From the test scores, the top 3 important features in the dataset are ranked from feature 3 to 4 to 1 and to 2 in order. The data scientist can choose to drop the second column and observe the effect on the model performance.

We can transform the dataset to subset only the important features.

The result drops the second column of the dataset.

Recursive Feature Elimination (RFE)

RFE is used together with a learning model to recursively select the desired number of top performing features.

Let's use RFE with **LinearRegression**.

```
# import packages
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
from sklearn import datasets
# load dataset
data = datasets.load_boston()
# separate features and target
X = data.data
y = data.target
```

```
# feature engineering
linear_reg = LinearRegression()
rfe = RFE(estimator=linear_reg, n_features_to_select=6)
rfe_fit = rfe.fit(X, y)
# print the feature ranking
rfe_fit.ranking_
'Output': array([3, 5, 4, 1, 1, 1, 8, 1, 2, 6, 1, 7, 1])
```

From the result, the 4th, 5th, 6th, 8th, 11th, and 13th features are the top 6 features in the Boston dataset.

Feature Importances

Tree-based or ensemble methods in Scikit-learn have a **feature_importances_** attribute which can be used to drop irrelevant features in the dataset using the **SelectFromModel** module contained in the **sklearn.feature_selection** package.

Let's used the ensemble method AdaBoostClassifier in this example.

```
# import packages
from sklearn.ensemble import AdaBoostClassifier
from sklearn.feature_selection import SelectFromModel
from sklearn import datasets
# load dataset
data = datasets.load_iris()
# separate features and target
X = data.data
y = data.target
# original data shape
X.shape
# feature engineering
ada_boost_classifier = AdaBoostClassifier()
ada_boost_classifier.fit(X, y)
```