CS575 Project_Apple dataset

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Downloading & Exporting the dataset

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

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

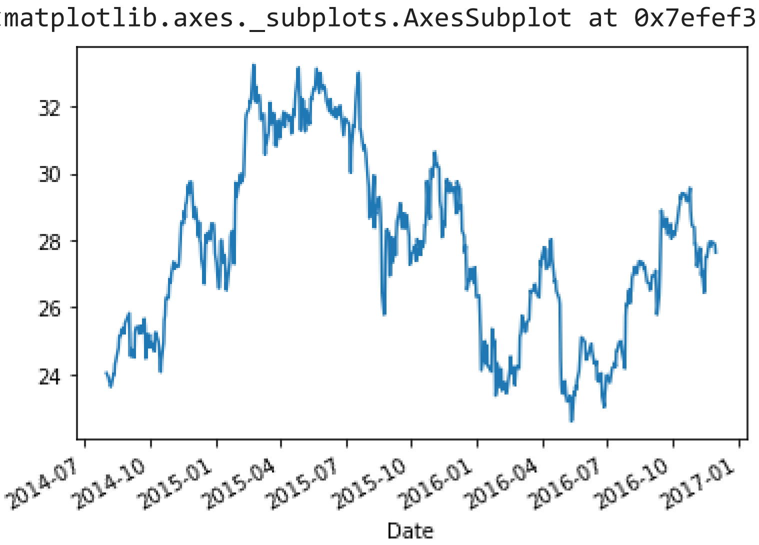
```
#print first few lines of data
print(apple.head())
```

```
                 High        Low       Open      Close       Volume  Adj Close
Date
2014-08-01  24.155001  23.702499  23.725000  24.032499  194044000.0  21.657644
2014-08-04  24.145000  23.792500  24.092501  23.897499  159832000.0  21.535982
2014-08-05  23.920000  23.590000  23.840000  23.780001  223732000.0  21.430096
2014-08-06  23.870001  23.677500  23.687500  23.740000  154232000.0  21.394049
2014-08-07  23.987499  23.525000  23.732500  23.620001  186844000.0  21.391787
```

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

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7efef3bc0850>
```



Statistical analysis like ACF, PACF, ADF, KPSS Test

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

```
#ADF Test

def adf_test(atr):

    #Perform Dickey-Fuller test:
    timeseries = apple[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                  -2.170605
p-value                          0.217087
#Lags Used                       0.000000
Number of Observations Used    588.000000
Critical Value (1%)             -3.441520
Critical Value (5%)             -2.866468
Critical Value (10%)            -2.569394
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

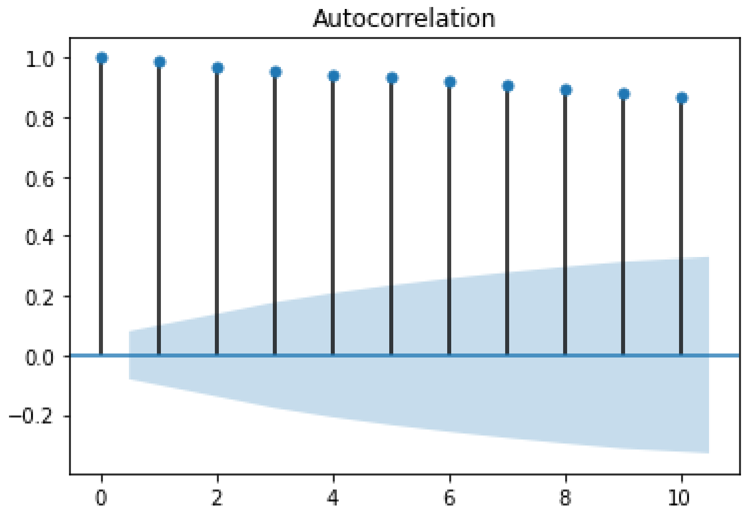
so we cant reject the null hypothesis so the time series is non stationary.

```
#KPSS Test

def kpss_test(atr):
    timeseries = apple[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            0.655743
p-value                   0.017569
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)
```

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(apple['Close'].dropna(), lags=10)
plt.show()
```




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

Partial Autocorrelation

```
#Differencing to make data as stationary

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

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

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

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

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

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

Exponential

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

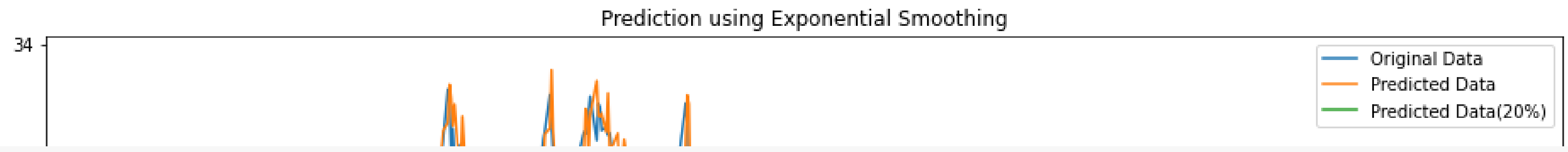
```
n = int(len(apple["Close"])*0.8)
data = apple['Close'].to_numpy()
train2 = data[:n]
test2 = data[n:]
date = (apple.index)
```

```
Exp_model = ExponentialSmoothing(apple.Close,trend='mul',seasonal='mul',seasonal_periods=4)
apple['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)
```

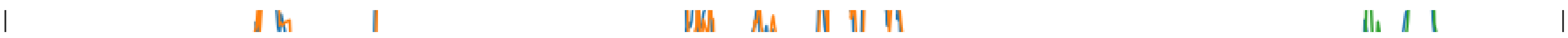
```
plt.figure(figsize=(16,8))
plt.plot(date,data, label='Original Data')
plt.plot(date[:n],apple.Pred_Exp[:n], label='Predicted Data')
plt.plot(date[n:],apple.Pred_Exp[n:], label='Predicted Data(20%)')
plt.legend()
plt.title('Prediction using Exponential Smoothing')
```

```
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(apple.Pred_Exp[n:])),2)))
print('MSE value using Exponential Smoothing model: ',rmse2)
```

```
MSE value using Exponential Smoothing model:  0.14894212244684166
```



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('Apple_stock.csv')
df.head()
```

	Date	High	Low	Open	Close	Volume	Adj Close
0	2014-08-01	24.155001	23.702499	23.725000	24.032499	194044000.0	21.657644
1	2014-08-04	24.145000	23.792500	24.092501	23.897499	159832000.0	21.535982
2	2014-08-05	23.920000	23.590000	23.840000	23.780001	223732000.0	21.430096
3	2014-08-06	23.870001	23.677500	23.687500	23.740000	154232000.0	21.394049
4	2014-08-07	23.987499	23.525000	23.732500	23.620001	186844000.0	21.391787

```
# 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()
```

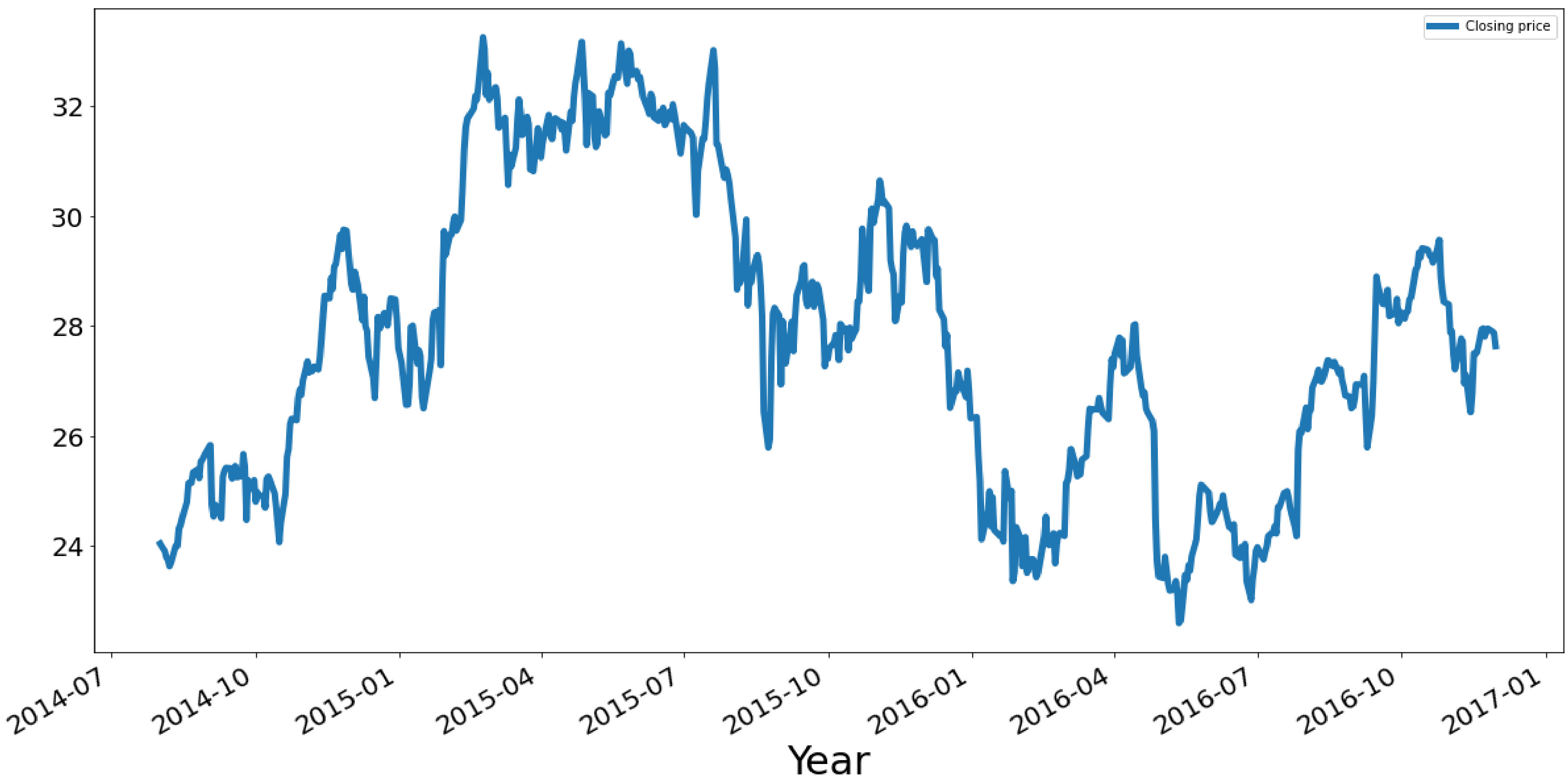
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 589 entries, 0 to 588
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype         
---  ------  --------------  -----         
 0   Date    589 non-null    datetime64[ns]
 1   Close   589 non-null    float64       
dtypes: datetime64[ns](1), 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	24.032499
2014-08-04	23.897499
2014-08-05	23.780001
2014-08-06	23.740000
2014-08-07	23.620001

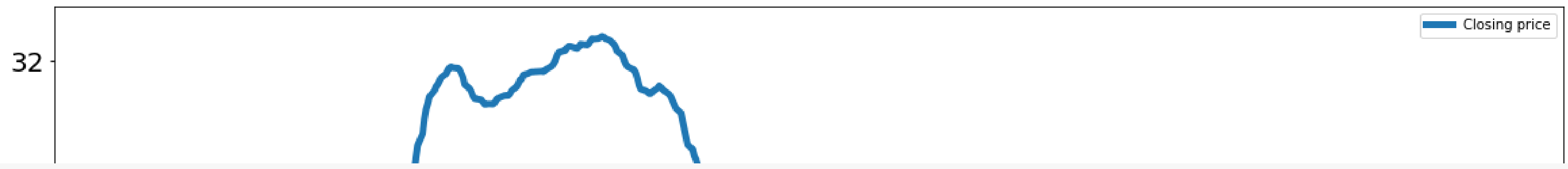
```
# Plot
df.plot(figsize=(20,10), linewidth=5,fontsize=20);
plt.xlabel('Year', fontsize=30)
```

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



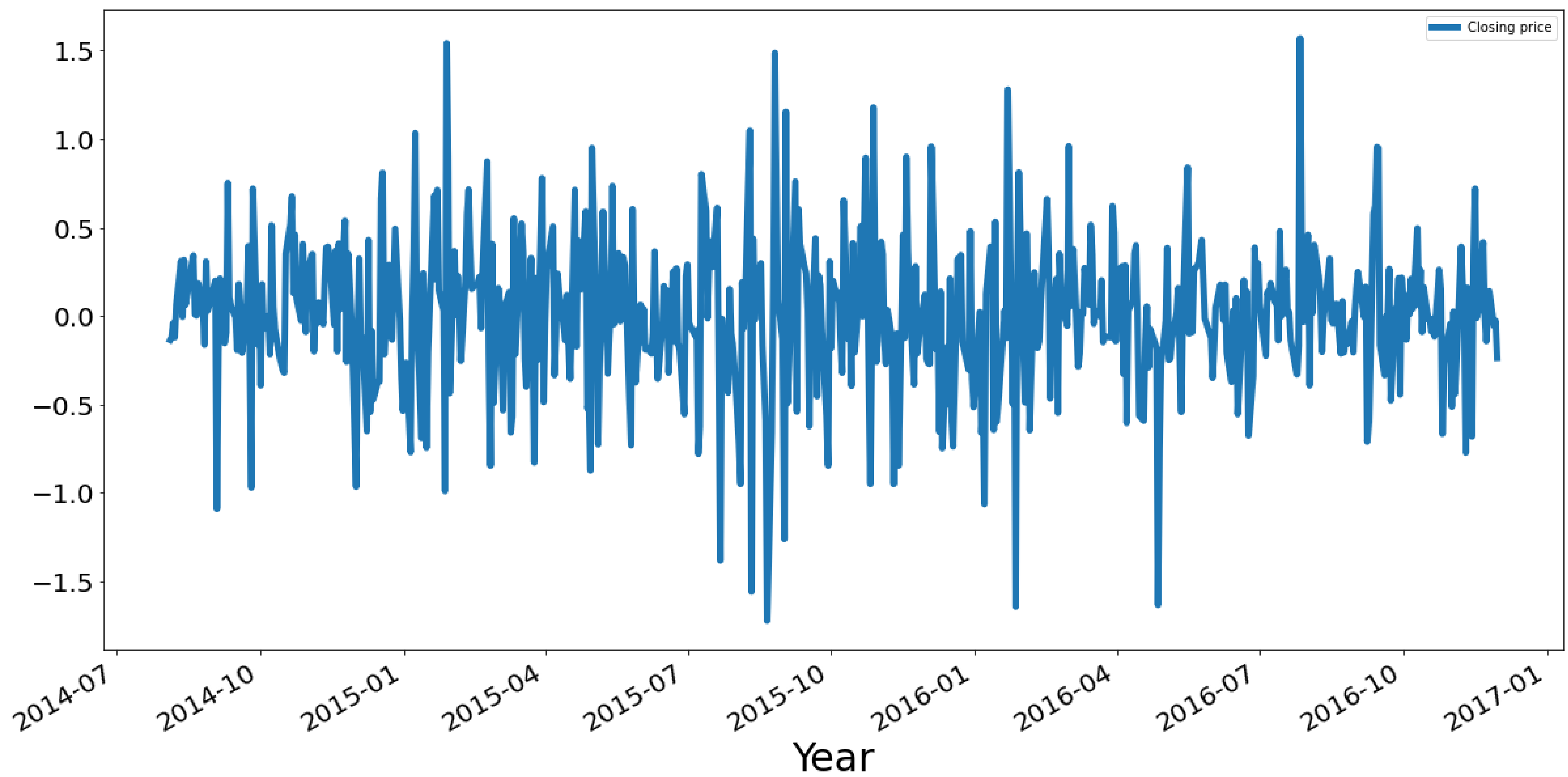

```
# Seeing the trend more clearly
df.rolling(24).mean().plot(figsize=(20,10), linewidth=5,fontsize=20);
plt.xlabel('Year', fontsize=30)
# Overall a rise here
```

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



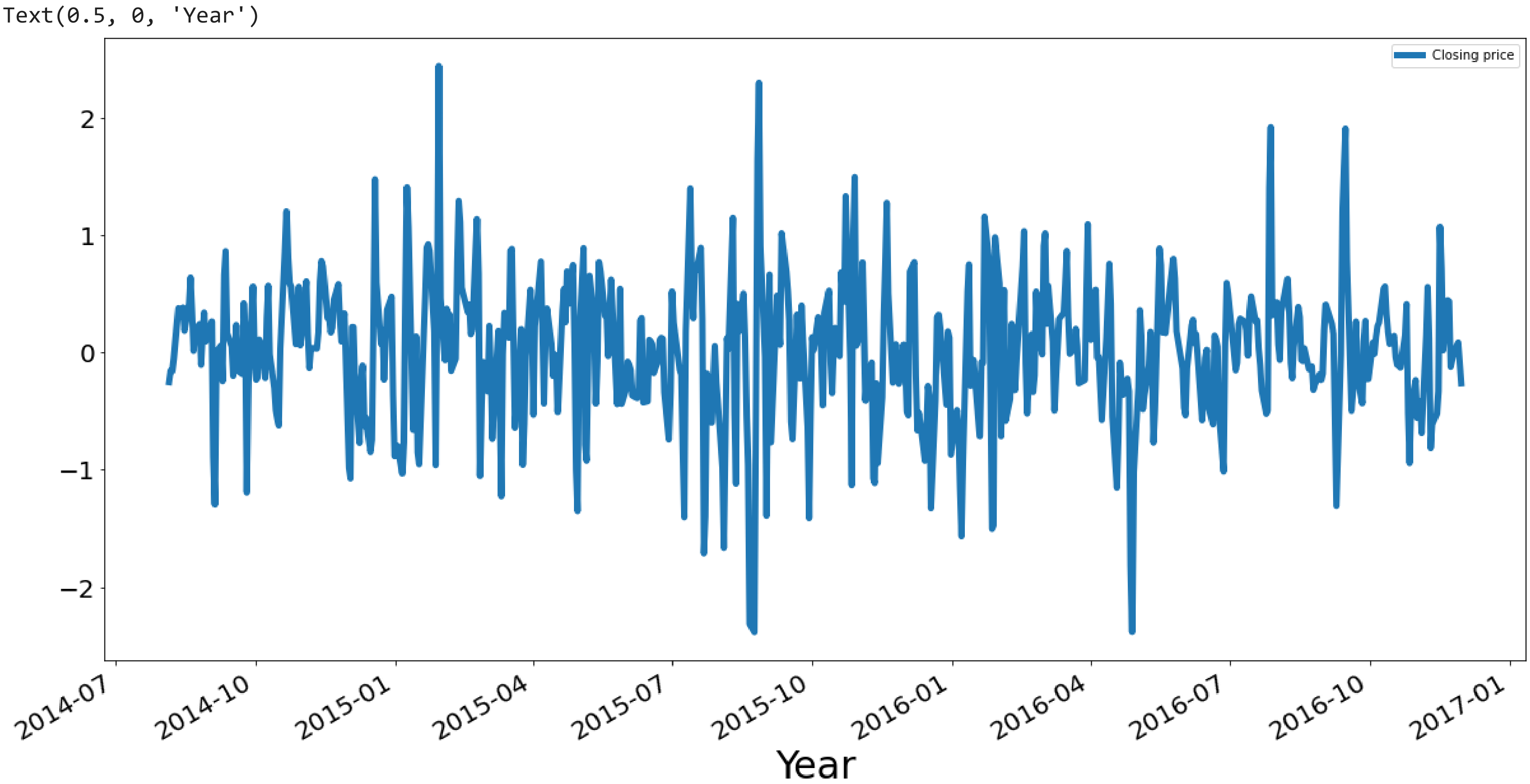

```
# We can see that there is no specific seasonality here
# Removing trend
df.diff().plot(figsize=(20,10), linewidth=5,fontsize=20);
plt.xlabel('Year', fontsize=30)
```

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



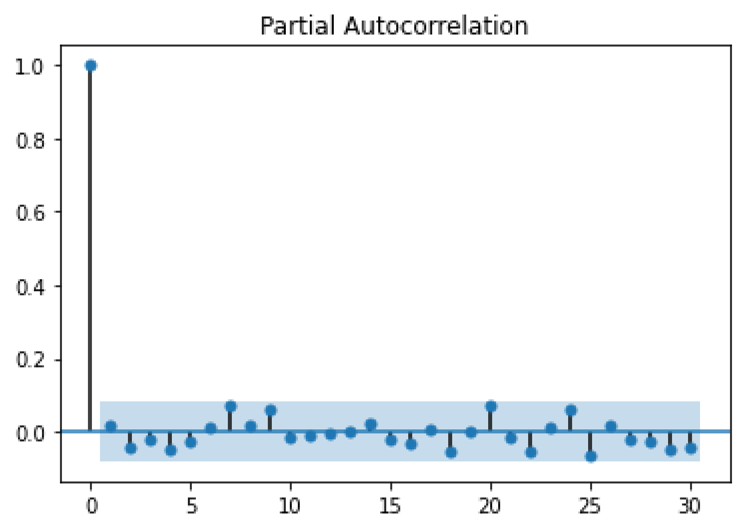

```
# 2nd order differencing
df.diff(periods=2).plot(figsize=(20,10), linewidth=5,fontsize=20);
plt.xlabel('Year', fontsize=30)
```

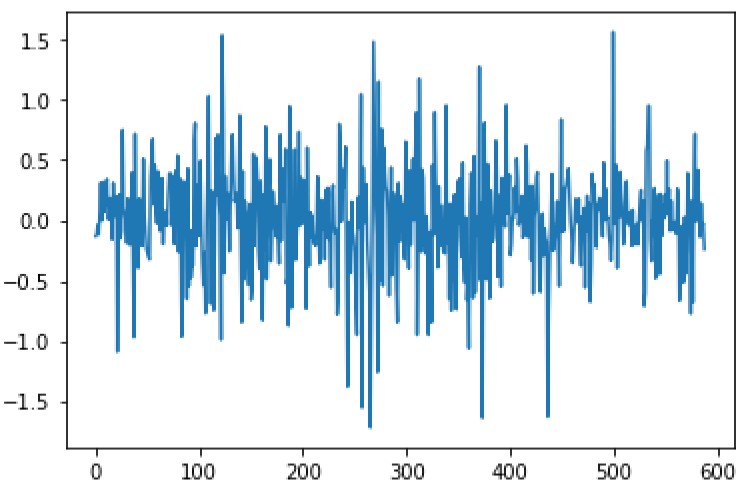
```
Text(0.5, 0, 'Year')
```

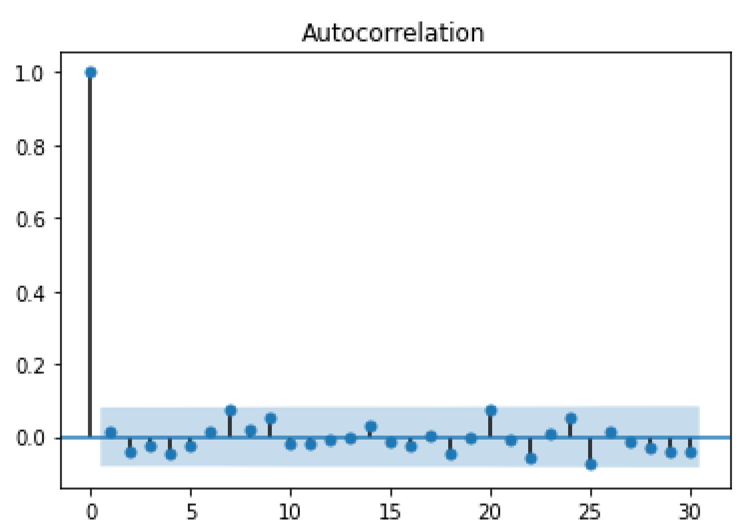


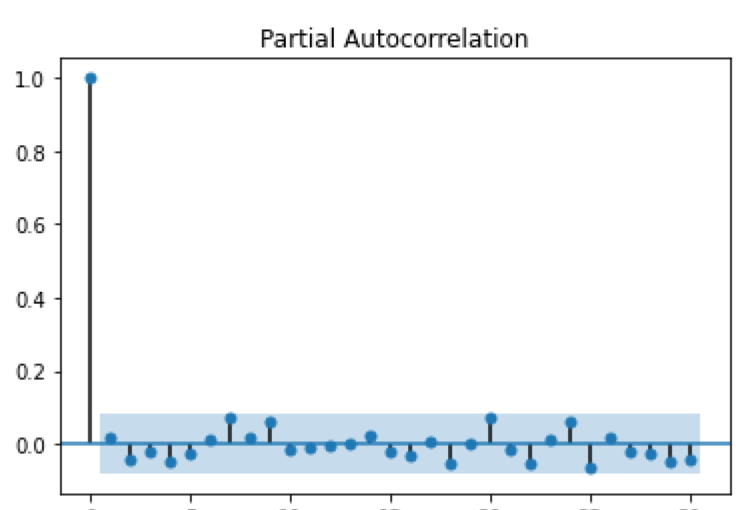

```
# Let's take a look at its auto-corelation plots
```

```
# 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)
```









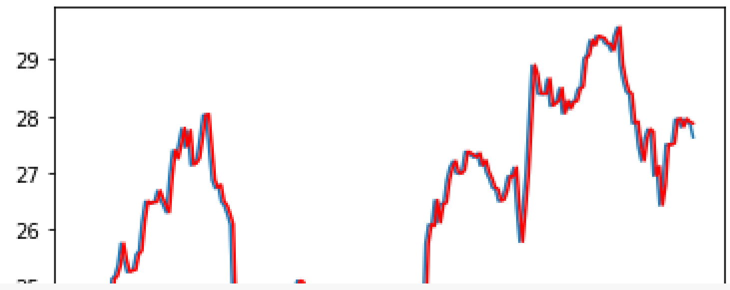

```
# Forecasting
from sklearn.metrics import mean_squared_error
from statsmodels.tsa.arima_model import ARIMA
df = df.astype(np.float64)
Y = df.values
size = int(len(Y)*0.66)
```

```
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=24.160329, expected=24.530001
predicted=24.531283, expected=24.065001
predicted=24.065084, expected=24.010000
predicted=24.009943, expected=24.219999
predicted=24.220479, expected=23.672501
predicted=23.671582, expected=24.025000
predicted=24.024981, expected=24.190001
predicted=24.190400, expected=24.227501
predicted=24.227995, expected=24.172501
predicted=24.172854, expected=25.132500
predicted=25.135270, expected=25.187500
predicted=25.190402, expected=25.375000
predicted=25.378365, expected=25.752501
predicted=25.756801, expected=25.467501
predicted=25.471079, expected=25.257500
predicted=25.260547, expected=25.280001
predicted=25.283096, expected=25.292500
predicted=25.295618, expected=25.565001
predicted=25.568784, expected=25.629999
predicted=25.633934, expected=26.145000
predicted=26.150191, expected=26.492500
predicted=26.498530, expected=26.450001
predicted=26.455912, expected=26.480000
predicted=26.485969, expected=26.477501
predicted=26.483450, expected=26.680000
predicted=26.686426, expected=26.532499
predicted=26.538553, expected=26.417500
predicted=26.423260, expected=26.297501
predicted=26.302958, expected=26.920000
predicted=26.926941, expected=27.389999
predicted=27.398051, expected=27.247499
predicted=27.255191, expected=27.497499
predicted=27.505769, expected=27.780001
predicted=27.788923, expected=27.452499
predicted=27.460623, expected=27.740000
predicted=27.748785, expected=27.135000
predicted=27.142335, expected=27.165001
predicted=27.172389, expected=27.254999
predicted=27.262582, expected=27.610001
predicted=27.618399, expected=28.010000
predicted=28.019315, expected=28.025000
predicted=28.034328, expected=27.462500
predicted=27.470495, expected=26.870001
predicted=26.876600, expected=26.727501
predicted=26.733754, expected=26.782499
predicted=26.788865, expected=26.492500
predicted=26.498182, expected=26.420000
predicted=26.425501, expected=26.270000
predicted=26.275144, expected=26.087500
predicted=26.092213, expected=24.455000
predicted=24.455967, expected=23.707500
predicted=23.706758, expected=23.434999
predicted=23.433638, expected=23.410000
predicted=23.408585, expected=23.795000
predicted=23.794462, expected=23.547501
predicted=23.546403, expected=23.309999
predicted=23.308369, expected=23.180000
predicted=23.178080, expected=23.197500
```

```
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
```

```
0.12134588182661789
```

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('Apple_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()
```

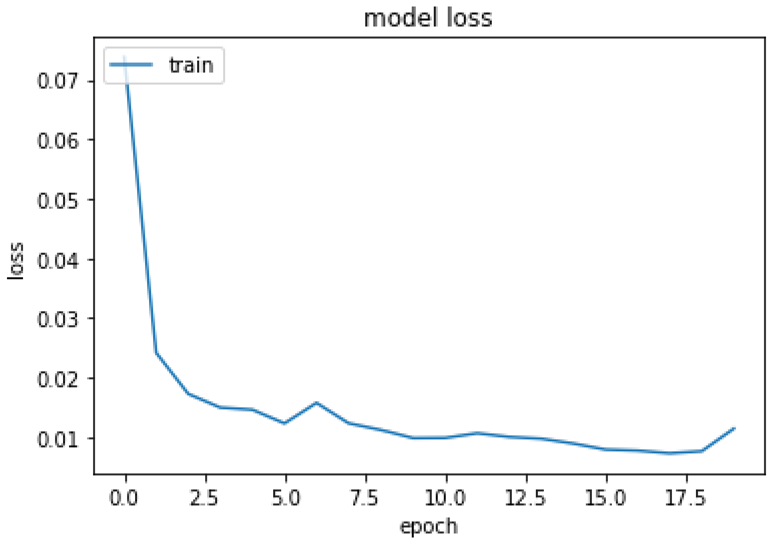
```
model.add(LSTM(units=100, return_sequences = True, input_shape =(X_train.shape[1],1)))
model.add(Dropout(0.2))

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: 0.0738
Epoch 2/20
17/17 - 3s - loss: 0.0242
Epoch 3/20
17/17 - 3s - loss: 0.0173
Epoch 4/20
17/17 - 3s - loss: 0.0150
Epoch 5/20
17/17 - 3s - loss: 0.0146
Epoch 6/20
17/17 - 3s - loss: 0.0123
Epoch 7/20
17/17 - 3s - loss: 0.0158
Epoch 8/20
17/17 - 3s - loss: 0.0123
Epoch 9/20
17/17 - 3s - loss: 0.0112
Epoch 10/20
17/17 - 3s - loss: 0.0098
Epoch 11/20
17/17 - 3s - loss: 0.0099
Epoch 12/20
17/17 - 3s - loss: 0.0107
Epoch 13/20
17/17 - 3s - loss: 0.0100
Epoch 14/20
17/17 - 3s - loss: 0.0097
Epoch 15/20
17/17 - 3s - loss: 0.0089
Epoch 16/20
17/17 - 3s - loss: 0.0079
Epoch 17/20
17/17 - 3s - loss: 0.0077
Epoch 18/20
17/17 - 3s - loss: 0.0073
Epoch 19/20
17/17 - 3s - loss: 0.0076
Epoch 20/20
17/17 - 3s - loss: 0.0114
```

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('Apple_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
```

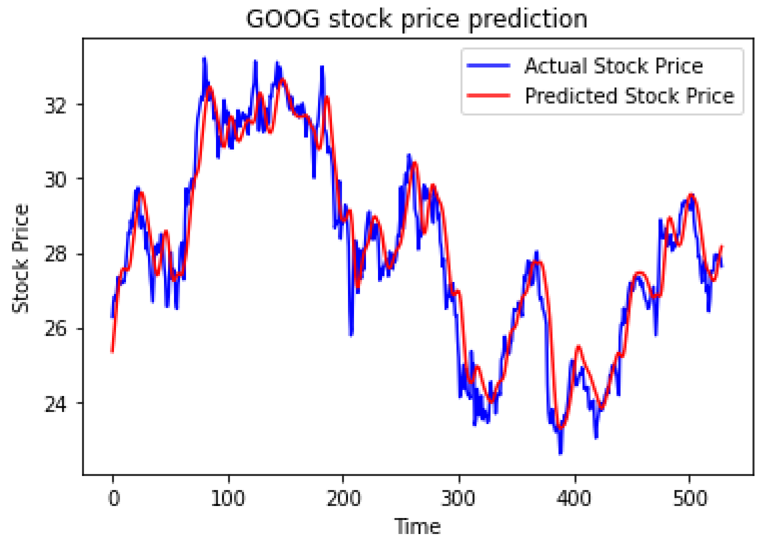
```
(529, 60, 1)
```

```
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
```

```
0.6218421248657574
```