# EvalML Documentation

***Release 0.12.0***

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# CONTENTS

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 3.6+. It can be installed by running the following command:

```
pip install evalml
```

## 1.1 Core vs Optional 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 Windows

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.

CHAPTER

# TWO

# START

In this guide, we'll show how you can use EvalML to automatically find the best pipeline for predicting whether a patient has breast cancer. 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
```

```
2020-08-03 19:09:12,591 featuretools - WARNING    Featuretools failed to load plugin␣
↪nlp_primitives from library nlp_primitives. For a full stack trace, set logging to␣
↪debug.
```

```
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.12.0/
↪lib/python3.7/site-packages/evalml/pipelines/components/transformers/preprocessing/
↪text_featurizer.py:31: RuntimeWarning: No text columns were given to TextFeaturizer,
↪ component will have no effect
  warnings.warn("No text columns were given to TextFeaturizer, component will have no␣
↪effect", RuntimeWarning)
```

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

[2]:
```
X, y = evalml.demos.load_breast_cancer()
```

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.

[3]:
```
automl = AutoMLSearch(problem_type="binary", objective="f1", max_pipelines=5)
```

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, test_
↪size=.2)
```

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*.

[5]:
```
automl.search(X_train, y_train)
```

```
Generating pipelines to search over...
*****************************
* Beginning pipeline search *
*****************************

Optimizing for F1.
Greater score is better.

Searching up to 5 pipelines.
Allowed model families: linear_model, random_forest, catboost, xgboost
```

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

```
(1/5) Mode Baseline Binary Classification P... Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean F1: 0.000
(2/5) CatBoost Classifier w/ Imputer           Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean F1: 0.908
(3/5) XGBoost Classifier w/ Imputer            Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean F1: 0.936
(4/5) Random Forest Classifier w/ Imputer      Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean F1: 0.941
(5/5) Logistic Regression Classifier w/ Imp... Elapsed:00:02
        Starting cross validation
        Finished cross validation - mean F1: 0.963

Search finished after 00:03
Best pipeline: Logistic Regression Classifier w/ Imputer + Standard Scaler
Best pipeline F1: 0.962611
```

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.

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

[6]:
```
   id                                     pipeline_name     score  \
0   4  Logistic Regression Classifier w/ Imputer + St...  0.962611
1   3               Random Forest Classifier w/ Imputer  0.940612
2   2                     XGBoost Classifier w/ Imputer  0.936003
3   1                    CatBoost Classifier w/ Imputer  0.907790
4   0       Mode Baseline Binary Classification Pipeline  0.000000

   high_variance_cv                                         parameters
0             False  {'Imputer': {'categorical_impute_strategy': 'm...
1             False  {'Imputer': {'categorical_impute_strategy': 'm...
2             False  {'Imputer': {'categorical_impute_strategy': 'm...
3             False  {'Imputer': {'categorical_impute_strategy': 'm...
4             False      {'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:

[7]:
```
automl.describe_pipeline(3)
```

```
*************************************
* Random Forest Classifier w/ Imputer *
*************************************

Problem Type: Binary Classification
Model Family: Random Forest

Pipeline Steps
==============
1. Imputer
         * categorical_impute_strategy : most_frequent
         * numeric_impute_strategy : mean
         * fill_value : None
2. Random Forest Classifier
         * n_estimators : 100
         * max_depth : 6
         * n_jobs : -1

Training
========
Training for Binary Classification problems.
Total training time (including CV): 1.4 seconds

Cross Validation
----------
                F1  Accuracy Binary  Balanced Accuracy Binary  Precision    AUC  Log␣
↪Loss Binary  MCC Binary # Training # Testing
0            0.922             0.941                     0.939      0.914 0.990       ␣
↪    0.123       0.874    303.000   152.000
1            0.966             0.974                     0.975      0.949 0.997       ␣
↪    0.098       0.945    303.000   152.000
2            0.935             0.954                     0.941      0.980 0.987       ␣
↪    0.146       0.901    304.000   151.000
mean         0.941             0.956                     0.952      0.948 0.991       ␣
↪    0.122       0.907          -         -
std          0.023             0.017                     0.021      0.033 0.005       ␣
↪    0.024       0.036          -         -
coef of var 0.024              0.017                     0.022      0.035 0.005       ␣
↪    0.198       0.039          -         -
```

We can also view the pipeline parameters directly:

[8]:
```
pipeline = automl.get_pipeline(3)
print(pipeline.parameters)
```

```
{'Imputer': {'categorical_impute_strategy': 'most_frequent',␣
↪'numeric_impute_strategy': 'mean', 'fill_value': None}, '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:

[9]:
```
pipeline = automl.best_pipeline
pipeline.fit(X_train, y_train)
pipeline.score(X_holdout, y_holdout, ["f1"])
```

[9]:
```
OrderedDict([('F1', 0.9761904761904762)])
```

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

[10]:
```
pipeline.graph()
```

[10]:

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 is over 4x better than using a generic machine learning metric like AUC.

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

```
2020-08-03 19:08:26,030 featuretools - WARNING    Featuretools failed to load plugin␣
↪nlp_primitives from library nlp_primitives. For a full stack trace, set logging to␣
↪debug.
```

```
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.12.0/
↪lib/python3.7/site-packages/evalml/pipelines/components/transformers/preprocessing/
↪text_featurizer.py:31: RuntimeWarning: No text columns were given to TextFeaturizer,
↪ component will have no effect
  warnings.warn("No text columns were given to TextFeaturizer, component will have no␣
↪effect", RuntimeWarning)
```

### 3.1.1 Configure "Cost of Fraud"

To optimize the pipelines toward the specific business needs of this model, you can set your 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 a holdout set

[3]:
```
X, y = evalml.demos.load_fraud(n_rows=2500)
```

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

Number of training examples: 2500
Labels
False    85.92%
True     14.08%
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]:
```
X = X.drop(['datetime', 'expiration_date', 'country', 'region', 'provider'], axis=1)

X_train, X_holdout, y_train, y_holdout = evalml.preprocessing.split_data(X, y, test_
↪size=0.2, random_state=0)

print(X.dtypes)
```

```
card_id               int64
store_id              int64
amount                int64
currency             object
customer_present       bool
lat                 float64
lng                 float64
dtype: object
```

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

[5]:
```
automl = AutoMLSearch(problem_type='binary',
                      objective=fraud_objective,
                      additional_objectives=['auc', 'f1', 'precision'],
                      max_pipelines=5,
                      optimize_thresholds=True)

automl.search(X_train, y_train)
```

```
Generating pipelines to search over...
*****************************
* Beginning pipeline search *
*****************************
```

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

Searching up to 5 pipelines.
Allowed model families: random_forest, catboost, xgboost, linear_model
```

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

```
(1/5) Mode Baseline Binary Classification P... Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean Fraud Cost: 0.023
(2/5) CatBoost Classifier w/ Imputer           Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean Fraud Cost: 0.002
(3/5) XGBoost Classifier w/ Imputer + One H... Elapsed:00:01
        Starting cross validation
        Finished cross validation - mean Fraud Cost: 0.007
(4/5) Random Forest Classifier w/ Imputer +... Elapsed:00:02
        Starting cross validation
        Finished cross validation - mean Fraud Cost: 0.002
(5/5) Logistic Regression Classifier w/ Imp... Elapsed:00:04
        Starting cross validation
        Finished cross validation - mean Fraud Cost: 0.016

Search finished after 00:06
Best pipeline: CatBoost Classifier w/ Imputer
Best pipeline Fraud Cost: 0.002316
```

### 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 fraud detection objective we defined

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

[6]:

| | id | pipeline_name | score | high_variance_cv | parameters |
|---|---|---|---|---|---|
| 0 | 1 | CatBoost Classifier w/ Imputer | 0.002316 | False | {'Imputer': {'categorical_impute_strategy': 'm... |
| 1 | 3 | Random Forest Classifier w/ Imputer + One Hot ... | 0.002316 | False | {'Imputer': {'categorical_impute_strategy': 'm... |
| 2 | 2 | XGBoost Classifier w/ Imputer + One Hot Encoder | 0.007152 | True | {'Imputer': {'categorical_impute_strategy': 'm... |
| 3 | 4 | Logistic Regression Classifier w/ Imputer + On... | 0.015898 | True | {'Imputer': {'categorical_impute_strategy': 'm... |
| 4 | 0 | Mode Baseline Binary Classification Pipeline | 0.022830 | True | {'Baseline Classifier': {'strategy': 'mode'}} |

to select the best pipeline we can run

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

### Describe pipeline

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

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

```
*************************************************************
* Random Forest Classifier w/ Imputer + One Hot Encoder *
*************************************************************

Problem Type: Binary Classification
Model Family: Random Forest

Pipeline Steps
==============
1. Imputer
         * categorical_impute_strategy : most_frequent
         * numeric_impute_strategy : mean
         * fill_value : None
2. One Hot Encoder
         * top_n : 10
         * categories : None
         * drop : None
         * handle_unknown : ignore
         * handle_missing : error
3. Random Forest Classifier
         * n_estimators : 100
         * max_depth : 6
         * n_jobs : -1

Training
========
Training for Binary Classification problems.
Objective to optimize binary classification pipeline thresholds for: <evalml.
↪objectives.fraud_cost.FraudCost object at 0x7fbc2d11d8d0>
Total training time (including CV): 2.3 seconds

Cross Validation
----------
              Fraud Cost    AUC     F1  Precision # Training # Testing
0                  0.002 0.869 0.247      0.141   1066.000   667.000
1                  0.002 0.863 0.247      0.141   1066.000   667.000
2                  0.002 0.856 0.247      0.141   1067.000   666.000
mean               0.002 0.862 0.247      0.141          -         -
std                0.000 0.006 0.000      0.000          -         -
coef of var        0.055 0.007 0.001      0.001          -         -
```

## 3.1.3 Evaluate on hold out

Finally, we retrain the best pipeline on all of the training data and evaluate on the holdout

[9]:
```
best_pipeline.fit(X_train, y_train)
```

```
[9]: <evalml.pipelines.utils.make_pipeline.<locals>.GeneratedPipeline at 0x7fbc2c77eba8>
```

Now, we can score the pipeline on the hold out data using both the fraud cost score and the AUC.

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

```
[10]: OrderedDict([('AUC', 0.8225415282392027),
                   ('Fraud Cost', 0.004329350526560073)])
```

### 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.

```
[11]: automl_auc = AutoMLSearch(problem_type='binary',
                                objective='auc',
                                additional_objectives=['f1', 'precision'],
                                max_pipelines=5,
                                optimize_thresholds=True)

      automl_auc.search(X_train, y_train)
```

```
Generating pipelines to search over...
*****************************
* Beginning pipeline search *
*****************************

Optimizing for AUC.
Greater score is better.

Searching up to 5 pipelines.
Allowed model families: random_forest, catboost, xgboost, linear_model
```

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

```
(1/5) Mode Baseline Binary Classification P... Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean AUC: 0.500
(2/5) CatBoost Classifier w/ Imputer           Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean AUC: 0.844
(3/5) XGBoost Classifier w/ Imputer + One H... Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean AUC: 0.851
(4/5) Random Forest Classifier w/ Imputer +... Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean AUC: 0.850
(5/5) Logistic Regression Classifier w/ Imp... Elapsed:00:02
        Starting cross validation
        Finished cross validation - mean AUC: 0.805

Search finished after 00:02
```

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```
Best pipeline: XGBoost Classifier w/ Imputer + One Hot Encoder
Best pipeline AUC: 0.851122
```

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

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

[12]:
```
   id                                     pipeline_name     score  \
0   2    XGBoost Classifier w/ Imputer + One Hot Encoder  0.851122
1   3  Random Forest Classifier w/ Imputer + One Hot ...  0.849773
2   1                    CatBoost Classifier w/ Imputer  0.843946
3   4  Logistic Regression Classifier w/ Imputer + On...  0.804897
4   0       Mode Baseline Binary Classification Pipeline  0.500000

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

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

# train on the full training data
best_pipeline_auc.fit(X_train, y_train)
```

[13]:
```
<evalml.pipelines.utils.make_pipeline.<locals>.GeneratedPipeline at 0x7fbc28ffde80>
```

[14]:
```
# get the fraud score on holdout data
best_pipeline_auc.score(X_holdout, y_holdout,  objectives=["auc", fraud_objective])
```

[14]:
```
OrderedDict([('AUC', 0.8529235880398671),
             ('Fraud Cost', 0.004329350526560073)])
```

[15]:
```
# fraud score on fraud optimized again
best_pipeline.score(X_holdout, y_holdout, objectives=["auc", fraud_objective])
```

[15]:
```
OrderedDict([('AUC', 0.8225415282392027),
             ('Fraud Cost', 0.004329350526560073)])
```

When we optimize for AUC, we can see that the AUC score from this pipeline is better than the AUC score from the pipeline optimized for fraud cost. However, the losses due to fraud are over 3% of the total transaction amount when optimized for AUC and under 1% when optimized for fraud cost. As a result, we lose more than 2% of the total transaction amount by not optimizing for fraud cost specifically.

This happens because optimizing for AUC does not take into account the user-specified `retry_percentage`, `interchange_fee`, `fraud_payout_percentage` values. 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 over 6x better than using a generic machine learning metric like AUC.

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

```
2020-08-03 19:08:41,059 featuretools - WARNING    Featuretools failed to load plugin␣
↪nlp_primitives from library nlp_primitives. For a full stack trace, set logging to␣
↪debug.
```

```
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.12.0/
↪lib/python3.7/site-packages/evalml/pipelines/components/transformers/preprocessing/
↪text_featurizer.py:31: RuntimeWarning: No text columns were given to TextFeaturizer,
↪ component will have no effect
  warnings.warn("No text columns were given to TextFeaturizer, component will have no␣
↪effect", RuntimeWarning)
```

### 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=1000,
    false_positives=-10
)
```

### 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

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',
```

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```
        '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
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
```

### 3.2.3 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

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

[4]:
```
X_train, X_holdout, y_train, y_holdout = evalml.preprocessing.split_data(X, y, test_
↪size=0.2, random_state=0)

print(X.dtypes)
```

```
job         object
state       object
zip        float64
action      object
amount     float64
dtype: object
```

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

[5]:
```
automl = AutoMLSearch(problem_type='binary',
                      objective=lead_scoring_objective,
                      additional_objectives=['auc'],
                      max_pipelines=5,
                      optimize_thresholds=True)

automl.search(X_train, y_train)
```

```
Generating pipelines to search over...
******************************
* Beginning pipeline search *
******************************

Optimizing for Lead Scoring.
Greater score is better.

Searching up to 5 pipelines.
Allowed model families: linear_model, catboost, random_forest, xgboost
```

```
FigureWidget({
    'data': [{'mode': 'lines+markers',
```

(continues on next page)

(continued from previous page)

```
             'name': 'Best Score',
             'type'...
```

```
(1/5) Mode Baseline Binary Classification P... Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean Lead Scoring: 0.000
(2/5) CatBoost Classifier w/ Imputer           Elapsed:00:01
        Starting cross validation
        Finished cross validation - mean Lead Scoring: 29.276
(3/5) XGBoost Classifier w/ Imputer + One H... Elapsed:00:01
        Starting cross validation
        Finished cross validation - mean Lead Scoring: 41.205
(4/5) Random Forest Classifier w/ Imputer +... Elapsed:00:03
        Starting cross validation
        Finished cross validation - mean Lead Scoring: 41.187
(5/5) Logistic Regression Classifier w/ Imp... Elapsed:00:05
        Starting cross validation
        Finished cross validation - mean Lead Scoring: 41.019

Search finished after 00:07
Best pipeline: XGBoost Classifier w/ Imputer + One Hot Encoder
Best pipeline Lead Scoring: 41.204697
```

### 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

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

[6]:
```
   id                                     pipeline_name      score  \
0   2    XGBoost Classifier w/ Imputer + One Hot Encoder  41.204697
1   3  Random Forest Classifier w/ Imputer + One Hot ...  41.187437
2   4  Logistic Regression Classifier w/ Imputer + On...  41.019034
3   1                    CatBoost Classifier w/ Imputer  29.275734
4   0       Mode Baseline Binary Classification Pipeline   0.000000

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

to select the best pipeline we can run

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

### Describe pipeline

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

[8]:
```
automl.describe_pipeline(automl.rankings.iloc[0]["id"])
```

```
*************************************************
* XGBoost Classifier w/ Imputer + One Hot Encoder *
*************************************************

Problem Type: Binary Classification
Model Family: XGBoost

Pipeline Steps
==============
1. Imputer
         * categorical_impute_strategy : most_frequent
         * numeric_impute_strategy : mean
         * fill_value : None
2. One Hot Encoder
         * top_n : 10
         * categories : None
         * drop : None
         * handle_unknown : ignore
         * handle_missing : error
3. XGBoost Classifier
         * eta : 0.1
         * max_depth : 6
         * min_child_weight : 1
         * n_estimators : 100

Training
========
Training for Binary Classification problems.
Objective to optimize binary classification pipeline thresholds for: <evalml.
↪objectives.lead_scoring.LeadScoring object at 0x7f7ecb3d9978>
Total training time (including CV): 1.5 seconds

Cross Validation
----------
             Lead Scoring   AUC # Training # Testing
0                  39.826 0.722   2479.000  1550.000
1                  41.948 0.713   2479.000  1550.000
2                  41.840 0.679   2480.000  1549.000
mean               41.205 0.705          -         -
std                 1.195 0.023          -         -
coef of var         0.029 0.032          -         -
```

### 3.2.4 Evaluate on hold out

Finally, we retrain the best pipeline on all of the training data and evaluate on the holdout

```
[9]: best_pipeline.fit(X_train, y_train)
```

```
[9]: <evalml.pipelines.utils.make_pipeline.<locals>.GeneratedPipeline at 0x7f7ec6e2cf28>
```

Now, we can score the pipeline on the hold out data using both the lead scoring score and the AUC.

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

```
[10]: OrderedDict([('AUC', 0.6662964641885766),
              ('Lead Scoring', -0.051590713671539126)])
```

### 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(problem_type='binary',
                                 objective='auc',
                                 additional_objectives=[],
                                 max_pipelines=5,
                                 optimize_thresholds=True)

automl_auc.search(X_train, y_train)
```

```
Generating pipelines to search over...
*****************************
* Beginning pipeline search *
*****************************

Optimizing for AUC.
Greater score is better.

Searching up to 5 pipelines.
Allowed model families: linear_model, catboost, random_forest, xgboost
```

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

```
(1/5) Mode Baseline Binary Classification P... Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean AUC: 0.500
(2/5) CatBoost Classifier w/ Imputer           Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean AUC: 0.582
(3/5) XGBoost Classifier w/ Imputer + One H... Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean AUC: 0.728
(4/5) Random Forest Classifier w/ Imputer +... Elapsed:00:01
        Starting cross validation
        Finished cross validation - mean AUC: 0.725
(5/5) Logistic Regression Classifier w/ Imp... Elapsed:00:02
        Starting cross validation
        Finished cross validation - mean AUC: 0.700

Search finished after 00:02
Best pipeline: XGBoost Classifier w/ Imputer + One Hot Encoder
Best pipeline AUC: 0.728289
```

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

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

[12]:
```
   id                                    pipeline_name     score  \
0   2    XGBoost Classifier w/ Imputer + One Hot Encoder  0.728289
1   3  Random Forest Classifier w/ Imputer + One Hot ...  0.725217
2   4  Logistic Regression Classifier w/ Imputer + On...  0.700140
```

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```
3   1                    CatBoost Classifier w/ Imputer  0.581861
4   0       Mode Baseline Binary Classification Pipeline  0.500000

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

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

# train on the full training data
best_pipeline_auc.fit(X_train, y_train)
```

[13]:
```
<evalml.pipelines.utils.make_pipeline.<locals>.GeneratedPipeline at 0x7f7ec764b0f0>
```

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

[14]:
```
OrderedDict([('AUC', 0.6662964641885766),
             ('Lead Scoring', -0.051590713671539126)])
```

When we optimize for AUC, we can see that the AUC score from this pipeline is better than the AUC score from the pipeline optimized for lead scoring. However, the revenue per lead gained was only $7 per lead when optimized for AUC and was $45 when optimized for lead scoring. As a result, we would gain up to 6x 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.

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.

#### 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.

[1]:
```
import evalml

X, y = evalml.demos.load_breast_cancer()

automl = evalml.automl.AutoMLSearch(problem_type='binary')
automl.search(X, y)
```

```
2020-08-03 19:09:23,274 featuretools - WARNING    Featuretools failed to load plugin␣
↪nlp_primitives from library nlp_primitives. For a full stack trace, set logging to␣
↪debug.
Using default limit of max_pipelines=5.

Generating pipelines to search over...
*****************************
* Beginning pipeline search *
*****************************

Optimizing for Log Loss Binary.
Lower score is better.

Searching up to 5 pipelines.
Allowed model families: random_forest, linear_model, xgboost, catboost
```

```
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.12.0/
↪lib/python3.7/site-packages/evalml/pipelines/components/transformers/preprocessing/
↪text_featurizer.py:31: RuntimeWarning: No text columns were given to TextFeaturizer,
↪ component will have no effect
  warnings.warn("No text columns were given to TextFeaturizer, component will have no␣
↪effect", RuntimeWarning)
```

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

```
(1/5) Mode Baseline Binary Classification P... Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 12.868
(2/5) CatBoost Classifier w/ Imputer           Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.390
(3/5) XGBoost Classifier w/ Imputer            Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.101
(4/5) Random Forest Classifier w/ Imputer      Elapsed:00:00
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.123
(5/5) Logistic Regression Classifier w/ Imp... Elapsed:00:02
        Starting cross validation
        Finished cross validation - mean Log Loss Binary: 0.091

Search finished after 00:03
```

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```
Best pipeline: Logistic Regression Classifier w/ Imputer + Standard Scaler
Best pipeline Log Loss Binary: 0.091164
```

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

By default, AutoML will search a fixed number of pipeline and parameter pairs (5). 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.*

#### Using custom pipelines

EvalML's AutoML algorithm generates a set of pipelines to search with. To provide a custom set instead, set allowed_pipelines to a list of *custom pipeline* classes. Note: this will prevent AutoML from generating other pipelines to search over.

[2]:
```
from evalml.pipelines import MulticlassClassificationPipeline

class CustomMulticlassClassificationPipeline(MulticlassClassificationPipeline):
    component_graph = ['Simple Imputer', 'Random Forest Classifier']

automl_custom = evalml.automl.AutoMLSearch(problem_type='multiclass', allowed_
↪pipelines=[CustomMulticlassClassificationPipeline])
```

```
Using default limit of max_pipelines=5.
```

#### 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.

### 4.1.3 View Rankings

A summary of all the pipelines built can be returned as a pandas DataFrame which is sorted by score.

[3]:
```
automl.rankings
```

[3]:
```
   id                                     pipeline_name      score  \
0   4  Logistic Regression Classifier w/ Imputer + St...   0.091164
1   2                      XGBoost Classifier w/ Imputer   0.100965
2   3                Random Forest Classifier w/ Imputer   0.122537
3   1                     CatBoost Classifier w/ Imputer   0.390101
4   0       Mode Baseline Binary Classification Pipeline  12.868443

   high_variance_cv                                         parameters
0             False  {'Imputer': {'categorical_impute_strategy': 'm...
1              True  {'Imputer': {'categorical_impute_strategy': 'm...
2             False  {'Imputer': {'categorical_impute_strategy': 'm...
3             False  {'Imputer': {'categorical_impute_strategy': 'm...
4             False      {'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`.

[4]:
```
automl.describe_pipeline(1)
```

```
*********************************
* CatBoost Classifier w/ Imputer *
*********************************

Problem Type: Binary Classification
Model Family: CatBoost

Pipeline Steps
==============
1. Imputer
         * categorical_impute_strategy : most_frequent
         * numeric_impute_strategy : mean
         * fill_value : None
2. CatBoost Classifier
         * n_estimators : 10
         * eta : 0.03
         * max_depth : 6
         * bootstrap_type : None

Training
========
Training for Binary Classification problems.
Total training time (including CV): 0.4 seconds

Cross Validation
----------
             Log Loss Binary  Accuracy Binary  Balanced Accuracy Binary    F1 
↪Precision   AUC  MCC Binary # Training # Testing
0                      0.398            0.926                     0.910 0.896      0.
↪952 0.984       0.843    379.000   190.000
1                      0.391            0.963                     0.954 0.949      0.
↪985 0.996       0.922    379.000   190.000
2                      0.382            0.963                     0.965 0.951      0.
↪932 0.989       0.922    380.000   189.000
mean                   0.390            0.951                     0.943 0.932      0.
↪956 0.989       0.895          -         -
std                    0.008            0.021                     0.029 0.031      0.
↪027 0.006       0.046          -         -
coef of var            0.020            0.022                     0.031 0.034      0.
↪028 0.006       0.051          -         -
```

### 4.1.5 Get Pipeline

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

[5]:
```
pipeline = automl.get_pipeline(1)
print(pipeline.name)
print(pipeline.parameters)
```

```
CatBoost Classifier w/ Imputer
{'Imputer': {'categorical_impute_strategy': 'most_frequent',␣
↪'numeric_impute_strategy': 'mean', 'fill_value': None}, 'CatBoost Classifier':␣
↪{'n_estimators': 10, 'eta': 0.03, 'max_depth': 6, 'bootstrap_type': None}}
```

#### Get best pipeline

If we specifically want to get the best pipeline, there is a convenient accessor for that.

[6]:
```
best_pipeline = automl.best_pipeline
print(best_pipeline.name)
print(best_pipeline.parameters)
```

```
Logistic Regression Classifier w/ Imputer + Standard Scaler
{'Imputer': {'categorical_impute_strategy': 'most_frequent',␣
↪'numeric_impute_strategy': 'mean', 'fill_value': None}, 'Logistic Regression␣
↪Classifier': {'penalty': 'l2', 'C': 1.0, 'n_jobs': -1}}
```

### 4.1.6 Access raw results

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

[7]:
```
automl.results
```

[7]:
```
{'pipeline_results': {0: {'id': 0,
   'pipeline_name': 'Mode Baseline Binary Classification Pipeline',
   'pipeline_class': evalml.pipelines.classification.baseline_binary.
↪ModeBaselineBinaryPipeline,
   'pipeline_summary': 'Baseline Classifier',
   'parameters': {'Baseline Classifier': {'strategy': 'mode'}},
   'score': 12.868443394958925,
   'high_variance_cv': False,
   'training_time': 0.0262908935546875,
   'cv_data': [{'all_objective_scores': OrderedDict([('Log Loss Binary',
                12.906595389677152),
               ('Accuracy Binary', 0.6263157894736842),
               ('Balanced Accuracy Binary', 0.5),
               ('F1', 0.0),
               ('Precision', 0.0),
               ('AUC', 0.5),
               ('MCC Binary', 0.0),
               ('# Training', 379),
               ('# Testing', 190)]),
     'score': 12.906595389677152,
     'binary_classification_threshold': 0.5},
    {'all_objective_scores': OrderedDict([('Log Loss Binary',
                12.906595389677149),
               ('Accuracy Binary', 0.6263157894736842),
               ('Balanced Accuracy Binary', 0.5),
               ('F1', 0.0),
               ('Precision', 0.0),
               ('AUC', 0.5),
               ('MCC Binary', 0.0),
               ('# Training', 379),
```

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```
                ('# Testing', 190)]),
   'score': 12.906595389677149,
   'binary_classification_threshold': 0.5},
  {'all_objective_scores': OrderedDict([('Log Loss Binary',
                12.792139405522475),
               ('Accuracy Binary', 0.6296296296296297),
               ('Balanced Accuracy Binary', 0.5),
               ('F1', 0.0),
               ('Precision', 0.0),
               ('AUC', 0.5),
               ('MCC Binary', 0.0),
               ('# Training', 380),
               ('# Testing', 189)]),
   'score': 12.792139405522475,
   'binary_classification_threshold': 0.5}]},
1: {'id': 1,
 'pipeline_name': 'CatBoost Classifier w/ Imputer',
 'pipeline_class': evalml.pipelines.utils.make_pipeline.<locals>.GeneratedPipeline,
 'pipeline_summary': 'CatBoost Classifier w/ Imputer',
 'parameters': {'Imputer': {'categorical_impute_strategy': 'most_frequent',
   'numeric_impute_strategy': 'mean',
   'fill_value': None},
  'CatBoost Classifier': {'n_estimators': 10,
   'eta': 0.03,
   'max_depth': 6,
   'bootstrap_type': None}},
 'score': 0.3901007526814435,
 'high_variance_cv': False,
 'training_time': 0.4076406955718994,
 'cv_data': [{'all_objective_scores': OrderedDict([('Log Loss Binary',
                0.3976961654004939),
               ('Accuracy Binary', 0.9263157894736842),
               ('Balanced Accuracy Binary', 0.9099301692507988),
               ('F1', 0.8955223880597014),
               ('Precision', 0.9523809523809523),
               ('AUC', 0.9835483489170316),
               ('MCC Binary', 0.8425009463611858),
               ('# Training', 379),
               ('# Testing', 190)]),
   'score': 0.3976961654004939,
   'binary_classification_threshold': 0.5},
  {'all_objective_scores': OrderedDict([('Log Loss Binary',
                0.39058702666377215),
               ('Accuracy Binary', 0.9631578947368421),
               ('Balanced Accuracy Binary', 0.9535447982009706),
               ('F1', 0.948905109489051),
               ('Precision', 0.9848484848484849),
               ('AUC', 0.9958574979287491),
               ('MCC Binary', 0.9216584956231404),
               ('# Training', 379),
               ('# Testing', 190)]),
   'score': 0.39058702666377215,
   'binary_classification_threshold': 0.5},
  {'all_objective_scores': OrderedDict([('Log Loss Binary',
                0.38201906598006447),
               ('Accuracy Binary', 0.9629629629629629),
               ('Balanced Accuracy Binary', 0.9647058823529412),
```

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```
                ('F1', 0.9510489510489512),
                ('Precision', 0.9315068493150684),
                ('AUC', 0.9885954381752702),
                ('MCC Binary', 0.9218075091290715),
                ('# Training', 380),
                ('# Testing', 189)]),
   'score': 0.38201906598006447,
   'binary_classification_threshold': 0.5}]},
 2: {'id': 2,
  'pipeline_name': 'XGBoost Classifier w/ Imputer',
  'pipeline_class': evalml.pipelines.utils.make_pipeline.<locals>.GeneratedPipeline,
  'pipeline_summary': 'XGBoost Classifier w/ Imputer',
  'parameters': {'Imputer': {'categorical_impute_strategy': 'most_frequent',
    'numeric_impute_strategy': 'mean',
    'fill_value': None},
   'XGBoost Classifier': {'eta': 0.1,
    'max_depth': 6,
    'min_child_weight': 1,
    'n_estimators': 100}},
  'score': 0.10096524696588778,
  'high_variance_cv': True,
  'training_time': 0.319899320602417,
  'cv_data': [{'all_objective_scores': OrderedDict([('Log Loss Binary',
                 0.11449877552314368),
                ('Accuracy Binary', 0.9578947368421052),
                ('Balanced Accuracy Binary', 0.9521836903775595),
                ('F1', 0.9428571428571428),
                ('Precision', 0.9565217391304348),
                ('AUC', 0.9915966386554622),
                ('MCC Binary', 0.9097672817424011),
                ('# Training', 379),
                ('# Testing', 190)]),
    'score': 0.11449877552314368,
    'binary_classification_threshold': 0.5},
   {'all_objective_scores': OrderedDict([('Log Loss Binary',
                 0.07421586432028562),
                ('Accuracy Binary', 0.9736842105263158),
                ('Balanced Accuracy Binary', 0.9676293052432241),
                ('F1', 0.9640287769784172),
                ('Precision', 0.9852941176470589),
                ('AUC', 0.9959758551307847),
                ('MCC Binary', 0.943843520216036),
                ('# Training', 379),
                ('# Testing', 190)]),
    'score': 0.07421586432028562,
    'binary_classification_threshold': 0.5},
   {'all_objective_scores': OrderedDict([('Log Loss Binary',
                 0.11418110105423404),
                ('Accuracy Binary', 0.9576719576719577),
                ('Balanced Accuracy Binary', 0.9605042016806722),
                ('F1', 0.9444444444444445),
                ('Precision', 0.9189189189189189),
                ('AUC', 0.9885954381752701),
                ('MCC Binary', 0.9112159507396058),
                ('# Training', 380),
                ('# Testing', 189)]),
    'score': 0.11418110105423404,
```

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```
    'binary_classification_threshold': 0.5}]},
 3: {'id': 3,
  'pipeline_name': 'Random Forest Classifier w/ Imputer',
  'pipeline_class': evalml.pipelines.utils.make_pipeline.<locals>.GeneratedPipeline,
  'pipeline_summary': 'Random Forest Classifier w/ Imputer',
  'parameters': {'Imputer': {'categorical_impute_strategy': 'most_frequent',
    'numeric_impute_strategy': 'mean',
    'fill_value': None},
   'Random Forest Classifier': {'n_estimators': 100,
    'max_depth': 6,
    'n_jobs': -1}},
  'score': 0.12253681387225622,
  'high_variance_cv': False,
  'training_time': 1.412430763244629,
  'cv_data': [{'all_objective_scores': OrderedDict([('Log Loss Binary',
                 0.13984688783161606),
                ('Accuracy Binary', 0.9421052631578948),
                ('Balanced Accuracy Binary', 0.9338975026630371),
                ('F1', 0.920863309352518),
                ('Precision', 0.9411764705882353),
                ('AUC', 0.9893478518167831),
                ('MCC Binary', 0.8757606542930872),
                ('# Training', 379),
                ('# Testing', 190)]),
    'score': 0.13984688783161606,
    'binary_classification_threshold': 0.5},
   {'all_objective_scores': OrderedDict([('Log Loss Binary',
                 0.12010721015394288),
                ('Accuracy Binary', 0.9631578947368421),
                ('Balanced Accuracy Binary', 0.9563853710498283),
                ('F1', 0.9496402877697842),
                ('Precision', 0.9705882352941176),
                ('AUC', 0.9893478518167831),
                ('MCC Binary', 0.9211492315750531),
                ('# Training', 379),
                ('# Testing', 190)]),
    'score': 0.12010721015394288,
    'binary_classification_threshold': 0.5},
   {'all_objective_scores': OrderedDict([('Log Loss Binary',
                 0.10765634363120972),
                ('Accuracy Binary', 0.9735449735449735),
                ('Balanced Accuracy Binary', 0.973109243697479),
                ('F1', 0.9645390070921985),
                ('Precision', 0.9577464788732394),
                ('AUC', 0.9927971188475391),
                ('MCC Binary', 0.9435040132749904),
                ('# Training', 380),
                ('# Testing', 189)]),
    'score': 0.10765634363120972,
    'binary_classification_threshold': 0.5}]},
 4: {'id': 4,
  'pipeline_name': 'Logistic Regression Classifier w/ Imputer + Standard Scaler',
  'pipeline_class': evalml.pipelines.utils.make_pipeline.<locals>.GeneratedPipeline,
  'pipeline_summary': 'Logistic Regression Classifier w/ Imputer + Standard Scaler',
  'parameters': {'Imputer': {'categorical_impute_strategy': 'most_frequent',
    'numeric_impute_strategy': 'mean',
    'fill_value': None},
```

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```
    'Logistic Regression Classifier': {'penalty': 'l2',
     'C': 1.0,
     'n_jobs': -1}},
   'score': 0.09116380517655302,
   'high_variance_cv': False,
   'training_time': 1.0162370204925537,
   'cv_data': [{'all_objective_scores': OrderedDict([('Log Loss Binary',
                  0.09347817517438466),
                 ('Accuracy Binary', 0.9789473684210527),
                 ('Balanced Accuracy Binary', 0.9775121316132087),
                 ('F1', 0.971830985915493),
                 ('Precision', 0.971830985915493),
                 ('AUC', 0.9936087110900698),
                 ('MCC Binary', 0.9550242632264173),
                 ('# Training', 379),
                 ('# Testing', 190)]),
     'score': 0.09347817517438466,
     'binary_classification_threshold': 0.5},
    {'all_objective_scores': OrderedDict([('Log Loss Binary',
                  0.08320464479579016),
                 ('Accuracy Binary', 0.9736842105263158),
                 ('Balanced Accuracy Binary', 0.9647887323943662),
                 ('F1', 0.9635036496350364),
                 ('Precision', 1.0),
                 ('AUC', 0.9975144987572494),
                 ('MCC Binary', 0.9445075449666159),
                 ('# Training', 379),
                 ('# Testing', 190)]),
     'score': 0.08320464479579016,
     'binary_classification_threshold': 0.5},
    {'all_objective_scores': OrderedDict([('Log Loss Binary',
                  0.09680859555948422),
                 ('Accuracy Binary', 0.9735449735449735),
                 ('Balanced Accuracy Binary', 0.9760504201680673),
                 ('F1', 0.9650349650349651),
                 ('Precision', 0.9452054794520548),
                 ('AUC', 0.9906362545018007),
                 ('MCC Binary', 0.9443109474170326),
                 ('# Training', 380),
                 ('# Testing', 189)]),
     'score': 0.09680859555948422,
     'binary_classification_threshold': 0.5}]}},
  'search_order': [0, 1, 2, 3, 4]}
```


## 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_objectives` method to get a list of which objectives are included with EvalML for each problem type:

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

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

```
2020-08-03 19:10:21,910 featuretools - WARNING    Featuretools failed to load plugin␣
↪nlp_primitives from library nlp_primitives. For a full stack trace, set logging to␣
↪debug.
Accuracy Binary
Balanced Accuracy Binary
F1
Precision
AUC
Log Loss Binary
MCC Binary
```

```
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.12.0/
↪lib/python3.7/site-packages/evalml/pipelines/components/transformers/preprocessing/
↪text_featurizer.py:31: RuntimeWarning: No text columns were given to TextFeaturizer,
↪ component will have no effect
  warnings.warn("No text columns were given to TextFeaturizer, component will have no␣
↪effect", RuntimeWarning)
```

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

### 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.

### Example: Fraud Detection

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

[2]:
```
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

    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:
```

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```
                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)

        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
```

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```
        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)
```

```
2020-08-03 19:09:31,854 featuretools - WARNING    Featuretools failed to load plugin␣
↪nlp_primitives from library nlp_primitives. For a full stack trace, set logging to␣
↪debug.
```

```
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.12.0/
↪lib/python3.7/site-packages/evalml/pipelines/components/transformers/preprocessing/
↪text_featurizer.py:31: RuntimeWarning: No text columns were given to TextFeaturizer,
↪ component will have no effect
  warnings.warn("No text columns were given to TextFeaturizer, component will have no␣
↪effect", RuntimeWarning)
```

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

[2]:
```
imp = SimpleImputer(impute_strategy="mean")
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: Text Featurization Component
Transformer: Drop Null Columns Transformer
Transformer: DateTime Featurization Component
Transformer: Select Columns Transformer
Transformer: Drop Columns Transformer
Transformer: Standard Scaler
Transformer: Imputer
Transformer: Per Column Imputer
Transformer: Simple Imputer
Transformer: RF Regressor Select From Model
Transformer: RF Classifier Select From Model
Transformer: One Hot Encoder
```

### 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:
```

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```
    if issubclass(component, Estimator):
        print(f"Estimator: {component.name}")
```

```
Estimator: Baseline Regressor
Estimator: Extra Trees Regressor
Estimator: XGBoost Regressor
Estimator: CatBoost Regressor
Estimator: Random Forest Regressor
Estimator: Linear Regressor
Estimator: Elastic Net Regressor
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]:
```
import pandas as pd
from evalml.pipelines.components import Transformer

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_state=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.
                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)
```

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

    def fit(self, X, y=None):
        pct_null_threshold = self.parameters["pct_null_threshold"]
        if not isinstance(X, pd.DataFrame):
            X = pd.DataFrame(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
        """

        if not isinstance(X, pd.DataFrame):
            X = pd.DataFrame(X)
        return X.drop(columns=self._cols_to_drop, axis=1)
```

### Required fields

For a transformer you must provide a class attribute `name` indicating a human-readable name.

### 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_state` 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.
- `transform()` - after fitting a component, the `transform()` method will take in new data and transform accordingly. 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]

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

        Arguments:
            strategy (str): method used to predict. Valid options are "mean", "median
↪". Defaults to "mean".
            random_state (int, np.random.RandomState): seed for the random number␣
↪generator

        """
        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_state=random_state)

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

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

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

    @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.array (float): an array of zeroes

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

### Required fields

- `name` indicating 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

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:
 ['random_forest', 'xgboost', 'linear_model', 'catboost', 'extra_trees', 'baseline', 'none']
Problem Types:
 ['binary', 'multiclass', 'regression']
```

### 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_state` 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_state=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_state=random_state)

    @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.

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.

[10]:
```
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."""
```

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```
    name = "Linear Regressor"
    hyperparameter_ranges = {
        'fit_intercept': [True, False],
        'normalize': [True, False]
    }
    model_family = ModelFamily.LINEAR_MODEL
    supported_problem_types = [ProblemTypes.REGRESSION]

    def __init__(self, fit_intercept=True, normalize=False, n_jobs=-1, random_state=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_state=random_state)

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

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

Each component and pipeline class 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 Class Definition

Pipeline definitions must inherit from the proper pipeline base class, `RegressionPipeline`, `BinaryClassificationPipeline` or `MulticlassClassificationPipeline`. They must also include a `component_graph` list as a class variable containing the sequence of components to be fit and evaluated. Each component in the graph can be provided as either a string name or as a reference to the component class.

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

class CustomMulticlassClassificationPipeline(MulticlassClassificationPipeline):
    component_graph = ['Simple Imputer', 'Random Forest Classifier']
```

```
2020-08-03 19:10:26,106 featuretools - WARNING    Featuretools failed to load plugin␣
↪nlp_primitives from library nlp_primitives. For a full stack trace, set logging to␣
↪debug.
```

```
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.12.0/
↪lib/python3.7/site-packages/evalml/pipelines/components/transformers/preprocessing/
↪text_featurizer.py:31: RuntimeWarning: No text columns were given to TextFeaturizer,
↪ component will have no effect
  warnings.warn("No text columns were given to TextFeaturizer, component will have no␣
↪effect", RuntimeWarning)
```

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

[2]:
```
from evalml.pipelines.components import Transformer

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

    def __init__(self, parameter_1, random_state):
        transformer = ThirdPartyTransformer(parameter_1)
        parameters = {"parameter_1": parameter_1}
        super().__init__(parameters=parameters,
                         component_obj=transformer,
                         random_state=random_state)

class␣
↪CustomComponentMulticlassClassificationPipeline(MulticlassClassificationPipeline):
    component_graph = [NewTransformer, 'Random Forest Classifier']
```

### 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.

[3]:
```
from evalml.demos import load_wine
X, y = load_wine()

pipeline = CustomMulticlassClassificationPipeline({})
pipeline.fit(X, y)
print(pipeline.predict(X))
print(pipeline.score(X, y, objectives=['log_loss_multi']))
```

```
0      class_0
1      class_0
2      class_0
```

(continues on next page)

(continued from previous page)

```
3      class_0
4      class_0
        ...
173    class_2
174    class_2
175    class_2
176    class_2
177    class_2
Length: 178, dtype: object
OrderedDict([('Log Loss Multiclass', 0.04132737017536148)])
```

### 4.4.3 Custom Name

By default, a pipeline class's name property is the result of adding spaces between each Pascal case capitalization in the class name. E.g. `LogisticRegressionPipeline.name` will return 'Logistic Regression Pipeline'. Therefore, we suggest custom pipelines use Pascal case for their class names.

If you'd like to override the pipeline classes name attribute so it isn't derived from the class name, you can set the custom_name attribute, like so:

[4]:
```
from evalml.pipelines import MulticlassClassificationPipeline

class CustomPipeline(MulticlassClassificationPipeline):
    component_graph = ['Simple Imputer', 'One Hot Encoder', 'Logistic Regression␣
↪Classifier']
    custom_name = 'A custom pipeline name'

print(CustomPipeline.name)
```

```
A custom pipeline name
```

### 4.4.4 Override Component Hyperparameter Ranges

To specify custom hyperparameter ranges, set the `custom_hyperparameters` property to be a dictionary where each key-value pair consists of a parameter name and range. AutoML will use this dictionary to override the hyperparameter ranges collected from each component in the component graph.

[5]:
```
class CustomPipeline(MulticlassClassificationPipeline):
    component_graph = ['Simple Imputer', 'One Hot Encoder', 'Standard Scaler',
↪'Logistic Regression Classifier']

print("Without custom hyperparameters:")
print(CustomPipeline.hyperparameters)

class CustomPipeline(MulticlassClassificationPipeline):
        component_graph = ['Simple Imputer', 'One Hot Encoder', 'Standard Scaler',
↪'Logistic Regression Classifier']
        custom_hyperparameters = {
        'Simple Imputer' : {
            'impute_strategy': ['most_frequent']
        }
    }

print()
```

(continues on next page)

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```
print("With custom hyperparameters:")
print(CustomPipeline.hyperparameters)
```

```
Without custom hyperparameters:
{'Simple Imputer': {'impute_strategy': ['mean', 'median', 'most_frequent']}, 'One Hot␣
↪Encoder': {}, 'Standard Scaler': {}, 'Logistic Regression Classifier': {'penalty':␣
↪['l2'], 'C': Real(low=0.01, high=10, prior='uniform', transform='identity')}}

With custom hyperparameters:
{'Simple Imputer': {'impute_strategy': ['most_frequent']}, 'One Hot Encoder': {},␣
↪'Standard Scaler': {}, 'Logistic Regression Classifier': {'penalty': ['l2'], 'C':␣
↪Real(low=0.01, high=10, prior='uniform', transform='identity')}}
```

To initialize our new custom pipeline class, we must pass in a `parameters` argument. If we want to use the defaults for each component, we can simply pass in an empty dictionary.

[6]:
```
CustomPipeline(parameters={})
```

[6]:
```
<__main__.CustomPipeline at 0x7fbbb7472d68>
```

### 4.4.5 Pipeline Parameters

You can also pass in custom parameters. The parameters dictionary needs to be in the format of a two-layered dictionary where the first key-value pair is the component name and component parameters dictionary. The component parameters dictionary consists of a key value pair of parameter name and parameter values. An example will be shown below and component parameters can be found *here*.

[7]:
```
parameters = {
        'Simple Imputer': {
            'impute_strategy': 'mean'
        },
        'Logistic Regression Classifier': {
            'penalty': 'l2',
            'C': 1.0,
        }
    }

cp = CustomPipeline(parameters=parameters, random_state=5)
```

### 4.4.6 Pipeline Description

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

[8]:
```
cp.graph()
```

[8]:

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

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

```
********************
* Custom Pipeline *
```

(continues on next page)

(continued from previous page)

```
********************

Problem Type: Multiclass Classification
Model Family: Linear

Pipeline Steps
==============
1. Simple Imputer
         * impute_strategy : mean
         * fill_value : None
2. One Hot Encoder
         * top_n : 10
         * categories : None
         * drop : None
         * handle_unknown : ignore
         * handle_missing : error
3. Standard Scaler
4. Logistic Regression Classifier
         * penalty : l2
         * C : 1.0
         * n_jobs : -1
```

## 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.

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

[1]:
```
import evalml

class RFBinaryClassificationPipeline(evalml.pipelines.BinaryClassificationPipeline):
    component_graph = ['Simple Imputer', 'Random Forest Classifier']

X, y = evalml.demos.load_breast_cancer()

pipeline = RFBinaryClassificationPipeline({})
pipeline.fit(X, y)
print(pipeline.score(X, y, objectives=['log_loss_binary']))
```

```
2020-08-03 19:09:43,140 featuretools - WARNING    Featuretools failed to load plugin␣
↪nlp_primitives from library nlp_primitives. For a full stack trace, set logging to␣
↪debug.
```

```
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.12.0/
↪lib/python3.7/site-packages/evalml/pipelines/components/transformers/preprocessing/
↪text_featurizer.py:31: RuntimeWarning: No text columns were given to TextFeaturizer,
↪ component will have no effect
  warnings.warn("No text columns were given to TextFeaturizer, component will have no␣
↪effect", RuntimeWarning)
```

```
OrderedDict([('Log Loss Binary', 0.038403828027876195)])
```

### 4.5.1 Feature Importance

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

[2]:
```
pipeline.feature_importance
```

[2]:

| | feature | importance |
|---|---|---|
| 0 | worst perimeter | 0.176488 |
| 1 | worst concave points | 0.125260 |
| 2 | worst radius | 0.124161 |
| 3 | mean concave points | 0.086443 |
| 4 | worst area | 0.072465 |
| 5 | mean concavity | 0.072320 |
| 6 | mean perimeter | 0.056685 |
| 7 | mean area | 0.049599 |
| 8 | area error | 0.037229 |
| 9 | worst concavity | 0.028181 |
| 10 | mean radius | 0.023294 |
| 11 | radius error | 0.019457 |
| 12 | worst texture | 0.014990 |
| 13 | perimeter error | 0.014103 |
| 14 | mean texture | 0.013618 |
| 15 | worst compactness | 0.011310 |
| 16 | worst smoothness | 0.011139 |
| 17 | worst fractal dimension | 0.008118 |
| 18 | worst symmetry | 0.007818 |
| 19 | mean smoothness | 0.006152 |
| 20 | concave points error | 0.005887 |
| 21 | fractal dimension error | 0.005059 |
| 22 | concavity error | 0.004510 |
| 23 | smoothness error | 0.004493 |
| 24 | texture error | 0.004476 |
| 25 | mean compactness | 0.004050 |
| 26 | compactness error | 0.003559 |
| 27 | mean symmetry | 0.003243 |
| 28 | symmetry error | 0.003124 |
| 29 | mean fractal dimension | 0.002768 |

We can also create a bar plot of the feature importances

[3]:
```
pipeline.graph_feature_importance()
```

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

### 4.5.2 Permutation Importance

We can also compute and plot the permutation importance of the pipeline.

[4]:
```
evalml.pipelines.calculate_permutation_importance(pipeline, X, y, 'log_loss_binary')
```

[4]:
```
                    feature  importance
0            worst perimeter    0.078033
1               worst radius    0.074341
2       worst concave points    0.068313
3                 worst area    0.067733
4        mean concave points    0.041261
5            worst concavity    0.037533
6             mean concavity    0.036664
7                 area error    0.035838
8             mean perimeter    0.025783
9                  mean area    0.025203
10            worst texture    0.016211
11          perimeter error    0.011738
12             mean texture    0.011716
13             radius error    0.010910
14              mean radius    0.010775
15        worst compactness    0.008322
16         worst smoothness    0.008281
17          mean smoothness    0.005707
18           worst symmetry    0.004454
19  worst fractal dimension    0.003889
20          concavity error    0.003858
21        compactness error    0.003572
22     concave points error    0.003449
23          mean compactness    0.003173
24         smoothness error    0.003172
25  fractal dimension error    0.002618
26            texture error    0.002533
27   mean fractal dimension    0.002228
28           symmetry error    0.002126
29            mean symmetry    0.001786
```

[5]:
```
evalml.pipelines.graph_permutation_importance(pipeline, X, y, 'log_loss_binary')
```

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

### 4.5.3 Confusion Matrix

For binary or multiclass classification, we can view a confusion matrix of the classifier's predictions

[6]:
```
y_pred = pipeline.predict(X)
evalml.pipelines.graph_utils.graph_confusion_matrix(y, y_pred)
```

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

### 4.5.4 Precision-Recall Curve

For binary classification, we can view the precision-recall curve of the pipeline.

[7]:
```
# get the predicted probabilities associated with the "true" label
y = y.map({'malignant': 0, 'benign': 1})
y_pred_proba = pipeline.predict_proba(X)["benign"]
evalml.pipelines.graph_utils.graph_precision_recall_curve(y, y_pred_proba)
```

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

### 4.5.5 ROC Curve

For binary and multiclass classification, we can view the Receiver Operating Characteristic (ROC) curve of the pipeline.

[8]:
```
# get the predicted probabilities associated with the "benign" label
y_pred_proba = pipeline.predict_proba(X)["benign"]
evalml.pipelines.graph_utils.graph_roc_curve(y, y_pred_proba)
```

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

### 4.5.6 Explaining Individual Predictions

We can explain why the model made an individual prediction with the `explain_prediction` function. This will use the Shapley Additive Explanations (SHAP) algorithms 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 (must correspond to one row of the input data) and the training data. 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%.

[9]:
```
from evalml.pipelines.prediction_explanations import explain_prediction

table = explain_prediction(pipeline=pipeline, input_features=X.iloc[3:4],
                           training_data=X, include_shap_values=True)
print(table)
```

```
Positive Label

    Feature Name       Contribution to Prediction   SHAP Value
============================================================
worst concave points               ++                  0.200
mean concave points                +                   0.110
   mean concavity                  +                   0.080
     worst area                    -                   -0.030
  worst perimeter                  -                   -0.050
    worst radius                   -                   -0.050
```

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.

This functionality is currently **not supported** for **XGBoost** models or **CatBoost multiclass** classifiers.

## 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 such as abnormal and missing data 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 the `HighlyNullDataCheck()` data check, 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_threshold=0.8)

for message in null_check.validate(X):
    print (message.message)
```

```
2020-08-03 19:09:37,372 featuretools - WARNING    Featuretools failed to load plugin␣
↪nlp_primitives from library nlp_primitives. For a full stack trace, set logging to␣
↪debug.
Column '2' is 80.0% or more null
```

```
/home/docs/checkouts/readthedocs.org/user_builds/feature-labs-inc-evalml/envs/v0.12.0/
↪lib/python3.7/site-packages/evalml/pipelines/components/transformers/preprocessing/
↪text_featurizer.py:31: RuntimeWarning: No text columns were given to TextFeaturizer,
↪ component will have no effect
  warnings.warn("No text columns were given to TextFeaturizer, component will have no␣
↪effect", RuntimeWarning)
```

### 4.6.2 Abnormal Data

EvalML provides two data checks to check for abnormal data: `OutliersDataCheck()` and `IDColumnsDataCheck()`.

#### 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.

[2]:
```
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)

for message in id_col_check.validate(X):
    print (message.message)
```

```
Column 'id' is 90.0% or more likely to be an ID column
Column 'user_number' is 90.0% or more likely to be an ID column
```

### 4.6.3 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 Isolation Forests to notify you if a sample can be considered an outlier.

Below we generate a random dataset with some outliers.

[3]:
```
data = np.random.randn(100, 100)
X = pd.DataFrame(data=data)

# generate some outliers in rows 3, 25, 55, and 72
X.iloc[3, :] = pd.Series(np.random.randn(100) * 10)
X.iloc[25, :] = pd.Series(np.random.randn(100) * 20)
X.iloc[55, :] = pd.Series(np.random.randn(100) * 100)
X.iloc[72, :] = pd.Series(np.random.randn(100) * 100)
```

We then utilize `OutliersDataCheck()` to rediscover these outliers.

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

outliers_check = OutliersDataCheck()

for message in outliers_check.validate(X):
    print (message.message)
```

```
Row '3' is likely to have outlier data
Row '25' is likely to have outlier data
Row '44' is likely to have outlier data
Row '55' is likely to have outlier data
Row '72' is likely to have outlier data
```

### 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`.

[5]:
```
from evalml.data_checks import DataCheck
from evalml.data_checks.data_check_message import DataCheckError

class ZeroVarianceDataCheck(DataCheck):
    def validate(self, X, y):
        if not isinstance(X, pd.DataFrame):
            X = pd.DataFrame(X)
        warning_msg = "Column '{}' has zero variance"
        return [DataCheckError(warning_msg.format(column), self.name) for column in X.
↪columns if len(X[column].unique()) == 1]
```

## 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.

## 4.8 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*.

### 4.8.3 Q: How does EvalML handle categorical encoding?

EvalML provides a *one-hot-encoding component* 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*.

### 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_fraud* | Load credit card fraud dataset. |
| *load_wine* | Load wine dataset. |
| *load_breast_cancer* | Load breast cancer dataset. |
| *load_diabetes* | Load diabetes dataset. |

### 5.1.1 evalml.demos.load_fraud

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, y

**Return type** pd.DataFrame, pd.Series

### 5.1.2 evalml.demos.load_wine

evalml.demos.**load_wine**()

Load wine dataset. Multiclass problem

**Returns** X, y

**Return type** pd.DataFrame, pd.Series

### 5.1.3 evalml.demos.load_breast_cancer

evalml.demos.**load_breast_cancer**()

Load breast cancer dataset. Multiclass problem

**Returns** X, y

**Return type** pd.DataFrame, pd.Series

### 5.1.4 evalml.demos.load_diabetes

evalml.demos.**load_diabetes**()

Load diabetes dataset. Regression problem

**Returns** X, y

**Return type** pd.DataFrame, pd.Series

## 5.2 Preprocessing

Utilities to preprocess data before using evalml.

| | |
|---|---|
| *drop_nan_target_rows* | Drops rows in X and y when row in the target y has a value of NaN. |
| *label_distribution* | Get the label distributions. |
| *load_data* | Load features and labels from file. |
| *number_of_features* | Get the number of features for specific dtypes. |
| *split_data* | Splits data into train and test sets. |

### 5.2.1 evalml.preprocessing.drop_nan_target_rows

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*) – Data to transform
- **y** (*pd.Series*) – Target values

**Returns** Transformed X (and y, if passed in) with rows that had a NaN value removed.

**Return type** pd.DataFrame

### 5.2.2 evalml.preprocessing.label_distribution

evalml.preprocessing.**label_distribution**(*labels*)

Get the label distributions.

**Parameters** **labels** (*pd.Series*) – Label values

**Returns** Label values and their frequency distribution as percentages.

**Return type** pd.Series

### 5.2.3 evalml.preprocessing.load_data

evalml.preprocessing.**load_data**(*path*, *index*, *label*, *n_rows=None*, *drop=None*, *verbose=True*, ***kwargs*)

Load features and labels from file.

**Parameters**

- **path** (*str*) – Path to file or a http/ftp/s3 URL

- **index** (*str*) – Column for index
- **label** (*str*) – Column for labels
- **n_rows** (*int*) – Number of rows to return
- **drop** (*list*) – List of columns to drop
- **verbose** (*bool*) – If True, prints information about features and labels

**Returns** features and labels

**Return type** pd.DataFrame, pd.Series

### 5.2.4 evalml.preprocessing.number_of_features

evalml.preprocessing.**number_of_features**(*dtypes*)

Get the number of features for specific dtypes.

**Parameters** **dtypes** (*pd.Series*) – dtypes to get the number of features for

**Returns** dtypes and the number of features for each input type

**Return type** pd.Series

### 5.2.5 evalml.preprocessing.split_data

evalml.preprocessing.**split_data**(*X*, *y*, *regression=False*, *test_size=0.2*, *random_state=None*)

Splits data into train and test sets.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]
- **y** (*pd.Series*) – labels of length [n_samples]
- **regression** (*bool*) – if true, do not use stratified split
- **test_size** (*float*) – percent of train set to holdout for testing
- **random_state** (*int, np.random.RandomState*) – seed for the random number generator

**Returns** features and labels each split into train and test sets

**Return type** pd.DataFrame, pd.DataFrame, pd.Series, pd.Series

## 5.3 AutoML

### 5.3.1 AutoML Search Classes

| | |
|---|---|
| *AutoMLSearch* | Automated Pipeline search. |

### evalml.automl.AutoMLSearch

# evalml.automl.automl_search.AutoMLSearch

**class** evalml.automl.**AutoMLSearch**(*problem_type=None*, *objective='auto'*, *max_pipelines=None*, *max_time=None*, *patience=None*, *tolerance=None*, *data_split=None*, *allowed_pipelines=None*, *allowed_model_families=None*, *start_iteration_callback=None*, *add_result_callback=None*, *additional_objectives=None*, *random_state=0*, *n_jobs=-1*, *tuner_class=None*, *verbose=True*, *optimize_thresholds=False*)

Automated Pipeline search.

#### Methods

| | |
|---|---|
| *__init__* | Automated pipeline search |
| *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. |
| *describe_pipeline* | Describe a pipeline |
| *get_pipeline* | 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. |
| *load* | Loads AutoML object at file path |
| *save* | Saves AutoML object at file path |
| *search* | Find the best pipeline for the data set. |

#### evalml.automl.AutoMLSearch.__init__

AutoMLSearch.**__init__**(*problem_type=None*, *objective='auto'*, *max_pipelines=None*, *max_time=None*, *patience=None*, *tolerance=None*, *data_split=None*, *allowed_pipelines=None*, *allowed_model_families=None*, *start_iteration_callback=None*, *add_result_callback=None*, *additional_objectives=None*, *random_state=0*, *n_jobs=-1*, *tuner_class=None*, *verbose=True*, *optimize_thresholds=False*)

Automated pipeline search

**Parameters**

- **problem_type** (*str or ProblemTypes*) – Choice of 'regression', 'binary', or 'multiclass', depending on the desired problem type.
- **objective** (*str, ObjectiveBase*) – The objective to optimize for. When set to auto, chooses: LogLossBinary for binary classification problems, LogLossMulticlass for multiclass classification problems, and R2 for regression problems.
- **max_pipelines** (*int*) – Maximum number of pipelines to search. If max_pipelines and max_time is not set, then max_pipelines will default to max_pipelines 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_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. Setting this field will cause allowed_model_families to be ignored.
- **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_split** (*sklearn.model_selection.BaseCrossValidator*) – data splitting method to use. Defaults to StratifiedKFold.
- **tuner_class** – the tuner class to use. Defaults to scikit-optimize tuner
- **start_iteration_callback** (*callable*) – function called before each pipeline training iteration. Passed two parameters: pipeline_class, parameters.
- **add_result_callback** (*callable*) – function called after each pipeline training iteration. Passed two parameters: results, trained_pipeline.
- **additional_objectives** (*list*) – Custom set of objectives to score on. Will override default objectives for problem type if not empty.
- **random_state** (*int, np.random.RandomState*) – The random seed/state. 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.
- **verbose** (*boolean*) – If True, turn verbosity on. Defaults to True

### evalml.automl.AutoMLSearch.add_to_rankings

AutoMLSearch.**add_to_rankings**(*pipeline*, *X*, *y*)

Fits and evaluates a given pipeline then adds the results to the automl rankings with the requirement that automl search has been run. Please use the same data as previous runs of automl search. If pipeline already exists in rankings this method will return *None*.

**Parameters**

- **pipeline** (PipelineBase) – pipeline to train and evaluate.
- **X** (*pd.DataFrame*) – the input training data of shape [n_samples, n_features].
- **y** (*pd.Series*) – the target training labels of length [n_samples].

### evalml.automl.AutoMLSearch.describe_pipeline

AutoMLSearch.**describe_pipeline**(*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.

### evalml.automl.AutoMLSearch.get_pipeline

AutoMLSearch.**get_pipeline**(*pipeline_id*, *random_state=0*)

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
- **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

**Returns** untrained pipeline instance associated with the provided ID

**Return type** *PipelineBase*

### evalml.automl.AutoMLSearch.load

**static** AutoMLSearch.**load**(*file_path*)

Loads AutoML object at file path

**Parameters** **file_path** (*str*) – location to find file to load

**Returns** AutoSearchBase object

### evalml.automl.AutoMLSearch.save

AutoMLSearch.**save**(*file_path*)

Saves AutoML object at file path

**Parameters** **file_path** (*str*) – location to save file

**Returns** None

#### evalml.automl.AutoMLSearch.search

AutoMLSearch.**search**(*X*, *y*, *data_checks='auto'*, *feature_types=None*, *show_iteration_plot=True*)

Find the best pipeline for the data set.

**Parameters**

- **X** (*pd.DataFrame*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target training labels of length [n_samples]
- **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.
- **data_checks** (DataChecks, *list(Datacheck), str, None*) – A collection of data checks to run before automl search. If data checks produce any errors, an exception will be thrown before the search begins. If "disabled" or None, no data checks will be done. If set to "auto", DefaultDataChecks will be done. Default value is set to "auto".

**Returns** self

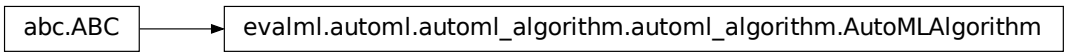
#### Attributes

| | |
|---|---|
| best_pipeline | Returns an untrained instance of the best pipeline and parameters found during automl search. |
| data_check_results | |
| full_rankings | Returns a pandas.DataFrame with scoring results from all pipelines searched |
| has_searched | Returns *True* if search has been ran and *False* if not |
| 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*. |

### 5.3.2 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. |

### evalml.automl.automl_algorithm.AutoMLAlgorithm




**class** evalml.automl.automl_algorithm.**AutoMLAlgorithm**(*allowed_pipelines=None*, *max_pipelines=None*, *tuner_class=None*, *random_state=0*)

Base class for the automl algorithms which power evalml.

#### Methods

| | |
|---|---|
| *__init__* | This class represents an automated machine learning (AutoML) algorithm. |
| *add_result* | Register results from evaluating a pipeline |
| *next_batch* | Get the next batch of pipelines to evaluate |

#### evalml.automl.automl_algorithm.AutoMLAlgorithm.__init__

AutoMLAlgorithm.**__init__**(*allowed_pipelines=None*, *max_pipelines=None*, *tuner_class=None*, *random_state=0*)

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.
- **max_pipelines** (*int*) – The maximum number of pipelines 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_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

#### evalml.automl.automl_algorithm.AutoMLAlgorithm.add_result

AutoMLAlgorithm.**add_result**(*score_to_minimize*, *pipeline*)

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.

#### evalml.automl.automl_algorithm.AutoMLAlgorithm.next_batch

AutoMLAlgorithm.**next_batch**()

Get the next batch of pipelines to evaluate

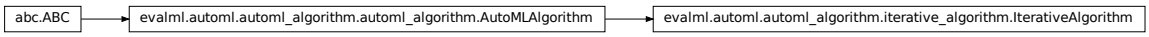
**Returns** a list of instances of PipelineBase subclasses, ready to be trained and evaluated.

**Return type** list(*PipelineBase*)

#### Attributes

| | |
|---|---|
| batch_number | Returns the number of batches which have been recommended so far. |
| pipeline_number | Returns the number of pipelines which have been recommended so far. |

### evalml.automl.automl_algorithm.IterativeAlgorithm




**class** evalml.automl.automl_algorithm.**IterativeAlgorithm**(*allowed_pipelines=None*, *max_pipelines=None*, *tuner_class=None*, *random_state=0*, *pipelines_per_batch=5*, *n_jobs=-1*, *number_features=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.

#### Methods

| | |
|---|---|
| *__init__* | 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. |
| *add_result* | Register results from evaluating a pipeline |
| *next_batch* | Get the next batch of pipelines to evaluate |

### evalml.automl.automl_algorithm.IterativeAlgorithm.__init__

IterativeAlgorithm.**__init__**(*allowed_pipelines=None*, *max_pipelines=None*, *tuner_class=None*, *random_state=0*, *pipelines_per_batch=5*, *n_jobs=-1*, *number_features=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 subclasses indicating the pipelines allowed in the search. The default of None indicates all pipelines for this problem type are allowed.
- **max_pipelines** (*int*) – The maximum number of pipelines 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_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.
- **pipelines_per_batch** (*int*) – the number of pipelines to be evaluated in each batch, after the first batch.
- **n_jobs** (*int or None*) – Non-negative integer describing level of parallelism used for pipelines.
- **number_features** (*int*) – The number of columns in the input features.

### evalml.automl.automl_algorithm.IterativeAlgorithm.add_result

IterativeAlgorithm.**add_result**(*score_to_minimize*, *pipeline*)

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.

### evalml.automl.automl_algorithm.IterativeAlgorithm.next_batch

IterativeAlgorithm.**next_batch**()

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*)

#### Attributes

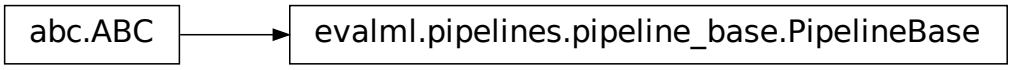
| | |
|---|---|
| batch_number | Returns the number of batches which have been recommended so far. |
| pipeline_number | Returns the number of pipelines which have been recommended so far. |

## 5.4 Pipelines

### 5.4.1 Pipeline Base Classes

| | |
|---|---|
| *PipelineBase* | Base class for all pipelines. |
| *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. |

#### evalml.pipelines.PipelineBase




**class** evalml.pipelines.**PipelineBase**(*parameters*, *random_state=0*)

Base class for all pipelines.

#### Methods

| | |
|---|---|
| *__init__* | Machine learning pipeline made out of transformers and a estimator. |
| *clone* | Constructs a new pipeline with the same parameters and components. |
| *describe* | Outputs pipeline details including component parameters |
| *fit* | Build a model |
| *get_component* | Returns component by name |
| *graph* | Generate an image representing the pipeline graph |

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| | |
|---|---|
| *graph_feature_importance* | Generate a bar graph of the pipeline's feature importance |
| *load* | Loads pipeline at file path |
| *predict* | Make predictions using selected features. |
| *save* | Saves pipeline at file path |
| *score* | Evaluate model performance on current and additional objectives |

### evalml.pipelines.PipelineBase.__init__

PipelineBase.**__init__**(*parameters*, *random_state=0*)

Machine learning pipeline made out of transformers and a estimator.

**Required Class Variables:** component_graph (list): List of components in order. Accepts strings or ComponentBase subclasses in the list

**Parameters**

- **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.
- **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

### evalml.pipelines.PipelineBase.clone

PipelineBase.**clone**(*random_state=0*)

Constructs a new pipeline with the same parameters and components.

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this pipeline with identical parameters and components

### evalml.pipelines.PipelineBase.describe

PipelineBase.**describe**()

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

### evalml.pipelines.PipelineBase.fit

PipelineBase.**fit**(*X*, *y*)

Build a model

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.PipelineBase.get_component

PipelineBase.**get_component**(*name*)

Returns component by name

**Parameters** **name** (*str*) – name of component

**Returns** component to return

**Return type** Component

### evalml.pipelines.PipelineBase.graph

PipelineBase.**graph**(*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

### evalml.pipelines.PipelineBase.graph_feature_importance

PipelineBase.**graph_feature_importance**(*show_all_features=False*)

Generate a bar graph of the pipeline's feature importance

**Parameters** **show_all_features** (*bool, optional*) – If true, graph features with an importance value of zero. Defaults to false.

**Returns** plotly.Figure, a bar graph showing features and their corresponding importance

### evalml.pipelines.PipelineBase.load

**static** PipelineBase.**load**(*file_path*)

Loads pipeline at file path

**Parameters** **file_path** (*str*) – location to load file

**Returns** PipelineBase object

### evalml.pipelines.PipelineBase.predict

PipelineBase.**predict**(*X*, *objective=None*)

Make predictions using selected features.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

### evalml.pipelines.PipelineBase.save

PipelineBase.**save**(*file_path*)

Saves pipeline at file path

**Parameters** **file_path** (*str*) – location to save file

**Returns** None

### evalml.pipelines.PipelineBase.score

PipelineBase.**score**(*X*, *y*, *objectives*)

Evaluate model performance on current and additional objectives

**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

## evalml.pipelines.ClassificationPipeline


**class** evalml.pipelines.**ClassificationPipeline**(*parameters*, *random_state=0*)

Pipeline subclass for all classification pipelines.

### Methods

| | |
|---|---|
| *__init__* | Machine learning classification pipeline made out of transformers and a classifier. |
| *clone* | Constructs a new pipeline with the same parameters and components. |
| *describe* | Outputs pipeline details including component parameters |

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Table 13 – continued from previous page

| | |
|---|---|
| *fit* | Build a classification model. For string and categorical targets, classes are sorted |
| *get_component* | Returns component by name |
| *graph* | Generate an image representing the pipeline graph |
| *graph_feature_importance* | Generate a bar graph of the pipeline's feature importance |
| *load* | Loads pipeline at file path |
| *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 |

### evalml.pipelines.ClassificationPipeline.__init__

ClassificationPipeline.**__init__**(*parameters*, *random_state=0*)

Machine learning classification pipeline made out of transformers and a classifier.

**Required Class Variables:** component_graph (list): List of components in order. Accepts strings or ComponentBase subclasses in the list

**Parameters**

- **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.
- **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

### evalml.pipelines.ClassificationPipeline.clone

ClassificationPipeline.**clone**(*random_state=0*)

Constructs a new pipeline with the same parameters and components.

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this pipeline with identical parameters and components

### evalml.pipelines.ClassificationPipeline.describe

ClassificationPipeline.**describe**()

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

### evalml.pipelines.ClassificationPipeline.fit

ClassificationPipeline.**fit**(*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.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.ClassificationPipeline.get_component

ClassificationPipeline.**get_component**(*name*)

Returns component by name

**Parameters** **name** (*str*) – name of component

**Returns** component to return

**Return type** Component

### evalml.pipelines.ClassificationPipeline.graph

ClassificationPipeline.**graph**(*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

### evalml.pipelines.ClassificationPipeline.graph_feature_importance

ClassificationPipeline.**graph_feature_importance**(*show_all_features=False*)

Generate a bar graph of the pipeline's feature importance

**Parameters** **show_all_features** (*bool, optional*) – If true, graph features with an importance value of zero. Defaults to false.

**Returns** plotly.Figure, a bar graph showing features and their corresponding importance

### evalml.pipelines.ClassificationPipeline.load

**static** ClassificationPipeline.**load**(*file_path*)

Loads pipeline at file path

**Parameters** **file_path** (*str*) – location to load file

**Returns** PipelineBase object

### evalml.pipelines.ClassificationPipeline.predict

ClassificationPipeline.**predict**(*X*, *objective=None*)
Make predictions using selected features.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

### evalml.pipelines.ClassificationPipeline.predict_proba

ClassificationPipeline.**predict_proba**(*X*)
Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]

**Returns** probability estimates

**Return type** pd.DataFrame

### evalml.pipelines.ClassificationPipeline.save

ClassificationPipeline.**save**(*file_path*)
Saves pipeline at file path

**Parameters** **file_path** (*str*) – location to save file

**Returns** None

### evalml.pipelines.ClassificationPipeline.score

ClassificationPipeline.**score**(*X*, *y*, *objectives*)
Evaluate model performance on objectives

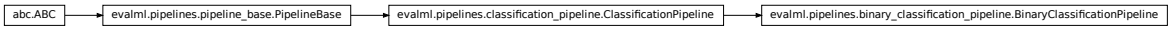
**Parameters**

- **X** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]
- **y** (*pd.Series*) – true labels of length [n_samples]
- **objectives** (*list*) – list of objectives to score

**Returns** ordered dictionary of objective scores

**Return type** dict

### evalml.pipelines.BinaryClassificationPipeline




**class** evalml.pipelines.**BinaryClassificationPipeline**(*parameters*, *random_state=0*)

Pipeline subclass for all binary classification pipelines.

#### Methods

| | |
|---|---|
| *__init__* | Machine learning classification pipeline made out of transformers and a classifier. |
| *clone* | Constructs a new pipeline with the same parameters and components. |
| *describe* | Outputs pipeline details including component parameters |
| *fit* | Build a classification model. For string and categorical targets, classes are sorted |
| *get_component* | Returns component by name |
| *graph* | Generate an image representing the pipeline graph |
| *graph_feature_importance* | Generate a bar graph of the pipeline's feature importance |
| *load* | Loads pipeline at file path |
| *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 |

#### evalml.pipelines.BinaryClassificationPipeline.__init__

BinaryClassificationPipeline.**__init__**(*parameters*, *random_state=0*)

Machine learning classification pipeline made out of transformers and a classifier.

**Required Class Variables:** component_graph (list): List of components in order. Accepts strings or ComponentBase subclasses in the list

**Parameters**

- **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.
- **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

#### evalml.pipelines.BinaryClassificationPipeline.clone

BinaryClassificationPipeline.**clone**(*random_state=0*)

Constructs a new pipeline with the same parameters and components.

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this pipeline with identical parameters and components

### evalml.pipelines.BinaryClassificationPipeline.describe

BinaryClassificationPipeline.**describe**()

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

### evalml.pipelines.BinaryClassificationPipeline.fit

BinaryClassificationPipeline.**fit**(*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.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.BinaryClassificationPipeline.get_component

BinaryClassificationPipeline.**get_component**(*name*)

Returns component by name

**Parameters** **name** (*str*) – name of component

**Returns** component to return

**Return type** Component

### evalml.pipelines.BinaryClassificationPipeline.graph

BinaryClassificationPipeline.**graph**(*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

### evalml.pipelines.BinaryClassificationPipeline.graph_feature_importance

BinaryClassificationPipeline.**graph_feature_importance**(*show_all_features=False*)
Generate a bar graph of the pipeline's feature importance

**Parameters** **show_all_features** (*bool, optional*) – If true, graph features with an importance value of zero. Defaults to false.

**Returns** plotly.Figure, a bar graph showing features and their corresponding importance

### evalml.pipelines.BinaryClassificationPipeline.load

**static** BinaryClassificationPipeline.**load**(*file_path*)
Loads pipeline at file path

**Parameters** **file_path** (*str*) – location to load file

**Returns** PipelineBase object

### evalml.pipelines.BinaryClassificationPipeline.predict

BinaryClassificationPipeline.**predict**(*X*, *objective=None*)
Make predictions using selected features.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

### evalml.pipelines.BinaryClassificationPipeline.predict_proba

BinaryClassificationPipeline.**predict_proba**(*X*)
Make probability estimates for labels. Assumes that the column at index 1 represents the positive label case.

**Parameters** **X** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]

**Returns** probability estimates

**Return type** pd.DataFrame

### evalml.pipelines.BinaryClassificationPipeline.save

BinaryClassificationPipeline.**save**(*file_path*)
Saves pipeline at file path

**Parameters** **file_path** (*str*) – location to save file

**Returns** None

### evalml.pipelines.BinaryClassificationPipeline.score

BinaryClassificationPipeline.**score**(*X*, *y*, *objectives*)

Evaluate model performance on objectives

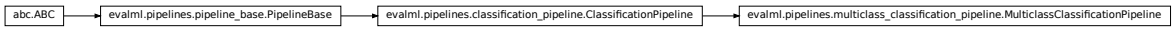
**Parameters**

- **X** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]
- **y** (*pd.Series*) – true labels of length [n_samples]
- **objectives** (*list*) – list of objectives to score

**Returns** ordered dictionary of objective scores

**Return type** dict

## evalml.pipelines.MulticlassClassificationPipeline




**class** evalml.pipelines.**MulticlassClassificationPipeline**(*parameters*, *random_state=0*)

Pipeline subclass for all multiclass classification pipelines.

### Methods

| | |
|---|---|
| *__init__* | Machine learning classification pipeline made out of transformers and a classifier. |
| *clone* | Constructs a new pipeline with the same parameters and components. |
| *describe* | Outputs pipeline details including component parameters |
| *fit* | Build a classification model. For string and categorical targets, classes are sorted |
| *get_component* | Returns component by name |
| *graph* | Generate an image representing the pipeline graph |
| *graph_feature_importance* | Generate a bar graph of the pipeline's feature importance |
| *load* | Loads pipeline at file path |
| *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 |

### evalml.pipelines.MulticlassClassificationPipeline.__init__

MulticlassClassificationPipeline.**__init__**(*parameters*, *random_state=0*)

Machine learning classification pipeline made out of transformers and a classifier.

**Required Class Variables:** component_graph (list): List of components in order. Accepts strings or

ComponentBase subclasses in the list

**Parameters**

- **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.
- **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

### evalml.pipelines.MulticlassClassificationPipeline.clone

MulticlassClassificationPipeline.**clone**(*random_state=0*)

Constructs a new pipeline with the same parameters and components.

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this pipeline with identical parameters and components

### evalml.pipelines.MulticlassClassificationPipeline.describe

MulticlassClassificationPipeline.**describe**()

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

### evalml.pipelines.MulticlassClassificationPipeline.fit

MulticlassClassificationPipeline.**fit**(*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.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.MulticlassClassificationPipeline.get_component

MulticlassClassificationPipeline.**get_component**(*name*)

Returns component by name

**Parameters** **name** (*str*) – name of component

**Returns** component to return

**Return type** Component

### evalml.pipelines.MulticlassClassificationPipeline.graph

`MulticlassClassificationPipeline.`**`graph`**(*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

### evalml.pipelines.MulticlassClassificationPipeline.graph_feature_importance

`MulticlassClassificationPipeline.`**`graph_feature_importance`**(*show_all_features=False*)

Generate a bar graph of the pipeline's feature importance

**Parameters** **`show_all_features`** (*`bool, optional`*) – If true, graph features with an importance value of zero. Defaults to false.

**Returns** plotly.Figure, a bar graph showing features and their corresponding importance

### evalml.pipelines.MulticlassClassificationPipeline.load

**`static`** `MulticlassClassificationPipeline.`**`load`**(*file_path*)

Loads pipeline at file path

**Parameters** **`file_path`** (*`str`*) – location to load file

**Returns** PipelineBase object

### evalml.pipelines.MulticlassClassificationPipeline.predict

`MulticlassClassificationPipeline.`**`predict`**(*X*, *objective=None*)

Make predictions using selected features.

**Parameters**

- **`X`** (*`pd.DataFrame or np.array`*) – 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

### evalml.pipelines.MulticlassClassificationPipeline.predict_proba

`MulticlassClassificationPipeline.`**`predict_proba`**(*X*)

Make probability estimates for labels.

**Parameters** **`X`** (*`pd.DataFrame or np.array`*) – data of shape [n_samples, n_features]

**Returns** probability estimates

**Return type** pd.DataFrame

### evalml.pipelines.MulticlassClassificationPipeline.save

`MulticlassClassificationPipeline.`**`save`**(*file_path*)

Saves pipeline at file path

**Parameters** **`file_path`** (*str*) – location to save file

**Returns** None

### evalml.pipelines.MulticlassClassificationPipeline.score

`MulticlassClassificationPipeline.`**`score`**(*X*, *y*, *objectives*)

Evaluate model performance on objectives

**Parameters**

- **`X`** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]
- **`y`** (*pd.Series*) – true labels of length [n_samples]
- **`objectives`** (*list*) – list of objectives to score

**Returns** ordered dictionary of objective scores

**Return type** dict

## evalml.pipelines.RegressionPipeline


**class** `evalml.pipelines.`**`RegressionPipeline`**(*parameters*, *random_state=0*)

Pipeline subclass for all regression pipelines.

### Methods

| | |
|---|---|
| *__init__* | Machine learning pipeline made out of transformers and a estimator. |
| *clone* | Constructs a new pipeline with the same parameters and components. |
| *describe* | Outputs pipeline details including component parameters |
| *fit* | Build a regression model. |
| *get_component* | Returns component by name |
| *graph* | Generate an image representing the pipeline graph |

Continued on next page

Table 16 – continued from previous page

| | |
|---|---|
| *graph_feature_importance* | Generate a bar graph of the pipeline's feature importance |
| *load* | Loads pipeline at file path |
| *predict* | Make predictions using selected features. |
| *save* | Saves pipeline at file path |
| *score* | Evaluate model performance on current and additional objectives |

### evalml.pipelines.RegressionPipeline.__init__

RegressionPipeline.**__init__**(*parameters*, *random_state=0*)

Machine learning pipeline made out of transformers and a estimator.

**Required Class Variables:** component_graph (list): List of components in order. Accepts strings or ComponentBase subclasses in the list

**Parameters**

- **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.
- **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

### evalml.pipelines.RegressionPipeline.clone

RegressionPipeline.**clone**(*random_state=0*)

Constructs a new pipeline with the same parameters and components.

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this pipeline with identical parameters and components

### evalml.pipelines.RegressionPipeline.describe

RegressionPipeline.**describe**()

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

### evalml.pipelines.RegressionPipeline.fit

RegressionPipeline.**fit**(*X*, *y*)

Build a regression model.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.RegressionPipeline.get_component

RegressionPipeline.**get_component**(*name*)

Returns component by name

**Parameters** **name** (*str*) – name of component

**Returns** component to return

**Return type** Component

### evalml.pipelines.RegressionPipeline.graph

RegressionPipeline.**graph**(*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

### evalml.pipelines.RegressionPipeline.graph_feature_importance

RegressionPipeline.**graph_feature_importance**(*show_all_features=False*)

Generate a bar graph of the pipeline's feature importance

**Parameters** **show_all_features** (*bool, optional*) – If true, graph features with an importance value of zero. Defaults to false.

**Returns** plotly.Figure, a bar graph showing features and their corresponding importance

### evalml.pipelines.RegressionPipeline.load

**static** RegressionPipeline.**load**(*file_path*)

Loads pipeline at file path

**Parameters** **file_path** (*str*) – location to load file

**Returns** PipelineBase object

### evalml.pipelines.RegressionPipeline.predict

RegressionPipeline.**predict**(*X*, *objective=None*)

Make predictions using selected features.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

#### evalml.pipelines.RegressionPipeline.save

RegressionPipeline.**save**(*file_path*)

Saves pipeline at file path

**Parameters** **file_path** (*str*) – location to save file

**Returns** None

#### evalml.pipelines.RegressionPipeline.score

RegressionPipeline.**score**(*X*, *y*, *objectives*)

Evaluate model performance on current and additional objectives

**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

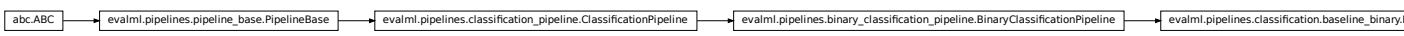
**Returns** ordered dictionary of objective scores

**Return type** dict

### 5.4.2 Classification Pipelines

| | |
|---|---|
| *BaselineBinaryPipeline* | Baseline Pipeline for binary classification. |
| *BaselineMulticlassPipeline* | Baseline Pipeline for multiclass classification. |
| *ModeBaselineBinaryPipeline* | Mode Baseline Pipeline for binary classification. |
| *ModeBaselineMulticlassPipeline* | Mode Baseline Pipeline for multiclass classification. |

#### evalml.pipelines.BaselineBinaryPipeline




**class** evalml.pipelines.**BaselineBinaryPipeline**(*parameters*, *random_state=0*)

Baseline Pipeline for binary classification.

**name = 'Baseline Classification Pipeline'**

**custom_name = 'Baseline Classification Pipeline'**

**summary = 'Baseline Classifier'**

```
component_graph = ['Baseline Classifier']
problem_type = 'binary'
model_family = 'baseline'
hyperparameters = {'Baseline Classifier':  {}}
custom_hyperparameters = None
default_parameters = {'Baseline Classifier':  {'strategy':  'mode'}}
```

### Instance attributes

| | |
|---|---|
| feature_importance | Return importance associated with each feature. |
| parameters | Returns parameter dictionary for this pipeline |
| threshold | |

### Methods:

| | |
|---|---|
| *__init__* | Machine learning classification pipeline made out of transformers and a classifier. |
| *clone* | Constructs a new pipeline with the same parameters and components. |
| *describe* | Outputs pipeline details including component parameters |
| *fit* | Build a classification model. For string and categorical targets, classes are sorted |
| *get_component* | Returns component by name |
| *graph* | Generate an image representing the pipeline graph |
| *graph_feature_importance* | Generate a bar graph of the pipeline's feature importance |
| *load* | Loads pipeline at file path |
| *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 |

### evalml.pipelines.BaselineBinaryPipeline.__init__

BaselineBinaryPipeline.**__init__**(*parameters*, *random_state=0*)

Machine learning classification pipeline made out of transformers and a classifier.

**Required Class Variables:** component_graph (list): List of components in order. Accepts strings or ComponentBase subclasses in the list

#### Parameters

- **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.
- **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

### evalml.pipelines.BaselineBinaryPipeline.clone

BaselineBinaryPipeline.**clone**(*random_state=0*)

Constructs a new pipeline with the same parameters and components.

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this pipeline with identical parameters and components

### evalml.pipelines.BaselineBinaryPipeline.describe

BaselineBinaryPipeline.**describe**()

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

### evalml.pipelines.BaselineBinaryPipeline.fit

BaselineBinaryPipeline.**fit**(*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.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.BaselineBinaryPipeline.get_component

BaselineBinaryPipeline.**get_component**(*name*)

Returns component by name

**Parameters** **name** (*str*) – name of component

**Returns** component to return

**Return type** Component

### evalml.pipelines.BaselineBinaryPipeline.graph

BaselineBinaryPipeline.**graph**(*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

### evalml.pipelines.BaselineBinaryPipeline.graph_feature_importance

BaselineBinaryPipeline.**graph_feature_importance**(*show_all_features=False*)

Generate a bar graph of the pipeline's feature importance

**Parameters** **show_all_features** (*bool, optional*) – If true, graph features with an importance value of zero. Defaults to false.

**Returns** plotly.Figure, a bar graph showing features and their corresponding importance

### evalml.pipelines.BaselineBinaryPipeline.load

**static** BaselineBinaryPipeline.**load**(*file_path*)

Loads pipeline at file path

**Parameters** **file_path** (*str*) – location to load file

**Returns** PipelineBase object

### evalml.pipelines.BaselineBinaryPipeline.predict

BaselineBinaryPipeline.**predict**(*X*, *objective=None*)

Make predictions using selected features.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

### evalml.pipelines.BaselineBinaryPipeline.predict_proba

BaselineBinaryPipeline.**predict_proba**(*X*)

Make probability estimates for labels. Assumes that the column at index 1 represents the positive label case.

**Parameters** **X** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]

**Returns** probability estimates

**Return type** pd.DataFrame

### evalml.pipelines.BaselineBinaryPipeline.save

BaselineBinaryPipeline.**save**(*file_path*)

Saves pipeline at file path

**Parameters** **file_path** (*str*) – location to save file

**Returns** None

### evalml.pipelines.BaselineBinaryPipeline.score

BaselineBinaryPipeline.**score**(*X*, *y*, *objectives*)
Evaluate model performance on objectives

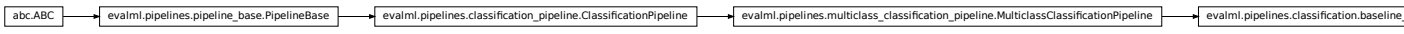
**Parameters**

- **X** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]
- **y** (*pd.Series*) – true labels of length [n_samples]
- **objectives** (*list*) – list of objectives to score

**Returns** ordered dictionary of objective scores

**Return type** dict

## evalml.pipelines.BaselineMulticlassPipeline




**class** evalml.pipelines.**BaselineMulticlassPipeline**(*parameters*, *random_state=0*)
Baseline Pipeline for multiclass classification.

**name = 'Baseline Multiclass Classification Pipeline'**

**custom_name = 'Baseline Multiclass Classification Pipeline'**

**summary = 'Baseline Classifier'**

**component_graph = ['Baseline Classifier']**

**problem_type = 'multiclass'**

**model_family = 'baseline'**

**hyperparameters = {'Baseline Classifier': {}}**

**custom_hyperparameters = None**

**default_parameters = {'Baseline Classifier': {'strategy': 'mode'}}**

### Instance attributes

| | |
|---|---|
| feature_importance | Return importance associated with each feature. |
| parameters | Returns parameter dictionary for this pipeline |

### Methods:

| | |
|---|---|
| __init__ | Machine learning classification pipeline made out of transformers and a classifier. |

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Table 21 – continued from previous page

| | |
|---|---|
| *clone* | Constructs a new pipeline with the same parameters and components. |
| *describe* | Outputs pipeline details including component parameters |
| *fit* | Build a classification model. For string and categorical targets, classes are sorted |
| *get_component* | Returns component by name |
| *graph* | Generate an image representing the pipeline graph |
| *graph_feature_importance* | Generate a bar graph of the pipeline's feature importance |
| *load* | Loads pipeline at file path |
| *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 |

### evalml.pipelines.BaselineMulticlassPipeline.__init__

BaselineMulticlassPipeline.**__init__**(*parameters*, *random_state=0*)

Machine learning classification pipeline made out of transformers and a classifier.

**Required Class Variables:** component_graph (list): List of components in order. Accepts strings or ComponentBase subclasses in the list

**Parameters**

- **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.
- **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

### evalml.pipelines.BaselineMulticlassPipeline.clone

BaselineMulticlassPipeline.**clone**(*random_state=0*)

Constructs a new pipeline with the same parameters and components.

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this pipeline with identical parameters and components

### evalml.pipelines.BaselineMulticlassPipeline.describe

BaselineMulticlassPipeline.**describe**()

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

### evalml.pipelines.BaselineMulticlassPipeline.fit

BaselineMulticlassPipeline.**fit**(*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.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.BaselineMulticlassPipeline.get_component

BaselineMulticlassPipeline.**get_component**(*name*)

Returns component by name

**Parameters** **name** (*str*) – name of component

**Returns** component to return

**Return type** Component

### evalml.pipelines.BaselineMulticlassPipeline.graph

BaselineMulticlassPipeline.**graph**(*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

### evalml.pipelines.BaselineMulticlassPipeline.graph_feature_importance

BaselineMulticlassPipeline.**graph_feature_importance**(*show_all_features=False*)

Generate a bar graph of the pipeline's feature importance

**Parameters** **show_all_features** (*bool, optional*) – If true, graph features with an importance value of zero. Defaults to false.

**Returns** plotly.Figure, a bar graph showing features and their corresponding importance

### evalml.pipelines.BaselineMulticlassPipeline.load

**static** BaselineMulticlassPipeline.**load**(*file_path*)

Loads pipeline at file path

**Parameters** **file_path** (*str*) – location to load file

**Returns** PipelineBase object

### evalml.pipelines.BaselineMulticlassPipeline.predict

BaselineMulticlassPipeline.**predict**(*X*, *objective=None*)

Make predictions using selected features.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

### evalml.pipelines.BaselineMulticlassPipeline.predict_proba

BaselineMulticlassPipeline.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]

**Returns** probability estimates

**Return type** pd.DataFrame

### evalml.pipelines.BaselineMulticlassPipeline.save

BaselineMulticlassPipeline.**save**(*file_path*)

Saves pipeline at file path

**Parameters** **file_path** (*str*) – location to save file

**Returns** None

### evalml.pipelines.BaselineMulticlassPipeline.score

BaselineMulticlassPipeline.**score**(*X*, *y*, *objectives*)

Evaluate model performance on objectives

**Parameters**

- **X** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]
- **y** (*pd.Series*) – true labels of length [n_samples]
- **objectives** (*list*) – list of objectives to score

**Returns** ordered dictionary of objective scores

**Return type** dict

## evalml.pipelines.ModeBaselineBinaryPipeline

**class** evalml.pipelines.**ModeBaselineBinaryPipeline**(*parameters*, *random_state=0*)

Mode Baseline Pipeline for binary classification.

**name = 'Mode Baseline Binary Classification Pipeline'**

**custom_name = 'Mode Baseline Binary Classification Pipeline'**

**summary = 'Baseline Classifier'**

**component_graph = ['Baseline Classifier']**

**problem_type = 'binary'**

**model_family = 'baseline'**

**hyperparameters = {'Baseline Classifier': {}}**

**custom_hyperparameters = {'strategy': ['mode']}**

**default_parameters = {'Baseline Classifier': {'strategy': 'mode'}}**

### Instance attributes

| | |
|---|---|
| feature_importance | Return importance associated with each feature. |
| parameters | Returns parameter dictionary for this pipeline |
| threshold | |

### Methods:

| | |
|---|---|
| *__init__* | Machine learning classification pipeline made out of transformers and a classifier. |
| *clone* | Constructs a new pipeline with the same parameters and components. |
| *describe* | Outputs pipeline details including component parameters |
| *fit* | Build a classification model. For string and categorical targets, classes are sorted |
| *get_component* | Returns component by name |
| *graph* | Generate an image representing the pipeline graph |
| *graph_feature_importance* | Generate a bar graph of the pipeline's feature importance |
| *load* | Loads pipeline at file path |
| *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 |

### evalml.pipelines.ModeBaselineBinaryPipeline.__init__

ModeBaselineBinaryPipeline.**__init__**(*parameters*, *random_state=0*)

Machine learning classification pipeline made out of transformers and a classifier.

**Required Class Variables:** component_graph (list): List of components in order. Accepts strings or ComponentBase subclasses in the list

**Parameters**

- **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.
- **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

### evalml.pipelines.ModeBaselineBinaryPipeline.clone

ModeBaselineBinaryPipeline.**clone**(*random_state=0*)

Constructs a new pipeline with the same parameters and components.

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this pipeline with identical parameters and components

### evalml.pipelines.ModeBaselineBinaryPipeline.describe

ModeBaselineBinaryPipeline.**describe**()

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

### evalml.pipelines.ModeBaselineBinaryPipeline.fit

ModeBaselineBinaryPipeline.**fit**(*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.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.ModeBaselineBinaryPipeline.get_component

ModeBaselineBinaryPipeline.**get_component**(*name*)

Returns component by name

**Parameters** **name** (*str*) – name of component

**Returns** component to return

**Return type** Component

### evalml.pipelines.ModeBaselineBinaryPipeline.graph

ModeBaselineBinaryPipeline.**graph**(*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

### evalml.pipelines.ModeBaselineBinaryPipeline.graph_feature_importance

ModeBaselineBinaryPipeline.**graph_feature_importance**(*show_all_features=False*)

Generate a bar graph of the pipeline's feature importance

**Parameters** **show_all_features** (*bool, optional*) – If true, graph features with an importance value of zero. Defaults to false.

**Returns** plotly.Figure, a bar graph showing features and their corresponding importance

### evalml.pipelines.ModeBaselineBinaryPipeline.load

**static** ModeBaselineBinaryPipeline.**load**(*file_path*)

Loads pipeline at file path

**Parameters** **file_path** (*str*) – location to load file

**Returns** PipelineBase object

### evalml.pipelines.ModeBaselineBinaryPipeline.predict

ModeBaselineBinaryPipeline.**predict**(*X*, *objective=None*)

Make predictions using selected features.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

### evalml.pipelines.ModeBaselineBinaryPipeline.predict_proba

ModeBaselineBinaryPipeline.**predict_proba**(*X*)

Make probability estimates for labels. Assumes that the column at index 1 represents the positive label case.

**Parameters** **X** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]

**Returns** probability estimates

**Return type** pd.DataFrame

### evalml.pipelines.ModeBaselineBinaryPipeline.save

ModeBaselineBinaryPipeline.**save**(*file_path*)

Saves pipeline at file path

**Parameters** **file_path** (*str*) – location to save file

**Returns** None

### evalml.pipelines.ModeBaselineBinaryPipeline.score

ModeBaselineBinaryPipeline.**score**(*X*, *y*, *objectives*)

Evaluate model performance on objectives

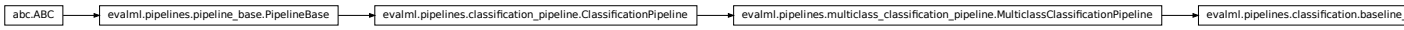
**Parameters**

- **X** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]
- **y** (*pd.Series*) – true labels of length [n_samples]
- **objectives** (*list*) – list of objectives to score

**Returns** ordered dictionary of objective scores

**Return type** dict

## evalml.pipelines.ModeBaselineMulticlassPipeline




**class** evalml.pipelines.**ModeBaselineMulticlassPipeline**(*parameters*, *random_state=0*)

Mode Baseline Pipeline for multiclass classification.

```
name = 'Mode Baseline Multiclass Classification Pipeline'
custom_name = 'Mode Baseline Multiclass Classification Pipeline'
summary = 'Baseline Classifier'
component_graph = ['Baseline Classifier']
problem_type = 'multiclass'
model_family = 'baseline'
hyperparameters = {'Baseline Classifier': {}}
custom_hyperparameters = {'strategy': ['mode']}
default_parameters = {'Baseline Classifier': {'strategy': 'mode'}}
```

### Instance attributes

| | |
|---|---|
| feature_importance | Return importance associated with each feature. |

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| | |
|---|---|
| parameters | Returns parameter dictionary for this pipeline |

### Methods:

| | |
|---|---|
| *__init__* | Machine learning classification pipeline made out of transformers and a classifier. |
| *clone* | Constructs a new pipeline with the same parameters and components. |
| *describe* | Outputs pipeline details including component parameters |
| *fit* | Build a classification model. For string and categorical targets, classes are sorted |
| *get_component* | Returns component by name |
| *graph* | Generate an image representing the pipeline graph |
| *graph_feature_importance* | Generate a bar graph of the pipeline's feature importance |
| *load* | Loads pipeline at file path |
| *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 |

### evalml.pipelines.ModeBaselineMulticlassPipeline.__init__

ModeBaselineMulticlassPipeline.**__init__**(*parameters*, *random_state=0*)

Machine learning classification pipeline made out of transformers and a classifier.

**Required Class Variables:** component_graph (list): List of components in order. Accepts strings or ComponentBase subclasses in the list

**Parameters**

- **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.
- **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

### evalml.pipelines.ModeBaselineMulticlassPipeline.clone

ModeBaselineMulticlassPipeline.**clone**(*random_state=0*)

Constructs a new pipeline with the same parameters and components.

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this pipeline with identical parameters and components

### evalml.pipelines.ModeBaselineMulticlassPipeline.describe

ModeBaselineMulticlassPipeline.**describe**()

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

### evalml.pipelines.ModeBaselineMulticlassPipeline.fit

ModeBaselineMulticlassPipeline.**fit**(*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.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.ModeBaselineMulticlassPipeline.get_component

ModeBaselineMulticlassPipeline.**get_component**(*name*)

Returns component by name

**Parameters** **name** (*str*) – name of component

**Returns** component to return

**Return type** Component

### evalml.pipelines.ModeBaselineMulticlassPipeline.graph

ModeBaselineMulticlassPipeline.**graph**(*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

### evalml.pipelines.ModeBaselineMulticlassPipeline.graph_feature_importance

ModeBaselineMulticlassPipeline.**graph_feature_importance**(*show_all_features=False*)

Generate a bar graph of the pipeline's feature importance

**Parameters** **show_all_features** (*bool, optional*) – If true, graph features with an importance value of zero. Defaults to false.

**Returns** plotly.Figure, a bar graph showing features and their corresponding importance

### evalml.pipelines.ModeBaselineMulticlassPipeline.load

**static** ModeBaselineMulticlassPipeline.**load**(*file_path*)

Loads pipeline at file path

**Parameters** **file_path** (*str*) – location to load file

**Returns** PipelineBase object

### evalml.pipelines.ModeBaselineMulticlassPipeline.predict

ModeBaselineMulticlassPipeline.**predict**(*X*, *objective=None*)

Make predictions using selected features.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

### evalml.pipelines.ModeBaselineMulticlassPipeline.predict_proba

ModeBaselineMulticlassPipeline.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]

**Returns** probability estimates

**Return type** pd.DataFrame

### evalml.pipelines.ModeBaselineMulticlassPipeline.save

ModeBaselineMulticlassPipeline.**save**(*file_path*)

Saves pipeline at file path

**Parameters** **file_path** (*str*) – location to save file

**Returns** None

### evalml.pipelines.ModeBaselineMulticlassPipeline.score

ModeBaselineMulticlassPipeline.**score**(*X*, *y*, *objectives*)

Evaluate model performance on objectives

**Parameters**

- **X** (*pd.DataFrame or np.array*) – data of shape [n_samples, n_features]
- **y** (*pd.Series*) – true labels of length [n_samples]
- **objectives** (*list*) – list of objectives to score

**Returns** ordered dictionary of objective scores

**Return type** dict

### 5.4.3 Regression Pipelines

| | |
|---|---|
| *BaselineRegressionPipeline* | Baseline Pipeline for regression problems. |
| *MeanBaselineRegressionPipeline* | Baseline Pipeline for regression problems. |

#### evalml.pipelines.BaselineRegressionPipeline


**class** evalml.pipelines.**BaselineRegressionPipeline**(*parameters*, *random_state=0*)

Baseline Pipeline for regression problems.

**name = 'Baseline Regression Pipeline'**

**custom_name = None**

**summary = 'Baseline Regressor'**

**component_graph = ['Baseline Regressor']**

**problem_type = 'regression'**

**model_family = 'baseline'**

**hyperparameters = {'Baseline Regressor': {}}**

**custom_hyperparameters = None**

**default_parameters = {'Baseline Regressor': {'strategy': 'mean'}}**

##### Instance attributes

| | |
|---|---|
| feature_importance | Return importance associated with each feature. |
| parameters | Returns parameter dictionary for this pipeline |

##### Methods:

| | |
|---|---|
| *__init__* | Machine learning pipeline made out of transformers and a estimator. |
| *clone* | Constructs a new pipeline with the same parameters and components. |

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| | |
|---|---|
| *describe* | Outputs pipeline details including component parameters |
| *fit* | Build a regression model. |
| *get_component* | Returns component by name |
| *graph* | Generate an image representing the pipeline graph |
| *graph_feature_importance* | Generate a bar graph of the pipeline's feature importance |
| *load* | Loads pipeline at file path |
| *predict* | Make predictions using selected features. |
| *save* | Saves pipeline at file path |
| *score* | Evaluate model performance on current and additional objectives |

### evalml.pipelines.BaselineRegressionPipeline.__init__

BaselineRegressionPipeline.**__init__**(*parameters*, *random_state=0*)

Machine learning pipeline made out of transformers and a estimator.

**Required Class Variables:** component_graph (list): List of components in order. Accepts strings or ComponentBase subclasses in the list

**Parameters**

- **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.
- **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

### evalml.pipelines.BaselineRegressionPipeline.clone

BaselineRegressionPipeline.**clone**(*random_state=0*)

Constructs a new pipeline with the same parameters and components.

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this pipeline with identical parameters and components

### evalml.pipelines.BaselineRegressionPipeline.describe

BaselineRegressionPipeline.**describe**()

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

### evalml.pipelines.BaselineRegressionPipeline.fit

BaselineRegressionPipeline.**fit**(*X*, *y*)
Build a regression model.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.BaselineRegressionPipeline.get_component

BaselineRegressionPipeline.**get_component**(*name*)
Returns component by name

**Parameters** **name** (*str*) – name of component

**Returns** component to return

**Return type** Component

### evalml.pipelines.BaselineRegressionPipeline.graph

BaselineRegressionPipeline.**graph**(*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

### evalml.pipelines.BaselineRegressionPipeline.graph_feature_importance

BaselineRegressionPipeline.**graph_feature_importance**(*show_all_features=False*)
Generate a bar graph of the pipeline's feature importance

**Parameters** **show_all_features** (*bool, optional*) – If true, graph features with an importance value of zero. Defaults to false.

**Returns** plotly.Figure, a bar graph showing features and their corresponding importance

### evalml.pipelines.BaselineRegressionPipeline.load

**static** BaselineRegressionPipeline.**load**(*file_path*)
Loads pipeline at file path

**Parameters** **file_path** (*str*) – location to load file

**Returns** PipelineBase object

### evalml.pipelines.BaselineRegressionPipeline.predict

BaselineRegressionPipeline.**predict**(*X*, *objective=None*)

Make predictions using selected features.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

### evalml.pipelines.BaselineRegressionPipeline.save

BaselineRegressionPipeline.**save**(*file_path*)

Saves pipeline at file path

**Parameters** **file_path** (*str*) – location to save file

**Returns** None

### evalml.pipelines.BaselineRegressionPipeline.score

BaselineRegressionPipeline.**score**(*X*, *y*, *objectives*)

Evaluate model performance on current and additional objectives

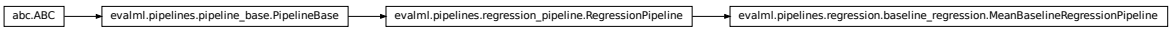
**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

## evalml.pipelines.MeanBaselineRegressionPipeline




**class** evalml.pipelines.**MeanBaselineRegressionPipeline**(*parameters*, *random_state=0*)

Baseline Pipeline for regression problems.

**name = 'Mean Baseline Regression Pipeline'**

**custom_name = None**

**summary = 'Baseline Regressor'**

**component_graph = ['Baseline Regressor']**

```
problem_type = 'regression'
model_family = 'baseline'
hyperparameters = {'Baseline Regressor': {}}
custom_hyperparameters = {'strategy': ['mean']}
default_parameters = {'Baseline Regressor': {'strategy': 'mean'}}
```

### Instance attributes

| | |
|---|---|
| feature_importance | Return importance associated with each feature. |
| parameters | Returns parameter dictionary for this pipeline |

### Methods:

| | |
|---|---|
| *__init__* | Machine learning pipeline made out of transformers and a estimator. |
| *clone* | Constructs a new pipeline with the same parameters and components. |
| *describe* | Outputs pipeline details including component parameters |
| *fit* | Build a regression model. |
| *get_component* | Returns component by name |
| *graph* | Generate an image representing the pipeline graph |
| *graph_feature_importance* | Generate a bar graph of the pipeline's feature importance |
| *load* | Loads pipeline at file path |
| *predict* | Make predictions using selected features. |
| *save* | Saves pipeline at file path |
| *score* | Evaluate model performance on current and additional objectives |

### evalml.pipelines.MeanBaselineRegressionPipeline.__init__

MeanBaselineRegressionPipeline.**__init__**(*parameters*, *random_state=0*)

Machine learning pipeline made out of transformers and a estimator.

**Required Class Variables:** component_graph (list): List of components in order. Accepts strings or ComponentBase subclasses in the list

#### Parameters

- **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.
- **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

### evalml.pipelines.MeanBaselineRegressionPipeline.clone

MeanBaselineRegressionPipeline.**clone**(*random_state=0*)

Constructs a new pipeline with the same parameters and components.

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this pipeline with identical parameters and components

### evalml.pipelines.MeanBaselineRegressionPipeline.describe

MeanBaselineRegressionPipeline.**describe**()

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

### evalml.pipelines.MeanBaselineRegressionPipeline.fit

MeanBaselineRegressionPipeline.**fit**(*X*, *y*)

Build a regression model.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.MeanBaselineRegressionPipeline.get_component

MeanBaselineRegressionPipeline.**get_component**(*name*)

Returns component by name

**Parameters** **name** (*str*) – name of component

**Returns** component to return

**Return type** Component

### evalml.pipelines.MeanBaselineRegressionPipeline.graph

MeanBaselineRegressionPipeline.**graph**(*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

### evalml.pipelines.MeanBaselineRegressionPipeline.graph_feature_importance

MeanBaselineRegressionPipeline.**graph_feature_importance**(*show_all_features=False*)
Generate a bar graph of the pipeline's feature importance

**Parameters** **show_all_features** (*bool, optional*) – If true, graph features with an importance value of zero. Defaults to false.

**Returns** plotly.Figure, a bar graph showing features and their corresponding importance

### evalml.pipelines.MeanBaselineRegressionPipeline.load

**static** MeanBaselineRegressionPipeline.**load**(*file_path*)
Loads pipeline at file path

**Parameters** **file_path** (*str*) – location to load file

**Returns** PipelineBase object

### evalml.pipelines.MeanBaselineRegressionPipeline.predict

MeanBaselineRegressionPipeline.**predict**(*X*, *objective=None*)
Make predictions using selected features.

**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

### evalml.pipelines.MeanBaselineRegressionPipeline.save

MeanBaselineRegressionPipeline.**save**(*file_path*)
Saves pipeline at file path

**Parameters** **file_path** (*str*) – location to save file

**Returns** None

### evalml.pipelines.MeanBaselineRegressionPipeline.score

MeanBaselineRegressionPipeline.**score**(*X*, *y*, *objectives*)
Evaluate model performance on current and additional objectives

**Parameters**

- **X** (*pd.DataFrame or np.array*) – 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

### 5.4.4 Pipeline Graph Utils

| | |
|---|---|
| *precision_recall_curve* | Given labels and binary classifier predicted probabilities, compute and return the data representing a precision-recall curve. |
| *graph_precision_recall_curve* | Generate and display a precision-recall plot. |
| *roc_curve* | Given labels and classifier predicted probabilities, compute and return the data representing a Receiver Operating Characteristic (ROC) curve. |
| *graph_roc_curve* | Generate and display a Receiver Operating Characteristic (ROC) plot. |
| *confusion_matrix* | Confusion matrix for binary and multiclass classification. |
| *normalize_confusion_matrix* | Normalizes a confusion matrix. |
| *graph_confusion_matrix* | Generate and display a confusion matrix plot. |
| *calculate_permutation_importance* | Calculates permutation importance for features. |
| *graph_permutation_importance* | Generate a bar graph of the pipeline's permutation importance. |

#### evalml.pipelines.precision_recall_curve

evalml.pipelines.**precision_recall_curve**(*y_true*, *y_pred_proba*)

Given labels and binary classifier predicted probabilities, compute and return the data representing a precision-recall curve.

**Parameters**

- **y_true** (*pd.Series or np.array*) – true binary labels.
- **y_pred_proba** (*pd.Series or np.array*) – predictions from a binary classifier, before thresholding has been applied. Note this should be the predicted probability for the "true" label.

**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.pipelines.graph_precision_recall_curve

evalml.pipelines.**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.array*) – true binary labels.
- **y_pred_proba** (*pd.Series or np.array*) – 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.pipelines.roc_curve

evalml.pipelines.**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.

**Parameters**

- **y_true** (*pd.Series or np.array*) – true labels.
- **y_pred_proba** (*pd.Series or np.array*) – predictions from a classifier, before thresholding has been applied. Note that 1 dimensional input is expected.

**Returns**

**Dictionary containing 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** dict

### evalml.pipelines.graph_roc_curve

evalml.pipelines.**graph_roc_curve**(*y_true*, *y_pred_proba*, *custom_class_names=None*, *title_addition=None*)

Generate and display a Receiver Operating Characteristic (ROC) plot.

**Parameters**

- **y_true** (*pd.Series or np.array*) – true labels.
- **y_pred_proba** (*pd.Series or np.array*) – 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.pipelines.confusion_matrix

evalml.pipelines.**confusion_matrix**(*y_true*, *y_predicted*, *normalize_method='true'*)

Confusion matrix for binary and multiclass classification.

**Parameters**

- **y_true** (*pd.Series or np.array*) – true binary labels.
- **y_pred** (*pd.Series or np.array*) – predictions from a binary classifier.
- **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** confusion matrix

**Return type** np.array

### evalml.pipelines.normalize_confusion_matrix

evalml.pipelines.**normalize_confusion_matrix**(*conf_mat*, *normalize_method='true'*)

Normalizes a confusion matrix.

**Parameters**

- **conf_mat** (*pd.DataFrame or np.array*) – 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** A normalized version of the input confusion matrix.

### evalml.pipelines.graph_confusion_matrix

evalml.pipelines.**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.array*) – true binary labels.
- **y_pred** (*pd.Series or np.array*) – predictions from a binary classifier.
- **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'.
- **title_addition** (*str or None*) – if not None, append to plot title. Default None.

**Returns** plotly.Figure representing the confusion matrix plot generated

#### evalml.pipelines.calculate_permutation_importance

evalml.pipelines.**calculate_permutation_importance**(*pipeline*, *X*, *y*, *objective*, *n_repeats=5*, *n_jobs=None*, *random_state=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 labels
- **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.
- **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

**Returns** Mean feature importance scores over 5 shuffles.

#### evalml.pipelines.graph_permutation_importance

evalml.pipelines.**graph_permutation_importance**(*pipeline*, *X*, *y*, *objective*, *show_all_features=False*)

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 labels
- **objective** (*str, ObjectiveBase*) – Objective to score on
- **show_all_features** (*bool, optional*) – If True, graph features with a permutation importance value of zero. Defaults to False.

**Returns** plotly.Figure, a bar graph showing features and their respective permutation importance.

### 5.4.5 Pipeline Utils

| | |
|---|---|
| *make_pipeline* | Given input data, target data, an estimator class and the problem type, |

#### evalml.pipelines.utils.make_pipeline

evalml.pipelines.utils.**make_pipeline**(*X*, *y*, *estimator*, *problem_type*)

**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 labels of length [n_samples]
- **estimator** (Estimator) – estimator for pipeline
- **problem_type** – problem type for pipeline to generate

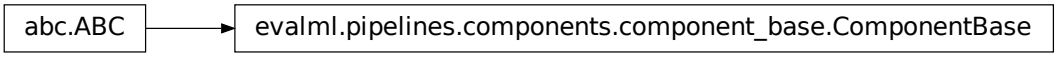
## 5.5 Components

### 5.5.1 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. |
| *Estimator* | A component that fits and predicts given data. |

#### evalml.pipelines.components.ComponentBase




**class** evalml.pipelines.components.**ComponentBase**(*parameters=None*, *component_obj=None*, *random_state=0*, ***kwargs*)

Base class for all components.

##### Methods

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |

### evalml.pipelines.components.ComponentBase.__init__

ComponentBase.**__init__**(*parameters=None*, *component_obj=None*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.ComponentBase.clone

ComponentBase.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.ComponentBase.describe

ComponentBase.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.ComponentBase.fit

ComponentBase.**fit**(*X*, *y=None*)

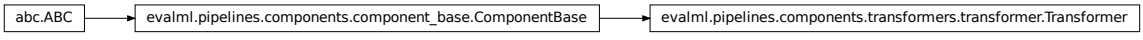
Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

## evalml.pipelines.components.Transformer



**class** evalml.pipelines.components.**Transformer**(*parameters=None*, *component_obj=None*, *random_state=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.

### Methods

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *fit_transform* | Fits on X and transforms X |
| *transform* | Transforms data X |

#### evalml.pipelines.components.Transformer.__init__

Transformer.**__init__**(*parameters=None*, *component_obj=None*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

#### evalml.pipelines.components.Transformer.clone

Transformer.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

#### evalml.pipelines.components.Transformer.describe

Transformer.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.Transformer.fit

Transformer.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.Transformer.fit_transform

Transformer.**fit_transform**(*X*, *y=None*)

Fits on X and transforms X

**Parameters**

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd. DataFrame*) – Labels to fit and transform

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.Transformer.transform

Transformer.**transform**(*X*, *y=None*)

Transforms data X

**Parameters**

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Input Labels

**Returns** Transformed X

**Return type** pd.DataFrame

## evalml.pipelines.components.Estimator


**class** evalml.pipelines.components.**Estimator**(*parameters=None*, *component_obj=None*, *random_state=0*, ***kwargs*)

A component that fits and predicts given data.

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 Estimator component.

### Methods

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *predict* | Make predictions using selected features. |
| *predict_proba* | Make probability estimates for labels. |

#### evalml.pipelines.components.Estimator.__init__

Estimator.**__init__**(*parameters=None*, *component_obj=None*, *random_state=0*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

#### evalml.pipelines.components.Estimator.clone

Estimator.**clone**(*random_state=0*)
Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

#### evalml.pipelines.components.Estimator.describe

Estimator.**describe**(*print_name=False*, *return_dict=False*)
Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

#### evalml.pipelines.components.Estimator.fit

Estimator.**fit**(*X*, *y=None*)
Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

#### evalml.pipelines.components.Estimator.predict

Estimator.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

#### evalml.pipelines.components.Estimator.predict_proba

Estimator.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

### 5.5.2 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. |

#### evalml.pipelines.components.utils.allowed_model_families

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.get_estimators

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]

### 5.5.3 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. |
| *OneHotEncoder* | One-hot encoder to encode non-numeric data. |
| *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* | Standardize features: removes mean and scales 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 featurize DateTime columns. |
| *TextFeaturizer* | Transformer that can automatically featurize text columns. |

#### evalml.pipelines.components.DropColumns


**class** evalml.pipelines.components.**DropColumns**(*columns=None*, *random_state=0*, ***kwargs*)

Drops specified columns in input data.

**name = 'Drop Columns Transformer'**

**model_family = 'none'**

**hyperparameter_ranges = {}**

**default_parameters = {'columns': None}**

### Instance attributes

| | |
|---|---|
| parameters | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *__init__* | Initalizes an transformer that drops specified columns in input data. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | 'Fits' the transformer by checking if the column names are present in the dataset. |
| *fit_transform* | Fit transformer to data, then transform data. |
| *transform* | Transforms data X by dropping columns. |

### evalml.pipelines.components.DropColumns.__init__

DropColumns.**__init__**(*columns=None*, *random_state=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 drop.

### evalml.pipelines.components.DropColumns.clone

DropColumns.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.DropColumns.describe

DropColumns.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.DropColumns.fit

DropColumns.**fit**(*X*, *y=None*)

'Fits' the transformer by checking if the column names are present in the dataset.

**Parameters**

- **X** (*pd.DataFrame*) – Data to check.
- **y** (*pd.Series, optional*) – Targets.

**Returns** None.

### evalml.pipelines.components.DropColumns.fit_transform

DropColumns.**fit_transform**(*X*, *y=None*)

Fit transformer to data, then transform data.

**Parameters**

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Targets.

**Returns** Transformed X.

**Return type** pd.DataFrame

### evalml.pipelines.components.DropColumns.transform

DropColumns.**transform**(*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

## evalml.pipelines.components.SelectColumns


**class** evalml.pipelines.components.**SelectColumns**(*columns=None*, *random_state=0*, ***kwargs*)

Selects specified columns in input data.

**name = 'Select Columns Transformer'**

**model_family = 'none'**

**hyperparameter_ranges = {}**

**default_parameters = {'columns': None}**

### Instance attributes

| | |
|---|---|
| parameters | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *__init__* | Initalizes an transformer that drops specified columns in input data. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | 'Fits' the transformer by checking if the column names are present in the dataset. |
| *fit_transform* | Fit transformer to data, then transform data. |
| *transform* | Transforms data X by selecting columns. |

### evalml.pipelines.components.SelectColumns.__init__

SelectColumns.**__init__**(*columns=None*, *random_state=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 drop.

### evalml.pipelines.components.SelectColumns.clone

SelectColumns.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.SelectColumns.describe

SelectColumns.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.SelectColumns.fit

SelectColumns.**fit**(*X*, *y=None*)

'Fits' the transformer by checking if the column names are present in the dataset.

**Parameters**

- **X** (*pd.DataFrame*) – Data to check.
- **y** (*pd.Series, optional*) – Targets.

**Returns** None.

### evalml.pipelines.components.SelectColumns.fit_transform

SelectColumns.**fit_transform**(*X*, *y=None*)

Fit transformer to data, then transform data.

**Parameters**

- **X** (*pd.DataFrame*) – Data to transform.
- **y** (*pd.Series, optional*) – Targets.

**Returns** Transformed X.

**Return type** pd.DataFrame

### evalml.pipelines.components.SelectColumns.transform

SelectColumns.**transform**(*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

## evalml.pipelines.components.OneHotEncoder


**class** evalml.pipelines.components.**OneHotEncoder**(*top_n=10*, *categories=None*, *drop=None*, *handle_unknown='ignore'*, *handle_missing='error'*, *random_state=0*, ***kwargs*)

One-hot encoder to encode non-numeric data.

**name = 'One Hot Encoder'**

```
model_family = 'none'
hyperparameter_ranges = {}
default_parameters = {'categories': None, 'drop': None, 'handle_missing': 'error',
```

### Instance attributes

| | |
|---|---|
| parameters | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *__init__* | Initalizes an transformer that encodes categorical features in a one-hot numeric array." |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *fit_transform* | Fits on X and transforms X |
| *get_feature_names* | Returns names of transformed and added columns |
| *transform* | One-hot encode the input DataFrame. |

### evalml.pipelines.components.OneHotEncoder.__init__

OneHotEncoder.**__init__**(*top_n=10*, *categories=None*, *drop=None*, *handle_unknown='ignore'*, *handle_missing='error'*, *random_state=0*, ***kwargs*)

Initalizes an 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.
- **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*) – Method ("first" or "if_binary") to use to drop one category per feature. Can also be a list specifying which method to use for each feature. Defaults to None.
- **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".

### evalml.pipelines.components.OneHotEncoder.clone

OneHotEncoder.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.OneHotEncoder.describe

OneHotEncoder.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.OneHotEncoder.fit

OneHotEncoder.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.OneHotEncoder.fit_transform

OneHotEncoder.**fit_transform**(*X*, *y=None*)

Fits on X and transforms X

**Parameters**

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd. DataFrame*) – Labels to fit and transform

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.OneHotEncoder.get_feature_names

OneHotEncoder.**get_feature_names**()

Returns names of transformed and added columns

**Returns** list of feature names not including dropped features

**Return type** list

### evalml.pipelines.components.OneHotEncoder.transform

OneHotEncoder.**transform**(*X*, *y=None*)

One-hot encode the input DataFrame.

**Parameters**

- **X** (*pd.DataFrame*) – Dataframe of features.
- **y** (*pd.Series*) – Ignored.

**Returns** Transformed dataframe, where each categorical feature has been encoded into numerical columns using one-hot encoding.

## evalml.pipelines.components.PerColumnImputer


**class** evalml.pipelines.components.**PerColumnImputer**(*impute_strategies=None*, *default_impute_strategy='most_frequent'*, *random_state=0*, ***kwargs*)

Imputes missing data according to a specified imputation strategy per column

**name = 'Per Column Imputer'**

**model_family = 'none'**

**hyperparameter_ranges = {}**

**default_parameters = {'default_impute_strategy': 'most_frequent', 'impute_strategies'**

### Instance attributes

| | |
|---|---|
| parameters | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *__init__* | Initializes a transformer that imputes missing data according to the specified imputation strategy per column.” |

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Table 46 – continued from previous page

| | |
|---|---|
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits imputers on data X |
| *fit_transform* | Fits imputer on data X then imputes missing values in X |
| *transform* | Transforms data X by imputing missing values |

### evalml.pipelines.components.PerColumnImputer.__init__

PerColumnImputer.**__init__**(*impute_strategies=None*, *default_impute_strategy='most_frequent'*, *random_state=0*, ***kwargs*)

Initializes a transformer that imputes missing data according to the 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 "most_frequent" for all columns.

  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.

- **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"

### evalml.pipelines.components.PerColumnImputer.clone

PerColumnImputer.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.PerColumnImputer.describe

PerColumnImputer.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.PerColumnImputer.fit

PerColumnImputer.**fit**(*X*, *y=None*)

Fits imputers on data X

**Parameters**

- **X** (*pd.DataFrame*) – Data to fit
- **y** (*pd.Series, optional*) – Input Labels

**Returns** self

### evalml.pipelines.components.PerColumnImputer.fit_transform

PerColumnImputer.**fit_transform**(*X*, *y=None*)

Fits imputer on data X then imputes missing values in X

**Parameters**

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Labels to fit and transform

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.PerColumnImputer.transform

PerColumnImputer.**transform**(*X*, *y=None*)

Transforms data X by imputing missing values

**Parameters**

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Input Labels

**Returns** Transformed X

**Return type** pd.DataFrame

## evalml.pipelines.components.Imputer


**class** evalml.pipelines.components.**Imputer**(*categorical_impute_strategy='most_frequent'*, *numeric_impute_strategy='mean'*, *fill_value=None*, *random_state=0*, ***kwargs*)

Imputes missing data according to a specified imputation strategy.

**name = 'Imputer'**

**model_family = 'none'**

**hyperparameter_ranges = {'categorical_impute_strategy': ['most_frequent'], 'numeric_i**

```
default_parameters = {'categorical_impute_strategy':  'most_frequent', 'fill_value':  N
```

### Instance attributes

| | |
|---|---|
| parameters | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *__init__* | Initalizes an transformer that imputes missing data according to the specified imputation strategy." |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits imputer to data |
| *fit_transform* | Fits on X and transforms X |
| *transform* | Transforms data X by imputing missing values |

### evalml.pipelines.components.Imputer.__init__

Imputer.**__init__**(*categorical_impute_strategy='most_frequent'*, *numeric_impute_strategy='mean'*, *fill_value=None*, *random_state=0*, ***kwargs*)

Initalizes an transformer that imputes missing data according to the 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 dtypes. Valid values include "mean", "median", "most_frequent", and "constant".
- **fill_value** (*string*) – When impute_strategy == "constant", fill_value is used to replace missing data. Defaults to 0 when imputing data and "missing_value" for strings or object data types.

### evalml.pipelines.components.Imputer.clone

Imputer.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.Imputer.describe

Imputer.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.Imputer.fit

Imputer.**fit**(*X*, *y=None*)

Fits imputer to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.Imputer.fit_transform

Imputer.**fit_transform**(*X*, *y=None*)

Fits on X and transforms X

**Parameters**

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd. DataFrame*) – Labels to fit and transform

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.Imputer.transform

Imputer.**transform**(*X*, *y=None*)

Transforms data X by imputing missing values

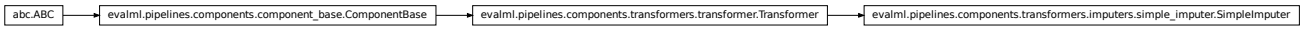
**Parameters**

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Input Labels

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.SimpleImputer




**class** evalml.pipelines.components.**SimpleImputer**(*impute_strategy='most_frequent'*, *fill_value=None*, *random_state=0*, ***kwargs*)

Imputes missing data according to a specified imputation strategy.

**name = 'Simple Imputer'**

**model_family = 'none'**

**hyperparameter_ranges = {'impute_strategy': ['mean', 'median', 'most_frequent']}**

**default_parameters = {'fill_value': None, 'impute_strategy': 'most_frequent'}**

#### Instance attributes

| | |
|---|---|
| parameters | Returns the parameters which were used to initialize the component |

#### Methods:

| | |
|---|---|
| *__init__* | Initalizes an transformer that imputes missing data according to the specified imputation strategy." |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits imputer to data |
| *fit_transform* | Fits on X and transforms X |
| *transform* | Transforms data X by imputing missing values |

#### evalml.pipelines.components.SimpleImputer.__init__

SimpleImputer.**__init__**(*impute_strategy='most_frequent'*, *fill_value=None*, *random_state=0*, ***kwargs*)

Initalizes an transformer that imputes missing data according to the 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.

### evalml.pipelines.components.SimpleImputer.clone

SimpleImputer.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.SimpleImputer.describe

SimpleImputer.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.SimpleImputer.fit

SimpleImputer.**fit**(*X*, *y=None*)

Fits imputer to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.SimpleImputer.fit_transform

SimpleImputer.**fit_transform**(*X*, *y=None*)

Fits on X and transforms X

**Parameters**

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd. DataFrame*) – Labels to fit and transform

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.SimpleImputer.transform

SimpleImputer.**transform**(*X*, *y=None*)
Transforms data X by imputing missing values

**Parameters**

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Input Labels

**Returns** Transformed X

**Return type** pd.DataFrame

## evalml.pipelines.components.StandardScaler


**class** evalml.pipelines.components.**StandardScaler**(*random_state=0*, ***kwargs*)
Standardize features: removes mean and scales to unit variance.

**name = 'Standard Scaler'**

**model_family = 'none'**

**hyperparameter_ranges = {}**

**default_parameters = {}**

### Instance attributes

| | |
|---|---|
| parameters | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *fit_transform* | Fits on X and transforms X |
| *transform* | Transforms data X |

### evalml.pipelines.components.StandardScaler.__init__

StandardScaler.**__init__**(*random_state=0*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.StandardScaler.clone

StandardScaler.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.StandardScaler.describe

StandardScaler.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.StandardScaler.fit

StandardScaler.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.StandardScaler.fit_transform

StandardScaler.**fit_transform**(*X*, *y=None*)

Fits on X and transforms X

**Parameters**

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd. DataFrame*) – Labels to fit and transform

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.StandardScaler.transform

StandardScaler.**transform**(*X*, *y=None*)
Transforms data X

**Parameters**

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Input Labels

**Returns** Transformed X

**Return type** pd.DataFrame

## evalml.pipelines.components.RFRegressorSelectFromModel


**class** evalml.pipelines.components.**RFRegressorSelectFromModel**(*number_features=None*, *n_estimators=10*, *max_depth=None*, *percent_features=0.5*, *threshold=-inf*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Selects top features based on importance weights using a Random Forest regressor.

```
name = 'RF Regressor Select From Model'
model_family = 'none'
hyperparameter_ranges = {'percent_features':  Real(low=0.01, high=1, prior='uniform',
default_parameters = {'max_depth':  None, 'n_estimators':  10, 'n_jobs':  -1, 'number_
```

### Instance attributes

| | |
|---|---|
| parameters | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |

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Table 54 – continued from previous page

| | |
|---|---|
| *fit_transform* | Fits feature selector on data X then transforms X by selecting features |
| *get_names* | Get names of selected features. |
| *transform* | Transforms data X by selecting features |

### evalml.pipelines.components.RFRegressorSelectFromModel.__init__

RFRegressorSelectFromModel.**__init__**(*number_features=None*, *n_estimators=10*, *max_depth=None*, *percent_features=0.5*, *threshold=-inf*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.RFRegressorSelectFromModel.clone

RFRegressorSelectFromModel.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.RFRegressorSelectFromModel.describe

RFRegressorSelectFromModel.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.RFRegressorSelectFromModel.fit

RFRegressorSelectFromModel.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.RFRegressorSelectFromModel.fit_transform

RFRegressorSelectFromModel.**fit_transform**(*X*, *y=None*)

Fits feature selector on data X then transforms X by selecting features

**Parameters**

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Labels to fit and transform

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.RFRegressorSelectFromModel.get_names

RFRegressorSelectFromModel.**get_names**()

Get names of selected features.

**Returns** list of the names of features selected

### evalml.pipelines.components.RFRegressorSelectFromModel.transform

RFRegressorSelectFromModel.**transform**(*X*, *y=None*)

Transforms data X by selecting features

**Parameters**

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Input Labels

**Returns** Transformed X

**Return type** pd.DataFrame

## evalml.pipelines.components.RFClassifierSelectFromModel


**class** evalml.pipelines.components.**RFClassifierSelectFromModel**(*number_features=None*, *n_estimators=10*, *max_depth=None*, *percent_features=0.5*, *threshold=-inf*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Selects top features based on importance weights using a Random Forest classifier.

**name = 'RF Classifier Select From Model'**

**model_family = 'none'**

```
hyperparameter_ranges = {'percent_features': Real(low=0.01, high=1, prior='uniform',
default_parameters = {'max_depth': None, 'n_estimators': 10, 'n_jobs': -1, 'number_
```

### Instance attributes

| | |
|---|---|
| `parameters` | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *`__init__`* | Initialize self. |
| *`clone`* | Constructs a new component with the same parameters |
| *`describe`* | Describe a component and its parameters |
| *`fit`* | Fits component to data |
| *`fit_transform`* | Fits feature selector on data X then transforms X by selecting features |
| *`get_names`* | Get names of selected features. |
| *`transform`* | Transforms data X by selecting features |

### evalml.pipelines.components.RFClassifierSelectFromModel.__init__

RFClassifierSelectFromModel.**__init__**(*number_features=None*, *n_estimators=10*, *max_depth=None*, *percent_features=0.5*, *threshold=-inf*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.RFClassifierSelectFromModel.clone

RFClassifierSelectFromModel.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.RFClassifierSelectFromModel.describe

RFClassifierSelectFromModel.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.RFClassifierSelectFromModel.fit

RFClassifierSelectFromModel.**fit**(*X*, *y=None*)
Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.RFClassifierSelectFromModel.fit_transform

RFClassifierSelectFromModel.**fit_transform**(*X*, *y=None*)
Fits feature selector on data X then transforms X by selecting features

**Parameters**

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd.Series*) – Labels to fit and transform

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.RFClassifierSelectFromModel.get_names

RFClassifierSelectFromModel.**get_names**()
Get names of selected features.

**Returns** list of the names of features selected

### evalml.pipelines.components.RFClassifierSelectFromModel.transform

RFClassifierSelectFromModel.**transform**(*X*, *y=None*)
Transforms data X by selecting features

**Parameters**

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Input Labels

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.DropNullColumns


**class** evalml.pipelines.components.**DropNullColumns**(*pct_null_threshold=1.0*, *random_state=0*, ***kwargs*)

Transformer to drop features whose percentage of NaN values exceeds a specified threshold

**name = 'Drop Null Columns Transformer'**

**model_family = 'none'**

**hyperparameter_ranges = {}**

**default_parameters = {'pct_null_threshold': 1.0}**

#### Instance attributes

| | |
|---|---|
| parameters | Returns the parameters which were used to initialize the component |

#### Methods:

| | |
|---|---|
| *__init__* | Initalizes an transformer to drop features whose percentage of NaN values exceeds a specified threshold. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *fit_transform* | Fits on X and transforms X |
| *transform* | Transforms data X by dropping columns that exceed the threshold of null values. |

#### evalml.pipelines.components.DropNullColumns.__init__

DropNullColumns.**__init__**(*pct_null_threshold=1.0*, *random_state=0*, ***kwargs*)

Initalizes an 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.

#### evalml.pipelines.components.DropNullColumns.clone

DropNullColumns.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.DropNullColumns.describe

DropNullColumns.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.DropNullColumns.fit

DropNullColumns.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.DropNullColumns.fit_transform

DropNullColumns.**fit_transform**(*X*, *y=None*)

Fits on X and transforms X

**Parameters**

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd. DataFrame*) – Labels to fit and transform

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.DropNullColumns.transform

DropNullColumns.**transform**(*X*, *y=None*)

Transforms data X by dropping columns that exceed the threshold of null values. :param X: Data to transform :type X: pd.DataFrame :param y: Targets :type y: pd.Series, optional

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.DateTimeFeaturizer


**class** evalml.pipelines.components.**DateTimeFeaturizer**(*features_to_extract=None*, *random_state=0*, ***kwargs*)

Transformer that can automatically featurize DateTime columns.

**name = 'DateTime Featurization Component'**

**model_family = 'none'**

**hyperparameter_ranges = {}**

**default_parameters = {'features_to_extract': ['year', 'month', 'day_of_week', 'hour']**

#### Instance attributes

| | |
|---|---|
| parameters | Returns the parameters which were used to initialize the component |

#### Methods:

| | |
|---|---|
| *__init__* | Extracts features from DateTime columns |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *fit_transform* | Fits on X and transforms X |
| *transform* | Transforms data X by creating new features using existing DateTime columns, and then dropping those DateTime columns |

#### evalml.pipelines.components.DateTimeFeaturizer.__init__

DateTimeFeaturizer.**__init__**(*features_to_extract=None*, *random_state=0*, ***kwargs*)

Extracts features from DateTime columns

**Parameters**

- **features_to_extract** (*list*) – list of features to extract. Valid options include "year", "month", "day_of_week", "hour".
- **random_state** (*int, np.random.RandomState*) – Seed for the random number generator.

#### evalml.pipelines.components.DateTimeFeaturizer.clone

DateTimeFeaturizer.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.DateTimeFeaturizer.describe

DateTimeFeaturizer.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.DateTimeFeaturizer.fit

DateTimeFeaturizer.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.DateTimeFeaturizer.fit_transform

DateTimeFeaturizer.**fit_transform**(*X*, *y=None*)

Fits on X and transforms X

**Parameters**

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd. DataFrame*) – Labels to fit and transform

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.DateTimeFeaturizer.transform

DateTimeFeaturizer.**transform**(*X*, *y=None*)

Transforms data X by creating new features using existing DateTime columns, and then dropping those DateTime columns

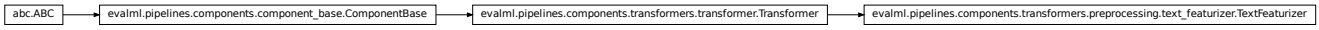
**Parameters**

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Input Labels

**Returns** Transformed X

**Return type** pd.DataFrame

### evalml.pipelines.components.TextFeaturizer




**class** evalml.pipelines.components.**TextFeaturizer**(*text_columns=None*, *random_state=0*, ***kwargs*)

Transformer that can automatically featurize text columns.

**name = 'Text Featurization Component'**

**model_family = 'none'**

**hyperparameter_ranges = {}**

**default_parameters = {'text_columns': []}**

#### Instance attributes

| | |
|---|---|
| parameters | Returns the parameters which were used to initialize the component |

#### Methods:

| | |
|---|---|
| *__init__* | Extracts features from text columns using featuretools' nlp_primitives |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *fit_transform* | Fits on X and transforms X |
| *transform* | Transforms data X by creating new features using existing text columns |

#### evalml.pipelines.components.TextFeaturizer.__init__

TextFeaturizer.**__init__**(*text_columns=None*, *random_state=0*, ***kwargs*)

Extracts features from text columns using featuretools' nlp_primitives

**Parameters**

- **text_colums** (*list*) – list of *pd.DataFrame* column names that contain text.
- **random_state** (*int, np.random.RandomState*) – Seed for the random number generator.

### evalml.pipelines.components.TextFeaturizer.clone

TextFeaturizer.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.TextFeaturizer.describe

TextFeaturizer.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.TextFeaturizer.fit

TextFeaturizer.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.TextFeaturizer.fit_transform

TextFeaturizer.**fit_transform**(*X*, *y=None*)

Fits on X and transforms X

**Parameters**

- **X** (*pd.DataFrame*) – Data to fit and transform
- **y** (*pd. DataFrame*) – Labels to fit and transform

**Returns** Transformed X

**Return type** pd.DataFrame

#### evalml.pipelines.components.TextFeaturizer.transform

TextFeaturizer.**transform**(*X*, *y=None*)

Transforms data X by creating new features using existing text columns

**Parameters**

- **X** (*pd.DataFrame*) – Data to transform
- **y** (*pd.Series, optional*) – Input Labels

**Returns** Transformed X

**Return type** pd.DataFrame

### 5.5.4 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. |
| *ExtraTreesClassifier* | Extra Trees Classifier. |
| *RandomForestClassifier* | Random Forest Classifier. |
| *LogisticRegressionClassifier* | Logistic Regression Classifier. |
| *XGBoostClassifier* | XGBoost Classifier. |
| *BaselineClassifier* | Classifier that predicts using the specified strategy. |

#### evalml.pipelines.components.CatBoostClassifier


**class** evalml.pipelines.components.**CatBoostClassifier**(*n_estimators=10*, *eta=0.03*, *max_depth=6*, *bootstrap_type=None*, *random_state=0*, ***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/

**name = 'CatBoost Classifier'**

**model_family = 'catboost'**

**supported_problem_types = [<ProblemTypes.BINARY: 'binary'>, <ProblemTypes.MULTICLASS:**

**hyperparameter_ranges = {'eta': Real(low=1e-06, high=1, prior='uniform', transform='i**

**default_parameters = {'bootstrap_type': None, 'eta': 0.03, 'max_depth': 6, 'n_estima**

### Instance attributes

| | |
|---|---|
| SEED_MAX | |
| SEED_MIN | |
| feature_importance | Return an attribute of instance, which is of type owner. |
| parameters | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *predict* | Make predictions using selected features. |
| *predict_proba* | Make probability estimates for labels. |

### evalml.pipelines.components.CatBoostClassifier.__init__

CatBoostClassifier.**__init__**(*n_estimators=10*, *eta=0.03*, *max_depth=6*, *bootstrap_type=None*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.CatBoostClassifier.clone

CatBoostClassifier.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.CatBoostClassifier.describe

CatBoostClassifier.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.CatBoostClassifier.fit

CatBoostClassifier.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.CatBoostClassifier.predict

CatBoostClassifier.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

### evalml.pipelines.components.CatBoostClassifier.predict_proba

CatBoostClassifier.**predict_proba**(*X*)

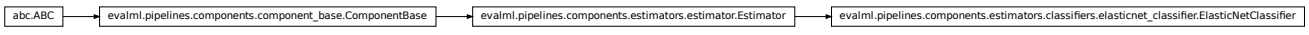
Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

## evalml.pipelines.components.ElasticNetClassifier




**class** evalml.pipelines.components.**ElasticNetClassifier**(*alpha=0.5*, *l1_ratio=0.5*, *n_jobs=-1*, *max_iter=1000*, *random_state=0*, ***kwargs*)

Elastic Net Classifier.

**name = 'Elastic Net Classifier'**

**model_family = 'linear_model'**

**supported_problem_types = [<ProblemTypes.BINARY: 'binary'>, <ProblemTypes.MULTICLASS:**

**hyperparameter_ranges = {'alpha': Real(low=0, high=1, prior='uniform', transform='ide**

**default_parameters = {'alpha': 0.5, 'l1_ratio': 0.5, 'max_iter': 1000, 'n_jobs': -**

### Instance attributes

| | |
|---|---|
| `feature_importance` | Return an attribute of instance, which is of type owner. |
| `parameters` | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *`__init__`* | Initialize self. |
| *`clone`* | Constructs a new component with the same parameters |
| *`describe`* | Describe a component and its parameters |
| *`fit`* | Fits component to data |
| *`predict`* | Make predictions using selected features. |
| *`predict_proba`* | Make probability estimates for labels. |

### evalml.pipelines.components.ElasticNetClassifier.__init__

`ElasticNetClassifier.`**`__init__`**(*alpha=0.5*, *l1_ratio=0.5*, *n_jobs=-1*, *max_iter=1000*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.ElasticNetClassifier.clone

`ElasticNetClassifier.`**`clone`**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **`random_state`** (*`int`*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.ElasticNetClassifier.describe

`ElasticNetClassifier.`**`describe`**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **`print_name`** (*`bool, optional`*) – whether to print name of component
- **`return_dict`** (*`bool, optional`*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.ElasticNetClassifier.fit

ElasticNetClassifier.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.ElasticNetClassifier.predict

ElasticNetClassifier.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

### evalml.pipelines.components.ElasticNetClassifier.predict_proba

ElasticNetClassifier.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

## evalml.pipelines.components.ExtraTreesClassifier


**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_state=0*, ***kwargs*)

Extra Trees Classifier.

**name = 'Extra Trees Classifier'**

**model_family = 'extra_trees'**

**supported_problem_types = [<ProblemTypes.BINARY: 'binary'>, <ProblemTypes.MULTICLASS:**

```
hyperparameter_ranges = {'max_depth':  Integer(low=4, high=10, prior='uniform', transf
default_parameters = {'max_depth':  6, 'max_features':  'auto', 'min_samples_split':  2
```

### Instance attributes

| | |
|---|---|
| feature_importance | Return an attribute of instance, which is of type owner. |
| parameters | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *predict* | Make predictions using selected features. |
| *predict_proba* | Make probability estimates for labels. |

### evalml.pipelines.components.ExtraTreesClassifier.__init__

ExtraTreesClassifier.**__init__**(*n_estimators=100*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.ExtraTreesClassifier.clone

ExtraTreesClassifier.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.ExtraTreesClassifier.describe

ExtraTreesClassifier.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.ExtraTreesClassifier.fit

ExtraTreesClassifier.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.ExtraTreesClassifier.predict

ExtraTreesClassifier.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

### evalml.pipelines.components.ExtraTreesClassifier.predict_proba

ExtraTreesClassifier.**predict_proba**(*X*)

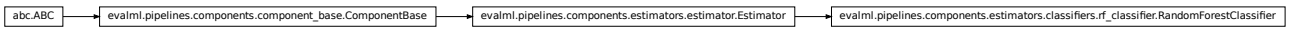
Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

## evalml.pipelines.components.RandomForestClassifier




**class** evalml.pipelines.components.**RandomForestClassifier**(*n_estimators=100*, *max_depth=6*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Random Forest Classifier.

**name = 'Random Forest Classifier'**

**model_family = 'random_forest'**

**supported_problem_types = [<ProblemTypes.BINARY: 'binary'>, <ProblemTypes.MULTICLASS:**

**hyperparameter_ranges = {'max_depth': Integer(low=1, high=10, prior='uniform', transf**

**default_parameters = {'max_depth': 6, 'n_estimators': 100, 'n_jobs': -1}**

### Instance attributes

| | |
|---|---|
| `feature_importance` | Return an attribute of instance, which is of type owner. |
| `parameters` | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *`__init__`* | Initialize self. |
| *`clone`* | Constructs a new component with the same parameters |
| *`describe`* | Describe a component and its parameters |
| *`fit`* | Fits component to data |
| *`predict`* | Make predictions using selected features. |
| *`predict_proba`* | Make probability estimates for labels. |

### evalml.pipelines.components.RandomForestClassifier.__init__

RandomForestClassifier.**__init__**(*n_estimators=100*, *max_depth=6*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.RandomForestClassifier.clone

RandomForestClassifier.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.RandomForestClassifier.describe

RandomForestClassifier.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.RandomForestClassifier.fit

RandomForestClassifier.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.RandomForestClassifier.predict

RandomForestClassifier.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

### evalml.pipelines.components.RandomForestClassifier.predict_proba

RandomForestClassifier.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

## evalml.pipelines.components.LogisticRegressionClassifier


**class** evalml.pipelines.components.**LogisticRegressionClassifier**(*penalty='l2'*, *C=1.0*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Logistic Regression Classifier.

**name = 'Logistic Regression Classifier'**

**model_family = 'linear_model'**

**supported_problem_types = [<ProblemTypes.BINARY: 'binary'>, <ProblemTypes.MULTICLASS:**

**hyperparameter_ranges = {'C': Real(low=0.01, high=10, prior='uniform', transform='iden**

**default_parameters = {'C': 1.0, 'n_jobs': -1, 'penalty': 'l2'}**

### Instance attributes

| | |
|---|---|
| feature_importance | Return an attribute of instance, which is of type owner. |
| parameters | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *predict* | Make predictions using selected features. |
| *predict_proba* | Make probability estimates for labels. |

### evalml.pipelines.components.LogisticRegressionClassifier.__init__

LogisticRegressionClassifier.**__init__**(*penalty='l2'*, *C=1.0*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.LogisticRegressionClassifier.clone

LogisticRegressionClassifier.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.LogisticRegressionClassifier.describe

LogisticRegressionClassifier.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.LogisticRegressionClassifier.fit

LogisticRegressionClassifier.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.LogisticRegressionClassifier.predict

LogisticRegressionClassifier.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

### evalml.pipelines.components.LogisticRegressionClassifier.predict_proba

LogisticRegressionClassifier.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

## evalml.pipelines.components.XGBoostClassifier


**class** evalml.pipelines.components.**XGBoostClassifier**(*eta=0.1*, *max_depth=6*, *min_child_weight=1*, *n_estimators=100*, *random_state=0*, ***kwargs*)

XGBoost Classifier.

**name = 'XGBoost Classifier'**

**model_family = 'xgboost'**

**supported_problem_types = [<ProblemTypes.BINARY: 'binary'>, <ProblemTypes.MULTICLASS:**

**hyperparameter_ranges = {'eta': Real(low=1e-06, high=1, prior='uniform', transform='i**

**default_parameters = {'eta': 0.1, 'max_depth': 6, 'min_child_weight': 1, 'n_estimat**

### Instance attributes

| | |
|---|---|
| SEED_MAX | |
| SEED_MIN | |
| feature_importance | Return an attribute of instance, which is of type owner. |
| parameters | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *predict* | Make predictions using selected features. |
| *predict_proba* | Make probability estimates for labels. |

### evalml.pipelines.components.XGBoostClassifier.__init__

XGBoostClassifier.**__init__**(*eta=0.1*, *max_depth=6*, *min_child_weight=1*, *n_estimators=100*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.XGBoostClassifier.clone

XGBoostClassifier.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.XGBoostClassifier.describe

XGBoostClassifier.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.XGBoostClassifier.fit

XGBoostClassifier.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.XGBoostClassifier.predict

XGBoostClassifier.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

### evalml.pipelines.components.XGBoostClassifier.predict_proba

XGBoostClassifier.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

## evalml.pipelines.components.BaselineClassifier


**class** evalml.pipelines.components.**BaselineClassifier**(*strategy='mode'*, *random_state=0*, ***kwargs*)

Classifier that predicts using the specified strategy.

This is useful as a simple baseline classifier to compare with other classifiers.

**name = 'Baseline Classifier'**

**model_family = 'baseline'**

**supported_problem_types = [<ProblemTypes.BINARY: 'binary'>, <ProblemTypes.MULTICLASS:**

**hyperparameter_ranges = {}**

**default_parameters = {'strategy': 'mode'}**

### Instance attributes

| | |
|---|---|
| classes_ | Returns class labels. |
| feature_importance | Return an attribute of instance, which is of type owner. |
| parameters | Returns the parameters which were used to initialize the component |

### Methods:

| | |
|---|---|
| *__init__* | Baseline classifier that uses a simple strategy to make predictions. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *predict* | Make predictions using selected features. |
| *predict_proba* | Make probability estimates for labels. |

### evalml.pipelines.components.BaselineClassifier.__init__

BaselineClassifier.**__init__**(*strategy='mode'*, *random_state=0*, ***kwargs*)

Baseline classifier that uses a simple strategy to make predictions.

**Parameters**

- **strategy** (*str*) – method used to predict. Valid options are "mode", "random" and "random_weighted". Defaults to "mode".
- **random_state** (*int, np.random.RandomState*) – seed for the random number generator

### evalml.pipelines.components.BaselineClassifier.clone

BaselineClassifier.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.BaselineClassifier.describe

BaselineClassifier.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

#### evalml.pipelines.components.BaselineClassifier.fit

BaselineClassifier.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

#### evalml.pipelines.components.BaselineClassifier.predict

BaselineClassifier.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

#### evalml.pipelines.components.BaselineClassifier.predict_proba

BaselineClassifier.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

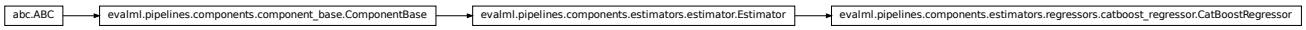
**Return type** pd.DataFrame

### Regressors

Regressors are components that output a predicted target value.

| | |
|---|---|
| *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* | Regressor that predicts using the specified strategy. |

### evalml.pipelines.components.CatBoostRegressor




**class** evalml.pipelines.components.**CatBoostRegressor**(*n_estimators=10*, *eta=0.03*, *max_depth=6*, *bootstrap_type=None*, *random_state=0*, ***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/

**name = 'CatBoost Regressor'**

**model_family = 'catboost'**

**supported_problem_types = [<ProblemTypes.REGRESSION: 'regression'>]**

**hyperparameter_ranges = {'eta': Real(low=1e-06, high=1, prior='uniform', transform='i**

**default_parameters = {'bootstrap_type': None, 'eta': 0.03, 'max_depth': 6, 'n_estima**

#### Instance attributes

| | |
|---|---|
| SEED_MAX | |
| SEED_MIN | |
| feature_importance | Return an attribute of instance, which is of type owner. |
| parameters | Returns the parameters which were used to initialize the component |

#### Methods:

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Build a model |
| *predict* | Make predictions using selected features. |
| *predict_proba* | Make probability estimates for labels. |

#### evalml.pipelines.components.CatBoostRegressor.__init__

CatBoostRegressor.**__init__**(*n_estimators=10*, *eta=0.03*, *max_depth=6*, *bootstrap_type=None*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.CatBoostRegressor.clone

CatBoostRegressor.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.CatBoostRegressor.describe

CatBoostRegressor.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.CatBoostRegressor.fit

CatBoostRegressor.**fit**(*X*, *y=None*)

Build a model

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.CatBoostRegressor.predict

CatBoostRegressor.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

### evalml.pipelines.components.CatBoostRegressor.predict_proba

CatBoostRegressor.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

### evalml.pipelines.components.ElasticNetRegressor


**class** evalml.pipelines.components.**ElasticNetRegressor**(*alpha=0.5*, *l1_ratio=0.5*, *max_iter=1000*, *normalize=False*, *random_state=0*, ***kwargs*)

Elastic Net Regressor.

**name = 'Elastic Net Regressor'**

**model_family = 'linear_model'**

**supported_problem_types = [<ProblemTypes.REGRESSION: 'regression'>]**

**hyperparameter_ranges = {'alpha': Real(low=0, high=1, prior='uniform', transform='ide**

**default_parameters = {'alpha': 0.5, 'l1_ratio': 0.5, 'max_iter': 1000, 'normalize':**

#### Instance attributes

| | |
|---|---|
| feature_importance | Return an attribute of instance, which is of type owner. |
| parameters | Returns the parameters which were used to initialize the component |

#### Methods:

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *predict* | Make predictions using selected features. |
| *predict_proba* | Make probability estimates for labels. |

#### evalml.pipelines.components.ElasticNetRegressor.__init__

ElasticNetRegressor.**__init__**(*alpha=0.5*, *l1_ratio=0.5*, *max_iter=1000*, *normalize=False*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.ElasticNetRegressor.clone

ElasticNetRegressor.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.ElasticNetRegressor.describe

ElasticNetRegressor.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.ElasticNetRegressor.fit

ElasticNetRegressor.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.ElasticNetRegressor.predict

ElasticNetRegressor.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

### evalml.pipelines.components.ElasticNetRegressor.predict_proba

ElasticNetRegressor.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

### evalml.pipelines.components.LinearRegressor


**class** evalml.pipelines.components.**LinearRegressor**(*fit_intercept=True*, *normalize=False*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Linear Regressor.

**name = 'Linear Regressor'**

**model_family = 'linear_model'**

**supported_problem_types = [<ProblemTypes.REGRESSION: 'regression'>]**

**hyperparameter_ranges = {'fit_intercept': [True, False], 'normalize': [True, False]}**

**default_parameters = {'fit_intercept': True, 'n_jobs': -1, 'normalize': False}**

#### Instance attributes

| | |
|---|---|
| feature_importance | Return an attribute of instance, which is of type owner. |
| parameters | Returns the parameters which were used to initialize the component |

#### Methods:

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *predict* | Make predictions using selected features. |
| *predict_proba* | Make probability estimates for labels. |

#### evalml.pipelines.components.LinearRegressor.__init__

LinearRegressor.**__init__**(*fit_intercept=True*, *normalize=False*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.LinearRegressor.clone

LinearRegressor.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.LinearRegressor.describe

LinearRegressor.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.LinearRegressor.fit

LinearRegressor.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.LinearRegressor.predict

LinearRegressor.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

### evalml.pipelines.components.LinearRegressor.predict_proba

LinearRegressor.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

### evalml.pipelines.components.ExtraTreesRegressor


**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_state=0*, ***kwargs*)

Extra Trees Regressor.

**name = 'Extra Trees Regressor'**

**model_family = 'extra_trees'**

**supported_problem_types = [<ProblemTypes.REGRESSION: 'regression'>]**

**hyperparameter_ranges = {'max_depth': Integer(low=4, high=10, prior='uniform', transf**

**default_parameters = {'max_depth': 6, 'max_features': 'auto', 'min_samples_split':**

#### Instance attributes

| | |
|---|---|
| feature_importance | Return an attribute of instance, which is of type owner. |
| parameters | Returns the parameters which were used to initialize the component |

#### Methods:

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *predict* | Make predictions using selected features. |
| *predict_proba* | Make probability estimates for labels. |

#### evalml.pipelines.components.ExtraTreesRegressor.__init__

ExtraTreesRegressor.**__init__**(*n_estimators=100*, *max_features='auto'*, *max_depth=6*, *min_samples_split=2*, *min_weight_fraction_leaf=0.0*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.ExtraTreesRegressor.clone

ExtraTreesRegressor.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.ExtraTreesRegressor.describe

ExtraTreesRegressor.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.ExtraTreesRegressor.fit

ExtraTreesRegressor.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.ExtraTreesRegressor.predict

ExtraTreesRegressor.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

### evalml.pipelines.components.ExtraTreesRegressor.predict_proba

ExtraTreesRegressor.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

### evalml.pipelines.components.RandomForestRegressor


**class** evalml.pipelines.components.**RandomForestRegressor**(*n_estimators=100*, *max_depth=6*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Random Forest Regressor.

**name = 'Random Forest Regressor'**

**model_family = 'random_forest'**

**supported_problem_types = [<ProblemTypes.REGRESSION: 'regression'>]**

**hyperparameter_ranges = {'max_depth': Integer(low=1, high=32, prior='uniform', transf**

**default_parameters = {'max_depth': 6, 'n_estimators': 100, 'n_jobs': -1}**

#### Instance attributes

| | |
|---|---|
| feature_importance | Return an attribute of instance, which is of type owner. |
| parameters | Returns the parameters which were used to initialize the component |

#### Methods:

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *predict* | Make predictions using selected features. |
| *predict_proba* | Make probability estimates for labels. |

#### evalml.pipelines.components.RandomForestRegressor.__init__

RandomForestRegressor.**__init__**(*n_estimators=100*, *max_depth=6*, *n_jobs=-1*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.RandomForestRegressor.clone

RandomForestRegressor.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.RandomForestRegressor.describe

RandomForestRegressor.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.RandomForestRegressor.fit

RandomForestRegressor.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.RandomForestRegressor.predict

RandomForestRegressor.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

### evalml.pipelines.components.RandomForestRegressor.predict_proba

RandomForestRegressor.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

### evalml.pipelines.components.XGBoostRegressor


**class** evalml.pipelines.components.**XGBoostRegressor**(*eta=0.1*, *max_depth=6*, *min_child_weight=1*, *n_estimators=100*, *random_state=0*, ***kwargs*)

XGBoost Regressor.

**name = 'XGBoost Regressor'**

**model_family = 'xgboost'**

**supported_problem_types = [<ProblemTypes.REGRESSION: 'regression'>]**

**hyperparameter_ranges = {'eta': Real(low=1e-06, high=1, prior='uniform', transform='i**

**default_parameters = {'eta': 0.1, 'max_depth': 6, 'min_child_weight': 1, 'n_estimat**

#### Instance attributes

| | |
|---|---|
| SEED_MAX | |
| SEED_MIN | |
| feature_importance | Return an attribute of instance, which is of type owner. |
| parameters | Returns the parameters which were used to initialize the component |

#### Methods:

| | |
|---|---|
| *__init__* | Initialize self. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *predict* | Make predictions using selected features. |
| *predict_proba* | Make probability estimates for labels. |

#### evalml.pipelines.components.XGBoostRegressor.__init__

XGBoostRegressor.**__init__**(*eta=0.1*, *max_depth=6*, *min_child_weight=1*, *n_estimators=100*, *random_state=0*, ***kwargs*)

Initialize self. See help(type(self)) for accurate signature.

### evalml.pipelines.components.XGBoostRegressor.clone

XGBoostRegressor.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.XGBoostRegressor.describe

XGBoostRegressor.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.XGBoostRegressor.fit

XGBoostRegressor.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.XGBoostRegressor.predict

XGBoostRegressor.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

### evalml.pipelines.components.XGBoostRegressor.predict_proba

XGBoostRegressor.**predict_proba**(*X*)

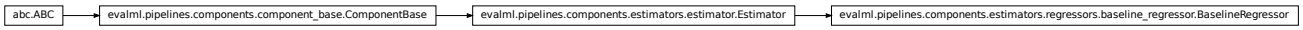
Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

### evalml.pipelines.components.BaselineRegressor




**class** evalml.pipelines.components.**BaselineRegressor**(*strategy='mean'*, *random_state=0*, ***kwargs*)

Regressor that predicts using the specified strategy.

This is useful as a simple baseline regressor to compare with other regressors.

**name = 'Baseline Regressor'**

**model_family = 'baseline'**

**supported_problem_types = [<ProblemTypes.REGRESSION: 'regression'>]**

**hyperparameter_ranges = {}**

**default_parameters = {'strategy': 'mean'}**

#### Instance attributes

| | |
|---|---|
| feature_importance | Return an attribute of instance, which is of type owner. |
| parameters | Returns the parameters which were used to initialize the component |

#### Methods:

| | |
|---|---|
| *__init__* | Baseline regressor that uses a simple strategy to make predictions. |
| *clone* | Constructs a new component with the same parameters |
| *describe* | Describe a component and its parameters |
| *fit* | Fits component to data |
| *predict* | Make predictions using selected features. |
| *predict_proba* | Make probability estimates for labels. |

#### evalml.pipelines.components.BaselineRegressor.__init__

BaselineRegressor.**__init__**(*strategy='mean'*, *random_state=0*, ***kwargs*)

Baseline regressor that uses a simple strategy to make predictions.

**Parameters**

- **strategy** (*str*) – method used to predict. Valid options are "mean", "median". Defaults to "mean".

- **random_state** (*int, np.random.RandomState*) – seed for the random number generator

### evalml.pipelines.components.BaselineRegressor.clone

BaselineRegressor.**clone**(*random_state=0*)

Constructs a new component with the same parameters

**Parameters** **random_state** (*int*) – the value to seed the random state with. Can also be a RandomState instance. Defaults to 0.

**Returns** A new instance of this component with identical parameters

### evalml.pipelines.components.BaselineRegressor.describe

BaselineRegressor.**describe**(*print_name=False*, *return_dict=False*)

Describe a component and its parameters

**Parameters**

- **print_name** (*bool, optional*) – whether to print name of component
- **return_dict** (*bool, optional*) – whether to return description as dictionary in the format {"name": name, "parameters": parameters}

**Returns** prints and returns dictionary

**Return type** None or dict

### evalml.pipelines.components.BaselineRegressor.fit

BaselineRegressor.**fit**(*X*, *y=None*)

Fits component to data

**Parameters**

- **X** (*pd.DataFrame or np.array*) – the input training data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target training labels of length [n_samples]

**Returns** self

### evalml.pipelines.components.BaselineRegressor.predict

BaselineRegressor.**predict**(*X*)

Make predictions using selected features.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** estimated labels

**Return type** pd.Series

#### evalml.pipelines.components.BaselineRegressor.predict_proba

BaselineRegressor.**predict_proba**(*X*)

Make probability estimates for labels.

**Parameters** **X** (*pd.DataFrame*) – features

**Returns** probability estimates

**Return type** pd.DataFrame

## 5.6 Prediction Explanations

| | |
|---|---|
| *explain_prediction* | Creates table summarizing the top_k positive and top_k negative contributing features to the prediction of a single datapoint. |

### 5.6.1 evalml.pipelines.prediction_explanations.explain_prediction

evalml.pipelines.prediction_explanations.**explain_prediction**(*pipeline*, *input_features*, *top_k=3*, *training_data=None*, *include_shap_values=False*)

Creates table summarizing the top_k positive and top_k negative contributing features to the prediction of a single datapoint.

XGBoost models and 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 features - needs to correspond to data the pipeline was fit on.
- **top_k** (*int*) – How many of the highest/lowest features to include in the table.
- **training_data** (*pd.DataFrame*) – Training data the pipeline was fit on. This is required for non-tree estimators because we need a sample of training data for the KernelSHAP algorithm.
- **include_shap_values** (*bool*) – Whether the SHAP values should be included in an extra column in the output.

**Returns** Table

**Return type** str

## 5.7 Objective Functions

### 5.7.1 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. |

### evalml.objectives.ObjectiveBase


**class** evalml.objectives.**ObjectiveBase**

Base class for all objectives.

#### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

#### evalml.objectives.ObjectiveBase.objective_function

**classmethod** ObjectiveBase.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

#### evalml.objectives.ObjectiveBase.score

ObjectiveBase.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

#### evalml.objectives.ObjectiveBase.validate_inputs

ObjectiveBase.**validate_inputs**(*y_true*, *y_predicted*)
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### evalml.objectives.BinaryClassificationObjective


**class** evalml.objectives.**BinaryClassificationObjective**
Base class for all binary classification objectives.

problem_type (ProblemTypes): Type of problem this objective is. Set to ProblemTypes.BINARY. can_optimize_threshold (bool): Determines if threshold used by objective can be optimized or not.

#### Methods

| | |
|---|---|
| *decision_function* | Apply a learned threshold to predicted probabilities to get predicted classes. |
| *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. |
| *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. |

### evalml.objectives.BinaryClassificationObjective.decision_function

BinaryClassificationObjective.**decision_function**(*ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

**Parameters**

- **ypred_proba** (*list*) – 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

### evalml.objectives.BinaryClassificationObjective.objective_function

**classmethod** BinaryClassificationObjective.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.BinaryClassificationObjective.optimize_threshold

BinaryClassificationObjective.**optimize_threshold**(*ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

**Parameters**

- **ypred_proba** (*list*) – The classifier's predicted probabilities
- **y_true** (*list*) – 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

### evalml.objectives.BinaryClassificationObjective.score

BinaryClassificationObjective.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

#### evalml.objectives.BinaryClassificationObjective.validate_inputs

BinaryClassificationObjective.**validate_inputs**(*y_true*, *y_predicted*)
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### evalml.objectives.MulticlassClassificationObjective


**class** evalml.objectives.**MulticlassClassificationObjective**
Base class for all multiclass classification objectives.

problem_type (ProblemTypes): Type of problem this objective is. Set to ProblemTypes.MULTICLASS.

#### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

#### evalml.objectives.MulticlassClassificationObjective.objective_function

**classmethod** MulticlassClassificationObjective.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.MulticlassClassificationObjective.score

MulticlassClassificationObjective.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.MulticlassClassificationObjective.validate_inputs

MulticlassClassificationObjective.**validate_inputs**(*y_true*, *y_predicted*)

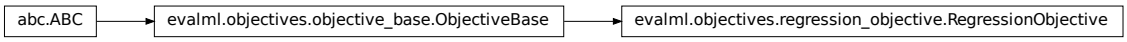
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.RegressionObjective




**class** evalml.objectives.**RegressionObjective**

Base class for all regression objectives.

problem_type (ProblemTypes): Type of problem this objective is. Set to ProblemTypes.REGRESSION.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *score* | Returns a numerical score indicating performance based on the differences between the predicted and actual values. |

Continued on next page

Table 98 – continued from previous page

| | |
|---|---|
| *validate_inputs* | Validates the input based on a few simple checks. |

#### evalml.objectives.RegressionObjective.objective_function

**classmethod** RegressionObjective.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

#### evalml.objectives.RegressionObjective.score

RegressionObjective.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

#### evalml.objectives.RegressionObjective.validate_inputs

RegressionObjective.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

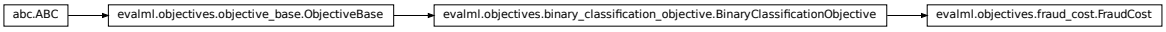
- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### 5.7.2 Domain-Specific Objectives

| | |
|---|---|
| *FraudCost* | Score the percentage of money lost of the total transaction amount process due to fraud. |
| *LeadScoring* | Lead scoring. |

### evalml.objectives.FraudCost




**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.

#### Methods

| | |
|---|---|
| *__init__* | Create instance of FraudCost |
| *decision_function* | Determine if a transaction is fraud given predicted probabilities, threshold, and dataframe with transaction amount. |
| *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. |
| *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. |

#### evalml.objectives.FraudCost.__init__

FraudCost.**__init__**(*retry_percentage=0.5*, *interchange_fee=0.02*, *fraud_payout_percentage=1.0*, *amount_col='amount'*)

Create instance of FraudCost

**Parameters**

- **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"

#### evalml.objectives.FraudCost.decision_function

FraudCost.**decision_function**(*ypred_proba*, *threshold=0.0*, *X=None*)

Determine if a transaction is fraud given predicted probabilities, threshold, and dataframe with transaction amount.

**Parameters**

- **ypred_proba** (*pd.Series*) – Predicted probablities
- **X** (*pd.DataFrame*) – Dataframe containing transaction amount
- **threshold** (*float*) – Dollar threshold to determine if transaction is fraud

**Returns** Series of predicted fraud labels using X and threshold

**Return type** pd.Series

### evalml.objectives.FraudCost.objective_function

FraudCost.**objective_function**(*y_true*, *y_predicted*, *X*)

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*) – dataframe with transaction amounts

**Returns** amount lost to fraud per transaction

**Return type** float

### evalml.objectives.FraudCost.optimize_threshold

FraudCost.**optimize_threshold**(*ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

**Parameters**

- **ypred_proba** (*list*) – The classifier's predicted probabilities
- **y_true** (*list*) – 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

### evalml.objectives.FraudCost.score

FraudCost.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.FraudCost.validate_inputs

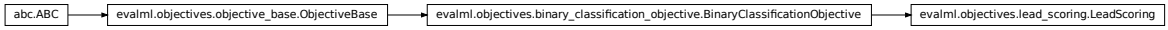
FraudCost.**validate_inputs**(*y_true*, *y_predicted*)
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.LeadScoring




**class** evalml.objectives.**LeadScoring**(*true_positives=1*, *false_positives=-1*)
Lead scoring.

### Methods

| | |
|---|---|
| *__init__* | Create instance. |
| *decision_function* | Apply a learned threshold to predicted probabilities to get predicted classes. |
| *objective_function* | Calculate the profit per lead. |
| *optimize_threshold* | Learn a binary classification threshold which optimizes the current objective. |
| *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. |

### evalml.objectives.LeadScoring.__init__

LeadScoring.**__init__**(*true_positives=1*, *false_positives=-1*)
Create instance.

**Parameters**

- **true_positives** (*int*) – reward for a true positive
- **false_positives** (*int*) – cost for a false positive. Should be negative.

### evalml.objectives.LeadScoring.decision_function

LeadScoring.**decision_function**(*ypred_proba*, *threshold=0.5*, *X=None*)
Apply a learned threshold to predicted probabilities to get predicted classes.

**Parameters**

- **ypred_proba** (*list*) – 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

### evalml.objectives.LeadScoring.objective_function

LeadScoring.**objective_function**(*y_true*, *y_predicted*, *X=None*)

Calculate the profit per lead.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted labels
- **y_true** (*pd.Series*) – true labels
- **X** (*pd.DataFrame*) – None, not used.

**Returns** profit per lead

**Return type** float

### evalml.objectives.LeadScoring.optimize_threshold

LeadScoring.**optimize_threshold**(*ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

**Parameters**

- **ypred_proba** (*list*) – The classifier's predicted probabilities
- **y_true** (*list*) – 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

### evalml.objectives.LeadScoring.score

LeadScoring.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

#### evalml.objectives.LeadScoring.validate_inputs

LeadScoring.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### 5.7.3 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. |
| *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. |

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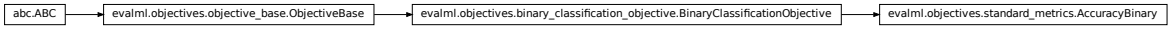
| | |
|---|---|
| *RecallWeighted* | Recall score for multiclass classification using weighted averaging. |

### evalml.objectives.AccuracyBinary




**class** evalml.objectives.**AccuracyBinary**

Accuracy score for binary classification.

#### Methods

| | |
|---|---|
| *decision_function* | Apply a learned threshold to predicted probabilities to get predicted classes. |
| *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. |
| *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. |

#### evalml.objectives.AccuracyBinary.decision_function

AccuracyBinary.**decision_function**(*ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

**Parameters**

- **ypred_proba** (*list*) – 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

#### evalml.objectives.AccuracyBinary.objective_function

AccuracyBinary.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.AccuracyBinary.optimize_threshold

AccuracyBinary.**optimize_threshold**(*ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

**Parameters**

- **ypred_proba** (*list*) – The classifier's predicted probabilities
- **y_true** (*list*) – 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

### evalml.objectives.AccuracyBinary.score

AccuracyBinary.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.AccuracyBinary.validate_inputs

AccuracyBinary.**validate_inputs**(*y_true*, *y_predicted*)

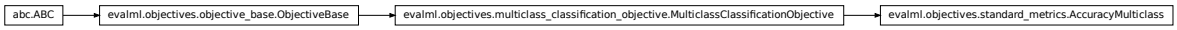
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### evalml.objectives.AccuracyMulticlass




**class** evalml.objectives.**AccuracyMulticlass**

Accuracy score for multiclass classification.

#### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

#### evalml.objectives.AccuracyMulticlass.objective_function

AccuracyMulticlass.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

#### evalml.objectives.AccuracyMulticlass.score

AccuracyMulticlass.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.AccuracyMulticlass.validate_inputs

AccuracyMulticlass.**validate_inputs**(*y_true*, *y_predicted*)

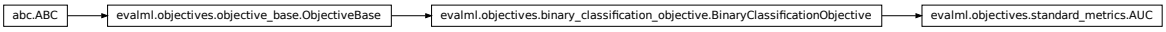
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.AUC




**class** evalml.objectives.**AUC**

AUC score for binary classification.

### Methods

| | |
|---|---|
| *decision_function* | Apply a learned threshold to predicted probabilities to get predicted classes. |
| *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. |
| *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. |

### evalml.objectives.AUC.decision_function

AUC.**decision_function**(*ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

**Parameters**

- **ypred_proba** (*list*) – 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

### evalml.objectives.AUC.objective_function

AUC.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.AUC.optimize_threshold

AUC.**optimize_threshold**(*ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

**Parameters**

- **ypred_proba** (*list*) – The classifier's predicted probabilities
- **y_true** (*list*) – 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

### evalml.objectives.AUC.score

AUC.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.AUC.validate_inputs

AUC.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### evalml.objectives.AUCMacro


**class** evalml.objectives.**AUCMacro**

AUC score for multiclass classification using macro averaging.

#### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

#### evalml.objectives.AUCMacro.objective_function

AUCMacro.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

#### evalml.objectives.AUCMacro.score

AUCMacro.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

#### evalml.objectives.AUCMacro.validate_inputs

AUCMacro.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### evalml.objectives.AUCMicro


**class** evalml.objectives.**AUCMicro**

AUC score for multiclass classification using micro averaging.

#### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

#### evalml.objectives.AUCMicro.objective_function

AUCMicro.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

#### evalml.objectives.AUCMicro.score

AUCMicro.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.AUCMicro.validate_inputs

AUCMicro.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.AUCWeighted


**class** evalml.objectives.**AUCWeighted**

AUC Score for multiclass classification using weighted averaging.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.AUCWeighted.objective_function

AUCWeighted.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.AUCWeighted.score

AUCWeighted.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.AUCWeighted.validate_inputs

AUCWeighted.**validate_inputs**(*y_true*, *y_predicted*)

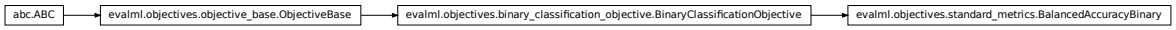
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.BalancedAccuracyBinary




**class** evalml.objectives.**BalancedAccuracyBinary**

Balanced accuracy score for binary classification.

### Methods

| | |
|---|---|
| *decision_function* | Apply a learned threshold to predicted probabilities to get predicted classes. |
| *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. |
| *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. |

### evalml.objectives.BalancedAccuracyBinary.decision_function

BalancedAccuracyBinary.**decision_function**(*ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

**Parameters**

- **ypred_proba** (*list*) – 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

### evalml.objectives.BalancedAccuracyBinary.objective_function

BalancedAccuracyBinary.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.BalancedAccuracyBinary.optimize_threshold

BalancedAccuracyBinary.**optimize_threshold**(*ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

**Parameters**

- **ypred_proba** (*list*) – The classifier's predicted probabilities
- **y_true** (*list*) – 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

### evalml.objectives.BalancedAccuracyBinary.score

BalancedAccuracyBinary.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.BalancedAccuracyBinary.validate_inputs

BalancedAccuracyBinary.**validate_inputs**(*y_true*, *y_predicted*)

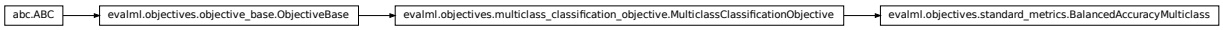
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.BalancedAccuracyMulticlass




**class** evalml.objectives.**BalancedAccuracyMulticlass**

Balanced accuracy score for multiclass classification.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.BalancedAccuracyMulticlass.objective_function

BalancedAccuracyMulticlass.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.BalancedAccuracyMulticlass.score

BalancedAccuracyMulticlass.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.BalancedAccuracyMulticlass.validate_inputs

BalancedAccuracyMulticlass.**validate_inputs**(*y_true*, *y_predicted*)

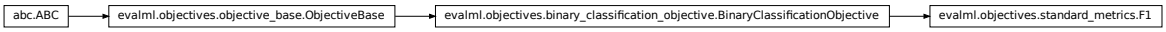
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.F1




**class** evalml.objectives.**F1**

F1 score for binary classification.

### Methods

| | |
|---|---|
| *decision_function* | Apply a learned threshold to predicted probabilities to get predicted classes. |
| *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. |
| *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. |

### evalml.objectives.F1.decision_function

F1.**decision_function**(*ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

**Parameters**

- **ypred_proba** (*list*) – 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

### evalml.objectives.F1.objective_function

F1.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.F1.optimize_threshold

F1.**optimize_threshold**(*ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

**Parameters**

- **ypred_proba** (*list*) – The classifier's predicted probabilities
- **y_true** (*list*) – 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

### evalml.objectives.F1.score

F1.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.F1.validate_inputs

F1.**validate_inputs**(*y_true*, *y_predicted*)

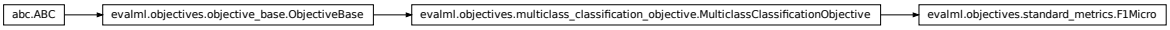
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.F1Micro




**class** evalml.objectives.**F1Micro**

F1 score for multiclass classification using micro averaging.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.F1Micro.objective_function

F1Micro.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

#### evalml.objectives.F1Micro.score

F1Micro.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

#### evalml.objectives.F1Micro.validate_inputs

F1Micro.**validate_inputs**(*y_true*, *y_predicted*)

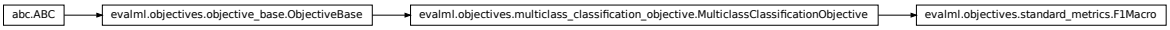
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### evalml.objectives.F1Macro




**class** evalml.objectives.**F1Macro**

F1 score for multiclass classification using macro averaging.

#### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

#### evalml.objectives.F1Macro.objective_function

F1Macro.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.F1Macro.score

F1Macro.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.F1Macro.validate_inputs

F1Macro.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.F1Weighted


**class** evalml.objectives.**F1Weighted**

F1 score for multiclass classification using weighted averaging.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.F1Weighted.objective_function

F1Weighted.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.F1Weighted.score

F1Weighted.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.F1Weighted.validate_inputs

F1Weighted.**validate_inputs**(*y_true*, *y_predicted*)

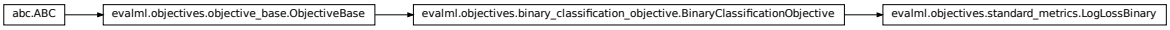
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### evalml.objectives.LogLossBinary




**class** evalml.objectives.**LogLossBinary**

Log Loss for binary classification.

#### Methods

| | |
|---|---|
| *decision_function* | Apply a learned threshold to predicted probabilities to get predicted classes. |
| *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. |
| *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. |

#### evalml.objectives.LogLossBinary.decision_function

LogLossBinary.**decision_function**(*ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

**Parameters**

- **ypred_proba** (*list*) – 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

#### evalml.objectives.LogLossBinary.objective_function

LogLossBinary.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.LogLossBinary.optimize_threshold

LogLossBinary.**optimize_threshold**(*ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

**Parameters**

- **ypred_proba** (*list*) – The classifier's predicted probabilities
- **y_true** (*list*) – 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

### evalml.objectives.LogLossBinary.score

LogLossBinary.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.LogLossBinary.validate_inputs

LogLossBinary.**validate_inputs**(*y_true*, *y_predicted*)

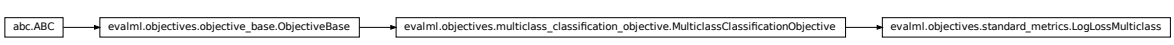
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.LogLossMulticlass




**class** evalml.objectives.**LogLossMulticlass**

Log Loss for multiclass classification.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.LogLossMulticlass.objective_function

LogLossMulticlass.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.LogLossMulticlass.score

LogLossMulticlass.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.LogLossMulticlass.validate_inputs

LogLossMulticlass.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### evalml.objectives.MCCBinary


**class** evalml.objectives.**MCCBinary**

Matthews correlation coefficient for binary classification.

#### Methods

| | |
|---|---|
| *decision_function* | Apply a learned threshold to predicted probabilities to get predicted classes. |
| *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. |
| *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. |

#### evalml.objectives.MCCBinary.decision_function

MCCBinary.**decision_function**(*ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

**Parameters**

- **ypred_proba** (*list*) – 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

#### evalml.objectives.MCCBinary.objective_function

MCCBinary.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.MCCBinary.optimize_threshold

MCCBinary.**optimize_threshold**(*ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

**Parameters**

- **ypred_proba** (*list*) – The classifier's predicted probabilities
- **y_true** (*list*) – 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

### evalml.objectives.MCCBinary.score

MCCBinary.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.MCCBinary.validate_inputs

MCCBinary.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.MCCMulticlass


**class** evalml.objectives.**MCCMulticlass**

Matthews correlation coefficient for multiclass classification.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.MCCMulticlass.objective_function

MCCMulticlass.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.MCCMulticlass.score

MCCMulticlass.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.MCCMulticlass.validate_inputs

MCCMulticlass.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### evalml.objectives.Precision


**class** evalml.objectives.**Precision**

Precision score for binary classification.

#### Methods

| | |
|---|---|
| *decision_function* | Apply a learned threshold to predicted probabilities to get predicted classes. |
| *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. |
| *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. |

#### evalml.objectives.Precision.decision_function

Precision.**decision_function**(*ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

**Parameters**

- **ypred_proba** (*list*) – 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

#### evalml.objectives.Precision.objective_function

Precision.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.Precision.optimize_threshold

Precision.**optimize_threshold**(*ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

**Parameters**

- **ypred_proba** (*list*) – The classifier's predicted probabilities
- **y_true** (*list*) – 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

### evalml.objectives.Precision.score

Precision.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.Precision.validate_inputs

Precision.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.PrecisionMicro


**class** evalml.objectives.**PrecisionMicro**

Precision score for multiclass classification using micro averaging.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.PrecisionMicro.objective_function

PrecisionMicro.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.PrecisionMicro.score

PrecisionMicro.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.PrecisionMicro.validate_inputs

PrecisionMicro.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### evalml.objectives.PrecisionMacro


**class** evalml.objectives.**PrecisionMacro**

Precision score for multiclass classification using macro averaging.

#### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

#### evalml.objectives.PrecisionMacro.objective_function

PrecisionMacro.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

#### evalml.objectives.PrecisionMacro.score

PrecisionMacro.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.PrecisionMacro.validate_inputs

PrecisionMacro.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.PrecisionWeighted


**class** evalml.objectives.**PrecisionWeighted**

Precision score for multiclass classification using weighted averaging.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.PrecisionWeighted.objective_function

PrecisionWeighted.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.PrecisionWeighted.score

PrecisionWeighted.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

#### evalml.objectives.PrecisionWeighted.validate_inputs

PrecisionWeighted.**validate_inputs**(*y_true*, *y_predicted*)

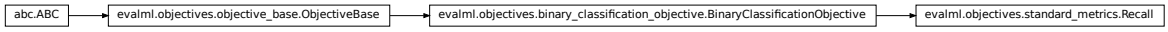
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### evalml.objectives.Recall




**class** evalml.objectives.**Recall**

Recall score for binary classification.

#### Methods

| | |
|---|---|
| *decision_function* | Apply a learned threshold to predicted probabilities to get predicted classes. |
| *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. |
| *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. |

#### evalml.objectives.Recall.decision_function

Recall.**decision_function**(*ypred_proba*, *threshold=0.5*, *X=None*)

Apply a learned threshold to predicted probabilities to get predicted classes.

**Parameters**

- **ypred_proba** (*list*) – 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

### evalml.objectives.Recall.objective_function

Recall.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.Recall.optimize_threshold

Recall.**optimize_threshold**(*ypred_proba*, *y_true*, *X=None*)

Learn a binary classification threshold which optimizes the current objective.

**Parameters**

- **ypred_proba** (*list*) – The classifier's predicted probabilities
- **y_true** (*list*) – 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

### evalml.objectives.Recall.score

Recall.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.Recall.validate_inputs

Recall.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.RecallMicro


**class** evalml.objectives.**RecallMicro**

Recall score for multiclass classification using micro averaging.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.RecallMicro.objective_function

RecallMicro.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.RecallMicro.score

RecallMicro.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.RecallMicro.validate_inputs

RecallMicro.**validate_inputs**(*y_true*, *y_predicted*)

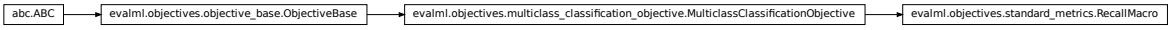
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.RecallMacro




**class** evalml.objectives.**RecallMacro**

Recall score for multiclass classification using macro averaging.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.RecallMacro.objective_function

RecallMacro.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.RecallMacro.score

RecallMacro.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.RecallMacro.validate_inputs

RecallMacro.**validate_inputs**(*y_true*, *y_predicted*)

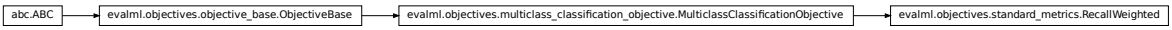
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.RecallWeighted




**class** evalml.objectives.**RecallWeighted**

Recall score for multiclass classification using weighted averaging.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.RecallWeighted.objective_function

RecallWeighted.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

#### evalml.objectives.RecallWeighted.score

RecallWeighted.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

#### evalml.objectives.RecallWeighted.validate_inputs

RecallWeighted.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### 5.7.4 Regression Objectives

| | |
|---|---|
| *R2* | Coefficient of determination for regression. |
| *MAE* | Mean absolute error for regression. |
| *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. |

### evalml.objectives.R2


**class** evalml.objectives.**R2**

Coefficient of determination for regression.

#### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

#### evalml.objectives.R2.objective_function

R2.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

#### evalml.objectives.R2.score

R2.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.R2.validate_inputs

R2.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.MAE


**class** evalml.objectives.**MAE**

Mean absolute error for regression.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.MAE.objective_function

MAE.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.MAE.score

MAE.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

#### evalml.objectives.MAE.validate_inputs

MAE.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### evalml.objectives.MSE


**class** evalml.objectives.**MSE**

Mean squared error for regression.

#### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

#### evalml.objectives.MSE.objective_function

MSE.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.MSE.score

MSE.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.MSE.validate_inputs

MSE.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.MeanSquaredLogError


**class** evalml.objectives.**MeanSquaredLogError**

Mean squared log error for regression.

Only valid for nonnegative inputs. Otherwise, will throw a ValueError

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.MeanSquaredLogError.objective_function

MeanSquaredLogError.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.MeanSquaredLogError.score

MeanSquaredLogError.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.MeanSquaredLogError.validate_inputs

MeanSquaredLogError.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.MedianAE


**class** evalml.objectives.**MedianAE**

Median absolute error for regression.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.MedianAE.objective_function

MedianAE.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.MedianAE.score

MedianAE.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.MedianAE.validate_inputs

MedianAE.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

### evalml.objectives.MaxError


**class** evalml.objectives.**MaxError**

Maximum residual error for regression.

#### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

#### evalml.objectives.MaxError.objective_function

MaxError.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

#### evalml.objectives.MaxError.score

MaxError.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.MaxError.validate_inputs

MaxError.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.ExpVariance


**class** evalml.objectives.**ExpVariance**

Explained variance score for regression.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.ExpVariance.objective_function

ExpVariance.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.ExpVariance.score

ExpVariance.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.ExpVariance.validate_inputs

ExpVariance.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.RootMeanSquaredError


**class** evalml.objectives.**RootMeanSquaredError**

Root mean squared error for regression.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

### evalml.objectives.RootMeanSquaredError.objective_function

RootMeanSquaredError.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

### evalml.objectives.RootMeanSquaredError.score

RootMeanSquaredError.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

### evalml.objectives.RootMeanSquaredError.validate_inputs

RootMeanSquaredError.**validate_inputs**(*y_true*, *y_predicted*)

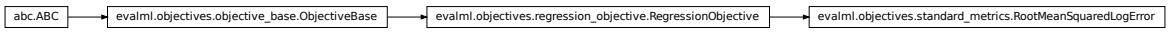
Validates the input based on a few simple checks.

**Parameters**

- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## evalml.objectives.RootMeanSquaredLogError




**class** evalml.objectives.**RootMeanSquaredLogError**

Root mean squared log error for regression.

Only valid for nonnegative inputs.Otherwise, will throw a ValueError.

### Methods

| | |
|---|---|
| *objective_function* | Computes the relative value of the provided predictions compared to the actual labels, according a specified metric |
| *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. |

#### evalml.objectives.RootMeanSquaredLogError.objective_function

RootMeanSquaredLogError.**objective_function**(*y_true*, *y_predicted*, *X=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.array): extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** numerical value used to calculate score

#### evalml.objectives.RootMeanSquaredLogError.score

RootMeanSquaredLogError.**score**(*y_true*, *y_predicted*, *X=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.array*) – extra data of shape [n_samples, n_features] necessary to calculate score

**Returns** score

#### evalml.objectives.RootMeanSquaredLogError.validate_inputs

RootMeanSquaredLogError.**validate_inputs**(*y_true*, *y_predicted*)

Validates the input based on a few simple checks.

**Parameters**

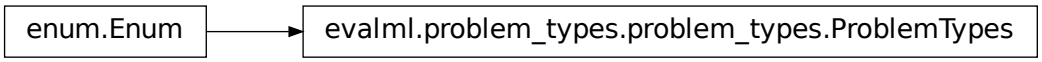
- **y_predicted** (*pd.Series*) – predicted values of length [n_samples]
- **y_true** (*pd.Series*) – actual class labels of length [n_samples]

**Returns** None

## 5.8 Problem Types

| | |
|---|---|
| *ProblemTypes* | Enum for type of machine learning problem: BINARY, MULTICLASS, or REGRESSION. |

### 5.8.1 evalml.problem_types.ProblemTypes




**class** evalml.problem_types.**ProblemTypes**
Enum for type of machine learning problem: BINARY, MULTICLASS, or REGRESSION.

| | |
|---|---|
| *handle_problem_types* | Handles problem_type by either returning the ProblemTypes or converting from a str. |

### 5.8.2 evalml.problem_types.handle_problem_types

evalml.problem_types.**handle_problem_types**(*problem_type*)
Handles problem_type by either returning the ProblemTypes or converting from a str.

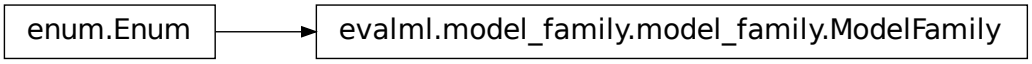
**Parameters** **problem_type** (*str or ProblemTypes*) – problem type that needs to be handled

**Returns** ProblemTypes

## 5.9 Model Family

| | |
|---|---|
| *ModelFamily* | Enum for family of machine learning models. |

### 5.9.1 evalml.model_family.ModelFamily




**class** evalml.model_family.**ModelFamily**
Enum for family of machine learning models.

| | |
|---|---|
| *handle_model_family* | Handles model_family by either returning the ModelFamily or converting from a str :param model_family: model type that needs to be handled :type model_family: str or ModelFamily |

### 5.9.2 evalml.model_family.handle_model_family

evalml.model_family.**handle_model_family**(*model_family*)

Handles model_family by either returning the ModelFamily or converting from a str :param model_family: model type that needs to be handled :type model_family: str or ModelFamily

**Returns** ModelFamily

## 5.10 Tuners

| | |
|---|---|
| *Tuner* | Defines API for Tuners. |
| *SKOptTuner* | Bayesian Optimizer. |
| *GridSearchTuner* | Grid Search Optimizer. |
| *RandomSearchTuner* | Random Search Optimizer. |

### 5.10.1 evalml.tuners.Tuner


**class** evalml.tuners.**Tuner**(*pipeline_hyperparameter_ranges*, *random_state=0*)

Defines API for Tuners.

Tuners implement different strategies for sampling from a search space. They're used in EvalML to search the space of pipeline hyperparameters.

#### Methods

| | |
|---|---|
| *__init__* | Base Tuner class |

Continued on next page

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| | |
|---|---|
| *add* | Register a set of hyperparameters with the score obtained from training a pipeline with those hyperparameters. |
| *is_search_space_exhausted* | Optional. |
| *propose* | Returns a suggested set of parameters to train and score a pipeline with, based off the search space dimensions and prior samples. |

### evalml.tuners.Tuner.__init__

Tuner.**__init__**(*pipeline_hyperparameter_ranges*, *random_state=0*)

Base Tuner class

**Parameters**

- **pipeline_hyperparameter_ranges** (*dict*) – a set of hyperparameter ranges corresponding to a pipeline's parameters
- **random_state** (*int, np.random.RandomState*) – The random state

### evalml.tuners.Tuner.add

Tuner.**add**(*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

### evalml.tuners.Tuner.is_search_space_exhausted

Tuner.**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.

**Returns** Returns true if all possible parameters in a search space has been scored.

**Return type** bool

### evalml.tuners.Tuner.propose

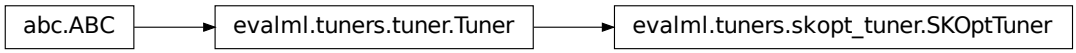
Tuner.**propose**()

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

### 5.10.2 evalml.tuners.SKOptTuner




**class** evalml.tuners.**SKOptTuner**(*pipeline_hyperparameter_ranges*, *random_state=0*)

Bayesian Optimizer.

#### Methods

| | |
|---|---|
| *__init__* | Init SkOptTuner |
| *add* | Add score to sample |
| *is_search_space_exhausted* | Optional. |
| *propose* | Returns a suggested set of parameters to train and score a pipeline with, based off the search space dimensions and prior samples. |

#### evalml.tuners.SKOptTuner.__init__

SKOptTuner.**__init__**(*pipeline_hyperparameter_ranges*, *random_state=0*)

Init SkOptTuner

**Parameters**

- **pipeline_hyperparameter_ranges** (*dict*) – a set of hyperparameter ranges corresponding to a pipeline's parameters
- **random_state** (*int, np.random.RandomState*) – The random state

#### evalml.tuners.SKOptTuner.add

SKOptTuner.**add**(*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

#### evalml.tuners.SKOptTuner.is_search_space_exhausted

SKOptTuner.**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.

**Returns** Returns true if all possible parameters in a search space has been scored.

**Return type** bool

#### evalml.tuners.SKOptTuner.propose

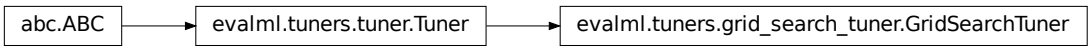
SKOptTuner.**propose**()

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

### 5.10.3 evalml.tuners.GridSearchTuner




**class** evalml.tuners.**GridSearchTuner**(*pipeline_hyperparameter_ranges*, *n_points=10*, *random_state=0*)

Grid Search Optimizer.

#### 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

| | |
|---|---|
| *__init__* | Generate all of the possible points to search for in the grid |
| *add* | Not applicable to grid search tuner as generated parameters are not dependent on scores of previous parameters. |
| *is_search_space_exhausted* | Checks if it is possible to generate a set of valid parameters. |
| *propose* | Returns parameters from _grid_points iterations |

#### evalml.tuners.GridSearchTuner.__init__

GridSearchTuner.**__init__**(*pipeline_hyperparameter_ranges*, *n_points=10*, *random_state=0*)

Generate all of the possible points to search for in the grid

**Parameters**

- **pipeline_hyperparameter_ranges** (*dict*) – a set of hyperparameter ranges corresponding to a pipeline's parameters
- **n_points** – The number of points to sample from along each dimension defined in the `space` argument
- **random_state** – Unused in this class

#### evalml.tuners.GridSearchTuner.add

`GridSearchTuner.`**`add`**(*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

#### evalml.tuners.GridSearchTuner.is_search_space_exhausted

`GridSearchTuner.`**`is_search_space_exhausted`**`()`

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

#### evalml.tuners.GridSearchTuner.propose

`GridSearchTuner.`**`propose`**`()`

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

### 5.10.4 evalml.tuners.RandomSearchTuner

**class** evalml.tuners.**RandomSearchTuner**(*pipeline_hyperparameter_ranges*, *random_state=0*, *with_replacement=False*, *replacement_max_attempts=10*)

Random Search Optimizer.

### Example

```
>>> tuner = RandomSearchTuner({'My Component': {'param a': [0.0, 10.0], 'param b
↪': ['a', 'b', 'c']}}, random_state=42)
>>> proposal = tuner.propose()
>>> assert proposal.keys() == {'My Component'}
>>> assert proposal['My Component'] == {'param a': 3.7454011884736254, 'param b':
↪'c'}
```

### Methods

| | |
|---|---|
| *__init__* | Sets up check for duplication if needed. |
| *add* | Not applicable to random search tuner as generated parameters are not dependent on scores of previous parameters. |
| *is_search_space_exhausted* | Checks if it is possible to generate a set of valid parameters. |
| *propose* | Generate a unique set of parameters. |

#### evalml.tuners.RandomSearchTuner.__init__

RandomSearchTuner.**__init__**(*pipeline_hyperparameter_ranges*, *random_state=0*, *with_replacement=False*, *replacement_max_attempts=10*)

Sets up check for duplication if needed.

**Parameters**

- **pipeline_hyperparameter_ranges** (*dict*) – a set of hyperparameter ranges corresponding to a pipeline's parameters
- **random_state** – Unused in this class
- **with_replacement** – If false, only unique hyperparameters will be shown
- **replacement_max_attempts** – The maximum number of tries to get a unique set of random parameters. Only used if tuner is initalized with with_replacement=True

#### evalml.tuners.RandomSearchTuner.add

RandomSearchTuner.**add**(*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

#### evalml.tuners.RandomSearchTuner.is_search_space_exhausted

RandomSearchTuner.**is_search_space_exhausted**()

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

#### evalml.tuners.RandomSearchTuner.propose

RandomSearchTuner.**propose**()

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

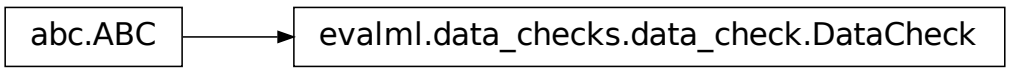
**Return type** dict

## 5.11 Data Checks

### 5.11.1 Data Check Classes

| | |
|---|---|
| *DataCheck* | Base class for all data checks. |
| *InvalidTargetDataCheck* | Checks if the target labels contain missing or invalid data. |
| *HighlyNullDataCheck* | Checks if there are any highly-null columns in the input. |
| *IDColumnsDataCheck* | Check if any of the features are likely to be ID columns. |
| *LabelLeakageDataCheck* | Check if any of the features are highly correlated with the target. |
| *OutliersDataCheck* | Checks if there are any outliers in input data by using an Isolation Forest to obtain the anomaly score of each index and then using IQR to determine score anomalies. |
| *NoVarianceDataCheck* | Check if any of the features or labels have no variance. |

#### evalml.data_checks.DataCheck



**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.

**name = 'DataCheck'**

#### Instance attributes

---

#### Methods:

| | |
|---|---|
| *validate* | Inspects and validates the input data, runs any necessary calculations or algorithms, and returns a list of warnings and errors if applicable. |

#### evalml.data_checks.DataCheck.validate

DataCheck.**validate**(*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.

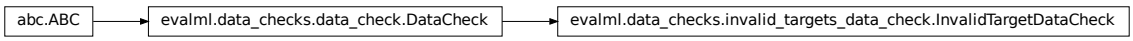
**Parameters**

- **X** (*pd.DataFrame*) – the input data of shape [n_samples, n_features]
- **y** (*pd.Series, optional*) – the target data of length [n_samples]

**Returns** list of DataCheckError and DataCheckWarning objects

**Return type** list (*DataCheckMessage*)

### evalml.data_checks.InvalidTargetDataCheck




**class** evalml.data_checks.**InvalidTargetDataCheck**

Checks if the target labels contain missing or invalid data.

**name = 'InvalidTargetDataCheck'**

#### Instance attributes

---

#### Methods:

| | |
|---|---|
| *validate* | Checks if the target labels contain missing or invalid data. |

### evalml.data_checks.InvalidTargetDataCheck.validate

InvalidTargetDataCheck.**validate**(*X*, *y*)

Checks if the target labels contain missing or invalid data.

**Parameters**

- **X** (*pd.DataFrame, pd.Series, np.array, list*) – Features. Ignored.
- **y** – Target labels to check for invalid data.

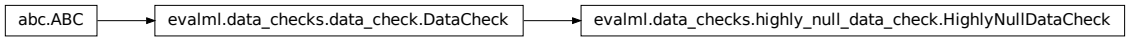
**Returns** list with DataCheckErrors if any invalid data is found in target labels.

**Return type** list (*DataCheckError*)

#### Example

```
>>> X = pd.DataFrame({})
>>> y = pd.Series([0, 1, None, None])
>>> target_check = InvalidTargetDataCheck()
>>> assert target_check.validate(X, y) == [DataCheckError("2 row(s) (50.0%) of target values are null", "InvalidTargetDataCheck")]
```

## evalml.data_checks.HighlyNullDataCheck




**class** evalml.data_checks.**HighlyNullDataCheck**(*pct_null_threshold=0.95*)

Checks if there are any highly-null columns in the input.

**name = 'HighlyNullDataCheck'**

#### Instance attributes

—

#### Methods:

| | |
|---|---|
| *__init__* | Checks if there are any highly-null columns in the input. |
| *validate* | Checks if there are any highly-null columns in the input. |

#### evalml.data_checks.HighlyNullDataCheck.__init__

HighlyNullDataCheck.**__init__**(*pct_null_threshold=0.95*)

Checks if there are any highly-null columns in the input.

**Parameters** **pct_null_threshold** (*float*) – If the percentage of NaN values in an input feature exceeds this amount, that feature will be considered highly-null. Defaults to 0.95.

#### evalml.data_checks.HighlyNullDataCheck.validate

HighlyNullDataCheck.**validate**(*X*, *y=None*)

Checks if there are any highly-null columns in the input.

**Parameters**

- **X** (*pd.DataFrame, pd.Series, np.array, list*) – features
- **y** – Ignored.

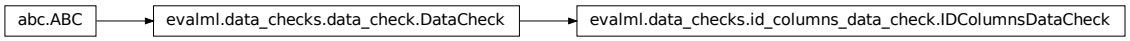
**Returns** list with a DataCheckWarning if there are any highly-null columns.

**Return type** list (*DataCheckWarning*)

#### Example

```
>>> df = pd.DataFrame({
...     'lots_of_null': [None, None, None, None, 5],
...     'no_null': [1, 2, 3, 4, 5]
... })
>>> null_check = HighlyNullDataCheck(pct_null_threshold=0.8)
>>> assert null_check.validate(df) == [DataCheckWarning("Column 'lots_of_null
↪' is 80.0% or more null", "HighlyNullDataCheck")]
```

### evalml.data_checks.IDColumnsDataCheck




**class** evalml.data_checks.**IDColumnsDataCheck**(*id_threshold=1.0*)

Check if any of the features are likely to be ID columns.

**name = 'IDColumnsDataCheck'**

#### Instance attributes

—

#### Methods:

| | |
|---|---|
| *__init__* | Check if any of the features are likely to be ID columns. |
| *validate* | Check if any of the features are likely to be ID columns. |

### evalml.data_checks.IDColumnsDataCheck.__init__

IDColumnsDataCheck.**__init__**(*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.

### evalml.data_checks.IDColumnsDataCheck.validate

IDColumnsDataCheck.**validate**(*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 not float / boolean)

**Parameters**

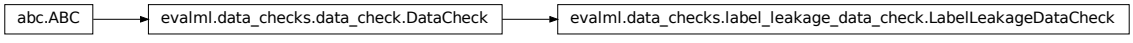
- **X** (*pd.DataFrame*) – The input features to check
- **threshold** (*float*) – the probability threshold to be considered an ID column. Defaults to 1.0

**Returns** A dictionary of features with column name or index and their probability of being ID columns

#### Example

```
>>> 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) == [DataCheckWarning("Column 'df_id' is␣
↪100.0% or more likely to be an ID column", "IDColumnsDataCheck")]
```

## evalml.data_checks.LabelLeakageDataCheck



**class** evalml.data_checks.**LabelLeakageDataCheck**(*pct_corr_threshold=0.95*)

Check if any of the features are highly correlated with the target.

**name = 'LabelLeakageDataCheck'**

### Instance attributes

—

### Methods:

| | |
|---|---|
| *__init__* | Check if any of the features are highly correlated with the target. |
| *validate* | Check if any of the features are highly correlated with the target. |

### evalml.data_checks.LabelLeakageDataCheck.__init__

LabelLeakageDataCheck.**__init__**(*pct_corr_threshold=0.95*)

Check if any of the features are highly correlated with the target.

Currently only supports binary and numeric targets and features.

**Parameters** **pct_corr_threshold** (*float*) – The correlation threshold to be considered leakage. Defaults to 0.95.

### evalml.data_checks.LabelLeakageDataCheck.validate

LabelLeakageDataCheck.**validate**(*X*, *y*)

Check if any of the features are highly correlated with the target.

Currently only supports binary and numeric targets and features.

**Parameters**

- **X** (*pd.DataFrame*) – The input features to check
- **y** (*pd.Series*) – The labels

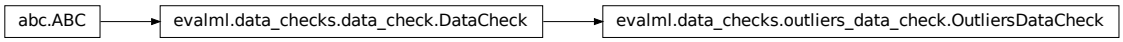
**Returns** list with a DataCheckWarning if there is label leakage detected.

**Return type** list (*DataCheckWarning*)

### Example

```
>>> 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])
>>> label_leakage_check = LabelLeakageDataCheck(pct_corr_threshold=0.8)
>>> assert label_leakage_check.validate(X, y) == [DataCheckWarning("Column
↪'leak' is 80.0% or more correlated with the target", "LabelLeakageDataCheck
↪")]
```

### evalml.data_checks.OutliersDataCheck




**class** evalml.data_checks.**OutliersDataCheck**(*random_state=0*)

Checks if there are any outliers in input data by using an Isolation Forest to obtain the anomaly score of each index and then using IQR to determine score anomalies. Indices with score anomalies are considered outliers.

**name = 'OutliersDataCheck'**

#### Instance attributes

—

#### Methods:

| | |
|---|---|
| *__init__* | Checks if there are any outliers in the input data. |
| *validate* | Checks if there are any outliers in a dataframe by using an Isolation Forest to obtain the anomaly score of each index and then using IQR to determine score anomalies. |

#### evalml.data_checks.OutliersDataCheck.__init__

OutliersDataCheck.**__init__**(*random_state=0*)

Checks if there are any outliers in the input data.

**Parameters** **random_state** (*int, np.random.RandomState*) – The random seed/state. Defaults to 0.

#### evalml.data_checks.OutliersDataCheck.validate

OutliersDataCheck.**validate**(*X*, *y=None*)

Checks if there are any outliers in a dataframe by using an Isolation Forest to obtain the anomaly score of each index and then using IQR to determine score anomalies. Indices with score anomalies are considered outliers.

**Parameters**

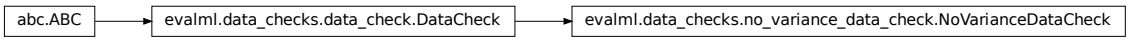
- **X** (*pd.DataFrame*) – features
- **y** – Ignored.

**Returns** A set of indices that may have outlier data.

#### Example

```
>>> df = pd.DataFrame({
...     'x': [1, 2, 3, 40, 5],
...     'y': [6, 7, 8, 990, 10],
...     'z': [-1, -2, -3, -1201, -4]
... })
>>> outliers_check = OutliersDataCheck()
>>> assert outliers_check.validate(df) == [DataCheckWarning("Row '3' is␣
↪likely to have outlier data", "OutliersDataCheck")]
```

### evalml.data_checks.NoVarianceDataCheck




**class** evalml.data_checks.**NoVarianceDataCheck**(*count_nan_as_value=False*)

Check if any of the features or labels have no variance.

**name = 'NoVarianceDataCheck'**

#### Instance attributes

—

#### Methods:

| | |
|---|---|
| *__init__* | Check if any of the features or labels have no variance. |
| *validate* | Check if any of the features or if the labels have no variance (1 unique value). |

#### evalml.data_checks.NoVarianceDataCheck.__init__

NoVarianceDataCheck.**__init__**(*count_nan_as_value=False*)

Check if any of the features or labels have no variance.

**Parameters** **count_nan_as_value** (*bool*) – If True, missing values will be counted as their own unique value. If set to True, a feature that has one unique value and all other data is missing, a DataCheckWarning will be returned instead of an error. Defaults to False.

#### evalml.data_checks.NoVarianceDataCheck.validate

NoVarianceDataCheck.**validate**(*X*, *y*)

Check if any of the features or if the labels have no variance (1 unique value).

**Parameters**

- **X** (*pd.DataFrame*) – The input features.
- **y** (*pd.Series*) – The labels.

**Returns** list (DataCheckWarning or DataCheckError), list of warnings/errors corresponding to features or labels with no variance.

| | |
|---|---|
| *DataChecks* | A collection of data checks. |
| *DefaultDataChecks* | A collection of basic data checks that is used by AutoML by default. |

### evalml.data_checks.DataChecks

## evalml.data_checks.data_checks.DataChecks

**class** evalml.data_checks.**DataChecks**(*data_checks=None*)

A collection of data checks.

#### Methods

| | |
|---|---|
| *__init__* | A collection of data checks. |
| *validate* | Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable. |

#### evalml.data_checks.DataChecks.__init__

DataChecks.**__init__**(*data_checks=None*)

A collection of data checks.

**Parameters** **data_checks** (*list (DataCheck)*) – list of DataCheck objects

#### evalml.data_checks.DataChecks.validate

DataChecks.**validate**(*X*, *y=None*)

Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable.

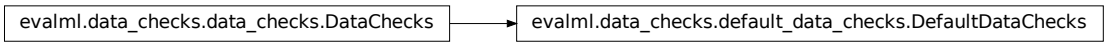
**Parameters**

- **X** (*pd.DataFrame*) – the input data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target labels of length [n_samples]

**Returns** list containing DataCheckMessage objects

**Return type** list (*DataCheckMessage*)

### evalml.data_checks.DefaultDataChecks




**class** evalml.data_checks.**DefaultDataChecks**(*data_checks=None*)

A collection of basic data checks that is used by AutoML by default.

Includes HighlyNullDataCheck, IDColumnsDataCheck, LabelLeakageDataCheck, InvalidTargetDataCheck, and NoVarianceDataCheck.

#### Methods

| | |
|---|---|
| *__init__* | A collection of basic data checks. |
| *validate* | Inspects and validates the input data against data checks and returns a list of warnings and errors if applicable. |

#### evalml.data_checks.DefaultDataChecks.__init__

DefaultDataChecks.**__init__**(*data_checks=None*)

A collection of basic data checks.

**Parameters** **data_checks** (*list (DataCheck)*) – Ignored.

#### evalml.data_checks.DefaultDataChecks.validate

DefaultDataChecks.**validate**(*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*) – the input data of shape [n_samples, n_features]
- **y** (*pd.Series*) – the target labels of length [n_samples]

**Returns** list containing DataCheckMessage objects

**Return type** list (*DataCheckMessage*)

### 5.11.2 Data Check Messages

| | |
|---|---|
| *DataCheckMessage* | Base class for all DataCheckMessages. |
| *DataCheckError* | DataCheckMessage subclass for errors returned by data checks. |
| *DataCheckWarning* | DataCheckMessage subclass for warnings returned by data checks. |

#### evalml.data_checks.DataCheckMessage

evalml.data_checks.data_check_message.DataCheckMessage

**class** evalml.data_checks.**DataCheckMessage**(*message*, *data_check_name*)

Base class for all DataCheckMessages.

**message_type = None**

#### Methods:

| | |
|---|---|
| *__init__* | Message returned by a DataCheck, tagged by name." |
| *__str__* | String representation of data check message, equivalent to self.message attribute. |
| *__eq__* | Checks for equality. |

#### evalml.data_checks.DataCheckMessage.__init__

DataCheckMessage.**__init__**(*message*, *data_check_name*)

Message returned by a DataCheck, tagged by name."

**Parameters**

- **message** (*str*) – Message string
- **data_check_name** (*str*) – Name of data check

#### evalml.data_checks.DataCheckMessage.__str__

DataCheckMessage.**__str__**()

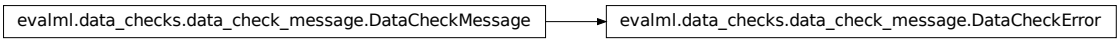
String representation of data check message, equivalent to self.message attribute.

#### evalml.data_checks.DataCheckMessage.__eq__

DataCheckMessage.**__eq__**(*other*)

Checks for equality. Two DataCheckMessage objs are considered equivalent if their message type and message are equivalent.

### evalml.data_checks.DataCheckError




**class** evalml.data_checks.**DataCheckError**(*message*, *data_check_name*)

DataCheckMessage subclass for errors returned by data checks.

**message_type = 'error'**

#### Methods:

| | |
|---|---|
| *__init__* | Message returned by a DataCheck, tagged by name.” |
| *__str__* | String representation of data check message, equivalent to self.message attribute. |
| *__eq__* | Checks for equality. |

#### evalml.data_checks.DataCheckError.__init__

DataCheckError.**__init__**(*message*, *data_check_name*)

Message returned by a DataCheck, tagged by name.”

**Parameters**

- **message** (*str*) – Message string
- **data_check_name** (*str*) – Name of data check

#### evalml.data_checks.DataCheckError.__str__

DataCheckError.**__str__**()

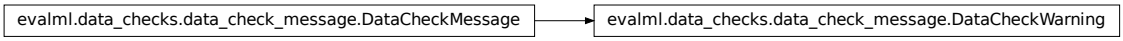
String representation of data check message, equivalent to self.message attribute.

#### evalml.data_checks.DataCheckError.__eq__

DataCheckError.**__eq__**(*other*)

Checks for equality. Two DataCheckMessage objs are considered equivalent if their message type and message are equivalent.

#### evalml.data_checks.DataCheckWarning




**class** evalml.data_checks.**DataCheckWarning**(*message*, *data_check_name*)

DataCheckMessage subclass for warnings returned by data checks.

**message_type = 'warning'**

##### Methods:

| | |
|---|---|
| *__init__* | Message returned by a DataCheck, tagged by name." |
| *__str__* | String representation of data check message, equivalent to self.message attribute. |
| *__eq__* | Checks for equality. |

##### evalml.data_checks.DataCheckWarning.__init__

DataCheckWarning.**__init__**(*message*, *data_check_name*)

Message returned by a DataCheck, tagged by name."

**Parameters**

- **message** (*str*) – Message string
- **data_check_name** (*str*) – Name of data check

##### evalml.data_checks.DataCheckWarning.__str__

DataCheckWarning.**__str__**()

String representation of data check message, equivalent to self.message attribute.

##### evalml.data_checks.DataCheckWarning.__eq__

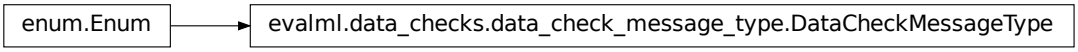
DataCheckWarning.**__eq__**(*other*)

Checks for equality. Two DataCheckMessage objs are considered equivalent if their message type and message are equivalent.

### 5.11.3 Data Check Message Types

| | |
|---|---|
| *DataCheckMessageType* | Enum for type of data check message: WARNING or ERROR. |

#### evalml.data_checks.DataCheckMessageType




**class** evalml.data_checks.**DataCheckMessageType**
Enum for type of data check message: WARNING or ERROR.

## 5.12 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. |

### 5.12.1 evalml.utils.import_or_raise

evalml.utils.**import_or_raise**(*library*, *error_msg=None*)
Attempts to import the requested library by name. If the import fails, raises an ImportError.

**Parameters**

- **library** (*str*) – the name of the library
- **error_msg** (*str*) – error message to return if the import fails

### 5.12.2 evalml.utils.convert_to_seconds

evalml.utils.**convert_to_seconds**(*input_str*)
Converts a string describing a length of time to its length in seconds.

### 5.12.3 evalml.utils.get_random_state

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.

### 5.12.4 evalml.utils.get_random_seed

evalml.utils.**get_random_seed**(*random_state*, *min_bound=0*, *max_bound=2147483647*)

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

CHAPTER

SIX

# RELEASE NOTES

**Future Releases**

- Enhancements
- Fixes
- Changes
- Documentation Changes
- Testing Changes

**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
- **Documentation Changes**
  - Update 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
  - Update FAQ section formatting #997
  - Update release process documentation #1003
- **Testing Changes**
  - Moved *predict_proba* and *predict* tests regarding string / categorical targets to *test_pipelines.py* #972
  - Fix 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/multiseries 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 PipelinePlots 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

# INDEX

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