Stock_Market_Prediction

August 13, 2018

1 Predicting the Stock Market Prices

1.0.1 Data Description:

In this mission, we'll be working with a csv file containing index prices. Each row in the file contains a **daily record of the price of the S&P500 Index from 1950 to 2015**. The dataset is stored in sphist.csv.

The columns of the dataset are:

```
Date -- The date of the record.
Open -- The opening price of the day (when trading starts).
High -- The highest trade price during the day.
Low -- The lowest trade price during the day.
Close -- The closing price for the day (when trading is finished).
Volume -- The number of shares traded.
Adj Close -- The daily closing price, adjusted for corporate actions.
```

We'll be using this dataset to develop a predictive model. We'll train the model with data from 1950-2012, and try to make predictions from 2013-2015.

```
In [18]: import pandas as pd
         from datetime import datetime

         # used to format headings
         bold = '\033[1m'
         end = '\033[0m'

         # Read the s&p 500 input data set and sorting based on date.
         sp500 = pd.read_csv("sphist.csv", index_col=False)
         sp500["Date"] = pd.to_datetime(sp500["Date"])
         sp_sorted = sp500.sort_values("Date")

         # To do feature engineering - take mean of previous rows
         temps = pd.DataFrame(sp_sorted.Close)

         # need to shift by 1 coz otherwise it will add up present value also
         # Adding present value to the mean is same as giving the
         # predicted value (outcome)along with the training data.
```

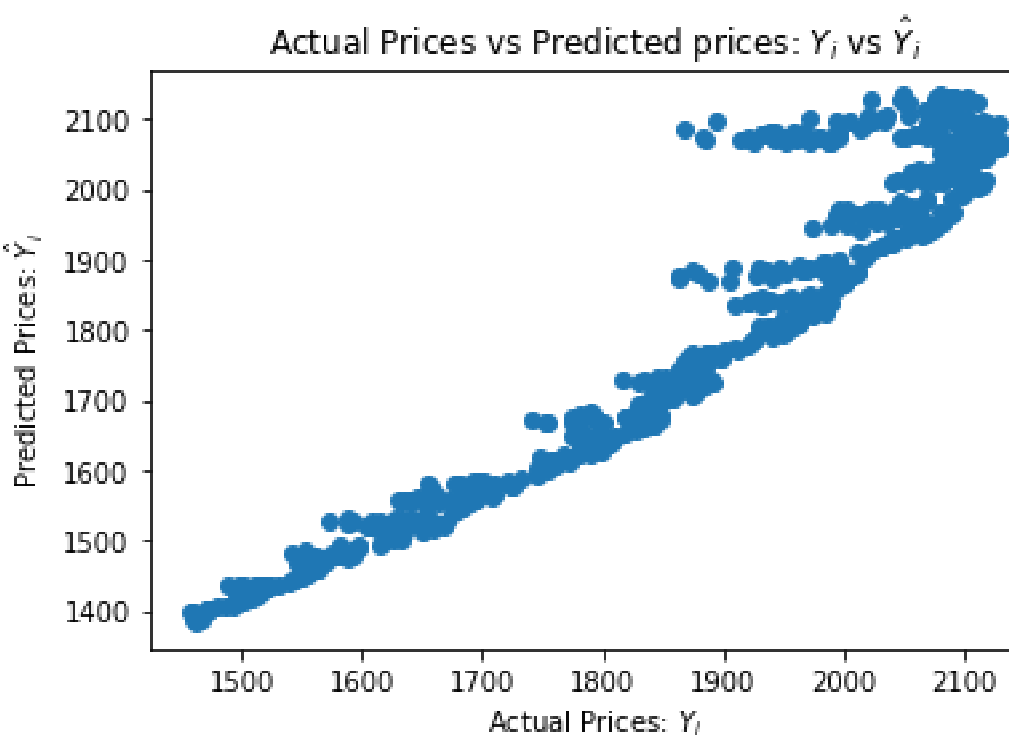
```python
# This will hurt prediction model
shifted = temps.shift(1)

# The average price for the past 365 days.
# The standard deviation of the price over the past 365 days
window = shifted.rolling(window=365)
means_365 = window.mean()
std_365 = window.std()
sp_sorted['mean_365'] = means_365
sp_sorted['std_365'] = std_365

# The ratio between the average price
# for the past 5 days, and the average
# price for the past 365 days.
window = shifted.rolling(window=5)
means_5 = window.mean()
sp_sorted['mean_5by365'] = means_5/ means_365

# Some of the indicators use 365 days of historical data, and the dataset starts
# on 1950-01-03. Thus, any rows that fall before 1951-01-03 don't have enough
# historical data to compute all the indicators.
sp_augmented = sp_sorted[sp_sorted["Date"] > datetime(year=1951, month=1, day=2)]

# Use the dropna method to remove any rows with NaN values.
# Pass in the axis=0 argument to drop rows.
sp_augmented = sp_augmented.dropna(axis = 0)

print("\n\n*** Dataset After Augmented Values ***")
print(sp_augmented.head(5))

# Train dataset would contain rows with a date less than 2013-01-01
train = sp_augmented[sp_augmented["Date"] < datetime(year=2013, month=1, day=1)]
test = sp_augmented[sp_augmented["Date"] >= datetime(year=2013, month=1, day=1)]

# Separate Train dataset
y_train = train['Close']
x_train = train.drop(
    ['Close', 'High', 'Low', 'Open', 'Volume', 'Adj Close', 'Date'], axis=1)

# Separate Test dataset
y_test = test['Close']
x_test = test.drop(
    ['Close', 'High', 'Low', 'Open', 'Volume', 'Adj Close', 'Date'], axis=1)


print("\n\n*** Train Dataset Outcome Variables ***")
print(y_train.head(10))
print("\n\n*** Train Dataset Input Variables ***")
```

```
print(x_train.head(10))
```

```
*** Dataset After Augmented Values ***
            Date       Open       High        Low      Close     Volume  \
16224 1951-06-19  22.020000  22.020000  22.020000  22.020000  1100000.0
16223 1951-06-20  21.910000  21.910000  21.910000  21.910000  1120000.0
16222 1951-06-21  21.780001  21.780001  21.780001  21.780001  1100000.0
16221 1951-06-22  21.549999  21.549999  21.549999  21.549999  1340000.0
16220 1951-06-25  21.290001  21.290001  21.290001  21.290001  2440000.0

       Adj Close   mean_365   std_365  mean_5by365
16224  22.020000  19.447726  1.790253     1.120954
16223  21.910000  19.462411  1.789307     1.125246
16222  21.780001  19.476274  1.788613     1.128142
16221  21.549999  19.489562  1.787659     1.126757
16220  21.290001  19.502082  1.786038     1.121008


*** Train Dataset Outcome Variables ***
16224    22.020000
16223    21.910000
16222    21.780001
16221    21.549999
16220    21.290001
16219    21.299999
16218    21.370001
16217    21.100000
16216    20.959999
16215    21.100000
Name: Close, dtype: float64


*** Train Dataset Input Variables ***
        mean_365   std_365  mean_5by365
16224  19.447726  1.790253     1.120954
16223  19.462411  1.789307     1.125246
16222  19.476274  1.788613     1.128142
16221  19.489562  1.787659     1.126757
16220  19.502082  1.786038     1.121008
16219  19.513617  1.783946     1.112556
16218  19.525315  1.781613     1.104515
16217  19.537041  1.779624     1.098324
16216  19.548932  1.775513     1.090699
16215  19.560685  1.770595     1.084011
```

```
In [19]: from sklearn.linear_model import LinearRegression
```

```
import matplotlib.pyplot as plt

# Importing the statistics module
from statistics import mean
from statistics import median

lm = LinearRegression()
lm.fit(x_train, y_train)

y_pred = lm.predict(x_test)

plt.scatter(y_test, y_pred)
plt.xlabel("Actual Prices: $Y_i$")
plt.ylabel("Predicted Prices: $\hat{Y}_i$")
plt.title("Actual Prices vs Predicted prices: $Y_i$ vs $\hat{Y}_i$")
plt.show()

# Calculating the error
delta_y = y_test - y_pred;
print("Mean Absolute Error (MAE) = " + str(mean(abs(delta_y))))
```




```
Mean Absolute Error (MAE) = 98.94921147104225
```

The above MAE error metric is not interpretable, since the value of MAE can range from 0 to infinity. We can't understand how good the model performed. Hence it would be better to compute Percentage error and even better would be to compute median (instead of mean) so that the perturbation caused by outliers could be eliminated.

Median Absolute Percentage Error (MAPE) would be a far more intrepretable metric, resilient to outliers.

In [20]:
```
# Calculating the percentage error
delta_y_percentage = (y_test - y_pred)/ y_test;

print(bold + "Median Absolute Percentage Error (MAPE) = " +
          str(round(median(abs(delta_y_percentage)), 2)*100) + "%" + end)
```

```
Median Absolute Percentage Error (MAPE) = 6.0%
```

2 Conclusion

1) **The Actual and Predicted prices are almost linear. Hence the prediction model is working fine**, though the error can be further reduced with a better model such as randomforest or using feature engineering techniques such as previous volume, highest/ lowest price in the past year etc.

2) An improvement to the above linear regression model is **to predict the % change of prices, over a period of one week or one month, if we invest today**. In the above logic, we predict the closing price of the very next day, which is not so reliable, because stock markets are mostly stable (especially for a stable stock index like S&P).

3) For a financial company, another way to reframe this problem would be **to perceive the problem as a classification problem, instead of regression problem.** If we can predict, whether the price of a particular stock would go up or down, on next day or a period of time then such a system is very useful.