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# DATA SCIENCE AND BUSINESS ANALYTICS INTERN

# Task 7: Stock Market Prediction using Numerical and Textual Analysis

Create a hybrid model for stock price or performance prediction using numerical analysis of historical stock prices, and sentimental analysis of news headlines. The stock to analyze and predict is SENSEX (S&P BSE SENSEX)

### **Import the Important Libraries**

#### In [168]:

```
# Import the libraries
import os
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
from statsmodels.tsa.arima model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
import nltk
import re
from textblob import TextBlob
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean squared error
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor
from sklearn.tree import DecisionTreeRegressor
import xgboost
import lightgbm
```

#### In [131]:

```
# For reading stock data from yahoo
from pandas_datareader.data import DataReader
# For time stamps
from datetime import datetime
```

#### In [132]:

```
# Load the first dataset
columns=['Date','Category','News']
ndf = pd.read_csv("D:\india-news-headlines.csv",names=columns)
```

#### In [133]:

```
print('Showing part of the whole dataset:')
ndf.head(5)
```

Showing part of the whole dataset:

#### Out[133]:

	Date	Category	News
0	publish_date	headline_category	headline_text
1	20010101	sports.wwe	win over cena satisfying but defeating underta
2	20010102	unknown	Status quo will not be disturbed at Ayodhya; s
3	20010102	unknown	Fissures in Hurriyat over Pak visit
4	20010102	unknown	America's unwanted heading for India?

#### In [134]:

```
ndf.drop(0, inplace=True)
ndf.drop('Category', axis = 1, inplace=True)
print('Showing part of the whole dataset:')
ndf.head(-5)
```

Showing part of the whole dataset:

#### Out[134]:

	Date	News
1	20010101	win over cena satisfying but defeating underta
2	20010102	Status quo will not be disturbed at Ayodhya; s
3	20010102	Fissures in Hurriyat over Pak visit
4	20010102	America's unwanted heading for India?
5	20010102	For bigwigs; it is destination Goa
3297163	20200630	vehicle of up stf team bringing gangster vikas
3297164	20200630	sushant singh rajputs demise fans trend cbifor
3297165	20200630	amitabh bachchans grandson agastya nanda prepp
3297166	20200630	icse isc result 2020 when where to check class
3297167	20200630	up govt imposes weekend restrictions from tonight

3297167 rows × 2 columns

#### In [135]:

```
# Load the second dataset
hisdf = pd.read_csv("D:\BSESN.csv")
hisdf.head(-5)
```

#### Out[135]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2015- 12-14	24935.599609	25194.150391	24867.730469	25150.349609	25150.349609	11600.0
1	2015- 12-15	25186.679688	25342.779297	25075.539063	25320.439453	25320.439453	9700.0
2	2015- 12-16	25402.470703	25572.900391	25372.470703	25494.369141	25494.369141	10800.0
3	2015- 12-17	25596.630859	25831.310547	25448.320313	25803.779297	25803.779297	22700.0
4	2015- 12-18	25764.669922	25789.509766	25481.509766	25519.220703	25519.220703	10400.0
1224	2020- 11-27	44325.031250	44407.281250	43995.410156	44149.718750	44149.718750	15700.0
1225	2020- 12-01	44435.828125	44730.789063	44118.101563	44655.441406	44655.441406	16000.0
1226	2020- 12-02	44729.519531	44729.640625	44169.968750	44618.039063	44618.039063	16000.0
1227	2020- 12-03	44902.019531	44953.011719	44551.421875	44632.648438	44632.648438	30700.0
1228	2020- 12-04	44665.910156	45148.281250	44665.910156	45079.550781	45079.550781	27600.0
1220 1	OWS X	7 columns					

1229 rows × 7 columns

# **Common Dataset Exploration**

```
In [136]:
# Check for common information of the first datast
ndf["Date"] = pd.to_datetime(ndf["Date"],format='%Y%m%d')
ndf.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3297172 entries, 1 to 3297172
Data columns (total 2 columns):
   Column Dtype
0
    Date
            datetime64[ns]
            object
 1
    News
dtypes: datetime64[ns](1), object(1)
memory usage: 75.5+ MB
```

#### In [137]:

```
# Group the headlines for each day
ndf['News'] = ndf.groupby(['Date']).transform(lambda x : ' '.join(x))
ndf = ndf.drop_duplicates()
ndf.reset_index(inplace=True,drop=True)
```

#### In [138]:

ndf

#### Out[138]:

	Date	News
0	2001-01-01	win over cena satisfying but defeating underta
1	2001-01-02	Status quo will not be disturbed at Ayodhya; s
2	2001-01-03	Powerless north India gropes in the dark Think
3	2001-01-04	The string that pulled Stephen Hawking to Indi
4	2001-01-05	Light combat craft takes India into club class
7075	2020-06-26	Containment zone residents slam high prices ch
7076	2020-06-27	like me i wont let you have a toxic relationsh
7077	2020-06-28	Atanu Ghosh plans to rewrite old scripts to ma
7078	2020-06-29	6 hot and stylish bikini looks of Katrina Kaif
7079	2020-06-30	Detective Byomkesh Bakshy! Edge of Tomorrow Fi

7080 rows × 2 columns

#### In [139]:

```
# Check for any duplicated values
ndf.isnull().sum()
```

#### Out[139]:

Date 0 News 0 dtype: int64

#### In [140]:

```
len(ndf)
```

#### Out[140]:

7080

#### In [141]:

```
hisdf=hisdf[["Date","Open","High","Low","Close","Volume"]]
hisdf.head(-5)
```

#### Out[141]:

Date	Open	High	Low	Close	Volume
2015-12-14	24935.599609	25194.150391	24867.730469	25150.349609	11600.0
2015-12-15	25186.679688	25342.779297	25075.539063	25320.439453	9700.0
2015-12-16	25402.470703	25572.900391	25372.470703	25494.369141	10800.0
2015-12-17	25596.630859	25831.310547	25448.320313	25803.779297	22700.0
2015-12-18	25764.669922	25789.509766	25481.509766	25519.220703	10400.0
2020-11-27	44325.031250	44407.281250	43995.410156	44149.718750	15700.0
2020-12-01	44435.828125	44730.789063	44118.101563	44655.441406	16000.0
2020-12-02	44729.519531	44729.640625	44169.968750	44618.039063	16000.0
2020-12-03	44902.019531	44953.011719	44551.421875	44632.648438	30700.0
2020-12-04	44665.910156	45148.281250	44665.910156	45079.550781	27600.0
	2015-12-14 2015-12-15 2015-12-16 2015-12-17 2015-12-18  2020-11-27 2020-12-01 2020-12-02 2020-12-03	2015-12-14 24935.599609 2015-12-15 25186.679688 2015-12-16 25402.470703 2015-12-17 25596.630859 2015-12-18 25764.669922  2020-11-27 44325.031250 2020-12-01 44435.828125 2020-12-02 44729.519531 2020-12-03 44902.019531	2015-12-14       24935.599609       25194.150391         2015-12-15       25186.679688       25342.779297         2015-12-16       25402.470703       25572.900391         2015-12-17       25596.630859       25831.310547         2015-12-18       25764.669922       25789.509766              2020-11-27       44325.031250       44407.281250         2020-12-01       44435.828125       44730.789063         2020-12-02       44729.519531       44729.640625         2020-12-03       44902.019531       44953.011719	2015-12-14       24935.599609       25194.150391       24867.730469         2015-12-15       25186.679688       25342.779297       25075.539063         2015-12-16       25402.470703       25572.900391       25372.470703         2015-12-17       25596.630859       25831.310547       25448.320313         2015-12-18       25764.669922       25789.509766       25481.509766               2020-11-27       44325.031250       44407.281250       43995.410156         2020-12-01       44435.828125       44730.789063       44118.101563         2020-12-02       44729.519531       44729.640625       44169.968750         2020-12-03       44902.019531       44953.011719       44551.421875	2015-12-14       24935.599609       25194.150391       24867.730469       25150.349609         2015-12-15       25186.679688       25342.779297       25075.539063       25320.439453         2015-12-16       25402.470703       25572.900391       25372.470703       25494.369141         2015-12-17       25596.630859       25831.310547       25448.320313       25803.779297         2015-12-18       25764.669922       25789.509766       25481.509766       25519.220703                2020-11-27       44325.031250       44407.281250       43995.410156       44149.718750         2020-12-01       44435.828125       44730.789063       44118.101563       44655.441406         2020-12-02       44729.519531       44729.640625       44169.968750       44618.039063         2020-12-03       44902.019531       44953.011719       44551.421875       44632.648438

1229 rows × 6 columns

#### In [142]:

```
# Check for common information of the second dataset
hisdf["Date"]= pd.to_datetime(hisdf["Date"])
hisdf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1234 entries, 0 to 1233
Data columns (total 6 columns):
    Column Non-Null Count Dtype
            1234 non-null
 0
    Date
                            datetime64[ns]
            1229 non-null
                           float64
 1
    0pen
 2
            1229 non-null float64
    High
            1229 non-null float64
 3
    Low
            1229 non-null
                            float64
 4
    Close
    Volume 1229 non-null
 5
                            float64
dtypes: datetime64[ns](1), float64(5)
memory usage: 58.0 KB
```

#### In [143]:

#### hisdf.describe()

#### Out[143]:

	Open	High	Low	Close	Volume
count	1229.000000	1229.000000	1229.000000	1229.000000	1.229000e+03
mean	33612.537529	33770.774116	33378.082519	33568.855966	2.737271e+05
std	5145.385399	5155.580751	5113.753852	5134.402915	2.123753e+06
min	23060.390625	23142.960938	22494.609375	22951.830078	2.500000e+03
25%	29006.000000	29077.279297	28789.300781	28929.130859	1.050000e+04
50%	34167.531250	34351.339844	33949.460938	34142.148438	1.430000e+04
75%	37840.640625	38022.320313	37586.878906	37752.171875	1.980000e+04
max	46060.320313	46309.628906	45792.011719	46103.500000	3.181510e+07

#### In [144]:

```
# Check for duplicated values
hisdf.isnull().sum()
```

#### Out[144]:

Date 0
Open 5
High 5
Low 5
Close 5
Volume 5
dtype: int64

#### In [145]:

len(hisdf)

#### Out[145]:

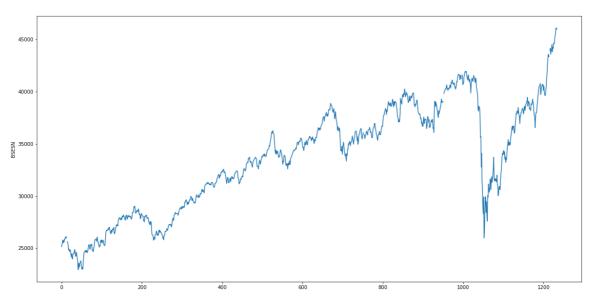
1234

#### In [147]:

```
# Figure plot
plt.figure(figsize=(20,10))
hisdf['Close'].plot()
plt.ylabel('BSESN')
```

#### Out[147]:

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



### **Remove Unwanted Characters from the News**

#### In [148]:

```
#removing unwanted characters from the News
ndf.replace("[^a-zA-Z']"," ",regex=True,inplace=True)
ndf["News"].head(5)
```

#### Out[148]:

- 0 win over cena satisfying but defeating underta...
- 1 Status quo will not be disturbed at Ayodhya s...
- 2 Powerless north India gropes in the dark Think...
- 3 The string that pulled Stephen Hawking to Indi...
- 4 Light combat craft takes India into club class...

Name: News, dtype: object

# **Historical Analysis**

### **Plot the Moving Average**

#### In [22]:

```
#Plotting moving average
close = hisdf['Close']

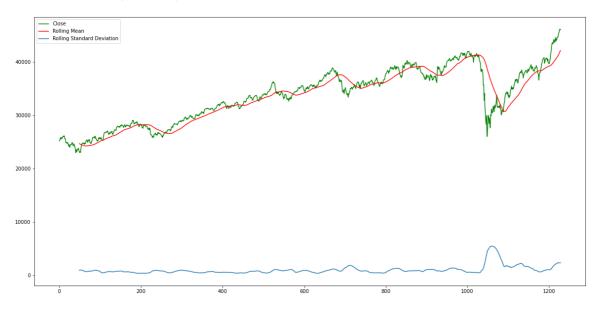
ma = close.rolling(window = 50).mean()
std = close.rolling(window = 50).std()

plt.figure(figsize=(20,10))
hisdf['Close'].plot(color='g',label='Close')
ma.plot(color = 'r',label='Rolling Mean')
std.plot(label = 'Rolling Standard Deviation')

plt.legend()
```

#### Out[22]:

<matplotlib.legend.Legend at 0x11c24c730>



# **Plot the Returns**

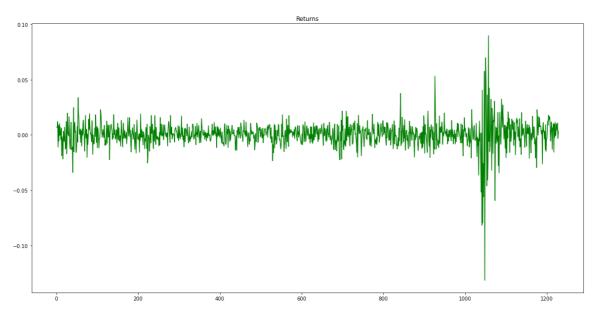
#### In [24]:

```
#Plotting returns
returns = close / close.shift(1) - 1

plt.figure(figsize = (20,10))
returns.plot(label='Return', color = 'g')
plt.title("Returns")
```

#### Out[24]:

#### Text(0.5, 1.0, 'Returns')



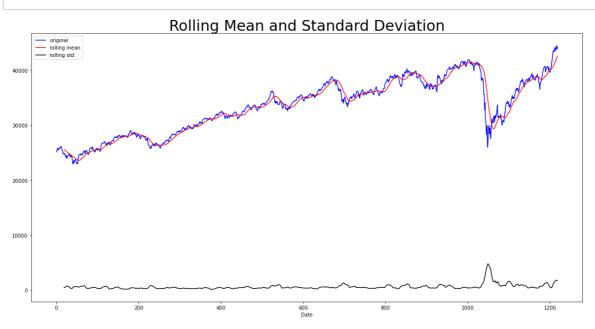
#### In [77]:

```
# Train test split
train = hisdf[:1219]
test = hisdf[1219:]
```

# **Rolling mean and Standard Deviation**

#### In [78]:

```
#Stationarity test
def test_stationarity(timeseries):
#Determine the rolling statistics
rolmean = timeseries.rolling(20).mean()
rolstd = timeseries.rolling(20).std()
#Plot rolling statistics:
plt.figure(figsize = (20,10))
plt.plot(timeseries, color = 'blue', label = 'original')
plt.plot(rolmean, color = 'r', label = 'rolling mean')
plt.plot(rolstd, color = 'black', label = 'rolling std')
plt.xlabel('Date')
plt.legend()
plt.title('Rolling Mean and Standard Deviation', fontsize = 30)
plt.show(block = False)
print('Results of dickey fuller test')
result = adfuller(timeseries, autolag = 'AIC')
labels = ['ADF Test Statistic','p-value','#Lags Used','Number of Observations Used']
for value, label in zip(result, labels):
  print(label+' : '+str(value) )
if result[1] <= 0.05:
  print("Strong evidence against the null hypothesis(Ho), reject the null hypothesis.
Data is stationary")
else:
   print("Weak evidence against null hypothesis, time series is non-stationary ")
test stationarity(train['Close'])
```



Results of dickey fuller test ADF Test Statistic : -1.2371986562284674 p-value : 0.6573926747294222 #Lags Used : 12

Number of Observations Used : 1206

Weak evidence against null hypothesis, time series is non-stationary

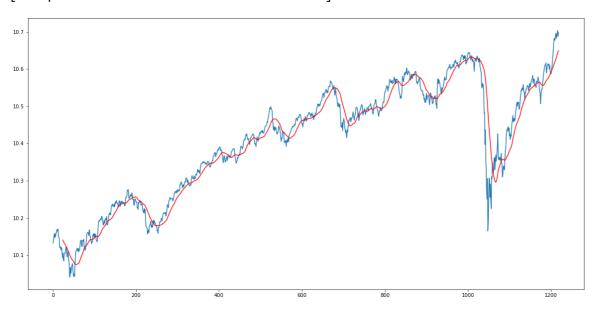
#### In [79]:

```
train_log = np.log(train['Close'])
test_log = np.log(test['Close'])

mav = train_log.rolling(24).mean()
plt.figure(figsize = (20,10))
plt.plot(train_log)
plt.plot(mav, color = 'red')
```

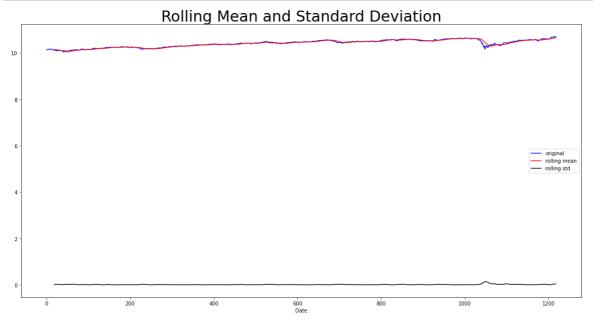
#### Out[79]:

#### [<matplotlib.lines.Line2D at 0x12f9369d0>]



#### In [80]:

```
train_log.dropna(inplace = True)
test_log.dropna(inplace = True)
test_stationarity(train_log)
```



Results of dickey fuller test

ADF Test Statistic : -1.3255659230909311

p-value : 0.6173962367893951

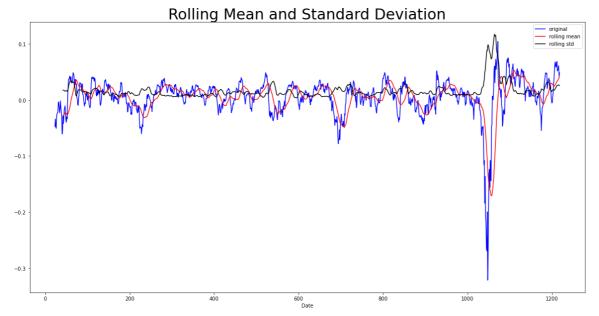
#Lags Used : 12

Number of Observations Used : 1206

Weak evidence against null hypothesis, time series is non-stationary

#### In [81]:

```
train_log_diff = train_log - mav
train_log_diff.dropna(inplace = True)
test_stationarity(train_log_diff)
```



Results of dickey fuller test

ADF Test Statistic : -7.069643762070366

p-value: 4.975591908076066e-10

#Lags Used : 12

Number of Observations Used: 1183

Strong evidence against the null hypothesis(Ho), reject the null hypothesi

s. Data is stationary

#### In [82]:

#Using auto arima to make predictions using log data
from pmdarima import auto\_arima

#### In [83]:

```
model = auto_arima(train_log, trace = True, error_action = 'ignore', suppress_warnings
= True)
model.fit(train_log)
predictions = model.predict(periods = len(test))
predictions = pd.DataFrame(predictions,index = test_log.index,columns=['Prediction'])
```

Performing stepwise search to minimize aic ARIMA(2,1,2)(0,0,0)[0] intercept : AIC=-7372.030, Time=0.71 sec ARIMA(0,1,0)(0,0,0)[0] intercept : AIC=-7379.211, Time=0.27 sec : AIC=-7382.510, Time=0.68 sec ARIMA(1,1,0)(0,0,0)[0] intercept ARIMA(0,1,1)(0,0,0)[0] intercept : AIC=-7382.013, Time=0.14 sec ARIMA(0,1,0)(0,0,0)[0]: AIC=-7379.290, Time=0.08 sec ARIMA(2,1,0)(0,0,0)[0] intercept : AIC=-7382.581, Time=0.24 sec : AIC=-7383.659, Time=0.58 sec ARIMA(3,1,0)(0,0,0)[0] intercept ARIMA(4,1,0)(0,0,0)[0] intercept : AIC=-7381.766, Time=0.29 sec ARIMA(3,1,1)(0,0,0)[0] intercept : AIC=-7381.633, Time=1.07 sec : AIC=-7380.186, Time=0.51 sec ARIMA(2,1,1)(0,0,0)[0] intercept ARIMA(4,1,1)(0,0,0)[0] intercept : AIC=-7379.695, Time=1.39 sec ARIMA(3,1,0)(0,0,0)[0]: AIC=-7383.838, Time=0.20 sec ARIMA(2,1,0)(0,0,0)[0] : AIC=-7382.575, Time=0.22 sec : AIC=-7381.915, Time=0.29 sec ARIMA(4,1,0)(0,0,0)[0] ARIMA(3,1,1)(0,0,0)[0]: AIC=-7381.817, Time=0.18 sec ARIMA(2,1,1)(0,0,0)[0]: AIC=-7380.746, Time=0.48 sec ARIMA(4,1,1)(0,0,0)[0]: AIC=-7379.857, Time=0.44 sec

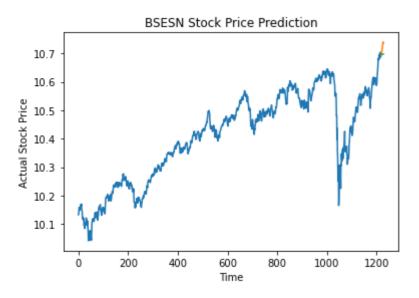
Best model: ARIMA(3,1,0)(0,0,0)[0] Total fit time: 7.762 seconds

#### In [87]:

```
plt.plot(train_log, label='Train')
plt.plot(test_log, label='Test')
plt.plot(predictions, label='Prediction')
plt.title('BSESN Stock Price Prediction')
plt.xlabel('Time')
plt.ylabel('Actual Stock Price')
```

#### Out[87]:

Text(0, 0.5, 'Actual Stock Price')



### **Error Calculation**

#### In [88]:

```
#Calculating error
rms = np.sqrt(mean_squared_error(test_log,predictions))
print("RMSE : ", rms)
```

RMSE: 0.026837616405067617

## **Textual Analysis**

#### In [89]:

```
#Functions to get the subjectivity and polarity
def getSubjectivity(text):
   return TextBlob(text).sentiment.subjectivity

def getPolarity(text):
   return TextBlob(text).sentiment.polarity
```

#### In [90]:

```
#Adding subjectivity and polarity columns
ndf['Subjectivity'] = ndf['News'].apply(getSubjectivity)
ndf['Polarity'] = ndf['News'].apply(getPolarity)
ndf
```

#### Out[90]:

	Date	News	Subjectivity	Polarity
0	2001-01-01	win over cena satisfying but defeating underta	0.633333	0.433333
1	2001-01-02	Status quo will not be disturbed at Ayodhya s	0.286859	0.143590
2	2001-01-03	Powerless north India gropes in the dark Think	0.392857	0.089286
3	2001-01-04	The string that pulled Stephen Hawking to Indi	0.445360	0.093039
4	2001-01-05	Light combat craft takes India into club class	0.480553	0.264024
7075	2020-06-26	Containment zone residents slam high prices ch	0.377957	0.060128
7076	2020-06-27	like me i wont let you have a toxic relationsh	0.390221	0.080373
7077	2020-06-28	Atanu Ghosh plans to rewrite old scripts to ma	0.397919	0.058824
7078	2020-06-29	hot and stylish bikini looks of Katrina Kaif	0.397084	0.065397
7079	2020-06-30	Detective Byomkesh Bakshy Edge of Tomorrow Fi	0.382257	0.072504

7080 rows × 4 columns

#### In [91]:

```
#Adding sentiment score to df_news
sia = SentimentIntensityAnalyzer()
```

#### In [92]:

```
ndf['Compound'] = [sia.polarity_scores(v)['compound'] for v in ndf['News']]
ndf['Negative'] = [sia.polarity_scores(v)['neg'] for v in ndf['News']]
ndf['Neutral'] = [sia.polarity_scores(v)['neu'] for v in ndf['News']]
ndf['Positive'] = [sia.polarity_scores(v)['pos'] for v in ndf['News']]
ndf
```

#### Out[92]:

	Date	News	Subjectivity	Polarity	Compound	Negative	Neutral	Positive
0	2001- 01-01	win over cena satisfying but defeating underta	0.633333	0.433333	-0.0000	0.230	0.473	0.297
1	2001- 01-02	Status quo will not be disturbed at Ayodhya s	0.286859	0.143590	-0.9792	0.121	0.809	0.071
2	2001- 01-03	Powerless north India gropes in the dark Think	0.392857	0.089286	-0.8910	0.156	0.735	0.109
3	2001- 01-04	The string that pulled Stephen Hawking to Indi	0.445360	0.093039	0.7543	0.104	0.792	0.104
4	2001- 01-05	Light combat craft takes India into club class	0.480553	0.264024	0.9645	0.142	0.694	0.164
7075	2020- 06-26	Containment zone residents slam high prices ch	0.377957	0.060128	-0.9999	0.170	0.738	0.092
7076	2020- 06-27	like me i wont let you have a toxic relationsh	0.390221	0.080373	-0.9999	0.162	0.743	0.095
7077	2020- 06-28	Atanu Ghosh plans to rewrite old scripts to ma	0.397919	0.058824	-0.9999	0.156	0.767	0.077
7078	2020- 06-29	hot and stylish bikini looks of Katrina Kaif	0.397084	0.065397	-0.9999	0.151	0.760	0.090
7079	2020- 06-30	Detective Byomkesh Bakshy Edge of Tomorrow Fi	0.382257	0.072504	-0.9999	0.141	0.786	0.073

7080 rows × 8 columns

# **Merge the Historical and Textual Data**

```
In [108]:
```

```
df_merge = pd.merge(hisdf, ndf, how='inner', on='Date')
df_merge
```

#### Out[108]:

	Date	Open	High	Low	Close	Volume	News
0	2015- 12-14	24935.599609	25194.150391	24867.730469	25150.349609	11600.0	things men do that make women fall deeper i
1	2015- 12-15	25186.679688	25342.779297	25075.539063	25320.439453	9700.0	Do looks matter at workplace Common running m
2	2015- 12-16	25402.470703	25572.900391	25372.470703	25494.369141	10800.0	In pics foods that make you smarter Dos and
3	2015- 12-17	25596.630859	25831.310547	25448.320313	25803.779297	22700.0	sex secrets every woman must know You too ca
4	2015- 12-18	25764.669922	25789.509766	25481.509766	25519.220703	10400.0	Stop making THESE diet disasters How to get s
1109	2020- 06-24	35679.738281	35706.550781	34794.929688	34868.980469	26600.0	I never thought I had a voice until today Vid
1110	2020- 06-25	34525.390625	35081.609375	34499.781250	34842.101563	24600.0	Truck firms look for new export markets to sel
1111	2020- 06-26	35144.781250	35254.878906	34910.339844	35171.269531	24800.0	Containment zone residents slam high prices ch
1112	2020- 06-29	34926.949219	35032.359375	34662.058594	34961.519531	18300.0	hot and stylish bikini looks of Katrina Kaif
1113	2020- 06-30	35168.300781	35233.910156	34812.800781	34915.800781	18500.0	Detective Byomkesh Bakshy Edge of Tomorrow Fi

1114 rows × 13 columns

# **Create Dataset for Model Training**

#### In [113]:

```
dfmerge1 = df_merge[['Close','Subjectivity', 'Polarity', 'Compound', 'Negative', 'Neutr
al', 'Positive']]
dfmerge1
```

#### Out[113]:

	Close	Subjectivity	Polarity	Compound	Negative	Neutral	Positive
0	25150.349609	0.472105	0.100389	-0.9996	0.153	0.719	0.128
1	25320.439453	0.421103	0.074733	-0.9999	0.149	0.745	0.106
2	25494.369141	0.434933	0.111113	-0.9724	0.107	0.786	0.107
3	25803.779297	0.389598	0.058890	-0.9997	0.150	0.735	0.115
4	25519.220703	0.412045	0.071201	-0.9999	0.161	0.726	0.113
1109	34868.980469	0.385245	0.087935	-0.9999	0.139	0.782	0.080
1110	34842.101563	0.398419	0.028698	-0.9999	0.145	0.789	0.066
1111	35171.269531	0.377957	0.060128	-0.9999	0.170	0.738	0.092
1112	34961.519531	0.397084	0.065397	-0.9999	0.151	0.760	0.090
1113	34915.800781	0.382257	0.072504	-0.9999	0.141	0.786	0.073

1114 rows × 7 columns

### **Normalize Data**

#### In [115]:

```
scaler = MinMaxScaler()

df = pd.DataFrame(scaler.fit_transform(dfmerge1))

df.columns = dfmerge1.columns

df.index = dfmerge1.index

df.head()
```

#### Out[115]:

	Close	Subjectivity	Polarity	Compound	Negative	Neutral	Positive
0	0.115707	1.000000	0.804262	0.000200	0.496063	0.131034	0.837209
1	0.124658	0.637680	0.618084	0.000050	0.464567	0.310345	0.581395
2	0.133812	0.735928	0.882084	0.013803	0.133858	0.593103	0.593023
3	0.150096	0.413875	0.503113	0.000150	0.472441	0.241379	0.686047
4	0.135120	0.573336	0.592454	0.000050	0.559055	0.179310	0.662791

```
In [116]:
```

```
X=df.drop('Close',axis=1)
X
```

#### Out[116]:

	Subjectivity	Polarity	Compound	Negative	Neutral	Positive
0	1.000000	0.804262	0.000200	0.496063	0.131034	0.837209
1	0.637680	0.618084	0.000050	0.464567	0.310345	0.581395
2	0.735928	0.882084	0.013803	0.133858	0.593103	0.593023
3	0.413875	0.503113	0.000150	0.472441	0.241379	0.686047
4	0.573336	0.592454	0.000050	0.559055	0.179310	0.662791
1109	0.382947	0.713887	0.000050	0.385827	0.565517	0.279070
1110	0.476536	0.284023	0.000050	0.433071	0.613793	0.116279
1111	0.331174	0.512097	0.000050	0.629921	0.262069	0.418605
1112	0.467056	0.550338	0.000050	0.480315	0.413793	0.395349
1113	0.361724	0.601906	0.000050	0.401575	0.593103	0.197674

1114 rows × 6 columns

#### In [118]:

```
Y=df['Close']
Y
```

#### Out[118]:

```
0.115707
1
        0.124658
2
        0.133812
3
        0.150096
        0.135120
1109
        0.627192
1110
        0.625777
1111
        0.643101
1112
        0.632062
        0.629656
1113
Name: Close, Length: 1114, dtype: float64
```

# **Split the Dataset into Train & Test Data**

```
In [119]:
```

```
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state =
0)
x_train.shape
```

#### Out[119]:

(891, 6)

#### In [149]:

```
x_train[:10]
```

#### Out[149]:

	Subjectivity	Polarity	Compound	Negative	Neutral	Positive
927	0.484416	0.739807	0.00005	0.590551	0.144828	0.674419
876	0.265810	0.484699	0.00005	0.598425	0.241379	0.511628
1050	0.402516	0.605501	0.00015	0.440945	0.344828	0.558140
1081	0.393804	0.604870	0.00015	0.377953	0.448276	0.476744
658	0.484525	0.393420	0.00005	0.307087	0.648276	0.244186
622	0.362822	0.174151	0.00000	0.677165	0.213793	0.430233
965	0.421373	0.338042	0.00005	0.566929	0.393103	0.302326
818	0.298472	0.603939	0.00005	0.535433	0.420690	0.302326
787	0.356953	0.474171	0.00005	0.566929	0.379310	0.302326
920	0.466131	0.428890	0.00010	0.433071	0.448276	0.395349

# RandomForestRegressor Model

#### In [150]:

```
rf = RandomForestRegressor()
rf.fit(x_train, y_train)
prediction=rf.predict(x_test)
```

```
In [151]:
```

```
print(prediction[:10])
print(y_test[:10])
print('Mean Squared error: ',mean_squared_error(prediction,y_test))
[0.59204602 0.77743871 0.46716064 0.73144085 0.25611568 0.33254211
 0.63953336 0.683319
                       0.59969559 0.26583055]
1006
        0.966906
1109
        0.627192
        0.299075
187
896
        0.723549
413
        0.465435
501
        0.578316
546
        0.591144
881
        0.839169
959
        0.903342
268
        0.228219
Name: Close, dtype: float64
Mean Squared error: 0.05257968397499098
```

## **DecisionTreeRegressor Model**

```
In [153]:
```

```
dtr = DecisionTreeRegressor()
dtr.fit(x_train, y_train)
predictions = dtr.predict(x_test)
```

```
In [154]:
```

```
print(predictions[:10])
print(y_test[:10])
print('Mean Squared error: ',mean_squared_error(predictions,y_test))

[0.46121848 0.98284344 0.69232194 0.71547783 0.19176137 0.28527224
    0.88757586 0.69698498 0.23569794 0.11570669]
```

```
0.966906
1006
1109
        0.627192
187
        0.299075
896
        0.723549
        0.465435
413
        0.578316
501
546
        0.591144
        0.839169
881
959
        0.903342
268
        0.228219
Name: Close, dtype: float64
Mean Squared error: 0.10831900809236311
```

### AdaBoostRegressor Model

```
In [165]:
```

```
adb = AdaBoostRegressor()
adb.fit(x_train, y_train)
```

#### Out[165]:

AdaBoostRegressor()

#### In [167]:

```
predictions = adb.predict(x_test)
print(mean_squared_error(predictions, y_test))
```

0.05492347045438241

### **LGBMRegressor Model**

```
In [163]:
```

```
gbm = lightgbm.LGBMRegressor()
gbm.fit(x_train, y_train)
```

#### Out[163]:

LGBMRegressor()

#### In [160]:

```
predictions = gbm.predict(x_test)
print(mean_squared_error(predictions, y_test))
```

0.0583079056070462

### **XGBRegressor Model**

```
In [162]:
```

```
xgb = xgboost.XGBRegressor()
xgb.fit(x_train, y_train)
```

#### Out[162]:

#### In [164]:

```
predictions = xgb.predict(x_test)
print(mean_squared_error(predictions, y_test))
```

0.05968830860645931

### Conclusion

- RandomForest = 0.05257968397499098
- DecisionTree = 0.10831900809236311
- AdaBoost = 0.05492347045438241
- LightGBM = 0.0583079056070462
- XGBoost = 0.05968830860645931 From here we can see that RandomForestRegressor shows a better performance than the others