Multivariate Linear Regression and Sentiment Analysis using Amazon.

Overview

This project source code file analyzes amazon stock data using technical indicators retireeved from Alpha Vantage. Then, a multivariate linear regression model is used to see which of those technical indicators is the best predictor of stock closing price. Moreover, through the power of natural language processing, sentiment analysis using twitter's API was done to see how public opinion affects the closing price, and whether the two models are related.

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Importing all the libraries required for the project.

In [1]:
```
# Import libraries
from urllib.request import urlopen, Request
from bs4 import BeautifulSoup
import os
import pandas as pd
import seaborn as sb
import nltk
sb.set()
import matplotlib.pyplot as plt
%matplotlib inline
# NLTK VADER for sentiment analysis
from nltk.sentiment.vader import SentimentIntensityAnalyzer
nltk.download('vader_lexicon')
finwiz_url = 'https://finviz.com/quote.ashx?t='

from alpha_vantage.timeseries import TimeSeries
from alpha_vantage.fundamentaldata import FundamentalData
from alpha_vantage.techindicators import TechIndicators
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\Neel\AppData\Roaming\nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

In [2]:
```
pip install alpha_vantage
```

```
Requirement already satisfied: alpha_vantage in c:\users\neel\anaconda3\lib\sit
e-packages (2.3.1)
Requirement already satisfied: requests in c:\users\neel\anaconda3\lib\site-pac
kages (from alpha_vantage) (2.24.0)
Requirement already satisfied: aiohttp in c:\users\neel\anaconda3\lib\site-pack
ages (from alpha_vantage) (3.7.4.post0)
Requirement already satisfied: idna<3,>=2.5 in c:\users\neel\anaconda3\lib\site
-packages (from requests->alpha_vantage) (2.10)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\neel\anaconda3\li
b\site-packages (from requests->alpha_vantage) (2020.6.20)
Requirement already satisfied: chardet<4,>=3.0.2 in c:\users\neel\anaconda3\lib
\site-packages (from requests->alpha_vantage) (3.0.4)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in c:\us
ers\neel\anaconda3\lib\site-packages (from requests->alpha_vantage) (1.25.11)
Requirement already satisfied: attrs>=17.3.0 in c:\users\neel\anaconda3\lib\sit
e-packages (from aiohttp->alpha_vantage) (20.3.0)
Requirement already satisfied: typing-extensions>=3.6.5 in c:\users\neel\anacon
da3\lib\site-packages (from aiohttp->alpha_vantage) (3.7.4.3)
Requirement already satisfied: multidict<7.0,>=4.5 in c:\users\neel\anaconda3\l
ib\site-packages (from aiohttp->alpha_vantage) (5.1.0)
Requirement already satisfied: yarl<2.0,>=1.0 in c:\users\neel\anaconda3\lib\si
te-packages (from aiohttp->alpha_vantage) (1.6.3)
Requirement already satisfied: async-timeout<4.0,>=3.0 in c:\users\neel\anacond
a3\lib\site-packages (from aiohttp->alpha_vantage) (3.0.1)
Note: you may need to restart the kernel to use updated packages.
```

In [3]:
```
pip install vaderSentiment
```

```
Requirement already satisfied: vaderSentiment in c:\users\neel\anaconda3\lib\si
te-packages (3.3.2)
Requirement already satisfied: requests in c:\users\neel\anaconda3\lib\site-pac
kages (from vaderSentiment) (2.24.0)
Requirement already satisfied: chardet<4,>=3.0.2 in c:\users\neel\anaconda3\lib
\site-packages (from requests->vaderSentiment) (3.0.4)
Requirement already satisfied: idna<3,>=2.5 in c:\users\neel\anaconda3\lib\site
-packages (from requests->vaderSentiment) (2.10)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in c:\us
ers\neel\anaconda3\lib\site-packages (from requests->vaderSentiment) (1.25.11)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\neel\anaconda3\li
b\site-packages (from requests->vaderSentiment) (2020.6.20)
Note: you may need to restart the kernel to use updated packages.
```

Utility Code to get datasets

Function to get the basic stock prices(open,close,high,low) of a company's stock

In [4]:
```
def get_intraday():
  key = '84E88MB3ZLGNJO2H'
  outputsize = 'compact'
  symbol = input('Ticker : ')
  typ = input('Data type- "daily", "weekly", "monthly", "interval" : ')

  ts = TimeSeries(key,output_format='pandas')

  if typ == 'daily':
    state = ts.get_daily_adjusted(symbol,outputsize=outputsize)[0]
  elif typ == 'weekly':
    state = ts.get_weekly_adjusted(symbol)[0]
  elif typ == 'monthly':
    state = ts.get_monthly_adjusted(symbol)[0]
  elif typ == 'interval':
    interval = input('Interval-1min, 5min, 15min, 30min, 60min : ')
    state = ts.get_intraday(symbol, interval=interval, outputsize=outputsize)[0]
  else:
    print('Wrong entry')
  return state
```

Function to get the fundamental data(income statement,balance sheet,etc.) of a company

In [5]:
```
def get_fundamental():
  key = '84E88MB3ZLGNJO2H'
  symbol = input('Ticker : ')
  period = input('Period- annual, quarterly : ')
  statement = input('Statement- balance sheet, income statement, cash flow : ')

  fd = FundamentalData(key,output_format = 'pandas')

  if period == 'annual':
    if statement == 'balance sheet':
      state = fd.get_balance_sheet_annual(symbol)[0].T[2:]
      state.columns = list(fd.get_balance_sheet_annual(symbol)[0].T.iloc[0])
    elif statement == 'income statement':
      state = fd.get_income_statement_annual(symbol)[0].T[2:]
      state.columns = list(fd.get_income_statement_annual(symbol)[0].T.iloc[0])
    elif statement == 'cash flow':
      state = fd.get_cash_flow_annual(symbol)[0].T[2:]
      state.columns = list(fd.get_cash_flow_annual(symbol)[0].T.iloc[0])
    else:
      print('Wrong Entry')

  elif period == 'quarterly':
    if statement == 'balance sheet':
      state = fd.get_balance_sheet_quarterly(symbol)[0].T[2:]
      state.columns = list(fd.get_balance_sheet_quarterly(symbol)[0].T.iloc[0])
    elif statement == 'income statement':
      state = fd.get_income_statement_quarterly(symbol)[0].T[2:]
      state.columns = list(fd.get_income_statement_quarterly(symbol)[0].T.iloc[0
    elif statement == 'cash flow':
      state = fd.get_cash_flow_quarterly(symbol)[0].T[2:]
      state.columns = list(fd.get_cash_flow_quarterly(symbol)[0].T.iloc[0])
    else:
          print('Wrong Entry')
  return state
```

Function to get the technical indicators(SMA,EMA,VWAP,etc.) of a company

In [6]:
```
def get_tech():
  key = '84E88MB3ZLGNJO2H'
  symbol = input('Ticker : ')
  outputsize = 'compact'
  interval =input('Interval- 1min,5min,15min,30min,60min,daily,weekly,monthly : '
  time = input('Time Period : ')
  tech_indi = input('Technical Indicator- SMA,EMA,VWAP,MACD,Stochastic Oscillator

  ti = TechIndicators(key,output_format='pandas')

  if tech_indi == 'SMA':
    state = ti.get_sma(symbol, interval=interval, time_period=time, series_type='
  elif tech_indi == 'EMA':
    state = ti.get_ema(symbol, interval=interval, time_period=time, series_type='
  elif tech_indi == 'VWAP':
    state = ti.get_vwap(symbol, interval=interval)[0]
  elif tech_indi == 'MACD':
    state = ti.get_macd(symbol, interval=interval, series_type='close')[0]
  elif tech_indi == 'Stochastic Oscillator':
    state = ti.get_stoch(symbol, interval=interval)[0]
  elif tech_indi == 'RSI':
    state = ti.get_rsi(symbol, interval=interval, time_period=time, series_type='
  elif tech_indi == 'Bollinger bands':
    state = ti.get_bbands(symbol, interval=interval, time_period=time, series_typ
  else:
    print('Wrong Entry')
  return state
```

Importing of relevant datasets required

In [7]:
```python
#get Amazon daliy stock info
amzn_daily = get_intraday()
amzn_daily.info()
amzn_daily.head()
```

```
Ticker : AMZN
Data type- "daily", "weekly", "monthly", "interval" : daily
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 100 entries, 2021-04-22 to 2020-11-27
Data columns (total 8 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   1. open              100 non-null    float64
 1   2. high              100 non-null    float64
 2   3. low               100 non-null    float64
 3   4. close             100 non-null    float64
 4   5. adjusted close    100 non-null    float64
 5   6. volume            100 non-null    float64
 6   7. dividend amount   100 non-null    float64
 7   8. split coefficient 100 non-null    float64
dtypes: float64(8)
memory usage: 7.0 KB
```

Out[7]:

date	1. open	2. high	3. low	4. close	5. adjusted close	6. volume	7. dividend amount	8. split coefficient
2021-04-22	3371.68	3372.8700	3301.4500	3309.04	3309.04	2580590.0	0.0	1.0
2021-04-21	3316.00	3362.8600	3303.8061	3362.02	3362.02	2211166.0	0.0	1.0
2021-04-20	3373.60	3382.9900	3316.0000	3334.69	3334.69	2623032.0	0.0	1.0
2021-04-19	3390.33	3435.9333	3360.1600	3372.01	3372.01	2725405.0	0.0	1.0
2021-04-16	3380.00	3406.8000	3355.5900	3399.44	3399.44	3186049.0	0.0	1.0

In [8]:
```
#extract only CLOSE from amzn_daily
amzn_close=pd.DataFrame(amzn_daily['4. close'])
amzn_close.info()
amzn_close.head()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 100 entries, 2021-04-22 to 2020-11-27
Data columns (total 1 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   4. close  100 non-null    float64
dtypes: float64(1)
memory usage: 1.6 KB
```

Out[8]:

	4. close
date	
2021-04-22	3309.04
2021-04-21	3362.02
2021-04-20	3334.69
2021-04-19	3372.01
2021-04-16	3399.44

In [10]:
```
#get Techincal indicator - EMA
amzn_ema=get_tech()
amzn_ema.info()
amzn_ema.head()
```

```
Ticker : AMZN
Interval- 1min,5min,15min,30min,60min,daily,weekly,monthly : daily
Time Period : 5
Technical Indicator- SMA,EMA,VWAP,MACD,Stochastic Oscillator,RSI,Bollinger band
s :EMA
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 5399 entries, 1999-11-05 to 2021-04-22
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   EMA     5399 non-null   float64
dtypes: float64(1)
memory usage: 84.4 KB
```

Out[10]:

date	EMA
1999-11-05	65.8760
1999-11-08	69.9173
1999-11-09	70.2149
1999-11-10	70.8099
1999-11-11	71.5400

In [11]:
```
#get Technical indicator - SMA
amzn_sma=get_tech()
amzn_sma.info()
amzn_sma.head()
```

```
Ticker : AMZN
Interval- 1min,5min,15min,30min,60min,daily,weekly,monthly : daily
Time Period : 5
Technical Indicator- SMA,EMA,VWAP,MACD,Stochastic Oscillator,RSI,Bollinger band
s :SMA
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 5399 entries, 1999-11-05 to 2021-04-22
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   SMA     5399 non-null   float64
dtypes: float64(1)
memory usage: 84.4 KB
```

Out[11]:

date	SMA
1999-11-05	65.876
1999-11-08	67.650
1999-11-09	68.524
1999-11-10	69.762
1999-11-11	71.750

In [12]:
```
#manipulation of individaul datasets for combination in later part
amzn_close['ticks'] = range(1,len(amzn_close.index.values)+1)
lastweekclose=amzn_close[amzn_close.ticks<=7]
amzn_close=amzn_close.reindex(index=amzn_close.index[::-1])
amzn_close=amzn_close.drop('ticks',axis=1)
amzn_close['ticks'] = range(1,len(amzn_close.index.values)+1)

amzn_sma['Ticks'] = range(1,len(amzn_sma.index.values)+1)
amzn_sma=amzn_sma[amzn_sma.Ticks>=5299]
amzn_sma=amzn_sma.drop('Ticks',axis=1)
amzn_sma['Ticks'] = range(1,len(amzn_sma.index.values)+1)

amzn_ema['Ticks1'] = range(1,len(amzn_ema.index.values)+1)
amzn_ema=amzn_ema[amzn_ema.Ticks1>=5299]
amzn_ema=amzn_ema.drop('Ticks1',axis=1)
amzn_ema['Ticks1']=range(1,len(amzn_ema.index.values)+1)


close = amzn_close
ema = amzn_ema
sma = amzn_sma
```

In [13]:
```
close
```

Out[13]:

	4. close	ticks
date		
2020-11-27	3195.34	1
2020-11-30	3168.04	2
2020-12-01	3220.08	3
2020-12-02	3203.53	4
2020-12-03	3186.73	5
...	...	...
2021-04-16	3399.44	96
2021-04-19	3372.01	97
2021-04-20	3334.69	98
2021-04-21	3362.02	99
2021-04-22	3309.04	100

100 rows × 2 columns

In [14]:
```
sma
```

Out[14]:

	SMA	Ticks
date		
2020-11-25	3123.588	1
2020-11-27	3139.252	2
2020-11-30	3152.980	3
2020-12-01	3177.318	4
2020-12-02	3194.412	5
...	...	...
2021-04-16	3378.184	97
2021-04-19	3376.708	98
2021-04-20	3363.646	99
2021-04-21	3369.450	100
2021-04-22	3355.440	101

101 rows × 2 columns

In [15]:
```
ema
```

Out[15]:

date	EMA	Ticks1
2020-11-25	3136.3242	1
2020-11-27	3155.9962	2
2020-11-30	3160.0108	3
2020-12-01	3180.0339	4
2020-12-02	3187.8659	5
...	...	...
2021-04-16	3368.4423	97
2021-04-19	3369.6315	98
2021-04-20	3357.9844	99
2021-04-21	3359.3296	100
2021-04-22	3342.5664	101

101 rows × 2 columns

In [16]:
```
#creating joint dataframe with all the variables obtained
jointDF = pd.concat([ema,sma,close], axis = 1)
jointDF=jointDF.drop(jointDF.index[0])
tempDF = jointDF
tempDF = tempDF.drop(['Ticks','Ticks1','ticks'],axis=1)
tempDF.columns=['EMA','SMA','CLOSE']
tempDF.info()
tempDF.head()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 100 entries, 2020-11-27 to 2021-04-22
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   EMA     100 non-null    float64
 1   SMA     100 non-null    float64
 2   CLOSE   100 non-null    float64
dtypes: float64(3)
memory usage: 3.1 KB
```

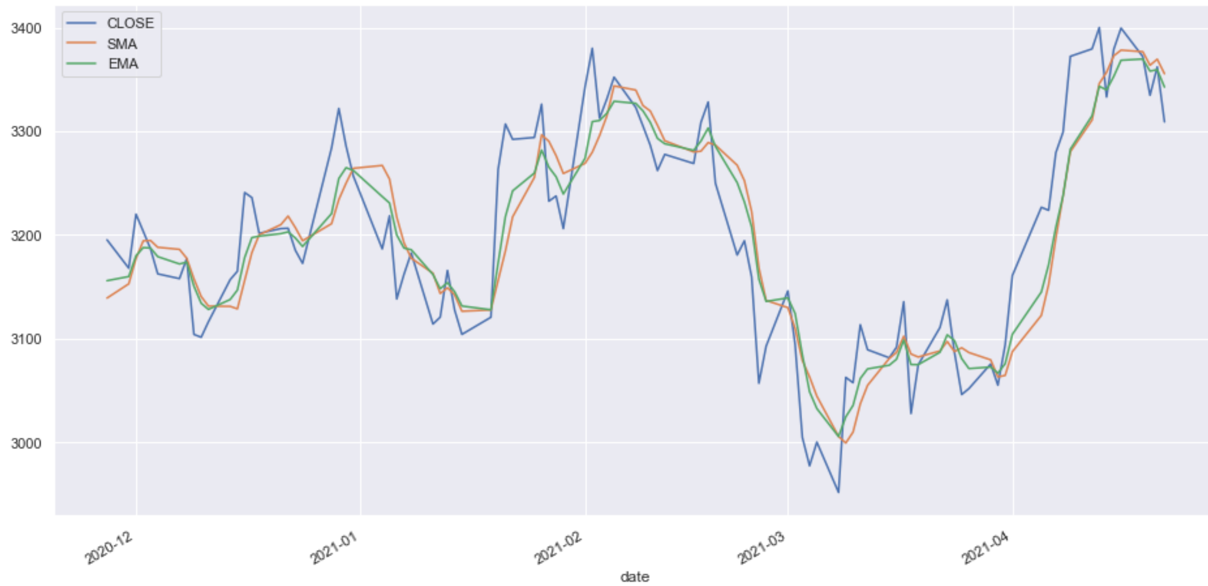
Out[16]:

	EMA	SMA	CLOSE
date			
2020-11-27	3155.9962	3139.252	3195.34
2020-11-30	3160.0108	3152.980	3168.04
2020-12-01	3180.0339	3177.318	3220.08
2020-12-02	3187.8659	3194.412	3203.53
2020-12-03	3187.4873	3194.744	3186.73

Plots of the Closing price and technical indicators against dates

In [17]:
```
#ploting time series of all variables
tempDF[['CLOSE','SMA','EMA']].plot(label='AMZN',figsize=(16,8))
```

Out[17]: <AxesSubplot:xlabel='date'>

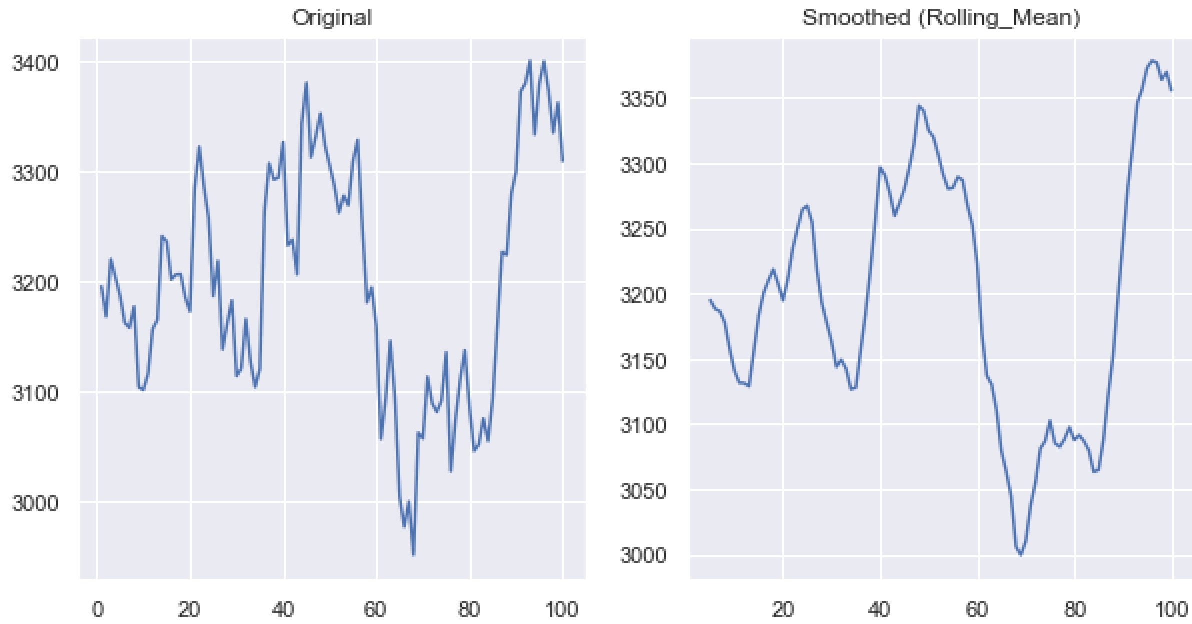


In [18]:
```
amzn_close['Rolling_Mean'] = amzn_close['4. close'].rolling(window = 5).mean()
amzn_close.head(5)
```

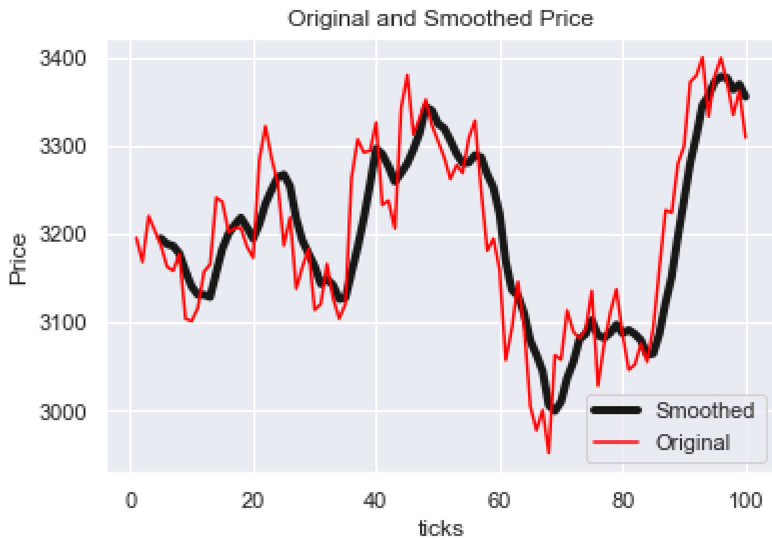
Out[18]:

date	4. close	ticks	Rolling_Mean
2020-11-27	3195.34	1	NaN
2020-11-30	3168.04	2	NaN
2020-12-01	3220.08	3	NaN
2020-12-02	3203.53	4	NaN
2020-12-03	3186.73	5	3194.744

In [19]:
```
fig, axes = plt.subplots(nrows = 1, ncols = 2, figsize = (10,5));
axes[0].plot('ticks', '4. close', data = amzn_close);
axes[0].set_title('Original')
axes[1].plot('ticks', 'Rolling_Mean', data = amzn_close);
axes[1].set_title('Smoothed (Rolling_Mean)');
```

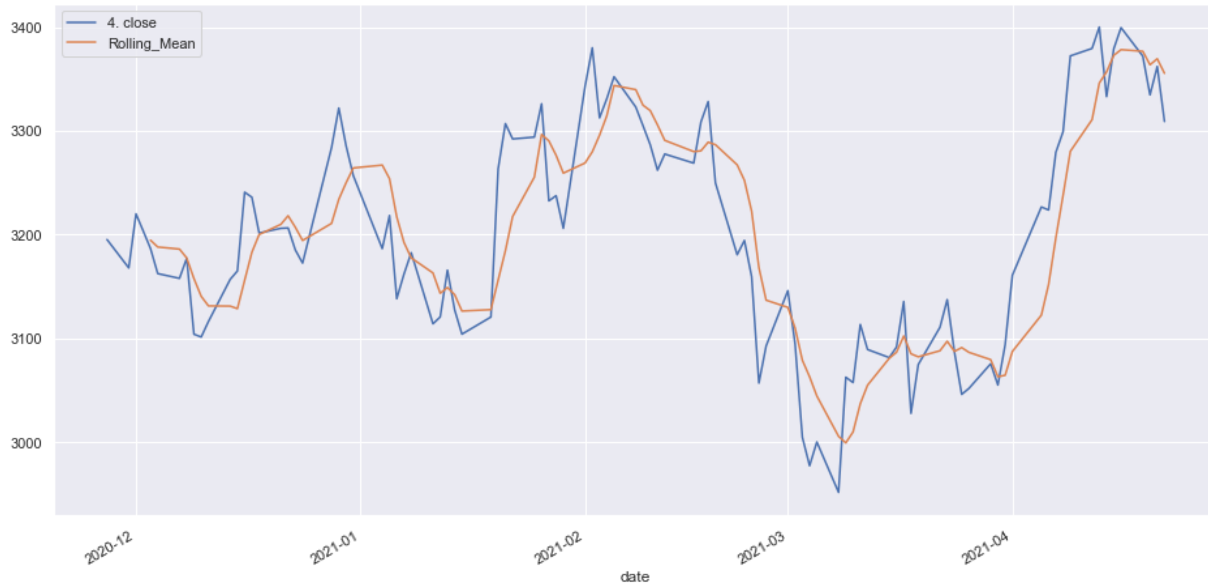


In [20]:
```
fig = plt.figure();
ax = fig.add_subplot(111);
ax.plot(amzn_close['ticks'], amzn_close['Rolling_Mean'], color = (0,0,0), linewic
ax.plot(amzn_close['ticks'], amzn_close['4. close'], color = (1,0,0), label = 'Or
ax.set_title('Original and Smoothed Price')
ax.set_xlabel('ticks')
ax.set_ylabel('Price')
ax.legend(loc='lower right');
```



In [21]:
```
amzn_close[['4. close','Rolling_Mean']].plot(label='AMZN',figsize=(16,8))
```

Out[21]: <AxesSubplot:xlabel='date'>



Exploratory Analysis on the variables obtained

In [22]:
```
#statistical analysis of variables
tempDF.describe()
```

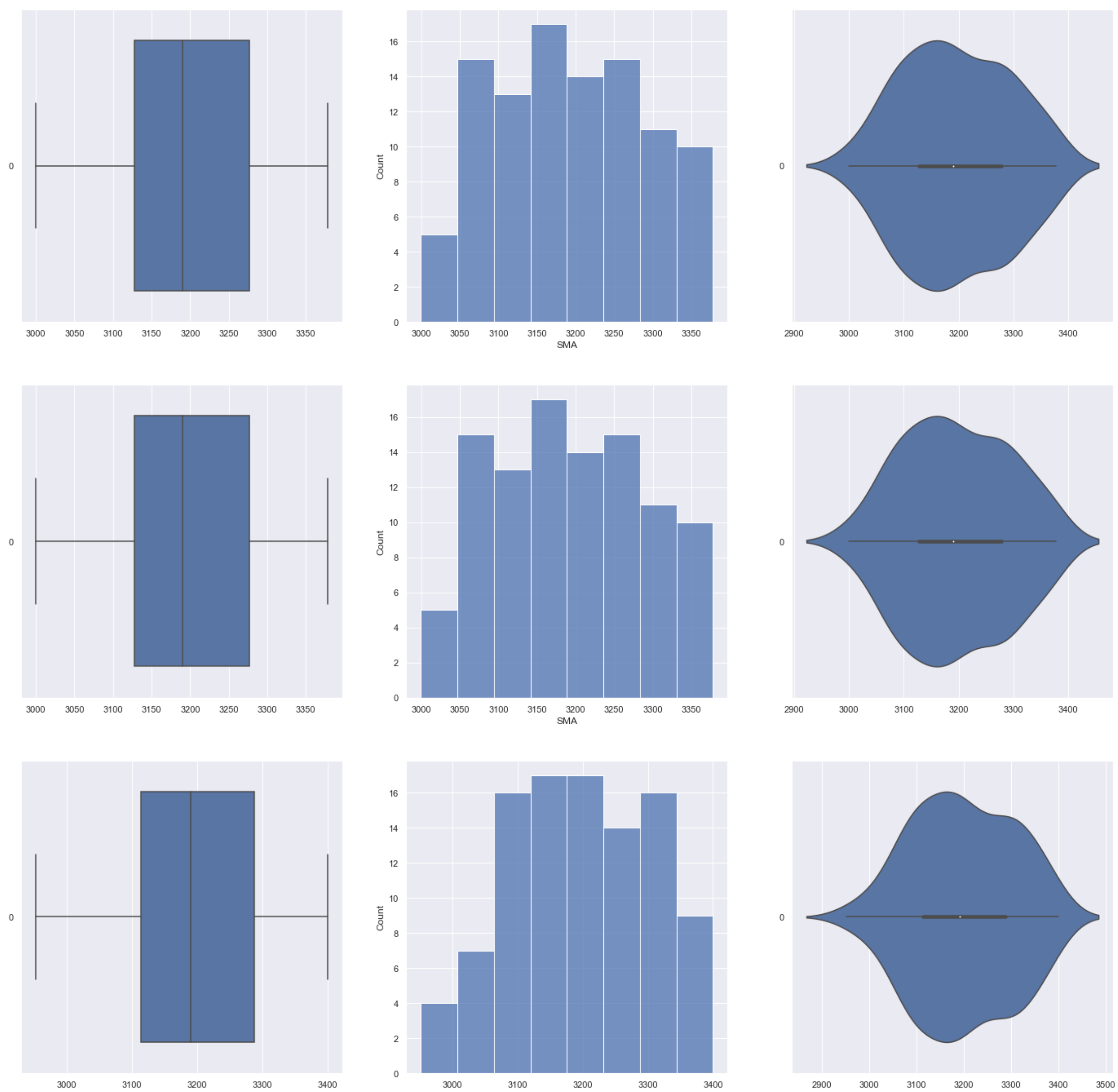
Out[22]:

	EMA	SMA	CLOSE
count	100.000000	100.000000	100.000000
mean	3195.172063	3195.350960	3199.296900
std	92.855277	96.804861	106.973344
min	3005.835900	2999.566000	2951.950000
25%	3130.761400	3127.512500	3114.055000
50%	3187.676600	3190.357000	3190.615000
75%	3267.561400	3277.348000	3287.992500
max	3369.631500	3378.184000	3400.000000

Plots to describe each independent variable

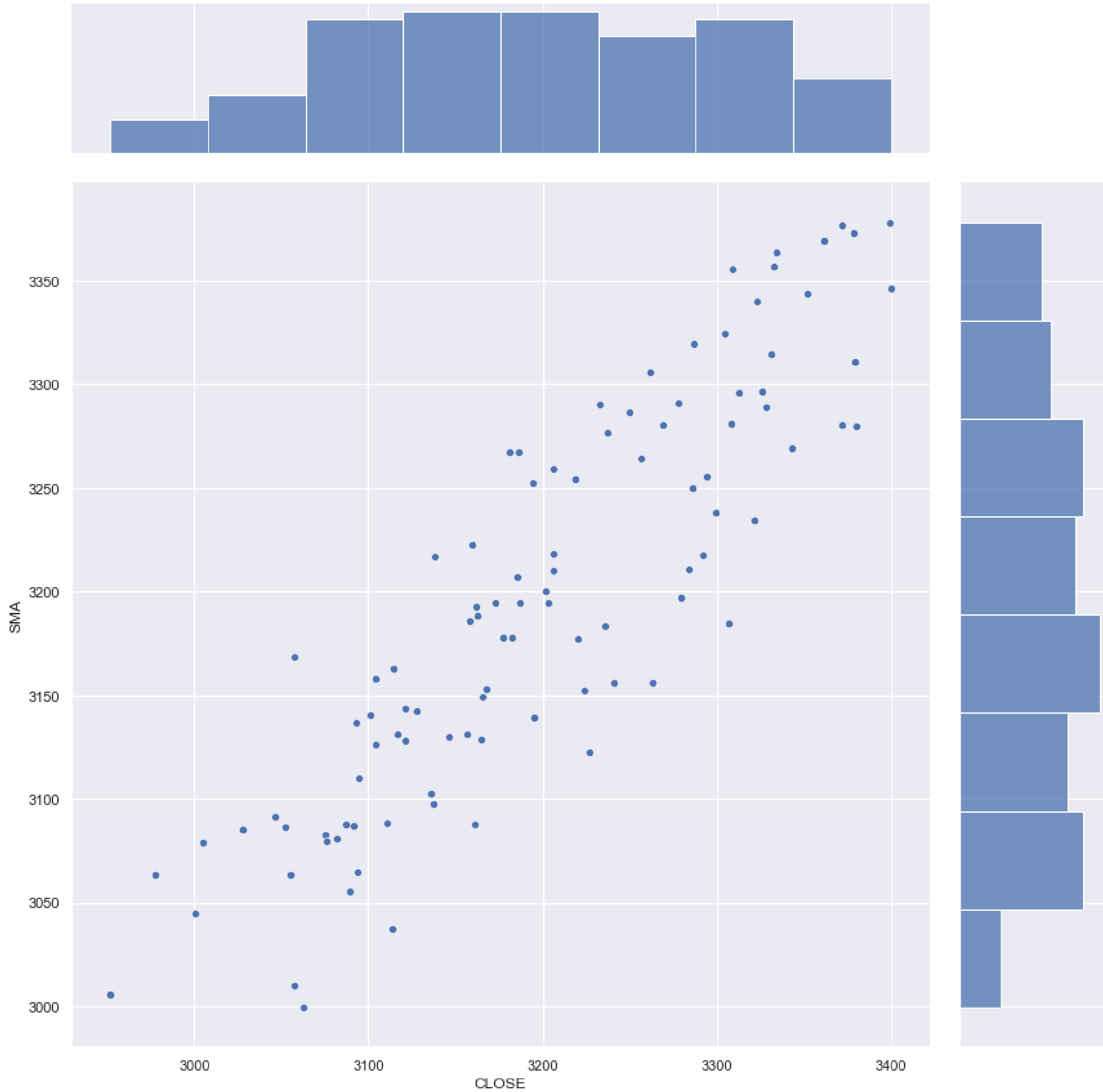
In [23]:
```python
#uni-Variate description of individual variables
f, axes = plt.subplots(3, 3, figsize=(24, 24))

# Plot the basic uni-variate figures for SMA
sb.boxplot(data = tempDF['SMA'], orient = "h", ax = axes[0,0])
sb.histplot(data = tempDF['SMA'], ax = axes[0,1])
sb.violinplot(data = tempDF['SMA'], orient = "h", ax = axes[0,2])

# Plot the basic uni-variate figures for EMA
sb.boxplot(data = tempDF['SMA'], orient = "h", ax = axes[1,0])
sb.histplot(data = tempDF['SMA'], ax = axes[1,1])
sb.violinplot(data = tempDF['SMA'], orient = "h", ax = axes[1,2])

# Plot the basic uni-variate figures for 4. close
sb.boxplot(data = tempDF['CLOSE'], orient = "h", ax = axes[2,0])
sb.histplot(data = tempDF['CLOSE'], ax = axes[2,1])
sb.violinplot(data = tempDF['CLOSE'], orient = "h", ax = axes[2,2])
```

Out[23]: <AxesSubplot:>



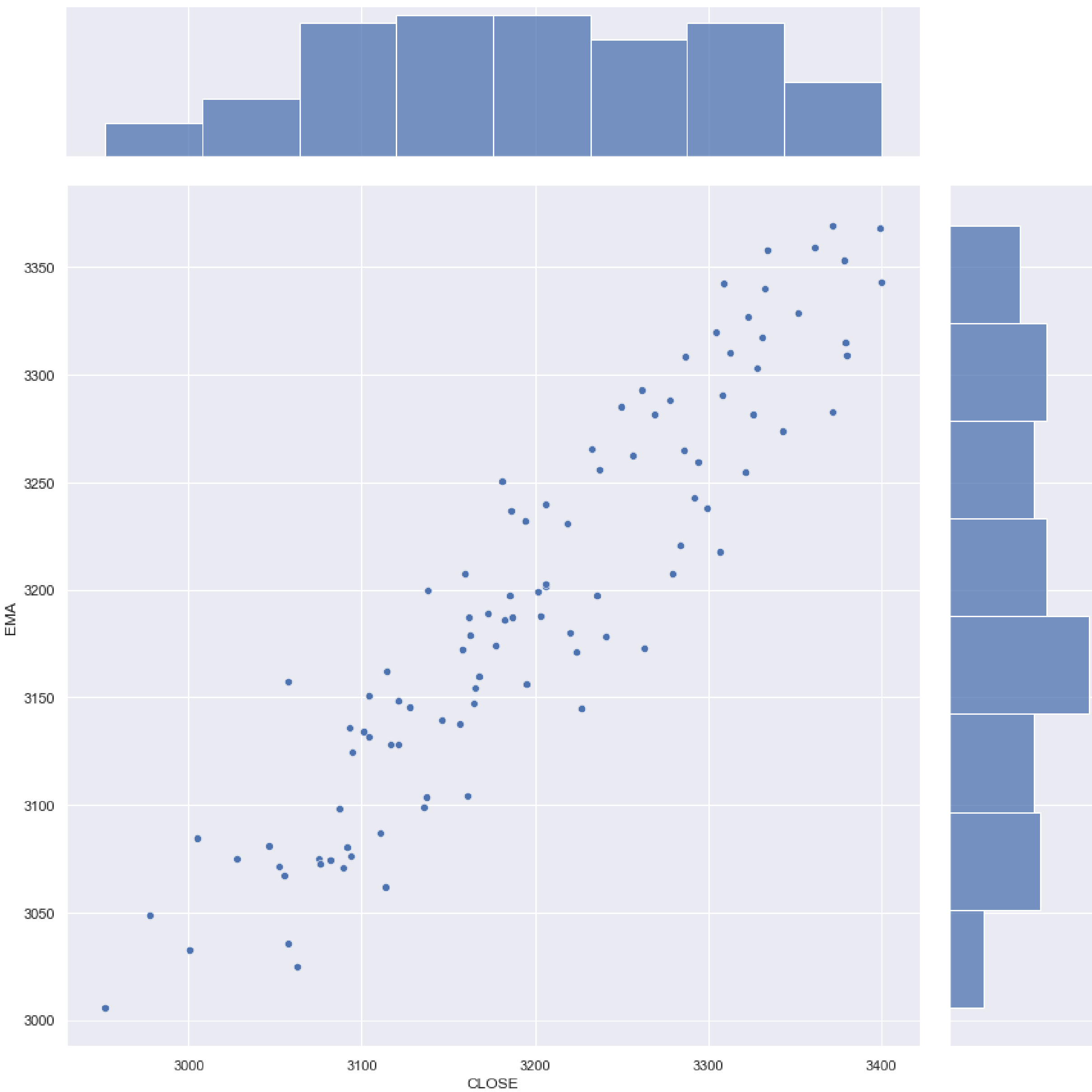
In [24]:
```
#jointplot for SMA vs CLOSE
sb.jointplot(data = tempDF, x = "CLOSE", y = "SMA", height = 12)
```

Out[24]:
```
<seaborn.axisgrid.JointGrid at 0x19686b7cfd0>
```



In [25]:
```
#jointplot of EMA vs CLOSE
f = plt.figure(figsize=(12, 8))
sb.jointplot(data = tempDF, x = "CLOSE", y = "EMA", height = 12)
```

Out[25]:
```
<seaborn.axisgrid.JointGrid at 0x196853fdc70>

<Figure size 864x576 with 0 Axes>
```



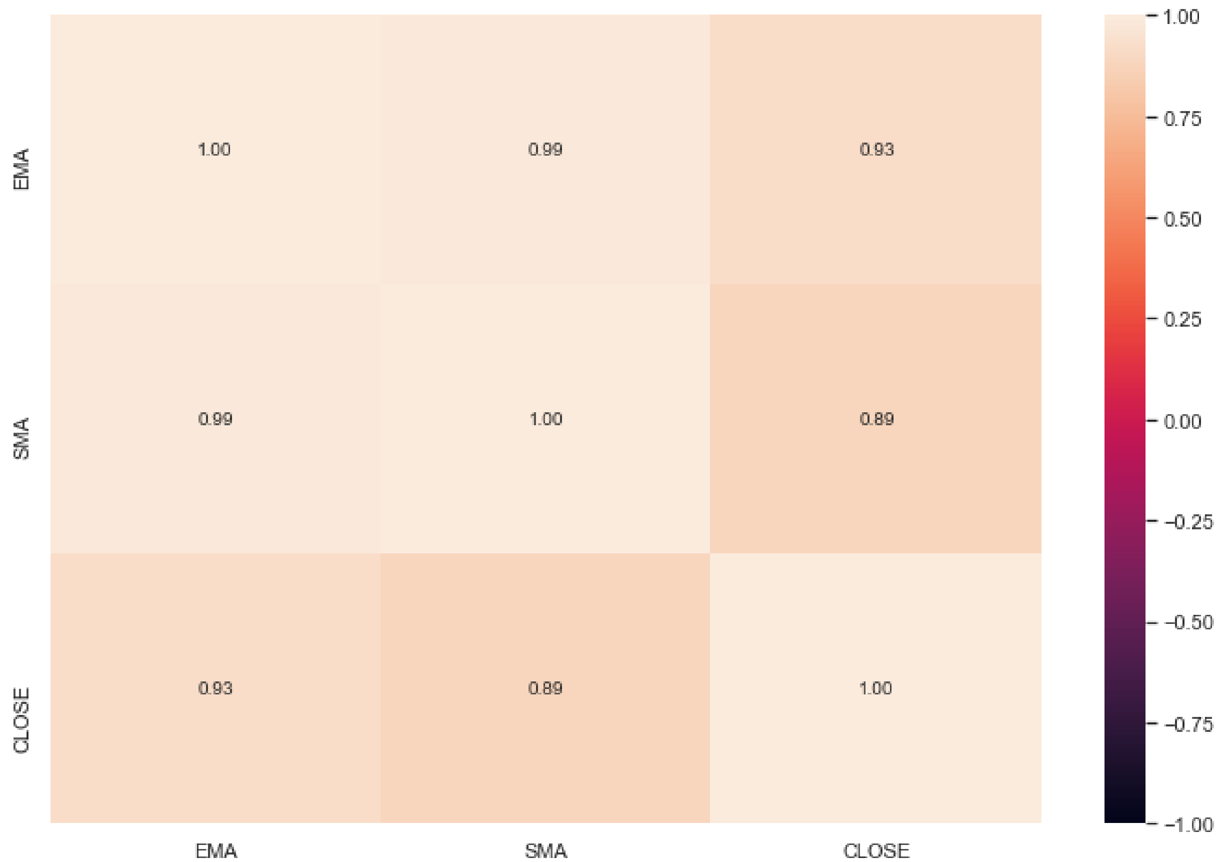
In [26]:
```
#print correlation matrix
tempDF.corr()
```

Out[26]:

	EMA	SMA	CLOSE
EMA	1.000000	0.990768	0.928028
SMA	0.990768	1.000000	0.885281
CLOSE	0.928028	0.885281	1.000000

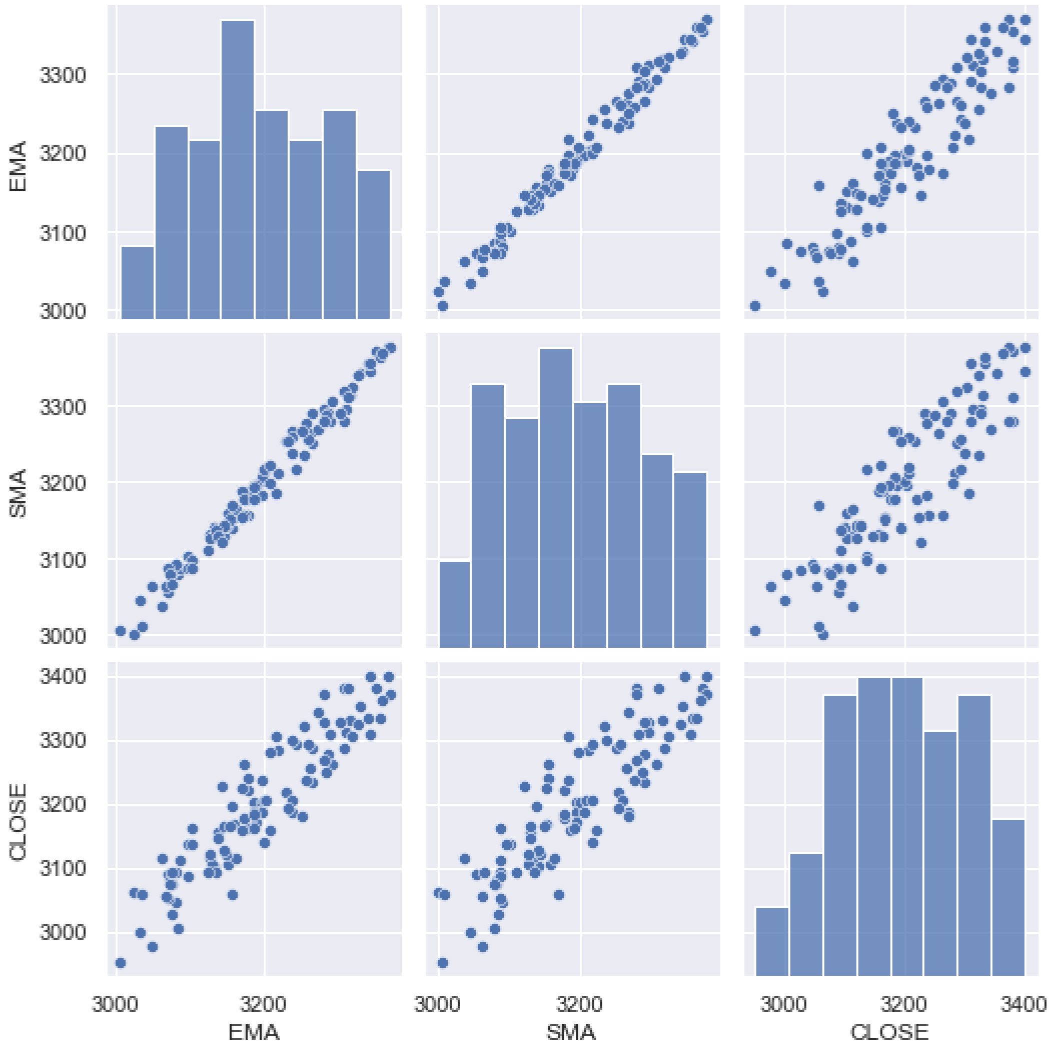
In [27]:
```
#heatmap for visualisation of correlation materix on variables
f = plt.figure(figsize=(12, 8))
sb.heatmap(tempDF.corr(), vmin = -1, vmax = 1, annot = True, fmt = ".2f")
```

Out[27]: <AxesSubplot:>



In [28]:
```
#pairplots of variables
sb.pairplot(data = tempDF)
```

Out[28]: <seaborn.axisgrid.PairGrid at 0x19686b66190>



Machine Learning on Dataset

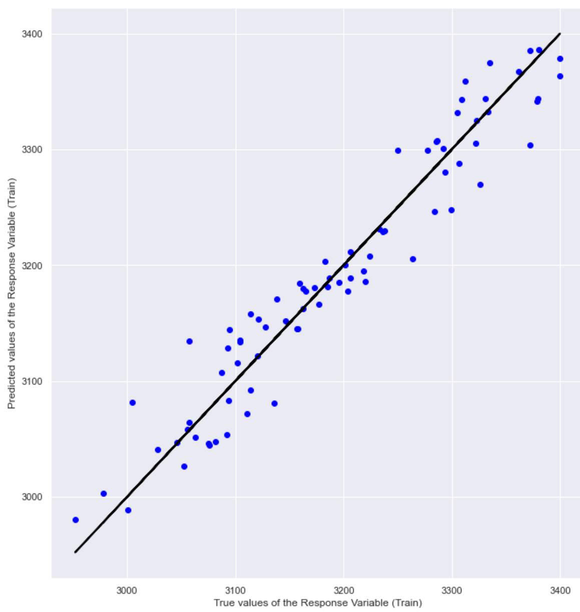
In [29]:
```
#extrraction of X and Y vraribles for regression
y = pd.DataFrame(tempDF["CLOSE"])
X = pd.DataFrame(tempDF[["SMA","EMA"]])

# Split the Dataset into Train and Test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20)

# Check the sample sizes
print("Train Set :", y_train.shape, X_train.shape)
print("Test Set  :", y_test.shape, X_test.shape)
print("\n")

# Linear Regression using Train Data
linreg = LinearRegression()         # create the linear regression object
linreg.fit(X_train, y_train)        # train the linear regression model

# Coefficients of the Linear Regression line
print('Intercept of Regression \t: b = ', linreg.intercept_)
print('Coefficients of Regression \t: a = ', linreg.coef_)
print()

# Print the Coefficients against Predictors
pd.DataFrame(list(zip(X_train.columns, linreg.coef_[0])), columns = ["Predictors'
```

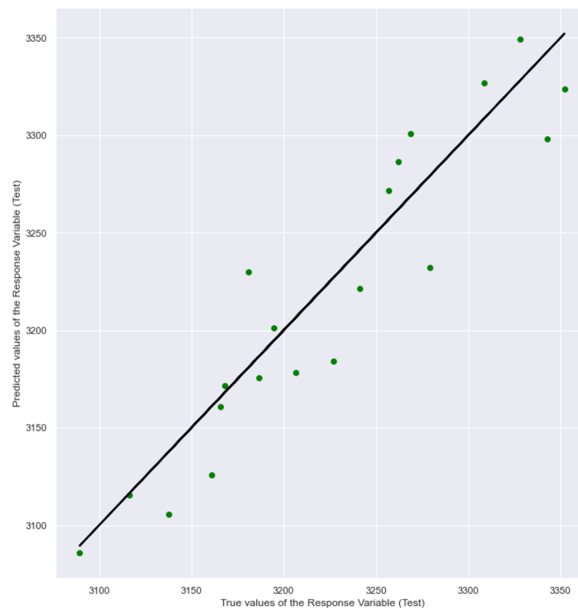
```
Train Set : (80, 1) (80, 2)
Test Set  : (20, 1) (20, 2)


Intercept of Regression         : b =  [-472.33542431]
Coefficients of Regression      : a =  [[-1.91800736  3.06682915]]
```

Out[29]:

	Predictors	Coefficients
0	SMA	-1.918007
1	EMA	3.066829

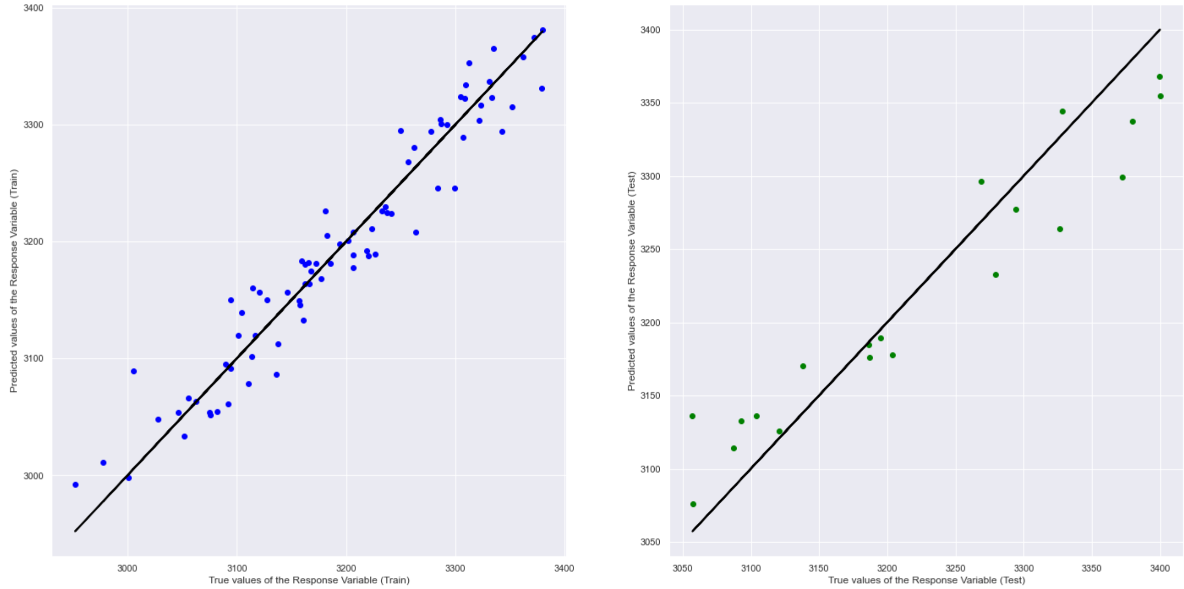
In [30]:
```
#Multi-Variate Regression
y_train_pred = linreg.predict(X_train)
y_test_pred = linreg.predict(X_test)

f, axes = plt.subplots(1, 2, figsize=(24, 12))
axes[0].scatter(y_train, y_train_pred, color = "blue")
axes[0].plot(y_train, y_train, 'w-', linewidth = 2, color = "black")
axes[0].set_xlabel("True values of the Response Variable (Train)")
axes[0].set_ylabel("Predicted values of the Response Variable (Train)")
axes[1].scatter(y_test, y_test_pred, color = "green")
axes[1].plot(y_test, y_test, 'w-', linewidth = 2 , color = "black")
axes[1].set_xlabel("True values of the Response Variable (Test)")
axes[1].set_ylabel("Predicted values of the Response Variable (Test)")
plt.show()
```





In [31]:
```
y = pd.DataFrame(tempDF["CLOSE"])
X = pd.DataFrame(tempDF[["SMA", "EMA"]])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20)

linreg = LinearRegression()
linreg.fit(X_train, y_train)

print('Intercept of Regression \t: b = ', linreg.intercept_)
print('Coefficients of Regression \t: a = ', linreg.coef_)
print()

print(pd.DataFrame(list(zip(X_train.columns, linreg.coef_[0])), columns = ["Predi
print()

y_train_pred = linreg.predict(X_train)
y_test_pred = linreg.predict(X_test)

f, axes = plt.subplots(1, 2, figsize=(24, 12))
axes[0].scatter(y_train, y_train_pred, color = "blue")
axes[0].plot(y_train, y_train, 'w-', linewidth = 2, color = "black")
axes[0].set_xlabel("True values of the Response Variable (Train)")
axes[0].set_ylabel("Predicted values of the Response Variable (Train)")
axes[1].scatter(y_test, y_test_pred, color = "green")
axes[1].plot(y_test, y_test, 'w-', linewidth = 2, color = "black")
axes[1].set_xlabel("True values of the Response Variable (Test)")
axes[1].set_ylabel("Predicted values of the Response Variable (Test)")
plt.show()

print("Goodness of Fit of Model \tTrain Dataset")
print("Explained Variance (R^2) \t:", linreg.score(X_train, y_train))
print("Mean Squared Error (MSE) \t:", mean_squared_error(y_train, y_train_pred))
print()

print("Goodness of Fit of Model \tTest Dataset")
print("Explained Variance (R^2) \t:", linreg.score(X_test, y_test))
print("Mean Squared Error (MSE) \t:", mean_squared_error(y_test, y_test_pred))
print()
```

```
Intercept of Regression         : b =  [-281.00149364]
Coefficients of Regression      : a =  [[-1.97866737  3.06774909]]

  Predictors  Coefficients
0        SMA     -1.978667
1        EMA      3.067749
```




```
Goodness of Fit of Model        Train Dataset
Explained Variance (R^2)        : 0.9319575223166396
Mean Squared Error (MSE)        : 723.625268264944

Goodness of Fit of Model        Test Dataset
Explained Variance (R^2)        : 0.8905591597110687
Mean Squared Error (MSE)        : 1460.7889918355045
```

We can observe the coefficients of regression we obtained. We have a coefficient of -2.260 for the SMA 3.408 for the EMA. This tells us the dependence of the closing price on each independent variable,i.e, if we were to observe the closing price by holding all the independent variables except for SMA constant, the closing price would change by a factor of 3.408.

From the regression analysis performed,we can observe that the test dataset has an R squared value of 0.890 and a Mean Squared Error of 911.381. This shows us that SMA and EMA are very good predictors of the closing price of a stock. This is in line with what we expect to see in the real world as technical indicators are generally the best predictors of the value of a particular stock.

Sentimemtal Analysis

In [32]:
```
news_tables = {}


url = finwiz_url + 'AMZN'
req = Request(url=url,headers={'user-agent': 'my-app/0.0.1'})
response = urlopen(req)
# Read the contents of the file into 'html'
html = BeautifulSoup(response)
# Find 'news-table' in the Soup and load it into 'news_table'
news_table = html.find(id='news-table')
# Add the table to our dictionary
news_tables['AMZN'] = news_table
```

In [33]:
```
# Read one single day of headlines for 'AMZN'
amzn = news_tables['AMZN']
# Get all the table rows tagged in HTML with <tr> into 'amzn_tr'
amzn_tr = amzn.findAll('tr')

for i, table_row in enumerate(amzn_tr):
    # Read the text of the element 'a' into 'link_text'
    a_text = table_row.a.text
    # Read the text of the element 'td' into 'data_text'
    td_text = table_row.td.text
    # Print the contents of 'link_text' and 'data_text'
    print(a_text)
    print(td_text)
    # Lets say we want to see 4 rows of data for now, printing head 4 rows:
    if i == 3:
        break
```

```
Facebook taking very aggressive measures to remove vaccine misinformation: Caro
lyn Everson
Apr-23-21 06:00AM
3 Robinhood Stocks That Cathie Woods Owns -- and You Should Too
05:52AM
Xiaomi Said to Mull Investing in AI Chipmaker Black Sesame
12:24AM
3 Great Growth Stocks to Buy Now at a Discount
Apr-22-21 07:06PM
```

In [34]:
```
parsed_news = []

# Iterate through the news
for file_name, news_table in news_tables.items():
    # Iterate through all tr tags in 'news_table'
    for x in news_table.findAll('tr'):
        # read the text from each tr tag into text
        # get text from a only
        text = x.a.get_text()
        # splite text in the td tag into a list
        date_scrape = x.td.text.split()
        # if the length of 'date_scrape' is 1, load 'time' as the only element

        if len(date_scrape) == 1:
            time = date_scrape[0]

        # else load 'date' as the 1st element and 'time' as the second
        else:
            date = date_scrape[0]
            time = date_scrape[1]
        # Extract the ticker from the file name, get the string up to the 1st '_
        ticker = file_name.split('_')[0]

        # Append ticker, date, time and headline as a list to the 'parsed_news' l
        parsed_news.append([ticker, date, time, text])

parsed_news
```

Out[34]:
```
[['AMZN',
  'Apr-23-21',
  '06:00AM',
  'Facebook taking very aggressive measures to remove vaccine misinformation:
Carolyn Everson'],
 ['AMZN',
  'Apr-23-21',
  '05:52AM',
  '3 Robinhood Stocks That Cathie Woods Owns -- and You Should Too'],
 ['AMZN',
  'Apr-23-21',
  '12:24AM',
  'Xiaomi Said to Mull Investing in AI Chipmaker Black Sesame'],
 ['AMZN',
  'Apr-22-21',
  '07:06PM',
  '3 Great Growth Stocks to Buy Now at a Discount'],
 ['AMZN',
  'Apr-22-21',
```

In [35]:
```
# Instantiate the sentiment intensity analyzer
vader = SentimentIntensityAnalyzer()

# Set column names
columns = ['ticker', 'date', 'time', 'headline']

# Convert the parsed_news list into a DataFrame called 'parsed_and_scored_news'
parsed_and_scored_news = pd.DataFrame(parsed_news, columns=columns)

# Iterate through the headlines and get the polarity scores using vader
scores = parsed_and_scored_news['headline'].apply(vader.polarity_scores).tolist()

# Convert the 'scores' list of dicts into a DataFrame
scores_df = pd.DataFrame(scores)

# Join the DataFrames of the news and the list of dicts
parsed_and_scored_news = parsed_and_scored_news.join(scores_df, rsuffix='_right')

# Convert the date column from string to datetime
parsed_and_scored_news['date'] = pd.to_datetime(parsed_and_scored_news.date).dt.d

parsed_and_scored_news.head(20)
```

Out[35]:

	ticker	date	time	headline	neg	neu	pos	compound
0	AMZN	2021-04-23	06:00AM	Facebook taking very aggressive measures to re...	0.318	0.682	0.000	-0.4927
1	AMZN	2021-04-23	05:52AM	3 Robinhood Stocks That Cathie Woods Owns -- a...	0.000	1.000	0.000	0.0000
2	AMZN	2021-04-23	12:24AM	Xiaomi Said to Mull Investing in AI Chipmaker ...	0.000	1.000	0.000	0.0000
3	AMZN	2021-04-22	07:06PM	3 Great Growth Stocks to Buy Now at a Discount	0.000	0.472	0.528	0.7717
4	AMZN	2021-04-22	06:35PM	Is Kroger Stock A Buy Right Now? Here's What E...	0.000	1.000	0.000	0.0000
5	AMZN	2021-04-22	05:08PM	Microsofts Big Deal and Coinbases Big Debut	0.000	1.000	0.000	0.0000
6	AMZN	2021-04-22	03:21PM	Amazon Targets Automated Checkout In Regular S...	0.000	0.805	0.195	0.1779
7	AMZN	2021-04-22	02:37PM	AeroFarms Serves Up High-Growth Greens Investo...	0.000	0.829	0.171	0.1139
8	AMZN	2021-04-22	02:30PM	Top mistakes graduating college students make ...	0.188	0.677	0.135	-0.1779
9	AMZN	2021-04-22	02:00PM	Amazon to Open London Hair Salon: Another Step...	0.171	0.698	0.132	-0.1280
10	AMZN	2021-04-22	01:06PM	DISH Stock Extends Rally on Amazon Deal. Heres...	0.000	0.789	0.211	0.2960
11	AMZN	2021-04-22	12:33PM	Amazon (AMZN) Reports Next Week: Wall Street E...	0.000	0.650	0.350	0.5106
12	AMZN	2021-04-22	11:50AM	Why Clean Energy Stock Moved Higher Today and...	0.139	0.511	0.350	0.4404

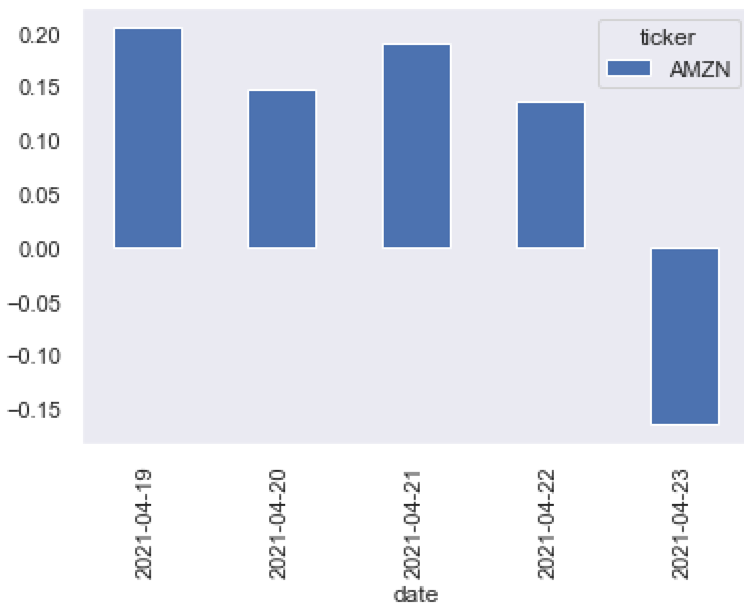
	ticker	date	time	headline	neg	neu	pos	compound
13	AMZN	2021-04-22	11:20AM	President Biden's Tax Proposal Targets Big Tec...	0.000	0.775	0.225	0.4404
14	AMZN	2021-04-22	10:20AM	Influencers with Andy Serwer: Carolyn Everson	0.000	1.000	0.000	0.0000
15	AMZN	2021-04-22	10:00AM	Chinese Billionaire Chen Tianqiaos Top 10 Stoc...	0.000	0.795	0.205	0.2023
16	AMZN	2021-04-22	09:51AM	Azure, Teams & Xbox Adoption to Aid Microsoft ...	0.000	1.000	0.000	0.0000
17	AMZN	2021-04-22	08:49AM	Amazons AWS Partners With DISH Network	0.180	0.820	0.000	-0.0258
18	AMZN	2021-04-22	08:45AM	3 Lessons From Jeff Bezos' Final Letter to Sha...	0.000	0.855	0.145	0.1779
19	AMZN	2021-04-22	08:30AM	4 Top Retail Picks for 2021	0.000	0.690	0.310	0.2023

In [36]:
```
parsed_and_scored_news.shape
```

Out[36]:
```
(100, 8)
```

In [37]:

```
# Group by date and ticker columns from scored_news and calculate the mean
mean_scores = parsed_and_scored_news.groupby(['ticker','date']).mean()

# Unstack the column ticker
mean_scores = mean_scores.unstack()

# Get the cross-section of compound in the 'columns' axis
mean_scores = mean_scores.xs('compound', axis="columns").transpose()

# Plot a bar chart with pandas
#f = plt.figure(figsize =  (12,36))
#sb.histplot(x = parsed_and_scored_news['compound'], y = parsed_and_scored_news[

# Plot a bar chart with pandas
mean_scores.plot(kind = 'bar')
plt.grid()
```



In [38]:

```
mean_scores['Ticks'] = range(1,len(mean_scores.index.values)+1)
mean_scores
```

Out[38]:

ticker	AMZN	Ticks
date		
2021-04-19	0.204621	1
2021-04-20	0.147082	2
2021-04-21	0.189422	3
2021-04-22	0.136767	4
2021-04-23	-0.164233	5

In [39]:
```
lastweekclose=amzn_close[amzn_close.ticks>=96]
lastweekclose
```

Out[39]:

	4. close	ticks	Rolling_Mean
date			
2021-04-16	3399.44	96	3378.184
2021-04-19	3372.01	97	3376.708
2021-04-20	3334.69	98	3363.646
2021-04-21	3362.02	99	3369.450
2021-04-22	3309.04	100	3355.440

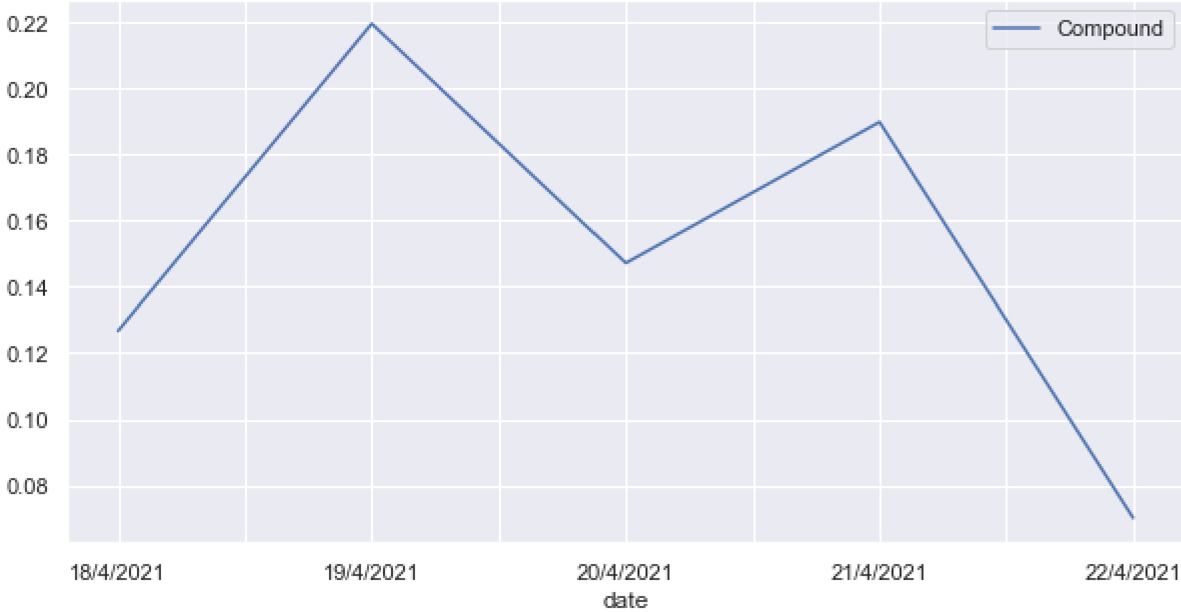
In [40]:
```
lastwclose = pd.read_csv('Close.csv')
compound=pd.read_csv('Compound.csv')
joinDF=pd.concat([compound,lastwclose], axis = 1)
joinDF=joinDF.drop('Date',axis=1)
joinDF
```

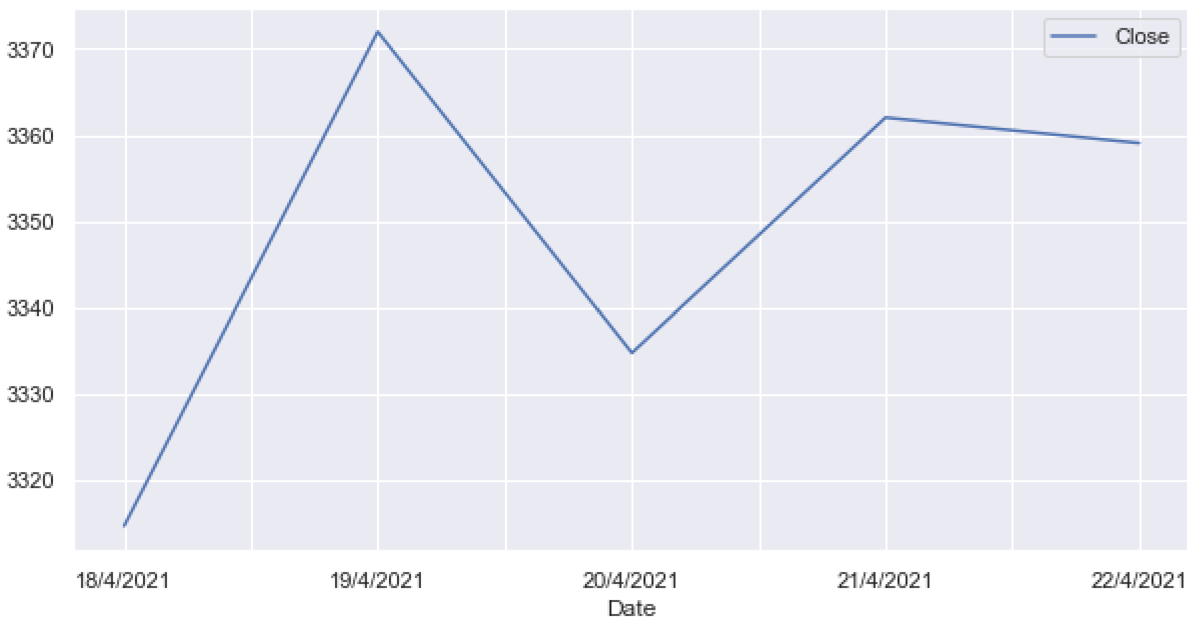
Out[40]:

	date	Compound	Close
0	18/4/2021	0.1267	3314.56
1	19/4/2021	0.2194	3372.01
2	20/4/2021	0.1471	3334.69
3	21/4/2021	0.1897	3362.02
4	22/4/2021	0.0702	3359.05

In [41]:
```
compound.set_index('date').plot(figsize=(10,5), grid=True)
lastwclose.set_index('Date').plot(figsize=(10,5),grid=True)
```

Out[41]: <AxesSubplot:xlabel='Date'>





In the above plots, the first plot shows the variation of sentiments with respect to time in the last week. The second chart shows the variation of closing price with respect to time in the last week.We see a quite a strong correlation between sentiments and predicted price.

In [ ]: