

Sweetviz is designed to describe each variable and measure the degree of association among variables. This example uses the `train.csv` and `test.csv` files from the Titanic dataset.

```
1  !pip install sweetviz
2  import sweetviz
3  import pandas as pd
4  train = pd.read_csv("/content/train.csv")
5  test = pd.read_csv("/content/test.csv")

1  my_report = sweetviz.compare([train, "Train"], [test, "Test"], "Survived")

1  my_report.show_html("Report.html") # Not providing a filename will default to SWEETVIZ_REPORT.html

1  pip install lime

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```

Using LIME with a RandomForest Model

```
1  from sklearn.datasets import load_boston
2  import sklearn.ensemble
3  import numpy as np
4  from sklearn.model_selection import train_test_split
5  import lime
6  import lime.lime_tabular

1  boston = load_boston()

1  print(boston['DESCR'])
```



```

.. _boston_dataset:

Boston house prices dataset
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**Data Set Characteristics:**

:Number of Instances: 506

:Number of Attributes: 13 numeric/categorical predictive. Median Value (attribute 14) is usually the target variable.

:Attribute Information (in order):
- CRIM      per capita crime rate by town
- ZN        proportion of residential land zoned for lots over 25,000 sq.ft.
- INDUS     proportion of non-retail business acres per town
- CHAS      Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
- NOX       nitric oxides concentration (parts per 10 million)
- RM        average number of rooms per dwelling
- AGE       proportion of owner-occupied units built prior to 1940

1  rf = sklearn.ensemble.RandomForestRegressor(n_estimators=1000)
2  train, test, labels_train, labels_test = train_test_split(boston.data, boston.target, train_size=0.80)
3  rf.fit(train, labels_train)

➤ RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                        max_depth=None, max_features='auto', max_leaf_nodes=None,
                        max_samples=None, min_impurity_decrease=0.0,
                        min_impurity_split=None, min_samples_leaf=1,
                        min_samples_split=2, min_weight_fraction_leaf=0.0,
                        n_estimators=1000, n_jobs=None, oob_score=False,
                        random_state=None, verbose=0, warm_start=False)

-----

1  print('Random Forest MSError', np.mean((rf.predict(test) - labels_test) ** 2))

➤ Random Forest MSError 7.070716154117681

The Boston house price data of New Bedford, Duxbury, and Dedham.

1  print('MSError when predicting the mean', np.mean((labels_train.mean() - labels_test) ** 2))

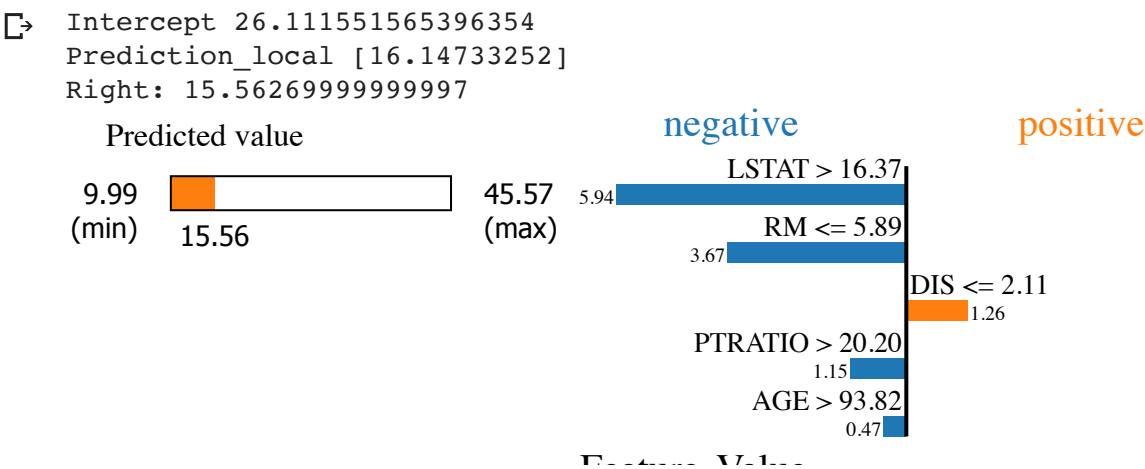
➤ MSError when predicting the mean 68.7759456493116

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1  categorical_features = np.argwhere(
2      np.array([len(set(boston.data[:,x]))
3                  for x in range(boston.data.shape[1])]) <= 10).flatten()

1  explainer = lime.lime_tabular.LimeTabularExplainer(train,
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Using LIME with a Linear Regression

```

1  import pandas as pd
2  from pandas import DataFrame
3  boston = load_boston()
4  boston.feature_names
5  dfx = pd.DataFrame(boston.data, columns = boston.feature_names)
6  dfy = pd.DataFrame(boston.target, columns = ['target'])

1  from sklearn.model_selection import train_test_split
2  X_train, y_train, X_test, y_test=train_test_split(boston.data, boston.target)

```

```
1 from sklearn.linear_model import LinearRegression
2 lr=LinearRegression()
3 lr.fit(dfx,dfy)

[ ]> LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

1 categorical_features = np.argwhere(
2     np.array([len(set(boston.data[:,x]))
3         for x in range(boston.data.shape[1])]) <= 10).flatten()

1 i = 100
2
3 exp = explainer.explain_instance(test[i], lr.predict, num_features=5)
4 exp.show_in_notebook(show_table=True)

[ ]> Intercept 27.60191921042433
Prediction_local [22.19441596]
Right: 18.938685923806553
```

