Tesla_GayathriGopalan

September 18, 2021

1 Forecasting of Tesla Stock Prices (TSLA) using Time Series (ARIMA) model and Predictive Analysis of Tesla Stock Prices using Neural Networks (LSTM RNN)- Financial Analysis and Visualization

We are going to apply a fundamental time series modelling technique to Tesla's stock price using Python.We calculate the hit rate after building the model and applying to the test data. In order to improve the accurracy and predictive efficiency of the model, we are going to incorporate the rolling window concept- Moving average (MA) to it and build the model. We perform Feature engineering in order to formulate useful features from existing data following the target to be learned and the machine learning model used. (It involves transforming data to forms that better relate to the underlying target to be learned.)

What is TIME SERIES- ARIMA model?

Auto Regressive Integrated Moving Average model An ARIMA model is a class of statistical models for analyzing and forecasting time series data.

Selling shoes- we want to predict how many are sold next -Time vs sold- we notice a trend- but a time series needs to have a constant mean overtime Mean is shifting upwards We use in situations where there is a moving avg/mean. I stands for Integrated

We are going to calculate difference betweenn 2 timestamps- we create a new time series Z(t)= a(t+1)- a(t). (To go from one point of linear function to next we keep adding a constant) Now Time series is no longer stationary- ARIMA(p,d,q): p- AR, q- MA, d- integrated part (difference) We need a(k)- no of shoes sold in that time

https://machinelearningmastery.com/arima-for-time-series-forecasting-with-python/

What is LSTM RNN model?

https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Table of Contents

Preliminary analysis:

Exploring the dataset

Visualizations (Graphs)

Rolling mean/moving window (smoothen curve & reduce outliers)

Summary

Building a trading strategy:

Calculating profit

Analysing income

Calculating the risk of price drop

Building the model- Data Wrangling/ Data muging

Deciding the model technique to be bulit

Splitting data - Testing and traing dataset

Scatter plot matrix

Forming ARIMA model

Running ARIMA model on Training data

Plot residuals (Actual – Fitted)

Fit model to the test data

Conclusion

2 Preliminary Analysis

1. Lets look into the metadata of the dataset & understand:

- `date` - Date of the stock
- `#open`- Opening price of the stock in the market that day
- `#high`- Highest price of the stock in the market that day
- `#low`- Lowest price of the stock in the market that day
- `#close`- The closing price is the raw price, which is just the cash value of the last transacted price before the market closes.
- `#Adj Close`- Adjusted closing price, taking splits etc into account The adjusted closing price amends a stock's closing price to reflect that stock's value after accounting for any corporate actions. It is often used when examining historical returns or doing a detailed analysis of past performance.

Adjusting Prices for Stock Splits A stock split is a corporate action intended to make the firm's shares more affordable for average investors. A stock split does not change a company's total market capitalization, but it does affect the company's stock price.

For example, a company's board of directors may decide to split the company's stock 3-for-1. Therefore, the company's shares outstanding increase by a multiple of three, while its share price is divided by three. Suppose a stock closed at 300 the day before its stock split. In this case, the closing price is adjusted to $100 ($300 divided by 3) per share to maintain a consistent standard of comparison. Similarly, all other previous closing prices for that company would be divided by three to obtain the adjusted closing prices.

- `#Volume`- Trading volume

2.1 2. Importing Libraries

[ ]:
```
pip install pandas_datareader
```

[ ]:
```
pip install keras
```

[ ]:
```
pip install tensorflow
```

[ ]:
```
pip install pmdarima
```

[161]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from pmdarima import ARIMA
from matplotlib.dates import DateFormatter
from pandas_datareader import data
import statsmodels.api as sm
from pylab import rcParams
from pmdarima import auto_arima
from pandas import read_csv
import itertools
%matplotlib inline
plt.style.use('fivethirtyeight')
import math
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error

import warnings
import numpy
warnings.filterwarnings("ignore")
from statsmodels.tsa.arima_model import ARIMA
```

2.2 3. Exploring the dataset

First, we need to import the data. We download the dataset from https://www.kaggle.com/timoboz/tesla-stock-data-from-2010-to-2020. We are going to use close price for analysis

[47]:
```
# df= pd.read_csv('/Users/Gaya/Dropbox/My Mac (Gayas-MacBook-Pro.local)/
↪Downloads/TSLA.csv')
df = pd.read_csv('TSLA.csv')
print(df.head())
```

```
         Date       Open   High        Low      Close  Adj Close    Volume
0  2010-06-29  19.000000  25.00  17.540001  23.889999  23.889999  18766300
1  2010-06-30  25.790001  30.42  23.299999  23.830000  23.830000  17187100
```

```
2   2010-07-01   25.000000   25.92   20.270000   21.959999   21.959999    8218800
3   2010-07-02   23.000000   23.10   18.709999   19.200001   19.200001    5139800
4   2010-07-06   20.000000   20.00   15.830000   16.110001   16.110001    6866900
```

[48]:
```
df.tail(3)
```

[48]:
```
            Date        Open        High        Low       Close   Adj Close  \
2413  2020-01-30  632.419983  650.880005  618.00000  640.809998  640.809998
2414  2020-01-31  640.000000  653.000000  632.52002  650.570007  650.570007
2415  2020-02-03  673.690002  786.140015  673.52002  780.000000  780.000000

        Volume
2413  29005700
2414  15719300
2415  47065000
```

2.3 4. Dealing with missing values

Let us look into the standard deviation of the dataset we currently have

[49]:
```
df.shape
```

[49]:
```
(2416, 7)
```

[50]:
```
df.describe()
```

[50]:
```
              Open         High          Low        Close    Adj Close  \
count  2416.000000  2416.000000  2416.000000  2416.000000  2416.000000
mean    186.271147   189.578224   182.916639   186.403651   186.403651
std     118.740163   120.892329   116.857591   119.136020   119.136020
min      16.139999    16.629999    14.980000    15.800000    15.800000
25%      34.342498    34.897501    33.587501    34.400002    34.400002
50%     213.035004   216.745002   208.870002   212.960007   212.960007
75%     266.450012   270.927513   262.102501   266.774994   266.774994
max     673.690002   786.140015   673.520020   780.000000   780.000000

             Volume
count  2.416000e+03
mean   5.572722e+06
std    4.987809e+06
min    1.185000e+05
25%    1.899275e+06
50%    4.578400e+06
75%    7.361150e+06
max    4.706500e+07
```

[51]:
```
# dropna- Removes missing values
df2= df.dropna()
```

[52]:
```python
df2.describe()
```

[52]:
```
              Open         High          Low        Close    Adj Close  \
count  2416.000000  2416.000000  2416.000000  2416.000000  2416.000000
mean    186.271147   189.578224   182.916639   186.403651   186.403651
std     118.740163   120.892329   116.857591   119.136020   119.136020
min      16.139999    16.629999    14.980000    15.800000    15.800000
25%      34.342498    34.897501    33.587501    34.400002    34.400002
50%     213.035004   216.745002   208.870002   212.960007   212.960007
75%     266.450012   270.927513   262.102501   266.774994   266.774994
max     673.690002   786.140015   673.520020   780.000000   780.000000

             Volume
count  2.416000e+03
mean   5.572722e+06
std    4.987809e+06
min    1.185000e+05
25%    1.899275e+06
50%    4.578400e+06
75%    7.361150e+06
max    4.706500e+07
```

[53]:
```python
df2.shape
```

[53]:
```
(2416, 7)
```

There are no missing values, we can proceed to next step. However, we can cross check with the missing values function too

[54]:
```python
print(f"""Tesla Missing Values: {df.isna().any(axis=1).sum()}\n
       {df[df.isna().any(axis=1)].index}""")
```

```
Tesla Missing Values: 0

       Int64Index([], dtype='int64')
```

[55]:
```python
# Filling missing values

def fill_missing(df):
    return df.fillna(method='ffill').fillna(method='bfill')
```

[56]:
```python
df= fill_missing(df)
print(f"""Tesla Missing Values: {df.isna().any(axis=1).sum()}""")
```

```
Tesla Missing Values: 0
```

2.3.1 Now there are 0 missing values…Lets carry on with the next step

[57]:
```python
# Setting date as index

df.set_index('Date')
```

[57]:
```
                  Open        High         Low       Close   Adj Close  \
Date
2010-06-29   19.000000   25.000000   17.540001   23.889999   23.889999
2010-06-30   25.790001   30.420000   23.299999   23.830000   23.830000
2010-07-01   25.000000   25.920000   20.270000   21.959999   21.959999
2010-07-02   23.000000   23.100000   18.709999   19.200001   19.200001
2010-07-06   20.000000   20.000000   15.830000   16.110001   16.110001
…                  …           …           …           …           …
2020-01-28  568.489990  576.809998  558.080017  566.900024  566.900024
2020-01-29  575.690002  589.799988  567.429993  580.989990  580.989990
2020-01-30  632.419983  650.880005  618.000000  640.809998  640.809998
2020-01-31  640.000000  653.000000  632.520020  650.570007  650.570007
2020-02-03  673.690002  786.140015  673.520020  780.000000  780.000000

              Volume
Date
2010-06-29  18766300
2010-06-30  17187100
2010-07-01   8218800
2010-07-02   5139800
2010-07-06   6866900
…                …
2020-01-28  11788500
2020-01-29  17801500
2020-01-30  29005700
2020-01-31  15719300
2020-02-03  47065000

[2416 rows x 6 columns]
```

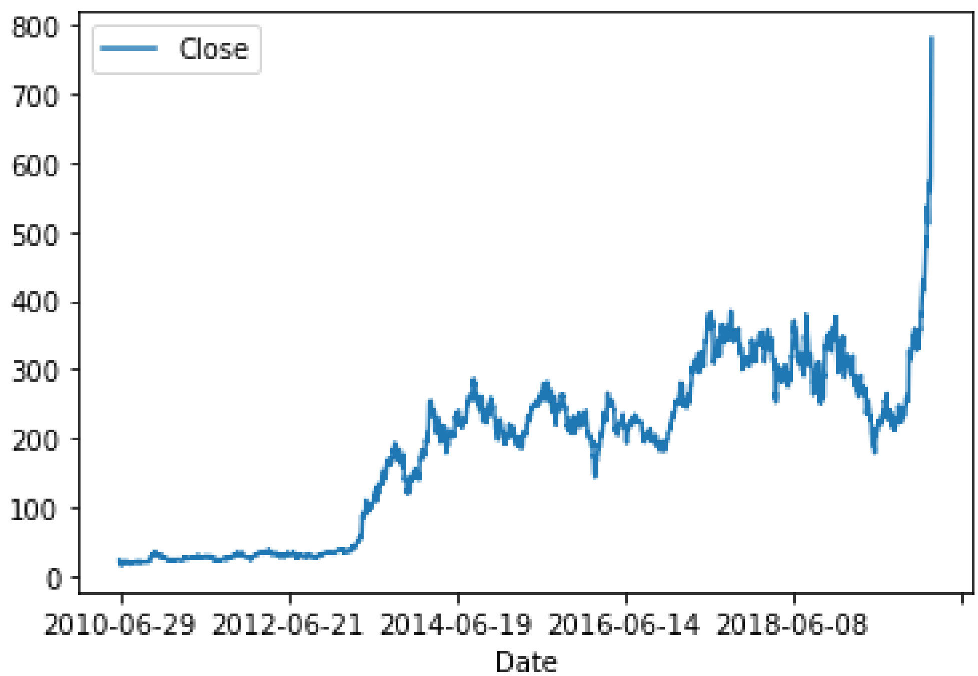
[58]:
```python
datetime_series = pd.to_datetime(df['Date'])
datetime_index = pd.DatetimeIndex(datetime_series.values)

df=df.set_index(datetime_index)
```

2.3.2 Analysing the stock trend from the Closing price

[59]:
```python
# Stock line data graph

plt.figure(figsize=(10, 10), dpi=80)

# figure(figsize=(10,8)) would create an inch-by-inch image,
```

```
# which would be 80-by-80 pixels unless you also give a different dpi argument.

df.plot.line(x='Date',y='Close')
plt.show()

# Matplotlib.pyplot is a collection of functions that make matplotlib work like␣
↪MATLAB.
# Each pyplot function makes some change to a figure: e.g., creates a figure,␣
↪creates a plotting area in a figure, plots some lines in a plotting area,
# decorates the plot with labels, etc.
```

```
<Figure size 800x800 with 0 Axes>
```



2.4 5. Implementing Rolling window

Rolling-window analysis of a time-series model assesses:

- The stability of the model over time. A common time-series model assumption is that the coefficients are constant with respect to time. Checking for instability amounts to examining whether the coefficients are time-invariant.
- The forecast accuracy of the model.(predictive performance)

`dataframe.rolling() function:` It provides the feature of rolling window calculations. The concept of rolling window calculation is most primarily used in signal processing and time series data.

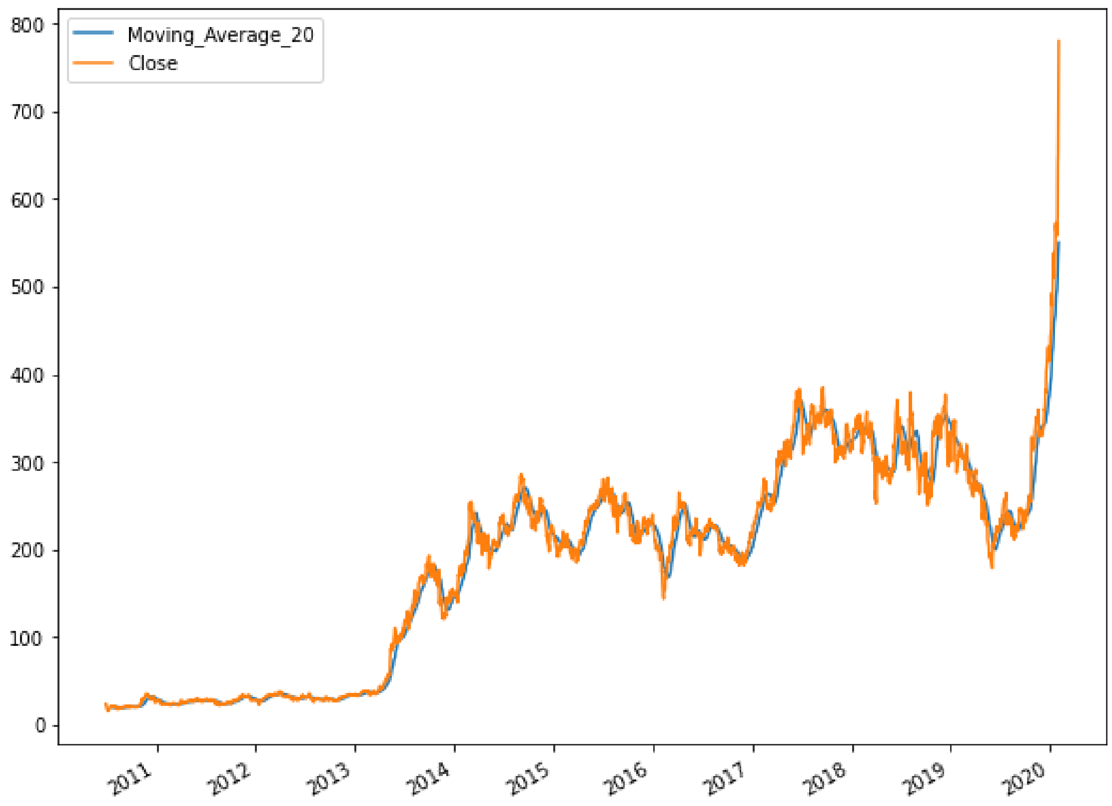
We take a window size of k at a time and perform some desired mathematical operation on it. A window of size k means k consecutive values at a time. In a very simple case all the 'k' values are equally weighted.

2.4.1 What is moving average?

A moving average is a calculation used to analyze data points by creating a series of averages of different subsets of the full data set. In finance, a moving average (MA) is a stock indicator that is commonly used in technical analysis.

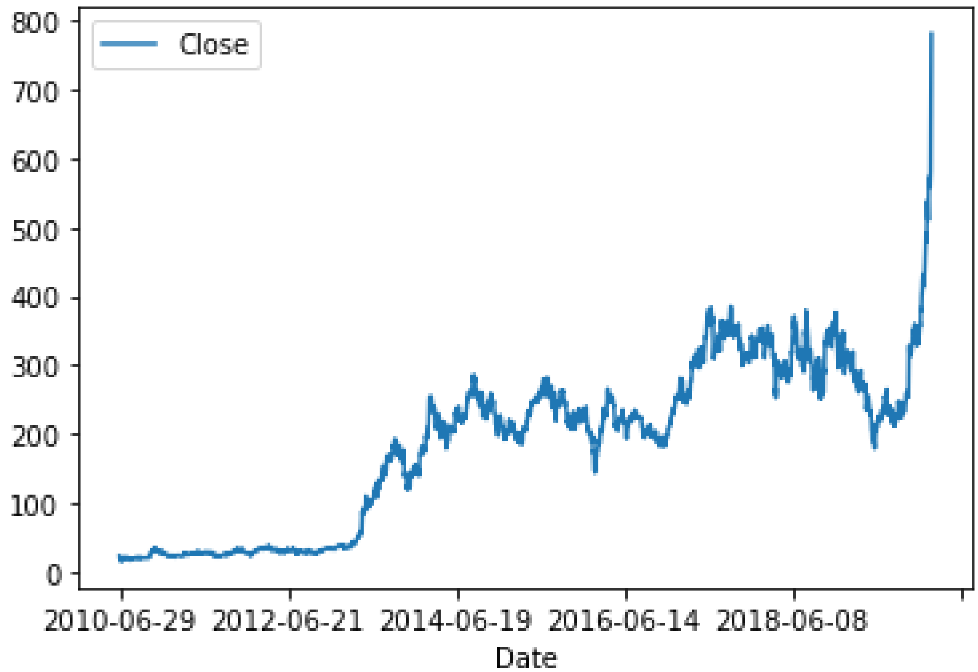
The moving average is calculated by adding a stock's prices over a certain period and dividing the sum by the total number of periods. For example, a trader wants to calculate the SMA for stock ABC by looking at the high of day over five periods

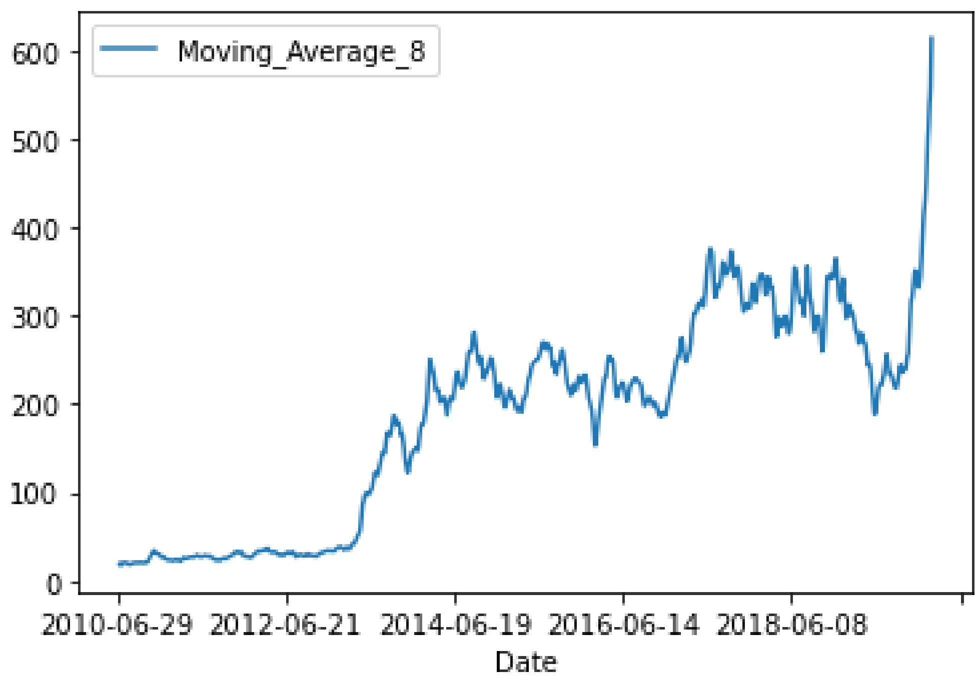
[60]:
```python
df['Moving_Average_8'] = df['Close'].rolling(8).mean()
df['Moving_Average_20'] = df['Close'].rolling(20).mean()
df['Moving_Average_50'] = df['Close'].rolling(50).mean()

# pandas creates subseries of all the different data contained within the␣
 ↪window size defined- Then we
# can cal a mean out of that- we nned a positional argument window: How big␣
 ↪should the subseries be for
# calculating the movinng avg- For eg, if its 5, each data point in the MA␣
 ↪column calculated on subset
# of 5

# By default pandas will use the outer value as the starting point- Thats the␣
 ↪reason of missing values

#Plot the moving average
plt.figure(figsize=(10, 8))


df['Moving_Average_20'].plot(label='Moving_Average_20')
df['Close'].plot(label='Close')
plt.legend()
plt.show()
```



[61]:

```
df.plot.line(x='Date',y='Close')
df.plot.line(x='Date',y='Moving_Average_8')
plt.legend()
plt.show()
```





We can see that the moving average smoothens out the variations of dataset- so we can ignore the variations The above is a ten year chart of Tesla Stock from 2010 to 2020 with moving averages. The blue line is the shorter, a 20-day moving average. We can see there is a growing trend and a spike.

We have calculated MA for last 8, 10 and 20 windows/days. It smoothes out the curve by Constantly updating the average price. We very unlikely for the trend to deviate outside the resistance point.

[62]:
```
df.Moving_Average_20= df.Moving_Average_20.fillna(0)
df.Moving_Average_50= df.Moving_Average_50.fillna(0)
df.Moving_Average_8= df.Moving_Average_8.fillna(0)

# Filling the NaN values in MA
```

[63]:
```
df
```

[63]:
```
                  Date        Open        High         Low       Close  \
2010-06-29  2010-06-29   19.000000   25.000000   17.540001   23.889999
2010-06-30  2010-06-30   25.790001   30.420000   23.299999   23.830000
2010-07-01  2010-07-01   25.000000   25.920000   20.270000   21.959999
2010-07-02  2010-07-02   23.000000   23.100000   18.709999   19.200001
2010-07-06  2010-07-06   20.000000   20.000000   15.830000   16.110001
…                …         …           …          …          …
2020-01-28  2020-01-28  568.489990  576.809998  558.080017  566.900024
2020-01-29  2020-01-29  575.690002  589.799988  567.429993  580.989990
2020-01-30  2020-01-30  632.419983  650.880005  618.000000  640.809998
2020-01-31  2020-01-31  640.000000  653.000000  632.520020  650.570007
2020-02-03  2020-02-03  673.690002  786.140015  673.520020  780.000000

             Adj Close    Volume  Moving_Average_8  Moving_Average_20  \
2010-06-29   23.889999  18766300          0.000000           0.000000
2010-06-30   23.830000  17187100          0.000000           0.000000
2010-07-01   21.959999   8218800          0.000000           0.000000
2010-07-02   19.200001   5139800          0.000000           0.000000
2010-07-06   16.110001   6866900          0.000000           0.000000
…                 …         …                …                  …
2020-01-28  566.900024  11788500        550.336258         503.125003
2020-01-29  580.989990  17801500        558.773758         511.439502
2020-01-30  640.809998  29005700        575.062508         522.563503
2020-01-31  650.570007  15719300        587.983757         533.579002
2020-02-03  780.000000  47065000        614.288757         550.428502

            Moving_Average_50
2010-06-29           0.000000
2010-06-30           0.000000
2010-07-01           0.000000
2010-07-02           0.000000
2010-07-06           0.000000
…                         …
2020-01-28         418.773402
2020-01-29         423.406202
```

```
2020-01-30          429.179001
2020-01-31          435.190602
2020-02-03          443.600202

[2416 rows x 10 columns]
```

2.4.2 Moving average wrt Stocks:

- A moving average (MA) is a stock indicator that is commonly used in technical analysis.
- The reason for calculating the moving average of a stock is to help smooth out the price data over a specified period of time by creating a constantly updated average price.
- By calculating the moving average, the impacts of random, short-term fluctuations on the price of a stock over a specified time-frame are mitigated.

MACD: - The moving average convergence divergence (MACD) is used by traders to monitor the relationship between two moving averages. It is generally calculated by subtracting a 26-day exponential moving average from a 12-day exponential moving average.

- When the MACD is positive, the short-term average is located above the long-term average. This an indication of upward momentum. When the short-term average is below the long-term average, this is a sign that the momentum is downward. Many traders will also watch for a move above or below the zero line. A move above zero is a signal to buy, while a cross below zero is a signal to sell.

Now let us create a MACD

[64]:
```
df['MACD']=[1 if df.loc[i, 'Moving_Average_8']>df.loc[i, 'Moving_Average_20']␣
↪and df.loc[i, 'Moving_Average_50'] else 0
          for i in df.index]
```

3 Building a trading strategy: Feature Engineering

Here we can try to answer questions we have- can we expect a profit ? Is investing going to be a risk ? How much are we going to gain of we invest continuously? What is the market strength of the stock?

3.1 1. Daily Returns

In general, stocks should have a high return and stabilty over time.There is more than 10% drop during certain years. In such cases, investors who are risk averse can better avoid this stock. In case they want to still invest, look into the long time ROI (cummulative returns). A correlation analysis with other stocks can also be done. Personal discretion and competitor stock analysis plays a role here, as its totally subjective.

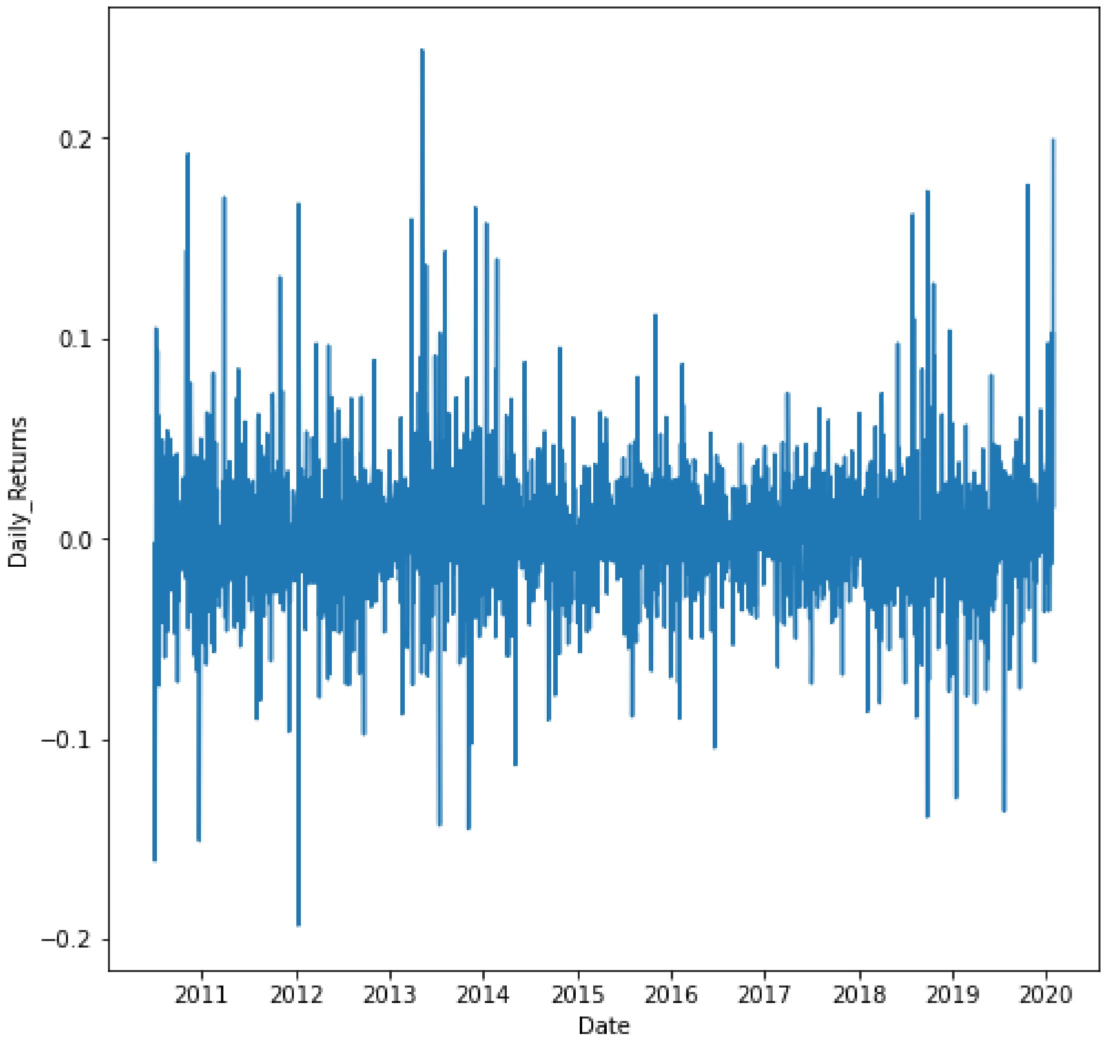
3.2 2. Calculating the Price difference & Daily returns

[65]:
```
df['Price Difference']= df['Close'].shift(-1)-df['Close']
print(df['Price Difference'])
```

```
2010-06-29     -0.059999
2010-06-30     -1.870001
2010-07-01     -2.759998
2010-07-02     -3.090000
2010-07-06     -0.310001
                 …
2020-01-28     14.089966
2020-01-29     59.820008
2020-01-30      9.760009
2020-01-31    129.429993
2020-02-03           NaN
Name: Price Difference, Length: 2416, dtype: float64
```

[66]:
```
# Calculating Daily returns
df['Daily_Returns'] = df['Price Difference'] /df['Close']
```

[67]:
```
# df['Daily_Returns'].plot(xlabel='Date' ,ylabel='Daily_Returns')
import matplotlib.dates as mdates

fig,ax= plt.subplots(figsize=(8,8))

# plt.plot(df['Date'].tolist(),df['Daily_Returns'].tolist())

plt.plot(df.index, df['Daily_Returns'])
plt.ylabel('Daily_Returns')
plt.xlabel('Date')

plt.show()

# Looking into the daily returns
```



3.3 3. Profits

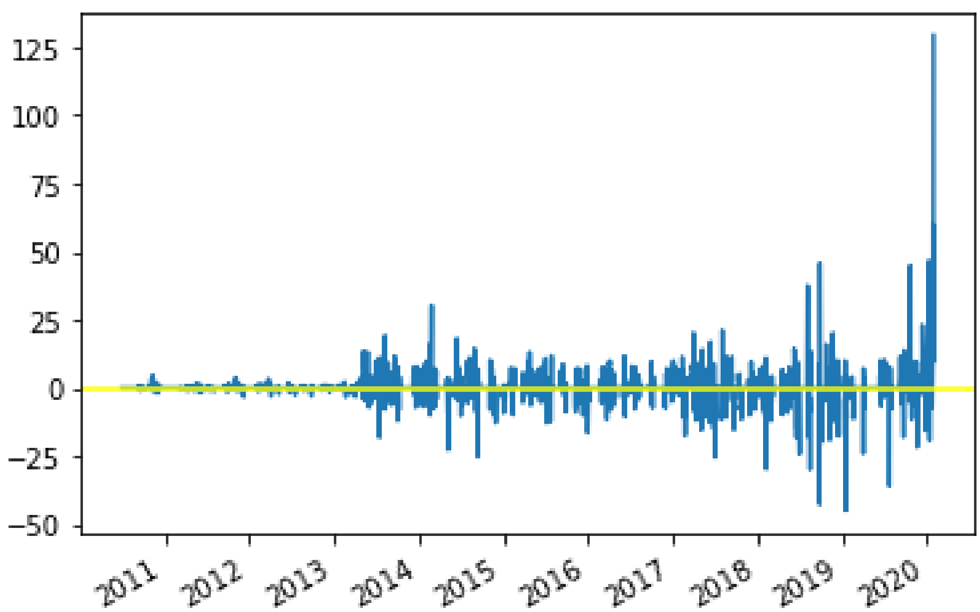
Profits are calculated as closing price of tomorrow- Closing price of today

[68]:
```
# df['Close_Tomorrow']=df['Close'].shift(-1)
# df[['Close_Tomorrow','Close']]
# df['Profit']= [df.loc[i,'Close_Tomorrow']- df.loc[i, 'Close'] for i in df.
↪index]
# df[['Close_Tomorrow','Close','Profit']]

# # print(df.loc[df.index[0], 'Close'])
# # print(df.loc[df.index[0],'Close_Tomorrow'])
# # print(df.loc[df.index[0],'MACD'])

# df['Profit'].plot()
```

```
# plt.axhline(y=0, color='red')

# Debugging
```

[69]:
```
df['Close_Tomorrow']=df['Close'].shift(-1)
df['Profit']= [df.loc[i,'Close_Tomorrow']- df.loc[i, 'Close']
              if df.loc[i, 'MACD']== 1 else 0 for i in df.index]
df['Profit'].plot()
plt.axhline(y=0, color='yellow')
```

[69]:
```
<matplotlib.lines.Line2D at 0x7fecc6ba43a0>
```



3.4 4. Investment Overtime

[70]:
```
df['Investment_Returns_OT']= df['Profit'].cumsum()
```

[71]:
```
df['Investment_Returns_OT'].tail()
```

[71]:
```
2020-01-28    366.350151
2020-01-29    426.170159
2020-01-30    435.930168
2020-01-31    565.360161
2020-02-03           NaN
Name: Investment_Returns_OT, dtype: float64
```

[72]:
```
df['Investment_Returns_OT'].plot()
plt.title('Total money you have made: {}'.format(df.loc[df.index[-2],␣
↪'Investment_Returns_OT']))
```

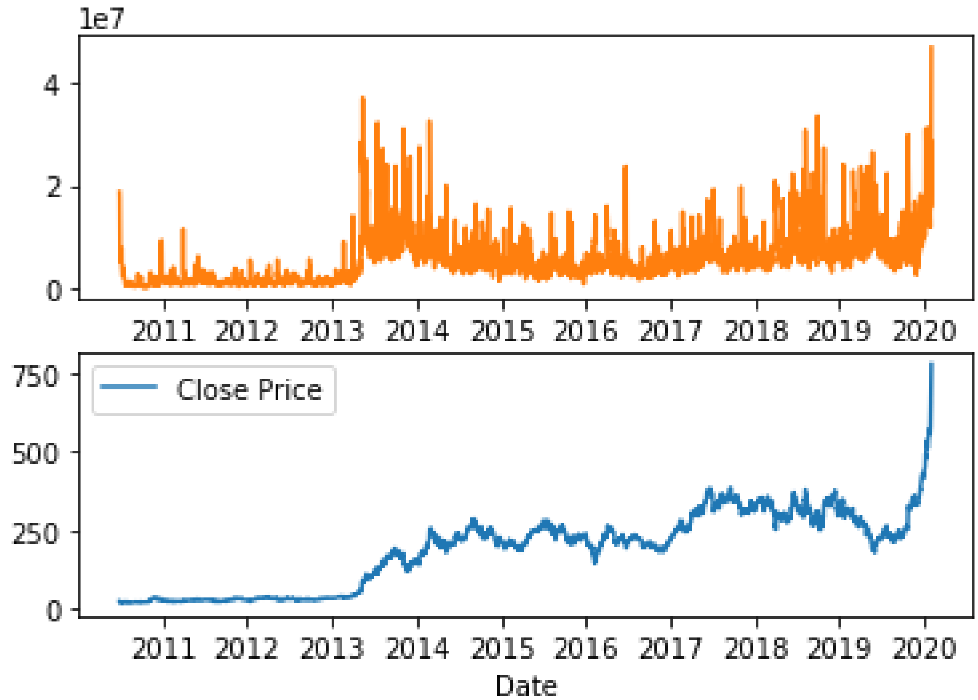
[72]: Text(0.5, 1.0, 'Total money you have made: 565.3601609999998')

From the above, we can get to know that we have a ROI of 565.36 dollars if we invested from 2010 to 2020. #### It would be wise to run this by other stocks and check it would be profitable overtime. The returns have gone done significantly from 2018 to 2020 during the pandemic. It has tremondously spiked only in 2020

3.5 5. Volume

[73]:
```
# plt.plot(df['Volume'])
# plt.axes([0.05,])

fig, axs= plt.subplots(2)
axs[0].plot(df.index,df['Volume'],'tab:orange', label='Volume')

axs[1].plot(df.index,df['Close'], label='Close Price')

plt.xlabel('Date')

plt.legend()
plt.show()
```

```
# tolist- Converts a column into list
```



From the above we can decipher how volume has affected the close price over the years. Initially when the volume of stocks were less, the close price is lesser too.

Volume can be an indicator of market strength, as rising markets on increasing volume are typically viewed as strong and healthy, which is what happened here

3.5.1 How do we analyse Volume to gain profits

- `Trend analysis and confirmation:` A rising market should see rising volume. Buyers require increasing numbers and increasing enthusiasm in order to keep pushing prices higher. Increasing price and decreasing volume might suggest a lack of interest, and this is a warning of a potential reversal.A price drop (or rise) on large volume is a stronger signal that something in the stock has fundamentally changed.

When prices fall on increasing volume, the trend is gathering strength to the downside. When prices reach new highs (or no lows) on decreasing volume, watch out; a reversal might be taking shape.

So I would suggest investing in this is not a bad idea based on Volume

4 Deciding model to be built

Apart from understanding the above features that influence the stock analysis in helping whether we need to invest or not, it would be more helpful if we build a forecasting model that helps us understand clearly Let us build 2 models:

Forecasting Using ARIMA Model

Predictive Analysis Using LSTM-RNN (Long Term Short Memory Model- Recurrent neural network)

4.1 1- Forecasting Using ARIMA Model

4.2 Import data set for 'Tesla' and To compare it with 'Volkswagen'

[212]:
```
symbol = ['VOW3.DE', 'TSLA']
source = 'yahoo'
start_date = '2010-06-29'
end_date = '2021-02-03'
stock = data.DataReader(symbol, source, start_date, end_date)

vw = stock.xs('VOW3.DE', level='Symbols', axis=1)
tesla = stock.xs('TSLA', level='Symbols', axis=1)
```

[213]:
```
df=pd.read_csv('TSLA_arima.csv', index_col='Date', parse_dates=True)
df=df.dropna()
print('Shape of data',df.shape)
df.head(10)
```

```
Shape of data (2416, 6)
```

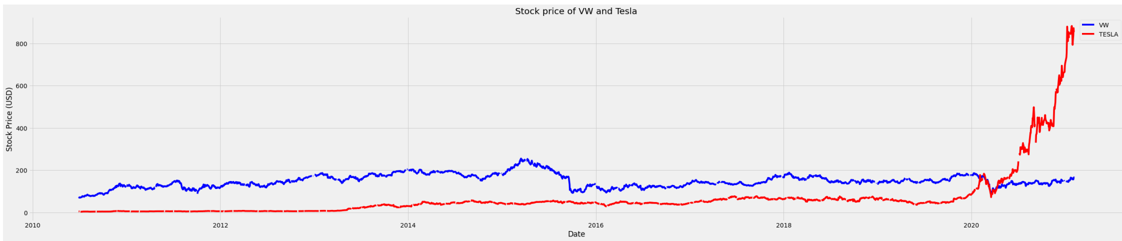
[213]:

	Open	High	Low	Close	Adj Close	Volume
Date						
2010-06-29	19.000000	25.000000	17.540001	23.889999	23.889999	18766300
2010-06-30	25.790001	30.420000	23.299999	23.830000	23.830000	17187100
2010-01-07	25.000000	25.920000	20.270000	21.959999	21.959999	8218800
2010-02-07	23.000000	23.100000	18.709999	19.200001	19.200001	5139800
2010-06-07	20.000000	20.000000	15.830000	16.110001	16.110001	6866900
2010-07-07	16.400000	16.629999	14.980000	15.800000	15.800000	6921700
2010-08-07	16.139999	17.520000	15.570000	17.459999	17.459999	7711400
2010-09-07	17.580000	17.900000	16.549999	17.400000	17.400000	4050600
2010-12-07	17.950001	18.070000	17.000000	17.049999	17.049999	2202500
2010-07-13	17.389999	18.639999	16.900000	18.139999	18.139999	2680100

4.3 Plot graph for both 'Tesla' and 'Valkswagen'

[214]:
```
def plot_df(df, x, y, title="", xlabel='Date', ylabel='Value', dpi=100):
    plt.plot(x, y)
    plt.gca().set(title=title, xlabel=xlabel, ylabel=ylabel)
    plt.show()
```

```python
rcParams['figure.figsize'] = 40, 8
plt.plot(vw.index, vw['Close'], 'b-', label = 'VW')
plt.plot(tesla.index, tesla['Close'], 'r-', label = 'TESLA')
plt.xlabel('Date'); plt.ylabel('Stock Price (USD)')
plt.title('Stock price of VW and Tesla')
plt.legend();
```



4.3.1 From above graph we can see that in 2020 Tesla took over the Valkswagen but these are Tesla's adjusted prices as Tesle splitted from 1 share to 5 shares, else it took over the stock price of Valkswagen in 2015 only. In 2020 it took over the Market Capitalization of the Valkswagen and reached to the second position after Genreal Moters.

4.4 Finding 'Missing Values' and Treating them for both 'Tesla' and 'Valkswagen'

[215]:
```python
print(f"""Tesla Missing Values: {tesla.isna().any(axis=1).sum()}\n{tesla[tesla.
↪isna().any(axis=1)].index} \n
Volkswagen MissingaValues: {vw.isna().any(axis=1).sum()}\n{vw[vw.isna().
↪any(axis=1)].index}""")
```

```
Tesla Missing Values: 70
DatetimeIndex(['2010-07-05', '2010-09-06', '2010-11-25', '2011-01-17',
               '2011-02-21', '2011-05-30', '2011-07-04', '2011-09-05',
               '2011-11-24', '2012-01-02', '2012-01-16', '2012-02-20',
               '2012-05-28', '2012-07-04', '2012-09-03', '2012-10-29',
               '2012-10-30', '2012-11-22', '2013-01-21', '2013-02-18',
               '2013-05-27', '2013-07-04', '2013-09-02', '2013-11-28',
               '2014-01-20', '2014-02-17', '2014-05-26', '2014-07-04',
               '2014-09-01', '2014-11-27', '2015-01-19', '2015-02-16',
               '2015-07-03', '2015-09-07', '2015-11-26', '2015-12-25',
               '2016-01-18', '2016-02-15', '2016-05-30', '2016-07-04',
               '2016-09-05', '2016-11-24', '2017-01-02', '2017-01-16',
               '2017-02-20', '2017-05-29', '2017-07-04', '2017-09-04',
               '2017-11-23', '2018-01-15', '2018-02-19', '2018-05-28',
               '2018-07-04', '2018-09-03', '2018-11-22', '2018-12-05',
               '2019-01-21', '2019-02-18', '2019-05-27', '2019-07-04',
```

```
                 '2019-09-02', '2019-11-28', '2020-01-20', '2020-02-17',
                 '2020-05-25', '2020-07-03', '2020-09-07', '2020-11-26',
                 '2021-01-18', '2021-02-04'],
                dtype='datetime64[ns]', name='Date', freq=None)

Volkswagen MissingaValues: 49
DatetimeIndex(['2010-12-31', '2011-04-25', '2011-10-03', '2012-04-09',
               '2012-05-01', '2012-10-03', '2012-12-24', '2012-12-26',
               '2012-12-31', '2013-04-01', '2013-05-01', '2013-10-03',
               '2013-12-24', '2013-12-26', '2013-12-31', '2014-04-21',
               '2014-05-01', '2014-10-03', '2014-12-24', '2014-12-26',
               '2014-12-31', '2015-04-06', '2015-05-01', '2015-12-24',
               '2015-12-31', '2016-03-28', '2016-05-16', '2016-10-03',
               '2017-04-17', '2017-05-01', '2017-12-26', '2018-04-02',
               '2018-05-01', '2018-10-03', '2018-12-24', '2018-12-26',
               '2018-12-31', '2019-04-22', '2019-05-01', '2019-06-10',
               '2019-10-03', '2019-12-24', '2019-12-26', '2019-12-31',
               '2020-04-13', '2020-05-01', '2020-06-01', '2020-12-24',
               '2020-12-31'],
              dtype='datetime64[ns]', name='Date', freq=None)
```

[216]:
```
def fill_missing(df):
    return df.fillna(method='ffill').fillna(method='bfill')
```

[217]:
```
tesla, vw = fill_missing(tesla), fill_missing(vw)
print(f"""Tesla Missing Values: {tesla.isna().any(axis=1).sum()}
Volkswagen Missing Values: {vw.isna().any(axis=1).sum()}""")
```

```
Tesla Missing Values: 0
Volkswagen Missing Values: 0
```

[218]:
```
tesla.head(10)
```

[218]:

Attributes	Adj Close	Close	High	Low	Open	Volume
Date						
2010-06-29	4.778	4.778	5.000	3.508	3.800	93831500.0
2010-06-30	4.766	4.766	6.084	4.660	5.158	85935500.0
2010-07-01	4.392	4.392	5.184	4.054	5.000	41094000.0
2010-07-02	3.840	3.840	4.620	3.742	4.600	25699000.0
2010-07-05	3.840	3.840	4.620	3.742	4.600	25699000.0
2010-07-06	3.222	3.222	4.000	3.166	4.000	34334500.0
2010-07-07	3.160	3.160	3.326	2.996	3.280	34608500.0
2010-07-08	3.492	3.492	3.504	3.114	3.228	38557000.0
2010-07-09	3.480	3.480	3.580	3.310	3.516	20253000.0
2010-07-12	3.410	3.410	3.614	3.400	3.590	11012500.0

[219]:
```
vw.head(10)
```

[219]:

Attributes	Adj Close	Close	High	Low	Open	Volume
Date						
2010-06-29	57.800720	73.430000	75.139999	72.809998	74.849998	1233377.0
2010-06-30	56.974213	72.379997	74.709999	72.220001	73.519997	1153137.0
2010-07-01	55.077171	69.970001	71.699997	69.970001	71.500000	1475203.0
2010-07-02	55.155884	70.070000	71.500000	70.000000	71.000000	704130.0
2010-07-05	55.100780	70.000000	70.849998	69.809998	70.470001	387599.0
2010-07-06	56.187054	71.379997	71.970001	70.589996	70.589996	665857.0
2010-07-07	56.076859	71.239998	71.650002	70.059998	70.449997	767184.0
2010-07-08	56.084717	71.250000	71.970001	70.849998	71.629997	756306.0
2010-07-09	56.769558	72.120003	72.440002	70.919998	71.250000	535715.0
2010-07-12	57.635422	73.220001	73.870003	72.500000	72.690002	852286.0

4.5 Check the Time Series Components.

4.5.1 There are two types of Time series "Additive Time Series" and "Multiplicative Time Series". Our graph is not like Multiplicative Time Series, so let's Assume our Time Series as Additive Time Series.

There are Three components of Time series.

1. Trend: the movement of the data on a larger scale (moving average)

2.Seasonality: repeated seasonal fluctuations

3.Residual: any fluctuations not captured from trend or seasonality (should be random)

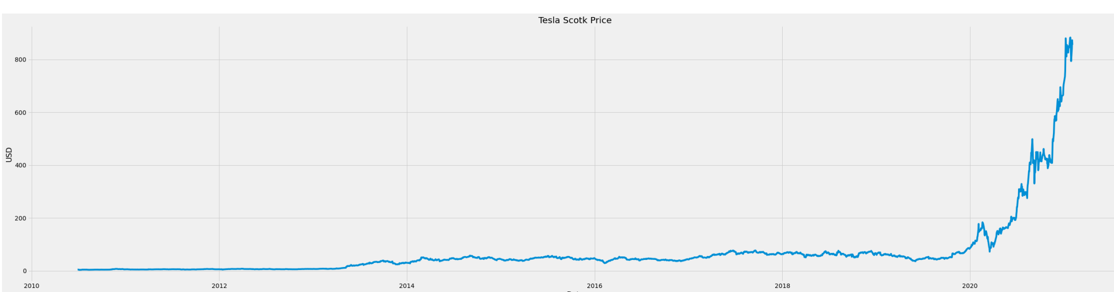
Our Time Series Model we assumed Additive Time Series so it will add this three components.

Trend + Seasonality + Residual.

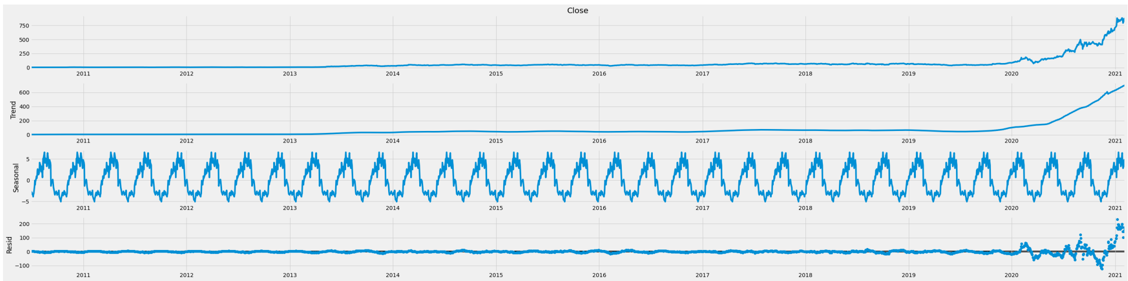
4.5.2 Let's again see the overall graph again and then extract the three components of it.

[220]:

```
rcParams['figure.figsize'] = 40, 10
plot_df(tesla, tesla.index , tesla['Close'], title='Tesla Scotk␣
↪Price',ylabel='USD')
```



[221]:
```python
decomposition = sm.tsa.seasonal_decompose(tesla['Close'], model='additive',␣
↪freq=7*4*3,extrapolate_trend='freq')
fig = decomposition.plot()
plt.show()
```



4.5.3 We can see above that Trend is smooth and pattern is in Seasonality this is the good sighn else we need to try different combinations. (Here we used 7 * 4 * 3 combination.)

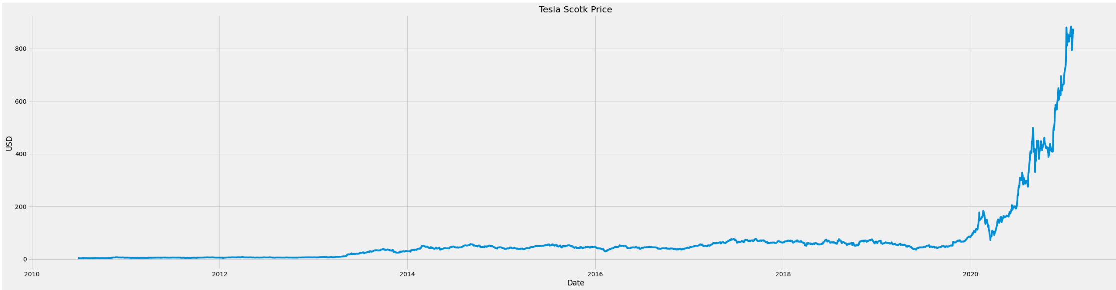
[222]:
```python
tesla_rc = pd.concat([decomposition.seasonal, decomposition.resid,␣
↪decomposition.trend, decomposition.observed], axis=1)
tesla_rc.columns = ['seasonal', 'residual', 'trend', 'observation']
tesla_rc['total'] = tesla_rc['seasonal'] + tesla_rc['residual'] +␣
↪tesla_rc['trend']
tesla_rc.head()
```

[222]:

	seasonal	residual	trend	observation	total
Date					
2010-06-29	-2.523436	4.138202	3.163234	4.778	4.778
2010-06-30	-2.753384	4.336255	3.183129	4.766	4.766
2010-07-01	-3.362628	4.551604	3.203024	4.392	4.392
2010-07-02	-2.875951	3.493032	3.222919	3.840	3.840
2010-07-05	-3.431242	4.028428	3.242814	3.840	3.840

4.6 Check the Time Series is Stationary or Non-stationary.

[223]:
```python
plot_df(tesla, tesla.index , tesla['Close'], title='Tesla Scotk␣
↪Price',ylabel='USD')
```



[224]:
```
from statsmodels.tsa.stattools import adfuller
adf_test = adfuller(tesla['Close'])
print(f"""
ADF Value : {adf_test[0]}
P Value : {adf_test[1]}
""")
```

```
ADF Value : 9.095638248788477
P Value : 1.0
```

4.6.1 When we do adfuller test our ADF Value shall be negative and the p-Value <0.05, but we are getting ADF Value positive and p-Value 1.0 which is >0.05 (much higher). So we can say that our data set is Non-stationary.

4.7 Change Time Series into Stationary

4.7.1 Log Transformation

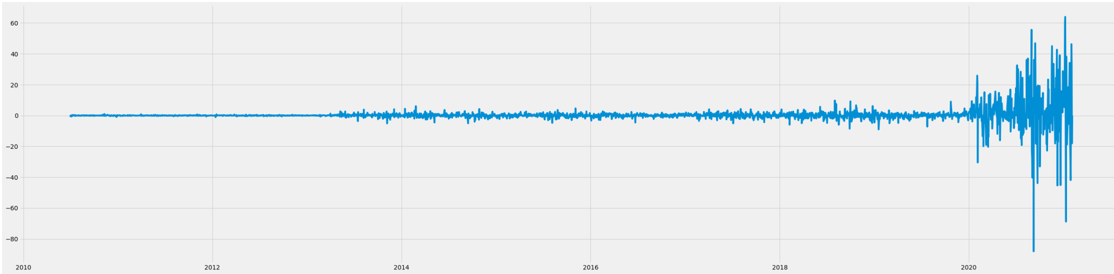
[225]:
```
from statsmodels.tsa.stattools import adfuller
adf_test = adfuller(np.log(tesla['Close']))
print(f"""
ADF Value : {adf_test[0]}
P Value : {adf_test[1]}
""")
```

```
ADF Value : 0.8425289463774092
P Value : 0.9922925548810414
```

4.7.2 Log Transformation is not enough as still ADF Value is positive and p-Value is too high, so lets do Differentiation

[226]:
```
plt.plot(tesla['Close'].diff(1).fillna(0))
```

[226]:
```
[<matplotlib.lines.Line2D at 0x7feca9d91520>]
```



[227]:
```python
from statsmodels.tsa.stattools import adfuller
adf_test = adfuller(np.log(tesla['Close']).diff(1).fillna(0))
adf_test = adfuller((tesla['Close']).diff(1).fillna(0))
print(f"""
ADF Value : {adf_test[0]}
P Value : {adf_test[1]}
""")
```

```
ADF Value : -6.639258845051617
P Value : 5.46229458993005e-09
```

4.7.3 Now we can see after Differentiation ADF Value is negative and p-Value is too small <0.05 so now the Time Series is Stationary.

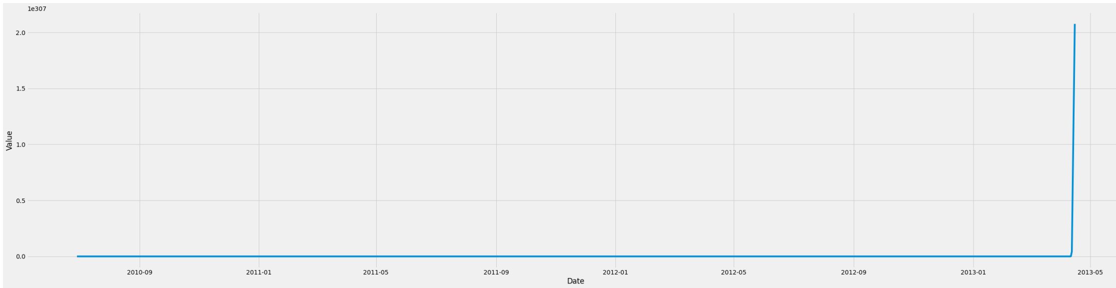
[228]:
```python
tesla_st = tesla.diff(1).fillna(0)
tesla_st.head()
```

[228]:

Attributes	Adj Close	Close	High	Low	Open	Volume
Date						
2010-06-29	0.000	0.000	0.000	0.000	0.000	0.0
2010-06-30	-0.012	-0.012	1.084	1.152	1.358	-7896000.0
2010-07-01	-0.374	-0.374	-0.900	-0.606	-0.158	-44841500.0
2010-07-02	-0.552	-0.552	-0.564	-0.312	-0.400	-15395000.0
2010-07-05	0.000	0.000	0.000	0.000	0.000	0.0

4.7.4 Above data set shows differentiated values, which are suitable for Time Series. The values are changed in the data set because we did the differentiation but we can solve that by using cumsum. Also we need to input initial data to transform as we changed previously nan, to zero.

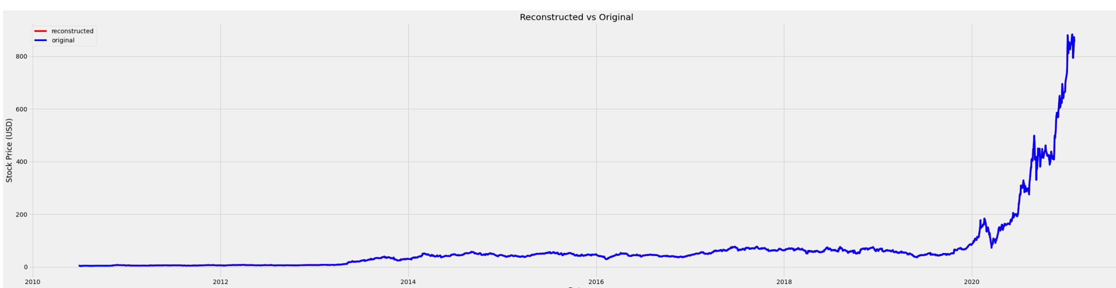
[229]:
```python
tesla_reconstruct = tesla_st.copy()
tesla_reconstruct = tesla_reconstruct.cumsum()
plot_df(tesla_reconstruct, tesla_reconstruct.index, tesla_reconstruct.cumsum().
 ↪apply(np.exp)['Close'])
```



[230]:
```
tesla_reconstruct = tesla_st.copy()
tesla_reconstruct.iloc[0,:] = tesla.iloc[0,:]
tesla_reconstruct = tesla_reconstruct.cumsum()
```

4.7.5 Now let's check whether its the same with original data or not?

[231]:
```
plt.plot(tesla.index, tesla_reconstruct['Close'], 'r-',  label='reconstructed')
plt.plot(tesla.index, tesla['Close'], 'b-', label = 'original')
plt.xlabel('Date'); plt.ylabel('Stock Price (USD)')
plt.title('Reconstructed vs Original')
plt.legend();
```



4.7.6 Based on the graph and manual check both data fream original and constructed are same so next step is to split the data set in to Training data set and Testing data set let's do it.

4.8 Step-08 Figure out order for ARIMA MODEL

[232]:
```
stepwise_fit = auto_arima(tesla_reconstruct['Close'], trace=True,␣
↪suppress_warnings=True)
stepwise_fit.summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(2,2,2)(0,0,0)[0]             : AIC=17310.048, Time=0.68 sec
 ARIMA(0,2,0)(0,0,0)[0]             : AIC=19358.182, Time=0.04 sec
```

```
 ARIMA(1,2,0)(0,0,0)[0]             : AIC=18660.317, Time=0.06 sec
 ARIMA(0,2,1)(0,0,0)[0]             : AIC=inf, Time=0.13 sec
 ARIMA(1,2,2)(0,0,0)[0]             : AIC=inf, Time=0.39 sec
 ARIMA(2,2,1)(0,0,0)[0]             : AIC=17346.412, Time=0.41 sec
 ARIMA(3,2,2)(0,0,0)[0]             : AIC=17304.677, Time=0.81 sec
 ARIMA(3,2,1)(0,0,0)[0]             : AIC=17339.068, Time=0.43 sec
 ARIMA(4,2,2)(0,0,0)[0]             : AIC=17305.925, Time=1.01 sec
 ARIMA(3,2,3)(0,0,0)[0]             : AIC=17306.503, Time=1.25 sec
 ARIMA(2,2,3)(0,0,0)[0]             : AIC=17308.081, Time=0.82 sec
 ARIMA(4,2,1)(0,0,0)[0]             : AIC=17336.071, Time=0.67 sec
 ARIMA(4,2,3)(0,0,0)[0]             : AIC=inf, Time=2.20 sec
 ARIMA(3,2,2)(0,0,0)[0] intercept   : AIC=17304.801, Time=2.13 sec

Best model:  ARIMA(3,2,2)(0,0,0)[0]
Total fit time: 11.031 seconds
```

[232]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 2739
Model:               SARIMAX(3, 2, 2)   Log Likelihood               -8646.338
Date:                Sun, 08 Aug 2021   AIC                          17304.677
Time:                        12:39:38   BIC                          17340.164
Sample:                             0   HQIC                         17317.501
                               - 2739
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.9920      0.007   -140.947      0.000      -1.006      -0.978
ar.L2         -0.1463      0.006    -23.622      0.000      -0.158      -0.134
ar.L3         -0.0549      0.006     -8.854      0.000      -0.067      -0.043
ma.L1         -0.0259      0.005     -4.791      0.000      -0.036      -0.015
ma.L2         -0.9511      0.005   -177.551      0.000      -0.962      -0.941
sigma2        32.4168      0.170    190.272      0.000      32.083      32.751
================================================================================
===
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):
365646.44
Prob(Q):                              0.99   Prob(JB):
0.00
Heteroskedasticity (H):             309.32   Skew:
-0.44
Prob(H) (two-sided):                  0.00   Kurtosis:
59.62
================================================================================
```

```
===

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

4.9 Split the data set into Training data set and Testing data set.

4.9.1 Note: In stock Market 9 days for short, 50 days for medium and 100 days for long term moving average taken in to consideration so we are taking testing data set as 100 and we will see the graph by keeping it 50 also.

[233]:
```
tesla_reconstruct.head()
```

[233]:
```
Attributes  Adj Close  Close   High    Low   Open      Volume
Date
2010-06-29      4.778  4.778  5.000  3.508  3.800  93831500.0
2010-06-30      4.766  4.766  6.084  4.660  5.158  85935500.0
2010-07-01      4.392  4.392  5.184  4.054  5.000  41094000.0
2010-07-02      3.840  3.840  4.620  3.742  4.600  25699000.0
2010-07-05      3.840  3.840  4.620  3.742  4.600  25699000.0
```

[234]:
```
print('Shape of data',tesla_reconstruct.shape)
```

```
Shape of data (2739, 6)
```

[235]:
```
print(tesla_reconstruct.shape)
train=tesla_reconstruct.iloc[:-100]
test=tesla_reconstruct.iloc[-100:]
print(train.shape,test.shape)
```

```
(2739, 6)
(2639, 6) (100, 6)
```

4.10 Train the Model.

[236]:
```
model=ARIMA(train['Close'], order= (3,2,2))
model= model.fit()
model.summary()
```

[236]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                             ARIMA Model Results
==============================================================================
Dep. Variable:               D2.Close   No. Observations:                 2637
Model:                 ARIMA(3, 2, 2)   Log Likelihood               -7275.947
Method:                       css-mle   S.D. of innovations              3.817
Date:                Sun, 08 Aug 2021   AIC                          14565.894
```

```
Time:                        12:39:40   BIC                          14607.035
Sample:                             2   HQIC                         14580.790

================================================================================
==
                     coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
--
const              0.0009      0.001      1.240      0.215      -0.001
0.002
ar.L1.D2.Close    -0.7787      0.062    -12.566      0.000      -0.900
-0.657
ar.L2.D2.Close    -0.0351      0.026     -1.324      0.186      -0.087
0.017
ar.L3.D2.Close     0.1449      0.027      5.410      0.000       0.092
0.197
ma.L1.D2.Close    -0.2129      0.062     -3.451      0.001      -0.334
-0.092
ma.L2.D2.Close    -0.7714      0.061    -12.675      0.000      -0.891
-0.652
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1           -1.3326           -0.7734j            1.5408           -0.4163
AR.2           -1.3326           +0.7734j            1.5408            0.4163
AR.3            2.9073           -0.0000j            2.9073           -0.0000
MA.1            1.0089           +0.0000j            1.0089            0.0000
MA.2           -1.2849           +0.0000j            1.2849            0.5000
-----------------------------------------------------------------------------
"""
```

4.11 Test the model on Testing data set "test"

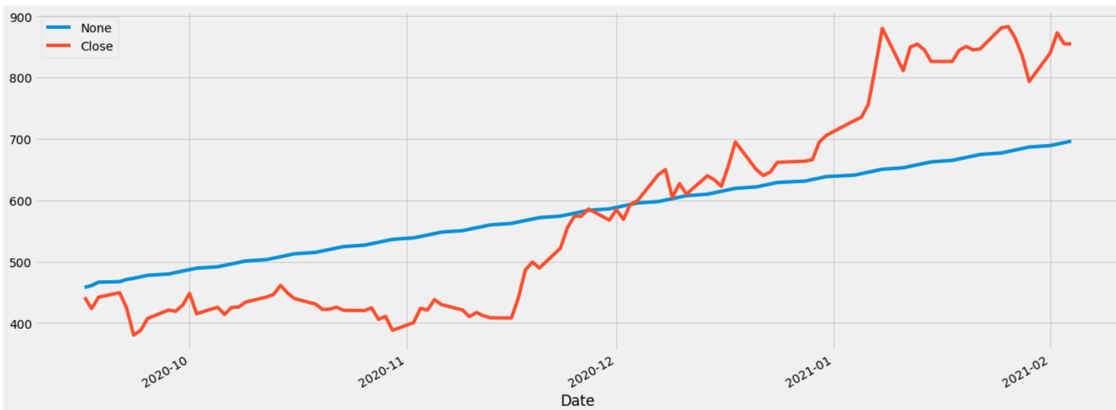
[237]:
```python
start=len(train)
end=len(train)+len(test)-1
pred=model.predict(start=start,end=end,typ='levels')
pred.index=tesla.index[start:end+1]
print(pred)
```

```
Date
2020-09-16    457.889297
2020-09-17    461.183749
2020-09-18    466.588390
2020-09-21    467.331865
2020-09-22    470.932065
                 …
```

```
2021-01-29    686.654321
2021-02-01    689.071128
2021-02-02    691.488858
2021-02-03    693.907511
2021-02-04    696.327086
Length: 100, dtype: float64
```

[238]:
```
pred.plot(legend=True)
test['Close'].plot(legend=True, figsize=(20,8))
```

[238]: `<AxesSubplot:xlabel='Date'>`



4.11.1 Let's repeat the step 9,10 and 11 for 50 days also

[239]:
```
tesla_reconstruct.head()
```

[239]:

Attributes	Adj Close	Close	High	Low	Open	Volume
Date						
2010-06-29	4.778	4.778	5.000	3.508	3.800	93831500.0
2010-06-30	4.766	4.766	6.084	4.660	5.158	85935500.0
2010-07-01	4.392	4.392	5.184	4.054	5.000	41094000.0
2010-07-02	3.840	3.840	4.620	3.742	4.600	25699000.0
2010-07-05	3.840	3.840	4.620	3.742	4.600	25699000.0

[240]:
```
print('Shape of data',tesla_reconstruct.shape)
```

```
Shape of data (2739, 6)
```

[241]:
```
print(tesla_reconstruct.shape)
train=tesla_reconstruct.iloc[:-50]
test=tesla_reconstruct.iloc[-50:]
print(train.shape,test.shape)
```

```
(2739, 6)
(2689, 6) (50, 6)
```

[242]:

```
model=ARIMA(train['Close'], order= (3,2,2))
model= model.fit()
model.summary()
```

[242]:

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                             ARIMA Model Results
==============================================================================
Dep. Variable:               D2.Close   No. Observations:                 2687
Model:                 ARIMA(3, 2, 2)   Log Likelihood               -7816.866
Method:                       css-mle   S.D. of innovations              4.434
Date:                Sun, 08 Aug 2021   AIC                          15647.733
Time:                        12:39:58   BIC                          15689.006
Sample:                             2   HQIC                         15662.662

================================================================================
==
                     coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
--
const              0.0009      0.001      1.302      0.193      -0.000
0.002
ar.L1.D2.Close    -0.8649      0.030    -28.940      0.000      -0.923
-0.806
ar.L2.D2.Close    -0.0549      0.026     -2.088      0.037      -0.106
-0.003
ar.L3.D2.Close     0.0447      0.022      2.032      0.042       0.002
0.088
ma.L1.D2.Close    -0.0906      0.023     -3.909      0.000      -0.136
-0.045
ma.L2.D2.Close    -0.8957      0.023    -39.121      0.000      -0.941
-0.851
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1           -1.4442           +0.0000j            1.4442            0.5000
AR.2           -2.8206           +0.0000j            2.8206            0.5000
AR.3            5.4927           +0.0000j            5.4927            0.0000
MA.1            1.0072           +0.0000j            1.0072            0.0000
MA.2           -1.1084           +0.0000j            1.1084            0.5000
-----------------------------------------------------------------------------
"""
```

[243]:

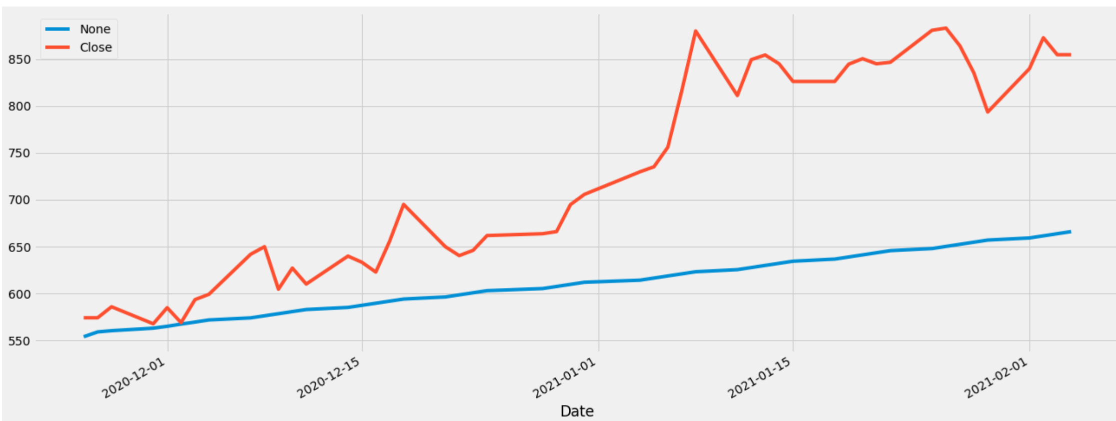
```
start=len(train)
end=len(train)+len(test)-1
pred=model.predict(start=start,end=end,typ='levels')
pred.index=tesla.index[start:end+1]
print(pred)
```

```
Date
2020-11-25    553.794264
2020-11-26    558.930310
2020-11-27    560.239125
2020-11-30    562.921394
2020-12-01    564.927853
2020-12-02    567.274026
2020-12-03    569.426483
2020-12-04    571.699271
2020-12-07    573.895431
2020-12-08    576.144238
2020-12-09    578.358725
2020-12-10    580.598213
2020-12-11    582.821947
2020-12-14    585.058033
2020-12-15    587.287050
2020-12-16    589.522431
2020-12-17    591.754880
2020-12-18    593.990832
2020-12-21    596.225832
2020-12-22    598.462965
2020-12-23    600.700094
2020-12-24    602.938698
2020-12-28    605.177754
2020-12-29    607.417971
2020-12-30    609.658857
2020-12-31    611.900753
2021-01-04    614.143423
2021-01-05    616.387030
2021-01-06    618.631462
2021-01-07    620.876796
2021-01-08    623.122978
2021-01-11    625.370046
2021-01-12    627.617974
2021-01-13    629.866780
2021-01-14    632.116451
2021-01-15    634.366997
2021-01-18    636.618410
2021-01-19    638.870695
2021-01-20    641.123850
2021-01-21    643.377876
2021-01-22    645.632772
```

```
2021-01-25    647.888539
2021-01-26    650.145176
2021-01-27    652.402684
2021-01-28    654.661062
2021-01-29    656.920311
2021-02-01    659.180430
2021-02-02    661.441420
2021-02-03    663.703280
2021-02-04    665.966010
dtype: float64
```

[244]:
```python
pred.plot(legend=True)
test['Close'].plot(legend=True, figsize=(20,8))
```

[244]: <AxesSubplot:xlabel='Date'>



[256]:
```python
from sklearn.metrics import mean_squared_error
from math import sqrt

print(tesla.iloc[start:end+1]['Close'].mean())
rmse=sqrt(mean_squared_error(pred,tesla.iloc[start:end+1]['Close']))
print(rmse)
```

```
727.0053991699219
141.00128715909202
```

First we check the mean value of the test set which comes out to be 727.00. And the root mean squared error for this particular model should come to around 141.00128. Also you should care about is that your root mean squared should be very smaller than the mean value of test set. In this case we can see

The average error is gonna be roughly (141.00128/727.00539)*100 = 19.39% of the actual value.

4.12 Conclusion of ARIMA Model

4.12.1 We can see that 100 days moving average gives us more clear idea about the stock movement and long term trend. here we can predict that due to covid it was traded below the prediction line in 2020 September to December Quarter but once vaccine rolled out and global sentiment became positive in Deciember 2020 it crossed the prediction line and since then it above the prediction (Means performed batter than its average) in December 2020 and Jan 2021. Moreover it's trend line (direction of the prediction line) is in upward direction so it is still a good stock to invest. But as it is above the prediction line we can say that it is a bit costly compared to the overall expectation of our model.

4.13 Future Price Prediction from February 2021 to July 2021

4.13.1 Here we will do the same exercise but we will keep training dataset as our complete data set and Testing with the values from Feb 2021 to July 2021 all will be in this one step just to see the prediction line with the actual.

[136]:
```
symbol = ['TSLA']
source = 'yahoo'
start_date = '2010-06-29'
end_date = '2021-07-20'
stock = data.DataReader(symbol, source, start_date, end_date)
tesla = stock.xs('TSLA', level='Symbols', axis=1)
```

[137]:
```
df=pd.read_csv('TSLA_arima.csv', index_col='Date', parse_dates=True)
df=df.dropna()
print('Shape of data',df.shape)
df.head(10)
```

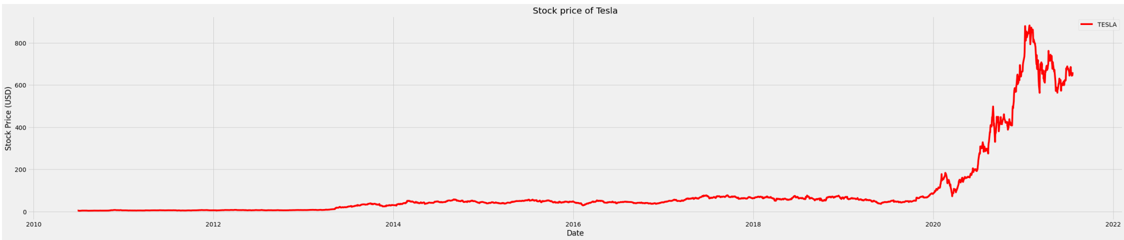
```
Shape of data (2416, 6)
```

[137]:

	Open	High	Low	Close	Adj Close	Volume
Date						
2010-06-29	19.000000	25.000000	17.540001	23.889999	23.889999	18766300
2010-06-30	25.790001	30.420000	23.299999	23.830000	23.830000	17187100
2010-01-07	25.000000	25.920000	20.270000	21.959999	21.959999	8218800
2010-02-07	23.000000	23.100000	18.709999	19.200001	19.200001	5139800
2010-06-07	20.000000	20.000000	15.830000	16.110001	16.110001	6866900
2010-07-07	16.400000	16.629999	14.980000	15.800000	15.800000	6921700
2010-08-07	16.139999	17.520000	15.570000	17.459999	17.459999	7711400
2010-09-07	17.580000	17.900000	16.549999	17.400000	17.400000	4050600
2010-12-07	17.950001	18.070000	17.000000	17.049999	17.049999	2202500
2010-07-13	17.389999	18.639999	16.900000	18.139999	18.139999	2680100

[138]:
```
def plot_df(df, x, y, title="", xlabel='Date', ylabel='Value', dpi=100):
    plt.plot(x, y)
    plt.gca().set(title=title, xlabel=xlabel, ylabel=ylabel)
    plt.show()
```

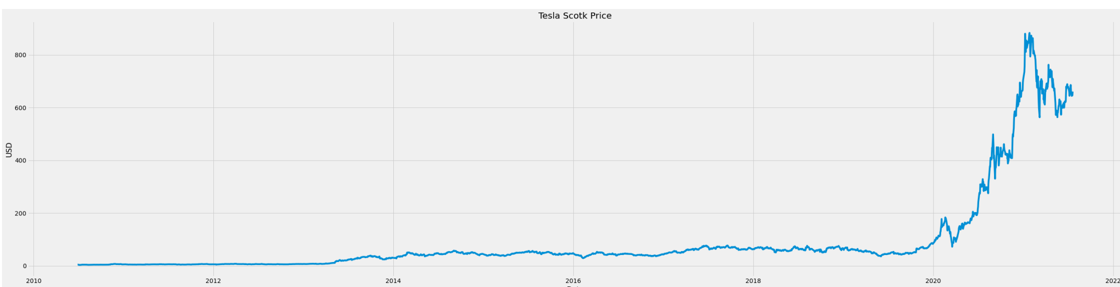
```
rcParams['figure.figsize'] = 40, 8
plt.plot(tesla.index, tesla['Close'], 'r-', label = 'TESLA')
plt.xlabel('Date'); plt.ylabel('Stock Price (USD)')
plt.title('Stock price of Tesla')
plt.legend();
```



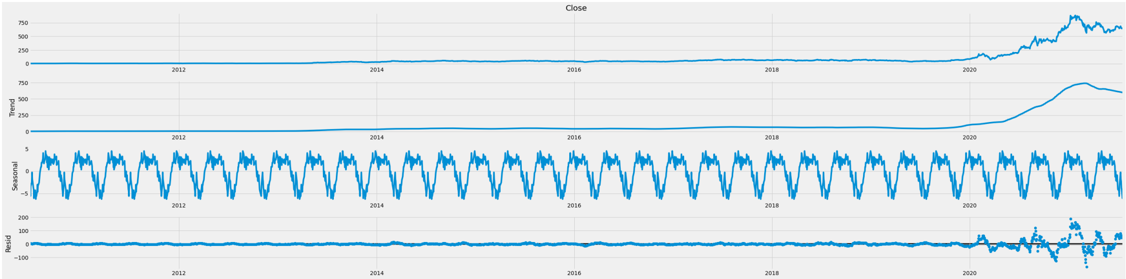
[139]:
```
print(f"""Tesla Missing Values: {tesla.isna().any(axis=1).sum()}\n{tesla[tesla.
↪isna().any(axis=1)].index}""")
```

```
Tesla Missing Values: 0
DatetimeIndex([], dtype='datetime64[ns]', name='Date', freq=None)
```

[140]:
```
rcParams['figure.figsize'] = 40, 10
plot_df(tesla, tesla.index , tesla['Close'], title='Tesla Scotk␣
↪Price',ylabel='USD')
```



[141]:
```
decomposition = sm.tsa.seasonal_decompose(tesla['Close'], model='additive',␣
↪freq=7*4*3,extrapolate_trend='freq')
fig = decomposition.plot()
plt.show()
```

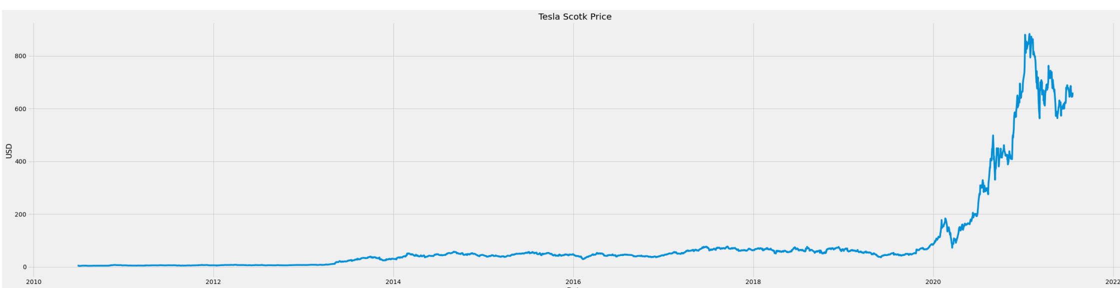



```
[142]: tesla_rc = pd.concat([decomposition.seasonal, decomposition.resid,␣
        ↪decomposition.trend, decomposition.observed], axis=1)
       tesla_rc.columns = ['seasonal', 'residual', 'trend', 'observation']
       tesla_rc['total'] = tesla_rc['seasonal'] + tesla_rc['residual'] +␣
        ↪tesla_rc['trend']
       tesla_rc.head()
```

[142]:

	seasonal	residual	trend	observation	total
Date					
2010-06-29	-4.060276	5.586953	3.251323	4.778	4.778
2010-06-30	-4.395862	5.891510	3.270352	4.766	4.766
2010-07-01	-5.574872	6.677491	3.289382	4.392	4.392
2010-07-02	-3.379229	3.910818	3.308411	3.840	3.840
2010-07-06	-2.491316	2.385874	3.327441	3.222	3.222

```
[143]: plot_df(tesla, tesla.index , tesla['Close'], title='Tesla Scotk␣
        ↪Price',ylabel='USD')
```

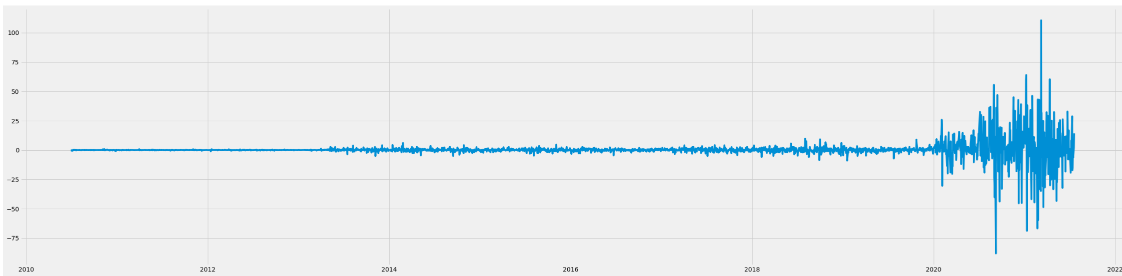



```
[144]: from statsmodels.tsa.stattools import adfuller
       adf_test = adfuller(tesla['Close'])
       print(f"""
       ADF Value : {adf_test[0]}
       P Value : {adf_test[1]}
       """)
```

```
ADF Value : 1.2319418969622373
P Value : 0.9961993094904104
```

[145]:
```python
plt.plot(tesla['Close'].diff(1).fillna(0))
```

[145]: [<matplotlib.lines.Line2D at 0x7feccae27f10>]



[146]:
```python
from statsmodels.tsa.stattools import adfuller
adf_test = adfuller(np.log(tesla['Close']).diff(1).fillna(0))
adf_test = adfuller((tesla['Close']).diff(1).fillna(0))
print(f"""
ADF Value : {adf_test[0]}
P Value : {adf_test[1]}
""")
```

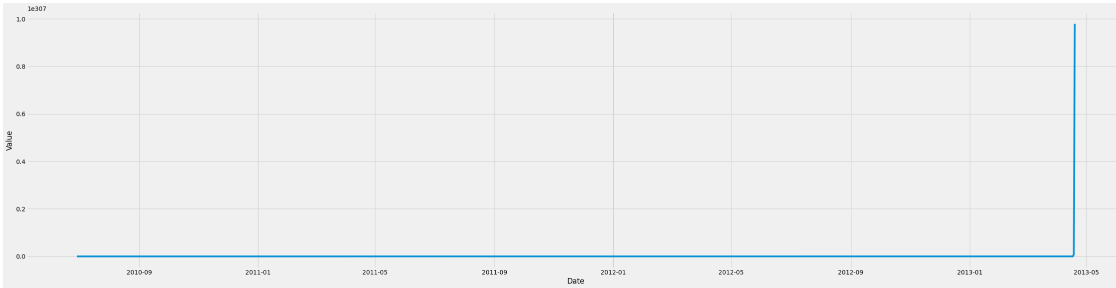
```
ADF Value : -9.177185248047586
P Value : 2.303220877653622e-15
```

[147]:
```python
tesla_st = tesla.diff(1).fillna(0)
tesla_st.head()
```

[147]:

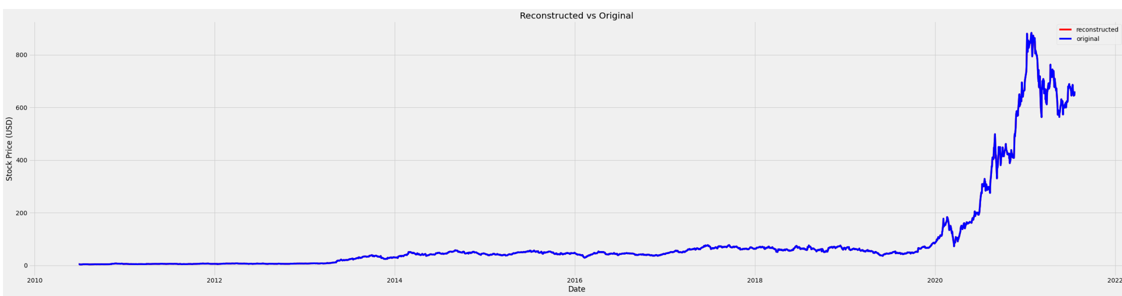
Attributes	Adj Close	Close	High	Low	Open	Volume
Date						
2010-06-29	0.000	0.000	0.000	0.000	0.000	0.0
2010-06-30	-0.012	-0.012	1.084	1.152	1.358	-7896000.0
2010-07-01	-0.374	-0.374	-0.900	-0.606	-0.158	-44841500.0
2010-07-02	-0.552	-0.552	-0.564	-0.312	-0.400	-15395000.0
2010-07-06	-0.618	-0.618	-0.620	-0.576	-0.600	8635500.0

[148]:
```python
tesla_reconstruct = tesla_st.copy()
tesla_reconstruct = tesla_reconstruct.cumsum()
plot_df(tesla_reconstruct, tesla_reconstruct.index, tesla_reconstruct.cumsum().
 ↪apply(np.exp)['Close'])
```



[149]:
```
tesla_reconstruct = tesla_st.copy()
tesla_reconstruct.iloc[0,:] = tesla.iloc[0,:]
tesla_reconstruct = tesla_reconstruct.cumsum()
```

[150]:
```
plt.plot(tesla.index, tesla_reconstruct['Close'], 'r-',  label='reconstructed')
plt.plot(tesla.index, tesla['Close'], 'b-', label = 'original')
plt.xlabel('Date'); plt.ylabel('Stock Price (USD)')
plt.title('Reconstructed vs Original')
plt.legend();
```



[151]:
```
stepwise_fit = auto_arima(tesla_reconstruct['Close'], trace=True, suppress_warnings=True)
stepwise_fit.summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(2,2,2)(0,0,0)[0]             : AIC=inf, Time=0.90 sec
 ARIMA(0,2,0)(0,0,0)[0]             : AIC=21264.132, Time=0.04 sec
 ARIMA(1,2,0)(0,0,0)[0]             : AIC=20362.268, Time=0.07 sec
 ARIMA(0,2,1)(0,0,0)[0]             : AIC=inf, Time=0.26 sec
 ARIMA(2,2,0)(0,0,0)[0]             : AIC=19869.808, Time=0.13 sec
 ARIMA(3,2,0)(0,0,0)[0]             : AIC=19669.473, Time=0.19 sec
 ARIMA(4,2,0)(0,0,0)[0]             : AIC=19644.774, Time=0.23 sec
 ARIMA(5,2,0)(0,0,0)[0]             : AIC=19522.033, Time=0.34 sec
 ARIMA(5,2,1)(0,0,0)[0]             : AIC=inf, Time=1.08 sec
 ARIMA(4,2,1)(0,0,0)[0]             : AIC=inf, Time=1.22 sec
```

```
ARIMA(5,2,0)(0,0,0)[0] intercept   : AIC=19524.033, Time=0.63 sec

Best model:  ARIMA(5,2,0)(0,0,0)[0]
Total fit time: 5.097 seconds
```

[151]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 2784
Model:               SARIMAX(5, 2, 0)   Log Likelihood               -9755.016
Date:                Sun, 08 Aug 2021   AIC                          19522.033
Time:                        11:31:38   BIC                          19557.619
Sample:                             0   HQIC                         19534.882
                               - 2784
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.8935      0.006   -145.877      0.000      -0.906      -0.882
ar.L2         -0.7323      0.007   -102.320      0.000      -0.746      -0.718
ar.L3         -0.4867      0.008    -62.985      0.000      -0.502      -0.472
ar.L4         -0.2813      0.007    -39.210      0.000      -0.295      -0.267
ar.L5         -0.2097      0.005    -38.622      0.000      -0.220      -0.199
sigma2        65.0168      0.396    164.002      0.000      64.240      65.794
================================================================================
===
Ljung-Box (L1) (Q):                   2.18   Jarque-Bera (JB):
266060.69
Prob(Q):                              0.14   Prob(JB):
0.00
Heteroskedasticity (H):             412.26   Skew:
0.59
Prob(H) (two-sided):                  0.00   Kurtosis:
50.89
================================================================================
===

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

[152]:
```python
tesla_reconstruct.head()
```

[152]:
```
Attributes  Adj Close  Close   High    Low   Open      Volume
Date
2010-06-29      4.778  4.778  5.000  3.508  3.800  93831500.0
```

```
2010-06-30      4.766  4.766  6.084  4.660  5.158  85935500.0
2010-07-01      4.392  4.392  5.184  4.054  5.000  41094000.0
2010-07-02      3.840  3.840  4.620  3.742  4.600  25699000.0
2010-07-06      3.222  3.222  4.000  3.166  4.000  34334500.0
```

[153]:
```python
print('Shape of data',tesla_reconstruct.shape)
```

```
Shape of data (2784, 6)
```

[154]:
```python
print(tesla_reconstruct.shape)
train=tesla_reconstruct.iloc[:-115]
test=tesla_reconstruct.iloc[-115:]
print(train.shape,test.shape)
```

```
(2784, 6)
(2669, 6) (115, 6)
```

[155]:
```python
model=ARIMA(train['Close'], order= (5,2,0))
model= model.fit()
model.summary()
```

[155]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                             ARIMA Model Results
==============================================================================
Dep. Variable:               D2.Close   No. Observations:                 2667
Model:                 ARIMA(5, 2, 0)   Log Likelihood               -8709.208
Method:                       css-mle   S.D. of innovations              6.337
Date:                Sun, 08 Aug 2021   AIC                          17432.417
Time:                        11:32:10   BIC                          17473.638
Sample:                             2   HQIC                         17447.333

================================================================================
==
                     coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
--
const              0.0017      0.036      0.047      0.962      -0.069
0.072
ar.L1.D2.Close    -0.8613      0.019    -44.784      0.000      -0.899
-0.824
ar.L2.D2.Close    -0.7147      0.025    -28.354      0.000      -0.764
-0.665
ar.L3.D2.Close    -0.4745      0.028    -16.957      0.000      -0.529
-0.420
ar.L4.D2.Close    -0.2314      0.026     -8.851      0.000      -0.283
-0.180
```

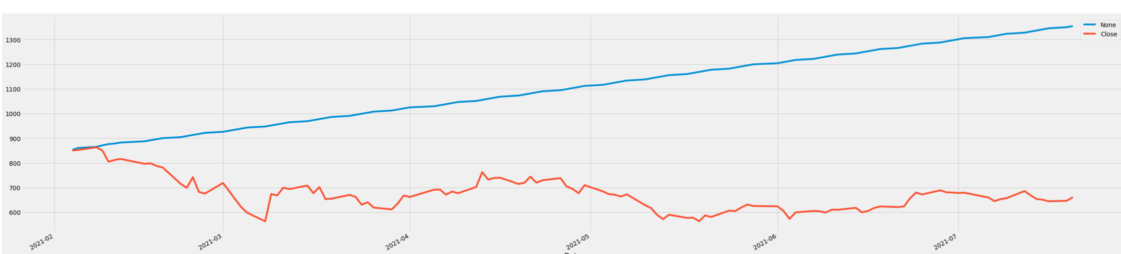
```
ar.L5.D2.Close    -0.1241      0.020     -6.225      0.000      -0.163
-0.085
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            0.5093          -1.4525j            1.5392           -0.1963
AR.2            0.5093          +1.4525j            1.5392            0.1963
AR.3           -1.4699          -0.0000j            1.4699           -0.5000
AR.4           -0.7068          -1.3469j            1.5211           -0.3269
AR.5           -0.7068          +1.3469j            1.5211            0.3269
-----------------------------------------------------------------------------
"""
```

[156]:
```python
start=len(train)
end=len(train)+len(test)-1
pred=model.predict(start=start,end=end,typ='levels')
pred.index=tesla.index[start:end+1]
print(pred)
```

```
Date
2021-02-04     852.518257
2021-02-05     860.678577
2021-02-08     864.934646
2021-02-09     871.088797
2021-02-10     876.154321
                 ...
2021-07-14    1336.761393
2021-07-15    1341.213108
2021-07-16    1345.666530
2021-07-19    1350.121661
2021-07-20    1354.578499
Length: 115, dtype: float64
```

[157]:
```python
pred.plot(legend=True)
test['Close'].plot(legend=True)
```

[157]:
```
<AxesSubplot:xlabel='Date'>
```



As you can see we saw upward trend only in the TESLA and our model predicted accordingly for remaining 115 days

and our prediction gone totally wrong as the stock changed the trend from upward to downward and sideward. The stock price is

depending on the so many parameters and we took in to consideration only the Closing price with respect to time so we got such

difference in our projection. We must take care other parameters.

So, learning from this project is,

1. We can build the model for sure but to enrich it we need more significant variables which are affacting the stock price, so same

format can be used with more significant variables majority variables we can get from Yahoo finance with free or very little monthly fees.

2. We know that price is dynamic and it absorbs all the current events so, there must be 3 types of variables taken in to

consideration, Long term (Which we took in to consideration price movement, 200 days Moving average), Medium term (like bonus,

dividend, Government overall policy for the sector, Conmany's order book, Management, Company's future plans and cliantage, Margins,

Top line and Bottom line, ROE (Return on Equity), 50 days and 100 days Moving Averages. etc.) and Also short term (like volume, open

interest, market sentiment overall and for that perticular sector and company, P/E, Moving averages like 3 days, 9 days and 14 days)

3. This was our first try to analyze the price movement and it taught us a lot, like more you add the valuable input and more accuracy you achieve.

4. We shall also try other models like Neural Network which might be useful in short term prediction as it is trained to check the

previous day price and current day price difference Delta and more the data it's pattern prediction capacity is high, so that is also a very good tool.

4.14 2- Predictive Analysis Using LSTM-RNN (Long Term Short Memory Model- Recurrent neural network)

Before we do anything, it is a good idea to fix the random number seed to ensure our results are reproducible.

4.14.1 Fix Random Seed for reproducibilty

[180]:
```
# fix random seed for reproducibility
numpy.random.seed(7)
```

4.14.2 Loading the dataset

[181]:
```
# We can then extract the NumPy array from the dataframe and
# convert the integer values to floating point values, which are more suitable␣
↪for modeling with a neural network

# load the dataset
tesla = pd.read_csv('TSLA.csv', usecols=['Close'], engine='python')
dataset = tesla.values
dataset = dataset.astype('float32')
```

[182]:
```
dataset
```

[182]:
```
array([[ 23.89],
       [ 23.83],
       [ 21.96],
       …,
       [640.81],
       [650.57],
       [780.  ]], dtype=float32)
```

The goal of normalization is to change the values of numeric columns in the dataset to a common scale, without distorting differences in the ranges of values.

LSTMs are sensitive to the scale of the input data, specifically when the sigmoid (default) or tanh activation functions are used. It can be a good practice to rescale the data to the range of 0-to-1, also called normalizing. We can easily normalize the dataset using the MinMaxScaler preprocessing class from the scikit-learn library.

[183]:
```
tesla.head(3)
```

[183]:

	Close
0	23.889999
1	23.830000
2	21.959999

4.14.3 Normalizing the dataset

LSTMs are sensitive to the scale of the input data, specifically when the sigmoid (default) or tanh activation functions are used. It's great to rescale / normalize the data to the range of 0-to-1. It can be done using the MinMaxScaler preprocessing class from the scikit-learn library.

[184]:
```
scaler = MinMaxScaler(feature_range=(0, 1))
dataset = scaler.fit_transform(dataset)
```

4.14.4 Splitting dataset into Testing and Training

With time series data, the sequence of values is important. We can split the ordered dataset into train and test datasets. The code below calculates the index of the split point and separates the data into the training datasets with 80% of the observations, leaving the remaining 20% for testing the model.

We can modify the train- test percentage according to the result we obtain

[264]:
```
train_size = int(len(dataset) * 0.80)
test_size = len(dataset) - train_size
train, test = dataset[0:train_size,:], dataset[train_size:len(dataset),:]
print(len(train), len(test))
```

```
1932 484
```

[265]:
```
train
```

[265]:
```
array([[0.01058623],
       [0.01050772],
       [0.00806071],
       …,
       [0.43861553],
       [0.42823866],
       [0.41236585]], dtype=float32)
```

4.14.5 Converting an array of values into a dataset matrix

[267]:
```
def create_dataset(dataset, look_back=1):
    dataX, dataY = [], []
    for i in range(len(dataset)-look_back-1):
#         print('Loop:', i,i+look_back)
#         print('X',dataset[i:(i+look_back), 0])
#         print('Y',dataset[(i+look_back), 0])
        a = dataset[i:(i+look_back), 0]
        dataX.append(a)
        dataY.append(dataset[i + look_back, 0])
    return numpy.array(dataX), numpy.array(dataY)
```

The function takes two arguments: the dataset, which is a NumPy array that we want to convert into a dataset, and the look_back, which is the number of previous time steps to use as input variables to predict the next time period — in this case defaulted to 1.

This default will create a dataset where X is the number of passengers at a given time (t) and Y is the number of passengers at the next time (t + 1).

It can be configured, and we will by constructing a differently shaped dataset in the next section.

4.14.6 Reshaping model

[268]:
```
# reshape into X=t and Y=t+1
look_back = 1
trainX, trainY = create_dataset(train, look_back)
testX, testY = create_dataset(test, look_back)
```

[269]:
```
# reshape input to be [samples, time steps, features]
trainX = numpy.reshape(trainX, (trainX.shape[0], 1, trainX.shape[1]))
testX = numpy.reshape(testX, (testX.shape[0], 1, testX.shape[1]))
```

4.14.7 Create and fit LSTM Network

The network has a visible layer with 1 input, a hidden layer with 3 LSTM blocks or neurons, and an output layer that makes a single value prediction. The default sigmoid activation function is used for the LSTM blocks. The network is trained for 100 epochs and a batch size of 32 is used.

[285]:
```
model = Sequential()
model.add(LSTM(3, input_shape=(1, look_back)))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam', metrics=['accuracy'])
model.fit(trainX, trainY, epochs=200, batch_size=7, verbose=1)
```

```
Epoch 1/200
276/276 [==============================] - 2s 1ms/step - loss: 0.0427 -
accuracy: 3.5471e-04
Epoch 2/200
276/276 [==============================] - 0s 997us/step - loss: 0.0194 -
accuracy: 2.6037e-04
Epoch 3/200
276/276 [==============================] - 0s 1ms/step - loss: 0.0137 -
accuracy: 1.0932e-04
Epoch 4/200
276/276 [==============================] - 0s 1ms/step - loss: 0.0069 -
accuracy: 1.2329e-04
Epoch 5/200
276/276 [==============================] - 0s 1ms/step - loss: 0.0019 -
accuracy: 8.4897e-04
Epoch 6/200
276/276 [==============================] - 0s 1ms/step - loss: 2.3639e-04 -
accuracy: 1.0021e-04
Epoch 7/200
```

```
276/276 [==============================] - 0s 1ms/step - loss: 7.2284e-05 -
accuracy: 4.5207e-04
Epoch 8/200
276/276 [==============================] - 0s 1ms/step - loss: 6.0629e-05 -
accuracy: 9.3482e-05
Epoch 9/200
276/276 [==============================] - 0s 1ms/step - loss: 6.1434e-05 -
accuracy: 7.1403e-04
Epoch 10/200
276/276 [==============================] - 0s 1ms/step - loss: 6.6593e-05 -
accuracy: 3.2246e-04
Epoch 11/200
276/276 [==============================] - 0s 1ms/step - loss: 5.9394e-05 -
accuracy: 2.0870e-05
Epoch 12/200
276/276 [==============================] - 0s 971us/step - loss: 5.7355e-05 -
accuracy: 3.5102e-04
Epoch 13/200
276/276 [==============================] - 0s 996us/step - loss: 6.0237e-05 -
accuracy: 0.0012
Epoch 14/200
276/276 [==============================] - 0s 994us/step - loss: 5.6607e-05 -
accuracy: 8.2083e-04
Epoch 15/200
276/276 [==============================] - 0s 991us/step - loss: 5.2111e-05 -
accuracy: 2.9871e-04
Epoch 16/200
276/276 [==============================] - 0s 1ms/step - loss: 5.4254e-05 -
accuracy: 1.1284e-05
Epoch 17/200
276/276 [==============================] - 0s 1ms/step - loss: 5.1524e-05 -
accuracy: 3.8126e-04
Epoch 18/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7336e-05 -
accuracy: 3.4013e-04
Epoch 19/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7161e-05 -
accuracy: 1.0021e-04
Epoch 20/200
276/276 [==============================] - 0s 1ms/step - loss: 4.9181e-05 -
accuracy: 2.0220e-04
Epoch 21/200
276/276 [==============================] - 0s 1ms/step - loss: 4.9215e-05 -
accuracy: 4.8700e-05
Epoch 22/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7398e-05 -
accuracy: 0.0013
Epoch 23/200
```

```
276/276 [==============================] - 0s 1ms/step - loss: 4.7595e-05 -
accuracy: 5.5556e-04
Epoch 24/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6070e-05 -
accuracy: 3.5102e-04
Epoch 25/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7440e-05 -
accuracy: 8.8904e-04
Epoch 26/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6996e-05 -
accuracy: 2.0496e-04
Epoch 27/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6373e-05 -
accuracy: 3.6592e-04
Epoch 28/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7687e-05 -
accuracy: 2.1332e-04
Epoch 29/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4264e-05 -
accuracy: 5.6105e-04
Epoch 30/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7981e-05 -
accuracy: 1.9945e-04
Epoch 31/200
276/276 [==============================] - 0s 1ms/step - loss: 5.4050e-05 -
accuracy: 4.8700e-05
Epoch 32/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1384e-05 -
accuracy: 2.5425e-04
Epoch 33/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1847e-05 -
accuracy: 1.4745e-04
Epoch 34/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6933e-05 -
accuracy: 2.2809e-05
Epoch 35/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2685e-05 -
accuracy: 9.5715e-05
Epoch 36/200
276/276 [==============================] - 0s 1ms/step - loss: 4.0100e-05 -
accuracy: 4.5656e-04
Epoch 37/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3960e-05 -
accuracy: 3.3654e-04
Epoch 38/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5878e-05 -
accuracy: 2.2469e-04
Epoch 39/200
```

```
276/276 [==============================] - 0s 1ms/step - loss: 4.3359e-05 -
accuracy: 4.6564e-04
Epoch 40/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7845e-05 -
accuracy: 3.5471e-04
Epoch 41/200
276/276 [==============================] - 0s 1ms/step - loss: 5.3745e-05 -
accuracy: 1.0021e-04
Epoch 42/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2280e-05 -
accuracy: 6.3826e-04
Epoch 43/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1593e-05 -
accuracy: 8.1178e-04
Epoch 44/200
276/276 [==============================] - 0s 1ms/step - loss: 3.9262e-05 -
accuracy: 1.9673e-04
Epoch 45/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1902e-05 -
accuracy: 6.3826e-04
Epoch 46/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3011e-05 -
accuracy: 5.6164e-06
Epoch 47/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6520e-05 -
accuracy: 2.7284e-04
Epoch 48/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1124e-05 -
accuracy: 6.5305e-05
Epoch 49/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7753e-05 -
accuracy: 0.0011
Epoch 50/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6151e-05 -
accuracy: 0.0012
Epoch 51/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2091e-05 -
accuracy: 4.9391e-04
Epoch 52/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6053e-05 -
accuracy: 1.2565e-04
Epoch 53/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4821e-05 -
accuracy: 0.0010
Epoch 54/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5310e-05 -
accuracy: 0.0018
Epoch 55/200
```

```
276/276 [==============================] - 0s 1ms/step - loss: 5.0618e-05 -
accuracy: 6.4470e-04
Epoch 56/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2945e-05 -
accuracy: 5.6105e-04
Epoch 57/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3769e-05 -
accuracy: 3.4598e-05
Epoch 58/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7161e-05 -
accuracy: 0.0016
Epoch 59/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5184e-05 -
accuracy: 9.7995e-04
Epoch 60/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6799e-05 -
accuracy: 5.0747e-05
Epoch 61/200
276/276 [==============================] - 0s 1ms/step - loss: 4.9299e-05 -
accuracy: 0.0012
Epoch 62/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2197e-05 -
accuracy: 1.1162e-04
Epoch 63/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1836e-05 -
accuracy: 2.3926e-04
Epoch 64/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1666e-05 -
accuracy: 2.4520e-04
Epoch 65/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4141e-05 -
accuracy: 1.7802e-04
Epoch 66/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7768e-05 -
accuracy: 2.0496e-04
Epoch 67/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3433e-05 -
accuracy: 4.3451e-04
Epoch 68/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2850e-05 -
accuracy: 1.4993e-04
Epoch 69/200
276/276 [==============================] - 0s 1ms/step - loss: 3.8550e-05 -
accuracy: 4.3022e-04
Epoch 70/200
276/276 [==============================] - 0s 1ms/step - loss: 4.9870e-05 -
accuracy: 7.6059e-04
Epoch 71/200
```

```
276/276 [==============================] - 0s 1ms/step - loss: 4.8776e-05 -
accuracy: 7.5961e-05
Epoch 72/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2477e-05 -
accuracy: 0.0014
Epoch 73/200
276/276 [==============================] - 0s 882us/step - loss: 5.1366e-05 -
accuracy: 1.1626e-04
Epoch 74/200
276/276 [==============================] - 0s 869us/step - loss: 4.3448e-05 -
accuracy: 4.9391e-04
Epoch 75/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4590e-05 -
accuracy: 0.0012
Epoch 76/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4381e-05 -
accuracy: 2.7600e-04
Epoch 77/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2273e-05 -
accuracy: 1.0702e-04
Epoch 78/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5052e-05 -
accuracy: 2.6709e-05
Epoch 79/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3595e-05 -
accuracy: 4.0595e-05
Epoch 80/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5164e-05 -
accuracy: 4.2609e-05
Epoch 81/200
276/276 [==============================] - 0s 1ms/step - loss: 4.0133e-05 -
accuracy: 1.8939e-05
Epoch 82/200
276/276 [==============================] - 0s 1ms/step - loss: 4.9976e-05 -
accuracy: 6.7820e-04
Epoch 83/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1025e-05 -
accuracy: 2.4820e-04
Epoch 84/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6863e-05 -
accuracy: 0.0019
Epoch 85/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6617e-05 -
accuracy: 3.0638e-05
Epoch 86/200
276/276 [==============================] - 0s 1ms/step - loss: 4.9776e-05 -
accuracy: 2.5730e-04
Epoch 87/200
```

```
276/276 [==============================] - 0s 1ms/step - loss: 4.2983e-05 -
accuracy: 4.0925e-04
Epoch 88/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5006e-05 -
accuracy: 4.1753e-04
Epoch 89/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6116e-05 -
accuracy: 6.3200e-05
Epoch 90/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3205e-05 -
accuracy: 9.1031e-04
Epoch 91/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3525e-05 -
accuracy: 6.3826e-04
Epoch 92/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5976e-05 -
accuracy: 2.4222e-04
Epoch 93/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1253e-05 -
accuracy: 2.6037e-04
Epoch 94/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3919e-05 -
accuracy: 1.2093e-04
Epoch 95/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6071e-05 -
accuracy: 7.9415e-04
Epoch 96/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6926e-05 -
accuracy: 4.3022e-04
Epoch 97/200
276/276 [==============================] - 0s 1ms/step - loss: 4.8090e-05 -
accuracy: 6.3189e-04
Epoch 98/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3918e-05 -
accuracy: 2.3046e-04
Epoch 99/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1923e-05 -
accuracy: 3.8910e-04
Epoch 100/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3897e-05 -
accuracy: 0.0014
Epoch 101/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3874e-05 -
accuracy: 3.5471e-04
Epoch 102/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3980e-05 -
accuracy: 3.1556e-04
Epoch 103/200
```

```
276/276 [==============================] - 0s 1ms/step - loss: 4.5477e-05 -
accuracy: 8.6862e-04
Epoch 104/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2370e-05 -
accuracy: 0.0010
Epoch 105/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5340e-05 -
accuracy: 1.7540e-04
Epoch 106/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3917e-05 -
accuracy: 1.7014e-05
Epoch 107/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7041e-05 -
accuracy: 1.7020e-04
Epoch 108/200
276/276 [==============================] - 0s 1ms/step - loss: 5.1524e-05 -
accuracy: 9.7995e-04
Epoch 109/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3189e-05 -
accuracy: 4.2609e-05
Epoch 110/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1868e-05 -
accuracy: 1.1284e-05
Epoch 111/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4529e-05 -
accuracy: 0.0012
Epoch 112/200
276/276 [==============================] - 0s 1ms/step - loss: 5.0431e-05 -
accuracy: 3.3654e-04
Epoch 113/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1009e-05 -
accuracy: 4.1753e-04
Epoch 114/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3953e-05 -
accuracy: 0.0016
Epoch 115/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3544e-05 -
accuracy: 3.5102e-04
Epoch 116/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3611e-05 -
accuracy: 4.2595e-04
Epoch 117/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4798e-05 -
accuracy: 4.4763e-04
Epoch 118/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5376e-05 -
accuracy: 3.8516e-04
Epoch 119/200
```

```
276/276 [==============================] - 0s 1ms/step - loss: 4.8068e-05 -
accuracy: 0.0019
Epoch 120/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1490e-05 -
accuracy: 2.1052e-04
Epoch 121/200
276/276 [==============================] - 0s 1ms/step - loss: 4.8095e-05 -
accuracy: 5.5013e-04
Epoch 122/200
276/276 [==============================] - 0s 1ms/step - loss: 5.0044e-05 -
accuracy: 7.7710e-04
Epoch 123/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2521e-05 -
accuracy: 2.2469e-04
Epoch 124/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1882e-05 -
accuracy: 8.3942e-04
Epoch 125/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4192e-05 -
accuracy: 2.4755e-05
Epoch 126/200
276/276 [==============================] - 0s 1ms/step - loss: 4.8391e-05 -
accuracy: 7.5254e-04
Epoch 127/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5086e-05 -
accuracy: 0.0011
Epoch 128/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1705e-05 -
accuracy: 4.7025e-04
Epoch 129/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2434e-05 -
accuracy: 2.5730e-04
Epoch 130/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1379e-05 -
accuracy: 5.4476e-04
Epoch 131/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1381e-05 -
accuracy: 1.7014e-05
Epoch 132/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3373e-05 -
accuracy: 2.4222e-04
Epoch 133/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6440e-05 -
accuracy: 0.0021
Epoch 134/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6651e-05 -
accuracy: 6.3200e-05
Epoch 135/200
```

```
276/276 [==============================] - 0s 996us/step - loss: 4.3334e-05 -
accuracy: 1.2329e-04
Epoch 136/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3710e-05 -
accuracy: 5.1365e-04
Epoch 137/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6935e-05 -
accuracy: 1.9401e-04
Epoch 138/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4847e-05 -
accuracy: 2.8239e-04
Epoch 139/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4410e-05 -
accuracy: 3.8516e-04
Epoch 140/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7223e-05 -
accuracy: 2.9871e-04
Epoch 141/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2475e-05 -
accuracy: 3.8516e-04
Epoch 142/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2664e-05 -
accuracy: 6.9224e-04
Epoch 143/200
276/276 [==============================] - 0s 1ms/step - loss: 5.1720e-05 -
accuracy: 0.0016
Epoch 144/200
276/276 [==============================] - 0s 1ms/step - loss: 4.9415e-05 -
accuracy: 1.4008e-04
Epoch 145/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4807e-05 -
accuracy: 3.5102e-04
Epoch 146/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6698e-05 -
accuracy: 1.3282e-04
Epoch 147/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1958e-05 -
accuracy: 0.0012
Epoch 148/200
276/276 [==============================] - 0s 1ms/step - loss: 3.9379e-05 -
accuracy: 4.0595e-05
Epoch 149/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4050e-05 -
accuracy: 7.4460e-04
Epoch 150/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1197e-05 -
accuracy: 2.9871e-04
Epoch 151/200
```

```
276/276 [==============================] - 0s 1ms/step - loss: 4.8970e-05 -
accuracy: 8.4897e-04
Epoch 152/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4440e-05 -
accuracy: 5.3945e-04
Epoch 153/200
276/276 [==============================] - 0s 1ms/step - loss: 4.9955e-05 -
accuracy: 8.2462e-05
Epoch 154/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4538e-05 -
accuracy: 4.8432e-04
Epoch 155/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1300e-05 -
accuracy: 1.6763e-04
Epoch 156/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2459e-05 -
accuracy: 2.0496e-04
Epoch 157/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5641e-05 -
accuracy: 0.0010
Epoch 158/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6853e-05 -
accuracy: 1.0932e-04
Epoch 159/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2144e-05 -
accuracy: 6.5123e-04
Epoch 160/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4399e-05 -
accuracy: 6.7418e-05
Epoch 161/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3932e-05 -
accuracy: 0.0013
Epoch 162/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2306e-05 -
accuracy: 4.0516e-04
Epoch 163/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3962e-05 -
accuracy: 6.7820e-04
Epoch 164/200
276/276 [==============================] - 0s 1ms/step - loss: 5.0056e-05 -
accuracy: 4.4763e-04
Epoch 165/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6656e-05 -
accuracy: 1.1393e-04
Epoch 166/200
276/276 [==============================] - 0s 1ms/step - loss: 4.8454e-05 -
accuracy: 8.5870e-04
Epoch 167/200
```

```
276/276 [==============================] - 0s 1ms/step - loss: 4.3993e-05 -
accuracy: 1.0702e-04
Epoch 168/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2490e-05 -
accuracy: 1.0702e-04
Epoch 169/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5616e-05 -
accuracy: 9.3878e-06
Epoch 170/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2084e-05 -
accuracy: 4.7958e-04
Epoch 171/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4624e-05 -
accuracy: 4.8432e-04
Epoch 172/200
276/276 [==============================] - 0s 1ms/step - loss: 4.4221e-05 -
accuracy: 0.0012
Epoch 173/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1004e-05 -
accuracy: 0.0010
Epoch 174/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6513e-05 -
accuracy: 0.0015
Epoch 175/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3250e-05 -
accuracy: 2.2757e-04
Epoch 176/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6262e-05 -
accuracy: 1.4252e-04
Epoch 177/200
276/276 [==============================] - 0s 1ms/step - loss: 5.5981e-05 -
accuracy: 1.2803e-04
Epoch 178/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5142e-05 -
accuracy: 3.8588e-05
Epoch 179/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7859e-05 -
accuracy: 5.6164e-06
Epoch 180/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3205e-05 -
accuracy: 5.0865e-04
Epoch 181/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6602e-05 -
accuracy: 5.0865e-04
Epoch 182/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1263e-05 -
accuracy: 8.6842e-05
Epoch 183/200
```

```
276/276 [==============================] - 0s 1ms/step - loss: 4.5230e-05 -
accuracy: 4.6564e-04
Epoch 184/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1718e-05 -
accuracy: 6.3189e-04
Epoch 185/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5482e-05 -
accuracy: 4.9878e-04
Epoch 186/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1131e-05 -
accuracy: 3.7738e-04
Epoch 187/200
276/276 [==============================] - 0s 1ms/step - loss: 4.1559e-05 -
accuracy: 9.2128e-04
Epoch 188/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3324e-05 -
accuracy: 6.2560e-04
Epoch 189/200
276/276 [==============================] - 0s 1ms/step - loss: 4.6109e-05 -
accuracy: 3.8516e-04
Epoch 190/200
276/276 [==============================] - 0s 1ms/step - loss: 4.0800e-05 -
accuracy: 0.0013
Epoch 191/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7096e-05 -
accuracy: 3.7738e-04
Epoch 192/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5367e-05 -
accuracy: 5.6660e-04
Epoch 193/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2817e-05 -
accuracy: 7.8119e-05
Epoch 194/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7690e-05 -
accuracy: 6.1939e-04
Epoch 195/200
276/276 [==============================] - 0s 999us/step - loss: 5.2191e-05 -
accuracy: 4.5656e-04
Epoch 196/200
276/276 [==============================] - 0s 1ms/step - loss: 4.7123e-05 -
accuracy: 5.3945e-04
Epoch 197/200
276/276 [==============================] - 0s 1ms/step - loss: 4.3947e-05 -
accuracy: 1.0474e-04
Epoch 198/200
276/276 [==============================] - 0s 1ms/step - loss: 4.2991e-05 -
accuracy: 2.9212e-04
Epoch 199/200
```

```
276/276 [==============================] - 0s 1ms/step - loss: 4.4694e-05 -
accuracy: 6.9541e-05
Epoch 200/200
276/276 [==============================] - 0s 1ms/step - loss: 4.5964e-05 -
accuracy: 7.4460e-04
```

[285]: <keras.callbacks.History at 0x7fec7c455820>

Once the model is fit, we can estimate the performance of the model on the train and test datasets. Accuracy is meaningless in a regression problem, The model fitting history (not shown here) shows a decreasing loss.

4.14.8 Model accuracy evaluation

Let's evaluate now the model performance in the same training set, using the appropriate Keras built-in function

[272]:
```
score=model.evaluate(trainX, trainY, verbose=0)
score
```

[272]: [4.164217898505 74e-05, 0.0005181347369216383]

The exact contents of the score array depend on what exactly we have requested during model compilation; in our case here, the first element is the loss (MSE), and the second one is the "accuracy". Usually accuracies are compared to a baseline accuracy of another (simple) algorithm, so that you can see whether the task is just very easy or your LSTM is very good.

The MSE(loss) is 4.16. There is no correct value for MSE. Simply put, the lower the value the better and 0 means the model is perfect. Since there is no correct answer, the MSE's basic value is in selecting one prediction model over another. This is low, but the model can do better by inclusing more data points and training it in different ways

4.14.9 Making Predictions and Calculating root mean square

[260]:
```
# make predictions
trainPredict = model.predict(trainX)
testPredict = model.predict(testX)
# invert predictions
trainPredict = scaler.inverse_transform(trainPredict)
trainY = scaler.inverse_transform([trainY])
testPredict = scaler.inverse_transform(testPredict)
testY = scaler.inverse_transform([testY])
# calculate root mean squared error
trainScore = math.sqrt(mean_squared_error(trainY[0], trainPredict[:,0]))
print('Train Score: %.2f RMSE' % (trainScore))
testScore = math.sqrt(mean_squared_error(testY[0], testPredict[:,0]))
print('Test Score: %.2f RMSE' % (testScore))
```

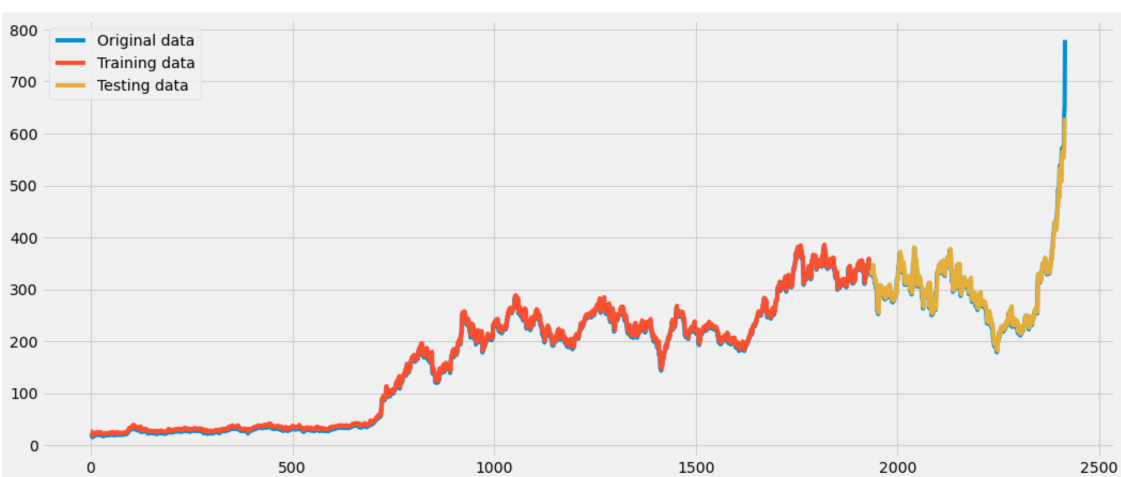
```
Train Score: 5.86 RMSE
Test Score: 11.35 RMSE
```

We can see that the model has an average error of about 6 stock closing prices (in thousands) on the training dataset, and about 11 stock closing prices (in thousands) on the test dataset, which is pretty good as average error is too low.

Lower values of RMSE indicate better fit.

4.14.10 Visualizations and Plotting

[261]:
```
# shift train predictions for plotting
trainPredictPlot = numpy.empty_like(dataset)
trainPredictPlot[:, :] = numpy.nan
trainPredictPlot[look_back:len(trainPredict)+look_back, :] = trainPredict

# shift test predictions for plotting
testPredictPlot = numpy.empty_like(dataset)
testPredictPlot[:, :] = numpy.nan
testPredictPlot[len(trainPredict)+(look_back*2)+1:len(dataset)-1, :] =␣
 ↪testPredict

# plot baseline and predictions
plt.figure(figsize=(16, 7))
plt.plot(scaler.inverse_transform(dataset), label='Original data')
plt.plot(trainPredictPlot, label='Training data')
plt.plot(testPredictPlot, label='Testing data')

# plt.figure(figsize=(16, 7))
# plt.plot(scaled_dataset, label='Original data')
# plt.plot(sup, label='Training data')
# plt.plot(test_results, label='Testing data')
# plt.legend()
# plt.show()

plt.legend()
plt.show()
```



4.15 We can deduce from the graph that LSTM model yields better prediction. ALso, from the actual error for ARIMA model was 19.39% of the actual value, whereas, the LSTM model had a lesser error rate as it had lesser loss and stable accuracy