CS575 Project_Google dataset

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Downloading & Exporting the dataset

```
from pandas_datareader import data as pdr
from datetime import datetime
```

```
#download data
google = pdr.DataReader('GOOGL', 'yahoo', start=datetime(2014, 8, 1), end=datetime(2016, 11, 30))
```

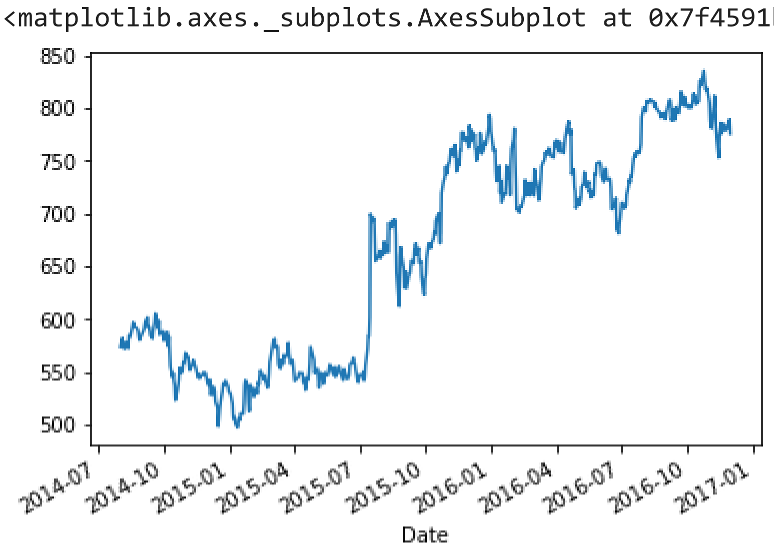
```
#print first few lines of data
print(google.head())
```

```
                  High         Low        Open       Close   Volume   Adj Close
Date
2014-08-01  583.429993  570.299988  578.549988  573.599976  2213300  573.599976
2014-08-04  583.820007  572.260010  576.510010  582.270020  1519400  582.270020
2014-08-05  580.200012  570.309998  579.380005  573.140015  1643800  573.140015
2014-08-06  578.640015  567.450012  569.500000  574.489990  1322800  574.489990
2014-08-07  578.309998  569.429993  576.049988  571.809998  1163000  571.809998
```

```
#export and save as csv files
google.to_csv('Google_stock.csv', sep=',')
```

```
#Visulaizing the close data
import matplotlib.pyplot as plt
google["Close"].plot()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4591b1a1d0>
```



Statistical analysis like ACF, PACF, ADF, KPSS Test

```
#Importing libraries
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller,kpss
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is deprecat
  import pandas.util.testing as tm
```

```
#ADF Test

def adf_test(atr):

    #Perform Dickey-Fuller test:
    timeseries = google[atr].dropna()
    print ('Results of Dickey-Fuller Test for ',atr,'\n')
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used','Number of Observations Used'])
    for key,value in dftest[4].items():
       dfoutput['Critical Value (%s)'%key] = value
    print(dfoutput)
```

```
#apply adf test on the series
adf_test('Close')
```

```
Results of Dickey-Fuller Test for  Close

Test Statistic                  -1.092577
p-value                          0.718023
#Lags Used                       3.000000
Number of Observations Used    585.000000
Critical Value (1%)             -3.441578
Critical Value (5%)             -2.866493
Critical Value (10%)            -2.569408
dtype: float64
```

The p value obtained is greater than significance level of 0.05 and test statistic is higher than any of the critical values

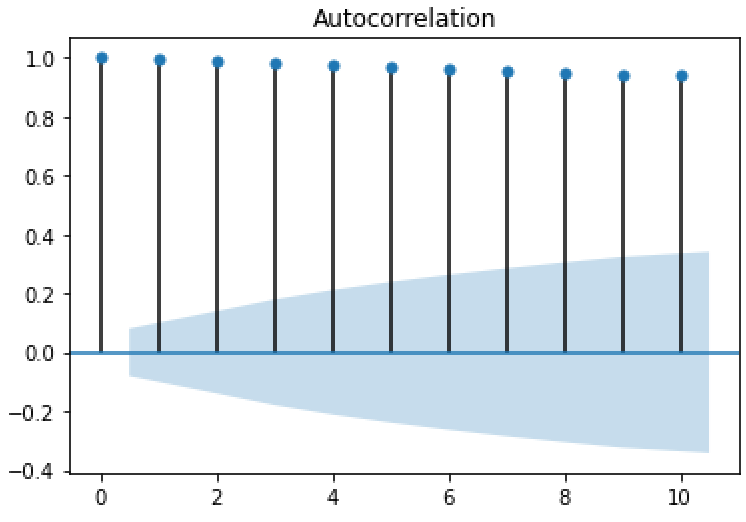
so we cant reject the null hypothesis so the time series is non stationary.

```
#KPSS Test

def kpss_test(atr):
    timeseries = google[atr].dropna()
    print ('Results of KPSS Test for ',atr)
    kpsstest = kpss(timeseries, regression='c')
    kpss_output = pd.Series(kpsstest[0:3], index=['Test Statistic','p-value','Lags Used'])
    for key,value in kpsstest[3].items():
        kpss_output['Critical Value (%s)'%key] = value
    print (kpss_output)

kpss_test('Close')
```

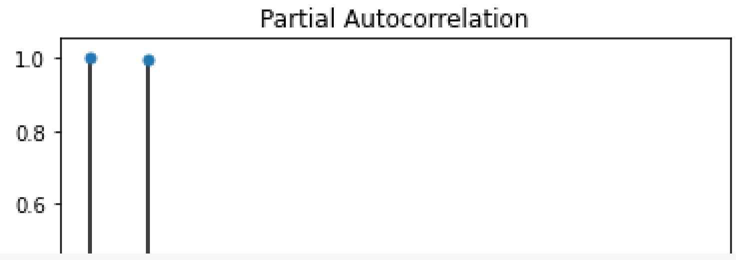
```
Results of KPSS Test for  Close
Test Statistic            2.648792
p-value                   0.010000
Lags Used                19.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/stattools.py:1685: FutureWarning: The behavior of using lags=Nor
  warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/stattools.py:1709: InterpolationWarning: p-value is smaller thar
  warn("p-value is smaller than the indicated p-value", InterpolationWarning)
```

The p value is significant less than 0.05 hence we can reject the null hypothesis so series is non stationary

```
# ACF Test of differenced data
plot_acf(google['Close'].dropna(), lags=10)
plt.show()
```

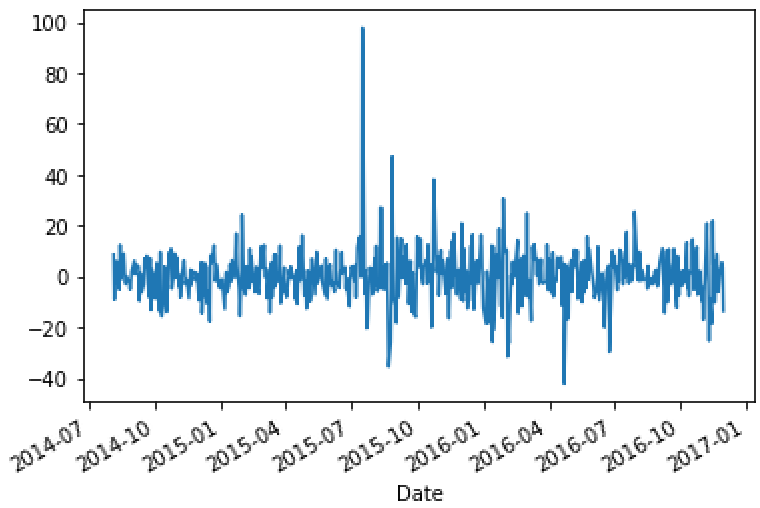



```
# PACF Test of differenced data
plot_pacf(google['Close'].dropna(), lags=10)
plt.show()
```




```
#Differencing to make data as stationary

#Differencing the data
google['diff'] = google['Close'].diff(periods=1)

#Visulaizing the differenced data
google["diff"].plot()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f45cd919a90>
```



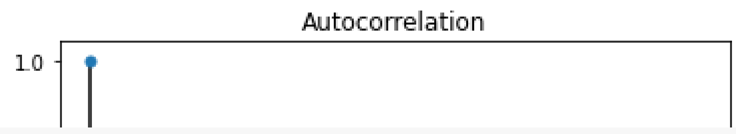

```
# ADF Test of differenced data
adf_test('diff')
```

```
Results of Dickey-Fuller Test for  diff

Test Statistic                 -1.479016e+01
p-value                         2.177423e-27
#Lags Used                      2.000000e+00
Number of Observations Used     5.850000e+02
Critical Value (1%)            -3.441578e+00
Critical Value (5%)            -2.866493e+00
Critical Value (10%)           -2.569408e+00
dtype: float64
```

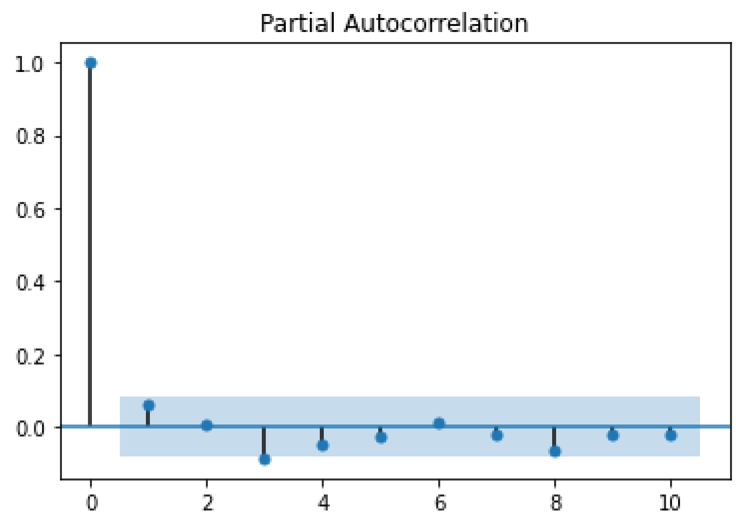
```
# KPSS Test of differenced data
kpss_test('diff')
```

```
Results of KPSS Test for  diff
Test Statistic            0.073196
p-value                   0.100000
Lags Used                19.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/stattools.py:1685: FutureWarning: The behavior of using lags=Nor
  warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/stattools.py:1711: InterpolationWarning: p-value is greater thar
  warn("p-value is greater than the indicated p-value", InterpolationWarning)
```

```
# ACF Test of differenced data
plot_acf(google['diff'].dropna(), lags=10)
plt.show()
```




```
# PACF Test of differenced data
plot_pacf(google['diff'].dropna(), lags=10)
plt.show()
```



Exponential

```
import numpy as np
from statsmodels.tsa.holtwinters import ExponentialSmoothing
```

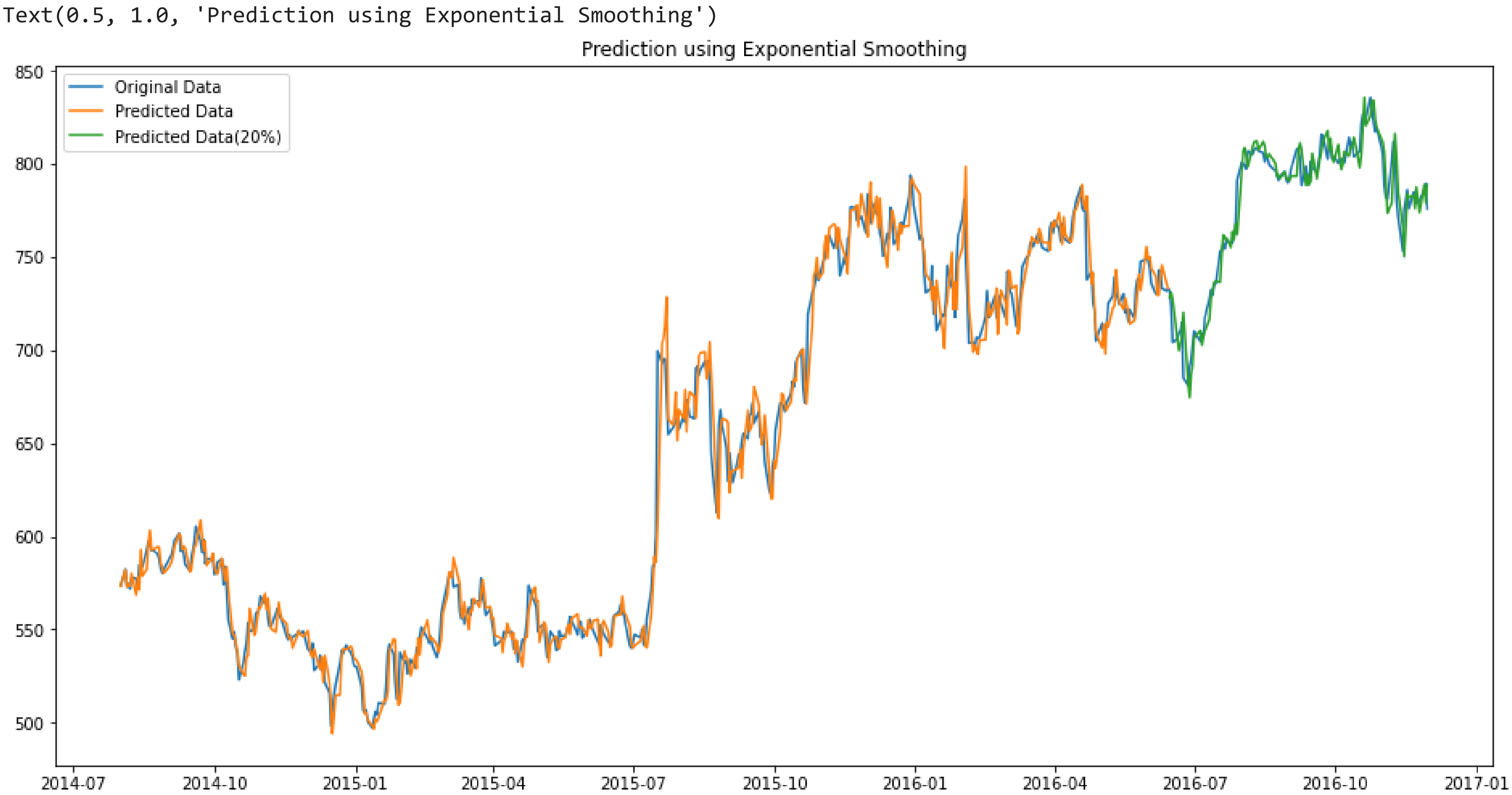
```
n = int(len(google["Close"])*0.8)
data = google['Close'].to_numpy()
train2 = data[:n]
test2 = data[n:]
date = (google.index)
```

```
Exp_model = ExponentialSmoothing(google.Close,trend='mul',seasonal='mul',seasonal_periods=4)
google['Pred_Exp'] = Exp_model.fit(smoothing_level = 0.9,smoothing_slope= 0.1,smoothing_seasonal = 0.2).fittedvalues.shift(0
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:219: ValueWarning: A date index has been provi
  ' ignored when e.g. forecasting.', ValueWarning)
```

```
plt.figure(figsize=(16,8))
plt.plot(date,data, label='Original Data')
plt.plot(date[:n],google.Pred_Exp[:n], label='Predicted Data')
plt.plot(date[n:],google.Pred_Exp[n:], label='Predicted Data(20%)')
plt.legend()
plt.title('Prediction using Exponential Smoothing')
```

```
Text(0.5, 1.0, 'Prediction using Exponential Smoothing')
```




```
#Calculation of MSE for comparing the model
```

```
rmse2 = (np.mean(np.power((np.array(test2)-np.array(google.Pred_Exp[n:])),2)))
print('MSE value using Exponential Smoothing model: ',rmse2)
```

```
MSE value using Exponential Smoothing model:  91.8678384539808
```

ARIMA

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from pandas.plotting import lag_plot
from pandas import datetime
from statsmodels.tsa.arima_model import ARIMA
from sklearn.metrics import mean_squared_error
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: FutureWarning: The pandas.datetime class is deprecated
  """
```

```
# Importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
# Importing data
df = pd.read_csv('Google_stock.csv')
df.head()
```

	Date	High	Low	Open	Close	Volume	Adj Close
0	2014-08-01	583.429993	570.299988	578.549988	573.599976	2213300	573.599976
1	2014-08-04	583.820007	572.260010	576.510010	582.270020	1519400	582.270020
2	2014-08-05	580.200012	570.309998	579.380005	573.140015	1643800	573.140015
3	2014-08-06	578.640015	567.450012	569.500000	574.489990	1322800	574.489990
4	2014-08-07	578.309998	569.429993	576.049988	571.809998	1163000	571.809998

```
# Extracting the required columns
df = df[['Date', 'Close']]
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 589 entries, 0 to 588
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Date    589 non-null    object
 1   Close   589 non-null    float64
dtypes: float64(1), object(1)
memory usage: 9.3+ KB
```

```
# Changing the Date column to proper DateTime object
df.Date = pd.to_datetime(df.Date)
df.info()
```

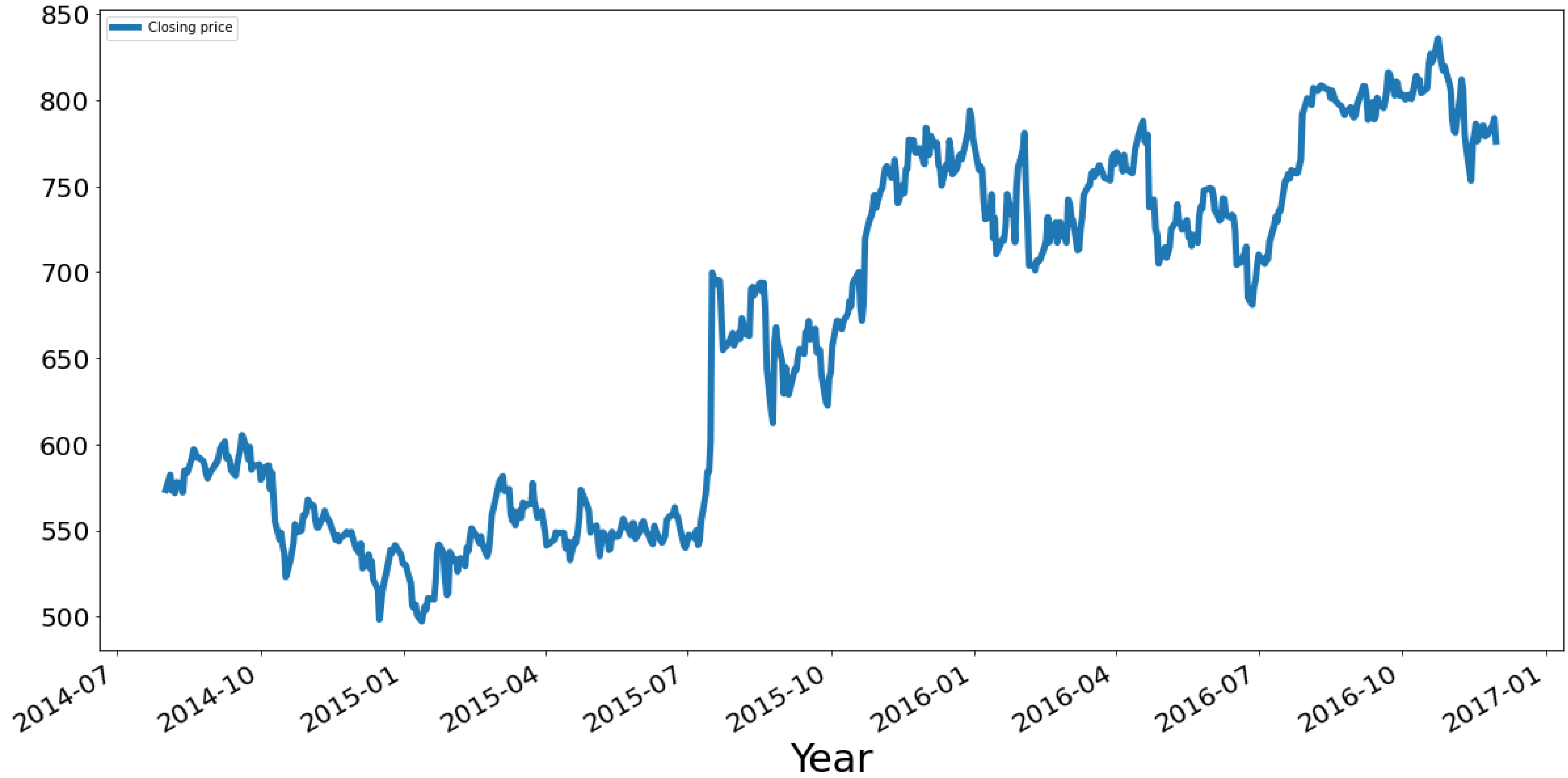
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 589 entries, 0 to 588
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Date    589 non-null    datetime64[ns]
 1   Close   589 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 9.3 KB
```

```
# Making Date column to be the index
df.columns=['Date','Closing price']
df.set_index('Date', inplace=True)
df.head()
```

	Closing price
Date	
2014-08-01	573.599976

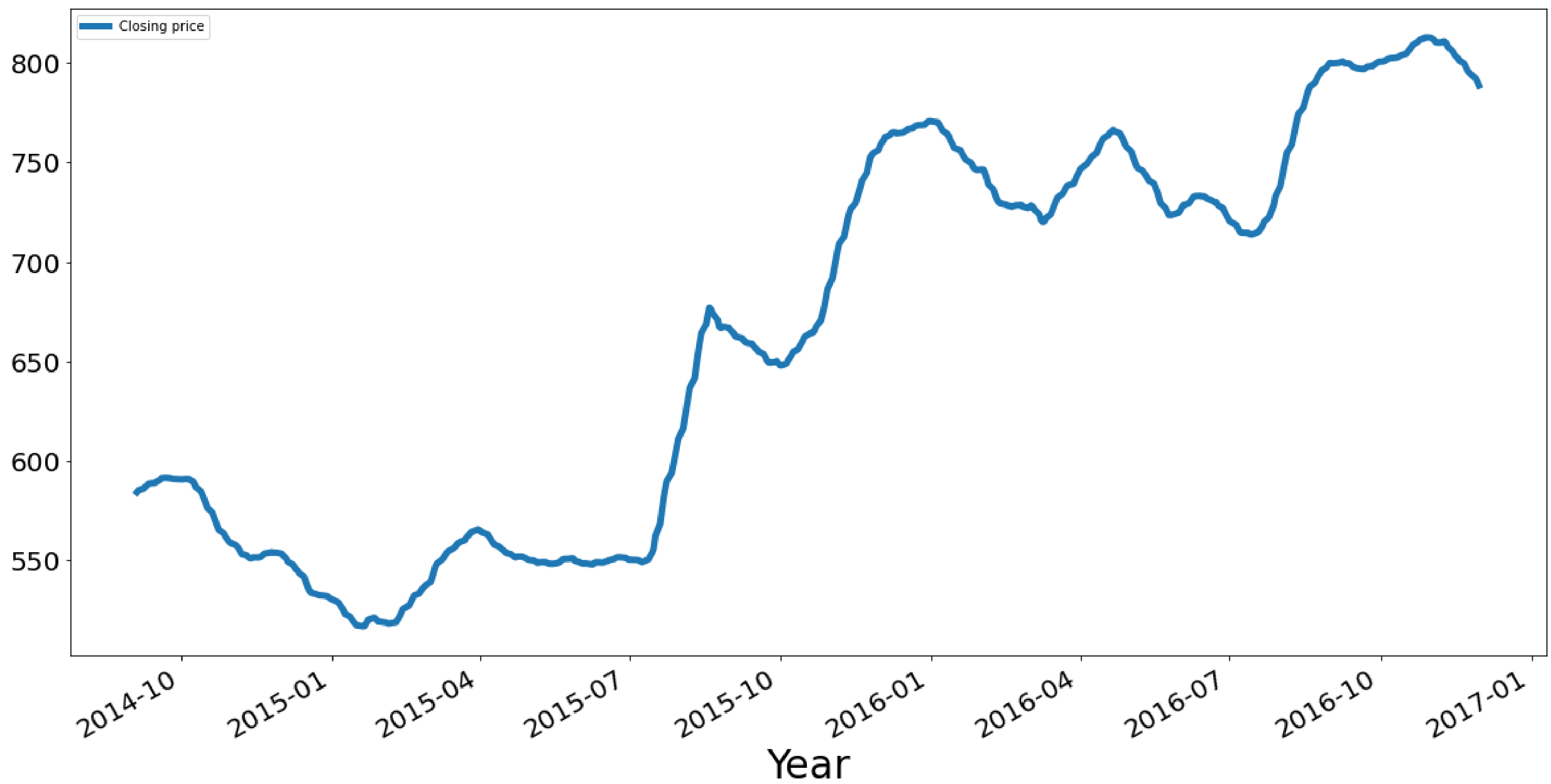
```
# Plot
df.plot(figsize=(20,10), linewidth=5,fontsize=20);
plt.xlabel('Year', fontsize=30)
```

```
Text(0.5, 0, 'Year')
```




```
# Seeing the trend more clearly
df.rolling(24).mean().plot(figsize=(20,10), linewidth=5,fontsize=20);
plt.xlabel('Year', fontsize=30)
# Overall a rise here
```

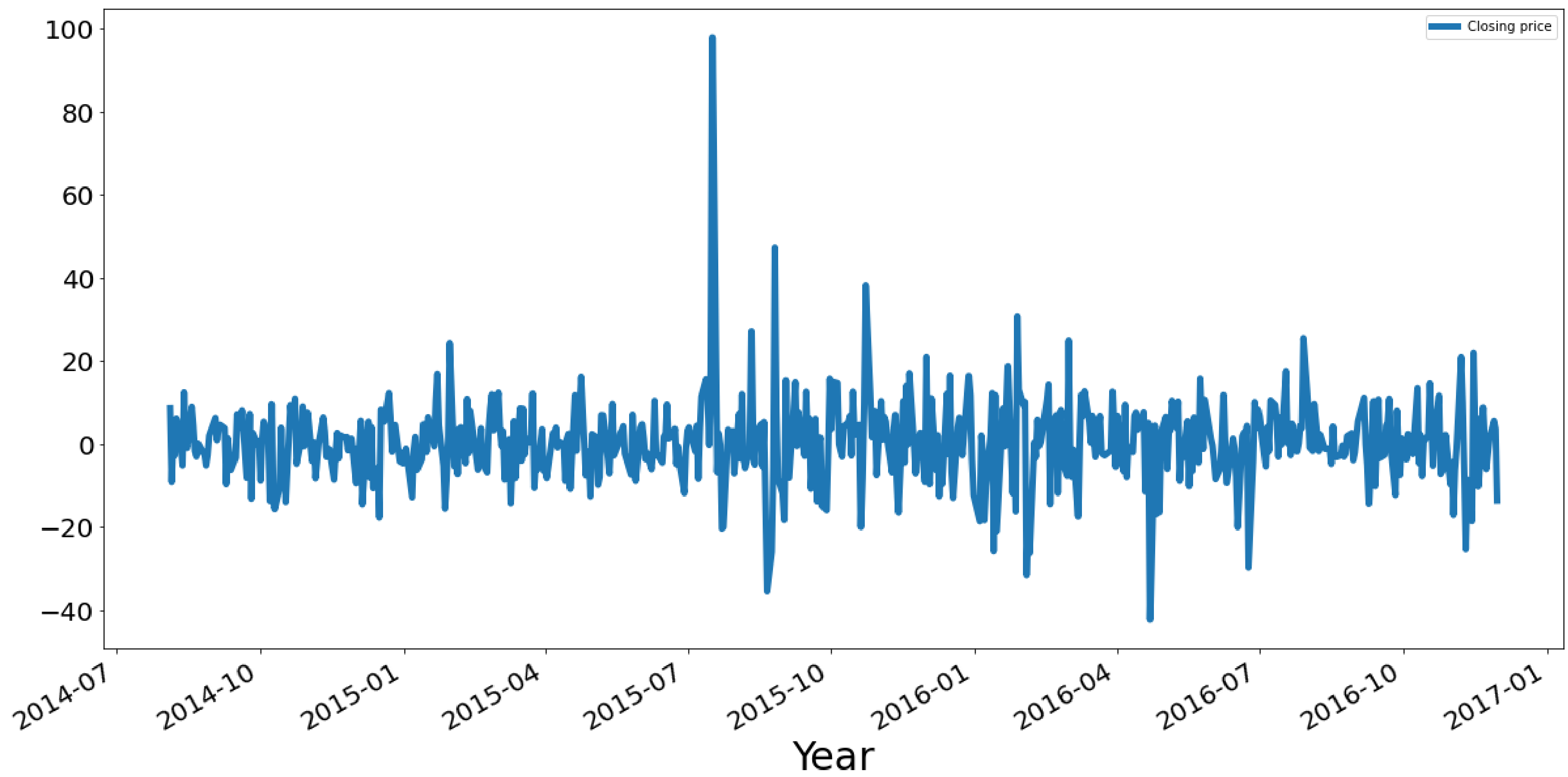
```
Text(0.5, 0, 'Year')
```




```
# We can see that there is no specific seasonality here
```

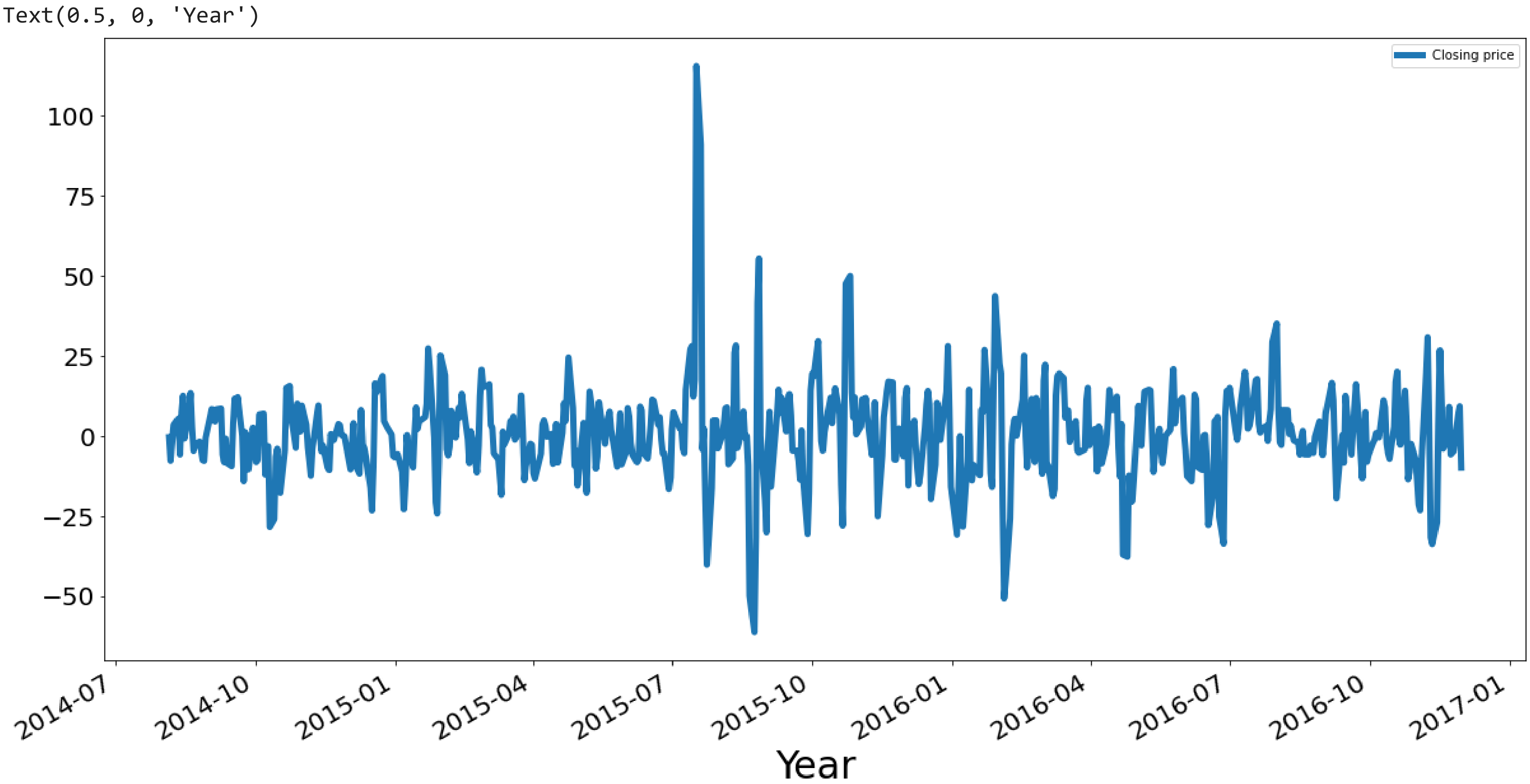
```
# We can see that there is no specific seasonality here
# Removing trend
df.diff().plot(figsize=(20,10), linewidth=5,fontsize=20);
plt.xlabel('Year', fontsize=30)
```

```
Text(0.5, 0, 'Year')
```



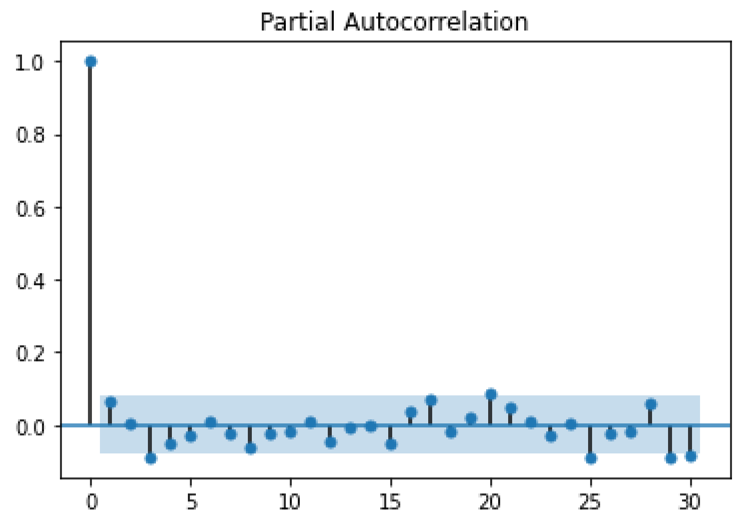

```
# 2nd order differencing
df.diff(periods=2).plot(figsize=(20,10), linewidth=5,fontsize=20);
plt.xlabel('Year', fontsize=30)
```

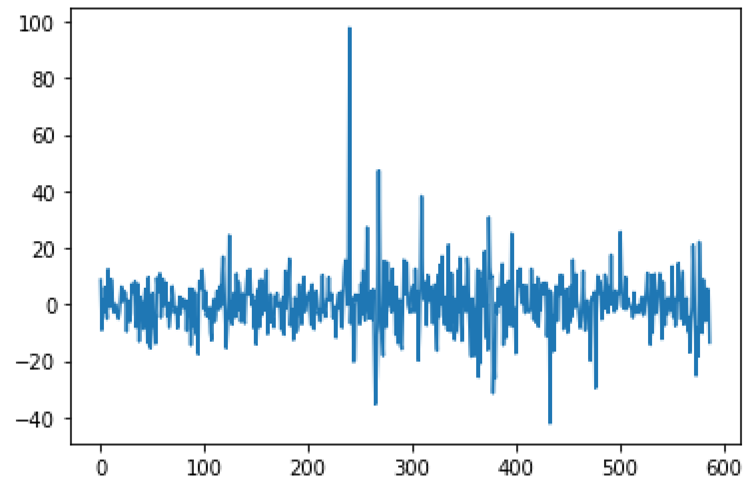
```
Text(0.5, 0, 'Year')
```

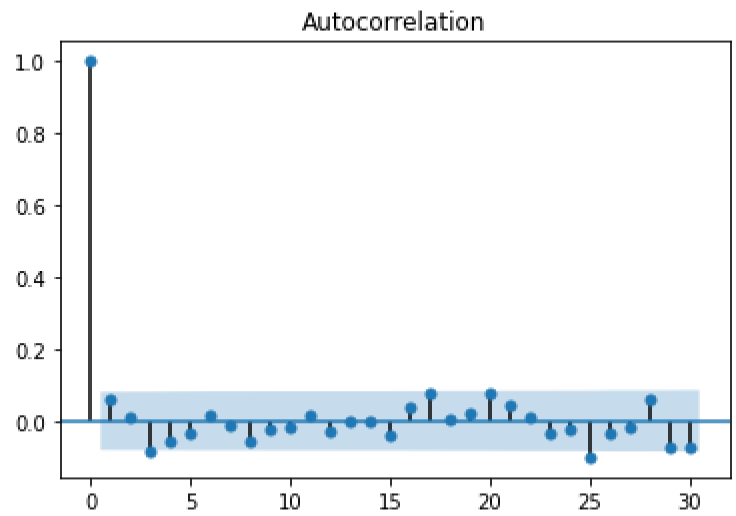


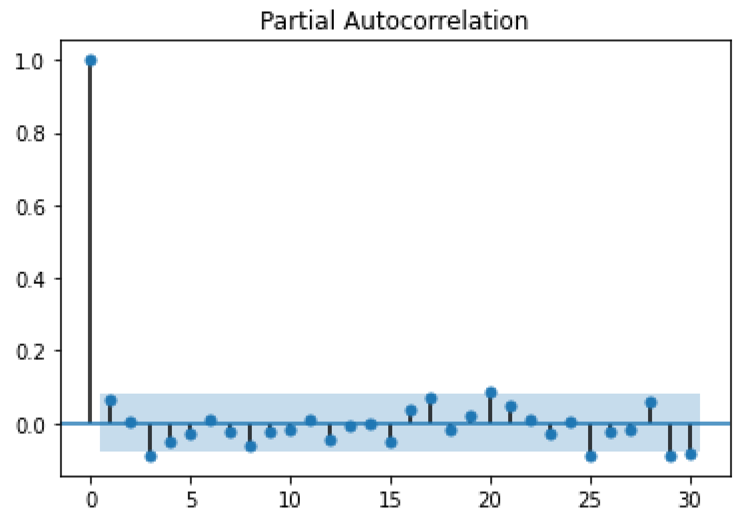

```
# Let's take a look at its auto-corelation plots
# Before that we'll have to do manual differencing
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

def difference(data, lag):
    diff= []

    for i in range(lag, len(data)):
```

```
        value = data[i] - data[i-lag]
        diff.append(value)
    return pd.Series(diff)

df_close = df['Closing price']
X = df_close.values
diff = difference(X,1)
plt.plot(diff)
df_diff = pd.DataFrame(diff)
plot_acf(df_diff, lags=30)
plot_pacf(df_diff, lags=30)
```









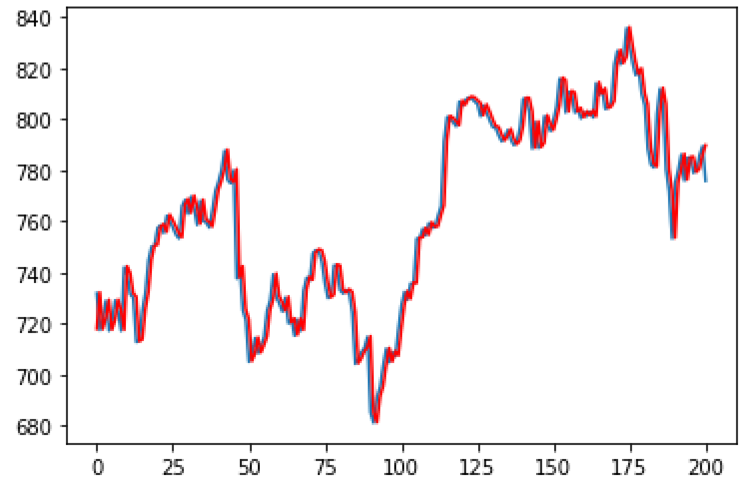

```
# Forecasting
from sklearn.metrics import mean_squared_error
from statsmodels.tsa.arima_model import ARIMA
df = df.astype(np.float64)
Y = df.values
size = int(len(Y)*0.66)
train, test = Y[0:size], Y[size:len(Y)]
```

```
history = [x for x in train]
predictions = list()

for t in range(len(test)):
```

```
    model = ARIMA(history, order=(0,1,0))
    model_fit = model.fit(disp=0)
    output = model_fit.forecast()
    pred = output[0]
    predictions.append(pred)
    obs = test[t]
    history.append(obs)
    print('predicted=%f, expected=%f'%(pred, obs))
```

```
predicted=718.012211, expected=731.969971
predicted=732.378141, expected=717.510010
predicted=717.879958, expected=722.109985
predicted=722.490780, expected=729.049988
predicted=729.447558, expected=717.289978
predicted=717.656534, expected=720.900024
predicted=721.274834, expected=729.119995
predicted=729.514716, expected=724.859985
predicted=725.242922, expected=717.219971
predicted=717.582647, expected=742.169983
predicted=742.594593, expected=739.479980
predicted=739.896764, expected=731.590027
predicted=731.985992, expected=730.219971
predicted=730.611521, expected=712.799988
predicted=713.147120, expected=713.530029
predicted=713.878114, expected=725.409973
predicted=725.786673, expected=732.169983
predicted=732.562483, expected=744.869995
predicted=745.292884, expected=750.239990
predicted=750.675064, expected=750.570007
predicted=751.004823, expected=757.359985
predicted=757.810378, expected=758.479980
predicted=758.932010, expected=755.409973
predicted=755.853412, expected=762.159973
predicted=762.618757, expected=760.049988
predicted=760.502537, expected=757.559998
predicted=758.005421, expected=754.840027
predicted=755.277805, expected=753.280029
predicted=753.712993, expected=765.890015
predicted=766.352250, expected=768.340027
predicted=768.807029, expected=762.900024
predicted=763.352895, expected=769.669983
predicted=770.137930, expected=765.119995
predicted=765.575995, expected=758.570007
predicted=759.009366, expected=768.070007
predicted=768.530837, expected=760.119995
predicted=760.560941, expected=759.469971
predicted=759.908343, expected=757.539978
/usr/local/lib/python3.7/dist-packages/statsmodels/base/model.py:512: ConvergenceWarning: Maximum Likelihood optimiz
  "Check mle_retvals", ConvergenceWarning)
/usr/local/lib/python3.7/dist-packages/statsmodels/base/model.py:512: ConvergenceWarning: Maximum Likelihood optimiz
  "Check mle_retvals", ConvergenceWarning)
predicted=757.972778, expected=764.320007
predicted=764.767707, expected=771.909973
predicted=772.374399, expected=775.390015
predicted=775.861487, expected=780.000000
predicted=780.481119, expected=787.679993
predicted=788.177853, expected=776.250000
predicted=776.720186, expected=774.919983
predicted=775.386001, expected=780.000000
predicted=780.476674, expected=737.770020
predicted=738.148292, expected=742.210022
predicted=742.597631, expected=725.369995
predicted=725.718091, expected=721.460022
predicted=721.798374, expected=705.059998
predicted=705.360135, expected=707.880005
predicted=708.185882, expected=714.409973
predicted=714.729996, expected=708.440002
```

```
plt.plot(test)
plt.plot(predictions, color='red')
plt.show()
```



```
#Calculation of MSE for comparing the model
difference_array = np.subtract(test, predictions)
squared_array = np.square(difference_array)
mse = squared_array.mean()
mse
```

```
76.00429273259594
```

LSTM

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense,LSTM,Dropout
```

importing the training data

```
data = pd.read_csv('Google_stock.csv')
```

choosing the close column

```
data["Close"]=pd.to_numeric(data.Close,errors='coerce') #turning the Close column to numeric
data = data.dropna() #romeving the NA values
trainData = data.iloc[:,4:5].values #selecting only the closing prices for training
```

scaling the values in the range of 0-1 for best preformances

```
sc = MinMaxScaler(feature_range=(0,1))
trainData = sc.fit_transform(trainData)
trainData.shape
```

```
(589, 1)
```

preparing the data for LSTM

since its a time series problem we took 60 as timestep for our learning : given 60 closing values as an input data the 61st value is our output

```
X_train = []
y_train = []

for i in range (60,589): #60 : timestep // 1149 : length of the data
    X_train.append(trainData[i-60:i,0])
    y_train.append(trainData[i,0])

X_train,y_train = np.array(X_train),np.array(y_train)
```

ps : LSTM take a 3D tensor (seq_len,timestep,batch_size)

```
X_train = np.reshape(X_train,(X_train.shape[0],X_train.shape[1],1)) #adding the batch_size axis
X_train.shape
```

```
(529, 60, 1)
```

building the model

```
model = Sequential()

model.add(LSTM(units=100, return_sequences = True, input_shape =(X_train.shape[1],1)))
model.add(Dropout(0.2))

model.add(LSTM(units=100, return_sequences = True))
model.add(Dropout(0.2))

model.add(LSTM(units=100, return_sequences = True))
model.add(Dropout(0.2))
```

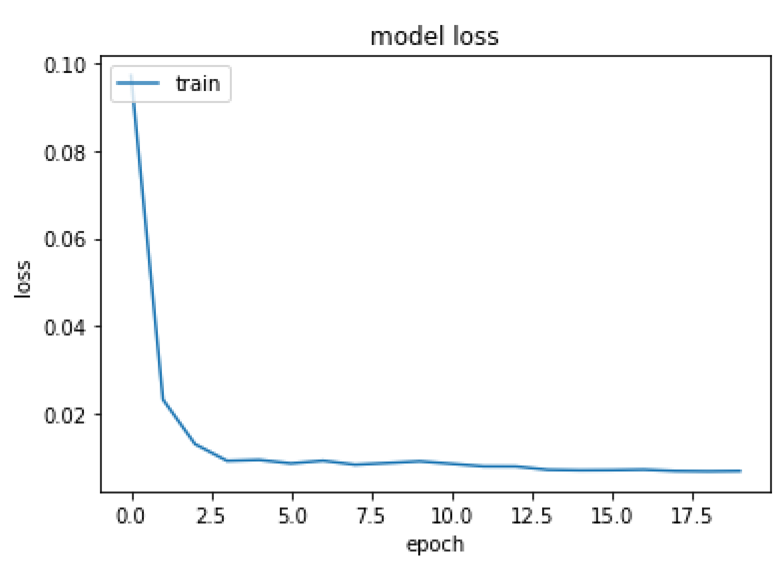
```
model.add(LSTM(units=100, return_sequences = False))
model.add(Dropout(0.2))

model.add(Dense(units =1))
model.compile(optimizer='adam',loss="mean_squared_error")
```

```
hist = model.fit(X_train, y_train, epochs = 20, batch_size = 32, verbose=2)
```

```
Epoch 1/20
17/17 - 10s - loss: 0.0973
Epoch 2/20
17/17 - 3s - loss: 0.0231
Epoch 3/20
17/17 - 3s - loss: 0.0129
Epoch 4/20
17/17 - 3s - loss: 0.0091
Epoch 5/20
17/17 - 3s - loss: 0.0093
Epoch 6/20
17/17 - 3s - loss: 0.0085
Epoch 7/20
17/17 - 3s - loss: 0.0091
Epoch 8/20
17/17 - 3s - loss: 0.0082
Epoch 9/20
17/17 - 3s - loss: 0.0086
Epoch 10/20
17/17 - 3s - loss: 0.0090
Epoch 11/20
17/17 - 3s - loss: 0.0084
Epoch 12/20
17/17 - 3s - loss: 0.0078
Epoch 13/20
17/17 - 3s - loss: 0.0078
Epoch 14/20
17/17 - 3s - loss: 0.0070
Epoch 15/20
17/17 - 3s - loss: 0.0069
Epoch 16/20
17/17 - 3s - loss: 0.0069
Epoch 17/20
17/17 - 3s - loss: 0.0071
Epoch 18/20
17/17 - 3s - loss: 0.0067
Epoch 19/20
17/17 - 3s - loss: 0.0067
Epoch 20/20
17/17 - 3s - loss: 0.0067
```

ploting the training loss

```
plt.plot(hist.history['loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train'], loc='upper left')
plt.show()
```



testing the model on new data

```
testData = pd.read_csv('Google_stock.csv') #importing the test data
testData["Close"]=pd.to_numeric(testData.Close,errors='coerce') #turning the close column to numerical type
testData = testData.dropna() #droping the NA values
testData = testData.iloc[:,4:5] #selecting the closing prices for testing
```

```
y_test = testData.iloc[60:,0:].values #selecting the labels
#input array for the model
inputClosing = testData.iloc[:,0:].values
inputClosing_scaled = sc.transform(inputClosing)
inputClosing_scaled.shape
X_test = []
length = len(testData)
timestep = 60
for i in range(timestep,length): #doing the same preivous preprocessing
    X_test.append(inputClosing_scaled[i-timestep:i,0])
X_test = np.array(X_test)
X_test = np.reshape(X_test,(X_test.shape[0],X_test.shape[1],1))
X_test.shape
```

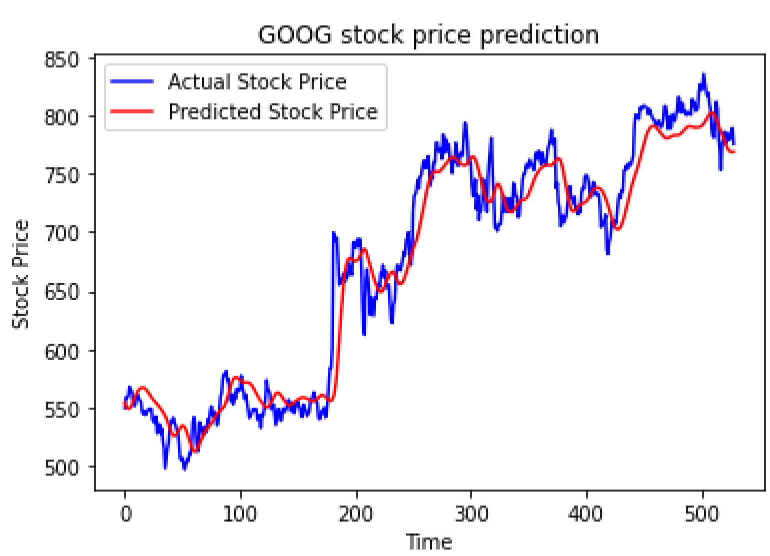
```
(529, 60, 1)
```

```
y_pred = model.predict(X_test) #predicting the new values
```

```
predicted_price = sc.inverse_transform(y_pred) #inversing the scaling transformation for ploting
```

ploting the results

```
plt.plot(y_test, color = 'blue', label = 'Actual Stock Price')
plt.plot(predicted_price, color = 'red', label = 'Predicted Stock Price')
plt.title('GOOG stock price prediction')
plt.xlabel('Time')
plt.ylabel('Stock Price')
plt.legend()
plt.show()
```




```
#Calculation of MSE for comparing the model
difference_array = np.subtract(y_test, predicted_price)
squared_array = np.square(difference_array)
mse = squared_array.mean()
mse
```

```
563.0632418355867
```