Supervised Algorithms

---

1. Importing dependencies

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
```

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

2. Loading the Dataset

In [3]:
```
df = pd.read_csv('HistoricalQuotes.csv')
```

In [4]:
```
df.head(5)
```

Out[4]:

	Date	Close/Last	Volume	Open	High	Low
0	02/28/2020	$273.36	106721200	$257.26	$278.41	$256.37
1	02/27/2020	$273.52	80151380	$281.1	$286	$272.96
2	02/26/2020	$292.65	49678430	$286.53	$297.88	$286.5
3	02/25/2020	$288.08	57668360	$300.95	$302.53	$286.13
4	02/24/2020	$298.18	55548830	$297.26	$304.18	$289.23

3. EDA

In [5]:
```
df.dtypes
```

Out[5]:
```
Date            object
 Close/Last     object
 Volume          int64
 Open           object
 High           object
 Low            object
dtype: object
```

In [6]:
```
df.duplicated().sum()
```

Out[6]:
```
0
```

In [7]:
```
df.isna().sum()
```

Out[7]:
```
Date           0
 Close/Last    0
 Volume        0
 Open          0
 High          0
 Low           0
dtype: int64
```

In [8]:
```
df = df.rename(columns={' Close/Last': 'Close', ' Volume': 'Volume', ' Open': 'Ope
```

In [9]:
```
df['Close'] = df['Close'].replace({'\$':''}, regex = True)
df['Open'] = df['Open'].replace({'\$':''}, regex = True)
df['High'] = df['High'].replace({'\$':''}, regex = True)
df['Low'] = df['Low'].replace({'\$':''}, regex = True)
```

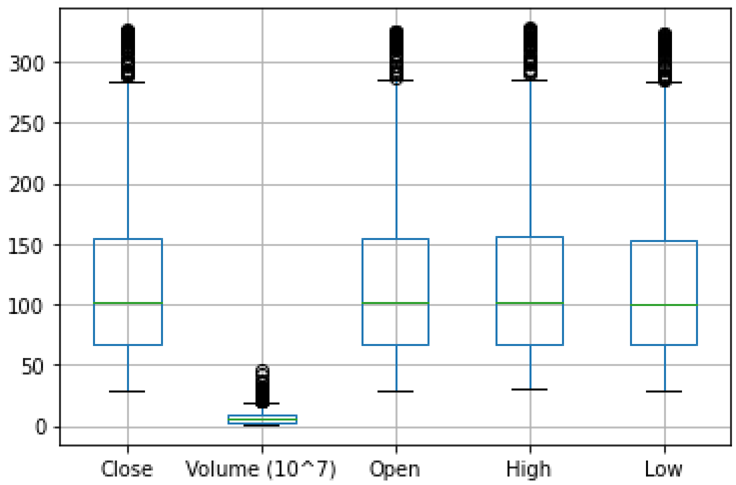
In [10]:
```
from sklearn.impute import SimpleImputer
imp = SimpleImputer()
```

In [11]:
```
imp.fit(df.iloc[:, 1:])
df.iloc[:,1:] = imp.transform(df.iloc[:,1:])
```

In [12]:
```
df['Volume'] = df['Volume'] / 10000000
df.rename(columns = {'Volume':'Volume (10^7)'}, inplace=True)
```

In [13]:
```
df.boxplot()
```

Out[13]: <AxesSubplot:>



In [14]:
```
df.describe()
```

Out[14]:

	Close	Volume (10^7)	Open	High	Low
count	2518.000000	2518.000000	2518.000000	2518.000000	2518.000000
mean	114.769522	7.258009	114.728443	115.766415	113.690582
std	60.662405	5.663113	60.546893	61.134456	60.085105
min	29.835700	1.136205	29.392800	29.928600	28.464300
25%	66.822475	3.053027	66.877150	67.475300	66.372950
50%	101.090000	5.295469	101.115000	102.085000	100.350000
75%	154.630000	9.861006	154.610000	155.735000	153.325000
max	327.200000	46.244233	324.740000	327.850000	323.350000

4. Implementing Auto-ARIMA

In [15]:
```
df1 = df
```

In [16]:
```
df1['Date'] = pd.to_datetime(df1.Date,format='%m/%d/%Y')
df1.index = df1['Date']
```

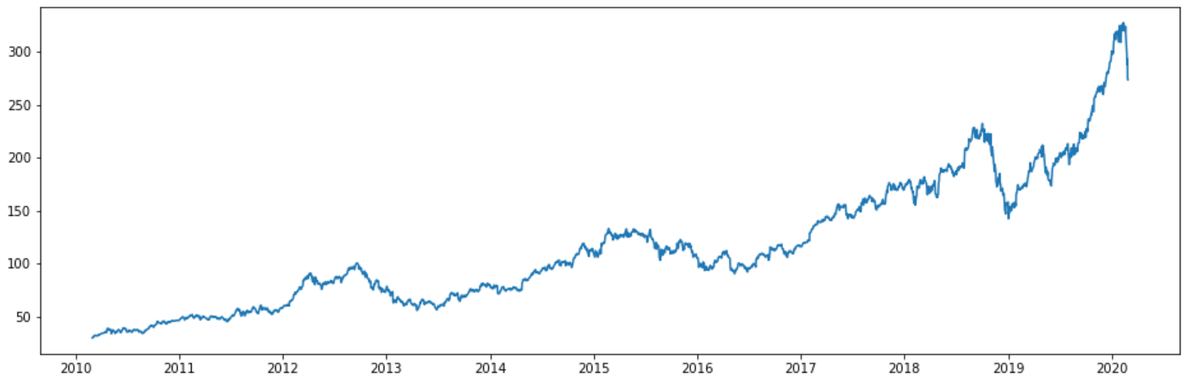
In [17]:
```
df1.head(5)
```

Out[17]:

Date	Date	Close	Volume (10^7)	Open	High	Low
2020-02-28	2020-02-28	273.36	10.672120	257.26	278.41	256.37
2020-02-27	2020-02-27	273.52	8.015138	281.10	286.00	272.96
2020-02-26	2020-02-26	292.65	4.967843	286.53	297.88	286.50
2020-02-25	2020-02-25	288.08	5.766836	300.95	302.53	286.13
2020-02-24	2020-02-24	298.18	5.554883	297.26	304.18	289.23

In [114…
```
plt.figure(figsize=(16,5))
plt.plot(df1['Close'], label='Close Price history')
```

Out[114]:
```
[<matplotlib.lines.Line2D at 0x2978e4afc10>]
```



In [21]:
```
from pmdarima.arima import auto_arima
```

In [108…
```
data = df1.sort_index(ascending=True, axis=0)

new_data = pd.DataFrame(index=range(0,len(df1)),columns=['Date', 'Close'])

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

#### Creating predictions for the validation set and check the RMSE using the actu
train = new_data[:1763]
valid = new_data[1763:]

y_train = train['Close']
y_valid = valid['Close']

model = auto_arima(y_train, start_p=1, start_q=1,max_p=3, max_q=3, m=12,start_P=0,
model.fit(y_train)
```

```
Performing stepwise search to minimize aic
 ARIMA(1,1,1)(0,1,1)[12]             : AIC=inf, Time=8.98 sec
 ARIMA(0,1,0)(0,1,0)[12]             : AIC=7254.752, Time=0.12 sec
 ARIMA(1,1,0)(1,1,0)[12]             : AIC=6701.535, Time=0.37 sec
 ARIMA(0,1,1)(0,1,1)[12]             : AIC=inf, Time=5.17 sec
 ARIMA(1,1,0)(0,1,0)[12]             : AIC=7255.748, Time=0.12 sec
 ARIMA(1,1,0)(2,1,0)[12]             : AIC=6537.920, Time=0.76 sec
 ARIMA(1,1,0)(2,1,1)[12]             : AIC=inf, Time=11.56 sec
 ARIMA(1,1,0)(1,1,1)[12]             : AIC=inf, Time=4.63 sec
 ARIMA(0,1,0)(2,1,0)[12]             : AIC=6538.133, Time=0.57 sec
 ARIMA(2,1,0)(2,1,0)[12]             : AIC=6538.814, Time=2.76 sec
 ARIMA(1,1,1)(2,1,0)[12]             : AIC=6539.477, Time=2.70 sec
 ARIMA(0,1,1)(2,1,0)[12]             : AIC=6537.811, Time=1.43 sec
 ARIMA(0,1,1)(1,1,0)[12]             : AIC=6701.462, Time=0.70 sec
 ARIMA(0,1,1)(2,1,1)[12]             : AIC=inf, Time=9.72 sec
 ARIMA(0,1,1)(1,1,1)[12]             : AIC=inf, Time=6.63 sec
 ARIMA(0,1,2)(2,1,0)[12]             : AIC=6538.958, Time=0.90 sec
 ARIMA(1,1,2)(2,1,0)[12]             : AIC=6539.759, Time=2.17 sec
 ARIMA(0,1,1)(2,1,0)[12] intercept   : AIC=6539.791, Time=3.18 sec

Best model:  ARIMA(0,1,1)(2,1,0)[12]
Total fit time: 62.546 seconds
```

Out[108]:

```
ARIMA(order=(0, 1, 1), scoring_args={}, seasonal_order=(2, 1, 0, 12),
      suppress_warnings=True, with_intercept=False)
```

In [109…

```python
forecast = model.predict(n_periods=755)
forecast = pd.DataFrame(forecast,index = y_valid.index,columns=['Prediction'])
```

In [110…

```python
rms_arima=np.sqrt(np.mean(np.power((np.array(y_valid)-np.array(forecast)),2)))
print(f"The Root Mean Square Value : {rms_arima}")
```

```
The Root Mean Square Value : 216.45229926579114
```

In [111…

```python
mae_arima = np.mean(np.absolute(np.array(y_valid)-np.array(forecast)))
print(f"The Mean Absolute Error Value : {mae_arima}")
```

```
The Mean Absolute Error Value : 179.4031199945296
```

In [112…

```python
mape_arima = np.mean(np.absolute(1-(np.array(forecast) / np.array(y_valid))))
print(f"The Mean Absolute Percentage Error Value : {mape_arima}")
```

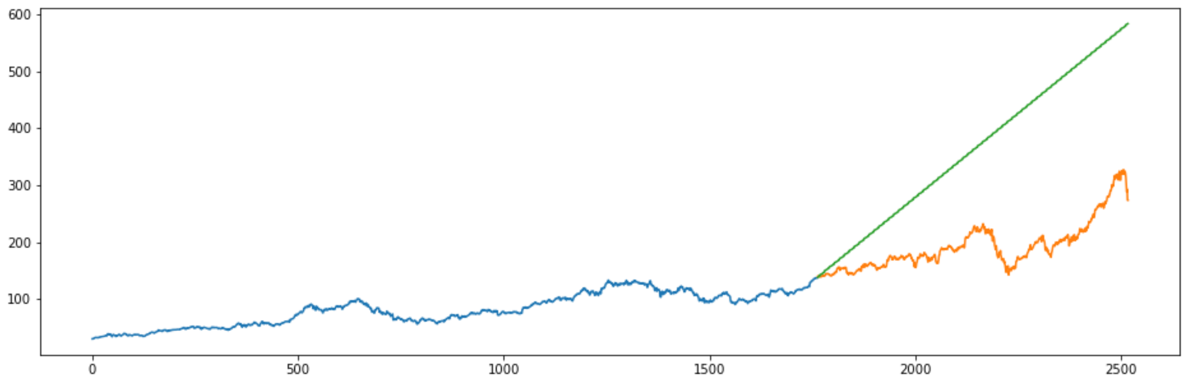
```
The Mean Absolute Percentage Error Value : 0.999106978163917
```

In [113…

```python
#plot
plt.figure(figsize=(16,5))
plt.plot(y_train)
plt.plot(y_valid)
plt.plot(forecast['Prediction'])
```

Out[113]:

```
[<matplotlib.lines.Line2D at 0x297caccbf70>]
```



5. Implementing XGBoost

In [31]:
```
import xgboost as xg
from sklearn.model_selection import train_test_split
```

In [32]:
```
df2 = df
df2 = df2.sort_index(ascending=True, axis=0)
```

In [33]:
```
df2.head(5)
```

Out[33]:

Date	Date	Close	Volume (10^7)	Open	High	Low
2010-03-01	2010-03-01	29.8557	13.731204	29.3928	29.9286	29.3500
2010-03-02	2010-03-02	29.8357	14.148628	29.9900	30.1186	29.6771
2010-03-03	2010-03-03	29.9043	9.284649	29.8486	29.9814	29.7057
2010-03-04	2010-03-04	30.1014	8.959191	29.8971	30.1314	29.8043
2010-03-05	2010-03-05	31.2786	22.464743	30.7057	31.3857	30.6614

In [34]:
```
X, y= df2.drop(['Close', 'Date'], axis=1), df2['Close']
```

In [35]:
```
# Splitting
train_X, test_X, train_y, test_y = train_test_split(X, y, test_size = 0.3, shuffle
```

In [36]:
```
# Train and test set are converted to DMatrix objects,
# as it is required by learning API.
train_dmatrix = xg.DMatrix(data = train_X, label = train_y)
test_dmatrix = xg.DMatrix(data = test_X, label = test_y)
```

In [37]:
```
# Parameter dictionary specifying base learner
param = {"booster":"gblinear", "objective":"reg:squarederror"}
```

In [38]:
```
xgb_r = xg.train(params = param, dtrain = train_dmatrix, num_boost_round = 10)
pred = xgb_r.predict(test_dmatrix)
```

In [39]:
```
from sklearn.metrics import mean_squared_error as MSE
```

In [40]:
```
# RMSE Computation
rmse = np.sqrt(MSE(test_y, pred))
print("RMSE : % f" %(rmse))
```

```
RMSE :  14.770982
```

In [84]:
```
mae_xgb = np.mean(np.absolute(np.array(test_y)-np.array(pred)))
print(f"The Mean Absolute Error Value for XGBoost is : {mae_xgb}")
```

```
The Mean Absolute Error Value for XGBoost is : 13.105213104732455
```

In [85]:
```
mape_xgb = np.mean(np.absolute(1-(np.array(pred) / np.array(test_y))))
print(f"The Mean Absolute Percentage Error Value : {mape_xgb}")
```

```
The Mean Absolute Percentage Error Value : 0.06445964187570392
```

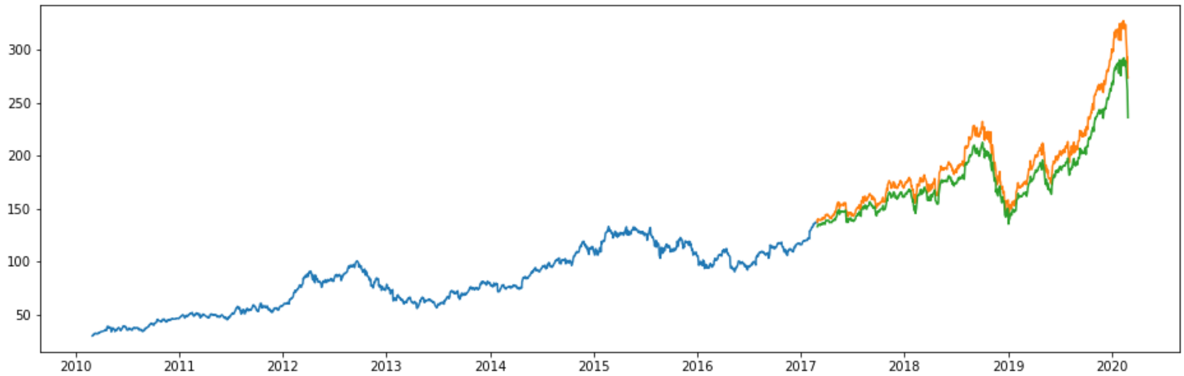
In [41]:
```
predDF = pd.DataFrame(np.squeeze(pred))
```

In [51]:
```
pred2 = pred
test_y1 = test_y
```

In [60]:
```
pred2.index = test_y1.index
```

In [68]:
```
plt.figure(figsize=(16, 5))
plt.plot(train_y)
plt.plot(test_y)
plt.plot(pred2)
```

Out[68]:
```
[<matplotlib.lines.Line2D at 0x29777bc69d0>]
```



6. Implementing LSTM

In [69]:
```
#importing required libraries
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense, Dropout, LSTM
```

In [94]:
```
df3 = df
```

In [95]:
```
#creating dataframe
data = df3.sort_index(ascending=True, axis=0)
new_data = pd.DataFrame(index=range(0,len(df)),columns=['Date', 'Close'])
for i in range(0,len(data)):
    new_data['Date'][i] = data['Date'][i]
    new_data['Close'][i] = data['Close'][i]
```

In [96]:
```
#setting index
new_data.index = new_data.Date
new_data.drop('Date', axis=1, inplace=True)
```

In [97]:
```
#creating train and test sets
dataset = new_data.values

train = dataset[:1763,:]
valid = dataset[1763:,:]
```

In [98]:
```
#converting dataset into x_train and y_train
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(dataset)

x_train, y_train = [], []
for i in range(60,len(train)):
    x_train.append(scaled_data[i-60:i,0])
    y_train.append(scaled_data[i,0])
```

```python
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 [78]:

```python
# create and fit the LSTM network
model = Sequential()
model.add(LSTM(units=50, return_sequences=True, input_shape=(x_train.shape[1],1)))
model.add(LSTM(units=50))
model.add(Dense(1))

model.compile(loss='mean_squared_error', optimizer='adam')
model.fit(x_train, y_train, epochs=10, batch_size=1, verbose=2)
```

```
Epoch 1/10
1703/1703 - 27s - loss: 3.2942e-04 - 27s/epoch - 16ms/step
Epoch 2/10
1703/1703 - 23s - loss: 1.2283e-04 - 23s/epoch - 13ms/step
Epoch 3/10
1703/1703 - 23s - loss: 9.3385e-05 - 23s/epoch - 13ms/step
Epoch 4/10
1703/1703 - 23s - loss: 6.6746e-05 - 23s/epoch - 13ms/step
Epoch 5/10
1703/1703 - 23s - loss: 6.1734e-05 - 23s/epoch - 13ms/step
Epoch 6/10
1703/1703 - 24s - loss: 5.4501e-05 - 24s/epoch - 14ms/step
Epoch 7/10
1703/1703 - 25s - loss: 4.8025e-05 - 25s/epoch - 15ms/step
Epoch 8/10
1703/1703 - 24s - loss: 4.9326e-05 - 24s/epoch - 14ms/step
Epoch 9/10
1703/1703 - 23s - loss: 4.9830e-05 - 23s/epoch - 14ms/step
Epoch 10/10
1703/1703 - 23s - loss: 4.6900e-05 - 23s/epoch - 14ms/step
```

Out[78]:

```
<keras.callbacks.History at 0x2977e5eff10>
```

In [99]:

```python
#predicting values, using past 60 from the train data
inputs = new_data[len(new_data) - len(valid) - 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))
closing_price = model.predict(X_test)
closing_price = scaler.inverse_transform(closing_price)
```

```
24/24 [==============================] - 0s 12ms/step
```

In [100…

```python
rms=np.sqrt(np.mean(np.power((valid-closing_price),2)))
print(f"The Root Mean Square Value : {rms}")
```

```
The Root Mean Square Value : 5.633869531903566
```

In [103…

```python
mae_lstm = np.mean(np.absolute(np.array(closing_price)-np.array(valid)))
print(f"The Mean Absolute Error Value for LSTM is : {mae_lstm}")
```

```
The Mean Absolute Error Value for LSTM is : 3.5884187569523474
```

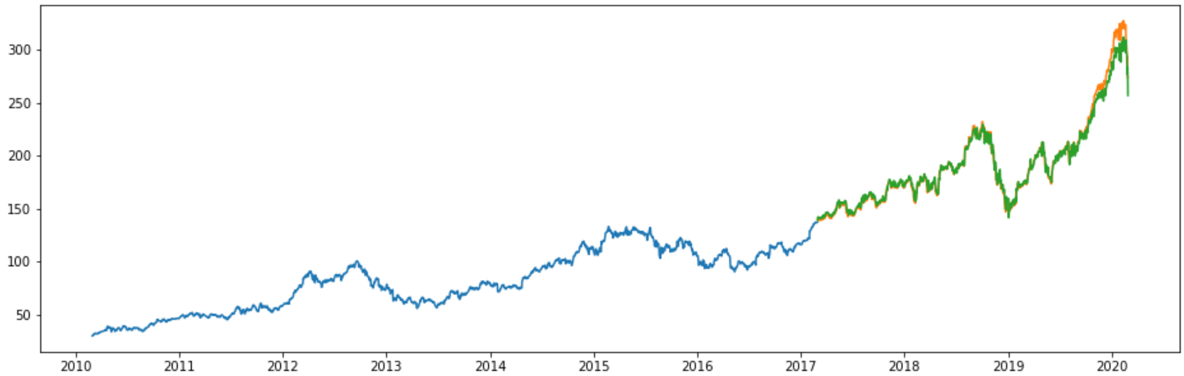
In [104…

```python
mape_lstm = np.mean(np.absolute(1-(np.array(closing_price) / np.array(valid))))
print(f"The Mean Absolute Percentage Error Value : {mape_lstm}")
```

```
The Mean Absolute Percentage Error Value : 0.016842609935427074
```

In [82]:
```
#for plotting
train = new_data[:1763]
valid = new_data[1763:]
valid['Predictions'] = closing_price
plt.figure(figsize=(16, 5))
plt.plot(train['Close'])
plt.plot(valid[['Close','Predictions']])
```

Out[82]:
```
[<matplotlib.lines.Line2D at 0x2977f852bb0>,
 <matplotlib.lines.Line2D at 0x2977f852c40>]
```



7. Supervised Algorithms Results

Parameter	Auto-ARIMA	XGBoost	LSTM
Root Mean Square Error	216.45	14.77	5.63
Mean Absolute Error	179.40	13.10	3.58
Mean Absolute Percentage Error	0.99	0.064	0.016