Artificial Intelligence and Machine Learning Fundamentals

Activity 6: Stock Price Prediction with Quadratic and Cubic Linear Polynomial Regression with Multiple Variables

This section will discuss how to perform linear, polynomial, and support vector regression with scikit-learn. We will also learn to predict the best fit model for a given task. We will be assuming that you are a software engineer at a financial institution and your employer wants to know whether linear regression, or support vector regression is a better fit for predicting stock prices. You will have to load all data of the S&P 500 from a data source. Then build a regressor using linear regression, cubic polynomial linear regression, and a support vector regression with a polynomial kernel of degree 3. Then separate training and test data. Plot the test labels and the prediction results and compare them with the y=x line. And finally, compare how well the three models score.

Let's load the S&P 500 index data using Quandl, then prepare the data for prediction.

You can read the process in the Predicting the Future section of the topic Linear Regression with Multiple Variables.

```
import quandl
import numpy as np
from sklearn import preprocessing
from sklearn import model_selection
from sklearn import linear_model
from sklearn.preprocessing import PolynomialFeatures
from matplotlib import pyplot as plot
from sklearn import svm
data_frame = quandl.get("YALE/SPCOMP")
data_frame[['Long Interest Rate', 'Real Price',
'Real Dividend', 'Cyclically Adjusted PE Ratio']]
data_frame.fillna(-100, inplace=True)
# We shift the price data to be predicted 20 years
forward
data_frame['Real Price Label'] =
data_frame['RealPrice'].shift(-240)
# Then exclude the label column from the features
features = np.array(data_frame.drop('Real Price Label',
1))
# We scale before dropping the last 240 rows from the
features
scaled_features = preprocessing.scale(features)
# Save the last 240 rows before dropping them
scaled_features_latest240 = scaled_features[-240:]
# Exclude the last 240 rows from the data used for #
# modelbuilding
scaled_features = scaled_features[:-240]
# Now we can drop the last 240 rows from the data frame
data_frame.dropna(inplace=True)
```

```
# Then build the labels from the remaining data
label = np.array(data_frame['Real Price Label'])
# The rest of the model building stays
(features_train,
features_test,
label_train,
label_test
) = model_selection.train_test_split(
scaled_features,
label,
test_size=0.1
)
```

Let's first use a polynomial of degree 1 for the evaluation of the model and for the prediction. We are still recreating the main example from the second topic.

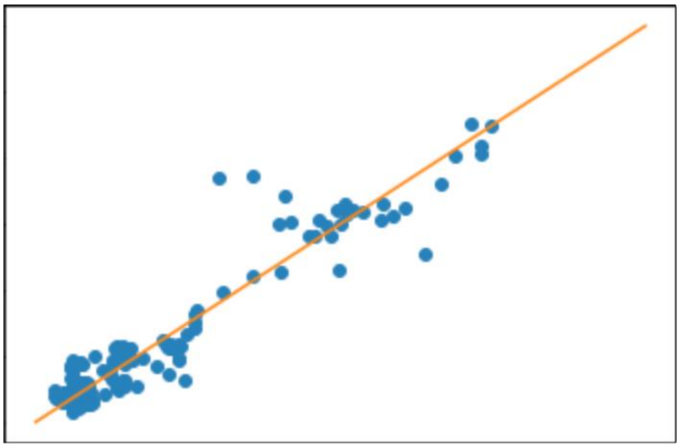
```
model = linear_model.LinearRegression()
model.fit(features_train, label_train)
model.score(features_test, label_test)
```

1. The output is as follows:

    0.8978136465083912

2. The output always depends on the test data, so the values may differ after each run.

    ```
    label_predicted = model.predict(features_test)
    plot.plot(
    label_test, label_predicted, 'o',
    [0, 3000], [0, 3000]
    ```



The closer the dots are to the y=x line, the less error the model works with.

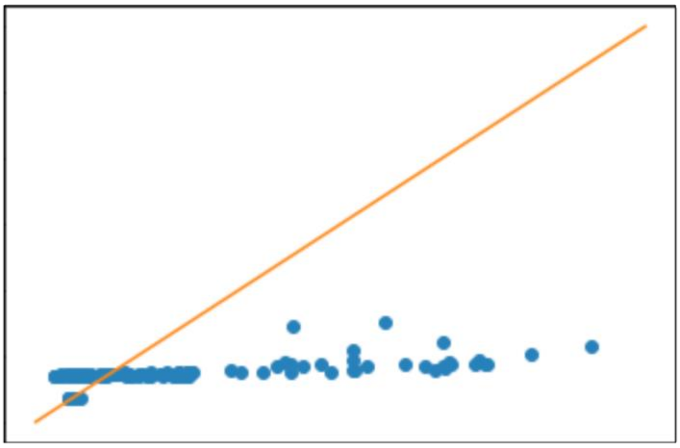
It is now time to perform a linear multiple regression with quadratic polynomials. The only change is in the Linear Regression model

```
poly_regressor = PolynomialFeatures(degree=3)
poly_scaled_features =
poly_regressor.fit_transform(scaled_features)
(poly_features_train,
poly_features_test,
poly_label_train,
poly_label_test) = model_selection.train_test_split(
poly_scaled_features,
label,
```

```
test_size=0.1)
model = linear_model.LinearRegression()
model.fit(poly_features_train, poly_label_train)
print('Polynomial model score: ', model.score(
poly_features_test, poly_label_test))
print('\n')
poly_label_predicted = model.predict(poly_features_test)
plot.plot(
poly_label_test, poly_label_predicted, 'o',
[0, 3000], [0, 3000]
)
```

The model is performing surprisingly well on test data. Therefore, we can already suspect our polynomials are overfitting for scenarios used in training and testing. We will now perform a Support Vector regression with a polynomial kernel of degree 3.

```
model = svm.SVR(kernel='poly')
model.fit(features_train, label_train)
label_predicted = model.predict(features_test)
plot.plot(
label_test, label_predicted, 'o',
[0,3000], [0,3000]
)
```



```
model.score(features_test, label_test)
```

The output will be **0.06388628722032952**.

We will now perform a Support Vector regression with a polynomial kernel of degree 3.