stock_market_analysis

June 15, 2019

```
In [41]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         from fastai.tabular import add_datepart
         from keras.models import Sequential
         from keras.layers import Activation, Dense, Dropout, LSTM
         from sklearn import neighbors
         from sklearn.model_selection import train_test_split, GridSearchCV
         from sklearn.preprocessing import MinMaxScaler
```

```
In [2]: import warnings
        warnings.filterwarnings("ignore")
```

```
In [3]: microsoft_dataset = "../dataset/EOD-MSFT.csv"
        tata_dataset = "../dataset/NSE-TATAGLOBAL11.csv"
        haineken_dataset = "../dataset/EURONEXT-HEIA.csv"
```

```
In [4]: scaler = MinMaxScaler(feature_range=(0, 1))
```

```
In [5]: df = pd.read_csv(microsoft_dataset)
        df.head()
```

```
Out[5]:          Date   Open     High     Low  Close      Volume  Dividend  Split  \
        0  2017-12-28  85.90  85.9300  85.550  85.72  10594344.0       0.0    1.0
        1  2017-12-27  85.65  85.9800  85.215  85.71  14678025.0       0.0    1.0
        2  2017-12-26  85.31  85.5346  85.030  85.40   9891237.0       0.0    1.0
        3  2017-12-22  85.40  85.6300  84.920  85.51  14145841.0       0.0    1.0
        4  2017-12-21  86.05  86.1000  85.400  85.50  17990745.0       0.0    1.0

            Adj_Open   Adj_High    Adj_Low  Adj_Close  Adj_Volume
        0  83.768909  83.798164  83.427592  83.593374  10594344.0
        1  83.525111  83.846924  83.100903  83.583622  14678025.0
        2  83.193546  83.412574  82.920492  83.281313   9891237.0
        3  83.281313  83.505607  82.813221  83.388584  14145841.0
        4  83.915187  83.963947  83.281313  83.378832  17990745.0
```

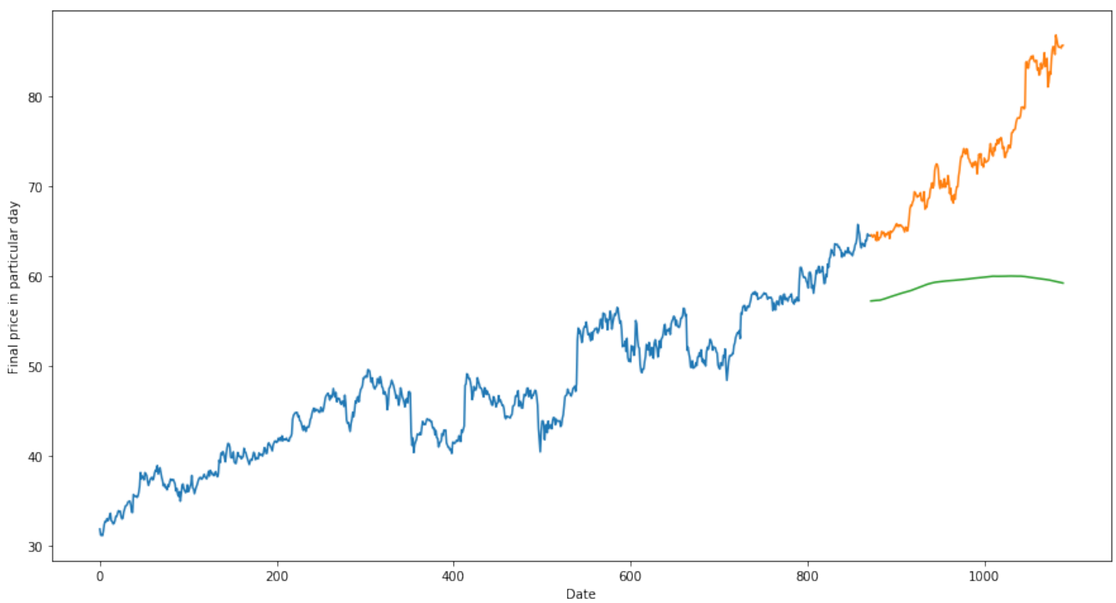
```
In [6]: df["Date"] = pd.to_datetime(df.Date, format="%Y-%m-%d")
        df.index = df["Date"]
```

```python
plt.figure(figsize=(15, 8))
plt.plot(df["Close"])
plt.xlabel("Date")
plt.ylabel("Final price in particular day")
plt.show()
```

Moving avarage prediction

```python
In [7]: def process_dataframe(df):
            data = df.sort_index(ascending=True, axis=0)
            processed_data = pd.DataFrame(index=range(0, len(df)), columns=["Date", "Close"])

            for i in range(0, len(data)):
                processed_data["Date"][i] = data["Date"][i]
                processed_data["Close"][i] = data["Close"][i]

            return processed_data


        def plot_predictions(train_data, test_data, predictions):
            test_data.loc[:, "Predictions"] = predictions
            plt.figure(figsize=(15, 8))
            plt.plot(train_data['Close'])
            plt.plot(test_data[['Close','Predictions']])
            plt.xlabel("Date")
            plt.ylabel("Final price in particular day")
            plt.show()
```

```
In [8]: lr_data = process_dataframe(df)

In [9]: train_data, test_data = train_test_split(lr_data, test_size=0.2, shuffle=False)

In [10]: def moving_avg(train_data, test_len):
             predictions = []
             train_len = train_data.shape[0]
             for i in range(0, test_len):
                 a = train_data["Close"][train_len-test_len+i:].sum() + sum(predictions)
                 b = a / test_len
                 predictions.append(b)
             return predictions

In [11]: mv_avg_predictions = moving_avg(train_data, test_data.shape[0])
         r_mean_square = np.sqrt(np.mean(np.power((np.array(test_data["Close"] - mv_avg_predic

In [12]: r_mean_square

Out[12]: 15.183666454508193

In [13]: plot_predictions(train_data, test_data, mv_avg_predictions)
```



Moving avarage apporach is easy to implement, but in stock marker spectrium predicted data is not looking reaslistic at all. I will skip linear regresion approach. There is a high change that model will overfit to the date and month column, the model will probably consider the value from the same date a month ago, or the same date/month a year ago.

KNN -> k-nearest neighbours Based on independet variables find similarity between new data and old data. I will use preimplemented KNN from sklearn library.

```
In [14]: df['Date'] = pd.to_datetime(df.Date,format='%Y-%m-%d')
         df.index = df['Date']

         knn_data = process_dataframe(df)
```

```
In [15]: add_datepart(knn_data, "Date")
         knn_data.drop("Elapsed", axis=1, inplace=True)
```

```
In [16]: train_data, test_data = train_test_split(knn_data, test_size=0.2, shuffle=False)
```

```
In [17]: x_train_scaled = scaler.fit_transform(train_data.drop('Close', axis=1))
         x_test_scaled = scaler.fit_transform(test_data.drop('Close', axis=1))
         x_train = pd.DataFrame(x_train_scaled)
         x_test = pd.DataFrame(x_test_scaled)
         y_train = train_data['Close']
         y_test = test_data['Close']
```

```
In [18]: parameters = {'n_neighbors': [2, 3, 4, 5, 6, 7, 8, 9]}
         knn = neighbors.KNeighborsRegressor()
         model = GridSearchCV(knn, parameters, cv=5)
```

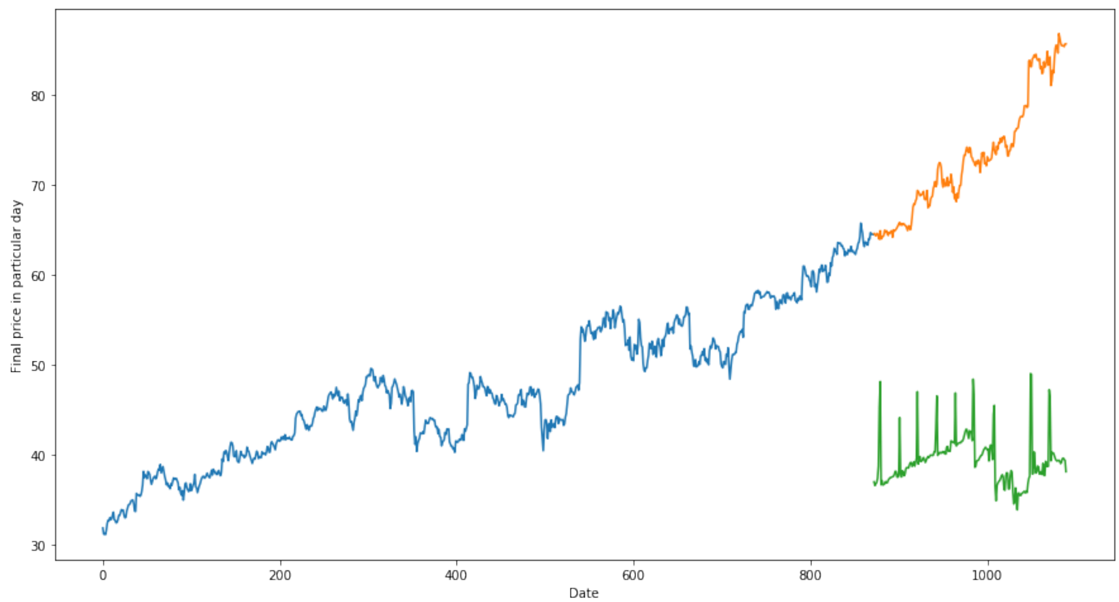
```
In [19]: model.fit(x_train, y_train)
         predictions = model.predict(x_test)
```

```
In [20]: r_mean_square = np.sqrt(np.mean(np.power((np.array(y_test) - np.array(predictions)),
```

```
In [21]: r_mean_square
```

```
Out[21]: 34.54203483310681
```

```
In [22]: plot_predictions(train_data, test_data, predictions)
```



KNN prediction is not accurate as we can see ://

LSTM - Long Short Term Memory LSTM is artificial recurrent neural network (RNN) architecture used in the field of deep learning. LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell.

```
In [67]: lstm_data = process_dataframe(df)

         lstm_data.index = lstm_data.Date
         lstm_data.drop('Date', axis=1, inplace=True)

In [68]: train_data, test_data =train_test_split(lstm_data, test_size=0.2, shuffle=False)
         scaled_data = scaler.fit_transform(lstm_data)

In [69]: x_train, y_train = [], []
         for i in range(60, len(train_data)):
             x_train.append(scaled_data[i-60:i,0])
             y_train.append(scaled_data[i,0])
         x_train, y_train = np.array(x_train), np.array(y_train)

         x_train = np.reshape(x_train, (x_train.shape[0],x_train.shape[1],1))

In [70]: class LSTMNet:
             @staticmethod
             def build(height: int):
                 input_shape = (height, 1)

                 model  = Sequential()
                 model.add(LSTM(50, return_sequences=True, input_shape=input_shape))
                 model.add(LSTM(50))
                 model.add(Dense(1))

                 return model

In [71]: height  = x_train.shape[1]
         model  = LSTMNet.build(height)
         model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_13 (LSTM)               (None, 60, 50)            10400
_________________________________________________________________
lstm_14 (LSTM)               (None, 50)                20200
```

```
-----------------------------------------------------------------
dense_7 (Dense)              (None, 1)                 51
=================================================================
Total params: 30,651
Trainable params: 30,651
Non-trainable params: 0
_________________________________________________________________
```

In [72]:
```python
model.compile(loss='mean_squared_error', optimizer='adam', metrics=['accuracy'])
model.fit(x_train, y_train, epochs=1, batch_size=1, verbose=2)
```

```
Epoch 1/1
 - 86s - loss: 0.0018 - acc: 0.0000e+00
```

Out[72]:
```
<keras.callbacks.History at 0x249c1ffccc0>
```

In [73]:
```python
inputs = lstm_data[len(lstm_data) - len(test_data) - 60:].values
inputs = inputs.reshape(-1,1)
inputs  = scaler.transform(inputs)

X_test = []
for i in range(60, inputs.shape[0]):
    X_test.append(inputs[i-60:i, 0])
X_test = np.array(X_test)

X_test = np.reshape(X_test, (X_test.shape[0],X_test.shape[1],1))
```

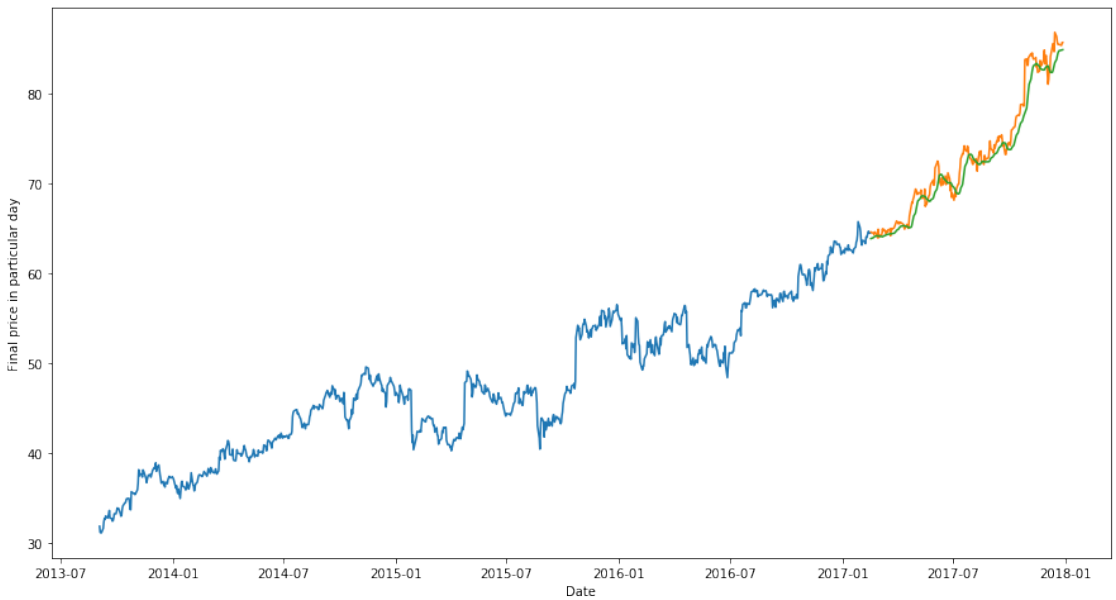
In [74]:
```python
predictions = model.predict(X_test)
predictions = scaler.inverse_transform(predictions)
```

In [75]:
```python
r_mean_square=np.sqrt(np.mean(np.power((test_data - predictions), 2)))
```

In [76]:
```python
r_mean_square
```

Out[76]:
```
Close    1.47423
dtype: float64
```

In [77]:
```python
plot_predictions(train_data, test_data, predictions)
```



Final price in particular day
Date
30
40
50
60
70
80
2013-07
2014-01
2014-07
2015-01
2015-07
2016-01
2016-07
2017-01
2017-07
2018-01

In [ ]: