EvalML Documentation

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Alteryx, Inc.

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CONTENTS

EvalML is an AutoML library that builds, optimizes, and evaluates machine learning pipelines using domain-specific objective functions.

Combined with Featuretools and Compose, EvalML can be used to create end-to-end supervised machine learning solutions.

CHAPTER

ONE

INSTALL

EvalML is available for Python 3.7 and 3.8 with experimental support 3.9. It can be installed with pip or conda.

1.1 Pip with all dependencies

To install evalml with pip, run the following command:

```
pip install evalml
```

1.2 Pip with core dependencies

EvalML includes several optional dependencies. The `xgboost` and `catboost` packages support pipelines built around those modeling libraries. The `plotly` and `ipywidgets` packages support plotting functionality in automl searches. These dependencies are recommended, and are included with EvalML by default but are not required in order to install and use EvalML.

EvalML's core dependencies are listed in `core-requirements.txt` in the source code, and optional requirements are isted in `requirements.txt`.

To install EvalML with only the core required dependencies, download the EvalML source from pypi to access the requirements files. Then run the following:

```
pip install evalml --no-dependencies
pip install -r core-requirements.txt
```

1.2.1 Add-ons

Update checker Receive automatic notifications of new EvalML releases

```
pip install evalml[update_checker]
```

1.3 Conda with all dependencies

To install evalml with conda run the following command:

```
conda install -c conda-forge evalml
```

1.4 Conda with core dependencies

To install evalml with only core dependencies run the following command:

```
conda install -c conda-forge evalml-core
```

1.5 Windows

Additionally, if you are using `pip` to install EvalML, it is recommended you first install the following packages using conda: * `numba` (needed for `shap` and prediction explanations). Install with `conda install -c conda-forge numba` * `graphviz` if you're using EvalML's plotting utilities. Install with `conda install -c conda-forge python-graphviz`

The XGBoost library may not be pip-installable in some Windows environments. If you are encountering installation issues, please try installing XGBoost from Github before installing EvalML or install evalml with conda.

1.6 Mac

In order to run on Mac, LightGBM requires the `OpenMP` library to be installed, which can be done with HomeBrew by running

```
brew install libomp
```

Additionally, `graphviz` can be installed by running

```
brew install graphviz
```

1.7 Python 3.9 support

Evalml can still be installed with pip in python 3.9 but note that `sktime`, one of our dependencies, will not be installed because that library does not yet support python 3.9. This means the `PolynomialDetrending` component will not be usable in python 3.9. You can try to install `sktime` from source in python 3.9 to use the `PolynomialDetrending` component but be warned that we only test it in python 3.7 and 3.8.

CHAPTER

TWO

START

In this guide, we'll show how you can use EvalML to automatically find the best pipeline for predicting whether or not a credit card transaction is fradulent. Along the way, we'll highlight EvalML's built-in tools and features for understanding and interacting with the search process.

[1]:
```
import evalml
from evalml import AutoMLSearch
from evalml.utils import infer_feature_types
```

First, we load in the features and outcomes we want to use to train our model.

[2]:
```
X, y = evalml.demos.load_fraud(n_rows=250)
```

```
             Number of Features
Boolean                       1
Categorical                   6
Numeric                       5

Number of training examples: 250
Targets
False    88.40%
True     11.60%
Name: fraud, dtype: object
```

First, we will clean the data. Since EvalML accepts a pandas input, it can run type inference on this data directly. Since we'd like to change the types inferred by EvalML, we can use the `infer_feature_types` utility method. Here's what we're going to do with the following dataset:

- Reformat the `expiration_date` column so it reflects a more familiar date format.
- Cast the `lat` and `lng` columns from float to str.
- Use `infer_feature_types` to specify what types certain columns should be. For example, to avoid having the `provider` column be inferred as natural language text, we have specified it as a categorical column instead.

The `infer_feature_types` utility method takes a pandas or numpy input and converts it to a pandas dataframe with a Woodwork accessor, providing us with flexibility to cast the data as necessary.

[3]:
```
X.ww['expiration_date'] = X['expiration_date'].apply(lambda x: '20{}-01-{}'.format(x.
↪split("/")[1], x.split("/")[0]))
X = infer_feature_types(X, feature_types= {'store_id': 'categorical',
                                           'expiration_date': 'datetime',
                                           'lat': 'categorical',
                                           'lng': 'categorical',
                                           'provider': 'categorical'})
X.ww
```

[3]:
```
                  Physical Type Logical Type Semantic Tag(s)
Column
card_id                   int64      Integer     ['numeric']
store_id                  int64      Integer     ['numeric']
datetime          datetime64[ns]     Datetime              []
amount                    int64      Integer     ['numeric']
currency               category  Categorical    ['category']
customer_present           bool      Boolean              []
expiration_date        category  Categorical    ['category']
provider               category  Categorical    ['category']
lat                     float64       Double     ['numeric']
lng                     float64       Double     ['numeric']
region                 category  Categorical    ['category']
country                category  Categorical    ['category']
```

In order to validate the results of the pipeline creation and optimization process, we will save some of our data as a holdout set.

[4]:
```
X_train, X_holdout, y_train, y_holdout = evalml.preprocessing.split_data(X, y,␣
↪problem_type='binary', test_size=.2)
```

Note: To provide data to EvalML, it is recommended that you initialize a woodwork accessor so that you control how EvalML will treat each feature, such as as a numeric feature, a categorical feature, a text feature or other type of feature. Consult the the Woodwork project for help on how to do this. Here, `split_data()` returns dataframes with woodwork accessors.

EvalML has many options to configure the pipeline search. At the minimum, we need to define an objective function. For simplicity, we will use the F1 score in this example. However, the real power of EvalML is in using domain-specific *objective functions* or *building your own*.

Below EvalML utilizes Bayesian optimization (EvalML's default optimizer) to search and find the best pipeline defined by the given objective.

EvalML provides a number of parameters to control the search process. `max_batches` is one of the parameters which controls the stopping criterion for the AutoML search. It indicates the maximum number of rounds of AutoML to evaluate, where each round may train and score a variable number of pipelines. In this example, `max_batches` is set to 1.

** Graphing methods, like AutoMLSearch, on Jupyter Notebook and Jupyter Lab require ipywidgets to be installed.

** If graphing on Jupyter Lab, jupyterlab-plotly required. To download this, make sure you have npm installed.

[5]:
```
automl = AutoMLSearch(X_train=X_train, y_train=y_train,
                      problem_type='binary', objective='f1', max_batches=1)
```

```
Generating pipelines to search over...
8 pipelines ready for search.
```

When we call `search()`, the search for the best pipeline will begin. There is no need to wrangle with missing data or categorical variables as EvalML includes various preprocessing steps (like imputation, one-hot encoding, feature selection) to ensure you're getting the best results. As long as your data is in a single table, EvalML can handle it. If not, you can reduce your data to a single table by utilizing Featuretools and its Entity Sets.

You can find more information on pipeline components and how to integrate your own custom pipelines into EvalML *here*.

[6]:
```
automl.search()
```

```
*****************************
* Beginning pipeline search *
*****************************

Optimizing for F1.
Greater score is better.

Using SequentialEngine to train and score pipelines.
Searching up to 1 batches for a total of 9 pipelines.
Allowed model families: decision_tree, random_forest, xgboost, catboost, linear_model,
↪ extra_trees, lightgbm
```

```
FigureWidget({
    'data': [{'mode': 'lines+markers',
              'name': 'Best Score',
              'type'...
```

```
Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean F1: 0.000

*****************************
* Evaluating Batch Number 1 *
*****************************

Elastic Net Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean F1: 0.263
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Elastic Net Classifier w/ Imputer + DateTime Featurization Component + One␣
↪Hot Encoder + SMOTENC Oversampler + Standard Scaler may not perform as estimated on␣
↪unseen data.
Decision Tree Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean F1: 0.448
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Decision Tree Classifier w/ Imputer + DateTime Featurization Component + One␣
↪Hot Encoder + SMOTENC Oversampler may not perform as estimated on unseen data.
Random Forest Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean F1: 0.500
LightGBM Classifier w/ Imputer + DateTime Featurization Component + One Hot Encoder +␣
↪SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean F1: 0.417
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        LightGBM Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler may not perform as estimated on unseen data.
Logistic Regression Classifier w/ Imputer + DateTime Featurization Component + One␣
↪Hot Encoder + SMOTENC Oversampler + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean F1: 0.233
```

```
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/xgboost/sklearn.py:1146: UserWarning:

The use of label encoder in XGBClassifier is deprecated and will be removed in a␣
↪future release. To remove this warning, do the following: 1) Pass option use_label_
↪encoder=False when constructing XGBClassifier object; and 2) Encode your labels (y)␣
↪as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].

[21:21:12] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default␣
↪evaluation metric used with the objective 'binary:logistic' was changed from 'error
↪' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old␣
↪behavior.
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/xgboost/sklearn.py:1146: UserWarning:

The use of label encoder in XGBClassifier is deprecated and will be removed in a␣
↪future release. To remove this warning, do the following: 1) Pass option use_label_
↪encoder=False when constructing XGBClassifier object; and 2) Encode your labels (y)␣
↪as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].

[21:21:13] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default␣
↪evaluation metric used with the objective 'binary:logistic' was changed from 'error
↪' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old␣
↪behavior.
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/xgboost/sklearn.py:1146: UserWarning:

The use of label encoder in XGBClassifier is deprecated and will be removed in a␣
↪future release. To remove this warning, do the following: 1) Pass option use_label_
↪encoder=False when constructing XGBClassifier object; and 2) Encode your labels (y)␣
↪as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].

[21:21:14] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default␣
↪evaluation metric used with the objective 'binary:logistic' was changed from 'error
↪' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old␣
↪behavior.
XGBoost Classifier w/ Imputer + DateTime Featurization Component + One Hot Encoder +␣
↪SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean F1: 0.372
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        XGBoost Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler may not perform as estimated on unseen data.
Extra Trees Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean F1: 0.263
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Extra Trees Classifier w/ Imputer + DateTime Featurization Component + One␣
↪Hot Encoder + SMOTENC Oversampler may not perform as estimated on unseen data.
CatBoost Classifier w/ Imputer + DateTime Featurization Component + SMOTENC␣
↪Oversampler:
        Starting cross validation
        Finished cross validation - mean F1: 0.646
        High coefficient of variation (cv >= 0.2) within cross validation scores.
```

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```
       CatBoost Classifier w/ Imputer + DateTime Featurization Component + SMOTENC␣
↪Oversampler may not perform as estimated on unseen data.

Search finished after 00:22
Best pipeline: CatBoost Classifier w/ Imputer + DateTime Featurization Component +␣
↪SMOTENC Oversampler
Best pipeline F1: 0.646154
```

We also provide *a standalone ``search`* method <../generated/evalml.automl.search.html>`__ which does all of the above in a single line, and returns the `AutoMLSearch` instance and data check results. If there were data check errors, AutoML will not be run and no `AutoMLSearch` instance will be returned.

After the search is finished we can view all of the pipelines searched, ranked by score. Internally, EvalML performs cross validation to score the pipelines. If it notices a high variance across cross validation folds, it will warn you. EvalML also provides additional *data checks* to analyze your data to assist you in producing the best performing pipeline.

[7]:
```
automl.rankings
```

[7]:
```
   id                                     pipeline_name  search_order  \
0   8  CatBoost Classifier w/ Imputer + DateTime Feat...             8
1   3  Random Forest Classifier w/ Imputer + DateTime...             3
2   2  Decision Tree Classifier w/ Imputer + DateTime...             2
3   4  LightGBM Classifier w/ Imputer + DateTime Feat...             4
4   6  XGBoost Classifier w/ Imputer + DateTime Featu...             6
5   7  Extra Trees Classifier w/ Imputer + DateTime F...             7
6   1  Elastic Net Classifier w/ Imputer + DateTime F...             1
7   5  Logistic Regression Classifier w/ Imputer + Da...             5
8   0       Mode Baseline Binary Classification Pipeline             0

   mean_cv_score  standard_deviation_cv_score  validation_score  \
0       0.646154                     0.213175          0.769231
1       0.500000                     0.100000          0.400000
2       0.447992                     0.328221          0.769231
3       0.416667                     0.144338          0.500000
4       0.372222                     0.256219          0.666667
5       0.263091                     0.233224          0.444444
6       0.262500                     0.073006          0.266667
7       0.232828                     0.044955          0.266667
8       0.000000                     0.000000          0.000000

   percent_better_than_baseline  high_variance_cv  \
0                     64.615385              True
1                     50.000000             False
2                     44.799226              True
3                     41.666667              True
4                     37.222222              True
5                     26.309068              True
6                     26.250000              True
7                     23.282828             False
8                      0.000000             False

                                        parameters
0  {'Imputer': {'categorical_impute_strategy': 'm...
1  {'Imputer': {'categorical_impute_strategy': 'm...
2  {'Imputer': {'categorical_impute_strategy': 'm...
3  {'Imputer': {'categorical_impute_strategy': 'm...
```

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```
4  {'Imputer': {'categorical_impute_strategy': 'm...
5  {'Imputer': {'categorical_impute_strategy': 'm...
6  {'Imputer': {'categorical_impute_strategy': 'm...
7  {'Imputer': {'categorical_impute_strategy': 'm...
8      {'Baseline Classifier': {'strategy': 'mode'}}
```

If we are interested in see more details about the pipeline, we can view a summary description using the `id` from the rankings table:

[8]:
```
automl.describe_pipeline(3)
```

```
*************************************************************************************************
* Random Forest Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler *
*************************************************************************************************

Problem Type: binary
Model Family: Random Forest

Pipeline Steps
==============
1. Imputer
         * categorical_impute_strategy : most_frequent
         * numeric_impute_strategy : mean
         * categorical_fill_value : None
         * numeric_fill_value : None
2. DateTime Featurization Component
         * features_to_extract : ['year', 'month', 'day_of_week', 'hour']
         * encode_as_categories : False
         * date_index : None
3. One Hot Encoder
         * top_n : 10
         * features_to_encode : None
         * categories : None
         * drop : if_binary
         * handle_unknown : ignore
         * handle_missing : error
4. SMOTENC Oversampler
         * sampling_ratio : 0.25
         * k_neighbors_default : 5
         * n_jobs : -1
         * sampling_ratio_dict : None
         * categorical_features : [3, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21,␣
↪22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42,␣
↪43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59]
         * k_neighbors : 5
5. Random Forest Classifier
         * n_estimators : 100
         * max_depth : 6
         * n_jobs : -1

Training
========
Training for binary problems.
Objective to optimize binary classification pipeline thresholds for: <evalml.
↪objectives.standard_metrics.F1 object at 0x7f70d023e5b0>
```

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```
Total training time (including CV): 2.7 seconds

Cross Validation
----------------
                F1  MCC Binary  Log Loss Binary  Gini   AUC  Precision  Balanced␣
↪Accuracy Binary  Accuracy Binary # Training # Validation
0            0.400        0.476           0.264 0.648 0.824      1.000
↪     0.625             0.910         133           67
1            0.500        0.490           0.333 0.424 0.712      0.750
↪     0.679             0.910         133           67
2            0.600        0.634           0.260 0.758 0.879      1.000
↪     0.714             0.939         134           66
mean         0.500        0.533           0.286 0.610 0.805      0.917
↪     0.673             0.920           -           -
std          0.100        0.087           0.041 0.170 0.085      0.144
↪     0.045             0.017           -           -
coef of var  0.200        0.163           0.144 0.279 0.106      0.157
↪     0.067             0.018           -           -
```

We can also view the pipeline parameters directly:

[9]:
```
pipeline = automl.get_pipeline(3)
print(pipeline.parameters)
```

```
{'Imputer': {'categorical_impute_strategy': 'most_frequent', 'numeric_impute_strategy
↪': 'mean', 'categorical_fill_value': None, 'numeric_fill_value': None}, 'DateTime␣
↪Featurization Component': {'features_to_extract': ['year', 'month', 'day_of_week',
↪'hour'], 'encode_as_categories': False, 'date_index': None}, 'One Hot Encoder': {
↪'top_n': 10, 'features_to_encode': None, 'categories': None, 'drop': 'if_binary',
↪'handle_unknown': 'ignore', 'handle_missing': 'error'}, 'SMOTENC Oversampler': {
↪'sampling_ratio': 0.25, 'k_neighbors_default': 5, 'n_jobs': -1, 'sampling_ratio_dict
↪': None, 'categorical_features': [3, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21,
↪ 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42,
↪ 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59], 'k_neighbors':
↪ 5}, 'Random Forest Classifier': {'n_estimators': 100, 'max_depth': 6, 'n_jobs': -1}
↪}
```

We can now select the best pipeline and score it on our holdout data:

[10]:
```
pipeline = automl.best_pipeline
pipeline.score(X_holdout, y_holdout, ["f1"])
```

[10]:
```
OrderedDict([('F1', 0.5)])
```

We can also visualize the structure of the components contained by the pipeline:

[11]:
```
pipeline.graph()
```

[11]:

CHAPTER

THREE

TUTORIALS

Below are examples of how to apply EvalML to a variety of problems:

3.1 Building a Fraud Prediction Model with EvalML

In this demo, we will build an optimized fraud prediction model using EvalML. To optimize the pipeline, we will set up an objective function to minimize the percentage of total transaction value lost to fraud. At the end of this demo, we also show you how introducing the right objective during the training results in a much better than using a generic machine learning metric like AUC.

[1]:
```
import evalml
from evalml import AutoMLSearch
from evalml.objectives import FraudCost
```

3.1.1 Configure "Cost of Fraud"

To optimize the pipelines toward the specific business needs of this model, we can set our own assumptions for the cost of fraud. These parameters are

- `retry_percentage` - what percentage of customers will retry a transaction if it is declined?
- `interchange_fee` - how much of each successful transaction do you collect?
- `fraud_payout_percentage` - the percentage of fraud will you be unable to collect
- `amount_col` - the column in the data the represents the transaction amount

Using these parameters, EvalML determines attempt to build a pipeline that will minimize the financial loss due to fraud.

[2]:
```
fraud_objective = FraudCost(retry_percentage=.5,
                            interchange_fee=.02,
                            fraud_payout_percentage=.75,
                            amount_col='amount')
```

3.1.2 Search for best pipeline

In order to validate the results of the pipeline creation and optimization process, we will save some of our data as the holdout set.

[3]:
```
X, y = evalml.demos.load_fraud(n_rows=5000)
```

```
             Number of Features
Boolean                       1
Categorical                   6
Numeric                       5

Number of training examples: 5000
Targets
False    86.20%
True     13.80%
Name: fraud, dtype: object
```

EvalML natively supports one-hot encoding. Here we keep 1 out of the 6 categorical columns to decrease computation time.

[4]:
```
cols_to_drop = ['datetime', 'expiration_date', 'country', 'region', 'provider']
for col in cols_to_drop:
    X.ww.pop(col)

X_train, X_holdout, y_train, y_holdout = evalml.preprocessing.split_data(X, y,␣
↪problem_type='binary', test_size=0.2, random_seed=0)

X.ww
```

[4]:
```
                 Physical Type Logical Type Semantic Tag(s)
Column
card_id                  int64      Integer     ['numeric']
store_id                 int64      Integer     ['numeric']
amount                   int64      Integer     ['numeric']
currency              category  Categorical    ['category']
customer_present          bool      Boolean              []
lat                     float64       Double     ['numeric']
lng                     float64       Double     ['numeric']
```

Because the fraud labels are binary, we will use `AutoMLSearch(X_train=X_train, y_train=y_train, problem_type='binary')`. When we call `.search()`, the search for the best pipeline will begin.

[5]:
```
automl = AutoMLSearch(X_train=X_train, y_train=y_train,
                      problem_type='binary',
                      objective=fraud_objective,
                      additional_objectives=['auc', 'f1', 'precision'],
                      allowed_model_families=["random_forest", "linear_model"],
                      max_batches=1,
                      optimize_thresholds=True)

automl.search()
```

```
Generating pipelines to search over...
3 pipelines ready for search.

*****************************
* Beginning pipeline search *
*****************************
```

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```
Optimizing for Fraud Cost.
Lower score is better.

Using SequentialEngine to train and score pipelines.
Searching up to 1 batches for a total of 4 pipelines.
Allowed model families: random_forest, linear_model
```

```
FigureWidget({
    'data': [{'mode': 'lines+markers',
              'name': 'Best Score',
              'type'...
```

```
Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean Fraud Cost: 0.790

*****************************
* Evaluating Batch Number 1 *
*****************************

Elastic Net Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler + Standard␣
↪Scaler:
        Starting cross validation
        Finished cross validation - mean Fraud Cost: 0.286
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Elastic Net Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler +␣
↪Standard Scaler may not perform as estimated on unseen data.
Random Forest Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean Fraud Cost: 0.289
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Random Forest Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler␣
↪may not perform as estimated on unseen data.
Logistic Regression Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler +␣
↪Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Fraud Cost: 0.286
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Logistic Regression Classifier w/ Imputer + One Hot Encoder + SMOTENC␣
↪Oversampler + Standard Scaler may not perform as estimated on unseen data.

Search finished after 00:14
Best pipeline: Elastic Net Classifier w/ Imputer + One Hot Encoder + SMOTENC␣
↪Oversampler + Standard Scaler
Best pipeline Fraud Cost: 0.285505
```

View rankings and select pipelines

Once the fitting process is done, we can see all of the pipelines that were searched, ranked by their score on the fraud detection objective we defined.

[6]:
```
automl.rankings
```

[6]:
```
   id                                     pipeline_name  search_order  \
0   1  Elastic Net Classifier w/ Imputer + One Hot En...             1
1   3  Logistic Regression Classifier w/ Imputer + On...             3
2   2  Random Forest Classifier w/ Imputer + One Hot ...             2
3   0       Mode Baseline Binary Classification Pipeline             0

   mean_cv_score  standard_deviation_cv_score  validation_score  \
0       0.285505                     0.436205          0.040953
1       0.285505                     0.436205          0.040953
2       0.289310                     0.434436          0.790953
3       0.789648                     0.001136          0.790953

   percent_better_than_baseline  high_variance_cv  \
0                     50.414342              True
1                     50.414342              True
2                     50.033835              True
3                      0.000000             False

                                          parameters
0  {'Imputer': {'categorical_impute_strategy': 'm...
1  {'Imputer': {'categorical_impute_strategy': 'm...
2  {'Imputer': {'categorical_impute_strategy': 'm...
3      {'Baseline Classifier': {'strategy': 'mode'}}
```

To select the best pipeline we can call `automl.best_pipeline`.

[7]:
```
best_pipeline = automl.best_pipeline
```

Describe pipelines

We can get more details about any pipeline created during the search process, including how it performed on other objective functions, by calling the `describe_pipeline` method and passing the `id` of the pipeline of interest.

[8]:
```
automl.describe_pipeline(automl.rankings.iloc[1]["id"])
```

```
*****************************************************************************************************
* Logistic Regression Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler +␣
↪Standard Scaler *
*****************************************************************************************************

Problem Type: binary
Model Family: Linear

Pipeline Steps
==============
1. Imputer
         * categorical_impute_strategy : most_frequent
         * numeric_impute_strategy : mean
         * categorical_fill_value : None
```

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```
        * numeric_fill_value : None
2. One Hot Encoder
        * top_n : 10
        * features_to_encode : None
        * categories : None
        * drop : if_binary
        * handle_unknown : ignore
        * handle_missing : error
3. SMOTENC Oversampler
        * sampling_ratio : 0.25
        * k_neighbors_default : 5
        * n_jobs : -1
        * sampling_ratio_dict : None
        * categorical_features : [3, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]
        * k_neighbors : 5
4. Standard Scaler
5. Logistic Regression Classifier
        * penalty : l2
        * C : 1.0
        * n_jobs : -1
        * multi_class : auto
        * solver : lbfgs

Training
========
Training for binary problems.
Objective to optimize binary classification pipeline thresholds for: <evalml.
↪objectives.fraud_cost.FraudCost object at 0x7fcbfdc05c40>
Total training time (including CV): 3.9 seconds

Cross Validation
----------------
             Fraud Cost    AUC     F1  Precision # Training # Validation
0                 0.041  0.854  0.011      1.000      2,666        1,334
1                 0.789  0.799  0.000      0.000      2,667        1,333
2                 0.026  0.828  0.355      0.228      2,667        1,333
mean              0.286  0.827  0.122      0.409          -            -
std               0.436  0.027  0.202      0.524          -            -
coef of var       1.528  0.033  1.656      1.280          -            -
```

3.1.3 Evaluate on holdout data

Finally, since the best pipeline is already trained, we evaluate it on the holdout data.

Now, we can score the pipeline on the holdout data using both our fraud cost objective and the AUC (Area under the ROC Curve) objective.

[9]:
```
best_pipeline.score(X_holdout, y_holdout, objectives=["auc", fraud_objective])
```

[9]:
```
OrderedDict([('AUC', 0.8097111537038906),
             ('Fraud Cost', 0.0015780080694855455)])
```

3.1.4 Why optimize for a problem-specific objective?

To demonstrate the importance of optimizing for the right objective, let's search for another pipeline using AUC, a common machine learning metric. After that, we will score the holdout data using the fraud cost objective to see how the best pipelines compare.

[10]:
```
automl_auc = AutoMLSearch(X_train=X_train, y_train=y_train,
                          problem_type='binary',
                          objective='auc',
                          additional_objectives=['f1', 'precision'],
                          max_batches=1,
                          allowed_model_families=["random_forest", "linear_model"],
                          optimize_thresholds=True)

automl_auc.search()
```

```
Generating pipelines to search over...
3 pipelines ready for search.

*****************************
* Beginning pipeline search *
*****************************

Optimizing for AUC.
Greater score is better.

Using SequentialEngine to train and score pipelines.
Searching up to 1 batches for a total of 4 pipelines.
Allowed model families: random_forest, linear_model
```

```
FigureWidget({
    'data': [{'mode': 'lines+markers',
              'name': 'Best Score',
              'type'...
```

```
Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean AUC: 0.500

*****************************
* Evaluating Batch Number 1 *
*****************************

Elastic Net Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler + Standard␣
↪Scaler:
        Starting cross validation
        Finished cross validation - mean AUC: 0.827
Random Forest Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean AUC: 0.853
Logistic Regression Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler +␣
↪Standard Scaler:
        Starting cross validation
        Finished cross validation - mean AUC: 0.827

Search finished after 00:07
Best pipeline: Random Forest Classifier w/ Imputer + One Hot Encoder + SMOTENC␣
↪Oversampler
```

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```
Best pipeline AUC: 0.853164
```

Like before, we can look at the rankings of all of the pipelines searched and pick the best pipeline.

[11]:
```
automl_auc.rankings
```

[11]:
```
   id                                     pipeline_name  search_order  \
0   2  Random Forest Classifier w/ Imputer + One Hot ...             2
1   1  Elastic Net Classifier w/ Imputer + One Hot En...             1
2   3  Logistic Regression Classifier w/ Imputer + On...             3
3   0       Mode Baseline Binary Classification Pipeline             0

   mean_cv_score  standard_deviation_cv_score  validation_score  \
0       0.853164                     0.010011          0.863894
1       0.827102                     0.027002          0.853667
2       0.826675                     0.027444          0.853544
3       0.500000                     0.000000          0.500000

   percent_better_than_baseline  high_variance_cv  \
0                     35.316397             False
1                     32.710221             False
2                     32.667497             False
3                      0.000000             False

                                        parameters
0  {'Imputer': {'categorical_impute_strategy': 'm...
1  {'Imputer': {'categorical_impute_strategy': 'm...
2  {'Imputer': {'categorical_impute_strategy': 'm...
3      {'Baseline Classifier': {'strategy': 'mode'}}
```

[12]:
```
best_pipeline_auc = automl_auc.best_pipeline
```

[13]:
```
# get the fraud score on holdout data
best_pipeline_auc.score(X_holdout, y_holdout,  objectives=["auc", fraud_objective])
```

[13]:
```
OrderedDict([('AUC', 0.8644456773933219),
             ('Fraud Cost', 0.026054721586011263)])
```

[14]:
```
# fraud score on fraud optimized again
best_pipeline.score(X_holdout, y_holdout, objectives=["auc", fraud_objective])
```

[14]:
```
OrderedDict([('AUC', 0.8097111537038906),
             ('Fraud Cost', 0.0015780080694855455)])
```

When we optimize for AUC, we can see that the AUC score from this pipeline performs better compared to the AUC score from the pipeline optimized for fraud cost; however, the losses due to fraud are a much larger percentage of the total transaction amount when optimized for AUC and much smaller when optimized for fraud cost. As a result, we lose a noticable percentage of the total transaction amount by not optimizing for fraud cost specifically.

Optimizing for AUC does not take into account the user-specified `retry_percentage`, `interchange_fee`, `fraud_payout_percentage` values, which could explain the decrease in fraud performance. Thus, the best pipelines may produce the highest AUC but may not actually reduce the amount loss due to your specific type fraud.

This example highlights how performance in the real world can diverge greatly from machine learning metrics.

3.2 Building a Lead Scoring Model with EvalML

In this demo, we will build an optimized lead scoring model using EvalML. To optimize the pipeline, we will set up an objective function to maximize the revenue generated with true positives while taking into account the cost of false positives. At the end of this demo, we also show you how introducing the right objective during the training is significantly better than using a generic machine learning metric like AUC.

[1]:
```
import evalml
from evalml import AutoMLSearch
from evalml.objectives import LeadScoring
```

3.2.1 Configure LeadScoring

To optimize the pipelines toward the specific business needs of this model, you can set your own assumptions for how much value is gained through true positives and the cost associated with false positives. These parameters are

- `true_positive` - dollar amount to be gained with a successful lead
- `false_positive` - dollar amount to be lost with an unsuccessful lead

Using these parameters, EvalML builds a pileline that will maximize the amount of revenue per lead generated.

[2]:
```
lead_scoring_objective = LeadScoring(
    true_positives=100,
    false_positives=-5
)
```

3.2.2 Dataset

We will be utilizing a dataset detailing a customer's job, country, state, zip, online action, the dollar amount of that action and whether they were a successful lead.

[3]:
```
from urllib.request import urlopen
import pandas as pd
import woodwork as ww
customers_data = urlopen('https://featurelabs-static.s3.amazonaws.com/lead_scoring_ml_
↪apps/customers.csv')
interactions_data = urlopen('https://featurelabs-static.s3.amazonaws.com/lead_scoring_
↪ml_apps/interactions.csv')
leads_data = urlopen('https://featurelabs-static.s3.amazonaws.com/lead_scoring_ml_
↪apps/previous_leads.csv')
customers = pd.read_csv(customers_data)
interactions = pd.read_csv(interactions_data)
leads = pd.read_csv(leads_data)

X = customers.merge(interactions, on='customer_id').merge(leads, on='customer_id')
y = X['label']
X = X.drop(['customer_id', 'date_registered', 'birthday','phone', 'email',
            'owner', 'company', 'id', 'time_x',
            'session', 'referrer', 'time_y', 'label', 'country'], axis=1)
display(X.head())
```

```
                      job state      zip     action  amount
0        Engineer, mining    NY  60091.0  page_view     NaN
1  Psychologist, forensic    CA      NaN   purchase  135.23
```

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```
2  Psychologist, forensic    CA      NaN  page_view     NaN
3          Air cabin crew   NaN  60091.0   download     NaN
4          Air cabin crew   NaN  60091.0  page_view     NaN
```

We will convert our data into Woodwork data structures. Doing so enables us to have more control over the types passed to and inferred by AutoML.

[4]:
```
X.ww.init(semantic_tags={'job': 'category'}, logical_types={'job': 'Categorical'})
y = ww.init_series(y)
X.ww
```

[4]:
```
       Physical Type Logical Type Semantic Tag(s)
Column
job         category  Categorical    ['category']
state       category  Categorical    ['category']
zip          float64       Double     ['numeric']
action      category  Categorical    ['category']
amount       float64       Double     ['numeric']
```

3.2.3 Search for the best pipeline

In order to validate the results of the pipeline creation and optimization process, we will save some of our data as a holdout set.

EvalML natively supports one-hot encoding and imputation so the above `NaN` and categorical values will be taken care of.

[5]:
```
X_train, X_holdout, y_train, y_holdout = evalml.preprocessing.split_data(X, y,␣
↪problem_type='binary', test_size=0.2, random_seed=0)

X.ww
```

[5]:
```
       Physical Type Logical Type Semantic Tag(s)
Column
job         category  Categorical    ['category']
state       category  Categorical    ['category']
zip          float64       Double     ['numeric']
action      category  Categorical    ['category']
amount       float64       Double     ['numeric']
```

Because the lead scoring labels are binary, we will use set the problem type to "binary". When we call `.search()`, the search for the best pipeline will begin.

[6]:
```
automl = AutoMLSearch(X_train=X_train, y_train=y_train,
                      problem_type='binary',
                      objective=lead_scoring_objective,
                      additional_objectives=['auc'],
                      allowed_model_families=["catboost", "random_forest", "linear_
↪model"],
                      max_batches=1)

automl.search()
```

```
Generating pipelines to search over...
4 pipelines ready for search.
```

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```
*****************************
* Beginning pipeline search *
*****************************

Optimizing for Lead Scoring.
Greater score is better.

Using SequentialEngine to train and score pipelines.
Searching up to 1 batches for a total of 5 pipelines.
Allowed model families: catboost, linear_model, random_forest
```

```
FigureWidget({
    'data': [{'mode': 'lines+markers',
              'name': 'Best Score',
              'type'...
```

```
Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean Lead Scoring: 0.000

*****************************
* Evaluating Batch Number 1 *
*****************************

Elastic Net Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler + Standard␣
↪Scaler:
        Starting cross validation
        Finished cross validation - mean Lead Scoring: 0.014
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Elastic Net Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler +␣
↪Standard Scaler may not perform as estimated on unseen data.
Random Forest Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean Lead Scoring: 0.015
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Random Forest Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler␣
↪may not perform as estimated on unseen data.
Logistic Regression Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler +␣
↪Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Lead Scoring: 0.014
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Logistic Regression Classifier w/ Imputer + One Hot Encoder + SMOTENC␣
↪Oversampler + Standard Scaler may not perform as estimated on unseen data.
CatBoost Classifier w/ Imputer + SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean Lead Scoring: 0.358
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        CatBoost Classifier w/ Imputer + SMOTENC Oversampler may not perform as␣
↪estimated on unseen data.

Search finished after 00:16
Best pipeline: CatBoost Classifier w/ Imputer + SMOTENC Oversampler
Best pipeline Lead Scoring: 0.358194
```

View rankings and select pipeline

Once the fitting process is done, we can see all of the pipelines that were searched, ranked by their score on the lead scoring objective we defined.

[7]:
```
automl.rankings
```

[7]:
```
   id                                     pipeline_name  search_order  \
0   4  CatBoost Classifier w/ Imputer + SMOTENC Overs...             4
1   2  Random Forest Classifier w/ Imputer + One Hot ...             2
2   1  Elastic Net Classifier w/ Imputer + One Hot En...             1
3   3  Logistic Regression Classifier w/ Imputer + On...             3
4   0       Mode Baseline Binary Classification Pipeline             0

   mean_cv_score  standard_deviation_cv_score  validation_score  \
0       0.358194                     0.328811         -0.016129
1       0.015067                     0.040868         -0.016129
2       0.013992                     0.041501         -0.016129
3       0.013992                     0.041501         -0.016129
4       0.000000                     0.000000          0.000000

   percent_better_than_baseline  high_variance_cv  \
0                           inf              True
1                           inf              True
2                           inf              True
3                           inf              True
4                           0.0             False

                                          parameters
0  {'Imputer': {'categorical_impute_strategy': 'm...
1  {'Imputer': {'categorical_impute_strategy': 'm...
2  {'Imputer': {'categorical_impute_strategy': 'm...
3  {'Imputer': {'categorical_impute_strategy': 'm...
4      {'Baseline Classifier': {'strategy': 'mode'}}
```

To select the best pipeline we can call `automl.best_pipeline`.

[8]:
```
best_pipeline = automl.best_pipeline
```

Describe pipeline

You can get more details about any pipeline, including how it performed on other objective functions by calling `.describe_pipeline()` and specifying the `id` of the pipeline.

[9]:
```
automl.describe_pipeline(automl.rankings.iloc[0]["id"])
```

```
*********************************************************
* CatBoost Classifier w/ Imputer + SMOTENC Oversampler *
*********************************************************

Problem Type: binary
Model Family: CatBoost

Pipeline Steps
==============
1. Imputer
```

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```
         * categorical_impute_strategy : most_frequent
         * numeric_impute_strategy : mean
         * categorical_fill_value : None
         * numeric_fill_value : None
2. SMOTENC Oversampler
         * sampling_ratio : 0.25
         * k_neighbors_default : 5
         * n_jobs : -1
         * sampling_ratio_dict : None
         * categorical_features : [0, 1, 3]
         * k_neighbors : 5
3. CatBoost Classifier
         * n_estimators : 10
         * eta : 0.03
         * max_depth : 6
         * bootstrap_type : None
         * silent : True
         * allow_writing_files : False
         * n_jobs : -1

Training
========
Training for binary problems.
Objective to optimize binary classification pipeline thresholds for: <evalml.
↪objectives.lead_scoring.LeadScoring object at 0x7f5803d87df0>
Total training time (including CV): 1.3 seconds

Cross Validation
----------------
             Lead Scoring   AUC # Training # Validation
0                  -0.016 0.869      3,099        1,550
1                   0.490 0.887      3,099        1,550
2                   0.600 0.889      3,100        1,549
mean                0.358 0.882          -            -
std                 0.329 0.011          -            -
coef of var         0.918 0.012          -            -
```

3.2.4 Evaluate on hold out

Finally, since the best pipeline was trained on all of the training data, we evaluate it on the holdout dataset.

[10]:
```
best_pipeline_score = best_pipeline.score(X_holdout, y_holdout, objectives=["auc",␣
↪lead_scoring_objective])
best_pipeline_score
```

[10]:
```
OrderedDict([('AUC', 0.8585599879117558),
             ('Lead Scoring', 0.8469475494411006)])
```

3.2.5 Why optimize for a problem-specific objective?

To demonstrate the importance of optimizing for the right objective, let's search for another pipeline using AUC, a common machine learning metric. After that, we will score the holdout data using the lead scoring objective to see how the best pipelines compare.

[11]:
```
automl_auc = evalml.AutoMLSearch(X_train=X_train, y_train=y_train,
                                 problem_type='binary',
                                 objective='auc',
                                 additional_objectives=[lead_scoring_objective],
                                 allowed_model_families=["catboost", "random_forest",
↪"linear_model"],
                                 max_batches=1)

automl_auc.search()
```

```
Generating pipelines to search over...
4 pipelines ready for search.

*****************************
* Beginning pipeline search *
*****************************

Optimizing for AUC.
Greater score is better.

Using SequentialEngine to train and score pipelines.
Searching up to 1 batches for a total of 5 pipelines.
Allowed model families: catboost, linear_model, random_forest
```

```
FigureWidget({
    'data': [{'mode': 'lines+markers',
              'name': 'Best Score',
              'type'...
```

```
Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean AUC: 0.500

*****************************
* Evaluating Batch Number 1 *
*****************************

Elastic Net Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler + Standard␣
↪Scaler:
        Starting cross validation
        Finished cross validation - mean AUC: 0.653
Random Forest Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean AUC: 0.652
Logistic Regression Classifier w/ Imputer + One Hot Encoder + SMOTENC Oversampler +␣
↪Standard Scaler:
        Starting cross validation
        Finished cross validation - mean AUC: 0.653
CatBoost Classifier w/ Imputer + SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean AUC: 0.882
```

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```
Search finished after 00:11
Best pipeline: CatBoost Classifier w/ Imputer + SMOTENC Oversampler
Best pipeline AUC: 0.881709
```

[12]:
```
automl_auc.rankings
```

[12]:
```
   id                                     pipeline_name  search_order  \
0   4  CatBoost Classifier w/ Imputer + SMOTENC Overs...             4
1   3  Logistic Regression Classifier w/ Imputer + On...             3
2   1  Elastic Net Classifier w/ Imputer + One Hot En...             1
3   2  Random Forest Classifier w/ Imputer + One Hot ...             2
4   0       Mode Baseline Binary Classification Pipeline             0

   mean_cv_score  standard_deviation_cv_score  validation_score  \
0       0.881709                     0.010861          0.869201
1       0.653038                     0.035883          0.691832
2       0.652855                     0.035875          0.691582
3       0.651591                     0.059622          0.717764
4       0.500000                     0.000000          0.500000

   percent_better_than_baseline  high_variance_cv  \
0                     38.170947             False
1                     15.303770             False
2                     15.285487             False
3                     15.159098             False
4                      0.000000             False

                                        parameters
0  {'Imputer': {'categorical_impute_strategy': 'm...
1  {'Imputer': {'categorical_impute_strategy': 'm...
2  {'Imputer': {'categorical_impute_strategy': 'm...
3  {'Imputer': {'categorical_impute_strategy': 'm...
4      {'Baseline Classifier': {'strategy': 'mode'}}
```

Like before, we can look at the rankings and pick the best pipeline.

[13]:
```
best_pipeline_auc = automl_auc.best_pipeline
```

[14]:
```
# get the auc and lead scoring score on holdout data
best_pipeline_auc_score = best_pipeline_auc.score(X_holdout, y_holdout,  objectives=[
↪"auc", lead_scoring_objective])
best_pipeline_auc_score
```

[14]:
```
OrderedDict([('AUC', 0.8585599879117558),
             ('Lead Scoring', 0.08168529664660361)])
```

[15]:
```
assert best_pipeline_score['Lead Scoring'] > best_pipeline_auc_score['Lead Scoring']
assert best_pipeline_auc_score['Lead Scoring'] >= 0
```

When we optimize for AUC, we can see that the AUC score from this pipeline is similar to the AUC score from the pipeline optimized for lead scoring. However, the revenue per lead is much smaller per lead when optimized for AUC and was much larger when optimized for lead scoring. As a result, we would have a huge gain on the amount of revenue if we optimized for lead scoring.

This happens because optimizing for AUC does not take into account the user-specified `true_positive` (dollar amount to be gained with a successful lead) and `false_positive` (dollar amount to be lost with an unsuccessful

lead) values. Thus, the best pipelines may produce the highest AUC but may not actually generate the most revenue through lead scoring.

This example highlights how performance in the real world can diverge greatly from machine learning metrics.

3.3 Using the Cost-Benefit Matrix Objective

The Cost-Benefit Matrix (`CostBenefitMatrix`) objective is an objective that assigns costs to each of the quadrants of a confusion matrix to quantify the cost of being correct or incorrect.

3.3.1 Confusion Matrix

Confusion matrices are tables that summarize the number of correct and incorrectly-classified predictions, broken down by each class. They allow us to quickly understand the performance of a classification model and where the model gets "confused" when it is making predictions. For the binary classification problem, there are four possible combinations of prediction and actual target values possible:

- true positives (correct positive assignments)
- true negatives (correct negative assignments)
- false positives (incorrect positive assignments)
- false negatives (incorrect negative assignments)

An example of how to calculate a confusion matrix can be found *here*.

3.3.2 Cost-Benefit Matrix

Although the confusion matrix is an incredibly useful visual for understanding our model, each prediction that is correctly or incorrectly classified is treated equally. For example, for detecting breast cancer, the confusion matrix does not take into consideration that it could be much more costly to incorrectly classify a malignant tumor as benign than it is to incorrectly classify a benign tumor as malignant. This is where the cost-benefit matrix shines: it uses the cost of each of the four possible outcomes to weigh each outcome differently. By scoring using the cost-benefit matrix, we can measure the score of the model by a concrete unit that is more closely related to the goal of the model. In the below example, we will show how the cost-benefit matrix objective can be used, and how it can give us better real-world impact when compared to using other standard machine learning objectives.

3.3.3 Customer Churn Example

Data

In this example, we will be using a customer churn data set taken from Kaggle.

This dataset includes records of over 7000 customers, and includes customer account information, demographic information, services they signed up for, and whether or not the customer "churned" or left within the last month.

The target we want to predict is whether the customer churned ("Yes") or did not churn ("No"). In the dataset, approximately 73.5% of customers did not churn, and 26.5% did. We will refer to the customers who churned as the "positive" class and the customers who did not churn as the "negative" class.

[1]:
```
from evalml.demos.churn import load_churn
from evalml.preprocessing import split_data

X, y = load_churn()
X.ww.set_types({'PaymentMethod':'Categorical', 'Contract': 'Categorical'}) # Update␣
↪data types Woodwork did not correctly infer
X_train, X_holdout, y_train, y_holdout = split_data(X, y, problem_type='binary', test_
↪size=0.3, random_seed=0)
```

```
             Number of Features
Categorical                  16
Numeric                       3

Number of training examples: 7043
Targets
No     73.46%
Yes    26.54%
Name: Churn, dtype: object
```

In this example, let's say that correctly identifying customers who will churn (true positive case) will give us a net profit of $400, because it allows us to intervene, incentivize the customer to stay, and sign a new contract. Incorrectly classifying customers who were not going to churn as customers who will churn (false positive case) will cost $100 to represent the marketing and effort used to try to retain the user. Not identifying customers who will churn (false negative case) will cost us $200 to represent the lost in revenue from losing a customer. Finally, correctly identifying customers who will not churn (true negative case) will not cost us anything ($0), as nothing needs to be done for that customer.

We can represent these values in our `CostBenefitMatrix` objective, where a negative value represents a cost and a positive value represents a profit–note that this means that the greater the score, the more profit we will make.

[2]:
```
from evalml.objectives import CostBenefitMatrix
cost_benefit_matrix = CostBenefitMatrix(true_positive=400,
                                        true_negative=0,
                                        false_positive=-100,
                                        false_negative=-200)
```

AutoML Search with Log Loss

First, let us run AutoML search to train pipelines using the default objective for binary classification (log loss).

[3]:
```
from evalml import AutoMLSearch
automl = AutoMLSearch(X_train=X_train, y_train=y_train, problem_type='binary',␣
↪objective='log loss binary',
                      max_iterations=5)
automl.search()

ll_pipeline = automl.best_pipeline
ll_pipeline.score(X_holdout, y_holdout, ['log loss binary'])
```

```
Generating pipelines to search over...
8 pipelines ready for search.

*****************************
* Beginning pipeline search *
*****************************
```

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```
Optimizing for Log Loss Binary.
Lower score is better.

Using SequentialEngine to train and score pipelines.
Searching up to 5 pipelines.
Allowed model families: linear_model, extra_trees, catboost, lightgbm, random_forest,␣
↪xgboost, decision_tree
```

```
FigureWidget({
    'data': [{'mode': 'lines+markers',
              'name': 'Best Score',
              'type'...
```

```
Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 9.164

*****************************
* Evaluating Batch Number 1 *
*****************************

Elastic Net Classifier w/ Imputer + One Hot Encoder + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.424
Decision Tree Classifier w/ Imputer + One Hot Encoder:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.628
Random Forest Classifier w/ Imputer + One Hot Encoder:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.426
LightGBM Classifier w/ Imputer + One Hot Encoder:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.471

Search finished after 00:11
Best pipeline: Elastic Net Classifier w/ Imputer + One Hot Encoder + Standard Scaler
Best pipeline Log Loss Binary: 0.424184
```

[3]:
```
OrderedDict([('Log Loss Binary', 0.4193730950794927)])
```

When we train our pipelines using log loss as our primary objective, we try to find pipelines that minimize log loss. However, our ultimate goal in training models is to find a model that gives us the most profit, so let's score our pipeline on the cost benefit matrix (using the costs outlined above) to determine the profit we would earn from the predictions made by this model:

[4]:
```
ll_pipeline_score = ll_pipeline.score(X_holdout, y_holdout, [cost_benefit_matrix])
print (ll_pipeline_score)
```

```
OrderedDict([('Cost Benefit Matrix', 53.43114055844771)])
```

[5]:
```
# Calculate total profit across all customers using pipeline optimized for Log Loss
total_profit_ll = ll_pipeline_score['Cost Benefit Matrix'] * len(X)
print (total_profit_ll)
```

```
376315.5229531472
```

AutoML Search with Cost-Benefit Matrix

Let's try rerunning our AutoML search, but this time using the cost-benefit matrix as our primary objective to optimize.

[6]:
```
automl = AutoMLSearch(X_train=X_train, y_train=y_train, problem_type='binary',␣
↪objective=cost_benefit_matrix,
                      max_iterations=5)
automl.search()

cbm_pipeline = automl.best_pipeline
```

```
Generating pipelines to search over...
8 pipelines ready for search.

*****************************
* Beginning pipeline search *
*****************************

Optimizing for Cost Benefit Matrix.
Greater score is better.

Using SequentialEngine to train and score pipelines.
Searching up to 5 pipelines.
Allowed model families: linear_model, extra_trees, catboost, lightgbm, random_forest,␣
↪xgboost, decision_tree
```

```
FigureWidget({
    'data': [{'mode': 'lines+markers',
              'name': 'Best Score',
              'type'...
```

```
Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean Cost Benefit Matrix: -53.063

*****************************
* Evaluating Batch Number 1 *
*****************************

Elastic Net Classifier w/ Imputer + One Hot Encoder + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Cost Benefit Matrix: 59.392
Decision Tree Classifier w/ Imputer + One Hot Encoder:
        Starting cross validation
        Finished cross validation - mean Cost Benefit Matrix: 52.982
Random Forest Classifier w/ Imputer + One Hot Encoder:
        Starting cross validation
        Finished cross validation - mean Cost Benefit Matrix: 59.048
LightGBM Classifier w/ Imputer + One Hot Encoder:
        Starting cross validation
        Finished cross validation - mean Cost Benefit Matrix: 50.692
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        LightGBM Classifier w/ Imputer + One Hot Encoder may not perform as estimated␣
↪on unseen data.

Search finished after 00:16
Best pipeline: Elastic Net Classifier w/ Imputer + One Hot Encoder + Standard Scaler
Best pipeline Cost Benefit Matrix: 59.391831
```

Now, if we calculate the cost-benefit matrix score on our best pipeline, we see that with this pipeline optimized for our cost-benefit matrix objective, we are able to generate more profit per customer. Across our 7043 customers, we generate much more profit using this best pipeline! Custom objectives like `CostBenefitMatrix` are just one example of how using EvalML can help find pipelines that can perform better on real-world problems, rather than on arbitrary standard statistical metrics.

[7]:
```
cbm_pipeline_score = cbm_pipeline.score(X_holdout, y_holdout, [cost_benefit_matrix])
print (cbm_pipeline_score)
```

```
OrderedDict([('Cost Benefit Matrix', 61.57122574538572)])
```

[8]:
```
# Calculate total profit across all customers using pipeline optimized for␣
↪CostBenefitMatrix
total_profit_cbm = cbm_pipeline_score['Cost Benefit Matrix'] * len(X)
print (total_profit_cbm)
```

```
433646.1429247516
```

[9]:
```
# Calculate difference in profit made using both pipelines
profit_diff = total_profit_cbm - total_profit_ll
print (profit_diff)
```

```
57330.619971604436
```

Finally, we can graph the confusion matrices for both pipelines to better understand why the pipeline trained using the cost-benefit matrix is able to correctly classify more samples than the pipeline trained with log loss: we were able to correctly predict more cases where the customer would have churned (true positive), allowing us to intervene and prevent those customers from leaving.

[10]:
```
from evalml.model_understanding.graphs import graph_confusion_matrix

# pipeline trained with log loss
y_pred = ll_pipeline.predict(X_holdout)
graph_confusion_matrix(y_holdout, y_pred)
```

Data type cannot be displayed: application/vnd.plotly.v1+json, text/html

[11]:
```
# pipeline trained with cost-benefit matrix
y_pred = cbm_pipeline.predict(X_holdout)
graph_confusion_matrix(y_holdout, y_pred)
```

Data type cannot be displayed: application/vnd.plotly.v1+json, text/html

3.4 Using Text Data with EvalML

In this demo, we will show you how to use EvalML to build models which use text data.

[1]:
```
import evalml
from evalml import AutoMLSearch
```

3.4.1 Dataset

We will be utilizing a dataset of SMS text messages, some of which are categorized as spam, and others which are not ("ham"). This dataset is originally from Kaggle, but modified to produce a slightly more even distribution of spam to ham.

[2]:
```
from urllib.request import urlopen
import pandas as pd

input_data = urlopen('https://featurelabs-static.s3.amazonaws.com/spam_text_messages_
↪modified.csv')
data = pd.read_csv(input_data)[:750]

X = data.drop(['Category'], axis=1)
y = data['Category']

display(X.head())
```

```
                                             Message
0  Free entry in 2 a wkly comp to win FA Cup fina...
1  FreeMsg Hey there darling it's been 3 week's n...
2  WINNER!! As a valued network customer you have...
3  Had your mobile 11 months or more? U R entitle...
4  SIX chances to win CASH! From 100 to 20,000 po...
```

The ham vs spam distribution of the data is 3:1, so any machine learning model must get above 75% accuracy in order to perform better than a trivial baseline model which simply classifies everything as ham.

[3]:
```
y.value_counts(normalize=True)
```

[3]:
```
spam    0.593333
ham     0.406667
Name: Category, dtype: float64
```

In order to properly utilize Woodwork's 'Natural Language' typing, we need to pass this argument in during initialization. Otherwise, this will be treated as an 'Unknown' type and dropped in the search.

[4]:
```
X.ww.init(logical_types={"Message": "NaturalLanguage"})
```

3.4.2 Search for best pipeline

In order to validate the results of the pipeline creation and optimization process, we will save some of our data as a holdout set.

[5]:
```
X_train, X_holdout, y_train, y_holdout = evalml.preprocessing.split_data(X, y,␣
↪problem_type='binary', test_size=0.2, random_seed=0)
```

EvalML uses Woodwork to automatically detect which columns are text columns, so you can run search normally, as you would if there was no text data. We can print out the logical type of the `Message` column and assert that it is indeed inferred as a natural language column.

[6]:
```
X_train.ww
```

[6]:
```
        Physical Type     Logical Type Semantic Tag(s)
Column
Message        string  NaturalLanguage              []
```

Because the spam/ham labels are binary, we will use `AutoMLSearch(X_train=X_train, y_train=y_train, problem_type='binary')`. When we call `.search()`, the search for the best pipeline will begin.

[7]:
```
automl = AutoMLSearch(X_train=X_train, y_train=y_train,
                      problem_type='binary',
                      max_batches=1,
                      optimize_thresholds=True)

automl.search()
```

```
Generating pipelines to search over...
8 pipelines ready for search.

*****************************
* Beginning pipeline search *
*****************************

Optimizing for Log Loss Binary.
Lower score is better.

Using SequentialEngine to train and score pipelines.
Searching up to 1 batches for a total of 9 pipelines.
Allowed model families: random_forest, lightgbm, catboost, decision_tree, xgboost,␣
↪linear_model, extra_trees
```

```
FigureWidget({
    'data': [{'mode': 'lines+markers',
              'name': 'Best Score',
              'type'...
```

```
Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 14.046

*****************************
* Evaluating Batch Number 1 *
*****************************
```

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```
Elastic Net Classifier w/ Text Featurization Component + Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.350
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Elastic Net Classifier w/ Text Featurization Component + Imputer + Standard␣
↪Scaler may not perform as estimated on unseen data.
Decision Tree Classifier w/ Text Featurization Component + Imputer:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 3.386
Random Forest Classifier w/ Text Featurization Component + Imputer:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.221
LightGBM Classifier w/ Text Featurization Component + Imputer:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.292
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        LightGBM Classifier w/ Text Featurization Component + Imputer may not perform␣
↪as estimated on unseen data.
Logistic Regression Classifier w/ Text Featurization Component + Imputer + Standard␣
↪Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.350
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Logistic Regression Classifier w/ Text Featurization Component + Imputer +␣
↪Standard Scaler may not perform as estimated on unseen data.
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/xgboost/sklearn.py:1146: UserWarning:

The use of label encoder in XGBClassifier is deprecated and will be removed in a␣
↪future release. To remove this warning, do the following: 1) Pass option use_label_
↪encoder=False when constructing XGBClassifier object; and 2) Encode your labels (y)␣
↪as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].

[21:20:05] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default␣
↪evaluation metric used with the objective 'binary:logistic' was changed from 'error
↪' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old␣
↪behavior.
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/xgboost/sklearn.py:1146: UserWarning:

The use of label encoder in XGBClassifier is deprecated and will be removed in a␣
↪future release. To remove this warning, do the following: 1) Pass option use_label_
↪encoder=False when constructing XGBClassifier object; and 2) Encode your labels (y)␣
↪as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].

[21:20:06] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default␣
↪evaluation metric used with the objective 'binary:logistic' was changed from 'error
↪' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old␣
↪behavior.
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/xgboost/sklearn.py:1146: UserWarning:

The use of label encoder in XGBClassifier is deprecated and will be removed in a␣
↪future release. To remove this warning, do the following: 1) Pass option use_label_
↪encoder=False when constructing XGBClassifier object; and 2) Encode your labels (y)␣
↪as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
```

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```
[21:20:07] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default␣
↪evaluation metric used with the objective 'binary:logistic' was changed from 'error
↪' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old␣
↪behavior.
XGBoost Classifier w/ Text Featurization Component + Imputer:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.266
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        XGBoost Classifier w/ Text Featurization Component + Imputer may not perform␣
↪as estimated on unseen data.
Extra Trees Classifier w/ Text Featurization Component + Imputer:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.292
CatBoost Classifier w/ Text Featurization Component + Imputer:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.589

Search finished after 00:28
Best pipeline: Random Forest Classifier w/ Text Featurization Component + Imputer
Best pipeline Log Loss Binary: 0.221422
```

View rankings and select pipeline

Once the fitting process is done, we can see all of the pipelines that were searched.

[8]:
```
automl.rankings
```

[8]:

	id	pipeline_name	search_order	mean_cv_score	standard_deviation_cv_score	validation_score	percent_better_than_baseline	high_variance_cv
0	3	Random Forest Classifier w/ Text Featurization...	3	0.221422	0.040958	0.221587	98.423568	False
1	6	XGBoost Classifier w/ Text Featurization Compo...	6	0.266164	0.106501	0.242896	98.105025	True
2	4	LightGBM Classifier w/ Text Featurization Comp...	4	0.291768	0.114862	0.291521	97.922737	True
3	7	Extra Trees Classifier w/ Text Featurization C...	7	0.292373	0.029893	0.325764	97.918427	False
4	5	Logistic Regression Classifier w/ Text Featuri...	5	0.350340	0.074833	0.349271		
5	1	Elastic Net Classifier w/ Text Featurization C...	1	0.350471	0.074886	0.349437		
6	8	CatBoost Classifier w/ Text Featurization Comp...	8	0.588944	0.004016	0.592259		
7	2	Decision Tree Classifier w/ Text Featurization...	2	3.385551	0.672118	3.708759		
8	0	Mode Baseline Binary Classification Pipeline	0	14.045769	0.099705	13.988204		

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```
4                     97.505728             True
5                     97.504795             True
6                     95.806967            False
7                     75.896294            False
8                      0.000000            False

                                          parameters
0  {'Imputer': {'categorical_impute_strategy': 'm...
1  {'Imputer': {'categorical_impute_strategy': 'm...
2  {'Imputer': {'categorical_impute_strategy': 'm...
3  {'Imputer': {'categorical_impute_strategy': 'm...
4  {'Imputer': {'categorical_impute_strategy': 'm...
5  {'Imputer': {'categorical_impute_strategy': 'm...
6  {'Imputer': {'categorical_impute_strategy': 'm...
7  {'Imputer': {'categorical_impute_strategy': 'm...
8      {'Baseline Classifier': {'strategy': 'mode'}}
```

To select the best pipeline we can call `automl.best_pipeline`.

[9]:
```
best_pipeline = automl.best_pipeline
```

Describe pipeline

You can get more details about any pipeline, including how it performed on other objective functions.

[10]:
```
automl.describe_pipeline(automl.rankings.iloc[0]["id"])
```

```
*****************************************************************************
* Random Forest Classifier w/ Text Featurization Component + Imputer *
*****************************************************************************

Problem Type: binary
Model Family: Random Forest

Pipeline Steps
==============
1. Text Featurization Component
2. Imputer
         * categorical_impute_strategy : most_frequent
         * numeric_impute_strategy : mean
         * categorical_fill_value : None
         * numeric_fill_value : None
3. Random Forest Classifier
         * n_estimators : 100
         * max_depth : 6
         * n_jobs : -1

Training
========
Training for binary problems.
Total training time (including CV): 3.4 seconds

Cross Validation
----------------
             Log Loss Binary  MCC Binary  Gini   AUC  Precision    F1  Balanced␣
↪Accuracy Binary  Accuracy Binary # Training # Validation
```

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```
0                    0.222       0.817 0.950 0.975       0.862 0.893
↪    0.913           0.910        400           200
1                    0.180       0.875 0.970 0.985       0.937 0.925
↪    0.936           0.940        400           200
2                    0.262       0.783 0.925 0.963       0.918 0.865
↪    0.883           0.895        400           200
mean                 0.221       0.825 0.948 0.974       0.906 0.894
↪    0.910           0.915          -             -
std                  0.041       0.047 0.023 0.011       0.039 0.030
↪    0.026           0.023          -             -
coef of var          0.185       0.057 0.024 0.012       0.043 0.034
↪    0.029           0.025          -             -
```

[11]:
```
best_pipeline.graph()
```

[11]:

Notice above that there is a `Text Featurization Component` as the first step in the pipeline. AutoMLSearch uses the woodwork accessor to recognize that `'Message'` is a text column, and converts this text into numerical values that can be handled by the estimator.

3.4.3 Evaluate on holdout

Now, we can score the pipeline on the holdout data using the core objectives for binary classification problems.

[12]:
```
scores = best_pipeline.score(X_holdout, y_holdout,  objectives=evalml.objectives.get_
↪core_objectives('binary'))
print(f'Accuracy Binary: {scores["Accuracy Binary"]}')
```

```
Accuracy Binary: 0.96
```

As you can see, this model performs relatively well on this dataset, even on unseen data.

3.4.4 What does the Text Featurization Component do?

Machine learning models cannot handle non-numeric data. Any text must be broken down into numeric features that provide useful information about that text. The Text Featurization component first normalizes your text by removing any punctuation and other non-alphanumeric characters and converting any capital letters to lowercase. From there, it passes the text into featuretools' nlp_primitives `dfs` search, resulting in several informative features that replace the original column in your dataset: Diversity Score, Mean Characters per Word, Polarity Score, and LSA (Latent Semantic Analysis).

Diversity Score is the ratio of unique words to total words.

Mean Characters per Word is the average number of letters in each word.

Polarity Score is a prediction of how "polarized" the text is, on a scale from -1 (extremely negative) to 1 (extremely positive).

Latent Semantic Analysis is an abstract representation of how important each word is with respect to the entire text, reduced down into two values per text. While the other text features are each a single column, this feature adds two columns to your data, `LSA(column_name)[0]` and `LSA(column_name)[1]`.

Let's see what this looks like with our spam/ham example.

[13]:
```
best_pipeline.input_feature_names
```

[13]:
```
{'Text Featurization Component': ['Message'],
 'Imputer': ['DIVERSITY_SCORE(Message)',
  'MEAN_CHARACTERS_PER_WORD(Message)',
  'POLARITY_SCORE(Message)',
  'LSA(Message)[0]',
  'LSA(Message)[1]'],
 'Random Forest Classifier': ['DIVERSITY_SCORE(Message)',
  'MEAN_CHARACTERS_PER_WORD(Message)',
  'POLARITY_SCORE(Message)',
  'LSA(Message)[0]',
  'LSA(Message)[1]']}
```

Here, the Text Featurization component takes in a single "Message" column, but then the next component in the pipeline, the Imputer, receives five columns of input. These five columns are the result of featurizing the text-type "Message" column. Most importantly, these featurized columns are what ends up passed in to the estimator.

If the dataset had any non-text columns, those would be left alone by this process. If the dataset had more than one text column, each would be broken into these five feature columns independently.

The features, more directly

Rather than just checking the new column names, let's examine the output of this component directly. We can see this by running the component on its own.

[14]:
```
text_featurizer = evalml.pipelines.components.TextFeaturizer()
X_featurized = text_featurizer.fit_transform(X_train)
```

Now we can compare the input data to the output from the text featurizer:

[15]:
```
X_train.head()
```

[15]:
```
                                              Message
296  Sunshine Hols. To claim ur med holiday send a ...
652                                Yup ü not comin :-(
526  Hello hun how ru? Its here by the way. Im good...
571  I tagged MY friends that you seemed to count a...
472                       What happened to our yo date?
```

[16]:
```
X_featurized.head()
```

[16]:
```
     DIVERSITY_SCORE(Message)  MEAN_CHARACTERS_PER_WORD(Message)  \
296                       1.0                          4.344828
652                       1.0                          3.000000
526                       1.0                          3.363636
571                       0.8                          4.083333
472                       1.0                          3.833333

     POLARITY_SCORE(Message)  LSA(Message)[0]  LSA(Message)[1]
296                    0.003         0.150556        -0.072443
652                    0.000         0.017340        -0.005411
526                    0.162         0.169954         0.022670
571                    0.681         0.144713         0.036799
472                    0.000         0.109373        -0.042754
```

These numeric values now represent important information about the original text that the estimator at the end of the pipeline can successfully use to make predictions.

3.4.5 Why encode text this way?

To demonstrate the importance of text-specific modeling, let's train a model with the same dataset, without letting `AutoMLSearch` detect the text column. We can change this by explicitly setting the data type of the `'Message'` column in Woodwork to `Categorical` using the utility method `infer_feature_types`.

[17]:
```
from evalml.utils import infer_feature_types
X = infer_feature_types(X, {'Message': 'Categorical'})
X_train, X_holdout, y_train, y_holdout = evalml.preprocessing.split_data(X, y,␣
↪problem_type='binary', test_size=0.2, random_seed=0)
```

[18]:
```
automl_no_text = AutoMLSearch(X_train=X_train, y_train=y_train,
                              problem_type='binary',
                              max_batches=1,
                              optimize_thresholds=True)

automl_no_text.search()
```

```
Generating pipelines to search over...
8 pipelines ready for search.

*****************************
* Beginning pipeline search *
*****************************

Optimizing for Log Loss Binary.
Lower score is better.

Using SequentialEngine to train and score pipelines.
Searching up to 1 batches for a total of 9 pipelines.
Allowed model families: random_forest, lightgbm, catboost, decision_tree, xgboost,␣
↪linear_model, extra_trees
```

```
FigureWidget({
    'data': [{'mode': 'lines+markers',
              'name': 'Best Score',
              'type'...
```

```
Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 14.046

*****************************
* Evaluating Batch Number 1 *
*****************************

Elastic Net Classifier w/ Text Featurization Component + Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.350
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Elastic Net Classifier w/ Text Featurization Component + Imputer + Standard␣
↪Scaler may not perform as estimated on unseen data.
Decision Tree Classifier w/ Text Featurization Component + Imputer:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 3.386
Random Forest Classifier w/ Text Featurization Component + Imputer:
        Starting cross validation
```

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```
        Finished cross validation - mean Log Loss Binary: 0.221
LightGBM Classifier w/ Text Featurization Component + Imputer:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.292
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        LightGBM Classifier w/ Text Featurization Component + Imputer may not perform␣
↪as estimated on unseen data.
Logistic Regression Classifier w/ Text Featurization Component + Imputer + Standard␣
↪Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.350
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Logistic Regression Classifier w/ Text Featurization Component + Imputer +␣
↪Standard Scaler may not perform as estimated on unseen data.
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/xgboost/sklearn.py:1146: UserWarning:

The use of label encoder in XGBClassifier is deprecated and will be removed in a␣
↪future release. To remove this warning, do the following: 1) Pass option use_label_
↪encoder=False when constructing XGBClassifier object; and 2) Encode your labels (y)␣
↪as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].

[21:20:33] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default␣
↪evaluation metric used with the objective 'binary:logistic' was changed from 'error
↪' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old␣
↪behavior.
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/xgboost/sklearn.py:1146: UserWarning:

The use of label encoder in XGBClassifier is deprecated and will be removed in a␣
↪future release. To remove this warning, do the following: 1) Pass option use_label_
↪encoder=False when constructing XGBClassifier object; and 2) Encode your labels (y)␣
↪as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].

[21:20:34] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default␣
↪evaluation metric used with the objective 'binary:logistic' was changed from 'error
↪' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old␣
↪behavior.
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/xgboost/sklearn.py:1146: UserWarning:

The use of label encoder in XGBClassifier is deprecated and will be removed in a␣
↪future release. To remove this warning, do the following: 1) Pass option use_label_
↪encoder=False when constructing XGBClassifier object; and 2) Encode your labels (y)␣
↪as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].

[21:20:35] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default␣
↪evaluation metric used with the objective 'binary:logistic' was changed from 'error
↪' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old␣
↪behavior.
XGBoost Classifier w/ Text Featurization Component + Imputer:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.266
        High coefficient of variation (cv >= 0.2) within cross validation scores.
```

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```
        XGBoost Classifier w/ Text Featurization Component + Imputer may not perform␣
↪as estimated on unseen data.
Extra Trees Classifier w/ Text Featurization Component + Imputer:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.292
CatBoost Classifier w/ Text Featurization Component + Imputer:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.589

Search finished after 00:25
Best pipeline: Random Forest Classifier w/ Text Featurization Component + Imputer
Best pipeline Log Loss Binary: 0.221422
```

Like before, we can look at the rankings and pick the best pipeline.

[19]:
```
automl_no_text.rankings
```

[19]:

	id	pipeline_name	search_order	mean_cv_score	standard_deviation_cv_score	validation_score	percent_better_than_baseline	high_variance_cv	parameters
0	3	Random Forest Classifier w/ Text Featurization...	3	0.221422	0.040958	0.221587	98.423568	False	{'Imputer': {'categorical_impute_strategy': 'm...
1	6	XGBoost Classifier w/ Text Featurization Compo...	6	0.266164	0.106501	0.242896	98.105025	True	{'Imputer': {'categorical_impute_strategy': 'm...
2	4	LightGBM Classifier w/ Text Featurization Comp...	4	0.291768	0.114862	0.291521	97.922737	True	{'Imputer': {'categorical_impute_strategy': 'm...
3	7	Extra Trees Classifier w/ Text Featurization C...	7	0.292373	0.029893	0.325764	97.918427	False	{'Imputer': {'categorical_impute_strategy': 'm...
4	5	Logistic Regression Classifier w/ Text Featuri...	5	0.350340	0.074833	0.349271	97.505728	True	{'Imputer': {'categorical_impute_strategy': 'm...
5	1	Elastic Net Classifier w/ Text Featurization C...	1	0.350471	0.074886	0.349437	97.504795	True	{'Imputer': {'categorical_impute_strategy': 'm...
6	8	CatBoost Classifier w/ Text Featurization Comp...	8	0.588944	0.004016	0.592259	95.806967	False	{'Imputer': {'categorical_impute_strategy': 'm...
7	2	Decision Tree Classifier w/ Text Featurization...	2	3.385551	0.672118	3.708759	75.896294	False	{'Imputer': {'categorical_impute_strategy': 'm...
8	0	Mode Baseline Binary Classification Pipeline	0	14.045769	0.099705	13.988204	0.000000	False	{'Imputer': {'categorical_impute_strategy': 'm...

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```
6  {'Imputer': {'categorical_impute_strategy': 'm...
7  {'Imputer': {'categorical_impute_strategy': 'm...
8      {'Baseline Classifier': {'strategy': 'mode'}}
```

[20]:
```
best_pipeline_no_text = automl_no_text.best_pipeline
```

Here, changing the data type of the text column removed the `Text Featurization Component` from the pipeline.

[21]:
```
best_pipeline_no_text.graph()
```

[21]:

[22]:
```
automl_no_text.describe_pipeline(automl_no_text.rankings.iloc[0]["id"])
```

```
*****************************************************************************
* Random Forest Classifier w/ Text Featurization Component + Imputer *
*****************************************************************************

Problem Type: binary
Model Family: Random Forest

Pipeline Steps
==============
1. Text Featurization Component
2. Imputer
         * categorical_impute_strategy : most_frequent
         * numeric_impute_strategy : mean
         * categorical_fill_value : None
         * numeric_fill_value : None
3. Random Forest Classifier
         * n_estimators : 100
         * max_depth : 6
         * n_jobs : -1

Training
========
Training for binary problems.
Total training time (including CV): 3.4 seconds

Cross Validation
----------------
             Log Loss Binary  MCC Binary  Gini   AUC  Precision    F1  Balanced␣
↪Accuracy Binary  Accuracy Binary # Training # Validation
0                      0.222       0.817 0.950 0.975      0.862 0.893                ␣
↪    0.913             0.910         400           200
1                      0.180       0.875 0.970 0.985      0.937 0.925                ␣
↪    0.936             0.940         400           200
2                      0.262       0.783 0.925 0.963      0.918 0.865                ␣
↪    0.883             0.895         400           200
mean                   0.221       0.825 0.948 0.974      0.906 0.894                ␣
↪    0.910             0.915           -             -
std                    0.041       0.047 0.023 0.011      0.039 0.030                ␣
↪    0.026             0.023           -             -
coef of var            0.185       0.057 0.024 0.012      0.043 0.034                ␣
↪    0.029             0.025           -             -
```

[23]:
```
# get standard performance metrics on holdout data
scores = best_pipeline_no_text.score(X_holdout, y_holdout, objectives=evalml.
↪objectives.get_core_objectives('binary'))
print(f'Accuracy Binary: {scores["Accuracy Binary"]}')
```

```
Accuracy Binary: 0.96
```

Without the `Text Featurization Component`, the `'Message'` column was treated as a categorical column, and therefore the conversion of this text to numerical features happened in the `One Hot Encoder`. The best pipeline encoded the top 10 most frequent "categories" of these texts, meaning 10 text messages were one-hot encoded and all the others were dropped. Clearly, this removed almost all of the information from the dataset, as we can see the `best_pipeline_no_text` performs very similarly to randomly guessing "ham" in every case.

CHAPTER

FOUR

USER GUIDE

These guides include in-depth descriptions and explanations of EvalML's features.

4.1 Automated Machine Learning (AutoML) Search

4.1.1 Background

Machine Learning

Machine learning (ML) is the process of constructing a mathematical model of a system based on a sample dataset collected from that system.

One of the main goals of training an ML model is to teach the model to separate the signal present in the data from the noise inherent in system and in the data collection process. If this is done effectively, the model can then be used to make accurate predictions about the system when presented with new, similar data. Additionally, introspecting on an ML model can reveal key information about the system being modeled, such as which inputs and transformations of the inputs are most useful to the ML model for learning the signal in the data, and are therefore the most predictive.

There are a variety of ML problem types. Supervised learning describes the case where the collected data contains an output value to be modeled and a set of inputs with which to train the model. EvalML focuses on training supervised learning models.

EvalML supports three common supervised ML problem types. The first is regression, where the target value to model is a continuous numeric value. Next are binary and multiclass classification, where the target value to model consists of two or more discrete values or categories. The choice of which supervised ML problem type is most appropriate depends on domain expertise and on how the model will be evaluated and used.

EvalML is currently building support for supervised time series problems: time series regression, time series binary classification, and time series multiclass classification. While we've added some features to tackle these kinds of problems, our functionality is still being actively developed so please be mindful of that before using it.

AutoML and Search

AutoML is the process of automating the construction, training and evaluation of ML models. Given a data and some configuration, AutoML searches for the most effective and accurate ML model or models to fit the dataset. During the search, AutoML will explore different combinations of model type, model parameters and model architecture.

An effective AutoML solution offers several advantages over constructing and tuning ML models by hand. AutoML can assist with many of the difficult aspects of ML, such as avoiding overfitting and underfitting, imbalanced data, detecting data leakage and other potential issues with the problem setup, and automatically applying best-practice data cleaning, feature engineering, feature selection and various modeling techniques. AutoML can also leverage

search algorithms to optimally sweep the hyperparameter search space, resulting in model performance which would be difficult to achieve by manual training.

4.1.2 AutoML in EvalML

EvalML supports all of the above and more.

In its simplest usage, the AutoML search interface requires only the input data, the target data and a `problem_type` specifying what kind of supervised ML problem to model.

** Graphing methods, like AutoMLSearch, on Jupyter Notebook and Jupyter Lab require ipywidgets to be installed.

** If graphing on Jupyter Lab, jupyterlab-plotly required. To download this, make sure you have npm installed.

[1]:
```
import evalml
from evalml.utils import infer_feature_types
X, y = evalml.demos.load_fraud(n_rows=250)
```

```
             Number of Features
Boolean                       1
Categorical                   6
Numeric                       5

Number of training examples: 250
Targets
False    88.40%
True     11.60%
Name: fraud, dtype: object
```

To provide data to EvalML, it is recommended that you initialize a Woodwork accessor on your data. This allows you to easily control how EvalML will treat each of your features before training a model.

EvalML also accepts `pandas` input, and will run type inference on top of the input `pandas` data. If you'd like to change the types inferred by EvalML, you can use the `infer_feature_types` utility method, which takes pandas or numpy input and converts it to a Woodwork data structure. The `feature_types` parameter can be used to specify what types specific columns should be.

Feature types such as `Natural Language` must be specified in this way, otherwise Woodwork will infer it as `Unknown` type and drop it during the AutoMLSearch.

In the example below, we reformat a couple features to make them easily consumable by the model, and then specify that the provider, which would have otherwise been inferred as a column with natural language, is a categorical column.

[2]:
```
X.ww['expiration_date'] = X['expiration_date'].apply(lambda x: '20{}-01-{}'.format(x.
↪split("/")[1], x.split("/")[0]))
X = infer_feature_types(X, feature_types= {'store_id': 'categorical',
                                           'expiration_date': 'datetime',
                                           'lat': 'categorical',
                                           'lng': 'categorical',
                                           'provider': 'categorical'})
```

In order to validate the results of the pipeline creation and optimization process, we will save some of our data as a holdout set.

[3]:
```
X_train, X_holdout, y_train, y_holdout = evalml.preprocessing.split_data(X, y,␣
↪problem_type='binary', test_size=.2)
```

Data Checks

Before calling `AutoMLSearch.search`, we should run some sanity checks on our data to ensure that the input data being passed will not run into some common issues before running a potentially time-consuming search. EvalML has various data checks that makes this easy. Each data check will return a collection of warnings and errors if it detects potential issues with the input data. This allows users to inspect their data to avoid confusing errors that may arise during the search process. You can learn about each of the data checks available through our *data checks guide*

Here, we will run the `DefaultDataChecks` class, which contains a series of data checks that are generally useful.

[4]:
```
from evalml.data_checks import DefaultDataChecks

data_checks = DefaultDataChecks("binary", "log loss binary")
data_checks.validate(X_train, y_train)
```

[4]:
```
{'warnings': [], 'errors': [], 'actions': []}
```

Since there were no warnings or errors returned, we can safely continue with the search process.

[5]:
```
automl = evalml.automl.AutoMLSearch(X_train=X_train, y_train=y_train, problem_type=
↪'binary')
automl.search()
```

```
Using default limit of max_batches=1.

Generating pipelines to search over...
8 pipelines ready for search.

*****************************
* Beginning pipeline search *
*****************************

Optimizing for Log Loss Binary.
Lower score is better.

Using SequentialEngine to train and score pipelines.
Searching up to 1 batches for a total of 9 pipelines.
Allowed model families: linear_model, lightgbm, decision_tree, extra_trees, catboost,␣
↪xgboost, random_forest
```

```
FigureWidget({
    'data': [{'mode': 'lines+markers',
              'name': 'Best Score',
              'type'...
```

```
Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 3.970

*****************************
* Evaluating Batch Number 1 *
*****************************

Elastic Net Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.512
Decision Tree Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler:
```

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```
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 2.957
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Decision Tree Classifier w/ Imputer + DateTime Featurization Component + One␣
↪Hot Encoder + SMOTENC Oversampler may not perform as estimated on unseen data.
Random Forest Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.286
LightGBM Classifier w/ Imputer + DateTime Featurization Component + One Hot Encoder +␣
↪SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.309
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        LightGBM Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler may not perform as estimated on unseen data.
Logistic Regression Classifier w/ Imputer + DateTime Featurization Component + One␣
↪Hot Encoder + SMOTENC Oversampler + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.552
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/xgboost/sklearn.py:1146: UserWarning:

The use of label encoder in XGBClassifier is deprecated and will be removed in a␣
↪future release. To remove this warning, do the following: 1) Pass option use_label_
↪encoder=False when constructing XGBClassifier object; and 2) Encode your labels (y)␣
↪as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].

[21:21:45] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default␣
↪evaluation metric used with the objective 'binary:logistic' was changed from 'error
↪' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old␣
↪behavior.
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/xgboost/sklearn.py:1146: UserWarning:

The use of label encoder in XGBClassifier is deprecated and will be removed in a␣
↪future release. To remove this warning, do the following: 1) Pass option use_label_
↪encoder=False when constructing XGBClassifier object; and 2) Encode your labels (y)␣
↪as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].

[21:21:46] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default␣
↪evaluation metric used with the objective 'binary:logistic' was changed from 'error
↪' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old␣
↪behavior.
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/xgboost/sklearn.py:1146: UserWarning:

The use of label encoder in XGBClassifier is deprecated and will be removed in a␣
↪future release. To remove this warning, do the following: 1) Pass option use_label_
↪encoder=False when constructing XGBClassifier object; and 2) Encode your labels (y)␣
↪as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].

[21:21:47] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default␣
↪evaluation metric used with the objective 'binary:logistic' was changed from 'error
↪' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old␣
↪behavior.
```

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```
XGBoost Classifier w/ Imputer + DateTime Featurization Component + One Hot Encoder +␣
↪SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.279
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        XGBoost Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler may not perform as estimated on unseen data.
Extra Trees Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.338
CatBoost Classifier w/ Imputer + DateTime Featurization Component + SMOTENC␣
↪Oversampler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.602

Search finished after 00:22
```

```
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/xgboost/sklearn.py:1146: UserWarning:

The use of label encoder in XGBClassifier is deprecated and will be removed in a␣
↪future release. To remove this warning, do the following: 1) Pass option use_label_
↪encoder=False when constructing XGBClassifier object; and 2) Encode your labels (y)␣
↪as integers starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
```

```
[21:21:52] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default␣
↪evaluation metric used with the objective 'binary:logistic' was changed from 'error
↪' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old␣
↪behavior.
Best pipeline: XGBoost Classifier w/ Imputer + DateTime Featurization Component + One␣
↪Hot Encoder + SMOTENC Oversampler
Best pipeline Log Loss Binary: 0.278707
```

The AutoML search will log its progress, reporting each pipeline and parameter set evaluated during the search.

There are a number of mechanisms to control the AutoML search time. One way is to set the `max_batches` parameter which controls the maximum number of rounds of AutoML to evaluate, where each round may train and score a variable number of pipelines. Another way is to set the `max_iterations` parameter which controls the maximum number of candidate models to be evaluated during AutoML. By default, AutoML will search for a single batch. The first pipeline to be evaluated will always be a baseline model representing a trivial solution.

The AutoML interface supports a variety of other parameters. For a comprehensive list, please *refer to the API reference.*

We also provide *a standalone search method* which does all of the above in a single line, and returns the `AutoMLSearch` instance and data check results. If there were data check errors, AutoML will not be run and no `AutoMLSearch` instance will be returned.

Detecting Problem Type

EvalML includes a simple method, `detect_problem_type`, to help determine the problem type given the target data.

This function can return the predicted problem type as a ProblemType enum, choosing from ProblemType.BINARY, ProblemType.MULTICLASS, and ProblemType.REGRESSION. If the target data is invalid (for instance when there is only 1 unique label), the function will throw an error instead.

[6]:
```
import pandas as pd
from evalml.problem_types import detect_problem_type

y_binary = pd.Series([0, 1, 1, 0, 1, 1])
detect_problem_type(y_binary)
```

[6]:
```
<ProblemTypes.BINARY: 'binary'>
```

Objective parameter

AutoMLSearch takes in an `objective` parameter to determine which `objective` to optimize for. By default, this parameter is set to `auto`, which allows AutoML to choose `LogLossBinary` for binary classification problems, `LogLossMulticlass` for multiclass classification problems, and `R2` for regression problems.

It should be noted that the `objective` parameter is only used in ranking and helping choose the pipelines to iterate over, but is not used to optimize each individual pipeline during fit-time.

To get the default objective for each problem type, you can use the `get_default_primary_search_objective` function.

[7]:
```
from evalml.automl import get_default_primary_search_objective

binary_objective = get_default_primary_search_objective("binary")
multiclass_objective = get_default_primary_search_objective("multiclass")
regression_objective = get_default_primary_search_objective("regression")

print(binary_objective.name)
print(multiclass_objective.name)
print(regression_objective.name)
```

```
Log Loss Binary
Log Loss Multiclass
R2
```

Using custom pipelines

EvalML's AutoML algorithm generates a set of pipelines to search with. To provide a custom set instead, set allowed_component_graphs to a dictionary of custom component graphs. `AutoMLSearch` will use these to generate `Pipeline` instances. Note: this will prevent AutoML from generating other pipelines to search over.

[8]:
```
from evalml.pipelines import MulticlassClassificationPipeline


automl_custom = evalml.automl.AutoMLSearch(X_train=X_train,
                                           y_train=y_train,
                                           problem_type='multiclass',
```

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```
                                                allowed_component_graphs={"My_pipeline": [
↪'Simple Imputer', 'Random Forest Classifier'],
                                                                          "My_other_
↪pipeline": ['One Hot Encoder', 'Random Forest Classifier']})
```

```
Using default limit of max_batches=1.

2 pipelines ready for search.
```

```
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/evalml/automl/automl_search.py:676:␣
↪ParameterNotUsedWarning:

Parameters for components {'SMOTENC Oversampler'} will not be used to instantiate the␣
↪pipeline since they don't appear in the pipeline
```

Stopping the search early

To stop the search early, hit `Ctrl-C`. This will bring up a prompt asking for confirmation. Responding with `y` will immediately stop the search. Responding with `n` will continue the search.

Callback functions

`AutoMLSearch` supports several callback functions, which can be specified as parameters when initializing an `AutoMLSearch` object. They are:

- `start_iteration_callback`
- `add_result_callback`
- `error_callback`

Start Iteration Callback

Users can set `start_iteration_callback` to set what function is called before each pipeline training iteration. This callback function must take three positional parameters: the pipeline class, the pipeline parameters, and the `AutoMLSearch` object.

[9]:
```
## start_iteration_callback example function
def start_iteration_callback_example(pipeline_class, pipeline_params, automl_obj):
    print ("Training pipeline with the following parameters:", pipeline_params)
```

Add Result Callback

Users can set `add_result_callback` to set what function is called after each pipeline training iteration. This callback function must take three positional parameters: a dictionary containing the training results for the new pipeline, an untrained_pipeline containing the parameters used during training, and the `AutoMLSearch` object.

[10]:
```
## add_result_callback example function
def add_result_callback_example(pipeline_results_dict, untrained_pipeline, automl_
↪obj):
    print ("Results for trained pipeline with the following parameters:", pipeline_
↪results_dict)
```

Error Callback

Users can set the `error_callback` to set what function called when `search()` errors and raises an `Exception`. This callback function takes three positional parameters: the `Exception raised`, the traceback, and the `AutoMLSearch object`. This callback function must also accept `kwargs`, so `AutoMLSearch` is able to pass along other parameters used by default.

Evalml defines several error callback functions, which can be found under `evalml.automl.callbacks`. They are:

- `silent_error_callback`
- `raise_error_callback`
- `log_and_save_error_callback`
- `raise_and_save_error_callback`
- `log_error_callback` (default used when `error_callback` is None)

[11]:
```
# error_callback example; this is implemented in the evalml library
def raise_error_callback(exception, traceback, automl, **kwargs):
    """Raises the exception thrown by the AutoMLSearch object. Also logs the␣
↪exception as an error."""
    logger.error(f'AutoMLSearch raised a fatal exception: {str(exception)}')
    logger.error("\n".join(traceback))
    raise exception
```

4.1.3 View Rankings

A summary of all the pipelines built can be returned as a pandas DataFrame which is sorted by score. The score column contains the average score across all cross-validation folds while the validation_score column is computed from the first cross-validation fold.

[12]:
```
automl.rankings
```

[12]:

	id	pipeline_name	search_order	\
0	6	XGBoost Classifier w/ Imputer + DateTime Featu...	6	
1	3	Random Forest Classifier w/ Imputer + DateTime...	3	
2	4	LightGBM Classifier w/ Imputer + DateTime Feat...	4	
3	7	Extra Trees Classifier w/ Imputer + DateTime F...	7	
4	1	Elastic Net Classifier w/ Imputer + DateTime F...	1	
5	5	Logistic Regression Classifier w/ Imputer + Da...	5	
6	8	CatBoost Classifier w/ Imputer + DateTime Feat...	8	

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```
7   2  Decision Tree Classifier w/ Imputer + DateTime...              2
8   0       Mode Baseline Binary Classification Pipeline              0

   mean_cv_score  standard_deviation_cv_score  validation_score  \
0       0.278707                     0.190725          0.202638
1       0.285613                     0.041116          0.263695
2       0.308636                     0.203878          0.234947
3       0.338286                     0.009381          0.329015
4       0.511808                     0.074992          0.590517
5       0.551960                     0.082695          0.628646
6       0.601819                     0.007246          0.593693
7       2.956956                     3.084439          0.651557
8       3.970423                     0.266060          4.124033

   percent_better_than_baseline  high_variance_cv  \
0                     92.980409              True
1                     92.806475             False
2                     92.226623              True
3                     91.479857             False
4                     87.109474             False
5                     86.098206             False
6                     84.842444             False
7                     25.525413              True
8                      0.000000             False

                                        parameters
0  {'Imputer': {'categorical_impute_strategy': 'm...
1  {'Imputer': {'categorical_impute_strategy': 'm...
2  {'Imputer': {'categorical_impute_strategy': 'm...
3  {'Imputer': {'categorical_impute_strategy': 'm...
4  {'Imputer': {'categorical_impute_strategy': 'm...
5  {'Imputer': {'categorical_impute_strategy': 'm...
6  {'Imputer': {'categorical_impute_strategy': 'm...
7  {'Imputer': {'categorical_impute_strategy': 'm...
8      {'Baseline Classifier': {'strategy': 'mode'}}
```

4.1.4 Describe Pipeline

Each pipeline is given an `id`. We can get more information about any particular pipeline using that `id`. Here, we will get more information about the pipeline with `id = 1`.

[13]:
```
automl.describe_pipeline(1)
```

```
*****************************************************************************************
* Elastic Net Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler + Standard Scaler *
*****************************************************************************************

Problem Type: binary
Model Family: Linear

Pipeline Steps
==============
1. Imputer
```

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```
         * categorical_impute_strategy : most_frequent
         * numeric_impute_strategy : mean
         * categorical_fill_value : None
         * numeric_fill_value : None
2. DateTime Featurization Component
         * features_to_extract : ['year', 'month', 'day_of_week', 'hour']
         * encode_as_categories : False
         * date_index : None
3. One Hot Encoder
         * top_n : 10
         * features_to_encode : None
         * categories : None
         * drop : if_binary
         * handle_unknown : ignore
         * handle_missing : error
4. SMOTENC Oversampler
         * sampling_ratio : 0.25
         * k_neighbors_default : 5
         * n_jobs : -1
         * sampling_ratio_dict : None
         * categorical_features : [3, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21,␣
↪22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42,␣
↪43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59]
         * k_neighbors : 5
5. Standard Scaler
6. Elastic Net Classifier
         * penalty : elasticnet
         * C : 1.0
         * l1_ratio : 0.15
         * n_jobs : -1
         * multi_class : auto
         * solver : saga

Training
========
Training for binary problems.
Total training time (including CV): 2.7 seconds

Cross Validation
----------------
             Log Loss Binary  MCC Binary  Gini   AUC  Precision    F1  Balanced␣
↪Accuracy Binary  Accuracy Binary # Training # Validation
0                      0.591       0.175 0.195 0.597      0.286 0.267                ␣
↪    0.583            0.836        133           67
1                      0.441       0.296 0.419 0.710      0.500 0.333                ␣
↪    0.608            0.881        133           67
2                      0.504       0.035 0.259 0.630      0.120 0.188                ␣
↪    0.528            0.606        134           66
mean                   0.512       0.169 0.291 0.646      0.302 0.263                ␣
↪    0.573            0.774          -             -
std                    0.075       0.130 0.116 0.058      0.191 0.073                ␣
↪    0.041            0.147          -             -
coef of var            0.147       0.772 0.397 0.090      0.631 0.278                ␣
↪    0.072            0.190          -             -
```

4.1.5 Get Pipeline

We can get the object of any pipeline via their `id` as well:

[14]:
```
pipeline = automl.get_pipeline(1)
print(pipeline.name)
print(pipeline.parameters)
```

```
Elastic Net Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler + Standard Scaler
{'Imputer': {'categorical_impute_strategy': 'most_frequent', 'numeric_impute_strategy
↪': 'mean', 'categorical_fill_value': None, 'numeric_fill_value': None}, 'DateTime␣
↪Featurization Component': {'features_to_extract': ['year', 'month', 'day_of_week',
↪'hour'], 'encode_as_categories': False, 'date_index': None}, 'One Hot Encoder': {
↪'top_n': 10, 'features_to_encode': None, 'categories': None, 'drop': 'if_binary',
↪'handle_unknown': 'ignore', 'handle_missing': 'error'}, 'SMOTENC Oversampler': {
↪'sampling_ratio': 0.25, 'k_neighbors_default': 5, 'n_jobs': -1, 'sampling_ratio_dict
↪': None, 'categorical_features': [3, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21,
↪ 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42,
↪ 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59], 'k_neighbors':
↪ 5}, 'Elastic Net Classifier': {'penalty': 'elasticnet', 'C': 1.0, 'l1_ratio': 0.15,
↪ 'n_jobs': -1, 'multi_class': 'auto', 'solver': 'saga'}}
```

Get best pipeline

If you specifically want to get the best pipeline, there is a convenient accessor for that. The pipeline returned is already fitted on the input X, y data that we passed to AutoMLSearch. To turn off this default behavior, set `train_best_pipeline=False` when initializing AutoMLSearch.

[15]:
```
best_pipeline = automl.best_pipeline
print(best_pipeline.name)
print(best_pipeline.parameters)
best_pipeline.predict(X_train)
```

```
XGBoost Classifier w/ Imputer + DateTime Featurization Component + One Hot Encoder +␣
↪SMOTENC Oversampler
{'Imputer': {'categorical_impute_strategy': 'most_frequent', 'numeric_impute_strategy
↪': 'mean', 'categorical_fill_value': None, 'numeric_fill_value': None}, 'DateTime␣
↪Featurization Component': {'features_to_extract': ['year', 'month', 'day_of_week',
↪'hour'], 'encode_as_categories': False, 'date_index': None}, 'One Hot Encoder': {
↪'top_n': 10, 'features_to_encode': None, 'categories': None, 'drop': 'if_binary',
↪'handle_unknown': 'ignore', 'handle_missing': 'error'}, 'SMOTENC Oversampler': {
↪'sampling_ratio': 0.25, 'k_neighbors_default': 5, 'n_jobs': -1, 'sampling_ratio_dict
↪': None, 'categorical_features': [3, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21,
↪ 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42,
↪ 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59], 'k_neighbors':
↪ 5}, 'XGBoost Classifier': {'eta': 0.1, 'max_depth': 6, 'min_child_weight': 1, 'n_
↪estimators': 100, 'n_jobs': -1}}
```

[15]:
```
0      False
1      False
2      False
3       True
4      False
       ...
195    False
196    False
```

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```
197    False
198    False
199    False
Name: fraud, Length: 200, dtype: bool
```

4.1.6 Training and Scoring Multiple Pipelines using AutoMLSearch

AutoMLSearch will automatically fit the best pipeline on the entire training data. It also provides an easy API for training and scoring other pipelines.

If you'd like to train one or more pipelines on the entire training data, you can use the `train_pipelines`method

Similarly, if you'd like to score one or more pipelines on a particular dataset, you can use the `train_pipelines`method

[16]:
```
trained_pipelines = automl.train_pipelines([automl.get_pipeline(i) for i in [0, 1,␣
↪2]])
trained_pipelines
```

[16]:
```
{'Mode Baseline Binary Classification Pipeline': pipeline =␣
↪BinaryClassificationPipeline(component_graph={'Baseline Classifier': ['Baseline␣
↪Classifier', 'X', 'y']}, parameters={'Baseline Classifier':{'strategy': 'mode'}},␣
↪custom_name='Mode Baseline Binary Classification Pipeline', random_seed=0),
 'Elastic Net Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler + Standard Scaler': pipeline =␣
↪BinaryClassificationPipeline(component_graph={'Imputer': ['Imputer', 'X', 'y'],
↪'DateTime Featurization Component': ['DateTime Featurization Component', 'Imputer.x
↪', 'y'], 'One Hot Encoder': ['One Hot Encoder', 'DateTime Featurization Component.x
↪', 'y'], 'SMOTENC Oversampler': ['SMOTENC Oversampler', 'One Hot Encoder.x', 'y'],
↪'Standard Scaler': ['Standard Scaler', 'SMOTENC Oversampler.x', 'SMOTENC␣
↪Oversampler.y'], 'Elastic Net Classifier': ['Elastic Net Classifier', 'Standard␣
↪Scaler.x', 'SMOTENC Oversampler.y']}, parameters={'Imputer':{'categorical_impute_
↪strategy': 'most_frequent', 'numeric_impute_strategy': 'mean', 'categorical_fill_
↪value': None, 'numeric_fill_value': None}, 'DateTime Featurization Component':{
↪'features_to_extract': ['year', 'month', 'day_of_week', 'hour'], 'encode_as_
↪categories': False, 'date_index': None}, 'One Hot Encoder':{'top_n': 10, 'features_
↪to_encode': None, 'categories': None, 'drop': 'if_binary', 'handle_unknown': 'ignore
↪', 'handle_missing': 'error'}, 'SMOTENC Oversampler':{'sampling_ratio': 0.25, 'k_
↪neighbors_default': 5, 'n_jobs': -1, 'sampling_ratio_dict': None, 'categorical_
↪features': [3, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26,␣
↪27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47,␣
↪48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59], 'k_neighbors': 5}, 'Elastic Net␣
↪Classifier':{'penalty': 'elasticnet', 'C': 1.0, 'l1_ratio': 0.15, 'n_jobs': -1,
↪'multi_class': 'auto', 'solver': 'saga'}}, random_seed=0),
 'Decision Tree Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler': pipeline = BinaryClassificationPipeline(component_
↪graph={'Imputer': ['Imputer', 'X', 'y'], 'DateTime Featurization Component': [
↪'DateTime Featurization Component', 'Imputer.x', 'y'], 'One Hot Encoder': ['One Hot␣
↪Encoder', 'DateTime Featurization Component.x', 'y'], 'SMOTENC Oversampler': [
↪'SMOTENC Oversampler', 'One Hot Encoder.x', 'y'], 'Decision Tree Classifier': [
↪'Decision Tree Classifier', 'SMOTENC Oversampler.x', 'SMOTENC Oversampler.y']},␣
↪parameters={'Imputer':{'categorical_impute_strategy': 'most_frequent', 'numeric_
↪impute_strategy': 'mean', 'categorical_fill_value': None, 'numeric_fill_value':␣
↪None}, 'DateTime Featurization Component':{'features_to_extract': ['year', 'month',
↪'day_of_week', 'hour'], 'encode_as_categories': False, 'date_index': None}, 'One␣
↪Hot Encoder':{'top_n': 10, 'features_to_encode': None, 'categories': None, 'drop':
↪'if_binary', 'handle_unknown': 'ignore', 'handle_missing': 'error'}, 'SMOTENC␣
↪Oversampler':{'sampling_ratio': 0.25, 'k_neighbors_default': 5, 'n_jobs': -1,
↪'sampling_ratio_dict': None, 'categorical_features': [3, 10, 11, 12, 13, 14, 15, 16,
↪ 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37,
↪ 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58,
↪ 59], 'k_neighbors': 5}, 'Decision Tree Classifier':{'criterion': 'gini', 'max_
↪features': 'auto', 'max_depth': 6, 'min_samples_split': 2, 'min_weight_fraction_leaf
```

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[17]:
```
pipeline_holdout_scores = automl.score_pipelines([trained_pipelines[name] for name in␣
↪trained_pipelines.keys()],
                                                 X_holdout,
                                                 y_holdout,
                                                 ['Accuracy Binary', 'F1', 'AUC'])
pipeline_holdout_scores
```

[17]:
```
{'Mode Baseline Binary Classification Pipeline': OrderedDict([('Accuracy Binary',
                0.88),
               ('F1', 0.0),
               ('AUC', 0.5)]),
 'Elastic Net Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler + Standard Scaler': OrderedDict([('Accuracy Binary',
                0.66),
               ('F1', 0.19047619047619044),
               ('AUC', 0.5265151515151515)]),
 'Decision Tree Classifier w/ Imputer + DateTime Featurization Component + One Hot␣
↪Encoder + SMOTENC Oversampler': OrderedDict([('Accuracy Binary',
                0.92),
               ('F1', 0.6),
               ('AUC', 0.7234848484848486)])}
```

4.1.7 Saving AutoMLSearch and pipelines from AutoMLSearch

There are two ways to save results from AutoMLSearch.

- You can save the AutoMLSearch object itself, calling `.save(<filepath>)` to do so. This will allow you to save the AutoMLSearch state and reload all pipelines from this.
- If you want to save a pipeline from AutoMLSearch for future use, pipeline classes themselves have a `.save(<filepath>)` method.

[18]:
```
# saving the entire automl search
automl.save("automl.cloudpickle")
automl2 = evalml.automl.AutoMLSearch.load("automl.cloudpickle")
# saving the best pipeline using .save()
best_pipeline.save("pipeline.cloudpickle")
best_pipeline_copy = evalml.pipelines.PipelineBase.load("pipeline.cloudpickle")
```

4.1.8 Limiting the AutoML Search Space

The AutoML search algorithm first trains each component in the pipeline with their default values. After the first iteration, it then tweaks the parameters of these components using the pre-defined hyperparameter ranges that these components have. To limit the search over certain hyperparameter ranges, you can specify a `custom_hyperparameters` argument with your `AutoMLSearch` parameters. These parameters will limit the hyperparameter search space.

Hyperparameter ranges can be found through the API reference for each component. Parameter arguments must be specified as dictionaries, but the associated values can be single values or `skopt.space` Real, Integer, Categorical values.

If however you'd like to specify certain values for the initial batch of the AutoML search algorithm, you can use the `pipeline_parameters` argument. This will set the initial batch's component parameters to the values passed by

this argument.

[19]:
```
from evalml import AutoMLSearch
from evalml.demos import load_fraud
from skopt.space import Categorical
from evalml.model_family import ModelFamily
import woodwork as ww

X, y = load_fraud(n_rows=1000)

# example of setting parameter to just one value
custom_hyperparameters = {'Imputer': {
    'numeric_impute_strategy': 'mean'
}}


# limit the numeric impute strategy to include only `median` and `most_frequent`
# `mean` is the default value for this argument, but it doesn't need to be included␣
↪in the specified hyperparameter range for this to work
custom_hyperparameters = {'Imputer': {
    'numeric_impute_strategy': Categorical(['median', 'most_frequent'])
}}
# set the initial batch numeric impute strategy strategy to 'median'
pipeline_parameters = {'Imputer': {
    'numeric_impute_strategy': 'median'
}}

# using this custom hyperparameter means that our Imputer components in these␣
↪pipelines will only search through
# 'median' and 'most_frequent' strategies for 'numeric_impute_strategy', and the␣
↪initial batch parameter will be
# set to 'median'
automl_constrained = AutoMLSearch(X_train=X, y_train=y, problem_type='binary',␣
↪pipeline_parameters=pipeline_parameters,
                                  custom_hyperparameters=custom_hyperparameters)
```

```
             Number of Features
Boolean                       1
Categorical                   6
Numeric                       5

Number of training examples: 1000
Targets
False    85.90%
True     14.10%
Name: fraud, dtype: object
Using default limit of max_batches=1.

Generating pipelines to search over...
8 pipelines ready for search.
```

4.1.9 Imbalanced Data

The AutoML search algorithm now has functionality to handle imbalanced data during classification! AutoMLSearch now provides two additional parameters, `sampler_method` and `sampler_balanced_ratio`, that allow you to let AutoMLSearch know whether to sample imbalanced data, and how to do so. `sampler_method` takes in either `Undersampler`, `Oversampler`, `auto`, or None as the sampler to use, and `sampler_balanced_ratio` specifies the `minority/majority` ratio that you want to sample to. Details on the Undersampler and Oversampler components can be found in the documentation.

This can be used for imbalanced datasets, like the fraud dataset, which has a 'minority:majority' ratio of < 0.2.

[20]:
```
automl_auto = AutoMLSearch(X_train=X, y_train=y, problem_type='binary')
automl_auto.allowed_pipelines[-1]
```

```
Using default limit of max_batches=1.

Generating pipelines to search over...
8 pipelines ready for search.
```

[20]:
```
pipeline = BinaryClassificationPipeline(component_graph={'Imputer': ['Imputer', 'X',
↪'y'], 'DateTime Featurization Component': ['DateTime Featurization Component',
↪'Imputer.x', 'y'], 'One Hot Encoder': ['One Hot Encoder', 'DateTime Featurization␣
↪Component.x', 'y'], 'SMOTENC Oversampler': ['SMOTENC Oversampler', 'One Hot Encoder.
↪x', 'y'], 'Standard Scaler': ['Standard Scaler', 'SMOTENC Oversampler.x', 'SMOTENC␣
↪Oversampler.y'], 'Logistic Regression Classifier': ['Logistic Regression Classifier
↪', 'Standard Scaler.x', 'SMOTENC Oversampler.y']}, parameters={'Imputer':{
↪'categorical_impute_strategy': 'most_frequent', 'numeric_impute_strategy': 'mean',
↪'categorical_fill_value': None, 'numeric_fill_value': None}, 'DateTime␣
↪Featurization Component':{'features_to_extract': ['year', 'month', 'day_of_week',
↪'hour'], 'encode_as_categories': False, 'date_index': None}, 'One Hot Encoder':{
↪'top_n': 10, 'features_to_encode': None, 'categories': None, 'drop': 'if_binary',
↪'handle_unknown': 'ignore', 'handle_missing': 'error'}, 'SMOTENC Oversampler':{
↪'sampling_ratio': 0.25, 'k_neighbors_default': 5, 'n_jobs': -1, 'sampling_ratio_dict
↪': None}, 'Logistic Regression Classifier':{'penalty': 'l2', 'C': 1.0, 'n_jobs': -1,
↪ 'multi_class': 'auto', 'solver': 'lbfgs'}}, random_seed=0)
```

The SMOTENC Oversampler is chosen as the default sampling component here, since the `sampler_balanced_ratio = 0.25`. If you specified a lower ratio, for instance `sampler_balanced_ratio = 0.1`, then there would be no sampling component added here. This is because if a ratio of 0.1 would be considered balanced, then a ratio of 0.2 would also be balanced.

[21]:
```
automl_auto_ratio = AutoMLSearch(X_train=X, y_train=y, problem_type='binary', sampler_
↪balanced_ratio=0.1)
automl_auto_ratio.allowed_pipelines[-1]
```

```
Using default limit of max_batches=1.

Generating pipelines to search over...
8 pipelines ready for search.
```

[21]:
```
pipeline = BinaryClassificationPipeline(component_graph={'Imputer': ['Imputer', 'X',
↪'y'], 'DateTime Featurization Component': ['DateTime Featurization Component',
↪'Imputer.x', 'y'], 'One Hot Encoder': ['One Hot Encoder', 'DateTime Featurization␣
↪Component.x', 'y'], 'Standard Scaler': ['Standard Scaler', 'One Hot Encoder.x', 'y
↪'], 'Logistic Regression Classifier': ['Logistic Regression Classifier', 'Standard␣
↪Scaler.x', 'y']}, parameters={'Imputer':{'categorical_impute_strategy': 'most_
↪frequent', 'numeric_impute_strategy': 'mean', 'categorical_fill_value': None,
↪'numeric_fill_value': None}, 'DateTime Featurization Component':{'features_to_
↪extract': ['year', 'month', 'day_of_week', 'hour'], 'encode_as_categories': False,
↪'date_index': None}, 'One Hot Encoder':{'top_n': 10, 'features_to_encode': None,
↪'categories': None, 'drop': 'if_binary', 'handle_unknown': 'ignore', 'handle_missing
↪': 'error'}, 'Logistic Regression Classifier':{'penalty': 'l2', 'C': 1.0, 'n_jobs':␣
↪-1, 'multi_class': 'auto', 'solver': 'lbfgs'}}, random_seed=0)
```

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Additionally, you can add more fine-grained sampling ratios by passing in a `sampling_ratio_dict` in pipeline parameters. For this dictionary, AutoMLSearch expects the keys to be int values from 0 to `n-1` for the classes, and the values would be the `sampler_balanced_ratio` associated with each target. This dictionary would override the AutoML argument `sampler_balanced_ratio`. Below, you can see the scenario for Oversampler component on this dataset. Note that the logic for Undersamplers is included in the commented section.

[22]:
```
# In this case, the majority class is the negative class
# for the oversampler, we don't want to oversample this class, so class 0 (majority)␣
↪will have a ratio of 1 to itself
# for the minority class 1, we want to oversample it to have a minority/majority␣
↪ratio of 0.5, which means we want minority to have 1/2 the samples as the minority
sampler_ratio_dict = {0: 1, 1: 0.5}
pipeline_parameters = {"SMOTENC Oversampler": {"sampler_balanced_ratio": sampler_
↪ratio_dict}}
automl_auto_ratio_dict = AutoMLSearch(X_train=X, y_train=y, problem_type='binary',␣
↪pipeline_parameters=pipeline_parameters)
automl_auto_ratio_dict.allowed_pipelines[-1]

# Undersampler case
# we don't want to undersample this class, so class 1 (minority) will have a ratio of␣
↪1 to itself
# for the majority class 0, we want to undersample it to have a minority/majority␣
↪ratio of 0.5, which means we want majority to have 2x the samples as the minority
# sampler_ratio_dict = {0: 0.5, 1: 1}
# pipeline_parameters = {"SMOTENC Oversampler": {"sampler_balanced_ratio": sampler_
↪ratio_dict}}
# automl_auto_ratio_dict = AutoMLSearch(X_train=X, y_train=y, problem_type='binary',␣
↪pipeline_parameters=pipeline_parameters)
```

```
Using default limit of max_batches=1.

Generating pipelines to search over...
8 pipelines ready for search.
```

[22]:
```
pipeline = BinaryClassificationPipeline(component_graph={'Imputer': ['Imputer', 'X',
↪'y'], 'DateTime Featurization Component': ['DateTime Featurization Component',
↪'Imputer.x', 'y'], 'One Hot Encoder': ['One Hot Encoder', 'DateTime Featurization␣
↪Component.x', 'y'], 'SMOTENC Oversampler': ['SMOTENC Oversampler', 'One Hot Encoder.
↪x', 'y'], 'Standard Scaler': ['Standard Scaler', 'SMOTENC Oversampler.x', 'SMOTENC␣
↪Oversampler.y'], 'Logistic Regression Classifier': ['Logistic Regression Classifier
↪', 'Standard Scaler.x', 'SMOTENC Oversampler.y']}, parameters={'Imputer':{
↪'categorical_impute_strategy': 'most_frequent', 'numeric_impute_strategy': 'mean',
↪'categorical_fill_value': None, 'numeric_fill_value': None}, 'DateTime␣
↪Featurization Component':{'features_to_extract': ['year', 'month', 'day_of_week',
↪'hour'], 'encode_as_categories': False, 'date_index': None}, 'One Hot Encoder':{
↪'top_n': 10, 'features_to_encode': None, 'categories': None, 'drop': 'if_binary',
↪'handle_unknown': 'ignore', 'handle_missing': 'error'}, 'SMOTENC Oversampler':{
↪'sampling_ratio': 0.25, 'k_neighbors_default': 5, 'n_jobs': -1, 'sampling_ratio_dict
↪': None, 'sampler_balanced_ratio': {0: 1, 1: 0.5}}, 'Logistic Regression Classifier
↪':{'penalty': 'l2', 'C': 1.0, 'n_jobs': -1, 'multi_class': 'auto', 'solver': 'lbfgs
↪'}}, random_seed=0)
```

4.1.10 Adding ensemble methods to AutoML

Stacking

Stacking is an ensemble machine learning algorithm that involves training a model to best combine the predictions of several base learning algorithms. First, each base learning algorithms is trained using the given data. Then, the combining algorithm or meta-learner is trained on the predictions made by those base learning algorithms to make a final prediction.

AutoML enables stacking using the `ensembling` flag during initalization; this is set to `False` by default. The stacking ensemble pipeline runs in its own batch after a whole cycle of training has occurred (each allowed pipeline trains for one batch). Note that this means **a large number of iterations may need to run before the stacking ensemble runs**. It is also important to note that **only the first CV fold is calculated for stacking ensembles** because the model internally uses CV folds.

[23]:
```
X, y = evalml.demos.load_breast_cancer()

automl_with_ensembling = AutoMLSearch(X_train=X, y_train=y,
                                      problem_type="binary",
                                      allowed_model_families=[ModelFamily.LINEAR_
↪MODEL],
                                      max_batches=4,
                                      ensembling=True)
automl_with_ensembling.search()
```

```
         Number of Features
Numeric                  30

Number of training examples: 569
Targets
benign       62.74%
malignant    37.26%
Name: target, dtype: object
Generating pipelines to search over...
2 pipelines ready for search.
Ensembling will run every 3 batches.

*****************************
* Beginning pipeline search *
*****************************

Optimizing for Log Loss Binary.
Lower score is better.

Using SequentialEngine to train and score pipelines.
Searching up to 4 batches for a total of 14 pipelines.
Allowed model families: linear_model
```

```
FigureWidget({
    'data': [{'mode': 'lines+markers',
              'name': 'Best Score',
              'type'...
```

```
Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 12.868
```

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```
*****************************
* Evaluating Batch Number 1 *
*****************************

Elastic Net Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.077
Logistic Regression Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.077
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Logistic Regression Classifier w/ Imputer + Standard Scaler may not perform␣
↪as estimated on unseen data.

*****************************
* Evaluating Batch Number 2 *
*****************************

Logistic Regression Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.097
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Logistic Regression Classifier w/ Imputer + Standard Scaler may not perform␣
↪as estimated on unseen data.
Logistic Regression Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.085
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Logistic Regression Classifier w/ Imputer + Standard Scaler may not perform␣
↪as estimated on unseen data.
Logistic Regression Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.097
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Logistic Regression Classifier w/ Imputer + Standard Scaler may not perform␣
↪as estimated on unseen data.
Logistic Regression Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.091
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Logistic Regression Classifier w/ Imputer + Standard Scaler may not perform␣
↪as estimated on unseen data.
Logistic Regression Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.080

*****************************
* Evaluating Batch Number 3 *
*****************************

Elastic Net Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.075
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Elastic Net Classifier w/ Imputer + Standard Scaler may not perform as␣
↪estimated on unseen data.
Elastic Net Classifier w/ Imputer + Standard Scaler:
```

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```
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.075
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Elastic Net Classifier w/ Imputer + Standard Scaler may not perform as␣
↪estimated on unseen data.
Elastic Net Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.079
Elastic Net Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.076
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Elastic Net Classifier w/ Imputer + Standard Scaler may not perform as␣
↪estimated on unseen data.
Elastic Net Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.075
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Elastic Net Classifier w/ Imputer + Standard Scaler may not perform as␣
↪estimated on unseen data.

*****************************
* Evaluating Batch Number 4 *
*****************************

Sklearn Stacked Ensemble Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.123

Search finished after 00:26
Best pipeline: Elastic Net Classifier w/ Imputer + Standard Scaler
Best pipeline Log Loss Binary: 0.075387
```

We can view more information about the stacking ensemble pipeline (which was the best performing pipeline) by calling `.describe()`.

[24]:
```
automl_with_ensembling.best_pipeline.describe()
```

```

*******************************************************
* Elastic Net Classifier w/ Imputer + Standard Scaler *
*******************************************************

Problem Type: binary
Model Family: Linear
Number of features: 30

Pipeline Steps
==============
1. Imputer
         * categorical_impute_strategy : most_frequent
         * numeric_impute_strategy : median
         * categorical_fill_value : None
         * numeric_fill_value : None
2. Standard Scaler
3. Elastic Net Classifier
         * penalty : elasticnet
```

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```
        * C : 8.123565600467177
        * l1_ratio : 0.47997717237505744
        * n_jobs : -1
        * multi_class : auto
        * solver : saga
```

4.1.11 Access raw results

The `AutoMLSearch` class records detailed results information under the `results` field, including information about the cross-validation scoring and parameters.

[25]:
```
automl.results
```

[25]:
```
{'pipeline_results': {0: {'id': 0,
   'pipeline_name': 'Mode Baseline Binary Classification Pipeline',
   'pipeline_class': evalml.pipelines.binary_classification_pipeline.
↪BinaryClassificationPipeline,
   'pipeline_summary': 'Baseline Classifier',
   'parameters': {'Baseline Classifier': {'strategy': 'mode'}},
   'mean_cv_score': 3.970423187263591,
   'standard_deviation_cv_score': 0.26606000431837074,
   'high_variance_cv': False,
   'training_time': 0.9233007431030273,
   'cv_data': [{'all_objective_scores': OrderedDict([('Log Loss Binary',
                 4.124033002377396),
                ('MCC Binary', 0.0),
                ('Gini', 0.0),
                ('AUC', 0.5),
                ('Precision', 0.0),
                ('F1', 0.0),
                ('Balanced Accuracy Binary', 0.5),
                ('Accuracy Binary', 0.8805970149253731),
                ('# Training', 133),
                ('# Validation', 67)]),
     'mean_cv_score': 4.124033002377396,
     'binary_classification_threshold': 9.16384630183206e-53},
    {'all_objective_scores': OrderedDict([('Log Loss Binary',
                 4.124033002377395),
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                ('Gini', 0.0),
                ('AUC', 0.5),
                ('Precision', 0.0),
                ('F1', 0.0),
                ('Balanced Accuracy Binary', 0.5),
                ('Accuracy Binary', 0.8805970149253731),
                ('# Training', 133),
                ('# Validation', 67)]),
     'mean_cv_score': 4.124033002377395,
     'binary_classification_threshold': 9.16384630183206e-53},
    {'all_objective_scores': OrderedDict([('Log Loss Binary',
                 3.6632035570359824),
                ('MCC Binary', 0.0),
                ('Gini', 0.0),
                ('AUC', 0.5),
                ('Precision', 0.0),
```

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```
                 ('F1', 0.0),
                 ('Balanced Accuracy Binary', 0.5),
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                 ('# Training', 134),
                 ('# Validation', 66)]),
    'mean_cv_score': 3.6632035570359824,
    'binary_classification_threshold': 9.16384630183206e-53}],
  'percent_better_than_baseline_all_objectives': {'Log Loss Binary': 0,
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   'Gini': 0,
   'AUC': 0,
   'Precision': 0,
   'F1': 0,
   'Balanced Accuracy Binary': 0,
   'Accuracy Binary': 0},
  'percent_better_than_baseline': 0,
  'validation_score': 4.124033002377396},
 1: {'id': 1,
  'pipeline_name': 'Elastic Net Classifier w/ Imputer + DateTime Featurization␣
↪Component + One Hot Encoder + SMOTENC Oversampler + Standard Scaler',
  'pipeline_class': evalml.pipelines.binary_classification_pipeline.
↪BinaryClassificationPipeline,
  'pipeline_summary': 'Elastic Net Classifier w/ Imputer + DateTime Featurization␣
↪Component + One Hot Encoder + SMOTENC Oversampler + Standard Scaler',
  'parameters': {'Imputer': {'categorical_impute_strategy': 'most_frequent',
    'numeric_impute_strategy': 'mean',
    'categorical_fill_value': None,
    'numeric_fill_value': None},
   'DateTime Featurization Component': {'features_to_extract': ['year',
     'month',
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     'hour'],
    'encode_as_categories': False,
    'date_index': None},
   'One Hot Encoder': {'top_n': 10,
    'features_to_encode': None,
    'categories': None,
    'drop': 'if_binary',
    'handle_unknown': 'ignore',
    'handle_missing': 'error'},
   'SMOTENC Oversampler': {'sampling_ratio': 0.25,
    'k_neighbors_default': 5,
    'n_jobs': -1,
    'sampling_ratio_dict': None,
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    'C': 1.0,
    'l1_ratio': 0.15,
    'n_jobs': -1,
    'multi_class': 'auto',
    'solver': 'saga'}},
  'mean_cv_score': 0.5118084226551022,
  'standard_deviation_cv_score': 0.07499222153032764,
  'high_variance_cv': False,
  'training_time': 2.723395347595215,
  'cv_data': [{'all_objective_scores': OrderedDict([('Log Loss Binary',
                 0.590516914375052),
                ('MCC Binary', 0.17518582316850065),
                ('Gini', 0.19491525423728806),
                ('AUC', 0.597457627118644),
                ('Precision', 0.2857142857142857),
                ('F1', 0.26666666666666666),
                ('Balanced Accuracy Binary', 0.5826271186440678),
```

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```
                ('Accuracy Binary', 0.835820895522388),
                ('# Training', 133),
                ('# Validation', 67)]),
    'mean_cv_score': 0.590516914375052,
    'binary_classification_threshold': 0.48089822234602875},
   {'all_objective_scores': OrderedDict([('Log Loss Binary',
                 0.44118816828058105),
                ('MCC Binary', 0.2957528252716689),
                ('Gini', 0.4194915254237288),
                ('AUC', 0.7097457627118644),
                ('Precision', 0.5),
                ('F1', 0.3333333333333333),
                ('Balanced Accuracy Binary', 0.6080508474576272),
                ('Accuracy Binary', 0.8805970149253731),
                ('# Training', 133),
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    'mean_cv_score': 0.44118816828058105,
    'binary_classification_threshold': 0.7518116371406225},
   {'all_objective_scores': OrderedDict([('Log Loss Binary',
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    'binary_classification_threshold': 0.10568708806540947}],
  'percent_better_than_baseline_all_objectives': {'Log Loss Binary': 87.
↪10947426720426,
   'MCC Binary': inf,
   'Gini': inf,
   'AUC': 14.558111380145277,
   'Precision': 30.19047619047619,
   'F1': 26.25,
   'Balanced Accuracy Binary': 7.284100080710254,
   'Accuracy Binary': -11.08849690939243},
  'percent_better_than_baseline': 87.10947426720426,
  'validation_score': 0.590516914375052},
 2: {'id': 2,
  'pipeline_name': 'Decision Tree Classifier w/ Imputer + DateTime Featurization␣
↪Component + One Hot Encoder + SMOTENC Oversampler',
  'pipeline_class': evalml.pipelines.binary_classification_pipeline.
↪BinaryClassificationPipeline,
  'pipeline_summary': 'Decision Tree Classifier w/ Imputer + DateTime Featurization␣
↪Component + One Hot Encoder + SMOTENC Oversampler',
  'parameters': {'Imputer': {'categorical_impute_strategy': 'most_frequent',
    'numeric_impute_strategy': 'mean',
    'categorical_fill_value': None,
    'numeric_fill_value': None},
   'DateTime Featurization Component': {'features_to_extract': ['year',
     'month',
     'day_of_week',
     'hour'],
```

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```
    'encode_as_categories': False,
    'date_index': None},
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    'handle_missing': 'error'},
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    'n_jobs': -1,
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```

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      54,
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     'k_neighbors': 5},
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     'max_features': 'auto',
     'max_depth': 6,
     'min_samples_split': 2,
     'min_weight_fraction_leaf': 0.0}},
   'mean_cv_score': 2.956956288246977,
   'standard_deviation_cv_score': 3.084438905133218,
   'high_variance_cv': True,
   'training_time': 2.2004153728485107,
   'cv_data': [{'all_objective_scores': OrderedDict([('Log Loss Binary',
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                 ('F1', 0.7692307692307693),
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                  1.7585681792927779),
                 ('MCC Binary', 0.4208952550769721),
                 ('Gini', 0.379237288135593),
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                 ('Precision', 0.6),
                 ('F1', 0.4615384615384615),
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↪52541256225873,
```

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    'MCC Binary': inf,
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    'F1': 44.79922593130141,
    'Balanced Accuracy Binary': 11.097659402744153,
    'Accuracy Binary': -17.21694557515452},
   'percent_better_than_baseline': 25.52541256225873,
   'validation_score': 0.651556943513563},
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   'pipeline_name': 'Random Forest Classifier w/ Imputer + DateTime Featurization␣
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   'pipeline_class': evalml.pipelines.binary_classification_pipeline.
↪BinaryClassificationPipeline,
   'pipeline_summary': 'Random Forest Classifier w/ Imputer + DateTime Featurization␣
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   'parameters': {'Imputer': {'categorical_impute_strategy': 'most_frequent',
     'numeric_impute_strategy': 'mean',
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     'numeric_fill_value': None},
    'DateTime Featurization Component': {'features_to_extract': ['year',
      'month',
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     'encode_as_categories': False,
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    'One Hot Encoder': {'top_n': 10,
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     'drop': 'if_binary',
     'handle_unknown': 'ignore',
     'handle_missing': 'error'},
    'SMOTENC Oversampler': {'sampling_ratio': 0.25,
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  'mean_cv_score': 0.6018191346985708,
  'standard_deviation_cv_score': 0.007246095254215931,
  'high_variance_cv': False,
  'training_time': 1.103830099105835,
  'cv_data': [{'all_objective_scores': OrderedDict([('Log Loss Binary',
                0.5936927052183711),
               ('MCC Binary', 0.7712055916006633),
               ('Gini', 0.7796610169491525),
               ('AUC', 0.8898305084745762),
```

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```
                 ('Precision', 1.0),
                 ('F1', 0.7692307692307693),
                 ('Balanced Accuracy Binary', 0.8125),
                 ('Accuracy Binary', 0.9552238805970149),
                 ('# Training', 133),
                 ('# Validation', 67)]),
    'mean_cv_score': 0.5936927052183711,
    'binary_classification_threshold': 0.498623875482405},
   {'all_objective_scores': OrderedDict([('Log Loss Binary',
                 0.6076076767585368),
                 ('MCC Binary', 0.47636443708895493),
                 ('Gini', 0.12076271186440679),
                 ('AUC', 0.5603813559322034),
                 ('Precision', 1.0),
                 ('F1', 0.4),
                 ('Balanced Accuracy Binary', 0.625),
                 ('Accuracy Binary', 0.9104477611940298),
                 ('# Training', 133),
                 ('# Validation', 67)]),
    'mean_cv_score': 0.6076076767585368,
    'binary_classification_threshold': 0.5007469614241519},
   {'all_objective_scores': OrderedDict([('Log Loss Binary',
                 0.6041570221188047),
                 ('MCC Binary', 0.7469064529073725),
                 ('Gini', 0.8692493946731235),
                 ('AUC', 0.9346246973365617),
                 ('Precision', 0.8333333333333334),
                 ('F1', 0.7692307692307692),
                 ('Balanced Accuracy Binary', 0.8486682808716708),
                 ('Accuracy Binary', 0.9545454545454546),
                 ('# Training', 134),
                 ('# Validation', 66)]),
    'mean_cv_score': 0.6041570221188047,
    'binary_classification_threshold': 0.47437131050216075}],
  'percent_better_than_baseline_all_objectives': {'Log Loss Binary': 84.
↪84244358059615,
   'MCC Binary': inf,
   'Gini': inf,
   'AUC': 29.49455205811139,
   'Precision': 94.44444444444446,
   'F1': 64.61538461538461,
   'Balanced Accuracy Binary': 26.205609362389026,
   'Accuracy Binary': 5.502789084878645},
  'percent_better_than_baseline': 84.84244358059615,
  'validation_score': 0.5936927052183711}},
 'search_order': [0, 1, 2, 3, 4, 5, 6, 7, 8]}
```

4.1.12 Parallel AutoML

By default, all pipelines in an AutoML batch are evaluated in series. Pipelines can be evaluated in parallel to improve performance during AutoML search. This is accomplished by a futures style submission and evaluation of pipelines in a batch. As of this writing, the pipelines use a threaded model for concurrent evaluation. This is similar to the currently implemented `n_jobs` parameter in the estimators, which uses increased numbers of threads to train and evaluate estimators.

Parallelism with Concurrent Futures

The `EngineBase` class is robust and extensible enough to support futures-like implementations from a variety of libraries. The `CFEngine` extends the `EngineBase` to use the native Python concurrent.futures library. The `CFEngine` supports both thread- and process-level parallelism. The type of parallelism can be chosen using either the `ThreadPoolExecutor` or the `ProcessPoolExecutor`. If either executor is passed a `max_workers` parameter, it will set the number of processes and threads spawned. If not, the default number of processes will be equal to the number of processors available and the number of threads set to five times the number of processors available.

[26]:
```
from concurrent.futures import ThreadPoolExecutor

from evalml.automl.engine import CFEngine
from evalml.automl.engine.cf_engine import CFClient

# Use thread-level parallelism
threaded_cf_engine = CFEngine(CFClient(ThreadPoolExecutor()))

automl_cf_threaded = AutoMLSearch(X_train=X, y_train=y,
                                  problem_type="binary",
                                  allowed_model_families=[ModelFamily.LINEAR_MODEL],
                                  engine=threaded_cf_engine)
automl_cf_threaded.search(show_iteration_plot = False)
```

```
Using default limit of max_batches=1.

Generating pipelines to search over...
2 pipelines ready for search.

*****************************
* Beginning pipeline search *
*****************************

Optimizing for Log Loss Binary.
Lower score is better.

Using CFEngine to train and score pipelines.
Searching up to 1 batches for a total of 3 pipelines.
Allowed model families: linear_model

Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 12.868

*****************************
* Evaluating Batch Number 1 *
*****************************
```

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```
Elastic Net Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.077
Logistic Regression Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.077
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Logistic Regression Classifier w/ Imputer + Standard Scaler may not perform␣
↪as estimated on unseen data.

Search finished after 00:04
Best pipeline: Logistic Regression Classifier w/ Imputer + Standard Scaler
Best pipeline Log Loss Binary: 0.076807
```

Note: the cell demonstrating process-level parallelism is commented out due to incompatibility with our ReadTheDocs build. It can be run successfully locally.

```
from concurrent.futures import ProcessPoolExecutor

# Repeat the process but using process-level parallelism
process_cf_engine = CFEngine(CFClient(ProcessPoolExecutor()))

automl_cf_process = AutoMLSearch(X_train=X, y_train=y,
                                 problem_type="binary",
                                 engine=process_cf_engine)
automl_cf_process.search(show_iteration_plot = False)
```

Parallelism with Dask

Thread or process level parallelism can be explicitly invoked for the `DaskEngine` (as well as the `CFEngine`). The `processes` can be set to `True` and the number of processes set using `n_workers`. If `processes` is set to `False`, then the resulting parallelism will be threaded and `n_workers` will represent the threads used. Examples of both follow.

[27]:
```
from dask.distributed import Client, LocalCluster

from evalml.automl.engine import DaskEngine

dask_engine_p2 = DaskEngine(Client(LocalCluster(processes=True, n_workers = 2)))
automl_dask_p2 = AutoMLSearch(X_train=X, y_train=y,
                              problem_type="binary",
                              allowed_model_families=[ModelFamily.LINEAR_MODEL],
                              engine=dask_engine_p2)
automl_dask_p2.search(show_iteration_plot = False)
del(dask_engine_p2)
```

```
Using default limit of max_batches=1.

Generating pipelines to search over...
2 pipelines ready for search.

*****************************
* Beginning pipeline search *
*****************************
```

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```
Optimizing for Log Loss Binary.
Lower score is better.

Using DaskEngine to train and score pipelines.
Searching up to 1 batches for a total of 3 pipelines.
Allowed model families: linear_model

Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 12.868

*****************************
* Evaluating Batch Number 1 *
*****************************

Elastic Net Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.077
Logistic Regression Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.077
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Logistic Regression Classifier w/ Imputer + Standard Scaler may not perform␣
↪as estimated on unseen data.

Search finished after 00:09
Best pipeline: Logistic Regression Classifier w/ Imputer + Standard Scaler
Best pipeline Log Loss Binary: 0.076807
```

[28]:
```
dask_engine_t4 = DaskEngine(Client(LocalCluster(processes=False, n_workers = 4)))

automl_dask_t4 = AutoMLSearch(X_train=X, y_train=y,
                              problem_type="binary",
                              allowed_model_families=[ModelFamily.LINEAR_MODEL],
                              engine=dask_engine_t4)
automl_dask_t4.search(show_iteration_plot = False)
```

```
Using default limit of max_batches=1.

Generating pipelines to search over...
2 pipelines ready for search.

*****************************
* Beginning pipeline search *
*****************************

Optimizing for Log Loss Binary.
Lower score is better.

Using DaskEngine to train and score pipelines.
Searching up to 1 batches for a total of 3 pipelines.
Allowed model families: linear_model

Evaluating Baseline Pipeline: Mode Baseline Binary Classification Pipeline
```

```
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.30.1/
↪lib/python3.8/site-packages/distributed/node.py:160: UserWarning:

Port 8787 is already in use.
Perhaps you already have a cluster running?
Hosting the HTTP server on port 41335 instead
```

```
Mode Baseline Binary Classification Pipeline:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 12.868

*****************************
* Evaluating Batch Number 1 *
*****************************

Elastic Net Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.077
Logistic Regression Classifier w/ Imputer + Standard Scaler:
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.077
        High coefficient of variation (cv >= 0.2) within cross validation scores.
        Logistic Regression Classifier w/ Imputer + Standard Scaler may not perform␣
↪as estimated on unseen data.

Search finished after 00:05
Best pipeline: Logistic Regression Classifier w/ Imputer + Standard Scaler
Best pipeline Log Loss Binary: 0.076807
```

As we can see, a significant performance gain can result from simply using something other than the default `SequentialEngine`, ranging from a 100% speed up with multiple processes to 250% speedup with multiple threads!

[29]:
```
print("Sequential search duration: %s" % str(automl.search_duration))
print("Concurrent futures (threaded) search duration: %s" % str(automl_cf_threaded.
↪search_duration))
print("Dask (two processes) search duration: %s" % str(automl_dask_p2.search_
↪duration))
print("Dask (four threads)search duration: %s" % str(automl_dask_t4.search_duration))
```

```
Sequential search duration: 22.637789726257324
Concurrent futures (threaded) search duration: 4.5792765617370605
Dask (two processes) search duration: 9.308585405349731
Dask (four threads)search duration: 5.546856164932251
```

4.2 Objectives

4.2.1 Overview

One of the key choices to make when training an ML model is what metric to choose by which to measure the efficacy of the model at learning the signal. Such metrics are useful for comparing how well the trained models generalize to new similar data.

This choice of metric is a key component of AutoML because it defines the cost function the AutoML search will seek to optimize. In EvalML, these metrics are called **objectives**. AutoML will seek to minimize (or maximize)

the objective score as it explores more pipelines and parameters and will use the feedback from scoring pipelines to tune the available hyperparameters and continue the search. Therefore, it is critical to have an objective function that represents how the model will be applied in the intended domain of use.

EvalML supports a variety of objectives from traditional supervised ML including mean squared error for regression problems and cross entropy or area under the ROC curve for classification problems. EvalML also allows the user to define a custom objective using their domain expertise, so that AutoML can search for models which provide the most value for the user's problem.

4.2.2 Core Objectives

Use the `get_core_objectives` method to get a list of which objectives are included with EvalML for each problem type:

[1]:
```
from evalml.objectives import get_core_objectives
from evalml.problem_types import ProblemTypes

for objective in get_core_objectives(ProblemTypes.BINARY):
    print(objective.name)
```

```
MCC Binary
Log Loss Binary
Gini
AUC
Precision
F1
Balanced Accuracy Binary
Accuracy Binary
```

EvalML defines a base objective class for each problem type: `RegressionObjective`, `BinaryClassificationObjective` and `MulticlassClassificationObjective`. All EvalML objectives are a subclass of one of these.

Binary Classification Objectives and Thresholds

All binary classification objectives have a `threshold` property. Some binary classification objectives like log loss and AUC are unaffected by the choice of binary classification threshold, because they score based on predicted probabilities or examine a range of threshold values. These metrics are defined with `score_needs_proba` set to False. For all other binary classification objectives, we can compute the optimal binary classification threshold from the predicted probabilities and the target.

[2]:
```
from evalml.pipelines import BinaryClassificationPipeline
from evalml.demos import load_fraud
from evalml.objectives import F1

X, y = load_fraud(n_rows=100)
X.ww.init(logical_types={"provider": "Categorical", "region": "Categorical"})
objective = F1()
pipeline = BinaryClassificationPipeline(component_graph=['Simple Imputer', 'DateTime␣
↪Featurization Component', 'One Hot Encoder', 'Random Forest Classifier'])
pipeline.fit(X, y)
print(pipeline.threshold)
print(pipeline.score(X, y, objectives=[objective]))

y_pred_proba = pipeline.predict_proba(X)[True]
```

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```
pipeline.threshold = objective.optimize_threshold(y_pred_proba, y)
print(pipeline.threshold)
print(pipeline.score(X, y, objectives=[objective]))
```

```
             Number of Features
Boolean                       1
Categorical                   6
Numeric                       5

Number of training examples: 100
Targets
False    91.00%
True      9.00%
Name: fraud, dtype: object
None
OrderedDict([('F1', 1.0)])
0.5202757772593112
OrderedDict([('F1', 1.0)])
```

4.2.3 Custom Objectives

Often times, the objective function is very specific to the use-case or business problem. To get the right objective to optimize requires thinking through the decisions or actions that will be taken using the model and assigning a cost/benefit to doing that correctly or incorrectly based on known outcomes in the training data.

Once you have determined the objective for your business, you can provide that to EvalML to optimize by defining a custom objective function.

Defining a Custom Objective Function

To create a custom objective class, we must define several elements:

- `name`: The printable name of this objective.
- `objective_function`: This function takes the predictions, true labels, and an optional reference to the inputs, and returns a score of how well the model performed.
- `greater_is_better`: `True` if a higher `objective_function` value represents a better solution, and otherwise `False`.
- `score_needs_proba`: Only for classification objectives. `True` if the objective is intended to function with predicted probabilities as opposed to predicted values (example: cross entropy for classifiers).
- `decision_function`: Only for binary classification objectives. This function takes predicted probabilities that were output from the model and a binary classification threshold, and returns predicted values.
- `perfect_score`: The score achieved by a perfect model on this objective.

Example: Fraud Detection

To give a concrete example, let's look at how the *fraud detection* objective function is built.

[3]:
```
from evalml.objectives.binary_classification_objective import␣
↪BinaryClassificationObjective
import pandas as pd


class FraudCost(BinaryClassificationObjective):
    """Score the percentage of money lost of the total transaction amount process due␣
↪to fraud"""
    name = "Fraud Cost"
    greater_is_better = False
    score_needs_proba = False
    perfect_score = 0.0

    def __init__(self, retry_percentage=.5, interchange_fee=.02,
                 fraud_payout_percentage=1.0, amount_col='amount'):
        """Create instance of FraudCost

        Arguments:
            retry_percentage (float): What percentage of customers that will retry a␣
↪transaction if it
                is declined. Between 0 and 1. Defaults to .5

            interchange_fee (float): How much of each successful transaction you can␣
↪collect.
                Between 0 and 1. Defaults to .02

            fraud_payout_percentage (float): Percentage of fraud you will not be able␣
↪to collect.
                Between 0 and 1. Defaults to 1.0

            amount_col (str): Name of column in data that contains the amount.␣
↪Defaults to "amount"
        """
        self.retry_percentage = retry_percentage
        self.interchange_fee = interchange_fee
        self.fraud_payout_percentage = fraud_payout_percentage
        self.amount_col = amount_col

    def decision_function(self, ypred_proba, threshold=0.0, X=None):
        """Determine if a transaction is fraud given predicted probabilities,␣
↪threshold, and dataframe with transaction amount

            Arguments:
                ypred_proba (pd.Series): Predicted probablities
                X (pd.DataFrame): Dataframe containing transaction amount
                threshold (float): Dollar threshold to determine if transaction is␣
↪fraud

            Returns:
                pd.Series: Series of predicted fraud labels using X and threshold
        """
        if not isinstance(X, pd.DataFrame):
            X = pd.DataFrame(X)
```

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```
        if not isinstance(ypred_proba, pd.Series):
            ypred_proba = pd.Series(ypred_proba)

        transformed_probs = (ypred_proba.values * X[self.amount_col])
        return transformed_probs > threshold

    def objective_function(self, y_true, y_predicted, X):
        """Calculate amount lost to fraud per transaction given predictions, true␣
↪values, and dataframe with transaction amount

            Arguments:
                y_predicted (pd.Series): predicted fraud labels
                y_true (pd.Series): true fraud labels
                X (pd.DataFrame): dataframe with transaction amounts

            Returns:
                float: amount lost to fraud per transaction
        """
        if not isinstance(X, pd.DataFrame):
            X = pd.DataFrame(X)

        if not isinstance(y_predicted, pd.Series):
            y_predicted = pd.Series(y_predicted)

        if not isinstance(y_true, pd.Series):
            y_true = pd.Series(y_true)

        # extract transaction using the amount columns in users data
        try:
            transaction_amount = X[self.amount_col]
        except KeyError:
            raise ValueError("`{}` is not a valid column in X.".format(self.amount_
↪col))

        # amount paid if transaction is fraud
        fraud_cost = transaction_amount * self.fraud_payout_percentage

        # money made from interchange fees on transaction
        interchange_cost = transaction_amount * (1 - self.retry_percentage) * self.
↪interchange_fee

        # calculate cost of missing fraudulent transactions
        false_negatives = (y_true & ~y_predicted) * fraud_cost

        # calculate money lost from fees
        false_positives = (~y_true & y_predicted) * interchange_cost

        loss = false_negatives.sum() + false_positives.sum()

        loss_per_total_processed = loss / transaction_amount.sum()

        return loss_per_total_processed
```

4.3 Components

Components are the lowest level of building blocks in EvalML. Each component represents a fundamental operation to be applied to data.

All components accept parameters as keyword arguments to their `__init__` methods. These parameters can be used to configure behavior.

Each component class definition must include a human-readable `name` for the component. Additionally, each component class may expose parameters for AutoML search by defining a `hyperparameter_ranges` attribute containing the parameters in question.

EvalML splits components into two categories: **transformers** and **estimators**.

4.3.1 Transformers

Transformers subclass the `Transformer` class, and define a `fit` method to learn information from training data and a `transform` method to apply a learned transformation to new data.

For example, an *imputer* is configured with the desired impute strategy to follow, for instance the mean value. The imputers `fit` method would learn the mean from the training data, and the `transform` method would fill the learned mean value in for any missing values in new data.

All transformers can execute `fit` and `transform` separately or in one step by calling `fit_transform`. Defining a custom `fit_transform` method can facilitate useful performance optimizations in some cases.

[1]:
```
import numpy as np
import pandas as pd
from evalml.pipelines.components import SimpleImputer

X = pd.DataFrame([[1, 2, 3], [1, np.nan, 3]])
display(X)
```

```
   0    1  2
0  1  2.0  3
1  1  NaN  3
```

[2]:
```
import woodwork as ww
imp = SimpleImputer(impute_strategy="mean")

X.ww.init()
X = imp.fit_transform(X)
display(X)
```

```
   0    1  2
0  1  2.0  3
1  1  2.0  3
```

Below is a list of all transformers included with EvalML:

[3]:
```
from evalml.pipelines.components.utils import all_components, Estimator, Transformer
for component in all_components():
    if issubclass(component, Transformer):
        print(f"Transformer: {component.name}")
```

```
Transformer: URL Featurizer
Transformer: Email Featurizer
Transformer: DFS Transformer
```

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```
Transformer: Delayed Feature Transformer
Transformer: Text Featurization Component
Transformer: LSA Transformer
Transformer: Drop Null Columns Transformer
Transformer: DateTime Featurization Component
Transformer: PCA Transformer
Transformer: Linear Discriminant Analysis Transformer
Transformer: Select Columns By Type Transformer
Transformer: Select Columns Transformer
Transformer: Drop Columns Transformer
Transformer: Undersampler
Transformer: SMOTEN Oversampler
Transformer: SMOTENC Oversampler
Transformer: SMOTE Oversampler
Transformer: Standard Scaler
Transformer: Target Imputer
Transformer: Imputer
Transformer: Per Column Imputer
Transformer: Simple Imputer
Transformer: RF Regressor Select From Model
Transformer: RF Classifier Select From Model
Transformer: Target Encoder
Transformer: One Hot Encoder
Transformer: Log Transformer
Transformer: Polynomial Detrender
```

4.3.2 Estimators

Each estimator wraps an ML algorithm. Estimators subclass the `Estimator` class, and define a `fit` method to learn information from training data and a `predict` method for generating predictions from new data. Classification estimators should also define a `predict_proba` method for generating predicted probabilities.

Estimator classes each define a `model_family` attribute indicating what type of model is used.

Here's an example of using the *LogisticRegressionClassifier* estimator to fit and predict on a simple dataset:

[4]:
```
from evalml.pipelines.components import LogisticRegressionClassifier

clf = LogisticRegressionClassifier()

X = X
y = [1, 0]

clf.fit(X, y)
clf.predict(X)
```

[4]:
```
0    0
1    0
dtype: int64
```

Below is a list of all estimators included with EvalML:

[5]:
```
from evalml.pipelines.components.utils import all_components, Estimator, Transformer
for component in all_components():
    if issubclass(component, Estimator):
        print(f"Estimator: {component.name}")
```

```
Estimator: Sklearn Stacked Ensemble Regressor
Estimator: Sklearn Stacked Ensemble Classifier
Estimator: ARIMA Regressor
Estimator: SVM Regressor
Estimator: Time Series Baseline Estimator
Estimator: Decision Tree Regressor
Estimator: Baseline Regressor
Estimator: Extra Trees Regressor
Estimator: XGBoost Regressor
Estimator: CatBoost Regressor
Estimator: Random Forest Regressor
Estimator: LightGBM Regressor
Estimator: Linear Regressor
Estimator: Elastic Net Regressor
Estimator: SVM Classifier
Estimator: KNN Classifier
Estimator: Decision Tree Classifier
Estimator: LightGBM Classifier
Estimator: Baseline Classifier
Estimator: Extra Trees Classifier
Estimator: Elastic Net Classifier
Estimator: CatBoost Classifier
Estimator: XGBoost Classifier
Estimator: Random Forest Classifier
Estimator: Logistic Regression Classifier
```

4.3.3 Defining Custom Components

EvalML allows you to easily create your own custom components by following the steps below.

Custom Transformers

Your transformer must inherit from the correct subclass. In this case *Transformer* for components that transform data. Next we will use EvalML's *DropNullColumns* as an example.

[6]:
```
from evalml.pipelines.components import Transformer
from evalml.utils import (
    infer_feature_types,
)

class DropNullColumns(Transformer):
    """Transformer to drop features whose percentage of NaN values exceeds a␣
↪specified threshold"""
    name = "Drop Null Columns Transformer"
    hyperparameter_ranges = {}

    def __init__(self, pct_null_threshold=1.0, random_seed=0, **kwargs):
        """Initalizes an transformer to drop features whose percentage of NaN values␣
↪exceeds a specified threshold.

        Arguments:
            pct_null_threshold(float): The percentage of NaN values in an input␣
↪feature to drop.
                Must be a value between [0, 1] inclusive. If equal to 0.0, will drop␣
↪columns with any null values.
```

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```
                If equal to 1.0, will drop columns with all null values. Defaults to␣
↪0.95.
        """
        if pct_null_threshold < 0 or pct_null_threshold > 1:
            raise ValueError("pct_null_threshold must be a float between 0 and 1,␣
↪inclusive.")
        parameters = {"pct_null_threshold": pct_null_threshold}
        parameters.update(kwargs)

        self._cols_to_drop = None
        super().__init__(parameters=parameters,
                         component_obj=None,
                         random_seed=random_seed)

    def fit(self, X, y=None):
        """Fits DropNullColumns component to data

        Arguments:
            X (pd.DataFrame): The input training data of shape [n_samples, n_features]
            y (pd.Series, optional): The target training data of length [n_samples]

        Returns:
            self
        """
        pct_null_threshold = self.parameters["pct_null_threshold"]
        X_t = infer_feature_types(X)
        percent_null = X_t.isnull().mean()
        if pct_null_threshold == 0.0:
            null_cols = percent_null[percent_null > 0]
        else:
            null_cols = percent_null[percent_null >= pct_null_threshold]
        self._cols_to_drop = list(null_cols.index)
        return self

    def transform(self, X, y=None):
        """Transforms data X by dropping columns that exceed the threshold of null␣
↪values.

        Arguments:
            X (pd.DataFrame): Data to transform
            y (pd.Series, optional): Ignored.

        Returns:
            pd.DataFrame: Transformed X
        """
        X_t = infer_feature_types(X)
        return X_t.drop(self._cols_to_drop)
```

Required fields

- `name`: A human-readable name.
- `modifies_features`: A boolean that specifies whether this component modifies (subsets or transforms) the features variable during `transform`.
- `modifies_target`: A boolean that specifies whether this component modifies (subsets or transforms) the target variable during `transform`.

Required methods

Likewise, there are select methods you need to override as `Transformer` is an abstract base class:

- `__init__()`: The `__init__()` method of your transformer will need to call `super().__init__()` and pass three parameters in: a `parameters` dictionary holding the parameters to the component, the `component_obj`, and the `random_seed` value. You can see that `component_obj` is set to `None` above and we will discuss `component_obj` in depth later on.
- `fit()`: The `fit()` method is responsible for fitting your component on training data. It should return the component object.
- `transform()`: After fitting a component, the `transform()` method will take in new data and transform accordingly. It should return a pandas dataframe with woodwork initialized. Note: a component must call `fit()` before `transform()`.

You can also call or override `fit_transform()` that combines `fit()` and `transform()` into one method.

Custom Estimators

Your estimator must inherit from the correct subclass. In this case *Estimator* for components that predict new target values. Next we will use EvalML's *BaselineRegressor* as an example.

[7]:
```
import numpy as np
import pandas as pd

from evalml.model_family import ModelFamily
from evalml.pipelines.components.estimators import Estimator
from evalml.problem_types import ProblemTypes


class BaselineRegressor(Estimator):
    """Regressor that predicts using the specified strategy.

    This is useful as a simple baseline regressor to compare with other regressors.
    """
    name = "Baseline Regressor"
    hyperparameter_ranges = {}
    model_family = ModelFamily.BASELINE
    supported_problem_types = [ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_
↪REGRESSION]

    def __init__(self, strategy="mean", random_seed=0, **kwargs):
        """Baseline regressor that uses a simple strategy to make predictions.

        Arguments:
```

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```
            strategy (str): Method used to predict. Valid options are "mean", "median
↪". Defaults to "mean".
            random_seed (int): Seed for the random number generator. Defaults to 0.

        """
        if strategy not in ["mean", "median"]:
            raise ValueError("'strategy' parameter must equal either 'mean' or 'median
↪'")
        parameters = {"strategy": strategy}
        parameters.update(kwargs)

        self._prediction_value = None
        self._num_features = None
        super().__init__(parameters=parameters,
                         component_obj=None,
                         random_seed=random_seed)

    def fit(self, X, y=None):
        if y is None:
            raise ValueError("Cannot fit Baseline regressor if y is None")
        X = infer_feature_types(X)
        y = infer_feature_types(y)

        if self.parameters["strategy"] == "mean":
            self._prediction_value = y.mean()
        elif self.parameters["strategy"] == "median":
            self._prediction_value = y.median()
        self._num_features = X.shape[1]
        return self

    def predict(self, X):
        X = infer_feature_types(X)
        predictions = pd.Series([self._prediction_value] * len(X))
        return infer_feature_types(predictions)

    @property
    def feature_importance(self):
        """Returns importance associated with each feature. Since baseline regressors␣
↪do not use input features to calculate predictions, returns an array of zeroes.

        Returns:
            np.ndarray (float): An array of zeroes

        """
        return np.zeros(self._num_features)
```

Required fields

- `name`: A human-readable name.
- `model_family` - EvalML *model_family* that this component belongs to
- `supported_problem_types` - list of EvalML *problem_types* that this component supports
- `modifies_features`: A boolean that specifies whether the return value from `predict` or `predict_proba` should be used as features.
- `modifies_target`: A boolean that specifies whether the return value from `predict` or `predict_proba` should be used as the target variable.

Model families and problem types include:

[8]:
```
from evalml.model_family import ModelFamily
from evalml.problem_types import ProblemTypes

print("Model Families:\n", [m.value for m in ModelFamily])
print("Problem Types:\n", [p.value for p in ProblemTypes])
```

```
Model Families:
 ['k_neighbors', 'random_forest', 'svm', 'xgboost', 'lightgbm', 'linear_model',
↪'catboost', 'extra_trees', 'ensemble', 'decision_tree', 'arima', 'baseline',
↪'prophet', 'none']
Problem Types:
 ['binary', 'multiclass', 'regression', 'time series regression', 'time series binary
↪', 'time series multiclass']
```

Required methods

- `__init__()` - the `__init__()` method of your estimator will need to call `super().__init__()` and pass three parameters in: a `parameters` dictionary holding the parameters to the component, the `component_obj`, and the `random_seed` value.
- `fit()` - the `fit()` method is responsible for fitting your component on training data.
- `predict()` - after fitting a component, the `predict()` method will take in new data and predict new target values. Note: a component must call `fit()` before `predict()`.
- `feature_importance` - `feature_importance` is a Python property that returns a list of importances associated with each feature.

If your estimator handles classification problems it also requires an additonal method:

- `predict_proba()` - this method predicts probability estimates for classification labels

Components Wrapping Third-Party Objects

The `component_obj` parameter is used for wrapping third-party objects and using them in component implementation. If you're using a `component_obj` you will need to define `__init__()` and pass in the relevant object that has also implemented the required methods mentioned above. However, if the `component_obj` does not follow EvalML component conventions, you may need to override methods as needed. Below is an example of EvalML's *LinearRegressor*.

[9]:
```
from sklearn.linear_model import LinearRegression as SKLinearRegression

from evalml.model_family import ModelFamily
from evalml.pipelines.components.estimators import Estimator
from evalml.problem_types import ProblemTypes

class LinearRegressor(Estimator):
    """Linear Regressor."""
    name = "Linear Regressor"
    model_family = ModelFamily.LINEAR_MODEL
    supported_problem_types = [ProblemTypes.REGRESSION]

    def __init__(self, fit_intercept=True, normalize=False, n_jobs=-1, random_seed=0,␣
↪**kwargs):
        parameters = {
            'fit_intercept': fit_intercept,
            'normalize': normalize,
            'n_jobs': n_jobs
        }
        parameters.update(kwargs)
        linear_regressor = SKLinearRegression(**parameters)
        super().__init__(parameters=parameters,
                         component_obj=linear_regressor,
                         random_seed=random_seed)

    @property
    def feature_importance(self):
        return self._component_obj.coef_
```

Hyperparameter Ranges for AutoML

`hyperparameter_ranges` is a dictionary mapping the parameter name (str) to an allowed range (SkOpt Space) for that parameter. Both lists and `skopt.space.Categorical` values are accepted for categorical spaces.

AutoML will perform a search over the allowed ranges for each parameter to select models which produce optimal performance within those ranges. AutoML gets the allowed ranges for each component from the component's `hyperparameter_ranges` class attribute. Any component parameter you add an entry for in `hyperparameter_ranges` will be included in the AutoML search. If parameters are omitted, AutoML will use the default value in all pipelines.

4.3.4 Generate Component Code

Once you have a component defined in EvalML, you can generate string Python code to recreate this component, which can then be saved and run elsewhere with EvalML. `generate_component_code` requires a component instance as the input. This method works for custom components as well, although it won't return the code required to define the custom component.

[10]:
```
from evalml.pipelines.components import LogisticRegressionClassifier
from evalml.pipelines.components.utils import generate_component_code

lr = LogisticRegressionClassifier(C=5)
code = generate_component_code(lr)
print(code)
```

```
from evalml.pipelines.components.estimators.classifiers.logistic_regression_
↪classifier import LogisticRegressionClassifier

logisticRegressionClassifier = LogisticRegressionClassifier(**{'penalty': 'l2', 'C':␣
↪5, 'n_jobs': -1, 'multi_class': 'auto', 'solver': 'lbfgs'})
```

[11]:
```
# this string can then be copy and pasted into a separate window and executed as␣
↪python code
exec(code)
```

[12]:
```
# We can also do this for custom components
from evalml.pipelines.components.utils import generate_component_code

myDropNull = DropNullColumns()
print(generate_component_code(myDropNull))
```

```
dropNullColumnsTransformer = DropNullColumns(**{'pct_null_threshold': 1.0})
```

Expectations for Custom Classification Components

EvalML expects the following from custom classification component implementations:

- Classification targets will range from 0 to n-1 and are integers.
- For classification estimators, the order of predict_proba's columns must match the order of the target, and the column names must be integers ranging from 0 to n-1

4.4 Pipelines

EvalML pipelines represent a sequence of operations to be applied to data, where each operation is either a data transformation or an ML modeling algorithm.

A pipeline holds a combination of one or more components, which will be applied to new input data in sequence.

Each component and pipeline supports a set of parameters which configure its behavior. The AutoML search process seeks to find the combination of pipeline structure and pipeline parameters which perform the best on the data.

4.4.1 Defining a Pipeline Instance

Pipeline instances can be instantiated using any of the following classes:

- `RegressionPipeline`
- `BinaryClassificationPipeline`
- `MulticlassClassificationPipeline`
- `TimeSeriesRegressionPipeline`
- `TimeSeriesBinaryClassificationPipeline`
- `TimeSeriesMulticlassClassificationPipeline`

The class you want to use will depend on your problem type. The only required parameter input for instantiating a pipeline instance is `component_graph`, which is either a list or a dictionary containing a sequence of components to be fit and evaluated.

A `component_graph` list is the default representation, which represents a linear order of transforming components with an estimator as the final component. A `component_graph` dictionary is used to represent a non-linear graph of components, where the key is a unique name for each component and the value is a list with the component's class as the first element and any parents of the component as the following element(s). For either `component_graph` format, each component can be provided as a reference to the component class for custom components, and as either a string name or as a reference to the component class for components defined in EvalML.

[1]:
```
from evalml.pipelines import MulticlassClassificationPipeline

component_graph_as_list = ['Imputer', 'Random Forest Classifier']
MulticlassClassificationPipeline(component_graph=component_graph_as_list)
```

[1]:
```
pipeline = MulticlassClassificationPipeline(component_graph={'Imputer': ['Imputer', 'X
↪', 'y'], 'Random Forest Classifier': ['Random Forest Classifier', 'Imputer.x', 'y']}
↪, parameters={'Imputer':{'categorical_impute_strategy': 'most_frequent', 'numeric_
↪impute_strategy': 'mean', 'categorical_fill_value': None, 'numeric_fill_value':␣
↪None}, 'Random Forest Classifier':{'n_estimators': 100, 'max_depth': 6, 'n_jobs': -
↪1}}, random_seed=0)
```

[2]:
```
component_graph_as_dict = {
    'Imputer': ['Imputer', 'X', 'y'],
    'Encoder': ['One Hot Encoder', 'Imputer.x', 'y'],
    'Random Forest Clf': ['Random Forest Classifier', 'Encoder.x', 'y'],
    'Elastic Net Clf': ['Elastic Net Classifier', 'Encoder.x', 'y'],
    'Final Estimator': ['Logistic Regression Classifier', 'Random Forest Clf.x',
↪'Elastic Net Clf.x', 'y']
}

MulticlassClassificationPipeline(component_graph=component_graph_as_dict)
```

[2]:
```
pipeline = MulticlassClassificationPipeline(component_graph={'Imputer': ['Imputer', 'X
↪', 'y'], 'Encoder': ['One Hot Encoder', 'Imputer.x', 'y'], 'Random Forest Clf': [
↪'Random Forest Classifier', 'Encoder.x', 'y'], 'Elastic Net Clf': ['Elastic Net␣
↪Classifier', 'Encoder.x', 'y'], 'Final Estimator': ['Logistic Regression Classifier
↪', 'Random Forest Clf.x', 'Elastic Net Clf.x', 'y']}, parameters={'Imputer':{
↪'categorical_impute_strategy': 'most_frequent', 'numeric_impute_strategy': 'mean',
↪'categorical_fill_value': None, 'numeric_fill_value': None}, 'Encoder':{'top_n': 10,
↪ 'features_to_encode': None, 'categories': None, 'drop': 'if_binary', 'handle_
↪unknown': 'ignore', 'handle_missing': 'error'}, 'Random Forest Clf':{'n_estimators':
↪ 100, 'max_depth': 6, 'n_jobs': -1}, 'Elastic Net Clf':{'penalty': 'elasticnet', 'C
↪': 1.0, 'l1_ratio': 0.15, 'n_jobs': -1, 'multi_class': 'auto', 'solver': 'saga'},
↪'Final Estimator':{'penalty': 'l2', 'C': 1.0, 'n_jobs': -1, 'multi_class': 'auto',
↪'solver': 'lbfgs'}}, random_seed=0)
```

If you're using your own *custom components* you can refer to them like so:

[3]:
```
from evalml.pipelines.components import Transformer

class NewTransformer(Transformer):
    name = 'New Transformer'
    hyperparameter_ranges = {
        "parameter_1":['a', 'b', 'c']
    }

    def __init__(self, parameter_1=1, random_seed=0):
        parameters = {"parameter_1": parameter_1}
        super().__init__(parameters=parameters,
                         random_seed=random_seed)
```

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```
MulticlassClassificationPipeline([NewTransformer, 'Random Forest Classifier'])
```

[3]:
```
pipeline = MulticlassClassificationPipeline(component_graph={'New Transformer':␣
↪[NewTransformer, 'X', 'y'], 'Random Forest Classifier': ['Random Forest Classifier',
↪ 'New Transformer.x', 'y']}, parameters={'New Transformer':{'parameter_1': 1},
↪'Random Forest Classifier':{'n_estimators': 100, 'max_depth': 6, 'n_jobs': -1}},␣
↪random_seed=0)
```

4.4.2 Pipeline Usage

All pipelines define the following methods:

- `fit` fits each component on the provided training data, in order.
- `predict` computes the predictions of the component graph on the provided data.
- `score` computes the value of *an objective* on the provided data.

[4]:
```
from evalml.demos import load_wine
X, y = load_wine()

pipeline = MulticlassClassificationPipeline(['Imputer', 'Random Forest Classifier'])
pipeline.fit(X, y)
print(pipeline.predict(X))
print(pipeline.score(X, y, objectives=['log loss multiclass']))
```

```
         Number of Features
Numeric                  13

Number of training examples: 178
Targets
class_1    39.89%
class_0    33.15%
class_2    26.97%
Name: target, dtype: object
0      class_0
1      class_0
2      class_0
3      class_0
4      class_0
        ...
173    class_2
174    class_2
175    class_2
176    class_2
177    class_2
Length: 178, dtype: category
Categories (3, object): ['class_0', 'class_1', 'class_2']
OrderedDict([('Log Loss Multiclass', 0.04132737017536148)])
```

4.4.3 Custom Name

By default, a pipeline's name is created using the component graph that makes up the pipeline. E.g. A pipeline with an imputer, one-hot encoder, and logistic regression classifier will have the name 'Logistic Regression Classifier w/ Imputer + One Hot Encoder'.

If you'd like to override the pipeline's name attribute, you can set the `custom_name` parameter when initalizing a pipeline, like so:

[5]:
```
component_graph = ['Imputer', 'One Hot Encoder', 'Logistic Regression Classifier']
pipeline = MulticlassClassificationPipeline(component_graph)
print("Pipeline with default name:", pipeline.name)


pipeline_with_name = MulticlassClassificationPipeline(component_graph, custom_name=
↪"My cool custom pipeline")
print("Pipeline with custom name:", pipeline_with_name.name)
```

```
Pipeline with default name: Logistic Regression Classifier w/ Imputer + One Hot␣
↪Encoder
Pipeline with custom name: My cool custom pipeline
```

4.4.4 Pipeline Parameters

You can also pass in custom parameters by using the `parameters` parameter, which will then be used when instantiating each component in `component_graph`. The parameters dictionary needs to be in the format of a two-layered dictionary where the key-value pairs are the component name and corresponding component parameters dictionary. The component parameters dictionary consists of (parameter name, parameter values) key-value pairs.

An example will be shown below. The API reference for component parameters can also be found [here] (../api_reference.rst#components).

[6]:
```
parameters = {
        'Imputer': {
            "categorical_impute_strategy": "most_frequent",
            "numeric_impute_strategy": "median"
        },
        'Logistic Regression Classifier': {
            'penalty': 'l2',
            'C': 1.0,
        }
    }
component_graph = ['Imputer', 'One Hot Encoder', 'Standard Scaler', 'Logistic␣
↪Regression Classifier']
MulticlassClassificationPipeline(component_graph=component_graph,␣
↪parameters=parameters)
```

[6]:
```
pipeline = MulticlassClassificationPipeline(component_graph={'Imputer': ['Imputer', 'X
↪', 'y'], 'One Hot Encoder': ['One Hot Encoder', 'Imputer.x', 'y'], 'Standard Scaler
↪': ['Standard Scaler', 'One Hot Encoder.x', 'y'], 'Logistic Regression Classifier':␣
↪['Logistic Regression Classifier', 'Standard Scaler.x', 'y']}, parameters={'Imputer
↪':{'categorical_impute_strategy': 'most_frequent', 'numeric_impute_strategy':
↪'median', 'categorical_fill_value': None, 'numeric_fill_value': None}, 'One Hot␣
↪Encoder':{'top_n': 10, 'features_to_encode': None, 'categories': None, 'drop': 'if_
↪binary', 'handle_unknown': 'ignore', 'handle_missing': 'error'}, 'Logistic␣
↪Regression Classifier':{'penalty': 'l2', 'C': 1.0, 'n_jobs': -1, 'multi_class':
↪'auto', 'solver': 'lbfgs'}}, random_seed=0)
```

4.4.5 Pipeline Description

You can call `.graph()` to see each component and its parameters. Each component takes in data and feeds it to the next.

[7]:
```
component_graph = ['Imputer', 'One Hot Encoder', 'Standard Scaler', 'Logistic␣
↪Regression Classifier']
pipeline = MulticlassClassificationPipeline(component_graph=component_graph,␣
↪parameters=parameters)
pipeline.graph()
```

[7]:

[8]:
```
component_graph_as_dict = {
    'Imputer': ['Imputer', 'X', 'y'],
    'Encoder': ['One Hot Encoder', 'Imputer.x', 'y'],
    'Random Forest Clf': ['Random Forest Classifier', 'Encoder.x', 'y'],
    'Elastic Net Clf': ['Elastic Net Classifier', 'Encoder.x', 'y'],
    'Final Estimator': ['Logistic Regression Classifier', 'Random Forest Clf.x',
↪'Elastic Net Clf.x', 'y']
}

nonlinear_pipeline = MulticlassClassificationPipeline(component_graph=component_graph_
↪as_dict)
nonlinear_pipeline.graph()
```

[8]:

You can see a textual representation of the pipeline by calling `.describe()`:

[9]:
```
pipeline.describe()
```

```
*********************************************************************************
* Logistic Regression Classifier w/ Imputer + One Hot Encoder + Standard Scaler *
*********************************************************************************

Problem Type: multiclass
Model Family: Linear

Pipeline Steps
==============
1. Imputer
         * categorical_impute_strategy : most_frequent
         * numeric_impute_strategy : median
         * categorical_fill_value : None
         * numeric_fill_value : None
2. One Hot Encoder
         * top_n : 10
         * features_to_encode : None
         * categories : None
         * drop : if_binary
         * handle_unknown : ignore
         * handle_missing : error
3. Standard Scaler
4. Logistic Regression Classifier
         * penalty : l2
         * C : 1.0
         * n_jobs : -1
         * multi_class : auto
         * solver : lbfgs
```

[10]:
```
nonlinear_pipeline.describe()
```

```
*********************************************************************************************
* Logistic Regression Classifier w/ Imputer + One Hot Encoder + Random Forest␣
↪Classifier + Elastic Net Classifier *
*********************************************************************************************

Problem Type: multiclass
Model Family: Linear

Pipeline Steps
==============
1. Imputer
         * categorical_impute_strategy : most_frequent
         * numeric_impute_strategy : mean
         * categorical_fill_value : None
         * numeric_fill_value : None
2. One Hot Encoder
         * top_n : 10
         * features_to_encode : None
         * categories : None
         * drop : if_binary
         * handle_unknown : ignore
         * handle_missing : error
3. Random Forest Classifier
         * n_estimators : 100
         * max_depth : 6
         * n_jobs : -1
4. Elastic Net Classifier
         * penalty : elasticnet
         * C : 1.0
         * l1_ratio : 0.15
         * n_jobs : -1
         * multi_class : auto
         * solver : saga
5. Logistic Regression Classifier
         * penalty : l2
         * C : 1.0
         * n_jobs : -1
         * multi_class : auto
         * solver : lbfgs
```

4.4.6 Component Graph

You can use `pipeline.get_component(name)` and provide the component name to access any component (API reference *here*):

[11]:
```
pipeline.get_component('Imputer')
```

[11]:
```
Imputer(categorical_impute_strategy='most_frequent', numeric_impute_strategy='median',
↪ categorical_fill_value=None, numeric_fill_value=None)
```

[12]:
```
nonlinear_pipeline.get_component('Elastic Net Clf')
```

[12]:
```
ElasticNetClassifier(penalty='elasticnet', C=1.0, l1_ratio=0.15, n_jobs=-1, multi_
↪class='auto', solver='saga')
```

Alternatively, you can index directly into the pipeline to get a component

[13]:
```
first_component = pipeline[0]
print(first_component.name)
```

```
Imputer
```

[14]:
```
nonlinear_pipeline['Final Estimator']
```

[14]:
```
LogisticRegressionClassifier(penalty='l2', C=1.0, n_jobs=-1, multi_class='auto',␣
↪solver='lbfgs')
```

4.4.7 Pipeline Estimator

EvalML enforces that the last component of a linear pipeline is an estimator. You can access this estimator directly by using `pipeline.estimator`.

[15]:
```
pipeline.estimator
```

[15]:
```
LogisticRegressionClassifier(penalty='l2', C=1.0, n_jobs=-1, multi_class='auto',␣
↪solver='lbfgs')
```

4.4.8 Input Feature Names

After a pipeline is fitted, you can access a pipeline's `input_feature_names` attribute to obtain a dictionary containing a list of feature names passed to each component of the pipeline. This could be especially useful for debugging where a feature might have been dropped or detecting unexpected behavior.

[16]:
```
pipeline = MulticlassClassificationPipeline(['Imputer', 'Random Forest Classifier'])
pipeline.fit(X, y)
pipeline.input_feature_names
```

[16]:
```
{'Imputer': ['alcohol',
  'malic_acid',
  'ash',
  'alcalinity_of_ash',
  'magnesium',
  'total_phenols',
  'flavanoids',
  'nonflavanoid_phenols',
  'proanthocyanins',
  'color_intensity',
  'hue',
  'od280/od315_of_diluted_wines',
  'proline'],
 'Random Forest Classifier': ['alcohol',
  'malic_acid',
  'ash',
  'alcalinity_of_ash',
  'magnesium',
  'total_phenols',
  'flavanoids',
  'nonflavanoid_phenols',
  'proanthocyanins',
  'color_intensity',
  'hue',
```

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```
 'od280/od315_of_diluted_wines',
 'proline']}
```

4.4.9 Saving and Loading Pipelines

You can save and load trained or untrained pipeline instances using the Python pickle format, like so:

[17]:
```
import pickle

pipeline_to_pickle = MulticlassClassificationPipeline(['Imputer', 'Random Forest␣
↪Classifier'])

with open("pipeline.pkl", 'wb') as f:
    pickle.dump(pipeline_to_pickle, f)

pickled_pipeline = None
with open('pipeline.pkl', 'rb') as f:
    pickled_pipeline = pickle.load(f)

assert pickled_pipeline == pipeline_to_pickle
pickled_pipeline.fit(X, y)
```

[17]:
```
pipeline = MulticlassClassificationPipeline(component_graph={'Imputer': ['Imputer', 'X
↪', 'y'], 'Random Forest Classifier': ['Random Forest Classifier', 'Imputer.x', 'y']}
↪, parameters={'Imputer':{'categorical_impute_strategy': 'most_frequent', 'numeric_
↪impute_strategy': 'mean', 'categorical_fill_value': None, 'numeric_fill_value':␣
↪None}, 'Random Forest Classifier':{'n_estimators': 100, 'max_depth': 6, 'n_jobs': -
↪1}}, random_seed=0)
```

4.4.10 Generate Code

Once you have instantiated a pipeline, you can generate string Python code to recreate this pipeline, which can then be saved and run elsewhere with EvalML. `generate_pipeline_code` requires a pipeline instance as the input. It can also handle custom components, but it won't return the code required to define the component. Note that any external libraries used in creating the pipeline instance will also need to be imported to execute the returned code.

Code generation is not yet supported for nonlinear pipelines.

[18]:
```
from evalml.pipelines.utils import generate_pipeline_code
from evalml.pipelines import MulticlassClassificationPipeline
import pandas as pd
from evalml.utils import infer_feature_types
from skopt.space import Integer

class MyDropNullColumns(Transformer):
    """Transformer to drop features whose percentage of NaN values exceeds a␣
↪specified threshold"""
    name = "My Drop Null Columns Transformer"
    hyperparameter_ranges = {}

    def __init__(self, pct_null_threshold=1.0, random_seed=0, **kwargs):
        """Initalizes an transformer to drop features whose percentage of NaN values␣
↪exceeds a specified threshold.
```

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```
        Arguments:
            pct_null_threshold(float): The percentage of NaN values in an input␣
↪feature to drop.
                Must be a value between [0, 1] inclusive. If equal to 0.0, will drop␣
↪columns with any null values.
                If equal to 1.0, will drop columns with all null values. Defaults to␣
↪0.95.
        """
        if pct_null_threshold < 0 or pct_null_threshold > 1:
            raise ValueError("pct_null_threshold must be a float between 0 and 1,␣
↪inclusive.")
        parameters = {"pct_null_threshold": pct_null_threshold}
        parameters.update(kwargs)

        self._cols_to_drop = None
        super().__init__(parameters=parameters,
                         component_obj=None,
                         random_seed=random_seed)

    def fit(self, X, y=None):
        pct_null_threshold = self.parameters["pct_null_threshold"]
        X = infer_feature_types(X)
        percent_null = X.isnull().mean()
        if pct_null_threshold == 0.0:
            null_cols = percent_null[percent_null > 0]
        else:
            null_cols = percent_null[percent_null >= pct_null_threshold]
        self._cols_to_drop = list(null_cols.index)
        return self

    def transform(self, X, y=None):
        """Transforms data X by dropping columns that exceed the threshold of null␣
↪values.
        Arguments:
            X (pd.DataFrame): Data to transform
            y (pd.Series, optional): Targets
        Returns:
            pd.DataFrame: Transformed X
        """

        X = infer_feature_types(X)
        return X.drop(columns=self._cols_to_drop)


pipeline_instance = MulticlassClassificationPipeline(['Imputer', MyDropNullColumns,
                                                       'DateTime Featurization␣
↪Component',
                                                       'Text Featurization Component',
                                                       'One Hot Encoder', 'Random␣
↪Forest Classifier'],
                                                      custom_name="Pipeline with␣
↪Custom Component",
                                                      random_seed=20)

code = generate_pipeline_code(pipeline_instance)
print(code)
```

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```
# This string can then be pasted into a separate window and run, although since the␣
↪pipeline has custom component `MyDropNullColumns`,
#      the code for that component must also be included
from evalml.demos import load_fraud
X, y = load_fraud(1000)
exec(code)
pipeline.fit(X, y)
```

```
from evalml.pipelines.multiclass_classification_pipeline import␣
↪MulticlassClassificationPipeline
pipeline = MulticlassClassificationPipeline(component_graph={'Imputer': ['Imputer', 'X
↪', 'y'], 'My Drop Null Columns Transformer': [MyDropNullColumns, 'Imputer.x', 'y'],
↪'DateTime Featurization Component': ['DateTime Featurization Component', 'My Drop␣
↪Null Columns Transformer.x', 'y'], 'Text Featurization Component': ['Text␣
↪Featurization Component', 'DateTime Featurization Component.x', 'y'], 'One Hot␣
↪Encoder': ['One Hot Encoder', 'Text Featurization Component.x', 'y'], 'Random␣
↪Forest Classifier': ['Random Forest Classifier', 'One Hot Encoder.x', 'y']},␣
↪parameters={'Imputer':{'categorical_impute_strategy': 'most_frequent', 'numeric_
↪impute_strategy': 'mean', 'categorical_fill_value': None, 'numeric_fill_value':␣
↪None}, 'My Drop Null Columns Transformer':{'pct_null_threshold': 1.0}, 'DateTime␣
↪Featurization Component':{'features_to_extract': ['year', 'month', 'day_of_week',
↪'hour'], 'encode_as_categories': False, 'date_index': None}, 'One Hot Encoder':{
↪'top_n': 10, 'features_to_encode': None, 'categories': None, 'drop': 'if_binary',
↪'handle_unknown': 'ignore', 'handle_missing': 'error'}, 'Random Forest Classifier':{
↪'n_estimators': 100, 'max_depth': 6, 'n_jobs': -1}}, custom_name='Pipeline with␣
↪Custom Component', random_seed=20)
             Number of Features
Boolean                       1
Categorical                   6
Numeric                       5

Number of training examples: 1000
Targets
False    85.90%
True     14.10%
Name: fraud, dtype: object
```

[18]:
```
pipeline = MulticlassClassificationPipeline(component_graph={'Imputer': ['Imputer', 'X
↪', 'y'], 'My Drop Null Columns Transformer': [MyDropNullColumns, 'Imputer.x', 'y'],
↪'DateTime Featurization Component': ['DateTime Featurization Component', 'My Drop␣
↪Null Columns Transformer.x', 'y'], 'Text Featurization Component': ['Text␣
↪Featurization Component', 'DateTime Featurization Component.x', 'y'], 'One Hot␣
↪Encoder': ['One Hot Encoder', 'Text Featurization Component.x', 'y'], 'Random␣
↪Forest Classifier': ['Random Forest Classifier', 'One Hot Encoder.x', 'y']},␣
↪parameters={'Imputer':{'categorical_impute_strategy': 'most_frequent', 'numeric_
↪impute_strategy': 'mean', 'categorical_fill_value': None, 'numeric_fill_value':␣
↪None}, 'My Drop Null Columns Transformer':{'pct_null_threshold': 1.0}, 'DateTime␣
↪Featurization Component':{'features_to_extract': ['year', 'month', 'day_of_week',
↪'hour'], 'encode_as_categories': False, 'date_index': None}, 'One Hot Encoder':{
↪'top_n': 10, 'features_to_encode': None, 'categories': None, 'drop': 'if_binary',
↪'handle_unknown': 'ignore', 'handle_missing': 'error'}, 'Random Forest Classifier':{
↪'n_estimators': 100, 'max_depth': 6, 'n_jobs': -1}}, custom_name='Pipeline with␣
↪Custom Component', random_seed=20)
```

4.5 Model Understanding

Simply examining a model's performance metrics is not enough to select a model and promote it for use in a production setting. While developing an ML algorithm, it is important to understand how the model behaves on the data, to examine the key factors influencing its predictions and to consider where it may be deficient. Determination of what "success" may mean for an ML project depends first and foremost on the user's domain expertise.

EvalML includes a variety of tools for understanding models, from graphing utilities to methods for explaining predictions.

** Graphing methods on Jupyter Notebook and Jupyter Lab require ipywidgets to be installed.

** If graphing on Jupyter Lab, jupyterlab-plotly required. To download this, make sure you have npm installed.

4.5.1 Graphing Utilities

First, let's train a pipeline on some data.

[1]:
```
import evalml
from evalml.pipelines import BinaryClassificationPipeline
X, y = evalml.demos.load_breast_cancer()

X_train, X_holdout, y_train, y_holdout = evalml.preprocessing.split_data(X, y,␣
↪problem_type='binary',
                                                                         test_size=0.
↪2, random_seed=0)


pipeline_binary = BinaryClassificationPipeline(['Simple Imputer', 'Random Forest␣
↪Classifier'])
pipeline_binary.fit(X_train, y_train)
print(pipeline_binary.score(X_holdout, y_holdout, objectives=['log loss binary']))
```

```
         Number of Features
Numeric                  30

Number of training examples: 569
Targets
benign       62.74%
malignant    37.26%
Name: target, dtype: object
OrderedDict([('Log Loss Binary', 0.1686746297113362)])
```

Feature Importance

We can get the importance associated with each feature of the resulting pipeline

[2]:
```
pipeline_binary.feature_importance
```

[2]:
```
                    feature  importance
0       mean concave points    0.138857
1           worst perimeter    0.137780
2      worst concave points    0.117782
3              worst radius    0.100584
4            mean concavity    0.086402
5                worst area    0.072027
```

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```
6            mean perimeter    0.046500
7          worst concavity    0.043408
8              mean radius    0.037664
9                mean area    0.033683
10           radius error    0.025036
11             area error    0.019324
12         worst texture    0.014754
13       worst compactness    0.014462
14            mean texture    0.013856
15       worst smoothness    0.013710
16         worst symmetry    0.011395
17        perimeter error    0.010284
18       mean compactness    0.008162
19        mean smoothness    0.008154
20  worst fractal dimension    0.007034
21  fractal dimension error    0.005502
22       compactness error    0.004953
23        smoothness error    0.004728
24           texture error    0.004384
25         symmetry error    0.004250
26   mean fractal dimension    0.004164
27         concavity error    0.004089
28           mean symmetry    0.003997
29    concave points error    0.003076
```

We can also create a bar plot of the feature importances

[3]:
```
pipeline_binary.graph_feature_importance()
```

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Permutation Importance

We can also compute and plot the permutation importance of the pipeline.

[4]:
```
from evalml.model_understanding import calculate_permutation_importance
calculate_permutation_importance(pipeline_binary, X_holdout, y_holdout, 'log loss␣
↪binary')
```

[4]:
```
                    feature  importance
0          worst perimeter    0.063657
1               worst area    0.045759
2             worst radius    0.041926
3      mean concave points    0.029325
4     worst concave points    0.021045
5          worst concavity    0.010105
6            worst texture    0.010044
7             mean texture    0.006178
8            mean symmetry    0.005857
9                mean area    0.004745
10       worst smoothness    0.003190
11             area error    0.003113
12         mean perimeter    0.002478
```

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```
13   mean fractal dimension    0.001981
14        compactness error    0.001968
15          concavity error    0.001947
16            texture error    0.000291
17         smoothness error   -0.000206
18          mean smoothness   -0.000745
19  fractal dimension error   -0.000835
20        worst compactness   -0.002392
21           mean concavity   -0.003188
22         mean compactness   -0.005377
23             radius error   -0.006229
24              mean radius   -0.006870
25  worst fractal dimension   -0.007415
26           symmetry error   -0.008175
27          perimeter error   -0.008980
28     concave points error   -0.010415
29           worst symmetry   -0.018645
```

[5]:
```
from evalml.model_understanding import graph_permutation_importance
graph_permutation_importance(pipeline_binary, X_holdout, y_holdout, 'log loss binary')
```

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Partial Dependence Plots

We can calculate the one-way partial dependence plots for a feature.

[6]:
```
from evalml.model_understanding.graphs import partial_dependence
partial_dependence(pipeline_binary, X_holdout, features='mean radius', grid_
↪resolution=5)
```

[6]:
```
   feature_values  partial_dependence class_label
0         9.69092            0.392453   malignant
1        12.40459            0.395962   malignant
2        15.11826            0.417396   malignant
3        17.83193            0.429542   malignant
4        20.54560            0.429717   malignant
```

[7]:
```
from evalml.model_understanding.graphs import graph_partial_dependence
graph_partial_dependence(pipeline_binary, X_holdout, features='mean radius', grid_
↪resolution=5)
```

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You can also compute the partial dependence for a categorical feature. We will demonstrate this on the fraud dataset.

[8]:
```
X_fraud, y_fraud = evalml.demos.load_fraud(100, verbose=False)
X_fraud.ww.init(logical_types={"provider": "Categorical", 'region': "Categorical"})

fraud_pipeline = BinaryClassificationPipeline(["DateTime Featurization Component",
↪"One Hot Encoder", "Random Forest Classifier"])
```

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```
fraud_pipeline.fit(X_fraud, y_fraud)

graph_partial_dependence(fraud_pipeline, X_fraud, features='provider')
```

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Two-way partial dependence plots are also possible and invoke the same API.

[9]:
```
partial_dependence(pipeline_binary, X_holdout, features=('worst perimeter', 'worst␣
↪radius'), grid_resolution=5)
```

[9]:
```
              10.6876  14.404924999999999  18.12225  21.839575   25.5569  \
69.140700   0.279038            0.282898  0.435179   0.435355  0.435355
94.334275   0.304335            0.308194  0.458283   0.458458  0.458458
119.527850  0.464455            0.468314  0.612137   0.616932  0.616932
144.721425  0.483437            0.487297  0.631120   0.635915  0.635915
169.915000  0.483437            0.487297  0.631120   0.635915  0.635915

            class_label
69.140700     malignant
94.334275     malignant
119.527850    malignant
144.721425    malignant
169.915000    malignant
```

[10]:
```
graph_partial_dependence(pipeline_binary, X_holdout, features=('worst perimeter',
↪'worst radius'), grid_resolution=5)
```

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Confusion Matrix

For binary or multiclass classification, we can view a confusion matrix of the classifier's predictions. In the DataFrame output of `confusion_matrix()`, the column header represents the predicted labels while row header represents the actual labels.

[11]:
```
from evalml.model_understanding.graphs import confusion_matrix
y_pred = pipeline_binary.predict(X_holdout)
confusion_matrix(y_holdout, y_pred)
```

[11]:
```
              benign  malignant
benign      0.930556   0.069444
malignant   0.023810   0.976190
```

[12]:
```
from evalml.model_understanding.graphs import graph_confusion_matrix
y_pred = pipeline_binary.predict(X_holdout)
graph_confusion_matrix(y_holdout, y_pred)
```

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Precision-Recall Curve

For binary classification, we can view the precision-recall curve of the pipeline.

[13]:
```
from evalml.model_understanding.graphs import graph_precision_recall_curve
# get the predicted probabilities associated with the "true" label
import woodwork as ww
y_encoded = y_holdout.ww.map({'benign': 0, 'malignant': 1})
y_pred_proba = pipeline_binary.predict_proba(X_holdout)["malignant"]
graph_precision_recall_curve(y_encoded, y_pred_proba)
```

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ROC Curve

For binary and multiclass classification, we can view the Receiver Operating Characteristic (ROC) curve of the pipeline.

[14]:
```
from evalml.model_understanding.graphs import graph_roc_curve
# get the predicted probabilities associated with the "malignant" label
y_pred_proba = pipeline_binary.predict_proba(X_holdout)["malignant"]
graph_roc_curve(y_encoded, y_pred_proba)
```

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The ROC curve can also be generated for multiclass classification problems. For multiclass problems, the graph will show a one-vs-many ROC curve for each class.

[15]:
```
from evalml.pipelines import MulticlassClassificationPipeline
X_multi, y_multi = evalml.demos.load_wine()

pipeline_multi = MulticlassClassificationPipeline(['Simple Imputer', 'Random Forest␣
↪Classifier'])
pipeline_multi.fit(X_multi, y_multi)

y_pred_proba = pipeline_multi.predict_proba(X_multi)
graph_roc_curve(y_multi, y_pred_proba)
```

```
         Number of Features
Numeric                  13

Number of training examples: 178
Targets
class_1    39.89%
class_0    33.15%
class_2    26.97%
Name: target, dtype: object
```

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Binary Objective Score vs. Threshold Graph

Some binary classification objectives (objectives that have `score_needs_proba` set to False) are sensitive to a decision threshold. For those objectives, we can obtain and graph the scores for thresholds from zero to one, calculated at evenly-spaced intervals determined by `steps`.

[16]:
```
from evalml.model_understanding.graphs import binary_objective_vs_threshold
binary_objective_vs_threshold(pipeline_binary, X_holdout, y_holdout, 'f1', steps=10)
```

[16]:
```
    threshold     score
0         0.0  0.538462
1         0.1  0.811881
2         0.2  0.891304
3         0.3  0.901099
4         0.4  0.931818
5         0.5  0.931818
6         0.6  0.941176
7         0.7  0.951220
8         0.8  0.936709
9         0.9  0.923077
10        1.0  0.000000
```

[17]:
```
from evalml.model_understanding.graphs import graph_binary_objective_vs_threshold
graph_binary_objective_vs_threshold(pipeline_binary, X_holdout, y_holdout, 'f1',␣
↪steps=100)
```

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Predicted Vs Actual Values Graph for Regression Problems

We can also create a scatterplot comparing predicted vs actual values for regression problems. We can specify an `outlier_threshold` to color values differently if the absolute difference between the actual and predicted values are outside of a given threshold.

[18]:
```
from evalml.model_understanding.graphs import graph_prediction_vs_actual
from evalml.pipelines import RegressionPipeline

X_regress, y_regress = evalml.demos.load_diabetes()
X_train, X_test, y_train, y_test = evalml.preprocessing.split_data(X_regress, y_
↪regress, problem_type='regression')

pipeline_regress = RegressionPipeline(['One Hot Encoder', 'Linear Regressor'])
pipeline_regress.fit(X_train, y_train)

y_pred = pipeline_regress.predict(X_test)
graph_prediction_vs_actual(y_test, y_pred, outlier_threshold=50)
```

```
         Number of Features
Numeric                  10

Number of training examples: 442
Targets
200.0     1.36%
72.0      1.36%
```

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```
90.0     1.13%
178.0    1.13%
71.0     1.13%
         ...
73.0     0.23%
222.0    0.23%
86.0     0.23%
79.0     0.23%
57.0     0.23%
Name: target, Length: 214, dtype: object
```

Data type cannot be displayed: application/vnd.plotly.v1+json, text/html

Now let's train a decision tree on some data.

[19]:
```
pipeline_dt = BinaryClassificationPipeline(['Simple Imputer', 'Decision Tree␣
↪Classifier'])
pipeline_dt.fit(X_train, y_train)
```

[19]:
```
pipeline = BinaryClassificationPipeline(component_graph={'Simple Imputer': ['Simple␣
↪Imputer', 'X', 'y'], 'Decision Tree Classifier': ['Decision Tree Classifier',
↪'Simple Imputer.x', 'y']}, parameters={'Simple Imputer':{'impute_strategy': 'most_
↪frequent', 'fill_value': None}, 'Decision Tree Classifier':{'criterion': 'gini',
↪'max_features': 'auto', 'max_depth': 6, 'min_samples_split': 2, 'min_weight_
↪fraction_leaf': 0.0}}, random_seed=0)
```

Tree Visualization

We can visualize the structure of the Decision Tree that was fit to that data, and save it if necessary.

[20]:
```
from evalml.model_understanding.graphs import visualize_decision_tree

visualize_decision_tree(pipeline_dt.estimator, max_depth=2, rotate=False, filled=True,
↪ filepath=None)
```

[20]:

4.5.2 Explaining Predictions

We can explain why the model made certain predictions with the *explain_predictions* function. This will use the Shapley Additive Explanations (SHAP) algorithm to identify the top features that explain the predicted value.

This function can explain both classification and regression models - all you need to do is provide the pipeline, the input features, and a list of rows corresponding to the indices of the input features you want to explain. The function will return a table that you can print summarizing the top 3 most positive and negative contributing features to the predicted value.

In the example below, we explain the prediction for the third data point in the data set. We see that the `worst concave points` feature increased the estimated probability that the tumor is malignant by 20% while the `worst radius` feature decreased the probability the tumor is malignant by 5%.

[21]:
```
from evalml.model_understanding.prediction_explanations import explain_predictions

table = explain_predictions(pipeline=pipeline_binary, input_features=X_holdout,␣
↪y=None, indices_to_explain=[3],
```

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```
                            top_k_features=6, include_shap_values=True)
print(table)
```

```
Random Forest Classifier w/ Simple Imputer

{'Simple Imputer': {'impute_strategy': 'most_frequent', 'fill_value': None}, 'Random␣
↪Forest Classifier': {'n_estimators': 100, 'max_depth': 6, 'n_jobs': -1}}

        1 of 1

                    Feature Name       Feature Value   Contribution to Prediction␣
↪SHAP Value
                ␣
↪================================================================================
                  worst concavity         0.18                     -                -
↪0.02
                  mean concavity          0.04                     -                -
↪0.03
                    worst area           599.50                    -                -
↪0.03
                   worst radius           14.04                    -                -
↪0.05
                mean concave points       0.03                     -                -
↪0.05
                  worst perimeter         92.80                    -                -
↪0.06
```

The interpretation of the table is the same for regression problems - but the SHAP value now corresponds to the change in the estimated value of the dependent variable rather than a change in probability. For multiclass classification problems, a table will be output for each possible class.

Below is an example of how you would explain three predictions with *explain_predictions*.

[22]:
```
from evalml.model_understanding.prediction_explanations import explain_predictions

report = explain_predictions(pipeline=pipeline_binary,
                             input_features=X_holdout, y=y_holdout, indices_to_
↪explain=[0, 4, 9], include_shap_values=True,
                             output_format='text')
print(report)
```

```
Random Forest Classifier w/ Simple Imputer

{'Simple Imputer': {'impute_strategy': 'most_frequent', 'fill_value': None}, 'Random␣
↪Forest Classifier': {'n_estimators': 100, 'max_depth': 6, 'n_jobs': -1}}

        1 of 3

                     Feature Name       Feature Value   Contribution to Prediction␣
↪SHAP Value
                ␣
↪================================================================================
                  worst perimeter         101.20                   -                ␣
↪-0.04
                worst concave points       0.06                    -                ␣
↪-0.05
```

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```
                mean concave points        0.01                    -
↪-0.05


       2 of 3

                   Feature Name       Feature Value   Contribution to Prediction
↪SHAP Value
↪==========================================================================
                    worst radius           11.94                   -
↪0.05
                  worst perimeter          80.78                   -
↪0.06
                mean concave points        0.02                    -
↪0.06


       3 of 3

                    Feature Name       Feature Value   Contribution to Prediction
↪SHAP Value
↪==========================================================================
                worst concave points       0.10                    -
↪-0.05
                  worst perimeter          99.21                   -
↪-0.06
                mean concave points        0.03                    -
↪-0.08
```

Explaining Best and Worst Predictions

When debugging machine learning models, it is often useful to analyze the best and worst predictions the model made. The *explain_predictions_best_worst* function can help us with this.

This function will display the output of *explain_predictions* for the best 2 and worst 2 predictions. By default, the best and worst predictions are determined by the absolute error for regression problems and cross entropy for classification problems.

We can specify our own ranking function by passing in a function to the `metric` parameter. This function will be called on `y_true` and `y_pred`. By convention, lower scores are better.

At the top of each table, we can see the predicted probabilities, target value, error, and row index for that prediction. For a regression problem, we would see the predicted value instead of predicted probabilities.

[23]:
```
from evalml.model_understanding.prediction_explanations import explain_predictions_
↪best_worst

report = explain_predictions_best_worst(pipeline=pipeline_binary, input_features=X_
↪holdout, y_true=y_holdout,
                                        include_shap_values=True, top_k_features=6,
↪num_to_explain=2)
```

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```
print(report)
```

```
Random Forest Classifier w/ Simple Imputer

{'Simple Imputer': {'impute_strategy': 'most_frequent', 'fill_value': None}, 'Random
↪Forest Classifier': {'n_estimators': 100, 'max_depth': 6, 'n_jobs': -1}}

        Best 1 of 2

                Predicted Probabilities: [benign: 1.0, malignant: 0.0]
                Predicted Value: benign
                Target Value: benign
                Cross Entropy: 0.0
                Index ID: 502

                    Feature Name       Feature Value   Contribution to Prediction
↪SHAP Value
                
↪=============================================================================
                   mean concavity          0.06                     -
↪-0.03
                    worst area           552.00                     -
↪-0.03
                worst concave points       0.08                     -
↪-0.05
                    worst radius           13.57                     -
↪-0.05
                mean concave points        0.03                     -
↪-0.05
                  worst perimeter          86.67                     -
↪-0.06


        Best 2 of 2

                Predicted Probabilities: [benign: 1.0, malignant: 0.0]
                Predicted Value: benign
                Target Value: benign
                Cross Entropy: 0.0
                Index ID: 52

                    Feature Name       Feature Value   Contribution to Prediction
↪SHAP Value
                
↪=============================================================================
                   mean concavity          0.02                     -
↪-0.02
                    worst area           527.20                     -
↪-0.03
                    worst radius           13.10                     -
↪-0.04
                worst concave points       0.06                     -
↪-0.04
                mean concave points        0.01                     -
↪-0.05
                  worst perimeter          83.67                     -
↪-0.06
```

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```
        Worst 1 of 2

                Predicted Probabilities: [benign: 0.266, malignant: 0.734]
                Predicted Value: malignant
                Target Value: benign
                Cross Entropy: 1.325
                Index ID: 363

                 Feature Name     Feature Value   Contribution to Prediction   SHAP␣
↪Value
                ␣
↪=============================================================================
                worst perimeter      117.20                   +                   0.13
                 worst radius         18.13                   +                   0.12
                  worst area         1009.00                   +                   0.11
                   mean area         838.10                   +                   0.06
                  mean radius         16.50                   +                   0.05
                worst concavity       0.17                    -                  -0.05


        Worst 2 of 2

                Predicted Probabilities: [benign: 1.0, malignant: 0.0]
                Predicted Value: benign
                Target Value: malignant
                Cross Entropy: 7.987
                Index ID: 135

                    Feature Name       Feature Value   Contribution to Prediction  ␣
↪SHAP Value
                ␣
↪=============================================================================
                   mean concavity          0.05                    -                ␣
↪-0.03
                     worst area           653.60                   -                ␣
↪-0.04
                worst concave points       0.09                    -                ␣
↪-0.05
                    worst radius           14.49                   -                ␣
↪-0.05
                  worst perimeter          92.04                   -                ␣
↪-0.06
                mean concave points        0.03                    -                ␣
↪-0.06
```

We use a custom metric (hinge loss) for selecting the best and worst predictions. See this example:

```
import numpy as np

def hinge_loss(y_true, y_pred_proba):

    probabilities = np.clip(y_pred_proba.iloc[:, 1], 0.001, 0.999)
```

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```
    y_true[y_true == 0] = -1

    return np.clip(1 - y_true * np.log(probabilities / (1 - probabilities)), a_min=0,␣
↪a_max=None)

report = explain_predictions_best_worst(pipeline=pipeline, input_features=X, y_true=y,
                                        include_shap_values=True, num_to_explain=5,␣
↪metric=hinge_loss)

print(report)
```

Changing Output Formats

Instead of getting the prediction explanations as text, you can get the report as a python dictionary or pandas dataframe. All you have to do is pass `output_format="dict"` or `output_format="dataframe"` to either `explain_prediction`, `explain_predictions`, or `explain_predictions_best_worst`.

Single prediction as a dictionary

[24]:
```
import json
single_prediction_report = explain_predictions(pipeline=pipeline_binary, input_
↪features=X_holdout, indices_to_explain=[3],
                                               y=y_holdout, top_k_features=6, include_
↪shap_values=True,
                                               output_format="dict")
print(json.dumps(single_prediction_report, indent=2))
```


```
{
  "explanations": [
    {
      "explanations": [
        {
          "feature_names": [
            "worst concavity",
            "mean concavity",
            "worst area",
            "worst radius",
            "mean concave points",
            "worst perimeter"
          ],
          "feature_values": [
            0.1791,
            0.038,
            599.5,
            14.04,
            0.034,
            92.8
          ],
          "qualitative_explanation": [
            "-",
            "-",
            "-",
            "-",
            "-",
```


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```
            "_"
          ],
          "quantitative_explanation": [
            -0.023008481104309524,
            -0.02621982146725469,
            -0.033821592020020774,
            -0.04666659740586632,
            -0.0541511910494414,
            -0.05523688273171911
          ],
          "drill_down": {},
          "class_name": "malignant",
          "expected_value": 0.3711208791208791
        }
      ]
    }
  ]
}
```


Single prediction as a dataframe

[25]:
```
single_prediction_report = explain_predictions(pipeline=pipeline_binary, input_
↪features=X_holdout,
                                               indices_to_explain=[3],
                                               y=y_holdout, top_k_features=6, include_
↪shap_values=True,
                                               output_format="dataframe")
single_prediction_report
```

[25]:
```
         feature_names  feature_values qualitative_explanation  \
0      worst concavity          0.1791                       -
1       mean concavity          0.0380                       -
2           worst area        599.5000                       -
3         worst radius         14.0400                       -
4  mean concave points          0.0340                       -
5      worst perimeter         92.8000                       -

   quantitative_explanation class_name  prediction_number
0                -0.023008  malignant                  0
1                -0.026220  malignant                  0
2                -0.033822  malignant                  0
3                -0.046667  malignant                  0
4                -0.054151  malignant                  0
5                -0.055237  malignant                  0
```

Best and worst predictions as a dictionary

[26]:
```
report = explain_predictions_best_worst(pipeline=pipeline_binary, input_features=X, y_
↪true=y,
                                        num_to_explain=1, top_k_features=6,
                                        include_shap_values=True, output_format="dict
↪")
print(json.dumps(report, indent=2))
```


```
{
  "explanations": [
    {
      "rank": {
        "prefix": "best",
        "index": 1
      },
      "predicted_values": {
        "probabilities": {
          "benign": 1.0,
          "malignant": 0.0
        },
        "predicted_value": "benign",
        "target_value": "benign",
        "error_name": "Cross Entropy",
        "error_value": 0.0001970443507070075,
        "index_id": 475
      },
      "explanations": [
        {
          "feature_names": [
            "mean concavity",
            "worst area",
            "worst radius",
            "worst concave points",
            "worst perimeter",
            "mean concave points"
          ],
          "feature_values": [
            0.05835,
            605.8,
            14.09,
            0.09783,
            93.22,
            0.03078
          ],
          "qualitative_explanation": [
            "-",
            "-",
            "-",
            "-",
            "-",
            "-"
          ],
          "quantitative_explanation": [
            -0.028481050954786636,
            -0.03050522196002462,
            -0.042922079201003216,
            -0.04429366151003684,
```


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```
            -0.05486784013962313,
            -0.05639460900233733
          ],
          "drill_down": {},
          "class_name": "malignant",
          "expected_value": 0.3711208791208791
        }
      ]
    },
    {
      "rank": {
        "prefix": "worst",
        "index": 1
      },
      "predicted_values": {
        "probabilities": {
          "benign": 1.0,
          "malignant": 0.0
        },
        "predicted_value": "benign",
        "target_value": "malignant",
        "error_name": "Cross Entropy",
        "error_value": 7.986911819330411,
        "index_id": 135
      },
      "explanations": [
        {
          "feature_names": [
            "mean concavity",
            "worst area",
            "worst concave points",
            "worst radius",
            "worst perimeter",
            "mean concave points"
          ],
          "feature_values": [
            0.04711,
            653.6,
            0.09331,
            14.49,
            92.04,
            0.02704
          ],
          "qualitative_explanation": [
            "-",
            "-",
            "-",
            "-",
            "-",
            "-"
          ],
          "quantitative_explanation": [
            -0.029936744551331215,
            -0.03748357654576422,
            -0.04553126236476177,
            -0.0483274199182721,
            -0.06039220265366764,
```


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```
            -0.060441902449258976
          ],
          "drill_down": {},
          "class_name": "malignant",
          "expected_value": 0.3711208791208791
        }
      ]
    }
  ]
}
```


Best and worst predictions as a dataframe

[27]:
```
report = explain_predictions_best_worst(pipeline=pipeline_binary, input_features=X_
↪holdout, y_true=y_holdout,
                                        num_to_explain=1, top_k_features=6,
                                        include_shap_values=True, output_format=
↪"dataframe")
report
```

[27]:

	feature_names	feature_values	qualitative_explanation	quantitative_explanation	class_name	label_benign_probability	label_malignant_probability	predicted_value	target_value	error_name
0	mean concavity	0.05928	-	-0.029022	malignant	1.0	0.0	benign	benign	Cross Entropy
1	worst area	552.00000	-	-0.034112	malignant	1.0	0.0	benign	benign	Cross Entropy
2	worst concave points	0.08411	-	-0.046896	malignant	1.0	0.0	benign	benign	Cross Entropy
3	worst radius	13.57000	-	-0.046928	malignant	1.0	0.0	benign	benign	Cross Entropy
4	mean concave points	0.03279	-	-0.052902	malignant	1.0	0.0	benign	benign	Cross Entropy
5	worst perimeter	86.67000	-	-0.064320	malignant	1.0	0.0	benign	benign	Cross Entropy
6	mean concavity	0.04711	-	-0.029937	malignant	1.0	0.0	benign	benign	Cross Entropy
7	worst area	653.60000	-	-0.037484	malignant	1.0	0.0	benign	benign	Cross Entropy
8	worst concave points	0.09331	-	-0.045531	malignant	1.0	0.0	benign	benign	Cross Entropy
9	worst radius	14.49000	-	-0.048327	malignant	1.0	0.0	benign	benign	Cross Entropy
10	worst perimeter	92.04000	-	-0.060392	malignant	1.0	0.0	benign	benign	Cross Entropy
11	mean concave points	0.02704	-	-0.060442	malignant	1.0	0.0	benign	benign	Cross Entropy

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```
6                           0.0          benign    malignant  Cross Entropy
7                           0.0          benign    malignant  Cross Entropy
8                           0.0          benign    malignant  Cross Entropy
9                           0.0          benign    malignant  Cross Entropy
10                          0.0          benign    malignant  Cross Entropy
11                          0.0          benign    malignant  Cross Entropy

    error_value  index_id  rank prefix
0      0.000197       502     1   best
1      0.000197       502     1   best
2      0.000197       502     1   best
3      0.000197       502     1   best
4      0.000197       502     1   best
5      0.000197       502     1   best
6      7.986912       135     1  worst
7      7.986912       135     1  worst
8      7.986912       135     1  worst
9      7.986912       135     1  worst
10     7.986912       135     1  worst
11     7.986912       135     1  worst
```

Force Plots

Force plots can be generated to predict single or multiple rows for binary, multiclass and regression problem types. Here's an example of predicting a single row on a binary classification dataset. The force plots show the predictive power of each of the features in making the negative ("Class: 0") prediction and the positive ("Class: 1") prediction.

[28]:
```
import shap

from evalml.model_understanding.force_plots import graph_force_plot

rows_to_explain = [0] # Should be a list of integer indices of the rows to explain.

results = graph_force_plot(pipeline_binary, rows_to_explain=rows_to_explain,
                           training_data=X_holdout, y=y_holdout)

for result in results:
    for cls in result:
        print("Class:", cls)
        display(result[cls]["plot"])
```

```
<IPython.core.display.HTML object>
```

```
Class: malignant
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f30a4ca1100>
```

Here's an example of a force plot explaining multiple predictions on a multiclass problem. These plots show the force plots for each row arranged as consecutive columns that can be ordered by the dropdown above. Clicking the column indicates which row explanation is underneath.

[29]:
```
rows_to_explain = [0,1,2,3,4] # Should be a list of integer indices of the rows to␣
↪explain.

results = graph_force_plot(pipeline_multi,
                           rows_to_explain=rows_to_explain,
```

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```
                            training_data=X_multi, y=y_multi)

for idx, result in enumerate(results):
    print("Row:", idx)
    for cls in result:
        print("Class:", cls)
        display(result[cls]["plot"])
```

```
<IPython.core.display.HTML object>
```

```
Row: 0
Class: class_0
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f3074e96370>
```

```
Class: class_1
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f306df89ca0>
```

```
Class: class_2
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f30754bcc10>
```

```
Row: 1
Class: class_0
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f3074ee03a0>
```

```
Class: class_1
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f30740f8760>
```

```
Class: class_2
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f306dffbd00>
```

```
Row: 2
Class: class_0
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f306dffb310>
```

```
Class: class_1
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f306dfe0fd0>
```

```
Class: class_2
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f306d76a8e0>
```

```
Row: 3
Class: class_0
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f306d76afd0>
```

```
Class: class_1
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f306d76ab20>
```

```
Class: class_2
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f306d76a730>
```

```
Row: 4
Class: class_0
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f306d76a5b0>
```

```
Class: class_1
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f306d76a4c0>
```

```
Class: class_2
```

```
<shap.plots._force.AdditiveForceVisualizer at 0x7f306df89b50>
```

4.6 Data Checks

EvalML provides data checks to help guide you in achieving the highest performing model. These utility functions help deal with problems such as overfitting, abnormal data, and missing data. These data checks can be found under `evalml/data_checks`. Below we will cover examples for each available data check in EvalML, as well as the `DefaultDataChecks` collection of data checks.

4.6.1 Missing Data

Missing data or rows with `NaN` values provide many challenges for machine learning pipelines. In the worst case, many algorithms simply will not run with missing data! EvalML pipelines contain imputation *components* to ensure that doesn't happen. Imputation works by approximating missing values with existing values. However, if a column contains a high number of missing values, a large percentage of the column would be approximated by a small percentage. This could potentially create a column without useful information for machine learning pipelines. By using `HighlyNullDataCheck`, EvalML will alert you to this potential problem by returning the columns that pass the missing values threshold.

[1]:
```
import numpy as np
import pandas as pd

from evalml.data_checks import HighlyNullDataCheck

X = pd.DataFrame([[1, 2, 3],
                  [0, 4, np.nan],
                  [1, 4, np.nan],
                  [9, 4, np.nan],
                  [8, 6, np.nan]])

null_check = HighlyNullDataCheck(pct_null_col_threshold=0.8, pct_null_row_threshold=0.
↪8)
results = null_check.validate(X)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Warning: Column '2' is 80.0% or more null
```

4.6.2 Abnormal Data

EvalML provides a few data checks to check for abnormal data:

- NoVarianceDataCheck
- ClassImbalanceDataCheck
- TargetLeakageDataCheck
- InvalidTargetDataCheck
- IDColumnsDataCheck
- OutliersDataCheck
- HighVarianceCVDataCheck
- MulticollinearityDataCheck
- UniquenessDataCheck
- TargetDistributionDataCheck
- DateTimeFormatDataCheck

Zero Variance

Data with zero variance indicates that all values are identical. If a feature has zero variance, it is not likely to be a useful feature. Similarly, if the target has zero variance, there is likely something wrong. NoVarianceDataCheck checks if the target or any feature has only one unique value and alerts you to any such columns.

[2]:
```
from evalml.data_checks import NoVarianceDataCheck
X = pd.DataFrame({"no var col": [0, 0, 0],
                  "good col":[0, 4, 1]})
y = pd.Series([1, 0, 1])
no_variance_data_check = NoVarianceDataCheck()
results = no_variance_data_check.validate(X, y)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Error: no var col has 1 unique value.
```

Note that you can set NaN to count as an unique value, but NoVarianceDataCheck will still return a warning if there is only one unique non-NaN value in a given column.

[3]:
```
from evalml.data_checks import NoVarianceDataCheck

X = pd.DataFrame({"no var col": [0, 0, 0],
                  "no var col with nan": [1, np.nan, 1],
                  "good col":[0, 4, 1]})
y = pd.Series([1, 0, 1])

no_variance_data_check = NoVarianceDataCheck(count_nan_as_value=True)
results = no_variance_data_check.validate(X, y)

for message in results['warnings']:
```

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```
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Warning: no var col with nan has two unique values including nulls. Consider encoding␣
↪the nulls for this column to be useful for machine learning.
Error: no var col has 1 unique value.
```

Class Imbalance

For classification problems, the distribution of examples across each class can vary. For small variations, this is normal and expected. However, when the number of examples for each class label is disproportionately biased or skewed towards a particular class (or classes), it can be difficult for machine learning models to predict well. In addition, having a low number of examples for a given class could mean that one or more of the CV folds generated for the training data could only have few or no examples from that class. This may cause the model to only predict the majority class and ultimately resulting in a poor-performant model.

`ClassImbalanceDataCheck` checks if the target labels are imbalanced beyond a specified threshold for a certain number of CV folds. It returns `DataCheckError` messages for any classes that have less samples than double the number of CV folds specified (since that indicates the likelihood of having at little to no samples of that class in a given fold), and `DataCheckWarning` messages for any classes that fall below the set threshold percentage.

[4]:
```
from evalml.data_checks import ClassImbalanceDataCheck

X = pd.DataFrame([[1, 2, 0, 1],
                  [4, 1, 9, 0],
                  [4, 4, 8, 3],
                  [9, 2, 7, 1]])
y = pd.Series([0, 1, 1, 1, 1])

class_imbalance_check = ClassImbalanceDataCheck(threshold=0.25, num_cv_folds=4)
results = class_imbalance_check.validate(X, y)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Warning: The following labels fall below 25% of the target: [0]
Warning: The following labels in the target have severe class imbalance because they␣
↪fall under 25% of the target and have less than 100 samples: [0]
Error: The number of instances of these targets is less than 2 * the number of cross␣
↪folds = 8 instances: [0, 1]
```

Target Leakage

Target leakage, also known as data leakage, can occur when you train your model on a dataset that includes information that should not be available at the time of prediction. This causes the model to score suspiciously well, but perform poorly in production. `TargetLeakageDataCheck` checks for features that could potentially be "leaking" information by calculating the Pearson correlation coefficient between each feature and the target to warn users if there are features are highly correlated with the target. Currently, only numerical features are considered.

[5]:
```
from evalml.data_checks import TargetLeakageDataCheck
X = pd.DataFrame({'leak': [10, 42, 31, 51, 61],
'x': [42, 54, 12, 64, 12],
'y': [12, 5, 13, 74, 24]})
y = pd.Series([10, 42, 31, 51, 40])

target_leakage_check = TargetLeakageDataCheck(pct_corr_threshold=0.8)
results = target_leakage_check.validate(X, y)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Warning: Column 'leak' is 80.0% or more correlated with the target
Warning: Column 'x' is 80.0% or more correlated with the target
Warning: Column 'y' is 80.0% or more correlated with the target
```

Invalid Target Data

The `InvalidTargetDataCheck` checks if the target data contains any missing or invalid values. Specifically:

- if any of the target values are missing, a `DataCheckError` message is returned
- if the specified problem type is a binary classification problem but there is more or less than two unique values in the target, a `DataCheckError` message is returned
- if binary classification target classes are numeric values not equal to {0, 1}, a `DataCheckError` message is returned because it can cause unpredictable behavior when passed to pipelines

[6]:
```
from evalml.data_checks import InvalidTargetDataCheck

X = pd.DataFrame({})
y = pd.Series([0, 1, None, None])

invalid_target_check = InvalidTargetDataCheck('binary', 'Log Loss Binary')
results = invalid_target_check.validate(X, y)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Warning: Input target and features have different lengths
Warning: Input target and features have mismatched indices
Error: 2 row(s) (50.0%) of target values are null
```

ID Columns

ID columns in your dataset provide little to no benefit to a machine learning pipeline as the pipeline cannot extrapolate useful information from unique identifiers. Thus, `IDColumnsDataCheck` reminds you if these columns exists. In the given example, 'user_number' and 'id' columns are both identified as potentially being unique identifiers that should be removed.

[7]:
```
from evalml.data_checks import IDColumnsDataCheck

X = pd.DataFrame([[0, 53, 6325, 5],[1, 90, 6325, 10],[2, 90, 18, 20]], columns=['user_
↪number', 'cost', 'revenue', 'id'])

id_col_check = IDColumnsDataCheck(id_threshold=0.9)
results = id_col_check.validate(X, y)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Warning: Column 'id' is 90.0% or more likely to be an ID column
Warning: Column 'user_number' is 90.0% or more likely to be an ID column
```

Multicollinearity

The `MulticollinearityDataCheck` data check is used in to detect if are any set of features that are likely to be multicollinear. Multicollinear features affect the performance of a model, but more importantly, it may greatly impact model interpretation. EvalML uses mutual information to determine collinearity.

[8]:
```
from evalml.data_checks import MulticollinearityDataCheck

y = pd.Series([1, 0, 2, 3, 4])
X = pd.DataFrame({'col_1': y,
                  'col_2': y * 3,
                  'col_3': ~y,
                  'col_4': y / 2,
                  'col_5': y + 1,
                  'not_collinear': [0, 1, 0, 0, 0]})

multi_check = MulticollinearityDataCheck(threshold=0.95)
results = multi_check.validate(X, y)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Warning: Columns are likely to be correlated: [('col_1', 'col_2'), ('col_1', 'col_3'),
↪ ('col_1', 'col_4'), ('col_1', 'col_5'), ('col_2', 'col_3'), ('col_2', 'col_4'), (
↪'col_2', 'col_5'), ('col_3', 'col_4'), ('col_3', 'col_5'), ('col_4', 'col_5')]
```

Uniqueness

The `UniquenessDataCheck` is used to detect columns with either too unique or not unique enough values. For regression type problems, the data is checked for a lower limit of uniqueness. For multiclass type problems, the data is checked for an upper limit.

[9]:
```
import pandas as pd
from evalml.data_checks import UniquenessDataCheck

X = pd.DataFrame({'most_unique': [float(x) for x in range(10)],  # [0,1,2,3,4,5,6,7,8,
↪9]
                  'more_unique': [x % 5 for x in range(10)],  # [0,1,2,3,4,0,1,2,3,4]
                  'unique': [x % 3 for x in range(10)],  # [0,1,2,0,1,2,0,1,2,0]
                  'less_unique': [x % 2 for x in range(10)],  # [0,1,0,1,0,1,0,1,0,1]
                  'not_unique': [float(1) for x in range(10)]})  # [1,1,1,1,1,1,1,1,1,
↪1]

uniqueness_check = UniquenessDataCheck(problem_type="regression",
                                       threshold=.5)
results = uniqueness_check.validate(X, y=None)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Warning: Input columns (not_unique) for regression problem type are not unique enough.
```

Sparsity

The `SparsityDataCheck` is used to identify features that contain a sparsity of values.

[10]:
```
from evalml.data_checks import SparsityDataCheck

X = pd.DataFrame({'most_sparse': [float(x) for x in range(10)],  # [0,1,2,3,4,5,6,7,8,
↪9]
                  'more_sparse': [x % 5 for x in range(10)],     # [0,1,2,3,4,0,1,2,3,
↪4]
                  'sparse': [x % 3 for x in range(10)],          # [0,1,2,0,1,2,0,1,2,
↪0]
                  'less_sparse': [x % 2 for x in range(10)],     # [0,1,0,1,0,1,0,1,0,
↪1]
                  'not_sparse': [float(1) for x in range(10)]})  # [1,1,1,1,1,1,1,1,1,
↪1]


sparsity_check = SparsityDataCheck(problem_type="multiclass",
                                   threshold=.4,
                                   unique_count_threshold=3)
results = sparsity_check.validate(X,y=None)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Warning: Input columns (most_sparse) for multiclass problem type are too sparse.
Warning: Input columns (more_sparse) for multiclass problem type are too sparse.
Warning: Input columns (sparse) for multiclass problem type are too sparse.
```

Outliers

Outliers are observations that differ significantly from other observations in the same sample. Many machine learning pipelines suffer in performance if outliers are not dropped from the training set as they are not representative of the data. `OutliersDataCheck()` uses IQR to notify you if a sample can be considered an outlier.

Below we generate a random dataset with some outliers.

[11]:
```
data = np.tile(np.arange(10) * 0.01, (100, 10))
X = pd.DataFrame(data=data)

# generate some outliers in columns 3, 25, 55, and 72
X.iloc[0, 3] = -10000
X.iloc[3, 25] = 10000
X.iloc[5, 55] = 10000
X.iloc[10, 72] = -10000
```

We then utilize `OutliersDataCheck()` to rediscover these outliers.

[12]:
```
from evalml.data_checks import OutliersDataCheck

outliers_check = OutliersDataCheck()
results = outliers_check.validate(X, y)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Warning: Column(s) '3', '25', '55', '72' are likely to have outlier data.
```

Target Distribution

Target data can come in a variety of distributions, such as Gaussian or Lognormal. When we work with machine learning models, we feed data into an estimator that learns from the training data provided. Sometimes the data can be significantly spread out with a long tail or outliers, which could lead to a lognormal distribution. This can cause machine learning model performance to suffer.

To help the estimators better understand the underlying relationships in the data between the features and the target, we can use the `TargetDistributionDataCheck`to identify such a distribution. If you use `AutoML.search` to try and find the best pipeline, it will automatically run this data check for you and, if a lognormal distribution is detected, will add a `LogTransformer` to your pipeline to help the model performance!

[13]:
```
from scipy.stats import lognorm
from evalml.data_checks import TargetDistributionDataCheck

data = np.tile(np.arange(10) * 0.01, (100, 10))
X = pd.DataFrame(data=data)
y = pd.Series(lognorm.rvs(s=0.4, loc=1, scale=1, size=100))
```

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```
target_dist_check = TargetDistributionDataCheck()
results = target_dist_check.validate(X, y)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Warning: Target may have a lognormal distribution.
```

Datetime Format

Datetime information is a necessary component of time series problems, but sometimes the data we deal with may contain flaws that make it impossible for time series models to work with them. For example, in order to identify a frequency in the datetime information there has to be equal interval spacing between data points i.e. January 1, 2021, January 3, 2021, January 5, 2021, ...etc which are separated by two days. If instead there are random jumps in the datetime data i.e. January 1, 2021, January 3, 2021, January 12, 2021, then a frequency can't be inferred. Another common issue with time series models are that they can't handle datetime information that isn't properly sorted. Datetime values that aren't monotonically increasing (sorted in ascending order) will encounter this issue and their frequency cannot be inferred.

To make it easy to verify that the datetime column you're working with is properly spaced and sorted, we can leverage the `DatetimeFormatDataCheck`. When initializing the data check, pass in the name of the column that contains your datetime information (or pass in "index" if it's found in either your X or y indices).

[14]:
```
from evalml.data_checks import DateTimeFormatDataCheck

X = pd.DataFrame(pd.date_range("January 1, 2021", periods=8, freq='2D'), columns=[
↪"dates"])
y = pd.Series([1, 2, 4, 2, 1, 2, 3, 1])

# Replaces the last entry with January 16th instead of January 15th
# so that the data is no longer evenly spaced.
X.iloc[7] = "January 16, 2021"

datetime_format_check = DateTimeFormatDataCheck(datetime_column="dates")
results = datetime_format_check.validate(X, y)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])

print("---------------------------------")

# Reverses the order of the index datetime values to be decreasing.
X = X[::-1]
results = datetime_format_check.validate(X, y)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Error: No frequency could be detected in dates, possibly due to uneven intervals.
--------------------------------
Error: No frequency could be detected in dates, possibly due to uneven intervals.
Error: Datetime values must be sorted in ascending order.
```

4.6.3 Data Check Messages

Each data check's `validate` method returns a list of `DataCheckMessage` objects indicating warnings or errors found; warnings are stored as a `DataCheckWarning` object (*API reference*) and errors are stored as a `DataCheckError` object (*API reference*). You can filter the messages returned by a data check by checking for the type of message returned. Below, `NoVarianceDataCheck` returns a list containing a `DataCheckWarning` and a `DataCheckError` message. We can determine which is which by checking the type of each message.

[15]:
```
from evalml.data_checks import NoVarianceDataCheck, DataCheckError, DataCheckWarning

X = pd.DataFrame({"no var col": [0, 0, 0],
                  "no var col with nan": [1, np.nan, 1],
                  "good col":[0, 4, 1]})
y = pd.Series([1, 0, 1])

no_variance_data_check = NoVarianceDataCheck(count_nan_as_value=True)
results = no_variance_data_check.validate(X, y)

for message in results['warnings']:
    print("Warning:", message['message'])

for message in results['errors']:
    print("Error:", message['message'])
```

```
Warning: no var col with nan has two unique values including nulls. Consider encoding␣
↪the nulls for this column to be useful for machine learning.
Error: no var col has 1 unique value.
```

4.6.4 Writing Your Own Data Check

If you would prefer to write your own data check, you can do so by extending the `DataCheck` class and implementing the `validate(self, X, y)` class method. Below, we've created a new `DataCheck`, `ZeroVarianceDataCheck`, which is similar to `NoVarianceDataCheck` defined in `EvalML`. The `validate(self, X, y)` method should return a dictionary with 'warnings' and 'errors' as keys mapping to list of warnings and errors, respectively.

[16]:
```
from evalml.data_checks import DataCheck

class ZeroVarianceDataCheck(DataCheck):
    def validate(self, X, y):
        messages = {'warnings': [], 'errors': []}
        if not isinstance(X, pd.DataFrame):
            X = pd.DataFrame(X)
        warning_msg = "Column '{}' has zero variance"
        messages['warnings'].extend([DataCheckError(warning_msg.format(column), self.
↪name) for column in X.columns if len(X[column].unique()) == 1])
```

4.6.5 Defining Collections of Data Checks

For convenience, EvalML provides a `DataChecks` class to represent a collection of data checks. We will go over `DefaultDataChecks` (*API reference*), a collection defined to check for some of the most common data issues.

Default Data Checks

`DefaultDataChecks` is a collection of data checks defined to check for some of the most common data issues. They include:

- `HighlyNullDataCheck`
- `IDColumnsDataCheck`
- `TargetLeakageDataCheck`
- `InvalidTargetDataCheck`
- `TargetDistributionDataCheck` (for regression problem types)
- `ClassImbalanceDataCheck` (for classification problem types)
- `NoVarianceDataCheck`
- `DateTimeNaNDataCheck`
- `NaturalLanguageNaNDataCheck`
- `DateTimeFormatDataCheck` (for time series problem types)

4.6.6 Writing Your Own Collection of Data Checks

If you would prefer to create your own collection of data checks, you could either write your own data checks class by extending the `DataChecks` class and setting the `self.data_checks` attribute to the list of `DataCheck` classes or objects, or you could pass that list of data checks to the constructor of the `DataChecks` class. Below, we create two identical collections of data checks using the two different methods.

[17]:
```
# Create a subclass of `DataChecks`
from evalml.data_checks import DataChecks, HighlyNullDataCheck,␣
↪InvalidTargetDataCheck, NoVarianceDataCheck, ClassImbalanceDataCheck,␣
↪TargetLeakageDataCheck
from evalml.problem_types import ProblemTypes, handle_problem_types

class MyCustomDataChecks(DataChecks):

    data_checks = [HighlyNullDataCheck, InvalidTargetDataCheck, NoVarianceDataCheck,␣
↪TargetLeakageDataCheck]

    def __init__(self, problem_type, objective):
        """
        A collection of basic data checks.
        Arguments:
            problem_type (str): The problem type that is being validated. Can be␣
↪regression, binary, or multiclass.
        """
        if handle_problem_types(problem_type) == ProblemTypes.REGRESSION:
            super().__init__(self.data_checks,
                             data_check_params={"InvalidTargetDataCheck": {"problem_
↪type": problem_type,
```

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```
                                                                    "objective
↪": objective}})
        else:
            super().__init__(self.data_checks + [ClassImbalanceDataCheck],
                             data_check_params={"InvalidTargetDataCheck": {"problem_
↪type": problem_type,
                                                                    "objective
↪": objective}})


custom_data_checks = MyCustomDataChecks(problem_type=ProblemTypes.REGRESSION,␣
↪objective="R2")
for data_check in custom_data_checks.data_checks:
    print(data_check.name)
```

```
HighlyNullDataCheck
InvalidTargetDataCheck
NoVarianceDataCheck
TargetLeakageDataCheck
```

[18]:
```
# Pass list of data checks to the `data_checks` parameter of DataChecks
same_custom_data_checks = DataChecks(data_checks=[HighlyNullDataCheck,␣
↪InvalidTargetDataCheck, NoVarianceDataCheck, TargetLeakageDataCheck],
                                     data_check_params={"InvalidTargetDataCheck": {
↪"problem_type": ProblemTypes.REGRESSION,

↪"objective": "R2"}})
for data_check in custom_data_checks.data_checks:
    print(data_check.name)
```

```
HighlyNullDataCheck
InvalidTargetDataCheck
NoVarianceDataCheck
TargetLeakageDataCheck
```

4.7 Utilities

4.7.1 Configuring Logging

EvalML uses the standard python logging package. By default, EvalML will log `INFO`-level logs and higher (warnings, errors and critical) to stdout, and will log everything to `evalml_debug.log` in the current working directory.

If you want to change the location of the logfile, before import, set the `EVALML_LOG_FILE` environment variable to specify a filename within an existing directory in which you have write permission. If you want to disable logging to the logfile, set `EVALML_LOG_FILE` to be empty. If the environment variable is set to an invalid location, EvalML will print a warning message to stdout and will not create a log file.

4.7.2 System Information

EvalML provides a command-line interface (CLI) tool prints the version of EvalML and core dependencies installed, as well as some basic system information. To use this tool, just run `evalml info` in your shell or terminal. This could be useful for debugging purposes or tracking down any version-related issues.

[1]:
```
!evalml info
```

```
EvalML version: 0.30.0
EvalML installation directory: /home/docs/checkouts/readthedocs.org/user_builds/
↪feature-labs-inc-evalml/envs/v0.30.1/lib/python3.8/site-packages/evalml

SYSTEM INFO
-----------
python: 3.8.6.final.0
python-bits: 64
OS: Linux
OS-release: 5.4.0-1035-aws
machine: x86_64
processor: x86_64
byteorder: little
LC_ALL: None
LANG: C.UTF-8
LOCALE: en_US.UTF-8
# of CPUS: 2
Available memory: 6.0G

INSTALLED VERSIONS
------------------
zict: 2.0.0
xgboost: 1.4.2
wrapt: 1.12.1
woodwork: 0.5.1
widgetsnbextension: 3.5.1
wheel: 0.37.0
webencodings: 0.5.1
wcwidth: 0.2.5
urllib3: 1.26.6
unidecode: 1.2.0
traitlets: 5.0.5
tqdm: 4.62.0
tornado: 6.1
toolz: 0.11.1
threadpoolctl: 2.2.0
texttable: 1.6.4
testpath: 0.5.0
terminado: 0.11.0
tenacity: 8.0.1
tblib: 1.7.0
statsmodels: 0.12.2
sphinxcontrib-websupport: 1.2.4
sphinxcontrib-serializinghtml: 1.1.5
sphinxcontrib-qthelp: 1.0.3
sphinxcontrib-jsmath: 1.0.1
sphinxcontrib-htmlhelp: 2.0.0
sphinxcontrib-devhelp: 1.0.2
sphinxcontrib-applehelp: 1.0.2
sphinx: 3.5.4
```

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```
sphinx-rtd-theme: 0.4.3
sphinx-autoapi: 1.8.3
soupsieve: 2.2.1
sortedcontainers: 2.4.0
snowballstemmer: 2.1.0
slicer: 0.0.7
sktime: 0.7.0
six: 1.16.0
shap: 0.39.0
setuptools: 57.4.0
send2trash: 1.8.0
seaborn: 0.11.1
scipy: 1.7.1
scikit-optimize: 0.8.1
scikit-learn: 0.24.2
requirements-parser: 0.2.0
requests: 2.26.0
regex: 2021.8.3
recommonmark: 0.5.0
readthedocs-sphinx-ext: 2.1.4
pyzmq: 22.2.1
pyyaml: 5.4.1
pytz: 2021.1
python-dateutil: 2.8.2
pyrsistent: 0.18.0
pyparsing: 2.4.7
pygments: 2.9.0
pydata-sphinx-theme: 0.6.3
pycparser: 2.20
pyaml: 21.8.3
ptyprocess: 0.7.0
psutil: 5.8.0
prompt-toolkit: 3.0.19
prometheus-client: 0.11.0
pmdarima: 1.8.0
plotly: 5.1.0
pip: 21.2.4
pillow: 8.3.1
pickleshare: 0.7.5
pexpect: 4.8.0
patsy: 0.5.1
partd: 1.2.0
parso: 0.8.2
pandocfilters: 1.4.3
pandas: 1.3.1
packaging: 21.0
numpy: 1.21.1
numba: 0.53.1
notebook: 6.4.3
nltk: 3.6.2
nlp-primitives: 1.1.0
networkx: 2.5.1
nest-asyncio: 1.5.1
nbsphinx: 0.8.7
nbformat: 5.1.3
nbconvert: 6.1.0
nbclient: 0.5.3
```

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```
msgpack: 1.0.2
mock: 1.0.1
mistune: 0.8.4
matplotlib: 3.4.3
matplotlib-inline: 0.1.2
markupsafe: 2.0.1
locket: 0.2.1
llvmlite: 0.36.0
lightgbm: 3.2.1
lazy-object-proxy: 1.6.0
kiwisolver: 1.3.1
kaleido: 0.2.1
jupyterlab-widgets: 1.0.0
jupyterlab-pygments: 0.1.2
jupyter-core: 4.7.1
jupyter-client: 6.1.12
jsonschema: 3.2.0
joblib: 1.0.1
jinja2: 3.0.1
jedi: 0.18.0
ipywidgets: 7.6.3
ipython: 7.26.0
ipython-genutils: 0.2.0
ipykernel: 6.1.0
imbalanced-learn: 0.8.0
imagesize: 1.2.0
idna: 3.2
heapdict: 1.0.1
graphviz: 0.17
future: 0.18.2
fsspec: 2021.7.0
featuretools: 0.26.1
evalml: 0.30.0
entrypoints: 0.3
docutils: 0.16
distributed: 2021.7.2
defusedxml: 0.7.1
decorator: 4.4.2
debugpy: 1.4.1
dask: 2021.7.2
cython: 0.29.17
cycler: 0.10.0
commonmark: 0.8.1
colorama: 0.4.4
cloudpickle: 1.6.0
click: 8.0.1
charset-normalizer: 2.0.4
cffi: 1.14.6
certifi: 2021.5.30
category-encoders: 2.2.2
catboost: 0.26.1
bleach: 4.0.0
beautifulsoup4: 4.9.3
backcall: 0.2.0
babel: 2.9.1
attrs: 21.2.0
async-generator: 1.10
```

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```
astroid: 2.6.6
argon2-cffi: 20.1.0
alabaster: 0.7.12
```

4.8 FAQ

4.8.1 Q: What is the difference between EvalML and other AutoML libraries?

EvalML optimizes machine learning pipelines on *custom practical objectives* instead of vague machine learning loss functions so that it will find the best pipelines for your specific needs. Furthermore, EvalML *pipelines* are able to take in all kinds of data (missing values, categorical, etc.) as long as the data are in a single table. EvalML also allows you to build your own pipelines with existing or custom components so you can have more control over the AutoML process. Moreover, EvalML also provides you with support in the form of *data checks* to ensure that you are aware of potential issues your data may cause with machine learning algorithms.

4.8.2 Q: How does EvalML handle missing values?

EvalML contains imputation components in its pipelines so that missing values are taken care of. EvalML optimizes over different types of imputation to search for the best possible pipeline. You can find more information about components *here* and in the API reference [here] (../generated/evalml.pipelines.components.Imputer.ipynb).

4.8.3 Q: How does EvalML handle categorical encoding?

EvalML provides a [one-hot-encoding component] (../generated/evalml.pipelines.components.OneHotEncoder.ipynb) in its pipelines for categorical variables. EvalML plans to support other encoders in the future.

4.8.4 Q: How does EvalML handle feature selection?

EvalML currently utilizes scikit-learn's SelectFromModel with a Random Forest classifier/regressor to handle feature selection. EvalML plans on supporting more feature selectors in the future. You can find more information in the API reference [here] (../generated/evalml.pipelines.components.RFClassifierSelectFromModel.ipynb).

4.8.5 Q: How is feature importance calculated?

Feature importance depends on the estimator used. Variable coefficients are used for regression-based estimators (Logistic Regression and Linear Regression) and Gini importance is used for tree-based estimators (Random Forest and XGBoost).

4.8.6 Q: How does hyperparameter tuning work?

EvalML tunes hyperparameters for its pipelines through Bayesian optimization. In the future we plan to support more optimization techniques such as random search.

4.8.7 Q: Can I create my own objective metric?

Yes you can! You can *create your own custom objective* so that EvalML optimizes the best model for your needs.

4.8.8 Q: How does EvalML avoid overfitting?

EvalML provides *data checks* to combat overfitting. Such data checks include detecting label leakage, unstable pipelines, hold-out datasets and cross validation. EvalML defaults to using Stratified K-Fold cross-validation for classification problems and K-Fold cross-validation for regression problems but allows you to utilize your own cross-validation methods as well.

4.8.9 Q: Can I create my own pipeline for EvalML?

Yes! EvalML allows you to create *custom pipelines* using modular components. This allows you to customize EvalML pipelines for your own needs or for AutoML.

4.8.10 Q: Does EvalML work with X algorithm?

EvalML is constantly improving and adding new components and will allow your own algorithms to be used as components in our pipelines.

CHAPTER

FIVE

API REFERENCE

5.1 Demo Datasets

load_breast_cancer	Load breast cancer dataset. Binary classification problem.
load_diabetes	Load diabetes dataset. Regression problem
load_fraud	Load credit card fraud dataset.
load_wine	Load wine dataset. Multiclass problem.
load_churn	Load credit card fraud dataset.

5.2 Preprocessing

Utilities to preprocess data before using evalml.

load_data	Load features and target from file.
drop_nan_target_rows	Drops rows in X and y when row in the target y has a value of NaN.
target_distribution	Get the target distributions.
number_of_features	Get the number of features of each specific dtype in a DataFrame.
split_data	Splits data into train and test sets.

5.3 Exceptions

MethodPropertyNotFoundError	Exception to raise when a class is does not have an expected method or property.
PipelineNotFoundError	An exception raised when a particular pipeline is not found in automl search results
ObjectiveNotFoundError	Exception to raise when specified objective does not exist.
MissingComponentError	An exception raised when a component is not found in all_components()

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Table 3 – continued from previous page

ComponentNotYetFittedError	An exception to be raised when predict/predict_proba/transform is called on a component without fitting first.
PipelineNotYetFittedError	An exception to be raised when predict/predict_proba/transform is called on a pipeline without fitting first.
AutoMLSearchException	Exception raised when all pipelines in an automl batch return a score of NaN for the primary objective.
EnsembleMissingPipelinesError	An exception raised when an ensemble is missing *estimators* (list) as a parameter.
PipelineScoreError	An exception raised when a pipeline errors while scoring any objective in a list of objectives.
DataCheckInitError	Exception raised when a data check can't initialize with the parameters given.
NullsInColumnWarning	Warning thrown when there are null values in the column of interest

5.4 AutoML

5.4.1 AutoML Search Interface

AutoMLSearch	Automated Pipeline search.

5.4.2 AutoML Utils

search	Given data and configuration, run an automl search.
get_default_primary_search_objective	Get the default primary search objective for a problem type.
make_data_splitter	Given the training data and ML problem parameters, compute a data splitting method to use during AutoML search.

5.4.3 AutoML Algorithm Classes

AutoMLAlgorithm	Base class for the AutoML algorithms which power EvalML.
IterativeAlgorithm	An automl algorithm which first fits a base round of pipelines with default parameters, then does a round of parameter tuning on each pipeline in order of performance.

5.4.4 AutoML Callbacks

silent_error_callback	No-op.
log_error_callback	Logs the exception thrown as an error. Will not throw. This is the default behavior for AutoMLSearch.
raise_error_callback	Raises the exception thrown by the AutoMLSearch object. Also logs the exception as an error.

5.5 Pipelines

5.5.1 Pipeline Base Classes

PipelineBase	Machine learning pipeline made out of transformers and a estimator.
ClassificationPipeline	Pipeline subclass for all classification pipelines.
BinaryClassificationPipeline	Pipeline subclass for all binary classification pipelines.
MulticlassClassificationPipeline	Pipeline subclass for all multiclass classification pipelines.
RegressionPipeline	Pipeline subclass for all regression pipelines.
TimeSeriesClassificationPipeline	Pipeline base class for time series classification problems.
TimeSeriesBinaryClassificationPipeline	Pipeline base class for time series binary classification problems.
TimeSeriesMulticlassClassificationPipeline	Pipeline base class for time series multiclass classification problems.
TimeSeriesRegressionPipeline	Pipeline base class for time series regression problems.

5.5.2 Pipeline Utils

make_pipeline	Given input data, target data, an estimator class and the problem type,
generate_pipeline_code	Creates and returns a string that contains the Python imports and code required for running the EvalML pipeline.

5.6 Components

5.6.1 Component Base Classes

Components represent a step in a pipeline.

ComponentBase	Base class for all components.
Transformer	A component that may or may not need fitting that transforms data.

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Table 10 – continued from previous page

Estimator	A component that fits and predicts given data.

5.6.2 Component Utils

allowed_model_families	List the model types allowed for a particular problem type.
get_estimators	Returns the estimators allowed for a particular problem type.
generate_component_code	Creates and returns a string that contains the Python imports and code required for running the EvalML component.

5.6.3 Transformers

Transformers are components that take in data as input and output transformed data.

DropColumns	Drops specified columns in input data.
SelectColumns	Selects specified columns in input data.
SelectByType	Selects columns by specified Woodwork logical type or semantic tag in input data.
OneHotEncoder	A transformer that encodes categorical features in a one-hot numeric array.
TargetEncoder	A transformer that encodes categorical features into target encodings.
PerColumnImputer	Imputes missing data according to a specified imputation strategy per column.
Imputer	Imputes missing data according to a specified imputation strategy.
SimpleImputer	Imputes missing data according to a specified imputation strategy.
StandardScaler	A transformer that standardizes input features by removing the mean and scaling to unit variance.
RFRegressorSelectFromModel	Selects top features based on importance weights using a Random Forest regressor.
RFClassifierSelectFromModel	Selects top features based on importance weights using a Random Forest classifier.
DropNullColumns	Transformer to drop features whose percentage of NaN values exceeds a specified threshold.
DateTimeFeaturizer	Transformer that can automatically extract features from datetime columns.
TextFeaturizer	Transformer that can automatically featurize text columns using featuretools' nlp_primitives.
DelayedFeatureTransformer	Transformer that delays input features and target variable for time series problems.
DFSTransformer	Featuretools DFS component that generates features for the input features.
PolynomialDetrender	Removes trends from time series by fitting a polynomial to the data.

continues on next page

Table 12 – continued from previous page

Undersampler	Initializes an undersampling transformer to downsample the majority classes in the dataset.
SMOTEOversampler	SMOTE Oversampler component. Works on numerical datasets only. This component is only run during training and not during predict.
SMOTENCOversampler	SMOTENC Oversampler component. Uses SMOTENC to generate synthetic samples. Works on a mix of numerical and categorical columns.
SMOTENOversampler	SMOTEN Oversampler component. Uses SMOTEN to generate synthetic samples. Works for purely categorical datasets.

5.6.4 Estimators

Classifiers

Classifiers are components that output a predicted class label.

CatBoostClassifier	CatBoost Classifier, a classifier that uses gradient-boosting on decision trees.
ElasticNetClassifier	Elastic Net Classifier. Uses Logistic Regression with elasticnet penalty as the base estimator.
ExtraTreesClassifier	Extra Trees Classifier.
RandomForestClassifier	Random Forest Classifier.
LightGBMClassifier	LightGBM Classifier.
LogisticRegressionClassifier	Logistic Regression Classifier.
XGBoostClassifier	XGBoost Classifier.
BaselineClassifier	Classifier that predicts using the specified strategy.
SklearnStackedEnsembleClassifier	Scikit-learn Stacked Ensemble Classifier.
DecisionTreeClassifier	Decision Tree Classifier.
KNeighborsClassifier	K-Nearest Neighbors Classifier.
SVMClassifier	Support Vector Machine Classifier.

Regressors

Regressors are components that output a predicted target value.

ARIMARegressor	Autoregressive Integrated Moving Average Model.
CatBoostRegressor	CatBoost Regressor, a regressor that uses gradient-boosting on decision trees.
ElasticNetRegressor	Elastic Net Regressor.
LinearRegressor	Linear Regressor.
ExtraTreesRegressor	Extra Trees Regressor.
RandomForestRegressor	Random Forest Regressor.
XGBoostRegressor	XGBoost Regressor.
BaselineRegressor	Baseline regressor that uses a simple strategy to make predictions.

continues on next page

Table 14 – continued from previous page

TimeSeriesBaselineEstimator	Time series estimator that predicts using the naive forecasting approach.
SklearnStackedEnsembleRegressor	Scikit-learn Stacked Ensemble Regressor.
DecisionTreeRegressor	Decision Tree Regressor.
LightGBMRegressor	LightGBM Regressor.
SVMRegressor	Support Vector Machine Regressor.

5.7 Model Understanding

5.7.1 Utility Methods

confusion_matrix	Confusion matrix for binary and multiclass classification.
normalize_confusion_matrix	Normalizes a confusion matrix.
precision_recall_curve	Given labels and binary classifier predicted probabilities, compute and return the data representing a precision-recall curve.
roc_curve	Given labels and classifier predicted probabilities, compute and return the data representing a Receiver Operating Characteristic (ROC) curve. Works with binary or multiclass problems.
calculate_permutation_importance	Calculates permutation importance for features.
calculate_permutation_importance_one_column	Calculates permutation importance for one column in the original dataframe.
binary_objective_vs_threshold	Computes objective score as a function of potential binary classification
get_prediction_vs_actual_over_time_data	Get the data needed for the prediction_vs_actual_over_time plot.
partial_dependence	Calculates one or two-way partial dependence. If a single integer or
get_prediction_vs_actual_data	Combines y_true and y_pred into a single dataframe and adds a column for outliers. Used in *graph_prediction_vs_actual()*.
get_linear_coefficients	Returns a dataframe showing the features with the greatest predictive power for a linear model.
t_sne	Get the transformed output after fitting X to the embedded space using t-SNE.

5.7.2 Graph Utility Methods

graph_precision_recall_curve	Generate and display a precision-recall plot.
graph_roc_curve	Generate and display a Receiver Operating Characteristic (ROC) plot for binary and multiclass classification problems.
graph_confusion_matrix	Generate and display a confusion matrix plot.

continues on next page

Table 16 – continued from previous page

graph_permutation_importance	Generate a bar graph of the pipeline's permutation importance.
graph_binary_objective_vs_threshold	Generates a plot graphing objective score vs. decision thresholds for a fitted binary classification pipeline.
graph_prediction_vs_actual	Generate a scatter plot comparing the true and predicted values. Used for regression plotting
graph_prediction_vs_actual_over_time	Plot the target values and predictions against time on the x-axis.
graph_partial_dependence	Create an one-way or two-way partial dependence plot. Passing a single integer or
graph_t_sne	Plot high dimensional data into lower dimensional space using t-SNE .

5.7.3 Prediction Explanations

explain_predictions	Creates a report summarizing the top contributing features for each data point in the input features.
explain_predictions_best_worst	Creates a report summarizing the top contributing features for the best and worst points in the dataset as measured by error to true labels.

5.8 Objectives

5.8.1 Objective Base Classes

ObjectiveBase	Base class for all objectives.
BinaryClassificationObjective	Base class for all binary classification objectives.
MulticlassClassificationObjective	Base class for all multiclass classification objectives.
RegressionObjective	Base class for all regression objectives.

5.8.2 Domain-Specific Objectives

FraudCost	Score the percentage of money lost of the total transaction amount process due to fraud.
LeadScoring	Lead scoring.
CostBenefitMatrix	Score using a cost-benefit matrix. Scores quantify the benefits of a given value, so greater numeric

5.8.3 Classification Objectives

AccuracyBinary	Accuracy score for binary classification.
AccuracyMulticlass	Accuracy score for multiclass classification.
AUC	AUC score for binary classification.
AUCMacro	AUC score for multiclass classification using macro averaging.
AUCMicro	AUC score for multiclass classification using micro averaging.
AUCWeighted	AUC Score for multiclass classification using weighted averaging.
Gini	Gini coefficient for binary classification.
BalancedAccuracyBinary	Balanced accuracy score for binary classification.
BalancedAccuracyMulticlass	Balanced accuracy score for multiclass classification.
F1	F1 score for binary classification.
F1Micro	F1 score for multiclass classification using micro averaging.
F1Macro	F1 score for multiclass classification using macro averaging.
F1Weighted	F1 score for multiclass classification using weighted averaging.
LogLossBinary	Log Loss for binary classification.
LogLossMulticlass	Log Loss for multiclass classification.
MCCBinary	Matthews correlation coefficient for binary classification.
MCCMulticlass	Matthews correlation coefficient for multiclass classification.
Precision	Precision score for binary classification.
PrecisionMicro	Precision score for multiclass classification using micro averaging.
PrecisionMacro	Precision score for multiclass classification using macro averaging.
PrecisionWeighted	Precision score for multiclass classification using weighted averaging.
Recall	Recall score for binary classification.
RecallMicro	Recall score for multiclass classification using micro averaging.
RecallMacro	Recall score for multiclass classification using macro averaging.
RecallWeighted	Recall score for multiclass classification using weighted averaging.

5.8.4 Regression Objectives

R2	Coefficient of determination for regression.
MAE	Mean absolute error for regression.
MAPE	Mean absolute percentage error for time series regression. Scaled by 100 to return a percentage.
MSE	Mean squared error for regression.
MeanSquaredLogError	Mean squared log error for regression.
MedianAE	Median absolute error for regression.
MaxError	Maximum residual error for regression.
ExpVariance	Explained variance score for regression.
RootMeanSquaredError	Root mean squared error for regression.
RootMeanSquaredLogError	Root mean squared log error for regression.

5.8.5 Objective Utils

get_all_objective_names	Get a list of the names of all objectives.
get_core_objectives	Returns all core objective instances associated with the given problem type.
get_core_objective_names	Get a list of all valid core objectives.
get_non_core_objectives	Get non-core objective classes.
get_objective	Returns the Objective class corresponding to a given objective name.

5.9 Problem Types

handle_problem_types	Handles problem_type by either returning the ProblemTypes or converting from a str.
detect_problem_type	Determine the type of problem is being solved based on the targets (binary vs multiclass classification, regression)
ProblemTypes	Enum defining the supported types of machine learning problems.

5.10 Model Family

handle_model_family	Handles model_family by either returning the ModelFamily or converting from a string
ModelFamily	Enum for family of machine learning models.

5.11 Tuners

Tuner	Defines API for base Tuner classes.
SKOptTuner	Bayesian Optimizer.
GridSearchTuner	Grid Search Optimizer, which generates all of the possible points to search for using a grid.
RandomSearchTuner	Random Search Optimizer.

5.12 Data Checks

5.12.1 Data Check Classes

DataCheck	Base class for all data checks. Data checks are a set of heuristics used to determine if there are problems with input data.
InvalidTargetDataCheck	Checks if the target data contains missing or invalid values.
HighlyNullDataCheck	Checks if there are any highly-null columns and rows in the input.
IDColumnsDataCheck	Check if any of the features are likely to be ID columns.
TargetLeakageDataCheck	Check if any of the features are highly correlated with the target by using mutual information or Pearson correlation.
OutliersDataCheck	Checks if there are any outliers in input data by using IQR to determine score anomalies. Columns with score anomalies are considered to contain outliers.
NoVarianceDataCheck	Check if the target or any of the features have no variance.
ClassImbalanceDataCheck	Check if any of the target labels are imbalanced, or if the number of values for each target are below 2 times the number of CV folds. Use for classification problems.
MulticollinearityDataCheck	Check if any set features are likely to be multicollinear.
DateTimeNaNDataCheck	Checks each column in the input for datetime features and will issue an error if NaN values are present.
NaturalLanguageNaNDataCheck	Checks each column in the input for natural language features and will issue an error if NaN values are present.
DateTimeFormatDataCheck	Checks if the datetime column has equally spaced intervals and is monotonically increasing or decreasing in order
DataChecks	A collection of data checks.
DefaultDataChecks	A collection of basic data checks that is used by AutoML by default.

5.12.2 Data Check Messages

DataCheckMessage	Base class for a message returned by a DataCheck, tagged by name.
DataCheckError	DataCheckMessage subclass for errors returned by data checks.
DataCheckWarning	DataCheckMessage subclass for warnings returned by data checks.

5.12.3 Data Check Message Types

DataCheckMessageType	Enum for type of data check message: WARNING or ERROR.

5.12.4 Data Check Message Codes

DataCheckMessageCode	Enum for data check message code.

5.13 Utils

5.13.1 General Utils

import_or_raise	Attempts to import the requested library by name.
convert_to_seconds	Converts a string describing a length of time to its length in seconds.
get_random_state	Generates a numpy.random.RandomState instance using seed.
get_random_seed	Given a numpy.random.RandomState object, generate an int representing a seed value for another random number generator. Or, if given an int, return that int.
pad_with_nans	Pad the beginning num_to_pad rows with nans.
drop_rows_with_nans	Drop rows that have any NaNs in all dataframes or series.
infer_feature_types	Create a Woodwork structure from the given list, pandas, or numpy input, with specified types for columns.
save_plot	Saves fig to filepath if specified, or to a default location if not.
is_all_numeric	Checks if the given DataFrame contains only numeric values
get_importable_subclasses	Get importable subclasses of a base class. Used to list all of our

Evalml

Subpackages

Automl

Subpackages

automl_algorithm

Submodules

automl_algorithm

Module Contents

Classes Summary

AutoMLAlgorithm	Base class for the AutoML algorithms which power EvalML.

Exceptions Summary

—

Contents

class evalml.automl.automl_algorithm.automl_algorithm.**AutoMLAlgorithm**(*allowed_pipelines=None*, *custom_hyperparameters=None*, *max_iterations=None*, *tuner_class=None*, *random_seed=0*)

Base class for the AutoML algorithms which power EvalML.

This class represents an automated machine learning (AutoML) algorithm. It encapsulates the decision-making logic behind an automl search, by both deciding which pipelines to evaluate next and by deciding what set of parameters to configure the pipeline with.

To use this interface, you must define a next_batch method which returns the next group of pipelines to evaluate on the training data. That method may access state and results recorded from the previous batches, although that information is not tracked in a general way in this base class. Overriding add_result is a convenient way to record pipeline evaluation info if necessary.

Parameters

- **allowed_pipelines** (*list(class)*) – A list of PipelineBase subclasses indicating the pipelines allowed in the search. The default of None indicates all pipelines for this problem type are allowed.

- **custom_hyperparameters** (*dict*) – Custom hyperparameter ranges specified for pipelines to iterate over.
- **max_iterations** (*int*) – The maximum number of iterations to be evaluated.
- **tuner_class** (*class*) – A subclass of Tuner, to be used to find parameters for each pipeline. The default of None indicates the SKOptTuner will be used.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Methods

add_result	Register results from evaluating a pipeline
batch_number	Returns the number of batches which have been recommended so far.
next_batch	Get the next batch of pipelines to evaluate
pipeline_number	Returns the number of pipelines which have been recommended so far.

add_result (*self*, *score_to_minimize*, *pipeline*, *trained_pipeline_results*)
Register results from evaluating a pipeline

Parameters

- **score_to_minimize** (*float*) – The score obtained by this pipeline on the primary objective, converted so that lower values indicate better pipelines.
- **pipeline** (*PipelineBase*) – The trained pipeline object which was used to compute the score.
- **trained_pipeline_results** (*dict*) – Results from training a pipeline.

property batch_number (*self*)
Returns the number of batches which have been recommended so far.

abstract next_batch (*self*)
Get the next batch of pipelines to evaluate

Returns a list of instances of PipelineBase subclasses, ready to be trained and evaluated.

Return type list(PipelineBase)

property pipeline_number (*self*)
Returns the number of pipelines which have been recommended so far.

exception evalml.automl.automl_algorithm.automl_algorithm.**AutoMLAlgorithmException**
Exception raised when an error is encountered during the computation of the automl algorithm

evalml_algorithm

Module Contents

Classes Summary

EvalMLAlgorithm	An automl algorithm that consists of two modes: fast and long, where fast is a subset of long.

Contents

class evalml.automl.automl_algorithm.evalml_algorithm.**EvalMLAlgorithm**(*X*, *y*, *problem_type*, *sampler_name*, *tuner_class=None*, *random_seed=0*, *pipeline_params=None*, *custom_hyperparameters=None*, *n_jobs=-1*, *text_in_ensembling=None*, *top_n=3*, *num_long_explore_pipelines=*
num_long_pipelines_per_batc

An automl algorithm that consists of two modes: fast and long, where fast is a subset of long.

1. **Naive pipelines:**
    a. run baseline with default preprocessing pipeline
    b. run naive linear model with default preprocessing pipeline
    c. run basic RF pipeline with default preprocessing pipeline
2. **Naive pipelines with feature selection**
    a. subsequent pipelines will use the selected features with a SelectedColumns transformer

At this point we have a single pipeline candidate for preprocessing and feature selection

3. **Pipelines with preprocessing components:**
    a. scan rest of estimators (our current batch 1).
4. First ensembling run

Fast mode ends here. Begin long mode.

6. **Run top 3 estimators:**
    a. Generate 50 random parameter sets. Run all 150 in one batch
7. Second ensembling run
8. **Repeat these indefinitely until stopping criterion is met:**
    a. For each of the previous top 3 estimators, sample 10 parameters from the tuner. Run all 30 in one batch
    b. Run ensembling

Methods

add_result	Register results from evaluating a pipeline. In batch number 2, the selected column names from the feature selector are taken to be used in a column selector. Information regarding the best pipeline is updated here as well.
batch_number	Returns the number of batches which have been recommended so far.
next_batch	Get the next batch of pipelines to evaluate
pipeline_number	Returns the number of pipelines which have been recommended so far.

add_result (*self*, *score_to_minimize*, *pipeline*, *trained_pipeline_results*)
Register results from evaluating a pipeline. In batch number 2, the selected column names from the feature selector are taken to be used in a column selector. Information regarding the best pipeline is updated here as well.

Parameters

- **score_to_minimize** (*float*) – The score obtained by this pipeline on the primary objective, converted so that lower values indicate better pipelines.
- **pipeline** (*PipelineBase*) – The trained pipeline object which was used to compute the score.
- **trained_pipeline_results** (*dict*) – Results from training a pipeline.

property batch_number (*self*)
Returns the number of batches which have been recommended so far.

next_batch (*self*)
Get the next batch of pipelines to evaluate

Returns a list of instances of PipelineBase subclasses, ready to be trained and evaluated.

Return type list(PipelineBase)

property pipeline_number (*self*)
Returns the number of pipelines which have been recommended so far.

iterative_algorithm

Module Contents

Classes Summary

IterativeAlgorithm	An automl algorithm which first fits a base round of pipelines with default parameters, then does a round of parameter tuning on each pipeline in order of performance.

Contents

class evalml.automl.automl_algorithm.iterative_algorithm.**IterativeAlgorithm**(*allowed_pipelines=N max_iterations=None tuner_class=None, random_seed=0, pipelines_per_batch= n_jobs=- 1, number_features=None, ensembling=False, text_in_ensembling=F pipeline_params=No custom_hyperparameters _estimator_family_order=No*

An automl algorithm which first fits a base round of pipelines with default parameters, then does a round of parameter tuning on each pipeline in order of performance.

Parameters

- **allowed_pipelines** (*list(class)*) – A list of PipelineBase instances indicating the pipelines allowed in the search. The default of None indicates all pipelines for this problem type are allowed.
- **max_iterations** (*int*) – The maximum number of iterations to be evaluated.
- **tuner_class** (*class*) – A subclass of Tuner, to be used to find parameters for each pipeline. The default of None indicates the SKOptTuner will be used.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **pipelines_per_batch** (*int*) – The number of pipelines to be evaluated in each batch, after the first batch. Defaults to 5.
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. Defaults to None.
- **number_features** (*int*) – The number of columns in the input features. Defaults to None.
- **ensembling** (*boolean*) – If True, runs ensembling in a separate batch after every allowed pipeline class has been iterated over. Defaults to False.
- **text_in_ensembling** (*boolean*) – If True and ensembling is True, then n_jobs will be set to 1 to avoid downstream sklearn stacking issues related to nltk. Defaults to None.
- **pipeline_params** (*dict or None*) – Pipeline-level parameters that should be passed to the proposed pipelines. Defaults to None.
- **custom_hyperparameters** (*dict or None*) – Custom hyperparameter ranges specified for pipelines to iterate over. Defaults to None.

- **_estimator_family_order** (*list(ModelFamily) or None*) – specify the sort order for the first batch. Defaults to None, which uses _ESTIMATOR_FAMILY_ORDER.

Methods

add_result	Register results from evaluating a pipeline
batch_number	Returns the number of batches which have been recommended so far.
next_batch	Get the next batch of pipelines to evaluate
pipeline_number	Returns the number of pipelines which have been recommended so far.

add_result (*self*, *score_to_minimize*, *pipeline*, *trained_pipeline_results*)
Register results from evaluating a pipeline

Parameters

- **score_to_minimize** (*float*) – The score obtained by this pipeline on the primary objective, converted so that lower values indicate better pipelines.
- **pipeline** (*PipelineBase*) – The trained pipeline object which was used to compute the score.
- **trained_pipeline_results** (*dict*) – Results from training a pipeline.

property batch_number (*self*)
Returns the number of batches which have been recommended so far.

next_batch (*self*)
Get the next batch of pipelines to evaluate

Returns a list of instances of PipelineBase subclasses, ready to be trained and evaluated.

Return type list(PipelineBase)

property pipeline_number (*self*)
Returns the number of pipelines which have been recommended so far.

Package Contents

Classes Summary

AutoMLAlgorithm	Base class for the AutoML algorithms which power EvalML.
EvalMLAlgorithm	An automl algorithm that consists of two modes: fast and long, where fast is a subset of long.
IterativeAlgorithm	An automl algorithm which first fits a base round of pipelines with default parameters, then does a round of parameter tuning on each pipeline in order of performance.

Exceptions Summary

—

Contents

class evalml.automl.automl_algorithm.**AutoMLAlgorithm**(*allowed_pipelines=None*, *custom_hyperparameters=None*, *max_iterations=None*, *tuner_class=None*, *random_seed=0*)

Base class for the AutoML algorithms which power EvalML.

This class represents an automated machine learning (AutoML) algorithm. It encapsulates the decision-making logic behind an automl search, by both deciding which pipelines to evaluate next and by deciding what set of parameters to configure the pipeline with.

To use this interface, you must define a next_batch method which returns the next group of pipelines to evaluate on the training data. That method may access state and results recorded from the previous batches, although that information is not tracked in a general way in this base class. Overriding add_result is a convenient way to record pipeline evaluation info if necessary.

Parameters

- **allowed_pipelines** (*list(class)*) – A list of PipelineBase subclasses indicating the pipelines allowed in the search. The default of None indicates all pipelines for this problem type are allowed.
- **custom_hyperparameters** (*dict*) – Custom hyperparameter ranges specified for pipelines to iterate over.
- **max_iterations** (*int*) – The maximum number of iterations to be evaluated.
- **tuner_class** (*class*) – A subclass of Tuner, to be used to find parameters for each pipeline. The default of None indicates the SKOptTuner will be used.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Methods

add_result	Register results from evaluating a pipeline
batch_number	Returns the number of batches which have been recommended so far.
next_batch	Get the next batch of pipelines to evaluate
pipeline_number	Returns the number of pipelines which have been recommended so far.

add_result(*self*, *score_to_minimize*, *pipeline*, *trained_pipeline_results*)

Register results from evaluating a pipeline

Parameters

- **score_to_minimize** (*float*) – The score obtained by this pipeline on the primary objective, converted so that lower values indicate better pipelines.
- **pipeline** (*PipelineBase*) – The trained pipeline object which was used to compute the score.
- **trained_pipeline_results** (*dict*) – Results from training a pipeline.

property batch_number(*self*)
Returns the number of batches which have been recommended so far.

abstract next_batch(*self*)
Get the next batch of pipelines to evaluate

Returns a list of instances of PipelineBase subclasses, ready to be trained and evaluated.

Return type list(PipelineBase)

property pipeline_number(*self*)
Returns the number of pipelines which have been recommended so far.

exception evalml.automl.automl_algorithm.**AutoMLAlgorithmException**
Exception raised when an error is encountered during the computation of the automl algorithm

class evalml.automl.automl_algorithm.**EvalMLAlgorithm**(*X*, *y*, *problem_type*, *sampler_name*, *tuner_class=None*, *random_seed=0*, *pipeline_params=None*, *custom_hyperparameters=None*, *n_jobs=-1*, *text_in_ensembling=None*, *top_n=3*, *num_long_explore_pipelines=50*, *num_long_pipelines_per_batch=10*)
An automl algorithm that consists of two modes: fast and long, where fast is a subset of long.

1. **Naive pipelines:**
    a. run baseline with default preprocessing pipeline
    b. run naive linear model with default preprocessing pipeline
    c. run basic RF pipeline with default preprocessing pipeline
2. **Naive pipelines with feature selection**
    a. subsequent pipelines will use the selected features with a SelectedColumns transformer

At this point we have a single pipeline candidate for preprocessing and feature selection

3. **Pipelines with preprocessing components:**
    a. scan rest of estimators (our current batch 1).
4. First ensembling run

Fast mode ends here. Begin long mode.

6. **Run top 3 estimators:**
    a. Generate 50 random parameter sets. Run all 150 in one batch
7. Second ensembling run
8. **Repeat these indefinitely until stopping criterion is met:**
    a. For each of the previous top 3 estimators, sample 10 parameters from the tuner. Run all 30 in one batch
    b. Run ensembling

Methods

add_result	Register results from evaluating a pipeline. In batch number 2, the selected column names from the feature selector are taken to be used in a column selector. Information regarding the best pipeline is updated here as well.
batch_number	Returns the number of batches which have been recommended so far.
next_batch	Get the next batch of pipelines to evaluate
pipeline_number	Returns the number of pipelines which have been recommended so far.

add_result(*self*, *score_to_minimize*, *pipeline*, *trained_pipeline_results*)
Register results from evaluating a pipeline. In batch number 2, the selected column names from the feature selector are taken to be used in a column selector. Information regarding the best pipeline is updated here as well.

Parameters

- **score_to_minimize** (*float*) – The score obtained by this pipeline on the primary objective, converted so that lower values indicate better pipelines.
- **pipeline** (*PipelineBase*) – The trained pipeline object which was used to compute the score.
- **trained_pipeline_results** (*dict*) – Results from training a pipeline.

property batch_number(*self*)
Returns the number of batches which have been recommended so far.

next_batch(*self*)
Get the next batch of pipelines to evaluate

Returns a list of instances of PipelineBase subclasses, ready to be trained and evaluated.

Return type list(PipelineBase)

property pipeline_number(*self*)
Returns the number of pipelines which have been recommended so far.

class evalml.automl.automl_algorithm.**IterativeAlgorithm**(*allowed_pipelines=None*, *max_iterations=None*, *tuner_class=None*, *random_seed=0*, *pipelines_per_batch=5*, *n_jobs=-1*, *number_features=None*, *ensembling=False*, *text_in_ensembling=False*, *pipeline_params=None*, *custom_hyperparameters=None*, *_estimator_family_order=None*)
An automl algorithm which first fits a base round of pipelines with default parameters, then does a round of parameter tuning on each pipeline in order of performance.

Parameters

- **allowed_pipelines** (*list(class)*) – A list of PipelineBase instances indicating the pipelines allowed in the search. The default of None indicates all pipelines for this problem type are allowed.
- **max_iterations** (*int*) – The maximum number of iterations to be evaluated.
- **tuner_class** (*class*) – A subclass of Tuner, to be used to find parameters for each pipeline. The default of None indicates the SKOptTuner will be used.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **pipelines_per_batch** (*int*) – The number of pipelines to be evaluated in each batch, after the first batch. Defaults to 5.
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. Defaults to None.
- **number_features** (*int*) – The number of columns in the input features. Defaults to None.
- **ensembling** (*boolean*) – If True, runs ensembling in a separate batch after every allowed pipeline class has been iterated over. Defaults to False.
- **text_in_ensembling** (*boolean*) – If True and ensembling is True, then n_jobs will be set to 1 to avoid downstream sklearn stacking issues related to nltk. Defaults to None.
- **pipeline_params** (*dict or None*) – Pipeline-level parameters that should be passed to the proposed pipelines. Defaults to None.
- **custom_hyperparameters** (*dict or None*) – Custom hyperparameter ranges specified for pipelines to iterate over. Defaults to None.
- **_estimator_family_order** (*list(ModelFamily) or None*) – specify the sort order for the first batch. Defaults to None, which uses _ESTIMATOR_FAMILY_ORDER.

Methods

add_result	Register results from evaluating a pipeline
batch_number	Returns the number of batches which have been recommended so far.
next_batch	Get the next batch of pipelines to evaluate
pipeline_number	Returns the number of pipelines which have been recommended so far.

add_result(*self*, *score_to_minimize*, *pipeline*, *trained_pipeline_results*)
Register results from evaluating a pipeline

Parameters

- **score_to_minimize** (*float*) – The score obtained by this pipeline on the primary objective, converted so that lower values indicate better pipelines.
- **pipeline** (*PipelineBase*) – The trained pipeline object which was used to compute the score.
- **trained_pipeline_results** (*dict*) – Results from training a pipeline.

property batch_number(*self*)
Returns the number of batches which have been recommended so far.

next_batch(*self*)

Get the next batch of pipelines to evaluate

Returns a list of instances of PipelineBase subclasses, ready to be trained and evaluated.

Return type list(PipelineBase)

property pipeline_number(*self*)
Returns the number of pipelines which have been recommended so far.

engine

Submodules

cf_engine

Module Contents

Classes Summary

CFClient	Custom CFClient API to match Dask's CFClient and allow context management.
CFComputation	A Future-like wrapper around jobs created by the CFEngine.
CFEngine	The concurrent.futures (CF) engine

Contents

class evalml.automl.engine.cf_engine.**CFClient**(*pool*)
Custom CFClient API to match Dask's CFClient and allow context management.

Methods

submit	Pass through to imitate Dask's Client API.

submit(*self*, **args*, ***kwargs*)
Pass through to imitate Dask's Client API.

class evalml.automl.engine.cf_engine.**CFComputation**(*future*)
A Future-like wrapper around jobs created by the CFEngine.

Methods

cancel	Cancel the current computation.
done	**returns** Whether the computation is done.
get_result	Gets the computation result.

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is_cancelled	**returns** Returns whether computation was cancelled.

cancel(*self*)
Cancel the current computation.

Returns

False if the call is currently being executed or finished running and cannot be cancelled. True if the call can be canceled.

Return type bool

done(*self*)

Returns Whether the computation is done.

Return type bool

get_result(*self*)
Gets the computation result. Will block until the computation is finished.

Raises

- **Exception** – If computation fails. Returns traceback.
- **cf.TimeoutError** – If computation takes longer than default timeout time.
- **cf.CancelledError** – If computation was canceled before completing.

Returns The result of the requested job.

property is_cancelled(*self*)

Returns Returns whether computation was cancelled.

Return type bool

class evalml.automl.engine.cf_engine.**CFEngine**(*client*)
The concurrent.futures (CF) engine

Methods

setup_job_log	
submit_evaluation_job	Send evaluation job to cluster.
submit_scoring_job	Send scoring job to cluster.
submit_training_job	Send training job to cluster.

static setup_job_log()

submit_evaluation_job(*self*, *automl_config*, *pipeline*, *X*, *y*) → *evalml.automl.engine.engine_base.EngineComputation*
Send evaluation job to cluster.

Parameters

- **automl_config** – structure containing data passed from AutoMLSearch instance
- **pipeline** (*pipeline.PipelineBase*) – pipeline to evaluate

- **X** (*pd.DataFrame*) – input data for modeling
- **y** (*pd.Series*) – target data for modeling

Returns

an object wrapping a reference to a future-like computation occurring in the resource pool

Return type *CFComputation*

submit_scoring_job(*self*, *automl_config*, *pipeline*, *X*, *y*, *objectives*) → *evalml.automl.engine.engine_base.EngineComputation*

Send scoring job to cluster.

Parameters

- **automl_config** – structure containing data passed from AutoMLSearch instance
- **pipeline** (*pipeline.PipelineBase*) – pipeline to train
- **X** (*pd.DataFrame*) – input data for modeling
- **y** (*pd.Series*) – target data for modeling

Returns

a object wrapping a reference to a future-like computation occurring in the resource pool

Return type *CFComputation*

submit_training_job(*self*, *automl_config*, *pipeline*, *X*, *y*) → *evalml.automl.engine.engine_base.EngineComputation*

Send training job to cluster.

Parameters

- **automl_config** – structure containing data passed from AutoMLSearch instance
- **pipeline** (*pipeline.PipelineBase*) – pipeline to train
- **X** (*pd.DataFrame*) – input data for modeling
- **y** (*pd.Series*) – target data for modeling

Returns

an object wrapping a reference to a future-like computation occurring in the resource pool

Return type *CFComputation*

dask_engine

Module Contents

Classes Summary

DaskComputation	A Future-like wrapper around jobs created by the DaskEngine.
DaskEngine	The dask engine

Contents

class evalml.automl.engine.dask_engine.**DaskComputation**(*dask_future*)
A Future-like wrapper around jobs created by the DaskEngine.

Parameters **dask_future** (*callable*) – Computation to do.

Methods

cancel	Cancel the current computation.
done	**returns** Whether the computation is done.
get_result	Gets the computation result.
is_cancelled	**returns** Returns whether computation was cancelled.

cancel(*self*)
Cancel the current computation.

done(*self*)

Returns Whether the computation is done.

Return type bool

get_result(*self*)
Gets the computation result. Will block until the computation is finished.

Raises **Exception** – If computation fails. Returns traceback.

property is_cancelled(*self*)

Returns Returns whether computation was cancelled.

Return type bool

class evalml.automl.engine.dask_engine.**DaskEngine**(*client*)
The dask engine

Methods

send_data_to_cluster	Send data to the cluster.
setup_job_log	
submit_evaluation_job	Send evaluation job to cluster.
submit_scoring_job	Send scoring job to cluster.
submit_training_job	Send training job to cluster.

send_data_to_cluster(*self*, *X*, *y*)
Send data to the cluster.

The implementation uses caching so the data is only sent once. This follows dask best practices.

Parameters

- **X** (*pd.DataFrame*) – input data for modeling

- **y** (*pd.Series*) – target data for modeling

Returns the modeling data

Return type dask.Future

static setup_job_log()

submit_evaluation_job(*self*, *automl_config*, *pipeline*, *X*, *y*) → *evalml.automl.engine.engine_base.EngineComputation*

Send evaluation job to cluster.

Parameters

- **automl_config** – structure containing data passed from AutoMLSearch instance
- **pipeline** (*pipeline.PipelineBase*) – pipeline to evaluate
- **X** (*pd.DataFrame*) – input data for modeling
- **y** (*pd.Series*) – target data for modeling

Returns

a object wrapping a reference to a future-like computation occurring in the dask cluster

Return type *DaskComputation*

submit_scoring_job(*self*, *automl_config*, *pipeline*, *X*, *y*, *objectives*) → *evalml.automl.engine.engine_base.EngineComputation*

Send scoring job to cluster.

Parameters

- **automl_config** – structure containing data passed from AutoMLSearch instance
- **pipeline** (*pipeline.PipelineBase*) – pipeline to train
- **X** (*pd.DataFrame*) – input data for modeling
- **y** (*pd.Series*) – target data for modeling

Returns

a object wrapping a reference to a future-like computation occurring in the dask cluster

Return type *DaskComputation*

submit_training_job(*self*, *automl_config*, *pipeline*, *X*, *y*) → *evalml.automl.engine.engine_base.EngineComputation*

Send training job to cluster.

Parameters

- **automl_config** – structure containing data passed from AutoMLSearch instance
- **pipeline** (*pipeline.PipelineBase*) – pipeline to train
- **X** (*pd.DataFrame*) – input data for modeling
- **y** (*pd.Series*) – target data for modeling

Returns

a object wrapping a reference to a future-like computation occurring in the dask cluster

Return type *DaskComputation*

engine_base

Module Contents

Classes Summary

EngineBase	Helper class that provides a standard way to create an ABC using
EngineComputation	Wrapper around the result of a (possibly asynchronous) engine computation.
JobLogger	Mimics the behavior of a python logging.Logger but stores all messages rather than actually logging them.

Functions

evaluate_pipeline	Function submitted to the submit_evaluation_job engine method.
score_pipeline	Wrapper around pipeline.score method to make it easy to score pipelines with dask.
train_and_score_pipeline	Given a pipeline, config and data, train and score the pipeline and return the CV or TV scores
train_pipeline	Train a pipeline and tune the threshold if necessary.

Contents

class evalml.automl.engine.engine_base.**EngineBase**

Helper class that provides a standard way to create an ABC using inheritance.

Methods

setup_job_log	
submit_evaluation_job	Submit job for pipeline evaluation during AutoMLSearch.
submit_scoring_job	Submit job for pipeline scoring.
submit_training_job	Submit job for pipeline training.

static setup_job_log()

abstract submit_evaluation_job(*self*, *automl_config*, *pipeline*, *X*, *y*)

Submit job for pipeline evaluation during AutoMLSearch.

abstract submit_scoring_job(*self*, *automl_config*, *pipeline*, *X*, *y*, *objectives*)

Submit job for pipeline scoring.

abstract submit_training_job(*self*, *automl_config*, *pipeline*, *X*, *y*)

Submit job for pipeline training.

class evalml.automl.engine.engine_base.**EngineComputation**

Wrapper around the result of a (possibly asynchronous) engine computation.

Methods

cancel	Cancel the computation.
done	Whether the computation is done.
get_result	Gets the computation result.

abstract cancel(*self*)
Cancel the computation.

abstract done(*self*)
Whether the computation is done.

abstract get_result(*self*)
Gets the computation result. Will block until the computation is finished.

Raises Exception: If computation fails. Returns traceback.

evalml.automl.engine.engine_base.**evaluate_pipeline**(*pipeline*, *automl_config*, *X*, *y*, *logger*)
Function submitted to the submit_evaluation_job engine method.

Parameters

- **pipeline** (*PipelineBase*) – The pipeline to score
- **automl_config** (*AutoMLConfig*) – The AutoMLSearch object, used to access config and the error callback
- **X** (*pd.DataFrame*) – Training features
- **y** (*pd.Series*) – Training target

Returns

First - A dict containing cv_score_mean, cv_scores, training_time and a cv_data structure with details. Second - The pipeline class we trained and scored. Third - the job logger instance with all the recorded messages.

Return type tuple of three items

class evalml.automl.engine.engine_base.**JobLogger**
Mimics the behavior of a python logging.Logger but stores all messages rather than actually logging them.

This is used during engine jobs so that log messages are recorded after the job completes. This is desired so that all of the messages for a single job are grouped together in the log.

Methods

debug	Store message at the debug level.
error	Store message at the error level.
info	Store message at the info level.
warning	Store message at the warning level.
write_to_logger	Write all the messages to the logger. First In First Out order.

debug(*self*, *msg*)
Store message at the debug level.

error(*self*, *msg*)
Store message at the error level.

info(*self*, *msg*)
Store message at the info level.

warning(*self*, *msg*)
Store message at the warning level.

write_to_logger(*self*, *logger*)
Write all the messages to the logger. First In First Out order.

evalml.automl.engine.engine_base.**score_pipeline**(*pipeline*, *X*, *y*, *objectives*, *X_schema=None*, *y_schema=None*)
Wrapper around pipeline.score method to make it easy to score pipelines with dask.

Arguments: pipeline (PipelineBase): The pipeline to score. X (pd.DataFrame): Features to score on. y (pd.Series): Target used to calcualte scores. X_schema (ww.TableSchema): Schema for features. y_schema (ww.ColumnSchema): Schema for columns.

Returns dict containing pipeline scores.

evalml.automl.engine.engine_base.**train_and_score_pipeline**(*pipeline*, *automl_config*, *full_X_train*, *full_y_train*, *logger*)
Given a pipeline, config and data, train and score the pipeline and return the CV or TV scores

Parameters

- **pipeline** (*PipelineBase*) – The pipeline to score
- **automl_config** (*AutoMLSearch*) – The AutoMLSearch object, used to access config and the error callback
- **full_X_train** (*pd.DataFrame*) – Training features
- **full_y_train** (*pd.Series*) – Training target

Returns

First - A dict containing cv_score_mean, cv_scores, training_time and a cv_data structure with details. Second - The pipeline class we trained and scored. Third - the job logger instance with all the recorded messages.

Return type tuple of three items

evalml.automl.engine.engine_base.**train_pipeline**(*pipeline*, *X*, *y*, *automl_config*, *schema=True*)
Train a pipeline and tune the threshold if necessary.

Parameters

- **pipeline** (*PipelineBase*) – Pipeline to train.
- **X** (*pd.DataFrame*) – Features to train on.
- **y** (*pd.Series*) – Target to train on.
- **automl_config** (*AutoMLSearch*) – The AutoMLSearch object, used to access config and the error callback
- **schema** (*bool*) – Whether to use the schemas for X and y

Returns trained pipeline.

Return type pipeline (PipelineBase)

sequential_engine

Module Contents

Classes Summary

SequentialComputation	A Future-like api for jobs created by the SequentialEngine, an Engine that sequentially computes the submitted jobs.
SequentialEngine	The default engine for the AutoML search. Trains and scores pipelines locally and sequentially.

Contents

class evalml.automl.engine.sequential_engine.**SequentialComputation**(*work*, ***kwargs*)

A Future-like api for jobs created by the SequentialEngine, an Engine that sequentially computes the submitted jobs.

In order to separate the engine from the AutoMLSearch loop, we need the sequential computations to behave the same way as concurrent computations from AutoMLSearch's point-of-view. One way to do this is by delaying the computation in the sequential engine until get_result is called. Since AutoMLSearch will call get_result only when the computation is "done", by always returning True in done() we make sure that get_result is called in the order that the jobs are submitted. So the computations happen sequentially!

Parameters **work** (*callable*) – Computation that should be done by the engine.

Methods

cancel	Cancel the current computation.
done	Whether the computation is done.
get_result	Gets the computation result.

cancel(*self*)
Cancel the current computation.

done(*self*)
Whether the computation is done.

get_result(*self*)
Gets the computation result. Will block until the computation is finished.

Raises Exception: If computation fails. Returns traceback.

class evalml.automl.engine.sequential_engine.**SequentialEngine**
The default engine for the AutoML search. Trains and scores pipelines locally and sequentially.

Methods

setup_job_log	
submit_evaluation_job	Submit job for pipeline evaluation during AutoMLSearch.

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submit_scoring_job	Submit job for pipeline scoring.
submit_training_job	Submit job for pipeline training.

static setup_job_log()

submit_evaluation_job(*self*, *automl_config*, *pipeline*, *X*, *y*)
Submit job for pipeline evaluation during AutoMLSearch.

submit_scoring_job(*self*, *automl_config*, *pipeline*, *X*, *y*, *objectives*)
Submit job for pipeline scoring.

submit_training_job(*self*, *automl_config*, *pipeline*, *X*, *y*)
Submit job for pipeline training.

Package Contents

Classes Summary

CFEngine	The concurrent.futures (CF) engine
DaskEngine	The dask engine
EngineBase	Helper class that provides a standard way to create an ABC using
EngineComputation	Wrapper around the result of a (possibly asynchronous) engine computation.
SequentialEngine	The default engine for the AutoML search. Trains and scores pipelines locally and sequentially.

Functions

evaluate_pipeline	Function submitted to the submit_evaluation_job engine method.
train_and_score_pipeline	Given a pipeline, config and data, train and score the pipeline and return the CV or TV scores
train_pipeline	Train a pipeline and tune the threshold if necessary.

Contents

class evalml.automl.engine.**CFEngine**(*client*)
The concurrent.futures (CF) engine

Methods

setup_job_log	

submit_evaluation_job	Send evaluation job to cluster.
submit_scoring_job	Send scoring job to cluster.
submit_training_job	Send training job to cluster.

static setup_job_log()

submit_evaluation_job(*self*, *automl_config*, *pipeline*, *X*, *y*) → *evalml.automl.engine.engine_base.EngineComputation*

Send evaluation job to cluster.

Parameters

- **automl_config** – structure containing data passed from AutoMLSearch instance
- **pipeline** (*pipeline.PipelineBase*) – pipeline to evaluate
- **X** (*pd.DataFrame*) – input data for modeling
- **y** (*pd.Series*) – target data for modeling

Returns

an object wrapping a reference to a future-like computation occurring in the resource pool

Return type CFComputation

submit_scoring_job(*self*, *automl_config*, *pipeline*, *X*, *y*, *objectives*) → *evalml.automl.engine.engine_base.EngineComputation*

Send scoring job to cluster.

Parameters

- **automl_config** – structure containing data passed from AutoMLSearch instance
- **pipeline** (*pipeline.PipelineBase*) – pipeline to train
- **X** (*pd.DataFrame*) – input data for modeling
- **y** (*pd.Series*) – target data for modeling

Returns

a object wrapping a reference to a future-like computation occurring in the resource pool

Return type CFComputation

submit_training_job(*self*, *automl_config*, *pipeline*, *X*, *y*) → *evalml.automl.engine.engine_base.EngineComputation*

Send training job to cluster.

Parameters

- **automl_config** – structure containing data passed from AutoMLSearch instance
- **pipeline** (*pipeline.PipelineBase*) – pipeline to train
- **X** (*pd.DataFrame*) – input data for modeling
- **y** (*pd.Series*) – target data for modeling

Returns

an object wrapping a reference to a future-like computation occurring in the resource pool

Return type CFComputation

class evalml.automl.engine.**DaskEngine**(*client*)

The dask engine

Methods

send_data_to_cluster	Send data to the cluster.
setup_job_log	

submit_evaluation_job	Send evaluation job to cluster.
submit_scoring_job	Send scoring job to cluster.
submit_training_job	Send training job to cluster.

send_data_to_cluster(*self*, *X*, *y*)
Send data to the cluster.

The implementation uses caching so the data is only sent once. This follows dask best practices.

Parameters

- **X** (*pd.DataFrame*) – input data for modeling
- **y** (*pd.Series*) – target data for modeling

Returns the modeling data

Return type dask.Future

static setup_job_log()

submit_evaluation_job(*self*, *automl_config*, *pipeline*, *X*, *y*) → *evalml.automl.engine.engine_base.EngineComputation*
Send evaluation job to cluster.

Parameters

- **automl_config** – structure containing data passed from AutoMLSearch instance
- **pipeline** (*pipeline.PipelineBase*) – pipeline to evaluate
- **X** (*pd.DataFrame*) – input data for modeling
- **y** (*pd.Series*) – target data for modeling

Returns

a object wrapping a reference to a future-like computation occurring in the dask cluster

Return type DaskComputation

submit_scoring_job(*self*, *automl_config*, *pipeline*, *X*, *y*, *objectives*) → *evalml.automl.engine.engine_base.EngineComputation*
Send scoring job to cluster.

Parameters

- **automl_config** – structure containing data passed from AutoMLSearch instance
- **pipeline** (*pipeline.PipelineBase*) – pipeline to train
- **X** (*pd.DataFrame*) – input data for modeling
- **y** (*pd.Series*) – target data for modeling

Returns

a object wrapping a reference to a future-like computation occurring in the dask cluster

Return type DaskComputation

submit_training_job(*self*, *automl_config*, *pipeline*, *X*, *y*) → *evalml.automl.engine.engine_base.EngineComputation*

Send training job to cluster.

Parameters

- **automl_config** – structure containing data passed from AutoMLSearch instance
- **pipeline** (*pipeline.PipelineBase*) – pipeline to train
- **X** (*pd.DataFrame*) – input data for modeling
- **y** (*pd.Series*) – target data for modeling

Returns

a object wrapping a reference to a future-like computation occurring in the dask cluster

Return type DaskComputation

class evalml.automl.engine.**EngineBase**

Helper class that provides a standard way to create an ABC using inheritance.

Methods

setup_job_log	
submit_evaluation_job	Submit job for pipeline evaluation during AutoMLSearch.
submit_scoring_job	Submit job for pipeline scoring.
submit_training_job	Submit job for pipeline training.

static setup_job_log()

abstract submit_evaluation_job(*self*, *automl_config*, *pipeline*, *X*, *y*)

Submit job for pipeline evaluation during AutoMLSearch.

abstract submit_scoring_job(*self*, *automl_config*, *pipeline*, *X*, *y*, *objectives*)

Submit job for pipeline scoring.

abstract submit_training_job(*self*, *automl_config*, *pipeline*, *X*, *y*)

Submit job for pipeline training.

class evalml.automl.engine.**EngineComputation**

Wrapper around the result of a (possibly asynchronous) engine computation.

Methods

cancel	Cancel the computation.
done	Whether the computation is done.
get_result	Gets the computation result.

abstract cancel(*self*)

Cancel the computation.

abstract done(*self*)

Whether the computation is done.

abstract get_result(*self*)

Gets the computation result. Will block until the computation is finished.

Raises Exception: If computation fails. Returns traceback.

evalml.automl.engine.**evaluate_pipeline**(*pipeline*, *automl_config*, *X*, *y*, *logger*)
Function submitted to the submit_evaluation_job engine method.

Parameters

- **pipeline** (*PipelineBase*) – The pipeline to score
- **automl_config** (*AutoMLConfig*) – The AutoMLSearch object, used to access config and the error callback
- **X** (*pd.DataFrame*) – Training features
- **y** (*pd.Series*) – Training target

Returns

First - A dict containing cv_score_mean, cv_scores, training_time and a cv_data structure with details. Second - The pipeline class we trained and scored. Third - the job logger instance with all the recorded messages.

Return type tuple of three items

class evalml.automl.engine.**SequentialEngine**
The default engine for the AutoML search. Trains and scores pipelines locally and sequentially.

Methods

setup_job_log	
submit_evaluation_job	Submit job for pipeline evaluation during AutoMLSearch.
submit_scoring_job	Submit job for pipeline scoring.
submit_training_job	Submit job for pipeline training.

static setup_job_log()

submit_evaluation_job(*self*, *automl_config*, *pipeline*, *X*, *y*)
Submit job for pipeline evaluation during AutoMLSearch.

submit_scoring_job(*self*, *automl_config*, *pipeline*, *X*, *y*, *objectives*)
Submit job for pipeline scoring.

submit_training_job(*self*, *automl_config*, *pipeline*, *X*, *y*)
Submit job for pipeline training.

evalml.automl.engine.**train_and_score_pipeline**(*pipeline*, *automl_config*, *full_X_train*, *full_y_train*, *logger*)
Given a pipeline, config and data, train and score the pipeline and return the CV or TV scores

Parameters

- **pipeline** (*PipelineBase*) – The pipeline to score
- **automl_config** (*AutoMLSearch*) – The AutoMLSearch object, used to access config and the error callback
- **full_X_train** (*pd.DataFrame*) – Training features
- **full_y_train** (*pd.Series*) – Training target

Returns

First - A dict containing cv_score_mean, cv_scores, training_time and a cv_data structure with details. Second - The pipeline class we trained and scored. Third - the job logger instance with all

the recorded messages.

Return type tuple of three items

evalml.automl.engine.**train_pipeline**(*pipeline*, *X*, *y*, *automl_config*, *schema=True*)

Train a pipeline and tune the threshold if necessary.

Parameters

- **pipeline** (*PipelineBase*) – Pipeline to train.
- **X** (*pd.DataFrame*) – Features to train on.
- **y** (*pd.Series*) – Target to train on.
- **automl_config** (*AutoMLSearch*) – The AutoMLSearch object, used to access config and the error callback
- **schema** (*bool*) – Whether to use the schemas for X and y

Returns trained pipeline.

Return type pipeline (PipelineBase)

Submodules

automl_search

Module Contents

Classes Summary

AutoMLSearch	Automated Pipeline search.

Functions

search	Given data and configuration, run an automl search.

Attributes Summary

logger

Contents

class evalml.automl.automl_search.**AutoMLSearch**(*X_train=None*, *y_train=None*, *problem_type=None*, *objective='auto'*, *max_iterations=None*, *max_time=None*, *patience=None*, *tolerance=None*, *data_splitter=None*, *allowed_component_graphs=None*, *allowed_model_families=None*, *start_iteration_callback=None*, *add_result_callback=None*, *error_callback=None*, *additional_objectives=None*, *alternate_thresholding_objective='F1'*, *random_seed=0*, *n_jobs=-1*, *tuner_class=None*, *optimize_thresholds=True*, *ensembling=False*, *max_batches=None*, *problem_configuration=None*, *train_best_pipeline=True*, *pipeline_parameters=None*, *custom_hyperparameters=None*, *sampler_method='auto'*, *sampler_balanced_ratio=0.25*, *_ensembling_split_size=0.2*, *_pipelines_per_batch=5*, *engine=None*)

Automated Pipeline search.

Parameters

- **X_train** (*pd.DataFrame*) – The input training data of shape [n_samples, n_features]. Required.
- **y_train** (*pd.Series*) – The target training data of length [n_samples]. Required for supervised learning tasks.
- **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.
- **objective** (*str, ObjectiveBase*) – The objective to optimize for. Used to propose and rank pipelines, but not for optimizing each pipeline during fit-time. When set to 'auto', chooses:
  - LogLossBinary for binary classification problems,
  - LogLossMulticlass for multiclass classification problems, and
  - R2 for regression problems.
- **max_iterations** (*int*) – Maximum number of iterations to search. If max_iterations and max_time is not set, then max_iterations will default to max_iterations of 5.
- **max_time** (*int, str*) – Maximum time to search for pipelines. This will not start a new pipeline search after the duration has elapsed. If it is an integer, then the time will be in seconds. For strings, time can be specified as seconds, minutes, or hours.
- **patience** (*int*) – Number of iterations without improvement to stop search early. Must be positive. If None, early stopping is disabled. Defaults to None.

- **tolerance** (*float*) – Minimum percentage difference to qualify as score improvement for early stopping. Only applicable if patience is not None. Defaults to None.
- **allowed_component_graphs** (*dict*) – A dictionary of lists or ComponentGraphs indicating the component graphs allowed in the search. The format should follow { "Name_0": [list_of_components], "Name_1": [ComponentGraph(...)] }

  The default of None indicates all pipeline component graphs for this problem type are allowed. Setting this field will cause allowed_model_families to be ignored.

  e.g. allowed_component_graphs = { "My_Graph": ["Imputer", "One Hot Encoder", "Random Forest Classifier"] }
- **allowed_model_families** (*list(str, ModelFamily)*) – The model families to search. The default of None searches over all model families. Run evalml.pipelines.components.utils.allowed_model_families("binary") to see options. Change *binary* to *multiclass* or *regression* depending on the problem type. Note that if allowed_pipelines is provided, this parameter will be ignored.
- **data_splitter** (*sklearn.model_selection.BaseCrossValidator*) – Data splitting method to use. Defaults to StratifiedKFold.
- **tuner_class** – The tuner class to use. Defaults to SKOptTuner.
- **optimize_thresholds** (*bool*) – Whether or not to optimize the binary pipeline threshold. Defaults to True.
- **start_iteration_callback** (*callable*) – Function called before each pipeline training iteration. Callback function takes three positional parameters: The pipeline instance and the AutoMLSearch object.
- **add_result_callback** (*callable*) – Function called after each pipeline training iteration. Callback function takes three positional parameters: A dictionary containing the training results for the new pipeline, an untrained_pipeline containing the parameters used during training, and the AutoMLSearch object.
- **error_callback** (*callable*) – Function called when *search()* errors and raises an Exception. Callback function takes three positional parameters: the Exception raised, the traceback, and the AutoMLSearch object. Must also accepts kwargs, so AutoMLSearch is able to pass along other appropriate parameters by default. Defaults to None, which will call *log_error_callback*.
- **additional_objectives** (*list*) – Custom set of objectives to score on. Will override default objectives for problem type if not empty.
- **alternate_thresholding_objective** (*str*) – The objective to use for thresholding binary classification pipelines if the main objective provided isn't tuneable. Defaults to F1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used.
- **ensembling** (*boolean*) – If True, runs ensembling in a separate batch after every allowed pipeline class has been iterated over. If the number of unique pipelines to search over per batch is one, ensembling will not run. Defaults to False.
- **max_batches** (*int*) – The maximum number of batches of pipelines to search. Parameters max_time, and max_iterations have precedence over stopping the search.

- **problem_configuration** (*dict, None*) – Additional parameters needed to configure the search. For example, in time series problems, values should be passed in for the date_index, gap, and max_delay variables.
- **train_best_pipeline** (*boolean*) – Whether or not to train the best pipeline before returning it. Defaults to True.
- **pipeline_parameters** (*dict*) – A dict of the parameters used to initialize a pipeline with. Keys should consist of the component names and values should specify parameter values

  e.g. pipeline_parameters = { 'Imputer' : { 'numeric_impute_strategy': 'most_frequent' } }
- **custom_hyperparameters** (*dict*) – A dict of the hyperparameter ranges used to iterate over during search. Keys should consist of the component names and values should specify a singular value or skopt.Space.

  e.g. custom_hyperparameters = { 'Imputer' : { 'numeric_impute_strategy': Categorical(['most_frequent', 'median']) } }
- **sampler_method** (*str*) – The data sampling component to use in the pipelines if the problem type is classification and the target balance is smaller than the sampler_balanced_ratio. Either 'auto', which will use our preferred sampler for the data, 'Undersampler', 'Oversampler', or None. Defaults to 'auto'.
- **sampler_balanced_ratio** (*float*) – The minority:majority class ratio that we consider balanced, so a 1:4 ratio would be equal to 0.25. If the class balance is larger than this provided value, then we will not add a sampler since the data is then considered balanced. Overrides the *sampler_ratio* of the samplers. Defaults to 0.25.
- **_ensembling_split_size** (*float*) – The amount of the training data we'll set aside for training ensemble metalearners. Only used when ensembling is True. Must be between 0 and 1, exclusive. Defaults to 0.2
- **_pipelines_per_batch** (*int*) – The number of pipelines to train for every batch after the first one. The first batch will train a baseline pipline + one of each pipeline family allowed in the search.
- **engine** (*EngineBase or None*) – The engine instance used to evaluate pipelines. If None, a SequentialEngine will be used.

Methods

add_to_rankings	Fits and evaluates a given pipeline then adds the results to the automl rankings with the requirement that automl search has been run.
best_pipeline	Returns a trained instance of the best pipeline and parameters found during automl search. If *train_best_pipeline* is set to False, returns an untrained pipeline instance.
describe_pipeline	Describe a pipeline
full_rankings	Returns a pandas.DataFrame with scoring results from all pipelines searched
get_pipeline	Given the ID of a pipeline training result, returns an untrained instance of the specified pipeline
load	Loads AutoML object at file path
plot	

continues on next page

Table 68 – continued from previous page

rankings	Returns a pandas.DataFrame with scoring results from the highest-scoring set of parameters used with each pipeline.
results	Class that allows access to a copy of the results from *automl_search*.
save	Saves AutoML object at file path
score_pipelines	Score a list of pipelines on the given holdout data.
search	Find the best pipeline for the data set.
train_pipelines	Train a list of pipelines on the training data.

add_to_rankings (*self*, *pipeline*)
Fits and evaluates a given pipeline then adds the results to the automl rankings with the requirement that automl search has been run.

Parameters **pipeline** (*PipelineBase*) – pipeline to train and evaluate.

property best_pipeline (*self*)
Returns a trained instance of the best pipeline and parameters found during automl search. If *train_best_pipeline* is set to False, returns an untrained pipeline instance.

Returns A trained instance of the best pipeline and parameters found during automl search. If *train_best_pipeline* is set to False, returns an untrained pipeline instance.

Return type PipelineBase

describe_pipeline (*self*, *pipeline_id*, *return_dict=False*)
Describe a pipeline

Parameters

- **pipeline_id** (*int*) – pipeline to describe
- **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Description of specified pipeline. Includes information such as type of pipeline components, problem, training time, cross validation, etc.

property full_rankings (*self*)
Returns a pandas.DataFrame with scoring results from all pipelines searched

get_pipeline (*self*, *pipeline_id*)
Given the ID of a pipeline training result, returns an untrained instance of the specified pipeline initialized with the parameters used to train that pipeline during automl search.

Parameters **pipeline_id** (*int*) – pipeline to retrieve

Returns untrained pipeline instance associated with the provided ID

Return type PipelineBase

static load (*file_path*, *pickle_type='cloudpickle'*)
Loads AutoML object at file path

Parameters

- **file_path** (*str*) – location to find file to load
- **{"pickle"** (*pickle_type*) – the pickling library to use. Currently not used since the standard pickle library can handle cloudpickles.

- **"cloudpickle"}** – the pickling library to use. Currently not used since the standard pickle library can handle cloudpickles.

Returns AutoSearchBase object

property plot (*self*)

property rankings (*self*)
Returns a pandas.DataFrame with scoring results from the highest-scoring set of parameters used with each pipeline.

property results (*self*)
Class that allows access to a copy of the results from *automl_search*.

Returns: dict containing *pipeline_results*: a dict with results from each pipeline, and *search_order*: a list describing the order the pipelines were searched.

save (*self*, *file_path*, *pickle_type='cloudpickle'*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves AutoML object at file path

Parameters

- **file_path** (*str*) – location to save file
- **{"pickle"** (*pickle_type*) – the pickling library to use.
- **"cloudpickle"}** – the pickling library to use.
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score_pipelines (*self*, *pipelines*, *X_holdout*, *y_holdout*, *objectives*)
Score a list of pipelines on the given holdout data.

Parameters

- **pipelines** (*list(PipelineBase)*) – List of pipelines to train.
- **X_holdout** (*pd.DataFrame*) – Holdout features.
- **y_holdout** (*pd.Series*) – Holdout targets for scoring.
- **objectives** (*list(str), list(ObjectiveBase)*) – Objectives used for scoring.

Returns Dictionary keyed by pipeline name that maps to a dictionary of scores. Note that the any pipelines that error out during scoring will not be included in the dictionary but the exception and stacktrace will be displayed in the log.

Return type Dict[str, Dict[str, float]]

search (*self*, *show_iteration_plot=True*)
Find the best pipeline for the data set.

Parameters

- **feature_types** (*list, optional*) – list of feature types, either numerical or categorical. Categorical features will automatically be encoded
- **show_iteration_plot** (*boolean, True*) – Shows an iteration vs. score plot in Jupyter notebook. Disabled by default in non-Jupyter enviroments.

train_pipelines (*self*, *pipelines*)
Train a list of pipelines on the training data.

This can be helpful for training pipelines once the search is complete.

Parameters **pipelines** (*list(PipelineBase)*) – List of pipelines to train.

Returns Dictionary keyed by pipeline name that maps to the fitted pipeline. Note that the any pipelines that error out during training will not be included in the dictionary but the exception and stacktrace will be displayed in the log.

Return type Dict[str, PipelineBase]

evalml.automl.automl_search.**logger**

evalml.automl.automl_search.**search**(*X_train=None*, *y_train=None*, *problem_type=None*, *objective='auto'*, *problem_configuration=None*, ***kwargs*)

Given data and configuration, run an automl search.

This method will run EvalML's default suite of data checks. If the data checks produce errors, the data check results will be returned before running the automl search. In that case we recommend you alter your data to address these errors and try again.

This method is provided for convenience. If you'd like more control over when each of these steps is run, consider making calls directly to the various pieces like the data checks and AutoMLSearch, instead of using this method.

Parameters

- **X_train** (*pd.DataFrame*) – The input training data of shape [n_samples, n_features]. Required.
- **y_train** (*pd.Series*) – The target training data of length [n_samples]. Required for supervised learning tasks.
- **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.
- **objective** (*str, ObjectiveBase*) – The objective to optimize for. Used to propose and rank pipelines, but not for optimizing each pipeline during fit-time. When set to 'auto', chooses:
  - LogLossBinary for binary classification problems,
  - LogLossMulticlass for multiclass classification problems, and
  - R2 for regression problems.
- **problem_configuration** (*dict*) – Additional parameters needed to configure the search. For example,
- **time series problems** (*in*) –
- **should be passed in for the date_index** (*values*) –
- **gap** –
- **max_delay variables.** (*and*) –

Other keyword arguments which are provided will be passed to AutoMLSearch.

Returns the automl search object containing pipelines and rankings, and the results from running the data checks. If the data check results contain errors, automl search will not be run and an automl search object will not be returned.

Return type (*AutoMLSearch*, dict)

callbacks

Module Contents

Functions

log_error_callback	Logs the exception thrown as an error. Will not throw. This is the default behavior for AutoMLSearch.
raise_error_callback	Raises the exception thrown by the AutoMLSearch object. Also logs the exception as an error.
silent_error_callback	No-op.

Attributes Summary

logger	

Contents

evalml.automl.callbacks.**log_error_callback**(*exception*, *traceback*, *automl*, ***kwargs*)
Logs the exception thrown as an error. Will not throw. This is the default behavior for AutoMLSearch.

evalml.automl.callbacks.**logger**

evalml.automl.callbacks.**raise_error_callback**(*exception*, *traceback*, *automl*, ***kwargs*)
Raises the exception thrown by the AutoMLSearch object. Also logs the exception as an error.

evalml.automl.callbacks.**silent_error_callback**(*exception*, *traceback*, *automl*, ***kwargs*)
No-op.

pipeline_search_plots

Module Contents

Classes Summary

PipelineSearchPlots	Plots for the AutoMLSearch class.
SearchIterationPlot	

Contents

class evalml.automl.pipeline_search_plots.**PipelineSearchPlots**(*results*, *objective*)

Plots for the AutoMLSearch class.

Methods

search_iteration_plot	Shows a plot of the best score at each iteration using data gathered during training.

search_iteration_plot(*self*, *interactive_plot=False*)

Shows a plot of the best score at each iteration using data gathered during training.

Returns plot

class evalml.automl.pipeline_search_plots.**SearchIterationPlot**(*results*, *objective*)

Methods

update	

update(*self*, *results*, *objective*)

utils

Module Contents

Functions

check_all_pipeline_names_unique	Checks whether all the pipeline names are unique.
get_best_sampler_for_data	Returns the name of the sampler component to use for AutoMLSearch.
get_default_primary_search_objective	Get the default primary search objective for a problem type.
get_pipelines_from_component_graphs	Returns created pipelines from passed component graphs based on the specified problem type.
make_data_splitter	Given the training data and ML problem parameters, compute a data splitting method to use during AutoML search.
tune_binary_threshold	Tunes the threshold of a binary pipeline to the X and y thresholding data

Attributes Summary

AutoMLConfig

Contents

evalml.automl.utils.**AutoMLConfig**

evalml.automl.utils.**check_all_pipeline_names_unique**(*pipelines*)

Checks whether all the pipeline names are unique.

Parameters **pipelines** (*list(PipelineBase)*) – List of pipelines to check if all names are unique.

Returns None

Raises **ValueError** – if any pipeline names are duplicated.

evalml.automl.utils.**get_best_sampler_for_data**(*X*, *y*, *sampler_method*, *sampler_balanced_ratio*)

Returns the name of the sampler component to use for AutoMLSearch.

Parameters

- **X** (*pd.DataFrame*) – The input feature data
- **y** (*pd.Series*) – The input target data
- **sampler_method** (*str*) – The sampler_type argument passed to AutoMLSearch
- **sampler_balanced_ratio** (*float*) – The ratio of min:majority targets that we would consider balanced, or should balance the classes to.

Returns The string name of the sampling component to use, or None if no sampler is necessary

Return type str, None

evalml.automl.utils.**get_default_primary_search_objective**(*problem_type*)

Get the default primary search objective for a problem type.

Parameters **problem_type** (*str or ProblemType*) – problem type of interest.

Returns primary objective instance for the problem type.

Return type ObjectiveBase

evalml.automl.utils.**get_pipelines_from_component_graphs**(*component_graphs_dict*, *problem_type*, *parameters=None*, *random_seed=0*)

Returns created pipelines from passed component graphs based on the specified problem type.

Parameters

- **component_graphs_dict** (*dict*) – The dict of component graphs.
- **problem_type** (*str or ProblemType*) – The problem type for which pipelines will be created.
- **parameters** (*dict or None*) – Pipeline-level parameters that should be passed to the proposed pipelines.

- **random_seed** (*int*) – Random seed.

Returns List of pipelines made from the passed component graphs.

Return type list

evalml.automl.utils.**make_data_splitter**(*X*, *y*, *problem_type*, *problem_configuration=None*, *n_splits=3*, *shuffle=True*, *random_seed=0*)

Given the training data and ML problem parameters, compute a data splitting method to use during AutoML search.

Parameters

- **X** (*pd.DataFrame*) – The input training data of shape [n_samples, n_features].
- **y** (*pd.Series*) – The target training data of length [n_samples].
- **problem_type** (*ProblemType*) – The type of machine learning problem.
- **problem_configuration** (*dict, None*) – Additional parameters needed to configure the search. For example, in time series problems, values should be passed in for the date_index, gap, and max_delay variables. Defaults to None.
- **n_splits** (*int, None*) – The number of CV splits, if applicable. Defaults to 3.
- **shuffle** (*bool*) – Whether or not to shuffle the data before splitting, if applicable. Defaults to True.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns Data splitting method.

Return type sklearn.model_selection.BaseCrossValidator

evalml.automl.utils.**tune_binary_threshold**(*pipeline*, *objective*, *problem_type*, *X_threshold_tuning*, *y_threshold_tuning*)

Tunes the threshold of a binary pipeline to the X and y thresholding data

Parameters

- **pipeline** (*Pipeline*) – Pipeline instance to threshold.
- **objective** (*ObjectiveBase*) – The objective we want to tune with. If not tuneable and best_pipeline is True, will use F1.
- **problem_type** (*ProblemType*) – The problem type of the pipeline.
- **X_threshold_tuning** (*pd.DataFrame*) – Features to tune pipeline to.
- **y_threshold_tuning** (*pd.Series*) – Target data to tune pipeline to.

Package Contents

Classes Summary

AutoMLSearch	Automated Pipeline search.
EngineBase	Helper class that provides a standard way to create an ABC using
SequentialEngine	The default engine for the AutoML search. Trains and scores pipelines locally and sequentially.

Functions

get_default_primary_search_objective	Get the default primary search objective for a problem type.
make_data_splitter	Given the training data and ML problem parameters, compute a data splitting method to use during AutoML search.
search	Given data and configuration, run an automl search.
tune_binary_threshold	Tunes the threshold of a binary pipeline to the X and y thresholding data

Contents

class evalml.automl.**AutoMLSearch**(*X_train=None*, *y_train=None*, *problem_type=None*, *objective='auto'*, *max_iterations=None*, *max_time=None*, *patience=None*, *tolerance=None*, *data_splitter=None*, *allowed_component_graphs=None*, *allowed_model_families=None*, *start_iteration_callback=None*, *add_result_callback=None*, *error_callback=None*, *additional_objectives=None*, *alternate_thresholding_objective='F1'*, *random_seed=0*, *n_jobs=- 1*, *tuner_class=None*, *optimize_thresholds=True*, *ensembling=False*, *max_batches=None*, *problem_configuration=None*, *train_best_pipeline=True*, *pipeline_parameters=None*, *custom_hyperparameters=None*, *sampler_method='auto'*, *sampler_balanced_ratio=0.25*, *_ensembling_split_size=0.2*, *_pipelines_per_batch=5*, *engine=None*)

Automated Pipeline search.

Parameters

- **X_train** (*pd.DataFrame*) – The input training data of shape [n_samples, n_features]. Required.
- **y_train** (*pd.Series*) – The target training data of length [n_samples]. Required for supervised learning tasks.
- **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.
- **objective** (*str, ObjectiveBase*) – The objective to optimize for. Used to propose and rank pipelines, but not for optimizing each pipeline during fit-time. When set to 'auto', chooses:
  - LogLossBinary for binary classification problems,
  - LogLossMulticlass for multiclass classification problems, and
  - R2 for regression problems.
- **max_iterations** (*int*) – Maximum number of iterations to search. If max_iterations and max_time is not set, then max_iterations will default to max_iterations of 5.
- **max_time** (*int, str*) – Maximum time to search for pipelines. This will not start a new pipeline search after the duration has elapsed. If it is an integer, then the time will be in

seconds. For strings, time can be specified as seconds, minutes, or hours.

- **patience** (*int*) – Number of iterations without improvement to stop search early. Must be positive. If None, early stopping is disabled. Defaults to None.
- **tolerance** (*float*) – Minimum percentage difference to qualify as score improvement for early stopping. Only applicable if patience is not None. Defaults to None.
- **allowed_component_graphs** (*dict*) – A dictionary of lists or ComponentGraphs indicating the component graphs allowed in the search. The format should follow { "Name_0": [list_of_components], "Name_1": [ComponentGraph(...)] }

  The default of None indicates all pipeline component graphs for this problem type are allowed. Setting this field will cause allowed_model_families to be ignored.

  e.g. allowed_component_graphs = { "My_Graph": ["Imputer", "One Hot Encoder", "Random Forest Classifier"] }
- **allowed_model_families** (*list(str, ModelFamily)*) – The model families to search. The default of None searches over all model families. Run evalml.pipelines.components.utils.allowed_model_families("binary") to see options. Change *binary* to *multiclass* or *regression* depending on the problem type. Note that if allowed_pipelines is provided, this parameter will be ignored.
- **data_splitter** (*sklearn.model_selection.BaseCrossValidator*) – Data splitting method to use. Defaults to StratifiedKFold.
- **tuner_class** – The tuner class to use. Defaults to SKOptTuner.
- **optimize_thresholds** (*bool*) – Whether or not to optimize the binary pipeline threshold. Defaults to True.
- **start_iteration_callback** (*callable*) – Function called before each pipeline training iteration. Callback function takes three positional parameters: The pipeline instance and the AutoMLSearch object.
- **add_result_callback** (*callable*) – Function called after each pipeline training iteration. Callback function takes three positional parameters: A dictionary containing the training results for the new pipeline, an untrained_pipeline containing the parameters used during training, and the AutoMLSearch object.
- **error_callback** (*callable*) – Function called when *search()* errors and raises an Exception. Callback function takes three positional parameters: the Exception raised, the traceback, and the AutoMLSearch object. Must also accepts kwargs, so AutoMLSearch is able to pass along other appropriate parameters by default. Defaults to None, which will call *log_error_callback*.
- **additional_objectives** (*list*) – Custom set of objectives to score on. Will override default objectives for problem type if not empty.
- **alternate_thresholding_objective** (*str*) – The objective to use for thresholding binary classification pipelines if the main objective provided isn't tuneable. Defaults to F1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used.

- **ensembling** (*boolean*) – If True, runs ensembling in a separate batch after every allowed pipeline class has been iterated over. If the number of unique pipelines to search over per batch is one, ensembling will not run. Defaults to False.
- **max_batches** (*int*) – The maximum number of batches of pipelines to search. Parameters max_time, and max_iterations have precedence over stopping the search.
- **problem_configuration** (*dict, None*) – Additional parameters needed to configure the search. For example, in time series problems, values should be passed in for the date_index, gap, and max_delay variables.
- **train_best_pipeline** (*boolean*) – Whether or not to train the best pipeline before returning it. Defaults to True.
- **pipeline_parameters** (*dict*) – A dict of the parameters used to initialize a pipeline with. Keys should consist of the component names and values should specify parameter values

  e.g. pipeline_parameters = { 'Imputer' : { 'numeric_impute_strategy': 'most_frequent' } }
- **custom_hyperparameters** (*dict*) – A dict of the hyperparameter ranges used to iterate over during search. Keys should consist of the component names and values should specify a singular value or skopt.Space.

  e.g. custom_hyperparameters = { 'Imputer' : { 'numeric_impute_strategy': Categorical(['most_frequent', 'median']) } }
- **sampler_method** (*str*) – The data sampling component to use in the pipelines if the problem type is classification and the target balance is smaller than the sampler_balanced_ratio. Either 'auto', which will use our preferred sampler for the data, 'Undersampler', 'Oversampler', or None. Defaults to 'auto'.
- **sampler_balanced_ratio** (*float*) – The minority:majority class ratio that we consider balanced, so a 1:4 ratio would be equal to 0.25. If the class balance is larger than this provided value, then we will not add a sampler since the data is then considered balanced. Overrides the *sampler_ratio* of the samplers. Defaults to 0.25.
- **_ensembling_split_size** (*float*) – The amount of the training data we'll set aside for training ensemble metalearners. Only used when ensembling is True. Must be between 0 and 1, exclusive. Defaults to 0.2
- **_pipelines_per_batch** (*int*) – The number of pipelines to train for every batch after the first one. The first batch will train a baseline pipline + one of each pipeline family allowed in the search.
- **engine** (*EngineBase or None*) – The engine instance used to evaluate pipelines. If None, a SequentialEngine will be used.

Methods

add_to_rankings	Fits and evaluates a given pipeline then adds the results to the automl rankings with the requirement that automl search has been run.
best_pipeline	Returns a trained instance of the best pipeline and parameters found during automl search. If *train_best_pipeline* is set to False, returns an untrained pipeline instance.
describe_pipeline	Describe a pipeline

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Table 78 – continued from previous page

full_rankings	Returns a pandas.DataFrame with scoring results from all pipelines searched
get_pipeline	Given the ID of a pipeline training result, returns an untrained instance of the specified pipeline
load	Loads AutoML object at file path
plot	
rankings	Returns a pandas.DataFrame with scoring results from the highest-scoring set of parameters used with each pipeline.
results	Class that allows access to a copy of the results from *automl_search*.
save	Saves AutoML object at file path
score_pipelines	Score a list of pipelines on the given holdout data.
search	Find the best pipeline for the data set.
train_pipelines	Train a list of pipelines on the training data.

add_to_rankings (*self*, *pipeline*)
Fits and evaluates a given pipeline then adds the results to the automl rankings with the requirement that automl search has been run.

Parameters **pipeline** (*PipelineBase*) – pipeline to train and evaluate.

property best_pipeline (*self*)
Returns a trained instance of the best pipeline and parameters found during automl search. If *train_best_pipeline* is set to False, returns an untrained pipeline instance.

Returns A trained instance of the best pipeline and parameters found during automl search. If *train_best_pipeline* is set to False, returns an untrained pipeline instance.

Return type PipelineBase

describe_pipeline (*self*, *pipeline_id*, *return_dict=False*)
Describe a pipeline

Parameters

- **pipeline_id** (*int*) – pipeline to describe
- **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Description of specified pipeline. Includes information such as type of pipeline components, problem, training time, cross validation, etc.

property full_rankings (*self*)
Returns a pandas.DataFrame with scoring results from all pipelines searched

get_pipeline (*self*, *pipeline_id*)
Given the ID of a pipeline training result, returns an untrained instance of the specified pipeline initialized with the parameters used to train that pipeline during automl search.

Parameters **pipeline_id** (*int*) – pipeline to retrieve

Returns untrained pipeline instance associated with the provided ID

Return type PipelineBase

static load (*file_path*, *pickle_type='cloudpickle'*)
Loads AutoML object at file path

Parameters

- **file_path** (*str*) – location to find file to load
- **{"pickle"** (*pickle_type*) – the pickling library to use. Currently not used since the standard pickle library can handle cloudpickles.
- **"cloudpickle"}** – the pickling library to use. Currently not used since the standard pickle library can handle cloudpickles.

Returns AutoSearchBase object

property plot (*self*)

property rankings (*self*)
Returns a pandas.DataFrame with scoring results from the highest-scoring set of parameters used with each pipeline.

property results (*self*)
Class that allows access to a copy of the results from *automl_search*.

Returns: dict containing *pipeline_results*: a dict with results from each pipeline, and *search_order*: a list describing the order the pipelines were searched.

save (*self*, *file_path*, *pickle_type='cloudpickle'*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves AutoML object at file path

Parameters

- **file_path** (*str*) – location to save file
- **{"pickle"** (*pickle_type*) – the pickling library to use.
- **"cloudpickle"}** – the pickling library to use.
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score_pipelines (*self*, *pipelines*, *X_holdout*, *y_holdout*, *objectives*)
Score a list of pipelines on the given holdout data.

Parameters

- **pipelines** (*list(PipelineBase)*) – List of pipelines to train.
- **X_holdout** (*pd.DataFrame*) – Holdout features.
- **y_holdout** (*pd.Series*) – Holdout targets for scoring.
- **objectives** (*list(str), list(ObjectiveBase)*) – Objectives used for scoring.

Returns Dictionary keyed by pipeline name that maps to a dictionary of scores. Note that the any pipelines that error out during scoring will not be included in the dictionary but the exception and stacktrace will be displayed in the log.

Return type Dict[str, Dict[str, float]]

search (*self*, *show_iteration_plot=True*)
Find the best pipeline for the data set.

Parameters

- **feature_types** (*list, optional*) – list of feature types, either numerical or categorical. Categorical features will automatically be encoded

- **show_iteration_plot** (*boolean, True*) – Shows an iteration vs. score plot in Jupyter notebook. Disabled by default in non-Jupyter enviroments.

train_pipelines(*self*, *pipelines*)
Train a list of pipelines on the training data.

This can be helpful for training pipelines once the search is complete.

Parameters **pipelines** (*list(PipelineBase)*) – List of pipelines to train.

Returns Dictionary keyed by pipeline name that maps to the fitted pipeline. Note that the any pipelines that error out during training will not be included in the dictionary but the exception and stacktrace will be displayed in the log.

Return type Dict[str, PipelineBase]

class evalml.automl.**EngineBase**
Helper class that provides a standard way to create an ABC using inheritance.

Methods

setup_job_log	
submit_evaluation_job	Submit job for pipeline evaluation during AutoMLSearch.
submit_scoring_job	Submit job for pipeline scoring.
submit_training_job	Submit job for pipeline training.

static setup_job_log()

abstract submit_evaluation_job(*self*, *automl_config*, *pipeline*, *X*, *y*)
Submit job for pipeline evaluation during AutoMLSearch.

abstract submit_scoring_job(*self*, *automl_config*, *pipeline*, *X*, *y*, *objectives*)
Submit job for pipeline scoring.

abstract submit_training_job(*self*, *automl_config*, *pipeline*, *X*, *y*)
Submit job for pipeline training.

evalml.automl.**get_default_primary_search_objective**(*problem_type*)
Get the default primary search objective for a problem type.

Parameters **problem_type** (*str or ProblemType*) – problem type of interest.

Returns primary objective instance for the problem type.

Return type ObjectiveBase

evalml.automl.**make_data_splitter**(*X*, *y*, *problem_type*, *problem_configuration=None*, *n_splits=3*, *shuffle=True*, *random_seed=0*)
Given the training data and ML problem parameters, compute a data splitting method to use during AutoML search.

Parameters

- **X** (*pd.DataFrame*) – The input training data of shape [n_samples, n_features].
- **y** (*pd.Series*) – The target training data of length [n_samples].
- **problem_type** (*ProblemType*) – The type of machine learning problem.
- **problem_configuration** (*dict, None*) – Additional parameters needed to configure the search. For example, in time series problems, values should be passed in for the

date_index, gap, and max_delay variables. Defaults to None.

- **n_splits** (*int, None*) – The number of CV splits, if applicable. Defaults to 3.
- **shuffle** (*bool*) – Whether or not to shuffle the data before splitting, if applicable. Defaults to True.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns Data splitting method.

Return type sklearn.model_selection.BaseCrossValidator

evalml.automl.**search**(*X_train=None*, *y_train=None*, *problem_type=None*, *objective='auto'*, *problem_configuration=None*, ***kwargs*)

Given data and configuration, run an automl search.

This method will run EvalML's default suite of data checks. If the data checks produce errors, the data check results will be returned before running the automl search. In that case we recommend you alter your data to address these errors and try again.

This method is provided for convenience. If you'd like more control over when each of these steps is run, consider making calls directly to the various pieces like the data checks and AutoMLSearch, instead of using this method.

Parameters

- **X_train** (*pd.DataFrame*) – The input training data of shape [n_samples, n_features]. Required.
- **y_train** (*pd.Series*) – The target training data of length [n_samples]. Required for supervised learning tasks.
- **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.
- **objective** (*str, ObjectiveBase*) – The objective to optimize for. Used to propose and rank pipelines, but not for optimizing each pipeline during fit-time. When set to 'auto', chooses:
  - LogLossBinary for binary classification problems,
  - LogLossMulticlass for multiclass classification problems, and
  - R2 for regression problems.
- **problem_configuration** (*dict*) – Additional parameters needed to configure the search. For example,
- **time series problems** (*in*) –
- **should be passed in for the date_index** (*values*) –
- **gap** –
- **max_delay variables.** (*and*) –

Other keyword arguments which are provided will be passed to AutoMLSearch.

Returns the automl search object containing pipelines and rankings, and the results from running the data checks. If the data check results contain errors, automl search will not be run and an automl search object will not be returned.

Return type (*AutoMLSearch*, dict)

class evalml.automl.**SequentialEngine**

The default engine for the AutoML search. Trains and scores pipelines locally and sequentially.

Methods

setup_job_log	
submit_evaluation_job	Submit job for pipeline evaluation during AutoMLSearch.
submit_scoring_job	Submit job for pipeline scoring.
submit_training_job	Submit job for pipeline training.

static setup_job_log()

submit_evaluation_job(*self*, *automl_config*, *pipeline*, *X*, *y*)

Submit job for pipeline evaluation during AutoMLSearch.

submit_scoring_job(*self*, *automl_config*, *pipeline*, *X*, *y*, *objectives*)

Submit job for pipeline scoring.

submit_training_job(*self*, *automl_config*, *pipeline*, *X*, *y*)

Submit job for pipeline training.

evalml.automl.**tune_binary_threshold**(*pipeline*, *objective*, *problem_type*, *X_threshold_tuning*, *y_threshold_tuning*)

Tunes the threshold of a binary pipeline to the X and y thresholding data

Parameters

- **pipeline** (*Pipeline*) – Pipeline instance to threshold.
- **objective** (*ObjectiveBase*) – The objective we want to tune with. If not tuneable and best_pipeline is True, will use F1.
- **problem_type** (*ProblemType*) – The problem type of the pipeline.
- **X_threshold_tuning** (*pd.DataFrame*) – Features to tune pipeline to.
- **y_threshold_tuning** (*pd.Series*) – Target data to tune pipeline to.

Data Checks

Submodules

class_imbalance_data_check

Module Contents

Classes Summary

ClassImbalanceDataCheck	Check if any of the target labels are imbalanced, or if the number of values for each target are below 2 times the number of CV folds. Use for classification problems.

Contents

class evalml.data_checks.class_imbalance_data_check.**ClassImbalanceDataCheck**(*threshold=0.1*, *min_samples=100*, *num_cv_folds=3*)

Check if any of the target labels are imbalanced, or if the number of values for each target are below 2 times the number of CV folds. Use for classification problems.

Parameters

- **threshold** (*float*) – The minimum threshold allowed for class imbalance before a warning is raised. This threshold is calculated by comparing the number of samples in each class to the sum of samples in that class and the majority class. For example, a multiclass case with [900, 900, 100] samples per classes 0, 1, and 2, respectively, would have a 0.10 threshold for class 2 (100 / (900 + 100)). Defaults to 0.10.
- **min_samples** (*int*) – The minimum number of samples per accepted class. If the minority class is both below the threshold and min_samples, then we consider this severely imbalanced. Must be greater than 0. Defaults to 100.
- **num_cv_folds** (*int*) – The number of cross-validation folds. Must be positive. Choose 0 to ignore this warning. Defaults to 3.

Methods

name	Returns a name describing the data check.
validate	Checks if any target labels are imbalanced beyond a threshold for binary and multiclass problems

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y*)

Checks if any target labels are imbalanced beyond a threshold for binary and multiclass problems

Ignores NaN values in target labels if they appear.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features. Ignored.
- **y** (*pd.Series, np.ndarray*) – Target labels to check for imbalanced data.

Returns

Dictionary with DataCheckWarnings if imbalance in classes is less than the threshold, and DataCheckErrors if the number of values for each target is below 2 * num_cv_folds.

Return type dict

Example

```
>>> import pandas as pd
>>> X = pd.DataFrame()
>>> y = pd.Series([0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
>>> target_check = ClassImbalanceDataCheck(threshold=0.10)
>>> assert target_check.validate(X, y) == {"errors": [{"message": "The number␣
↪of instances of these targets is less than 2 * the number of cross folds =␣
↪6 instances: [0]",
↪         "data_check_name": "ClassImbalanceDataCheck",
↪                                                "level": "error",
↪                                                       "code": "CLASS_
↪IMBALANCE_BELOW_FOLDS",
↪              "details": {"target_values": [0]}}],
↪                            "warnings": [{"message": "The following labels␣
↪fall below 10% of the target: [0]",
↪                           "data_check_name": "ClassImbalanceDataCheck",
↪                                                             "level":
↪"warning",
↪ "code": "CLASS_IMBALANCE_BELOW_THRESHOLD",
↪                                    "details": {"target_values": [0]}},
↪                                                          {"message":
↪"The following labels in the target have severe class imbalance because␣
↪they fall under 10% of the target and have less than 100 samples: [0]",
↪                                                             "data_check_
↪name": "ClassImbalanceDataCheck",
↪                          "level": "warning",
↪                                    "code": "CLASS_IMBALANCE_SEVERE",
↪                                                          "details": {
↪"target_values": [0]}}],
↪ "actions": []}
```

data_check

Module Contents

Classes Summary

DataCheck	Base class for all data checks. Data checks are a set of heuristics used to determine if there are problems with input data.

Contents

class evalml.data_checks.data_check.**DataCheck**

Base class for all data checks. Data checks are a set of heuristics used to determine if there are problems with input data.

Methods

name	Returns a name describing the data check.

continues on next page

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validate	Inspects and validates the input data, runs any necessary calculations or algorithms, and returns a list of warnings and errors if applicable.

name (*cls*)
Returns a name describing the data check.

abstract validate (*self*, *X*, *y=None*)
Inspects and validates the input data, runs any necessary calculations or algorithms, and returns a list of warnings and errors if applicable.

Parameters

- **X** (*pd.DataFrame*) – The input data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – The target data of length [n_samples]

Returns Dictionary of DataCheckError and DataCheckWarning messages

Return type dict (DataCheckMessage)

data_check_action

Module Contents

Classes Summary

DataCheckAction	A recommended action returned by a DataCheck.

Contents

class evalml.data_checks.data_check_action.**DataCheckAction** (*action_code*, *metadata=None*)
A recommended action returned by a DataCheck.

Parameters

- **action_code** (*DataCheckActionCode*) – Action code associated with the action.
- **metadata** (*dict, optional*) – Additional useful information associated with the action. Defaults to None.

Methods

to_dict

to_dict (*self*)

data_check_action_code

Module Contents

Classes Summary

DataCheckActionCode	Enum for data check action code.

Contents

class evalml.data_checks.data_check_action_code.**DataCheckActionCode**

Enum for data check action code.

Attributes

DROP_COL	Action code for dropping a column.
DROP_ROWS	Action code for dropping rows.
IMPUTE_COL	Action code for imputing a column.
TRANSFORM_TARGET	Action code for transforming the target data.

Methods

name	The name of the Enum member.
value	The value of the Enum member.

name (*self*)

The name of the Enum member.

value (*self*)

The value of the Enum member.

data_check_message

Module Contents

Classes Summary

DataCheckError	DataCheckMessage subclass for errors returned by data checks.
DataCheckMessage	Base class for a message returned by a DataCheck, tagged by name.
DataCheckWarning	DataCheckMessage subclass for warnings returned by data checks.

Contents

class evalml.data_checks.data_check_message.**DataCheckError**(*message*, *data_check_name*, *message_code=None*, *details=None*)

DataCheckMessage subclass for errors returned by data checks.

Attributes

message_type	DataCheckMessageType.ERROR

Methods

to_dict

to_dict(*self*)

class evalml.data_checks.data_check_message.**DataCheckMessage**(*message*, *data_check_name*, *message_code=None*, *details=None*)

Base class for a message returned by a DataCheck, tagged by name.

Parameters

- **message** (*str*) – Message string
- **data_check_name** (*str*) – Name of data check
- **message_code** (*DataCheckMessageCode*) – Message code associated with message. Defaults to None.
- **details** (*dict*) – Additional useful information associated with the message. Defaults to None.

Attributes

message_type	None

Methods

to_dict

to_dict(*self*)

class evalml.data_checks.data_check_message.**DataCheckWarning**(*message*, *data_check_name*, *message_code=None*, *details=None*)

DataCheckMessage subclass for warnings returned by data checks.

Attributes

message_type	DataCheckMessageType.WARNING

Methods

to_dict

to_dict(*self*)

data_check_message_code

Module Contents

Classes Summary

DataCheckMessageCode	Enum for data check message code.

Contents

class evalml.data_checks.data_check_message_code.**DataCheckMessageCode**
Enum for data check message code.

Attributes

CLASS_IMBALANCE_BELOW_FOLDS	Message code for when number of values for each target is below 2 * number of CV folds.
CLASS_IMBALANCE_BELOW_THRESHOLD	Message code for when balance in classes is less than the threshold.
CLASS_IMBALANCE_SEVERE	Message code for when balance in classes is less than the threshold and minimum class is less than minimum number of accepted samples.
DATETIME_HAS_NAN	Message code for when input datetime columns contain NaN values.
DATETIME_HAS_UNEVEN_INTERVALS	Message code for when the datetime values have uneven intervals.
DATETIME_INFORMATION_NOT_FOUND	Message code for when datetime information can not be found or is in an unaccepted format.
DATETIME_IS_NOT_MONOTONIC	Message code for when the datetime values are not monotonically increasing.
HAS_ID_COLUMN	Message code for data that has ID columns.
HAS_OUTLIERS	Message code for when outliers are detected.
HIGH_VARIANCE	Message code for when high variance is detected for cross-validation.
HIGHLY_NULL_COLS	Message code for highly null columns.
HIGHLY_NULL_ROWS	Message code for highly null rows.
IS_MULTICOLLINEAR	Message code for when data is potentially multicollinear.
MISMATCHED_INDICES	Message code for when input target and features have mismatched indices.

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MISMATCHED_INDICES_ORDER	Message code for when input target and features have mismatched indices order. The two inputs have the same index values, but shuffled.
MISMATCHED_LENGTHS	Message code for when input target and features have different lengths.
NATURAL_LANGUAGE_HAS_NAN	Message code for when input natural language columns contain NaN values.
NO_VARIANCE	Message code for when data has no variance (1 unique value).
NO_VARIANCE_WITH_NULL	Message code for when data has one unique value and NaN values.
NOT_UNIQUE_ENOUGH	Message code for when data does not possess enough unique values.
TARGET_BINARY_NOT_TWO_UNIQUE_VALUES	Message code for target data for a binary classification problem that does not have two unique values.
TARGET_HAS_NULL	Message code for target data that has null values.
TARGET_INCOMPATIBLE_OBJECTIVE	Message code for target data that has incompatible values for the specified objective
TARGET_IS_EMPTY_OR_FULLY_NULL	Message code for target data that is empty or has all null values.
TARGET_IS_NONE	Message code for when target is None.
TARGET_LEAKAGE	Message code for when target leakage is detected.
TARGET_LOGNORMAL_DISTRIBUTION	Message code for target data with a lognormal distribution.
TARGET_MULTICLASS_HIGH_UNIQUE_CLASS	Message code for target data for a multi classification problem that has an abnormally large number of unique classes relative to the number of target values.
TARGET_MULTICLASS_NOT_ENOUGH_CLASSES	Message code for target data for a multi classification problem that does not have more than two unique classes.
TARGET_MULTICLASS_NOT_TWO_EXAMPLES_PER_CLASS	Message code for target data for a multi classification problem that does not have two examples per class.
TARGET_UNSUPPORTED_PROBLEM_TYPE	Message code for target data that is being checked against an unsupported problem type.
TARGET_UNSUPPORTED_TYPE	Message code for target data that is of an unsupported type.
TOO_SPARSE	Message code for when multiclass data has values that are too sparsely populated.
TOO_UNIQUE	Message code for when data possesses too many unique values.

Methods

name	The name of the Enum member.
value	The value of the Enum member.

name (*self*)
The name of the Enum member.

value (*self*)
The value of the Enum member.

data_check_message_type

Module Contents

Classes Summary

DataCheckMessageType	Enum for type of data check message: WARNING or ERROR.

Contents

class evalml.data_checks.data_check_message_type.**DataCheckMessageType**

Enum for type of data check message: WARNING or ERROR.

Attributes

ERROR	Error message returned by a data check.
WARNING	Warning message returned by a data check.

Methods

name	The name of the Enum member.
value	The value of the Enum member.

name (*self*)

The name of the Enum member.

value (*self*)

The value of the Enum member.

data_checks

Module Contents

Classes Summary

DataChecks	A collection of data checks.

Contents

class evalml.data_checks.data_checks.**DataChecks**(*data_checks=None*, *data_check_params=None*)

A collection of data checks.

Methods

validate	Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable.

validate(*self*, *X*, *y=None*)

Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target data of length [n_samples]

Returns Dictionary containing DataCheckMessage objects

Return type dict

datetime_format_data_check

Module Contents

Classes Summary

DateTimeFormatDataCheck	Checks if the datetime column has equally spaced intervals and is monotonically increasing or decreasing in order

Contents

class evalml.data_checks.datetime_format_data_check.**DateTimeFormatDataCheck**(*datetime_column='in*

Checks if the datetime column has equally spaced intervals and is monotonically increasing or decreasing in order to be supported by time series estimators.

Parameters **datetime_column** (*str, int*) – The name of the datetime column. If the datetime values are in the index, then pass "index".

Methods

name	Returns a name describing the data check.
validate	Checks if the target data has equal intervals and is sorted.

name(*cls*)

Returns a name describing the data check.

validate (*self*, *X*, *y*)
Checks if the target data has equal intervals and is sorted.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features.
- **y** (*pd.Series, np.ndarray*) – Target data.

Returns List with DataCheckErrors if unequal intervals are found in the datetime column.

Return type dict (DataCheckError)

Example

```
>>> from pandas as pd
>>> X = pd.DataFrame(pd.date_range("January 1, 2021", periods=8), columns=[
↪"dates"])
>>> y = pd.Series([1, 2, 4, 2, 1, 2, 3, 1])
>>> X.iloc[7] = "January 9, 2021"
>>> datetime_format_check = DateTimeFormatDataCheck()
>>> assert datetime_format_check.validate(X, y) == {"errors": [{"message":
↪"No frequency could be detected in dates, possibly due to uneven intervals.
↪",                                                                    "data_
↪check_name": "EqualIntervalDataCheck",                                    ⌟
↪                                "level": "error",                         ⌟
↪                                         "code": "DATETIME_HAS_UNEVEN_
↪INTERVALS",                                                               ⌟
↪   "details": {}}],
↪"warnings": [],
↪"actions": []}
```

datetime_nan_data_check

Module Contents

Classes Summary

DateTimeNaNDataCheck	Checks each column in the input for datetime features and will issue an error if NaN values are present.

Attributes Summary

error_contains_nan

Contents

class evalml.data_checks.datetime_nan_data_check.**DateTimeNaNDataCheck**

Checks each column in the input for datetime features and will issue an error if NaN values are present.

Methods

name	Returns a name describing the data check.
validate	Checks if any datetime columns contain NaN values.

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y=None*)

Checks if any datetime columns contain NaN values.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features.
- **y** (*pd.Series, np.ndarray*) – Ignored. Defaults to None.

Returns dict with a DataCheckError if NaN values are present in datetime columns.

Return type dict

Example

```
>>> import pandas as pd
>>> import woodwork as ww
>>> import numpy as np
>>> dates = np.arange(np.datetime64('2017-01-01'), np.datetime64('2017-01-08
↪'))
>>> dates[0] = np.datetime64('NaT')
>>> df = pd.DataFrame(dates, columns=['index'])
>>> df.ww.init()
>>> dt_nan_check = DateTimeNaNDataCheck()
>>> assert dt_nan_check.validate(df) == {"warnings": [],
...                                      "actions": [],
...                                      "errors":␣
↪[DataCheckError(message='Input datetime column(s) (index) contains NaN␣
↪values. Please impute NaN values or drop these rows or columns.',
...                                                                  data_
↪check_name=DateTimeNaNDataCheck.name,
...                                                                  ␣
↪message_code=DataCheckMessageCode.DATETIME_HAS_NAN,
...                                                                  ␣
↪details={"columns": 'index'}).to_dict()]}
```

evalml.data_checks.datetime_nan_data_check.**error_contains_nan = Input datetime column(s) (**

default_data_checks

Module Contents

Classes Summary

DefaultDataChecks	A collection of basic data checks that is used by AutoML by default.

Contents

class evalml.data_checks.default_data_checks.**DefaultDataChecks**(*problem_type*, *objective*, *n_splits=3*, *datetime_column=None*)

A collection of basic data checks that is used by AutoML by default. Includes:

- *HighlyNullDataCheck*
- *HighlyNullRowsDataCheck*
- *IDColumnsDataCheck*
- *TargetLeakageDataCheck*
- *InvalidTargetDataCheck*
- *NoVarianceDataCheck*
- *ClassImbalanceDataCheck* (for classification problem types)
- *DateTimeNaNDataCheck*
- *NaturalLanguageNaNDataCheck*
- *TargetDistributionDataCheck* (for regression problem types)
- *DateTimeFormatDataCheck* (for time series problem types)

Parameters

- **problem_type** (*str*) – The problem type that is being validated. Can be regression, binary, or multiclass.
- **objective** (*str or ObjectiveBase*) – Name or instance of the objective class.
- **n_splits** (*int*) – The number of splits as determined by the data splitter being used. Defaults to 3.
- **datetime_column** (*str*) – The name of the column containing datetime information to be used for time series problems.
- **to "index" indicating that the datetime information is in the index of X or y.** (*Default*) –

Methods

validate	Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable.

validate (*self*, *X*, *y=None*)
Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target data of length [n_samples]

Returns Dictionary containing DataCheckMessage objects

Return type dict

highly_null_data_check

Module Contents

Classes Summary

HighlyNullDataCheck	Checks if there are any highly-null columns and rows in the input.

Contents

class evalml.data_checks.highly_null_data_check.**HighlyNullDataCheck**(*pct_null_col_threshold=0.95*, *pct_null_row_threshold=0.95*)
Checks if there are any highly-null columns and rows in the input.

Parameters

- **pct_null_col_threshold** (*float*) – If the percentage of NaN values in an input feature exceeds this amount, that column will be considered highly-null. Defaults to 0.95.
- **pct_null_row_threshold** (*float*) – If the percentage of NaN values in an input row exceeds this amount, that row will be considered highly-null. Defaults to 0.95.

Methods

name	Returns a name describing the data check.
validate	Checks if there are any highly-null columns or rows in the input.

name (*cls*)
Returns a name describing the data check.

validate (*self*, *X*, *y=None*)
Checks if there are any highly-null columns or rows in the input.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features.
- **y** (*pd.Series, np.ndarray*) – Ignored.

Returns dict with a DataCheckWarning if there are any highly-null columns or rows.

Return type dict

Example

```
>>> import pandas as pd
>>> class SeriesWrap():
...     def __init__(self, series):
...         self.series = series
...
...     def __eq__(self, series_2):
...         return all(self.series.eq(series_2.series))
...
>>> df = pd.DataFrame({
...     'lots_of_null': [None, None, None, None, 5],
...     'no_null': [1, 2, 3, 4, 5]
... })
>>> null_check = HighlyNullDataCheck(pct_null_col_threshold=0.50, pct_null_
↪row_threshold=0.50)
>>> validation_results = null_check.validate(df)
>>> validation_results['warnings'][0]['details']['pct_null_cols'] =␣
↪SeriesWrap(validation_results['warnings'][0]['details']['pct_null_cols'])
>>> highly_null_rows = SeriesWrap(pd.Series([0.5, 0.5, 0.5, 0.5]))
>>> assert validation_results== {"errors": [],
↪            "warnings": [{"message": "4 out of 5 rows are more than 50.0%␣
↪null",                                                                "data_
↪check_name": "HighlyNullDataCheck",
↪                    "level": "warning",
↪                       "code": "HIGHLY_NULL_ROWS",
↪                                  "details": {"pct_null_cols": highly_null_
↪rows}},                                                                {"message
↪": "Column 'lots_of_null' is 50.0% or more null",
↪                                  "data_check_name": "HighlyNullDataCheck",
↪                                                  "level": "warning
↪",                                                     "code":
↪"HIGHLY_NULL_COLS",
↪   "details": {"column": "lots_of_null", "pct_null_rows": 0.8}}],
↪                                  "actions": [{"code": "DROP_ROWS", "metadata
↪": {"rows": [0, 1, 2, 3]}},
↪       {"code": "DROP_COL",
↪           "metadata": {"column": "lots_of_null"}}]}
```

id_columns_data_check

Module Contents

Classes Summary

IDColumnsDataCheck	Check if any of the features are likely to be ID columns.

Contents

class evalml.data_checks.id_columns_data_check.**IDColumnsDataCheck**(*id_threshold=1.0*)

Check if any of the features are likely to be ID columns.

Parameters **id_threshold** (*float*) – The probability threshold to be considered an ID column. Defaults to 1.0.

Methods

name	Returns a name describing the data check.
validate	Check if any of the features are likely to be ID columns. Currently performs these simple checks:

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y=None*)

Check if any of the features are likely to be ID columns. Currently performs these simple checks:

- column name is "id"
- column name ends in "_id"
- column contains all unique values (and is categorical / integer type)

Parameters **X** (*pd.DataFrame, np.ndarray*) – The input features to check

Returns A dictionary of features with column name or index and their probability of being ID columns

Return type dict

Example

```
>>> import pandas as pd
>>> df = pd.DataFrame({
...     'df_id': [0, 1, 2, 3, 4],
...     'x': [10, 42, 31, 51, 61],
...     'y': [42, 54, 12, 64, 12]
... })
>>> id_col_check = IDColumnsDataCheck()
>>> assert id_col_check.validate(df) == {"errors": [],
↪                                      "warnings": [{"message": "Column 'df_id' is␣
↪100.0% or more likely to be an ID column",
↪                                                   "data_check_name": "IDColumnsDataCheck",␣
↪                                                   "level": "warning",␣
↪ "code": "HAS_ID_COLUMN",␣
↪                                                   "details": {"column": "df_id"}}],␣
↪                                                   "actions": [{"code": "DROP_COL",␣
↪                                                                "metadata": {"column": "df_id
↪"}}]}
```

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invalid_targets_data_check

Module Contents

Classes Summary

InvalidTargetDataCheck	Checks if the target data contains missing or invalid values.

Contents

class evalml.data_checks.invalid_targets_data_check.**InvalidTargetDataCheck**(*problem_type*, *objective*, *n_unique=100*)

Checks if the target data contains missing or invalid values.

Parameters

- **problem_type** (*str or ProblemTypes*) – The specific problem type to data check for. e.g. 'binary', 'multiclass', 'regression, 'time series regression'
- **objective** (*str or ObjectiveBase*) – Name or instance of the objective class.
- **n_unique** (*int*) – Number of unique target values to store when problem type is binary and target incorrectly has more than 2 unique values. Non-negative integer. If None, stores all unique values. Defaults to 100.

Attributes

multiclass_continuous_threshold	0.05

Methods

name	Returns a name describing the data check.
validate	Checks if the target data contains missing or invalid values.

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y*)

Checks if the target data contains missing or invalid values.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features. Ignored.

- **y** (*pd.Series, np.ndarray*) – Target data to check for invalid values.

Returns List with DataCheckErrors if any invalid values are found in the target data.

Return type dict (DataCheckError)

Example

```
>>> import pandas as pd
>>> X = pd.DataFrame({"col": [1, 2, 3, 1]})
>>> y = pd.Series([0, 1, None, None])
>>> target_check = InvalidTargetDataCheck('binary', 'Log Loss Binary')
>>> assert target_check.validate(X, y) == {"errors": [{"message": "2 row(s) (50.0%) of target values are null",
↪                           "data_check_name": "InvalidTargetDataCheck",
↪                                                "level": "error",
↪                                                "code": "TARGET_HAS_NULL",
↪                "details": {"num_null_rows": 2, "pct_null_rows": 50}}],
↪                                              "warnings": [],
↪                                            "actions": [{'code': 'IMPUTE_COL',
↪'metadata': {'column': None, 'impute_strategy': 'most_frequent', 'is_target': True}}]}
```

multicollinearity_data_check

Module Contents

Classes Summary

MulticollinearityDataCheck	Check if any set features are likely to be multicollinear.

Contents

class evalml.data_checks.multicollinearity_data_check.**MulticollinearityDataCheck**(*threshold=0.9*)

Check if any set features are likely to be multicollinear.

Parameters **threshold** (*float*) – The threshold to be considered. Defaults to 0.9.

Methods

name	Returns a name describing the data check.
validate	Check if any set of features are likely to be multicollinear.

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y=None*)

Check if any set of features are likely to be multicollinear.

Parameters **X** (*pd.DataFrame, np.ndarray*) – The input features to check

Returns dict with a DataCheckWarning if there are any potentially multicollinear columns.

Return type dict

natural_language_nan_data_check

Module Contents

Classes Summary

NaturalLanguageNaNDataCheck	Checks each column in the input for natural language features and will issue an error if NaN values are present.

Attributes Summary

error_contains_nan

Contents

evalml.data_checks.natural_language_nan_data_check.**error_contains_nan = Input natural langu**

class evalml.data_checks.natural_language_nan_data_check.**NaturalLanguageNaNDataCheck**

Checks each column in the input for natural language features and will issue an error if NaN values are present.

Methods

name	Returns a name describing the data check.
validate	Checks if any natural language columns contain NaN values.

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y=None*)

Checks if any natural language columns contain NaN values.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features.
- **y** (*pd.Series, np.ndarray*) – Ignored. Defaults to None.

Returns dict with a DataCheckError if NaN values are present in natural language columns.

Return type dict

Example

```
>>> import pandas as pd
>>> import woodwork as ww
>>> import numpy as np
>>> data = pd.DataFrame()
>>> data['A'] = [None, "string_that_is_long_enough_for_natural_language"]
>>> data['B'] = ['string_that_is_long_enough_for_natural_language', 'string_
↪that_is_long_enough_for_natural_language']
>>> data['C'] = np.random.randint(0, 3, size=len(data))
>>> data.ww.init(logical_types={'A': 'NaturalLanguage', 'B': 'NaturalLanguage
↪'})
>>> nl_nan_check = NaturalLanguageNaNDataCheck()
>>> assert nl_nan_check.validate(data) == {
...         "warnings": [],
...         "actions": [],
...         "errors": [DataCheckError(message='Input natural language␣
↪column(s) (A) contains NaN values. Please impute NaN values or drop these␣
↪rows or columns.',
...                         data_check_name=NaturalLanguageNaNDataCheck.name,
...                         message_code=DataCheckMessageCode.NATURAL_LANGUAGE_
↪HAS_NAN,
...                         details={"columns": 'A'}).to_dict()]
...     }
```

no_variance_data_check

Module Contents

Classes Summary

NoVarianceDataCheck	Check if the target or any of the features have no variance.

Attributes Summary

logger

Contents

evalml.data_checks.no_variance_data_check.**logger**

class evalml.data_checks.no_variance_data_check.**NoVarianceDataCheck**(*count_nan_as_value=False*)

Check if the target or any of the features have no variance.

Parameters **count_nan_as_value** (*bool*) – If True, missing values will be counted as their own unique value. Additionally, if true, will return a DataCheckWarning instead of an error if the feature has mostly missing data and only one unique value. Defaults to False.

Methods

name	Returns a name describing the data check.
validate	Check if the target or any of the features have no variance (1 unique value).

name (*cls*)
Returns a name describing the data check.

validate (*self*, *X*, *y*)
Check if the target or any of the features have no variance (1 unique value).

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input features.
- **y** (*pd.Series, np.ndarray*) – The target data.

Returns dict of warnings/errors corresponding to features or target with no variance.

Return type dict

outliers_data_check

Module Contents

Classes Summary

OutliersDataCheck	Checks if there are any outliers in input data by using IQR to determine score anomalies. Columns with score anomalies are considered to contain outliers.

Contents

class evalml.data_checks.outliers_data_check.**OutliersDataCheck**
Checks if there are any outliers in input data by using IQR to determine score anomalies. Columns with score anomalies are considered to contain outliers.

Methods

name	Returns a name describing the data check.
validate	Checks if there are any outliers in a dataframe by using IQR to determine column anomalies. Column with anomalies are considered to contain outliers.

name (*cls*)
Returns a name describing the data check.

validate (*self*, *X*, *y=None*)
Checks if there are any outliers in a dataframe by using IQR to determine column anomalies. Column with anomalies are considered to contain outliers.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features

- **y** (*pd.Series, np.ndarray*) – Ignored.

Returns A dictionary with warnings if any columns have outliers.

Return type dict

Example

```
>>> import pandas as pd
>>> df = pd.DataFrame({
...     'x': [1, 2, 3, 4, 5],
...     'y': [6, 7, 8, 9, 10],
...     'z': [-1, -2, -3, -1201, -4]
... })
>>> outliers_check = OutliersDataCheck()
>>> assert outliers_check.validate(df) == {"warnings": [{"message":
↪"Column(s) 'z' are likely to have outlier data.",
↪                                                    "data_check_name":
↪"OutliersDataCheck",
↪             "level": "warning",
↪                          "code": "HAS_OUTLIERS",
↪                                                  "details": {"columns": ["z"]}}],
↪                                                             "errors": [],
↪                                                "actions": []}
```

sparsity_data_check

Module Contents

Classes Summary

SparsityDataCheck	Checks if there are any columns with sparsely populated values in the input.

Attributes Summary

warning_too_unique

Contents

class evalml.data_checks.sparsity_data_check.**SparsityDataCheck**(*problem_type*, *threshold*, *unique_count_threshold=10*)

Checks if there are any columns with sparsely populated values in the input.

Parameters

- **problem_type** (*str or ProblemTypes*) – The specific problem type to data check for. 'multiclass' or 'time series multiclass' is the only accepted problem type.

- **threshold** (*float*) – The threshold value, or percentage of each column's unique values, below which, a column exhibits sparsity. Should be between 0 and 1.
- **unique_count_threshold** (*int*) – The minimum number of times a unique value has to be present in a column to not be considered "sparse." Defaults to 10.

Methods

name	Returns a name describing the data check.
sparsity_score	This function calculates a sparsity score for the given value counts by calculating the percentage of
validate	Calculates what percentage of each column's unique values exceed the count threshold and compare

name (*cls*)
Returns a name describing the data check.

static sparsity_score (*col*, *count_threshold=10*)
This function calculates a sparsity score for the given value counts by calculating the percentage of unique values that exceed the count_threshold.

Parameters

- **col** (*pd.Series*) – Feature values.
- **count_threshold** (*int*) – The number of instances below which a value is considered sparse. Default is 10.

Returns Sparsity score, or the percentage of the unique values that exceed count_threshold.

Return type (float)

validate (*self*, *X*, *y=None*)
Calculates what percentage of each column's unique values exceed the count threshold and compare that percentage to the sparsity threshold stored in the class instance.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features.
- **y** (*pd.Series, np.ndarray*) – Ignored.

Returns dict with a DataCheckWarning if there are any sparse columns.

Return type dict

Example

```
>>> import pandas as pd
>>> df = pd.DataFrame({
...     'sparse': [float(x) for x in range(100)],
...     'not_sparse': [float(1) for x in range(100)]
... })
>>> sparsity_check = SparsityDataCheck(problem_type="multiclass", threshold=0.
↪5, unique_count_threshold=10)
>>> assert sparsity_check.validate(df) == {"errors": [],
↪                                       "warnings": [{"message": "Input columns
↪(sparse) for multiclass problem type are too sparse.",
↪                                         "data_check_name": "SparsityDataCheck
↪",                                                    "level":
↪"warning",                                                    "code
↪": "TOO_SPARSE",
↪"details": {"column": "sparse", 'sparsity_score': 0.0}}],
↪                                       "actions": [{"code": "DROP_COL",
↪                                                    "metadata": {
↪"column": "sparse"}}]}
```

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```
evalml.data_checks.sparsity_data_check.warning_too_unique = Input columns ({}) for {} probl
```

target_distribution_data_check

Module Contents

Classes Summary

TargetDistributionDataCheck	Checks if the target data contains certain distributions that may need to be transformed prior training to

Contents

class evalml.data_checks.target_distribution_data_check.**TargetDistributionDataCheck**

Checks if the target data contains certain distributions that may need to be transformed prior training to improve model performance.

Methods

name	Returns a name describing the data check.
validate	Checks if the target data has a certain distribution.

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y*)

Checks if the target data has a certain distribution.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features. Ignored.
- **y** (*pd.Series, np.ndarray*) – Target data to check for underlying distributions.

Returns List with DataCheckErrors if certain distributions are found in the target data.

Return type dict (DataCheckError)

Example

```
>>> from scipy.stats import lognorm
>>> X = None
>>> y = [0.946, 0.972, 1.154, 0.954, 0.969, 1.222, 1.038, 0.999, 0.973, 0.897]
>>> target_check = TargetDistributionDataCheck()
>>> assert target_check.validate(X, y) == {"errors": [],
↪                                       "warnings": [{"message": "Target may have␣
↪a lognormal distribution.",
↪                     "data_check_name": "TargetDistributionDataCheck",
↪                                                          "level":
↪"warning",
↪  "code": "TARGET_LOGNORMAL_DISTRIBUTION",
↪                                       "details": {"shapiro-statistic/pvalue":
↪'0.84/0.045'}}],
↪"actions": [{'code': 'TRANSFORM_TARGET', 'metadata': {'column': None,
↪'transformation_strategy': 'lognormal', 'is_target': True}}]}
```

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target_leakage_data_check

Module Contents

Classes Summary

TargetLeakageDataCheck	Check if any of the features are highly correlated with the target by using mutual information or Pearson correlation.

Contents

class evalml.data_checks.target_leakage_data_check.**TargetLeakageDataCheck**(*pct_corr_threshold=0.9*, *method='mutual'*)

Check if any of the features are highly correlated with the target by using mutual information or Pearson correlation.

If *method='mutual'*, this data check uses mutual information and supports all target and feature types. Otherwise, if *method='pearson'*, it uses Pearson correlation and only supports binary with numeric and boolean dtypes. Pearson correlation returns a value in [-1, 1], while mutual information returns a value in [0, 1].

Parameters

- **pct_corr_threshold** (*float*) – The correlation threshold to be considered leakage. Defaults to 0.95.
- **method** (*string*) – The method to determine correlation. Use 'mutual' for mutual information, otherwise 'pearson' for Pearson correlation. Defaults to 'mutual'.

Methods

name	Returns a name describing the data check.
validate	Check if any of the features are highly correlated with the target by using mutual information or Pearson correlation.

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y*)

Check if any of the features are highly correlated with the target by using mutual information or Pearson correlation.

If *method='mutual'*, supports all target and feature types. Otherwise, if *method='pearson'* only supports binary with numeric and boolean dtypes. Pearson correlation returns a value in [-1, 1], while mutual information returns a value in [0, 1].

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input features to check
- **y** (*pd.Series, np.ndarray*) – The target data

Returns dict with a DataCheckWarning if target leakage is detected.

Return type dict (DataCheckWarning)

Example

```
>>> import pandas as pd
>>> X = pd.DataFrame({
...     'leak': [10, 42, 31, 51, 61],
...     'x': [42, 54, 12, 64, 12],
...     'y': [13, 5, 13, 74, 24],
... })
>>> y = pd.Series([10, 42, 31, 51, 40])
>>> target_leakage_check = TargetLeakageDataCheck(pct_corr_threshold=0.95)
>>> assert target_leakage_check.validate(X, y) == {"warnings": [{"message":
↪"Column 'leak' is 95.0% or more correlated with the target",
↪                                                            "data_check_
↪name": "TargetLeakageDataCheck",
↪                                  "level": "warning",
↪                                                  "code": "TARGET_LEAKAGE
↪",
↪   "details": {"column": "leak"}}],
↪                     "errors": [],
↪                     "actions": [{"code": "DROP_COL",
↪                                                   "metadata": {"column":
↪ "leak"}}]}
```

uniqueness_data_check

Module Contents

Classes Summary

UniquenessDataCheck	Checks if there are any columns in the input that are either too unique for classification problems

Attributes Summary

warning_not_unique_enough
warning_too_unique

Contents

class evalml.data_checks.uniqueness_data_check.**UniquenessDataCheck**(*problem_type*, *threshold=0.5*)

Checks if there are any columns in the input that are either too unique for classification problems or not unique enough for regression problems.

Parameters

- **problem_type** (*str or ProblemTypes*) – The specific problem type to data check for. e.g. 'binary', 'multiclass', 'regression, 'time series regression'
- **threshold** (*float*) – The threshold to set as an upper bound on uniqueness for classification type problems or lower bound on for regression type problems. Defaults to 0.50.

Methods

name	Returns a name describing the data check.
uniqueness_score	This function calculates a uniqueness score for the provided field. NaN values are
validate	Checks if there are any columns in the input that are too unique in the case of classification

name(*cls*)

Returns a name describing the data check.

static uniqueness_score(*col*)

This function calculates a uniqueness score for the provided field. NaN values are not considered as unique values in the calculation.

Based on the Herfindahl–Hirschman Index.

Parameters **col** (*pd.Series*) – Feature values.

Returns Uniqueness score.

Return type (float)

validate(*self*, *X*, *y=None*)

Checks if there are any columns in the input that are too unique in the case of classification problems or not unique enough in the case of regression problems.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features.
- **y** (*pd.Series, np.ndarray*) – Ignored. Defaults to None.

Returns

dict with a DataCheckWarning if there are any too unique or not unique enough columns.

Return type dict

Example

```
>>> import pandas as pd
>>> df = pd.DataFrame({
...     'regression_unique_enough': [float(x) for x in range(100)],
...     'regression_not_unique_enough': [float(1) for x in range(100)]
... })
>>> uniqueness_check = UniquenessDataCheck(problem_type="regression",␣
↪threshold=0.8)
>>> assert uniqueness_check.validate(df) == {"errors": [],                    ␣
↪                                          "warnings": [{"message": "Input␣
↪columns (regression_not_unique_enough) for regression problem type are not␣
↪unique enough.",                                                           ␣
↪     "data_check_name": "UniquenessDataCheck",                             ␣
↪                                    "level": "warning",                    ␣
↪                                            "code": "NOT_UNIQUE_ENOUGH",   ␣
↪                                                    "details": {
↪"column": "regression_not_unique_enough", 'uniqueness_score': 0.0}}],      ␣
↪                                                  "actions": [{"code":
↪"DROP_COL",                                                                ␣
↪     "metadata": {"column": "regression_not_unique_enough"}}]}
```

evalml.data_checks.uniqueness_data_check.**warning_not_unique_enough = Input columns ({}) for**

evalml.data_checks.uniqueness_data_check.**warning_too_unique = Input columns ({}) for {} pro**

utils

Module Contents

Classes Summary

EmptyDataChecks	A collection of data checks.

Contents

class evalml.data_checks.utils.**EmptyDataChecks**(*data_checks=None*)

A collection of data checks.

Methods

validate	Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable.

validate(*self*, *X*, *y=None*)

Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input data of shape [n_samples, n_features]

- **y** (*pd.Series, np.ndarray*) – The target data of length [n_samples]

Returns Dictionary containing DataCheckMessage objects

Return type dict

Package Contents

Classes Summary

ClassImbalanceDataCheck	Check if any of the target labels are imbalanced, or if the number of values for each target are below 2 times the number of CV folds. Use for classification problems.
DataCheck	Base class for all data checks. Data checks are a set of heuristics used to determine if there are problems with input data.
DataCheckAction	A recommended action returned by a DataCheck.
DataCheckActionCode	Enum for data check action code.
DataCheckError	DataCheckMessage subclass for errors returned by data checks.
DataCheckMessage	Base class for a message returned by a DataCheck, tagged by name.
DataCheckMessageCode	Enum for data check message code.
DataCheckMessageType	Enum for type of data check message: WARNING or ERROR.
DataChecks	A collection of data checks.
DataCheckWarning	DataCheckMessage subclass for warnings returned by data checks.
DateTimeFormatDataCheck	Checks if the datetime column has equally spaced intervals and is monotonically increasing or decreasing in order
DateTimeNaNDataCheck	Checks each column in the input for datetime features and will issue an error if NaN values are present.
DefaultDataChecks	A collection of basic data checks that is used by AutoML by default.
EmptyDataChecks	A collection of data checks.
HighlyNullDataCheck	Checks if there are any highly-null columns and rows in the input.
IDColumnsDataCheck	Check if any of the features are likely to be ID columns.
InvalidTargetDataCheck	Checks if the target data contains missing or invalid values.
MulticollinearityDataCheck	Check if any set features are likely to be multicollinear.
NaturalLanguageNaNDataCheck	Checks each column in the input for natural language features and will issue an error if NaN values are present.
NoVarianceDataCheck	Check if the target or any of the features have no variance.
OutliersDataCheck	Checks if there are any outliers in input data by using IQR to determine score anomalies. Columns with score anomalies are considered to contain outliers.

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Table 135 – continued from previous page

SparsityDataCheck	Checks if there are any columns with sparsely populated values in the input.
TargetDistributionDataCheck	Checks if the target data contains certain distributions that may need to be transformed prior training to
TargetLeakageDataCheck	Check if any of the features are highly correlated with the target by using mutual information or Pearson correlation.
UniquenessDataCheck	Checks if there are any columns in the input that are either too unique for classification problems

Contents

class evalml.data_checks.**ClassImbalanceDataCheck**(*threshold=0.1*, *min_samples=100*, *num_cv_folds=3*)

Check if any of the target labels are imbalanced, or if the number of values for each target are below 2 times the number of CV folds. Use for classification problems.

Parameters

- **threshold** (*float*) – The minimum threshold allowed for class imbalance before a warning is raised. This threshold is calculated by comparing the number of samples in each class to the sum of samples in that class and the majority class. For example, a multiclass case with [900, 900, 100] samples per classes 0, 1, and 2, respectively, would have a 0.10 threshold for class 2 (100 / (900 + 100)). Defaults to 0.10.
- **min_samples** (*int*) – The minimum number of samples per accepted class. If the minority class is both below the threshold and min_samples, then we consider this severely imbalanced. Must be greater than 0. Defaults to 100.
- **num_cv_folds** (*int*) – The number of cross-validation folds. Must be positive. Choose 0 to ignore this warning. Defaults to 3.

Methods

name	Returns a name describing the data check.
validate	Checks if any target labels are imbalanced beyond a threshold for binary and multiclass problems

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y*)

Checks if any target labels are imbalanced beyond a threshold for binary and multiclass problems

Ignores NaN values in target labels if they appear.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features. Ignored.
- **y** (*pd.Series, np.ndarray*) – Target labels to check for imbalanced data.

Returns

Dictionary with DataCheckWarnings if imbalance in classes is less than the threshold, and DataCheckErrors if the number of values for each target is below 2 * num_cv_folds.

Return type dict

Example

```
>>> import pandas as pd
>>> X = pd.DataFrame()
>>> y = pd.Series([0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
>>> target_check = ClassImbalanceDataCheck(threshold=0.10)
>>> assert target_check.validate(X, y) == {"errors": [{"message": "The number␣
↪of instances of these targets is less than 2 * the number of cross folds =␣
↪6 instances: [0]",
↪         "data_check_name": "ClassImbalanceDataCheck",
↪                                                "level": "error",
↪                                                        "code": "CLASS_
↪IMBALANCE_BELOW_FOLDS",
↪              "details": {"target_values": [0]}}],
↪                           "warnings": [{"message": "The following labels␣
↪fall below 10% of the target: [0]",
↪                           "data_check_name": "ClassImbalanceDataCheck",
↪                                                             "level":
↪"warning",
↪ "code": "CLASS_IMBALANCE_BELOW_THRESHOLD",
↪                                  "details": {"target_values": [0]}},
↪                                                          {"message":
↪"The following labels in the target have severe class imbalance because␣
↪they fall under 10% of the target and have less than 100 samples: [0]",
↪                                                             "data_check_
↪name": "ClassImbalanceDataCheck",
↪                         "level": "warning",
↪                                  "code": "CLASS_IMBALANCE_SEVERE",
↪                                                        "details": {
↪"target_values": [0]}}],
↪ "actions": []}
```

class evalml.data_checks.**DataCheck**

Base class for all data checks. Data checks are a set of heuristics used to determine if there are problems with input data.

Methods

name	Returns a name describing the data check.
validate	Inspects and validates the input data, runs any necessary calculations or algorithms, and returns a list of warnings and errors if applicable.

name(*cls*)

Returns a name describing the data check.

abstract validate(*self*, *X*, *y=None*)

Inspects and validates the input data, runs any necessary calculations or algorithms, and returns a list of warnings and errors if applicable.

Parameters

- **X** (*pd.DataFrame*) – The input data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – The target data of length [n_samples]

Returns Dictionary of DataCheckError and DataCheckWarning messages

Return type dict (*DataCheckMessage*)

class evalml.data_checks.**DataCheckAction**(*action_code*, *metadata=None*)

A recommended action returned by a DataCheck.

Parameters

- **action_code** (DataCheckActionCode) – Action code associated with the action.
- **metadata** (*dict, optional*) – Additional useful information associated with the action. Defaults to None.

Methods

to_dict	

to_dict(*self*)

class evalml.data_checks.**DataCheckActionCode**

Enum for data check action code.

Attributes

DROP_COL	Action code for dropping a column.
DROP_ROWS	Action code for dropping rows.
IMPUTE_COL	Action code for imputing a column.
TRANSFORM_TARGET	Action code for transforming the target data.

Methods

name	The name of the Enum member.
value	The value of the Enum member.

name(*self*)

The name of the Enum member.

value(*self*)

The value of the Enum member.

class evalml.data_checks.**DataCheckError**(*message*, *data_check_name*, *message_code=None*, *details=None*)

DataCheckMessage subclass for errors returned by data checks.

Attributes

message_type	DataCheckMessageType.ERROR

Methods

to_dict

to_dict(*self*)

class evalml.data_checks.**DataCheckMessage**(*message*, *data_check_name*, *message_code=None*, *details=None*)

Base class for a message returned by a DataCheck, tagged by name.

Parameters

- **message** (*str*) – Message string
- **data_check_name** (*str*) – Name of data check
- **message_code** (DataCheckMessageCode) – Message code associated with message. Defaults to None.
- **details** (*dict*) – Additional useful information associated with the message. Defaults to None.

Attributes

message_type	None

Methods

to_dict

to_dict(*self*)

class evalml.data_checks.**DataCheckMessageCode**

Enum for data check message code.

Attributes

CLASS_IMBALANCE_BELOW_FOLDS	Message code for when the number of values for each target is below 2 * number of CV folds.
CLASS_IMBALANCE_BELOW_THRESHOLD	Message code for when balance in classes is less than the threshold.
CLASS_IMBALANCE_SEVERE	Message code for when balance in classes is less than the threshold and minimum class is less than minimum number of accepted samples.
DATETIME_HAS_NAN	Message code for when input datetime columns contain NaN values.
DATETIME_HAS_UNEVEN_INTERVALS	Message code for when the datetime values have uneven intervals.
DATETIME_INFORMATION_NOT_FOUND	Message code for when datetime information can not be found or is in an unaccepted format.
DATETIME_IS_NOT_MONOTONIC	Message code for when the datetime values are not monotonically increasing.
HAS_ID_COLUMN	Message code for data that has ID columns.
HAS_OUTLIERS	Message code for when outliers are detected.
HIGH_VARIANCE	Message code for when high variance is detected for cross-validation.
HIGHLY_NULL_COLS	Message code for highly null columns.

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HIGHLY_NULL_ROWS	Message code for highly null rows.
IS_MULTICOLLINEAR	Message code for when data is potentially multicollinear.
MISMATCHED_INDICES	Message code for when input target and features have mismatched indices.
MISMATCHED_INDICES_ORDER	Message code for when input target and features have mismatched indices order. The two inputs have the same index values, but shuffled.
MISMATCHED_LENGTHS	Message code for when input target and features have different lengths.
NATURAL_LANGUAGE_HAS_NAN	Message code for when input natural language columns contain NaN values.
NO_VARIANCE	Message code for when data has no variance (1 unique value).
NO_VARIANCE_WITH_NULL	Message code for when data has one unique value and NaN values.
NOT_UNIQUE_ENOUGH	Message code for when data does not possess enough unique values.
TARGET_BINARY_NOT_TWO_UNIQUE_VALUES	Message code for target data for a binary classification problem that does not have two unique values.
TARGET_HAS_NULL	Message code for target data that has null values.
TARGET_INCOMPATIBLE_OBJECTIVE	Message code for target data that has incompatible values for the specified objective
TARGET_IS_EMPTY_OR_FULLY_NULL	Message code for target data that is empty or has all null values.
TARGET_IS_NONE	Message code for when target is None.
TARGET_LEAKAGE	Message code for when target leakage is detected.
TARGET_LOGNORMAL_DISTRIBUTION	Message code for target data with a lognormal distribution.
TARGET_MULTICLASS_HIGH_UNIQUE_CLASS	Message code for target data for a multi classification problem that has an abnormally large number of unique classes relative to the number of target values.
TARGET_MULTICLASS_NOT_ENOUGH_CLASSES	Message code for target data for a multi classification problem that does not have more than 1 unique class.
TARGET_MULTICLASS_NOT_TWO_EXAMPLES_PER_CLASS	Message code for target data for a multi classification problem that does not have two examples per class.
TARGET_UNSUPPORTED_PROBLEM_TYPE	Message code for target data that is being checked against an unsupported problem type.
TARGET_UNSUPPORTED_TYPE	Message code for target data that is of an unsupported type.
TOO_SPARSE	Message code for when multiclass data has values that are too sparsely populated.
TOO_UNIQUE	Message code for when data possesses too many unique values.

Methods

name	The name of the Enum member.
value	The value of the Enum member.

name(*self*)
The name of the Enum member.

value(*self*)
The value of the Enum member.

class evalml.data_checks.**DataCheckMessageType**

Enum for type of data check message: WARNING or ERROR.

Attributes

ERROR	Error message returned by a data check.
WARNING	Warning message returned by a data check.

Methods

name	The name of the Enum member.
value	The value of the Enum member.

name (*self*)
The name of the Enum member.

value (*self*)
The value of the Enum member.

class evalml.data_checks.**DataChecks**(*data_checks=None*, *data_check_params=None*)
A collection of data checks.

Methods

validate	Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable.

validate(*self*, *X*, *y=None*)
Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target data of length [n_samples]

Returns Dictionary containing DataCheckMessage objects

Return type dict

class evalml.data_checks.**DataCheckWarning**(*message*, *data_check_name*, *message_code=None*, *details=None*)
DataCheckMessage subclass for warnings returned by data checks.

Attributes

message_type	DataCheckMessageType.WARNING

Methods

to_dict

to_dict(*self*)

class evalml.data_checks.**DateTimeFormatDataCheck**(*datetime_column='index'*)

Checks if the datetime column has equally spaced intervals and is monotonically increasing or decreasing in order to be supported by time series estimators.

Parameters **datetime_column** (*str, int*) – The name of the datetime column. If the datetime values are in the index, then pass "index".

Methods

name	Returns a name describing the data check.
validate	Checks if the target data has equal intervals and is sorted.

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y*)

Checks if the target data has equal intervals and is sorted.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features.
- **y** (*pd.Series, np.ndarray*) – Target data.

Returns List with DataCheckErrors if unequal intervals are found in the datetime column.

Return type dict (*DataCheckError*)

Example

```
>>> from pandas as pd
>>> X = pd.DataFrame(pd.date_range("January 1, 2021", periods=8), columns=[
↪"dates"])
>>> y = pd.Series([1, 2, 4, 2, 1, 2, 3, 1])
>>> X.iloc[7] = "January 9, 2021"
>>> datetime_format_check = DateTimeFormatDataCheck()
>>> assert datetime_format_check.validate(X, y) == {"errors": [{"message":
↪"No frequency could be detected in dates, possibly due to uneven intervals.
↪",                                                                    "data_
↪check_name": "EqualIntervalDataCheck",                                    ␣
↪                                "level": "error",                         ␣
↪                                         "code": "DATETIME_HAS_UNEVEN_
↪INTERVALS",                                                               ␣
↪   "details": {}}],
↪"warnings": [],
↪"actions": []}
```

class evalml.data_checks.**DateTimeNaNDataCheck**

Checks each column in the input for datetime features and will issue an error if NaN values are present.

Methods

name	Returns a name describing the data check.
validate	Checks if any datetime columns contain NaN values.

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y=None*)

Checks if any datetime columns contain NaN values.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features.
- **y** (*pd.Series, np.ndarray*) – Ignored. Defaults to None.

Returns dict with a DataCheckError if NaN values are present in datetime columns.

Return type dict

Example

```
>>> import pandas as pd
>>> import woodwork as ww
>>> import numpy as np
>>> dates = np.arange(np.datetime64('2017-01-01'), np.datetime64('2017-01-08
↪'))
>>> dates[0] = np.datetime64('NaT')
>>> df = pd.DataFrame(dates, columns=['index'])
>>> df.ww.init()
>>> dt_nan_check = DateTimeNaNDataCheck()
>>> assert dt_nan_check.validate(df) == {"warnings": [],
...                                      "actions": [],
...                                      "errors":␣
↪[DataCheckError(message='Input datetime column(s) (index) contains NaN␣
↪values. Please impute NaN values or drop these rows or columns.',
...                                                                  data_
↪check_name=DateTimeNaNDataCheck.name,
...                                                                  ␣
↪message_code=DataCheckMessageCode.DATETIME_HAS_NAN,
...                                                                  ␣
↪details={"columns": 'index'}).to_dict()]}
```

class evalml.data_checks.**DefaultDataChecks**(*problem_type*, *objective*, *n_splits=3*, *datetime_column=None*)

A collection of basic data checks that is used by AutoML by default. Includes:

- *HighlyNullDataCheck*
- *HighlyNullRowsDataCheck*
- *IDColumnsDataCheck*
- *TargetLeakageDataCheck*
- *InvalidTargetDataCheck*
- *NoVarianceDataCheck*
- *ClassImbalanceDataCheck* (for classification problem types)
- *DateTimeNaNDataCheck*
- *NaturalLanguageNaNDataCheck*
- *TargetDistributionDataCheck* (for regression problem types)
- *DateTimeFormatDataCheck* (for time series problem types)

Parameters

- **problem_type** (*str*) – The problem type that is being validated. Can be regression, binary, or multiclass.
- **objective** (*str or ObjectiveBase*) – Name or instance of the objective class.
- **n_splits** (*int*) – The number of splits as determined by the data splitter being used. Defaults to 3.
- **datetime_column** (*str*) – The name of the column containing datetime information to be used for time series problems.
- **to "index" indicating that the datetime information is in the index of X or y.** (*Default*) –

Methods

validate	Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable.

validate(*self*, *X*, *y=None*)

Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target data of length [n_samples]

Returns Dictionary containing DataCheckMessage objects

Return type dict

class evalml.data_checks.**EmptyDataChecks**(*data_checks=None*)

A collection of data checks.

Methods

validate	Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable.

validate(*self*, *X*, *y=None*)

Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target data of length [n_samples]

Returns Dictionary containing DataCheckMessage objects

Return type dict

class evalml.data_checks.**HighlyNullDataCheck**(*pct_null_col_threshold=0.95*, *pct_null_row_threshold=0.95*)

Checks if there are any highly-null columns and rows in the input.

Parameters

- **pct_null_col_threshold** (*float*) – If the percentage of NaN values in an input feature exceeds this amount, that column will be considered highly-null. Defaults to 0.95.
- **pct_null_row_threshold** (*float*) – If the percentage of NaN values in an input row exceeds this amount, that row will be considered highly-null. Defaults to 0.95.

Methods

name	Returns a name describing the data check.
validate	Checks if there are any highly-null columns or rows in the input.

name (*cls*)
Returns a name describing the data check.

validate (*self*, *X*, *y=None*)
Checks if there are any highly-null columns or rows in the input.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features.
- **y** (*pd.Series, np.ndarray*) – Ignored.

Returns dict with a DataCheckWarning if there are any highly-null columns or rows.

Return type dict

Example

```
>>> import pandas as pd
>>> class SeriesWrap():
...     def __init__(self, series):
...         self.series = series
...
...     def __eq__(self, series_2):
...         return all(self.series.eq(series_2.series))
...
>>> df = pd.DataFrame({
...     'lots_of_null': [None, None, None, None, 5],
...     'no_null': [1, 2, 3, 4, 5]
... })
>>> null_check = HighlyNullDataCheck(pct_null_col_threshold=0.50, pct_null_
↪row_threshold=0.50)
>>> validation_results = null_check.validate(df)
>>> validation_results['warnings'][0]['details']['pct_null_cols'] =␣
↪SeriesWrap(validation_results['warnings'][0]['details']['pct_null_cols'])
>>> highly_null_rows = SeriesWrap(pd.Series([0.5, 0.5, 0.5, 0.5]))
>>> assert validation_results== {"errors": [],
↪             "warnings": [{"message": "4 out of 5 rows are more than 50.0%␣
↪null",                                                                "data_
↪check_name": "HighlyNullDataCheck",
↪                    "level": "warning",
↪                       "code": "HIGHLY_NULL_ROWS",
↪                                "details": {"pct_null_cols": highly_null_
↪rows}},                                                                {"message
↪": "Column 'lots_of_null' is 50.0% or more null",
↪                                "data_check_name": "HighlyNullDataCheck",
↪                                                   "level": "warning
↪",                                                                    "code":
↪"HIGHLY_NULL_COLS",
↪   "details": {"column": "lots_of_null", "pct_null_rows": 0.8}}],
↪                                "actions": [{"code": "DROP_ROWS", "metadata
↪": {"rows": [0, 1, 2, 3]}},
```

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class evalml.data_checks.**IDColumnsDataCheck**(*id_threshold=1.0*)

Check if any of the features are likely to be ID columns.

Parameters **id_threshold** (*float*) – The probability threshold to be considered an ID column. Defaults to 1.0.

Methods

name	Returns a name describing the data check.
validate	Check if any of the features are likely to be ID columns. Currently performs these simple checks:

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y=None*)

Check if any of the features are likely to be ID columns. Currently performs these simple checks:

- column name is "id"
- column name ends in "_id"
- column contains all unique values (and is categorical / integer type)

Parameters **X** (*pd.DataFrame, np.ndarray*) – The input features to check

Returns A dictionary of features with column name or index and their probability of being ID columns

Return type dict

Example

```
>>> import pandas as pd
>>> df = pd.DataFrame({
...     'df_id': [0, 1, 2, 3, 4],
...     'x': [10, 42, 31, 51, 61],
...     'y': [42, 54, 12, 64, 12]
... })
>>> id_col_check = IDColumnsDataCheck()
>>> assert id_col_check.validate(df) == {"errors": [],
↪                                "warnings": [{"message": "Column 'df_id' is␣
↪100.0% or more likely to be an ID column",
↪                                    "data_check_name": "IDColumnsDataCheck",
↪                                                       "level":
↪"warning",
↪ "code": "HAS_ID_COLUMN",
↪                "details": {"column": "df_id"}}],
↪                           "actions": [{"code": "DROP_COL",
↪                                        "metadata": {"column": "df_id
↪"}}]}
```

class evalml.data_checks.**InvalidTargetDataCheck**(*problem_type*, *objective*, *n_unique=100*)

Checks if the target data contains missing or invalid values.

Parameters

- **problem_type** (*str or ProblemTypes*) – The specific problem type to data check for. e.g. 'binary', 'multiclass', 'regression, 'time series regression'
- **objective** (*str or ObjectiveBase*) – Name or instance of the objective class.
- **n_unique** (*int*) – Number of unique target values to store when problem type is binary and target incorrectly has more than 2 unique values. Non-negative integer. If None, stores all unique values. Defaults to 100.

Attributes

multi-class_continuous_threshold	0.05

Methods

name	Returns a name describing the data check.
validate	Checks if the target data contains missing or invalid values.

name (*cls*)
Returns a name describing the data check.

validate (*self*, *X*, *y*)
Checks if the target data contains missing or invalid values.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features. Ignored.
- **y** (*pd.Series, np.ndarray*) – Target data to check for invalid values.

Returns List with DataCheckErrors if any invalid values are found in the target data.

Return type dict (*DataCheckError*)

Example

```
>>> import pandas as pd
>>> X = pd.DataFrame({"col": [1, 2, 3, 1]})
>>> y = pd.Series([0, 1, None, None])
>>> target_check = InvalidTargetDataCheck('binary', 'Log Loss Binary')
>>> assert target_check.validate(X, y) == {"errors": [{"message": "2 row(s)␣
↪(50.0%) of target values are null",
↪                           "data_check_name": "InvalidTargetDataCheck",
↪                                                  "level": "error
↪",
↪ "TARGET_HAS_NULL",
↪          "details": {"num_null_rows": 2, "pct_null_rows": 50}}],
↪                                          "warnings": [],
↪                                    "actions": [{'code': 'IMPUTE_COL',
↪'metadata': {'column': None, 'impute_strategy': 'most_frequent', 'is_target
↪': True}}]}
```

class evalml.data_checks.**MulticollinearityDataCheck** (*threshold=0.9*)
Check if any set features are likely to be multicollinear.

Parameters **threshold** (*float*) – The threshold to be considered. Defaults to 0.9.

Methods

name	Returns a name describing the data check.
validate	Check if any set of features are likely to be multicollinear.

name (*cls*)
Returns a name describing the data check.

validate (*self*, *X*, *y=None*)
Check if any set of features are likely to be multicollinear.

Parameters **X** (*pd.DataFrame, np.ndarray*) – The input features to check

Returns dict with a DataCheckWarning if there are any potentially multicollinear columns.

Return type dict

class evalml.data_checks.**NaturalLanguageNaNDataCheck**
Checks each column in the input for natural language features and will issue an error if NaN values are present.

Methods

name	Returns a name describing the data check.
validate	Checks if any natural language columns contain NaN values.

name (*cls*)
Returns a name describing the data check.

validate (*self*, *X*, *y=None*)
Checks if any natural language columns contain NaN values.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features.
- **y** (*pd.Series, np.ndarray*) – Ignored. Defaults to None.

Returns dict with a DataCheckError if NaN values are present in natural language columns.

Return type dict

Example

```
>>> import pandas as pd
>>> import woodwork as ww
>>> import numpy as np
>>> data = pd.DataFrame()
>>> data['A'] = [None, "string_that_is_long_enough_for_natural_language"]
>>> data['B'] = ['string_that_is_long_enough_for_natural_language', 'string_
↪that_is_long_enough_for_natural_language']
>>> data['C'] = np.random.randint(0, 3, size=len(data))
>>> data.ww.init(logical_types={'A': 'NaturalLanguage', 'B': 'NaturalLanguage
↪'})
>>> nl_nan_check = NaturalLanguageNaNDataCheck()
```

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```
>>> assert nl_nan_check.validate(data) == {
...         "warnings": [],
...         "actions": [],
...         "errors": [DataCheckError(message='Input natural language␣
↪column(s) (A) contains NaN values. Please impute NaN values or drop these␣
↪rows or columns.',
...                         data_check_name=NaturalLanguageNaNDataCheck.name,
...                         message_code=DataCheckMessageCode.NATURAL_LANGUAGE_
↪HAS_NAN,
...                         details={"columns": 'A'}).to_dict()]
...     }
```

class evalml.data_checks.**NoVarianceDataCheck**(*count_nan_as_value=False*)

Check if the target or any of the features have no variance.

Parameters **count_nan_as_value** (*bool*) – If True, missing values will be counted as their own unique value. Additionally, if true, will return a DataCheckWarning instead of an error if the feature has mostly missing data and only one unique value. Defaults to False.

Methods

name	Returns a name describing the data check.
validate	Check if the target or any of the features have no variance (1 unique value).

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y*)

Check if the target or any of the features have no variance (1 unique value).

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input features.
- **y** (*pd.Series, np.ndarray*) – The target data.

Returns dict of warnings/errors corresponding to features or target with no variance.

Return type dict

class evalml.data_checks.**OutliersDataCheck**

Checks if there are any outliers in input data by using IQR to determine score anomalies. Columns with score anomalies are considered to contain outliers.

Methods

name	Returns a name describing the data check.
validate	Checks if there are any outliers in a dataframe by using IQR to determine column anomalies. Column with anomalies are considered to contain outliers.

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y=None*)

Checks if there are any outliers in a dataframe by using IQR to determine column anomalies. Column with anomalies are considered to contain outliers.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features
- **y** (*pd.Series, np.ndarray*) – Ignored.

Returns A dictionary with warnings if any columns have outliers.

Return type dict

Example

```
>>> import pandas as pd
>>> df = pd.DataFrame({
...     'x': [1, 2, 3, 4, 5],
...     'y': [6, 7, 8, 9, 10],
...     'z': [-1, -2, -3, -1201, -4]
... })
>>> outliers_check = OutliersDataCheck()
>>> assert outliers_check.validate(df) == {"warnings": [{"message":
↪"Column(s) 'z' are likely to have outlier data.",
↪                                                    "data_check_name":
↪"OutliersDataCheck",
↪             "level": "warning",
↪                          "code": "HAS_OUTLIERS",
↪                                                "details": {"columns": ["z"]}}],
↪                                                          "errors": [],
↪                                                  "actions": []}
```

class evalml.data_checks.**SparsityDataCheck**(*problem_type*, *threshold*, *unique_count_threshold=10*)

Checks if there are any columns with sparsely populated values in the input.

Parameters

- **problem_type** (*str or ProblemTypes*) – The specific problem type to data check for. 'multiclass' or 'time series multiclass' is the only accepted problem type.
- **threshold** (*float*) – The threshold value, or percentage of each column's unique values, below which, a column exhibits sparsity. Should be between 0 and 1.
- **unique_count_threshold** (*int*) – The minimum number of times a unique value has to be present in a column to not be considered "sparse." Defaults to 10.

Methods

name	Returns a name describing the data check.
sparsity_score	This function calculates a sparsity score for the given value counts by calculating the percentage of
validate	Calculates what percentage of each column's unique values exceed the count threshold and compare

name(*cls*)

Returns a name describing the data check.

static sparsity_score(*col*, *count_threshold=10*)

This function calculates a sparsity score for the given value counts by calculating the percentage of unique values that exceed the count_threshold.

Parameters

- **col** (*pd.Series*) – Feature values.
- **count_threshold** (*int*) – The number of instances below which a value is considered sparse. Default is 10.

Returns Sparsity score, or the percentage of the unique values that exceed count_threshold.

Return type (float)

validate(*self*, *X*, *y=None*)

Calculates what percentage of each column's unique values exceed the count threshold and compare that percentage to the sparsity threshold stored in the class instance.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features.
- **y** (*pd.Series, np.ndarray*) – Ignored.

Returns dict with a DataCheckWarning if there are any sparse columns.

Return type dict

Example

```
>>> import pandas as pd
>>> df = pd.DataFrame({
...     'sparse': [float(x) for x in range(100)],
...     'not_sparse': [float(1) for x in range(100)]
... })
>>> sparsity_check = SparsityDataCheck(problem_type="multiclass", threshold=0.
↪5, unique_count_threshold=10)
>>> assert sparsity_check.validate(df) == {"errors": [],
↪                                       "warnings": [{"message": "Input columns
↪(sparse) for multiclass problem type are too sparse.",
↪                                         "data_check_name": "SparsityDataCheck
↪",                                                  "level":
↪"warning",                                                          "code
↪": "TOO_SPARSE",
↪"details": {"column": "sparse", 'sparsity_score': 0.0}}],
↪                                      "actions": [{"code": "DROP_COL",
↪                                                   "metadata": {
↪"column": "sparse"}}]}
```

class evalml.data_checks.**TargetDistributionDataCheck**

Checks if the target data contains certain distributions that may need to be transformed prior training to improve model performance.

Methods

name	Returns a name describing the data check.
validate	Checks if the target data has a certain distribution.

name(*cls*)

Returns a name describing the data check.

validate(*self*, *X*, *y*)

Checks if the target data has a certain distribution.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features. Ignored.
- **y** (*pd.Series, np.ndarray*) – Target data to check for underlying distributions.

Returns List with DataCheckErrors if certain distributions are found in the target data.

Return type dict (*DataCheckError*)

Example

```
>>> from scipy.stats import lognorm
>>> X = None
>>> y = [0.946, 0.972, 1.154, 0.954, 0.969, 1.222, 1.038, 0.999, 0.973, 0.897]
>>> target_check = TargetDistributionDataCheck()
>>> assert target_check.validate(X, y) == {"errors": [],
↪                                       "warnings": [{"message": "Target may have␣
↪a lognormal distribution.",
↪                    "data_check_name": "TargetDistributionDataCheck",
↪                                                          "level":
↪"warning",
↪  "code": "TARGET_LOGNORMAL_DISTRIBUTION",
↪                                        "details": {"shapiro-statistic/pvalue":
↪'0.84/0.045'}}],
↪"actions": [{'code': 'TRANSFORM_TARGET', 'metadata': {'column': None,
↪'transformation_strategy': 'lognormal', 'is_target': True}}]}
```

class evalml.data_checks.**TargetLeakageDataCheck**(*pct_corr_threshold=0.95*, *method='mutual'*)

Check if any of the features are highly correlated with the target by using mutual information or Pearson correlation.

If *method='mutual'*, this data check uses mutual information and supports all target and feature types. Otherwise, if *method='pearson'*, it uses Pearson correlation and only supports binary with numeric and boolean dtypes. Pearson correlation returns a value in [-1, 1], while mutual information returns a value in [0, 1].

Parameters

- **pct_corr_threshold** (*float*) – The correlation threshold to be considered leakage. Defaults to 0.95.
- **method** (*string*) – The method to determine correlation. Use 'mutual' for mutual information, otherwise 'pearson' for Pearson correlation. Defaults to 'mutual'.

Methods

name	Returns a name describing the data check.
validate	Check if any of the features are highly correlated with the target by using mutual information or Pearson correlation.

name(*cls*)
Returns a name describing the data check.

validate(*self*, *X*, *y*)
Check if any of the features are highly correlated with the target by using mutual information or Pearson correlation.

If *method='mutual'*, supports all target and feature types. Otherwise, if *method='pearson'* only supports binary with numeric and boolean dtypes. Pearson correlation returns a value in [-1, 1], while mutual information returns a value in [0, 1].

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input features to check
- **y** (*pd.Series, np.ndarray*) – The target data

Returns dict with a DataCheckWarning if target leakage is detected.

Return type dict (*DataCheckWarning*)

Example

```
>>> import pandas as pd
>>> X = pd.DataFrame({
...     'leak': [10, 42, 31, 51, 61],
...     'x': [42, 54, 12, 64, 12],
...     'y': [13, 5, 13, 74, 24],
... })
>>> y = pd.Series([10, 42, 31, 51, 40])
>>> target_leakage_check = TargetLeakageDataCheck(pct_corr_threshold=0.95)
>>> assert target_leakage_check.validate(X, y) == {"warnings": [{"message":
↪"Column 'leak' is 95.0% or more correlated with the target",
↪                                                              "data_check_
↪name": "TargetLeakageDataCheck",
↪                                    "level": "warning",
↪                                                  "code": "TARGET_LEAKAGE
↪",
↪   "details": {"column": "leak"}}],
↪                     "errors": [],
↪                     "actions": [{"code": "DROP_COL",
↪                                                   "metadata": {"column":
↪ "leak"}}]}
```

class evalml.data_checks.**UniquenessDataCheck**(*problem_type*, *threshold=0.5*)

Checks if there are any columns in the input that are either too unique for classification problems or not unique enough for regression problems.

Parameters

- **problem_type** (*str or ProblemTypes*) – The specific problem type to data check for. e.g. 'binary', 'multiclass', 'regression, 'time series regression'
- **threshold** (*float*) – The threshold to set as an upper bound on uniqueness for classification type problems or lower bound on for regression type problems. Defaults to 0.50.

Methods

name	Returns a name describing the data check.
uniqueness_score	This function calculates a uniqueness score for the provided field. NaN values are
validate	Checks if there are any columns in the input that are too unique in the case of classification

name(*cls*)

Returns a name describing the data check.

static uniqueness_score(*col*)

This function calculates a uniqueness score for the provided field. NaN values are not considered as unique values in the calculation.

Based on the Herfindahl–Hirschman Index.

Parameters **col** (*pd.Series*) – Feature values.

Returns Uniqueness score.

Return type (float)

validate(*self*, *X*, *y=None*)

Checks if there are any columns in the input that are too unique in the case of classification problems or not unique enough in the case of regression problems.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Features.
- **y** (*pd.Series, np.ndarray*) – Ignored. Defaults to None.

Returns

dict with a DataCheckWarning if there are any too unique or not unique enough columns.

Return type dict

Example

```
>>> import pandas as pd
>>> df = pd.DataFrame({
...     'regression_unique_enough': [float(x) for x in range(100)],
...     'regression_not_unique_enough': [float(1) for x in range(100)]
... })
>>> uniqueness_check = UniquenessDataCheck(problem_type="regression",␣
↪threshold=0.8)
>>> assert uniqueness_check.validate(df) == {"errors": [],␣
↪                                          "warnings": [{"message": "Input␣
↪columns (regression_not_unique_enough) for regression problem type are not␣
↪unique enough.",␣
↪     "data_check_name": "UniquenessDataCheck",␣
↪                                        "level": "warning",␣
↪                                               "code": "NOT_UNIQUE_ENOUGH",␣
↪                                                       "details": {
↪"column": "regression_not_unique_enough", 'uniqueness_score': 0.0}}],␣
↪                                                    "actions": [{"code":
↪"DROP_COL",␣
↪     "metadata": {"column": "regression_not_unique_enough"}}]}
```

Demos

Submodules

breast_cancer

Module Contents

Functions

load_breast_cancer	Load breast cancer dataset. Binary classification problem.

Contents

evalml.demos.breast_cancer.**load_breast_cancer**()

Load breast cancer dataset. Binary classification problem.

Returns X and y

Return type (pd.Dataframe, pd.Series)

churn

Module Contents

Functions

load_churn	Load credit card fraud dataset.

Contents

evalml.demos.churn.**load_churn**(*n_rows=None*, *verbose=True*)

Load credit card fraud dataset. The fraud dataset can be used for binary classification problems.

Parameters

- **n_rows** (*int*) – Number of rows from the dataset to return
- **verbose** (*bool*) – Whether to print information about features and labels

Returns X and y

Return type (pd.Dataframe, pd.Series)

diabetes

Module Contents

Functions

load_diabetes	Load diabetes dataset. Regression problem

Contents

evalml.demos.diabetes.**load_diabetes**()

Load diabetes dataset. Regression problem

Returns X and y

Return type (pd.Dataframe, pd.Series)

fraud

Module Contents

Functions

load_fraud	Load credit card fraud dataset.

Contents

evalml.demos.fraud.**load_fraud**(*n_rows=None*, *verbose=True*)

Load credit card fraud dataset. The fraud dataset can be used for binary classification problems.

Parameters

- **n_rows** (*int*) – Number of rows from the dataset to return
- **verbose** (*bool*) – Whether to print information about features and labels

Returns X and y

Return type (pd.Dataframe, pd.Series)

wine

Module Contents

Functions

load_wine	Load wine dataset. Multiclass problem.

Contents

evalml.demos.wine.**load_wine**()
Load wine dataset. Multiclass problem.

Returns X and y

Return type (pd.Dataframe, pd.Series)

Package Contents

Functions

load_breast_cancer	Load breast cancer dataset. Binary classification problem.
load_churn	Load credit card fraud dataset.
load_diabetes	Load diabetes dataset. Regression problem
load_fraud	Load credit card fraud dataset.
load_wine	Load wine dataset. Multiclass problem.

Contents

evalml.demos.**load_breast_cancer**()
Load breast cancer dataset. Binary classification problem.

Returns X and y

Return type (pd.Dataframe, pd.Series)

evalml.demos.**load_churn**(*n_rows=None*, *verbose=True*)

Load credit card fraud dataset. The fraud dataset can be used for binary classification problems.

Parameters

- **n_rows** (*int*) – Number of rows from the dataset to return
- **verbose** (*bool*) – Whether to print information about features and labels

Returns X and y

Return type (pd.Dataframe, pd.Series)

evalml.demos.**load_diabetes**()
Load diabetes dataset. Regression problem

Returns X and y

Return type (pd.Dataframe, pd.Series)

evalml.demos.**load_fraud**(*n_rows=None*, *verbose=True*)

Load credit card fraud dataset. The fraud dataset can be used for binary classification problems.

Parameters

- **n_rows** (*int*) – Number of rows from the dataset to return
- **verbose** (*bool*) – Whether to print information about features and labels

Returns X and y

Return type (pd.Dataframe, pd.Series)

evalml.demos.**load_wine**()
Load wine dataset. Multiclass problem.

Returns X and y

Return type (pd.Dataframe, pd.Series)

Exceptions

Submodules

exceptions

Module Contents

Classes Summary

PartialDependenceErrorCode	Enum identifying the type of error encountered in partial dependence.

Exceptions Summary

—

Contents

exception evalml.exceptions.exceptions.**AutoMLSearchException**
Exception raised when all pipelines in an automl batch return a score of NaN for the primary objective.

exception evalml.exceptions.exceptions.**ComponentNotYetFittedError**
An exception to be raised when predict/predict_proba/transform is called on a component without fitting first.

exception evalml.exceptions.exceptions.**DataCheckInitError**
Exception raised when a data check can't initialize with the parameters given.

exception evalml.exceptions.exceptions.**EnsembleMissingPipelinesError**
An exception raised when an ensemble is missing *estimators* (list) as a parameter.

exception evalml.exceptions.exceptions.**MethodPropertyNotFoundError**
Exception to raise when a class is does not have an expected method or property.

exception evalml.exceptions.exceptions.**MissingComponentError**
An exception raised when a component is not found in all_components()

exception evalml.exceptions.exceptions.**NoPositiveLabelException**
Exception when a particular classification label for the 'positive' class cannot be found in the column index or unique values

exception evalml.exceptions.exceptions.**NullsInColumnWarning**
Warning thrown when there are null values in the column of interest

exception evalml.exceptions.exceptions.**ObjectiveCreationError**
Exception when get_objective tries to instantiate an objective and required args are not provided.

exception evalml.exceptions.exceptions.**ObjectiveNotFoundError**
Exception to raise when specified objective does not exist.

exception evalml.exceptions.exceptions.**ParameterNotUsedWarning**(*components*)
Warning thrown when a pipeline parameter isn't used in a defined pipeline's component graph during initialization.

exception evalml.exceptions.exceptions.**PartialDependenceError**(*message*, *code*)
Exception raised for all errors that partial dependence can raise.

class evalml.exceptions.exceptions.**PartialDependenceErrorCode**
Enum identifying the type of error encountered in partial dependence.

Attributes

ALL_OTHER_ERRORS	all_other_errors
COMPUTED_PERCENTILES_TOO_CLOSE	computed_percentiles_too_close
FEATURE_IS_ALL_NANS	feature_is_all_nans
FEATURE_IS_MOSTLY_ONE_VALUE	feature_is_mostly_one_value
FEATURES_ARGUMENT_INCORRECT_TYPES	features_argument_incorrect_types
ICE_PLOT_REQUESTED_FOR_TWO_WAY_PLOT	ice_plot_requested_for_two_way_partial_dependence_plot
INVALID_CLASS_LABEL	invalid_class_label_requested_for_plot
INVALID_FEATURE_TYPE	invalid_feature_type
PIPELINE_IS_BASELINE	pipeline_is_baseline
TOO_MANY_FEATURES	too_many_features
TWO_WAY_REQUESTED_FOR_DATES	two_way_requested_for_dates
UNFITTED_PIPELINE	unfitted_pipeline

Methods

name	The name of the Enum member.
value	The value of the Enum member.

name (*self*)
The name of the Enum member.

value (*self*)
The value of the Enum member.

exception evalml.exceptions.exceptions.**PipelineNotFoundError**
An exception raised when a particular pipeline is not found in automl search results

exception evalml.exceptions.exceptions.**PipelineNotYetFittedError**
An exception to be raised when predict/predict_proba/transform is called on a pipeline without fitting first.

exception evalml.exceptions.exceptions.**PipelineScoreError**(*exceptions*, *scored_successfully*)
An exception raised when a pipeline errors while scoring any objective in a list of objectives.

Parameters

- **exceptions** (*dict*) – A dictionary mapping an objective name (str) to a tuple of the form (exception, traceback). All of the objectives that errored will be stored here.
- **scored_successfully** (*dict*) – A dictionary mapping an objective name (str) to a score value. All of the objectives that did not error will be stored here.

Package Contents

Classes Summary

PartialDependenceErrorCode	Enum identifying the type of error encountered in partial dependence.

Exceptions Summary

—

Contents

exception evalml.exceptions.**AutoMLSearchException**
Exception raised when all pipelines in an automl batch return a score of NaN for the primary objective.

exception evalml.exceptions.**ComponentNotYetFittedError**
An exception to be raised when predict/predict_proba/transform is called on a component without fitting first.

exception evalml.exceptions.**DataCheckInitError**
Exception raised when a data check can't initialize with the parameters given.

exception evalml.exceptions.**EnsembleMissingPipelinesError**
An exception raised when an ensemble is missing *estimators* (list) as a parameter.

exception evalml.exceptions.**MethodPropertyNotFoundError**
Exception to raise when a class is does not have an expected method or property.

exception evalml.exceptions.**MissingComponentError**
An exception raised when a component is not found in all_components()

exception evalml.exceptions.**NoPositiveLabelException**
Exception when a particular classification label for the 'positive' class cannot be found in the column index or unique values

exception evalml.exceptions.**NullsInColumnWarning**
Warning thrown when there are null values in the column of interest

exception evalml.exceptions.**ObjectiveCreationError**
Exception when get_objective tries to instantiate an objective and required args are not provided.

exception evalml.exceptions.**ObjectiveNotFoundError**
Exception to raise when specified objective does not exist.

exception evalml.exceptions.**ParameterNotUsedWarning**(*components*)
Warning thrown when a pipeline parameter isn't used in a defined pipeline's component graph during initialization.

exception evalml.exceptions.**PartialDependenceError**(*message*, *code*)
Exception raised for all errors that partial dependence can raise.

class evalml.exceptions.**PartialDependenceErrorCode**
Enum identifying the type of error encountered in partial dependence.

Attributes

ALL_OTHER_ERRORS	all_other_errors
COMPUTED_PERCENTILES_TOO_CLOSE	computed_percentiles_too_close
FEATURE_IS_ALL_NANS	feature_is_all_nans
FEATURE_IS_MOSTLY_ONE_VALUE	feature_is_mostly_one_value
FEATURES_ARGUMENT_INCORRECT_TYPES	features_argument_incorrect_types
ICE_PLOT_REQUESTED_FOR_TWO_WAY_PLOT	ice_plot_requested_for_two_way_partial_dependence_plot
INVALID_CLASS_LABEL	invalid_class_label_requested_for_plot
INVALID_FEATURE_TYPE	invalid_feature_type
PIPELINE_IS_BASELINE	pipeline_is_baseline
TOO_MANY_FEATURES	too_many_features
TWO_WAY_REQUESTED_FOR_DATES	two_way_requested_for_dates
UNFITTED_PIPELINE	unfitted_pipeline

Methods

name	The name of the Enum member.
value	The value of the Enum member.

name (*self*)
The name of the Enum member.

value (*self*)
The value of the Enum member.

exception evalml.exceptions.**PipelineNotFoundError**
An exception raised when a particular pipeline is not found in automl search results

exception evalml.exceptions.**PipelineNotYetFittedError**
An exception to be raised when predict/predict_proba/transform is called on a pipeline without fitting first.

exception evalml.exceptions.**PipelineScoreError**(*exceptions*, *scored_successfully*)
An exception raised when a pipeline errors while scoring any objective in a list of objectives.

Parameters

- **exceptions** (*dict*) – A dictionary mapping an objective name (str) to a tuple of the form (exception, traceback). All of the objectives that errored will be stored here.
- **scored_successfully** (*dict*) – A dictionary mapping an objective name (str) to a score value. All of the objectives that did not error will be stored here.

Model Family

Submodules

model_family

Module Contents

Classes Summary

ModelFamily	Enum for family of machine learning models.

Contents

class evalml.model_family.model_family.**ModelFamily**

Enum for family of machine learning models.

Attributes

ARIMA	ARIMA model family.
BASELINE	Baseline model family.
CATBOOST	CatBoost model family.
DECISION_TREE	Decision Tree model family.
ENSEMBLE	Ensemble model family.
EXTRA_TREES	Extra Trees model family.
K_NEIGHBORS	K Nearest Neighbors model family.
LIGHTGBM	LightGBM model family.
LINEAR_MODEL	Linear model family.
NONE	None
PROPHET	Prophet model family.
RANDOM_FOREST	Random Forest model family.
SVM	SVM model family.
XGBOOST	XGBoost model family.

Methods

is_tree_estimator	Checks whether the estimator's model family uses trees.
name	The name of the Enum member.
value	The value of the Enum member.

is_tree_estimator(*self*)

Checks whether the estimator's model family uses trees.

name (*self*)
The name of the Enum member.

value (*self*)
The value of the Enum member.

utils

Module Contents

Functions

handle_model_family	Handles model_family by either returning the ModelFamily or converting from a string

Contents

evalml.model_family.utils.**handle_model_family**(*model_family*)
Handles model_family by either returning the ModelFamily or converting from a string

Parameters **model_family** (*str or ModelFamily*) – Model type that needs to be handled

Returns ModelFamily

Package Contents

Classes Summary

ModelFamily	Enum for family of machine learning models.

Functions

handle_model_family	Handles model_family by either returning the ModelFamily or converting from a string

Contents

evalml.model_family.**handle_model_family**(*model_family*)
Handles model_family by either returning the ModelFamily or converting from a string

Parameters **model_family** (*str or ModelFamily*) – Model type that needs to be handled

Returns ModelFamily

class evalml.model_family.**ModelFamily**
Enum for family of machine learning models.

Attributes

ARIMA	ARIMA model family.
BASELINE	Baseline model family.
CATBOOST	CatBoost model family.
DECISION_TREE	Decision Tree model family.
ENSEMBLE	Ensemble model family.
EXTRA_TREES	Extra Trees model family.
K_NEIGHBORS	K Nearest Neighbors model family.
LIGHTGBM	LightGBM model family.
LINEAR_MODEL	Linear model family.
NONE	None
PROPHET	Prophet model family.
RANDOM_FOREST	Random Forest model family.
SVM	SVM model family.
XGBOOST	XGBoost model family.

Methods

is_tree_estimator	Checks whether the estimator's model family uses trees.
name	The name of the Enum member.
value	The value of the Enum member.

is_tree_estimator (*self*)
Checks whether the estimator's model family uses trees.

name (*self*)
The name of the Enum member.

value (*self*)
The value of the Enum member.

Model Understanding

Subpackages

prediction_explanations

Submodules

explainers

Module Contents

Classes Summary

ExplainPredictionsStage	Generic enumeration.

Functions

abs_error	Computes the absolute error per data point for regression problems.
cross_entropy	Computes Cross Entropy Loss per data point for classification problems.
explain_predictions	Creates a report summarizing the top contributing features for each data point in the input features.
explain_predictions_best_worst	Creates a report summarizing the top contributing features for the best and worst points in the dataset as measured by error to true labels.

Attributes Summary

DEFAULT_METRICS

Contents

evalml.model_understanding.prediction_explanations.explainers.**abs_error**(*y_true*, *y_pred*)

Computes the absolute error per data point for regression problems.

Parameters

- **y_true** (*pd.Series*) – True labels.
- **y_pred** (*pd.Series*) – Predicted values.

Returns np.ndarray

evalml.model_understanding.prediction_explanations.explainers.**cross_entropy**(*y_true*, *y_pred_proba*)

Computes Cross Entropy Loss per data point for classification problems.

Parameters

- **y_true** (*pd.Series*) – True labels encoded as ints.
- **y_pred_proba** (*pd.DataFrame*) – Predicted probabilities. One column per class.

Returns np.ndarray

evalml.model_understanding.prediction_explanations.explainers.**DEFAULT_METRICS**

evalml.model_understanding.prediction_explanations.explainers.**explain_predictions**(*pipeline*, *input_features*, *y*, *indices_to_exp*, *top_k_featur*, *include_shap_*, *include_expec*, *output_format=*

Creates a report summarizing the top contributing features for each data point in the input features.

XGBoost and Stacked Ensemble models, as well as CatBoost multiclass classifiers, are not currently supported.

Parameters

- **pipeline** (*PipelineBase*) – Fitted pipeline whose predictions we want to explain with SHAP.
- **input_features** (*pd.DataFrame*) – Dataframe of input data to evaluate the pipeline on.
- **y** (*pd.Series*) – Labels for the input data.
- **indices_to_explain** (*list(int)*) – List of integer indices to explain.
- **top_k_features** (*int*) – How many of the highest/lowest contributing feature to include in the table for each data point. Default is 3.
- **include_shap_values** (*bool*) – Whether SHAP values should be included in the table. Default is False.
- **include_expected_value** (*bool*) – Whether the expected value should be included in the table. Default is False.
- **output_format** (*str*) – Either "text", "dict", or "dataframe". Default is "text".

Returns

str, dict, or pd.DataFrame - A report explaining the top contributing features to each prediction for each row of
The report will include the feature names, prediction contribution, and SHAP Value (optional).

Raises

- **ValueError** – if input_features is empty.
- **ValueError** – if an output_format outside of "text", "dict" or "dataframe is provided.
- **ValueError** – if the requested index falls outside the input_feature's boundaries.

evalml.model_understanding.prediction_explanations.explainers.**explain_predictions_best_wors**

Creates a report summarizing the top contributing features for the best and worst points in the dataset as measured by error to true labels.

XGBoost and Stacked Ensemble models, as well as CatBoost multiclass classifiers, are not currently supported.

Parameters

- **pipeline** (*PipelineBase*) – Fitted pipeline whose predictions we want to explain with SHAP.
- **input_features** (*pd.DataFrame*) – Input data to evaluate the pipeline on.
- **y_true** (*pd.Series*) – True labels for the input data.
- **num_to_explain** (*int*) – How many of the best, worst, random data points to explain.
- **top_k_features** (*int*) – How many of the highest/lowest contributing feature to include in the table for each data point.
- **include_shap_values** (*bool*) – Whether SHAP values should be included in the table. Default is False.
- **metric** (*callable*) – The metric used to identify the best and worst points in the dataset. Function must accept the true labels and predicted value or probabilities as the only arguments and lower values must be better. By default, this will be the absolute error for regression problems and cross entropy loss for classification problems.
- **output_format** (*str*) – Either "text" or "dict". Default is "text".
- **callback** (*callable*) – Function to be called with incremental updates. Has the following parameters: - progress_stage: stage of computation - time_elapsed: total time in seconds that has elapsed since start of call

Returns

str, dict, or pd.DataFrame - A report explaining the top contributing features for the best/worst predictions in th
For each of the best/worst rows of input_features, the predicted values, true labels, metric value, feature names, prediction contribution, and SHAP Value (optional) will be listed.

Raises

- **ValueError** – if input_features does not have more than twice the requested features to explain.
- **ValueError** – if y_true and input_features have mismatched lengths.
- **ValueError** – if an output_format outside of "text", "dict" or "dataframe is provided.

class evalml.model_understanding.prediction_explanations.explainers.**ExplainPredictionsStage**
Generic enumeration.

Derive from this class to define new enumerations.

Attributes

COMPUTE_FEATURE_STAGE	compute_feature_stage
COMPUTE_SHAP_VALUES_STAGE	compute_shap_value_stage
DONE	done
PREDICT_STAGE	predict_stage
PREPROCESSING_STAGE	preprocessing_stage

Methods

name	The name of the Enum member.
value	The value of the Enum member.

name (*self*)
The name of the Enum member.

value (*self*)
The value of the Enum member.

Package Contents

Functions

explain_predictions	Creates a report summarizing the top contributing features for each data point in the input features.
explain_predictions_best_worst	Creates a report summarizing the top contributing features for the best and worst points in the dataset as measured by error to true labels.

Contents

evalml.model_understanding.prediction_explanations.**explain_predictions**(*pipeline*, *input_features*, *y*, *indices_to_explain*, *top_k_features=3*, *include_shap_values=False*, *include_expected_value=False*, *output_format='text'*)

Creates a report summarizing the top contributing features for each data point in the input features.

XGBoost and Stacked Ensemble models, as well as CatBoost multiclass classifiers, are not currently supported.

Parameters

- **pipeline** (*PipelineBase*) – Fitted pipeline whose predictions we want to explain with SHAP.
- **input_features** (*pd.DataFrame*) – Dataframe of input data to evaluate the pipeline on.
- **y** (*pd.Series*) – Labels for the input data.
- **indices_to_explain** (*list(int)*) – List of integer indices to explain.
- **top_k_features** (*int*) – How many of the highest/lowest contributing feature to include in the table for each data point. Default is 3.
- **include_shap_values** (*bool*) – Whether SHAP values should be included in the table. Default is False.
- **include_expected_value** (*bool*) – Whether the expected value should be included in the table. Default is False.
- **output_format** (*str*) – Either "text", "dict", or "dataframe". Default is "text".

Returns

str, dict, or pd.DataFrame - A report explaining the top contributing features to each prediction for each row of
The report will include the feature names, prediction contribution, and SHAP Value (optional).

Raises

- **ValueError** – if input_features is empty.
- **ValueError** – if an output_format outside of "text", "dict" or "dataframe is provided.
- **ValueError** – if the requested index falls outside the input_feature's boundaries.

evalml.model_understanding.prediction_explanations.**explain_predictions_best_worst**(*pipeline*, *input_features*, *y_true*, *num_to_explain*, *top_k_features=4*, *include_shap_values=False*, *metric=None*, *output_format='text'*, *callback=None*)

Creates a report summarizing the top contributing features for the best and worst points in the dataset as measured by error to true labels.

XGBoost and Stacked Ensemble models, as well as CatBoost multiclass classifiers, are not currently supported.

Parameters

- **pipeline** (*PipelineBase*) – Fitted pipeline whose predictions we want to explain with SHAP.
- **input_features** (*pd.DataFrame*) – Input data to evaluate the pipeline on.
- **y_true** (*pd.Series*) – True labels for the input data.
- **num_to_explain** (*int*) – How many of the best, worst, random data points to explain.
- **top_k_features** (*int*) – How many of the highest/lowest contributing feature to include in the table for each data point.
- **include_shap_values** (*bool*) – Whether SHAP values should be included in the table. Default is False.
- **metric** (*callable*) – The metric used to identify the best and worst points in the dataset. Function must accept the true labels and predicted value or probabilities as the only arguments and lower values must be better. By default, this will be the absolute error for regression problems and cross entropy loss for classification problems.
- **output_format** (*str*) – Either "text" or "dict". Default is "text".
- **callback** (*callable*) – Function to be called with incremental updates. Has the following parameters: - progress_stage: stage of computation - time_elapsed: total time in seconds that has elapsed since start of call

Returns

str, dict, or pd.DataFrame - A report explaining the top contributing features for the best/worst predictions in th
For each of the best/worst rows of input_features, the predicted values, true labels, metric value, feature names, prediction contribution, and SHAP Value (optional) will be listed.

Raises

- **ValueError** – if input_features does not have more than twice the requested features to explain.
- **ValueError** – if y_true and input_features have mismatched lengths.
- **ValueError** – if an output_format outside of "text", "dict" or "dataframe is provided.

Submodules

force_plots

Module Contents

Functions

force_plot	Function to generate the data required to build a force plot.
graph_force_plot	Function to generate force plots for the desired rows of the training data.

Contents

evalml.model_understanding.force_plots.**force_plot**(*pipeline*, *rows_to_explain*, *training_data*, *y*)

Function to generate the data required to build a force plot.

Parameters

- **pipeline** (*PipelineBase*) – The pipeline to generate the force plot for.
- **rows_to_explain** (*list(int)*) – A list of the indices of the training_data to explain.
- **training_data** (*pandas.DataFrame*) – The data used to train the pipeline.
- **y** (*pandas.Series*) – The target data.

Returns

list of dictionaries where each dict contains force plot data. Each dictionary entry represents the explanations for a single row.

For single row binary force plots:

[{'malignant': {'expected_value': 0.37, 'feature_names': ['worst concave points', 'worst perimeter', 'worst radius'], 'shap_values': [0.09, 0.09, 0.08], 'plot': AdditiveForceVisualizer}]

For two row binary force plots:

[{'malignant': {'expected_value': 0.37, 'feature_names': ['worst concave points', 'worst perimeter', 'worst radius'], 'shap_values': [0.09, 0.09, 0.08], 'plot': AdditiveForceVisualizer},

{'malignant': {'expected_value': 0.29, 'feature_names': ['worst concave points', 'worst perimeter', 'worst radius'], 'shap_values': [0.05, 0.03, 0.02], 'plot': AdditiveForceVisualizer}]

Return type list(dict())

Raises

- **TypeError** – if rows_to_explain is not a list.
- **TypeError** – if all values in rows_to_explain aren't integers.

evalml.model_understanding.force_plots.**graph_force_plot**(*pipeline*, *rows_to_explain*, *training_data*, *y*, *matplotlib=False*)

Function to generate force plots for the desired rows of the training data.

Parameters

- **pipeline** (*PipelineBase*) – The pipeline to generate the force plot for.
- **rows_to_explain** (*list(int)*) – A list of the indices indicating which of the rows of the training_data to explain.
- **training_data** (*pandas.DataFrame*) – The data used to train the pipeline.
- **y** (*pandas.Series*) – The target data for the pipeline.
- **matplotlib** (*bool*) – flag to display the force plot using matplotlib (outside of jupyter) Defaults to False.

Returns

The same as force_plot(), but with an additional key in each dictionary for the plot.

Return type list(dict(shap.AdditiveForceVisualizer))

graphs

Module Contents

Functions

binary_objective_vs_threshold	Computes objective score as a function of potential binary classification
confusion_matrix	Confusion matrix for binary and multiclass classification.
decision_tree_data_from_estimator	Return data for a fitted tree in a restructured format
decision_tree_data_from_pipeline	Return data for a fitted pipeline with in a restructured format
get_linear_coefficients	Returns a dataframe showing the features with the greatest predictive power for a linear model.
get_prediction_vs_actual_data	Combines y_true and y_pred into a single dataframe and adds a column for outliers. Used in *graph_prediction_vs_actual()*.
get_prediction_vs_actual_over_time_data	Get the data needed for the prediction_vs_actual_over_time plot.
graph_binary_objective_vs_threshold	Generates a plot graphing objective score vs. decision thresholds for a fitted binary classification pipeline.
graph_confusion_matrix	Generate and display a confusion matrix plot.
graph_partial_dependence	Create an one-way or two-way partial dependence plot. Passing a single integer or
graph_permutation_importance	Generate a bar graph of the pipeline's permutation importance.
graph_precision_recall_curve	Generate and display a precision-recall plot.
graph_prediction_vs_actual	Generate a scatter plot comparing the true and predicted values. Used for regression plotting

continues on next page

Table 186 – continued from previous page

graph_prediction_vs_actual_over_time	Plot the target values and predictions against time on the x-axis.
graph_roc_curve	Generate and display a Receiver Operating Characteristic (ROC) plot for binary and multiclass classification problems.
graph_t_sne	Plot high dimensional data into lower dimensional space using t-SNE .
normalize_confusion_matrix	Normalizes a confusion matrix.
partial_dependence	Calculates one or two-way partial dependence. If a single integer or
precision_recall_curve	Given labels and binary classifier predicted probabilities, compute and return the data representing a precision-recall curve.
roc_curve	Given labels and classifier predicted probabilities, compute and return the data representing a Receiver Operating Characteristic (ROC) curve. Works with binary or multiclass problems.
t_sne	Get the transformed output after fitting X to the embedded space using t-SNE.
visualize_decision_tree	Generate an image visualizing the decision tree

Contents

evalml.model_understanding.graphs.**binary_objective_vs_threshold**(*pipeline*, *X*, *y*, *objective*, *steps=100*)

Computes objective score as a function of potential binary classification decision thresholds for a fitted binary classification pipeline.

Parameters

- **pipeline** (*BinaryClassificationPipeline obj*) – Fitted binary classification pipeline
- **X** (*pd.DataFrame*) – The input data used to compute objective score
- **y** (*pd.Series*) – The target labels
- **objective** (*ObjectiveBase obj, str*) – Objective used to score
- **steps** (*int*) – Number of intervals to divide and calculate objective score at

Returns DataFrame with thresholds and the corresponding objective score calculated at each threshold

Return type pd.DataFrame

evalml.model_understanding.graphs.**confusion_matrix**(*y_true*, *y_predicted*, *normalize_method='true'*)

Confusion matrix for binary and multiclass classification.

Parameters

- **y_true** (*pd.Series or np.ndarray*) – True binary labels.
- **y_pred** (*pd.Series or np.ndarray*) – Predictions from a binary classifier.

- **normalize_method** (*{'true', 'pred', 'all', None}*) – Normalization method to use, if not None. Supported options are: 'true' to normalize by row, 'pred' to normalize by column, or 'all' to normalize by all values. Defaults to 'true'.

Returns Confusion matrix. The column header represents the predicted labels while row header represents the actual labels.

Return type pd.DataFrame

evalml.model_understanding.graphs.**decision_tree_data_from_estimator**(*estimator*)
Return data for a fitted tree in a restructured format

Parameters **estimator** (*ComponentBase*) – A fitted DecisionTree-based estimator.

Returns An OrderedDict of OrderedDicts describing a tree structure

Return type OrderedDict

evalml.model_understanding.graphs.**decision_tree_data_from_pipeline**(*pipeline_*)
Return data for a fitted pipeline with in a restructured format

Parameters **pipeline** (*PipelineBase*) – A pipeline with a DecisionTree-based estimator.

Returns An OrderedDict of OrderedDicts describing a tree structure

Return type OrderedDict

evalml.model_understanding.graphs.**get_linear_coefficients**(*estimator*, *features=None*)
Returns a dataframe showing the features with the greatest predictive power for a linear model.

Parameters

- **estimator** (*Estimator*) – Fitted linear model family estimator.
- **features** (*list[str]*) – List of feature names associated with the underlying data.

Returns Displaying the features by importance.

Return type pd.DataFrame

evalml.model_understanding.graphs.**get_prediction_vs_actual_data**(*y_true*, *y_pred*, *outlier_threshold=None*)
Combines y_true and y_pred into a single dataframe and adds a column for outliers. Used in *graph_prediction_vs_actual()*.

Parameters

- **y_true** (*pd.Series, or np.ndarray*) – The real target values of the data
- **y_pred** (*pd.Series, or np.ndarray*) – The predicted values outputted by the regression model.
- **outlier_threshold** (*int, float*) – A positive threshold for what is considered an outlier value. This value is compared to the absolute difference between each value of y_true and y_pred. Values within this threshold will be blue, otherwise they will be yellow. Defaults to None

Returns

- *prediction*: Predicted values from regression model.
- *actual*: Real target values.
- *outlier*: Colors indicating which values are in the threshold for what is considered an outlier value.

Return type pd.DataFrame with the following columns

evalml.model_understanding.graphs.**get_prediction_vs_actual_over_time_data**(*pipeline*, *X*, *y*, *dates*)

Get the data needed for the prediction_vs_actual_over_time plot.

Parameters

- **pipeline** (*TimeSeriesRegressionPipeline*) – Fitted time series regression pipeline.
- **X** (*pd.DataFrame*) – Features used to generate new predictions.
- **y** (*pd.Series*) – Target values to compare predictions against.
- **dates** (*pd.Series*) – Dates corresponding to target values and predictions.

Returns pd.DataFrame

evalml.model_understanding.graphs.**graph_binary_objective_vs_threshold**(*pipeline*, *X*, *y*, *objective*, *steps=100*)

Generates a plot graphing objective score vs. decision thresholds for a fitted binary classification pipeline.

Parameters

- **pipeline** (*PipelineBase or subclass*) – Fitted pipeline
- **X** (*pd.DataFrame*) – The input data used to score and compute scores
- **y** (*pd.Series*) – The target labels
- **objective** (*ObjectiveBase obj, str*) – Objective used to score, shown on the y-axis of the graph
- **steps** (*int*) – Number of intervals to divide and calculate objective score at

Returns plotly.Figure representing the objective score vs. threshold graph generated

evalml.model_understanding.graphs.**graph_confusion_matrix**(*y_true*, *y_pred*, *normalize_method='true'*, *title_addition=None*)

Generate and display a confusion matrix plot.

If *normalize_method* is set, hover text will show raw count, otherwise hover text will show count normalized with method 'true'.

Parameters

- **y_true** (*pd.Series or np.ndarray*) – True binary labels.
- **y_pred** (*pd.Series or np.ndarray*) – Predictions from a binary classifier.
- **normalize_method** (*{'true', 'pred', 'all', None}*) – Normalization method to use, if not None. Supported options are: 'true' to normalize by row, 'pred' to normalize by column, or 'all' to normalize by all values. Defaults to 'true'.
- **title_addition** (*str or None*) – if not None, append to plot title. Defaults to None.

Returns plotly.Figure representing the confusion matrix plot generated

evalml.model_understanding.graphs.**graph_partial_dependence**(*pipeline*, *X*, *features*, *class_label=None*, *grid_resolution=100*, *kind='average'*)

Create an one-way or two-way partial dependence plot. Passing a single integer or string as features will create a one-way partial dependence plot with the feature values plotted against the partial dependence. Passing features a tuple of int/strings will create a two-way partial dependence plot with a contour of feature[0] in the y-axis, feature[1] in the x-axis and the partial dependence in the z-axis.

Parameters

- **pipeline** (*PipelineBase or subclass*) – Fitted pipeline
- **X** (*pd.DataFrame, np.ndarray*) – The input data used to generate a grid of values for feature where partial dependence will be calculated at
- **features** (*int, string, tuple[int or string]*) – The target feature for which to create the partial dependence plot for. If features is an int, it must be the index of the feature to use. If features is a string, it must be a valid column name in X. If features is a tuple of strings, it must contain valid column int/names in X.
- **class_label** (*string, optional*) – Name of class to plot for multiclass problems. If None, will plot the partial dependence for each class. This argument does not change behavior for regression or binary classification pipelines. For binary classification, the partial dependence for the positive label will always be displayed. Defaults to None.
- **grid_resolution** (*int*) – Number of samples of feature(s) for partial dependence plot
- **{'average'** (*kind*) – Type of partial dependence to plot. 'average' creates a regular partial dependence (PD) graph, 'individual' creates an individual conditional expectation (ICE) plot, and 'both' creates a single-figure PD and ICE plot. ICE plots can only be shown for one-way partial dependence plots.
- **'individual'** – Type of partial dependence to plot. 'average' creates a regular partial dependence (PD) graph, 'individual' creates an individual conditional expectation (ICE) plot, and 'both' creates a single-figure PD and ICE plot. ICE plots can only be shown for one-way partial dependence plots.
- **'both'}** – Type of partial dependence to plot. 'average' creates a regular partial dependence (PD) graph, 'individual' creates an individual conditional expectation (ICE) plot, and 'both' creates a single-figure PD and ICE plot. ICE plots can only be shown for one-way partial dependence plots.

Returns figure object containing the partial dependence data for plotting

Return type plotly.graph_objects.Figure

Raises

- **PartialDependenceError** – if a graph is requested for a class name that isn't present in the pipeline.
- **PartialDependenceError** – if an ICE plot is requested for a two-way partial dependence.

evalml.model_understanding.graphs.**graph_permutation_importance**(*pipeline*, *X*, *y*, *objective*, *importance_threshold=0*)

Generate a bar graph of the pipeline's permutation importance.

Parameters

- **pipeline** (*PipelineBase or subclass*) – Fitted pipeline
- **X** (*pd.DataFrame*) – The input data used to score and compute permutation importance
- **y** (*pd.Series*) – The target data
- **objective** (*str, ObjectiveBase*) – Objective to score on
- **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their respective permutation importance.

evalml.model_understanding.graphs.**graph_precision_recall_curve**(*y_true*, *y_pred_proba*, *title_addition=None*)

Generate and display a precision-recall plot.

Parameters

- **y_true** (*pd.Series or np.ndarray*) – True binary labels.
- **y_pred_proba** (*pd.Series or np.ndarray*) – Predictions from a binary classifier, before thresholding has been applied. Note this should be the predicted probability for the "true" label.
- **title_addition** (*str or None*) – If not None, append to plot title. Default None.

Returns plotly.Figure representing the precision-recall plot generated

evalml.model_understanding.graphs.**graph_prediction_vs_actual**(*y_true*, *y_pred*, *outlier_threshold=None*)

Generate a scatter plot comparing the true and predicted values. Used for regression plotting

Parameters

- **y_true** (*pd.Series*) – The real target values of the data
- **y_pred** (*pd.Series*) – The predicted values outputted by the regression model.
- **outlier_threshold** (*int, float*) – A positive threshold for what is considered an outlier value. This value is compared to the absolute difference between each value of y_true and y_pred. Values within this threshold will be blue, otherwise they will be yellow. Defaults to None

Returns plotly.Figure representing the predicted vs. actual values graph

evalml.model_understanding.graphs.**graph_prediction_vs_actual_over_time**(*pipeline*, *X*, *y*, *dates*)

Plot the target values and predictions against time on the x-axis.

Parameters

- **pipeline** (*TimeSeriesRegressionPipeline*) – Fitted time series regression pipeline.
- **X** (*pd.DataFrame*) – Features used to generate new predictions.
- **y** (*pd.Series*) – Target values to compare predictions against.
- **dates** (*pd.Series*) – Dates corresponding to target values and predictions.

Returns Showing the prediction vs actual over time.

Return type plotly.Figure

evalml.model_understanding.graphs.**graph_roc_curve**(*y_true*, *y_pred_proba*, *custom_class_names=None*, *title_addition=None*)

Generate and display a Receiver Operating Characteristic (ROC) plot for binary and multiclass classification problems.

Parameters

- **y_true** (*pd.Series or np.ndarray*) – True labels.
- **y_pred_proba** (*pd.Series or np.ndarray*) – Predictions from a classifier, before thresholding has been applied. Note this should a one dimensional array with the predicted probability for the "true" label in the binary case.
- **custom_class_labels** (*list or None*) – If not None, custom labels for classes. Default None.
- **title_addition** (*str or None*) – if not None, append to plot title. Default None.

Returns plotly.Figure representing the ROC plot generated

evalml.model_understanding.graphs.**graph_t_sne**(*X*, *n_components=2*, *perplexity=30.0*, *learning_rate=200.0*, *metric='euclidean'*, *marker_line_width=2*, *marker_size=7*, ***kwargs*)

Plot high dimensional data into lower dimensional space using t-SNE .

Parameters

- **X** (*np.ndarray, pd.DataFrame*) – Data to be transformed. Must be numeric.
- **n_components** (*int, optional*) – Dimension of the embedded space.
- **perplexity** (*float, optional*) – Related to the number of nearest neighbors that is used in other manifold learning
- **Larger datasets usually require a larger perplexity. Consider selecting a value between 5 and 50.** (*algorithms.*) –
- **learning_rate** (*float, optional*) – Usually in the range [10.0, 1000.0]. If the cost function gets stuck in a bad
- **minimum** (*local*) –
- **the learning rate may help.** (*increasing*) –
- **metric** (*str, optional*) – The metric to use when calculating distance between instances in a feature array.
- **marker_line_width** (*int, optional*) – Determines the line width of the marker boundary.
- **marker_size** (*int, optional*) – Determines the size of the marker.

Returns plotly.Figure representing the transformed data

evalml.model_understanding.graphs.**normalize_confusion_matrix**(*conf_mat*, *normalize_method='true'*)

Normalizes a confusion matrix.

Parameters

- **conf_mat** (*pd.DataFrame or np.ndarray*) – Confusion matrix to normalize.

- **normalize_method** (*{'true', 'pred', 'all'}*) – Normalization method. Supported options are: 'true' to normalize by row, 'pred' to normalize by column, or 'all' to normalize by all values. Defaults to 'true'.

Returns normalized version of the input confusion matrix. The column header represents the predicted labels while row header represents the actual labels.

Return type pd.DataFrame

evalml.model_understanding.graphs.**partial_dependence**(*pipeline*, *X*, *features*, *percentiles=(0.05, 0.95)*, *grid_resolution=100*, *kind='average'*)

Calculates one or two-way partial dependence. If a single integer or string is given for features, one-way partial dependence is calculated. If a tuple of two integers or strings is given, two-way partial dependence is calculated with the first feature in the y-axis and second feature in the x-axis.

Parameters

- **pipeline** (*PipelineBase or subclass*) – Fitted pipeline
- **X** (*pd.DataFrame, np.ndarray*) – The input data used to generate a grid of values for feature where partial dependence will be calculated at
- **features** (*int, string, tuple[int or string]*) – The target feature for which to create the partial dependence plot for. If features is an int, it must be the index of the feature to use. If features is a string, it must be a valid column name in X. If features is a tuple of int/strings, it must contain valid column integers/names in X.
- **percentiles** (*tuple[float]*) – The lower and upper percentile used to create the extreme values for the grid. Must be in [0, 1]. Defaults to (0.05, 0.95).
- **grid_resolution** (*int*) – Number of samples of feature(s) for partial dependence plot. If this value is less than the maximum number of categories present in categorical data within X, it will be set to the max number of categories + 1. Defaults to 100.
- **{'average'** (*kind*) – The type of predictions to return. 'individual' will return the predictions for all of the points in the grid for each sample in X. 'average' will return the predictions for all of the points in the grid but averaged over all of the samples in X.
- **'individual'** – The type of predictions to return. 'individual' will return the predictions for all of the points in the grid for each sample in X. 'average' will return the predictions for all of the points in the grid but averaged over all of the samples in X.
- **'both'}** – The type of predictions to return. 'individual' will return the predictions for all of the points in the grid for each sample in X. 'average' will return the predictions for all of the points in the grid but averaged over all of the samples in X.

Returns

When *kind='average'*: DataFrame with averaged predictions for all points in the grid averaged over all samples of X and the values used to calculate those predictions.

When *kind='individual'*: DataFrame with individual predictions for all points in the grid for each sample of X and the values used to calculate those predictions. If a two-way partial dependence is calculated, then the result is a list of DataFrames with each DataFrame representing one sample's predictions.

When *kind='both'*: A tuple consisting of the averaged predictions (in a DataFrame) over all samples of X and the individual predictions (in a list of DataFrames) for each sample of X.

In the one-way case: The dataframe will contain two columns, "feature_values" (grid points at which the partial dependence was calculated) and "partial_dependence" (the partial dependence at that feature value). For classification problems, there will be a third column called "class_label" (the class label for which the partial dependence was calculated). For binary classification, the partial dependence is only calculated for the "positive" class.

In the two-way case: The data frame will contain grid_resolution number of columns and rows where the index and column headers are the sampled values of the first and second features, respectively, used to make the partial dependence contour. The values of the data frame contain the partial dependence data for each feature value pair.

Return type pd.DataFrame, list(pd.DataFrame), or tuple(pd.DataFrame, list(pd.DataFrame))

Raises

- **PartialDependenceError** – if the user provides a tuple of not exactly two features.
- **PartialDependenceError** – if the provided pipeline isn't fitted.
- **PartialDependenceError** – if the provided pipeline is a Baseline pipeline.
- **PartialDependenceError** – if any of the features passed in are completely NaN
- **PartialDependenceError** – if any of the features are low-variance. Defined as having one value occurring more than the upper percentile passed by the user. By default 95%.

evalml.model_understanding.graphs.**precision_recall_curve**(*y_true*, *y_pred_proba*, *pos_label_idx=- 1*)

Given labels and binary classifier predicted probabilities, compute and return the data representing a precision-recall curve.

Parameters

- **y_true** (*pd.Series or np.ndarray*) – True binary labels.
- **y_pred_proba** (*pd.Series or np.ndarray*) – Predictions from a binary classifier, before thresholding has been applied. Note this should be the predicted probability for the "true" label.
- **pos_label_idx** (*int*) – the column index corresponding to the positive class. If predicted probabilities are two-dimensional, this will be used to access the probabilities for the positive class.

Returns

Dictionary containing metrics used to generate a precision-recall plot, with the following keys:

- *precision*: Precision values.
- *recall*: Recall values.
- *thresholds*: Threshold values used to produce the precision and recall.
- *auc_score*: The area under the ROC curve.

Return type list

evalml.model_understanding.graphs.**roc_curve**(*y_true*, *y_pred_proba*)

Given labels and classifier predicted probabilities, compute and return the data representing a Receiver Operating Characteristic (ROC) curve. Works with binary or multiclass problems.

Parameters

- **y_true** (*pd.Series or np.ndarray*) – True labels.

- **y_pred_proba** (*pd.Series or np.ndarray*) – Predictions from a classifier, before thresholding has been applied.

Returns

A list of dictionaries (with one for each class) is returned. Binary classification problems return a list with one di

Each dictionary contains metrics used to generate an ROC plot with the following keys:

- *fpr_rate*: False positive rate.
- *tpr_rate*: True positive rate.
- *threshold*: Threshold values used to produce each pair of true/false positive rates.
- *auc_score*: The area under the ROC curve.

Return type list(dict)

evalml.model_understanding.graphs.**t_sne**(*X*, *n_components=2*, *perplexity=30.0*, *learning_rate=200.0*, *metric='euclidean'*, ***kwargs*)

Get the transformed output after fitting X to the embedded space using t-SNE.

Arguments: X (np.ndarray, pd.DataFrame): Data to be transformed. Must be numeric. n_components (int, optional): Dimension of the embedded space. perplexity (float, optional): Related to the number of nearest neighbors that is used in other manifold learning algorithms. Larger datasets usually require a larger perplexity. Consider selecting a value between 5 and 50. learning_rate (float, optional): Usually in the range [10.0, 1000.0]. If the cost function gets stuck in a bad local minimum, increasing the learning rate may help. metric (str, optional): The metric to use when calculating distance between instances in a feature array.

Returns np.ndarray (n_samples, n_components)

evalml.model_understanding.graphs.**visualize_decision_tree**(*estimator*, *max_depth=None*, *rotate=False*, *filled=False*, *filepath=None*)

Generate an image visualizing the decision tree

Parameters

- **estimator** (*ComponentBase*) – A fitted DecisionTree-based estimator.
- **max_depth** (*int, optional*) – The depth to which the tree should be displayed. If set to None (as by default),
- **is fully generated.** (*tree*) –
- **rotate** (*bool, optional*) – Orient tree left to right rather than top-down.
- **filled** (*bool, optional*) – Paint nodes to indicate majority class for classification, extremity of values for
- **regression** –
- **purity of node for multi-output.** (*or*) –
- **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph
- **not be saved.** (*will*) –

Returns DOT object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Source

permutation_importance

Module Contents

Functions

calculate_permutation_importance	Calculates permutation importance for features.
calculate_permutation_importance_one_column	Calculates permutation importance for one column in the original dataframe.

Contents

evalml.model_understanding.permutation_importance.**calculate_permutation_importance**(*pipeline*, *X*, *y*, *objective*, *n_repeats=*, *n_jobs=No*, *random_seed=*

Calculates permutation importance for features.

Parameters

- **pipeline** (*PipelineBase or subclass*) – Fitted pipeline.
- **X** (*pd.DataFrame*) – The input data used to score and compute permutation importance.
- **y** (*pd.Series*) – The target data.
- **objective** (*str, ObjectiveBase*) – Objective to score on.
- **n_repeats** (*int*) – Number of times to permute a feature. Defaults to 5.
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns Mean feature importance scores over a number of shuffles.

Return type pd.DataFrame

evalml.model_understanding.permutation_importance.**calculate_permutation_importance_one_colu**

Calculates permutation importance for one column in the original dataframe.

Parameters

- **pipeline** (*PipelineBase or subclass*) – Fitted pipeline.
- **X** (*pd.DataFrame*) – The input data used to score and compute permutation importance.
- **y** (*pd.Series*) – The target data.
- **col_name** (*str, int*) – The column in X to calculate permutation importance for.
- **objective** (*str, ObjectiveBase*) – Objective to score on.
- **n_repeats** (*int*) – Number of times to permute a feature. Defaults to 5.
- **fast** (*bool*) – Whether to use the fast method of calculating the permutation importance or not. Defaults to True.
- **precomputed_features** (*pd.DataFrame*) – Precomputed features necessary to calculate permutation importance using the fast method. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns Mean feature importance scores over a number of shuffles.

Return type float

Package Contents

Functions

binary_objective_vs_threshold	Computes objective score as a function of potential binary classification
calculate_permutation_importance	Calculates permutation importance for features.
calculate_permutation_importance_one_co	Calculates permutation importance for one column in the original dataframe.
confusion_matrix	Confusion matrix for binary and multiclass classification.
explain_predictions	Creates a report summarizing the top contributing features for each data point in the input features.

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explain_predictions_best_worst	Creates a report summarizing the top contributing features for the best and worst points in the dataset as measured by error to true labels.
get_linear_coefficients	Returns a dataframe showing the features with the greatest predictive power for a linear model.
get_prediction_vs_actual_data	Combines y_true and y_pred into a single dataframe and adds a column for outliers. Used in *graph_prediction_vs_actual()*.
get_prediction_vs_actual_over_time_data	Get the data needed for the prediction_vs_actual_over_time plot.
graph_binary_objective_vs_threshold	Generates a plot graphing objective score vs. decision thresholds for a fitted binary classification pipeline.
graph_confusion_matrix	Generate and display a confusion matrix plot.
graph_partial_dependence	Create an one-way or two-way partial dependence plot. Passing a single integer or
graph_permutation_importance	Generate a bar graph of the pipeline's permutation importance.
graph_precision_recall_curve	Generate and display a precision-recall plot.
graph_prediction_vs_actual	Generate a scatter plot comparing the true and predicted values. Used for regression plotting
graph_prediction_vs_actual_over_time	Plot the target values and predictions against time on the x-axis.
graph_roc_curve	Generate and display a Receiver Operating Characteristic (ROC) plot for binary and multiclass classification problems.
graph_t_sne	Plot high dimensional data into lower dimensional space using t-SNE .
normalize_confusion_matrix	Normalizes a confusion matrix.
partial_dependence	Calculates one or two-way partial dependence. If a single integer or
precision_recall_curve	Given labels and binary classifier predicted probabilities, compute and return the data representing a precision-recall curve.
roc_curve	Given labels and classifier predicted probabilities, compute and return the data representing a Receiver Operating Characteristic (ROC) curve. Works with binary or multiclass problems.
t_sne	Get the transformed output after fitting X to the embedded space using t-SNE.

Contents

evalml.model_understanding.**binary_objective_vs_threshold**(*pipeline*, *X*, *y*, *objective*, *steps=100*)

Computes objective score as a function of potential binary classification decision thresholds for a fitted binary classification pipeline.

Parameters

- **pipeline** (*BinaryClassificationPipeline obj*) – Fitted binary classification pipeline

- **X** (*pd.DataFrame*) – The input data used to compute objective score
- **y** (*pd.Series*) – The target labels
- **objective** (*ObjectiveBase obj, str*) – Objective used to score
- **steps** (*int*) – Number of intervals to divide and calculate objective score at

Returns DataFrame with thresholds and the corresponding objective score calculated at each threshold

Return type pd.DataFrame

evalml.model_understanding.**calculate_permutation_importance**(*pipeline*, *X*, *y*, *objective*, *n_repeats=5*, *n_jobs=None*, *random_seed=0*)

Calculates permutation importance for features.

Parameters

- **pipeline** (*PipelineBase or subclass*) – Fitted pipeline.
- **X** (*pd.DataFrame*) – The input data used to score and compute permutation importance.
- **y** (*pd.Series*) – The target data.
- **objective** (*str, ObjectiveBase*) – Objective to score on.
- **n_repeats** (*int*) – Number of times to permute a feature. Defaults to 5.
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns Mean feature importance scores over a number of shuffles.

Return type pd.DataFrame

evalml.model_understanding.**calculate_permutation_importance_one_column**(*pipeline*, *X*, *y*, *col_name*, *objective*, *n_repeats=5*, *fast=True*, *precomputed_features=None*, *random_seed=0*)

Calculates permutation importance for one column in the original dataframe.

Parameters

- **pipeline** (*PipelineBase or subclass*) – Fitted pipeline.
- **X** (*pd.DataFrame*) – The input data used to score and compute permutation importance.
- **y** (*pd.Series*) – The target data.
- **col_name** (*str, int*) – The column in X to calculate permutation importance for.

- **objective** (*str, ObjectiveBase*) – Objective to score on.
- **n_repeats** (*int*) – Number of times to permute a feature. Defaults to 5.
- **fast** (*bool*) – Whether to use the fast method of calculating the permutation importance or not. Defaults to True.
- **precomputed_features** (*pd.DataFrame*) – Precomputed features necessary to calculate permutation importance using the fast method. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns Mean feature importance scores over a number of shuffles.

Return type float

evalml.model_understanding.**confusion_matrix**(*y_true*, *y_predicted*, *normalize_method='true'*)

Confusion matrix for binary and multiclass classification.

Parameters

- **y_true** (*pd.Series or np.ndarray*) – True binary labels.
- **y_pred** (*pd.Series or np.ndarray*) – Predictions from a binary classifier.
- **normalize_method** (*{'true', 'pred', 'all', None}*) – Normalization method to use, if not None. Supported options are: 'true' to normalize by row, 'pred' to normalize by column, or 'all' to normalize by all values. Defaults to 'true'.

Returns Confusion matrix. The column header represents the predicted labels while row header represents the actual labels.

Return type pd.DataFrame

evalml.model_understanding.**explain_predictions**(*pipeline*, *input_features*, *y*, *indices_to_explain*, *top_k_features=3*, *include_shap_values=False*, *include_expected_value=False*, *output_format='text'*)

Creates a report summarizing the top contributing features for each data point in the input features.

XGBoost and Stacked Ensemble models, as well as CatBoost multiclass classifiers, are not currently supported.

Parameters

- **pipeline** (*PipelineBase*) – Fitted pipeline whose predictions we want to explain with SHAP.
- **input_features** (*pd.DataFrame*) – Dataframe of input data to evaluate the pipeline on.
- **y** (*pd.Series*) – Labels for the input data.
- **indices_to_explain** (*list(int)*) – List of integer indices to explain.
- **top_k_features** (*int*) – How many of the highest/lowest contributing feature to include in the table for each data point. Default is 3.
- **include_shap_values** (*bool*) – Whether SHAP values should be included in the table. Default is False.
- **include_expected_value** (*bool*) – Whether the expected value should be included in the table. Default is False.
- **output_format** (*str*) – Either "text", "dict", or "dataframe". Default is "text".

Returns

str, dict, or pd.DataFrame - A report explaining the top contributing features to each prediction for each row of
The report will include the feature names, prediction contribution, and SHAP Value (optional).

Raises

- **ValueError** – if input_features is empty.
- **ValueError** – if an output_format outside of "text", "dict" or "dataframe is provided.
- **ValueError** – if the requested index falls outside the input_feature's boundaries.

evalml.model_understanding.**explain_predictions_best_worst**(*pipeline*, *input_features*, *y_true*, *num_to_explain=5*, *top_k_features=3*, *include_shap_values=False*, *metric=None*, *output_format='text'*, *callback=None*)

Creates a report summarizing the top contributing features for the best and worst points in the dataset as measured by error to true labels.

XGBoost and Stacked Ensemble models, as well as CatBoost multiclass classifiers, are not currently supported.

Parameters

- **pipeline** (*PipelineBase*) – Fitted pipeline whose predictions we want to explain with SHAP.
- **input_features** (*pd.DataFrame*) – Input data to evaluate the pipeline on.
- **y_true** (*pd.Series*) – True labels for the input data.
- **num_to_explain** (*int*) – How many of the best, worst, random data points to explain.
- **top_k_features** (*int*) – How many of the highest/lowest contributing feature to include in the table for each data point.
- **include_shap_values** (*bool*) – Whether SHAP values should be included in the table. Default is False.
- **metric** (*callable*) – The metric used to identify the best and worst points in the dataset. Function must accept the true labels and predicted value or probabilities as the only arguments and lower values must be better. By default, this will be the absolute error for regression problems and cross entropy loss for classification problems.
- **output_format** (*str*) – Either "text" or "dict". Default is "text".
- **callback** (*callable*) – Function to be called with incremental updates. Has the following parameters: - progress_stage: stage of computation - time_elapsed: total time in seconds that has elapsed since start of call

Returns

str, dict, or pd.DataFrame - A report explaining the top contributing features for the best/worst predictions in th
For each of the best/worst rows of input_features, the predicted values, true labels, metric value, feature names, prediction contribution, and SHAP Value (optional) will be listed.

Raises

- **ValueError** – if input_features does not have more than twice the requested features to explain.

- **ValueError** – if y_true and input_features have mismatched lengths.
- **ValueError** – if an output_format outside of "text", "dict" or "dataframe is provided.

evalml.model_understanding.**get_linear_coefficients**(*estimator*, *features=None*)

Returns a dataframe showing the features with the greatest predictive power for a linear model.

Parameters

- **estimator** (*Estimator*) – Fitted linear model family estimator.
- **features** (*list[str]*) – List of feature names associated with the underlying data.

Returns Displaying the features by importance.

Return type pd.DataFrame

evalml.model_understanding.**get_prediction_vs_actual_data**(*y_true*, *y_pred*, *outlier_threshold=None*)

Combines y_true and y_pred into a single dataframe and adds a column for outliers. Used in *graph_prediction_vs_actual()*.

Parameters

- **y_true** (*pd.Series, or np.ndarray*) – The real target values of the data
- **y_pred** (*pd.Series, or np.ndarray*) – The predicted values outputted by the regression model.
- **outlier_threshold** (*int, float*) – A positive threshold for what is considered an outlier value. This value is compared to the absolute difference between each value of y_true and y_pred. Values within this threshold will be blue, otherwise they will be yellow. Defaults to None

Returns

- *prediction*: Predicted values from regression model.
- *actual*: Real target values.
- *outlier*: Colors indicating which values are in the threshold for what is considered an outlier value.

Return type pd.DataFrame with the following columns

evalml.model_understanding.**get_prediction_vs_actual_over_time_data**(*pipeline*, *X*, *y*, *dates*)

Get the data needed for the prediction_vs_actual_over_time plot.

Parameters

- **pipeline** (*TimeSeriesRegressionPipeline*) – Fitted time series regression pipeline.
- **X** (*pd.DataFrame*) – Features used to generate new predictions.
- **y** (*pd.Series*) – Target values to compare predictions against.
- **dates** (*pd.Series*) – Dates corresponding to target values and predictions.

Returns pd.DataFrame

evalml.model_understanding.**graph_binary_objective_vs_threshold**(*pipeline*, *X*, *y*, *objective*, *steps=100*)

Generates a plot graphing objective score vs. decision thresholds for a fitted binary classification pipeline.

Parameters

- **pipeline** (*PipelineBase or subclass*) – Fitted pipeline
- **X** (*pd.DataFrame*) – The input data used to score and compute scores
- **y** (*pd.Series*) – The target labels
- **objective** (*ObjectiveBase obj, str*) – Objective used to score, shown on the y-axis of the graph
- **steps** (*int*) – Number of intervals to divide and calculate objective score at

Returns plotly.Figure representing the objective score vs. threshold graph generated

evalml.model_understanding.**graph_confusion_matrix**(*y_true*, *y_pred*, *normalize_method='true'*, *title_addition=None*)

Generate and display a confusion matrix plot.

If *normalize_method* is set, hover text will show raw count, otherwise hover text will show count normalized with method 'true'.

Parameters

- **y_true** (*pd.Series or np.ndarray*) – True binary labels.
- **y_pred** (*pd.Series or np.ndarray*) – Predictions from a binary classifier.
- **normalize_method** (*{'true', 'pred', 'all', None}*) – Normalization method to use, if not None. Supported options are: 'true' to normalize by row, 'pred' to normalize by column, or 'all' to normalize by all values. Defaults to 'true'.
- **title_addition** (*str or None*) – if not None, append to plot title. Defaults to None.

Returns plotly.Figure representing the confusion matrix plot generated

evalml.model_understanding.**graph_partial_dependence**(*pipeline*, *X*, *features*, *class_label=None*, *grid_resolution=100*, *kind='average'*)

Create an one-way or two-way partial dependence plot. Passing a single integer or string as features will create a one-way partial dependence plot with the feature values plotted against the partial dependence. Passing features a tuple of int/strings will create a two-way partial dependence plot with a contour of feature[0] in the y-axis, feature[1] in the x-axis and the partial dependence in the z-axis.

Parameters

- **pipeline** (*PipelineBase or subclass*) – Fitted pipeline
- **X** (*pd.DataFrame, np.ndarray*) – The input data used to generate a grid of values for feature where partial dependence will be calculated at
- **features** (*int, string, tuple[int or string]*) – The target feature for which to create the partial dependence plot for. If features is an int, it must be the index of the feature to use. If features is a string, it must be a valid column name in X. If features is a tuple of strings, it must contain valid column int/names in X.
- **class_label** (*string, optional*) – Name of class to plot for multiclass problems. If None, will plot the partial dependence for each class. This argument does not change behavior for regression or binary classification pipelines. For binary classification, the partial dependence for the positive label will always be displayed. Defaults to None.
- **grid_resolution** (*int*) – Number of samples of feature(s) for partial dependence plot

- **{'average'** (*kind*) – Type of partial dependence to plot. 'average' creates a regular partial dependence (PD) graph, 'individual' creates an individual conditional expectation (ICE) plot, and 'both' creates a single-figure PD and ICE plot. ICE plots can only be shown for one-way partial dependence plots.
- **'individual'** – Type of partial dependence to plot. 'average' creates a regular partial dependence (PD) graph, 'individual' creates an individual conditional expectation (ICE) plot, and 'both' creates a single-figure PD and ICE plot. ICE plots can only be shown for one-way partial dependence plots.
- **'both'}** – Type of partial dependence to plot. 'average' creates a regular partial dependence (PD) graph, 'individual' creates an individual conditional expectation (ICE) plot, and 'both' creates a single-figure PD and ICE plot. ICE plots can only be shown for one-way partial dependence plots.

Returns figure object containing the partial dependence data for plotting

Return type plotly.graph_objects.Figure

Raises

- **PartialDependenceError** – if a graph is requested for a class name that isn't present in the pipeline.
- **PartialDependenceError** – if an ICE plot is requested for a two-way partial dependence.

evalml.model_understanding.**graph_permutation_importance**(*pipeline*, *X*, *y*, *objective*, *importance_threshold=0*)

Generate a bar graph of the pipeline's permutation importance.

Parameters

- **pipeline** (*PipelineBase or subclass*) – Fitted pipeline
- **X** (*pd.DataFrame*) – The input data used to score and compute permutation importance
- **y** (*pd.Series*) – The target data
- **objective** (*str, ObjectiveBase*) – Objective to score on
- **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their respective permutation importance.

evalml.model_understanding.**graph_precision_recall_curve**(*y_true*, *y_pred_proba*, *title_addition=None*)

Generate and display a precision-recall plot.

Parameters

- **y_true** (*pd.Series or np.ndarray*) – True binary labels.
- **y_pred_proba** (*pd.Series or np.ndarray*) – Predictions from a binary classifier, before thresholding has been applied. Note this should be the predicted probability for the "true" label.
- **title_addition** (*str or None*) – If not None, append to plot title. Default None.

Returns plotly.Figure representing the precision-recall plot generated

evalml.model_understanding.**graph_prediction_vs_actual**(*y_true*, *y_pred*, *outlier_threshold=None*)

Generate a scatter plot comparing the true and predicted values. Used for regression plotting

Parameters

- **y_true** (*pd.Series*) – The real target values of the data
- **y_pred** (*pd.Series*) – The predicted values outputted by the regression model.
- **outlier_threshold** (*int, float*) – A positive threshold for what is considered an outlier value. This value is compared to the absolute difference between each value of y_true and y_pred. Values within this threshold will be blue, otherwise they will be yellow. Defaults to None

Returns plotly.Figure representing the predicted vs. actual values graph

evalml.model_understanding.**graph_prediction_vs_actual_over_time**(*pipeline*, *X*, *y*, *dates*)

Plot the target values and predictions against time on the x-axis.

Parameters

- **pipeline** (*TimeSeriesRegressionPipeline*) – Fitted time series regression pipeline.
- **X** (*pd.DataFrame*) – Features used to generate new predictions.
- **y** (*pd.Series*) – Target values to compare predictions against.
- **dates** (*pd.Series*) – Dates corresponding to target values and predictions.

Returns Showing the prediction vs actual over time.

Return type plotly.Figure

evalml.model_understanding.**graph_roc_curve**(*y_true*, *y_pred_proba*, *custom_class_names=None*, *title_addition=None*)

Generate and display a Receiver Operating Characteristic (ROC) plot for binary and multiclass classification problems.

Parameters

- **y_true** (*pd.Series or np.ndarray*) – True labels.
- **y_pred_proba** (*pd.Series or np.ndarray*) – Predictions from a classifier, before thresholding has been applied. Note this should a one dimensional array with the predicted probability for the "true" label in the binary case.
- **custom_class_labels** (*list or None*) – If not None, custom labels for classes. Default None.
- **title_addition** (*str or None*) – if not None, append to plot title. Default None.

Returns plotly.Figure representing the ROC plot generated

evalml.model_understanding.**graph_t_sne**(*X*, *n_components=2*, *perplexity=30.0*, *learning_rate=200.0*, *metric='euclidean'*, *marker_line_width=2*, *marker_size=7*, ***kwargs*)

Plot high dimensional data into lower dimensional space using t-SNE .

Parameters

- **X** (*np.ndarray, pd.DataFrame*) – Data to be transformed. Must be numeric.
- **n_components** (*int, optional*) – Dimension of the embedded space.
- **perplexity** (*float, optional*) – Related to the number of nearest neighbors that is used in other manifold learning

- **Larger datasets usually require a larger perplexity. Consider selecting a value between 5 and 50.** (*algorithms.*) –
- **learning_rate** (*float, optional*) – Usually in the range [10.0, 1000.0]. If the cost function gets stuck in a bad
- **minimum** (*local*) –
- **the learning rate may help.** (*increasing*) –
- **metric** (*str, optional*) – The metric to use when calculating distance between instances in a feature array.
- **marker_line_width** (*int, optional*) – Determines the line width of the marker boundary.
- **marker_size** (*int, optional*) – Determines the size of the marker.

Returns plotly.Figure representing the transformed data

evalml.model_understanding.**normalize_confusion_matrix**(*conf_mat*, *normalize_method='true'*)

Normalizes a confusion matrix.

Parameters

- **conf_mat** (*pd.DataFrame or np.ndarray*) – Confusion matrix to normalize.
- **normalize_method** (*{'true', 'pred', 'all'}*) – Normalization method. Supported options are: 'true' to normalize by row, 'pred' to normalize by column, or 'all' to normalize by all values. Defaults to 'true'.

Returns normalized version of the input confusion matrix. The column header represents the predicted labels while row header represents the actual labels.

Return type pd.DataFrame

evalml.model_understanding.**partial_dependence**(*pipeline*, *X*, *features*, *percentiles=(0.05, 0.95)*, *grid_resolution=100*, *kind='average'*)

Calculates one or two-way partial dependence. If a single integer or string is given for features, one-way partial dependence is calculated. If a tuple of two integers or strings is given, two-way partial dependence is calculated with the first feature in the y-axis and second feature in the x-axis.

Parameters

- **pipeline** (*PipelineBase or subclass*) – Fitted pipeline
- **X** (*pd.DataFrame, np.ndarray*) – The input data used to generate a grid of values for feature where partial dependence will be calculated at
- **features** (*int, string, tuple[int or string]*) – The target feature for which to create the partial dependence plot for. If features is an int, it must be the index of the feature to use. If features is a string, it must be a valid column name in X. If features is a tuple of int/strings, it must contain valid column integers/names in X.
- **percentiles** (*tuple[float]*) – The lower and upper percentile used to create the extreme values for the grid. Must be in [0, 1]. Defaults to (0.05, 0.95).
- **grid_resolution** (*int*) – Number of samples of feature(s) for partial dependence plot. If this value is less than the maximum number of categories present in categorical data within X, it will be set to the max number of categories + 1. Defaults to 100.

- **{'average'** (*kind*) – The type of predictions to return. 'individual' will return the predictions for all of the points in the grid for each sample in X. 'average' will return the predictions for all of the points in the grid but averaged over all of the samples in X.
- **'individual'** – The type of predictions to return. 'individual' will return the predictions for all of the points in the grid for each sample in X. 'average' will return the predictions for all of the points in the grid but averaged over all of the samples in X.
- **'both'}** – The type of predictions to return. 'individual' will return the predictions for all of the points in the grid for each sample in X. 'average' will return the predictions for all of the points in the grid but averaged over all of the samples in X.

Returns

When *kind='average'*: DataFrame with averaged predictions for all points in the grid averaged over all samples of X and the values used to calculate those predictions.

When *kind='individual'*: DataFrame with individual predictions for all points in the grid for each sample of X and the values used to calculate those predictions. If a two-way partial dependence is calculated, then the result is a list of DataFrames with each DataFrame representing one sample's predictions.

When *kind='both'*: A tuple consisting of the averaged predictions (in a DataFrame) over all samples of X and the individual predictions (in a list of DataFrames) for each sample of X.

In the one-way case: The dataframe will contain two columns, "feature_values" (grid points at which the partial dependence was calculated) and "partial_dependence" (the partial dependence at that feature value). For classification problems, there will be a third column called "class_label" (the class label for which the partial dependence was calculated). For binary classification, the partial dependence is only calculated for the "positive" class.

In the two-way case: The data frame will contain grid_resolution number of columns and rows where the index and column headers are the sampled values of the first and second features, respectively, used to make the partial dependence contour. The values of the data frame contain the partial dependence data for each feature value pair.

Return type pd.DataFrame, list(pd.DataFrame), or tuple(pd.DataFrame, list(pd.DataFrame))

Raises

- **PartialDependenceError** – if the user provides a tuple of not exactly two features.
- **PartialDependenceError** – if the provided pipeline isn't fitted.
- **PartialDependenceError** – if the provided pipeline is a Baseline pipeline.
- **PartialDependenceError** – if any of the features passed in are completely NaN
- **PartialDependenceError** – if any of the features are low-variance. Defined as having one value occurring more than the upper percentile passed by the user. By default 95%.

evalml.model_understanding.**precision_recall_curve**(*y_true*, *y_pred_proba*, *pos_label_idx=- 1*)

Given labels and binary classifier predicted probabilities, compute and return the data representing a precision-recall curve.

Parameters

- **y_true** (*pd.Series or np.ndarray*) – True binary labels.
- **y_pred_proba** (*pd.Series or np.ndarray*) – Predictions from a binary classifier, before thresholding has been applied. Note this should be the predicted probability for the "true" label.

- **pos_label_idx** (*int*) – the column index corresponding to the positive class. If predicted probabilities are two-dimensional, this will be used to access the probabilities for the positive class.

Returns

Dictionary containing metrics used to generate a precision-recall plot, with the following keys:

- *precision*: Precision values.
- *recall*: Recall values.
- *thresholds*: Threshold values used to produce the precision and recall.
- *auc_score*: The area under the ROC curve.

Return type list

evalml.model_understanding.**roc_curve**(*y_true*, *y_pred_proba*)

Given labels and classifier predicted probabilities, compute and return the data representing a Receiver Operating Characteristic (ROC) curve. Works with binary or multiclass problems.

Parameters

- **y_true** (*pd.Series or np.ndarray*) – True labels.
- **y_pred_proba** (*pd.Series or np.ndarray*) – Predictions from a classifier, before thresholding has been applied.

Returns

A list of dictionaries (with one for each class) is returned. Binary classification problems return a list with one di

Each dictionary contains metrics used to generate an ROC plot with the following keys:

- *fpr_rate*: False positive rate.
- *tpr_rate*: True positive rate.
- *threshold*: Threshold values used to produce each pair of true/false positive rates.
- *auc_score*: The area under the ROC curve.

Return type list(dict)

evalml.model_understanding.**t_sne**(*X*, *n_components=2*, *perplexity=30.0*, *learning_rate=200.0*, *metric='euclidean'*, ***kwargs*)

Get the transformed output after fitting X to the embedded space using t-SNE.

Arguments: X (np.ndarray, pd.DataFrame): Data to be transformed. Must be numeric. n_components (int, optional): Dimension of the embedded space. perplexity (float, optional): Related to the number of nearest neighbors that is used in other manifold learning algorithms. Larger datasets usually require a larger perplexity. Consider selecting a value between 5 and 50. learning_rate (float, optional): Usually in the range [10.0, 1000.0]. If the cost function gets stuck in a bad local minimum, increasing the learning rate may help. metric (str, optional): The metric to use when calculating distance between instances in a feature array.

Returns np.ndarray (n_samples, n_components)

Objectives

Submodules

binary_classification_objective

Module Contents

Classes Summary

BinaryClassificationObjective	Base class for all binary classification objectives.

Contents

class evalml.objectives.binary_classification_objective.**BinaryClassificationObjective**

Base class for all binary classification objectives.

Attributes

problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
greater_is_better	Returns a boolean determining if a greater score indicates better model performance.
is_bounded_like_percentage	Returns whether this objective is bounded between 0 and 1, inclusive.
is_defined_for_problem_type	
name	Returns a name describing the objective.
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
perfect_score	Returns the score obtained by evaluating this objective on a perfect model.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.

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score_needs_proba	Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

property greater_is_better(*cls*)
Returns a boolean determining if a greater score indicates better model performance.

property is_bounded_like_percentage(*cls*)
Returns whether this objective is bounded between 0 and 1, inclusive.

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

property name(*cls*)
Returns a name describing the objective.

abstract classmethod objective_function(*cls*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

property perfect_score(*cls*)
Returns the score obtained by evaluating this objective on a perfect model.

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

property score_needs_proba(*cls*)
Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

cost_benefit_matrix

Module Contents

Classes Summary

CostBenefitMatrix	Score using a cost-benefit matrix. Scores quantify the benefits of a given value, so greater numeric

Contents

class evalml.objectives.cost_benefit_matrix.**CostBenefitMatrix**(*true_positive*, *true_negative*, *false_positive*, *false_negative*)

Score using a cost-benefit matrix. Scores quantify the benefits of a given value, so greater numeric scores represents a better score. Costs and scores can be negative, indicating that a value is not beneficial. For example, in the case of monetary profit, a negative cost and/or score represents loss of cash flow.

Parameters

- **true_positive** (*float*) – Cost associated with true positive predictions
- **true_negative** (*float*) – Cost associated with true negative predictions
- **false_positive** (*float*) – Cost associated with false positive predictions
- **false_negative** (*float*) – Cost associated with false negative predictions

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	Cost Benefit Matrix
perfect_score	None
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Calculates cost-benefit of the using the predicted and true values.

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optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Calculates cost-benefit of the using the predicted and true values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted labels
- **y_true** (*pd.Series*) – True labels
- **X** (*pd.DataFrame*) – Ignored.
- **sample_weight** (*pd.DataFrame*) – Ignored.

Returns Cost-benefit matrix score

Return type float

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

fraud_cost

Module Contents

Classes Summary

FraudCost	Score the percentage of money lost of the total transaction amount process due to fraud.

Contents

class evalml.objectives.fraud_cost.**FraudCost**(*retry_percentage=0.5*, *interchange_fee=0.02*, *fraud_payout_percentage=1.0*, *amount_col='amount'*)

Score the percentage of money lost of the total transaction amount process due to fraud.

Parameters

- **retry_percentage** (*float*) – What percentage of customers that will retry a transaction if it is declined. Between 0 and 1. Defaults to 0.5.
- **interchange_fee** (*float*) – How much of each successful transaction you pay. Between 0 and 1. Defaults to 0.02.
- **fraud_payout_percentage** (*float*) – Percentage of fraud you will not be able to collect. Between 0 and 1. Defaults to 1.0.
- **amount_col** (*str*) – Name of column in data that contains the amount. Defaults to "amount".

Attributes

greater_is_better	False
is_bounded_like_percentage	True
name	Fraud Cost
perfect_score	0.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Calculate amount lost to fraud per transaction given predictions, true values, and dataframe with transaction amount.
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)

Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X*, *sample_weight=None*)

Calculate amount lost to fraud per transaction given predictions, true values, and dataframe with transaction amount.

Parameters

- **y_predicted** (*pd.Series*) – Predicted fraud labels
- **y_true** (*pd.Series*) – True fraud labels
- **X** (*pd.DataFrame*) – Data with transaction amounts
- **sample_weight** (*pd.DataFrame*) – Ignored.

Returns Amount lost to fraud per transaction

Return type float

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.

- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

lead_scoring

Module Contents

Classes Summary

LeadScoring	Lead scoring.

Contents

class evalml.objectives.lead_scoring.**LeadScoring**(*true_positives=1*, *false_positives=-1*)
Lead scoring.

Parameters

- **true_positives** (*int*) – Reward for a true positive. Defaults to 1.
- **false_positives** (*int*) – Cost for a false positive. Should be negative. Defaults to -1.

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	Lead Scoring
perfect_score	None
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Calculate the profit per lead.
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)

Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Calculate the profit per lead.

Parameters

- **y_predicted** (*pd.Series*) – Predicted labels
- **y_true** (*pd.Series*) – True labels
- **X** (*pd.DataFrame*) – Ignored.
- **sample_weight** (*pd.DataFrame*) – Ignored.

Returns Profit per lead

Return type float

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

multiclass_classification_objective

Module Contents

Classes Summary

MulticlassClassificationObjective	Base class for all multiclass classification objectives.

Contents

class evalml.objectives.multiclass_classification_objective.**MulticlassClassificationObjecti**

Base class for all multiclass classification objectives.

Attributes

problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]

Methods

calculate_percent_difference	Calculate the percent difference between scores.
greater_is_better	Returns a boolean determining if a greater score indicates better model performance.
is_bounded_like_percentage	Returns whether this objective is bounded between 0 and 1, inclusive.
is_defined_for_problem_type	
name	Returns a name describing the objective.
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
perfect_score	Returns the score obtained by evaluating this objective on a perfect model.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.

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score_needs_proba	Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property greater_is_better(*cls*)
Returns a boolean determining if a greater score indicates better model performance.

property is_bounded_like_percentage(*cls*)
Returns whether this objective is bounded between 0 and 1, inclusive.

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

property name(*cls*)
Returns a name describing the objective.

abstract classmethod objective_function(*cls*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

property perfect_score(*cls*)
Returns the score obtained by evaluating this objective on a perfect model.

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

property score_needs_proba(*cls*)
Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

objective_base

Module Contents

Classes Summary

ObjectiveBase	Base class for all objectives.

Contents

class evalml.objectives.objective_base.**ObjectiveBase**
Base class for all objectives.

Attributes

problem_types	None

Methods

calculate_percent_difference	Calculate the percent difference between scores.
greater_is_better	Returns a boolean determining if a greater score indicates better model performance.
is_bounded_like_percentage	Returns whether this objective is bounded between 0 and 1, inclusive.

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is_defined_for_problem_type	
name	Returns a name describing the objective.
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
perfect_score	Returns the score obtained by evaluating this objective on a perfect model.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
score_needs_proba	Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property greater_is_better(*cls*)
Returns a boolean determining if a greater score indicates better model performance.

property is_bounded_like_percentage(*cls*)
Returns whether this objective is bounded between 0 and 1, inclusive.

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

property name(*cls*)
Returns a name describing the objective.

abstract classmethod objective_function(*cls*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

property perfect_score(*cls*)
Returns the score obtained by evaluating this objective on a perfect model.

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

property score_needs_proba(*cls*)
Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

regression_objective

Module Contents

Classes Summary

RegressionObjective	Base class for all regression objectives.

Contents

class evalml.objectives.regression_objective.**RegressionObjective**

Base class for all regression objectives.

Attributes

problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]

Methods

calculate_percent_difference	Calculate the percent difference between scores.
greater_is_better	Returns a boolean determining if a greater score indicates better model performance.
is_bounded_like_percentage	Returns whether this objective is bounded between 0 and 1, inclusive.
is_defined_for_problem_type	
name	Returns a name describing the objective.
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
perfect_score	Returns the score obtained by evaluating this objective on a perfect model.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
score_needs_proba	Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property greater_is_better(*cls*)
Returns a boolean determining if a greater score indicates better model performance.

property is_bounded_like_percentage(*cls*)
Returns whether this objective is bounded between 0 and 1, inclusive.

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

property name(*cls*)
Returns a name describing the objective.

abstract classmethod objective_function(*cls*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

property perfect_score(*cls*)
Returns the score obtained by evaluating this objective on a perfect model.

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

property score_needs_proba(*cls*)
Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

sensitivity_low_alert

Module Contents

Classes Summary

SensitivityLowAlert	Base class for all binary classification objectives.

Attributes Summary

logger

Contents

evalml.objectives.sensitivity_low_alert.**logger**

class evalml.objectives.sensitivity_low_alert.**SensitivityLowAlert**(*alert_rate=0.01*)

Base class for all binary classification objectives.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Sensitivity at Low Alert Rates
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Determine if an observation is high risk given an alert rate
is_defined_for_problem_type	
objective_function	Calculate sensitivity across all predictions, using the top alert_rate percent of observations as the predicted positive class
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.

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score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, ***kwargs*)
Determine if an observation is high risk given an alert rate

Parameters **ypred_proba** (*pd.Series*) – Predicted probabilities

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, ***kwargs*)
Calculate sensitivity across all predictions, using the top alert_rate percent of observations as the predicted positive class

Parameters

- **y_true** (*pd.Series*) – True labels
- **y_predicted** (*pd.Series*) – Predicted labels based on alert_rate

Returns sensitivity using the observations with the top scores as the predicted positive class

Return type float

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only (*cls*)
If True, this objective is only valid for positive data. Default False.

score (*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs (*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

standard_metrics

Module Contents

Classes Summary

AccuracyBinary	Accuracy score for binary classification.
AccuracyMulticlass	Accuracy score for multiclass classification.
AUC	AUC score for binary classification.
AUCMacro	AUC score for multiclass classification using macro averaging.
AUCMicro	AUC score for multiclass classification using micro averaging.
AUCWeighted	AUC Score for multiclass classification using weighted averaging.
BalancedAccuracyBinary	Balanced accuracy score for binary classification.
BalancedAccuracyMulticlass	Balanced accuracy score for multiclass classification.
ExpVariance	Explained variance score for regression.
F1	F1 score for binary classification.
F1Macro	F1 score for multiclass classification using macro averaging.
F1Micro	F1 score for multiclass classification using micro averaging.

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F1Weighted	F1 score for multiclass classification using weighted averaging.
Gini	Gini coefficient for binary classification.
LogLossBinary	Log Loss for binary classification.
LogLossMulticlass	Log Loss for multiclass classification.
MAE	Mean absolute error for regression.
MAPE	Mean absolute percentage error for time series regression. Scaled by 100 to return a percentage.
MaxError	Maximum residual error for regression.
MCCBinary	Matthews correlation coefficient for binary classification.
MCCMulticlass	Matthews correlation coefficient for multiclass classification.
MeanSquaredLogError	Mean squared log error for regression.
MedianAE	Median absolute error for regression.
MSE	Mean squared error for regression.
Precision	Precision score for binary classification.
PrecisionMacro	Precision score for multiclass classification using macro averaging.
PrecisionMicro	Precision score for multiclass classification using micro averaging.
PrecisionWeighted	Precision score for multiclass classification using weighted averaging.
R2	Coefficient of determination for regression.
Recall	Recall score for binary classification.
RecallMacro	Recall score for multiclass classification using macro averaging.
RecallMicro	Recall score for multiclass classification using micro averaging.
RecallWeighted	Recall score for multiclass classification using weighted averaging.
RootMeanSquaredError	Root mean squared error for regression.
RootMeanSquaredLogError	Root mean squared log error for regression.

Contents

class evalml.objectives.standard_metrics.**AccuracyBinary**

Accuracy score for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Accuracy Binary
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**AccuracyMulticlass**
Accuracy score for multiclass classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Accuracy Multiclass
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only (*cls*)
If True, this objective is only valid for positive data. Default False.

score (*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs (*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**AUC**
AUC score for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	AUC
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

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optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**AUCMacro**
AUC score for multiclass classification using macro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	AUC Macro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score

- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**AUCMicro**
AUC score for multiclass classification using micro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	AUC Micro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted

as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**AUCWeighted**
AUC Score for multiclass classification using weighted averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	AUC Weighted
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**BalancedAccuracyBinary**
Balanced accuracy score for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Balanced Accuracy Binary
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

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optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**BalancedAccuracyMulticlass**
Balanced accuracy score for multiclass classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Balanced Accuracy Multiclass
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score

- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**ExpVariance**
Explained variance score for regression.

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	ExpVariance
perfect_score	1.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted

as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**F1**
F1 score for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	F1
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)

Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)

If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)

Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**F1Macro**

F1 score for multiclass classification using macro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	F1 Macro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**F1Micro**
F1 score for multiclass classification using micro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	F1 Micro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	

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objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**F1Weighted**
F1 score for multiclass classification using weighted averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	F1 Weighted
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**Gini**
Gini coefficient for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	Gini
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)

Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**LogLossBinary**
Log Loss for binary classification.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	Log Loss Binary
perfect_score	0.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)

Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)

If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)

Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**LogLossMulticlass**

Log Loss for multiclass classification.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	Log Loss Multiclass
perfect_score	0.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**MAE**
Mean absolute error for regression.

Attributes

greater_is_better	False
is_bounded_like_percentage	True
name	MAE
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	

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objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**MAPE**
Mean absolute percentage error for time series regression. Scaled by 100 to return a percentage.

Only valid for nonzero inputs. Otherwise, will throw a ValueError

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	Mean Absolute Percentage Error
perfect_score	0.0
problem_types	[ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*self*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**MaxError**
Maximum residual error for regression.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	MaxError
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)

Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**MCCBinary**

Matthews correlation coefficient for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	MCC Binary
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)

Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only (*cls*)
If True, this objective is only valid for positive data. Default False.

score (*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs (*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**MCCMulticlass**
Matthews correlation coefficient for multiclass classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	MCC Multiclass
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.

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score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**MeanSquaredLogError**

Mean squared log error for regression.

Only valid for nonnegative inputs. Otherwise, will throw a ValueError

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	Mean Squared Log Error
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*self*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**MedianAE**
Median absolute error for regression.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	MedianAE
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score

- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**MSE**
Mean squared error for regression.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	MSE
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted

as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**Precision**
Precision score for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Precision
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)

Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)

If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)

Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**PrecisionMacro**

Precision score for multiclass classification using macro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Precision Macro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**PrecisionMicro**
Precision score for multiclass classification using micro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Precision Micro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	

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objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**PrecisionWeighted**
Precision score for multiclass classification using weighted averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Precision Weighted
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**R2**
Coefficient of determination for regression.

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	R2
perfect_score	1
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score

- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**Recall**
Recall score for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Recall
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)

Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)

If True, this objective is only valid for positive data. Default False.

score (*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs (*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**RecallMacro**
Recall score for multiclass classification using macro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Recall Macro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**RecallMicro**

Recall score for multiclass classification using micro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Recall Micro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only (*cls*)
If True, this objective is only valid for positive data. Default False.

score (*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs (*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**RecallWeighted**
Recall score for multiclass classification using weighted averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Recall Weighted
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.

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score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**RootMeanSquaredError**

Root mean squared error for regression.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	Root Mean Squared Error
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.standard_metrics.**RootMeanSquaredLogError**
Root mean squared log error for regression.

Only valid for nonnegative inputs.Otherwise, will throw a ValueError.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	Root Mean Squared Log Error
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.

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is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*self*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score

- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

time_series_regression_objective

Module Contents

Classes Summary

TimeSeriesRegressionObjective	Base class for all time series regression objectives.

Contents

class evalml.objectives.time_series_regression_objective.**TimeSeriesRegressionObjective**
Base class for all time series regression objectives.

Attributes

problem_types	[ProblemTypes.TIME_SERIES_REGRESSION]

Methods

calculate_percent_difference	Calculate the percent difference between scores.
greater_is_better	Returns a boolean determining if a greater score indicates better model performance.
is_bounded_like_percentage	Returns whether this objective is bounded between 0 and 1, inclusive.
is_defined_for_problem_type	
name	Returns a name describing the objective.
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
perfect_score	Returns the score obtained by evaluating this objective on a perfect model.
positive_only	If True, this objective is only valid for positive data. Default False.

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score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
score_needs_proba	Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property greater_is_better(*cls*)
Returns a boolean determining if a greater score indicates better model performance.

property is_bounded_like_percentage(*cls*)
Returns whether this objective is bounded between 0 and 1, inclusive.

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

property name(*cls*)
Returns a name describing the objective.

abstract classmethod objective_function(*cls*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

property perfect_score(*cls*)
Returns the score obtained by evaluating this objective on a perfect model.

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score (*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

property score_needs_proba (*cls*)
Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.

validate_inputs (*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

utils

Module Contents

Functions

get_all_objective_names	Get a list of the names of all objectives.
get_core_objective_names	Get a list of all valid core objectives.
get_core_objectives	Returns all core objective instances associated with the given problem type.
get_non_core_objectives	Get non-core objective classes.
get_objective	Returns the Objective class corresponding to a given objective name.

Contents

evalml.objectives.utils.**get_all_objective_names**()
Get a list of the names of all objectives.

Returns Objective names

Return type list (str)

evalml.objectives.utils.**get_core_objective_names**()
Get a list of all valid core objectives.

Returns Objective names.

Return type list[str]

evalml.objectives.utils.**get_core_objectives**(*problem_type*)
Returns all core objective instances associated with the given problem type.

Core objectives are designed to work out-of-the-box for any dataset.

Parameters **problem_type** (*str/ProblemTypes*) – Type of problem

Returns List of ObjectiveBase instances

evalml.objectives.utils.**get_non_core_objectives**()
Get non-core objective classes.

Non-core objectives are objectives that are domain-specific. Users typically need to configure these objectives before using them in AutoMLSearch.

Returns List of ObjectiveBase classes

evalml.objectives.utils.**get_objective**(*objective*, *return_instance=False*, ***kwargs*)
Returns the Objective class corresponding to a given objective name.

Parameters

- **objective** (*str or ObjectiveBase*) – Name or instance of the objective class.
- **return_instance** (*bool*) – Whether to return an instance of the objective. This only applies if objective is of type str. Note that the instance will be initialized with default arguments.
- **kwargs** (*Any*) – Any keyword arguments to pass into the objective. Only used when return_instance=True.

Returns ObjectiveBase if the parameter objective is of type ObjectiveBase. If objective is instead a valid objective name, function will return the class corresponding to that name. If return_instance is True, an instance of that objective will be returned.

Package Contents

Classes Summary

AccuracyBinary	Accuracy score for binary classification.
AccuracyMulticlass	Accuracy score for multiclass classification.
AUC	AUC score for binary classification.

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AUCMacro	AUC score for multiclass classification using macro averaging.
AUCMicro	AUC score for multiclass classification using micro averaging.
AUCWeighted	AUC Score for multiclass classification using weighted averaging.
BalancedAccuracyBinary	Balanced accuracy score for binary classification.
BalancedAccuracyMulticlass	Balanced accuracy score for multiclass classification.
BinaryClassificationObjective	Base class for all binary classification objectives.
CostBenefitMatrix	Score using a cost-benefit matrix. Scores quantify the benefits of a given value, so greater numeric
ExpVariance	Explained variance score for regression.
F1	F1 score for binary classification.
F1Macro	F1 score for multiclass classification using macro averaging.
F1Micro	F1 score for multiclass classification using micro averaging.
F1Weighted	F1 score for multiclass classification using weighted averaging.
FraudCost	Score the percentage of money lost of the total transaction amount process due to fraud.
Gini	Gini coefficient for binary classification.
LeadScoring	Lead scoring.
LogLossBinary	Log Loss for binary classification.
LogLossMulticlass	Log Loss for multiclass classification.
MAE	Mean absolute error for regression.
MAPE	Mean absolute percentage error for time series regression. Scaled by 100 to return a percentage.
MaxError	Maximum residual error for regression.
MCCBinary	Matthews correlation coefficient for binary classification.
MCCMulticlass	Matthews correlation coefficient for multiclass classification.
MeanSquaredLogError	Mean squared log error for regression.
MedianAE	Median absolute error for regression.
MSE	Mean squared error for regression.
MulticlassClassificationObjective	Base class for all multiclass classification objectives.
ObjectiveBase	Base class for all objectives.
Precision	Precision score for binary classification.
PrecisionMacro	Precision score for multiclass classification using macro averaging.
PrecisionMicro	Precision score for multiclass classification using micro averaging.
PrecisionWeighted	Precision score for multiclass classification using weighted averaging.
R2	Coefficient of determination for regression.
Recall	Recall score for binary classification.
RecallMacro	Recall score for multiclass classification using macro averaging.
RecallMicro	Recall score for multiclass classification using micro averaging.

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RecallWeighted	Recall score for multiclass classification using weighted averaging.
RegressionObjective	Base class for all regression objectives.
RootMeanSquaredError	Root mean squared error for regression.
RootMeanSquaredLogError	Root mean squared log error for regression.
SensitivityLowAlert	Base class for all binary classification objectives.

Functions

get_all_objective_names	Get a list of the names of all objectives.
get_core_objective_names	Get a list of all valid core objectives.
get_core_objectives	Returns all core objective instances associated with the given problem type.
get_non_core_objectives	Get non-core objective classes.
get_objective	Returns the Objective class corresponding to a given objective name.

Contents

class evalml.objectives.**AccuracyBinary**

Accuracy score for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Accuracy Binary
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.

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positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**AccuracyMulticlass**
Accuracy score for multiclass classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Accuracy Multiclass
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.

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is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score

- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**AUC**
AUC score for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	AUC
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)

Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)

If True, this objective is only valid for positive data. Default False.

score (*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs (*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**AUCMacro**
AUC score for multiclass classification using macro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	AUC Macro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**AUCMicro**

AUC score for multiclass classification using micro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	AUC Micro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**AUCWeighted**
AUC Score for multiclass classification using weighted averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	AUC Weighted
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.

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score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**BalancedAccuracyBinary**

Balanced accuracy score for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Balanced Accuracy Binary
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**BalancedAccuracyMulticlass**
Balanced accuracy score for multiclass classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Balanced Accuracy Multiclass
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**BinaryClassificationObjective**
Base class for all binary classification objectives.

Attributes

problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
greater_is_better	Returns a boolean determining if a greater score indicates better model performance.
is_bounded_like_percentage	Returns whether this objective is bounded between 0 and 1, inclusive.
is_defined_for_problem_type	
name	Returns a name describing the objective.
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
perfect_score	Returns the score obtained by evaluating this objective on a perfect model.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
score_needs_proba	Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)

Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

property greater_is_better(*cls*)
Returns a boolean determining if a greater score indicates better model performance.

property is_bounded_like_percentage(*cls*)
Returns whether this objective is bounded between 0 and 1, inclusive.

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

property name(*cls*)
Returns a name describing the objective.

abstract classmethod objective_function(*cls*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

property perfect_score(*cls*)
Returns the score obtained by evaluating this objective on a perfect model.

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]

- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

property score_needs_proba(*cls*)
Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**CostBenefitMatrix**(*true_positive*, *true_negative*, *false_positive*, *false_negative*)
Score using a cost-benefit matrix. Scores quantify the benefits of a given value, so greater numeric scores represents a better score. Costs and scores can be negative, indicating that a value is not beneficial. For example, in the case of monetary profit, a negative cost and/or score represents loss of cash flow.

Parameters

- **true_positive** (*float*) – Cost associated with true positive predictions
- **true_negative** (*float*) – Cost associated with true negative predictions
- **false_positive** (*float*) – Cost associated with false positive predictions
- **false_negative** (*float*) – Cost associated with false negative predictions

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	Cost Benefit Matrix
perfect_score	None
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.

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decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Calculates cost-benefit of the using the predicted and true values.
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Calculates cost-benefit of the using the predicted and true values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted labels
- **y_true** (*pd.Series*) – True labels
- **X** (*pd.DataFrame*) – Ignored.
- **sample_weight** (*pd.DataFrame*) – Ignored.

Returns Cost-benefit matrix score

Return type float

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**ExpVariance**
Explained variance score for regression.

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	ExpVariance
perfect_score	1.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**F1**
F1 score for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	F1
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

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optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**F1Macro**
F1 score for multiclass classification using macro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	F1 Macro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score

- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**F1Micro**
F1 score for multiclass classification using micro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	F1 Micro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted

as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**F1Weighted**
F1 score for multiclass classification using weighted averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	F1 Weighted
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only (*cls*)
If True, this objective is only valid for positive data. Default False.

score (*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs (*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**FraudCost** (*retry_percentage=0.5*, *interchange_fee=0.02*, *fraud_payout_percentage=1.0*, *amount_col='amount'*)
Score the percentage of money lost of the total transaction amount process due to fraud.

Parameters

- **retry_percentage** (*float*) – What percentage of customers that will retry a transaction if it is declined. Between 0 and 1. Defaults to 0.5.
- **interchange_fee** (*float*) – How much of each successful transaction you pay. Between 0 and 1. Defaults to 0.02.
- **fraud_payout_percentage** (*float*) – Percentage of fraud you will not be able to collect. Between 0 and 1. Defaults to 1.0.
- **amount_col** (*str*) – Name of column in data that contains the amount. Defaults to "amount".

Attributes

greater_is_better	False
is_bounded_like_percentage	True
name	Fraud Cost
perfect_score	0.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Calculate amount lost to fraud per transaction given predictions, true values, and dataframe with transaction amount.
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)

Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X*, *sample_weight=None*)
Calculate amount lost to fraud per transaction given predictions, true values, and dataframe with transaction amount.

Parameters

- **y_predicted** (*pd.Series*) – Predicted fraud labels
- **y_true** (*pd.Series*) – True fraud labels
- **X** (*pd.DataFrame*) – Data with transaction amounts
- **sample_weight** (*pd.DataFrame*) – Ignored.

Returns Amount lost to fraud per transaction

Return type float

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

evalml.objectives.**get_all_objective_names**()
Get a list of the names of all objectives.

Returns Objective names

Return type list (str)

evalml.objectives.**get_core_objective_names**()
Get a list of all valid core objectives.

Returns Objective names.

Return type list[str]

evalml.objectives.**get_core_objectives**(*problem_type*)
Returns all core objective instances associated with the given problem type.

Core objectives are designed to work out-of-the-box for any dataset.

Parameters **problem_type** (*str/ProblemTypes*) – Type of problem

Returns List of ObjectiveBase instances

evalml.objectives.**get_non_core_objectives**()
Get non-core objective classes.

Non-core objectives are objectives that are domain-specific. Users typically need to configure these objectives before using them in AutoMLSearch.

Returns List of ObjectiveBase classes

evalml.objectives.**get_objective**(*objective*, *return_instance=False*, ***kwargs*)
Returns the Objective class corresponding to a given objective name.

Parameters

- **objective** (*str or ObjectiveBase*) – Name or instance of the objective class.
- **return_instance** (*bool*) – Whether to return an instance of the objective. This only applies if objective is of type str. Note that the instance will be initialized with default arguments.
- **kwargs** (*Any*) – Any keyword arguments to pass into the objective. Only used when return_instance=True.

Returns ObjectiveBase if the parameter objective is of type ObjectiveBase. If objective is instead a valid objective name, function will return the class corresponding to that name. If return_instance is True, an instance of that objective will be returned.

class evalml.objectives.**Gini**
Gini coefficient for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	Gini
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**LeadScoring**(*true_positives=1*, *false_positives=- 1*)
Lead scoring.

Parameters

- **true_positives** (*int*) – Reward for a true positive. Defaults to 1.

- **false_positives** (*int*) – Cost for a false positive. Should be negative. Defaults to -1.

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	Lead Scoring
perfect_score	None
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Calculate the profit per lead.
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)

Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Calculate the profit per lead.

Parameters

- **y_predicted** (*pd.Series*) – Predicted labels
- **y_true** (*pd.Series*) – True labels
- **X** (*pd.DataFrame*) – Ignored.
- **sample_weight** (*pd.DataFrame*) – Ignored.

Returns Profit per lead

Return type float

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)

If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**LogLossBinary**
Log Loss for binary classification.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	Log Loss Binary
perfect_score	0.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**LogLossMulticlass**
Log Loss for multiclass classification.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	Log Loss Multiclass
perfect_score	0.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	True

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.

- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)

If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)

Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**MAE**

Mean absolute error for regression.

Attributes

greater_is_better	False
is_bounded_like_percentage	True
name	MAE
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**MAPE**
Mean absolute percentage error for time series regression. Scaled by 100 to return a percentage.

Only valid for nonzero inputs. Otherwise, will throw a ValueError

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	Mean Absolute Percentage Error
perfect_score	0.0
problem_types	[ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.

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score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*self*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**MaxError**

Maximum residual error for regression.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	MaxError
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**MCCBinary**
Matthews correlation coefficient for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	MCC Binary
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.

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decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)

If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)

Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**MCCMulticlass**

Matthews correlation coefficient for multiclass classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	MCC Multiclass
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**MeanSquaredLogError**
Mean squared log error for regression.

Only valid for nonnegative inputs. Otherwise, will throw a ValueError

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	Mean Squared Log Error
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.

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score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference (*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type (*cls*, *problem_type*)

objective_function (*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only (*self*)
If True, this objective is only valid for positive data. Default False.

score (*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs (*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**MedianAE**

Median absolute error for regression.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	MedianAE
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**MSE**
Mean squared error for regression.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	MSE
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	

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objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**MulticlassClassificationObjective**
Base class for all multiclass classification objectives.

Attributes

problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]

Methods

calculate_percent_difference	Calculate the percent difference between scores.
greater_is_better	Returns a boolean determining if a greater score indicates better model performance.
is_bounded_like_percentage	Returns whether this objective is bounded between 0 and 1, inclusive.
is_defined_for_problem_type	
name	Returns a name describing the objective.
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
perfect_score	Returns the score obtained by evaluating this objective on a perfect model.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
score_needs_proba	Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property greater_is_better(*cls*)
Returns a boolean determining if a greater score indicates better model performance.

property is_bounded_like_percentage(*cls*)
Returns whether this objective is bounded between 0 and 1, inclusive.

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

property name(*cls*)
Returns a name describing the objective.

abstract classmethod objective_function(*cls*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

property perfect_score(*cls*)
Returns the score obtained by evaluating this objective on a perfect model.

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

property score_needs_proba(*cls*)
Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**ObjectiveBase**

Base class for all objectives.

Attributes

problem_types	None

Methods

calculate_percent_difference	Calculate the percent difference between scores.
greater_is_better	Returns a boolean determining if a greater score indicates better model performance.
is_bounded_like_percentage	Returns whether this objective is bounded between 0 and 1, inclusive.
is_defined_for_problem_type	
name	Returns a name describing the objective.
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
perfect_score	Returns the score obtained by evaluating this objective on a perfect model.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
score_needs_proba	Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all

other objectives, the difference will be normalized by the reference score.

Return type float

property greater_is_better(*cls*)
Returns a boolean determining if a greater score indicates better model performance.

property is_bounded_like_percentage(*cls*)
Returns whether this objective is bounded between 0 and 1, inclusive.

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

property name(*cls*)
Returns a name describing the objective.

abstract classmethod objective_function(*cls*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

property perfect_score(*cls*)
Returns the score obtained by evaluating this objective on a perfect model.

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

property score_needs_proba(*cls*)
Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]

- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**Precision**

Precision score for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Precision
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score

- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**PrecisionMacro**
Precision score for multiclass classification using macro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Precision Macro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted

as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**PrecisionMicro**
Precision score for multiclass classification using micro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Precision Micro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only (*cls*)
If True, this objective is only valid for positive data. Default False.

score (*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs (*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**PrecisionWeighted**
Precision score for multiclass classification using weighted averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Precision Weighted
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.

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score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**R2**

Coefficient of determination for regression.

Attributes

greater_is_better	True
is_bounded_like_percentage	False
name	R2
perfect_score	1
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**Recall**
Recall score for binary classification.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Recall
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.

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decision_function	Apply a learned threshold to predicted probabilities to get predicted classes.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

Parameters

- **ypred_proba** (*pd.Series, np.ndarray*) – The classifier's predicted probabilities
- **threshold** (*float, optional*) – Threshold used to make a prediction. Defaults to 0.5.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns predictions

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)

If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)

Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**RecallMacro**

Recall score for multiclass classification using macro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Recall Macro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**RecallMicro**
Recall score for multiclass classification using micro averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Recall Micro
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.

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score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**RecallWeighted**

Recall score for multiclass classification using weighted averaging.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Recall Weighted
perfect_score	1.0
problem_types	[ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_MULTICLASS]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)

Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)

Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**RegressionObjective**
Base class for all regression objectives.

Attributes

problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]

Methods

calculate_percent_difference	Calculate the percent difference between scores.
greater_is_better	Returns a boolean determining if a greater score indicates better model performance.
is_bounded_like_percentage	Returns whether this objective is bounded between 0 and 1, inclusive.
is_defined_for_problem_type	
name	Returns a name describing the objective.

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objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
perfect_score	Returns the score obtained by evaluating this objective on a perfect model.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
score_needs_proba	Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property greater_is_better(*cls*)
Returns a boolean determining if a greater score indicates better model performance.

property is_bounded_like_percentage(*cls*)
Returns whether this objective is bounded between 0 and 1, inclusive.

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

property name(*cls*)
Returns a name describing the objective.

abstract classmethod objective_function(*cls*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

property perfect_score(*cls*)
Returns the score obtained by evaluating this objective on a perfect model.

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

property score_needs_proba(*cls*)
Returns a boolean determining if the score() method needs probability estimates. This should be true for objectives which work with predicted probabilities, like log loss or AUC, and false for objectives which compare predicted class labels to the actual labels, like F1 or correlation.

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**RootMeanSquaredError**
Root mean squared error for regression.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	Root Mean Squared Error
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	

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objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**RootMeanSquaredLogError**
Root mean squared log error for regression.

Only valid for nonnegative inputs.Otherwise, will throw a ValueError.

Attributes

greater_is_better	False
is_bounded_like_percentage	False
name	Root Mean Squared Log Error
perfect_score	0.0
problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
is_defined_for_problem_type	
objective_function	Computes the relative value of the provided predictions compared to the actual labels, according a specified metric
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Computes the relative value of the provided predictions compared to the actual labels, according a specified metric

Arguments: y_predicted (pd.Series): Predicted values of length [n_samples] y_true (pd.Series): Actual class labels of length [n_samples] X (pd.DataFrame or np.ndarray): Extra data of shape [n_samples, n_features] necessary to calculate score sample_weight (pd.DataFrame or np.ndarray): Sample weights used in computing objective value result

Returns Numerical value used to calculate score

positive_only(*self*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

class evalml.objectives.**SensitivityLowAlert**(*alert_rate=0.01*)
Base class for all binary classification objectives.

Attributes

greater_is_better	True
is_bounded_like_percentage	True
name	Sensitivity at Low Alert Rates
perfect_score	1.0
problem_types	[ProblemTypes.BINARY, ProblemTypes.TIME_SERIES_BINARY]
score_needs_proba	False

Methods

calculate_percent_difference	Calculate the percent difference between scores.
can_optimize_threshold	Returns a boolean determining if we can optimize the binary classification objective threshold.
decision_function	Determine if an observation is high risk given an alert rate
is_defined_for_problem_type	
objective_function	Calculate sensitivity across all predictions, using the top alert_rate percent of observations as the predicted positive class
optimize_threshold	Learn a binary classification threshold which optimizes the current objective.
positive_only	If True, this objective is only valid for positive data. Default False.
score	Returns a numerical score indicating performance based on the differences between the predicted and actual values.
validate_inputs	Validates the input based on a few simple checks.

classmethod calculate_percent_difference(*cls*, *score*, *baseline_score*)
Calculate the percent difference between scores.

Parameters

- **score** (*float*) – A score. Output of the score method of this objective.
- **baseline_score** (*float*) – A score. Output of the score method of this objective. In practice, this is the score achieved on this objective with a baseline estimator.

Returns

The percent difference between the scores. Note that for objectives that can be interpreted as percentages, this will be the difference between the reference score and score. For all other objectives, the difference will be normalized by the reference score.

Return type float

property can_optimize_threshold(*cls*)
Returns a boolean determining if we can optimize the binary classification objective threshold. This will be false for any objective that works directly with predicted probabilities, like log loss and AUC. Otherwise, it will be true.

decision_function(*self*, *ypred_proba*, ***kwargs*)
Determine if an observation is high risk given an alert rate

Parameters **ypred_proba** (*pd.Series*) – Predicted probabilities

classmethod is_defined_for_problem_type(*cls*, *problem_type*)

objective_function(*self*, *y_true*, *y_predicted*, ***kwargs*)
Calculate sensitivity across all predictions, using the top alert_rate percent of observations as the predicted positive class

Parameters

- **y_true** (*pd.Series*) – True labels
- **y_predicted** (*pd.Series*) – Predicted labels based on alert_rate

Returns sensitivity using the observations with the top scores as the predicted positive class

Return type float

optimize_threshold(*self*, *ypred_proba*, *y_true*, *X=None*)
Learn a binary classification threshold which optimizes the current objective.

Parameters

- **ypred_proba** (*pd.Series*) – The classifier's predicted probabilities
- **y_true** (*pd.Series*) – The ground truth for the predictions.
- **X** (*pd.DataFrame, optional*) – Any extra columns that are needed from training data.

Returns Optimal threshold for this objective

positive_only(*cls*)
If True, this objective is only valid for positive data. Default False.

score(*self*, *y_true*, *y_predicted*, *X=None*, *sample_weight=None*)
Returns a numerical score indicating performance based on the differences between the predicted and actual values.

Parameters

- **y_predicted** (*pd.Series*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]
- **X** (*pd.DataFrame or np.ndarray*) – Extra data of shape [n_samples, n_features] necessary to calculate score
- **sample_weight** (*pd.DataFrame or np.ndarray*) – Sample weights used in computing objective value result

Returns score

validate_inputs(*self*, *y_true*, *y_predicted*)
Validates the input based on a few simple checks.

Parameters

- **y_predicted** (*pd.Series, or pd.DataFrame*) – Predicted values of length [n_samples]
- **y_true** (*pd.Series*) – Actual class labels of length [n_samples]

Returns None

Pipelines

Subpackages

components

Subpackages

ensemble

Submodules

sklearn_stacked_ensemble_base

Module Contents

Classes Summary

SklearnStackedEnsembleBase	Stacked Ensemble Base Class.

Contents

class evalml.pipelines.components.ensemble.sklearn_stacked_ensemble_base.**SklearnStackedEnse**

Stacked Ensemble Base Class.

Parameters

- **input_pipelines** (*list(PipelineBase or subclass obj)*) – List of pipeline instances to use as the base estimators. This must not be None or an empty list or else EnsembleMissingPipelinesError will be raised.
- **final_estimator** (*Estimator or subclass*) – The estimator used to combine the base estimators.
- **cv** (*int, cross-validation generator or an iterable*) – Determines the cross-validation splitting strategy used to train final_estimator. For int/None inputs, if the estimator is a classifier and y is either binary or multiclass, StratifiedKFold is used. In all other cases, KFold is used. Possible inputs for cv are:
  - None: 5-fold cross validation
  - int: the number of folds in a (Stratified) KFold
  - An scikit-learn cross-validation generator object
  - An iterable yielding (train, test) splits
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Defaults to -1. - Note: there could be some multi-process errors thrown for values of *n_jobs != 1*. If this is the case, please use *n_jobs = 1*.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.ENSEMBLE
modifies_features	True
modifies_target	False
predict_uses_y	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for stacked ensemble classes.
describe	Describe a component and its parameters
feature_importance	Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor
fit	Fits component to data
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path
supported_problem_types	Problem types this estimator supports

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for stacked ensemble classes.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name (*cls*)
Returns string name of this component

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

property supported_problem_types (*cls*)
Problem types this estimator supports

sklearn_stacked_ensemble_classifier

Module Contents

Classes Summary

SklearnStackedEnsembleClassifier	Scikit-learn Stacked Ensemble Classifier.

Contents

class evalml.pipelines.components.ensemble.sklearn_stacked_ensemble_classifier.**SklearnStacl**

Scikit-learn Stacked Ensemble Classifier.

Parameters

- **input_pipelines** (*list(PipelineBase or subclass obj)*) – List of pipeline instances to use as the base estimators. This must not be None or an empty list or else EnsembleMissingPipelinesError will be raised.
- **final_estimator** (*Estimator or subclass*) – The classifier used to combine the base estimators. If None, uses LogisticRegressionClassifier.
- **cv** (*int, cross-validation generator or an iterable*) – Determines the cross-validation splitting strategy used to train final_estimator. For int/None inputs, if the estimator is a classifier and y is either binary or multiclass, StratifiedKFold is used. Defaults to None. Possible inputs for cv are:
  - None: 3-fold cross validation
  - int: the number of folds in a (Stratified) KFold
  - An scikit-learn cross-validation generator object
  - An iterable yielding (train, test) splits
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Defaults to -1. - Note: there could be some multi-process errors thrown for values of *n_jobs != 1*. If this is the case, please use *n_jobs = 1*.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.ENSEMBLE
modifies_features	True
modifies_target	False
name	Sklearn Stacked Ensemble Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for stacked ensemble classes.
describe	Describe a component and its parameters
feature_importance	Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for stacked ensemble classes.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

sklearn_stacked_ensemble_regressor

Module Contents

Classes Summary

SklearnStackedEnsembleRegressor	Scikit-learn Stacked Ensemble Regressor.

Contents

class evalml.pipelines.components.ensemble.sklearn_stacked_ensemble_regressor.**SklearnStacke**

Scikit-learn Stacked Ensemble Regressor.

Parameters

- **input_pipelines** (*list(PipelineBase or subclass obj)*) – List of pipeline instances to use as the base estimators. This must not be None or an empty list or else EnsembleMissingPipelinesError will be raised.
- **final_estimator** (*Estimator or subclass*) – The regressor used to combine the base estimators. If None, uses LinearRegressor.
- **cv** (*int, cross-validation generator or an iterable*) – Determines the cross-validation splitting strategy used to train final_estimator. For int/None inputs, KFold is used. Defaults to None. Possible inputs for cv are:
  - None: 3-fold cross validation
  - int: the number of folds in a (Stratified) KFold
  - An scikit-learn cross-validation generator object
  - An iterable yielding (train, test) splits
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Defaults to -1. - Note: there could be some multi-process errors thrown for values of *n_jobs != 1*. If this is the case, please use *n_jobs = 1*.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.ENSEMBLE
modifies_features	True
modifies_target	False
name	Sklearn Stacked Ensemble Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for stacked ensemble classes.
describe	Describe a component and its parameters
feature_importance	Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for stacked ensemble classes.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

Package Contents

Classes Summary

SklearnStackedEnsembleBase	Stacked Ensemble Base Class.
SklearnStackedEnsembleClassifier	Scikit-learn Stacked Ensemble Classifier.
SklearnStackedEnsembleRegressor	Scikit-learn Stacked Ensemble Regressor.

Contents

class evalml.pipelines.components.ensemble.**SklearnStackedEnsembleBase**(*input_pipelines=None*, *final_estimator=None*, *cv=None*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Stacked Ensemble Base Class.

Parameters

- **input_pipelines** (*list(PipelineBase or subclass obj)*) – List of pipeline instances to use as the base estimators. This must not be None or an empty list or else EnsembleMissingPipelinesError will be raised.
- **final_estimator** (*Estimator or subclass*) – The estimator used to combine the base estimators.
- **cv** (*int, cross-validation generator or an iterable*) – Determines the cross-validation splitting strategy used to train final_estimator. For int/None inputs, if the estimator is a classifier and y is either binary or multiclass, StratifiedKFold is used. In all other cases, KFold is used. Possible inputs for cv are:
  - None: 5-fold cross validation
  - int: the number of folds in a (Stratified) KFold
  - An scikit-learn cross-validation generator object
  - An iterable yielding (train, test) splits
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Defaults to -1. - Note: there could be some multi-process errors thrown for values of *n_jobs != 1*. If this is the case, please use *n_jobs = 1*.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.ENSEMBLE
modifies_features	True
modifies_target	False
predict_uses_y	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for stacked ensemble classes.
describe	Describe a component and its parameters
feature_importance	Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor
fit	Fits component to data
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path
supported_problem_types	Problem types this estimator supports

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for stacked ensemble classes.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name (*cls*)
Returns string name of this component

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

property supported_problem_types (*cls*)
Problem types this estimator supports

class evalml.pipelines.components.ensemble.**SklearnStackedEnsembleClassifier**(*input_pipelines=None*, *final_estimator=None*, *cv=None*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Scikit-learn Stacked Ensemble Classifier.

Parameters

- **input_pipelines** (*list(PipelineBase or subclass obj)*) – List of pipeline instances to use as the base estimators. This must not be None or an empty list or else EnsembleMissingPipelinesError will be raised.
- **final_estimator** (*Estimator or subclass*) – The classifier used to combine the base estimators. If None, uses LogisticRegressionClassifier.
- **cv** (*int, cross-validation generator or an iterable*) – Determines the cross-validation splitting strategy used to train final_estimator. For int/None inputs, if the estimator is a classifier and y is either binary or multiclass, StratifiedKFold is used. Defaults to None. Possible inputs for cv are:
  - None: 3-fold cross validation
  - int: the number of folds in a (Stratified) KFold
  - An scikit-learn cross-validation generator object
  - An iterable yielding (train, test) splits
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Defaults to -1. - Note: there could be some multi-process errors thrown for values of *n_jobs != 1*. If this is the case, please use *n_jobs = 1*.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.ENSEMBLE
modifies_features	True
modifies_target	False
name	Sklearn Stacked Ensemble Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for stacked ensemble classes.
describe	Describe a component and its parameters
feature_importance	Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for stacked ensemble classes.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.ensemble.**SklearnStackedEnsembleRegressor**(*input_pipelines=None*, *final_estimator=None*, *cv=None*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Scikit-learn Stacked Ensemble Regressor.

Parameters

- **input_pipelines** (*list(PipelineBase or subclass obj)*) – List of pipeline instances to use as the base estimators. This must not be None or an empty list or else EnsembleMissingPipelinesError will be raised.
- **final_estimator** (*Estimator or subclass*) – The regressor used to combine the base estimators. If None, uses LinearRegressor.
- **cv** (*int, cross-validation generator or an iterable*) – Determines the cross-validation splitting strategy used to train final_estimator. For int/None inputs, KFold is used. Defaults to None. Possible inputs for cv are:

  - None: 3-fold cross validation
  - int: the number of folds in a (Stratified) KFold
  - An scikit-learn cross-validation generator object
  - An iterable yielding (train, test) splits
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Defaults to -1. - Note: there could be some multi-process errors thrown for values of *n_jobs != 1*. If this is the case, please use *n_jobs = 1*.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.ENSEMBLE
modifies_features	True
modifies_target	False
name	Sklearn Stacked Ensemble Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for stacked ensemble classes.
describe	Describe a component and its parameters
feature_importance	Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for stacked ensemble classes.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

estimators

Subpackages

classifiers

Submodules

baseline_classifier

Module Contents

Classes Summary

BaselineClassifier	Classifier that predicts using the specified strategy.

Contents

class evalml.pipelines.components.estimators.classifiers.baseline_classifier.**BaselineClassi**

Classifier that predicts using the specified strategy.

This is useful as a simple baseline classifier to compare with other classifiers.

Parameters

- **strategy** (*str*) – Method used to predict. Valid options are "mode", "random" and "random_weighted". Defaults to "mode".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.BASELINE
modifies_features	True
modifies_target	False
name	Baseline Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS]

Methods

*classes_*	Returns class labels. Will return None before fitting.
clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature. Since baseline classifiers do not use input features to calculate predictions, returns an array of zeroes.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

property classes_(*self*)
Returns class labels. Will return None before fitting.

Returns Class names

Return type list[str] or list(float)

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature. Since baseline classifiers do not use input features to calculate predictions, returns an array of zeroes.

Returns An array of zeroes

Return type np.ndarray (float)

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

catboost_classifier

Module Contents

Classes Summary

CatBoostClassifier	CatBoost Classifier, a classifier that uses gradient-boosting on decision trees.

Contents

class evalml.pipelines.components.estimators.classifiers.catboost_classifier.**CatBoostClassi**

CatBoost Classifier, a classifier that uses gradient-boosting on decision trees. CatBoost is an open-source library and natively supports categorical features.

For more information, check out https://catboost.ai/

Parameters

- **n_estimators** (*float*) – The maximum number of trees to build. Defaults to 10.
- **eta** (*float*) – The learning rate. Defaults to 0.03.
- **max_depth** (*int*) – The maximum tree depth for base learners. Defaults to 6.
- **bootstrap_type** (*string*) – Defines the method for sampling the weights of objects. Available methods are 'Bayesian', 'Bernoulli', 'MVS'. Defaults to None.
- **silent** (*boolean*) – Whether to use the "silent" logging mode. Defaults to True.
- **allow_writing_files** (*boolean*) – Whether to allow writing snapshot files while training. Defaults to False.

- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(4, 100), "eta": Real(0.000001, 1), "max_depth": Integer(4, 10),}
model_family	ModelFamily.CATBOOST
modifies_features	True
modifies_target	False
name	CatBoost Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

decision_tree_classifier

Module Contents

Classes Summary

DecisionTreeClassifier	Decision Tree Classifier.

Contents

class evalml.pipelines.components.estimators.classifiers.decision_tree_classifier.**DecisionT**

Decision Tree Classifier.

Parameters

- **criterion** (*{"gini", "entropy"}*) – The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain. Defaults to "gini".
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.

– If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.

Defaults to 2.

- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "criterion": ["gini", "entropy"], "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.DECISION_TREE
modifies_features	True
modifies_target	False
name	Decision Tree Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

elasticnet_classifier

Module Contents

Classes Summary

ElasticNetClassifier	Elastic Net Classifier. Uses Logistic Regression with elasticnet penalty as the base estimator.

Contents

class evalml.pipelines.components.estimators.classifiers.elasticnet_classifier.**ElasticNetC**

Elastic Net Classifier. Uses Logistic Regression with elasticnet penalty as the base estimator.

Parameters

- **penalty** (*{"l1", "l2", "elasticnet", "none"}*) – The norm used in penalization. Defaults to "elasticnet".
- **C** (*float*) – Inverse of regularization strength. Must be a positive float. Defaults to 1.0.
- **l1_ratio** (*float*) – The mixing parameter, with 0 <= l1_ratio <= 1. Only used if penalty='elasticnet'. Setting l1_ratio=0 is equivalent to using penalty='l2', while setting l1_ratio=1 is equivalent to using penalty='l1'. For 0 < l1_ratio <1, the penalty is a combination of L1 and L2. Defaults to 0.15.
- **multi_class** (*{"auto", "ovr", "multinomial"}*) – If the option chosen is "ovr", then a binary problem is fit for each label. For "multinomial" the loss minimised is the multinomial loss fit across the entire probability distribution, even when the data is binary. "multinomial" is unavailable when solver="liblinear". "auto" selects "ovr" if the data is binary, or if solver="liblinear", and otherwise selects "multinomial". Defaults to "auto".
- **solver** (*{"newton-cg", "lbfgs", "liblinear", "sag", "saga"}*) – Algorithm to use in the optimization problem. For small datasets, "liblinear" is a good

choice, whereas “sag” and “saga” are faster for large ones. For multiclass problems, only “newton-cg”, “sag”, “saga” and “lbfgs” handle multinomial loss; “liblinear” is limited to one-versus-rest schemes.

– ”newton-cg”, “lbfgs”, “sag” and “saga” handle L2 or no penalty

– ”liblinear” and “saga” also handle L1 penalty

– ”saga” also supports “elasticnet” penalty

– ”liblinear” does not support setting penalty=’none’

Defaults to “saga”.

- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “C”: Real(0.01, 10), “l1_ratio”: Real(0, 1)}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Elastic Net Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

et_classifier

Module Contents

Classes Summary

ExtraTreesClassifier	Extra Trees Classifier.

Contents

class evalml.pipelines.components.estimators.classifiers.et_classifier.**ExtraTreesClassifier**

Extra Trees Classifier.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).

- If "log2", then max_features=log2(n_features).
- If None, then max_features = n_features.

The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".

- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.
- **to 2.** (*Defaults*) –
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.EXTRA_TREES
modifies_features	True
modifies_target	False
name	Extra Trees Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component

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predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

kneighbors_classifier

Module Contents

Classes Summary

KNeighborsClassifier	K-Nearest Neighbors Classifier.

Contents

class evalml.pipelines.components.estimators.classifiers.kneighbors_classifier.**KNeighborsC**

K-Nearest Neighbors Classifier.

Parameters

- **n_neighbors** (*int*) – Number of neighbors to use by default. Defaults to 5.

- **weights** (*{'uniform', 'distance'} or callable*) – Weight function used in prediction. Can be:
  - 'uniform' : uniform weights. All points in each neighborhood are weighted equally.
  - 'distance' : weight points by the inverse of their distance. in this case, closer neighbors of a query point will have a greater influence than neighbors which are further away.
  - [callable] : a user-defined function which accepts an array of distances, and returns an array of the same shape containing the weights.

  Defaults to "uniform".
- **algorithm** (*{'auto', 'ball_tree', 'kd_tree', 'brute'}*) – Algorithm used to compute the nearest neighbors:
  - 'ball_tree' will use BallTree
  - 'kd_tree' will use KDTree
  - 'brute' will use a brute-force search.

  'auto' will attempt to decide the most appropriate algorithm based on the values passed to fit method. Defaults to "auto". Note: fitting on sparse input will override the setting of this parameter, using brute force.
- **leaf_size** (*int*) – Leaf size passed to BallTree or KDTree. This can affect the speed of the construction and query, as well as the memory required to store the tree. The optimal value depends on the nature of the problem. Defaults to 30.
- **p** (*int*) – Power parameter for the Minkowski metric. When p = 1, this is equivalent to using manhattan_distance (l1), and euclidean_distance (l2) for p = 2. For arbitrary p, minkowski_distance (l_p) is used. Defaults to 2.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_neighbors": Integer(2, 12), "weights": ["uniform", "distance"], "algorithm": ["auto", "ball_tree", "kd_tree", "brute"], "leaf_size": Integer(10, 30), "p": Integer(1, 5),}
model_family	ModelFamily.K_NEIGHBORS
modifies_features	True
modifies_target	False
name	KNN Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters

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feature_importance	Returns array of 0's matching the input number of features as feature_importance is
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns array of 0's matching the input number of features as feature_importance is not defined for KNN classifiers.

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

lightgbm_classifier

Module Contents

Classes Summary

LightGBMClassifier	LightGBM Classifier.

Contents

class evalml.pipelines.components.estimators.classifiers.lightgbm_classifier.**LightGBMClassi**

LightGBM Classifier.

Parameters

- **boosting_type** (*string*) – Type of boosting to use. Defaults to "gbdt". - 'gbdt' uses traditional Gradient Boosting Decision Tree - "dart", uses Dropouts meet Multiple Additive Regression Trees - "goss", uses Gradient-based One-Side Sampling - "rf", uses Random Forest
- **learning_rate** (*float*) – Boosting learning rate. Defaults to 0.1.
- **n_estimators** (*int*) – Number of boosted trees to fit. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners, <=0 means no limit. Defaults to 0.
- **num_leaves** (*int*) – Maximum tree leaves for base learners. Defaults to 31.
- **min_child_samples** (*int*) – Minimum number of data needed in a child (leaf). Defaults to 20.
- **bagging_fraction** (*float*) – LightGBM will randomly select a subset of features on each iteration (tree) without resampling if this is smaller than 1.0. For example, if set to 0.8, LightGBM will select 80% of features before training each tree. This can be used to speed up training and deal with overfitting. Defaults to 0.9.
- **bagging_freq** (*int*) – Frequency for bagging. 0 means bagging is disabled. k means perform bagging at every k iteration. Every k-th iteration, LightGBM will randomly select bagging_fraction * 100 % of the data to use for the next k iterations. Defaults to 0.
- **n_jobs** (*int or None*) – Number of threads to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “learning_rate”: Real(0.000001, 1), “boosting_type”: [“gbdt”, “dart”, “goss”, “rf”], “n_estimators”: Integer(10, 100), “max_depth”: Integer(0, 10), “num_leaves”: Integer(2, 100), “min_child_samples”: Integer(1, 100), “bagging_fraction”: Real(0.000001, 1), “bagging_freq”: Integer(0, 1),}
model_family	ModelFamily.LIGHTGBM
modifies_features	True
modifies_target	False
name	LightGBM Classifier
predict_uses_y	False
SEED_MAX	SEED_BOUNDS.max_bound
SEED_MIN	0
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file

- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

logistic_regression_classifier

Module Contents

Classes Summary

LogisticRegressionClassifier	Logistic Regression Classifier.

Contents

class evalml.pipelines.components.estimators.classifiers.logistic_regression_classifier.**Log**

Logistic Regression Classifier.

Parameters

- **penalty** (*{"l1", "l2", "elasticnet", "none"}*) – The norm used in penalization. Defaults to "l2".
- **C** (*float*) – Inverse of regularization strength. Must be a positive float. Defaults to 1.0.
- **multi_class** (*{"auto", "ovr", "multinomial"}*) – If the option chosen is "ovr", then a binary problem is fit for each label. For "multinomial" the loss minimised is the multinomial loss fit across the entire probability distribution, even when the data is binary. "multinomial" is unavailable when solver="liblinear". "auto" selects "ovr" if the data is binary, or if solver="liblinear", and otherwise selects "multinomial". Defaults to "auto".
- **solver** (*{"newton-cg", "lbfgs", "liblinear", "sag", "saga"}*) – Algorithm to use in the optimization problem. For small datasets, "liblinear" is a good choice, whereas "sag" and "saga" are faster for large ones. For multiclass problems, only "newton-cg", "sag", "saga" and "lbfgs" handle multinomial loss; "liblinear" is limited to one-versus-rest schemes.
  - "newton-cg", "lbfgs", "sag" and "saga" handle L2 or no penalty
  - "liblinear" and "saga" also handle L1 penalty
  - "saga" also supports "elasticnet" penalty
  - "liblinear" does not support setting penalty='none'

  Defaults to "lbfgs".

- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "penalty": ["l2"], "C": Real(0.01, 10),}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Logistic Regression Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

rf_classifier

Module Contents

Classes Summary

RandomForestClassifier	Random Forest Classifier.

Contents

class evalml.pipelines.components.estimators.classifiers.rf_classifier.**RandomForestClassifi**

Random Forest Classifier.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyper-parame-ter_ranges	{ “n_estimators”: Integer(10, 1000), “max_depth”: Integer(1, 10),}
model_family	ModelFamily.RANDOM_FOREST
modi-fies_features	True
modi-fies_target	False
name	Random Forest Classifier
pre-dict_uses_y	False
sup-ported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, Problem-Types.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)

Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

svm_classifier

Module Contents

Classes Summary

SVMClassifier	Support Vector Machine Classifier.

Contents

class evalml.pipelines.components.estimators.classifiers.svm_classifier.**SVMClassifier**(*C=1.0, kernel='rbf', gamma='scale', probability=True, random_state=0, **kwargs*)

Support Vector Machine Classifier.

Parameters

- **C** (*float*) – The regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive. The penalty is a squared l2 penalty. Defaults to 1.0.
- **kernel** (*{"linear", "poly", "rbf", "sigmoid", "precomputed"}*) – Specifies the kernel type to be used in the algorithm. Defaults to "rbf".
- **gamma** (*{"scale", "auto"} or float*) – Kernel coefficient for "rbf", "poly" and "sigmoid". Defaults to "scale". - If gamma='scale' (default) is passed then it uses 1 / (n_features * X.var()) as value of gamma - if "auto", uses 1 / n_features
- **probability** (*boolean*) – Whether to enable probability estimates. Defaults to True.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0, 10), "kernel": ["linear", "poly", "rbf", "sigmoid", "precomputed"], "gamma": ["scale", "auto"],}
model_family	ModelFamily.SVM
modifies_features	True
modifies_target	False
name	SVM Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Feature importance only works with linear kernels.

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Table 319 – continued from previous page

fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Feature importance only works with linear kernels. If the kernel isn't linear, we return a numpy array of zeros

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

xgboost_classifier

Module Contents

Classes Summary

XGBoostClassifier	XGBoost Classifier.

Contents

class evalml.pipelines.components.estimators.classifiers.xgboost_classifier.**XGBoostClassif**

XGBoost Classifier.

Parameters

- **eta** (*float*) – Boosting learning rate. Defaults to 0.1.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **min_child_weight** (*float*) – Minimum sum of instance weight (hessian) needed in a child. Defaults to 1.0
- **n_estimators** (*int*) – Number of gradient boosted trees. Equivalent to number of boosting rounds. Defaults to 100.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.

Attributes

hyperparameter_ranges	{ "eta": Real(0.000001, 1), "max_depth": Integer(1, 10), "min_child_weight": Real(1, 10), "n_estimators": Integer(1, 1000),}
model_family	ModelFamily.XGBOOST
modifies_features	True
modifies_target	False
name	XGBoost Classifier
predict_uses_y	False
SEED_MAX	None
SEED_MIN	None
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.

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Table 321 – continued from previous page

fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

Package Contents

Classes Summary

BaselineClassifier	Classifier that predicts using the specified strategy.
CatBoostClassifier	CatBoost Classifier, a classifier that uses gradient-boosting on decision trees.
DecisionTreeClassifier	Decision Tree Classifier.
ElasticNetClassifier	Elastic Net Classifier. Uses Logistic Regression with elasticnet penalty as the base estimator.
ExtraTreesClassifier	Extra Trees Classifier.
KNeighborsClassifier	K-Nearest Neighbors Classifier.
LightGBMClassifier	LightGBM Classifier.
LogisticRegressionClassifier	Logistic Regression Classifier.
RandomForestClassifier	Random Forest Classifier.
SVMClassifier	Support Vector Machine Classifier.
XGBoostClassifier	XGBoost Classifier.

Contents

class evalml.pipelines.components.estimators.classifiers.**BaselineClassifier**(*strategy='mode'*, *random_seed=0*, ***kwargs*)

Classifier that predicts using the specified strategy.

This is useful as a simple baseline classifier to compare with other classifiers.

Parameters

- **strategy** (*str*) – Method used to predict. Valid options are "mode", "random" and "random_weighted". Defaults to "mode".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.BASELINE
modifies_features	True
modifies_target	False
name	Baseline Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS]

Methods

*classes_*	Returns class labels. Will return None before fitting.
clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature. Since baseline classifiers do not use input features to calculate predictions, returns an array of zeroes.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

property classes_(*self*)

Returns class labels. Will return None before fitting.

Returns Class names

Return type list[str] or list(float)

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature. Since baseline classifiers do not use input features to calculate predictions, returns an array of zeroes.

Returns An array of zeroes

Return type np.ndarray (float)

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.classifiers.**CatBoostClassifier**(*n_estimators=10*, *eta=0.03*, *max_depth=6*, *bootstrap_type=None*, *silent=True*, *allow_writing_files=Fa* *random_seed=0*, *n_jobs=-1*, ***kwargs*)
CatBoost Classifier, a classifier that uses gradient-boosting on decision trees. CatBoost is an open-source library and natively supports categorical features.

For more information, check out https://catboost.ai/

Parameters

- **n_estimators** (*float*) – The maximum number of trees to build. Defaults to 10.
- **eta** (*float*) – The learning rate. Defaults to 0.03.
- **max_depth** (*int*) – The maximum tree depth for base learners. Defaults to 6.
- **bootstrap_type** (*string*) – Defines the method for sampling the weights of objects. Available methods are 'Bayesian', 'Bernoulli', 'MVS'. Defaults to None.
- **silent** (*boolean*) – Whether to use the "silent" logging mode. Defaults to True.
- **allow_writing_files** (*boolean*) – Whether to allow writing snapshot files while training. Defaults to False.

- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(4, 100), "eta": Real(0.000001, 1), "max_depth": Integer(4, 10),}
model_family	ModelFamily.CATBOOST
modifies_features	True
modifies_target	False
name	CatBoost Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.classifiers.**DecisionTreeClassifier**(*criterion='gini'*, *max_features='*, *max_depth=6*, *min_samples_s*, *min_weight_fra*, *random_seed=0*, ***kwargs*)

Decision Tree Classifier.

Parameters

- **criterion** (*{"gini", "entropy"}*) – The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain. Defaults to "gini".
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.

  Defaults to 2.
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "criterion": ["gini", "entropy"], "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.DECISION_TREE
modifies_features	True
modifies_target	False
name	Decision Tree Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.classifiers.**ElasticNetClassifier**(*penalty='elasticnet'*, *C=1.0*, *l1_ratio=0.15*, *multi_class='auto'*, *solver='saga'*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Elastic Net Classifier. Uses Logistic Regression with elasticnet penalty as the base estimator.

Parameters

- **penalty** (*{"l1", "l2", "elasticnet", "none"}*) – The norm used in penalization. Defaults to "elasticnet".
- **C** (*float*) – Inverse of regularization strength. Must be a positive float. Defaults to 1.0.
- **l1_ratio** (*float*) – The mixing parameter, with 0 <= l1_ratio <= 1. Only used if penalty='elasticnet'. Setting l1_ratio=0 is equivalent to using penalty='l2', while setting l1_ratio=1 is equivalent to using penalty='l1'. For 0 < l1_ratio <1, the penalty is a combination of L1 and L2. Defaults to 0.15.
- **multi_class** (*{"auto", "ovr", "multinomial"}*) – If the option chosen is "ovr", then a binary problem is fit for each label. For "multinomial" the loss minimised is the multinomial loss fit across the entire probability distribution, even when the data is binary. "multinomial" is unavailable when solver="liblinear". "auto" selects "ovr" if the data is binary, or if solver="liblinear", and otherwise selects "multinomial". Defaults to "auto".
- **solver** (*{"newton-cg", "lbfgs", "liblinear", "sag", "saga"}*) – Algorithm to use in the optimization problem. For small datasets, "liblinear" is a good choice, whereas "sag" and "saga" are faster for large ones. For multiclass problems, only "newton-cg", "sag", "saga" and "lbfgs" handle multinomial loss; "liblinear" is limited to one-versus-rest schemes.
  - "newton-cg", "lbfgs", "sag" and "saga" handle L2 or no penalty
  - "liblinear" and "saga" also handle L1 penalty
  - "saga" also supports "elasticnet" penalty
  - "liblinear" does not support setting penalty='none'

  Defaults to "saga".
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0.01, 10), "l1_ratio": Real(0, 1)}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Elastic Net Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.classifiers.**ExtraTreesClassifier**(*n_estimators=100*, *max_features='au*, *max_depth=6*, *min_samples_split*, *min_weight_fracti*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Extra Trees Classifier.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.
- **to 2.** (*Defaults*) –
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.EXTRA_TREES
modifies_features	True
modifies_target	False
name	Extra Trees Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.classifiers.**KNeighborsClassifier**(*n_neighbors=5*, *weights='uniform'*, *algorithm='auto'*, *leaf_size=30*, *p=2*, *random_seed=0*, ***kwargs*)

K-Nearest Neighbors Classifier.

Parameters

- **n_neighbors** (*int*) – Number of neighbors to use by default. Defaults to 5.
- **weights** (*{'uniform', 'distance'} or callable*) – Weight function used in prediction. Can be:
  - 'uniform' : uniform weights. All points in each neighborhood are weighted equally.
  - 'distance' : weight points by the inverse of their distance. in this case, closer neighbors of a query point will have a greater influence than neighbors which are further away.
  - [callable] : a user-defined function which accepts an array of distances, and returns an array of the same shape containing the weights.

  Defaults to "uniform".
- **algorithm** (*{'auto', 'ball_tree', 'kd_tree', 'brute'}*) – Algorithm used to compute the nearest neighbors:
  - 'ball_tree' will use BallTree
  - 'kd_tree' will use KDTree
  - 'brute' will use a brute-force search.

  'auto' will attempt to decide the most appropriate algorithm based on the values passed to fit method. Defaults to "auto". Note: fitting on sparse input will override the setting of this parameter, using brute force.
- **leaf_size** (*int*) – Leaf size passed to BallTree or KDTree. This can affect the speed of the construction and query, as well as the memory required to store the tree. The optimal value depends on the nature of the problem. Defaults to 30.
- **p** (*int*) – Power parameter for the Minkowski metric. When p = 1, this is equivalent to using manhattan_distance (l1), and euclidean_distance (l2) for p = 2. For arbitrary p, minkowski_distance (l_p) is used. Defaults to 2.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “n_neighbors”: Integer(2, 12), “weights”: [“uniform”, “distance”], “algorithm”: [“auto”, “ball_tree”, “kd_tree”, “brute”], “leaf_size”: Integer(10, 30), “p”: Integer(1, 5),}
model_family	ModelFamily.K_NEIGHBORS
modifies_features	True
modifies_target	False
name	KNN Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns array of 0’s matching the input number of features as feature_importance is
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns array of 0's matching the input number of features as feature_importance is not defined for KNN classifiers.

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.classifiers.**LightGBMClassifier**(*boosting_type='gbdt'*, *learning_rate=0.1*, *n_estimators=100*, *max_depth=0*, *num_leaves=31*, *min_child_samples=2*, *bagging_fraction=0.9*, *bagging_freq=0*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

LightGBM Classifier.

Parameters

- **boosting_type** (*string*) – Type of boosting to use. Defaults to "gbdt". - 'gbdt' uses traditional Gradient Boosting Decision Tree - "dart", uses Dropouts meet Multiple Additive Regression Trees - "goss", uses Gradient-based One-Side Sampling - "rf", uses Random Forest
- **learning_rate** (*float*) – Boosting learning rate. Defaults to 0.1.
- **n_estimators** (*int*) – Number of boosted trees to fit. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners, <=0 means no limit. Defaults to 0.
- **num_leaves** (*int*) – Maximum tree leaves for base learners. Defaults to 31.
- **min_child_samples** (*int*) – Minimum number of data needed in a child (leaf). Defaults to 20.
- **bagging_fraction** (*float*) – LightGBM will randomly select a subset of features on each iteration (tree) without resampling if this is smaller than 1.0. For example, if set to 0.8, LightGBM will select 80% of features before training each tree. This can be used to speed up training and deal with overfitting. Defaults to 0.9.
- **bagging_freq** (*int*) – Frequency for bagging. 0 means bagging is disabled. k means perform bagging at every k iteration. Every k-th iteration, LightGBM will randomly select bagging_fraction * 100 % of the data to use for the next k iterations. Defaults to 0.
- **n_jobs** (*int or None*) – Number of threads to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “learning_rate”: Real(0.000001, 1), “boosting_type”: [“gbdt”, “dart”, “goss”, “rf”], “n_estimators”: Integer(10, 100), “max_depth”: Integer(0, 10), “num_leaves”: Integer(2, 100), “min_child_samples”: Integer(1, 100), “bagging_fraction”: Real(0.000001, 1), “bagging_freq”: Integer(0, 1),}
model_family	ModelFamily.LIGHTGBM
modifies_features	True
modifies_target	False
name	LightGBM Classifier
predict_uses_y	False
SEED_MAX	SEED_BOUNDS.max_bound
SEED_MIN	0
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file

- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.classifiers.**LogisticRegressionClassifier**(*penalty='l2'*, *C=1.0*, *multi_class='auto'*, *solver='lbfgs'*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Logistic Regression Classifier.

Parameters

- **penalty** (*{"l1", "l2", "elasticnet", "none"}*) – The norm used in penalization. Defaults to "l2".
- **C** (*float*) – Inverse of regularization strength. Must be a positive float. Defaults to 1.0.
- **multi_class** (*{"auto", "ovr", "multinomial"}*) – If the option chosen is "ovr", then a binary problem is fit for each label. For "multinomial" the loss minimised is the multinomial loss fit across the entire probability distribution, even when the data is binary. "multinomial" is unavailable when solver="liblinear". "auto" selects "ovr" if the data is binary, or if solver="liblinear", and otherwise selects "multinomial". Defaults to "auto".
- **solver** (*{"newton-cg", "lbfgs", "liblinear", "sag", "saga"}*) – Algorithm to use in the optimization problem. For small datasets, "liblinear" is a good choice, whereas "sag" and "saga" are faster for large ones. For multiclass problems, only "newton-cg", "sag", "saga" and "lbfgs" handle multinomial loss; "liblinear" is limited to one-versus-rest schemes.
  - "newton-cg", "lbfgs", "sag" and "saga" handle L2 or no penalty
  - "liblinear" and "saga" also handle L1 penalty
  - "saga" also supports "elasticnet" penalty
  - "liblinear" does not support setting penalty='none'

  Defaults to "lbfgs".
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "penalty": ["l2"], "C": Real(0.01, 10),}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Logistic Regression Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.classifiers.**RandomForestClassifier**(*n_estimators=100*, *max_depth=6*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Random Forest Classifier.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_depth": Integer(1, 10),}
model_family	ModelFamily.RANDOM_FOREST
modifies_features	True
modifies_target	False
name	Random Forest Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.classifiers.**SVMClassifier**(*C=1.0*, *kernel='rbf'*, *gamma='scale'*, *probability=True*, *random_seed=0*, ***kwargs*)

Support Vector Machine Classifier.

Parameters

- **C** (*float*) – The regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive. The penalty is a squared l2 penalty. Defaults to 1.0.
- **kernel** (*{"linear", "poly", "rbf", "sigmoid", "precomputed"}*) – Specifies the kernel type to be used in the algorithm. Defaults to "rbf".
- **gamma** (*{"scale", "auto"} or float*) – Kernel coefficient for "rbf", "poly" and "sigmoid". Defaults to "scale". - If gamma='scale' (default) is passed then it uses 1 / (n_features * X.var()) as value of gamma - if "auto", uses 1 / n_features
- **probability** (*boolean*) – Whether to enable probability estimates. Defaults to True.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0, 10), "kernel": ["linear", "poly", "rbf", "sigmoid", "precomputed"], "gamma": ["scale", "auto"],}
model_family	ModelFamily.SVM
modifies_features	True
modifies_target	False
name	SVM Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Feature importance only works with linear kernels.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Feature importance only works with linear kernels. If the kernel isn't linear, we return a numpy array of zeros

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.classifiers.**XGBoostClassifier**(*eta=0.1*, *max_depth=6*, *min_child_weight=1*, *n_estimators=100*, *random_seed=0*, *n_jobs=-1*, ***kwargs*)

XGBoost Classifier.

Parameters

- **eta** (*float*) – Boosting learning rate. Defaults to 0.1.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **min_child_weight** (*float*) – Minimum sum of instance weight (hessian) needed in a child. Defaults to 1.0
- **n_estimators** (*int*) – Number of gradient boosted trees. Equivalent to number of boosting rounds. Defaults to 100.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.

Attributes

hyperparameter_ranges	{ “eta”: Real(0.000001, 1), “max_depth”: Integer(1, 10), “min_child_weight”: Real(1, 10), “n_estimators”: Integer(1, 1000),}
model_family	ModelFamily.XGBOOST
modifies_features	True
modifies_target	False
name	XGBoost Classifier
predict_uses_y	False
SEED_MAX	None
SEED_MIN	None
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path

continues on next page

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needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

regressors

Submodules

arima_regressor

Module Contents

Classes Summary

ARIMARegressor	Autoregressive Integrated Moving Average Model.

Contents

class evalml.pipelines.components.estimators.regressors.arima_regressor.**ARIMARegressor**(*date_
trend
*start_
d=0,
*start_
*max_
*max_
*max_
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Autoregressive Integrated Moving Average Model. The three parameters (p, d, q) are the AR order, the degree of differencing, and the MA order. More information here: https://www.statsmodels.org/devel/generated/statsmodels.tsa.arima_model.ARIMA.html

Currently ARIMARegressor isn't supported via conda install. It's recommended that it be installed via PyPI.

Parameters

- **date_index** (*str*) – Specifies the name of the column in X that provides the datetime objects. Defaults to None.
- **trend** (*str*) – Controls the deterministic trend. Options are ['n', 'c', 't', 'ct'] where 'c' is a constant term, 't' indicates a linear trend, and 'ct' is both. Can also be an iterable when defining a polynomial, such as [1, 1, 0, 1].
- **start_p** (*int*) – Minimum Autoregressive order. Defaults to 2.
- **d** (*int*) – Minimum Differencing degree. Defaults to 0.
- **start_q** (*int*) – Minimum Moving Average order. Defaults to 2.
- **max_p** (*int*) – Maximum Autoregressive order. Defaults to 5.
- **max_d** (*int*) – Maximum Differencing degree. Defaults to 2.
- **max_q** (*int*) – Maximum Moving Average order. Defaults to 5.
- **seasonal** (*boolean*) – Whether to fit a seasonal model to ARIMA. Defaults to True.
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “start_p”: Integer(1, 3), “d”: Integer(0, 2), “start_q”: Integer(1, 3), “max_p”: Integer(3, 10), “max_d”: Integer(2, 5), “max_q”: Integer(3, 10), “seasonal”: [True, False],}
model_family	ModelFamily.ARIMA
modifies_features	True
modifies_target	False
name	ARIMA Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns array of 0’s with a length of 1 as feature_importance is not defined for ARIMA regressor.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns array of 0's with a length of 1 as feature_importance is not defined for ARIMA regressor.

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

baseline_regressor

Module Contents

Classes Summary

BaselineRegressor	Baseline regressor that uses a simple strategy to make predictions.

Contents

class evalml.pipelines.components.estimators.regressors.baseline_regressor.**BaselineRegresso**

Baseline regressor that uses a simple strategy to make predictions. This is useful as a simple baseline regressor to compare with other regressors.

Parameters

- **strategy** (*str*) – Method used to predict. Valid options are "mean", "median". Defaults to "mean".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.BASELINE
modifies_features	True
modifies_target	False
name	Baseline Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature. Since baseline regressors do not use input features to calculate predictions, returns an array of zeroes.
fit	Fits component to data

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Table 337 – continued from previous page

load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature. Since baseline regressors do not use input features to calculate predictions, returns an array of zeroes.

Returns An array of zeroes

Return type np.ndarray (float)

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

catboost_regressor

Module Contents

Classes Summary

CatBoostRegressor	CatBoost Regressor, a regressor that uses gradient-boosting on decision trees.

Contents

class evalml.pipelines.components.estimators.regressors.catboost_regressor.**CatBoostRegresso**

CatBoost Regressor, a regressor that uses gradient-boosting on decision trees. CatBoost is an open-source library and natively supports categorical features.

For more information, check out https://catboost.ai/

Parameters

- **n_estimators** (*float*) – The maximum number of trees to build. Defaults to 10.
- **eta** (*float*) – The learning rate. Defaults to 0.03.
- **max_depth** (*int*) – The maximum tree depth for base learners. Defaults to 6.
- **bootstrap_type** (*string*) – Defines the method for sampling the weights of objects. Available methods are 'Bayesian', 'Bernoulli', 'MVS'. Defaults to None.
- **silent** (*boolean*) – Whether to use the "silent" logging mode. Defaults to True.
- **allow_writing_files** (*boolean*) – Whether to allow writing snapshot files while training. Defaults to False.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(4, 100), "eta": Real(0.000001, 1), "max_depth": Integer(4, 10),}
model_family	ModelFamily.CATBOOST
modifies_features	True
modifies_target	False
name	CatBoost Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)

Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

decision_tree_regressor

Module Contents

Classes Summary

DecisionTreeRegressor	Decision Tree Regressor.

Contents

class evalml.pipelines.components.estimators.regressors.decision_tree_regressor.**DecisionTre**

Decision Tree Regressor.

Parameters

- **criterion** (*{"mse", "friedman_mse", "mae", "poisson"}*) – The function to measure the quality of a split. Supported criteria are:
  - "mse" for the mean squared error, which is equal to variance reduction as feature selection criterion and minimizes the L2 loss using the mean of each terminal node
  - "friedman_mse", which uses mean squared error with Friedman"s improvement score for potential splits
  - "mae" for the mean absolute error, which minimizes the L1 loss using the median of each terminal node,
  - "poisson" which uses reduction in Poisson deviance to find splits.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features.
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.

  Defaults to 2.
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "criterion": ["mse", "friedman_mse", "mae"], "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.DECISION_TREE
modifies_features	True
modifies_target	False
name	Decision Tree Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

elasticnet_regressor

Module Contents

Classes Summary

ElasticNetRegressor	Elastic Net Regressor.

Contents

class evalml.pipelines.components.estimators.regressors.elasticnet_regressor.**ElasticNetRegr**

Elastic Net Regressor.

Parameters

- **alpha** (*float*) – Constant that multiplies the penalty terms. Defaults to 0.0001.
- **l1_ratio** (*float*) – The mixing parameter, with 0 <= l1_ratio <= 1. Only used if penalty='elasticnet'. Setting l1_ratio=0 is equivalent to using penalty='l2', while setting l1_ratio=1 is equivalent to using penalty='l1'. For 0 < l1_ratio <1, the penalty is a combination of L1 and L2. Defaults to 0.15.
- **max_iter** (*int*) – The maximum number of iterations. Defaults to 1000.
- **normalize** (*boolean*) – If True, the regressors will be normalized before regression by subtracting the mean and dividing by the l2-norm. Defaults to False.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "alpha": Real(0, 1), "l1_ratio": Real(0, 1),}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Elastic Net Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)

Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

et_regressor

Module Contents

Classes Summary

ExtraTreesRegressor	Extra Trees Regressor.

Contents

class evalml.pipelines.components.estimators.regressors.et_regressor.**ExtraTreesRegressor**(*n_*
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m
m
*n_*

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***

Extra Trees Regressor.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.
- **to 2.** (*Defaults*) –
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “n_estimators”: Integer(10, 1000), “max_features”: [“auto”, “sqrt”, “log2”], “max_depth”: Integer(4, 10),}
model_family	ModelFamily.EXTRA_TREES
modifies_features	True
modifies_target	False
name	Extra Trees Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

lightgbm_regressor

Module Contents

Classes Summary

LightGBMRegressor	LightGBM Regressor.

Contents

class evalml.pipelines.components.estimators.regressors.lightgbm_regressor.**LightGBMRegresso**

LightGBM Regressor.

Parameters

- **boosting_type** (*string*) – Type of boosting to use. Defaults to "gbdt". - 'gbdt' uses traditional Gradient Boosting Decision Tree - "dart", uses Dropouts meet Multiple Additive Regression Trees - "goss", uses Gradient-based One-Side Sampling - "rf", uses Random Forest
- **learning_rate** (*float*) – Boosting learning rate. Defaults to 0.1.
- **n_estimators** (*int*) – Number of boosted trees to fit. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners, <=0 means no limit. Defaults to 0.
- **num_leaves** (*int*) – Maximum tree leaves for base learners. Defaults to 31.
- **min_child_samples** (*int*) – Minimum number of data needed in a child (leaf). Defaults to 20.
- **bagging_fraction** (*float*) – LightGBM will randomly select a subset of features on each iteration (tree) without resampling if this is smaller than 1.0. For example, if set to 0.8, LightGBM will select 80% of features before training each tree. This can be used to speed up training and deal with overfitting. Defaults to 0.9.
- **bagging_freq** (*int*) – Frequency for bagging. 0 means bagging is disabled. k means perform bagging at every k iteration. Every k-th iteration, LightGBM will randomly select

bagging_fraction * 100 % of the data to use for the next k iterations. Defaults to 0.

- **n_jobs** (*int or None*) – Number of threads to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "learning_rate": Real(0.000001, 1), "boosting_type": ["gbdt", "dart", "goss", "rf"], "n_estimators": Integer(10, 100), "max_depth": Integer(0, 10), "num_leaves": Integer(2, 100), "min_child_samples": Integer(1, 100), "bagging_fraction": Real(0.000001, 1), "bagging_freq": Integer(0, 1),}
model_family	ModelFamily.LIGHTGBM
modifies_features	True
modifies_target	False
name	LightGBM Regressor
predict_uses_y	False
SEED_MAX	SEED_BOUNDS.max_bound
SEED_MIN	0
supported_problem_types	[ProblemTypes.REGRESSION]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

linear_regressor

Module Contents

Classes Summary

LinearRegressor	Linear Regressor.

Contents

class evalml.pipelines.components.estimators.regressors.linear_regressor.**LinearRegressor**(*fit*
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***

Linear Regressor.

Parameters

- **fit_intercept** (*boolean*) – Whether to calculate the intercept for this model. If set to False, no intercept will be used in calculations (i.e. data is expected to be centered). Defaults to True.
- **normalize** (*boolean*) – If True, the regressors will be normalized before regression by subtracting the mean and dividing by the l2-norm. This parameter is ignored when fit_intercept is set to False. Defaults to False.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "fit_intercept": [True, False], "normalize": [True, False]}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Linear Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

prophet_regressor

Module Contents

Classes Summary

ProphetRegressor	Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.

Contents

class evalml.pipelines.components.estimators.regressors.prophet_regressor.**ProphetRegressor**

Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well.

More information here: https://facebook.github.io/prophet/

Attributes

hyperparameter_ranges	{ “changepoint_prior_scale”: Real(0.001, 0.5), “seasonality_prior_scale”: Real(0.01, 10), “holidays_prior_scale”: Real(0.01, 10), “seasonality_mode”: [“additive”, “multiplicative”],}
model_family	ModelFamily.PROPHET
modifies_features	True
modifies_target	False
name	Prophet Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION]

Methods

build_prophet_df	
clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns array of 0’s with len(1) as feature_importance is not defined for Prophet regressor.
fit	Fits component to data
get_params	
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

static build_prophet_df(*X*, *y=None*, *date_column='ds'*)

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns array of 0's with len(1) as feature_importance is not defined for Prophet regressor.

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

get_params(*self*)

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file

- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

rf_regressor

Module Contents

Classes Summary

RandomForestRegressor	Random Forest Regressor.

Contents

class evalml.pipelines.components.estimators.regressors.rf_regressor.**RandomForestRegressor**

Random Forest Regressor.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_depth": Integer(1, 32),}
model_family	ModelFamily.RANDOM_FOREST
modifies_features	True
modifies_target	False
name	Random Forest Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

svm_regressor

Module Contents

Classes Summary

SVMRegressor	Support Vector Machine Regressor.

Contents

class evalml.pipelines.components.estimators.regressors.svm_regressor.**SVMRegressor**(*C=1.0*, *kernel='rbf'*, *gamma='s*
random_seed=
***kwargs*)

Support Vector Machine Regressor.

Parameters

- **C** (*float*) – The regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive. The penalty is a squared l2 penalty. Defaults to 1.0.
- **kernel** (*{"linear", "poly", "rbf", "sigmoid", "precomputed"}*) – Specifies the kernel type to be used in the algorithm. Defaults to "rbf".
- **gamma** (*{"scale", "auto"} or float*) – Kernel coefficient for "rbf", "poly" and "sigmoid". Defaults to "scale". - If gamma='scale' (default) is passed then it uses 1 / (n_features * X.var()) as value of gamma - if "auto", uses 1 / n_features
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0, 10), "kernel": ["linear", "poly", "rbf", "sigmoid", "precomputed"], "gamma": ["scale", "auto"],}
model_family	ModelFamily.SVM
modifies_features	True
modifies_target	False
name	SVM Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Feature importance only works with linear kernels.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component

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predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Feature importance only works with linear kernels. If the kernel isn't linear, we return a numpy array of zeros

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

time_series_baseline_estimator

Module Contents

Classes Summary

TimeSeriesBaselineEstimator	Time series estimator that predicts using the naive forecasting approach.

Contents

class evalml.pipelines.components.estimators.regressors.time_series_baseline_estimator.**Time**

Time series estimator that predicts using the naive forecasting approach.

This is useful as a simple baseline estimator for time series problems.

Parameters

- **gap** (*int*) – Gap between prediction date and target date and must be a positive integer. If gap is 0, target date will be shifted ahead by 1 time period. Defaults to 1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.BASELINE
modifies_features	True
modifies_target	False
name	Time Series Baseline Estimator
predict_uses_y	True
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Since baseline estimators do not use input features to calculate predictions, returns an array of zeroes.

Returns an array of zeroes

Return type np.ndarray (float)

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*, *y=None*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

xgboost_regressor

Module Contents

Classes Summary

XGBoostRegressor	XGBoost Regressor.

Contents

class evalml.pipelines.components.estimators.regressors.xgboost_regressor.**XGBoostRegressor**

XGBoost Regressor.

Parameters

- **eta** (*float*) – Boosting learning rate. Defaults to 0.1.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **min_child_weight** (*float*) – Minimum sum of instance weight (hessian) needed in a child. Defaults to 1.0
- **n_estimators** (*int*) – Number of gradient boosted trees. Equivalent to number of boosting rounds. Defaults to 100.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.

Attributes

hyperparameter_ranges	{ "eta": Real(0.000001, 1), "max_depth": Integer(1, 20), "min_child_weight": Real(1, 10), "n_estimators": Integer(1, 1000),}
model_family	ModelFamily.XGBOOST
modifies_features	True
modifies_target	False
name	XGBoost Regressor
predict_uses_y	False
SEED_MAX	None
SEED_MIN	None
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

Package Contents

Classes Summary

ARIMARegressor	Autoregressive Integrated Moving Average Model.
BaselineRegressor	Baseline regressor that uses a simple strategy to make predictions.
CatBoostRegressor	CatBoost Regressor, a regressor that uses gradient-boosting on decision trees.
DecisionTreeRegressor	Decision Tree Regressor.
ElasticNetRegressor	Elastic Net Regressor.
ExtraTreesRegressor	Extra Trees Regressor.
LightGBMRegressor	LightGBM Regressor.
LinearRegressor	Linear Regressor.
ProphetRegressor	Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.
RandomForestRegressor	Random Forest Regressor.
SVMRegressor	Support Vector Machine Regressor.
TimeSeriesBaselineEstimator	Time series estimator that predicts using the naive forecasting approach.
XGBoostRegressor	XGBoost Regressor.

Contents

class evalml.pipelines.components.estimators.regressors.**ARIMARegressor**(*date_index=None*, *trend=None*, *start_p=2*, *d=0*, *start_q=2*, *max_p=5*, *max_d=2*, *max_q=5*, *seasonal=True*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Autoregressive Integrated Moving Average Model. The three parameters (p, d, q) are the AR order, the degree of differencing, and the MA order. More information here: https://www.statsmodels.org/devel/generated/statsmodels.tsa.arima_model.ARIMA.html

Currently ARIMARegressor isn't supported via conda install. It's recommended that it be installed via PyPI.

Parameters

- **date_index** (*str*) – Specifies the name of the column in X that provides the datetime objects. Defaults to None.
- **trend** (*str*) – Controls the deterministic trend. Options are ['n', 'c', 't', 'ct'] where 'c'

is a constant term, 't' indicates a linear trend, and 'ct' is both. Can also be an iterable when defining a polynomial, such as [1, 1, 0, 1].

- **start_p** (*int*) – Minimum Autoregressive order. Defaults to 2.
- **d** (*int*) – Minimum Differencing degree. Defaults to 0.
- **start_q** (*int*) – Minimum Moving Average order. Defaults to 2.
- **max_p** (*int*) – Maximum Autoregressive order. Defaults to 5.
- **max_d** (*int*) – Maximum Differencing degree. Defaults to 2.
- **max_q** (*int*) – Maximum Moving Average order. Defaults to 5.
- **seasonal** (*boolean*) – Whether to fit a seasonal model to ARIMA. Defaults to True.
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "start_p": Integer(1, 3), "d": Integer(0, 2), "start_q": Integer(1, 3), "max_p": Integer(3, 10), "max_d": Integer(2, 5), "max_q": Integer(3, 10), "seasonal": [True, False],}
model_family	ModelFamily.ARIMA
modifies_features	True
modifies_target	False
name	ARIMA Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns array of 0's with a length of 1 as feature_importance is not defined for ARIMA regressor.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns array of 0's with a length of 1 as feature_importance is not defined for ARIMA regressor.

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.regressors.**BaselineRegressor**(*strategy='mean'*, *random_seed=0*, ***kwargs*)
Baseline regressor that uses a simple strategy to make predictions. This is useful as a simple baseline regressor to compare with other regressors.

Parameters

- **strategy** (*str*) – Method used to predict. Valid options are "mean", "median". Defaults to "mean".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.BASELINE
modifies_features	True
modifies_target	False
name	Baseline Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature. Since baseline regressors do not use input features to calculate predictions, returns an array of zeroes.

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fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature. Since baseline regressors do not use input features to calculate predictions, returns an array of zeroes.

Returns An array of zeroes

Return type np.ndarray (float)

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.regressors.**CatBoostRegressor**(*n_estimators=10*, *eta=0.03*, *max_depth=6*, *bootstrap_type=None*, *silent=False*, *allow_writing_files=False*, *random_seed=0*, *n_jobs=-1*, ***kwargs*)
CatBoost Regressor, a regressor that uses gradient-boosting on decision trees. CatBoost is an open-source library and natively supports categorical features.

For more information, check out https://catboost.ai/

Parameters

- **n_estimators** (*float*) – The maximum number of trees to build. Defaults to 10.
- **eta** (*float*) – The learning rate. Defaults to 0.03.
- **max_depth** (*int*) – The maximum tree depth for base learners. Defaults to 6.

- **bootstrap_type** (*string*) – Defines the method for sampling the weights of objects. Available methods are 'Bayesian', 'Bernoulli', 'MVS'. Defaults to None.
- **silent** (*boolean*) – Whether to use the "silent" logging mode. Defaults to True.
- **allow_writing_files** (*boolean*) – Whether to allow writing snapshot files while training. Defaults to False.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(4, 100), "eta": Real(0.000001, 1), "max_depth": Integer(4, 10),}
model_family	ModelFamily.CATBOOST
modifies_features	True
modifies_target	False
name	CatBoost Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.regressors.**DecisionTreeRegressor**(*criterion='mse'*, *max_features='aut*
max_depth=6, *min_samples_split*
min_weight_fracti
random_seed=0, ***kwargs*)

Decision Tree Regressor.

Parameters

- **criterion** (*{"mse", "friedman_mse", "mae", "poisson"}*) – The function to measure the quality of a split. Supported criteria are:
  - "mse" for the mean squared error, which is equal to variance reduction as feature selection criterion and minimizes the L2 loss using the mean of each terminal node
  - "friedman_mse", which uses mean squared error with Friedman"s improvement score for potential splits
  - "mae" for the mean absolute error, which minimizes the L1 loss using the median of each terminal node,
  - "poisson" which uses reduction in Poisson deviance to find splits.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features.
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.

– If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.

Defaults to 2.

- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "criterion": ["mse", "friedman_mse", "mae"], "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.DECISION_TREE
modifies_features	True
modifies_target	False
name	Decision Tree Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.regressors.**ElasticNetRegressor**(*alpha=0.0001*, *l1_ratio=0.15*, *max_iter=1000*, *normalize=False*, *random_seed=0*, ***kwargs*)

Elastic Net Regressor.

Parameters

- **alpha** (*float*) – Constant that multiplies the penalty terms. Defaults to 0.0001.
- **l1_ratio** (*float*) – The mixing parameter, with 0 <= l1_ratio <= 1. Only used if penalty='elasticnet'. Setting l1_ratio=0 is equivalent to using penalty='l2', while setting l1_ratio=1 is equivalent to using penalty='l1'. For 0 < l1_ratio <1, the penalty is a combination of L1 and L2. Defaults to 0.15.
- **max_iter** (*int*) – The maximum number of iterations. Defaults to 1000.
- **normalize** (*boolean*) – If True, the regressors will be normalized before regression by subtracting the mean and dividing by the l2-norm. Defaults to False.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "alpha": Real(0, 1), "l1_ratio": Real(0, 1),}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Elastic Net Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.

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default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.regressors.**ExtraTreesRegressor**(*n_estimators=100*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Extra Trees Regressor.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.

  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".

- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.
- **to 2.** (*Defaults*) –
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.EXTRA_TREES
modifies_features	True
modifies_target	False
name	Extra Trees Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data

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load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.regressors.**LightGBMRegressor**(*boosting_type='gbdt'*, *learning_rate=0.1*, *n_estimators=20*, *max_depth=0*, *num_leaves=31*, *min_child_samples=20*, *bagging_fraction=0.9*, *bagging_freq=0*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
LightGBM Regressor.

Parameters

- **boosting_type** (*string*) – Type of boosting to use. Defaults to "gbdt". - 'gbdt' uses traditional Gradient Boosting Decision Tree - "dart", uses Dropouts meet Multiple Additive Regression Trees - "goss", uses Gradient-based One-Side Sampling - "rf", uses Random Forest

- **learning_rate** (*float*) – Boosting learning rate. Defaults to 0.1.
- **n_estimators** (*int*) – Number of boosted trees to fit. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners, <=0 means no limit. Defaults to 0.
- **num_leaves** (*int*) – Maximum tree leaves for base learners. Defaults to 31.
- **min_child_samples** (*int*) – Minimum number of data needed in a child (leaf). Defaults to 20.
- **bagging_fraction** (*float*) – LightGBM will randomly select a subset of features on each iteration (tree) without resampling if this is smaller than 1.0. For example, if set to 0.8, LightGBM will select 80% of features before training each tree. This can be used to speed up training and deal with overfitting. Defaults to 0.9.
- **bagging_freq** (*int*) – Frequency for bagging. 0 means bagging is disabled. k means perform bagging at every k iteration. Every k-th iteration, LightGBM will randomly select bagging_fraction * 100 % of the data to use for the next k iterations. Defaults to 0.
- **n_jobs** (*int or None*) – Number of threads to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “learning_rate”: Real(0.000001, 1), “boosting_type”: [“gbdt”, “dart”, “goss”, “rf”], “n_estimators”: Integer(10, 100), “max_depth”: Integer(0, 10), “num_leaves”: Integer(2, 100), “min_child_samples”: Integer(1, 100), “bagging_fraction”: Real(0.000001, 1), “bagging_freq”: Integer(0, 1),}
model_family	ModelFamily.LIGHTGBM
modifies_features	True
modifies_target	False
name	LightGBM Regressor
predict_uses_y	False
SEED_MAX	SEED_BOUNDS.max_bound
SEED_MIN	0
supported_problem_types	[ProblemTypes.REGRESSION]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before

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Table 367 – continued from previous page

parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform,

or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.regressors.**LinearRegressor**(*fit_intercept=True*, *normalize=False*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Linear Regressor.

Parameters

- **fit_intercept** (*boolean*) – Whether to calculate the intercept for this model. If set to False, no intercept will be used in calculations (i.e. data is expected to be centered). Defaults to True.
- **normalize** (*boolean*) – If True, the regressors will be normalized before regression by subtracting the mean and dividing by the l2-norm. This parameter is ignored when fit_intercept is set to False. Defaults to False.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "fit_intercept": [True, False], "normalize": [True, False]}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Linear Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.regressors.**ProphetRegressor**(*date_column='ds'*, *changepoint_prior_scale=0.05*, *seasonality_prior_scale=10*, *holidays_prior_scale=10*, *seasonality_mode='additive'*, *random_seed=0*, *stan_backend='CMDSTA*
***kwargs*)

Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well.

More information here: https://facebook.github.io/prophet/

Attributes

hyperparameter_ranges	{ "changepoint_prior_scale": Real(0.001, 0.5), "seasonality_prior_scale": Real(0.01, 10), "holidays_prior_scale": Real(0.01, 10), "seasonality_mode": ["additive", "multiplicative"],}
model_family	ModelFamily.PROPHET
modifies_features	True
modifies_target	False
name	Prophet Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION]

Methods

build_prophet_df	
clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns array of 0's with len(1) as feature_importance is not defined for Prophet regressor.
fit	Fits component to data

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get_params	
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

static build_prophet_df(*X*, *y=None*, *date_column='ds'*)

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns array of 0's with len(1) as feature_importance is not defined for Prophet regressor.

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

get_params(*self*)

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.regressors.**RandomForestRegressor**(*n_estimators=100*, *max_depth=6*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Random Forest Regressor.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “n_estimators”: Integer(10, 1000), “max_depth”: Integer(1, 32),}
model_family	ModelFamily.RANDOM_FOREST
modifies_features	True
modifies_target	False
name	Random Forest Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.regressors.**SVMRegressor**(*C=1.0*, *kernel='rbf'*, *gamma='scale'*, *random_seed=0*, ***kwargs*)

Support Vector Machine Regressor.

Parameters

- **C** (*float*) – The regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive. The penalty is a squared l2 penalty. Defaults to 1.0.
- **kernel** (*{"linear", "poly", "rbf", "sigmoid", "precomputed"}*) – Specifies the kernel type to be used in the algorithm. Defaults to "rbf".
- **gamma** (*{"scale", "auto"} or float*) – Kernel coefficient for "rbf", "poly" and "sigmoid". Defaults to "scale". - If gamma='scale' (default) is passed then it uses 1 / (n_features * X.var()) as value of gamma - if "auto", uses 1 / n_features
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0, 10), "kernel": ["linear", "poly", "rbf", "sigmoid", "precomputed"], "gamma": ["scale", "auto"],}
model_family	ModelFamily.SVM
modifies_features	True
modifies_target	False
name	SVM Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Feature importance only works with linear kernels.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.

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save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Feature importance only works with linear kernels. If the kernel isn't linear, we return a numpy array of zeros

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.regressors.**TimeSeriesBaselineEstimator**(*gap=1*, *random_seed*, ***kwargs*)

Time series estimator that predicts using the naive forecasting approach.

This is useful as a simple baseline estimator for time series problems.

Parameters

- **gap** (*int*) – Gap between prediction date and target date and must be a positive integer. If gap is 0, target date will be shifted ahead by 1 time period. Defaults to 1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.BASELINE
modifies_features	True
modifies_target	False
name	Time Series Baseline Estimator
predict_uses_y	True
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)

Returns importance associated with each feature.

Since baseline estimators do not use input features to calculate predictions, returns an array of zeroes.

Returns an array of zeroes

Return type np.ndarray (float)

fit (*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*, *y=None*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.regressors.**XGBoostRegressor**(*eta=0.1*, *max_depth=6*, *min_child_weight=1*, *n_estimators=100*, *random_seed=0*, *n_jobs=-1*, ***kwargs*)
XGBoost Regressor.

Parameters

- **eta** (*float*) – Boosting learning rate. Defaults to 0.1.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **min_child_weight** (*float*) – Minimum sum of instance weight (hessian) needed in a child. Defaults to 1.0

- **n_estimators** (*int*) – Number of gradient boosted trees. Equivalent to number of boosting rounds. Defaults to 100.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.

Attributes

hyperparameter_ranges	{ "eta": Real(0.000001, 1), "max_depth": Integer(1, 20), "min_child_weight": Real(1, 10), "n_estimators": Integer(1, 1000),}
model_family	ModelFamily.XGBOOST
modifies_features	True
modifies_target	False
name	XGBoost Regressor
predict_uses_y	False
SEED_MAX	None
SEED_MIN	None
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

Submodules

estimator

Module Contents

Classes Summary

Estimator	A component that fits and predicts given data.

Contents

class evalml.pipelines.components.estimators.estimator.**Estimator**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)

A component that fits and predicts given data.

To implement a new Estimator, define your own class which is a subclass of Estimator, including a name and a list of acceptable ranges for any parameters to be tuned during the automl search (hyperparameters). Define an *__init__* method which sets up any necessary state and objects. Make sure your *__init__* only uses standard keyword arguments and calls *super().__init__()* with a parameters dict. You may also override the *fit*, *transform*, *fit_transform* and other methods in this class if appropriate.

To see some examples, check out the definitions of any Estimator component.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
predict_uses_y	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path
supported_problem_types	Problem types this estimator supports

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name (*cls*)
Returns string name of this component

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

property supported_problem_types (*cls*)
Problem types this estimator supports

Package Contents

Classes Summary

ARIMARegressor	Autoregressive Integrated Moving Average Model.
BaselineClassifier	Classifier that predicts using the specified strategy.
BaselineRegressor	Baseline regressor that uses a simple strategy to make predictions.
CatBoostClassifier	CatBoost Classifier, a classifier that uses gradient-boosting on decision trees.
CatBoostRegressor	CatBoost Regressor, a regressor that uses gradient-boosting on decision trees.
DecisionTreeClassifier	Decision Tree Classifier.
DecisionTreeRegressor	Decision Tree Regressor.
ElasticNetClassifier	Elastic Net Classifier. Uses Logistic Regression with elasticnet penalty as the base estimator.
ElasticNetRegressor	Elastic Net Regressor.
Estimator	A component that fits and predicts given data.
ExtraTreesClassifier	Extra Trees Classifier.
ExtraTreesRegressor	Extra Trees Regressor.
KNeighborsClassifier	K-Nearest Neighbors Classifier.
LightGBMClassifier	LightGBM Classifier.
LightGBMRegressor	LightGBM Regressor.
LinearRegressor	Linear Regressor.
LogisticRegressionClassifier	Logistic Regression Classifier.
ProphetRegressor	Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.
RandomForestClassifier	Random Forest Classifier.
RandomForestRegressor	Random Forest Regressor.
SVMClassifier	Support Vector Machine Classifier.
SVMRegressor	Support Vector Machine Regressor.
TimeSeriesBaselineEstimator	Time series estimator that predicts using the naive forecasting approach.
XGBoostClassifier	XGBoost Classifier.
XGBoostRegressor	XGBoost Regressor.

Contents

class evalml.pipelines.components.estimators.**ARIMARegressor**(*date_index=None*, *trend=None*, *start_p=2*, *d=0*, *start_q=2*, *max_p=5*, *max_d=2*, *max_q=5*, *seasonal=True*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Autoregressive Integrated Moving Average Model. The three parameters (p, d, q) are the AR order, the degree of differencing, and the MA order. More information here: https://www.statsmodels.org/devel/generated/statsmodels.tsa.arima_model.ARIMA.html

Currently ARIMARegressor isn't supported via conda install. It's recommended that it be installed via PyPI.

Parameters

- **date_index** (*str*) – Specifies the name of the column in X that provides the datetime objects. Defaults to None.
- **trend** (*str*) – Controls the deterministic trend. Options are ['n', 'c', 't', 'ct'] where 'c' is a constant term, 't' indicates a linear trend, and 'ct' is both. Can also be an iterable when defining a polynomial, such as [1, 1, 0, 1].
- **start_p** (*int*) – Minimum Autoregressive order. Defaults to 2.
- **d** (*int*) – Minimum Differencing degree. Defaults to 0.
- **start_q** (*int*) – Minimum Moving Average order. Defaults to 2.
- **max_p** (*int*) – Maximum Autoregressive order. Defaults to 5.
- **max_d** (*int*) – Maximum Differencing degree. Defaults to 2.
- **max_q** (*int*) – Maximum Moving Average order. Defaults to 5.
- **seasonal** (*boolean*) – Whether to fit a seasonal model to ARIMA. Defaults to True.
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “start_p”: Integer(1, 3), “d”: Integer(0, 2), “start_q”: Integer(1, 3), “max_p”: Integer(3, 10), “max_d”: Integer(2, 5), “max_q”: Integer(3, 10), “seasonal”: [True, False],}
model_family	ModelFamily.ARIMA
modifies_features	True
modifies_target	False
name	ARIMA Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns array of 0’s with a length of 1 as feature_importance is not defined for ARIMA regressor.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns array of 0's with a length of 1 as feature_importance is not defined for ARIMA regressor.

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**BaselineClassifier**(*strategy='mode'*, *random_seed=0*, ***kwargs*)
Classifier that predicts using the specified strategy.

This is useful as a simple baseline classifier to compare with other classifiers.

Parameters

- **strategy** (*str*) – Method used to predict. Valid options are "mode", "random" and "random_weighted". Defaults to "mode".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.BASELINE
modifies_features	True
modifies_target	False
name	Baseline Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS]

Methods

*classes_*	Returns class labels. Will return None before fitting.
clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature. Since baseline classifiers do not use input features to calculate predictions, returns an array of zeroes.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

property classes_(*self*)

Returns class labels. Will return None before fitting.

Returns Class names

Return type list[str] or list(float)

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature. Since baseline classifiers do not use input features to calculate predictions, returns an array of zeroes.

Returns An array of zeroes

Return type np.ndarray (float)

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**BaselineRegressor** (*strategy='mean'*, *random_seed=0*, ***kwargs*)
Baseline regressor that uses a simple strategy to make predictions. This is useful as a simple baseline regressor to compare with other regressors.

Parameters

- **strategy** (*str*) – Method used to predict. Valid options are "mean", "median". Defaults to "mean".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.BASELINE
modifies_features	True
modifies_target	False
name	Baseline Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature. Since baseline regressors do not use input features to calculate predictions, returns an array of zeroes.

continues on next page

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fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature. Since baseline regressors do not use input features to calculate predictions, returns an array of zeroes.

Returns An array of zeroes

Return type np.ndarray (float)

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**CatBoostClassifier**(*n_estimators=10*, *eta=0.03*, *max_depth=6*, *bootstrap_type=None*, *silent=True*, *allow_writing_files=False*, *random_seed=0*, *n_jobs=-1*, ***kwargs*)
CatBoost Classifier, a classifier that uses gradient-boosting on decision trees. CatBoost is an open-source library and natively supports categorical features.

For more information, check out https://catboost.ai/

Parameters

- **n_estimators** (*float*) – The maximum number of trees to build. Defaults to 10.
- **eta** (*float*) – The learning rate. Defaults to 0.03.
- **max_depth** (*int*) – The maximum tree depth for base learners. Defaults to 6.

- **bootstrap_type** (*string*) – Defines the method for sampling the weights of objects. Available methods are 'Bayesian', 'Bernoulli', 'MVS'. Defaults to None.
- **silent** (*boolean*) – Whether to use the "silent" logging mode. Defaults to True.
- **allow_writing_files** (*boolean*) – Whether to allow writing snapshot files while training. Defaults to False.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(4, 100), "eta": Real(0.000001, 1), "max_depth": Integer(4, 10),}
model_family	ModelFamily.CATBOOST
modifies_features	True
modifies_target	False
name	CatBoost Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**CatBoostRegressor**(*n_estimators=10*, *eta=0.03*, *max_depth=6*, *bootstrap_type=None*, *silent=False*, *allow_writing_files=False*, *random_seed=0*, *n_jobs=-1*, ***kwargs*)
CatBoost Regressor, a regressor that uses gradient-boosting on decision trees. CatBoost is an open-source library and natively supports categorical features.

For more information, check out https://catboost.ai/

Parameters

- **n_estimators** (*float*) – The maximum number of trees to build. Defaults to 10.
- **eta** (*float*) – The learning rate. Defaults to 0.03.
- **max_depth** (*int*) – The maximum tree depth for base learners. Defaults to 6.
- **bootstrap_type** (*string*) – Defines the method for sampling the weights of objects. Available methods are 'Bayesian', 'Bernoulli', 'MVS'. Defaults to None.
- **silent** (*boolean*) – Whether to use the "silent" logging mode. Defaults to True.
- **allow_writing_files** (*boolean*) – Whether to allow writing snapshot files while training. Defaults to False.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “n_estimators”: Integer(4, 100), “eta”: Real(0.000001, 1), “max_depth”: Integer(4, 10),}
model_family	ModelFamily.CATBOOST
modifies_features	True
modifies_target	False
name	CatBoost Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**DecisionTreeClassifier**(*criterion='gini'*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *random_seed=0*, ***kwargs*)

Decision Tree Classifier.

Parameters

- **criterion** (*{"gini", "entropy"}*) – The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain. Defaults to "gini".
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.

  Defaults to 2.
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "criterion": ["gini", "entropy"], "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.DECISION_TREE
modifies_features	True
modifies_target	False
name	Decision Tree Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**DecisionTreeRegressor**(*criterion='mse'*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *random_seed=0*, ***kwargs*)

Decision Tree Regressor.

Parameters

- **criterion** (*{"mse", "friedman_mse", "mae", "poisson"}*) – The function to measure the quality of a split. Supported criteria are:
  - "mse" for the mean squared error, which is equal to variance reduction as feature selection criterion and minimizes the L2 loss using the mean of each terminal node
  - "friedman_mse", which uses mean squared error with Friedman"s improvement score for potential splits
  - "mae" for the mean absolute error, which minimizes the L1 loss using the median of each terminal node,
  - "poisson" which uses reduction in Poisson deviance to find splits.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features.
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.

  Defaults to 2.
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “criterion”: [“mse”, “friedman_mse”, “mae”], “max_features”: [“auto”, “sqrt”, “log2”], “max_depth”: Integer(4, 10),}
model_family	ModelFamily.DECISION_TREE
modifies_features	True
modifies_target	False
name	Decision Tree Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**ElasticNetClassifier**(*penalty='elasticnet'*, *C=1.0*, *l1_ratio=0.15*, *multi_class='auto'*, *solver='saga'*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Elastic Net Classifier. Uses Logistic Regression with elasticnet penalty as the base estimator.

Parameters

- **penalty** (*{"l1", "l2", "elasticnet", "none"}*) – The norm used in penalization. Defaults to "elasticnet".
- **C** (*float*) – Inverse of regularization strength. Must be a positive float. Defaults to 1.0.
- **l1_ratio** (*float*) – The mixing parameter, with 0 <= l1_ratio <= 1. Only used if penalty='elasticnet'. Setting l1_ratio=0 is equivalent to using penalty='l2', while setting l1_ratio=1 is equivalent to using penalty='l1'. For 0 < l1_ratio <1, the penalty is a combination of L1 and L2. Defaults to 0.15.
- **multi_class** (*{"auto", "ovr", "multinomial"}*) – If the option chosen is "ovr", then a binary problem is fit for each label. For "multinomial" the loss minimised is the multinomial loss fit across the entire probability distribution, even when the data is binary. "multinomial" is unavailable when solver="liblinear". "auto" selects "ovr" if the data is binary, or if solver="liblinear", and otherwise selects "multinomial". Defaults to "auto".
- **solver** (*{"newton-cg", "lbfgs", "liblinear", "sag", "saga"}*) – Algorithm to use in the optimization problem. For small datasets, "liblinear" is a good choice, whereas "sag" and "saga" are faster for large ones. For multiclass problems, only "newton-cg", "sag", "saga" and "lbfgs" handle multinomial loss; "liblinear" is limited to one-versus-rest schemes.
  - "newton-cg", "lbfgs", "sag" and "saga" handle L2 or no penalty
  - "liblinear" and "saga" also handle L1 penalty
  - "saga" also supports "elasticnet" penalty
  - "liblinear" does not support setting penalty='none'

  Defaults to "saga".
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0.01, 10), "l1_ratio": Real(0, 1)}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Elastic Net Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**ElasticNetRegressor**(*alpha=0.0001*, *l1_ratio=0.15*, *max_iter=1000*, *normalize=False*, *random_seed=0*, ***kwargs*)

Elastic Net Regressor.

Parameters

- **alpha** (*float*) – Constant that multiplies the penalty terms. Defaults to 0.0001.
- **l1_ratio** (*float*) – The mixing parameter, with 0 <= l1_ratio <= 1. Only used if penalty='elasticnet'. Setting l1_ratio=0 is equivalent to using penalty='l2', while setting l1_ratio=1 is equivalent to using penalty='l1'. For 0 < l1_ratio <1, the penalty is a combination of L1 and L2. Defaults to 0.15.
- **max_iter** (*int*) – The maximum number of iterations. Defaults to 1000.
- **normalize** (*boolean*) – If True, the regressors will be normalized before regression by subtracting the mean and dividing by the l2-norm. Defaults to False.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "alpha": Real(0, 1), "l1_ratio": Real(0, 1),}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Elastic Net Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component

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predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**Estimator**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)
A component that fits and predicts given data.

To implement a new Estimator, define your own class which is a subclass of Estimator, including a name and a list of acceptable ranges for any parameters to be tuned during the automl search (hyperparameters). Define an *__init__* method which sets up any necessary state and objects. Make sure your *__init__* only uses standard keyword arguments and calls *super().__init__()* with a parameters dict. You may also override the *fit*, *transform*, *fit_transform* and other methods in this class if appropriate.

To see some examples, check out the definitions of any Estimator component.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
predict_uses_y	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path
supported_problem_types	Problem types this estimator supports

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]

- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

property supported_problem_types(*cls*)
Problem types this estimator supports

class evalml.pipelines.components.estimators.**ExtraTreesClassifier**(*n_estimators=100*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Extra Trees Classifier.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.
- **to 2.** (*Defaults*) –
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.EXTRA_TREES
modifies_features	True
modifies_target	False
name	Extra Trees Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**ExtraTreesRegressor**(*n_estimators=100*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
Extra Trees Regressor.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.

- If "auto", then max_features=sqrt(n_features).
- If "sqrt", then max_features=sqrt(n_features).
- If "log2", then max_features=log2(n_features).
- If None, then max_features = n_features.

The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".

- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.
- **to 2.** (*Defaults*) –
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.EXTRA_TREES
modifies_features	True
modifies_target	False
name	Extra Trees Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path

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needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**KNeighborsClassifier**(*n_neighbors=5*, *weights='uniform'*, *algorithm='auto'*, *leaf_size=30*, *p=2*, *random_seed=0*, ***kwargs*)

K-Nearest Neighbors Classifier.

Parameters

- **n_neighbors** (*int*) – Number of neighbors to use by default. Defaults to 5.
- **weights** (*{'uniform', 'distance'} or callable*) – Weight function used in prediction. Can be:
  - 'uniform' : uniform weights. All points in each neighborhood are weighted equally.
  - 'distance' : weight points by the inverse of their distance. in this case, closer neighbors of a query point will have a greater influence than neighbors which are further away.
  - [callable] : a user-defined function which accepts an array of distances, and returns an array of the same shape containing the weights.

  Defaults to "uniform".
- **algorithm** (*{'auto', 'ball_tree', 'kd_tree', 'brute'}*) – Algorithm used to compute the nearest neighbors:

- 'ball_tree' will use BallTree
- 'kd_tree' will use KDTree
- 'brute' will use a brute-force search.

'auto' will attempt to decide the most appropriate algorithm based on the values passed to fit method. Defaults to "auto". Note: fitting on sparse input will override the setting of this parameter, using brute force.

- **leaf_size** (*int*) – Leaf size passed to BallTree or KDTree. This can affect the speed of the construction and query, as well as the memory required to store the tree. The optimal value depends on the nature of the problem. Defaults to 30.
- **p** (*int*) – Power parameter for the Minkowski metric. When p = 1, this is equivalent to using manhattan_distance (l1), and euclidean_distance (l2) for p = 2. For arbitrary p, minkowski_distance (l_p) is used. Defaults to 2.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_neighbors": Integer(2, 12), "weights": ["uniform", "distance"], "algorithm": ["auto", "ball_tree", "kd_tree", "brute"], "leaf_size": Integer(10, 30), "p": Integer(1, 5),}
model_family	ModelFamily.K_NEIGHBORS
modifies_features	True
modifies_target	False
name	KNN Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns array of 0's matching the input number of features as feature_importance is
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns array of 0's matching the input number of features as feature_importance is not defined for KNN classifiers.

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**LightGBMClassifier**(*boosting_type='gbdt'*, *learning_rate=0.1*, *n_estimators=100*, *max_depth=0*, *num_leaves=31*, *min_child_samples=20*, *bagging_fraction=0.9*, *bagging_freq=0*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

LightGBM Classifier.

Parameters

- **boosting_type** (*string*) – Type of boosting to use. Defaults to "gbdt". - 'gbdt' uses traditional Gradient Boosting Decision Tree - "dart", uses Dropouts meet Multiple Additive Regression Trees - "goss", uses Gradient-based One-Side Sampling - "rf", uses Random Forest
- **learning_rate** (*float*) – Boosting learning rate. Defaults to 0.1.
- **n_estimators** (*int*) – Number of boosted trees to fit. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners, <=0 means no limit. Defaults to 0.
- **num_leaves** (*int*) – Maximum tree leaves for base learners. Defaults to 31.
- **min_child_samples** (*int*) – Minimum number of data needed in a child (leaf). Defaults to 20.
- **bagging_fraction** (*float*) – LightGBM will randomly select a subset of features on each iteration (tree) without resampling if this is smaller than 1.0. For example, if set to 0.8, LightGBM will select 80% of features before training each tree. This can be used to speed up training and deal with overfitting. Defaults to 0.9.

- **bagging_freq** (*int*) – Frequency for bagging. 0 means bagging is disabled. k means perform bagging at every k iteration. Every k-th iteration, LightGBM will randomly select bagging_fraction * 100 % of the data to use for the next k iterations. Defaults to 0.
- **n_jobs** (*int or None*) – Number of threads to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "learning_rate": Real(0.000001, 1), "boosting_type": ["gbdt", "dart", "goss", "rf"], "n_estimators": Integer(10, 100), "max_depth": Integer(0, 10), "num_leaves": Integer(2, 100), "min_child_samples": Integer(1, 100), "bagging_fraction": Real(0.000001, 1), "bagging_freq": Integer(0, 1),}
model_family	ModelFamily.LIGHTGBM
modifies_features	True
modifies_target	False
name	LightGBM Classifier
predict_uses_y	False
SEED_MAX	SEED_BOUNDS.max_bound
SEED_MIN	0
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**LightGBMRegressor**(*boosting_type='gbdt'*, *learning_rate=0.1*, *n_estimators=20*, *max_depth=0*, *num_leaves=31*, *min_child_samples=20*, *bagging_fraction=0.9*, *bagging_freq=0*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)

LightGBM Regressor.

Parameters

- **boosting_type** (*string*) – Type of boosting to use. Defaults to "gbdt". - 'gbdt' uses traditional Gradient Boosting Decision Tree - "dart", uses Dropouts meet Multiple Additive Regression Trees - "goss", uses Gradient-based One-Side Sampling - "rf", uses Random Forest
- **learning_rate** (*float*) – Boosting learning rate. Defaults to 0.1.
- **n_estimators** (*int*) – Number of boosted trees to fit. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners, <=0 means no limit. Defaults to 0.
- **num_leaves** (*int*) – Maximum tree leaves for base learners. Defaults to 31.
- **min_child_samples** (*int*) – Minimum number of data needed in a child (leaf). Defaults to 20.
- **bagging_fraction** (*float*) – LightGBM will randomly select a subset of features on each iteration (tree) without resampling if this is smaller than 1.0. For example, if set to 0.8, LightGBM will select 80% of features before training each tree. This can be used to speed up training and deal with overfitting. Defaults to 0.9.
- **bagging_freq** (*int*) – Frequency for bagging. 0 means bagging is disabled. k means perform bagging at every k iteration. Every k-th iteration, LightGBM will randomly select bagging_fraction * 100 % of the data to use for the next k iterations. Defaults to 0.
- **n_jobs** (*int or None*) – Number of threads to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "learning_rate": Real(0.000001, 1), "boosting_type": ["gbdt", "dart", "goss", "rf"], "n_estimators": Integer(10, 100), "max_depth": Integer(0, 10), "num_leaves": Integer(2, 100), "min_child_samples": Integer(1, 100), "bagging_fraction": Real(0.000001, 1), "bagging_freq": Integer(0, 1),}
model_family	ModelFamily.LIGHTGBM
modifies_features	True
modifies_target	False
name	LightGBM Regressor
predict_uses_y	False
SEED_MAX	SEED_BOUNDS.max_bound
SEED_MIN	0
supported_problem_types	[ProblemTypes.REGRESSION]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file

- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**LinearRegressor**(*fit_intercept=True*, *normalize=False*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)

Linear Regressor.

Parameters

- **fit_intercept** (*boolean*) – Whether to calculate the intercept for this model. If set to False, no intercept will be used in calculations (i.e. data is expected to be centered). Defaults to True.
- **normalize** (*boolean*) – If True, the regressors will be normalized before regression by subtracting the mean and dividing by the l2-norm. This parameter is ignored when fit_intercept is set to False. Defaults to False.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "fit_intercept": [True, False], "normalize": [True, False]}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Linear Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.

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predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**LogisticRegressionClassifier**(*penalty='l2'*, *C=1.0*, *multi_class='auto'*, *solver='lbfgs'*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Logistic Regression Classifier.

Parameters

- **penalty** (*{"l1", "l2", "elasticnet", "none"}*) – The norm used in penalization. Defaults to "l2".
- **C** (*float*) – Inverse of regularization strength. Must be a positive float. Defaults to 1.0.
- **multi_class** (*{"auto", "ovr", "multinomial"}*) – If the option chosen is "ovr", then a binary problem is fit for each label. For "multinomial" the loss minimised is the multinomial loss fit across the entire probability distribution, even when the data is binary. "multinomial" is unavailable when solver="liblinear". "auto" selects "ovr" if the data is binary, or if solver="liblinear", and otherwise selects "multinomial". Defaults to "auto".
- **solver** (*{"newton-cg", "lbfgs", "liblinear", "sag", "saga"}*) – Algorithm to use in the optimization problem. For small datasets, "liblinear" is a good choice, whereas "sag" and "saga" are faster for large ones. For multiclass problems, only "newton-cg", "sag", "saga" and "lbfgs" handle multinomial loss; "liblinear" is limited to one-versus-rest schemes.
  - "newton-cg", "lbfgs", "sag" and "saga" handle L2 or no penalty
  - "liblinear" and "saga" also handle L1 penalty
  - "saga" also supports "elasticnet" penalty

– ”liblinear” does not support setting penalty='none'

Defaults to “lbfgs”.

- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “penalty”: [“l2”], “C”: Real(0.01, 10),}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Logistic Regression Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)

Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)

Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)

Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)

Returns the parameters which were used to initialize the component

predict(*self*, *X*)

Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)

Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**ProphetRegressor**(*date_column='ds'*, *changepoint_prior_scale=0.05*, *seasonality_prior_scale=10*, *holidays_prior_scale=10*, *seasonality_mode='additive'*, *random_seed=0*, *stan_backend='CMDSTANPY'*, ***kwargs*)

Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well.

More information here: https://facebook.github.io/prophet/

Attributes

hyperparameter_ranges	{ "changepoint_prior_scale": Real(0.001, 0.5), "seasonality_prior_scale": Real(0.01, 10), "holidays_prior_scale": Real(0.01, 10), "seasonality_mode": ["additive", "multiplicative"],}
model_family	ModelFamily.PROPHET
modifies_features	True
modifies_target	False
name	Prophet Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION]

Methods

build_prophet_df	
clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns array of 0's with len(1) as feature_importance is not defined for Prophet regressor.

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fit	Fits component to data
get_params	
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

static build_prophet_df(*X*, *y=None*, *date_column='ds'*)

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)

Returns array of 0's with len(1) as feature_importance is not defined for Prophet regressor.

fit(*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

get_params(*self*)

static load(*file_path*)

Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**RandomForestClassifier**(*n_estimators=100*, *max_depth=6*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Random Forest Classifier.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_depth": Integer(1, 10),}
model_family	ModelFamily.RANDOM_FOREST
modifies_features	True
modifies_target	False
name	Random Forest Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**RandomForestRegressor**(*n_estimators=100*, *max_depth=6*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Random Forest Regressor.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_depth": Integer(1, 32),}
model_family	ModelFamily.RANDOM_FOREST
modifies_features	True
modifies_target	False
name	Random Forest Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**SVMClassifier**(*C=1.0*, *kernel='rbf'*, *gamma='scale'*, *probability=True*, *random_seed=0*, ***kwargs*)

Support Vector Machine Classifier.

Parameters

- **C** (*float*) – The regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive. The penalty is a squared l2 penalty. Defaults to 1.0.
- **kernel** (*{"linear", "poly", "rbf", "sigmoid", "precomputed"}*) – Specifies the kernel type to be used in the algorithm. Defaults to "rbf".
- **gamma** (*{"scale", "auto"} or float*) – Kernel coefficient for "rbf", "poly" and "sigmoid". Defaults to "scale". - If gamma='scale' (default) is passed then it uses 1 / (n_features * X.var()) as value of gamma - if "auto", uses 1 / n_features
- **probability** (*boolean*) – Whether to enable probability estimates. Defaults to True.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0, 10), "kernel": ["linear", "poly", "rbf", "sigmoid", "precomputed"], "gamma": ["scale", "auto"],}
model_family	ModelFamily.SVM
modifies_features	True
modifies_target	False
name	SVM Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Feature importance only works with linear kernels.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)

Feature importance only works with linear kernels. If the kernel isn't linear, we return a numpy array of zeros

fit (*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**SVMRegressor**(*C=1.0*, *kernel='rbf'*, *gamma='scale'*, *random_seed=0*, ***kwargs*)

Support Vector Machine Regressor.

Parameters

- **C** (*float*) – The regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive. The penalty is a squared l2 penalty. Defaults to 1.0.
- **kernel** (*{"linear", "poly", "rbf", "sigmoid", "precomputed"}*) – Specifies the kernel type to be used in the algorithm. Defaults to "rbf".
- **gamma** (*{"scale", "auto"} or float*) – Kernel coefficient for "rbf", "poly" and "sigmoid". Defaults to "scale". - If gamma='scale' (default) is passed then it uses 1 / (n_features * X.var()) as value of gamma - if "auto", uses 1 / n_features
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0, 10), "kernel": ["linear", "poly", "rbf", "sigmoid", "precomputed"], "gamma": ["scale", "auto"],}
model_family	ModelFamily.SVM
modifies_features	True
modifies_target	False
name	SVM Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Feature importance only works with linear kernels.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Feature importance only works with linear kernels. If the kernel isn't linear, we return a numpy array of zeros

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**TimeSeriesBaselineEstimator**(*gap=1*, *random_seed=0*, ***kwargs*)

Time series estimator that predicts using the naive forecasting approach.

This is useful as a simple baseline estimator for time series problems.

Parameters

- **gap** (*int*) – Gap between prediction date and target date and must be a positive integer. If gap is 0, target date will be shifted ahead by 1 time period. Defaults to 1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.BASELINE
modifies_features	True
modifies_target	False
name	Time Series Baseline Estimator
predict_uses_y	True
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Since baseline estimators do not use input features to calculate predictions, returns an array of zeroes.

Returns an array of zeroes

Return type np.ndarray (float)

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*, *y=None*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**XGBoostClassifier** (*eta=0.1*, *max_depth=6*, *min_child_weight=1*, *n_estimators=100*, *random_seed=0*, *n_jobs=-1*, ***kwargs*)

XGBoost Classifier.

Parameters

- **eta** (*float*) – Boosting learning rate. Defaults to 0.1.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **min_child_weight** (*float*) – Minimum sum of instance weight (hessian) needed in a child. Defaults to 1.0
- **n_estimators** (*int*) – Number of gradient boosted trees. Equivalent to number of boosting rounds. Defaults to 100.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.

Attributes

hyperparameter_ranges	{ "eta": Real(0.000001, 1), "max_depth": Integer(1, 10), "min_child_weight": Real(1, 10), "n_estimators": Integer(1, 1000),}
model_family	ModelFamily.XGBOOST
modifies_features	True
modifies_target	False
name	XGBoost Classifier
predict_uses_y	False
SEED_MAX	None
SEED_MIN	None
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.estimators.**XGBoostRegressor**(*eta=0.1*, *max_depth=6*, *min_child_weight=1*, *n_estimators=100*, *random_seed=0*, *n_jobs=-1*, ***kwargs*)

XGBoost Regressor.

Parameters

- **eta** (*float*) – Boosting learning rate. Defaults to 0.1.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **min_child_weight** (*float*) – Minimum sum of instance weight (hessian) needed in a child. Defaults to 1.0
- **n_estimators** (*int*) – Number of gradient boosted trees. Equivalent to number of boosting rounds. Defaults to 100.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.

Attributes

hyperparameter_ranges	{ “eta”: Real(0.000001, 1), “max_depth”: Integer(1, 20), “min_child_weight”: Real(1, 10), “n_estimators”: Integer(1, 1000),}
model_family	ModelFamily.XGBOOST
modifies_features	True
modifies_target	False
name	XGBoost Regressor
predict_uses_y	False
SEED_MAX	None
SEED_MIN	None
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before

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parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform,

or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transformers

Subpackages

dimensionality_reduction

Submodules

lda

Module Contents

Classes Summary

LinearDiscriminantAnalysis	Reduces the number of features by using Linear Discriminant Analysis.

Contents

class evalml.pipelines.components.transformers.dimensionality_reduction.lda.**LinearDiscrimi**

Reduces the number of features by using Linear Discriminant Analysis.

Parameters

- **n_components** (*int*) – The number of features to maintain after computation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Linear Discriminant Analysis Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

pca

Module Contents

Classes Summary

PCA	Reduces the number of features by using Principal Component Analysis (PCA).

Contents

class evalml.pipelines.components.transformers.dimensionality_reduction.pca.**PCA**(*variance=0.95*, *n_components=*, *random_seed=0*, ***kwargs*)

Reduces the number of features by using Principal Component Analysis (PCA).

Parameters

- **variance** (*float*) – The percentage of the original data variance that should be preserved when reducing the number of features. Defaults to 0.95.
- **n_components** (*int*) – The number of features to maintain after computing SVD. Defaults to None, but will override variance variable if set.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	Real(0.25, 1)}:type: {"variance"
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	PCA Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform

- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

Package Contents

Classes Summary

LinearDiscriminantAnalysis	Reduces the number of features by using Linear Discriminant Analysis.
PCA	Reduces the number of features by using Principal Component Analysis (PCA).

Contents

class evalml.pipelines.components.transformers.dimensionality_reduction.**LinearDiscriminantA**

Reduces the number of features by using Linear Discriminant Analysis.

Parameters

- **n_components** (*int*) – The number of features to maintain after computation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Linear Discriminant Analysis Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.dimensionality_reduction.**PCA**(*variance=0.95*, *n_components=None*, *random_seed=0*, ***kwargs*)

Reduces the number of features by using Principal Component Analysis (PCA).

Parameters

- **variance** (*float*) – The percentage of the original data variance that should be preserved when reducing the number of features. Defaults to 0.95.
- **n_components** (*int*) – The number of features to maintain after computing SVD. Defaults to None, but will override variance variable if set.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	Real(0.25, 1)}:type: {"variance"
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	PCA Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

encoders

Submodules

onehot_encoder

Module Contents

Classes Summary

OneHotEncoder	A transformer that encodes categorical features in a one-hot numeric array.
OneHotEncoderMeta	A version of the ComponentBaseMeta class which includes validation on an additional one-hot-encoder-specific method *categories*.

Contents

class evalml.pipelines.components.transformers.encoders.onehot_encoder.**OneHotEncoder**(*top_n=1 features_to cat- e- gories= drop='if han- dle_unk han- dle_mis ran- dom_se **kwarg*

A transformer that encodes categorical features in a one-hot numeric array.

Parameters

- **top_n** (*int*) – Number of categories per column to encode. If None, all categories will be encoded. Otherwise, the *n* most frequent will be encoded and all others will be dropped. Defaults to 10.
- **features_to_encode** (*list[str]*) – List of columns to encode. All other columns will remain untouched. If None, all appropriate columns will be encoded. Defaults to None.
- **categories** (*list*) – A two dimensional list of categories, where *categories[i]* is a list of the categories for the column at index *i*. This can also be *None*, or *"auto"* if *top_n* is not None. Defaults to None.
- **drop** (*string, list*) – Method ("first" or "if_binary") to use to drop one category per feature. Can also be a list specifying which categories to drop for each feature. Defaults to 'if_binary'.
- **handle_unknown** (*string*) – Whether to ignore or error for unknown categories for a feature encountered during *fit* or *transform*. If either *top_n* or *categories* is used to limit the number of categories per column, this must be "ignore". Defaults to "ignore".
- **handle_missing** (*string*) – Options for how to handle missing (NaN) values encountered during *fit* or *transform*. If this is set to "as_category" and NaN values are within the *n* most frequent, "nan" values will be encoded as their own column. If this is set to "error", any missing values encountered will raise an error. Defaults to "error".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	One Hot Encoder

Methods

categories	Returns a list of the unique categories to be encoded for the particular feature, in order.
clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_feature_names	Return feature names for the categorical features after fitting.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	One-hot encode the input data.

categories (*self*, *feature_name*)
Returns a list of the unique categories to be encoded for the particular feature, in order.

Parameters **feature_name** (*str*) – the name of any feature provided to one-hot encoder during fit

Returns the unique categories, in the same dtype as they were provided during fit

Return type np.ndarray

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names(*self*)
Return feature names for the categorical features after fitting.

Feature names are formatted as {column name}_{category name}. In the event of a duplicate name, an integer will be added at the end of the feature name to distinguish it.

For example, consider a dataframe with a column called "A" and category "x_y" and another column called "A_x" with "y". In this example, the feature names would be "A_x_y" and "A_x_y_1".

Returns The feature names after encoding, provided in the same order as input_features.

Return type np.ndarray

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
One-hot encode the input data.

Parameters

- **X** (*pd.DataFrame*) – Features to one-hot encode.
- **y** (*pd.Series*) – Ignored.

Returns Transformed data, where each categorical feature has been encoded into numerical columns using one-hot encoding.

Return type pd.DataFrame

class evalml.pipelines.components.transformers.encoders.onehot_encoder.**OneHotEncoderMeta**

A version of the ComponentBaseMeta class which includes validation on an additional one-hot-encoder-specific method *categories*.

Attributes

FIT_METHODS	['fit', 'fit_transform']
METHODS_TO_CHECK	None
PROPERTIES_TO_CHECK	['feature_importance']

Methods

check_for_fit	*check_for_fit* wraps a method that validates if *self._is_fitted* is *True*.
register	Register a virtual subclass of an ABC.
set_fit	

classmethod check_for_fit(*cls*, *method*)

check_for_fit wraps a method that validates if *self._is_fitted* is *True*. It raises an exception if *False* and calls and returns the wrapped method if *True*.

register(*cls*, *subclass*)

Register a virtual subclass of an ABC.

Returns the subclass, to allow usage as a class decorator.

classmethod set_fit(*cls*, *method*)

target_encoder

Module Contents

Classes Summary

TargetEncoder	A transformer that encodes categorical features into target encodings.

Contents

class evalml.pipelines.components.transformers.encoders.target_encoder.**TargetEncoder**(*cols=No*
smooth-
ing=1.0
han-
dle_unk
han-
dle_mis
ran-
dom_se
***kwarg*

A transformer that encodes categorical features into target encodings.

Parameters

- **cols** (*list*) – Columns to encode. If None, all string columns will be encoded, otherwise only the columns provided will be encoded. Defaults to None
- **smoothing** (*float*) – The smoothing factor to apply. The larger this value is, the more influence the expected target value has on the resulting target encodings. Must be strictly larger than 0. Defaults to 1.0
- **handle_unknown** (*string*) – Determines how to handle unknown categories for a feature encountered. Options are 'value', 'error', nd 'return_nan'. Defaults to 'value', which replaces with the target mean
- **handle_missing** (*string*) – Determines how to handle missing values encountered during *fit* or *transform*. Options are 'value', 'error', and 'return_nan'. Defaults to 'value', which replaces with the target mean
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Target Encoder

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_feature_names	Return feature names for the input features after fitting.

continues on next page

Table 413 – continued from previous page

load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names (*self*)
Return feature names for the input features after fitting.

Returns The feature names after encoding

Return type np.array

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

Package Contents

Classes Summary

OneHotEncoder	A transformer that encodes categorical features in a one-hot numeric array.
TargetEncoder	A transformer that encodes categorical features into target encodings.

Contents

class evalml.pipelines.components.transformers.encoders.**OneHotEncoder**(*top_n=10*, *features_to_encode=None*, *categories=None*, *drop='if_binary'*, *handle_unknown='ignore'*, *handle_missing='error'*, *random_seed=0*, ***kwargs*)

A transformer that encodes categorical features in a one-hot numeric array.

Parameters

- **top_n** (*int*) – Number of categories per column to encode. If None, all categories will be encoded. Otherwise, the *n* most frequent will be encoded and all others will be dropped. Defaults to 10.
- **features_to_encode** (*list[str]*) – List of columns to encode. All other columns will remain untouched. If None, all appropriate columns will be encoded. Defaults to None.
- **categories** (*list*) – A two dimensional list of categories, where *categories[i]* is a list of the categories for the column at index *i*. This can also be *None*, or *"auto"* if *top_n* is not None. Defaults to None.
- **drop** (*string, list*) – Method ("first" or "if_binary") to use to drop one category per feature. Can also be a list specifying which categories to drop for each feature. Defaults to 'if_binary'.
- **handle_unknown** (*string*) – Whether to ignore or error for unknown categories for a feature encountered during *fit* or *transform*. If either *top_n* or *categories* is used to limit the number of categories per column, this must be "ignore". Defaults to "ignore".
- **handle_missing** (*string*) – Options for how to handle missing (NaN) values encountered during *fit* or *transform*. If this is set to "as_category" and NaN values are within the *n* most frequent, "nan" values will be encoded as their own column. If this is set to "error", any missing values encountered will raise an error. Defaults to "error".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	One Hot Encoder

Methods

categories	Returns a list of the unique categories to be encoded for the particular feature, in order.
clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_feature_names	Return feature names for the categorical features after fitting.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	One-hot encode the input data.

categories (*self*, *feature_name*)
Returns a list of the unique categories to be encoded for the particular feature, in order.

Parameters **feature_name** (*str*) – the name of any feature provided to one-hot encoder during fit

Returns the unique categories, in the same dtype as they were provided during fit

Return type np.ndarray

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names(*self*)
Return feature names for the categorical features after fitting.

Feature names are formatted as {column name}_{category name}. In the event of a duplicate name, an integer will be added at the end of the feature name to distinguish it.

For example, consider a dataframe with a column called "A" and category "x_y" and another column called "A_x" with "y". In this example, the feature names would be "A_x_y" and "A_x_y_1".

Returns The feature names after encoding, provided in the same order as input_features.

Return type np.ndarray

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
One-hot encode the input data.

Parameters

- **X** (*pd.DataFrame*) – Features to one-hot encode.

- **y** (*pd.Series*) – Ignored.

Returns Transformed data, where each categorical feature has been encoded into numerical columns using one-hot encoding.

Return type pd.DataFrame

class evalml.pipelines.components.transformers.encoders.**TargetEncoder**(*cols=None*, *smoothing=1.0*, *handle_unknown='value'*, *handle_missing='value'*, *random_seed=0*, ***kwargs*)

A transformer that encodes categorical features into target encodings.

Parameters

- **cols** (*list*) – Columns to encode. If None, all string columns will be encoded, otherwise only the columns provided will be encoded. Defaults to None
- **smoothing** (*float*) – The smoothing factor to apply. The larger this value is, the more influence the expected target value has on the resulting target encodings. Must be strictly larger than 0. Defaults to 1.0
- **handle_unknown** (*string*) – Determines how to handle unknown categories for a feature encountered. Options are 'value', 'error', nd 'return_nan'. Defaults to 'value', which replaces with the target mean
- **handle_missing** (*string*) – Determines how to handle missing values encountered during *fit* or *transform*. Options are 'value', 'error', and 'return_nan'. Defaults to 'value', which replaces with the target mean
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Target Encoder

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data

continues on next page

Table 416 – continued from previous page

fit_transform	Fits on X and transforms X
get_feature_names	Return feature names for the input features after fitting.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names (*self*)
Return feature names for the input features after fitting.

Returns The feature names after encoding

Return type np.array

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

feature_selection

Submodules

feature_selector

Module Contents

Classes Summary

FeatureSelector	Selects top features based on importance weights.

Contents

class evalml.pipelines.components.transformers.feature_selection.feature_selector.**FeatureSe**

Selects top features based on importance weights.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names(*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)
Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

rf_classifier_feature_selector

Module Contents

Classes Summary

RFClassifierSelectFromModel	Selects top features based on importance weights using a Random Forest classifier.

Contents

class evalml.pipelines.components.transformers.feature_selection.rf_classifier_feature_sele

Selects top features based on importance weights using a Random Forest classifier.

Parameters

- **number_features** (*int*) – The maximum number of features to select. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5. Defaults to None.
- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **percent_features** (*float*) – Percentage of features to use. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5.
- **threshold** (*string or float*) – The threshold value to use for feature selection. Features whose importance is greater or equal are kept while the others are discarded. If "median", then the threshold value is the median of the feature importances. A scaling factor (e.g., "1.25*mean") may also be used. Defaults to -np.inf.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "percent_features": Real(0.01, 1), "threshold": ["mean", -np.inf],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	RF Classifier Select From Model

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names(*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform,

or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)
Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

rf_regressor_feature_selector

Module Contents

Classes Summary

RFRegressorSelectFromModel	Selects top features based on importance weights using a Random Forest regressor.

Contents

class evalml.pipelines.components.transformers.feature_selection.rf_regressor_feature_selec

Selects top features based on importance weights using a Random Forest regressor.

Parameters

- **number_features** (*int*) – The maximum number of features to select. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5. Defaults to None.
- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **percent_features** (*float*) – Percentage of features to use. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5.
- **threshold** (*string or float*) – The threshold value to use for feature selection. Features whose importance is greater or equal are kept while the others are discarded. If "median", then the threshold value is the median of the feature importances. A scaling factor (e.g., "1.25*mean") may also be used. Defaults to -np.inf.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "percent_features": Real(0.01, 1), "threshold": ["mean", -np.inf],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	RF Regressor Select From Model

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names(*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

Package Contents

Classes Summary

FeatureSelector	Selects top features based on importance weights.
RFClassifierSelectFromModel	Selects top features based on importance weights using a Random Forest classifier.
RFRegressorSelectFromModel	Selects top features based on importance weights using a Random Forest regressor.

Contents

class evalml.pipelines.components.transformers.feature_selection.**FeatureSelector**(*parameters=N* *component_obj=Nor* *random_seed=0*, ***kwargs*)

Selects top features based on importance weights.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before

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parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names (*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.feature_selection.**RFClassifierSelectFromMode**

Selects top features based on importance weights using a Random Forest classifier.

Parameters

- **number_features** (*int*) – The maximum number of features to select. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5. Defaults to None.
- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **percent_features** (*float*) – Percentage of features to use. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5.
- **threshold** (*string or float*) – The threshold value to use for feature selection. Features whose importance is greater or equal are kept while the others are discarded. If "median", then the threshold value is the median of the feature importances. A scaling factor (e.g., "1.25*mean") may also be used. Defaults to -np.inf.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "percent_features": Real(0.01, 1), "threshold": ["mean", -np.inf],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	RF Classifier Select From Model

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names(*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform,

or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.feature_selection.**RFRegressorSelectFromModel**

Selects top features based on importance weights using a Random Forest regressor.

Parameters

- **number_features** (*int*) – The maximum number of features to select. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5. Defaults to None.
- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **percent_features** (*float*) – Percentage of features to use. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5.
- **threshold** (*string or float*) – The threshold value to use for feature selection. Features whose importance is greater or equal are kept while the others are discarded. If "median", then the threshold value is the median of the feature importances. A scaling factor (e.g., "1.25*mean") may also be used. Defaults to -np.inf.

- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "percent_features": Real(0.01, 1), "threshold": ["mean", -np.inf],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	RF Regressor Select From Model

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names(*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

imputers

Submodules

imputer

Module Contents

Classes Summary

Imputer	Imputes missing data according to a specified imputation strategy.

Contents

class evalml.pipelines.components.transformers.imputers.imputer.**Imputer**(*categorical_impute_strateg*
categorical_fill_value=None,
numeric_impute_strategy='me
numeric_fill_value=None,
random_seed=0,
***kwargs*)

Imputes missing data according to a specified imputation strategy.

Parameters

- **categorical_impute_strategy** (*string*) – Impute strategy to use for string, object, boolean, categorical dtypes. Valid values include “most_frequent” and “constant”.
- **numeric_impute_strategy** (*string*) – Impute strategy to use for numeric columns. Valid values include “mean”, “median”, “most_frequent”, and “constant”.
- **categorical_fill_value** (*string*) – When categorical_impute_strategy == “constant”, fill_value is used to replace missing data. The default value of None will fill with the

string "missing_value".

- **numeric_fill_value** (*int, float*) – When numeric_impute_strategy == "constant", fill_value is used to replace missing data. The default value of None will fill with 0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "categorical_impute_strategy": ["most_frequent"], "numeric_impute_strategy": ["mean", "median", "most_frequent"],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputer to data. 'None' values are converted to np.nan before imputation and are
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by imputing missing values. 'None' values are converted to np.nan before imputation and are

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)

Fits imputer to data. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)

Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)

Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)

Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)

Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)

Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)

Transforms data X by imputing missing values. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

per_column_imputer

Module Contents

Classes Summary

PerColumnImputer	Imputes missing data according to a specified imputation strategy per column.

Contents

class evalml.pipelines.components.transformers.imputers.per_column_imputer.**PerColumnImputer**

Imputes missing data according to a specified imputation strategy per column.

Parameters

- **impute_strategies** (*dict*) – Column and {"impute_strategy": strategy, "fill_value":value} pairings. Valid values for impute strategy include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types. Defaults to None, which uses "most_frequent" for all columns. When impute_strategy == "constant", fill_value is used to replace missing data. When None, uses 0 when imputing numerical data and "missing_value" for strings or object data types.
- **default_impute_strategy** (*str*) – Impute strategy to fall back on when none is provided for a certain column. Valid values include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types. Defaults to "most_frequent".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Per Column Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputers on input data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by imputing missing values.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits imputers on input data

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features] to fit.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]. Ignored.

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input data by imputing missing values.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features] to transform.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]. Ignored.

Returns Transformed X

Return type pd.DataFrame

simple_imputer

Module Contents

Classes Summary

SimpleImputer	Imputes missing data according to a specified imputation strategy.

Contents

class evalml.pipelines.components.transformers.imputers.simple_imputer.**SimpleImputer**(*impute_fill_valu ran- dom_se **kwarg*

Imputes missing data according to a specified imputation strategy.

Parameters

- **impute_strategy** (*string*) – Impute strategy to use. Valid values include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types.
- **fill_value** (*string*) – When impute_strategy == "constant", fill_value is used to replace missing data. Defaults to 0 when imputing numerical data and "missing_value" for strings or object data types.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "impute_strategy": ["mean", "median", "most_frequent"]}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Simple Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputer to data. 'None' values are converted to np.nan before imputation and are
fit_transform	Fits on X and transforms X

continues on next page

Table 432 – continued from previous page

load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input by imputing missing values. 'None' and np.nan values are treated as the same.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)

Fits imputer to data. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)

Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input by imputing missing values. 'None' and np.nan values are treated as the same.

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

target_imputer

Module Contents

Classes Summary

TargetImputer	Imputes missing target data according to a specified imputation strategy.
TargetImputerMeta	A version of the ComponentBaseMeta class which handles when input features is None

Contents

class evalml.pipelines.components.transformers.imputers.target_imputer.**TargetImputer**(*impute_ fill_valu ran- dom_se **kwarg*

Imputes missing target data according to a specified imputation strategy.

Parameters

- **impute_strategy** (*string*) – Impute strategy to use. Valid values include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types. Defaults to "most_frequent".
- **fill_value** (*string*) – When impute_strategy == "constant", fill_value is used to replace missing data. Defaults to None which uses 0 when imputing numerical data and "missing_value" for strings or object data types.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "impute_strategy": ["mean", "median", "most_frequent"]}
model_family	ModelFamily.NONE
modifies_features	False
modifies_target	True
name	Target Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputer to target data. 'None' values are converted to np.nan before imputation and are
fit_transform	Fits on and transforms the input target data.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input target data by imputing missing values. 'None' and np.nan values are treated as the same.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)

Fits imputer to target data. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]. Ignored.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples].

Returns self

fit_transform(*self*, *X*, *y*)
Fits on and transforms the input target data.

Parameters

- **X** (*pd.DataFrame*) – Features. Ignored.
- **y** (*pd.Series*) – Target data to impute.

Returns The original X, transformed y

Return type (pd.DataFrame, pd.Series)

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y*)
Transforms input target data by imputing missing values. 'None' and np.nan values are treated as the same.

Parameters

- **X** (*pd.DataFrame*) – Features. Ignored.
- **y** (*pd.Series*) – Target data to impute.

Returns The original X, transformed y

Return type (pd.DataFrame, pd.Series)

class evalml.pipelines.components.transformers.imputers.target_imputer.**TargetImputerMeta**
A version of the ComponentBaseMeta class which handles when input features is None

Attributes

FIT_METHODS	['fit', 'fit_transform']
METHODS_TO_CHECK	['predict', 'predict_proba', 'transform', 'inverse_transform']
PROPERTIES_TO_CHECK	['feature_importance']

Methods

check_for_fit	*check_for_fit* wraps a method that validates if *self._is_fitted* is *True*.
register	Register a virtual subclass of an ABC.
set_fit	

classmethod check_for_fit(*cls*, *method*)
check_for_fit wraps a method that validates if *self._is_fitted* is *True*. It raises an exception if *False* and calls and returns the wrapped method if *True*.

register(*cls*, *subclass*)
Register a virtual subclass of an ABC.

Returns the subclass, to allow usage as a class decorator.

classmethod set_fit(*cls*, *method*)

Package Contents

Classes Summary

Imputer	Imputes missing data according to a specified imputation strategy.
PerColumnImputer	Imputes missing data according to a specified imputation strategy per column.
SimpleImputer	Imputes missing data according to a specified imputation strategy.
TargetImputer	Imputes missing target data according to a specified imputation strategy.

Contents

class evalml.pipelines.components.transformers.imputers.**Imputer**(*categorical_impute_strategy='most_fre*
categorical_fill_value=None,
numeric_impute_strategy='mean',
numeric_fill_value=None,
random_seed=0,
***kwargs*)

Imputes missing data according to a specified imputation strategy.

Parameters

- **categorical_impute_strategy** (*string*) – Impute strategy to use for string, object, boolean, categorical dtypes. Valid values include "most_frequent" and "constant".
- **numeric_impute_strategy** (*string*) – Impute strategy to use for numeric columns. Valid values include "mean", "median", "most_frequent", and "constant".
- **categorical_fill_value** (*string*) – When categorical_impute_strategy == "constant", fill_value is used to replace missing data. The default value of None will fill with the string "missing_value".
- **numeric_fill_value** (*int, float*) – When numeric_impute_strategy == "constant", fill_value is used to replace missing data. The default value of None will fill with 0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “categorical_impute_strategy”: [“most_frequent”], “numeric_impute_strategy”: [“mean”, “median”, “most_frequent”],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputer to data. ‘None’ values are converted to np.nan before imputation and are
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by imputing missing values. ‘None’ values are converted to np.nan before imputation and are

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)

Fits imputer to data. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)

Transforms data X by imputing missing values. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.imputers.**PerColumnImputer**(*impute_strategies=None*, *default_impute_strategy='m*, *random_seed=0*, ***kwargs*)

Imputes missing data according to a specified imputation strategy per column.

Parameters

- **impute_strategies** (*dict*) – Column and {"impute_strategy": strategy, "fill_value":value} pairings. Valid values for impute strategy include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types. Defaults to None, which uses "most_frequent" for all columns. When impute_strategy == "constant", fill_value is used to replace missing data. When None, uses 0 when imputing numerical data and "missing_value" for strings or object data types.
- **default_impute_strategy** (*str*) – Impute strategy to fall back on when none is provided for a certain column. Valid values include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types. Defaults to "most_frequent".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Per Column Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputers on input data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by imputing missing values.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits imputers on input data

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features] to fit.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]. Ignored.

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input data by imputing missing values.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features] to transform.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.imputers.**SimpleImputer**(*impute_strategy='most_freque fill_value=None*, *random_seed=0*, ***kwargs*)

Imputes missing data according to a specified imputation strategy.

Parameters

- **impute_strategy** (*string*) – Impute strategy to use. Valid values include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types.
- **fill_value** (*string*) – When impute_strategy == "constant", fill_value is used to replace missing data. Defaults to 0 when imputing numerical data and "missing_value" for strings or object data types.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "impute_strategy": ["mean", "median", "most_frequent"]}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Simple Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputer to data. 'None' values are converted to np.nan before imputation and are

continues on next page

Table 439 – continued from previous page

fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input by imputing missing values. 'None' and np.nan values are treated as the same.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)

Fits imputer to data. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)

Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input by imputing missing values. 'None' and np.nan values are treated as the same.

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.imputers.**TargetImputer**(*impute_strategy='most_freque*
fill_value=None,
ran-
dom_seed=0,
***kwargs*)

Imputes missing target data according to a specified imputation strategy.

Parameters

- **impute_strategy** (*string*) – Impute strategy to use. Valid values include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types. Defaults to "most_frequent".
- **fill_value** (*string*) – When impute_strategy == "constant", fill_value is used to replace missing data. Defaults to None which uses 0 when imputing numerical data and "missing_value" for strings or object data types.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “impute_strategy”: [“mean”, “median”, “most_frequent”]}
model_family	ModelFamily.NONE
modifies_features	False
modifies_target	True
name	Target Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputer to target data. ‘None’ values are converted to np.nan before imputation and are
fit_transform	Fits on and transforms the input target data.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input target data by imputing missing values. ‘None’ and np.nan values are treated as the same.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)

Fits imputer to target data. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]. Ignored.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples].

Returns self

fit_transform(*self*, *X*, *y*)

Fits on and transforms the input target data.

Parameters

- **X** (*pd.DataFrame*) – Features. Ignored.
- **y** (*pd.Series*) – Target data to impute.

Returns The original X, transformed y

Return type (pd.DataFrame, pd.Series)

static load(*file_path*)

Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)

Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)

Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)

Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y*)

Transforms input target data by imputing missing values. 'None' and np.nan values are treated as the same.

Parameters

- **X** (*pd.DataFrame*) – Features. Ignored.
- **y** (*pd.Series*) – Target data to impute.

Returns The original X, transformed y

Return type (pd.DataFrame, pd.Series)

preprocessing

Submodules

datetime_featurizer

Module Contents

Classes Summary

DateTimeFeaturizer	Transformer that can automatically extract features from datetime columns.

Contents

class evalml.pipelines.components.transformers.preprocessing.datetime_featurizer.**DateTimeFe**

Transformer that can automatically extract features from datetime columns.

Parameters

- **features_to_extract** (*list*) – List of features to extract. Valid options include "year", "month", "day_of_week", "hour". Defaults to None.
- **encode_as_categories** (*bool*) – Whether day-of-week and month features should be encoded as pandas "category" dtype. This allows OneHotEncoders to encode these features. Defaults to False.
- **date_index** (*str*) – Name of the column containing the datetime information used to order the data. Ignored.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	DateTime Featurization Component

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_feature_names	Gets the categories of each datetime feature.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by creating new features using existing DateTime columns, and then dropping those DateTime columns

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names(*self*)
Gets the categories of each datetime feature.

Returns Dictionary, where each key-value pair is a column name and a dictionary mapping the unique feature values to their integer encoding.

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by creating new features using existing DateTime columns, and then dropping those DateTime columns

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

delayed_feature_transformer

Module Contents

Classes Summary

DelayedFeatureTransformer	Transformer that delays input features and target variable for time series problems.

Contents

class evalml.pipelines.components.transformers.preprocessing.delayed_feature_transformer.**De**

Transformer that delays input features and target variable for time series problems.

Parameters

- **date_index** (*str*) – Name of the column containing the datetime information used to order the data. Ignored.
- **max_delay** (*int*) – Maximum number of time units to delay each feature. Defaults to 2.
- **delay_features** (*bool*) – Whether to delay the input features. Defaults to True.
- **delay_target** (*bool*) – Whether to delay the target. Defaults to True.
- **gap** (*int*) – The number of time units between when the features are collected and when the target is collected. For example, if you are predicting the next time step's target, gap=1. This is only needed because when gap=0, we need to be sure to start the lagging of the target variable at 1. Defaults to 1.
- **random_seed** (*int*) – Seed for the random number generator. This transformer performs the same regardless of the random seed provided.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Delayed Feature Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the DelayFeatureTransformer.
fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Computes the delayed features for all features in X and y.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits the DelayFeatureTransformer.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Computes the delayed features for all features in X and y.

For each feature in X, it will add a column to the output dataframe for each delay in the (inclusive) range [1, max_delay]. The values of each delayed feature are simply the original feature shifted forward in time by the delay amount. For example, a delay of 3 units means that the feature value at row n will be taken from the n-3rd row of that feature

If y is not None, it will also compute the delayed values for the target variable.

Parameters

- **X** (*pd.DataFrame or None*) – Data to transform. None is expected when only the target variable is being used.
- **y** (*pd.Series, or None*) – Target.

Returns Transformed X.

Return type pd.DataFrame

drop_null_columns

Module Contents

Classes Summary

DropNullColumns	Transformer to drop features whose percentage of NaN values exceeds a specified threshold.

Contents

class evalml.pipelines.components.transformers.preprocessing.drop_null_columns.**DropNullColu**

Transformer to drop features whose percentage of NaN values exceeds a specified threshold.

Parameters

- **pct_null_threshold** (*float*) – The percentage of NaN values in an input feature to drop. Must be a value between [0, 1] inclusive. If equal to 0.0, will drop columns with any null values. If equal to 1.0, will drop columns with all null values. Defaults to 0.95.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Drop Null Columns Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by dropping columns that exceed the threshold of null values.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by dropping columns that exceed the threshold of null values.

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

featuretools

Module Contents

Classes Summary

DFSTransformer	Featuretools DFS component that generates features for the input features.

Contents

class evalml.pipelines.components.transformers.preprocessing.featuretools.**DFSTransformer**(*in*
ra
do
***

Featuretools DFS component that generates features for the input features.

Parameters

- **index** (*string*) – The name of the column that contains the indices. If no column with this name exists, then featuretools.EntitySet() creates a column with this name to serve as the index column. Defaults to 'index'.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	DFS Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the DFSTransformer Transformer component.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Computes the feature matrix for the input X using featuretools' dfs algorithm.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)

Fits the DFSTransformer Transformer component.

Parameters

- **X** (*pd.DataFrame, np.array*) – The input data to transform, of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)

Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform

- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Computes the feature matrix for the input X using featuretools' dfs algorithm.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data to transform. Has shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – Ignored.

Returns Feature matrix

Return type pd.DataFrame

log_transformer

Module Contents

Classes Summary

LogTransformer	Applies a log transformation to the target data.

Contents

class evalml.pipelines.components.transformers.preprocessing.log_transformer.**LogTransforme**

Applies a log transformation to the target data.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	False
modifies_target	True
name	Log Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the LogTransformer.
fit_transform	Log transforms the target variable.
inverse_transform	Inverts the transformation done by the transform method.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Log transforms the target variable.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits the LogTransformer.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Ignored.
- **y** (*pd.Series, optional*) – Ignored.

Returns self

fit_transform(*self*, *X*, *y=None*)
Log transforms the target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to log transform.

Returns

The input features are returned without modification. The target variable y is log transformed.

Return type tuple of pd.DataFrame, pd.Series

inverse_transform(*self*, *y*)
Inverts the transformation done by the transform method.

Arguments: y (pd.Series): Target transformed by this component.

Returns Target without the transformation.

Return type pd.Seriesø

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Log transforms the target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target data to log transform.

Returns

The input features are returned without modification. The target variable y is log transformed.

Return type tuple of pd.DataFrame, pd.Series

lsa

Module Contents

Classes Summary

LSA	Transformer to calculate the Latent Semantic Analysis Values of text input.

Contents

class evalml.pipelines.components.transformers.preprocessing.lsa.**LSA**(*random_seed=0*, ***kwargs*)
Transformer to calculate the Latent Semantic Analysis Values of text input.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	LSA Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters

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fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by applying the LSA pipeline.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by applying the LSA pipeline.

Parameters

- **X** (*pd.DataFrame*) – The data to transform.
- **y** (*pd.Series, optional*) – Ignored.

Returns

Transformed X. The original column is removed and replaced with two columns of the format *LSA(original_column_name)[feature_number]*, where *feature_number* is 0 or 1.

Return type pd.DataFrame

polynomial_detrender

Module Contents

Classes Summary

PolynomialDetrender	Removes trends from time series by fitting a polynomial to the data.

Contents

class evalml.pipelines.components.transformers.preprocessing.polynomial_detrender.**Polynomia**

Removes trends from time series by fitting a polynomial to the data.

Parameters

- **degree** (*int*) – Degree for the polynomial. If 1, linear model is fit to the data. If 2, quadratic model is fit, etc. Defaults to 1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "degree": Integer(1, 3)}
model_family	ModelFamily.NONE
modifies_features	False
modifies_target	True
name	Polynomial Detrender

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the PolynomialDetrender.
fit_transform	Removes fitted trend from target variable.
inverse_transform	Adds back fitted trend to target variable.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Removes fitted trend from target variable.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits the PolynomialDetrender.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to detrend.

Returns self

fit_transform(*self*, *X*, *y=None*)
Removes fitted trend from target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to detrend.

Returns

The first element are the input features returned without modification. The second element is the target variable y with the fitted trend removed.

Return type tuple of pd.DataFrame, pd.Series

inverse_transform(*self*, *y*)
Adds back fitted trend to target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable.

Returns

The first element are the input features returned without modification. The second element is the target variable y with the trend added back.

Return type tuple of pd.DataFrame, pd.Series

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Removes fitted trend from target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to detrend.

Returns

The input features are returned without modification. The target variable y is detrended

Return type tuple of pd.DataFrame, pd.Series

text_featurizer

Module Contents

Classes Summary

TextFeaturizer	Transformer that can automatically featurize text columns using featuretools' nlp_primitives.

Contents

class evalml.pipelines.components.transformers.preprocessing.text_featurizer.**TextFeaturizer**

Transformer that can automatically featurize text columns using featuretools' nlp_primitives.

Since models cannot handle non-numeric data, any text must be broken down into features that provide useful information about that text. This component splits each text column into several informative features: Diversity Score, Mean Characters per Word, Polarity Score, and LSA (Latent Semantic Analysis). Calling transform on this component will replace any text columns in the given dataset with these numeric columns.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Text Featurization Component

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by creating new features using existing text columns

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by creating new features using existing text columns

Parameters

- **X** (*pd.DataFrame*) – The data to transform.
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

text_transformer

Module Contents

Classes Summary

TextTransformer	Base class for all transformers working with text features.

Attributes Summary

logger	

Contents

evalml.pipelines.components.transformers.preprocessing.text_transformer.**logger**

class evalml.pipelines.components.transformers.preprocessing.text_transformer.**TextTransform**

Base class for all transformers working with text features.

Parameters

- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
name	Returns string name of this component

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needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

transform_primitive_components

Module Contents

Classes Summary

EmailFeaturizer	Transformer that can automatically extract features from emails.
URLFeaturizer	Transformer that can automatically extract features from URL.

Contents

class evalml.pipelines.components.transformers.preprocessing.transform_primitive_components

Transformer that can automatically extract features from emails.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Email Featurizer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.preprocessing.transform_primitive_components

Transformer that can automatically extract features from URL.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	URL Featurizer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

Package Contents

Classes Summary

DateTimeFeaturizer	Transformer that can automatically extract features from datetime columns.
DelayedFeatureTransformer	Transformer that delays input features and target variable for time series problems.
DFSTransformer	Featuretools DFS component that generates features for the input features.
DropNullColumns	Transformer to drop features whose percentage of NaN values exceeds a specified threshold.
EmailFeaturizer	Transformer that can automatically extract features from emails.
LogTransformer	Applies a log transformation to the target data.
LSA	Transformer to calculate the Latent Semantic Analysis Values of text input.
PolynomialDetrender	Removes trends from time series by fitting a polynomial to the data.
TextFeaturizer	Transformer that can automatically featurize text columns using featuretools' nlp_primitives.
TextTransformer	Base class for all transformers working with text features.
URLFeaturizer	Transformer that can automatically extract features from URL.

Contents

class evalml.pipelines.components.transformers.preprocessing.**DateTimeFeaturizer**(*features_to_ext*
en-
code_as_catego
date_index=No
ran-
dom_seed=0,
***kwargs*)

Transformer that can automatically extract features from datetime columns.

Parameters

- **features_to_extract** (*list*) – List of features to extract. Valid options include "year", "month", "day_of_week", "hour". Defaults to None.
- **encode_as_categories** (*bool*) – Whether day-of-week and month features should be encoded as pandas "category" dtype. This allows OneHotEncoders to encode these features. Defaults to False.
- **date_index** (*str*) – Name of the column containing the datetime information used to order the data. Ignored.

- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	DateTime Featurization Component

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_feature_names	Gets the categories of each datetime feature.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by creating new features using existing DateTime columns, and then dropping those DateTime columns

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names(*self*)
Gets the categories of each datetime feature.

Returns Dictionary, where each key-value pair is a column name and a dictionary mapping the unique feature values to their integer encoding.

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by creating new features using existing DateTime columns, and then dropping those DateTime columns

Parameters

- **X** (*pd.DataFrame*) – Data to transform

- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.preprocessing.**DelayedFeatureTransformer**(*date_
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***kw*

Transformer that delays input features and target variable for time series problems.

Parameters

- **date_index** (*str*) – Name of the column containing the datetime information used to order the data. Ignored.
- **max_delay** (*int*) – Maximum number of time units to delay each feature. Defaults to 2.
- **delay_features** (*bool*) – Whether to delay the input features. Defaults to True.
- **delay_target** (*bool*) – Whether to delay the target. Defaults to True.
- **gap** (*int*) – The number of time units between when the features are collected and when the target is collected. For example, if you are predicting the next time step's target, gap=1. This is only needed because when gap=0, we need to be sure to start the lagging of the target variable at 1. Defaults to 1.
- **random_seed** (*int*) – Seed for the random number generator. This transformer performs the same regardless of the random seed provided.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Delayed Feature Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the DelayFeatureTransformer.

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Table 465 – continued from previous page

fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Computes the delayed features for all features in X and y.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits the DelayFeatureTransformer.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Computes the delayed features for all features in X and y.

For each feature in X, it will add a column to the output dataframe for each delay in the (inclusive) range [1, max_delay]. The values of each delayed feature are simply the original feature shifted forward in time by the delay amount. For example, a delay of 3 units means that the feature value at row n will be taken from the n-3rd row of that feature

If y is not None, it will also compute the delayed values for the target variable.

Parameters

- **X** (*pd.DataFrame or None*) – Data to transform. None is expected when only the target variable is being used.
- **y** (*pd.Series, or None*) – Target.

Returns Transformed X.

Return type pd.DataFrame

class evalml.pipelines.components.transformers.preprocessing.**DFSTransformer**(*index='index'*, *random_seed=0*, ***kwargs*)

Featuretools DFS component that generates features for the input features.

Parameters

- **index** (*string*) – The name of the column that contains the indices. If no column with this name exists, then featuretools.EntitySet() creates a column with this name to serve as the index column. Defaults to 'index'.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	DFS Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the DFSTransformer Transformer component.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Computes the feature matrix for the input X using featuretools' dfs algorithm.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits the DFSTransformer Transformer component.

Parameters

- **X** (*pd.DataFrame, np.array*) – The input data to transform, of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Computes the feature matrix for the input X using featuretools' dfs algorithm.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data to transform. Has shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – Ignored.

Returns Feature matrix

Return type pd.DataFrame

class evalml.pipelines.components.transformers.preprocessing.**DropNullColumns**(*pct_null_threshold=0.95*, *random_seed=0*, ***kwargs*)
Transformer to drop features whose percentage of NaN values exceeds a specified threshold.

Parameters

- **pct_null_threshold** (*float*) – The percentage of NaN values in an input feature to drop. Must be a value between [0, 1] inclusive. If equal to 0.0, will drop columns with any null values. If equal to 1.0, will drop columns with all null values. Defaults to 0.95.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Drop Null Columns Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by dropping columns that exceed the threshold of null values.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by dropping columns that exceed the threshold of null values.

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.preprocessing.**EmailFeaturizer**(*random_seed=0*, ***kwargs*)
Transformer that can automatically extract features from emails.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Email Featurizer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.preprocessing.**LogTransformer**(*random_seed=0*)
Applies a log transformation to the target data.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	False
modifies_target	True
name	Log Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the LogTransformer.
fit_transform	Log transforms the target variable.
inverse_transform	Inverts the transformation done by the transform method.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Log transforms the target variable.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits the LogTransformer.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Ignored.
- **y** (*pd.Series, optional*) – Ignored.

Returns self

fit_transform(*self*, *X*, *y=None*)
Log transforms the target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to log transform.

Returns

The input features are returned without modification. The target variable y is log transformed.

Return type tuple of pd.DataFrame, pd.Series

inverse_transform(*self*, *y*)
Inverts the transformation done by the transform method.

Arguments: y (pd.Series): Target transformed by this component.

Returns Target without the transformation.

Return type pd.Seriesø

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Log transforms the target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target data to log transform.

Returns

The input features are returned without modification. The target variable y is log transformed.

Return type tuple of pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.preprocessing.**LSA**(*random_seed=0*, ***kwargs*)

Transformer to calculate the Latent Semantic Analysis Values of text input.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	LSA Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by applying the LSA pipeline.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by applying the LSA pipeline.

Parameters

- **X** (*pd.DataFrame*) – The data to transform.

- **y** (*pd.Series, optional*) – Ignored.

Returns

Transformed X. The original column is removed and replaced with two columns of the format *LSA(original_column_name)[feature_number]*, where *feature_number* is 0 or 1.

Return type pd.DataFrame

class evalml.pipelines.components.transformers.preprocessing.**PolynomialDetrender**(*degree=1*, *random_seed=0*, ***kwargs*)

Removes trends from time series by fitting a polynomial to the data.

Parameters

- **degree** (*int*) – Degree for the polynomial. If 1, linear model is fit to the data. If 2, quadratic model is fit, etc. Defaults to 1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "degree": Integer(1, 3)}
model_family	ModelFamily.NONE
modifies_features	False
modifies_target	True
name	Polynomial Detrender

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the PolynomialDetrender.
fit_transform	Removes fitted trend from target variable.
inverse_transform	Adds back fitted trend to target variable.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Removes fitted trend from target variable.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits the PolynomialDetrender.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to detrend.

Returns self

fit_transform(*self*, *X*, *y=None*)
Removes fitted trend from target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to detrend.

Returns

The first element are the input features returned without modification. The second element is the target variable y with the fitted trend removed.

Return type tuple of pd.DataFrame, pd.Series

inverse_transform(*self*, *y*)
Adds back fitted trend to target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable.

Returns

The first element are the input features returned without modification. The second element is the target variable y with the trend added back.

Return type tuple of pd.DataFrame, pd.Series

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Removes fitted trend from target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to detrend.

Returns

The input features are returned without modification. The target variable y is detrended

Return type tuple of pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.preprocessing.**TextFeaturizer**(*random_seed=0*, ***kwargs*)
Transformer that can automatically featurize text columns using featuretools' nlp_primitives.

Since models cannot handle non-numeric data, any text must be broken down into features that provide useful information about that text. This component splits each text column into several informative features: Diversity Score, Mean Characters per Word, Polarity Score, and LSA (Latent Semantic Analysis). Calling transform on this component will replace any text columns in the given dataset with these numeric columns.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Text Featurization Component

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by creating new features using existing text columns

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)

Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform

- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by creating new features using existing text columns

Parameters

- **X** (*pd.DataFrame*) – The data to transform.
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.preprocessing.**TextTransformer**(*component_obj=None*, *random_seed=0*, ***kwargs*)

Base class for all transformers working with text features.

Parameters

- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.preprocessing.**URLFeaturizer**(*random_seed=0*, ***kwargs*)
Transformer that can automatically extract features from URL.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	URL Featurizer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

samplers

Submodules

base_sampler

Module Contents

Classes Summary

BaseOversampler	Base Oversampler component. Used as the base class of all imbalance-learn oversampler components.
BaseSampler	Base Sampler component. Used as the base class of all sampler components.

Contents

class evalml.pipelines.components.transformers.samplers.base_sampler.**BaseOversampler**(*sampler*, *sampling_ratio*, *sampling_ratio_dict*, *k_neighbors_default*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Base Oversampler component. Used as the base class of all imbalance-learn oversampler components.

Parameters

- **sampler** (*obj*) – Sampler object to use.
- **sampling_ratio** (*float*) – This is the goal ratio of the minority to majority class, with range (0, 1]. A value of 0.25 means we want a 1:4 ratio of the minority to majority class after oversampling. We will create the a sampling dictionary using this ratio, with the keys corresponding to the class and the values responding to the number of samples. Defaults to 0.25.
- **sampling_ratio_dict** (*dict*) – A dictionary specifying the desired balanced ratio for each target value. For instance, in a binary case where class 1 is the minority, we could specify: *sampling_ratio_dict={0: 0.5, 1: 1}*, which means we would undersample class 0 to have twice the number of samples as class 1 (minority:majority ratio = 0.5), and don't sample class 1. Overrides sampling_ratio if provided. Defaults to None.
- **k_neighbors_default** (*int*) – The number of nearest neighbors used to construct synthetic samples. This is the default value used, but the actual k_neighbors value might be smaller if there are less samples. Defaults to 5.
- **n_jobs** (*int*) – The number of CPU cores to use. Defaults to -1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.

- **y** (*pd.Series*) – Target.

Returns self

fit_transform(*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.samplers.base_sampler.**BaseSampler**(*parameters=N*
com-
po-
nent_obj=Nor
ran-
dom_seed=0,
***kwargs*)

Base Sampler component. Used as the base class of all sampler components.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name (*cls*)
Returns string name of this component

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

oversamplers

Module Contents

Classes Summary

SMOTENCOversampler	SMOTENC Oversampler component. Uses SMOTENC to generate synthetic samples. Works on a mix of numerical and categorical columns.
SMOTENOversampler	SMOTEN Oversampler component. Uses SMOTEN to generate synthetic samples. Works for purely categorical datasets.
SMOTEOversampler	SMOTE Oversampler component. Works on numerical datasets only. This component is only run during training and not during predict.

Contents

class evalml.pipelines.components.transformers.samplers.oversamplers.**SMOTENCOversampler**(*sam*
k_n
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SMOTENC Oversampler component. Uses SMOTENC to generate synthetic samples. Works on a mix of numerical and categorical columns. Input data must be Woodwork type, and this component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – This is the goal ratio of the minority to majority class, with range (0, 1]. A value of 0.25 means we want a 1:4 ratio of the minority to majority class after oversampling. We will create the a sampling dictionary using this ratio, with the keys corresponding to the class and the values responding to the number of samples. Defaults to 0.25.
- **k_neighbors_default** (*int*) – The number of nearest neighbors used to construct synthetic samples. This is the default value used, but the actual k_neighbors value might be smaller if there are less samples. Defaults to 5.
- **n_jobs** (*int*) – The number of CPU cores to use. Defaults to -1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	SMOTENC Oversampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform(*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.samplers.oversamplers.**SMOTENOversampler**(*samp*
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SMOTEN Oversampler component. Uses SMOTEN to generate synthetic samples. Works for purely categorical

datasets. This component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – This is the goal ratio of the minority to majority class, with range (0, 1]. A value of 0.25 means we want a 1:4 ratio of the minority to majority class after oversampling. We will create the a sampling dictionary using this ratio, with the keys corresponding to the class and the values responding to the number of samples. Defaults to 0.25.
- **k_neighbors_default** (*int*) – The number of nearest neighbors used to construct synthetic samples. This is the default value used, but the actual k_neighbors value might be smaller if there are less samples. Defaults to 5.
- **n_jobs** (*int*) – The number of CPU cores to use. Defaults to -1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	SMOTEN Oversampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform(*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.samplers.oversamplers.**SMOTEOversampler**(*sampli*
k_neig
n_jobs

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***kwa*

SMOTE Oversampler component. Works on numerical datasets only. This component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – This is the goal ratio of the minority to majority class, with range (0, 1]. A value of 0.25 means we want a 1:4 ratio of the minority to majority class after oversampling. We will create the a sampling dictionary using this ratio, with the keys corresponding to the class and the values responding to the number of samples. Defaults to 0.25.
- **k_neighbors_default** (*int*) – The number of nearest neighbors used to construct synthetic samples. This is the default value used, but the actual k_neighbors value might be smaller if there are less samples. Defaults to 5.
- **n_jobs** (*int*) – The number of CPU cores to use. Defaults to -1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	SMOTE Oversampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X

continues on next page

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load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

undersampler

Module Contents

Classes Summary

Undersampler	Initializes an undersampling transformer to downsample the majority classes in the dataset.

Contents

class evalml.pipelines.components.transformers.samplers.undersampler.**Undersampler**(*sampling_ra*
sam-
*pling_ratio_*
min_samples
min_percent
ran-
dom_seed=0
***kwargs*)

Initializes an undersampling transformer to downsample the majority classes in the dataset.

This component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – The smallest minority:majority ratio that is accepted as 'balanced'. For instance, a 1:4 ratio would be represented as 0.25, while a 1:1 ratio is 1.0. Must be between 0 and 1, inclusive. Defaults to 0.25.
- **sampling_ratio_dict** (*dict*) – A dictionary specifying the desired balanced ratio for each target value. For instance, in a binary case where class 1 is the minority, we could specify: *sampling_ratio_dict={0: 0.5, 1: 1}*, which means we would undersample class 0 to have twice the number of samples as class 1 (minority:majority ratio = 0.5), and don't sample class 1. Overrides sampling_ratio if provided. Defaults to None.
- **min_samples** (*int*) – The minimum number of samples that we must have for any class, pre or post sampling. If a class must be downsampled, it will not be downsampled past this value. To determine severe imbalance, the minority class must occur less often than this and must have a class ratio below min_percentage. Must be greater than 0. Defaults to 100.
- **min_percentage** (*float*) – The minimum percentage of the minimum class to total dataset that we tolerate, as long as it is above min_samples. If min_percentage and min_samples are not met, treat this as severely imbalanced, and we will not resample the data. Must be between 0 and 0.5, inclusive. Defaults to 0.1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	Undersampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform(*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file

- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

Package Contents

Classes Summary

SMOTENCOversampler	SMOTENC Oversampler component. Uses SMOTENC to generate synthetic samples. Works on a mix of numerical and categorical columns.
SMOTENOversampler	SMOTEN Oversampler component. Uses SMOTEN to generate synthetic samples. Works for purely categorical datasets.
SMOTEOversampler	SMOTE Oversampler component. Works on numerical datasets only. This component is only run during training and not during predict.
Undersampler	Initializes an undersampling transformer to downsample the majority classes in the dataset.

Contents

class evalml.pipelines.components.transformers.samplers.**SMOTENCOversampler**(*sampling_ratio=0.25*, *k_neighbors_default=5*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

SMOTENC Oversampler component. Uses SMOTENC to generate synthetic samples. Works on a mix of numerical and categorical columns. Input data must be Woodwork type, and this component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – This is the goal ratio of the minority to majority class, with range (0, 1]. A value of 0.25 means we want a 1:4 ratio of the minority to majority class after oversampling. We will create the a sampling dictionary using this ratio, with the keys corresponding to the class and the values responding to the number of samples. Defaults to 0.25.

- **k_neighbors_default** (*int*) – The number of nearest neighbors used to construct synthetic samples. This is the default value used, but the actual k_neighbors value might be smaller if there are less samples. Defaults to 5.
- **n_jobs** (*int*) – The number of CPU cores to use. Defaults to -1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	SMOTENC Oversampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform(*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.samplers.**SMOTENOversampler**(*sampling_ratio=0.25*, *k_neighbors_default=5*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

SMOTEN Oversampler component. Uses SMOTEN to generate synthetic samples. Works for purely categorical datasets. This component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – This is the goal ratio of the minority to majority class, with range (0, 1]. A value of 0.25 means we want a 1:4 ratio of the minority to majority class after oversampling. We will create the a sampling dictionary using this ratio, with the keys corresponding to the class and the values responding to the number of samples. Defaults to 0.25.
- **k_neighbors_default** (*int*) – The number of nearest neighbors used to construct synthetic samples. This is the default value used, but the actual k_neighbors value might be smaller if there are less samples. Defaults to 5.
- **n_jobs** (*int*) – The number of CPU cores to use. Defaults to -1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	SMOTEN Oversampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path

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transform	Transforms the input data by sampling the data.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.samplers.**SMOTEOversampler**(*sampling_ratio=0.25*, *k_neighbors_default=5*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
SMOTE Oversampler component. Works on numerical datasets only. This component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – This is the goal ratio of the minority to majority class, with range (0, 1]. A value of 0.25 means we want a 1:4 ratio of the minority to majority class after oversampling. We will create the a sampling dictionary using this ratio, with the keys corresponding to the class and the values responding to the number of samples. Defaults to 0.25.
- **k_neighbors_default** (*int*) – The number of nearest neighbors used to construct synthetic samples. This is the default value used, but the actual k_neighbors value might be smaller if there are less samples. Defaults to 5.
- **n_jobs** (*int*) – The number of CPU cores to use. Defaults to -1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	SMOTE Oversampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform(*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.samplers.**Undersampler**(*sampling_ratio=0.25*, *sampling_ratio_dict=None*, *min_samples=100*, *min_percentage=0.1*, *random_seed=0*, ***kwargs*)
Initializes an undersampling transformer to downsample the majority classes in the dataset.

This component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – The smallest minority:majority ratio that is accepted as 'balanced'. For instance, a 1:4 ratio would be represented as 0.25, while a 1:1 ratio is 1.0. Must be between 0 and 1, inclusive. Defaults to 0.25.
- **sampling_ratio_dict** (*dict*) – A dictionary specifying the desired balanced ratio for each target value. For instance, in a binary case where class 1 is the minority, we could specify: *sampling_ratio_dict={0: 0.5, 1: 1}*, which means we would undersample class 0 to have twice the number of samples as class 1 (minority:majority ratio = 0.5), and don't sample class 1. Overrides sampling_ratio if provided. Defaults to None.
- **min_samples** (*int*) – The minimum number of samples that we must have for any class, pre or post sampling. If a class must be downsampled, it will not be downsampled past this value. To determine severe imbalance, the minority class must occur less often than this and must have a class ratio below min_percentage. Must be greater than 0. Defaults to 100.
- **min_percentage** (*float*) – The minimum percentage of the minimum class to total dataset that we tolerate, as long as it is above min_samples. If min_percentage and min_samples are not met, treat this as severely imbalanced, and we will not resample the data. Must be between 0 and 0.5, inclusive. Defaults to 0.1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	Undersampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform(*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

scalers

Submodules

standard_scaler

Module Contents

Classes Summary

StandardScaler	A transformer that standardizes input features by removing the mean and scaling to unit variance.

Contents

class evalml.pipelines.components.transformers.scalers.standard_scaler.**StandardScaler**(*rando*
***kwa*

A transformer that standardizes input features by removing the mean and scaling to unit variance.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Standard Scaler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform

- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

Package Contents

Classes Summary

StandardScaler	A transformer that standardizes input features by removing the mean and scaling to unit variance.

Contents

class evalml.pipelines.components.transformers.scalers.**StandardScaler**(*random_seed=0*, ***kwargs*)

A transformer that standardizes input features by removing the mean and scaling to unit variance.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Standard Scaler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

Submodules

column_selectors

Module Contents

Classes Summary

ColumnSelector	Initalizes an transformer that drops specified columns in input data.
DropColumns	Drops specified columns in input data.
SelectByType	Selects columns by specified Woodwork logical type or semantic tag in input data.
SelectColumns	Selects specified columns in input data.

Contents

class evalml.pipelines.components.transformers.column_selectors.**ColumnSelector**(*columns=None*, *random_seed=0*, ***kwargs*)

Initalizes an transformer that drops specified columns in input data.

Parameters

- **columns** (*list (string)*) – List of column names, used to determine which columns to select.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the transformer by checking if column names are present in the dataset.

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fit_transform	Fits on X and transforms X
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits the transformer by checking if column names are present in the dataset.

Parameters

- **X** (*pd.DataFrame*) – Data to check.
- **y** (*pd.Series, optional*) – Targets.

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.column_selectors.**DropColumns**(*columns=None*, *random_seed=0*, ***kwargs*)

Drops specified columns in input data.

Parameters

- **columns** (*list (string)*) – List of column names, used to determine which columns to drop.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Drop Columns Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the transformer by checking if column names are present in the dataset.
fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by dropping columns.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits the transformer by checking if column names are present in the dataset.

Parameters

- **X** (*pd.DataFrame*) – Data to check.
- **y** (*pd.Series, optional*) – Targets.

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by dropping columns.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Targets.

Returns Transformed X.

Return type pd.DataFrame

class evalml.pipelines.components.transformers.column_selectors.**SelectByType**(*column_types=None*, *random_seed=0*, ***kwargs*)

Selects columns by specified Woodwork logical type or semantic tag in input data.

Parameters

- **column_types** (*string, ww.LogicalType, list(string), list(ww.LogicalType)*) – List of Woodwork types or tags, used to determine which columns to select.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Select Columns By Type Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the transformer by checking if column names are present in the dataset.
fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits the transformer by checking if column names are present in the dataset.

Parameters

- **X** (*pd.DataFrame*) – Data to check.
- **y** (*pd.Series, optional*) – Targets.

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.column_selectors.**SelectColumns**(*columns=None*, *random_seed=0*, ***kwargs*)

Selects specified columns in input data.

Parameters

- **columns** (*list(string)*) – List of column names, used to determine which columns to select.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Select Columns Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the transformer by checking if column names are present in the dataset.
fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by selecting columns.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits the transformer by checking if column names are present in the dataset.

Parameters

- **X** (*pd.DataFrame*) – Data to check.
- **y** (*pd.Series, optional*) – Targets.

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by selecting columns.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Targets.

Returns Transformed X.

Return type pd.DataFrame

transformer

Module Contents

Classes Summary

TargetTransformer	A component that transforms the target.
Transformer	A component that may or may not need fitting that transforms data.

Contents

class evalml.pipelines.components.transformers.transformer.**TargetTransformer**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)

A component that transforms the target.

Attributes

model_family	ModelFamily.NONE
modifies_features	False
modifies_target	True

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
inverse_transform	Inverts the transformation done by the transform method.
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

abstract inverse_transform(*self*, *y*)
Inverts the transformation done by the transform method.

Arguments: y (pd.Series): Target transformed by this component.

Returns Target without the transformation.

Return type pd.Seriesø

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.

- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.transformer.**Transformer**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)

A component that may or may not need fitting that transforms data. These components are used before an estimator.

To implement a new Transformer, define your own class which is a subclass of Transformer, including a name and a list of acceptable ranges for any parameters to be tuned during the automl search (hyperparameters). Define an *__init__* method which sets up any necessary state and objects. Make sure your *__init__* only uses standard keyword arguments and calls *super().__init__()* with a parameters dict. You may also override the *fit*, *transform*, *fit_transform* and other methods in this class if appropriate.

To see some examples, check out the definitions of any Transformer component.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name (*cls*)
Returns string name of this component

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform,

or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

Package Contents

Classes Summary

DateTimeFeaturizer	Transformer that can automatically extract features from datetime columns.
DelayedFeatureTransformer	Transformer that delays input features and target variable for time series problems.
DFSTransformer	Featuretools DFS component that generates features for the input features.
DropColumns	Drops specified columns in input data.
DropNullColumns	Transformer to drop features whose percentage of NaN values exceeds a specified threshold.
EmailFeaturizer	Transformer that can automatically extract features from emails.
FeatureSelector	Selects top features based on importance weights.
Imputer	Imputes missing data according to a specified imputation strategy.
LinearDiscriminantAnalysis	Reduces the number of features by using Linear Discriminant Analysis.
LogTransformer	Applies a log transformation to the target data.
LSA	Transformer to calculate the Latent Semantic Analysis Values of text input.
OneHotEncoder	A transformer that encodes categorical features in a one-hot numeric array.

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PCA	Reduces the number of features by using Principal Component Analysis (PCA).
PerColumnImputer	Imputes missing data according to a specified imputation strategy per column.
PolynomialDetrender	Removes trends from time series by fitting a polynomial to the data.
RFClassifierSelectFromModel	Selects top features based on importance weights using a Random Forest classifier.
RFRegressorSelectFromModel	Selects top features based on importance weights using a Random Forest regressor.
SelectByType	Selects columns by specified Woodwork logical type or semantic tag in input data.
SelectColumns	Selects specified columns in input data.
SimpleImputer	Imputes missing data according to a specified imputation strategy.
SMOTENCOversampler	SMOTENC Oversampler component. Uses SMOTENC to generate synthetic samples. Works on a mix of numerical and categorical columns.
SMOTENOversampler	SMOTEN Oversampler component. Uses SMOTEN to generate synthetic samples. Works for purely categorical datasets.
SMOTEOversampler	SMOTE Oversampler component. Works on numerical datasets only. This component is only run during training and not during predict.
StandardScaler	A transformer that standardizes input features by removing the mean and scaling to unit variance.
TargetEncoder	A transformer that encodes categorical features into target encodings.
TargetImputer	Imputes missing target data according to a specified imputation strategy.
TextFeaturizer	Transformer that can automatically featurize text columns using featuretools' nlp_primitives.
Transformer	A component that may or may not need fitting that transforms data.
Undersampler	Initializes an undersampling transformer to downsample the majority classes in the dataset.
URLFeaturizer	Transformer that can automatically extract features from URL.

Contents

class evalml.pipelines.components.transformers.**DateTimeFeaturizer**(*features_to_extract=None*, *encode_as_categories=False*, *date_index=None*, *random_seed=0*, ***kwargs*)

Transformer that can automatically extract features from datetime columns.

Parameters

- **features_to_extract** (*list*) – List of features to extract. Valid options include "year", "month", "day_of_week", "hour". Defaults to None.
- **encode_as_categories** (*bool*) – Whether day-of-week and month features should be encoded as pandas "category" dtype. This allows OneHotEncoders to encode these features. Defaults to False.
- **date_index** (*str*) – Name of the column containing the datetime information used to order the data. Ignored.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	DateTime Featurization Component

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_feature_names	Gets the categories of each datetime feature.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by creating new features using existing DateTime columns, and then dropping those DateTime columns

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names (*self*)
Gets the categories of each datetime feature.

Returns Dictionary, where each key-value pair is a column name and a dictionary mapping the unique feature values to their integer encoding.

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file

- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)

Transforms data X by creating new features using existing DateTime columns, and then dropping those DateTime columns

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**DelayedFeatureTransformer**(*date_index=None*, *max_delay=2*, *delay_features=True*, *delay_target=True*, *gap=1*, *random_seed=0*, ***kwargs*)

Transformer that delays input features and target variable for time series problems.

Parameters

- **date_index** (*str*) – Name of the column containing the datetime information used to order the data. Ignored.
- **max_delay** (*int*) – Maximum number of time units to delay each feature. Defaults to 2.
- **delay_features** (*bool*) – Whether to delay the input features. Defaults to True.
- **delay_target** (*bool*) – Whether to delay the target. Defaults to True.
- **gap** (*int*) – The number of time units between when the features are collected and when the target is collected. For example, if you are predicting the next time step's target, gap=1. This is only needed because when gap=0, we need to be sure to start the lagging of the target variable at 1. Defaults to 1.
- **random_seed** (*int*) – Seed for the random number generator. This transformer performs the same regardless of the random seed provided.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Delayed Feature Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the DelayFeatureTransformer.
fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Computes the delayed features for all features in X and y.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits the DelayFeatureTransformer.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Computes the delayed features for all features in X and y.

For each feature in X, it will add a column to the output dataframe for each delay in the (inclusive) range [1, max_delay]. The values of each delayed feature are simply the original feature shifted forward in time by the delay amount. For example, a delay of 3 units means that the feature value at row n will be taken from the n-3rd row of that feature

If y is not None, it will also compute the delayed values for the target variable.

Parameters

- **X** (*pd.DataFrame or None*) – Data to transform. None is expected when only the target variable is being used.
- **y** (*pd.Series, or None*) – Target.

Returns Transformed X.

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**DFSTransformer**(*index='index'*, *random_seed=0*, ***kwargs*)
Featuretools DFS component that generates features for the input features.

Parameters

- **index** (*string*) – The name of the column that contains the indices. If no column with this name exists, then featuretools.EntitySet() creates a column with this name to serve as the index column. Defaults to 'index'.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	DFS Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the DFSTransformer Transformer component.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Computes the feature matrix for the input X using featuretools' dfs algorithm.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits the DFSTransformer Transformer component.

Parameters

- **X** (*pd.DataFrame, np.array*) – The input data to transform, of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Computes the feature matrix for the input X using featuretools' dfs algorithm.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data to transform. Has shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – Ignored.

Returns Feature matrix

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**DropColumns**(*columns=None*, *random_seed=0*, ***kwargs*)
Drops specified columns in input data.

Parameters

- **columns** (*list (string)*) – List of column names, used to determine which columns to drop.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Drop Columns Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the transformer by checking if column names are present in the dataset.
fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by dropping columns.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits the transformer by checking if column names are present in the dataset.

Parameters

- **X** (*pd.DataFrame*) – Data to check.
- **y** (*pd.Series, optional*) – Targets.

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by dropping columns.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Targets.

Returns Transformed X.

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**DropNullColumns**(*pct_null_threshold=1.0*, *random_seed=0*, ***kwargs*)
Transformer to drop features whose percentage of NaN values exceeds a specified threshold.

Parameters

- **pct_null_threshold** (*float*) – The percentage of NaN values in an input feature to drop. Must be a value between [0, 1] inclusive. If equal to 0.0, will drop columns with any null values. If equal to 1.0, will drop columns with all null values. Defaults to 0.95.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Drop Null Columns Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by dropping columns that exceed the threshold of null values.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by dropping columns that exceed the threshold of null values.

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**EmailFeaturizer**(*random_seed=0*, ***kwargs*)

Transformer that can automatically extract features from emails.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Email Featurizer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**FeatureSelector**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)

Selects top features based on importance weights.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names(*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)

Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)

Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**Imputer**(*categorical_impute_strategy='most_frequent'*, *categorical_fill_value=None*, *numeric_impute_strategy='mean'*, *numeric_fill_value=None*, *random_seed=0*, ***kwargs*)

Imputes missing data according to a specified imputation strategy.

Parameters

- **categorical_impute_strategy** (*string*) – Impute strategy to use for string, object, boolean, categorical dtypes. Valid values include “most_frequent” and “constant”.
- **numeric_impute_strategy** (*string*) – Impute strategy to use for numeric columns. Valid values include “mean”, “median”, “most_frequent”, and “constant”.
- **categorical_fill_value** (*string*) – When categorical_impute_strategy == “constant”, fill_value is used to replace missing data. The default value of None will fill with the string “missing_value”.
- **numeric_fill_value** (*int, float*) – When numeric_impute_strategy == “constant”, fill_value is used to replace missing data. The default value of None will fill with 0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “categorical_impute_strategy”: [“most_frequent”], “numeric_impute_strategy”: [“mean”, “median”, “most_frequent”],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputer to data. 'None' values are converted to np.nan before imputation and are
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by imputing missing values. 'None' values are converted to np.nan before imputation and are

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)

Fits imputer to data. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)

Transforms data X by imputing missing values. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**LinearDiscriminantAnalysis**(*n_components=None*, *random_seed=0*, ***kwargs*)

Reduces the number of features by using Linear Discriminant Analysis.

Parameters

- **n_components** (*int*) – The number of features to maintain after computation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Linear Discriminant Analysis Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**LogTransformer**(*random_seed=0*)
Applies a log transformation to the target data.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	False
modifies_target	True
name	Log Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the LogTransformer.
fit_transform	Log transforms the target variable.
inverse_transform	Inverts the transformation done by the transform method.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Log transforms the target variable.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits the LogTransformer.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Ignored.
- **y** (*pd.Series, optional*) – Ignored.

Returns self

fit_transform(*self*, *X*, *y=None*)
Log transforms the target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to log transform.

Returns

The input features are returned without modification. The target variable y is log transformed.

Return type tuple of pd.DataFrame, pd.Series

inverse_transform(*self*, *y*)
Inverts the transformation done by the transform method.

Arguments: y (pd.Series): Target transformed by this component.

Returns Target without the transformation.

Return type pd.Seriesø

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Log transforms the target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target data to log transform.

Returns

The input features are returned without modification. The target variable y is log transformed.

Return type tuple of pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.**LSA**(*random_seed=0*, ***kwargs*)

Transformer to calculate the Latent Semantic Analysis Values of text input.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	LSA Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by applying the LSA pipeline.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by applying the LSA pipeline.

Parameters

- **X** (*pd.DataFrame*) – The data to transform.

- **y** (*pd.Series, optional*) – Ignored.

Returns

Transformed X. The original column is removed and replaced with two columns of the format *LSA(original_column_name)[feature_number]*, where *feature_number* is 0 or 1.

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**OneHotEncoder**(*top_n=10*, *features_to_encode=None*, *categories=None*, *drop='if_binary'*, *handle_unknown='ignore'*, *handle_missing='error'*, *random_seed=0*, ***kwargs*)

A transformer that encodes categorical features in a one-hot numeric array.

Parameters

- **top_n** (*int*) – Number of categories per column to encode. If None, all categories will be encoded. Otherwise, the *n* most frequent will be encoded and all others will be dropped. Defaults to 10.
- **features_to_encode** (*list[str]*) – List of columns to encode. All other columns will remain untouched. If None, all appropriate columns will be encoded. Defaults to None.
- **categories** (*list*) – A two dimensional list of categories, where *categories[i]* is a list of the categories for the column at index *i*. This can also be *None*, or *"auto"* if *top_n* is not None. Defaults to None.
- **drop** (*string, list*) – Method ("first" or "if_binary") to use to drop one category per feature. Can also be a list specifying which categories to drop for each feature. Defaults to 'if_binary'.
- **handle_unknown** (*string*) – Whether to ignore or error for unknown categories for a feature encountered during *fit* or *transform*. If either *top_n* or *categories* is used to limit the number of categories per column, this must be "ignore". Defaults to "ignore".
- **handle_missing** (*string*) – Options for how to handle missing (NaN) values encountered during *fit* or *transform*. If this is set to "as_category" and NaN values are within the *n* most frequent, "nan" values will be encoded as their own column. If this is set to "error", any missing values encountered will raise an error. Defaults to "error".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	One Hot Encoder

Methods

categories	Returns a list of the unique categories to be encoded for the particular feature, in order.
clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_feature_names	Return feature names for the categorical features after fitting.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	One-hot encode the input data.

categories (*self*, *feature_name*)
Returns a list of the unique categories to be encoded for the particular feature, in order.

Parameters **feature_name** (*str*) – the name of any feature provided to one-hot encoder during fit

Returns the unique categories, in the same dtype as they were provided during fit

Return type np.ndarray

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names(*self*)
Return feature names for the categorical features after fitting.

Feature names are formatted as {column name}_{category name}. In the event of a duplicate name, an integer will be added at the end of the feature name to distinguish it.

For example, consider a dataframe with a column called "A" and category "x_y" and another column called "A_x" with "y". In this example, the feature names would be "A_x_y" and "A_x_y_1".

Returns The feature names after encoding, provided in the same order as input_features.

Return type np.ndarray

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
One-hot encode the input data.

Parameters

- **X** (*pd.DataFrame*) – Features to one-hot encode.
- **y** (*pd.Series*) – Ignored.

Returns Transformed data, where each categorical feature has been encoded into numerical columns using one-hot encoding.

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**PCA**(*variance=0.95*, *n_components=None*, *random_seed=0*, ***kwargs*)

Reduces the number of features by using Principal Component Analysis (PCA).

Parameters

- **variance** (*float*) – The percentage of the original data variance that should be preserved when reducing the number of features. Defaults to 0.95.
- **n_components** (*int*) – The number of features to maintain after computing SVD. Defaults to None, but will override variance variable if set.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	Real(0.25, 1)}:type: {"variance"
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	PCA Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**PerColumnImputer**(*impute_strategies=None*, *default_impute_strategy='most_frequent'*, *random_seed=0*, ***kwargs*)

Imputes missing data according to a specified imputation strategy per column.

Parameters

- **impute_strategies** (*dict*) – Column and {"impute_strategy": strategy, "fill_value":value} pairings. Valid values for impute strategy include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types. Defaults to None, which uses "most_frequent" for all columns. When impute_strategy == "constant", fill_value is used to replace missing data. When None, uses 0 when imputing numerical data and "missing_value" for strings or object data types.
- **default_impute_strategy** (*str*) – Impute strategy to fall back on when none is provided for a certain column. Valid values include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types. Defaults to "most_frequent".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Per Column Imputer

Methods

clone	Constructs a new component with the same parameters and random state.

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default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputers on input data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by imputing missing values.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits imputers on input data

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features] to fit.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]. Ignored.

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input data by imputing missing values.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features] to transform.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**PolynomialDetrender**(*degree=1*, *random_seed=0*, ***kwargs*)
Removes trends from time series by fitting a polynomial to the data.

Parameters

- **degree** (*int*) – Degree for the polynomial. If 1, linear model is fit to the data. If 2, quadratic model is fit, etc. Defaults to 1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "degree": Integer(1, 3)}
model_family	ModelFamily.NONE
modifies_features	False
modifies_target	True
name	Polynomial Detrender

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the PolynomialDetrender.
fit_transform	Removes fitted trend from target variable.
inverse_transform	Adds back fitted trend to target variable.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Removes fitted trend from target variable.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits the PolynomialDetrender.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to detrend.

Returns self

fit_transform(*self*, *X*, *y=None*)
Removes fitted trend from target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to detrend.

Returns

The first element are the input features returned without modification. The second element is the target variable y with the fitted trend removed.

Return type tuple of pd.DataFrame, pd.Series

inverse_transform(*self*, *y*)
Adds back fitted trend to target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable.

Returns

The first element are the input features returned without modification. The second element is the target variable y with the trend added back.

Return type tuple of pd.DataFrame, pd.Series

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Removes fitted trend from target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to detrend.

Returns

The input features are returned without modification. The target variable y is detrended

Return type tuple of pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.**RFClassifierSelectFromModel**(*number_features=None*, *n_estimators=10*, *max_depth=None*, *percent_features=0.5*, *threshold=-np.inf*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Selects top features based on importance weights using a Random Forest classifier.

Parameters

- **number_features** (*int*) – The maximum number of features to select. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5. Defaults to None.
- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **percent_features** (*float*) – Percentage of features to use. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5.
- **threshold** (*string or float*) – The threshold value to use for feature selection. Features whose importance is greater or equal are kept while the others are discarded. If "median", then the threshold value is the median of the feature importances. A scaling factor (e.g., "1.25*mean") may also be used. Defaults to -np.inf.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “percent_features”: Real(0.01, 1), “threshold”: [“mean”, -np.inf],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	RF Classifier Select From Model

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names (*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)
Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.

- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**RFRegressorSelectFromModel**(*number_features=None*, *n_estimators=10*, *max_depth=None*, *percent_features=0.5*, *threshold=-np.inf*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Selects top features based on importance weights using a Random Forest regressor.

Parameters

- **number_features** (*int*) – The maximum number of features to select. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5. Defaults to None.
- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **percent_features** (*float*) – Percentage of features to use. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5.
- **threshold** (*string or float*) – The threshold value to use for feature selection. Features whose importance is greater or equal are kept while the others are discarded. If "median", then the threshold value is the median of the feature importances. A scaling factor (e.g., "1.25*mean") may also be used. Defaults to -np.inf.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "percent_features": Real(0.01, 1), "threshold": ["mean", -np.inf],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	RF Regressor Select From Model

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names(*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**SelectByType**(*column_types=None*, *random_seed=0*, ***kwargs*)
Selects columns by specified Woodwork logical type or semantic tag in input data.

Parameters

- **column_types** (*string, ww.LogicalType, list(string), list(ww.LogicalType)*) – List of Woodwork types or tags, used to determine which columns to select.

- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Select Columns By Type Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the transformer by checking if column names are present in the dataset.
fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits the transformer by checking if column names are present in the dataset.

Parameters

- **X** (*pd.DataFrame*) – Data to check.
- **y** (*pd.Series, optional*) – Targets.

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**SelectColumns** (*columns=None*, *random_seed=0*, ***kwargs*)
Selects specified columns in input data.

Parameters

- **columns** (*list (string)*) – List of column names, used to determine which columns to select.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Select Columns Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the transformer by checking if column names are present in the dataset.
fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by selecting columns.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)

Fits the transformer by checking if column names are present in the dataset.

Parameters

- **X** (*pd.DataFrame*) – Data to check.
- **y** (*pd.Series, optional*) – Targets.

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by selecting columns.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Targets.

Returns Transformed X.

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**SimpleImputer**(*impute_strategy='most_frequent'*, *fill_value=None*, *random_seed=0*, ***kwargs*)
Imputes missing data according to a specified imputation strategy.

Parameters

- **impute_strategy** (*string*) – Impute strategy to use. Valid values include “mean”, “median”, “most_frequent”, “constant” for numerical data, and “most_frequent”, “constant” for object data types.

- **fill_value** (*string*) – When impute_strategy == "constant", fill_value is used to replace missing data. Defaults to 0 when imputing numerical data and "missing_value" for strings or object data types.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "impute_strategy": ["mean", "median", "most_frequent"]}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Simple Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputer to data. 'None' values are converted to np.nan before imputation and are
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input by imputing missing values. 'None' and np.nan values are treated as the same.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)

Fits imputer to data. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)

Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)

Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)

Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)

Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)

Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)

Transforms input by imputing missing values. 'None' and np.nan values are treated as the same.

Parameters

- **X** (*pd.DataFrame*) – Data to transform

- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**SMOTENCOversampler**(*sampling_ratio=0.25*, *k_neighbors_default=5*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

SMOTENC Oversampler component. Uses SMOTENC to generate synthetic samples. Works on a mix of numerical and categorical columns. Input data must be Woodwork type, and this component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – This is the goal ratio of the minority to majority class, with range (0, 1]. A value of 0.25 means we want a 1:4 ratio of the minority to majority class after oversampling. We will create the a sampling dictionary using this ratio, with the keys corresponding to the class and the values responding to the number of samples. Defaults to 0.25.
- **k_neighbors_default** (*int*) – The number of nearest neighbors used to construct synthetic samples. This is the default value used, but the actual k_neighbors value might be smaller if there are less samples. Defaults to 5.
- **n_jobs** (*int*) – The number of CPU cores to use. Defaults to -1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	SMOTENC Oversampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before

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parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.**SMOTENOversampler**(*sampling_ratio=0.25*, *k_neighbors_default=5*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
SMOTEN Oversampler component. Uses SMOTEN to generate synthetic samples. Works for purely categorical datasets. This component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – This is the goal ratio of the minority to majority class, with range (0, 1]. A value of 0.25 means we want a 1:4 ratio of the minority to majority class after oversampling. We will create the a sampling dictionary using this ratio, with the keys corresponding to the class and the values responding to the number of samples. Defaults to 0.25.
- **k_neighbors_default** (*int*) – The number of nearest neighbors used to construct synthetic samples. This is the default value used, but the actual k_neighbors value might be smaller if there are less samples. Defaults to 5.
- **n_jobs** (*int*) – The number of CPU cores to use. Defaults to -1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	SMOTEN Oversampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform(*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.**SMOTEOversampler**(*sampling_ratio=0.25*, *k_neighbors_default=5*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
SMOTE Oversampler component. Works on numerical datasets only. This component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – This is the goal ratio of the minority to majority class, with range (0, 1]. A value of 0.25 means we want a 1:4 ratio of the minority to majority class after oversampling. We will create the a sampling dictionary using this ratio, with the keys corresponding to the class and the values responding to the number of samples. Defaults to 0.25.
- **k_neighbors_default** (*int*) – The number of nearest neighbors used to construct synthetic samples. This is the default value used, but the actual k_neighbors value might be smaller if there are less samples. Defaults to 5.
- **n_jobs** (*int*) – The number of CPU cores to use. Defaults to -1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	SMOTE Oversampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform(*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.**StandardScaler**(*random_seed=0*, ***kwargs*)

A transformer that standardizes input features by removing the mean and scaling to unit variance.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Standard Scaler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**TargetEncoder**(*cols=None*, *smoothing=1.0*, *handle_unknown='value'*, *handle_missing='value'*, *random_seed=0*, ***kwargs*)

A transformer that encodes categorical features into target encodings.

Parameters

- **cols** (*list*) – Columns to encode. If None, all string columns will be encoded, otherwise only the columns provided will be encoded. Defaults to None
- **smoothing** (*float*) – The smoothing factor to apply. The larger this value is, the more influence the expected target value has on the resulting target encodings. Must be strictly larger than 0. Defaults to 1.0
- **handle_unknown** (*string*) – Determines how to handle unknown categories for a feature encountered. Options are 'value', 'error', nd 'return_nan'. Defaults to 'value', which replaces with the target mean
- **handle_missing** (*string*) – Determines how to handle missing values encountered during *fit* or *transform*. Options are 'value', 'error', and 'return_nan'. Defaults to 'value', which replaces with the target mean
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Target Encoder

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X

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get_feature_names	Return feature names for the input features after fitting.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names(*self*)
Return feature names for the input features after fitting.

Returns The feature names after encoding

Return type np.array

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**TargetImputer**(*impute_strategy='most_frequent'*, *fill_value=None*, *random_seed=0*, ***kwargs*)
Imputes missing target data according to a specified imputation strategy.

Parameters

- **impute_strategy** (*string*) – Impute strategy to use. Valid values include “mean”, “median”, “most_frequent”, “constant” for numerical data, and “most_frequent”, “constant” for object data types. Defaults to “most_frequent”.
- **fill_value** (*string*) – When impute_strategy == “constant”, fill_value is used to replace missing data. Defaults to None which uses 0 when imputing numerical data and “missing_value” for strings or object data types.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "impute_strategy": ["mean", "median", "most_frequent"]}
model_family	ModelFamily.NONE
modifies_features	False
modifies_target	True
name	Target Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputer to target data. 'None' values are converted to np.nan before imputation and are
fit_transform	Fits on and transforms the input target data.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input target data by imputing missing values. 'None' and np.nan values are treated as the same.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)

Fits imputer to target data. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]. Ignored.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples].

Returns self

fit_transform (*self*, *X*, *y*)

Fits on and transforms the input target data.

Parameters

- **X** (*pd.DataFrame*) – Features. Ignored.
- **y** (*pd.Series*) – Target data to impute.

Returns The original X, transformed y

Return type (pd.DataFrame, pd.Series)

static load (*file_path*)

Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)

Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)

Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)

Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y*)

Transforms input target data by imputing missing values. 'None' and np.nan values are treated as the same.

Parameters

- **X** (*pd.DataFrame*) – Features. Ignored.
- **y** (*pd.Series*) – Target data to impute.

Returns The original X, transformed y

Return type (pd.DataFrame, pd.Series)

class evalml.pipelines.components.transformers.**TextFeaturizer**(*random_seed=0*, ***kwargs*)

Transformer that can automatically featurize text columns using featuretools' nlp_primitives.

Since models cannot handle non-numeric data, any text must be broken down into features that provide useful information about that text. This component splits each text column into several informative features: Diversity Score, Mean Characters per Word, Polarity Score, and LSA (Latent Semantic Analysis). Calling transform on this component will replace any text columns in the given dataset with these numeric columns.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Text Featurization Component

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by creating new features using existing text columns

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by creating new features using existing text columns

Parameters

- **X** (*pd.DataFrame*) – The data to transform.

- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**Transformer**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)

A component that may or may not need fitting that transforms data. These components are used before an estimator.

To implement a new Transformer, define your own class which is a subclass of Transformer, including a name and a list of acceptable ranges for any parameters to be tuned during the automl search (hyperparameters). Define an *__init__* method which sets up any necessary state and objects. Make sure your *__init__* only uses standard keyword arguments and calls *super().__init__()* with a parameters dict. You may also override the *fit*, *transform*, *fit_transform* and other methods in this class if appropriate.

To see some examples, check out the definitions of any Transformer component.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.transformers.**Undersampler**(*sampling_ratio=0.25*, *sampling_ratio_dict=None*, *min_samples=100*, *min_percentage=0.1*, *random_seed=0*, ***kwargs*)
Initializes an undersampling transformer to downsample the majority classes in the dataset.

This component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – The smallest minority:majority ratio that is accepted as 'balanced'. For instance, a 1:4 ratio would be represented as 0.25, while a 1:1 ratio is 1.0. Must be between 0 and 1, inclusive. Defaults to 0.25.
- **sampling_ratio_dict** (*dict*) – A dictionary specifying the desired balanced ratio for each target value. For instance, in a binary case where class 1 is the minority, we could specify: *sampling_ratio_dict={0: 0.5, 1: 1}*, which means we would undersample class 0 to have twice the number of samples as class 1 (minority:majority ratio = 0.5), and don't sample class 1. Overrides sampling_ratio if provided. Defaults to None.
- **min_samples** (*int*) – The minimum number of samples that we must have for any class, pre or post sampling. If a class must be downsampled, it will not be downsampled past this value. To determine severe imbalance, the minority class must occur less often than this and must have a class ratio below min_percentage. Must be greater than 0. Defaults to 100.
- **min_percentage** (*float*) – The minimum percentage of the minimum class to total dataset that we tolerate, as long as it is above min_samples. If min_percentage and min_samples are not met, treat this as severely imbalanced, and we will not resample the data. Must be between 0 and 0.5, inclusive. Defaults to 0.1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	Undersampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform(*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.transformers.**URLFeaturizer**(*random_seed=0*, ***kwargs*)
Transformer that can automatically extract features from URL.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	URL Featurizer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

Submodules

component_base

Module Contents

Classes Summary

ComponentBase	Base class for all components.

Attributes Summary

logger

Contents

class evalml.pipelines.components.component_base.**ComponentBase**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)

Base class for all components.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
load	Loads component at file path
model_family	Returns ModelFamily of this component
modifies_features	Returns whether this component modifies (subsets or transforms) the features variable during transform.
modifies_target	Returns whether this component modifies (subsets or transforms) the target variable during transform.
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before

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parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property model_family (*cls*)
Returns ModelFamily of this component

property modifies_features (*cls*)
Returns whether this component modifies (subsets or transforms) the features variable during transform. For Estimator objects, this attribute determines if the return value from *predict* or *predict_proba* should be used as features or targets.

property modifies_target (*cls*)
Returns whether this component modifies (subsets or transforms) the target variable during transform. For Estimator objects, this attribute determines if the return value from *predict* or *predict_proba* should be used as features or targets.

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

evalml.pipelines.components.component_base.**logger**

component_base_meta

Module Contents

Classes Summary

ComponentBaseMeta	Metaclass that overrides creating a new component by wrapping methods with validators and setters

Contents

class evalml.pipelines.components.component_base_meta.**ComponentBaseMeta**
Metaclass that overrides creating a new component by wrapping methods with validators and setters

Attributes

FIT_METHODS	[‘fit’, ‘fit_transform’]
METHODS_TO_CHECK	[‘predict’, ‘predict_proba’, ‘transform’, ‘inverse_transform’]
PROPERTIES_TO_CHECK	[‘feature_importance’]

Methods

check_for_fit	*check_for_fit* wraps a method that validates if *self._is_fitted* is *True*.
register	Register a virtual subclass of an ABC.
set_fit	

classmethod check_for_fit(*cls*, *method*)
check_for_fit wraps a method that validates if *self._is_fitted* is *True*. It raises an exception if *False* and calls and returns the wrapped method if *True*.

register(*cls*, *subclass*)
Register a virtual subclass of an ABC.

Returns the subclass, to allow usage as a class decorator.

classmethod set_fit(*cls*, *method*)

utils

Module Contents

Classes Summary

WrappedSKClassifier	Scikit-learn classifier wrapper class.
WrappedSKRegressor	Scikit-learn regressor wrapper class.

Functions

all_components	
allowed_model_families	List the model types allowed for a particular problem type.
generate_component_code	Creates and returns a string that contains the Python imports and code required for running the EvalML component.
get_estimators	Returns the estimators allowed for a particular problem type.
handle_component_class	Standardizes input from a string name to a ComponentBase subclass if necessary.
make_balancing_dictionary	Makes dictionary for oversampler components. Find ratio of each class to the majority.
scikit_learn_wrapped_estimator	

Attributes Summary

logger	

Contents

evalml.pipelines.components.utils.**all_components**()

evalml.pipelines.components.utils.**allowed_model_families**(*problem_type*)
List the model types allowed for a particular problem type.

Parameters **problem_types** (*ProblemTypes or str*) – binary, multiclass, or regression

Returns a list of model families

Return type list[ModelFamily]

evalml.pipelines.components.utils.**generate_component_code**(*element*)
Creates and returns a string that contains the Python imports and code required for running the EvalML component.

Parameters **element** (*component instance*) – The instance of the component to generate string Python code for

Returns String representation of Python code that can be run separately in order to recreate the component instance. Does not include code for custom component implementation.

evalml.pipelines.components.utils.**get_estimators**(*problem_type*, *model_families=None*)
Returns the estimators allowed for a particular problem type.

Can also optionally filter by a list of model types.

Parameters

- **problem_type** (*ProblemTypes or str*) – problem type to filter for
- **model_families** (*list[ModelFamily] or list[str]*) – model families to filter for

Returns a list of estimator subclasses

Return type list[class]

evalml.pipelines.components.utils.**handle_component_class**(*component_class*)
Standardizes input from a string name to a ComponentBase subclass if necessary.

If a str is provided, will attempt to look up a ComponentBase class by that name and return a new instance. Otherwise if a ComponentBase subclass is provided, will return that without modification.

Parameters **component** (*str, ComponentBase*) – input to be standardized

Returns ComponentBase

evalml.pipelines.components.utils.**logger**

evalml.pipelines.components.utils.**make_balancing_dictionary**(*y*, *sampling_ratio*)
Makes dictionary for oversampler components. Find ratio of each class to the majority. If the ratio is smaller than the sampling_ratio, we want to oversample, otherwise, we don't want to sample at all, and we leave the data as is.

Parameters

- **y** (*pd.Series*) – Target data
- **sampling_ratio** (*float*) – The balanced ratio we want the samples to meet

Returns Dictionary where keys are the classes, and the corresponding values are the counts of samples for each class that will satisfy sampling_ratio.

evalml.pipelines.components.utils.**scikit_learn_wrapped_estimator**(*evalml_obj*)

class evalml.pipelines.components.utils.**WrappedSKClassifier**(*pipeline*)

Scikit-learn classifier wrapper class.

Methods

fit	Fits component to data
get_params	Get parameters for this estimator.
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
score	Return the mean accuracy on the given test data and labels.
set_params	Set the parameters of this estimator.

fit(*self*, *X*, *y*)

Fits component to data

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training data of length [n_samples]

Returns self

get_params(*self*, *deep=True*)

Get parameters for this estimator.

Parameters **deep** (*bool, default=True*) – If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns **params** – Parameter names mapped to their values.

Return type dict

predict(*self*, *X*)

Make predictions using selected features.

Parameters **X** (*pd.DataFrame*) – Features

Returns Predicted values

Return type np.ndarray

predict_proba(*self*, *X*)

Make probability estimates for labels.

Parameters **X** (*pd.DataFrame*) – Features

Returns Probability estimates

Return type np.ndarray

score(*self*, *X*, *y*, *sample_weight=None*)

Return the mean accuracy on the given test data and labels.

In multi-label classification, this is the subset accuracy which is a harsh metric since you require for each sample that each label set be correctly predicted.

Parameters

- **X** (*array-like of shape (n_samples, n_features)*) – Test samples.

- **y** (*array-like of shape (n_samples,) or (n_samples, n_outputs)*) – True labels for *X*.
- **sample_weight** (*array-like of shape (n_samples,), default=None*) – Sample weights.

Returns **score** – Mean accuracy of `self.predict(X)` wrt. *y*.

Return type float

set_params(*self*, ***params*)
Set the parameters of this estimator.

The method works on simple estimators as well as on nested objects (such as `Pipeline`). The latter have parameters of the form `<component>__<parameter>` so that it's possible to update each component of a nested object.

Parameters ****params** (*dict*) – Estimator parameters.

Returns **self** – Estimator instance.

Return type estimator instance

class evalml.pipelines.components.utils.**WrappedSKRegressor**(*pipeline*)
Scikit-learn regressor wrapper class.

Methods

fit	Fits component to data
get_params	Get parameters for this estimator.
predict	Make predictions using selected features.
score	Return the coefficient of determination R^2 of the
set_params	Set the parameters of this estimator.

fit(*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training data of length [n_samples]

Returns self

get_params(*self*, *deep=True*)
Get parameters for this estimator.

Parameters **deep** (*bool, default=True*) – If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns **params** – Parameter names mapped to their values.

Return type dict

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame*) – Features

Returns Predicted values

Return type np.ndarray

score (*self*, *X*, *y*, *sample_weight=None*)

Return the coefficient of determination R^2 of the prediction.

The coefficient R^2 is defined as $(1 - \frac{u}{v})$, where u is the residual sum of squares `((y_true - y_pred) ** 2).sum()` and v is the total sum of squares `((y_true - y_true.mean()) ** 2).sum()`. The best possible score is 1.0 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

Parameters

- **X** (*array-like of shape (n_samples, n_features)*) – Test samples. For some estimators this may be a precomputed kernel matrix or a list of generic objects instead with shape `(n_samples, n_samples_fitted)`, where `n_samples_fitted` is the number of samples used in the fitting for the estimator.
- **y** (*array-like of shape (n_samples,) or (n_samples, n_outputs)*) – True values for *X*.
- **sample_weight** (*array-like of shape (n_samples,), default=None*) – Sample weights.

Returns **score** – R^2 of `self.predict(X)` wrt. *y*.

Return type float

Notes

The R^2 score used when calling `score` on a regressor uses `multioutput='uniform_average'` from version 0.23 to keep consistent with default value of `r2_score()`. This influences the `score` method of all the multioutput regressors (except for `MultiOutputRegressor`).

set_params (*self*, ***params*)

Set the parameters of this estimator.

The method works on simple estimators as well as on nested objects (such as `Pipeline`). The latter have parameters of the form `<component>__<parameter>` so that it's possible to update each component of a nested object.

Parameters ****params** (*dict*) – Estimator parameters.

Returns **self** – Estimator instance.

Return type estimator instance

Package Contents

Classes Summary

ARIMARegressor	Autoregressive Integrated Moving Average Model.
BaselineClassifier	Classifier that predicts using the specified strategy.
BaselineRegressor	Baseline regressor that uses a simple strategy to make predictions.
CatBoostClassifier	CatBoost Classifier, a classifier that uses gradient-boosting on decision trees.

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CatBoostRegressor	CatBoost Regressor, a regressor that uses gradient-boosting on decision trees.
ComponentBase	Base class for all components.
ComponentBaseMeta	Metaclass that overrides creating a new component by wrapping methods with validators and setters
DateTimeFeaturizer	Transformer that can automatically extract features from datetime columns.
DecisionTreeClassifier	Decision Tree Classifier.
DecisionTreeRegressor	Decision Tree Regressor.
DelayedFeatureTransformer	Transformer that delays input features and target variable for time series problems.
DFSTransformer	Featuretools DFS component that generates features for the input features.
DropColumns	Drops specified columns in input data.
DropNullColumns	Transformer to drop features whose percentage of NaN values exceeds a specified threshold.
ElasticNetClassifier	Elastic Net Classifier. Uses Logistic Regression with elasticnet penalty as the base estimator.
ElasticNetRegressor	Elastic Net Regressor.
EmailFeaturizer	Transformer that can automatically extract features from emails.
Estimator	A component that fits and predicts given data.
ExtraTreesClassifier	Extra Trees Classifier.
ExtraTreesRegressor	Extra Trees Regressor.
FeatureSelector	Selects top features based on importance weights.
Imputer	Imputes missing data according to a specified imputation strategy.
KNeighborsClassifier	K-Nearest Neighbors Classifier.
LightGBMClassifier	LightGBM Classifier.
LightGBMRegressor	LightGBM Regressor.
LinearDiscriminantAnalysis	Reduces the number of features by using Linear Discriminant Analysis.
LinearRegressor	Linear Regressor.
LogisticRegressionClassifier	Logistic Regression Classifier.
LogTransformer	Applies a log transformation to the target data.
LSA	Transformer to calculate the Latent Semantic Analysis Values of text input.
OneHotEncoder	A transformer that encodes categorical features in a one-hot numeric array.
PCA	Reduces the number of features by using Principal Component Analysis (PCA).
PerColumnImputer	Imputes missing data according to a specified imputation strategy per column.
PolynomialDetrender	Removes trends from time series by fitting a polynomial to the data.
ProphetRegressor	Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.
RandomForestClassifier	Random Forest Classifier.
RandomForestRegressor	Random Forest Regressor.

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RFClassifierSelectFromModel	Selects top features based on importance weights using a Random Forest classifier.
RFRegressorSelectFromModel	Selects top features based on importance weights using a Random Forest regressor.
SelectByType	Selects columns by specified Woodwork logical type or semantic tag in input data.
SelectColumns	Selects specified columns in input data.
SimpleImputer	Imputes missing data according to a specified imputation strategy.
SklearnStackedEnsembleClassifier	Scikit-learn Stacked Ensemble Classifier.
SklearnStackedEnsembleRegressor	Scikit-learn Stacked Ensemble Regressor.
SMOTENCOversampler	SMOTENC Oversampler component. Uses SMOTENC to generate synthetic samples. Works on a mix of numerical and categorical columns.
SMOTENOversampler	SMOTEN Oversampler component. Uses SMOTEN to generate synthetic samples. Works for purely categorical datasets.
SMOTEOversampler	SMOTE Oversampler component. Works on numerical datasets only. This component is only run during training and not during predict.
StandardScaler	A transformer that standardizes input features by removing the mean and scaling to unit variance.
SVMClassifier	Support Vector Machine Classifier.
SVMRegressor	Support Vector Machine Regressor.
TargetEncoder	A transformer that encodes categorical features into target encodings.
TargetImputer	Imputes missing target data according to a specified imputation strategy.
TextFeaturizer	Transformer that can automatically featurize text columns using featuretools' nlp_primitives.
TimeSeriesBaselineEstimator	Time series estimator that predicts using the naive forecasting approach.
Transformer	A component that may or may not need fitting that transforms data.
Undersampler	Initializes an undersampling transformer to downsample the majority classes in the dataset.
URLFeaturizer	Transformer that can automatically extract features from URL.
XGBoostClassifier	XGBoost Classifier.
XGBoostRegressor	XGBoost Regressor.

Contents

class evalml.pipelines.components.**ARIMARegressor**(*date_index=None*, *trend=None*, *start_p=2*, *d=0*, *start_q=2*, *max_p=5*, *max_d=2*, *max_q=5*, *seasonal=True*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)

Autoregressive Integrated Moving Average Model. The three parameters (p, d, q) are the AR order, the degree of differencing, and the MA order. More information here: https://www.statsmodels.org/devel/generated/statsmodels.tsa.arima_model.ARIMA.html

Currently ARIMARegressor isn't supported via conda install. It's recommended that it be installed via PyPI.

Parameters

- **date_index** (*str*) – Specifies the name of the column in X that provides the datetime objects. Defaults to None.
- **trend** (*str*) – Controls the deterministic trend. Options are ['n', 'c', 't', 'ct'] where 'c' is a constant term, 't' indicates a linear trend, and 'ct' is both. Can also be an iterable when defining a polynomial, such as [1, 1, 0, 1].
- **start_p** (*int*) – Minimum Autoregressive order. Defaults to 2.
- **d** (*int*) – Minimum Differencing degree. Defaults to 0.
- **start_q** (*int*) – Minimum Moving Average order. Defaults to 2.
- **max_p** (*int*) – Maximum Autoregressive order. Defaults to 5.
- **max_d** (*int*) – Maximum Differencing degree. Defaults to 2.
- **max_q** (*int*) – Maximum Moving Average order. Defaults to 5.
- **seasonal** (*boolean*) – Whether to fit a seasonal model to ARIMA. Defaults to True.
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "start_p": Integer(1, 3), "d": Integer(0, 2), "start_q": Integer(1, 3), "max_p": Integer(3, 10), "max_d": Integer(2, 5), "max_q": Integer(3, 10), "seasonal": [True, False],}
model_family	ModelFamily.ARIMA
modifies_features	True
modifies_target	False
name	ARIMA Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns array of 0's with a length of 1 as feature_importance is not defined for ARIMA regressor.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before

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Table 543 – continued from previous page

parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns array of 0's with a length of 1 as feature_importance is not defined for ARIMA regressor.

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**BaselineClassifier** (*strategy='mode'*, *random_seed=0*, ***kwargs*)
Classifier that predicts using the specified strategy.

This is useful as a simple baseline classifier to compare with other classifiers.

Parameters

- **strategy** (*str*) – Method used to predict. Valid options are "mode", "random" and "random_weighted". Defaults to "mode".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.BASELINE
modifies_features	True
modifies_target	False
name	Baseline Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS]

Methods

*classes_*	Returns class labels. Will return None before fitting.

continues on next page

Table 544 – continued from previous page

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature. Since baseline classifiers do not use input features to calculate predictions, returns an array of zeroes.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

property classes_(*self*)
Returns class labels. Will return None before fitting.

Returns Class names

Return type list[str] or list(float)

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature. Since baseline classifiers do not use input features to calculate predictions, returns an array of zeroes.

Returns An array of zeroes

Return type np.ndarray (float)

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**BaselineRegressor** (*strategy='mean'*, *random_seed=0*, ***kwargs*)
Baseline regressor that uses a simple strategy to make predictions. This is useful as a simple baseline regressor to compare with other regressors.

Parameters

- **strategy** (*str*) – Method used to predict. Valid options are "mean", "median". Defaults to "mean".

- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.BASELINE
modifies_features	True
modifies_target	False
name	Baseline Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature. Since baseline regressors do not use input features to calculate predictions, returns an array of zeroes.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)

Returns importance associated with each feature. Since baseline regressors do not use input features to calculate predictions, returns an array of zeroes.

Returns An array of zeroes

Return type np.ndarray (float)

fit(*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)

Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)

Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)

Returns the parameters which were used to initialize the component

predict(*self*, *X*)

Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)

Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)

Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file

- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**CatBoostClassifier**(*n_estimators=10*, *eta=0.03*, *max_depth=6*, *bootstrap_type=None*, *silent=True*, *allow_writing_files=False*, *random_seed=0*, *n_jobs=- 1*, ***kwargs*)

CatBoost Classifier, a classifier that uses gradient-boosting on decision trees. CatBoost is an open-source library and natively supports categorical features.

For more information, check out https://catboost.ai/

Parameters

- **n_estimators** (*float*) – The maximum number of trees to build. Defaults to 10.
- **eta** (*float*) – The learning rate. Defaults to 0.03.
- **max_depth** (*int*) – The maximum tree depth for base learners. Defaults to 6.
- **bootstrap_type** (*string*) – Defines the method for sampling the weights of objects. Available methods are 'Bayesian', 'Bernoulli', 'MVS'. Defaults to None.
- **silent** (*boolean*) – Whether to use the "silent" logging mode. Defaults to True.
- **allow_writing_files** (*boolean*) – Whether to allow writing snapshot files while training. Defaults to False.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(4, 100), "eta": Real(0.000001, 1), "max_depth": Integer(4, 10),}
model_family	ModelFamily.CATBOOST
modifies_features	True
modifies_target	False
name	CatBoost Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters

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feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**CatBoostRegressor**(*n_estimators=10*, *eta=0.03*, *max_depth=6*, *bootstrap_type=None*, *silent=False*, *allow_writing_files=False*, *random_seed=0*, *n_jobs=-1*, ***kwargs*)
CatBoost Regressor, a regressor that uses gradient-boosting on decision trees. CatBoost is an open-source library and natively supports categorical features.

For more information, check out https://catboost.ai/

Parameters

- **n_estimators** (*float*) – The maximum number of trees to build. Defaults to 10.
- **eta** (*float*) – The learning rate. Defaults to 0.03.
- **max_depth** (*int*) – The maximum tree depth for base learners. Defaults to 6.
- **bootstrap_type** (*string*) – Defines the method for sampling the weights of objects. Available methods are 'Bayesian', 'Bernoulli', 'MVS'. Defaults to None.
- **silent** (*boolean*) – Whether to use the "silent" logging mode. Defaults to True.
- **allow_writing_files** (*boolean*) – Whether to allow writing snapshot files while training. Defaults to False.

- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(4, 100), "eta": Real(0.000001, 1), "max_depth": Integer(4, 10),}
model_family	ModelFamily.CATBOOST
modifies_features	True
modifies_target	False
name	CatBoost Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**ComponentBase**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)

Base class for all components.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
load	Loads component at file path
model_family	Returns ModelFamily of this component
modifies_features	Returns whether this component modifies (subsets or transforms) the features variable during transform.
modifies_target	Returns whether this component modifies (subsets or transforms) the target variable during transform.
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property model_family(*cls*)
Returns ModelFamily of this component

property modifies_features(*cls*)
Returns whether this component modifies (subsets or transforms) the features variable during transform. For Estimator objects, this attribute determines if the return value from *predict* or *predict_proba* should be used as features or targets.

property modifies_target(*cls*)
Returns whether this component modifies (subsets or transforms) the target variable during transform. For Estimator objects, this attribute determines if the return value from *predict* or *predict_proba* should be used as features or targets.

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**ComponentBaseMeta**
Metaclass that overrides creating a new component by wrapping methods with validators and setters

Attributes

FIT_METHODS	['fit', 'fit_transform']
METHODS_TO_CHECK	['predict', 'predict_proba', 'transform', 'inverse_transform']
PROPERTIES_TO_CHECK	['feature_importance']

Methods

check_for_fit	*check_for_fit* wraps a method that validates if *self._is_fitted* is *True*.
register	Register a virtual subclass of an ABC.
set_fit	

classmethod check_for_fit(*cls*, *method*)
check_for_fit wraps a method that validates if *self._is_fitted* is *True*. It raises an exception if *False* and calls and returns the wrapped method if *True*.

register(*cls*, *subclass*)
Register a virtual subclass of an ABC.

Returns the subclass, to allow usage as a class decorator.

classmethod set_fit(*cls*, *method*)

class evalml.pipelines.components.**DateTimeFeaturizer**(*features_to_extract=None*, *encode_as_categories=False*, *date_index=None*, *random_seed=0*, ***kwargs*)
Transformer that can automatically extract features from datetime columns.

Parameters

- **features_to_extract** (*list*) – List of features to extract. Valid options include "year", "month", "day_of_week", "hour". Defaults to None.
- **encode_as_categories** (*bool*) – Whether day-of-week and month features should be encoded as pandas "category" dtype. This allows OneHotEncoders to encode these features. Defaults to False.
- **date_index** (*str*) – Name of the column containing the datetime information used to order the data. Ignored.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	DateTime Featurization Component

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_feature_names	Gets the categories of each datetime feature.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by creating new features using existing DateTime columns, and then dropping those DateTime columns

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names (*self*)
Gets the categories of each datetime feature.

Returns Dictionary, where each key-value pair is a column name and a dictionary mapping the unique feature values to their integer encoding.

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)
Transforms data X by creating new features using existing DateTime columns, and then dropping those DateTime columns

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**DecisionTreeClassifier**(*criterion='gini'*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *random_seed=0*, ***kwargs*)

Decision Tree Classifier.

Parameters

- **criterion** (*{"gini", "entropy"}*) – The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain. Defaults to "gini".
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.

  Defaults to 2.
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "criterion": ["gini", "entropy"], "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.DECISION_TREE
modifies_features	True
modifies_target	False
name	Decision Tree Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**DecisionTreeRegressor**(*criterion='mse'*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *random_seed=0*, ***kwargs*)

Decision Tree Regressor.

Parameters

- **criterion** (*{"mse", "friedman_mse", "mae", "poisson"}*) – The function to measure the quality of a split. Supported criteria are:
  - "mse" for the mean squared error, which is equal to variance reduction as feature selection criterion and minimizes the L2 loss using the mean of each terminal node
  - "friedman_mse", which uses mean squared error with Friedman"s improvement score for potential splits
  - "mae" for the mean absolute error, which minimizes the L1 loss using the median of each terminal node,
  - "poisson" which uses reduction in Poisson deviance to find splits.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features.
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.

  Defaults to 2.
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “criterion”: [“mse”, “friedman_mse”, “mae”], “max_features”: [“auto”, “sqrt”, “log2”], “max_depth”: Integer(4, 10),}
model_family	ModelFamily.DECISION_TREE
modifies_features	True
modifies_target	False
name	Decision Tree Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**DelayedFeatureTransformer**(*date_index=None*, *max_delay=2*, *delay_features=True*, *delay_target=True*, *gap=1*, *random_seed=0*, ***kwargs*)

Transformer that delays input features and target variable for time series problems.

Parameters

- **date_index** (*str*) – Name of the column containing the datetime information used to order the data. Ignored.
- **max_delay** (*int*) – Maximum number of time units to delay each feature. Defaults to 2.
- **delay_features** (*bool*) – Whether to delay the input features. Defaults to True.
- **delay_target** (*bool*) – Whether to delay the target. Defaults to True.
- **gap** (*int*) – The number of time units between when the features are collected and when the target is collected. For example, if you are predicting the next time step's target, gap=1. This is only needed because when gap=0, we need to be sure to start the lagging of the target variable at 1. Defaults to 1.
- **random_seed** (*int*) – Seed for the random number generator. This transformer performs the same regardless of the random seed provided.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Delayed Feature Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the DelayFeatureTransformer.
fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Computes the delayed features for all features in X and y.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits the DelayFeatureTransformer.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file

- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)

Computes the delayed features for all features in X and y.

For each feature in X, it will add a column to the output dataframe for each delay in the (inclusive) range [1, max_delay]. The values of each delayed feature are simply the original feature shifted forward in time by the delay amount. For example, a delay of 3 units means that the feature value at row n will be taken from the n-3rd row of that feature

If y is not None, it will also compute the delayed values for the target variable.

Parameters

- **X** (*pd.DataFrame or None*) – Data to transform. None is expected when only the target variable is being used.
- **y** (*pd.Series, or None*) – Target.

Returns Transformed X.

Return type pd.DataFrame

class evalml.pipelines.components.**DFSTransformer**(*index='index'*, *random_seed=0*, ***kwargs*)

Featuretools DFS component that generates features for the input features.

Parameters

- **index** (*string*) – The name of the column that contains the indices. If no column with this name exists, then featuretools.EntitySet() creates a column with this name to serve as the index column. Defaults to 'index'.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	DFS Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the DFSTransformer Transformer component.
fit_transform	Fits on X and transforms X
load	Loads component at file path

continues on next page

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needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Computes the feature matrix for the input X using featuretools' dfs algorithm.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits the DFSTransformer Transformer component.

Parameters

- **X** (*pd.DataFrame, np.array*) – The input data to transform, of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Computes the feature matrix for the input X using featuretools' dfs algorithm.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data to transform. Has shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – Ignored.

Returns Feature matrix

Return type pd.DataFrame

class evalml.pipelines.components.**DropColumns**(*columns=None*, *random_seed=0*, ***kwargs*)
Drops specified columns in input data.

Parameters

- **columns** (*list(string)*) – List of column names, used to determine which columns to drop.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Drop Columns Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the transformer by checking if column names are present in the dataset.
fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by dropping columns.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits the transformer by checking if column names are present in the dataset.

Parameters

- **X** (*pd.DataFrame*) – Data to check.
- **y** (*pd.Series, optional*) – Targets.

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by dropping columns.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Targets.

Returns Transformed X.

Return type pd.DataFrame

class evalml.pipelines.components.**DropNullColumns**(*pct_null_threshold=1.0*, *random_seed=0*, ***kwargs*)
Transformer to drop features whose percentage of NaN values exceeds a specified threshold.

Parameters

- **pct_null_threshold** (*float*) – The percentage of NaN values in an input feature to drop. Must be a value between [0, 1] inclusive. If equal to 0.0, will drop columns with any null values. If equal to 1.0, will drop columns with all null values. Defaults to 0.95.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Drop Null Columns Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by dropping columns that exceed the threshold of null values.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)

Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform

- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by dropping columns that exceed the threshold of null values.

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**ElasticNetClassifier**(*penalty='elasticnet'*, *C=1.0*, *l1_ratio=0.15*, *multi_class='auto'*, *solver='saga'*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
Elastic Net Classifier. Uses Logistic Regression with elasticnet penalty as the base estimator.

Parameters

- **penalty** (*{"l1", "l2", "elasticnet", "none"}*) – The norm used in penalization. Defaults to "elasticnet".
- **C** (*float*) – Inverse of regularization strength. Must be a positive float. Defaults to 1.0.
- **l1_ratio** (*float*) – The mixing parameter, with 0 <= l1_ratio <= 1. Only used if penalty='elasticnet'. Setting l1_ratio=0 is equivalent to using penalty='l2', while setting l1_ratio=1 is equivalent to using penalty='l1'. For 0 < l1_ratio <1, the penalty is a combination of L1 and L2. Defaults to 0.15.

- **multi_class** (*{"auto", "ovr", "multinomial"}*) – If the option chosen is "ovr", then a binary problem is fit for each label. For "multinomial" the loss minimised is the multinomial loss fit across the entire probability distribution, even when the data is binary. "multinomial" is unavailable when solver="liblinear". "auto" selects "ovr" if the data is binary, or if solver="liblinear", and otherwise selects "multinomial". Defaults to "auto".
- **solver** (*{"newton-cg", "lbfgs", "liblinear", "sag", "saga"}*) – Algorithm to use in the optimization problem. For small datasets, "liblinear" is a good choice, whereas "sag" and "saga" are faster for large ones. For multiclass problems, only "newton-cg", "sag", "saga" and "lbfgs" handle multinomial loss; "liblinear" is limited to one-versus-rest schemes.
  - "newton-cg", "lbfgs", "sag" and "saga" handle L2 or no penalty
  - "liblinear" and "saga" also handle L1 penalty
  - "saga" also supports "elasticnet" penalty
  - "liblinear" does not support setting penalty='none'

  Defaults to "saga".
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0.01, 10), "l1_ratio": Real(0, 1)}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Elastic Net Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component

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predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**ElasticNetRegressor**(*alpha=0.0001*, *l1_ratio=0.15*, *max_iter=1000*, *normalize=False*, *random_seed=0*, ***kwargs*)
Elastic Net Regressor.

Parameters

- **alpha** (*float*) – Constant that multiplies the penalty terms. Defaults to 0.0001.
- **l1_ratio** (*float*) – The mixing parameter, with 0 <= l1_ratio <= 1. Only used if penalty='elasticnet'. Setting l1_ratio=0 is equivalent to using penalty='l2', while setting l1_ratio=1 is equivalent to using penalty='l1'. For 0 < l1_ratio <1, the penalty is a combination of L1 and L2. Defaults to 0.15.
- **max_iter** (*int*) – The maximum number of iterations. Defaults to 1000.
- **normalize** (*boolean*) – If True, the regressors will be normalized before regression by subtracting the mean and dividing by the l2-norm. Defaults to False.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “alpha”: Real(0, 1), “l1_ratio”: Real(0, 1),}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Elastic Net Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**EmailFeaturizer**(*random_seed=0*, ***kwargs*)

Transformer that can automatically extract features from emails.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Email Featurizer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**Estimator**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)

A component that fits and predicts given data.

To implement a new Estimator, define your own class which is a subclass of Estimator, including a name and a list of acceptable ranges for any parameters to be tuned during the automl search (hyperparameters). Define an *__init__* method which sets up any necessary state and objects. Make sure your *__init__* only uses standard keyword arguments and calls *super().__init__()* with a parameters dict. You may also override the *fit*, *transform*, *fit_transform* and other methods in this class if appropriate.

To see some examples, check out the definitions of any Estimator component.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
predict_uses_y	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path
supported_problem_types	Problem types this estimator supports

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name (*cls*)
Returns string name of this component

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

property supported_problem_types(*cls*)
Problem types this estimator supports

class evalml.pipelines.components.**ExtraTreesClassifier**(*n_estimators=100*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
Extra Trees Classifier.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.
- **to 2.** (*Defaults*) –

- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.EXTRA_TREES
modifies_features	True
modifies_target	False
name	Extra Trees Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**ExtraTreesRegressor**(*n_estimators=100*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)

Extra Trees Regressor.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.
- **to 2.** (*Defaults*) –
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “n_estimators”: Integer(10, 1000), “max_features”: [“auto”, “sqrt”, “log2”], “max_depth”: Integer(4, 10),}
model_family	ModelFamily.EXTRA_TREES
modifies_features	True
modifies_target	False
name	Extra Trees Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**FeatureSelector**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)

Selects top features based on importance weights.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names (*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name (*cls*)
Returns string name of this component

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)

Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**Imputer**(*categorical_impute_strategy='most_frequent'*, *categorical_fill_value=None*, *numeric_impute_strategy='mean'*, *numeric_fill_value=None*, *random_seed=0*, ***kwargs*)

Imputes missing data according to a specified imputation strategy.

Parameters

- **categorical_impute_strategy** (*string*) – Impute strategy to use for string, object, boolean, categorical dtypes. Valid values include "most_frequent" and "constant".
- **numeric_impute_strategy** (*string*) – Impute strategy to use for numeric columns. Valid values include "mean", "median", "most_frequent", and "constant".
- **categorical_fill_value** (*string*) – When categorical_impute_strategy == "constant", fill_value is used to replace missing data. The default value of None will fill with the string "missing_value".
- **numeric_fill_value** (*int, float*) – When numeric_impute_strategy == "constant", fill_value is used to replace missing data. The default value of None will fill with 0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "categorical_impute_strategy": ["most_frequent"], "numeric_impute_strategy": ["mean", "median", "most_frequent"],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputer to data. 'None' values are converted to np.nan before imputation and are
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by imputing missing values. 'None' values are converted to np.nan before imputation and are

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)

Fits imputer to data. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)

Transforms data X by imputing missing values. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**KNeighborsClassifier**(*n_neighbors=5*, *weights='uniform'*, *algorithm='auto'*, *leaf_size=30*, *p=2*, *random_seed=0*, ***kwargs*)

K-Nearest Neighbors Classifier.

Parameters

- **n_neighbors** (*int*) – Number of neighbors to use by default. Defaults to 5.
- **weights** (*{'uniform', 'distance'} or callable*) – Weight function used in prediction. Can be:
  - 'uniform' : uniform weights. All points in each neighborhood are weighted equally.

- 'distance' : weight points by the inverse of their distance. in this case, closer neighbors of a query point will have a greater influence than neighbors which are further away.
- [callable] : a user-defined function which accepts an array of distances, and returns an array of the same shape containing the weights.

Defaults to "uniform".

- **algorithm** (*{'auto', 'ball_tree', 'kd_tree', 'brute'}*) – Algorithm used to compute the nearest neighbors:
  - 'ball_tree' will use BallTree
  - 'kd_tree' will use KDTree
  - 'brute' will use a brute-force search.

  'auto' will attempt to decide the most appropriate algorithm based on the values passed to fit method. Defaults to "auto". Note: fitting on sparse input will override the setting of this parameter, using brute force.
- **leaf_size** (*int*) – Leaf size passed to BallTree or KDTree. This can affect the speed of the construction and query, as well as the memory required to store the tree. The optimal value depends on the nature of the problem. Defaults to 30.
- **p** (*int*) – Power parameter for the Minkowski metric. When p = 1, this is equivalent to using manhattan_distance (l1), and euclidean_distance (l2) for p = 2. For arbitrary p, minkowski_distance (l_p) is used. Defaults to 2.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_neighbors": Integer(2, 12), "weights": ["uniform", "distance"], "algorithm": ["auto", "ball_tree", "kd_tree", "brute"], "leaf_size": Integer(10, 30), "p": Integer(1, 5),}
model_family	ModelFamily.K_NEIGHBORS
modifies_features	True
modifies_target	False
name	KNN Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns array of 0's matching the input number of features as feature_importance is
fit	Fits component to data
load	Loads component at file path

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needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns array of 0's matching the input number of features as feature_importance is not defined for KNN classifiers.

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform,

or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**LightGBMClassifier**(*boosting_type='gbdt'*, *learning_rate=0.1*, *n_estimators=100*, *max_depth=0*, *num_leaves=31*, *min_child_samples=20*, *bagging_fraction=0.9*, *bagging_freq=0*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)
LightGBM Classifier.

Parameters

- **boosting_type** (*string*) – Type of boosting to use. Defaults to "gbdt". - 'gbdt' uses traditional Gradient Boosting Decision Tree - "dart", uses Dropouts meet Multiple Additive Regression Trees - "goss", uses Gradient-based One-Side Sampling - "rf", uses Random Forest
- **learning_rate** (*float*) – Boosting learning rate. Defaults to 0.1.
- **n_estimators** (*int*) – Number of boosted trees to fit. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners, <=0 means no limit. Defaults to 0.
- **num_leaves** (*int*) – Maximum tree leaves for base learners. Defaults to 31.
- **min_child_samples** (*int*) – Minimum number of data needed in a child (leaf). Defaults to 20.

- **bagging_fraction** (*float*) – LightGBM will randomly select a subset of features on each iteration (tree) without resampling if this is smaller than 1.0. For example, if set to 0.8, LightGBM will select 80% of features before training each tree. This can be used to speed up training and deal with overfitting. Defaults to 0.9.
- **bagging_freq** (*int*) – Frequency for bagging. 0 means bagging is disabled. k means perform bagging at every k iteration. Every k-th iteration, LightGBM will randomly select bagging_fraction * 100 % of the data to use for the next k iterations. Defaults to 0.
- **n_jobs** (*int or None*) – Number of threads to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "learning_rate": Real(0.000001, 1), "boosting_type": ["gbdt", "dart", "goss", "rf"], "n_estimators": Integer(10, 100), "max_depth": Integer(0, 10), "num_leaves": Integer(2, 100), "min_child_samples": Integer(1, 100), "bagging_fraction": Real(0.000001, 1), "bagging_freq": Integer(0, 1),}
model_family	ModelFamily.LIGHTGBM
modifies_features	True
modifies_target	False
name	LightGBM Classifier
predict_uses_y	False
SEED_MAX	SEED_BOUNDS.max_bound
SEED_MIN	0
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**LightGBMRegressor**(*boosting_type='gbdt'*, *learning_rate=0.1*, *n_estimators=20*, *max_depth=0*, *num_leaves=31*, *min_child_samples=20*, *bagging_fraction=0.9*, *bagging_freq=0*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

LightGBM Regressor.

Parameters

- **boosting_type** (*string*) – Type of boosting to use. Defaults to "gbdt". - 'gbdt' uses traditional Gradient Boosting Decision Tree - "dart", uses Dropouts meet Multiple Additive Regression Trees - "goss", uses Gradient-based One-Side Sampling - "rf", uses Random Forest
- **learning_rate** (*float*) – Boosting learning rate. Defaults to 0.1.
- **n_estimators** (*int*) – Number of boosted trees to fit. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners, <=0 means no limit. Defaults to 0.
- **num_leaves** (*int*) – Maximum tree leaves for base learners. Defaults to 31.
- **min_child_samples** (*int*) – Minimum number of data needed in a child (leaf). Defaults to 20.
- **bagging_fraction** (*float*) – LightGBM will randomly select a subset of features on each iteration (tree) without resampling if this is smaller than 1.0. For example, if set to 0.8, LightGBM will select 80% of features before training each tree. This can be used to speed up training and deal with overfitting. Defaults to 0.9.
- **bagging_freq** (*int*) – Frequency for bagging. 0 means bagging is disabled. k means perform bagging at every k iteration. Every k-th iteration, LightGBM will randomly select bagging_fraction * 100 % of the data to use for the next k iterations. Defaults to 0.
- **n_jobs** (*int or None*) – Number of threads to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “learning_rate”: Real(0.000001, 1), “boosting_type”: [“gbdt”, “dart”, “goss”, “rf”], “n_estimators”: Integer(10, 100), “max_depth”: Integer(0, 10), “num_leaves”: Integer(2, 100), “min_child_samples”: Integer(1, 100), “bagging_fraction”: Real(0.000001, 1), “bagging_freq”: Integer(0, 1),}
model_family	ModelFamily.LIGHTGBM
modifies_features	True
modifies_target	False
name	LightGBM Regressor
predict_uses_y	False
SEED_MAX	SEED_BOUNDS.max_bound
SEED_MIN	0
supported_problem_types	[ProblemTypes.REGRESSION]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file

- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**LinearDiscriminantAnalysis**(*n_components=None*, *random_seed=0*, ***kwargs*)

Reduces the number of features by using Linear Discriminant Analysis.

Parameters

- **n_components** (*int*) – The number of features to maintain after computation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Linear Discriminant Analysis Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**LinearRegressor**(*fit_intercept=True*, *normalize=False*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
Linear Regressor.

Parameters

- **fit_intercept** (*boolean*) – Whether to calculate the intercept for this model. If set to False, no intercept will be used in calculations (i.e. data is expected to be centered). Defaults to True.
- **normalize** (*boolean*) – If True, the regressors will be normalized before regression by subtracting the mean and dividing by the l2-norm. This parameter is ignored when fit_intercept is set to False. Defaults to False.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "fit_intercept": [True, False], "normalize": [True, False]}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Linear Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path

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needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**LogisticRegressionClassifier**(*penalty='l2'*, *C=1.0*, *multi_class='auto'*, *solver='lbfgs'*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)

Logistic Regression Classifier.

Parameters

- **penalty** (*{"l1", "l2", "elasticnet", "none"}*) – The norm used in penalization. Defaults to "l2".
- **C** (*float*) – Inverse of regularization strength. Must be a positive float. Defaults to 1.0.
- **multi_class** (*{"auto", "ovr", "multinomial"}*) – If the option chosen is "ovr", then a binary problem is fit for each label. For "multinomial" the loss minimised is the multinomial loss fit across the entire probability distribution, even when the data is binary. "multinomial" is unavailable when solver="liblinear". "auto" selects "ovr" if the data is binary, or if solver="liblinear", and otherwise selects "multinomial". Defaults to "auto".
- **solver** (*{"newton-cg", "lbfgs", "liblinear", "sag", "saga"}*) – Algorithm to use in the optimization problem. For small datasets, "liblinear" is a good choice, whereas "sag" and "saga" are faster for large ones. For multiclass problems, only "newton-cg", "sag", "saga" and "lbfgs" handle multinomial loss; "liblinear" is limited to one-versus-rest schemes.

- ”newton-cg”, “lbfgs”, “sag” and “saga” handle L2 or no penalty
- ”liblinear” and “saga” also handle L1 penalty
- ”saga” also supports “elasticnet” penalty
- ”liblinear” does not support setting penalty=’none’

Defaults to “lbfgs”.

- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “penalty”: [“l2”], “C”: Real(0.01, 10),}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Logistic Regression Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**LogTransformer**(*random_seed=0*)
Applies a log transformation to the target data.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	False
modifies_target	True
name	Log Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the LogTransformer.
fit_transform	Log transforms the target variable.
inverse_transform	Inverts the transformation done by the transform method.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Log transforms the target variable.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits the LogTransformer.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Ignored.
- **y** (*pd.Series, optional*) – Ignored.

Returns self

fit_transform(*self*, *X*, *y=None*)
Log transforms the target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to log transform.

Returns

The input features are returned without modification. The target variable y is log transformed.

Return type tuple of pd.DataFrame, pd.Series

inverse_transform(*self*, *y*)
Inverts the transformation done by the transform method.

Arguments: y (pd.Series): Target transformed by this component.

Returns Target without the transformation.

Return type pd.Seriesø

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Log transforms the target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target data to log transform.

Returns

The input features are returned without modification. The target variable y is log transformed.

Return type tuple of pd.DataFrame, pd.Series

class evalml.pipelines.components.**LSA**(*random_seed=0*, ***kwargs*)
Transformer to calculate the Latent Semantic Analysis Values of text input.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	LSA Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before

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parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by applying the LSA pipeline.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by applying the LSA pipeline.

Parameters

- **X** (*pd.DataFrame*) – The data to transform.
- **y** (*pd.Series, optional*) – Ignored.

Returns

Transformed X. The original column is removed and replaced with two columns of the format *LSA(original_column_name)[feature_number]*, where *feature_number* is 0 or 1.

Return type pd.DataFrame

class evalml.pipelines.components.**OneHotEncoder**(*top_n=10*, *features_to_encode=None*, *categories=None*, *drop='if_binary'*, *handle_unknown='ignore'*, *handle_missing='error'*, *random_seed=0*, ***kwargs*)
A transformer that encodes categorical features in a one-hot numeric array.

Parameters

- **top_n** (*int*) – Number of categories per column to encode. If None, all categories will be encoded. Otherwise, the *n* most frequent will be encoded and all others will be dropped. Defaults to 10.
- **features_to_encode** (*list[str]*) – List of columns to encode. All other columns will remain untouched. If None, all appropriate columns will be encoded. Defaults to None.
- **categories** (*list*) – A two dimensional list of categories, where *categories[i]* is a list of the categories for the column at index *i*. This can also be *None*, or *"auto"* if *top_n* is not None. Defaults to None.
- **drop** (*string, list*) – Method ("first" or "if_binary") to use to drop one category per feature. Can also be a list specifying which categories to drop for each feature. Defaults to 'if_binary'.
- **handle_unknown** (*string*) – Whether to ignore or error for unknown categories for a feature encountered during *fit* or *transform*. If either *top_n* or *categories* is used to limit the number of categories per column, this must be "ignore". Defaults to "ignore".

- **handle_missing** (*string*) – Options for how to handle missing (NaN) values encountered during *fit* or *transform*. If this is set to "as_category" and NaN values are within the *n* most frequent, "nan" values will be encoded as their own column. If this is set to "error", any missing values encountered will raise an error. Defaults to "error".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	One Hot Encoder

Methods

categories	Returns a list of the unique categories to be encoded for the particular feature, in order.
clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_feature_names	Return feature names for the categorical features after fitting.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	One-hot encode the input data.

categories (*self*, *feature_name*)
Returns a list of the unique categories to be encoded for the particular feature, in order.

Parameters **feature_name** (*str*) – the name of any feature provided to one-hot encoder during fit

Returns the unique categories, in the same dtype as they were provided during fit

Return type np.ndarray

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names (*self*)
Return feature names for the categorical features after fitting.

Feature names are formatted as {column name}_{category name}. In the event of a duplicate name, an integer will be added at the end of the feature name to distinguish it.

For example, consider a dataframe with a column called "A" and category "x_y" and another column called "A_x" with "y". In this example, the feature names would be "A_x_y" and "A_x_y_1".

Returns The feature names after encoding, provided in the same order as input_features.

Return type np.ndarray

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
One-hot encode the input data.

Parameters

- **X** (*pd.DataFrame*) – Features to one-hot encode.
- **y** (*pd.Series*) – Ignored.

Returns Transformed data, where each categorical feature has been encoded into numerical columns using one-hot encoding.

Return type pd.DataFrame

class evalml.pipelines.components.**PCA**(*variance=0.95*, *n_components=None*, *random_seed=0*, ***kwargs*)
Reduces the number of features by using Principal Component Analysis (PCA).

Parameters

- **variance** (*float*) – The percentage of the original data variance that should be preserved when reducing the number of features. Defaults to 0.95.
- **n_components** (*int*) – The number of features to maintain after computing SVD. Defaults to None, but will override variance variable if set.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	Real(0.25, 1)}:type: {"variance"
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	PCA Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform

- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**PerColumnImputer**(*impute_strategies=None*, *default_impute_strategy='most_frequent'*, *random_seed=0*, ***kwargs*)
Imputes missing data according to a specified imputation strategy per column.

Parameters

- **impute_strategies** (*dict*) – Column and {"impute_strategy": strategy, "fill_value":value} pairings. Valid values for impute strategy include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types. Defaults to None, which uses "most_frequent" for all columns. When impute_strategy == "constant", fill_value is used to replace missing data. When None, uses 0 when imputing numerical data and "missing_value" for strings or object data types.
- **default_impute_strategy** (*str*) – Impute strategy to fall back on when none is provided for a certain column. Valid values include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types. Defaults to "most_frequent".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Per Column Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputers on input data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by imputing missing values.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits imputers on input data

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features] to fit.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]. Ignored.

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input data by imputing missing values.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features] to transform.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**PolynomialDetrender**(*degree=1*, *random_seed=0*, ***kwargs*)
Removes trends from time series by fitting a polynomial to the data.

Parameters

- **degree** (*int*) – Degree for the polynomial. If 1, linear model is fit to the data. If 2, quadratic model is fit, etc. Defaults to 1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "degree": Integer(1, 3)}
model_family	ModelFamily.NONE
modifies_features	False
modifies_target	True
name	Polynomial Detrender

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the PolynomialDetrender.
fit_transform	Removes fitted trend from target variable.
inverse_transform	Adds back fitted trend to target variable.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Removes fitted trend from target variable.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits the PolynomialDetrender.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to detrend.

Returns self

fit_transform (*self*, *X*, *y=None*)
Removes fitted trend from target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to detrend.

Returns

The first element are the input features returned without modification. The second element is the target variable y with the fitted trend removed.

Return type tuple of pd.DataFrame, pd.Series

inverse_transform (*self*, *y*)
Adds back fitted trend to target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable.

Returns

The first element are the input features returned without modification. The second element is the target variable y with the trend added back.

Return type tuple of pd.DataFrame, pd.Series

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file

- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Removes fitted trend from target variable.

Parameters

- **X** (*pd.DataFrame, optional*) – Ignored.
- **y** (*pd.Series*) – Target variable to detrend.

Returns

The input features are returned without modification. The target variable y is detrended

Return type tuple of pd.DataFrame, pd.Series

class evalml.pipelines.components.**ProphetRegressor**(*date_column='ds'*, *changepoint_prior_scale=0.05*, *seasonality_prior_scale=10*, *holidays_prior_scale=10*, *seasonality_mode='additive'*, *random_seed=0*, *stan_backend='CMDSTANPY'*, ***kwargs*)
Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well.

More information here: https://facebook.github.io/prophet/

Attributes

hyperparameter_ranges	{ “changepoint_prior_scale”: Real(0.001, 0.5), “seasonality_prior_scale”: Real(0.01, 10), “holidays_prior_scale”: Real(0.01, 10), “seasonality_mode”: [“additive”, “multiplicative”],}
model_family	ModelFamily.PROPHET
modifies_features	True
modifies_target	False
name	Prophet Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION]

Methods

build_prophet_df	
clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.

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describe	Describe a component and its parameters
feature_importance	Returns array of 0's with len(1) as feature_importance is not defined for Prophet regressor.
fit	Fits component to data
get_params	
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

static build_prophet_df(*X*, *y=None*, *date_column='ds'*)

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)

Returns array of 0's with len(1) as feature_importance is not defined for Prophet regressor.

fit(*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

get_params(*self*)

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**RandomForestClassifier**(*n_estimators=100*, *max_depth=6*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
Random Forest Classifier.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “n_estimators”: Integer(10, 1000), “max_depth”: Integer(1, 10),}
model_family	ModelFamily.RANDOM_FOREST
modifies_features	True
modifies_target	False
name	Random Forest Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**RandomForestRegressor**(*n_estimators=100*, *max_depth=6*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Random Forest Regressor.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_depth": Integer(1, 32),}
model_family	ModelFamily.RANDOM_FOREST
modifies_features	True
modifies_target	False
name	Random Forest Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**RFClassifierSelectFromModel**(*number_features=None*, *n_estimators=10*, *max_depth=None*, *percent_features=0.5*, *threshold=-np.inf*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
Selects top features based on importance weights using a Random Forest classifier.

Parameters

- **number_features** (*int*) – The maximum number of features to select. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5. Defaults to None.
- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **percent_features** (*float*) – Percentage of features to use. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5.
- **threshold** (*string or float*) – The threshold value to use for feature selection. Features whose importance is greater or equal are kept while the others are discarded. If "median", then the threshold value is the median of the feature importances. A scaling factor (e.g., "1.25*mean") may also be used. Defaults to -np.inf.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "percent_features": Real(0.01, 1), "threshold": ["mean", -np.inf],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	RF Classifier Select From Model

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names (*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)
Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.

- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**RFRegressorSelectFromModel**(*number_features=None*, *n_estimators=10*, *max_depth=None*, *percent_features=0.5*, *threshold=-np.inf*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Selects top features based on importance weights using a Random Forest regressor.

Parameters

- **number_features** (*int*) – The maximum number of features to select. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5. Defaults to None.
- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **percent_features** (*float*) – Percentage of features to use. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5.
- **threshold** (*string or float*) – The threshold value to use for feature selection. Features whose importance is greater or equal are kept while the others are discarded. If "median", then the threshold value is the median of the feature importances. A scaling factor (e.g., "1.25*mean") may also be used. Defaults to -np.inf.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "percent_features": Real(0.01, 1), "threshold": ["mean", -np.inf],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	RF Regressor Select From Model

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters

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fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)

Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform

- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names(*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**SelectByType**(*column_types=None*, *random_seed=0*, ***kwargs*)
Selects columns by specified Woodwork logical type or semantic tag in input data.

Parameters

- **column_types** (*string, ww.LogicalType, list(string), list(ww.LogicalType)*) – List of Woodwork types or tags, used to determine which columns to select.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Select Columns By Type Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the transformer by checking if column names are present in the dataset.
fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)

Fits the transformer by checking if column names are present in the dataset.

Parameters

- **X** (*pd.DataFrame*) – Data to check.
- **y** (*pd.Series, optional*) – Targets.

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**SelectColumns**(*columns=None*, *random_seed=0*, ***kwargs*)
Selects specified columns in input data.

Parameters

- **columns** (*list(string)*) – List of column names, used to determine which columns to select.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Select Columns Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the transformer by checking if column names are present in the dataset.
fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X by selecting columns.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)

Fits the transformer by checking if column names are present in the dataset.

Parameters

- **X** (*pd.DataFrame*) – Data to check.
- **y** (*pd.Series, optional*) – Targets.

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by selecting columns.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Targets.

Returns Transformed X.

Return type pd.DataFrame

class evalml.pipelines.components.**SimpleImputer**(*impute_strategy='most_frequent'*, *fill_value=None*, *random_seed=0*, ***kwargs*)
Imputes missing data according to a specified imputation strategy.

Parameters

- **impute_strategy** (*string*) – Impute strategy to use. Valid values include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types.

- **fill_value** (*string*) – When impute_strategy == "constant", fill_value is used to replace missing data. Defaults to 0 when imputing numerical data and "missing_value" for strings or object data types.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "impute_strategy": ["mean", "median", "most_frequent"]}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Simple Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputer to data. 'None' values are converted to np.nan before imputation and are
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input by imputing missing values. 'None' and np.nan values are treated as the same.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component

- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)

Fits imputer to data. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)

Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)

Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)

Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)

Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)

Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)

Transforms input by imputing missing values. 'None' and np.nan values are treated as the same.

Parameters

- **X** (*pd.DataFrame*) – Data to transform

- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**SklearnStackedEnsembleClassifier**(*input_pipelines=None*, *final_estimator=None*, *cv=None*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Scikit-learn Stacked Ensemble Classifier.

Parameters

- **input_pipelines** (*list(PipelineBase or subclass obj)*) – List of pipeline instances to use as the base estimators. This must not be None or an empty list or else EnsembleMissingPipelinesError will be raised.
- **final_estimator** (*Estimator or subclass*) – The classifier used to combine the base estimators. If None, uses LogisticRegressionClassifier.
- **cv** (*int, cross-validation generator or an iterable*) – Determines the cross-validation splitting strategy used to train final_estimator. For int/None inputs, if the estimator is a classifier and y is either binary or multiclass, StratifiedKFold is used. Defaults to None. Possible inputs for cv are:
  - None: 3-fold cross validation
  - int: the number of folds in a (Stratified) KFold
  - An scikit-learn cross-validation generator object
  - An iterable yielding (train, test) splits
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Defaults to -1. - Note: there could be some multi-process errors thrown for values of *n_jobs != 1*. If this is the case, please use *n_jobs = 1*.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.ENSEMBLE
modifies_features	True
modifies_target	False
name	Sklearn Stacked Ensemble Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for stacked ensemble classes.
describe	Describe a component and its parameters
feature_importance	Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for stacked ensemble classes.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**SklearnStackedEnsembleRegressor**(*input_pipelines=None*, *final_estimator=None*, *cv=None*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
Scikit-learn Stacked Ensemble Regressor.

Parameters

- **input_pipelines** (*list(PipelineBase or subclass obj)*) – List of pipeline instances to use as the base estimators. This must not be None or an empty list or else EnsembleMissingPipelinesError will be raised.
- **final_estimator** (Estimator *or subclass*) – The regressor used to combine the base estimators. If None, uses LinearRegressor.

- **cv** (*int, cross-validation generator or an iterable*) – Determines the cross-validation splitting strategy used to train final_estimator. For int/None inputs, KFold is used. Defaults to None. Possible inputs for cv are:
  - None: 3-fold cross validation
  - int: the number of folds in a (Stratified) KFold
  - An scikit-learn cross-validation generator object
  - An iterable yielding (train, test) splits
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Defaults to -1. - Note: there could be some multi-process errors thrown for values of *n_jobs != 1*. If this is the case, please use *n_jobs = 1*.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.ENSEMBLE
modifies_features	True
modifies_target	False
name	Sklearn Stacked Ensemble Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for stacked ensemble classes.
describe	Describe a component and its parameters
feature_importance	Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for stacked ensemble classes.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**SMOTENCOversampler**(*sampling_ratio=0.25*, *k_neighbors_default=5*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)
SMOTENC Oversampler component. Uses SMOTENC to generate synthetic samples. Works on a mix of numerical and categorical columns. Input data must be Woodwork type, and this component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – This is the goal ratio of the minority to majority class, with range (0, 1]. A value of 0.25 means we want a 1:4 ratio of the minority to majority class after oversampling. We will create the a sampling dictionary using this ratio, with the keys corresponding to the class and the values responding to the number of samples. Defaults to 0.25.
- **k_neighbors_default** (*int*) – The number of nearest neighbors used to construct synthetic samples. This is the default value used, but the actual k_neighbors value might be smaller if there are less samples. Defaults to 5.
- **n_jobs** (*int*) – The number of CPU cores to use. Defaults to -1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	SMOTENC Oversampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X

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load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.**SMOTENOversampler**(*sampling_ratio=0.25*, *k_neighbors_default=5*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
SMOTEN Oversampler component. Uses SMOTEN to generate synthetic samples. Works for purely categorical datasets. This component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – This is the goal ratio of the minority to majority class, with range (0, 1]. A value of 0.25 means we want a 1:4 ratio of the minority to majority class after oversampling. We will create the a sampling dictionary using this ratio, with the keys corresponding to the class and the values responding to the number of samples. Defaults to 0.25.
- **k_neighbors_default** (*int*) – The number of nearest neighbors used to construct synthetic samples. This is the default value used, but the actual k_neighbors value might be smaller if there are less samples. Defaults to 5.
- **n_jobs** (*int*) – The number of CPU cores to use. Defaults to -1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	SMOTEN Oversampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform(*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.**SMOTEOversampler**(*sampling_ratio=0.25*, *k_neighbors_default=5*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
SMOTE Oversampler component. Works on numerical datasets only. This component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – This is the goal ratio of the minority to majority class, with range (0, 1]. A value of 0.25 means we want a 1:4 ratio of the minority to majority class after oversampling. We will create the a sampling dictionary using this ratio, with the keys corresponding to the class and the values responding to the number of samples. Defaults to 0.25.
- **k_neighbors_default** (*int*) – The number of nearest neighbors used to construct synthetic samples. This is the default value used, but the actual k_neighbors value might be smaller if there are less samples. Defaults to 5.
- **n_jobs** (*int*) – The number of CPU cores to use. Defaults to -1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	SMOTE Oversampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.**StandardScaler**(*random_seed=0*, ***kwargs*)

A transformer that standardizes input features by removing the mean and scaling to unit variance.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Standard Scaler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.

- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**SVMClassifier**(*C=1.0*, *kernel='rbf'*, *gamma='scale'*, *probability=True*, *random_seed=0*, ***kwargs*)

Support Vector Machine Classifier.

Parameters

- **C** (*float*) – The regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive. The penalty is a squared l2 penalty. Defaults to 1.0.
- **kernel** (*{"linear", "poly", "rbf", "sigmoid", "precomputed"}*) – Specifies the kernel type to be used in the algorithm. Defaults to "rbf".
- **gamma** (*{"scale", "auto"} or float*) – Kernel coefficient for "rbf", "poly" and "sigmoid". Defaults to "scale". - If gamma='scale' (default) is passed then it uses 1 / (n_features * X.var()) as value of gamma - if "auto", uses 1 / n_features
- **probability** (*boolean*) – Whether to enable probability estimates. Defaults to True.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0, 10), "kernel": ["linear", "poly", "rbf", "sigmoid", "precomputed"], "gamma": ["scale", "auto"],}
model_family	ModelFamily.SVM
modifies_features	True
modifies_target	False
name	SVM Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Feature importance only works with linear kernels.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component

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predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Feature importance only works with linear kernels. If the kernel isn't linear, we return a numpy array of zeros

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**SVMRegressor**(*C=1.0*, *kernel='rbf'*, *gamma='scale'*, *random_seed=0*, ***kwargs*)
Support Vector Machine Regressor.

Parameters

- **C** (*float*) – The regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive. The penalty is a squared l2 penalty. Defaults to 1.0.
- **kernel** (*{"linear", "poly", "rbf", "sigmoid", "precomputed"}*) – Specifies the kernel type to be used in the algorithm. Defaults to "rbf".
- **gamma** (*{"scale", "auto"} or float*) – Kernel coefficient for "rbf", "poly" and "sigmoid". Defaults to "scale". - If gamma='scale' (default) is passed then it uses 1 / (n_features * X.var()) as value of gamma - if "auto", uses 1 / n_features
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0, 10), "kernel": ["linear", "poly", "rbf", "sigmoid", "precomputed"], "gamma": ["scale", "auto"],}
model_family	ModelFamily.SVM
modifies_features	True
modifies_target	False
name	SVM Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Feature importance only works with linear kernels.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Feature importance only works with linear kernels. If the kernel isn't linear, we return a numpy array of zeros

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**TargetEncoder**(*cols=None*, *smoothing=1.0*, *handle_unknown='value'*, *handle_missing='value'*, *random_seed=0*, ***kwargs*)
A transformer that encodes categorical features into target encodings.

Parameters

- **cols** (*list*) – Columns to encode. If None, all string columns will be encoded, otherwise only the columns provided will be encoded. Defaults to None
- **smoothing** (*float*) – The smoothing factor to apply. The larger this value is, the more influence the expected target value has on the resulting target encodings. Must be strictly larger than 0. Defaults to 1.0
- **handle_unknown** (*string*) – Determines how to handle unknown categories for a feature encountered. Options are 'value', 'error', nd 'return_nan'. Defaults to 'value', which replaces with the target mean
- **handle_missing** (*string*) – Determines how to handle missing values encountered during *fit* or *transform*. Options are 'value', 'error', and 'return_nan'. Defaults to 'value', which replaces with the target mean

- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Target Encoder

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_feature_names	Return feature names for the input features after fitting.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names(*self*)
Return feature names for the input features after fitting.

Returns The feature names after encoding

Return type np.array

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.

- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**TargetImputer**(*impute_strategy='most_frequent', fill_value=None, random_seed=0, **kwargs*)

Imputes missing target data according to a specified imputation strategy.

Parameters

- **impute_strategy** (*string*) – Impute strategy to use. Valid values include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types. Defaults to "most_frequent".
- **fill_value** (*string*) – When impute_strategy == "constant", fill_value is used to replace missing data. Defaults to None which uses 0 when imputing numerical data and "missing_value" for strings or object data types.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "impute_strategy": ["mean", "median", "most_frequent"]}
model_family	ModelFamily.NONE
modifies_features	False
modifies_target	True
name	Target Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputer to target data. 'None' values are converted to np.nan before imputation and are
fit_transform	Fits on and transforms the input target data.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input target data by imputing missing values. 'None' and np.nan values are treated as the same.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y*)

Fits imputer to target data. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]. Ignored.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples].

Returns self

fit_transform(*self*, *X*, *y*)
Fits on and transforms the input target data.

Parameters

- **X** (*pd.DataFrame*) – Features. Ignored.
- **y** (*pd.Series*) – Target data to impute.

Returns The original X, transformed y

Return type (pd.DataFrame, pd.Series)

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y*)
Transforms input target data by imputing missing values. 'None' and np.nan values are treated as the same.

Parameters

- **X** (*pd.DataFrame*) – Features. Ignored.
- **y** (*pd.Series*) – Target data to impute.

Returns The original X, transformed y

Return type (pd.DataFrame, pd.Series)

class evalml.pipelines.components.**TextFeaturizer** (*random_seed=0*, ***kwargs*)
Transformer that can automatically featurize text columns using featuretools' nlp_primitives.

Since models cannot handle non-numeric data, any text must be broken down into features that provide useful information about that text. This component splits each text column into several informative features: Diversity Score, Mean Characters per Word, Polarity Score, and LSA (Latent Semantic Analysis). Calling transform on this component will replace any text columns in the given dataset with these numeric columns.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Text Featurization Component

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component

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save	Saves component at file path
transform	Transforms data X by creating new features using existing text columns

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X by creating new features using existing text columns

Parameters

- **X** (*pd.DataFrame*) – The data to transform.
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**TimeSeriesBaselineEstimator**(*gap=1*, *random_seed=0*, ***kwargs*)
Time series estimator that predicts using the naive forecasting approach.

This is useful as a simple baseline estimator for time series problems.

Parameters

- **gap** (*int*) – Gap between prediction date and target date and must be a positive integer. If gap is 0, target date will be shifted ahead by 1 time period. Defaults to 1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.BASELINE
modifies_features	True
modifies_target	False
name	Time Series Baseline Estimator
predict_uses_y	True
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Since baseline estimators do not use input features to calculate predictions, returns an array of zeroes.

Returns an array of zeroes

Return type np.ndarray (float)

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]

- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*, *y=None*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**Transformer**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)
A component that may or may not need fitting that transforms data. These components are used before an estimator.

To implement a new Transformer, define your own class which is a subclass of Transformer, including a name and a list of acceptable ranges for any parameters to be tuned during the automl search (hyperparameters). Define an *__init__* method which sets up any necessary state and objects. Make sure your *__init__* only uses standard keyword arguments and calls *super().__init__()* with a parameters dict. You may also override the *fit*, *transform*, *fit_transform* and other methods in this class if appropriate.

To see some examples, check out the definitions of any Transformer component.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.

- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name (*cls*)
Returns string name of this component

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform (*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**Undersampler**(*sampling_ratio=0.25*, *sampling_ratio_dict=None*, *min_samples=100*, *min_percentage=0.1*, *random_seed=0*, ***kwargs*)

Initializes an undersampling transformer to downsample the majority classes in the dataset.

This component is only run during training and not during predict.

Parameters

- **sampling_ratio** (*float*) – The smallest minority:majority ratio that is accepted as 'balanced'. For instance, a 1:4 ratio would be represented as 0.25, while a 1:1 ratio is 1.0. Must be between 0 and 1, inclusive. Defaults to 0.25.
- **sampling_ratio_dict** (*dict*) – A dictionary specifying the desired balanced ratio for each target value. For instance, in a binary case where class 1 is the minority, we could specify: *sampling_ratio_dict={0: 0.5, 1: 1}*, which means we would undersample class 0 to have twice the number of samples as class 1 (minority:majority ratio = 0.5), and don't sample class 1. Overrides sampling_ratio if provided. Defaults to None.
- **min_samples** (*int*) – The minimum number of samples that we must have for any class, pre or post sampling. If a class must be downsampled, it will not be downsampled past this value. To determine severe imbalance, the minority class must occur less often than this and must have a class ratio below min_percentage. Must be greater than 0. Defaults to 100.
- **min_percentage** (*float*) – The minimum percentage of the minimum class to total dataset that we tolerate, as long as it is above min_samples. If min_percentage and min_samples are not met, treat this as severely imbalanced, and we will not resample the data. Must be between 0 and 0.5, inclusive. Defaults to 0.1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	True
name	Undersampler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the sampler to the data.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before

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parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms the input data by sampling the data.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits the sampler to the data.

Parameters

- **X** (*pd.DataFrame*) – Input features.
- **y** (*pd.Series*) – Target.

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms the input data by sampling the data.

Parameters

- **X** (*pd.DataFrame*) – Training features.
- **y** (*pd.Series*) – Target.

Returns Transformed features and target.

Return type pd.DataFrame, pd.Series

class evalml.pipelines.components.**URLFeaturizer**(*random_seed=0*, ***kwargs*)
Transformer that can automatically extract features from URL.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	URL Featurizer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path

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needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.components.**XGBoostClassifier**(*eta=0.1*, *max_depth=6*, *min_child_weight=1*, *n_estimators=100*, *random_seed=0*, *n_jobs=-1*, ***kwargs*)
XGBoost Classifier.

Parameters

- **eta** (*float*) – Boosting learning rate. Defaults to 0.1.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **min_child_weight** (*float*) – Minimum sum of instance weight (hessian) needed in a child. Defaults to 1.0
- **n_estimators** (*int*) – Number of gradient boosted trees. Equivalent to number of boosting rounds. Defaults to 100.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.

Attributes

hyperparameter_ranges	{ "eta": Real(0.000001, 1), "max_depth": Integer(1, 10), "min_child_weight": Real(1, 10), "n_estimators": Integer(1, 1000),}
model_family	ModelFamily.XGBOOST
modifies_features	True
modifies_target	False
name	XGBoost Classifier
predict_uses_y	False
SEED_MAX	None
SEED_MIN	None
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.components.**XGBoostRegressor**(*eta=0.1*, *max_depth=6*, *min_child_weight=1*, *n_estimators=100*, *random_seed=0*, *n_jobs=-1*, ***kwargs*)

XGBoost Regressor.

Parameters

- **eta** (*float*) – Boosting learning rate. Defaults to 0.1.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **min_child_weight** (*float*) – Minimum sum of instance weight (hessian) needed in a child. Defaults to 1.0
- **n_estimators** (*int*) – Number of gradient boosted trees. Equivalent to number of boosting rounds. Defaults to 100.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.

Attributes

hyperparameter_ranges	{ “eta”: Real(0.000001, 1), “max_depth”: Integer(1, 20), “min_child_weight”: Real(1, 10), “n_estimators”: Integer(1, 1000),}
model_family	ModelFamily.XGBOOST
modifies_features	True
modifies_target	False
name	XGBoost Regressor
predict_uses_y	False
SEED_MAX	None
SEED_MIN	None
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.

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Table 601 – continued from previous page

predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

Submodules

binary_classification_pipeline

Module Contents

Classes Summary

BinaryClassificationPipeline	Pipeline subclass for all binary classification pipelines.

Contents

class evalml.pipelines.binary_classification_pipeline.**BinaryClassificationPipeline**(*component_graph*, *parameters=None*, *custom_name=None*, *random_seed=0*)

Pipeline subclass for all binary classification pipelines.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index

in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **custom_name** (*str*) – Custom name for the pipeline. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	ProblemTypes.BINARY

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
*classes_*	Gets the class names for the problem.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Build a classification model. For string and categorical targets, classes are sorted
get_component	Returns component by name
get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
optimize_threshold	Optimize the pipeline threshold given the objective to use. Only used for binary problems with objectives whose thresholds can be tuned.
parameters	Parameter dictionary for this pipeline.

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Table 603 – continued from previous page

predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels. Assumes that the column at index 1 represents the positive label case.
save	Saves pipeline at file path
score	Evaluate model performance on objectives
summary	A short summary of the pipeline structure, describing the list of components used.
threshold	Threshold used to make a prediction. Defaults to None.

can_tune_threshold_with_objective (*self*, *objective*)
Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (*PipelineBase*) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

property classes_ (*self*)
Gets the class names for the problem.

clone (*self*)
Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features (*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives (*objectives*)

property custom_name (*self*)
Custom name of the pipeline.

describe (*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance (*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit (*self*, *X*, *y*)

Build a classification model. For string and categorical targets, classes are sorted by sorted(set(y)) and then are mapped to values between 0 and n_classes-1.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training labels of length [n_samples]

Returns self

get_component (*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges (*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph (*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance (*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform (*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load (*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family (*self*)
Returns model family of this pipeline.

property name (*self*)
Name of the pipeline.

new (*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

optimize_threshold (*self*, *X*, *y*, *y_pred_proba*, *objective*)
Optimize the pipeline threshold given the objective to use. Only used for binary problems with objectives whose thresholds can be tuned.

Parameters

- **X** (*pd.DataFrame*) – Input features
- **y** (*pd.Series*) – Input target values
- **y_pred_proba** (*pd.Series*) – The predicted probabilities of the target outputted by the pipeline
- **objective** (*ObjectiveBase*) – The objective to threshold with. Must have a tunable threshold.

property parameters (*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict (*self*, *X*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]
- **objective** (*Object or string*) – The objective to use to make predictions

Returns Estimated labels

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels. Assumes that the column at index 1 represents the positive label case.

Parameters **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score(*self*, *X*, *y*, *objectives*)
Evaluate model performance on objectives

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series, or np.ndarray*) – True labels of length [n_samples]
- **objectives** (*list*) – List of objectives to score

Returns Ordered dictionary of objective scores

Return type dict

property summary(*self*)
A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

property threshold(*self*)
Threshold used to make a prediction. Defaults to None.

binary_classification_pipeline_mixin

Module Contents

Classes Summary

BinaryClassificationPipelineMixin

Contents

class evalml.pipelines.binary_classification_pipeline_mixin.**BinaryClassificationPipelineMi**
Methods

optimize_threshold	Optimize the pipeline threshold given the objective to use. Only used for binary problems with objectives whose thresholds can be tuned.
threshold	Threshold used to make a prediction. Defaults to None.

optimize_threshold(*self*, *X*, *y*, *y_pred_proba*, *objective*)
Optimize the pipeline threshold given the objective to use. Only used for binary problems with objectives whose thresholds can be tuned.

Parameters

- **X** (*pd.DataFrame*) – Input features
- **y** (*pd.Series*) – Input target values

- **y_pred_proba** (*pd.Series*) – The predicted probabilities of the target outputted by the pipeline
- **objective** (*ObjectiveBase*) – The objective to threshold with. Must have a tunable threshold.

property threshold(*self*)
Threshold used to make a prediction. Defaults to None.

classification_pipeline

Module Contents

Classes Summary

ClassificationPipeline	Pipeline subclass for all classification pipelines.

Contents

class evalml.pipelines.classification_pipeline.**ClassificationPipeline**(*component_graph*, *parameters=None*, *custom_name=None*, *random_seed=0*)

Pipeline subclass for all classification pipelines.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **custom_name** (*str*) – Custom name for the pipeline. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	None

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
*classes_*	Gets the class names for the problem.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Build a classification model. For string and categorical targets, classes are sorted
get_component	Returns component by name
get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves pipeline at file path
score	Evaluate model performance on objectives
summary	A short summary of the pipeline structure, describing the list of components used.

can_tune_threshold_with_objective(*self*, *objective*)
Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (*PipelineBase*) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

property classes_(*self*)
Gets the class names for the problem.

clone(*self*)
Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features (*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives (*objectives*)

property custom_name (*self*)
Custom name of the pipeline.

describe (*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance (*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit (*self*, *X*, *y*)

Build a classification model. For string and categorical targets, classes are sorted by sorted(set(y)) and then are mapped to values between 0 and n_classes-1.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training labels of length [n_samples]

Returns self

get_component (*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges (*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph (*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance(*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform(*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load(*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family(*self*)
Returns model family of this pipeline.

property name(*self*)
Name of the pipeline.

new(*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

property parameters(*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict(*self*, *X*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]
- **objective** (*Object or string*) – The objective to use to make predictions

Returns Estimated labels

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]

Returns Probability estimates

Return type pd.DataFrame

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score (*self*, *X*, *y*, *objectives*)
Evaluate model performance on objectives

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series, or np.ndarray*) – True labels of length [n_samples]
- **objectives** (*list*) – List of objectives to score

Returns Ordered dictionary of objective scores

Return type dict

property summary (*self*)
A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

component_graph

Module Contents

Classes Summary

ComponentGraph	Component graph for a pipeline as a directed acyclic graph (DAG).

Attributes Summary

logger	

Contents

class evalml.pipelines.component_graph.**ComponentGraph**(*component_dict=None*, *random_seed=0*)

Component graph for a pipeline as a directed acyclic graph (DAG).

Parameters

- **component_dict** (*dict*) – A dictionary which specifies the components and edges between components that should be used to create the component graph. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Example

```
>>> component_dict = {'imputer': ['Imputer'], 'ohe': ['One Hot Encoder', 'imputer.
↪x'], 'estimator_1': ['Random Forest Classifier', 'ohe.x'], 'estimator_2': [
↪'Decision Tree Classifier', 'ohe.x'], 'final': ['Logistic Regression Classifier
↪', 'estimator_1', 'estimator_2']}
>>> component_graph = ComponentGraph(component_dict)
```

Methods

compute_final_component_features	Transform all components save the final one, and gathers the data from any number of parents
compute_order	The order that components will be computed or called in.
default_parameters	The default parameter dictionary for this pipeline.
describe	Outputs component graph details including component parameters
fit	Fit each component in the graph.
fit_features	Fit all components save the final one, usually an estimator.
generate_order	Regenerated the topologically sorted order of the graph
get_component	Retrieves a single component object from the graph.
get_estimators	Gets a list of all the estimator components within this graph.
get_inputs	Retrieves all inputs for a given component.
get_last_component	Retrieves the component that is computed last in the graph, usually the final estimator.
graph	Generate an image representing the component graph
instantiate	Instantiates all uninstantiated components within the graph using the given parameters. An error will be

continues on next page

Table 610 – continued from previous page

inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
predict	Make predictions using selected features.

compute_final_component_features (*self*, *X*, *y=None*)
Transform all components save the final one, and gathers the data from any number of parents to get all the information that should be fed to the final component.

Parameters

- **X** (*pd.DataFrame*) – Data of shape [n_samples, n_features].
- **y** (*pd.Series*) – The target training data of length [n_samples]. Defaults to None.

Returns Transformed values.

Return type pd.DataFrame

property compute_order (*self*)
The order that components will be computed or called in.

property default_parameters (*self*)
The default parameter dictionary for this pipeline.

Returns Dictionary of all component default parameters.

Return type dict

describe (*self*, *return_dict=False*)
Outputs component graph details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about component graph. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

fit (*self*, *X*, *y*)
Fit each component in the graph.

Parameters

- **X** (*pd.DataFrame*) – The input training data of shape [n_samples, n_features].
- **y** (*pd.Series*) – The target training data of length [n_samples].

fit_features (*self*, *X*, *y*)
Fit all components save the final one, usually an estimator.

Parameters

- **X** (*pd.DataFrame*) – The input training data of shape [n_samples, n_features].
- **y** (*pd.Series*) – The target training data of length [n_samples].

Returns Transformed values.

Return type pd.DataFrame

classmethod generate_order (*cls*, *component_dict*)
Regenerated the topologically sorted order of the graph

get_component (*self*, *component_name*)
Retrieves a single component object from the graph.

Parameters **component_name** (*str*) – Name of the component to retrieve

Returns ComponentBase object

get_estimators(*self*)
Gets a list of all the estimator components within this graph.

Returns All estimator objects within the graph.

Return type list

get_inputs(*self*, *component_name*)
Retrieves all inputs for a given component.

Parameters **component_name** (*str*) – Name of the component to look up.

Returns List of inputs for the component to use.

Return type list[str]

get_last_component(*self*)
Retrieves the component that is computed last in the graph, usually the final estimator.

Returns ComponentBase object

graph(*self*, *name=None*, *graph_format=None*)
Generate an image representing the component graph

Parameters

- **name** (*str*) – Name of the graph. Defaults to None.
- **graph_format** (*str*) – file format to save the graph in. Defaults to None.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

instantiate(*self*, *parameters*)
Instantiates all uninstantiated components within the graph using the given parameters. An error will be raised if a component is already instantiated but the parameters dict contains arguments for that component.

Parameters **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary {} or None implies using all default values for component parameters.

inverse_transform(*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** – (pd.Series): Final component features

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame*) – Data of shape [n_samples, n_features].

Returns Predicted values.

Return type pd.Series

evalml.pipelines.component_graph.**logger**

multiclass_classification_pipeline

Module Contents

Classes Summary

MulticlassClassificationPipeline	Pipeline subclass for all multiclass classification pipelines.

Contents

class evalml.pipelines.multiclass_classification_pipeline.**MulticlassClassificationPipeline**

Pipeline subclass for all multiclass classification pipelines.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **custom_name** (*str*) – Custom name for the pipeline. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	ProblemTypes.MULTICLASS

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
*classes_*	Gets the class names for the problem.
clone	Constructs a new pipeline with the same components, parameters, and random state.

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Table 612 – continued from previous page

compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Build a classification model. For string and categorical targets, classes are sorted
get_component	Returns component by name
get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves pipeline at file path
score	Evaluate model performance on objectives
summary	A short summary of the pipeline structure, describing the list of components used.

can_tune_threshold_with_objective (*self*, *objective*)
Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (*PipelineBase*) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

property classes_ (*self*)
Gets the class names for the problem.

clone (*self*)
Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features (*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives(*objectives*)

property custom_name(*self*)
Custom name of the pipeline.

describe(*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance(*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit(*self*, *X*, *y*)

Build a classification model. For string and categorical targets, classes are sorted by sorted(set(y)) and then are mapped to values between 0 and n_classes-1.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training labels of length [n_samples]

Returns self

get_component(*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges(*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph(*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance(*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform(*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load(*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family(*self*)
Returns model family of this pipeline.

property name(*self*)
Name of the pipeline.

new(*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

property parameters(*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict(*self*, *X*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]
- **objective** (*Object or string*) – The objective to use to make predictions

Returns Estimated labels

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]

Returns Probability estimates

Return type pd.DataFrame

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score(*self*, *X*, *y*, *objectives*)
Evaluate model performance on objectives

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series, or np.ndarray*) – True labels of length [n_samples]
- **objectives** (*list*) – List of objectives to score

Returns Ordered dictionary of objective scores

Return type dict

property summary(*self*)
A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

pipeline_base

Module Contents

Classes Summary

PipelineBase	Machine learning pipeline made out of transformers and a estimator.

Attributes Summary

logger

Contents

evalml.pipelines.pipeline_base.**logger**

class evalml.pipelines.pipeline_base.**PipelineBase**(*component_graph*, *parameters=None*, *custom_name=None*, *random_seed=0*)

Machine learning pipeline made out of transformers and a estimator.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"].
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **custom_name** (*str*) – Custom name for the pipeline. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	None

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Build a model.
get_component	Returns component by name
get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.

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load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
save	Saves pipeline at file path
score	Evaluate model performance on current and additional objectives.
summary	A short summary of the pipeline structure, describing the list of components used.

can_tune_threshold_with_objective (*self*, *objective*)
Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (*PipelineBase*) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

clone (*self*)
Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features (*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives (*objectives*)

property custom_name (*self*)
Custom name of the pipeline.

describe (*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance (*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

abstract fit (*self*, *X*, *y*)
Build a model.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features].
- **y** (*pd.Series, np.ndarray*) – The target training data of length [n_samples].

Returns self

get_component (*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges (*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph (*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance (*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform (*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load (*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family (*self*)
Returns model family of this pipeline.

property name (*self*)
Name of the pipeline.

new (*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

property parameters (*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict (*self*, *X*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features].
- **objective** (*Object or string*) – The objective to use to make predictions.

Returns Predicted values.

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

abstract score (*self*, *X*, *y*, *objectives*)
Evaluate model performance on current and additional objectives.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features].
- **y** (*pd.Series, np.ndarray*) – True labels of length [n_samples].
- **objectives** (*list*) – Non-empty list of objectives to score on.

Returns Ordered dictionary of objective scores.

Return type dict

property summary (*self*)
A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

pipeline_meta

Module Contents

Classes Summary

PipelineBaseMeta	Metaclass that overrides creating a new pipeline by wrapping methods with validators and setters
TimeSeriesPipelineBaseMeta	Metaclass that overrides creating a new time series pipeline by wrapping methods with validators and setters

Contents

class evalml.pipelines.pipeline_meta.**PipelineBaseMeta**

Metaclass that overrides creating a new pipeline by wrapping methods with validators and setters

Attributes

FIT_METHODS	[‘fit’, ‘fit_transform’]
METHODS_TO_CHECK	[‘predict’, ‘predict_proba’, ‘transform’, ‘inverse_transform’]
PROPERTIES_TO_CHECK	[‘feature_importance’]

Methods

check_for_fit	*check_for_fit* wraps a method that validates if *self._is_fitted* is *True*.
register	Register a virtual subclass of an ABC.
set_fit	

classmethod check_for_fit(*cls*, *method*)

check_for_fit wraps a method that validates if *self._is_fitted* is *True*. It raises an exception if *False* and calls and returns the wrapped method if *True*.

register(*cls*, *subclass*)

Register a virtual subclass of an ABC.

Returns the subclass, to allow usage as a class decorator.

classmethod set_fit(*cls*, *method*)

class evalml.pipelines.pipeline_meta.**TimeSeriesPipelineBaseMeta**

Metaclass that overrides creating a new time series pipeline by wrapping methods with validators and setters

Attributes

FIT_METHODS	['fit', 'fit_transform']
METHODS_TO_CHECK	['predict', 'predict_proba', 'transform', 'inverse_transform']
PROPERTIES_TO_CHECK	['feature_importance']

Methods

check_for_fit	*check_for_fit* wraps a method that validates if *self._is_fitted* is *True*.
register	Register a virtual subclass of an ABC.
set_fit	

classmethod check_for_fit(*cls*, *method*)
check_for_fit wraps a method that validates if *self._is_fitted* is *True*. It raises an exception if *False* and calls and returns the wrapped method if *True*.

register(*cls*, *subclass*)
Register a virtual subclass of an ABC.

Returns the subclass, to allow usage as a class decorator.

classmethod set_fit(*cls*, *method*)

regression_pipeline

Module Contents

Classes Summary

RegressionPipeline	Pipeline subclass for all regression pipelines.

Contents

class evalml.pipelines.regression_pipeline.**RegressionPipeline**(*component_graph*, *parameters=None*, *custom_name=None*, *random_seed=0*)

Pipeline subclass for all regression pipelines.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that

component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.

- **custom_name** (*str*) – Custom name for the pipeline. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	ProblemTypes.REGRESSION

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Build a regression model.
get_component	Returns component by name
get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
save	Saves pipeline at file path
score	Evaluate model performance on current and additional objectives
summary	A short summary of the pipeline structure, describing the list of components used.

can_tune_threshold_with_objective(*self*, *objective*)

Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (*PipelineBase*) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

clone (*self*)
Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features (*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives (*objectives*)

property custom_name (*self*)
Custom name of the pipeline.

describe (*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance (*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit (*self*, *X*, *y*)
Build a regression model.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training data of length [n_samples]

Returns self

get_component (*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges (*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph (*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance (*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform (*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load (*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family (*self*)
Returns model family of this pipeline.

property name (*self*)
Name of the pipeline.

new (*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

property parameters (*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict (*self*, *X*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features].
- **objective** (*Object or string*) – The objective to use to make predictions.

Returns Predicted values.

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score (*self*, *X*, *y*, *objectives*)
Evaluate model performance on current and additional objectives

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series, or np.ndarray*) – True values of length [n_samples]
- **objectives** (*list*) – Non-empty list of objectives to score on

Returns Ordered dictionary of objective scores

Return type dict

property summary (*self*)
A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

time_series_classification_pipelines

Module Contents

Classes Summary

TimeSeriesBinaryClassificationPipeline	Pipeline base class for time series binary classification problems.
TimeSeriesClassificationPipeline	Pipeline base class for time series classification problems.
TimeSeriesMulticlassClassificationPipeline	Pipeline base class for time series multiclass classification problems.

Contents

class evalml.pipelines.time_series_classification_pipelines.**TimeSeriesBinaryClassificationP**

Pipeline base class for time series binary classification problems.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary {} implies using all default values for component parameters. Pipeline-level parameters such as date_index, gap, and max_delay must be specified with the "pipeline" key. For example: Pipeline(parameters={"pipeline": {"date_index": "Date", "max_delay": 4, "gap": 2}}).
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	None

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
*classes_*	Gets the class names for the problem.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Fit a time series classification pipeline.
get_component	Returns component by name

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get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
optimize_threshold	Optimize the pipeline threshold given the objective to use. Only used for binary problems with objectives whose thresholds can be tuned.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves pipeline at file path
score	Evaluate model performance on current and additional objectives.
summary	A short summary of the pipeline structure, describing the list of components used.
threshold	Threshold used to make a prediction. Defaults to None.

can_tune_threshold_with_objective (*self*, *objective*)
Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (*PipelineBase*) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

property classes_ (*self*)
Gets the class names for the problem.

clone (*self*)
Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features (*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives (*objectives*)

property custom_name (*self*)
Custom name of the pipeline.

describe (*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance (*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit (*self*, *X*, *y*)
Fit a time series classification pipeline.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training targets of length [n_samples]

Returns self

get_component (*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges (*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph (*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance (*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform(*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load(*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family(*self*)
Returns model family of this pipeline.

property name(*self*)
Name of the pipeline.

new(*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

optimize_threshold(*self*, *X*, *y*, *y_pred_proba*, *objective*)
Optimize the pipeline threshold given the objective to use. Only used for binary problems with objectives whose thresholds can be tuned.

Parameters

- **X** (*pd.DataFrame*) – Input features
- **y** (*pd.Series*) – Input target values
- **y_pred_proba** (*pd.Series*) – The predicted probabilities of the target outputted by the pipeline
- **objective** (*ObjectiveBase*) – The objective to threshold with. Must have a tunable threshold.

property parameters(*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict(*self*, *X*, *y=None*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]

- **y** (*pd.Series, np.ndarray, None*) – The target training targets of length [n_samples]
- **objective** (*Object or string*) – The objective to use to make predictions

Returns Predicted values.

Return type pd.Series

predict_proba(*self*, *X*, *y=None*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]

Returns Probability estimates

Return type pd.DataFrame

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score(*self*, *X*, *y*, *objectives*)
Evaluate model performance on current and additional objectives.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series*) – True labels of length [n_samples]
- **objectives** (*list*) – Non-empty list of objectives to score on

Returns Ordered dictionary of objective scores

Return type dict

property summary(*self*)
A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

property threshold(*self*)
Threshold used to make a prediction. Defaults to None.

class evalml.pipelines.time_series_classification_pipelines.**TimeSeriesClassificationPipeli**

Pipeline base class for time series classification problems.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary {} implies using all default values for component parameters. Pipeline-level parameters such as date_index, gap, and max_delay must be specified with the "pipeline" key. For example: Pipeline(parameters={"pipeline": {"date_index": "Date", "max_delay": 4, "gap": 2}}).
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	None

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
*classes_*	Gets the class names for the problem.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Fit a time series classification pipeline.
get_component	Returns component by name
get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.

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predict_proba	Make probability estimates for labels.
save	Saves pipeline at file path
score	Evaluate model performance on current and additional objectives.
summary	A short summary of the pipeline structure, describing the list of components used.

can_tune_threshold_with_objective (*self*, *objective*)
Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (*PipelineBase*) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

property classes_ (*self*)
Gets the class names for the problem.

clone (*self*)
Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features (*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives (*objectives*)

property custom_name (*self*)
Custom name of the pipeline.

describe (*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance (*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit (*self*, *X*, *y*)
Fit a time series classification pipeline.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training targets of length [n_samples]

Returns self

get_component (*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges (*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph (*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance (*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform (*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load (*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family (*self*)
Returns model family of this pipeline.

property name (*self*)
Name of the pipeline.

new (*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

property parameters(*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict(*self*, *X*, *y=None*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, None*) – The target training targets of length [n_samples]
- **objective** (*Object or string*) – The objective to use to make predictions

Returns Predicted values.

Return type pd.Series

predict_proba(*self*, *X*, *y=None*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]

Returns Probability estimates

Return type pd.DataFrame

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score(*self*, *X*, *y*, *objectives*)
Evaluate model performance on current and additional objectives.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series*) – True labels of length [n_samples]
- **objectives** (*list*) – Non-empty list of objectives to score on

Returns Ordered dictionary of objective scores

Return type dict

property summary(*self*)
A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

class evalml.pipelines.time_series_classification_pipelines.**TimeSeriesMulticlassClassificat**

Pipeline base class for time series multiclass classification problems.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary {} implies using all default values for component parameters. Pipeline-level parameters such as date_index, gap, and max_delay must be specified with the "pipeline" key. For example: Pipeline(parameters={"pipeline": {"date_index": "Date", "max_delay": 4, "gap": 2}}).
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	ProblemTypes.TIME_SERIES_MULTICLASS

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
*classes_*	Gets the class names for the problem.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Fit a time series classification pipeline.
get_component	Returns component by name

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get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves pipeline at file path
score	Evaluate model performance on current and additional objectives.
summary	A short summary of the pipeline structure, describing the list of components used.

can_tune_threshold_with_objective (*self*, *objective*)
Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (*PipelineBase*) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

property classes_ (*self*)
Gets the class names for the problem.

clone (*self*)
Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features (*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives (*objectives*)

property custom_name (*self*)
Custom name of the pipeline.

describe (*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance(*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit(*self*, *X*, *y*)
Fit a time series classification pipeline.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training targets of length [n_samples]

Returns self

get_component(*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges(*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph(*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance(*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform(*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load(*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family(*self*)
Returns model family of this pipeline.

property name(*self*)
Name of the pipeline.

new(*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

property parameters(*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict(*self*, *X*, *y=None*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, None*) – The target training targets of length [n_samples]
- **objective** (*Object or string*) – The objective to use to make predictions

Returns Predicted values.

Return type pd.Series

predict_proba(*self*, *X*, *y=None*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]

Returns Probability estimates

Return type pd.DataFrame

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score(*self*, *X*, *y*, *objectives*)
Evaluate model performance on current and additional objectives.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series*) – True labels of length [n_samples]
- **objectives** (*list*) – Non-empty list of objectives to score on

Returns Ordered dictionary of objective scores

Return type dict

property summary(*self*)
A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

time_series_regression_pipeline

Module Contents

Classes Summary

TimeSeriesRegressionPipeline	Pipeline base class for time series regression problems.

Contents

class evalml.pipelines.time_series_regression_pipeline.**TimeSeriesRegressionPipeline**(*componen*
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Pipeline base class for time series regression problems.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary {} implies us-

ing all default values for component parameters. Pipeline-level parameters such as date_index, gap, and max_delay must be specified with the "pipeline" key. For example: Pipeline(parameters={"pipeline": {"date_index": "Date", "max_delay": 4, "gap": 2}}).

- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	ProblemTypes.TIME_SERIES_REGRESSIO

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Fit a time series regression pipeline.
get_component	Returns component by name
get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
save	Saves pipeline at file path
score	Evaluate model performance on current and additional objectives.
summary	A short summary of the pipeline structure, describing the list of components used.

can_tune_threshold_with_objective(*self*, *objective*)

Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (*PipelineBase*) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

clone (*self*)
Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features (*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives (*objectives*)

property custom_name (*self*)
Custom name of the pipeline.

describe (*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance (*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit (*self*, *X*, *y*)
Fit a time series regression pipeline.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training targets of length [n_samples]

Returns self

get_component (*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges (*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph (*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance (*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform (*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load (*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family (*self*)
Returns model family of this pipeline.

property name (*self*)
Name of the pipeline.

new (*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

property parameters (*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict (*self*, *X*, *y=None*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, None*) – The target training targets of length [n_samples]
- **objective** (*Object or string*) – The objective to use to make predictions

Returns Predicted values.

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score(*self*, *X*, *y*, *objectives*)
Evaluate model performance on current and additional objectives.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series*) – True labels of length [n_samples]
- **objectives** (*list*) – Non-empty list of objectives to score on

Returns Ordered dictionary of objective scores

Return type dict

property summary(*self*)
A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

utils

Module Contents

Functions

generate_pipeline_code	Creates and returns a string that contains the Python imports and code required for running the EvalML pipeline.
make_pipeline	Given input data, target data, an estimator class and the problem type,

Attributes Summary

logger	

Contents

evalml.pipelines.utils.**generate_pipeline_code**(*element*)

Creates and returns a string that contains the Python imports and code required for running the EvalML pipeline.

Parameters **element** (*pipeline instance*) – The instance of the pipeline to generate string Python code

Returns String representation of Python code that can be run separately in order to recreate the pipeline instance. Does not include code for custom component implementation.

evalml.pipelines.utils.**logger**

evalml.pipelines.utils.**make_pipeline**(*X*, *y*, *estimator*, *problem_type*, *parameters=None*, *sampler_name=None*, *extra_components=None*)

Given input data, target data, an estimator class and the problem type, generates a pipeline class with a preprocessing chain which was recommended based on the inputs. The pipeline will be a subclass of the appropriate pipeline base class for the specified problem_type.

Parameters

- **X** (*pd.DataFrame*) – The input data of shape [n_samples, n_features]
- **y** (*pd.Series*) – The target data of length [n_samples]
- **estimator** (*Estimator*) – Estimator for pipeline
- **problem_type** (*ProblemTypes or str*) – Problem type for pipeline to generate
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters.
- **sampler_name** (*str*) – The name of the sampler component to add to the pipeline. Only used in classification problems. Defaults to None
- **extra_components** – List of extra components to be added after preprocessing components. Defaults to None.

Package Contents

Classes Summary

ARIMARegressor	Autoregressive Integrated Moving Average Model.
CatBoostClassifier	CatBoost Classifier, a classifier that uses gradient-boosting on decision trees.
CatBoostRegressor	CatBoost Regressor, a regressor that uses gradient-boosting on decision trees.

continues on next page

Table 629 – continued from previous page

ComponentGraph	Component graph for a pipeline as a directed acyclic graph (DAG).
DecisionTreeClassifier	Decision Tree Classifier.
DecisionTreeRegressor	Decision Tree Regressor.
DelayedFeatureTransformer	Transformer that delays input features and target variable for time series problems.
DFSTransformer	Featuretools DFS component that generates features for the input features.
ElasticNetClassifier	Elastic Net Classifier. Uses Logistic Regression with elasticnet penalty as the base estimator.
ElasticNetRegressor	Elastic Net Regressor.
Estimator	A component that fits and predicts given data.
ExtraTreesClassifier	Extra Trees Classifier.
ExtraTreesRegressor	Extra Trees Regressor.
FeatureSelector	Selects top features based on importance weights.
KNeighborsClassifier	K-Nearest Neighbors Classifier.
LightGBMClassifier	LightGBM Classifier.
LightGBMRegressor	LightGBM Regressor.
LinearRegressor	Linear Regressor.
LogisticRegressionClassifier	Logistic Regression Classifier.
MulticlassClassificationPipeline	Pipeline subclass for all multiclass classification pipelines.
OneHotEncoder	A transformer that encodes categorical features in a one-hot numeric array.
PerColumnImputer	Imputes missing data according to a specified imputation strategy per column.
PipelineBase	Machine learning pipeline made out of transformers and a estimator.
ProphetRegressor	Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.
RandomForestClassifier	Random Forest Classifier.
RandomForestRegressor	Random Forest Regressor.
RegressionPipeline	Pipeline subclass for all regression pipelines.
RFClassifierSelectFromModel	Selects top features based on importance weights using a Random Forest classifier.
RFRegressorSelectFromModel	Selects top features based on importance weights using a Random Forest regressor.
SimpleImputer	Imputes missing data according to a specified imputation strategy.
SklearnStackedEnsembleClassifier	Scikit-learn Stacked Ensemble Classifier.
SklearnStackedEnsembleRegressor	Scikit-learn Stacked Ensemble Regressor.
StandardScaler	A transformer that standardizes input features by removing the mean and scaling to unit variance.
SVMClassifier	Support Vector Machine Classifier.
SVMRegressor	Support Vector Machine Regressor.
TargetEncoder	A transformer that encodes categorical features into target encodings.
TimeSeriesBinaryClassificationPipeline	Pipeline base class for time series binary classification problems.

continues on next page

Table 629 – continued from previous page

TimeSeriesClassificationPipeline	Pipeline base class for time series classification problems.
TimeSeriesMulticlassClassificationPipeline	Pipeline base class for time series multiclass classification problems.
TimeSeriesRegressionPipeline	Pipeline base class for time series regression problems.
Transformer	A component that may or may not need fitting that transforms data.
XGBoostClassifier	XGBoost Classifier.
XGBoostRegressor	XGBoost Regressor.

Contents

class evalml.pipelines.**ARIMARegressor**(*date_index=None*, *trend=None*, *start_p=2*, *d=0*, *start_q=2*, *max_p=5*, *max_d=2*, *max_q=5*, *seasonal=True*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)

Autoregressive Integrated Moving Average Model. The three parameters (p, d, q) are the AR order, the degree of differencing, and the MA order. More information here: https://www.statsmodels.org/devel/generated/statsmodels.tsa.arima_model.ARIMA.html

Currently ARIMARegressor isn't supported via conda install. It's recommended that it be installed via PyPI.

Parameters

- **date_index** (*str*) – Specifies the name of the column in X that provides the datetime objects. Defaults to None.
- **trend** (*str*) – Controls the deterministic trend. Options are ['n', 'c', 't', 'ct'] where 'c' is a constant term, 't' indicates a linear trend, and 'ct' is both. Can also be an iterable when defining a polynomial, such as [1, 1, 0, 1].
- **start_p** (*int*) – Minimum Autoregressive order. Defaults to 2.
- **d** (*int*) – Minimum Differencing degree. Defaults to 0.
- **start_q** (*int*) – Minimum Moving Average order. Defaults to 2.
- **max_p** (*int*) – Maximum Autoregressive order. Defaults to 5.
- **max_d** (*int*) – Maximum Differencing degree. Defaults to 2.
- **max_q** (*int*) – Maximum Moving Average order. Defaults to 5.
- **seasonal** (*boolean*) – Whether to fit a seasonal model to ARIMA. Defaults to True.
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “start_p”: Integer(1, 3), “d”: Integer(0, 2), “start_q”: Integer(1, 3), “max_p”: Integer(3, 10), “max_d”: Integer(2, 5), “max_q”: Integer(3, 10), “seasonal”: [True, False],}
model_family	ModelFamily.ARIMA
modifies_features	True
modifies_target	False
name	ARIMA Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns array of 0’s with a length of 1 as feature_importance is not defined for ARIMA regressor.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns array of 0's with a length of 1 as feature_importance is not defined for ARIMA regressor.

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**CatBoostClassifier**(*n_estimators=10*, *eta=0.03*, *max_depth=6*, *bootstrap_type=None*, *silent=True*, *allow_writing_files=False*, *random_seed=0*, *n_jobs=- 1*, ***kwargs*)
CatBoost Classifier, a classifier that uses gradient-boosting on decision trees. CatBoost is an open-source library

and natively supports categorical features.

For more information, check out https://catboost.ai/

Parameters

- **n_estimators** (*float*) – The maximum number of trees to build. Defaults to 10.
- **eta** (*float*) – The learning rate. Defaults to 0.03.
- **max_depth** (*int*) – The maximum tree depth for base learners. Defaults to 6.
- **bootstrap_type** (*string*) – Defines the method for sampling the weights of objects. Available methods are 'Bayesian', 'Bernoulli', 'MVS'. Defaults to None.
- **silent** (*boolean*) – Whether to use the "silent" logging mode. Defaults to True.
- **allow_writing_files** (*boolean*) – Whether to allow writing snapshot files while training. Defaults to False.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(4, 100), "eta": Real(0.000001, 1), "max_depth": Integer(4, 10),}
model_family	ModelFamily.CATBOOST
modifies_features	True
modifies_target	False
name	CatBoost Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**CatBoostRegressor**(*n_estimators=10*, *eta=0.03*, *max_depth=6*, *bootstrap_type=None*, *silent=False*, *allow_writing_files=False*, *random_seed=0*, *n_jobs=- 1*, ***kwargs*)
CatBoost Regressor, a regressor that uses gradient-boosting on decision trees. CatBoost is an open-source library and natively supports categorical features.

For more information, check out https://catboost.ai/

Parameters

- **n_estimators** (*float*) – The maximum number of trees to build. Defaults to 10.
- **eta** (*float*) – The learning rate. Defaults to 0.03.
- **max_depth** (*int*) – The maximum tree depth for base learners. Defaults to 6.
- **bootstrap_type** (*string*) – Defines the method for sampling the weights of objects. Available methods are 'Bayesian', 'Bernoulli', 'MVS'. Defaults to None.
- **silent** (*boolean*) – Whether to use the "silent" logging mode. Defaults to True.
- **allow_writing_files** (*boolean*) – Whether to allow writing snapshot files while training. Defaults to False.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “n_estimators”: Integer(4, 100), “eta”: Real(0.000001, 1), “max_depth”: Integer(4, 10),}
model_family	ModelFamily.CATBOOST
modifies_features	True
modifies_target	False
name	CatBoost Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**ComponentGraph**(*component_dict=None*, *random_seed=0*)

Component graph for a pipeline as a directed acyclic graph (DAG).

Parameters

- **component_dict** (*dict*) – A dictionary which specifies the components and edges between components that should be used to create the component graph. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Example

```
>>> component_dict = {'imputer': ['Imputer'], 'ohe': ['One Hot Encoder', 'imputer.
↪x'], 'estimator_1': ['Random Forest Classifier', 'ohe.x'], 'estimator_2': [
↪'Decision Tree Classifier', 'ohe.x'], 'final': ['Logistic Regression Classifier
↪', 'estimator_1', 'estimator_2']}
>>> component_graph = ComponentGraph(component_dict)
```

Methods

compute_final_component_features	Transform all components save the final one, and gathers the data from any number of parents
compute_order	The order that components will be computed or called in.
default_parameters	The default parameter dictionary for this pipeline.
describe	Outputs component graph details including component parameters
fit	Fit each component in the graph.
fit_features	Fit all components save the final one, usually an estimator.
generate_order	Regenerated the topologically sorted order of the graph
get_component	Retrieves a single component object from the graph.
get_estimators	Gets a list of all the estimator components within this graph.
get_inputs	Retrieves all inputs for a given component.
get_last_component	Retrieves the component that is computed last in the graph, usually the final estimator.
graph	Generate an image representing the component graph
instantiate	Instantiates all uninstantiated components within the graph using the given parameters. An error will be
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
predict	Make predictions using selected features.

compute_final_component_features(*self*, *X*, *y=None*)

Transform all components save the final one, and gathers the data from any number of parents to get all the information that should be fed to the final component.

Parameters

- **X** (*pd.DataFrame*) – Data of shape [n_samples, n_features].
- **y** (*pd.Series*) – The target training data of length [n_samples]. Defaults to None.

Returns Transformed values.

Return type pd.DataFrame

property compute_order(*self*)
The order that components will be computed or called in.

property default_parameters(*self*)
The default parameter dictionary for this pipeline.

Returns Dictionary of all component default parameters.

Return type dict

describe(*self*, *return_dict=False*)
Outputs component graph details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about component graph. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

fit(*self*, *X*, *y*)
Fit each component in the graph.

Parameters

- **X** (*pd.DataFrame*) – The input training data of shape [n_samples, n_features].
- **y** (*pd.Series*) – The target training data of length [n_samples].

fit_features(*self*, *X*, *y*)
Fit all components save the final one, usually an estimator.

Parameters

- **X** (*pd.DataFrame*) – The input training data of shape [n_samples, n_features].
- **y** (*pd.Series*) – The target training data of length [n_samples].

Returns Transformed values.

Return type pd.DataFrame

classmethod generate_order(*cls*, *component_dict*)
Regenerated the topologically sorted order of the graph

get_component(*self*, *component_name*)
Retrieves a single component object from the graph.

Parameters **component_name** (*str*) – Name of the component to retrieve

Returns ComponentBase object

get_estimators(*self*)
Gets a list of all the estimator components within this graph.

Returns All estimator objects within the graph.

Return type list

get_inputs(*self*, *component_name*)
Retrieves all inputs for a given component.

Parameters **component_name** (*str*) – Name of the component to look up.

Returns List of inputs for the component to use.

Return type list[str]

get_last_component(*self*)
Retrieves the component that is computed last in the graph, usually the final estimator.

Returns ComponentBase object

graph(*self*, *name=None*, *graph_format=None*)
Generate an image representing the component graph

Parameters

- **name** (*str*) – Name of the graph. Defaults to None.
- **graph_format** (*str*) – file format to save the graph in. Defaults to None.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

instantiate(*self*, *parameters*)
Instantiates all uninstantiated components within the graph using the given parameters. An error will be raised if a component is already instantiated but the parameters dict contains arguments for that component.

Parameters **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary {} or None implies using all default values for component parameters.

inverse_transform(*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** – (pd.Series): Final component features

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame*) – Data of shape [n_samples, n_features].

Returns Predicted values.

Return type pd.Series

class evalml.pipelines.**DecisionTreeClassifier**(*criterion='gini'*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *random_seed=0*, ***kwargs*)
Decision Tree Classifier.

Parameters

- **criterion** (*{"gini", "entropy"}*) – The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain. Defaults to "gini".
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).

  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".

- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.

  Defaults to 2.
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "criterion": ["gini", "entropy"], "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.DECISION_TREE
modifies_features	True
modifies_target	False
name	Decision Tree Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.

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predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**DecisionTreeRegressor**(*criterion='mse'*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *random_seed=0*, ***kwargs*)
Decision Tree Regressor.

Parameters

- **criterion** (*{"mse", "friedman_mse", "mae", "poisson"}*) – The function to measure the quality of a split. Supported criteria are:
  - "mse" for the mean squared error, which is equal to variance reduction as feature selection criterion and minimizes the L2 loss using the mean of each terminal node
  - "friedman_mse", which uses mean squared error with Friedman"s improvement score for potential splits
  - "mae" for the mean absolute error, which minimizes the L1 loss using the median of each terminal node,
  - "poisson" which uses reduction in Poisson deviance to find splits.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features.

- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.

  Defaults to 2.
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “criterion”: [“mse”, “friedman_mse”, “mae”], “max_features”: [“auto”, “sqrt”, “log2”], “max_depth”: Integer(4, 10),}
model_family	ModelFamily.DECISION_TREE
modifies_features	True
modifies_target	False
name	Decision Tree Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**DelayedFeatureTransformer**(*date_index=None*, *max_delay=2*, *delay_features=True*, *delay_target=True*, *gap=1*, *random_seed=0*, ***kwargs*)
Transformer that delays input features and target variable for time series problems.

Parameters

- **date_index** (*str*) – Name of the column containing the datetime information used to order the data. Ignored.
- **max_delay** (*int*) – Maximum number of time units to delay each feature. Defaults to 2.
- **delay_features** (*bool*) – Whether to delay the input features. Defaults to True.
- **delay_target** (*bool*) – Whether to delay the target. Defaults to True.
- **gap** (*int*) – The number of time units between when the features are collected and when the target is collected. For example, if you are predicting the next time step's target, gap=1. This is only needed because when gap=0, we need to be sure to start the lagging of the target variable at 1. Defaults to 1.
- **random_seed** (*int*) – Seed for the random number generator. This transformer performs the same regardless of the random seed provided.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Delayed Feature Transformer
needs_fitting	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the DelayFeatureTransformer.
fit_transform	Fits on X and transforms X
load	Loads component at file path
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Computes the delayed features for all features in X and y.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits the DelayFeatureTransformer.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Computes the delayed features for all features in X and y.

For each feature in X, it will add a column to the output dataframe for each delay in the (inclusive) range [1, max_delay]. The values of each delayed feature are simply the original feature shifted forward in time by the delay amount. For example, a delay of 3 units means that the feature value at row n will be taken from the n-3rd row of that feature

If y is not None, it will also compute the delayed values for the target variable.

Parameters

- **X** (*pd.DataFrame or None*) – Data to transform. None is expected when only the target variable is being used.
- **y** (*pd.Series, or None*) – Target.

Returns Transformed X.

Return type pd.DataFrame

class evalml.pipelines.**DFSTransformer**(*index='index'*, *random_seed=0*, ***kwargs*)
Featuretools DFS component that generates features for the input features.

Parameters

- **index** (*string*) – The name of the column that contains the indices. If no column with this name exists, then featuretools.EntitySet() creates a column with this name to serve as the index column. Defaults to 'index'.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	DFS Transformer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits the DFSTransformer Transformer component.
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Computes the feature matrix for the input X using featuretools' dfs algorithm.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits the DFSTransformer Transformer component.

Parameters

- **X** (*pd.DataFrame, np.array*) – The input data to transform, of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Computes the feature matrix for the input X using featuretools' dfs algorithm.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data to transform. Has shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – Ignored.

Returns Feature matrix

Return type pd.DataFrame

class evalml.pipelines.**ElasticNetClassifier**(*penalty='elasticnet'*, *C=1.0*, *l1_ratio=0.15*, *multi_class='auto'*, *solver='saga'*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
Elastic Net Classifier. Uses Logistic Regression with elasticnet penalty as the base estimator.

Parameters

- **penalty** (*{"l1", "l2", "elasticnet", "none"}*) – The norm used in penalization. Defaults to "elasticnet".
- **C** (*float*) – Inverse of regularization strength. Must be a positive float. Defaults to 1.0.
- **l1_ratio** (*float*) – The mixing parameter, with 0 <= l1_ratio <= 1. Only used if penalty='elasticnet'. Setting l1_ratio=0 is equivalent to using penalty='l2', while setting l1_ratio=1 is equivalent to using penalty='l1'. For 0 < l1_ratio <1, the penalty is a combination of L1 and L2. Defaults to 0.15.
- **multi_class** (*{"auto", "ovr", "multinomial"}*) – If the option chosen is "ovr", then a binary problem is fit for each label. For "multinomial" the loss minimised is the multinomial loss fit across the entire probability distribution, even when the data is binary. "multinomial" is unavailable when solver="liblinear". "auto" selects "ovr" if the data is binary, or if solver="liblinear", and otherwise selects "multinomial". Defaults to "auto".
- **solver** (*{"newton-cg", "lbfgs", "liblinear", "sag", "saga"}*) – Algorithm to use in the optimization problem. For small datasets, "liblinear" is a good choice, whereas "sag" and "saga" are faster for large ones. For multiclass problems, only "newton-cg", "sag", "saga" and "lbfgs" handle multinomial loss; "liblinear" is limited to one-versus-rest schemes.
  - "newton-cg", "lbfgs", "sag" and "saga" handle L2 or no penalty
  - "liblinear" and "saga" also handle L1 penalty
  - "saga" also supports "elasticnet" penalty
  - "liblinear" does not support setting penalty='none'

  Defaults to "saga".
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0.01, 10), "l1_ratio": Real(0, 1)}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Elastic Net Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**ElasticNetRegressor**(*alpha=0.0001*, *l1_ratio=0.15*, *max_iter=1000*, *normalize=False*, *random_seed=0*, ***kwargs*)
Elastic Net Regressor.

Parameters

- **alpha** (*float*) – Constant that multiplies the penalty terms. Defaults to 0.0001.
- **l1_ratio** (*float*) – The mixing parameter, with 0 <= l1_ratio <= 1. Only used if penalty='elasticnet'. Setting l1_ratio=0 is equivalent to using penalty='l2', while setting l1_ratio=1 is equivalent to using penalty='l1'. For 0 < l1_ratio <1, the penalty is a combination of L1 and L2. Defaults to 0.15.
- **max_iter** (*int*) – The maximum number of iterations. Defaults to 1000.
- **normalize** (*boolean*) – If True, the regressors will be normalized before regression by subtracting the mean and dividing by the l2-norm. Defaults to False.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "alpha": Real(0, 1), "l1_ratio": Real(0, 1),}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Elastic Net Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**Estimator**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)

A component that fits and predicts given data.

To implement a new Estimator, define your own class which is a subclass of Estimator, including a name and a list of acceptable ranges for any parameters to be tuned during the automl search (hyperparameters). Define an *__init__* method which sets up any necessary state and objects. Make sure your *__init__* only uses standard keyword arguments and calls *super().__init__()* with a parameters dict. You may also override the *fit*, *transform*, *fit_transform* and other methods in this class if appropriate.

To see some examples, check out the definitions of any Estimator component.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
predict_uses_y	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path
supported_problem_types	Problem types this estimator supports

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name (*cls*)
Returns string name of this component

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

property supported_problem_types(*cls*)
Problem types this estimator supports

class evalml.pipelines.**ExtraTreesClassifier**(*n_estimators=100*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)
Extra Trees Classifier.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.
- **to 2.** (*Defaults*) –
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.

- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_features": ["auto", "sqrt", "log2"], "max_depth": Integer(4, 10),}
model_family	ModelFamily.EXTRA_TREES
modifies_features	True
modifies_target	False
name	Extra Trees Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**ExtraTreesRegressor**(*n_estimators=100*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Extra Trees Regressor.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_features** (*int, float or {"auto", "sqrt", "log2"}*) – The number of features to consider when looking for the best split:
  - If int, then consider max_features features at each split.
  - If float, then max_features is a fraction and int(max_features * n_features) features are considered at each split.
  - If "auto", then max_features=sqrt(n_features).
  - If "sqrt", then max_features=sqrt(n_features).
  - If "log2", then max_features=log2(n_features).
  - If None, then max_features = n_features.

  The search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features. Defaults to "auto".
- **max_depth** (*int*) – The maximum depth of the tree. Defaults to 6.
- **min_samples_split** (*int or float*) – The minimum number of samples required to split an internal node:
  - If int, then consider min_samples_split as the minimum number.
  - If float, then min_samples_split is a fraction and ceil(min_samples_split * n_samples) are the minimum number of samples for each split.
- **to 2.** (*Defaults*) –
- **min_weight_fraction_leaf** (*float*) – The minimum weighted fraction of the sum total of weights (of all the input samples) required to be at a leaf node. Defaults to 0.0.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “n_estimators”: Integer(10, 1000), “max_features”: [“auto”, “sqrt”, “log2”], “max_depth”: Integer(4, 10),}
model_family	ModelFamily.EXTRA_TREES
modifies_features	True
modifies_target	False
name	Extra Trees Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {“name”: name, “parameters”: parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**FeatureSelector**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)

Selects top features based on importance weights.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names(*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)

Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.**KNeighborsClassifier**(*n_neighbors=5*, *weights='uniform'*, *algorithm='auto'*, *leaf_size=30*, *p=2*, *random_seed=0*, ***kwargs*)

K-Nearest Neighbors Classifier.

Parameters

- **n_neighbors** (*int*) – Number of neighbors to use by default. Defaults to 5.
- **weights** (*{'uniform', 'distance'} or callable*) – Weight function used in prediction. Can be:
  - 'uniform' : uniform weights. All points in each neighborhood are weighted equally.
  - 'distance' : weight points by the inverse of their distance. in this case, closer neighbors of a query point will have a greater influence than neighbors which are further away.
  - [callable] : a user-defined function which accepts an array of distances, and returns an array of the same shape containing the weights.

  Defaults to "uniform".
- **algorithm** (*{'auto', 'ball_tree', 'kd_tree', 'brute'}*) – Algorithm used to compute the nearest neighbors:
  - 'ball_tree' will use BallTree
  - 'kd_tree' will use KDTree
  - 'brute' will use a brute-force search.

  'auto' will attempt to decide the most appropriate algorithm based on the values passed to fit method. Defaults to "auto". Note: fitting on sparse input will override the setting of this parameter, using brute force.
- **leaf_size** (*int*) – Leaf size passed to BallTree or KDTree. This can affect the speed of the construction and query, as well as the memory required to store the tree. The optimal value depends on the nature of the problem. Defaults to 30.
- **p** (*int*) – Power parameter for the Minkowski metric. When p = 1, this is equivalent to using manhattan_distance (l1), and euclidean_distance (l2) for p = 2. For arbitrary p, minkowski_distance (l_p) is used. Defaults to 2.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_neighbors": Integer(2, 12), "weights": ["uniform", "distance"], "algorithm": ["auto", "ball_tree", "kd_tree", "brute"], "leaf_size": Integer(10, 30), "p": Integer(1, 5),}
model_family	ModelFamily.K_NEIGHBORS
modifies_features	True
modifies_target	False
name	KNN Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns array of 0's matching the input number of features as feature_importance is
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns array of 0's matching the input number of features as feature_importance is not defined for KNN classifiers.

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**LightGBMClassifier**(*boosting_type='gbdt'*, *learning_rate=0.1*, *n_estimators=100*, *max_depth=0*, *num_leaves=31*, *min_child_samples=20*, *bagging_fraction=0.9*, *bagging_freq=0*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

LightGBM Classifier.

Parameters

- **boosting_type** (*string*) – Type of boosting to use. Defaults to "gbdt". - 'gbdt' uses traditional Gradient Boosting Decision Tree - "dart", uses Dropouts meet Multiple Additive Regression Trees - "goss", uses Gradient-based One-Side Sampling - "rf", uses Random Forest
- **learning_rate** (*float*) – Boosting learning rate. Defaults to 0.1.
- **n_estimators** (*int*) – Number of boosted trees to fit. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners, <=0 means no limit. Defaults to 0.
- **num_leaves** (*int*) – Maximum tree leaves for base learners. Defaults to 31.
- **min_child_samples** (*int*) – Minimum number of data needed in a child (leaf). Defaults to 20.
- **bagging_fraction** (*float*) – LightGBM will randomly select a subset of features on each iteration (tree) without resampling if this is smaller than 1.0. For example, if set to 0.8, LightGBM will select 80% of features before training each tree. This can be used to speed up training and deal with overfitting. Defaults to 0.9.
- **bagging_freq** (*int*) – Frequency for bagging. 0 means bagging is disabled. k means perform bagging at every k iteration. Every k-th iteration, LightGBM will randomly select bagging_fraction * 100 % of the data to use for the next k iterations. Defaults to 0.
- **n_jobs** (*int or None*) – Number of threads to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "learning_rate": Real(0.000001, 1), "boosting_type": ["gbdt", "dart", "goss", "rf"], "n_estimators": Integer(10, 100), "max_depth": Integer(0, 10), "num_leaves": Integer(2, 100), "min_child_samples": Integer(1, 100), "bagging_fraction": Real(0.000001, 1), "bagging_freq": Integer(0, 1),}
model_family	ModelFamily.LIGHTGBM
modifies_features	True
modifies_target	False
name	LightGBM Classifier
predict_uses_y	False
SEED_MAX	SEED_BOUNDS.max_bound
SEED_MIN	0
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**LightGBMRegressor**(*boosting_type='gbdt'*, *learning_rate=0.1*, *n_estimators=20*, *max_depth=0*, *num_leaves=31*, *min_child_samples=20*, *bagging_fraction=0.9*, *bagging_freq=0*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)
LightGBM Regressor.

Parameters

- **boosting_type** (*string*) – Type of boosting to use. Defaults to "gbdt". - 'gbdt' uses traditional Gradient Boosting Decision Tree - "dart", uses Dropouts meet Multiple Additive Regression Trees - "goss", uses Gradient-based One-Side Sampling - "rf", uses Random Forest
- **learning_rate** (*float*) – Boosting learning rate. Defaults to 0.1.
- **n_estimators** (*int*) – Number of boosted trees to fit. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners, <=0 means no limit. Defaults to 0.

- **num_leaves** (*int*) – Maximum tree leaves for base learners. Defaults to 31.
- **min_child_samples** (*int*) – Minimum number of data needed in a child (leaf). Defaults to 20.
- **bagging_fraction** (*float*) – LightGBM will randomly select a subset of features on each iteration (tree) without resampling if this is smaller than 1.0. For example, if set to 0.8, LightGBM will select 80% of features before training each tree. This can be used to speed up training and deal with overfitting. Defaults to 0.9.
- **bagging_freq** (*int*) – Frequency for bagging. 0 means bagging is disabled. k means perform bagging at every k iteration. Every k-th iteration, LightGBM will randomly select bagging_fraction * 100 % of the data to use for the next k iterations. Defaults to 0.
- **n_jobs** (*int or None*) – Number of threads to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "learning_rate": Real(0.000001, 1), "boosting_type": ["gbdt", "dart", "goss", "rf"], "n_estimators": Integer(10, 100), "max_depth": Integer(0, 10), "num_leaves": Integer(2, 100), "min_child_samples": Integer(1, 100), "bagging_fraction": Real(0.000001, 1), "bagging_freq": Integer(0, 1),}
model_family	ModelFamily.LIGHTGBM
modifies_features	True
modifies_target	False
name	LightGBM Regressor
predict_uses_y	False
SEED_MAX	SEED_BOUNDS.max_bound
SEED_MIN	0
supported_problem_types	[ProblemTypes.REGRESSION]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**LinearRegressor**(*fit_intercept=True*, *normalize=False*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)
Linear Regressor.

Parameters

- **fit_intercept** (*boolean*) – Whether to calculate the intercept for this model. If set to False, no intercept will be used in calculations (i.e. data is expected to be centered). Defaults to True.
- **normalize** (*boolean*) – If True, the regressors will be normalized before regression by subtracting the mean and dividing by the l2-norm. This parameter is ignored when fit_intercept is set to False. Defaults to False.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all threads. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ “fit_intercept”: [True, False], “normalize”: [True, False]}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Linear Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)

Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**LogisticRegressionClassifier**(*penalty='l2'*, *C=1.0*, *multi_class='auto'*, *solver='lbfgs'*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)
Logistic Regression Classifier.

Parameters

- **penalty** (*{"l1", "l2", "elasticnet", "none"}*) – The norm used in penalization. Defaults to "l2".
- **C** (*float*) – Inverse of regularization strength. Must be a positive float. Defaults to 1.0.
- **multi_class** (*{"auto", "ovr", "multinomial"}*) – If the option chosen is "ovr", then a binary problem is fit for each label. For "multinomial" the loss minimised is the multinomial loss fit across the entire probability distribution, even when the data is binary. "multinomial" is unavailable when solver="liblinear". "auto" selects "ovr" if the data is binary, or if solver="liblinear", and otherwise selects "multinomial". Defaults to "auto".
- **solver** (*{"newton-cg", "lbfgs", "liblinear", "sag", "saga"}*) – Algorithm to use in the optimization problem. For small datasets, "liblinear" is a good choice, whereas "sag" and "saga" are faster for large ones. For multiclass problems, only

"newton-cg", "sag", "saga" and "lbfgs" handle multinomial loss; "liblinear" is limited to one-versus-rest schemes.

- "newton-cg", "lbfgs", "sag" and "saga" handle L2 or no penalty
- "liblinear" and "saga" also handle L1 penalty
- "saga" also supports "elasticnet" penalty
- "liblinear" does not support setting penalty='none'

Defaults to "lbfgs".

- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "penalty": ["l2"], "C": Real(0.01, 10),}
model_family	ModelFamily.LINEAR_MODEL
modifies_features	True
modifies_target	False
name	Logistic Regression Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**MulticlassClassificationPipeline**(*component_graph*, *parameters=None*, *custom_name=None*, *random_seed=0*)

Pipeline subclass for all multiclass classification pipelines.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **custom_name** (*str*) – Custom name for the pipeline. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	ProblemTypes.MULTICLASS

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
*classes_*	Gets the class names for the problem.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.

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describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Build a classification model. For string and categorical targets, classes are sorted
get_component	Returns component by name
get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves pipeline at file path
score	Evaluate model performance on objectives
summary	A short summary of the pipeline structure, describing the list of components used.

can_tune_threshold_with_objective(*self*, *objective*)
Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (PipelineBase) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

property classes_(*self*)
Gets the class names for the problem.

clone(*self*)
Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features(*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives(*objectives*)

property custom_name (*self*)
Custom name of the pipeline.

describe (*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance (*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit (*self*, *X*, *y*)

Build a classification model. For string and categorical targets, classes are sorted by sorted(set(y)) and then are mapped to values between 0 and n_classes-1.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training labels of length [n_samples]

Returns self

get_component (*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges (*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph (*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance (*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform(*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load(*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family(*self*)
Returns model family of this pipeline.

property name(*self*)
Name of the pipeline.

new(*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

property parameters(*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict(*self*, *X*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]
- **objective** (*Object or string*) – The objective to use to make predictions

Returns Estimated labels

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]

Returns Probability estimates

Return type pd.DataFrame

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score(*self*, *X*, *y*, *objectives*)
Evaluate model performance on objectives

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series, or np.ndarray*) – True labels of length [n_samples]
- **objectives** (*list*) – List of objectives to score

Returns Ordered dictionary of objective scores

Return type dict

property summary(*self*)
A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

class evalml.pipelines.**OneHotEncoder**(*top_n=10*, *features_to_encode=None*, *categories=None*, *drop='if_binary'*, *handle_unknown='ignore'*, *handle_missing='error'*, *random_seed=0*, ***kwargs*)
A transformer that encodes categorical features in a one-hot numeric array.

Parameters

- **top_n** (*int*) – Number of categories per column to encode. If None, all categories will be encoded. Otherwise, the *n* most frequent will be encoded and all others will be dropped. Defaults to 10.
- **features_to_encode** (*list[str]*) – List of columns to encode. All other columns will remain untouched. If None, all appropriate columns will be encoded. Defaults to None.
- **categories** (*list*) – A two dimensional list of categories, where *categories[i]* is a list of the categories for the column at index *i*. This can also be *None*, or *"auto"* if *top_n* is not None. Defaults to None.
- **drop** (*string, list*) – Method ("first" or "if_binary") to use to drop one category per feature. Can also be a list specifying which categories to drop for each feature. Defaults to 'if_binary'.
- **handle_unknown** (*string*) – Whether to ignore or error for unknown categories for a feature encountered during *fit* or *transform*. If either *top_n* or *categories* is used to limit the number of categories per column, this must be "ignore". Defaults to "ignore".
- **handle_missing** (*string*) – Options for how to handle missing (NaN) values encountered during *fit* or *transform*. If this is set to "as_category" and NaN values are within the *n* most frequent, "nan" values will be encoded as their own column. If this is set to "error", any missing values encountered will raise an error. Defaults to "error".

- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	One Hot Encoder

Methods

categories	Returns a list of the unique categories to be encoded for the particular feature, in order.
clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_feature_names	Return feature names for the categorical features after fitting.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	One-hot encode the input data.

categories(*self*, *feature_name*)

Returns a list of the unique categories to be encoded for the particular feature, in order.

Parameters **feature_name** (*str*) – the name of any feature provided to one-hot encoder during fit

Returns the unique categories, in the same dtype as they were provided during fit

Return type np.ndarray

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names (*self*)
Return feature names for the categorical features after fitting.

Feature names are formatted as {column name}_{category name}. In the event of a duplicate name, an integer will be added at the end of the feature name to distinguish it.

For example, consider a dataframe with a column called "A" and category "x_y" and another column called "A_x" with "y". In this example, the feature names would be "A_x_y" and "A_x_y_1".

Returns The feature names after encoding, provided in the same order as input_features.

Return type np.ndarray

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
One-hot encode the input data.

Parameters

- **X** (*pd.DataFrame*) – Features to one-hot encode.
- **y** (*pd.Series*) – Ignored.

Returns Transformed data, where each categorical feature has been encoded into numerical columns using one-hot encoding.

Return type pd.DataFrame

class evalml.pipelines.**PerColumnImputer**(*impute_strategies=None*, *default_impute_strategy='most_frequent'*, *random_seed=0*, ***kwargs*)
Imputes missing data according to a specified imputation strategy per column.

Parameters

- **impute_strategies** (*dict*) – Column and {"impute_strategy": strategy, "fill_value":value} pairings. Valid values for impute strategy include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types. Defaults to None, which uses "most_frequent" for all columns. When impute_strategy == "constant", fill_value is used to replace missing data. When None, uses 0 when imputing numerical data and "missing_value" for strings or object data types.
- **default_impute_strategy** (*str*) – Impute strategy to fall back on when none is provided for a certain column. Valid values include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types. Defaults to "most_frequent".
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Per Column Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputers on input data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by imputing missing values.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits imputers on input data

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features] to fit.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]. Ignored.

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input data by imputing missing values.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features] to transform.
- **y** (*pd.Series, optional*) – The target training data of length [n_samples]. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.**PipelineBase**(*component_graph*, *parameters=None*, *custom_name=None*, *random_seed=0*)
Machine learning pipeline made out of transformers and a estimator.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"].
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **custom_name** (*str*) – Custom name for the pipeline. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	None

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Build a model.
get_component	Returns component by name
get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
save	Saves pipeline at file path
score	Evaluate model performance on current and additional objectives.
summary	A short summary of the pipeline structure, describing the list of components used.

can_tune_threshold_with_objective(*self*, *objective*)

Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (PipelineBase) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

clone(*self*)

Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features(*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives(*objectives*)

property custom_name(*self*)
Custom name of the pipeline.

describe(*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance(*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

abstract fit(*self*, *X*, *y*)
Build a model.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features].
- **y** (*pd.Series, np.ndarray*) – The target training data of length [n_samples].

Returns self

get_component(*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges(*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph(*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance(*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform(*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load(*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family(*self*)
Returns model family of this pipeline.

property name(*self*)
Name of the pipeline.

new(*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

property parameters(*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict(*self*, *X*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features].
- **objective** (*Object or string*) – The objective to use to make predictions.

Returns Predicted values.

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

abstract score(*self*, *X*, *y*, *objectives*)
Evaluate model performance on current and additional objectives.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features].
- **y** (*pd.Series, np.ndarray*) – True labels of length [n_samples].
- **objectives** (*list*) – Non-empty list of objectives to score on.

Returns Ordered dictionary of objective scores.

Return type dict

property summary(*self*)
A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

class evalml.pipelines.**ProphetRegressor**(*date_column='ds'*, *changepoint_prior_scale=0.05*, *seasonality_prior_scale=10*, *holidays_prior_scale=10*, *seasonality_mode='additive'*, *random_seed=0*, *stan_backend='CMDSTANPY'*, ***kwargs*)
Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well.

More information here: https://facebook.github.io/prophet/

Attributes

hyperparameter_ranges	{ “changepoint_prior_scale”: Real(0.001, 0.5), “seasonality_prior_scale”: Real(0.01, 10), “holidays_prior_scale”: Real(0.01, 10), “seasonality_mode”: [“additive”, “multiplicative”],}
model_family	ModelFamily.PROPHET
modifies_features	True
modifies_target	False
name	Prophet Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.TIME_SERIES_REGRESSION]

Methods

build_prophet_df	
clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns array of 0's with len(1) as feature_importance is not defined for Prophet regressor.
fit	Fits component to data
get_params	
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

static build_prophet_df(*X*, *y=None*, *date_column='ds'*)

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns array of 0's with len(1) as feature_importance is not defined for Prophet regressor.

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

get_params(*self*)

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*, *y=None*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**RandomForestClassifier**(*n_estimators=100*, *max_depth=6*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)
Random Forest Classifier.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_depth": Integer(1, 10),}
model_family	ModelFamily.RANDOM_FOREST
modifies_features	True
modifies_target	False
name	Random Forest Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**RandomForestRegressor**(*n_estimators=100*, *max_depth=6*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Random Forest Regressor.

Parameters

- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "n_estimators": Integer(10, 1000), "max_depth": Integer(1, 32),}
model_family	ModelFamily.RANDOM_FOREST
modifies_features	True
modifies_target	False
name	Random Forest Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**RegressionPipeline**(*component_graph*, *parameters=None*, *custom_name=None*, *random_seed=0*)
Pipeline subclass for all regression pipelines.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **custom_name** (*str*) – Custom name for the pipeline. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	ProblemTypes.REGRESSION

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Build a regression model.
get_component	Returns component by name

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get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
save	Saves pipeline at file path
score	Evaluate model performance on current and additional objectives
summary	A short summary of the pipeline structure, describing the list of components used.

can_tune_threshold_with_objective(*self*, *objective*)
Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (PipelineBase) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

clone(*self*)
Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features(*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives(*objectives*)

property custom_name(*self*)
Custom name of the pipeline.

describe(*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance (*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit (*self*, *X*, *y*)
Build a regression model.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training data of length [n_samples]

Returns self

get_component (*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges (*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph (*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance (*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform (*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load (*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family(*self*)
Returns model family of this pipeline.

property name(*self*)
Name of the pipeline.

new(*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

property parameters(*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict(*self*, *X*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features].
- **objective** (*Object or string*) – The objective to use to make predictions.

Returns Predicted values.

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score(*self*, *X*, *y*, *objectives*)
Evaluate model performance on current and additional objectives

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series, or np.ndarray*) – True values of length [n_samples]
- **objectives** (*list*) – Non-empty list of objectives to score on

Returns Ordered dictionary of objective scores

Return type dict

property summary(*self*)

A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

class evalml.pipelines.**RFClassifierSelectFromModel**(*number_features=None*, *n_estimators=10*, *max_depth=None*, *percent_features=0.5*, *threshold=-np.inf*, *n_jobs=-1*, *random_seed=0*, ***kwargs*)

Selects top features based on importance weights using a Random Forest classifier.

Parameters

- **number_features** (*int*) – The maximum number of features to select. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5. Defaults to None.
- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **percent_features** (*float*) – Percentage of features to use. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5.
- **threshold** (*string or float*) – The threshold value to use for feature selection. Features whose importance is greater or equal are kept while the others are discarded. If "median", then the threshold value is the median of the feature importances. A scaling factor (e.g., "1.25*mean") may also be used. Defaults to -np.inf.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "percent_features": Real(0.01, 1), "threshold": ["mean", -np.inf],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	RF Classifier Select From Model

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X

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get_names	Get names of selected features.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names(*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.**RFRegressorSelectFromModel**(*number_features=None*, *n_estimators=10*, *max_depth=None*, *percent_features=0.5*, *threshold=-np.inf*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)
Selects top features based on importance weights using a Random Forest regressor.

Parameters

- **number_features** (*int*) – The maximum number of features to select. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5. Defaults to None.
- **n_estimators** (*float*) – The number of trees in the forest. Defaults to 100.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.

- **percent_features** (*float*) – Percentage of features to use. If both percent_features and number_features are specified, take the greater number of features. Defaults to 0.5.
- **threshold** (*string or float*) – The threshold value to use for feature selection. Features whose importance is greater or equal are kept while the others are discarded. If "median", then the threshold value is the median of the feature importances. A scaling factor (e.g., "1.25*mean") may also be used. Defaults to -np.inf.
- **n_jobs** (*int or None*) – Number of jobs to run in parallel. -1 uses all processes. Defaults to -1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "percent_features": Real(0.01, 1), "threshold": ["mean", -np.inf],}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	RF Regressor Select From Model

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_names	Get names of selected features.
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_names(*self*)
Get names of selected features.

Returns List of the names of features selected

Return type list[str]

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)

Transforms input data by selecting features. If the component_obj does not have a transform method, will raise an MethodPropertyNotFoundError exception.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data. Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.**SimpleImputer**(*impute_strategy='most_frequent'*, *fill_value=None*, *random_seed=0*, ***kwargs*)

Imputes missing data according to a specified imputation strategy.

Parameters

- **impute_strategy** (*string*) – Impute strategy to use. Valid values include "mean", "median", "most_frequent", "constant" for numerical data, and "most_frequent", "constant" for object data types.
- **fill_value** (*string*) – When impute_strategy == "constant", fill_value is used to replace missing data. Defaults to 0 when imputing numerical data and "missing_value" for strings or object data types.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "impute_strategy": ["mean", "median", "most_frequent"]}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Simple Imputer

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits imputer to data. 'None' values are converted to np.nan before imputation and are
fit_transform	Fits on X and transforms X

continues on next page

Table 659 – continued from previous page

load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms input by imputing missing values. 'None' and np.nan values are treated as the same.

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y=None*)

Fits imputer to data. 'None' values are converted to np.nan before imputation and are treated as the same.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y=None*)

Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms input by imputing missing values. 'None' and np.nan values are treated as the same.

Parameters

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Ignored.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.**SklearnStackedEnsembleClassifier**(*input_pipelines=None*, *final_estimator=None*, *cv=None*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)
Scikit-learn Stacked Ensemble Classifier.

Parameters

- **input_pipelines** (*list(PipelineBase or subclass obj)*) – List of pipeline instances to use as the base estimators. This must not be None or an empty list or else EnsembleMissingPipelinesError will be raised.
- **final_estimator** (*Estimator or subclass*) – The classifier used to combine the base estimators. If None, uses LogisticRegressionClassifier.
- **cv** (*int, cross-validation generator or an iterable*) – Determines the cross-validation splitting strategy used to train final_estimator. For int/None inputs, if the estimator is a classifier and y is either binary or multiclass, StratifiedKFold is used. Defaults to None. Possible inputs for cv are:
  - None: 3-fold cross validation
  - int: the number of folds in a (Stratified) KFold
  - An scikit-learn cross-validation generator object
  - An iterable yielding (train, test) splits

- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Defaults to -1. - Note: there could be some multi-process errors thrown for values of *n_jobs != 1*. If this is the case, please use *n_jobs = 1*.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.ENSEMBLE
modifies_features	True
modifies_target	False
name	Sklearn Stacked Ensemble Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for stacked ensemble classes.
describe	Describe a component and its parameters
feature_importance	Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for stacked ensemble classes.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file

- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**SklearnStackedEnsembleRegressor**(*input_pipelines=None*, *final_estimator=None*, *cv=None*, *n_jobs=- 1*, *random_seed=0*, ***kwargs*)

Scikit-learn Stacked Ensemble Regressor.

Parameters

- **input_pipelines** (*list(PipelineBase or subclass obj)*) – List of pipeline instances to use as the base estimators. This must not be None or an empty list or else EnsembleMissingPipelinesError will be raised.
- **final_estimator** (*Estimator or subclass*) – The regressor used to combine the base estimators. If None, uses LinearRegressor.
- **cv** (*int, cross-validation generator or an iterable*) – Determines the cross-validation splitting strategy used to train final_estimator. For int/None inputs, KFold is used. Defaults to None. Possible inputs for cv are:
  - None: 3-fold cross validation
  - int: the number of folds in a (Stratified) KFold
  - An scikit-learn cross-validation generator object
  - An iterable yielding (train, test) splits
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Defaults to -1. - Note: there could be some multi-process errors thrown for values of *n_jobs != 1*. If this is the case, please use *n_jobs = 1*.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.ENSEMBLE
modifies_features	True
modifies_target	False
name	Sklearn Stacked Ensemble Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.

continues on next page

Table 661 – continued from previous page

default_parameters	Returns the default parameters for stacked ensemble classes.
describe	Describe a component and its parameters
feature_importance	Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for stacked ensemble classes.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Not implemented for SklearnStackedEnsembleClassifier and SklearnStackedEnsembleRegressor

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**StandardScaler**(*random_seed=0*, ***kwargs*)
A transformer that standardizes input features by removing the mean and scaling to unit variance.

Parameters **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Standard Scaler

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.

continues on next page

Table 662 – continued from previous page

describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.**SVMClassifier**(*C=1.0*, *kernel='rbf'*, *gamma='scale'*, *probability=True*, *random_seed=0*, ***kwargs*)
Support Vector Machine Classifier.

Parameters

- **C** (*float*) – The regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive. The penalty is a squared l2 penalty. Defaults to 1.0.
- **kernel** (*{"linear", "poly", "rbf", "sigmoid", "precomputed"}*) – Specifies the kernel type to be used in the algorithm. Defaults to “rbf”.
- **gamma** (*{"scale", "auto"} or float*) – Kernel coefficient for “rbf”, “poly” and “sigmoid”. Defaults to “scale”. - If gamma=’scale’ (default) is passed then it uses 1 / (n_features * X.var()) as value of gamma - if “auto”, uses 1 / n_features
- **probability** (*boolean*) – Whether to enable probability estimates. Defaults to True.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0, 10), "kernel": ["linear", "poly", "rbf", "sigmoid", "precomputed"], "gamma": ["scale", "auto"],}
model_family	ModelFamily.SVM
modifies_features	True
modifies_target	False
name	SVM Classifier
predict_uses_y	False
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Feature importance only works with linear kernels.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance(*self*)
Feature importance only works with linear kernels. If the kernel isn't linear, we return a numpy array of zeros

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**SVMRegressor**(*C=1.0*, *kernel='rbf'*, *gamma='scale'*, *random_seed=0*, ***kwargs*)
Support Vector Machine Regressor.

Parameters

- **C** (*float*) – The regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive. The penalty is a squared l2 penalty. Defaults to 1.0.
- **kernel** (*{"linear", "poly", "rbf", "sigmoid", "precomputed"}*) – Specifies the kernel type to be used in the algorithm. Defaults to "rbf".
- **gamma** (*{"scale", "auto"} or float*) – Kernel coefficient for "rbf", "poly" and "sigmoid". Defaults to "scale". - If gamma='scale' (default) is passed then it uses 1 / (n_features * X.var()) as value of gamma - if "auto", uses 1 / n_features
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{ "C": Real(0, 10), "kernel": ["linear", "poly", "rbf", "sigmoid", "precomputed"], "gamma": ["scale", "auto"],}
model_family	ModelFamily.SVM
modifies_features	True
modifies_target	False
name	SVM Regressor
predict_uses_y	False
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Feature importance only works with linear kernels.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Feature importance only works with linear kernels. If the kernel isn't linear, we return a numpy array of zeros

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**TargetEncoder**(*cols=None*, *smoothing=1.0*, *handle_unknown='value'*, *handle_missing='value'*, *random_seed=0*, ***kwargs*)
A transformer that encodes categorical features into target encodings.

Parameters

- **cols** (*list*) – Columns to encode. If None, all string columns will be encoded, otherwise only the columns provided will be encoded. Defaults to None
- **smoothing** (*float*) – The smoothing factor to apply. The larger this value is, the more influence the expected target value has on the resulting target encodings. Must be strictly larger than 0. Defaults to 1.0
- **handle_unknown** (*string*) – Determines how to handle unknown categories for a feature encountered. Options are 'value', 'error', nd 'return_nan'. Defaults to 'value', which replaces with the target mean
- **handle_missing** (*string*) – Determines how to handle missing values encountered during *fit* or *transform*. Options are 'value', 'error', and 'return_nan'. Defaults to 'value', which replaces with the target mean
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

hyperparameter_ranges	{}
model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False
name	Target Encoder

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
get_feature_names	Return feature names for the input features after fitting.

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load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone (*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit (*self*, *X*, *y*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform (*self*, *X*, *y*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

get_feature_names (*self*)
Return feature names for the input features after fitting.

Returns The feature names after encoding

Return type np.array

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.**TimeSeriesBinaryClassificationPipeline**(*component_graph*, *parameters=None*, *custom_name=None*, *random_seed=0*)

Pipeline base class for time series binary classification problems.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary {} implies using all default values for component parameters. Pipeline-level parameters such as date_index, gap, and max_delay must be specified with the "pipeline" key. For example: Pipeline(parameters={"pipeline": {"date_index": "Date", "max_delay": 4, "gap": 2}}).

- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	None

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
*classes_*	Gets the class names for the problem.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Fit a time series classification pipeline.
get_component	Returns component by name
get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
optimize_threshold	Optimize the pipeline threshold given the objective to use. Only used for binary problems with objectives whose thresholds can be tuned.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves pipeline at file path
score	Evaluate model performance on current and additional objectives.
summary	A short summary of the pipeline structure, describing the list of components used.
threshold	Threshold used to make a prediction. Defaults to None.

can_tune_threshold_with_objective (*self*, *objective*)
Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (PipelineBase) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

property classes_ (*self*)
Gets the class names for the problem.

clone (*self*)
Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features (*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives (*objectives*)

property custom_name (*self*)
Custom name of the pipeline.

describe (*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance (*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit (*self*, *X*, *y*)
Fit a time series classification pipeline.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training targets of length [n_samples]

Returns self

get_component (*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges(*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph(*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance(*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform(*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load(*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family(*self*)
Returns model family of this pipeline.

property name(*self*)
Name of the pipeline.

new(*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

optimize_threshold(*self*, *X*, *y*, *y_pred_proba*, *objective*)
Optimize the pipeline threshold given the objective to use. Only used for binary problems with objectives whose thresholds can be tuned.

Parameters

- **X** (*pd.DataFrame*) – Input features
- **y** (*pd.Series*) – Input target values
- **y_pred_proba** (*pd.Series*) – The predicted probabilities of the target outputted by the pipeline
- **objective** (*ObjectiveBase*) – The objective to threshold with. Must have a tunable threshold.

property parameters(*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict(*self*, *X*, *y=None*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, None*) – The target training targets of length [n_samples]
- **objective** (*Object or string*) – The objective to use to make predictions

Returns Predicted values.

Return type pd.Series

predict_proba(*self*, *X*, *y=None*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]

Returns Probability estimates

Return type pd.DataFrame

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score(*self*, *X*, *y*, *objectives*)
Evaluate model performance on current and additional objectives.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series*) – True labels of length [n_samples]

- **objectives** (*list*) – Non-empty list of objectives to score on

Returns Ordered dictionary of objective scores

Return type dict

property summary(*self*)
A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

property threshold(*self*)
Threshold used to make a prediction. Defaults to None.

class evalml.pipelines.**TimeSeriesClassificationPipeline**(*component_graph*, *parameters=None*, *custom_name=None*, *random_seed=0*)

Pipeline base class for time series classification problems.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary {} implies using all default values for component parameters. Pipeline-level parameters such as date_index, gap, and max_delay must be specified with the "pipeline" key. For example: Pipeline(parameters={"pipeline": {"date_index": "Date", "max_delay": 4, "gap": 2}}).
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	None

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
*classes_*	Gets the class names for the problem.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.

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fit	Fit a time series classification pipeline.
get_component	Returns component by name
get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves pipeline at file path
score	Evaluate model performance on current and additional objectives.
summary	A short summary of the pipeline structure, describing the list of components used.

can_tune_threshold_with_objective(*self*, *objective*)
Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (PipelineBase) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

property classes_(*self*)
Gets the class names for the problem.

clone(*self*)
Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features(*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives(*objectives*)

property custom_name(*self*)
Custom name of the pipeline.

describe(*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance(*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit(*self*, *X*, *y*)
Fit a time series classification pipeline.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training targets of length [n_samples]

Returns self

get_component(*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges(*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph(*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance(*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform(*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load(*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family(*self*)
Returns model family of this pipeline.

property name(*self*)
Name of the pipeline.

new(*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

property parameters(*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict(*self*, *X*, *y=None*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, None*) – The target training targets of length [n_samples]
- **objective** (*Object or string*) – The objective to use to make predictions

Returns Predicted values.

Return type pd.Series

predict_proba(*self*, *X*, *y=None*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]

Returns Probability estimates

Return type pd.DataFrame

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score(*self*, *X*, *y*, *objectives*)

Evaluate model performance on current and additional objectives.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series*) – True labels of length [n_samples]
- **objectives** (*list*) – Non-empty list of objectives to score on

Returns Ordered dictionary of objective scores

Return type dict

property summary(*self*)

A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

class evalml.pipelines.**TimeSeriesMulticlassClassificationPipeline**(*component_graph*, *parameters=None*, *custom_name=None*, *random_seed=0*)

Pipeline base class for time series multiclass classification problems.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary {} implies using all default values for component parameters. Pipeline-level parameters such as date_index, gap, and max_delay must be specified with the "pipeline" key. For example: Pipeline(parameters={"pipeline": {"date_index": "Date", "max_delay": 4, "gap": 2}}).
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	ProblemTypes.TIME_SERIES_MULTICLASS

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
*classes_*	Gets the class names for the problem.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Fit a time series classification pipeline.
get_component	Returns component by name
get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves pipeline at file path
score	Evaluate model performance on current and additional objectives.
summary	A short summary of the pipeline structure, describing the list of components used.

can_tune_threshold_with_objective(*self*, *objective*)

Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (PipelineBase) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

property classes_(*self*)

Gets the class names for the problem.

clone(*self*)

Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features (*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives (*objectives*)

property custom_name (*self*)
Custom name of the pipeline.

describe (*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance (*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit (*self*, *X*, *y*)
Fit a time series classification pipeline.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training targets of length [n_samples]

Returns self

get_component (*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges (*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph (*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance(*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform(*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load(*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family(*self*)
Returns model family of this pipeline.

property name(*self*)
Name of the pipeline.

new(*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

property parameters(*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict(*self*, *X*, *y=None*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray, None*) – The target training targets of length [n_samples]
- **objective** (*Object or string*) – The objective to use to make predictions

Returns Predicted values.

Return type pd.Series

predict_proba (*self*, *X*, *y=None*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]

Returns Probability estimates

Return type pd.DataFrame

save (*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score (*self*, *X*, *y*, *objectives*)
Evaluate model performance on current and additional objectives.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series*) – True labels of length [n_samples]
- **objectives** (*list*) – Non-empty list of objectives to score on

Returns Ordered dictionary of objective scores

Return type dict

property summary (*self*)
A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

class evalml.pipelines.**TimeSeriesRegressionPipeline** (*component_graph*, *parameters=None*, *custom_name=None*, *random_seed=0*)
Pipeline base class for time series regression problems.

Parameters

- **component_graph** (*list or dict*) – List of components in order. Accepts strings or ComponentBase subclasses in the list. Note that when duplicate components are specified in a list, the duplicate component names will be modified with the component's index in the list. For example, the component graph [Imputer, One Hot Encoder, Imputer, Logistic Regression Classifier] will have names ["Imputer", "One Hot Encoder", "Imputer_2", "Logistic Regression Classifier"]
- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary {} implies using all default values for component parameters. Pipeline-level parameters such as date_index, gap, and max_delay must be specified with the "pipeline" key. For example: Pipeline(parameters={"pipeline": {"date_index": "Date", "max_delay": 4, "gap": 2}}).
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

problem_type	ProblemTypes.TIME_SERIES_REGRESSIO

Methods

can_tune_threshold_with_objective	Determine whether the threshold of a binary classification pipeline can be tuned.
clone	Constructs a new pipeline with the same components, parameters, and random state.
compute_estimator_features	Transforms the data by applying all pre-processing components.
create_objectives	
custom_name	Custom name of the pipeline.
describe	Outputs pipeline details including component parameters
feature_importance	Importance associated with each feature. Features dropped by the feature selection are excluded.
fit	Fit a time series regression pipeline.
get_component	Returns component by name
get_hyperparameter_ranges	Returns hyperparameter ranges from all components as a dictionary.
graph	Generate an image representing the pipeline graph.
graph_feature_importance	Generate a bar graph of the pipeline's feature importance
inverse_transform	Apply component inverse_transform methods to estimator predictions in reverse order.
load	Loads pipeline at file path
model_family	Returns model family of this pipeline.
name	Name of the pipeline.
new	Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
parameters	Parameter dictionary for this pipeline.
predict	Make predictions using selected features.
save	Saves pipeline at file path
score	Evaluate model performance on current and additional objectives.
summary	A short summary of the pipeline structure, describing the list of components used.

can_tune_threshold_with_objective(*self*, *objective*)

Determine whether the threshold of a binary classification pipeline can be tuned.

Parameters

- **pipeline** (PipelineBase) – Binary classification pipeline.
- **objective** – Primary AutoMLSearch objective.

clone(*self*)

Constructs a new pipeline with the same components, parameters, and random state.

Returns A new instance of this pipeline with identical components, parameters, and random state.

compute_estimator_features (*self*, *X*, *y=None*)
Transforms the data by applying all pre-processing components.

Parameters **X** (*pd.DataFrame*) – Input data to the pipeline to transform.

Returns New transformed features.

Return type pd.DataFrame

static create_objectives (*objectives*)

property custom_name (*self*)
Custom name of the pipeline.

describe (*self*, *return_dict=False*)
Outputs pipeline details including component parameters

Parameters **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Dictionary of all component parameters if return_dict is True, else None

Return type dict

property feature_importance (*self*)
Importance associated with each feature. Features dropped by the feature selection are excluded.

Returns pd.DataFrame including feature names and their corresponding importance

fit (*self*, *X*, *y*)
Fit a time series regression pipeline.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*pd.Series, np.ndarray*) – The target training targets of length [n_samples]

Returns self

get_component (*self*, *name*)
Returns component by name

Parameters **name** (*str*) – Name of component

Returns Component to return

Return type Component

get_hyperparameter_ranges (*self*, *custom_hyperparameters*)
Returns hyperparameter ranges from all components as a dictionary.

Parameters **custom_hyperparameters** (*dict*) – Custom hyperparameters for the pipeline.

Returns Dictionary of hyperparameter ranges for each component in the pipeline.

Return type dict

graph (*self*, *filepath=None*)
Generate an image representing the pipeline graph.

Parameters **filepath** (*str, optional*) – Path to where the graph should be saved. If set to None (as by default), the graph will not be saved.

Returns Graph object that can be directly displayed in Jupyter notebooks.

Return type graphviz.Digraph

graph_feature_importance(*self*, *importance_threshold=0*)
Generate a bar graph of the pipeline's feature importance

Parameters **importance_threshold** (*float, optional*) – If provided, graph features with a permutation importance whose absolute value is larger than importance_threshold. Defaults to zero.

Returns plotly.Figure, a bar graph showing features and their corresponding importance

inverse_transform(*self*, *y*)
Apply component inverse_transform methods to estimator predictions in reverse order.

Components that implement inverse_transform are PolynomialDetrender, LabelEncoder (tbd).

Parameters **y** (*pd.Series*) – Final component features

static load(*file_path*)
Loads pipeline at file path

Parameters **file_path** (*str*) – location to load file

Returns PipelineBase object

property model_family(*self*)
Returns model family of this pipeline.

property name(*self*)
Name of the pipeline.

new(*self*, *parameters*, *random_seed=0*)

Constructs a new instance of the pipeline with the same component graph but with a different set of parameters.
Not to be confused with python's __new__ method.

Parameters

- **parameters** (*dict*) – Dictionary with component names as keys and dictionary of that component's parameters as values. An empty dictionary or None implies using all default values for component parameters. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns A new instance of this pipeline with identical components.

property parameters(*self*)
Parameter dictionary for this pipeline.

Returns Dictionary of all component parameters.

Return type dict

predict(*self*, *X*, *y=None*, *objective=None*)
Make predictions using selected features.

Parameters

- **X** (*pd.DataFrame, or np.ndarray*) – Data of shape [n_samples, n_features]

- **y** (*pd.Series, np.ndarray, None*) – The target training targets of length [n_samples]
- **objective** (*Object or string*) – The objective to use to make predictions

Returns Predicted values.

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)

Saves pipeline at file path

Parameters

- **file_path** (*str*) – location to save file
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score(*self*, *X*, *y*, *objectives*)

Evaluate model performance on current and additional objectives.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – Data of shape [n_samples, n_features]
- **y** (*pd.Series*) – True labels of length [n_samples]
- **objectives** (*list*) – Non-empty list of objectives to score on

Returns Ordered dictionary of objective scores

Return type dict

property summary(*self*)

A short summary of the pipeline structure, describing the list of components used. Example: Logistic Regression Classifier w/ Simple Imputer + One Hot Encoder

class evalml.pipelines.**Transformer**(*parameters=None*, *component_obj=None*, *random_seed=0*, ***kwargs*)

A component that may or may not need fitting that transforms data. These components are used before an estimator.

To implement a new Transformer, define your own class which is a subclass of Transformer, including a name and a list of acceptable ranges for any parameters to be tuned during the automl search (hyperparameters). Define an *__init__* method which sets up any necessary state and objects. Make sure your *__init__* only uses standard keyword arguments and calls *super().__init__()* with a parameters dict. You may also override the *fit*, *transform*, *fit_transform* and other methods in this class if appropriate.

To see some examples, check out the definitions of any Transformer component.

Parameters

- **parameters** (*dict*) – Dictionary of parameters for the component. Defaults to None.
- **component_obj** (*obj*) – Third-party objects useful in component implementation. Defaults to None.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Attributes

model_family	ModelFamily.NONE
modifies_features	True
modifies_target	False

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
fit	Fits component to data
fit_transform	Fits on X and transforms X
load	Loads component at file path
name	Returns string name of this component
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
save	Saves component at file path
transform	Transforms data X.

clone(*self*)
Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)
Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe(*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

fit(*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]

- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

fit_transform(*self*, *X*, *y=None*)
Fits on X and transforms X

Parameters

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Target data

Returns Transformed X

Return type pd.DataFrame

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

property name(*cls*)
Returns string name of this component

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

transform(*self*, *X*, *y=None*)
Transforms data X.

Parameters

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Target data.

Returns Transformed X

Return type pd.DataFrame

class evalml.pipelines.**XGBoostClassifier**(*eta=0.1*, *max_depth=6*, *min_child_weight=1*, *n_estimators=100*, *random_seed=0*, *n_jobs=- 1*, ***kwargs*)
XGBoost Classifier.

Parameters

- **eta** (*float*) – Boosting learning rate. Defaults to 0.1.

- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **min_child_weight** (*float*) – Minimum sum of instance weight (hessian) needed in a child. Defaults to 1.0
- **n_estimators** (*int*) – Number of gradient boosted trees. Equivalent to number of boosting rounds. Defaults to 100.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.

Attributes

hyperparameter_ranges	{ "eta": Real(0.000001, 1), "max_depth": Integer(1, 10), "min_child_weight": Real(1, 10), "n_estimators": Integer(1, 1000),}
model_family	ModelFamily.XGBOOST
modifies_features	True
modifies_target	False
name	XGBoost Classifier
predict_uses_y	False
SEED_MAX	None
SEED_MIN	None
supported_problem_types	[ProblemTypes.BINARY, ProblemTypes.MULTICLASS, ProblemTypes.TIME_SERIES_BINARY, ProblemTypes.TIME_SERIES_MULTICLASS,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone(*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters(*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)
Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)
Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)
Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load (*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting (*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters (*self*)
Returns the parameters which were used to initialize the component

predict (*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba (*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)

Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

class evalml.pipelines.**XGBoostRegressor**(*eta=0.1*, *max_depth=6*, *min_child_weight=1*, *n_estimators=100*, *random_seed=0*, *n_jobs=- 1*, ***kwargs*)

XGBoost Regressor.

Parameters

- **eta** (*float*) – Boosting learning rate. Defaults to 0.1.
- **max_depth** (*int*) – Maximum tree depth for base learners. Defaults to 6.
- **min_child_weight** (*float*) – Minimum sum of instance weight (hessian) needed in a child. Defaults to 1.0
- **n_estimators** (*int*) – Number of gradient boosted trees. Equivalent to number of boosting rounds. Defaults to 100.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **n_jobs** (*int*) – Number of parallel threads used to run xgboost. Note that creating thread contention will significantly slow down the algorithm. Defaults to -1.

Attributes

hyperparameter_ranges	{ “eta”: Real(0.000001, 1), “max_depth”: Integer(1, 20), “min_child_weight”: Real(1, 10), “n_estimators”: Integer(1, 1000),}
model_family	ModelFamily.XGBOOST
modifies_features	True
modifies_target	False
name	XGBoost Regressor
predict_uses_y	False
SEED_MAX	None
SEED_MIN	None
supported_problem_types	[ProblemTypes.REGRESSION, ProblemTypes.TIME_SERIES_REGRESSION,]

Methods

clone	Constructs a new component with the same parameters and random state.
default_parameters	Returns the default parameters for this component.
describe	Describe a component and its parameters
feature_importance	Returns importance associated with each feature.
fit	Fits component to data
load	Loads component at file path
needs_fitting	Returns boolean determining if component needs fitting before
parameters	Returns the parameters which were used to initialize the component
predict	Make predictions using selected features.
predict_proba	Make probability estimates for labels.
save	Saves component at file path

clone (*self*)

Constructs a new component with the same parameters and random state.

Returns A new instance of this component with identical parameters and random state.

default_parameters (*cls*)

Returns the default parameters for this component.

Our convention is that Component.default_parameters == Component().parameters.

Returns default parameters for this component.

Return type dict

describe (*self*, *print_name=False*, *return_dict=False*)

Describe a component and its parameters

Parameters

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

Returns prints and returns dictionary

Return type None or dict

property feature_importance (*self*)

Returns importance associated with each feature.

Returns Importance associated with each feature

Return type np.ndarray

fit (*self*, *X*, *y=None*)

Fits component to data

Parameters

- **X** (*list, pd.DataFrame or np.ndarray*) – The input training data of shape [n_samples, n_features]
- **y** (*list, pd.Series, np.ndarray, optional*) – The target training data of length [n_samples]

Returns self

static load(*file_path*)
Loads component at file path

Parameters **file_path** (*str*) – Location to load file

Returns ComponentBase object

needs_fitting(*self*)
Returns boolean determining if component needs fitting before calling predict, predict_proba, transform, or feature_importances. This can be overridden to False for components that do not need to be fit or whose fit methods do nothing.

property parameters(*self*)
Returns the parameters which were used to initialize the component

predict(*self*, *X*)
Make predictions using selected features.

Parameters **X** (*pd.DataFrame, np.ndarray*) – Data of shape [n_samples, n_features]

Returns Predicted values

Return type pd.Series

predict_proba(*self*, *X*)
Make probability estimates for labels.

Parameters **X** (*pd.DataFrame, or np.ndarray*) – Features

Returns Probability estimates

Return type pd.Series

save(*self*, *file_path*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves component at file path

Parameters

- **file_path** (*str*) – Location to save file
- **pickle_protocol** (*int*) – The pickle data stream format.

Returns None

Preprocessing

Subpackages

data_splitters

Submodules

balanced_classification_sampler

Module Contents

Classes Summary

BalancedClassificationSampler	Class for balanced classification downsampler.

Contents

class evalml.preprocessing.data_splitters.balanced_classification_sampler.**BalancedClassifi**

Class for balanced classification downsampler.

Parameters

- **sampling_ratio** (*float*) – The smallest minority:majority ratio that is accepted as 'balanced'. For instance, a 1:4 ratio would be represented as 0.25, while a 1:1 ratio is 1.0. Must be between 0 and 1, inclusive. Defaults to 0.25.
- **sampling_ratio_dict** (*dict*) – A dictionary specifying the desired balanced ratio for each target value. Overrides sampling_ratio if provided. Defaults to None.
- **min_samples** (*int*) – The minimum number of samples that we must have for any class, pre or post sampling. If a class must be downsampled, it will not be downsampled past this value. To determine severe imbalance, the minority class must occur less often than this and must have a class ratio below min_percentage. Must be greater than 0. Defaults to 100.
- **min_percentage** (*float*) – The minimum percentage of the minimum class to total dataset that we tolerate, as long as it is above min_samples. To determine severe imbalance, the minority class must have a class ratio below this and must occur less often than min_samples. Must be between 0 and 0.5, inclusive. Defaults to 0.1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Methods

fit_resample	Resampling technique for this sampler.

fit_resample(*self*, *X*, *y*)

Resampling technique for this sampler.

Parameters

- **X** (*pd.DataFrame*) – Training data to fit and resample
- **y** (*pd.Series*) – Training data targets to fit and resample

Returns Indices to keep for training data

Return type list

sampler_base

Module Contents

Classes Summary

SamplerBase	Base class for all custom samplers.

Contents

class evalml.preprocessing.data_splitters.sampler_base.**SamplerBase**(*random_seed=0*)

Base class for all custom samplers.

Parameters **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Methods

fit_resample	Resample the input data with this sampling strategy.

abstract fit_resample(*self*, *X*, *y*)

Resample the input data with this sampling strategy.

Parameters

- **X** (*pd.DataFrame*) – Training data to fit and resample.
- **y** (*pd.Series*) – Training data targets to fit and resample.

Returns resampled X and y data for oversampling or indices to keep for undersampling.

Return type Tuple(pd.DataFrame, pd.Series) or list

time_series_split

Module Contents

Classes Summary

TimeSeriesSplit	Rolling Origin Cross Validation for time series problems.

Contents

class evalml.preprocessing.data_splitters.time_series_split.**TimeSeriesSplit**(*max_delay=0*, *gap=0*, *date_index=None*, *n_splits=3*)

Rolling Origin Cross Validation for time series problems.

This class uses max_delay and gap values to take into account that evalml time series pipelines perform some feature and target engineering, e.g delaying input features and shifting the target variable by the desired amount. If the data that will be split already has all the features and appropriate target values, and then set max_delay and gap to 0.

Parameters

- **max_delay** (*int*) – Max delay value for feature engineering. Time series pipelines create delayed features from existing features. This process will introduce NaNs into the first max_delay number of rows. The splitter uses the last max_delay number of rows from the previous split as the first max_delay number of rows of the current split to avoid "throwing out" more data than in necessary. Defaults to 0.
- **gap** (*int*) – Gap used in time series problem. Time series pipelines shift the target variable by gap rows. Defaults to 0.
- **date_index** (*str*) – Name of the column containing the datetime information used to order the data. Defaults to None.
- **n_splits** (*int*) – number of data splits to make. Defaults to 3.

Methods

get_n_splits	Get the number of data splits.
split	Get the time series splits.

get_n_splits(*self*, *X=None*, *y=None*, *groups=None*)
Get the number of data splits.

split(*self*, *X*, *y=None*, *groups=None*)
Get the time series splits.

X and y are assumed to be sorted in ascending time order. This method can handle passing in empty or None X and y data but note that X and y cannot be None or empty at the same time.

Parameters

- **X** (*pd.DataFrame, None*) – Features to split.
- **y** (*pd.DataFrame, None*) – Target variable to split.
- **groups** – Ignored but kept for compatibility with sklearn api.

Returns Iterator of (train, test) indices tuples.

training_validation_split

Module Contents

Classes Summary

TrainingValidationSplit	Split the training data into training and validation sets.

Contents

class evalml.preprocessing.data_splitters.training_validation_split.**TrainingValidationSplit**

Split the training data into training and validation sets.

Parameters

- **test_size** (*float*) – What percentage of data points should be included in the validation set. Defalts to the complement of *train_size* if *train_size* is set, and 0.25 otherwise.
- **train_size** (*float*) – What percentage of data points should be included in the training set. Defaults to the complement of *test_size*
- **shuffle** (*boolean*) – Whether to shuffle the data before splitting. Defaults to False.
- **stratify** (*list*) – Splits the data in a stratified fashion, using this argument as class labels. Defaults to None.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Methods

get_n_splits	Returns the number of splits of this object
split	Divides the data into training and testing sets

static get_n_splits()
Returns the number of splits of this object

split(*self*, *X*, *y=None*)
Divides the data into training and testing sets

Parameters

- **X** (*pd.DataFrame*) – Dataframe of points to split
- **y** (*pd.Series*) – Series of points to split

Returns Indices to split data into training and test set

Return type list

Package Contents

Classes Summary

BalancedClassificationSampler	Class for balanced classification downsampler.
SamplerBase	Base class for all custom samplers.
TimeSeriesSplit	Rolling Origin Cross Validation for time series problems.
TrainingValidationSplit	Split the training data into training and validation sets.

Contents

class evalml.preprocessing.data_splitters.**BalancedClassificationSampler**(*sampling_ratio=0.25*, *sampling_ratio_dict=None*, *min_samples=100*, *min_percentage=0.1*, *random_seed=0*)

Class for balanced classification downsampler.

Parameters

- **sampling_ratio** (*float*) – The smallest minority:majority ratio that is accepted as 'balanced'. For instance, a 1:4 ratio would be represented as 0.25, while a 1:1 ratio is 1.0. Must be between 0 and 1, inclusive. Defaults to 0.25.
- **sampling_ratio_dict** (*dict*) – A dictionary specifying the desired balanced ratio for each target value. Overrides sampling_ratio if provided. Defaults to None.
- **min_samples** (*int*) – The minimum number of samples that we must have for any class, pre or post sampling. If a class must be downsampled, it will not be downsampled past this value. To determine severe imbalance, the minority class must occur less often than this and must have a class ratio below min_percentage. Must be greater than 0. Defaults to 100.
- **min_percentage** (*float*) – The minimum percentage of the minimum class to total dataset that we tolerate, as long as it is above min_samples. To determine severe imbalance, the minority class must have a class ratio below this and must occur less often than min_samples. Must be between 0 and 0.5, inclusive. Defaults to 0.1.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Methods

fit_resample	Resampling technique for this sampler.

fit_resample(*self*, *X*, *y*)

Resampling technique for this sampler.

Parameters

- **X** (*pd.DataFrame*) – Training data to fit and resample
- **y** (*pd.Series*) – Training data targets to fit and resample

Returns Indices to keep for training data

Return type list

class evalml.preprocessing.data_splitters.**SamplerBase**(*random_seed=0*)

Base class for all custom samplers.

Parameters **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Methods

fit_resample	Resample the input data with this sampling strategy.

abstract fit_resample(*self*, *X*, *y*)

Resample the input data with this sampling strategy.

Parameters

- **X** (*pd.DataFrame*) – Training data to fit and resample.
- **y** (*pd.Series*) – Training data targets to fit and resample.

Returns resampled X and y data for oversampling or indices to keep for undersampling.

Return type Tuple(pd.DataFrame, pd.Series) or list

class evalml.preprocessing.data_splitters.**TimeSeriesSplit**(*max_delay=0*, *gap=0*, *date_index=None*, *n_splits=3*)

Rolling Origin Cross Validation for time series problems.

This class uses max_delay and gap values to take into account that evalml time series pipelines perform some feature and target engineering, e.g delaying input features and shifting the target variable by the desired amount. If the data that will be split already has all the features and appropriate target values, and then set max_delay and gap to 0.

Parameters

- **max_delay** (*int*) – Max delay value for feature engineering. Time series pipelines create delayed features from existing features. This process will introduce NaNs into the first max_delay number of rows. The splitter uses the last max_delay number of rows from the previous split as the first max_delay number of rows of the current split to avoid "throwing out" more data than in necessary. Defaults to 0.
- **gap** (*int*) – Gap used in time series problem. Time series pipelines shift the target variable by gap rows. Defaults to 0.
- **date_index** (*str*) – Name of the column containing the datetime information used to order the data. Defaults to None.
- **n_splits** (*int*) – number of data splits to make. Defaults to 3.

Methods

get_n_splits	Get the number of data splits.
split	Get the time series splits.

get_n_splits(*self*, *X=None*, *y=None*, *groups=None*)

Get the number of data splits.

split(*self*, *X*, *y=None*, *groups=None*)

Get the time series splits.

X and y are assumed to be sorted in ascending time order. This method can handle passing in empty or

None X and y data but note that X and y cannot be None or empty at the same time.

Parameters

- **X** (*pd.DataFrame, None*) – Features to split.
- **y** (*pd.DataFrame, None*) – Target variable to split.
- **groups** – Ignored but kept for compatibility with sklearn api.

Returns Iterator of (train, test) indices tuples.

class evalml.preprocessing.data_splitters.**TrainingValidationSplit**(*test_size=None*, *train_size=None*, *shuffle=False*, *stratify=None*, *random_seed=0*)

Split the training data into training and validation sets.

Parameters

- **test_size** (*float*) – What percentage of data points should be included in the validation set. Defalts to the complement of *train_size* if *train_size* is set, and 0.25 otherwise.
- **train_size** (*float*) – What percentage of data points should be included in the training set. Defaults to the complement of *test_size*
- **shuffle** (*boolean*) – Whether to shuffle the data before splitting. Defaults to False.
- **stratify** (*list*) – Splits the data in a stratified fashion, using this argument as class labels. Defaults to None.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Methods

get_n_splits	Returns the number of splits of this object
split	Divides the data into training and testing sets

static get_n_splits()
Returns the number of splits of this object

split(*self*, *X*, *y=None*)
Divides the data into training and testing sets

Parameters

- **X** (*pd.DataFrame*) – Dataframe of points to split
- **y** (*pd.Series*) – Series of points to split

Returns Indices to split data into training and test set

Return type list

Submodules

utils

Module Contents

Functions

drop_nan_target_rows	Drops rows in X and y when row in the target y has a value of NaN.
load_data	Load features and target from file.
number_of_features	Get the number of features of each specific dtype in a DataFrame.
split_data	Splits data into train and test sets.
target_distribution	Get the target distributions.

Contents

evalml.preprocessing.utils.**drop_nan_target_rows**(*X*, *y*)

Drops rows in X and y when row in the target y has a value of NaN.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Data to transform
- **y** (*pd.Series, np.ndarray*) – Target data

Returns Transformed X (and y, if passed in) with rows that had a NaN value removed.

Return type pd.DataFrame, pd.DataFrame

evalml.preprocessing.utils.**load_data**(*path*, *index*, *target*, *n_rows=None*, *drop=None*, *verbose=True*, ***kwargs*)

Load features and target from file.

Parameters

- **path** (*str*) – Path to file or a http/ftp/s3 URL
- **index** (*str*) – Column for index
- **target** (*str*) – Column for target
- **n_rows** (*int*) – Number of rows to return
- **drop** (*list*) – List of columns to drop
- **verbose** (*bool*) – If True, prints information about features and target

Returns Features matrix and target

Return type pd.DataFrame, pd.Series

evalml.preprocessing.utils.**number_of_features**(*dtypes*)

Get the number of features of each specific dtype in a DataFrame.

Parameters **dtypes** (*pd.Series*) – DataFrame.dtypes to get the number of features for

Returns dtypes and the number of features for each input type

Return type pd.Series

evalml.preprocessing.utils.**split_data**(*X*, *y*, *problem_type*, *problem_configuration=None*, *test_size=0.2*, *random_seed=0*)

Splits data into train and test sets.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – data of shape [n_samples, n_features]
- **y** (*pd.Series, or np.ndarray*) – target data of length [n_samples]
- **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. see evalml.problem_types.problemtype.all_problem_types for a full list.
- **problem_configuration** (*dict*) – Additional parameters needed to configure the search. For example, in time series problems, values should be passed in for the date_index, gap, and max_delay variables.
- **test_size** (*float*) – What percentage of data points should be included in the test set. Defaults to 0.2 (20%).
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns Feature and target data each split into train and test sets

Return type pd.DataFrame, pd.DataFrame, pd.Series, pd.Series

evalml.preprocessing.utils.**target_distribution**(*targets*)

Get the target distributions.

Parameters **targets** (*pd.Series*) – Target data

Returns Target data and their frequency distribution as percentages.

Return type pd.Series

Package Contents

Classes Summary

TimeSeriesSplit	Rolling Origin Cross Validation for time series problems.
TrainingValidationSplit	Split the training data into training and validation sets.

Functions

drop_nan_target_rows	Drops rows in X and y when row in the target y has a value of NaN.
load_data	Load features and target from file.
number_of_features	Get the number of features of each specific dtype in a DataFrame.
split_data	Splits data into train and test sets.
target_distribution	Get the target distributions.

Contents

evalml.preprocessing.**drop_nan_target_rows**(*X*, *y*)

Drops rows in X and y when row in the target y has a value of NaN.

Parameters

- **X** (*pd.DataFrame, np.ndarray*) – Data to transform
- **y** (*pd.Series, np.ndarray*) – Target data

Returns Transformed X (and y, if passed in) with rows that had a NaN value removed.

Return type pd.DataFrame, pd.DataFrame

evalml.preprocessing.**load_data**(*path*, *index*, *target*, *n_rows=None*, *drop=None*, *verbose=True*, ***kwargs*)

Load features and target from file.

Parameters

- **path** (*str*) – Path to file or a http/ftp/s3 URL
- **index** (*str*) – Column for index
- **target** (*str*) – Column for target
- **n_rows** (*int*) – Number of rows to return
- **drop** (*list*) – List of columns to drop
- **verbose** (*bool*) – If True, prints information about features and target

Returns Features matrix and target

Return type pd.DataFrame, pd.Series

evalml.preprocessing.**number_of_features**(*dtypes*)

Get the number of features of each specific dtype in a DataFrame.

Parameters **dtypes** (*pd.Series*) – DataFrame.dtypes to get the number of features for

Returns dtypes and the number of features for each input type

Return type pd.Series

evalml.preprocessing.**split_data**(*X*, *y*, *problem_type*, *problem_configuration=None*, *test_size=0.2*, *random_seed=0*)

Splits data into train and test sets.

Parameters

- **X** (*pd.DataFrame or np.ndarray*) – data of shape [n_samples, n_features]
- **y** (*pd.Series, or np.ndarray*) – target data of length [n_samples]
- **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. see evalml.problem_types.problemtype.all_problem_types for a full list.
- **problem_configuration** (*dict*) – Additional parameters needed to configure the search. For example, in time series problems, values should be passed in for the date_index, gap, and max_delay variables.
- **test_size** (*float*) – What percentage of data points should be included in the test set. Defaults to 0.2 (20%).
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.

Returns Feature and target data each split into train and test sets

Return type pd.DataFrame, pd.DataFrame, pd.Series, pd.Series

evalml.preprocessing.**target_distribution**(*targets*)

Get the target distributions.

Parameters **targets** (*pd.Series*) – Target data

Returns Target data and their frequency distribution as percentages.

Return type pd.Series

class evalml.preprocessing.**TimeSeriesSplit**(*max_delay=0*, *gap=0*, *date_index=None*, *n_splits=3*)

Rolling Origin Cross Validation for time series problems.

This class uses max_delay and gap values to take into account that evalml time series pipelines perform some feature and target engineering, e.g delaying input features and shifting the target variable by the desired amount. If the data that will be split already has all the features and appropriate target values, and then set max_delay and gap to 0.

Parameters

- **max_delay** (*int*) – Max delay value for feature engineering. Time series pipelines create delayed features from existing features. This process will introduce NaNs into the first max_delay number of rows. The splitter uses the last max_delay number of rows from the previous split as the first max_delay number of rows of the current split to avoid "throwing out" more data than in necessary. Defaults to 0.
- **gap** (*int*) – Gap used in time series problem. Time series pipelines shift the target variable by gap rows. Defaults to 0.
- **date_index** (*str*) – Name of the column containing the datetime information used to order the data. Defaults to None.
- **n_splits** (*int*) – number of data splits to make. Defaults to 3.

Methods

get_n_splits	Get the number of data splits.
split	Get the time series splits.

get_n_splits(*self*, *X=None*, *y=None*, *groups=None*)

Get the number of data splits.

split(*self*, *X*, *y=None*, *groups=None*)

Get the time series splits.

X and y are assumed to be sorted in ascending time order. This method can handle passing in empty or None X and y data but note that X and y cannot be None or empty at the same time.

Parameters

- **X** (*pd.DataFrame, None*) – Features to split.
- **y** (*pd.DataFrame, None*) – Target variable to split.
- **groups** – Ignored but kept for compatibility with sklearn api.

Returns Iterator of (train, test) indices tuples.

class evalml.preprocessing.**TrainingValidationSplit**(*test_size=None*, *train_size=None*, *shuffle=False*, *stratify=None*, *random_seed=0*)

Split the training data into training and validation sets.

Parameters

- **test_size** (*float*) – What percentage of data points should be included in the validation set. Defalts to the complement of *train_size* if *train_size* is set, and 0.25 otherwise.
- **train_size** (*float*) – What percentage of data points should be included in the training set. Defaults to the complement of *test_size*
- **shuffle** (*boolean*) – Whether to shuffle the data before splitting. Defaults to False.
- **stratify** (*list*) – Splits the data in a stratified fashion, using this argument as class labels. Defaults to None.
- **random_seed** (*int*) – The seed to use for random sampling. Defaults to 0.

Methods

get_n_splits	Returns the number of splits of this object
split	Divides the data into training and testing sets

static get_n_splits()

Returns the number of splits of this object

split(*self*, *X*, *y=None*)

Divides the data into training and testing sets

Parameters

- **X** (*pd.DataFrame*) – Dataframe of points to split
- **y** (*pd.Series*) – Series of points to split

Returns Indices to split data into training and test set

Return type list

Problem Types

Submodules

problem_types

Module Contents

Classes Summary

ProblemTypes	Enum defining the supported types of machine learning problems.

Contents

class evalml.problem_types.problem_types.**ProblemTypes**

Enum defining the supported types of machine learning problems.

Attributes

BINARY	Binary classification problem.
MULTICLASS	Multiclass classification problem.
REGRESSION	Regression problem.
TIME_SERIES_BINARY	Time series binary classification problem.
TIME_SERIES_MULTICLASS	Time series multiclass classification problem.
TIME_SERIES_REGRESSION	Time series regression problem.

Methods

all_problem_types	Get a list of all defined problem types.
name	The name of the Enum member.
value	The value of the Enum member.

all_problem_types(*cls*)

Get a list of all defined problem types.

Returns list

Return type list(*ProblemTypes*)

name(*self*)

The name of the Enum member.

value(*self*)

The value of the Enum member.

utils

Module Contents

Functions

detect_problem_type	Determine the type of problem is being solved based on the targets (binary vs multiclass classification, regression)
handle_problem_types	Handles problem_type by either returning the ProblemTypes or converting from a str.
is_binary	Determines if the provided problem_type is a binary classification problem type
is_classification	Determines if the provided problem_type is a classification problem type

continues on next page

Table 693 – continued from previous page

is_multiclass	Determines if the provided problem_type is a multiclass classification problem type
is_regression	Determines if the provided problem_type is a regression problem type
is_time_series	Determines if the provided problem_type is a time series problem type

Contents

evalml.problem_types.utils.**detect_problem_type**(*y*)

Determine the type of problem is being solved based on the targets (binary vs multiclass classification, regression)
Ignores missing and null data

Parameters **y** (*pd.Series*) – the target labels to predict

Returns ProblemType Enum

Return type ProblemType

Example

```
>>> y = pd.Series([0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1])
>>> problem_type = detect_problem_type(y)
>>> assert problem_type == ProblemTypes.BINARY
```

evalml.problem_types.utils.**handle_problem_types**(*problem_type*)
Handles problem_type by either returning the ProblemTypes or converting from a str.

Parameters **problem_type** (*str or ProblemTypes*) – Problem type that needs to be handled

Returns ProblemTypes

evalml.problem_types.utils.**is_binary**(*problem_type*)
Determines if the provided problem_type is a binary classification problem type

Parameters **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.

Returns Whether or not the provided problem_type is a binary classification problem type.

Return type bool

evalml.problem_types.utils.**is_classification**(*problem_type*)
Determines if the provided problem_type is a classification problem type

Parameters **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.

Returns Whether or not the provided problem_type is a classification problem type.

Return type bool

evalml.problem_types.utils.**is_multiclass**(*problem_type*)
Determines if the provided problem_type is a multiclass classification problem type

Parameters **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.

Returns Whether or not the provided problem_type is a multiclass classification problem type.

Return type bool

evalml.problem_types.utils.**is_regression**(*problem_type*)
Determines if the provided problem_type is a regression problem type

Parameters **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.

Returns Whether or not the provided problem_type is a regression problem type.

Return type bool

evalml.problem_types.utils.**is_time_series**(*problem_type*)
Determines if the provided problem_type is a time series problem type

Parameters **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.

Returns Whether or not the provided problem_type is a time series problem type.

Return type bool

Package Contents

Classes Summary

ProblemTypes	Enum defining the supported types of machine learning problems.

Functions

detect_problem_type	Determine the type of problem is being solved based on the targets (binary vs multiclass classification, regression)
handle_problem_types	Handles problem_type by either returning the ProblemTypes or converting from a str.
is_binary	Determines if the provided problem_type is a binary classification problem type
is_classification	Determines if the provided problem_type is a classification problem type
is_multiclass	Determines if the provided problem_type is a multiclass classification problem type
is_regression	Determines if the provided problem_type is a regression problem type
is_time_series	Determines if the provided problem_type is a time series problem type

Contents

evalml.problem_types.**detect_problem_type**(*y*)

Determine the type of problem is being solved based on the targets (binary vs multiclass classification, regression)
Ignores missing and null data

Parameters **y** (*pd.Series*) – the target labels to predict

Returns ProblemType Enum

Return type ProblemType

Example

```
>>> y = pd.Series([0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1])
>>> problem_type = detect_problem_type(y)
>>> assert problem_type == ProblemTypes.BINARY
```

evalml.problem_types.**handle_problem_types**(*problem_type*)
Handles problem_type by either returning the ProblemTypes or converting from a str.

Parameters **problem_type** (*str or ProblemTypes*) – Problem type that needs to be handled

Returns ProblemTypes

evalml.problem_types.**is_binary**(*problem_type*)
Determines if the provided problem_type is a binary classification problem type

Parameters **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.

Returns Whether or not the provided problem_type is a binary classification problem type.

Return type bool

evalml.problem_types.**is_classification**(*problem_type*)
Determines if the provided problem_type is a classification problem type

Parameters **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.

Returns Whether or not the provided problem_type is a classification problem type.

Return type bool

evalml.problem_types.**is_multiclass**(*problem_type*)
Determines if the provided problem_type is a multiclass classification problem type

Parameters **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.

Returns Whether or not the provided problem_type is a multiclass classification problem type.

Return type bool

evalml.problem_types.**is_regression**(*problem_type*)
Determines if the provided problem_type is a regression problem type

Parameters **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.

Returns Whether or not the provided problem_type is a regression problem type.

Return type bool

evalml.problem_types.**is_time_series**(*problem_type*)

Determines if the provided problem_type is a time series problem type

Parameters **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.

Returns Whether or not the provided problem_type is a time series problem type.

Return type bool

class evalml.problem_types.**ProblemTypes**

Enum defining the supported types of machine learning problems.

Attributes

BINARY	Binary classification problem.
MULTICLASS	Multiclass classification problem.
REGRESSION	Regression problem.
TIME_SERIES_BINARY	Time series binary classification problem.
TIME_SERIES_MULTICLASS	Time series multiclass classification problem.
TIME_SERIES_REGRESSION	Time series regression problem.

Methods

all_problem_types	Get a list of all defined problem types.
name	The name of the Enum member.
value	The value of the Enum member.

all_problem_types(*cls*)

Get a list of all defined problem types.

Returns list

Return type list(*ProblemTypes*)

name(*self*)

The name of the Enum member.

value(*self*)

The value of the Enum member.

Tuners

Submodules

grid_search_tuner

Module Contents

Classes Summary

GridSearchTuner	Grid Search Optimizer, which generates all of the possible points to search for using a grid.

Contents

class evalml.tuners.grid_search_tuner.**GridSearchTuner**(*pipeline_hyperparameter_ranges*, *n_points=10*, *random_seed=0*)

Grid Search Optimizer, which generates all of the possible points to search for using a grid.

Parameters

- **pipeline_hyperparameter_ranges** (*dict*) – a set of hyperparameter ranges corresponding to a pipeline's parameters
- **n_points** (*int*) – The number of points to sample from along each dimension defined in the `space` argument. Defaults to 10.
- **random_seed** (*int*) – Seed for random number generator. Unused in this class, defaults to 0.

Example

```
>>> tuner = GridSearchTuner({'My Component': {'param a': [0.0, 10.0], 'param b': [
↪'a', 'b', 'c']}}, n_points=5)
>>> proposal = tuner.propose()
>>> assert proposal.keys() == {'My Component'}
>>> assert proposal['My Component'] == {'param a': 0.0, 'param b': 'a'}
```

Methods

add	Not applicable to grid search tuner as generated parameters are
is_search_space_exhausted	Checks if it is possible to generate a set of valid parameters. Stores generated parameters in
propose	Returns parameters from _grid_points iterations

add(*self*, *pipeline_parameters*, *score*)

Not applicable to grid search tuner as generated parameters are not dependent on scores of previous parameters.

Parameters

- **pipeline_parameters** (*dict*) – a dict of the parameters used to evaluate a pipeline
- **score** (*float*) – the score obtained by evaluating the pipeline with the provided parameters

is_search_space_exhausted(*self*)

Checks if it is possible to generate a set of valid parameters. Stores generated parameters in `self.curr_params` to be returned by `propose()`.

Raises **NoParamsException** – If a search space is exhausted, then this exception is thrown.

Returns If no more valid parameters exists in the search space, return false.

Return type bool

propose(*self*)

Returns parameters from _grid_points iterations

If all possible combinations of parameters have been scored, then `NoParamsException` is raised.

Returns proposed pipeline parameters

Return type dict

random_search_tuner

Module Contents

Classes Summary

RandomSearchTuner	Random Search Optimizer.

Contents

class evalml.tuners.random_search_tuner.**RandomSearchTuner**(*pipeline_hyperparameter_ranges*, *with_replacement=False*, *replacement_max_attempts=10*, *random_seed=0*)

Random Search Optimizer.

Parameters

- **pipeline_hyperparameter_ranges** (*dict*) – a set of hyperparameter ranges corresponding to a pipeline's parameters
- **with_replacement** (*bool*) – If false, only unique hyperparameters will be shown
- **replacement_max_attempts** (*int*) – The maximum number of tries to get a unique set of random parameters. Only used if tuner is initalized with with_replacement=True
- **random_seed** (*int*) – Seed for random number generator. Defaults to 0.

Example

```
>>> tuner = RandomSearchTuner({'My Component': {'param a': [0.0, 10.0], 'param b':
↪ ['a', 'b', 'c']}}, random_seed=42)
>>> proposal = tuner.propose()
>>> assert proposal.keys() == {'My Component'}
>>> assert proposal['My Component'] == {'param a': 3.7454011884736254, 'param b':
↪'c'}
```

Methods

add	Not applicable to random search tuner as generated parameters are
is_search_space_exhausted	Checks if it is possible to generate a set of valid parameters. Stores generated parameters in
propose	Generate a unique set of parameters.

add(*self*, *pipeline_parameters*, *score*)

Not applicable to random search tuner as generated parameters are not dependent on scores of previous parameters.

Parameters

- **pipeline_parameters** (*dict*) – A dict of the parameters used to evaluate a pipeline
- **score** (*float*) – The score obtained by evaluating the pipeline with the provided parameters

is_search_space_exhausted(*self*)

Checks if it is possible to generate a set of valid parameters. Stores generated parameters in `self.curr_params` to be returned by `propose()`.

Raises **NoParamsException** – If a search space is exhausted, then this exception is thrown.

Returns If no more valid parameters exists in the search space, return false.

Return type bool

propose(*self*)

Generate a unique set of parameters.

If tuner was initialized with `with_replacement=True` and the tuner is unable to generate a unique set of parameters after `replacement_max_attempts` tries, then `NoParamsException` is raised.

Returns Proposed pipeline parameters

Return type dict

skopt_tuner

Module Contents

Classes Summary

SKOptTuner	Bayesian Optimizer.

Attributes Summary

logger

Contents

evalml.tuners.skopt_tuner.**logger**

class evalml.tuners.skopt_tuner.**SKOptTuner**(*pipeline_hyperparameter_ranges*, *random_seed=0*)

Bayesian Optimizer.

Parameters

- **pipeline_hyperparameter_ranges** (*dict*) – A set of hyperparameter ranges corresponding to a pipeline's parameters.
- **random_seed** (*int*) – The seed for the random number generator. Defaults to 0.

Methods

add	Add score to sample.
is_search_space_exhausted	Optional. If possible search space for tuner is finite, this method indicates whether or not all possible parameters have been scored.
propose	Returns a suggested set of parameters to train and score a pipeline with, based off the search space dimensions and prior samples.

add(*self*, *pipeline_parameters*, *score*)

Add score to sample.

Parameters

- **pipeline_parameters** (*dict*) – A dict of the parameters used to evaluate a pipeline
- **score** (*float*) – The score obtained by evaluating the pipeline with the provided parameters

Returns None

is_search_space_exhausted(*self*)

Optional. If possible search space for tuner is finite, this method indicates whether or not all possible parameters have been scored.

Returns Returns true if all possible parameters in a search space has been scored.

Return type bool

propose(*self*)

Returns a suggested set of parameters to train and score a pipeline with, based off the search space dimensions and prior samples.

Returns Proposed pipeline parameters

Return type dict

tuner

Module Contents

Classes Summary

Tuner	Defines API for base Tuner classes.

Contents

class evalml.tuners.tuner.**Tuner**(*pipeline_hyperparameter_ranges*, *random_seed=0*)

Defines API for base Tuner classes.

Tuners implement different strategies for sampling from a search space. They're used in EvalML to search the space of pipeline hyperparameters.

Parameters

- **pipeline_hyperparameter_ranges** (*dict*) – a set of hyperparameter ranges corresponding to a pipeline's parameters.
- **random_seed** (*int*) – The random state. Defaults to 0.

Methods

add	Register a set of hyperparameters with the score obtained from training a pipeline with those hyperparameters.
is_search_space_exhausted	Optional. If possible search space for tuner is finite, this method indicates whether or not all possible parameters have been scored.
propose	Returns a suggested set of parameters to train and score a pipeline with, based off the search space dimensions and prior samples.

abstract add(*self*, *pipeline_parameters*, *score*)

Register a set of hyperparameters with the score obtained from training a pipeline with those hyperparameters.

Parameters

- **pipeline_parameters** (*dict*) – a dict of the parameters used to evaluate a pipeline
- **score** (*float*) – the score obtained by evaluating the pipeline with the provided parameters

Returns None

is_search_space_exhausted(*self*)

Optional. If possible search space for tuner is finite, this method indicates whether or not all possible parameters have been scored.

Returns Returns true if all possible parameters in a search space has been scored.

Return type bool

abstract propose(*self*)
Returns a suggested set of parameters to train and score a pipeline with, based off the search space dimensions and prior samples.

Returns Proposed pipeline parameters

Return type dict

tuner_exceptions

Module Contents

Contents

exception evalml.tuners.tuner_exceptions.**NoParamsException**
Raised when a tuner exhausts its search space and runs out of parameters to propose.

exception evalml.tuners.tuner_exceptions.**ParameterError**
Raised when a tuner encounters an error with the parameters being used with it.

Package Contents

Classes Summary

GridSearchTuner	Grid Search Optimizer, which generates all of the possible points to search for using a grid.
RandomSearchTuner	Random Search Optimizer.
SKOptTuner	Bayesian Optimizer.
Tuner	Defines API for base Tuner classes.

Exceptions Summary

—

Contents

class evalml.tuners.**GridSearchTuner**(*pipeline_hyperparameter_ranges*, *n_points=10*, *random_seed=0*)
Grid Search Optimizer, which generates all of the possible points to search for using a grid.

Parameters

- **pipeline_hyperparameter_ranges** (*dict*) – a set of hyperparameter ranges corresponding to a pipeline's parameters
- **n_points** (*int*) – The number of points to sample from along each dimension defined in the `space` argument. Defaults to 10.
- **random_seed** (*int*) – Seed for random number generator. Unused in this class, defaults to 0.

Example

```
>>> tuner = GridSearchTuner({'My Component': {'param a': [0.0, 10.0], 'param b': [
↪'a', 'b', 'c']}}, n_points=5)
>>> proposal = tuner.propose()
>>> assert proposal.keys() == {'My Component'}
>>> assert proposal['My Component'] == {'param a': 0.0, 'param b': 'a'}
```

Methods

add	Not applicable to grid search tuner as generated parameters are
is_search_space_exhausted	Checks if it is possible to generate a set of valid parameters. Stores generated parameters in
propose	Returns parameters from _grid_points iterations

add(*self*, *pipeline_parameters*, *score*)
Not applicable to grid search tuner as generated parameters are not dependent on scores of previous parameters.

Parameters

- **pipeline_parameters** (*dict*) – a dict of the parameters used to evaluate a pipeline
- **score** (*float*) – the score obtained by evaluating the pipeline with the provided parameters

is_search_space_exhausted(*self*)
Checks if it is possible to generate a set of valid parameters. Stores generated parameters in `self.curr_params` to be returned by `propose()`.

Raises ***NoParamsException*** – If a search space is exhausted, then this exception is thrown.

Returns If no more valid parameters exists in the search space, return false.

Return type bool

propose(*self*)
Returns parameters from _grid_points iterations

If all possible combinations of parameters have been scored, then `NoParamsException` is raised.

Returns proposed pipeline parameters

Return type dict

exception evalml.tuners.**NoParamsException**
Raised when a tuner exhausts its search space and runs out of parameters to propose.

exception evalml.tuners.**ParameterError**
Raised when a tuner encounters an error with the parameters being used with it.

class evalml.tuners.**RandomSearchTuner**(*pipeline_hyperparameter_ranges*, *with_replacement=False*, *replacement_max_attempts=10*, *random_seed=0*)
Random Search Optimizer.

Parameters

- **pipeline_hyperparameter_ranges** (*dict*) – a set of hyperparameter ranges corresponding to a pipeline's parameters

- **with_replacement** (*bool*) – If false, only unique hyperparameters will be shown
- **replacement_max_attempts** (*int*) – The maximum number of tries to get a unique set of random parameters. Only used if tuner is initalized with with_replacement=True
- **random_seed** (*int*) – Seed for random number generator. Defaults to 0.

Example

```
>>> tuner = RandomSearchTuner({'My Component': {'param a': [0.0, 10.0], 'param b':
↪ ['a', 'b', 'c']}}, random_seed=42)
>>> proposal = tuner.propose()
>>> assert proposal.keys() == {'My Component'}
>>> assert proposal['My Component'] == {'param a': 3.7454011884736254, 'param b':
↪'c'}
```

Methods

add	Not applicable to random search tuner as generated parameters are
is_search_space_exhausted	Checks if it is possible to generate a set of valid parameters. Stores generated parameters in
propose	Generate a unique set of parameters.

add(*self*, *pipeline_parameters*, *score*)
Not applicable to random search tuner as generated parameters are not dependent on scores of previous parameters.

Parameters

- **pipeline_parameters** (*dict*) – A dict of the parameters used to evaluate a pipeline
- **score** (*float*) – The score obtained by evaluating the pipeline with the provided parameters

is_search_space_exhausted(*self*)
Checks if it is possible to generate a set of valid parameters. Stores generated parameters in `self.curr_params` to be returned by `propose()`.

Raises ***NoParamsException*** – If a search space is exhausted, then this exception is thrown.

Returns If no more valid parameters exists in the search space, return false.

Return type bool

propose(*self*)
Generate a unique set of parameters.

If tuner was initialized with `with_replacement=True` and the tuner is unable to generate a unique set of parameters after `replacement_max_attempts` tries, then `NoParamsException` is raised.

Returns Proposed pipeline parameters

Return type dict

class evalml.tuners.**SKOptTuner**(*pipeline_hyperparameter_ranges*, *random_seed=0*)
Bayesian Optimizer.

Parameters

- **pipeline_hyperparameter_ranges** (*dict*) – A set of hyperparameter ranges corresponding to a pipeline's parameters.
- **random_seed** (*int*) – The seed for the random number generator. Defaults to 0.

Methods

add	Add score to sample.
is_search_space_exhausted	Optional. If possible search space for tuner is finite, this method indicates whether or not all possible parameters have been scored.
propose	Returns a suggested set of parameters to train and score a pipeline with, based off the search space dimensions and prior samples.

add(*self*, *pipeline_parameters*, *score*)
Add score to sample.

Parameters

- **pipeline_parameters** (*dict*) – A dict of the parameters used to evaluate a pipeline
- **score** (*float*) – The score obtained by evaluating the pipeline with the provided parameters

Returns None

is_search_space_exhausted(*self*)
Optional. If possible search space for tuner is finite, this method indicates whether or not all possible parameters have been scored.

Returns Returns true if all possible parameters in a search space has been scored.

Return type bool

propose(*self*)
Returns a suggested set of parameters to train and score a pipeline with, based off the search space dimensions and prior samples.

Returns Proposed pipeline parameters

Return type dict

class evalml.tuners.**Tuner**(*pipeline_hyperparameter_ranges*, *random_seed=0*)
Defines API for base Tuner classes.

Tuners implement different strategies for sampling from a search space. They're used in EvalML to search the space of pipeline hyperparameters.

Parameters

- **pipeline_hyperparameter_ranges** (*dict*) – a set of hyperparameter ranges corresponding to a pipeline's parameters.
- **random_seed** (*int*) – The random state. Defaults to 0.

Methods

add	Register a set of hyperparameters with the score obtained from training a pipeline with those hyperparameters.

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Table 711 – continued from previous page

is_search_space_exhausted	Optional. If possible search space for tuner is finite, this method indicates whether or not all possible parameters have been scored.
propose	Returns a suggested set of parameters to train and score a pipeline with, based off the search space dimensions and prior samples.

abstract add(*self*, *pipeline_parameters*, *score*)
Register a set of hyperparameters with the score obtained from training a pipeline with those hyperparameters.

Parameters

- **pipeline_parameters** (*dict*) – a dict of the parameters used to evaluate a pipeline
- **score** (*float*) – the score obtained by evaluating the pipeline with the provided parameters

Returns None

is_search_space_exhausted(*self*)
Optional. If possible search space for tuner is finite, this method indicates whether or not all possible parameters have been scored.

Returns Returns true if all possible parameters in a search space has been scored.

Return type bool

abstract propose(*self*)
Returns a suggested set of parameters to train and score a pipeline with, based off the search space dimensions and prior samples.

Returns Proposed pipeline parameters

Return type dict

Utils

Submodules

base_meta

Module Contents

Classes Summary

BaseMeta	Metaclass that overrides creating a new component or pipeline by wrapping methods with validators and setters

Contents

class evalml.utils.base_meta.**BaseMeta**

Metaclass that overrides creating a new component or pipeline by wrapping methods with validators and setters

Attributes

FIT_METHODS	['fit', 'fit_transform']
METHODS_TO_CHECK	['predict', 'predict_proba', 'transform', 'inverse_transform']
PROPERTIES_TO_CHECK	['feature_importance']

Methods

register	Register a virtual subclass of an ABC.
set_fit	

register(*cls*, *subclass*)

Register a virtual subclass of an ABC.

Returns the subclass, to allow usage as a class decorator.

classmethod set_fit(*cls*, *method*)

cli_utils

Module Contents

Functions

get_evalml_root	Gets location where evalml is installed.
get_installed_packages	Get dictionary mapping installed package names to their versions.
get_sys_info	Returns system information.
print_deps	Prints the version number of each dependency.
print_info	Prints information about the system, evalml, and dependencies of evalml.
print_sys_info	Prints system information.

Attributes Summary

logger	

Contents

evalml.utils.cli_utils.**get_evalml_root**()
Gets location where evalml is installed.

Returns Location where evalml is installed.

evalml.utils.cli_utils.**get_installed_packages**()
Get dictionary mapping installed package names to their versions.

Returns Dictionary mapping installed package names to their versions.

evalml.utils.cli_utils.**get_sys_info**()
Returns system information.

Returns List of tuples about system stats.

evalml.utils.cli_utils.**logger**

evalml.utils.cli_utils.**print_deps**()
Prints the version number of each dependency.

Returns None

evalml.utils.cli_utils.**print_info**()
Prints information about the system, evalml, and dependencies of evalml.

Returns None

evalml.utils.cli_utils.**print_sys_info**()
Prints system information.

Returns None

gen_utils

Module Contents

Classes Summary

classproperty	Allows function to be accessed as a class level property.

Functions

convert_to_seconds	Converts a string describing a length of time to its length in seconds.
deprecate_arg	Helper to raise warnings when a deprecated arg is used.
drop_rows_with_nans	Drop rows that have any NaNs in all dataframes or series.
get_importable_subclasses	Get importable subclasses of a base class. Used to list all of our
get_random_seed	Given a numpy.random.RandomState object, generate an int representing a seed value for another random number generator. Or, if given an int, return that int.
get_random_state	Generates a numpy.random.RandomState instance using seed.
import_or_raise	Attempts to import the requested library by name.
is_all_numeric	Checks if the given DataFrame contains only numeric values
jupyter_check	Get whether or not the code is being run in a Ipython environment (such as Jupyter Notebook or Jupyter Lab)
pad_with_nans	Pad the beginning num_to_pad rows with nans.
safe_repr	Convert the given value into a string that can safely be used for repr
save_plot	Saves fig to filepath if specified, or to a default location if not.

Attributes Summary

logger	
SEED_BOUNDS	

Contents

class evalml.utils.gen_utils.**classproperty**(*func*)

Allows function to be accessed as a class level property.

Example:

```
class LogisticRegressionBinaryPipeline(PipelineBase):
    component_graph = ['Simple Imputer', 'Logistic Regression Classifier']

    @classproperty
    def summary(cls):
    summary = ""
    for component in cls.component_graph:
        component = handle_component_class(component)
        summary += component.name + " + "
    return summary
```

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```
assert LogisticRegressionBinaryPipeline.summary == "Simple Imputer + Logistic␣
↪Regression Classifier + "
assert LogisticRegressionBinaryPipeline().summary == "Simple Imputer + Logistic␣
↪Regression Classifier + "
```

evalml.utils.gen_utils.**convert_to_seconds**(*input_str*)

Converts a string describing a length of time to its length in seconds.

evalml.utils.gen_utils.**deprecate_arg**(*old_arg*, *new_arg*, *old_value*, *new_value*)

Helper to raise warnings when a deprecated arg is used.

Parameters

- **old_arg** (*str*) – Name of old/deprecated argument.
- **new_arg** (*str*) – Name of new argument.
- **old_value** (*Any*) – Value the user passed in for the old argument.
- **new_value** (*Any*) – Value the user passed in for the new argument.

Returns old_value if not None, else new_value

evalml.utils.gen_utils.**drop_rows_with_nans**(**pd_data*)

Drop rows that have any NaNs in all dataframes or series.

Parameters ***pd_data** (*sequence of pd.Series or pd.DataFrame or None*) –

Returns list of pd.DataFrame or pd.Series or None

evalml.utils.gen_utils.**get_importable_subclasses**(*base_class*, *used_in_automl=True*)

Get importable subclasses of a base class. Used to list all of our estimators, transformers, components and pipelines dynamically.

Parameters

- **base_class** (*abc.ABCMeta*) – Base class to find all of the subclasses for.
- **args** (*list*) – Args used to instantiate the subclass. [{}] for a pipeline, and [] for all other classes.
- **used_in_automl** – Not all components/pipelines/estimators are used in automl search. If True, only include those subclasses that are used in the search. This would mean excluding classes related to ExtraTrees, ElasticNet, and Baseline estimators.

Returns List of subclasses.

evalml.utils.gen_utils.**get_random_seed**(*random_state*, *min_bound=SEED_BOUNDS.min_bound*, *max_bound=SEED_BOUNDS.max_bound*)

Given a numpy.random.RandomState object, generate an int representing a seed value for another random number generator. Or, if given an int, return that int.

To protect against invalid input to a particular library's random number generator, if an int value is provided, and it is outside the bounds "[min_bound, max_bound)", the value will be projected into the range between the min_bound (inclusive) and max_bound (exclusive) using modular arithmetic.

Parameters

- **random_state** (*int, numpy.random.RandomState*) – random state
- **min_bound** (*None, int*) – if not default of None, will be min bound when generating seed (inclusive). Must be less than max_bound.

- **max_bound** (*None, int*) – if not default of None, will be max bound when generating seed (exclusive). Must be greater than min_bound.

Returns seed for random number generator

Return type int

evalml.utils.gen_utils.**get_random_state**(*seed*)
Generates a numpy.random.RandomState instance using seed.

Parameters **seed** (*None, int, np.random.RandomState object*) – seed to use to generate numpy.random.RandomState. Must be between SEED_BOUNDS.min_bound and SEED_BOUNDS.max_bound, inclusive. Otherwise, an exception will be thrown.

evalml.utils.gen_utils.**import_or_raise**(*library*, *error_msg=None*, *warning=False*)
Attempts to import the requested library by name. If the import fails, raises an ImportError or warning.

Parameters

- **library** (*str*) – the name of the library
- **error_msg** (*str*) – error message to return if the import fails
- **warning** (*bool*) – if True, import_or_raise gives a warning instead of ImportError. Defaults to False.

evalml.utils.gen_utils.**is_all_numeric**(*df*)
Checks if the given DataFrame contains only numeric values

Parameters **df** (*pd.DataFrame*) – The DataFrame to check data types of.

Returns True if all the columns are numeric and are not missing any values, False otherwise.

evalml.utils.gen_utils.**jupyter_check**()
Get whether or not the code is being run in a Ipython environment (such as Jupyter Notebook or Jupyter Lab)

Parameters **None** –

Returns True if Ipython, False otherwise

Return type Boolean

evalml.utils.gen_utils.**logger**

evalml.utils.gen_utils.**pad_with_nans**(*pd_data*, *num_to_pad*)
Pad the beginning num_to_pad rows with nans.

Parameters **pd_data** (*pd.DataFrame or pd.Series*) – Data to pad.

Returns pd.DataFrame or pd.Series

evalml.utils.gen_utils.**safe_repr**(*value*)
Convert the given value into a string that can safely be used for repr

Parameters **value** – the item to convert

Returns String representation of the value

evalml.utils.gen_utils.**save_plot**(*fig*, *filepath=None*, *format='png'*, *interactive=False*, *return_filepath=False*)
Saves fig to filepath if specified, or to a default location if not.

Parameters

- **fig** (*Figure*) – Figure to be saved.
- **filepath** (*str or Path, optional*) – Location to save file. Default is with filename "test_plot".

- **format** (*str*) – Extension for figure to be saved as. Ignored if interactive is True and fig
- **of type plotly.Figure. Defaults to 'png'.** (*is*) –
- **interactive** (*bool, optional*) – If True and fig is of type plotly.Figure, saves the fig as interactive
- **of static** (*instead*) –
- **format will be set to 'html'. Defaults to False.** (*and*) –
- **return_filepath** (*bool, optional*) – Whether to return the final filepath the image is saved to. Defaults to False.

Returns String representing the final filepath the image was saved to if return_filepath is set to True. Defaults to None.

evalml.utils.gen_utils.**SEED_BOUNDS**

logger

Module Contents

Functions

get_logger	
log_subtitle	
log_title	
time_elapsed	How much time has elapsed since the search started.

Contents

evalml.utils.logger.**get_logger**(*name*)

evalml.utils.logger.**log_subtitle**(*logger*, *title*, *underline='='*)

evalml.utils.logger.**log_title**(*logger*, *title*)

evalml.utils.logger.**time_elapsed**(*start_time*)

How much time has elapsed since the search started.

Parameters **start_time** (*int*) – Time when search started.

Returns elapsed time formatted as a string [H:]MM:SS

Return type str

update_checker

Module Contents

Contents

evalml.utils.update_checker.**method**

woodwork_utils

Module Contents

Functions

infer_feature_types	Create a Woodwork structure from the given list, pandas, or numpy input, with specified types for columns.

Attributes Summary

numeric_and_boolean_ww

Contents

evalml.utils.woodwork_utils.**infer_feature_types**(*data*, *feature_types=None*)

Create a Woodwork structure from the given list, pandas, or numpy input, with specified types for columns.
If a column's type is not specified, it will be inferred by Woodwork.

Parameters

- **data** (*pd.DataFrame, pd.Series*) – Input data to convert to a Woodwork data structure.
- **feature_types** (*string, ww.logical_type obj, dict, optional*) – If data is a 2D structure, feature_types must be a dictionary mapping column names to the type of data represented in the column. If data is a 1D structure, then feature_types must be a Woodwork logical type or a string representing a Woodwork logical type ("Double", "Integer", "Boolean", "Categorical", "Datetime", "NaturalLanguage")

Returns A Woodwork data structure where the data type of each column was either specified or inferred.

evalml.utils.woodwork_utils.**numeric_and_boolean_ww**

Package Contents

Classes Summary

classproperty	Allows function to be accessed as a class level property.

Functions

convert_to_seconds	Converts a string describing a length of time to its length in seconds.
deprecate_arg	Helper to raise warnings when a deprecated arg is used.
drop_rows_with_nans	Drop rows that have any NaNs in all dataframes or series.
get_importable_subclasses	Get importable subclasses of a base class. Used to list all of our
get_logger	
get_random_seed	Given a numpy.random.RandomState object, generate an int representing a seed value for another random number generator. Or, if given an int, return that int.
get_random_state	Generates a numpy.random.RandomState instance using seed.
import_or_raise	Attempts to import the requested library by name.
infer_feature_types	Create a Woodwork structure from the given list, pandas, or numpy input, with specified types for columns.
is_all_numeric	Checks if the given DataFrame contains only numeric values
jupyter_check	Get whether or not the code is being run in a Ipython environment (such as Jupyter Notebook or Jupyter Lab)
log_subtitle	
log_title	
pad_with_nans	Pad the beginning num_to_pad rows with nans.
safe_repr	Convert the given value into a string that can safely be used for repr
save_plot	Saves fig to filepath if specified, or to a default location if not.

Attributes Summary

SEED_BOUNDS	

Contents

class evalml.utils.**classproperty**(*func*)

Allows function to be accessed as a class level property.

Example:

```
class LogisticRegressionBinaryPipeline(PipelineBase):
    component_graph = ['Simple Imputer', 'Logistic Regression Classifier']

    @classproperty
    def summary(cls):
    summary = ""
    for component in cls.component_graph:
        component = handle_component_class(component)
        summary += component.name + " + "
    return summary

assert LogisticRegressionBinaryPipeline.summary == "Simple Imputer + Logistic␣
↪Regression Classifier + "
assert LogisticRegressionBinaryPipeline().summary == "Simple Imputer + Logistic␣
↪Regression Classifier + "
```

evalml.utils.**convert_to_seconds**(*input_str*)

Converts a string describing a length of time to its length in seconds.

evalml.utils.**deprecate_arg**(*old_arg*, *new_arg*, *old_value*, *new_value*)

Helper to raise warnings when a deprecated arg is used.

Parameters

- **old_arg** (*str*) – Name of old/deprecated argument.
- **new_arg** (*str*) – Name of new argument.
- **old_value** (*Any*) – Value the user passed in for the old argument.
- **new_value** (*Any*) – Value the user passed in for the new argument.

Returns old_value if not None, else new_value

evalml.utils.**drop_rows_with_nans**(**pd_data*)

Drop rows that have any NaNs in all dataframes or series.

Parameters ***pd_data** (*sequence of pd.Series or pd.DataFrame or None*) –

Returns list of pd.DataFrame or pd.Series or None

evalml.utils.**get_importable_subclasses**(*base_class*, *used_in_automl=True*)

Get importable subclasses of a base class. Used to list all of our estimators, transformers, components and pipelines dynamically.

Parameters

- **base_class** (*abc.ABCMeta*) – Base class to find all of the subclasses for.
- **args** (*list*) – Args used to instantiate the subclass. [{}] for a pipeline, and [] for all other classes.
- **used_in_automl** – Not all components/pipelines/estimators are used in automl search. If True, only include those subclasses that are used in the search. This would mean excluding classes related to ExtraTrees, ElasticNet, and Baseline estimators.

Returns List of subclasses.

evalml.utils.**get_logger**(*name*)

evalml.utils.**get_random_seed**(*random_state*, *min_bound=SEED_BOUNDS.min_bound*, *max_bound=SEED_BOUNDS.max_bound*)

Given a numpy.random.RandomState object, generate an int representing a seed value for another random number generator. Or, if given an int, return that int.

To protect against invalid input to a particular library's random number generator, if an int value is provided, and it is outside the bounds "[min_bound, max_bound)", the value will be projected into the range between the min_bound (inclusive) and max_bound (exclusive) using modular arithmetic.

Parameters

- **random_state** (*int, numpy.random.RandomState*) – random state
- **min_bound** (*None, int*) – if not default of None, will be min bound when generating seed (inclusive). Must be less than max_bound.
- **max_bound** (*None, int*) – if not default of None, will be max bound when generating seed (exclusive). Must be greater than min_bound.

Returns seed for random number generator

Return type int

evalml.utils.**get_random_state**(*seed*)

Generates a numpy.random.RandomState instance using seed.

Parameters **seed** (*None, int, np.random.RandomState object*) – seed to use to generate numpy.random.RandomState. Must be between SEED_BOUNDS.min_bound and SEED_BOUNDS.max_bound, inclusive. Otherwise, an exception will be thrown.

evalml.utils.**import_or_raise**(*library*, *error_msg=None*, *warning=False*)

Attempts to import the requested library by name. If the import fails, raises an ImportError or warning.

Parameters

- **library** (*str*) – the name of the library
- **error_msg** (*str*) – error message to return if the import fails
- **warning** (*bool*) – if True, import_or_raise gives a warning instead of ImportError. Defaults to False.

evalml.utils.**infer_feature_types**(*data*, *feature_types=None*)

Create a Woodwork structure from the given list, pandas, or numpy input, with specified types for columns. If a column's type is not specified, it will be inferred by Woodwork.

Parameters

- **data** (*pd.DataFrame, pd.Series*) – Input data to convert to a Woodwork data structure.
- **feature_types** (*string, ww.logical_type obj, dict, optional*) – If data is a 2D structure, feature_types must be a dictionary mapping column names to the type of data represented in the column. If data is a 1D structure, then feature_types must be a Woodwork logical type or a string representing a Woodwork logical type ("Double", "Integer", "Boolean", "Categorical", "Datetime", "NaturalLanguage")

Returns A Woodwork data structure where the data type of each column was either specified or inferred.

evalml.utils.**is_all_numeric**(*df*)
Checks if the given DataFrame contains only numeric values

Parameters **df** (*pd.DataFrame*) – The DataFrame to check data types of.

Returns True if all the columns are numeric and are not missing any values, False otherwise.

evalml.utils.**jupyter_check**()
Get whether or not the code is being run in a Ipython environment (such as Jupyter Notebook or Jupyter Lab)

Parameters **None** –

Returns True if Ipython, False otherwise

Return type Boolean

evalml.utils.**log_subtitle**(*logger*, *title*, *underline='='*)

evalml.utils.**log_title**(*logger*, *title*)

evalml.utils.**pad_with_nans**(*pd_data*, *num_to_pad*)
Pad the beginning num_to_pad rows with nans.

Parameters **pd_data** (*pd.DataFrame or pd.Series*) – Data to pad.

Returns pd.DataFrame or pd.Series

evalml.utils.**safe_repr**(*value*)
Convert the given value into a string that can safely be used for repr

Parameters **value** – the item to convert

Returns String representation of the value

evalml.utils.**save_plot**(*fig*, *filepath=None*, *format='png'*, *interactive=False*, *return_filepath=False*)
Saves fig to filepath if specified, or to a default location if not.

Parameters

- **fig** (*Figure*) – Figure to be saved.
- **filepath** (*str or Path, optional*) – Location to save file. Default is with filename "test_plot".
- **format** (*str*) – Extension for figure to be saved as. Ignored if interactive is True and fig
- **of type plotly.Figure. Defaults to 'png'.** (*is*) –
- **interactive** (*bool, optional*) – If True and fig is of type plotly.Figure, saves the fig as interactive
- **of static** (*instead*) –
- **format will be set to 'html'. Defaults to False.** (*and*) –
- **return_filepath** (*bool, optional*) – Whether to return the final filepath the image is saved to. Defaults to False.

Returns String representing the final filepath the image was saved to if return_filepath is set to True. Defaults to None.

evalml.utils.**SEED_BOUNDS**

Package Contents

Classes Summary

AutoMLSearch	Automated Pipeline search.

Functions

search	Given data and configuration, run an automl search.

Contents

class evalml.**AutoMLSearch**(*X_train=None*, *y_train=None*, *problem_type=None*, *objective='auto'*, *max_iterations=None*, *max_time=None*, *patience=None*, *tolerance=None*, *data_splitter=None*, *allowed_component_graphs=None*, *allowed_model_families=None*, *start_iteration_callback=None*, *add_result_callback=None*, *error_callback=None*, *additional_objectives=None*, *alternate_thresholding_objective='F1'*, *random_seed=0*, *n_jobs=-1*, *tuner_class=None*, *optimize_thresholds=True*, *ensembling=False*, *max_batches=None*, *problem_configuration=None*, *train_best_pipeline=True*, *pipeline_parameters=None*, *custom_hyperparameters=None*, *sampler_method='auto'*, *sampler_balanced_ratio=0.25*, *_ensembling_split_size=0.2*, *_pipelines_per_batch=5*, *engine=None*)

Automated Pipeline search.

Parameters

- **X_train** (*pd.DataFrame*) – The input training data of shape [n_samples, n_features]. Required.
- **y_train** (*pd.Series*) – The target training data of length [n_samples]. Required for supervised learning tasks.
- **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.
- **objective** (*str, ObjectiveBase*) – The objective to optimize for. Used to propose and rank pipelines, but not for optimizing each pipeline during fit-time. When set to 'auto', chooses:
  - LogLossBinary for binary classification problems,
  - LogLossMulticlass for multiclass classification problems, and
  - R2 for regression problems.
- **max_iterations** (*int*) – Maximum number of iterations to search. If max_iterations and max_time is not set, then max_iterations will default to max_iterations of 5.
- **max_time** (*int, str*) – Maximum time to search for pipelines. This will not start a new pipeline search after the duration has elapsed. If it is an integer, then the time will be in seconds. For strings, time can be specified as seconds, minutes, or hours.

- **patience** (*int*) – Number of iterations without improvement to stop search early. Must be positive. If None, early stopping is disabled. Defaults to None.
- **tolerance** (*float*) – Minimum percentage difference to qualify as score improvement for early stopping. Only applicable if patience is not None. Defaults to None.
- **allowed_component_graphs** (*dict*) – A dictionary of lists or ComponentGraphs indicating the component graphs allowed in the search. The format should follow { "Name_0": [list_of_components], "Name_1": [ComponentGraph(...)] }

  The default of None indicates all pipeline component graphs for this problem type are allowed. Setting this field will cause allowed_model_families to be ignored.

  e.g. allowed_component_graphs = { "My_Graph": ["Imputer", "One Hot Encoder", "Random Forest Classifier"] }
- **allowed_model_families** (*list(str, ModelFamily)*) – The model families to search. The default of None searches over all model families. Run evalml.pipelines.components.utils.allowed_model_families("binary") to see options. Change *binary* to *multiclass* or *regression* depending on the problem type. Note that if allowed_pipelines is provided, this parameter will be ignored.
- **data_splitter** (*sklearn.model_selection.BaseCrossValidator*) – Data splitting method to use. Defaults to StratifiedKFold.
- **tuner_class** – The tuner class to use. Defaults to SKOptTuner.
- **optimize_thresholds** (*bool*) – Whether or not to optimize the binary pipeline threshold. Defaults to True.
- **start_iteration_callback** (*callable*) – Function called before each pipeline training iteration. Callback function takes three positional parameters: The pipeline instance and the AutoMLSearch object.
- **add_result_callback** (*callable*) – Function called after each pipeline training iteration. Callback function takes three positional parameters: A dictionary containing the training results for the new pipeline, an untrained_pipeline containing the parameters used during training, and the AutoMLSearch object.
- **error_callback** (*callable*) – Function called when *search()* errors and raises an Exception. Callback function takes three positional parameters: the Exception raised, the traceback, and the AutoMLSearch object. Must also accepts kwargs, so AutoMLSearch is able to pass along other appropriate parameters by default. Defaults to None, which will call *log_error_callback*.
- **additional_objectives** (*list*) – Custom set of objectives to score on. Will override default objectives for problem type if not empty.
- **alternate_thresholding_objective** (*str*) – The objective to use for thresholding binary classification pipelines if the main objective provided isn't tuneable. Defaults to F1.
- **random_seed** (*int*) – Seed for the random number generator. Defaults to 0.
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines. None and 1 are equivalent. If set to -1, all CPUs are used. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used.
- **ensembling** (*boolean*) – If True, runs ensembling in a separate batch after every allowed pipeline class has been iterated over. If the number of unique pipelines to search over per batch is one, ensembling will not run. Defaults to False.

- **max_batches** (*int*) – The maximum number of batches of pipelines to search. Parameters max_time, and max_iterations have precedence over stopping the search.
- **problem_configuration** (*dict, None*) – Additional parameters needed to configure the search. For example, in time series problems, values should be passed in for the date_index, gap, and max_delay variables.
- **train_best_pipeline** (*boolean*) – Whether or not to train the best pipeline before returning it. Defaults to True.
- **pipeline_parameters** (*dict*) – A dict of the parameters used to initialize a pipeline with. Keys should consist of the component names and values should specify parameter values

  e.g. pipeline_parameters = { 'Imputer' : { 'numeric_impute_strategy': 'most_frequent' } }
- **custom_hyperparameters** (*dict*) – A dict of the hyperparameter ranges used to iterate over during search. Keys should consist of the component names and values should specify a singular value or skopt.Space.

  e.g. custom_hyperparameters = { 'Imputer' : { 'numeric_impute_strategy': Categorical(['most_frequent', 'median']) } }
- **sampler_method** (*str*) – The data sampling component to use in the pipelines if the problem type is classification and the target balance is smaller than the sampler_balanced_ratio. Either 'auto', which will use our preferred sampler for the data, 'Undersampler', 'Oversampler', or None. Defaults to 'auto'.
- **sampler_balanced_ratio** (*float*) – The minority:majority class ratio that we consider balanced, so a 1:4 ratio would be equal to 0.25. If the class balance is larger than this provided value, then we will not add a sampler since the data is then considered balanced. Overrides the *sampler_ratio* of the samplers. Defaults to 0.25.
- **_ensembling_split_size** (*float*) – The amount of the training data we'll set aside for training ensemble metalearners. Only used when ensembling is True. Must be between 0 and 1, exclusive. Defaults to 0.2
- **_pipelines_per_batch** (*int*) – The number of pipelines to train for every batch after the first one. The first batch will train a baseline pipline + one of each pipeline family allowed in the search.
- **engine** (*EngineBase or None*) – The engine instance used to evaluate pipelines. If None, a SequentialEngine will be used.

Methods

add_to_rankings	Fits and evaluates a given pipeline then adds the results to the automl rankings with the requirement that automl search has been run.
best_pipeline	Returns a trained instance of the best pipeline and parameters found during automl search. If *train_best_pipeline* is set to False, returns an untrained pipeline instance.
describe_pipeline	Describe a pipeline
full_rankings	Returns a pandas.DataFrame with scoring results from all pipelines searched
get_pipeline	Given the ID of a pipeline training result, returns an untrained instance of the specified pipeline

continues on next page

Table 727 – continued from previous page

load	Loads AutoML object at file path
plot	
rankings	Returns a pandas.DataFrame with scoring results from the highest-scoring set of parameters used with each pipeline.
results	Class that allows access to a copy of the results from *automl_search*.
save	Saves AutoML object at file path
score_pipelines	Score a list of pipelines on the given holdout data.
search	Find the best pipeline for the data set.
train_pipelines	Train a list of pipelines on the training data.

add_to_rankings (*self*, *pipeline*)
Fits and evaluates a given pipeline then adds the results to the automl rankings with the requirement that automl search has been run.

Parameters **pipeline** (*PipelineBase*) – pipeline to train and evaluate.

property best_pipeline (*self*)
Returns a trained instance of the best pipeline and parameters found during automl search. If *train_best_pipeline* is set to False, returns an untrained pipeline instance.

Returns A trained instance of the best pipeline and parameters found during automl search. If *train_best_pipeline* is set to False, returns an untrained pipeline instance.

Return type PipelineBase

describe_pipeline (*self*, *pipeline_id*, *return_dict=False*)
Describe a pipeline

Parameters

- **pipeline_id** (*int*) – pipeline to describe
- **return_dict** (*bool*) – If True, return dictionary of information about pipeline. Defaults to False.

Returns Description of specified pipeline. Includes information such as type of pipeline components, problem, training time, cross validation, etc.

property full_rankings (*self*)
Returns a pandas.DataFrame with scoring results from all pipelines searched

get_pipeline (*self*, *pipeline_id*)
Given the ID of a pipeline training result, returns an untrained instance of the specified pipeline initialized with the parameters used to train that pipeline during automl search.

Parameters **pipeline_id** (*int*) – pipeline to retrieve

Returns untrained pipeline instance associated with the provided ID

Return type PipelineBase

static load (*file_path*, *pickle_type='cloudpickle'*)
Loads AutoML object at file path

Parameters

- **file_path** (*str*) – location to find file to load

- **{"pickle"** (*pickle_type*) – the pickling library to use. Currently not used since the standard pickle library can handle cloudpickles.
- **"cloudpickle"}** – the pickling library to use. Currently not used since the standard pickle library can handle cloudpickles.

Returns AutoSearchBase object

property plot (*self*)

property rankings (*self*)
Returns a pandas.DataFrame with scoring results from the highest-scoring set of parameters used with each pipeline.

property results (*self*)
Class that allows access to a copy of the results from *automl_search*.

Returns: dict containing *pipeline_results*: a dict with results from each pipeline, and *search_order*: a list describing the order the pipelines were searched.

save (*self*, *file_path*, *pickle_type='cloudpickle'*, *pickle_protocol=cloudpickle.DEFAULT_PROTOCOL*)
Saves AutoML object at file path

Parameters

- **file_path** (*str*) – location to save file
- **{"pickle"** (*pickle_type*) – the pickling library to use.
- **"cloudpickle"}** – the pickling library to use.
- **pickle_protocol** (*int*) – the pickle data stream format.

Returns None

score_pipelines (*self*, *pipelines*, *X_holdout*, *y_holdout*, *objectives*)
Score a list of pipelines on the given holdout data.

Parameters

- **pipelines** (*list(PipelineBase)*) – List of pipelines to train.
- **X_holdout** (*pd.DataFrame*) – Holdout features.
- **y_holdout** (*pd.Series*) – Holdout targets for scoring.
- **objectives** (*list(str), list(ObjectiveBase)*) – Objectives used for scoring.

Returns Dictionary keyed by pipeline name that maps to a dictionary of scores. Note that the any pipelines that error out during scoring will not be included in the dictionary but the exception and stacktrace will be displayed in the log.

Return type Dict[str, Dict[str, float]]

search (*self*, *show_iteration_plot=True*)
Find the best pipeline for the data set.

Parameters

- **feature_types** (*list, optional*) – list of feature types, either numerical or categorical. Categorical features will automatically be encoded
- **show_iteration_plot** (*boolean, True*) – Shows an iteration vs. score plot in Jupyter notebook. Disabled by default in non-Jupyter enviroments.

train_pipelines(*self*, *pipelines*)

Train a list of pipelines on the training data.

This can be helpful for training pipelines once the search is complete.

Parameters **pipelines** (*list(PipelineBase)*) – List of pipelines to train.

Returns Dictionary keyed by pipeline name that maps to the fitted pipeline. Note that the any pipelines that error out during training will not be included in the dictionary but the exception and stacktrace will be displayed in the log.

Return type Dict[str, PipelineBase]

evalml.**search**(*X_train=None*, *y_train=None*, *problem_type=None*, *objective='auto'*, *problem_configuration=None*, ***kwargs*)

Given data and configuration, run an automl search.

This method will run EvalML's default suite of data checks. If the data checks produce errors, the data check results will be returned before running the automl search. In that case we recommend you alter your data to address these errors and try again.

This method is provided for convenience. If you'd like more control over when each of these steps is run, consider making calls directly to the various pieces like the data checks and AutoMLSearch, instead of using this method.

Parameters

- **X_train** (*pd.DataFrame*) – The input training data of shape [n_samples, n_features]. Required.
- **y_train** (*pd.Series*) – The target training data of length [n_samples]. Required for supervised learning tasks.
- **problem_type** (*str or ProblemTypes*) – type of supervised learning problem. See evalml.problem_types.ProblemType.all_problem_types for a full list.
- **objective** (*str, ObjectiveBase*) – The objective to optimize for. Used to propose and rank pipelines, but not for optimizing each pipeline during fit-time. When set to 'auto', chooses:
  - LogLossBinary for binary classification problems,
  - LogLossMulticlass for multiclass classification problems, and
  - R2 for regression problems.
- **problem_configuration** (*dict*) – Additional parameters needed to configure the search. For example,
- **time series problems** (*in*) –
- **should be passed in for the date_index** (*values*) –
- **gap** –
- **max_delay variables.** (*and*) –

Other keyword arguments which are provided will be passed to AutoMLSearch.

Returns the automl search object containing pipelines and rankings, and the results from running the data checks. If the data check results contain errors, automl search will not be run and an automl search object will not be returned.

Return type (*AutoMLSearch*, dict)

CHAPTER

SIX

RELEASE NOTES

Future Release

- **Enhancements**
  - Added `DatetimeFormatDataCheck` for time series problems #2603
  - Added `ProphetRegressor` to estimators #2242
  - Updated `ComponentGraph` to handle not calling samplers' transform during predict, and updated samplers' transform methods s.t. `fit_transform` is equivalent to `fit(X, y).transform(X, y)` #2583
  - Updated `ComponentGraph` `_validate_component_dict` logic to be stricter about input values #2599
  - Patched bug in `xgboost` estimators where predicting on a feature matrix of only booleans would throw an exception. #2602
  - Updated `ARIMARegressor` to use relative forecasting to predict values #2613
  - Updated to support Woodwork 0.5.1 #2610
- **Fixes**
  - Updated `get_best_sampler_for_data` to consider all non-numeric datatypes as categorical for SMOTE #2590
  - Fixed inconsistent test results from *TargetDistributionDataCheck* #2608
  - Adopted vectorized pd.NA checking for Woodwork 0.5.1 support #2626
- **Changes**
  - Renamed SMOTE samplers to SMOTE oversampler #2595
  - Changed `partial_dependence` and `graph_partial_dependence` to raise a `PartialDependenceError` instead of `ValueError`. This is not a breaking change because `PartialDependenceError` is a subclass of `ValueError` #2604
  - Cleaned up code duplication in `ComponentGraph` #2612
- **Documentation Changes**
  - To avoid local docs build error, only add warning disable and download headers on ReadTheDocs builds, not locally #2617
- **Testing Changes**
  - Changed the lint CI job to only check against python 3.9 via the *-t* flag #2586
  - Installed Prophet in linux nightlies test and fixed `test_all_components` #2598

- Refactored and fixed all `make_pipeline` tests to assert correct order and address new Woodwork Unknown type inference #2572
- Removed `component_graphs` as a global variable in `test_component_graphs.py` #2609

Warning:

Breaking Changes

- Renamed SMOTE samplers to SMOTE oversampler. Please use `SMOTEOversampler`, `SMOTENCOversampler`, `SMOTENOversampler` instead of `SMOTESampler`, `SMOTENCSampler`, and `SMOTENSampler` #2595

v0.30.0 Aug. 3, 2021

- **Enhancements**
  - Added `LogTransformer` and `TargetDistributionDataCheck` #2487
  - Issue a warning to users when a pipeline parameter passed in isn't used in the pipeline #2564
  - Added Gini coefficient as an objective #2544
  - Added `repr` to `ComponentGraph` #2565
  - Added components to extract features from `URL` and `EmailAddress` Logical Types #2550
  - Added support for *NaN* values in `TextFeaturizer` #2532
  - Added `SelectByType` transformer #2531
  - Added separate thresholds for percent null rows and columns in `HighlyNullDataCheck` #2562
  - Added support for *NaN* natural language values #2577
- **Fixes**
  - Raised error message for types `URL`, `NaturalLanguage`, and `EmailAddress` in `partial_dependence` #2573
- **Changes**
  - Updated `PipelineBase` implementation for creating pipelines from a list of components #2549
  - Moved `get_hyperparameter_ranges` to `PipelineBase` class from automl/utils module #2546
  - Renamed `ComponentGraph`'s `get_parents` to `get_inputs` #2540
  - Removed `ComponentGraph.linearized_component_graph` and `ComponentGraph.from_list` #2556
  - Updated `ComponentGraph` to enforce requiring *.x* and *.y* inputs for each component in the graph #2563
  - Renamed existing ensembler implementation from `StackedEnsemblers` to `SklearnStackedEnsemblers` #2578
- **Documentation Changes**
  - Added documentation for `DaskEngine` and `CFEngine` parallel engines #2560

  - Improved detail of `TextFeaturizer` docstring and tutorial #2568

- **Testing Changes**
  - Added test that makes sure `split_data` does not shuffle for time series problems #2552

Warning:

Breaking Changes

- Moved `get_hyperparameter_ranges` to `PipelineBase` class from automl/utils module #2546
- Renamed `ComponentGraph`'s `get_parents` to `get_inputs` #2540
- Removed `ComponentGraph.linearized_component_graph` and `ComponentGraph.from_list` #2556
- Updated `ComponentGraph` to enforce requiring *.x* and *.y* inputs for each component in the graph #2563

v0.29.0 Jul. 21, 2021

- **Enhancements**
  - Updated 1-way partial dependence support for datetime features #2454
  - Added details on how to fix error caused by broken ww schema #2466
  - Added ability to use built-in pickle for saving AutoMLSearch #2463
  - Updated our components and component graphs to use latest features of ww 0.4.1, e.g. `concat_columns` and drop in-place. #2465
  - Added new, concurrent.futures based engine for parallel AutoML #2506
  - Added support for new Woodwork `Unknown` type in AutoMLSearch #2477
  - Updated our components with an attribute that describes if they modify features or targets and can be used in list API for pipeline initialization #2504
  - Updated `ComponentGraph` to accept X and y as inputs #2507
  - Removed unused `TARGET_BINARY_INVALID_VALUES` from `DataCheckMessageCode` enum and fixed formatting of objective documentation #2520
  - Added `EvalMLAlgorithm` #2525
  - Added support for *NaN* values in `TextFeaturizer` #2532
- **Fixes**
  - Fixed `FraudCost` objective and reverted threshold optimization method for binary classification to `Golden` #2450
  - Added custom exception message for partial dependence on features with scales that are too small #2455
  - Ensures the typing for Ordinal and Datetime ltypes are passed through _retain_custom_types_and_initalize_woodwork #2461
  - Updated to work with Pandas 1.3.0 #2442
  - Updated to work with sktime 0.7.0 #2499
- **Changes**

  - Updated XGBoost dependency to `>=1.4.2` #2484, #2498
  - Added a `DeprecationWarning` about deprecating the list API for `ComponentGraph` #2488
  - Updated `make_pipeline` for AutoML to create dictionaries, not lists, to initialize pipelines #2504
  - No longer installing graphviz on windows in our CI pipelines because release 0.17 breaks windows 3.7 #2516
- **Documentation Changes**
  - Moved docstrings from `__init__` to class pages, added missing docstrings for missing classes, and updated missing default values #2452
  - Build documentation with sphinx-autoapi #2458
  - Change `autoapi_ignore` to only ignore files in `evalml/tests/*` #2530
- **Testing Changes**
  - Fixed flaky dask tests #2471
  - Removed shellcheck action from `build_conda_pkg` action #2514
  - Added a tmp_dir fixture that deletes its contents after tests run #2505
  - Added a test that makes sure all pipelines in `AutoMLSearch` get the same data splits #2513
  - Condensed warning output in test logs #2521

Warning:

Breaking Changes

- *NaN* values in the *Natural Language* type are no longer supported by the Imputer with the pandas upgrade. #2477

v0.28.0 Jul. 2, 2021

- **Enhancements**
  - Added support for showing a Individual Conditional Expectations plot when graphing Partial Dependence #2386
  - Exposed `thread_count` for Catboost estimators as `n_jobs` parameter #2410
  - Updated Objectives API to allow for sample weighting #2433
- **Fixes**
  - Deleted unreachable line from `IterativeAlgorithm` #2464
- **Changes**
  - Pinned Woodwork version between 0.4.1 and 0.4.2 #2460
  - Updated psutils minimum version in requirements #2438
  - Updated `log_error_callback` to not include filepath in logged message #2429
- **Documentation Changes**
  - Sped up docs #2430
  - Removed mentions of `DataTable` and `DataColumn` from the docs #2445

- **Testing Changes**
  - Added slack integration for nightlies tests #2436
  - Changed `build_conda_pkg` CI job to run only when dependencies are updates #2446
  - Updated workflows to store pytest runtimes as test artifacts #2448
  - Added `AutoMLTestEnv` test fixture for making it easy to mock automl tests #2406

v0.27.0 Jun. 22, 2021

- **Enhancements**
  - Adds force plots for prediction explanations #2157
  - Removed self-reference from `AutoMLSearch` #2304
  - Added support for nonlinear pipelines for `generate_pipeline_code` #2332
  - Added `inverse_transform` method to pipelines #2256
  - Add optional automatic update checker #2350
  - Added `search_order` to `AutoMLSearch`'s `rankings` and `full_rankings` tables #2345
  - Updated threshold optimization method for binary classification #2315
  - Updated demos to pull data from S3 instead of including demo data in package #2387
  - Upgrade woodwork version to v0.4.1 #2379
- **Fixes**
  - Preserve user-specified woodwork types throughout pipeline fit/predict #2297
  - Fixed `ComponentGraph` appending target to `final_component_features` if there is a component that returns both X and y #2358
  - Fixed partial dependence graph method failing on multiclass problems when the class labels are numeric #2372
  - Added `thresholding_objective` argument to `AutoMLSearch` for binary classification problems #2320
  - Added change for `k_neighbors` parameter in SMOTE Oversamplers to automatically handle small samples #2375
  - Changed naming for `Logistic Regression Classifier` file #2399
  - Pinned pytest-timeout to fix minimum dependence checker #2425
  - Replaced `Elastic Net Classifier` base class with `Logistsic Regression` to avoid `NaN` outputs #2420
- **Changes**
  - Cleaned up `PipelineBase`'s `component_graph` and `_component_graph` attributes. Updated `PipelineBase` `__repr__` and added `__eq__` for `ComponentGraph` #2332
  - Added and applied `black` linting package to the EvalML repo in place of `autopep8` #2306
  - Separated *custom_hyperparameters* from pipelines and added them as an argument to `AutoMLSearch` #2317
  - Replaced *allowed_pipelines* with *allowed_component_graphs* #2364

  - Removed private method `_compute_features_during_fit` from `PipelineBase` #2359
  - Updated `compute_order` in `ComponentGraph` to be a read-only property #2408
  - Unpinned PyZMQ version in requirements.txt #2389
  - Uncapping LightGBM version in requirements.txt #2405
  - Updated minimum version of plotly #2415
  - Removed `SensitivityLowAlert` objective from core objectives #2418
- **Documentation Changes**
  - Fixed lead scoring weights in the demos documentation #2315
  - Fixed start page code and description dataset naming discrepancy #2370
- **Testing Changes**
  - Update minimum unit tests to run on all pull requests #2314
  - Pass token to authorize uploading of codecov reports #2344
  - Add `pytest-timeout`. All tests that run longer than 6 minutes will fail. #2374
  - Separated the dask tests out into separate github action jobs to isolate dask failures. #2376
  - Refactored dask tests #2377
  - Added the combined dask/non-dask unit tests back and renamed the dask only unit tests. #2382
  - Sped up unit tests and split into separate jobs #2365
  - Change CI job names, run lint for python 3.9, run nightlies on python 3.8 at 3am EST #2395 #2398
  - Set fail-fast to false for CI jobs that run for PRs #2402

Warning:

Breaking Changes

- *AutoMLSearch* will accept *allowed_component_graphs* instead of *allowed_pipelines* #2364
- Removed `PipelineBase`'s `_component_graph` attribute. Updated `PipelineBase` `__repr__` and added `__eq__` for `ComponentGraph` #2332
- *pipeline_parameters* will no longer accept *skopt.space* variables since hyperparameter ranges will now be specified through *custom_hyperparameters* #2317

v0.25.0 Jun. 01, 2021

- **Enhancements**
  - Upgraded minimum woodwork to version 0.3.1. Previous versions will not be supported #2181
  - Added a new callback parameter for `explain_predictions_best_worst` #2308
- Fixes
- **Changes**
  - Deleted the `return_pandas` flag from our demo data loaders #2181
  - Moved `default_parameters` to `ComponentGraph` from `PipelineBase` #2307

- **Documentation Changes**
  - Updated the release procedure documentation #2230
- **Testing Changes**
  - Ignoring `test_saving_png_file` while building conda package #2323

Warning:

Breaking Changes

- Deleted the `return_pandas` flag from our demo data loaders #2181
- Upgraded minimum woodwork to version 0.3.1. Previous versions will not be supported #2181
- Due to the weak-ref in woodwork, set the result of `infer_feature_types` to a variable before accessing woodwork #2181

v0.24.2 May. 24, 2021

- **Enhancements**
  - Added oversamplers to AutoMLSearch #2213 #2286
  - Added dictionary input functionality for `Undersampler` component #2271
  - Changed the default parameter values for `Elastic Net Classifier` and `Elastic Net Regressor` #2269
  - Added dictionary input functionality for the Oversampler components #2288
- **Fixes**
  - Set default *n_jobs* to 1 for *StackedEnsembleClassifier* and *StackedEnsembleRegressor* until fix for text-based parallelism in sklearn stacking can be found #2295
- **Changes**
  - Updated `start_iteration_callback` to accept a pipeline instance instead of a pipeline class and no longer accept pipeline parameters as a parameter #2290
  - Refactored `calculate_permutation_importance` method and add per-column permutation importance method #2302
  - Updated logging information in `AutoMLSearch.__init__` to clarify pipeline generation #2263
- **Documentation Changes**
  - Minor changes to the release procedure #2230
- **Testing Changes**
  - Use codecov action to update coverage reports #2238
  - Removed MarkupSafe dependency version pin from requirements.txt and moved instead into RTD docs build CI #2261

Warning:

Breaking Changes

- Updated `start_iteration_callback` to accept a pipeline instance instead of a pipeline class and no longer accept pipeline parameters as a parameter #2290
- Moved `default_parameters` to `ComponentGraph` from `PipelineBase`. A pipeline's `default_parameters` is now accessible via `pipeline.component_graph.default_parameters` #2307

v0.24.1 May. 16, 2021

- **Enhancements**
  - Integrated `ARIMARegressor` into AutoML #2009
  - Updated `HighlyNullDataCheck` to also perform a null row check #2222
  - Set `max_depth` to 1 in calls to featuretools dfs #2231
- **Fixes**
  - Removed data splitter sampler calls during training #2253
  - Set minimum required version for for pyzmq, colorama, and docutils #2254
  - Changed BaseSampler to return None instead of y #2272
- **Changes**
  - Removed ensemble split and indices in `AutoMLSearch` #2260
  - Updated pipeline `repr()` and `generate_pipeline_code` to return pipeline instances without generating custom pipeline class #2227
- **Documentation Changes**
  - Capped Sphinx version under 4.0.0 #2244
- **Testing Changes**
  - Change number of cores for pytest from 4 to 2 #2266
  - Add minimum dependency checker to generate minimum requirement files #2267
  - Add unit tests with minimum dependencies #2277

v0.24.0 May. 04, 2021

- **Enhancements**
  - Added *date_index* as a required parameter for TimeSeries problems #2217
  - Have the `OneHotEncoder` return the transformed columns as booleans rather than floats #2170
  - Added Oversampler transformer component to EvalML #2079
  - Added Undersampler to AutoMLSearch, as well as arguments `_sampler_method` and `sampler_balanced_ratio` #2128
  - Updated prediction explanations functions to allow pipelines with XGBoost estimators #2162
  - Added partial dependence for datetime columns #2180
  - Update precision-recall curve with positive label index argument, and fix for 2d predicted probabilities #2090
  - Add pct_null_rows to `HighlyNullDataCheck` #2211

  - Added a standalone AutoML *search* method for convenience, which runs data checks and then runs automl #2152
  - Make the first batch of AutoML have a predefined order, with linear models first and complex models last #2223 #2225
  - Added sampling dictionary support to `BalancedClassficationSampler` #2235
- **Fixes**
  - Fixed partial dependence not respecting grid resolution parameter for numerical features #2180
  - Enable prediction explanations for catboost for multiclass problems #2224
- **Changes**
  - Deleted baseline pipeline classes #2202
  - Reverting user specified date feature PR #2155 until *pmdarima* installation fix is found #2214
  - Updated pipeline API to accept component graph and other class attributes as instance parameters. Old pipeline API still works but will not be supported long-term. #2091
  - Removed all old datasplitters from EvalML #2193
  - Deleted `make_pipeline_from_components` #2218
- **Documentation Changes**
  - Renamed dataset to clarify that its gzipped but not a tarball #2183
  - Updated documentation to use pipeline instances instead of pipeline subclasses #2195
  - Updated contributing guide with a note about GitHub Actions permissions #2090
  - Updated automl and model understanding user guides #2090
- **Testing Changes**
  - Use machineFL user token for dependency update bot, and add more reviewers #2189

Warning:

Breaking Changes

- All baseline pipeline classes (`BaselineBinaryPipeline`, `BaselineMulticlassPipeline`, `BaselineRegressionPipeline`, etc.) have been deleted #2202
- Updated pipeline API to accept component graph and other class attributes as instance parameters. Old pipeline API still works but will not be supported long-term. Pipelines can now be initialized by specifying the component graph as the first parameter, and then passing in optional arguments such as `custom_name`, `parameters`, etc. For example, `BinaryClassificationPipeline([ "Random Forest Classifier"], parameters={}).` #2091
- Removed all old datasplitters from EvalML #2193
- Deleted utility method `make_pipeline_from_components` #2218

v0.23.0 Apr. 20, 2021

- **Enhancements**
  - Refactored `EngineBase` and `SequentialEngine` api. Adding `DaskEngine` #1975.
  - Added optional `engine` argument to `AutoMLSearch` #1975

  - Added a warning about how time series support is still in beta when a user passes in a time series problem to `AutoMLSearch` #2118
  - Added `NaturalLanguageNaNDataCheck` data check #2122
  - Added ValueError to `partial_dependence` to prevent users from computing partial dependence on columns with all NaNs #2120
  - Added standard deviation of cv scores to rankings table #2154
- **Fixes**
  - Fixed `BalancedClassificationDataCVSplit`, `BalancedClassificationDataTVSplit`, and `BalancedClassificationSampler` to use `minority:majority` ratio instead of `majority:minority` #2077
  - Fixed bug where two-way partial dependence plots with categorical variables were not working correctly #2117
  - Fixed bug where `hyperparameters` were not displaying properly for pipelines with a list `component_graph` and duplicate components #2133
  - Fixed bug where `pipeline_parameters` argument in `AutoMLSearch` was not applied to pipelines passed in as `allowed_pipelines` #2133
  - Fixed bug where `AutoMLSearch` was not applying custom hyperparameters to pipelines with a list `component_graph` and duplicate components #2133
- **Changes**
  - Removed `hyperparameter_ranges` from Undersampler and renamed `balanced_ratio` to `sampling_ratio` for samplers #2113
  - Renamed `TARGET_BINARY_NOT_TWO_EXAMPLES_PER_CLASS` data check message code to `TARGET_MULTICLASS_NOT_TWO_EXAMPLES_PER_CLASS` #2126
  - Modified one-way partial dependence plots of categorical features to display data with a bar plot #2117
  - Renamed `score` column for `automl.rankings` as `mean_cv_score` #2135
  - Remove 'warning' from docs tool output #2031
- **Documentation Changes**
  - Fixed `conf.py` file #2112
  - Added a sentence to the automl user guide stating that our support for time series problems is still in beta. #2118
  - Fixed documentation demos #2139
  - Update test badge in README to use GitHub Actions #2150
- **Testing Changes**
  - Fixed `test_describe_pipeline` for `pandas v1.2.4` #2129
  - Added a GitHub Action for building the conda package #1870 #2148

Warning:

Breaking Changes

- Renamed `balanced_ratio` to `sampling_ratio` for the `BalancedClassificationDataCVSplit`, `BalancedClassificationDataTVSplit`, `BalancedClassficationSampler`, and Undersampler #2113
- Deleted the "errors" key from automl results #1975
- Deleted the `raise_and_save_error_callback` and the `log_and_save_error_callback` #1975
- Fixed `BalancedClassificationDataCVSplit`, `BalancedClassificationDataTVSplit`, and `BalancedClassificationSampler` to use minority:majority ratio instead of majority:minority #2077

v0.22.0 Apr. 06, 2021

- **Enhancements**
  - Added a GitHub Action for `linux_unit_tests`#2013
  - Added recommended actions for `InvalidTargetDataCheck`, updated `_make_component_list_from_actions` to address new action, and added `TargetImputer` component #1989
  - Updated `AutoMLSearch._check_for_high_variance` to not emit `RuntimeWarning` #2024
  - Added exception when pipeline passed to `explain_predictions` is a `Stacked Ensemble` pipeline #2033
  - Added sensitivity at low alert rates as an objective #2001
  - Added `Undersampler` transformer component #2030
- **Fixes**
  - Updated Engine's `train_batch` to apply undersampling #2038
  - Fixed bug in where Time Series Classification pipelines were not encoding targets in `predict` and `predict_proba` #2040
  - Fixed data splitting errors if target is float for classification problems #2050
  - Pinned `docutils` to <0.17 to fix ReadtheDocs warning issues #2088
- **Changes**
  - Removed lists as acceptable hyperparameter ranges in `AutoMLSearch` #2028
  - Renamed "details" to "metadata" for data check actions #2008
- **Documentation Changes**
  - Catch and suppress warnings in documentation #1991 #2097
  - Change spacing in `start.ipynb` to provide clarity for `AutoMLSearch` #2078
  - Fixed start code on README #2108
- Testing Changes

v0.21.0 Mar. 24, 2021

- **Enhancements**
  - Changed `AutoMLSearch` to default `optimize_thresholds` to True #1943

  - Added multiple oversampling and undersampling sampling methods as data splitters for imbalanced classification #1775
  - Added params to balanced classification data splitters for visibility #1966
  - Updated `make_pipeline` to not add `Imputer` if input data does not have numeric or categorical columns #1967
  - Updated `ClassImbalanceDataCheck` to better handle multiclass imbalances #1986
  - Added recommended actions for the output of data check's `validate` method #1968
  - Added error message for `partial_dependence` when features are mostly the same value #1994
  - Updated `OneHotEncoder` to drop one redundant feature by default for features with two categories #1997
  - Added a `PolynomialDetrender` component #1992
  - Added `DateTimeNaNDataCheck` data check #2039
- **Fixes**
  - Changed best pipeline to train on the entire dataset rather than just ensemble indices for ensemble problems #2037
  - Updated binary classification pipelines to use objective decision function during scoring of custom objectives #1934
- **Changes**
  - Removed `data_checks` parameter, `data_check_results` and data checks logic from `AutoMLSearch` #1935
  - Deleted `random_state` argument #1985
  - Updated Woodwork version requirement to `v0.0.11` #1996
- Documentation Changes
- **Testing Changes**
  - Removed `build_docs` CI job in favor of RTD GH builder #1974
  - Added tests to confirm support for Python 3.9 #1724
  - Added tests to support Dask AutoML/Engine #1990
  - Changed `build_conda_pkg` job to use `latest_release_changes` branch in the feedstock. #1979

Warning:

Breaking Changes

- Changed `AutoMLSearch` to default `optimize_thresholds` to True #1943
- Removed `data_checks` parameter, `data_check_results` and data checks logic from `AutoMLSearch`. To run the data checks which were previously run by default in `AutoMLSearch`, please call `DefaultDataChecks().validate(X_train, y_train)` or take a look at our documentation for more examples. #1935
- Deleted `random_state` argument #1985

v0.20.0 Mar. 10, 2021

- **Enhancements**
  - Added a GitHub Action for Detecting dependency changes #1933
  - Create a separate CV split to train stacked ensembler on for AutoMLSearch #1814
  - Added a GitHub Action for Linux unit tests #1846
  - Added `ARIMARegressor` estimator #1894
  - Added `DataCheckAction` class and `DataCheckActionCode` enum #1896
  - Updated `Woodwork` requirement to `v0.0.10` #1900
  - Added `BalancedClassificationDataCVSplit` and `BalancedClassificationDataTVSplit` to AutoMLSearch #1875
  - Update default classification data splitter to use downsampling for highly imbalanced data #1875
  - Updated `describe_pipeline` to return more information, including `id` of pipelines used for ensemble models #1909
  - Added utility method to create list of components from a list of `DataCheckAction` #1907
  - Updated `validate` method to include a `action` key in returned dictionary for all `DataCheck``and ``DataChecks` #1916
  - Aggregating the shap values for predictions that we know the provenance of, e.g. OHE, text, and date-time. #1901
  - Improved error message when custom objective is passed as a string in `pipeline.score` #1941
  - Added `score_pipelines` and `train_pipelines` methods to `AutoMLSearch` #1913
  - Added support for `pandas` version 1.2.0 #1708
  - Added `score_batch` and `train_batch` abstact methods to `EngineBase` and implementations in `SequentialEngine` #1913
  - Added ability to handle index columns in `AutoMLSearch` and `DataChecks` #2138
- **Fixes**
  - Removed CI check for `check_dependencies_updated_linux` #1950
  - Added metaclass for time series pipelines and fix binary classification pipeline `predict` not using objective if it is passed as a named argument #1874
  - Fixed stack trace in prediction explanation functions caused by mixed string/numeric pandas column names #1871
  - Fixed stack trace caused by passing pipelines with duplicate names to `AutoMLSearch` #1932
  - Fixed `AutoMLSearch.get_pipelines` returning pipelines with the same attributes #1958
- **Changes**
  - Reversed GitHub Action for Linux unit tests until a fix for report generation is found #1920
  - Updated `add_results` in `AutoMLAlgorithm` to take in entire pipeline results dictionary from `AutoMLSearch` #1891
  - Updated `ClassImbalanceDataCheck` to look for severe class imbalance scenarios #1905
  - Deleted the `explain_prediction` function #1915

  - Removed `HighVarianceCVDataCheck` and convered it to an `AutoMLSearch` method instead #1928
  - Removed warning in `InvalidTargetDataCheck` returned when numeric binary classification targets are not (0, 1) #1959

- **Documentation Changes**
  - Updated `model_understanding.ipynb` to demo the two-way partial dependence capability #1919

- Testing Changes

Warning:

Breaking Changes

- Deleted the `explain_prediction` function #1915
- Removed `HighVarianceCVDataCheck` and convered it to an `AutoMLSearch` method instead #1928
- Added `score_batch` and `train_batch` abstact methods to `EngineBase`. These need to be implemented in Engine subclasses #1913

v0.19.0 Feb. 23, 2021

- **Enhancements**
  - Added a GitHub Action for Python windows unit tests #1844
  - Added a GitHub Action for checking updated release notes #1849
  - Added a GitHub Action for Python lint checks #1837
  - Adjusted `explain_prediction`, `explain_predictions` and `explain_predictions_best_worst` to handle timeseries problems. #1818
  - Updated `InvalidTargetDataCheck` to check for mismatched indices in target and features #1816
  - Updated `Woodwork` structures returned from components to support `Woodwork` logical type overrides set by the user #1784
  - Updated estimators to keep track of input feature names during `fit()` #1794
  - Updated `visualize_decision_tree` to include feature names in output #1813
  - Added `is_bounded_like_percentage` property for objectives. If true, the `calculate_percent_difference` method will return the absolute difference rather than relative difference #1809
  - Added full error traceback to AutoMLSearch logger file #1840
  - Changed `TargetEncoder` to preserve custom indices in the data #1836
  - Refactored `explain_predictions` and `explain_predictions_best_worst` to only compute features once for all rows that need to be explained #1843
  - Added custom random undersampler data splitter for classification #1857
  - Updated `OutliersDataCheck` implementation to calculate the probability of having no outliers #1855
  - Added `Engines` pipeline processing API #1838

- **Fixes**
  - Changed EngineBase random_state arg to random_seed and same for user guide docs #1889
- **Changes**
  - Modified `calculate_percent_difference` so that division by 0 is now inf rather than nan #1809
  - Removed `text_columns` parameter from `LSA` and `TextFeaturizer` components #1652
  - Added `random_seed` as an argument to our automl/pipeline/component API. Using `random_state` will raise a warning #1798
  - Added `DataCheckError` message in `InvalidTargetDataCheck` if input target is None and removed exception raised #1866
- Documentation Changes
- **Testing Changes**
  - Added back coverage for `_get_feature_provenance` in `TextFeaturizer` after `text_columns` was removed #1842
  - Pin graphviz version for windows builds #1847
  - Unpin graphviz version for windows builds #1851

Warning:

Breaking Changes

- Added a deprecation warning to `explain_prediction`. It will be deleted in the next release. #1860

v0.18.2 Feb. 10, 2021

- **Enhancements**
  - Added uniqueness score data check #1785
  - Added "dataframe" output format for prediction explanations #1781
  - Updated LightGBM estimators to handle `pandas.MultiIndex` #1770
  - Sped up permutation importance for some pipelines #1762
  - Added sparsity data check #1797
  - Confirmed support for threshold tuning for binary time series classification problems #1803
- Fixes
- Changes
- **Documentation Changes**
  - Added section on conda to the contributing guide #1771
  - Updated release process to reflect freezing *main* before perf tests #1787
  - Moving some prs to the right section of the release notes #1789
  - Tweak README.md. #1800
  - Fixed back arrow on install page docs #1795
  - Fixed docstring for *ClassImbalanceDataCheck.validate()* #1817

- Testing Changes

v0.18.1 Feb. 1, 2021

- **Enhancements**
  - Added `graph_t_sne` as a visualization tool for high dimensional data #1731
  - Added the ability to see the linear coefficients of features in linear models terms #1738
  - Added support for `scikit-learn v0.24.0` #1733
  - Added support for `scipy v1.6.0` #1752
  - Added SVM Classifier and Regressor to estimators #1714 #1761
- **Fixes**
  - Addressed bug with `partial_dependence` and categorical data with more categories than grid resolution #1748
  - Removed `random_state` arg from `get_pipelines` in `AutoMLSearch` #1719
  - Pinned pyzmq at less than 22.0.0 till we add support #1756
- **Changes**
  - Updated components and pipelines to return `Woodwork` data structures #1668
  - Updated `clone()` for pipelines and components to copy over random state automatically #1753
  - Dropped support for Python version 3.6 #1751
  - Removed deprecated `verbose` flag from `AutoMLSearch` parameters #1772
- **Documentation Changes**
  - Add Twitter and Github link to documentation toolbar #1754
  - Added Open Graph info to documentation #1758
- Testing Changes

Warning:

Breaking Changes

- Components and pipelines return `Woodwork` data structures instead of `pandas` data structures #1668
- Python 3.6 will not be actively supported due to discontinued support from EvalML dependencies.
- Deprecated `verbose` flag is removed for `AutoMLSearch` #1772

v0.18.0 Jan. 26, 2021

- **Enhancements**
  - Added RMSLE, MSLE, and MAPE to core objectives while checking for negative target values in `invalid_targets_data_check` #1574
  - Added validation checks for binary problems with regression-like datasets and multiclass problems without true multiclass targets in `invalid_targets_data_check` #1665
  - Added time series support for `make_pipeline` #1566
  - Added target name for output of pipeline `predict` method #1578
  - Added multiclass check to `InvalidTargetDataCheck` for two examples per class #1596

  - Added support for `graphviz v0.16` #1657
  - Enhanced time series pipelines to accept empty features #1651
  - Added KNN Classifier to estimators. #1650
  - Added support for list inputs for objectives #1663
  - Added support for `AutoMLSearch` to handle time series classification pipelines #1666
  - Enhanced `DelayedFeaturesTransformer` to encode categorical features and targets before delaying them #1691
  - Added 2-way dependence plots. #1690
  - Added ability to directly iterate through components within Pipelines #1583
- **Fixes**
  - Fixed inconsistent attributes and added Exceptions to docs #1673
  - Fixed `TargetLeakageDataCheck` to use Woodwork `mutual_information` rather than using Pandas' Pearson Correlation #1616
  - Fixed thresholding for pipelines in `AutoMLSearch` to only threshold binary classification pipelines #1622 #1626
  - Updated `load_data` to return Woodwork structures and update default parameter value for `index` to `None` #1610
  - Pinned scipy at < 1.6.0 while we work on adding support #1629
  - Fixed data check message formatting in `AutoMLSearch` #1633
  - Addressed stacked ensemble component for `scikit-learn` v0.24 support by setting `shuffle=True` for default CV #1613
  - Fixed bug where `Imputer` reset the index on `X` #1590
  - Fixed `AutoMLSearch` stacktrace when a cutom objective was passed in as a primary objective or additional objective #1575
  - Fixed custom index bug for `MAPE` objective #1641
  - Fixed index bug for `TextFeaturizer` and `LSA` components #1644
  - Limited `load_fraud` dataset loaded into `automl.ipynb` #1646
  - `add_to_rankings` updates `AutoMLSearch.best_pipeline` when necessary #1647
  - Fixed bug where time series baseline estimators were not receiving `gap` and `max_delay` in `AutoMLSearch` #1645
  - Fixed jupyter notebooks to help the RTD buildtime #1654
  - Added `positive_only` objectives to `non_core_objectives` #1661
  - Fixed stacking argument `n_jobs` for IterativeAlgorithm #1706
  - Updated CatBoost estimators to return self in `.fit()` rather than the underlying model for consistency #1701
  - Added ability to initialize pipeline parameters in `AutoMLSearch` constructor #1676
- **Changes**
  - Added labeling to `graph_confusion_matrix` #1632

  - Rerunning search for `AutoMLSearch` results in a message thrown rather than failing the search, and removed `has_searched` property #1647
  - Changed tuner class to allow and ignore single parameter values as input #1686
  - Capped LightGBM version limit to remove bug in docs #1711
  - Removed support for *np.random.RandomState* in EvalML #1727
- **Documentation Changes**
  - Update Model Understanding in the user guide to include `visualize_decision_tree` #1678
  - Updated docs to include information about `AutoMLSearch` callback parameters and methods #1577
  - Updated docs to prompt users to install graphiz on Mac #1656
  - Added `infer_feature_types` to the `start.ipynb` guide #1700
  - Added multicollinearity data check to API reference and docs #1707
- Testing Changes

Warning:

Breaking Changes

- Removed `has_searched` property from `AutoMLSearch` #1647
- Components and pipelines return `Woodwork` data structures instead of `pandas` data structures #1668
- Removed support for *np.random.RandomState* in EvalML. Rather than passing `np.random.RandomState` as component and pipeline random_state values, we use int random_seed #1727

v0.17.0 Dec. 29, 2020

- **Enhancements**
  - Added `save_plot` that allows for saving figures from different backends #1588
  - Added `LightGBM Regressor` to regression components #1459
  - Added `visualize_decision_tree` for tree visualization with `decision_tree_data_from_estimator` and `decision_tree_data_from_pipeline` to reformat tree structure output #1511
  - Added *DFS Transformer* component into transformer components #1454
  - Added `MAPE` to the standard metrics for time series problems and update objectives #1510
  - Added `graph_prediction_vs_actual_over_time` and `get_prediction_vs_actual_over_time_data` to the model understanding module for time series problems #1483
  - Added a `ComponentGraph` class that will support future pipelines as directed acyclic graphs #1415
  - Updated data checks to accept `Woodwork` data structures #1481
  - Added parameter to `InvalidTargetDataCheck` to show only top unique values rather than all unique values #1485
  - Added multicollinearity data check #1515

  - Added baseline pipeline and components for time series regression problems #1496
  - Added more information to users about ensembling behavior in `AutoMLSearch` #1527
  - Add woodwork support for more utility and graph methods #1544
  - Changed `DateTimeFeaturizer` to encode features as int #1479
  - Return trained pipelines from `AutoMLSearch.best_pipeline` #1547
  - Added utility method so that users can set feature types without having to learn about Woodwork directly #1555
  - Added Linear Discriminant Analysis transformer for dimensionality reduction #1331
  - Added multiclass support for `partial_dependence` and `graph_partial_dependence` #1554
  - Added `TimeSeriesBinaryClassificationPipeline` and `TimeSeriesMulticlassClassificationPipeline` classes #1528
  - Added `make_data_splitter` method for easier automl data split customization #1568
  - Integrated `ComponentGraph` class into Pipelines for full non-linear pipeline support #1543
  - Update `AutoMLSearch` constructor to take training data instead of `search` and `add_to_leaderboard` #1597
  - Update `split_data` helper args #1597
  - Add problem type utils `is_regression`, `is_classification`, `is_timeseries` #1597
  - Rename `AutoMLSearch` `data_split` arg to `data_splitter` #1569

- **Fixes**
  - Fix AutoML not passing CV folds to `DefaultDataChecks` for usage by `ClassImbalanceDataCheck` #1619
  - Fix Windows CI jobs: install `numba` via conda, required for `shap` #1490
  - Added custom-index support for *reset-index-get_prediction_vs_actual_over_time_data* #1494
  - Fix `generate_pipeline_code` to account for boolean and None differences between Python and JSON #1524 #1531
  - Set max value for plotly and xgboost versions while we debug CI failures with newer versions #1532
  - Undo version pinning for plotly #1533
  - Fix ReadTheDocs build by updating the version of `setuptools` #1561
  - Set `random_state` of data splitter in AutoMLSearch to take int to keep consistency in the resulting splits #1579
  - Pin sklearn version while we work on adding support #1594
  - Pin pandas at <1.2.0 while we work on adding support #1609
  - Pin graphviz at < 0.16 while we work on adding support #1609

- **Changes**
  - Reverting `save_graph` #1550 to resolve kaleido build issues #1585
  - Update circleci badge to apply to `main` #1489
  - Added script to generate github markdown for releases #1487

  - Updated selection using pandas `dtypes` to selecting using Woodwork logical types #1551
  - Updated dependencies to fix `ImportError: cannot import name 'MaskedArray' from 'sklearn.utils.fixes'` error and to address Woodwork and Featuretool dependencies #1540
  - Made `get_prediction_vs_actual_data()` a public method #1553
  - Updated `Woodwork` version requirement to v0.0.7 #1560
  - Move data splitters from `evalml.automl.data_splitters` to `evalml.preprocessing.data_splitters` #1597
  - Rename "# Testing" in automl log output to "# Validation" #1597
- **Documentation Changes**
  - Added partial dependence methods to API reference #1537
  - Updated documentation for confusion matrix methods #1611
- **Testing Changes**
  - Set `n_jobs=1` in most unit tests to reduce memory #1505

Warning:

Breaking Changes

- Updated minimal dependencies: `numpy>=1.19.1`, `pandas>=1.1.0`, `scikit-learn>=0.23.1`, `scikit-optimize>=0.8.1`
- Updated `AutoMLSearch.best_pipeline` to return a trained pipeline. Pass in `train_best_pipeline=False` to AutoMLSearch in order to return an untrained pipeline.
- Pipeline component instances can no longer be iterated through using `Pipeline.component_graph` #1543
- Update `AutoMLSearch` constructor to take training data instead of `search` and `add_to_leaderboard` #1597
- Update `split_data` helper args #1597
- Move data splitters from `evalml.automl.data_splitters` to `evalml.preprocessing.data_splitters` #1597
- Rename `AutoMLSearch` `data_split` arg to `data_splitter` #1569

v0.16.1 Dec. 1, 2020

- **Enhancements**
  - Pin woodwork version to v0.0.6 to avoid breaking changes #1484
  - Updated `Woodwork` to >=0.0.5 in `core-requirements.txt` #1473
  - Removed `copy_dataframe` parameter for `Woodwork`, updated `Woodwork` to >=0.0.6 in `core-requirements.txt` #1478
  - Updated `detect_problem_type` to use `pandas.api.is_numeric_dtype` #1476
- **Changes**
  - Changed `make clean` to delete coverage reports as a convenience for developers #1464
  - Set `n_jobs=-1` by default for stacked ensemble components #1472

- **Documentation Changes**
  - Updated pipeline and component documentation and demos to use `Woodwork` #1466
- **Testing Changes**
  - Update dependency update checker to use everything from core and optional dependencies #1480

v0.16.0 Nov. 24, 2020

- **Enhancements**
  - Updated pipelines and `make_pipeline` to accept `Woodwork` inputs #1393
  - Updated components to accept `Woodwork` inputs #1423
  - Added ability to freeze hyperparameters for `AutoMLSearch` #1284
  - Added `Target Encoder` into transformer components #1401
  - Added callback for error handling in `AutoMLSearch` #1403
  - Added the index id to the `explain_predictions_best_worst` output to help users identify which rows in their data are included #1365
  - The top_k features displayed in `explain_predictions_*` functions are now determined by the magnitude of shap values as opposed to the `top_k` largest and smallest shap values. #1374
  - Added a problem type for time series regression #1386
  - Added a `is_defined_for_problem_type` method to `ObjectiveBase` #1386
  - Added a `random_state` parameter to `make_pipeline_from_components` function #1411
  - Added `DelayedFeaturesTransformer` #1396
  - Added a `TimeSeriesRegressionPipeline` class #1418
  - Removed `core-requirements.txt` from the package distribution #1429
  - Updated data check messages to include a *"code"* and *"details"* fields #1451, #1462
  - Added a `TimeSeriesSplit` data splitter for time series problems #1441
  - Added a `problem_configuration` parameter to AutoMLSearch #1457
- **Fixes**
  - Fixed `IndexError` raised in `AutoMLSearch` when `ensembling = True` but only one pipeline to iterate over #1397
  - Fixed stacked ensemble input bug and LightGBM warning and bug in `AutoMLSearch` #1388
  - Updated enum classes to show possible enum values as attributes #1391
  - Updated calls to `Woodwork`'s `to_pandas()` to `to_series()` and `to_dataframe()` #1428
  - Fixed bug in OHE where column names were not guaranteed to be unique #1349
  - Fixed bug with percent improvement of `ExpVariance` objective on data with highly skewed target #1467
  - Fix SimpleImputer error which occurs when all features are bool type #1215
- **Changes**

  - Changed `OutliersDataCheck` to return the list of columns, rather than rows, that contain outliers #1377
  - Simplified and cleaned output for Code Generation #1371
  - Reverted changes from #1337 #1409
  - Updated data checks to return dictionary of warnings and errors instead of a list #1448
  - Updated `AutoMLSearch` to pass `Woodwork` data structures to every pipeline (instead of pandas DataFrames) #1450
  - Update `AutoMLSearch` to default to `max_batches=1` instead of `max_iterations=5` #1452
  - Updated _evaluate_pipelines to consolidate side effects #1410
- **Documentation Changes**
  - Added description of CLA to contributing guide, updated description of draft PRs #1402
  - Updated documentation to include all data checks, `DataChecks`, and usage of data checks in AutoML #1412
  - Updated docstrings from `np.array` to `np.ndarray` #1417
  - Added section on stacking ensembles in AutoMLSearch documentation #1425
- **Testing Changes**
  - Removed `category_encoders` from test-requirements.txt #1373
  - Tweak codecov.io settings again to avoid flakes #1413
  - Modified `make lint` to check notebook versions in the docs #1431
  - Modified `make lint-fix` to standardize notebook versions in the docs #1431
  - Use new version of pull request Github Action for dependency check (#1443)
  - Reduced number of workers for tests to 4 #1447

Warning:

Breaking Changes

- The `top_k` and `top_k_features` parameters in `explain_predictions_*` functions now return `k` features as opposed to `2 * k` features #1374
- Renamed `problem_type` to `problem_types` in `RegressionObjective`, `BinaryClassificationObjective`, and `MulticlassClassificationObjective` #1319
- Data checks now return a dictionary of warnings and errors instead of a list #1448

v0.15.0 Oct. 29, 2020

- **Enhancements**
  - Added stacked ensemble component classes (`StackedEnsembleClassifier`, `StackedEnsembleRegressor`) #1134
  - Added stacked ensemble components to `AutoMLSearch` #1253
  - Added `DecisionTreeClassifier` and `DecisionTreeRegressor` to AutoML #1255

  - Added `graph_prediction_vs_actual` in `model_understanding` for regression problems #1252
  - Added parameter to `OneHotEncoder` to enable filtering for features to encode for #1249
  - Added percent-better-than-baseline for all objectives to automl.results #1244
  - Added `HighVarianceCVDataCheck` and replaced synonymous warning in `AutoMLSearch` #1254
  - Added *PCA Transformer* component for dimensionality reduction #1270
  - Added `generate_pipeline_code` and `generate_component_code` to allow for code generation given a pipeline or component instance #1306
  - Added `PCA Transformer` component for dimensionality reduction #1270
  - Updated `AutoMLSearch` to support `Woodwork` data structures #1299
  - Added cv_folds to `ClassImbalanceDataCheck` and added this check to `DefaultDataChecks` #1333
  - Make `max_batches` argument to `AutoMLSearch.search` public #1320
  - Added text support to automl search #1062
  - Added `_pipelines_per_batch` as a private argument to `AutoMLSearch` #1355

- **Fixes**
  - Fixed ML performance issue with ordered datasets: always shuffle data in automl's default CV splits #1265
  - Fixed broken `evalml info` CLI command #1293
  - Fixed `boosting type='rf'` for LightGBM Classifier, as well as `num_leaves` error #1302
  - Fixed bug in `explain_predictions_best_worst` where a custom index in the target variable would cause a `ValueError` #1318
  - Added stacked ensemble estimators to to `evalml.pipelines.__init__` file #1326
  - Fixed bug in OHE where calls to transform were not deterministic if `top_n` was less than the number of categories in a column #1324
  - Fixed LightGBM warning messages during AutoMLSearch #1342
  - Fix warnings thrown during AutoMLSearch in `HighVarianceCVDataCheck` #1346
  - Fixed bug where TrainingValidationSplit would return invalid location indices for dataframes with a custom index #1348
  - Fixed bug where the AutoMLSearch `random_state` was not being passed to the created pipelines #1321

- **Changes**
  - Allow `add_to_rankings` to be called before AutoMLSearch is called #1250
  - Removed Graphviz from test-requirements to add to requirements.txt #1327
  - Removed `max_pipelines` parameter from `AutoMLSearch` #1264
  - Include editable installs in all install make targets #1335
  - Made pip dependencies *featuretools* and *nlp_primitives* core dependencies #1062
  - Removed *PartOfSpeechCount* from *TextFeaturizer* transform primitives #1062

  - Added warning for `partial_dependency` when the feature includes null values #1352

- **Documentation Changes**
  - Fixed and updated code blocks in Release Notes #1243
  - Added DecisionTree estimators to API Reference #1246
  - Changed class inheritance display to flow vertically #1248
  - Updated cost-benefit tutorial to use a holdout/test set #1159
  - Added `evalml info` command to documentation #1293
  - Miscellaneous doc updates #1269
  - Removed conda pre-release testing from the release process document #1282
  - Updates to contributing guide #1310
  - Added Alteryx footer to docs with Twitter and Github link #1312
  - Added documentation for evalml installation for Python 3.6 #1322
  - Added documentation changes to make the API Docs easier to understand #1323
  - Fixed documentation for `feature_importance` #1353
  - Added tutorial for running *AutoML* with text data #1357
  - Added documentation for woodwork integration with automl search #1361
- **Testing Changes**
  - Added tests for `jupyter_check` to handle IPython #1256
  - Cleaned up `make_pipeline` tests to test for all estimators #1257
  - Added a test to check conda build after merge to main #1247
  - Removed code that was lacking codecov for `__main__.py` and unnecessary #1293
  - Codecov: round coverage up instead of down #1334
  - Add DockerHub credentials to CI testing environment #1356
  - Add DockerHub credentials to conda testing environment #1363

Warning:

Breaking Changes

- Renamed `LabelLeakageDataCheck` to `TargetLeakageDataCheck` #1319
- `max_pipelines` parameter has been removed from `AutoMLSearch`. Please use `max_iterations` instead. #1264
- `AutoMLSearch.search()` will now log a warning if the input is not a `Woodwork` data structure (`pandas`, `numpy`) #1299
- Make `max_batches` argument to `AutoMLSearch.search` public #1320
- Removed unused argument *feature_types* from AutoMLSearch.search #1062

v0.14.1 Sep. 29, 2020

- **Enhancements**

  - Updated partial dependence methods to support calculating numeric columns in a dataset with non-numeric columns #1150
  - Added `get_feature_names` on `OneHotEncoder` #1193
  - Added `detect_problem_type` to `problem_type/utils.py` to automatically detect the problem type given targets #1194
  - Added LightGBM to `AutoMLSearch` #1199
  - Updated `scikit-learn` and `scikit-optimize` to use latest versions - 0.23.2 and 0.8.1 respectively #1141
  - Added `__str__` and `__repr__` for pipelines and components #1218
  - Included internal target check for both training and validation data in `AutoMLSearch` #1226
  - Added `ProblemTypes.all_problem_types` helper to get list of supported problem types #1219
  - Added `DecisionTreeClassifier` and `DecisionTreeRegressor` classes #1223
  - Added `ProblemTypes.all_problem_types` helper to get list of supported problem types #1219
  - `DataChecks` can now be parametrized by passing a list of `DataCheck` classes and a parameter dictionary #1167
  - Added first CV fold score as validation score in `AutoMLSearch.rankings` #1221
  - Updated `flake8` configuration to enable linting on `__init__.py` files #1234
  - Refined `make_pipeline_from_components` implementation #1204

- **Fixes**
  - Updated GitHub URL after migration to Alteryx GitHub org #1207
  - Changed Problem Type enum to be more similar to the string name #1208
  - Wrapped call to scikit-learn's partial dependence method in a `try`/`finally` block #1232

- **Changes**
  - Added `allow_writing_files` as a named argument to CatBoost estimators. #1202
  - Added `solver` and `multi_class` as named arguments to `LogisticRegressionClassifier` #1202
  - Replaced pipeline's `._transform` method to evaluate all the preprocessing steps of a pipeline with `.compute_estimator_features` #1231
  - Changed default large dataset train/test splitting behavior #1205

- **Documentation Changes**
  - Included description of how to access the component instances and features for pipeline user guide #1163
  - Updated API docs to refer to target as "target" instead of "labels" for non-classification tasks and minor docs cleanup #1160
  - Added Class Imbalance Data Check to `api_reference.rst` #1190 #1200
  - Added pipeline properties to API reference #1209
  - Clarified what the objective parameter in AutoML is used for in AutoML API reference and AutoML user guide #1222

  - Updated API docs to include `skopt.space.Categorical` option for component hyperparameter range definition #1228
  - Added install documentation for `libomp` in order to use LightGBM on Mac #1233
  - Improved description of `max_iterations` in documentation #1212
  - Removed unused code from sphinx conf #1235
- Testing Changes

Warning:

Breaking Changes

- `DefaultDataChecks` now accepts a `problem_type` parameter that must be specified #1167
- Pipeline's `._transform` method to evaluate all the preprocessing steps of a pipeline has been replaced with `.compute_estimator_features` #1231
- `get_objectives` has been renamed to `get_core_objectives`. This function will now return a list of valid objective instances #1230

v0.13.2 Sep. 17, 2020

- **Enhancements**
  - Added `output_format` field to explain predictions functions #1107
  - Modified `get_objective` and `get_objectives` to be able to return any objective in `evalml.objectives` #1132
  - Added a `return_instance` boolean parameter to `get_objective` #1132
  - Added `ClassImbalanceDataCheck` to determine whether target imbalance falls below a given threshold #1135
  - Added label encoder to LightGBM for binary classification #1152
  - Added labels for the row index of confusion matrix #1154
  - Added `AutoMLSearch` object as another parameter in search callbacks #1156
  - Added the corresponding probability threshold for each point displayed in `graph_roc_curve` #1161
  - Added `__eq__` for `ComponentBase` and `PipelineBase` #1178
  - Added support for multiclass classification for `roc_curve` #1164
  - Added `categories` accessor to `OneHotEncoder` for listing the categories associated with a feature #1182
  - Added utility function to create pipeline instances from a list of component instances #1176
- **Fixes**
  - Fixed XGBoost column names for partial dependence methods #1104
  - Removed dead code validating column type from `TextFeaturizer` #1122
  - Fixed issue where `Imputer` cannot fit when there is None in a categorical or boolean column #1144
  - `OneHotEncoder` preserves the custom index in the input data #1146

  - Fixed representation for `ModelFamily` #1165
  - Removed duplicate `nbsphinx` dependency in `dev-requirements.txt` #1168
  - Users can now pass in any valid kwargs to all estimators #1157
  - Remove broken accessor `OneHotEncoder.get_feature_names` and unneeded base class #1179
  - Removed LightGBM Estimator from AutoML models #1186
- **Changes**
  - Pinned `scikit-optimize` version to 0.7.4 #1136
  - Removed `tqdm` as a dependency #1177
  - Added lightgbm version 3.0.0 to `latest_dependency_versions.txt` #1185
  - Rename `max_pipelines` to `max_iterations` #1169
- **Documentation Changes**
  - Fixed API docs for `AutoMLSearch` `add_result_callback` #1113
  - Added a step to our release process for pushing our latest version to conda-forge #1118
  - Added warning for missing ipywidgets dependency for using `PipelineSearchPlots` on Jupyterlab #1145
  - Updated `README.md` example to load demo dataset #1151
  - Swapped mapping of breast cancer targets in `model_understanding.ipynb` #1170
- **Testing Changes**
  - Added test confirming `TextFeaturizer` never outputs null values #1122
  - Changed Python version of `Update Dependencies` action to 3.8.x #1137
  - Fixed release notes check-in test for `Update Dependencies` actions #1172

Warning:

Breaking Changes

- `get_objective` will now return a class definition rather than an instance by default #1132
- Deleted `OPTIONS` dictionary in `evalml.objectives.utils.py` #1132
- If specifying an objective by string, the string must now match the objective's name field, case-insensitive #1132
- **Passing "Cost Benefit Matrix", "Fraud Cost", "Lead Scoring", "Mean Squared Log Error",** "Recall", "Recall Macro", "Recall Micro", "Recall Weighted", or "Root Mean Squared Log Error" to `AutoMLSearch` will now result in a `ValueError` rather than an `ObjectiveNotFoundError` #1132
- Search callbacks `start_iteration_callback` and `add_results_callback` have changed to include a copy of the AutoMLSearch object as a third parameter #1156
- Deleted `OneHotEncoder.get_feature_names` method which had been broken for a while, in favor of pipelines' `input_feature_names` #1179
- Deleted empty base class `CategoricalEncoder` which `OneHotEncoder` component was inheriting from #1176

- Results from `roc_curve` will now return as a list of dictionaries with each dictionary representing a class #1164
- `max_pipelines` now raises a `DeprecationWarning` and will be removed in the next release. `max_iterations` should be used instead. #1169

v0.13.1 Aug. 25, 2020

- **Enhancements**
  - Added Cost-Benefit Matrix objective for binary classification #1038
  - Split `fill_value` into `categorical_fill_value` and `numeric_fill_value` for Imputer #1019
  - Added `explain_predictions` and `explain_predictions_best_worst` for explaining multiple predictions with SHAP #1016
  - Added new LSA component for text featurization #1022
  - Added guide on installing with conda #1041
  - Added a "cost-benefit curve" util method to graph cost-benefit matrix scores vs. binary classification thresholds #1081
  - Standardized error when calling transform/predict before fit for pipelines #1048
  - Added `percent_better_than_baseline` to AutoML search rankings and full rankings table #1050
  - Added one-way partial dependence and partial dependence plots #1079
  - Added "Feature Value" column to prediction explanation reports. #1064
  - Added LightGBM classification estimator #1082, #1114
  - Added `max_batches` parameter to `AutoMLSearch` #1087
- **Fixes**
  - Updated `TextFeaturizer` component to no longer require an internet connection to run #1022
  - Fixed non-deterministic element of `TextFeaturizer` transformations #1022
  - Added a StandardScaler to all ElasticNet pipelines #1065
  - Updated cost-benefit matrix to normalize score #1099
  - Fixed logic in `calculate_percent_difference` so that it can handle negative values #1100
- **Changes**
  - Added `needs_fitting` property to `ComponentBase` #1044
  - Updated references to data types to use datatype lists defined in `evalml.utils.gen_utils` #1039
  - Remove maximum version limit for SciPy dependency #1051
  - Moved `all_components` and other component importers into runtime methods #1045
  - Consolidated graphing utility methods under `evalml.utils.graph_utils` #1060
  - Made slight tweaks to how `TextFeaturizer` uses `featuretools`, and did some refactoring of that and of LSA #1090

  - Changed `show_all_features` parameter into `importance_threshold`, which allows for thresholding feature importance #1097, #1103

- **Documentation Changes**
  - Update `setup.py` URL to point to the github repo #1037
  - Added tutorial for using the cost-benefit matrix objective #1088
  - Updated `model_understanding.ipynb` to include documentation for using plotly on Jupyter Lab #1108
- **Testing Changes**
  - Refactor CircleCI tests to use matrix jobs (#1043)
  - Added a test to check that all test directories are included in evalml package #1054

Warning:

Breaking Changes

- `confusion_matrix` and `normalize_confusion_matrix` have been moved to `evalml.utils` #1038
- All graph utility methods previously under `evalml.pipelines.graph_utils` have been moved to `evalml.utils.graph_utils` #1060

v0.12.2 Aug. 6, 2020

- **Enhancements**
  - Add save/load method to components #1023
  - Expose pickle `protocol` as optional arg to save/load #1023
  - Updated estimators used in AutoML to include ExtraTrees and ElasticNet estimators #1030
- Fixes
- **Changes**
  - Removed `DeprecationWarning` for `SimpleImputer` #1018
- **Documentation Changes**
  - Add note about version numbers to release process docs #1034
- **Testing Changes**
  - Test files are now included in the evalml package #1029

v0.12.0 Aug. 3, 2020

- **Enhancements**
  - Added string and categorical targets support for binary and multiclass pipelines and check for numeric targets for `DetectLabelLeakage` data check #932
  - Added clear exception for regression pipelines if target datatype is string or categorical #960
  - Added target column names and class labels in `predict` and `predict_proba` output for pipelines #951
  - Added `_compute_shap_values` and `normalize_values` to `pipelines/explanations` module #958

  - Added `explain_prediction` feature which explains single predictions with SHAP #974
  - Added Imputer to allow different imputation strategies for numerical and categorical dtypes #991
  - Added support for configuring logfile path using env var, and don't create logger if there are filesystem errors #975
  - Updated catboost estimators' default parameters and automl hyperparameter ranges to speed up fit time #998

- **Fixes**
  - Fixed ReadtheDocs warning failure regarding embedded gif #943
  - Removed incorrect parameter passed to pipeline classes in `_add_baseline_pipelines` #941
  - Added universal error for calling `predict`, `predict_proba`, `transform`, and `feature_importances` before fitting #969, #994
  - Made `TextFeaturizer` component and pip dependencies `featuretools` and `nlp_primitives` optional #976
  - Updated imputation strategy in automl to no longer limit impute strategy to `most_frequent` for all features if there are any categorical columns #991
  - Fixed `UnboundLocalError` for `cv_pipeline` when automl search errors #996
  - Fixed `Imputer` to reset dataframe index to preserve behavior expected from `SimpleImputer` #1009

- **Changes**
  - Moved `get_estimators` to `evalml.pipelines.components.utils` #934
  - Modified Pipelines to raise `PipelineScoreError` when they encounter an error during scoring #936
  - Moved `evalml.model_families.list_model_families` to `evalml.pipelines.components.allowed_model_families` #959
  - Renamed `DateTimeFeaturization` to `DateTimeFeaturizer` #977
  - Added check to stop search and raise an error if all pipelines in a batch return NaN scores #1015

- **Documentation Changes**
  - Updated `README.md` #963
  - Reworded message when errors are returned from data checks in search #982
  - Added section on understanding model predictions with `explain_prediction` to User Guide #981
  - Added a section to the user guide and api reference about how XGBoost and CatBoost are not fully supported. #992
  - Added custom components section in user guide #993
  - Updated FAQ section formatting #997
  - Updated release process documentation #1003

- **Testing Changes**
  - Moved `predict_proba` and `predict` tests regarding string / categorical targets to `test_pipelines.py` #972

  - Fixed dependency update bot by updating python version to 3.7 to avoid frequent github version updates #1002

Warning:

Breaking Changes

- `get_estimators` has been moved to `evalml.pipelines.components.utils` (previously was under `evalml.pipelines.utils`) #934
- Removed the `raise_errors` flag in AutoML search. All errors during pipeline evaluation will be caught and logged. #936
- `evalml.model_families.list_model_families` has been moved to `evalml.pipelines.components.allowed_model_families` #959
- `TextFeaturizer`: the `featuretools` and `nlp_primitives` packages must be installed after installing evalml in order to use this component #976
- Renamed `DateTimeFeaturization` to `DateTimeFeaturizer` #977

v0.11.2 July 16, 2020

- **Enhancements**
  - Added `NoVarianceDataCheck` to `DefaultDataChecks` #893
  - Added text processing and featurization component `TextFeaturizer` #913, #924
  - Added additional checks to `InvalidTargetDataCheck` to handle invalid target data types #929
  - `AutoMLSearch` will now handle `KeyboardInterrupt` and prompt user for confirmation #915
- **Fixes**
  - Makes automl results a read-only property #919
- **Changes**
  - Deleted static pipelines and refactored tests involving static pipelines, removed `all_pipelines()` and `get_pipelines()` #904
  - Moved `list_model_families` to `evalml.model_family.utils` #903
  - Updated `all_pipelines`, `all_estimators`, `all_components` to use the same mechanism for dynamically generating their elements #898
  - Rename `master` branch to `main` #918
  - Add pypi release github action #923
  - Updated `AutoMLSearch.search` stdout output and logging and removed tqdm progress bar #921
  - Moved automl config checks previously in `search()` to init #933
- **Documentation Changes**
  - Reorganized and rewrote documentation #937
  - Updated to use pydata sphinx theme #937
  - Updated docs to use `release_notes` instead of `changelog` #942

- **Testing Changes**
  - Cleaned up fixture names and usages in tests #895

Warning:

Breaking Changes

- `list_model_families` has been moved to `evalml.model_family.utils` (previously was under `evalml.pipelines.utils`) #903
- `get_estimators` has been moved to `evalml.pipelines.components.utils` (previously was under `evalml.pipelines.utils`) #934
- Static pipeline definitions have been removed, but similar pipelines can still be constructed via creating an instance of `PipelineBase` #904
- `all_pipelines()` and `get_pipelines()` utility methods have been removed #904

v0.11.0 June 30, 2020

- **Enhancements**
  - Added multiclass support for ROC curve graphing #832
  - Added preprocessing component to drop features whose percentage of NaN values exceeds a specified threshold #834
  - Added data check to check for problematic target labels #814
  - Added PerColumnImputer that allows imputation strategies per column #824
  - Added transformer to drop specific columns #827
  - Added support for `categories`, `handle_error`, and `drop` parameters in `OneHotEncoder` #830 #897
  - Added preprocessing component to handle DateTime columns featurization #838
  - Added ability to clone pipelines and components #842
  - Define getter method for component `parameters` #847
  - Added utility methods to calculate and graph permutation importances #860, #880
  - Added new utility functions necessary for generating dynamic preprocessing pipelines #852
  - Added kwargs to all components #863
  - Updated `AutoSearchBase` to use dynamically generated preprocessing pipelines #870
  - Added SelectColumns transformer #873
  - Added ability to evaluate additional pipelines for automl search #874
  - Added `default_parameters` class property to components and pipelines #879
  - Added better support for disabling data checks in automl search #892
  - Added ability to save and load AutoML objects to file #888
  - Updated `AutoSearchBase.get_pipelines` to return an untrained pipeline instance #876
  - Saved learned binary classification thresholds in automl results cv data dict #876
- **Fixes**

  - Fixed bug where SimpleImputer cannot handle dropped columns #846
  - Fixed bug where PerColumnImputer cannot handle dropped columns #855
  - Enforce requirement that builtin components save all inputted values in their parameters dict #847
  - Don't list base classes in `all_components` output #847
  - Standardize all components to output pandas data structures, and accept either pandas or numpy #853
  - Fixed rankings and full_rankings error when search has not been run #894
- **Changes**
  - Update `all_pipelines` and `all_components` to try initializing pipelines/components, and on failure exclude them #849
  - Refactor `handle_components` to `handle_components_class`, standardize to `ComponentBase` subclass instead of instance #850
  - Refactor "blacklist"/"whitelist" to "allow"/"exclude" lists #854
  - Replaced `AutoClassificationSearch` and `AutoRegressionSearch` with `AutoMLSearch` #871
  - Renamed feature_importances and permutation_importances methods to use singular names (feature_importance and permutation_importance) #883
  - Updated `automl` default data splitter to train/validation split for large datasets #877
  - Added open source license, update some repo metadata #887
  - Removed dead code in `_get_preprocessing_components` #896
- **Documentation Changes**
  - Fix some typos and update the EvalML logo #872
- **Testing Changes**
  - Update the changelog check job to expect the new branching pattern for the deps update bot #836
  - Check that all components output pandas datastructures, and can accept either pandas or numpy #853
  - Replaced `AutoClassificationSearch` and `AutoRegressionSearch` with `AutoMLSearch` #871

Warning:

Breaking Changes

- Pipelines' static `component_graph` field must contain either `ComponentBase` subclasses or `str`, instead of `ComponentBase` subclass instances #850
- Rename `handle_component` to `handle_component_class`. Now standardizes to `ComponentBase` subclasses instead of `ComponentBase` subclass instances #850
- Renamed automl's `cv` argument to `data_split` #877
- Pipelines' and classifiers' `feature_importances` is renamed `feature_importance`, `graph_feature_importances` is renamed `graph_feature_importance` #883
- Passing `data_checks=None` to automl search will not perform any data checks as opposed to default checks. #892

- Pipelines to search for in AutoML are now determined automatically, rather than using the statically-defined pipeline classes. #870
- Updated `AutoSearchBase.get_pipelines` to return an untrained pipeline instance, instead of one which happened to be trained on the final cross-validation fold #876

v0.10.0 May 29, 2020

- **Enhancements**
  - Added baseline models for classification and regression, add functionality to calculate baseline models before searching in AutoML #746
  - Port over highly-null guardrail as a data check and define `DefaultDataChecks` and `DisableDataChecks` classes #745
  - Update `Tuner` classes to work directly with pipeline parameters dicts instead of flat parameter lists #779
  - Add Elastic Net as a pipeline option #812
  - Added new Pipeline option `ExtraTrees` #790
  - Added precicion-recall curve metrics and plot for binary classification problems in `evalml.pipeline.graph_utils` #794
  - Update the default automl algorithm to search in batches, starting with default parameters for each pipeline and iterating from there #793
  - Added `AutoMLAlgorithm` class and `IterativeAlgorithm` impl, separated from `AutoSearchBase` #793
- **Fixes**
  - Update pipeline `score` to return `nan` score for any objective which throws an exception during scoring #787
  - Fixed bug introduced in #787 where binary classification metrics requiring predicted probabilities error in scoring #798
  - CatBoost and XGBoost classifiers and regressors can no longer have a learning rate of 0 #795
- **Changes**
  - Cleanup pipeline `score` code, and cleanup codecov #711
  - Remove `pass` for abstract methods for codecov #730
  - Added __str__ for AutoSearch object #675
  - Add util methods to graph ROC and confusion matrix #720
  - Refactor `AutoBase` to `AutoSearchBase` #758
  - Updated AutoBase with `data_checks` parameter, removed previous `detect_label_leakage` parameter, and added functionality to run data checks before search in AutoML #765
  - Updated our logger to use Python's logging utils #763
  - Refactor most of `AutoSearchBase._do_iteration` impl into `AutoSearchBase._evaluate` #762
  - Port over all guardrails to use the new DataCheck API #789

  - Expanded `import_or_raise` to catch all exceptions #759
  - Adds RMSE, MSLE, RMSLE as standard metrics #788
  - Don't allow `Recall` to be used as an objective for AutoML #784
  - Removed feature selection from pipelines #819
  - Update default estimator parameters to make automl search faster and more accurate #793
- **Documentation Changes**
  - Add instructions to freeze `master` on `release.md` #726
  - Update release instructions with more details #727 #733
  - Add objective base classes to API reference #736
  - Fix components API to match other modules #747
- **Testing Changes**
  - Delete codecov yml, use codecov.io's default #732
  - Added unit tests for fraud cost, lead scoring, and standard metric objectives #741
  - Update codecov client #782
  - Updated AutoBase __str__ test to include no parameters case #783
  - Added unit tests for `ExtraTrees` pipeline #790
  - If codecov fails to upload, fail build #810
  - Updated Python version of dependency action #816
  - Update the dependency update bot to use a suffix when creating branches #817

Warning:

Breaking Changes

- The `detect_label_leakage` parameter for AutoML classes has been removed and replaced by a `data_checks` parameter #765
- Moved ROC and confusion matrix methods from `evalml.pipeline.plot_utils` to `evalml.pipeline.graph_utils` #720
- `Tuner` classes require a pipeline hyperparameter range dict as an init arg instead of a space definition #779
- `Tuner.propose` and `Tuner.add` work directly with pipeline parameters dicts instead of flat parameter lists #779
- `PipelineBase.hyperparameters` and `custom_hyperparameters` use pipeline parameters dict format instead of being represented as a flat list #779
- All guardrail functions previously under `evalml.guardrails.utils` will be removed and replaced by data checks #789
- `Recall` disallowed as an objective for AutoML #784
- `AutoSearchBase` parameter `tuner` has been renamed to `tuner_class` #793
- `AutoSearchBase` parameter `possible_pipelines` and `possible_model_families` have been renamed to `allowed_pipelines` and `allowed_model_families` #793

v0.9.0 Apr. 27, 2020

- **Enhancements**
  - Added `Accuracy` as an standard objective #624
  - Added verbose parameter to load_fraud #560
  - Added Balanced Accuracy metric for binary, multiclass #612 #661
  - Added XGBoost regressor and XGBoost regression pipeline #666
  - Added `Accuracy` metric for multiclass #672
  - Added objective name in `AutoBase.describe_pipeline` #686
  - Added `DataCheck` and `DataChecks`, `Message` classes and relevant subclasses #739
- **Fixes**
  - Removed direct access to `cls.component_graph` #595
  - Add testing files to .gitignore #625
  - Remove circular dependencies from `Makefile` #637
  - Add error case for `normalize_confusion_matrix()` #640
  - Fixed `XGBoostClassifier` and `XGBoostRegressor` bug with feature names that contain [,], or < #659
  - Update `make_pipeline_graph` to not accidentally create empty file when testing if path is valid #649
  - Fix pip installation warning about docsutils version, from boto dependency #664
  - Removed zero division warning for F1/precision/recall metrics #671
  - Fixed `summary` for pipelines without estimators #707
- **Changes**
  - Updated default objective for binary/multiclass classification to log loss #613
  - Created classification and regression pipeline subclasses and removed objective as an attribute of pipeline classes #405
  - Changed the output of `score` to return one dictionary #429
  - Created binary and multiclass objective subclasses #504
  - Updated objectives API #445
  - Removed call to `get_plot_data` from AutoML #615
  - Set `raise_error` to default to True for AutoML classes #638
  - Remove unnecessary "u" prefixes on some unicode strings #641
  - Changed one-hot encoder to return uint8 dtypes instead of ints #653
  - Pipeline `_name` field changed to `custom_name` #650
  - Removed `graphs.py` and moved methods into `PipelineBase` #657, #665
  - Remove s3fs as a dev dependency #664
  - Changed requirements-parser to be a core dependency #673

  - Replace `supported_problem_types` field on pipelines with `problem_type` attribute on base classes #678
  - Changed AutoML to only show best results for a given pipeline template in `rankings`, added `full_rankings` property to show all #682
  - Update `ModelFamily` values: don't list xgboost/catboost as classifiers now that we have regression pipelines for them #677
  - Changed AutoML's `describe_pipeline` to get problem type from pipeline instead #685
  - Standardize `import_or_raise` error messages #683
  - Updated argument order of objectives to align with sklearn's #698
  - Renamed `pipeline.feature_importance_graph` to `pipeline.graph_feature_importances` #700
  - Moved ROC and confusion matrix methods to `evalml.pipelines.plot_utils` #704
  - Renamed `MultiClassificationObjective` to `MulticlassClassificationObjective`, to align with pipeline naming scheme #715

- **Documentation Changes**
  - Fixed some sphinx warnings #593
  - Fixed docstring for `AutoClassificationSearch` with correct command #599
  - Limit readthedocs formats to pdf, not htmlzip and epub #594 #600
  - Clean up objectives API documentation #605
  - Fixed function on Exploring search results page #604
  - Update release process doc #567
  - `AutoClassificationSearch` and `AutoRegressionSearch` show inherited methods in API reference #651
  - Fixed improperly formatted code in breaking changes for changelog #655
  - Added configuration to treat Sphinx warnings as errors #660
  - Removed separate plotting section for pipelines in API reference #657, #665
  - Have leads example notebook load S3 files using https, so we can delete s3fs dev dependency #664
  - Categorized components in API reference and added descriptions for each category #663
  - Fixed Sphinx warnings about `BalancedAccuracy` objective #669
  - Updated API reference to include missing components and clean up pipeline docstrings #689
  - Reorganize API ref, and clarify pipeline sub-titles #688
  - Add and update preprocessing utils in API reference #687
  - Added inheritance diagrams to API reference #695
  - Documented which default objective AutoML optimizes for #699
  - Create seperate install page #701
  - Include more utils in API ref, like `import_or_raise` #704
  - Add more color to pipeline documentation #705

- **Testing Changes**
  - Matched install commands of `check_latest_dependencies` test and it's GitHub action #578
  - Added Github app to auto assign PR author as assignee #477
  - Removed unneeded conda installation of xgboost in windows checkin tests #618
  - Update graph tests to always use tmpfile dir #649
  - Changelog checkin test workaround for release PRs: If 'future release' section is empty of PR refs, pass check #658
  - Add changelog checkin test exception for `dep-update` branch #723

Warning: Breaking Changes

- Pipelines will now no longer take an objective parameter during instantiation, and will no longer have an objective attribute.
- `fit()` and `predict()` now use an optional `objective` parameter, which is only used in binary classification pipelines to fit for a specific objective.
- `score()` will now use a required `objectives` parameter that is used to determine all the objectives to score on. This differs from the previous behavior, where the pipeline's objective was scored on regardless.
- `score()` will now return one dictionary of all objective scores.
- `ROC` and `ConfusionMatrix` plot methods via `Auto(*).plot` have been removed by #615 and are replaced by `roc_curve` and `confusion_matrix` in `evamlm.pipelines.plot_utils` in #704
- `normalize_confusion_matrix` has been moved to `evalml.pipelines.plot_utils` #704
- Pipelines `_name` field changed to `custom_name`
- Pipelines `supported_problem_types` field is removed because it is no longer necessary #678
- Updated argument order of objectives' `objective_function` to align with sklearn #698
- `pipeline.feature_importance_graph` has been renamed to `pipeline.graph_feature_importances` in #700
- Removed unsupported `MSLE` objective #704

v0.8.0 Apr. 1, 2020

- **Enhancements**
  - Add normalization option and information to confusion matrix #484
  - Add util function to drop rows with NaN values #487
  - Renamed `PipelineBase.name` as `PipelineBase.summary` and redefined `PipelineBase.name` as class property #491
  - Added access to parameters in Pipelines with `PipelineBase.parameters` (used to be return of `PipelineBase.describe`) #501
  - Added `fill_value` parameter for `SimpleImputer` #509
  - Added functionality to override component hyperparameters and made pipelines take hyperparemeters from components #516
  - Allow `numpy.random.RandomState` for random_state parameters #556

- **Fixes**
  - Removed unused dependency `matplotlib`, and move `category_encoders` to test reqs #572
- **Changes**
  - Undo version cap in XGBoost placed in #402 and allowed all released of XGBoost #407
  - Support pandas 1.0.0 #486
  - Made all references to the logger static #503
  - Refactored `model_type` parameter for components and pipelines to `model_family` #507
  - Refactored `problem_types` for pipelines and components into `supported_problem_types` #515
  - Moved `pipelines/utils.save_pipeline` and `pipelines/utils.load_pipeline` to `PipelineBase.save` and `PipelineBase.load` #526
  - Limit number of categories encoded by `OneHotEncoder` #517
- **Documentation Changes**
  - Updated API reference to remove `PipelinePlot` and added moved `PipelineBase` plotting methods #483
  - Add code style and github issue guides #463 #512
  - Updated API reference for to surface class variables for pipelines and components #537
  - Fixed README documentation link #535
  - Unhid PR references in changelog #656
- **Testing Changes**
  - Added automated dependency check PR #482, #505
  - Updated automated dependency check comment #497
  - Have build_docs job use python executor, so that env vars are set properly #547
  - Added simple test to make sure `OneHotEncoder`'s top_n works with large number of categories #552
  - Run windows unit tests on PRs #557

Warning: Breaking Changes

- `AutoClassificationSearch` and `AutoRegressionSearch`'s `model_types` parameter has been refactored into `allowed_model_families`
- `ModelTypes` enum has been changed to `ModelFamily`
- Components and Pipelines now have a `model_family` field instead of `model_type`
- `get_pipelines` utility function now accepts `model_families` as an argument instead of `model_types`
- `PipelineBase.name` no longer returns structure of pipeline and has been replaced by `PipelineBase.summary`
- `PipelineBase.problem_types` and `Estimator.problem_types` has been renamed to `supported_problem_types`

- `pipelines/utils.save_pipeline` and `pipelines/utils.load_pipeline` moved to `PipelineBase.save` and `PipelineBase.load`

v0.7.0 Mar. 9, 2020

- **Enhancements**
  - Added emacs buffers to .gitignore #350
  - Add CatBoost (gradient-boosted trees) classification and regression components and pipelines #247
  - Added Tuner abstract base class #351
  - Added `n_jobs` as parameter for `AutoClassificationSearch` and `AutoRegressionSearch` #403
  - Changed colors of confusion matrix to shades of blue and updated axis order to match scikit-learn's #426
  - Added `PipelineBase .graph` and `.feature_importance_graph` methods, moved from previous location #423
  - Added support for python 3.8 #462
- **Fixes**
  - Fixed ROC and confusion matrix plots not being calculated if user passed own additional_objectives #276
  - Fixed ReadtheDocs `FileNotFoundError` exception for fraud dataset #439
- **Changes**
  - Added `n_estimators` as a tunable parameter for XGBoost #307
  - Remove unused parameter `ObjectiveBase.fit_needs_proba` #320
  - Remove extraneous parameter `component_type` from all components #361
  - Remove unused `rankings.csv` file #397
  - Downloaded demo and test datasets so unit tests can run offline #408
  - Remove `_needs_fitting` attribute from Components #398
  - Changed plot.feature_importance to show only non-zero feature importances by default, added optional parameter to show all #413
  - Refactored `PipelineBase` to take in parameter dictionary and moved pipeline metadata to class attribute #421
  - Dropped support for Python 3.5 #438
  - Removed unused `apply.py` file #449
  - Clean up `requirements.txt` to remove unused deps #451
  - Support installation without all required dependencies #459
- **Documentation Changes**
  - Update release.md with instructions to release to internal license key #354
- **Testing Changes**
  - Added tests for utils (and moved current utils to gen_utils) #297

  - Moved XGBoost install into it's own separate step on Windows using Conda #313
  - Rewind pandas version to before 1.0.0, to diagnose test failures for that version #325
  - Added dependency update checkin test #324
  - Rewind XGBoost version to before 1.0.0 to diagnose test failures for that version #402
  - Update dependency check to use a whitelist #417
  - Update unit test jobs to not install dev deps #455

Warning: Breaking Changes

- Python 3.5 will not be actively supported.

v0.6.0 Dec. 16, 2019

- **Enhancements**
  - Added ability to create a plot of feature importances #133
  - Add early stopping to AutoML using patience and tolerance parameters #241
  - Added ROC and confusion matrix metrics and plot for classification problems and introduce PipelineSearchPlots class #242
  - Enhanced AutoML results with search order #260
  - Added utility function to show system and environment information #300
- **Fixes**
  - Lower botocore requirement #235
  - Fixed decision_function calculation for `FraudCost` objective #254
  - Fixed return value of `Recall` metrics #264
  - Components return `self` on fit #289
- **Changes**
  - Renamed automl classes to `AutoRegressionSearch` and `AutoClassificationSearch` #287
  - Updating demo datasets to retain column names #223
  - Moving pipeline visualization to `PipelinePlot` class #228
  - Standarizing inputs as `pd.Dataframe` / `pd.Series` #130
  - Enforcing that pipelines must have an estimator as last component #277
  - Added `ipywidgets` as a dependency in `requirements.txt` #278
  - Added Random and Grid Search Tuners #240
- **Documentation Changes**
  - Adding class properties to API reference #244
  - Fix and filter FutureWarnings from scikit-learn #249, #257
  - Adding Linear Regression to API reference and cleaning up some Sphinx warnings #227
- **Testing Changes**

  - Added support for testing on Windows with CircleCI #226
  - Added support for doctests #233

Warning: Breaking Changes

- The `fit()` method for `AutoClassifier` and `AutoRegressor` has been renamed to `search()`.
- `AutoClassifier` has been renamed to `AutoClassificationSearch`
- `AutoRegressor` has been renamed to `AutoRegressionSearch`
- `AutoClassificationSearch.results` and `AutoRegressionSearch.results` now is a dictionary with `pipeline_results` and `search_order` keys. `pipeline_results` can be used to access a dictionary that is identical to the old `.results` dictionary. Whereas, `search_order` returns a list of the search order in terms of `pipeline_id`.
- Pipelines now require an estimator as the last component in `component_list`. Slicing pipelines now throws an `NotImplementedError` to avoid returning pipelines without an estimator.

v0.5.2 Nov. 18, 2019

- **Enhancements**
  - Adding basic pipeline structure visualization #211
- **Documentation Changes**
  - Added notebooks to build process #212

v0.5.1 Nov. 15, 2019

- **Enhancements**
  - Added basic outlier detection guardrail #151
  - Added basic ID column guardrail #135
  - Added support for unlimited pipelines with a `max_time` limit #70
  - Updated .readthedocs.yaml to successfully build #188
- **Fixes**
  - Removed MSLE from default additional objectives #203
  - Fixed `random_state` passed in pipelines #204
  - Fixed slow down in RFRegressor #206
- **Changes**
  - Pulled information for describe_pipeline from pipeline's new describe method #190
  - Refactored pipelines #108
  - Removed guardrails from Auto(*) #202, #208
- **Documentation Changes**
  - Updated documentation to show `max_time` enhancements #189
  - Updated release instructions for RTD #193
  - Added notebooks to build process #212
  - Added contributing instructions #213

  - Added new content #222

v0.5.0 Oct. 29, 2019

- **Enhancements**
  - Added basic one hot encoding #73
  - Use enums for model_type #110
  - Support for splitting regression datasets #112
  - Auto-infer multiclass classification #99
  - Added support for other units in `max_time` #125
  - Detect highly null columns #121
  - Added additional regression objectives #100
  - Show an interactive iteration vs. score plot when using fit() #134
- **Fixes**
  - Reordered `describe_pipeline` #94
  - Added type check for `model_type` #109
  - Fixed `s` units when setting string `max_time` #132
  - Fix objectives not appearing in API documentation #150
- **Changes**
  - Reorganized tests #93
  - Moved logging to its own module #119
  - Show progress bar history #111
  - Using `cloudpickle` instead of pickle to allow unloading of custom objectives #113
  - Removed render.py #154
- **Documentation Changes**
  - Update release instructions #140
  - Include additional_objectives parameter #124
  - Added Changelog #136
- **Testing Changes**
  - Code coverage #90
  - Added CircleCI tests for other Python versions #104
  - Added doc notebooks as tests #139
  - Test metadata for CircleCI and 2 core parallelism #137

v0.4.1 Sep. 16, 2019

- **Enhancements**
  - Added AutoML for classification and regressor using Autobase and Skopt #7 #9
  - Implemented standard classification and regression metrics #7
  - Added logistic regression, random forest, and XGBoost pipelines #7

  - Implemented support for custom objectives #15
  - Feature importance for pipelines #18
  - Serialization for pipelines #19
  - Allow fitting on objectives for optimal threshold #27
  - Added detect label leakage #31
  - Implemented callbacks #42
  - Allow for multiclass classification #21
  - Added support for additional objectives #79
- **Fixes**
  - Fixed feature selection in pipelines #13
  - Made `random_seed` usage consistent #45
- **Documentation Changes**
  - Documentation Changes
  - Added docstrings #6
  - Created notebooks for docs #6
  - Initialized readthedocs EvalML #6
  - Added favicon #38
- **Testing Changes**
  - Added testing for loading data #39

v0.2.0 Aug. 13, 2019

- **Enhancements**
  - Created fraud detection objective #4

v0.1.0 July. 31, 2019

- *First Release*
- **Enhancements**
  - Added lead scoring objecitve #1
  - Added basic classifier #1
- **Documentation Changes**
  - Initialized Sphinx for docs #1

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