adani

1 AdaniPowerltd.:-StockPriceForecasting

2 Stepsthatwearefollowintimeseries(Forecasting)

1. Data Ingesiton
2. EDA of the data
3. Processing of the data
4. Model Building
5. Model Evalution

[]:

```

```

3 DataIngesiton

[1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
import sys
import warnings
warnings.filterwarnings('ignore')
```

[2]:

```
# load the dataset (adani power limited)

data = pd.read_csv('Adani_power_LTD_data_file.csv')
data.head()
```

[2]:

	Date	Open	High	Low	Close	Adj Close \
0	2022/11/09	348.600006	366.000000	345.000000	365.799988	365.799988
1	2022/11/10	365.799988	377.000000	358.000000	371.399994	371.399994
2	2022/11/11	376.000000	378.000000	353.000000	360.200012	360.200012
3	2022/11/14	348.149994	365.049988	342.200012	359.799988	359.799988
4	2022/11/15	355.899994	358.500000	353.000000	357.049988	357.049988

Volume

```
0   389162
1   8
2   29386
3   62
4   34060
    69
    32380
    02
    126538
    2
```

[]:

4 Univariate Analysis

[3]:
```python
stock_data = data[['Date','Close']]
stock_data
```

[3]:

	Date	Close
0	2022/11/09	365.799988
1	2022/11/10	371.399994
2	2022/11/11	360.200012
3	2022/11/14	359.799988
4	2022/11/15	357.049988
..	...	...
245	2023/11/03	384.649994
246	2023/11/06	394.000000
247	2023/11/07	383.799988
248	2023/11/08	393.399994
249	2023/11/09	401.100006

[250 rows x 2 columns]

[4]:
```python
# checking the information
stock_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250 entries, 0 to 249
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Date    250 non-null    object
 1   Close   250 non-null    float64
dtypes: float64(1), object(1)
memory usage: 4.0+ KB
```

[5]:
```python
# convert data time [ Obj--> int ]

pd.to_datetime(stock_data.Date)
stock_data['Date'] = pd.to_datetime(stock_data.Date)
```

```
# now check the updated info()
stock_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250 entries, 0 to 249
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Date    250 non-null    datetime64[ns]
 1   Close   250 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 4.0 KB
```

[]:

[6]:
```
# set the date as a index
stock_data = stock_data.set_index('Date')
```

[7]:
```
stock_data
```

[7]:
```
                 Close
Date
2022-11-09  365.799988
2022-11-10  371.399994
2022-11-11  360.200012
2022-11-14  359.799988
2022-11-15  357.049988
...                ...
2023-11-03  384.649994
2023-11-06  394.000000
2023-11-07  383.799988
2023-11-08  393.399994
2023-11-09  401.100006

[250 rows x 1 columns]
```

[]:

4.1 Observation:

we convert this date column into index because of: 1. Retriving of the data will be easy

2. visualization will be easy

3. those lib has been degine in such a way it required date column as a index(scipy statsmodel)

[]:

5 EDAoftheData:

Steps:

1. Summary Statistics

- Compute summary statistics such as mean, median, mode, standard deviation, to get an overview of the data.

2. Visualize the Time Series Data

- Plot the Time Series data
- Plot the rolling mean and rolling standard deviation of the Time Series data.
- Decompose the Time Series Data check for any trends, seasonality, and Noise.
- Plot the decomposed components to get a better understanding of the Time Series data.

3. Stationarity Check

- Check for stationarity.
- Check for stationarity of the Time Series data using the Augmented Dickey-Fuller test.

4. Check for Autocorrelation

- Plot the autocorrelation function (ACF) and partial autocorrelation function (PACF) to identify the order of the ARIMA model.

5. Outlier Detection

- Detect and handle outliers using statistical methods or machine learning techniques.

6. Check for Autocorrelation

- Plot the autocorrelation function (ACF) and partial autocorrelation function (PACF) to identify the order of the ARIMA model.

[8]:
```
stock_data.describe()
```

[8]:

	Close
count	250.000000
mean	273.129200
std	65.525775
min	139.350006
25%	235.625004
50%	273.075012
75%	325.787506
max	401.100006

[9]:
```
stock_data.head(5)
```

[9]:

	Close
Date	
2022-11-09	365.799988

```
2022-11-10   371.39999
2022-11-11   4
2022-11-14   360.20001
2022-11-15   2
             359.79998
             8
             357.0499
             88
```

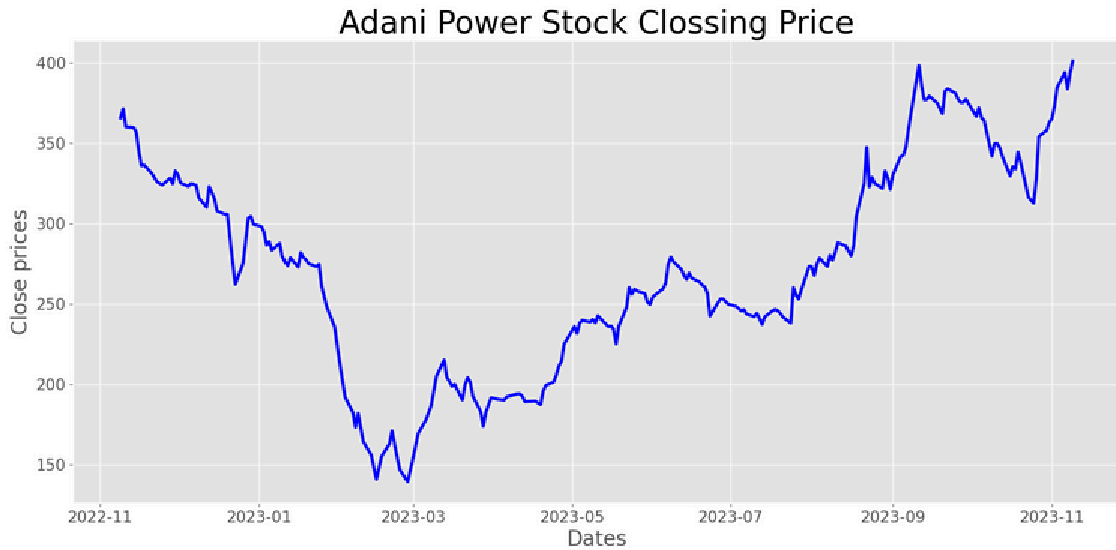
[]:

[10]:
```python
# Plot the Stock data
plt.plot(stock_data.Close)
```

[10]:
```
[<matplotlib.lines.Line2D at 0x1e1cd560f50>]
```

[11]:
```python
# making this plot more readable :
# plot the close price
plt.style.use('ggplot')
plt.figure(figsize=(18,8))
plt.grid(True)
plt.xlabel('Dates', fontsize= (20))
plt.xticks(fontsize = 15)
plt.ylabel('Close prices', fontsize = 20)
plt.yticks(fontsize= 15)
plt.plot(stock_data['Close'], linewidth = 3, color = 'blue')
```

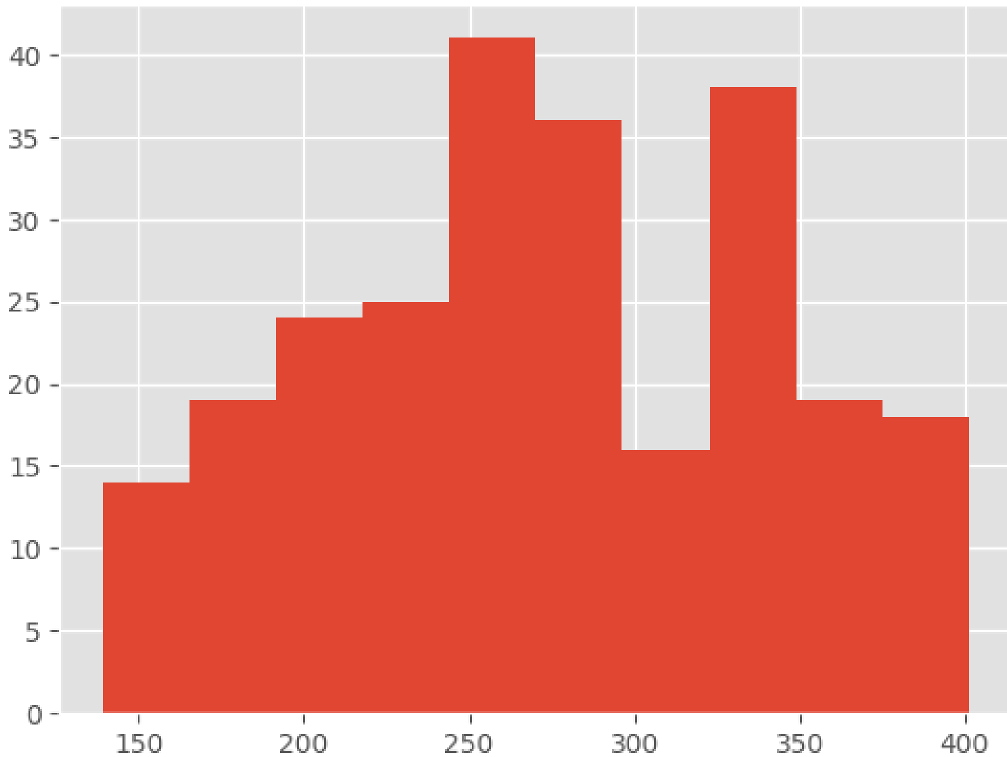
```
plt.title('Adani Power Stock Clossing Price', fontsize= 30 )
plt.show()
```



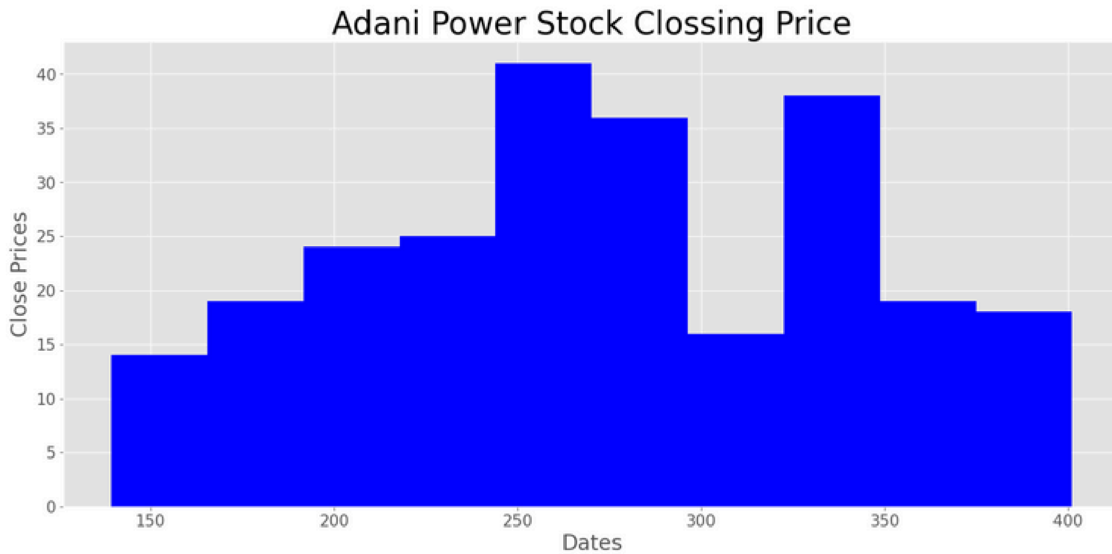
[]:

```
[12]: # Showing this stock data into histograme
plt.hist(stock_data.Close)
```

```
[12]: (array([14., 19., 24., 25., 41., 36., 16., 38., 19., 18.]),
 array([139.350006, 165.525006, 191.700006, 217.875006, 244.050006,
 270.225006, 296.400006, 322.575006, 348.750006, 374.925006,
 401.100006]),
 <BarContainer object of 10 artists>)
```



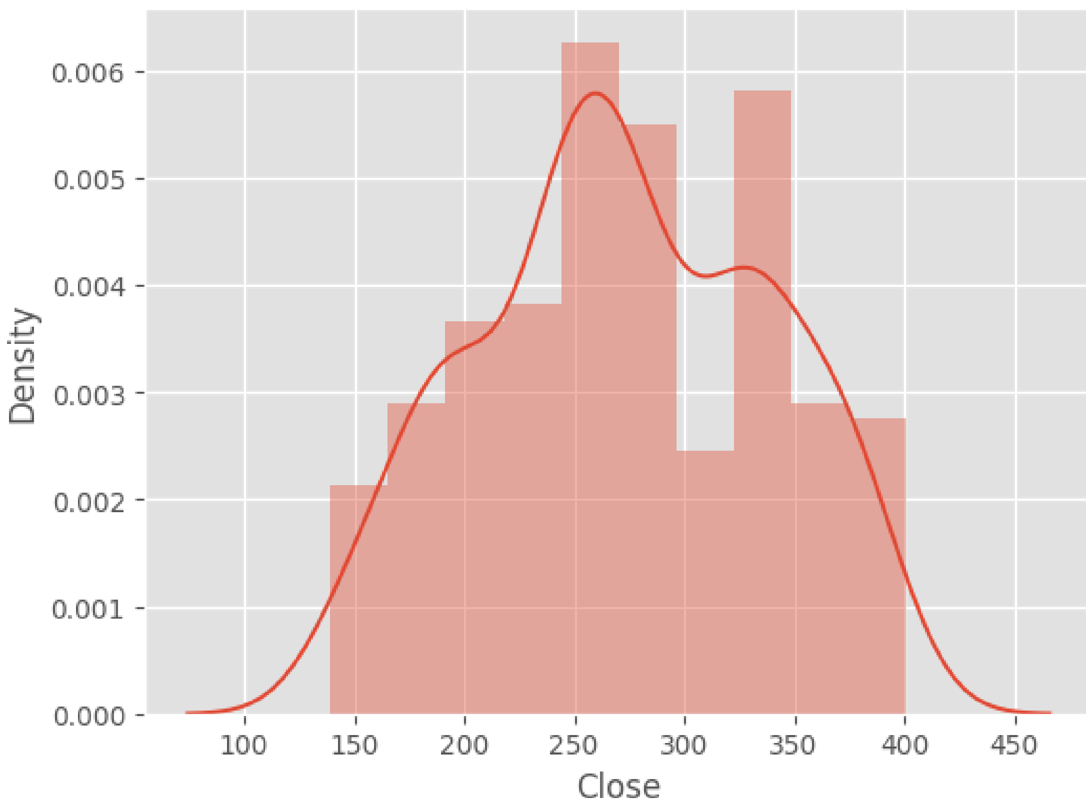
[13]:
```
# making histograme more readable
# plotting close price plt.style.use('ggplot')
plt.figure(figsize=(18,8)) plt.grid(True) plt.xlabel('Dates',
fontsize = 20) plt.xticks(fontsize = 15) plt.ylabel('Close
Prices', fontsize = 20) plt.yticks(fontsize = 15)
plt.hist(stock_data['Close'], linewidth = 3, color = 'blue')
plt.title('Adani Power Stock Clossing Price', fontsize = 30)
plt.show()
```



[]:

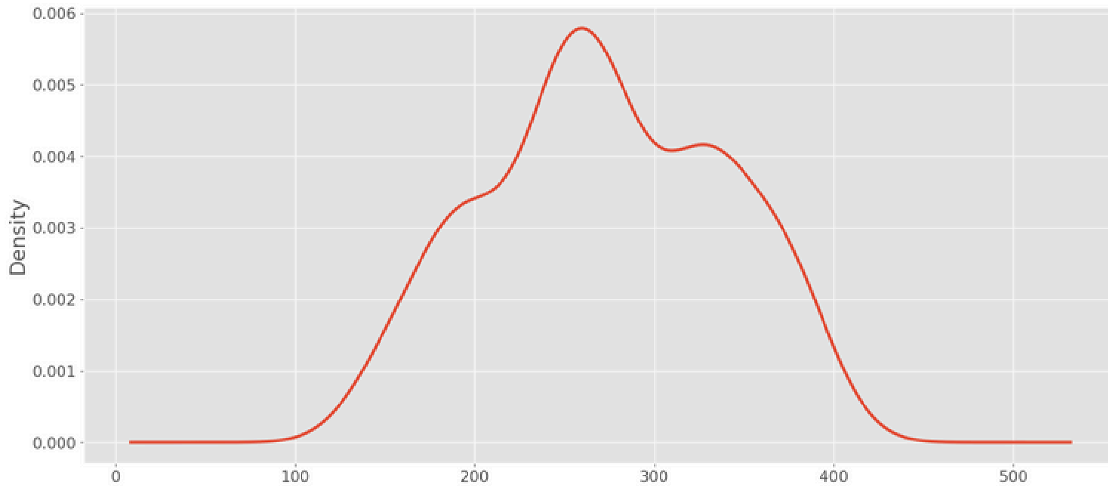
[14]:
```
# showing in displot aslo
import seaborn as sns
sns.distplot(stock_data.Close)
```

[14]: <Axes: xlabel='Close', ylabel='Density'>



[]:

```
[15]: # Distribution of the Close price
df_close = stock_data['Close']
df_close.plot(kind = 'kde',figsize = (18,8), linewidth= 3 )
plt.xticks(fontsize = 15)
plt.grid("both")
plt.ylabel('Density', fontsize = 20)
plt.yticks(fontsize = 15)
plt.show()
```



[]:

[16]:
```
# Plot the Rolling mean and Standard deviation of the Time Series Data
```

[17]:
```
stock_data['Close']
```

[17]:
```
Date
2022-11-09    365.799988
2022-11-10    371.399994
2022-11-11    360.200012
2022-11-14    359.799988
2022-11-15    357.049988
                 ...
2023-11-03    384.649994
2023-11-06    394.000000
2023-11-07    383.799988
2023-11-08    393.399994
2023-11-09    401.100006
Name: Close, Length: 250, dtype: float64
```

[18]:
```
# Rolling mean
stock_data['Close'].rolling(12)
```

[18]:
```
Rolling [window=12,center=False,axis=0,method=single]
```

[19]:
```
# check the rolling mean
rolmean = stock_data['Close'].rolling(12).mean()
rolmean
```

[19]:
```
Date
2022-11-09           NaN
2022-11-10           NaN
2022-11-11           NaN
2022-11-14           NaN
2022-11-15           NaN
                 ...
2023-11-03    347.595838
2023-11-06    352.600004
2023-11-07    355.879168
2023-11-08    360.470835
2023-11-09    365.525001
Name: Close, Length: 250, dtype: float64
```

[20]:
```python
# Check the rolling standard deviation
rolstd = stock_data['Close'].rolling(12).std()
rolstd
```

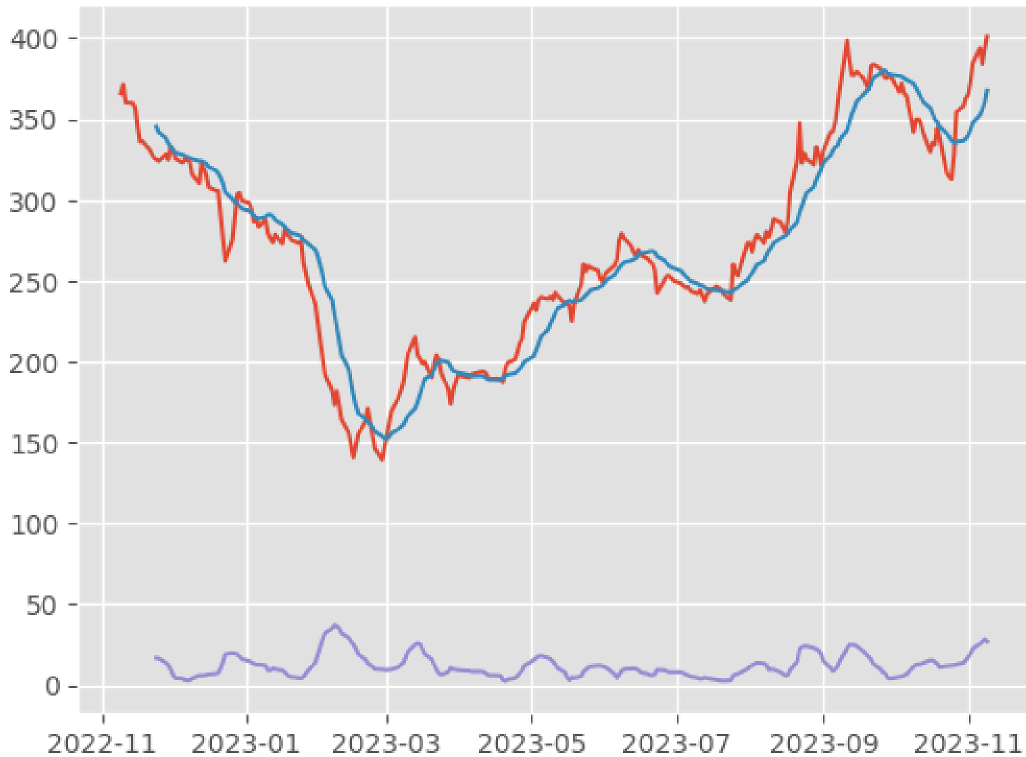
[20]:
```
Date
2022-11-09          NaN
2022-11-10          NaN
2022-11-11          NaN
2022-11-14          NaN
2022-11-15          NaN
                ...
2023-11-03    22.552848
2023-11-06    25.693257
2023-11-07    27.034590
2023-11-08    28.421093
2023-11-09    26.969857
Name: Close, Length: 250, dtype: float64
```

[ ]:

6 PlottingthedataBeforeSmoothning

[21]:
```python
# now plot those values
plt.plot(stock_data.Close)      ##timeseries data
plt.plot(rolmean)     ##rolling  mean
plt.plot(rolstd)           ##rolling  std
```

[21]: [<matplotlib.lines.Line2D at 0x1e1e2151550>]



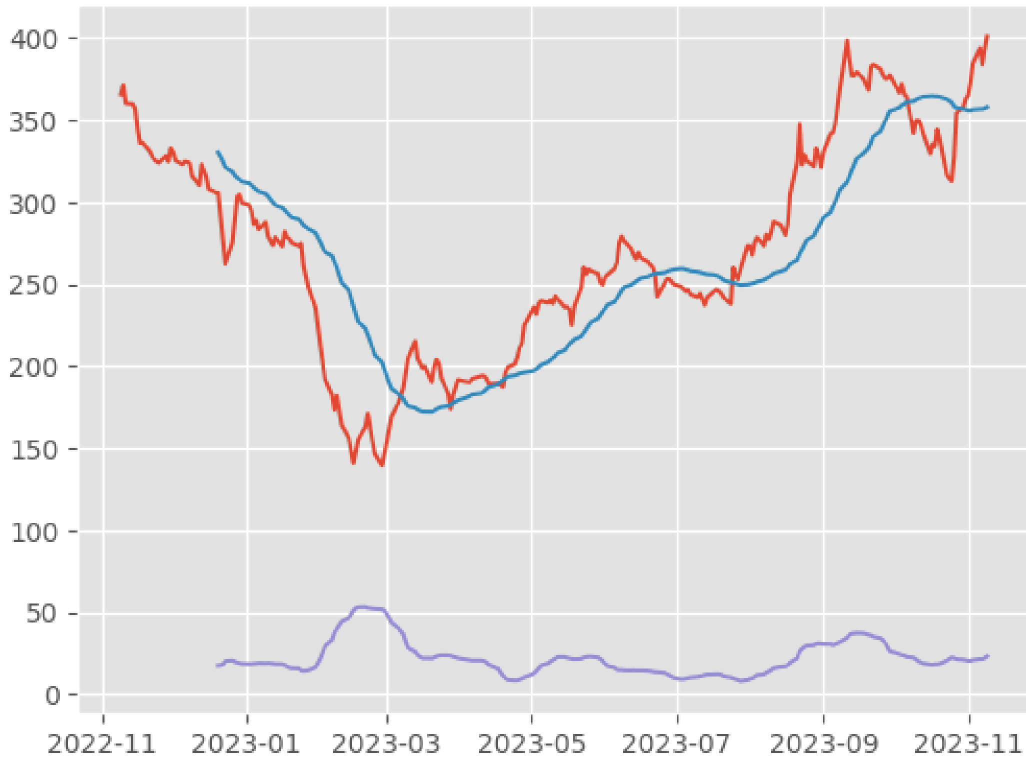
[]:

7 PlottingAfterSmoothning

[22]:
```
rolmean = stock_data['Close'].rolling(30).mean()        ## smoothning by changing the rolling mean values

rolstd = stock_data['Close'].rolling(30).std()          ## smoothning by changing the rolling std values
```

[23]:
```
# now plot those values after smothining
plt.plot(stock_data.Close)     ##timeseries data
plt.plot(rolmean)    ##rolling  mean
plt.plot(rolstd)          ##rolling  std
```

[23]: [<matplotlib.lines.Line2D at 0x1e1e2177fd0>]



[]:

8 Stationarity Check

[24]:
```
# importing the adfuller for checking the stationarity
from statsmodels.tsa.stattools import adfuller
adft = adfuller(stock_data.Close)
```

[25]:
```
adft
```

[25]:
```
(-0.875900424719507,
 0.795805131159639,
 1,
 248,
 {'1%': -3.4569962781990573,
 '5%': -2.8732659015936024,
 '10%': -2.573018897632674},
 1631.1543128405356)
```

[26]:
```
adft[0:4]
```

[26]: (-0.875900424719507, 0.795805131159639, 1, 248)

[27]:
```
## indexing on adft values
pd.Series(adft[0:4], index= ['test stats', 'P-value', 'lag', 'data points'])
```

[27]:
```
teststats        -0.875900
P-value           0.795805
lag               1.000000
datapoints      248.000000
dtype: float64
```

[]:

8.1 makeacriteriaforthep-value

null hypothesis = data is non stationary

P-value= 0.795805

$p < 0.05$ reject null hypothesis

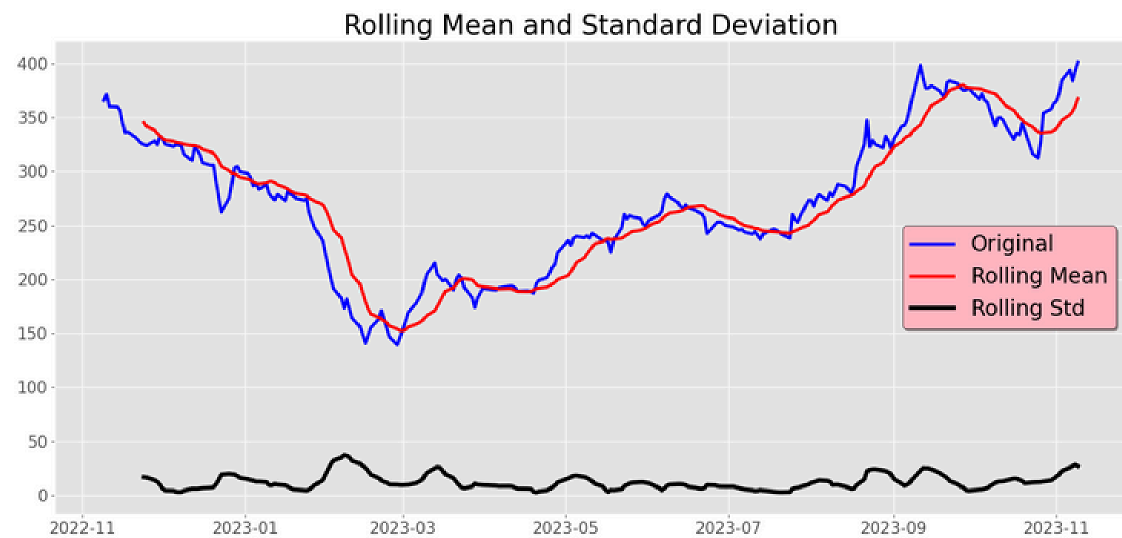
$p > 0.05$ accept null hypothesis

[]:

[28]:
```
# creating a function where all stationarity details shuould be present

#Test for staionarity
def test_stationarity(timeseries):
# Determing rolling statistics
rolmean = timeseries.rolling(12).mean() # rolling mean
rolstd = timeseries.rolling(12).std() # rolling standard deviation

# Plot rolling statistics:
plt.figure(figsize = (18,8))
plt.grid('both')
plt.plot(timeseries, color='blue',label='Original', linewidth = 3)
plt.plot(rolmean, color='red', label='Rolling Mean',linewidth = 3)
plt.plot(rolstd, color='black', label = 'Rolling Std',linewidth = 4)
plt.legend(loc='best', fontsize = 20,␣
  ↪shadow=True,facecolor='lightpink',edgecolor='k')

    plt.title('RollingMeanandStandardDeviation',fontsize=25)
    plt.xticks(fontsize = 15)
    plt.yticks(fontsize = 15)
    plt.show(block=False)
    print("Results of dickey fuller test")
    adft = adfuller(timeseries,autolag='AIC')
```

```
# output for adft will give us without defining what the values are.
# hence we manually write what values does it explains using a for loop
output = pd.Series(adft[0:4],index=['Test Statistics','p-value','No. of␣
lags used','Number of observations used'])

for key,values in adft[4].items():
    output['critical value (%s)'%key] = values
print(output)
```

[29]:
```
test_stationarity(stock_data.Close)
```



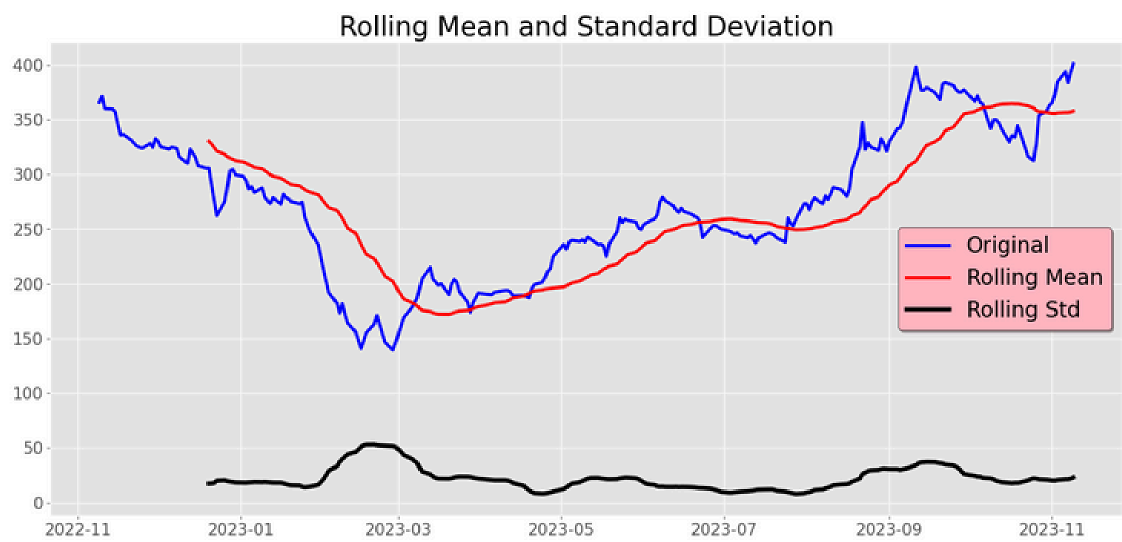

```
Results of dickey fuller test
TestStatistics                   -0.875900
p-value                           0.795805
No.oflags used                    1.000000
Number of observations used     248.000000
criticalvalue (1%)               -3.456996
criticalvalue (5%)               -2.873266
criticalvalue (10%)              -2.573019
dtype: float64
```

[]:

[30]:
```
## smothning on stock data

# creating a function where all stationarity details shuould be present

#Test for staionarity
def test_stationarity(timeseries):
```

```
# Determing rolling statistics rolmean =
timeseries.rolling(30).mean() # rolling mean rolstd =
timeseries.rolling(30).std() # rolling standard deviation

# Plot rolling statistics:
plt.figure(figsize = (18,8))
plt.grid('both')
plt.plot(timeseries, color='blue',label='Original', linewidth = 3)
plt.plot(rolmean, color='red', label='Rolling Mean',linewidth = 3)
plt.plot(rolstd, color='black', label = 'Rolling Std',linewidth = 4)
plt.legend(loc='best', fontsize = 20,␣
↪shadow=True,facecolor='lightpink',edgecolor='k')

plt.title('RollingMeanandStandardDeviation',fontsize=25)
plt.xticks(fontsize = 15)
plt.yticks(fontsize = 15)
plt.show(block=False)
print("Results of dickey fuller test")
adft = adfuller(timeseries,autolag='AIC')
# output for dft will give us without defining what the values are.
# hence we manually write what values does it explains using a for loop
output = pd.Series(adft[0:4],index=['Test Statistics','p-value','No. of␣
↪lagsused','Numberofobservationsused'])

forkey,valuesinadft[4].items():
    output['critical value (%s)'%key]= values
print(output)
```

[31]:
```
test_stationarity(stock_data.Close)
```



Results of dickey fuller test

Test Statistics	-0.875900
p-value	0.795805
No. of lags used	1.000000
Number of observations used	248.000000
critical value (1%)	-3.456996
critical value (5%)	-2.873266
critical value (10%)	-2.573019

dtype: float64

[]:

```

```

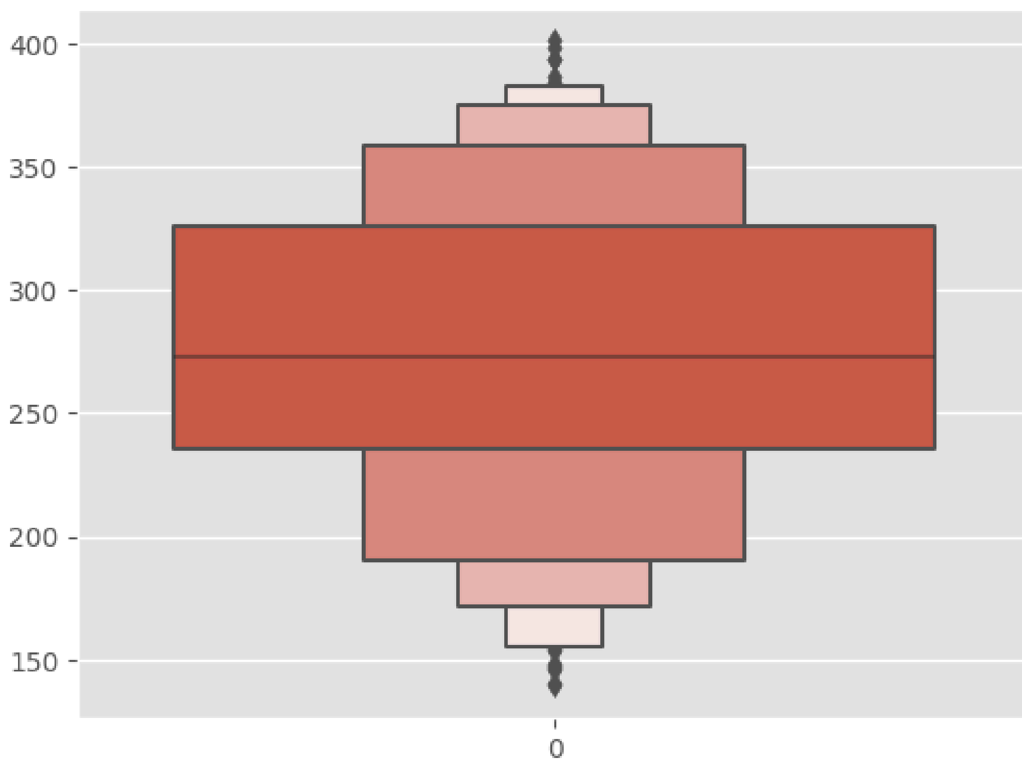
9 OutlierDectection

[32]:
```
# there is no missing value in the dataset
stock_data.Close.isnull().sum()
```

[32]: 0

[33]:
```
sns.boxenplot(stock_data.Close)
```

[33]: <Axes: >



[34]:
```
stock_data.Close.describe()
```

[34]:
```
count    250.000000
mean     273.129200
std       65.525775
min      139.350006
25%      235.625004
50%      273.075012
75%      325.787506
max      401.100006
Name: Close, dtype: float64
```

[35]:
```
# finding the IQR
iqr_25 = stock_data.Close.quantile(0.25)
iqr_75 = stock_data.Close.quantile(0.75)
```

[36]:
```
iqr_25
```

[36]: 235.62500375000002

[37]:
```
iqr_75
```

[37]: 325.787506

[38]:
```
iqr = iqr_75 - iqr_25
iqr
```

[38]: 90.16250224999999

[39]:
```
upper_limit = iqr_75 + 1.5*iqr
lower_limit = iqr_25 - 1.5*iqr
print('Upper Limit', upper_limit)
print('Lower Limit', lower_limit)
```

```
Upper Limit 461.031259375
Lower Limit 100.38125037500004
```

[40]:
```
stock_data[stock_data.Close > upper_limit]
```

[40]:
```
Empty DataFrame
Columns: [Close]
Index: []
```

[41]:
```
stock_data[stock_data.Close < lower_limit]
```

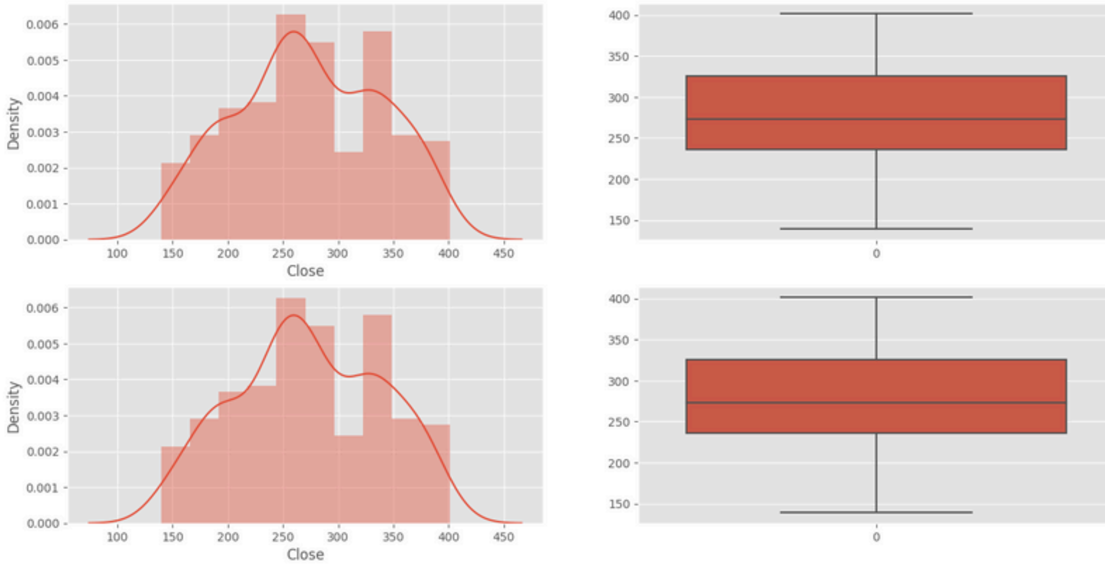
[41]: Empty DataFrame
Columns: [Close]
Index: []

[42]:
```
# Capping

new_df_cap = stock_data.copy()

new_df_cap['Close'] = np.where(
    new_df_cap['Close'] > upper_limit,
    upper_limit,
    np.where(
        new_df_cap['Close'] < lower_limit,
        lower_limit,
        new_df_cap['Close']
    )
)
```

[43]:
```
new_df_cap.shape
```

[43]: (250, 1)

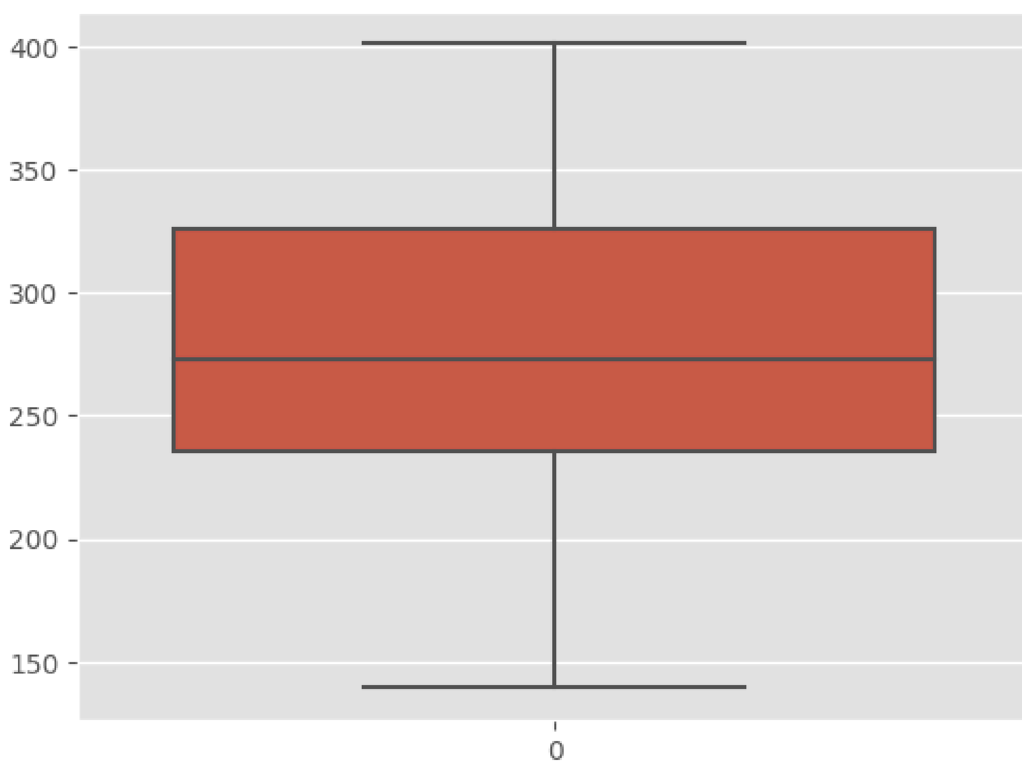
[44]:
```
# camparing

plt.figure(figsize=(16,8))
plt.subplot(2,2,1)
sns.distplot(stock_data['Close'])

plt.subplot(2,2,2)
sns.boxplot(stock_data['Close'])
plt.subplot(2,2,3)
sns.distplot(new_df_cap['Close'])
plt.subplot(2,2,4)
sns.boxplot(new_df_cap['Close'])
plt.show()
```



[]:

[45]:
```
sns.boxplot(stock_data['Close'])
```

[45]: <Axes: >



10 Observation:

now we capping all the outliers from the data set. now our data is completly outlier free.

[]:

```

```

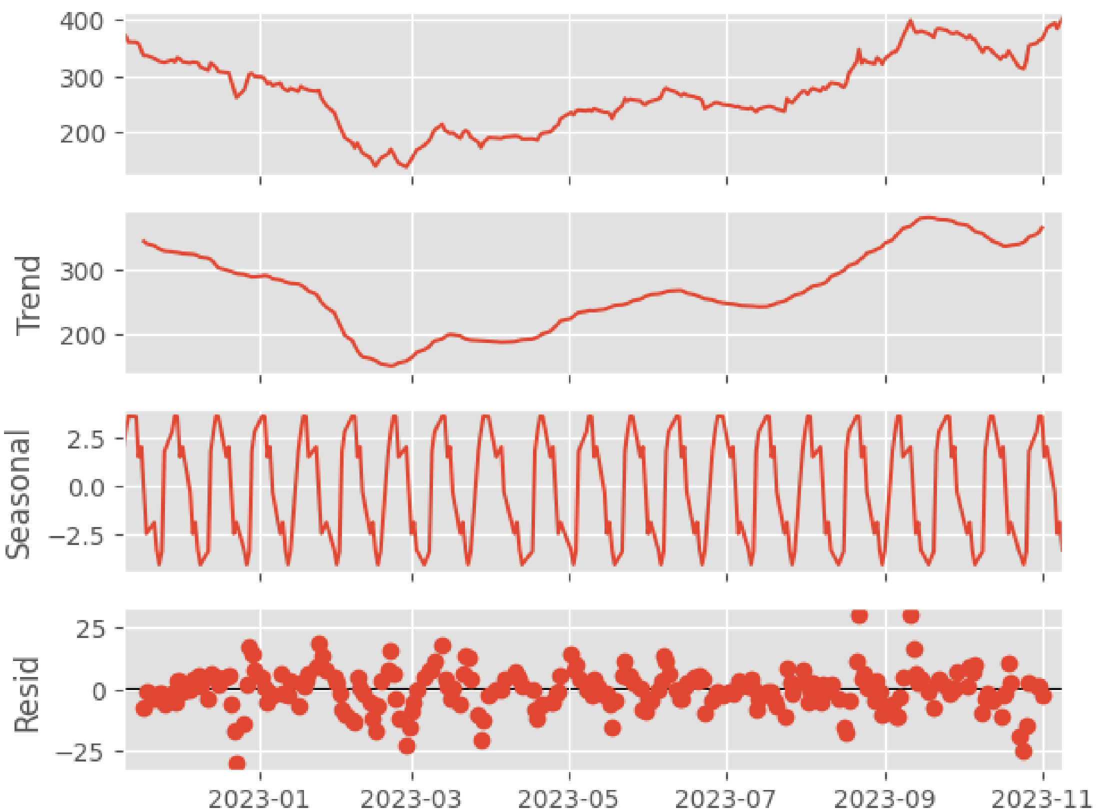
11 TimeseriesDecomposition

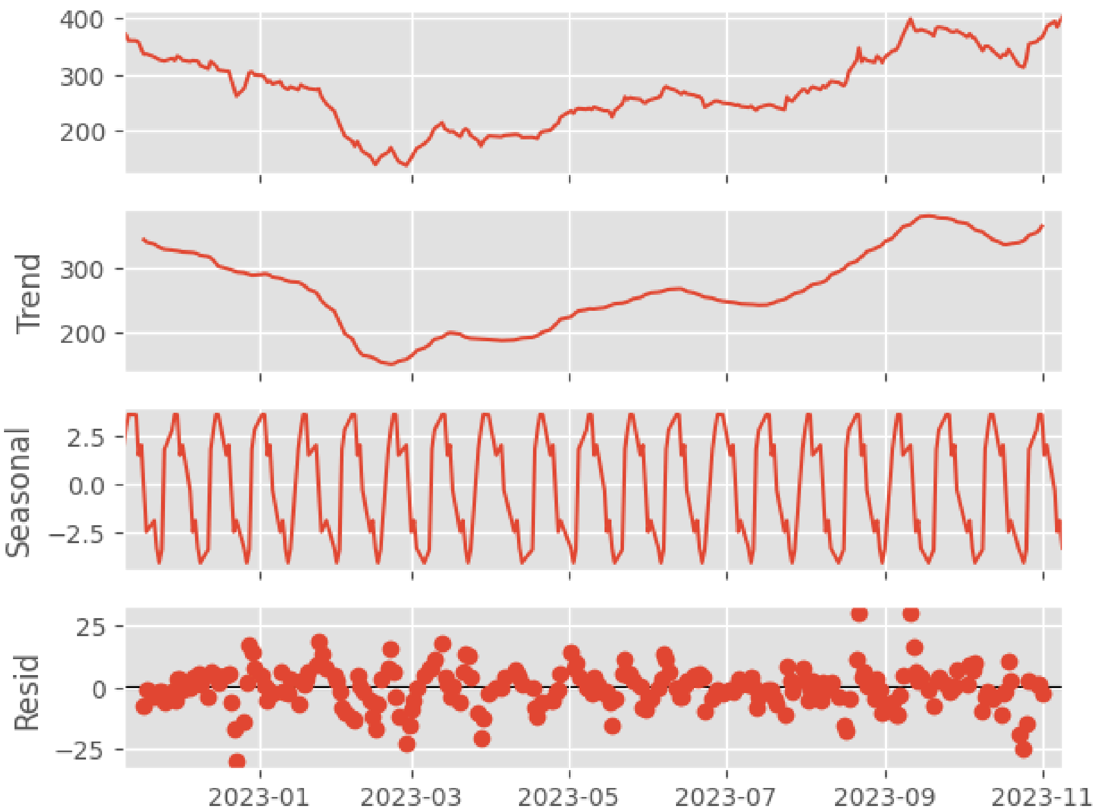
[46]:
```
from statsmodels.tsa.seasonal import seasonal_decompose

result = seasonal_decompose(stock_data[['Close']], period= 12)
result
```

[46]: <statsmodels.tsa.seasonal.DecomposeResult at 0x1e1e2528390>

[47]:
```
# plot the result
result.plot()
```

[47]:





12 Observation

1. Here we got two plot: one for additive and second for multiplicative, we can go with one also but defolt this go will both perametter, we can chage it with our conviniant.
2. And we also check seperatly the trend, seasonl, resid values with graph

[]:

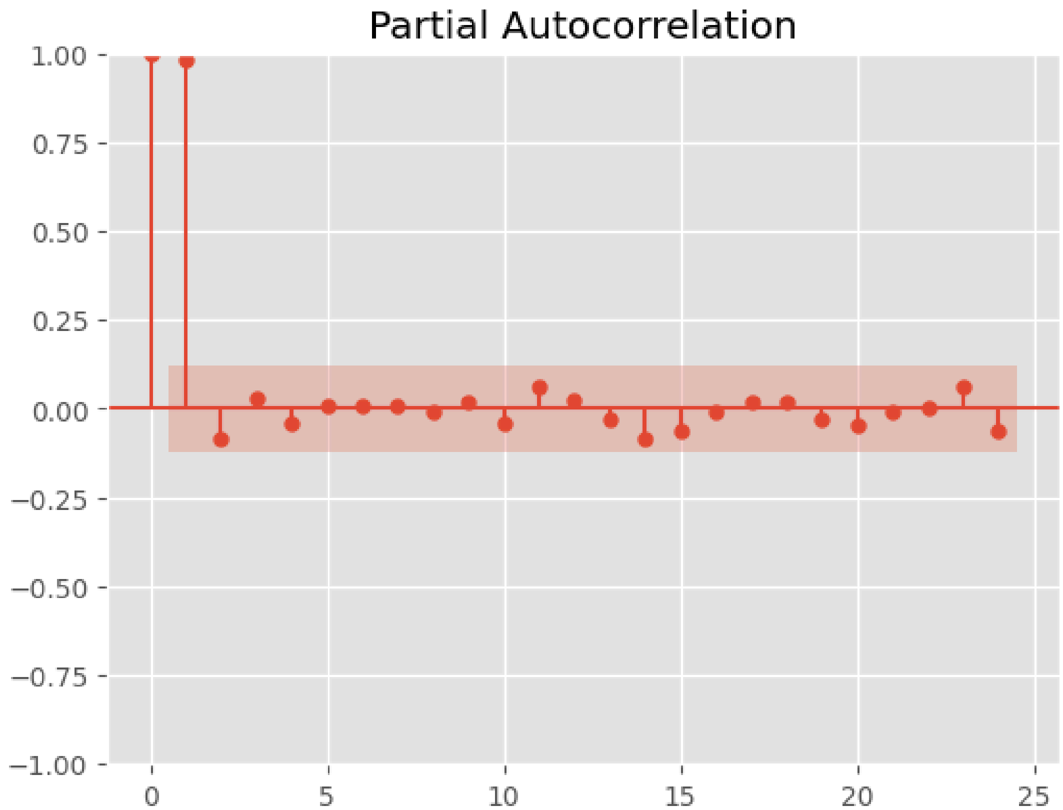
```
```

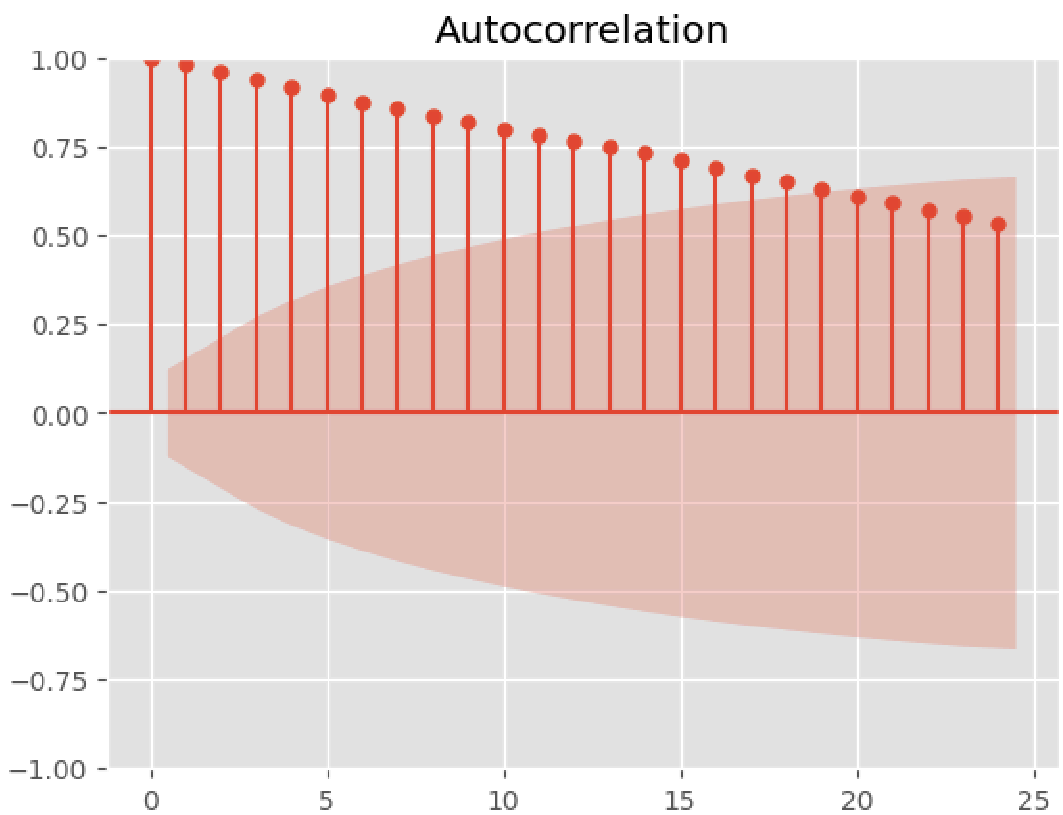
13 ACFANDPACF

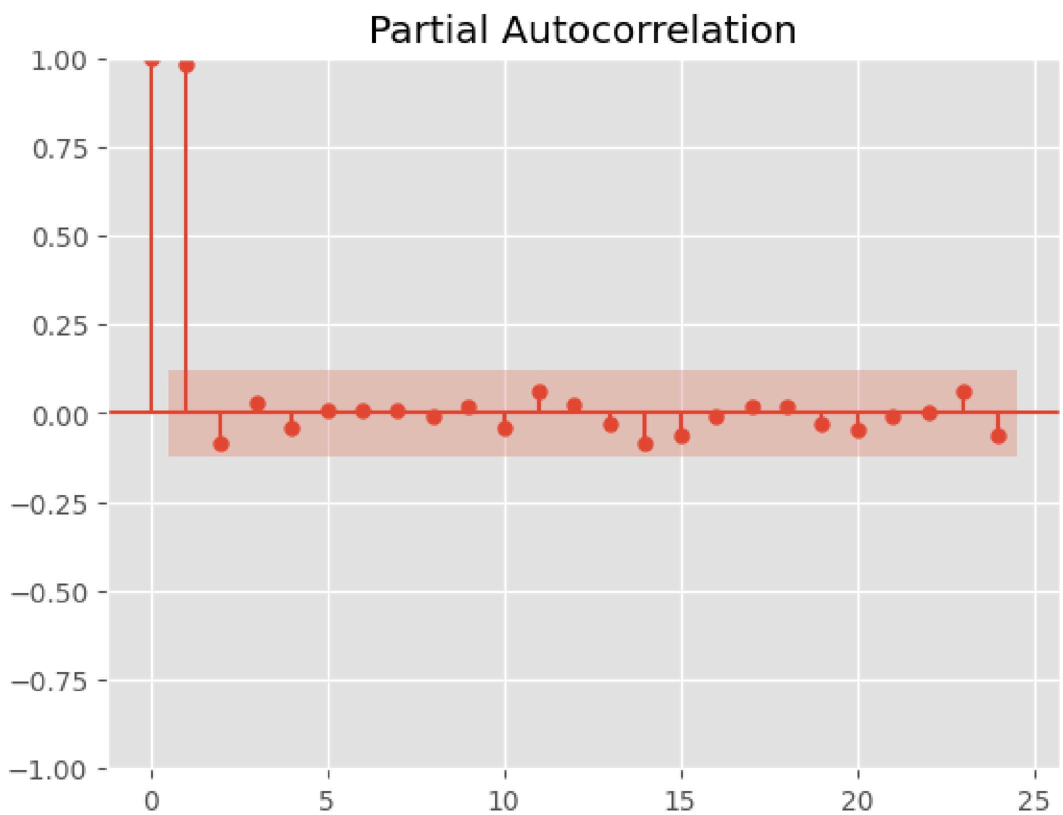
[48]:

```
from statsmodels.graphics.tsaplots import  plot_acf, plot_pacf
plot_acf(stock_data.Close)
plot_pacf(stock_data.Close)
```

[48]:


Partial Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25


Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25



[]:

14 Preprocessingofthedata

1. fill the miss(here not required)
2. convert data into stationary time series
3. if necessary then normalize the data(here not required)
4. split the data into train and test
5. clean the data by removing the outlier (here not required)

[49]:
```
# non stationary to stationary
df_close = stock_data['Close']
df_close
```

[49]:
```
Date
2022-11-09    365.799988
2022-11-10    371.399994
2022-11-11    360.200012
```

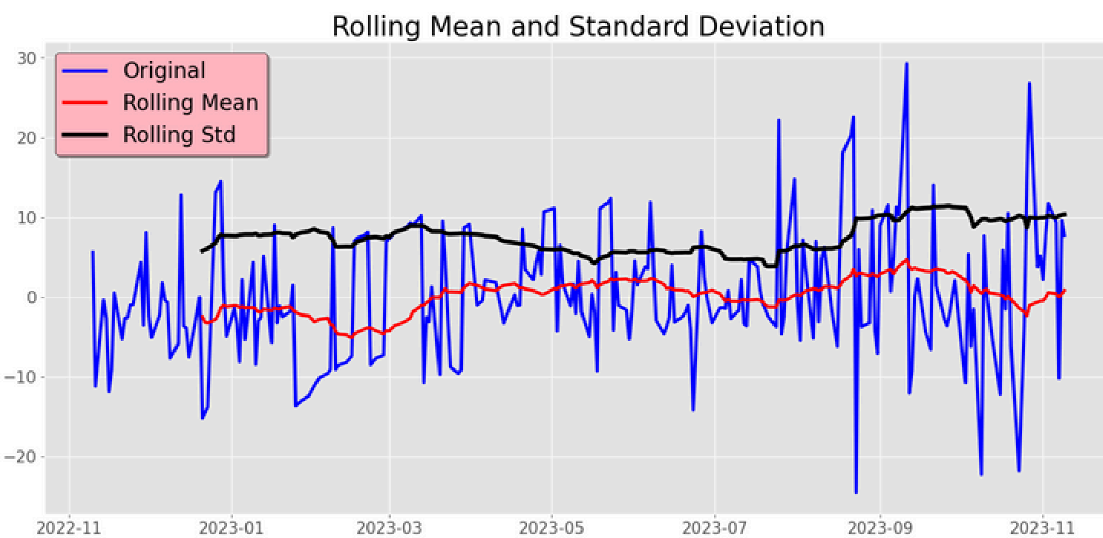
```
2022-11-14    359.79998
2022-11-15    8
2023-11-03    357.0499
2023-11-06    ...
2023-11-07    384.6499
2023-11-08    94
2023-11-09    394.0000
              00
              383.7999
              88
              393.39999
              4
              401.10000
              6
Name: Close, Length: 250, dtype: float64
```

[50]:
```python
df_close.diff(2)        ##chaningingvalues in  diff
```

[50]:
```
Date
2022-11-09          NaN
2022-11-10          NaN
2022-11-11    -5.599976
2022-11-14   -11.600006
2022-11-15    -3.150024
                 ...
2023-11-03    19.449982
2023-11-06    21.049988
2023-11-07    -0.850006
2023-11-08    -0.600006
2023-11-09    17.300018
Name: Close, Length: 250, dtype: float64
```

[51]:
```python
df_close = df_close.diff()
df_close = df_close.dropna()
```

[52]:
```python
# now passing df-close data into test-stationarity function
test_stationarity(df_close)
```



```
Results of dickey fuller test
TestStatistics                 -1.250145e+01
p-value                         2.800604e-23
No.oflags    used               0.000000e+00
Number of observations used     2.480000e+02
criticalvalue    (1%)          -3.456996e+00
criticalvalue    (5%)          -2.873266e+00
criticalvalue    (10%)         -2.573019e+00
dtype: float64
```

[53]:
```
# train test split our data
df_close[0:-40]     ##trainingdata
```

[53]:
```
Date
2022-11-10     5.600006
2022-11-11   -11.199982
2022-11-14    -0.400024
2022-11-15    -2.750000
2022-11-16   -11.899994
                ...
2023-09-05     0.700012
2023-09-06     5.099976
2023-09-07    11.250000
2023-09-08    10.350006
2023-09-11    29.250000
Name: Close, Length: 209, dtype: float64
```

[54]:
```
df_close[-40:]       ##testing data
```

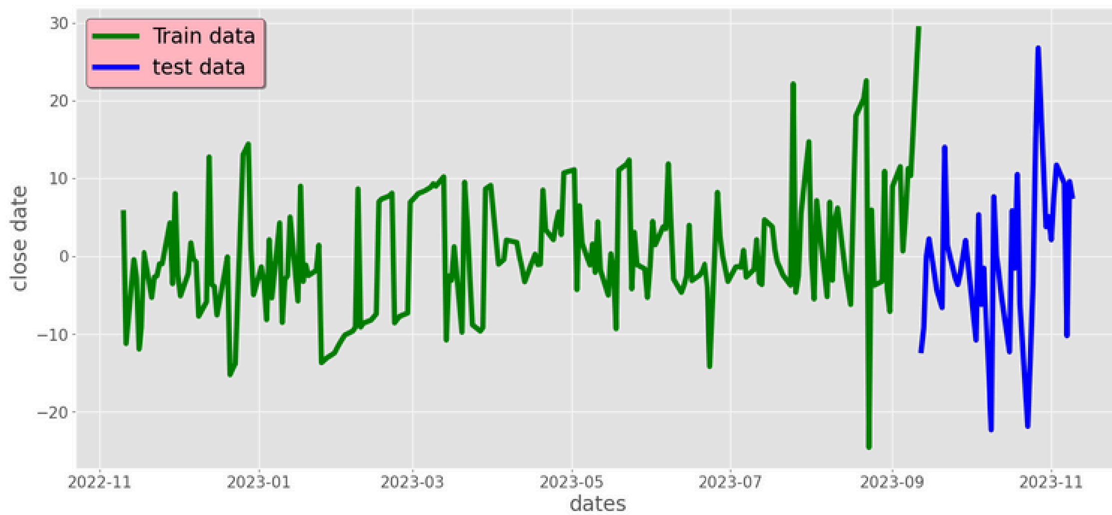
[54]:
```
Date
2023-09-12   -12.100006
2023-09-13    -9.199982
2023-09-14     0.049988
2023-09-15     2.250000
2023-09-18    -4.399994
2023-09-20    -6.600006
2023-09-21    14.050018
2023-09-22     1.449982
2023-09-25    -2.750000
2023-09-26    -3.649994
2023-09-27    -2.149994
2023-09-28     0.049988
2023-09-29     2.050018
2023-10-03   -10.750000
2023-10-04     5.349976
```

```
2023-10-05     -6.199982
2023-10-06     -1.550018
2023-10-09    -22.299988
2023-10-10      7.649994
2023-10-11      0.149994
2023-10-12     -2.549988
2023-10-13     -5.350006
2023-10-16    -12.250000
2023-10-17      5.850006
2023-10-18     -1.549988
2023-10-19     10.500000
2023-10-20     -6.150024
2023-10-23    -21.849976
2023-10-25     -3.750000
2023-10-26     14.649994
2023-10-27     26.799988
2023-10-30      3.800018
2023-10-31      5.099976
2023-11-01      2.150024
2023-11-02      7.750000
2023-11-03     11.699982
2023-11-06      9.350006
2023-11-07    -10.200012
2023-11-08      9.600006
2023-11-09      7.700012
Name: Close, dtype: float64
```

[55]:

```
##ploting the train test splited data into graph

# split data into train and testing data
train_data = df_close[0:-40]
test_data = df_close[-40:]
plt.figure(figsize= (18,8))
plt.grid(True)
plt.xlabel('dates', fontsize = 20 )
plt.ylabel('close date', fontsize = 20)
plt.xticks(fontsize = 15 )
plt.yticks(fontsize = 15 )
plt.plot(train_data, 'green', label = 'Train data', linewidth = 5)
plt.plot(test_data, 'blue', label = 'test data', linewidth = 5)
plt.legend(fontsize = 20, shadow = True, facecolor = 'lightpink', edgecolor = 'k')
```

[55]: <matplotlib.legend.Legend at 0x1e1e2485050>



[]:

15 ModelBuilding

[56]:
```
train_data= stock_data['Close'][0:-40]          ##traindata
test_data =stock_data['Close'][-40:]              ##testingdata
plt.figure(figsize=(18,8))   plt.grid(True)   plt.xlabel('Dates',   fontsize   =   20)
plt.ylabel('Closeing   Price',   fontsize   =   20)   plt.xticks(fontsize   =   15)
plt.yticks(fontsize   =   15)   plt.plot(train_data,  'green',   label   =  'train  data',
linewidth  =  5)  plt.plot(test_data,  'blue',  label  =  'test  data',  linewidth  =  5)
plt.legend(fontsize = 20, shadow = True, facecolor = 'lightpink', edgecolor =␣

↪'k')
```

[56]: <matplotlib.legend.Legend at 0x1e1e2dab9d0>

[57]:
```
stock_data['Close']
```

[57]:
```
Date
2022-11-09    365.799988
2022-11-10    371.399994
2022-11-11    360.200012
2022-11-14    359.799988
2022-11-15    357.049988
                 ...
2023-11-03    384.649994
2023-11-06    394.000000
2023-11-07    383.799988
2023-11-08    393.399994
2023-11-09    401.100006
Name: Close, Length: 250, dtype: float64
```

[58]:
```
249-40    ## 0-->209 == training data, 209-->249 == testing data
```

[58]: 209

[59]:
```
# importing the libraries
import statsmodels.api as sm
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error
```

[60]:
```
history = [x for x in train_data]
```

[61]:
```
# passing train data into the arima model
model = ARIMA(history, order= (1,1,1) )          ##p,d,q values ---> lags values
```

[62]:
```
model = model.fit()       ##fiting the model
```

[63]:
```
model.summary()
```

[63]:

Dep.Variable:	y	No.Observations:	210
Model:	ARIMA(1,1,1)	LogLikelihood AIC	-713.376
Date:	Thu,09Nov2023	BIC HQIC	1432.752
Time:	19:21:42		1442.779
Sample:	0		1436.806
CovarianceType:	-210		
	opg		

	coef	stderr	z	P>|z|	[0.025	0.975]
ar.L1	0.4868	0.168	2.893	0.004	45.621	62.276
sigma2	53.9485	4.249	12.697	0.000		

Ljung-Box(L1)(Q):	0.00	Jarque-Bera(JB):	26.51
Prob(Q):	0.98	Prob(JB):	0.00
Heteroskedasticity(H):	1.48	Skew:	0.16
Prob(H)(two-sided):	0.10	Kurtosis:	4.71

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

[]:

16 NowwewanttopredictOrForecastthenextvalue

[64]:
```
model.forecast()
```

[64]: array([407.18606043])

[65]:
```
# geting the MSE value
mean_squared_error([test_data[0]], model.forecast())
```

[65]: 436.22802153554466

[66]:
```
## geting the RMSE value
np.sqrt(mean_squared_error([test_data[0]], model.forecast()))
```

[66]: 20.886072429625074

[]:

[67]:
```
def train_arima_model(X, y, arima_order):
    history = [x for x in X]        ## prepare training dataset
    predictions= list()          ##makepredictionlist
```

```
    for t in range(len(y)):
        model = ARIMA(history, order= arima_order)
        model_fit = model.fit()
        yhat  =model_fit.forecast()[0]
        predictions.append(yhat)
        history.append(y[t])

    # calculate out of sample error
    rmse = np.sqrt(mean_squared_error(y, predictions))
    return rmse
```

[68]:
```
##evaluate different combinations of p,d,q values for an ARIMA model to get
↪thebestorderforARIMAmodel

defevaluate_models(dataset,test,p_values,d_values,q_values):
    dataset = dataset.astype('float32')
    best_score, best_cfg = float('inf'), None

    for p in p_values:
        for d in d_values:
            for q in q_values:
                order = (p,d,q)
                try:
                    rmse = train_arima_model(dataset, test, order)
                    if rmse < best_score:
                        best_score, best_cfg = rmse, order
                    print('ARIMA%s RMSE= %.3f'%(order, rmse))
                except:
                    continue
    print('Best ARIMA%s RMSE= %.3f'%(best_cfg, best_score))
```

[ ]:
```
import warnings
warnings.filterwarnings('ignore')
p_values = range(0,3)
d_values = range(0,3)
q_values = range(0,3)

evaluate_models(train_data, test_data, p_values, d_values, q_values)
```

```
ARIMA(0, 0, 0) RMSE= 100.786
ARIMA(0, 0, 1) RMSE= 52.635
ARIMA(0, 0, 2) RMSE= 44.402
ARIMA(0, 1, 0) RMSE= 9.550
ARIMA(0, 1, 1) RMSE= 9.727
ARIMA(0, 1, 2) RMSE= 9.878
ARIMA(0, 2, 0) RMSE= 13.903
```

ARIMA(0, 2, 1) RMSE= 10.235 ARIMA(0, 2, 2) RMSE= 10.088 ARIMA(1, 0, 0) RMSE= 9.548 ARIMA(1, 0, 1) RMSE= 9.720 ARIMA(1, 0, 2) RMSE= 9.872 ARIMA(1, 1, 0) RMSE= 9.869 ARIMA(1, 1, 1) RMSE= 9.950 ARIMA(1, 1, 2) RMSE= 9.952 ARIMA(1, 2, 0) RMSE= 12.823 ARIMA(1, 2, 1) RMSE= 10.118 ARIMA(1, 2, 2) RMSE= 10.140 ARIMA(2, 0, 0) RMSE= 9.864 ARIMA(2, 0, 1) RMSE= 9.952

[ ]:
```
#now with best arima values create our final model

history = [x for x in train_data]
predictions = list()
conf_list = list()
for t in range(len(test_data)):
    model = ARIMA(history,order=(1,0,0))
    model_fit = model.fit()
    fc = model_fit.forecast(alpha = 0.05)
    predictions.append(fc)
    history.append(test_data[t])
print('RMSE of ARIMA Model:', np.sqrt(mean_squared_error(test_data,
 predictions)))
```

17 Observation:

- For our model the best ARIMA Value is == **(1,0,0)**
- **RMSE of ARIMA** Model = **9.547**

[]:

[ ]:
```
## now ploting the predicted data

plt.figure(figsize=(18,8))
plt.grid(True)
plt.plot(range(len(test_data)),test_data, label = 'True Test Close Value',
 linewidth=5)
plt.plot(range(len(predictions)),predictions,label='Predictionsontest
 data',linewidth=5)
plt.xticks(fontsize=15)
plt.xticks(fontsize = 15)
plt.legend(fontsize = 20, shadow=True,facecolor='lightpink',edgecolor = 'k')
plt.show()
```

[]:

```
[ ]: # Now converted forecast values into series
fc_series = pd.Series(predictions, index= test_data.index)
```

18 Nowplotthefc-series

```
[ ]: plt.figure(figsize=(12,5), dpi=100)
plt.plot(train_data, label='Training', color = 'blue')
plt.plot(test_data, label='Test', color = 'green', linewidth = 3)
plt.plot(fc_series, label='Forecast', color = 'red')
plt.title('Forecast vs Actuals on test data')
plt.legend(loc='upper left', fontsize=8)
plt.show()
```

```
[ ]: # now plotting forecast the future calues in the plot
from statsmodels.graphics.tsaplots import plot_predict
fig = plt.figure(figsize=(18,8))
ax1 = fig.add_subplot(111)
plot_predict(result=model_fit,start=1, end=len(df_close)+60, ax = ax1)
plt.grid("both")
plt.legend(['Forecast','Close','95% confidence interval'],fontsize = 20,␣
↪shadow=True,facecolor='lightblue',edgecolor='k')

plt.show()
```

```
[ ]: # Let's check with SARIMA Model also

## evaluate parameters for sarimax
import warnings
warnings.filterwarnings('ignore')

history = [x for x in train_data]
predictions = list()
conf_list = list()
for t in range(len(test_data)):
    model = sm.tsa.statespace.SARIMAX(history, order = (0,1,0), seasonal_order␣
↪=(1,1,1,3))

    model_fit=model.fit()
    fc = model_fit.forecast()
    predictions.append(fc)
    history.append(test_data[t])
print('RMSE of SARIMA Model:', np.sqrt(mean_squared_error(test_data,␣
↪predictions)))
```

[ ]:
```
plt.figure(figsize=(18,8))
plt.title('Forecast vs Actual', fontsize = 25)
plt.plot(range(40), predictions, label = 'Predictions', linewidth = 4)
plt.plot(range(40), test_data, label = 'Close', linewidth = 4)
plt.legend(fontsize = 25, shadow=True,facecolor='lightpink',edgecolor = 'k')
```

19 Observation:

- in this Adani Power Limited stock price data there is no need to apply or include sessional factor beacause our actual data in zik-zak.
- we make sure that our order of arima is should be in correct format.
- Here we forecaste the Close price for the next 60 days.

[]:

[]:

[]:

[]:

[]: