Tesla Stock Price Forecasting with Time Series Analysis

Let's Begin

Importing all the necessary libraries

In [289…
```
# import important libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
import sys
```

Importing dataset

In [290…
```
data=pd.read_csv("TSLA.csv")
```

In [291…
```
data.head()
```

Out[291…

	Date	Open	High	Low	Close	Volume	Dividends	St Sp
0	2019-05-21	39.551998	41.480000	39.208000	41.015999	90019500	0	
1	2019-05-22	39.820000	40.787998	38.355999	38.546001	93426000	0	
2	2019-05-23	38.868000	39.894001	37.243999	39.098000	132735500	0	
3	2019-05-24	39.966000	39.995998	37.750000	38.125999	70683000	0	
4	2019-05-28	38.240002	39.000000	37.570000	37.740002	51564500	0	

In this project, we will perform a Univariate Time Series Analysis

In [292…
```
stock_data=data[["Date","Close"]]
```

In [293…
```
stock_data.head()
```

Out[293...

	Date	Close
0	2019-05-21	41.015999
1	2019-05-22	38.546001
2	2019-05-23	39.098000
3	2019-05-24	38.125999
4	2019-05-28	37.740002

Checking information of the data

In [294...
```
stock_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 758 entries, 0 to 757
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Date    758 non-null    object 
 1   Close   758 non-null    float64
dtypes: float64(1), object(1)
memory usage: 12.0+ KB
```

Convert ‘Date’ feature into Date time data type using pandas

In [295...
```
stock_data["Date"]=pd.to_datetime(stock_data["Date"])
```

In [296...
```
stock_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 758 entries, 0 to 757
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype         
---  ------  --------------  -----         
 0   Date    758 non-null    datetime64[ns]
 1   Close   758 non-null    float64       
dtypes: datetime64[ns](1), float64(1)
memory usage: 12.0 KB
```

Convert Date Column as Index Column

In [298...
```
stock_data=stock_data.set_index("Date")
```

In [353...
```
stock_data.head()
```

Out[353…

	Close
Date	
2019-05-21	41.015999
2019-05-22	38.546001
2019-05-23	39.098000
2019-05-24	38.125999
2019-05-28	37.740002

Exploratory Data Analysis(EDA)

Statistical Description

In [301…

```
stock_data.describe()
```

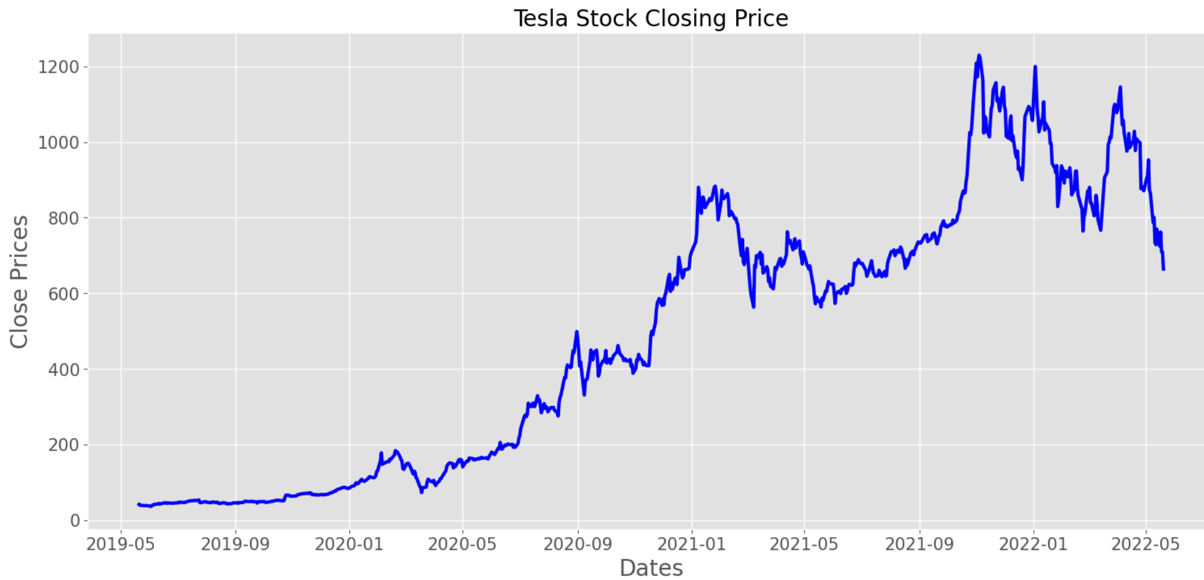
Out[301…

	Close
count	758.000000
mean	485.531513
std	353.160353
min	35.793999
25%	112.323500
50%	488.125000
75%	762.142502
max	1229.910034

Visualizing Trends for Closing Price

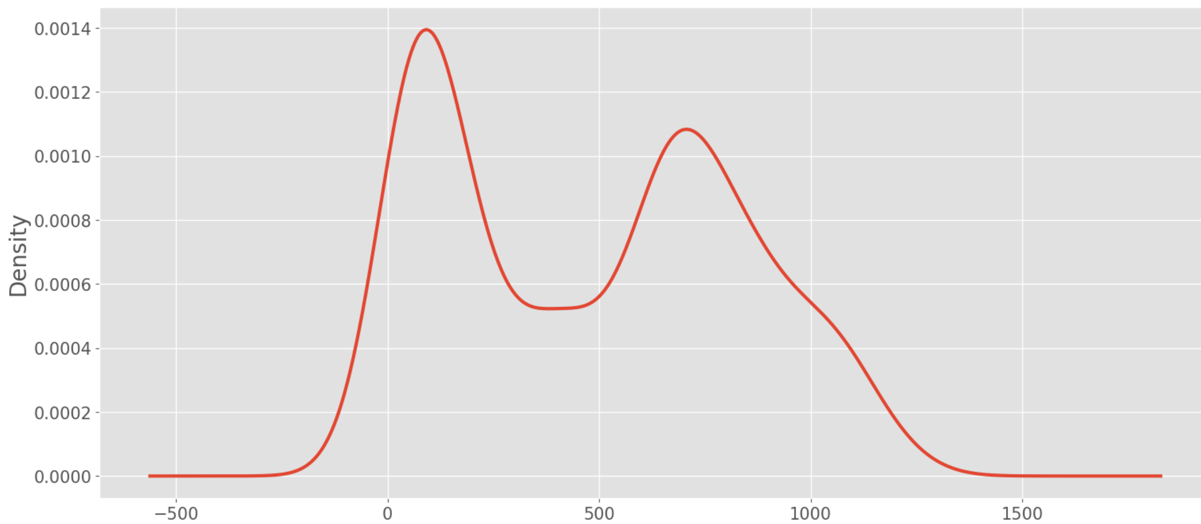
In [355…

```
# 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.plot(stock_data['Close'], linewidth = 3, color = 'blue')
plt.title('Tesla Stock Closing Price', fontsize = 20)
plt.show()
```



In [306…

```
# 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()
```



Identifying if Time Series Data is Stationary or Non-Stationary by testing Visualization based test and Statistics based test

Using Visualization Test

In [307…

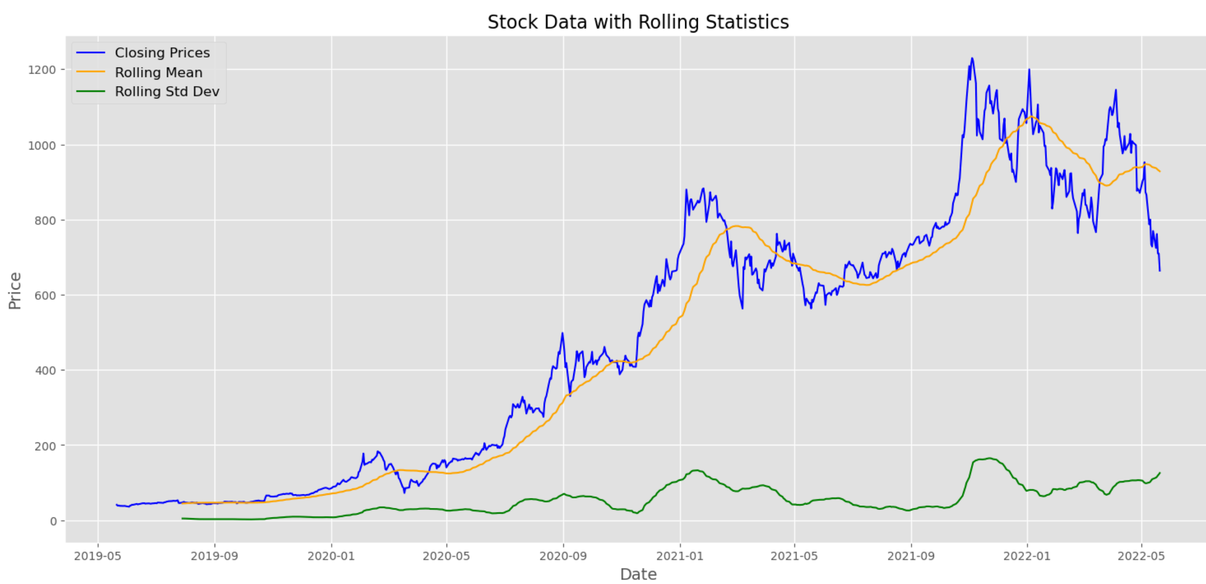
```
# Moving Average
rolmean=stock_data["Close"].rolling(48).mean()
```

In [308…

```
rolstd=stock_data["Close"].rolling(48).std()
```

In [ ]:

```
plt.figure(figsize=(18, 8))

# Plot the closing prices
plt.plot(stock_data.Close, label='Closing Prices', color='blue')

# Plot the rolling mean
plt.plot(rolmean, label='Rolling Mean', color='orange')

# Plot the rolling standard deviation
plt.plot(rolstd, label='Rolling Std Dev', color='green')

# Add title and labels
plt.title('Stock Data with Rolling Statistics', fontsize=16)
plt.xlabel('Date', fontsize=14)
plt.ylabel('Price', fontsize=14)

# Add legend for clarity
plt.legend(loc='best', fontsize=12)

# Display the plot
plt.show()
```



ADF(Augmented Decay-Fuller Test)

In [310…

```
#ADF(ada fullar test)
from statsmodels.tsa.stattools import adfuller
adft=adfuller(stock_data["Close"])
```

In [311…

```
pd.Series(adft[0:4],index=["test stats","p-value","lag","data points"])
```

Out[311…

```
test stats       -1.363009
p-value           0.599876
lag               9.000000
data points     748.000000
dtype: float64
```

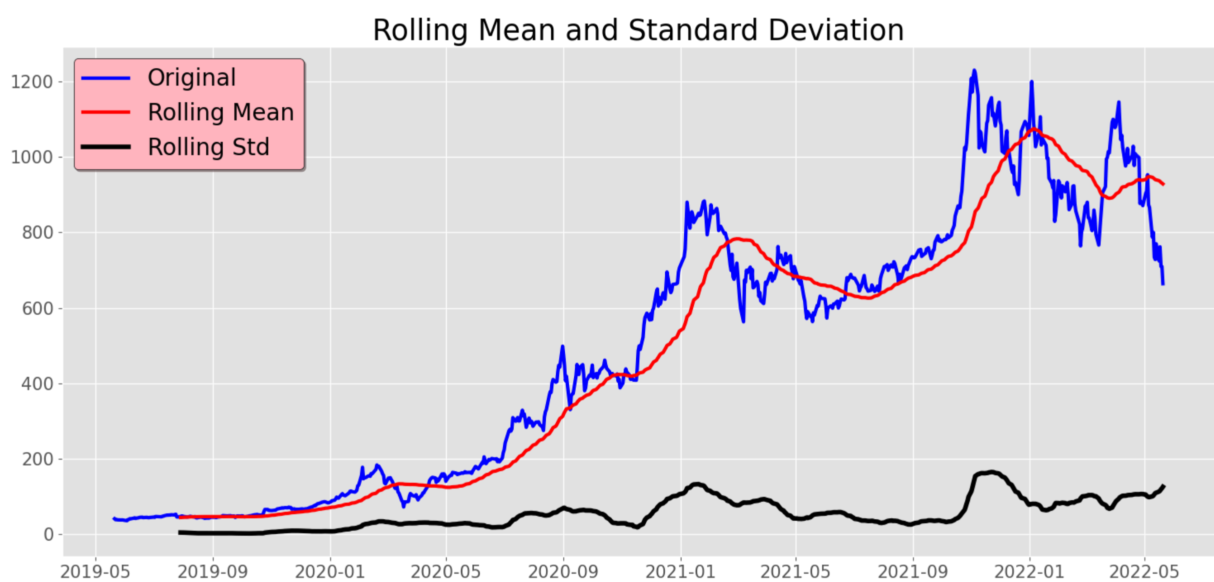
- The most important value is P-Value

In [312…

```
#Test for staionarity
def test_stationarity(timeseries):
    # Determing rolling statistics
    rolmean = timeseries.rolling(48).mean() # rolling mean
    rolstd = timeseries.rolling(48).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',
    plt.title('Rolling Mean and Standard Deviation', 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
    for key,values in adft[4].items():
        output['critical value (%s)'%key] =  values
    print(output)
```

In [313…

```
test_stationarity(stock_data.Close)
```



```
Results of dickey fuller test
Test Statistics                 -1.363009
p-value                          0.599876
No. of lags used                 9.000000
Number of observations used    748.000000
critical value (1%)             -3.439123
critical value (5%)             -2.865412
critical value (10%)            -2.568832
dtype: float64
```

- From Visualization based test, we can see:

1. Data is following Upward trend
2. Moving Average is not constant

- From ADF test, we can see p value is greater than 0.5

Hence, Time Series data is Non-Stationary and we will accept the null hypothesis

Time Series Decomposition

In [314…

```python
from statsmodels.tsa.seasonal import seasonal_decompose
result=seasonal_decompose(stock_data[["Close"]],period=12)
```

In [315…

```python
result.seasonal
```

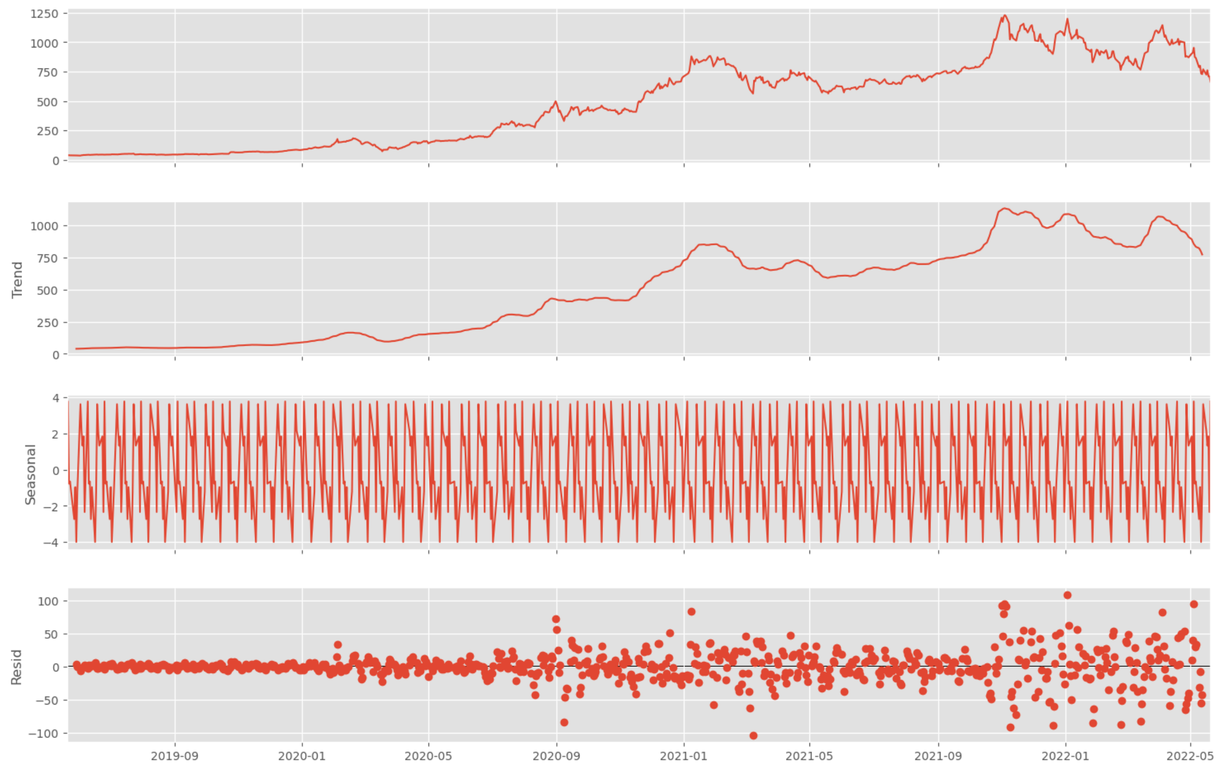
Out[315…

```
Date
2019-05-21   -2.346452
2019-05-22    3.768884
2019-05-23   -0.777006
2019-05-24   -0.654226
2019-05-28   -2.737845
                ...
2022-05-16    2.149519
2022-05-17    1.323680
2022-05-18    1.837638
2022-05-19   -2.346452
2022-05-20    3.768884
Name: seasonal, Length: 758, dtype: float64
```

In [363…

```python
# Additive
from statsmodels.tsa.seasonal import seasonal_decompose
result=seasonal_decompose(stock_data[["Close"]],period=12,model="additive")

fig=plt.figure(figsize=(20,10))
fig=result.plot()
fig.set_size_inches(17,10)
```

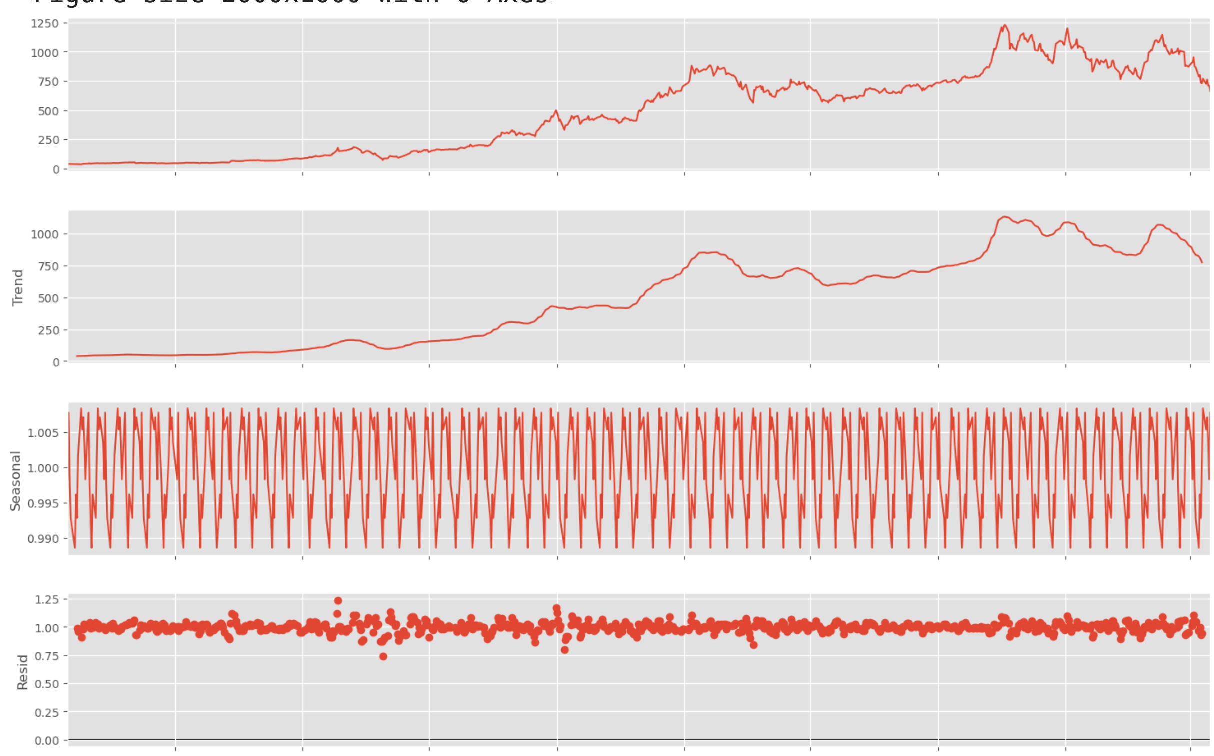
```
<Figure size 2000x1000 with 0 Axes>
```



In [364…

```
# Multiplicative
from statsmodels.tsa.seasonal import seasonal_decompose
result=seasonal_decompose(stock_data[["Close"]],period=12,model="multiplicat

fig=plt.figure(figsize=(20,10))
fig=result.plot()
fig.set_size_inches(17,10)
```

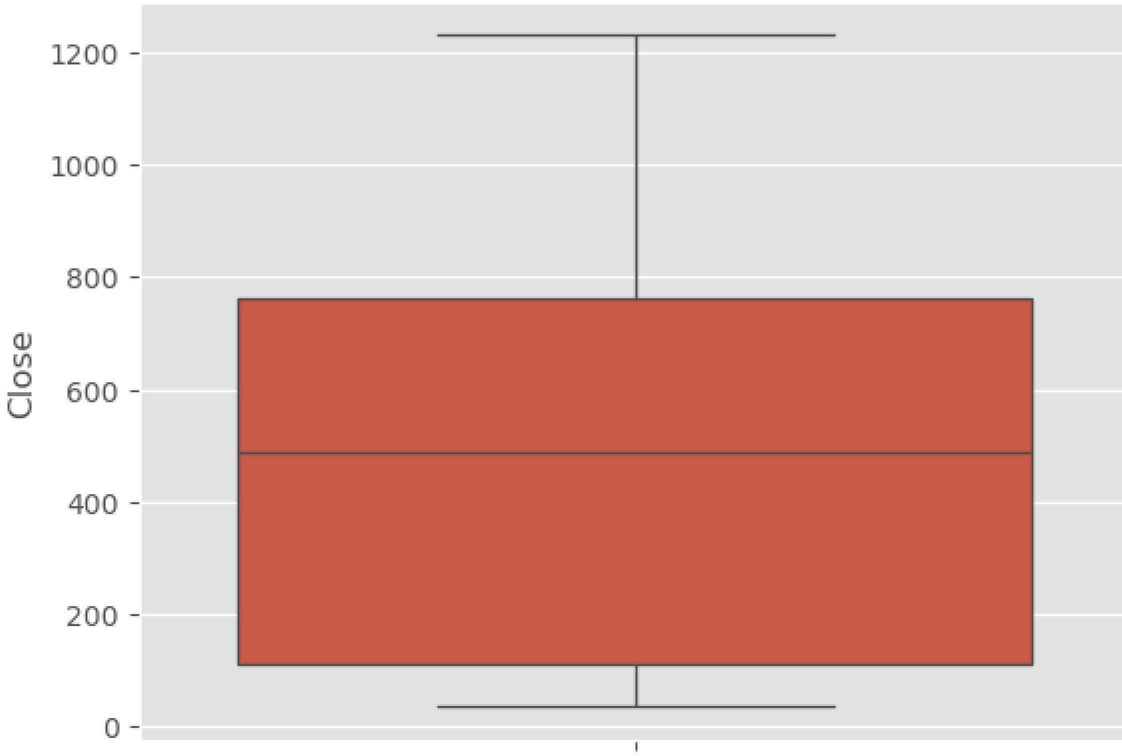
```
<Figure size 2000x1000 with 0 Axes>
```



Checking for outliers

In [319…
```
# Checking for Outliers
import seaborn as sns
sns.boxplot(stock_data.Close)
```

Out[319…
```
<Axes: ylabel='Close'>
```

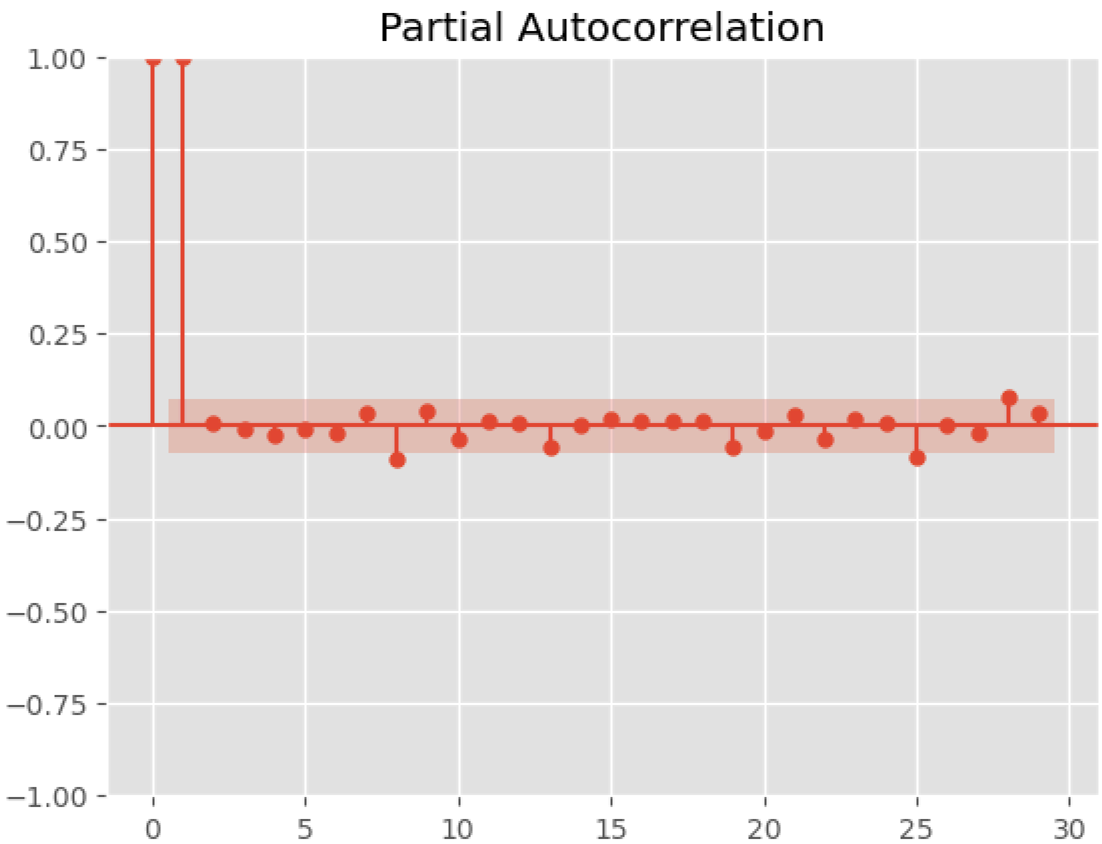


- Data has no outliers

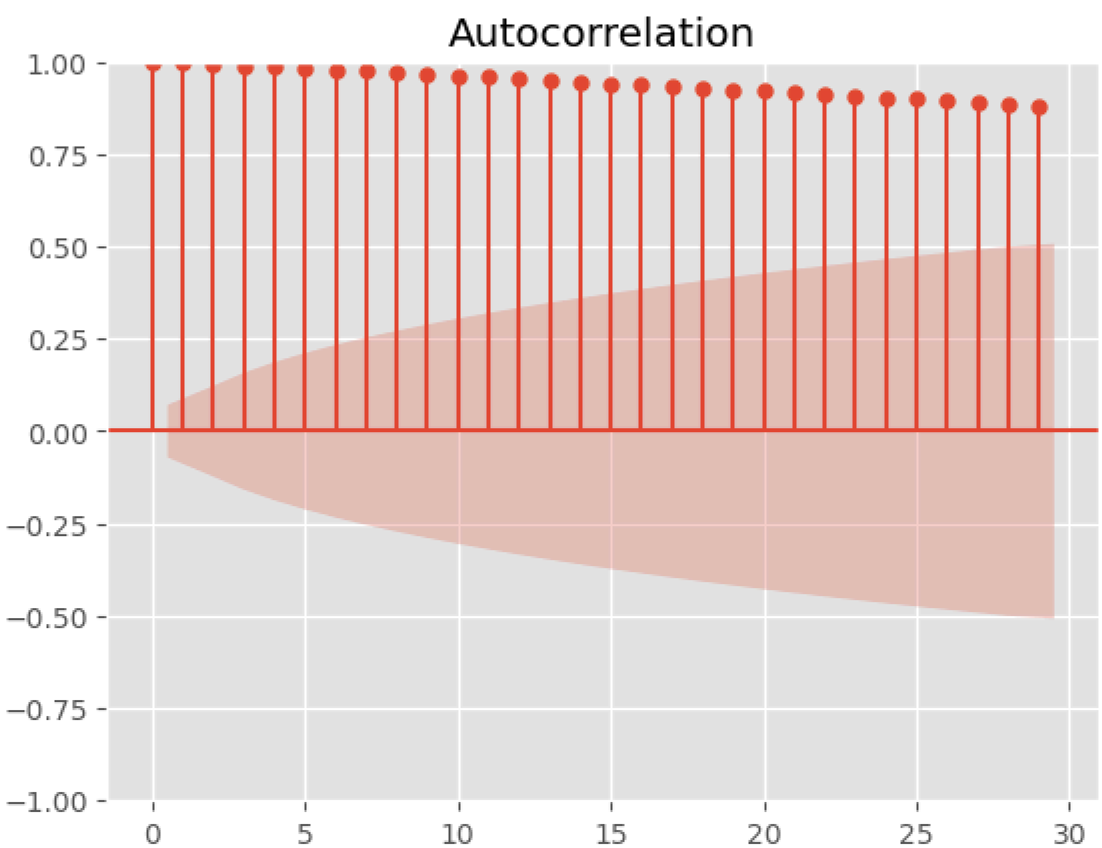
ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) are statistical tools used in time series analysis to identify relationships between observations in a time series dataset.

In [365…
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
plot_acf(stock_data.Close)
plot_pacf(stock_data.Close)
```

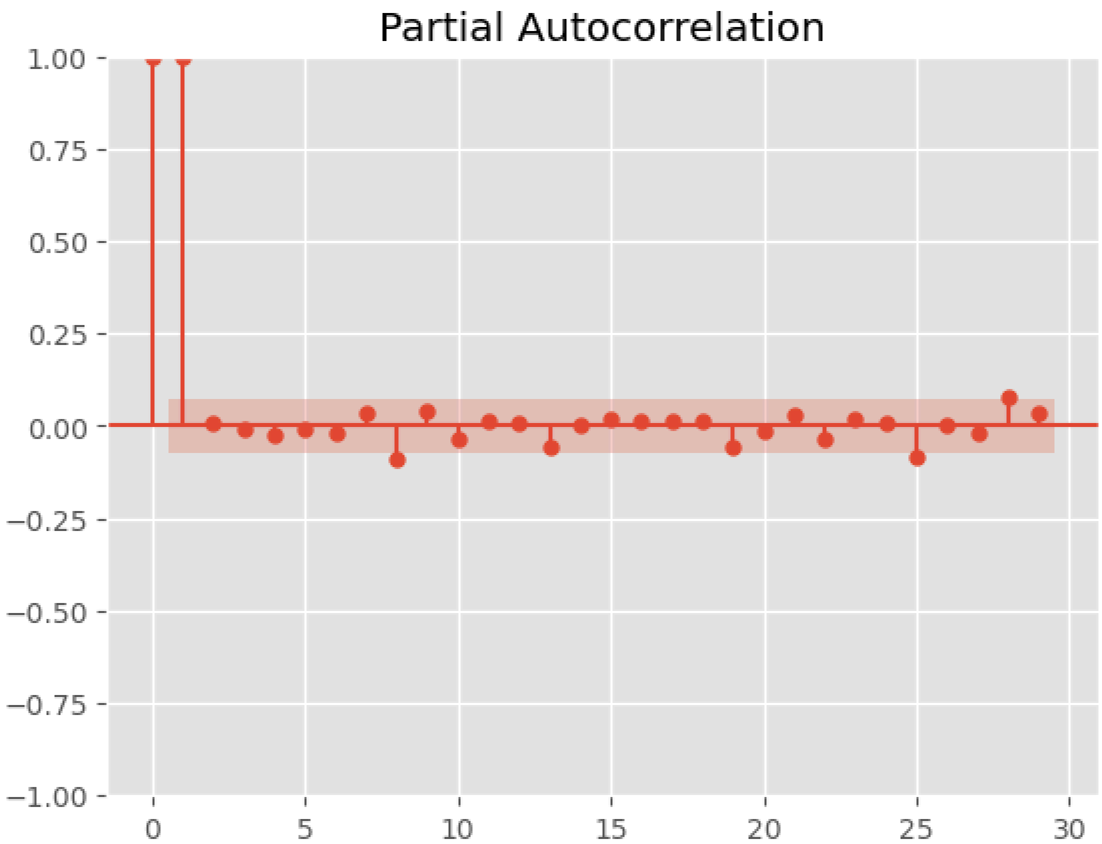
Out[365…



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
30



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
30

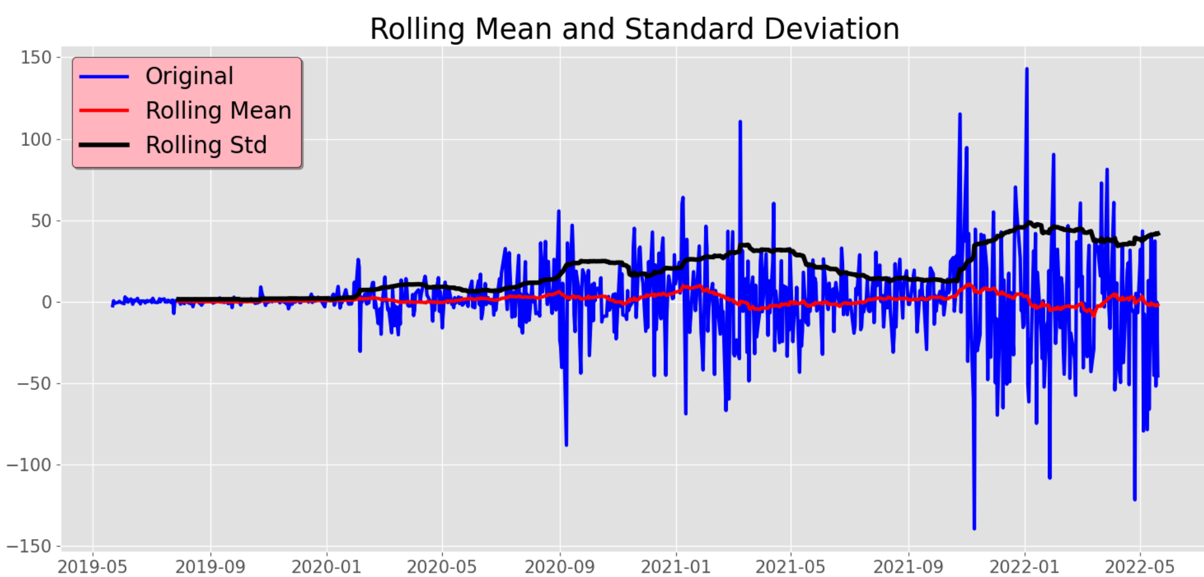


Data Transformation

Converting Non-Stationary data into stationary data

In [322…
```
df_close = df_close.diff()
df_close=df_close.dropna()
```

In [323…
```
test_stationarity(df_close)
```



```
Results of dickey fuller test
Test Statistics                  -8.324564e+00
p-value                           3.498786e-13
No. of lags used                  8.000000e+00
Number of observations used       7.480000e+02
critical value (1%)              -3.439123e+00
critical value (5%)              -2.865412e+00
critical value (10%)             -2.568832e+00
dtype: float64
```

- Now our data is stationary.
- Hence, will reject the null hypothesis

Model Building

In [326…

```
## Splitting data into training and testing dataset

train_data = df_close[0:-60]
test_data  = df_close[-60:]
plt.figure(figsize=(18,8))
plt.grid(True)
plt.xlabel('Dates', fontsize=20)
plt.ylabel('Closing Prices', fontsize=20)
plt.xticks(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')
```

Out[326…

```
<matplotlib.legend.Legend at 0x1dbd2ec73b0>
```

Applying ARIMA Model on the Time Series

In [327…

```
import statsmodels.api as sm
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

In [328…
```
history=[x for x in train_data]
```

In [329…
```
model=ARIMA(history,order=(1,1,1))
```

In [330…
```
model=model.fit()
```

In [331…
```
model.summary()
```

Out[331…

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	698
Model:	ARIMA(1, 1, 1)	**Log Likelihood**	-3150.350
Date:	Sun, 15 Dec 2024	**AIC**	6306.700
Time:	19:26:27	**BIC**	6320.340
Sample:	0	**HQIC**	6311.974
	- 698		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.2397	0.699	0.343	0.731	-1.129	1.609
ma.L1	-0.2713	0.690	-0.393	0.694	-1.623	1.080
sigma2	493.6767	11.690	42.231	0.000	470.765	516.588

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	2111.30
Prob(Q):	0.98	**Prob(JB):**	0.00
Heteroskedasticity (H):	31.69	**Skew:**	0.09
Prob(H) (two-sided):	0.00	**Kurtosis:**	11.52

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

In [332…
```
model.forecast()[0]
```

Out[332…
```
800.2043838663046
```

In [333…
```
test_data[0]
```

Out[333…
```
809.8699951171875
```

In [334…
```
mean_squared_error([test_data[0]],model.forecast())
```

Out[334… 93.42404085319363

In [335…
```
np.sqrt(mean_squared_error([test_data[0]],model.forecast()))
```

Out[335… 9.665611250882876

In [336…
```
def train_arima_model(X, y, arima_order):
    # prepare training dataset
    # make predictions list
    history = [x for x in X]
    predictions = list()
    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
```

In [337…
```
def evaluate_models(data, test, p_values, d_values, q_values):
    data = data.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(data, 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))
```

In [338…
```
# evaluate parameters
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=457.414
ARIMA(0, 0, 1) RMSE=241.164
ARIMA(0, 0, 2) RMSE=161.913
ARIMA(0, 1, 0) RMSE=39.516
ARIMA(0, 1, 1) RMSE=39.482
ARIMA(0, 1, 2) RMSE=39.617
ARIMA(0, 2, 0) RMSE=57.835
ARIMA(0, 2, 1) RMSE=39.611
ARIMA(0, 2, 2) RMSE=39.580
ARIMA(1, 0, 0) RMSE=39.477
ARIMA(1, 0, 1) RMSE=39.449
ARIMA(1, 0, 2) RMSE=39.584
ARIMA(1, 1, 0) RMSE=39.475
ARIMA(1, 1, 1) RMSE=39.555
ARIMA(1, 1, 2) RMSE=39.935
ARIMA(1, 2, 0) RMSE=46.184
ARIMA(1, 2, 1) RMSE=39.573
ARIMA(1, 2, 2) RMSE=39.731
ARIMA(2, 0, 0) RMSE=39.440
ARIMA(2, 0, 1) RMSE=39.494
ARIMA(2, 0, 2) RMSE=39.598
ARIMA(2, 1, 0) RMSE=39.635
ARIMA(2, 1, 1) RMSE=39.759
ARIMA(2, 1, 2) RMSE=39.658
ARIMA(2, 2, 0) RMSE=45.781
ARIMA(2, 2, 1) RMSE=39.739
ARIMA(2, 2, 2) RMSE=39.733
Best ARIMA(2, 0, 0) RMSE=39.440
```

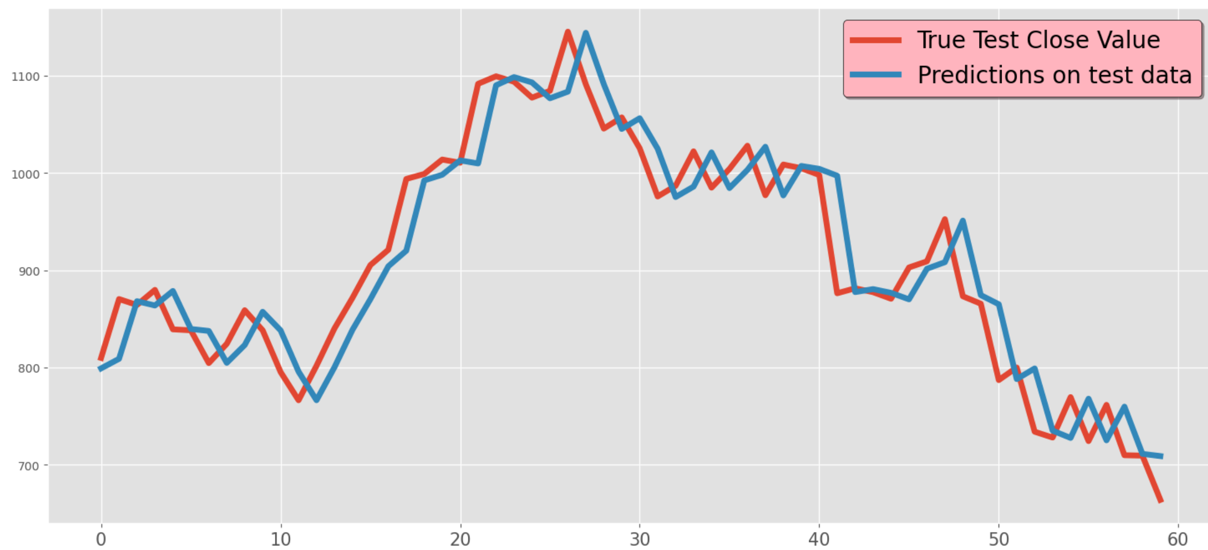
In [346…

```
history = [x for x in train_data]
predictions = list()
conf_list = list()
for t in range(len(test_data)):
    model = ARIMA(history,order=(2,0,0))
    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, predicti
```

```
RMSE of ARIMA Model: 39.43995729937915
```

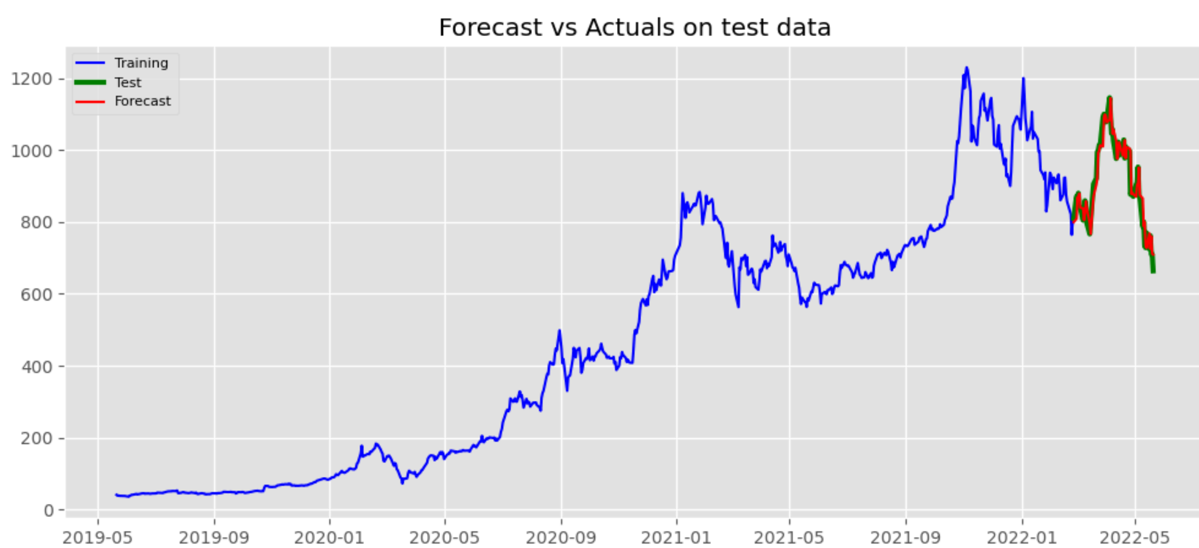
In [347…

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

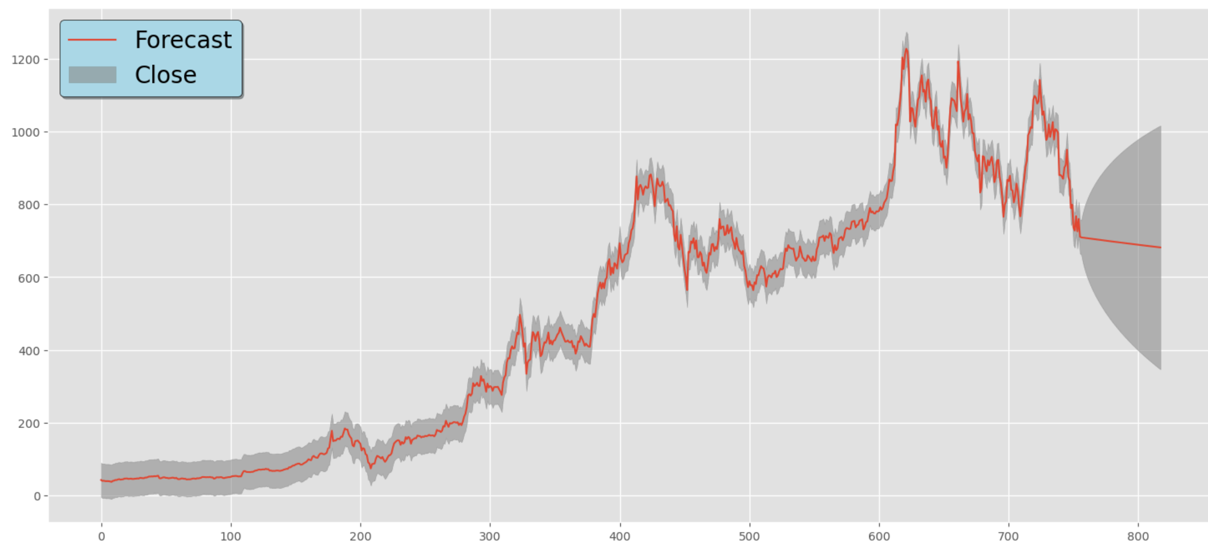


In [348…
```python
fc_series = pd.Series(predictions, index=test_data.index)
```

In [349…
```python
# Plot
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()
```



In [350…
```python
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, sha
plt.show()
```



Applying SARIMA Model on the Time Series

In [351…

```
# evaluate parameters
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_orc
    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, predict
```

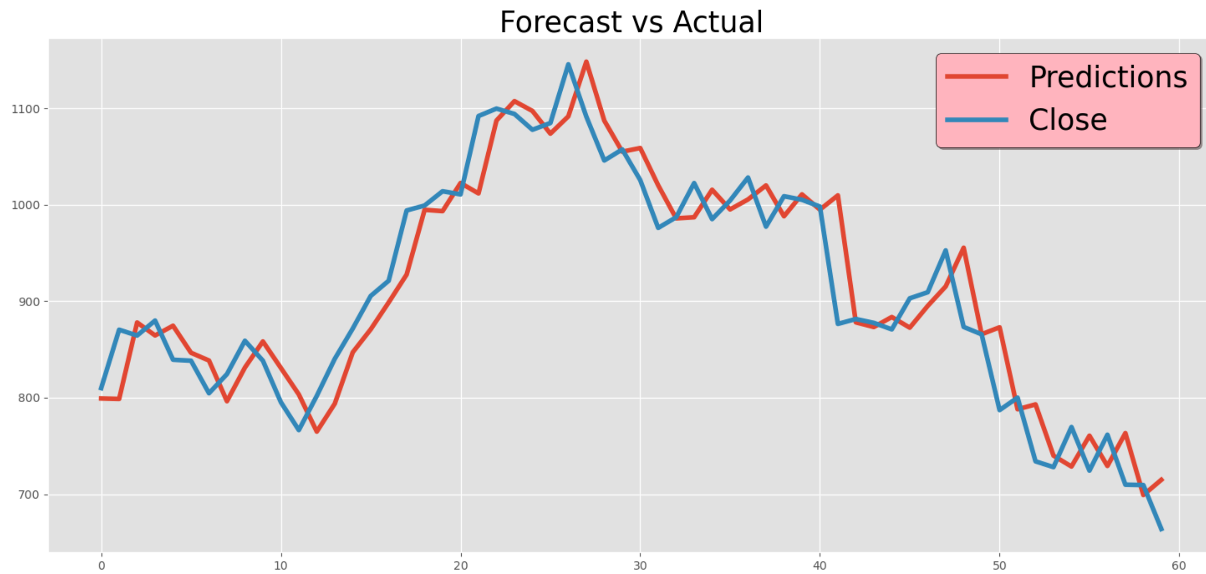
```
RMSE of SARIMA Model: 39.739481948001675
```

In [352…

```
plt.figure(figsize=(18,8))
plt.title('Forecast vs Actual', fontsize = 25)
plt.plot(range(60), predictions, label = 'Predictions', linewidth = 4)
plt.plot(range(60), test_data, label = 'Close', linewidth = 4)
plt.legend(fontsize = 25, shadow=True,facecolor='lightpink',edgecolor = 'k')
```

Out[352…

```
<matplotlib.legend.Legend at 0x1dbd2b738f0>
```



In [ ]:

This notebook was converted with convert.ploomber.io

Kshitija Chilbule