```
%%capture
!pip install prophet
!pip install -U statsmodels
!pip install colorama
```

```
##Importing Packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from statsmodels.tsa.seasonal import seasonal_decompose as sd
from scipy import stats
from statsmodels.graphics.gofplots import qqplot as qq
from scipy.stats import kurtosis
import scipy
from statsmodels.tsa.stattools import adfuller
from pylab import rcParams
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
from pandas.core.window.rolling import Rolling
from sklearn.model_selection import train_test_split as split
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
import statsmodels.api as sm
import warnings
import itertools
warnings.filterwarnings("ignore")
from statsmodels.stats.diagnostic import acorr_ljungbox
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error, median_absolute_error, mean_squared_log_error
                                    KFold, ShuffleSplit, StratifiedKFold, StratifiedShuffleSplit, TimeSeriesSplit
```

Saved successfully!

```
from matplotlib import pyplot
import os
import re
from colorama import Fore, Back, Style
import seaborn as sns
import plotly.express as px
import warnings
from matplotlib.patches import Patch
# ! pip install plotly
import plotly.graph_objects as go
import plotly.express as px
from plotly.subplots import make_subplots
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LSTM, GRU

from itertools import cycle
```

```
##Matplotlib Parameters
import matplotlib.ticker as ticker
rcParams['axes.labelsize'] = 12
rcParams['xtick.labelsize'] = 12
rcParams['ytick.labelsize'] = 12
plt.style.context('fivethirtyeight')
```

```
<contextlib._GeneratorContextManager at 0x7f04e5d75720>
```

```
data = pd.read_csv("AAPL.csv");
```

```
data.head()
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	2012-01-03	58.485714	58.928570	58.428570	58.747143	50.765709	75555200
1	2012-01-04	58.571430	59.240002	58.468571	59.062859	51.038536	65005500
2	2012-01-05	59.278572	59.792858	58.952858	59.718571	51.605175	67817400
3	2012-01-06	59.967144	60.392857	59.888573	60.342857	52.144630	79573200
4	2012-01-09	60.785713	61.107143	60.192856	60.247143	52.061932	98506100

```
data.describe()
```

	Open	High	Low	Close	Adj Close	Volume
count	2011.000000	2011.000000	2011.000000	2011.000000	2011.000000	2.011000e+03
mean	126.707469	127.827594	125.580258	126.741235	119.505548	5.949670e+07
std	50.483753	50.926301	50.124940	50.578369	52.438444	4.683856e+07
min	55.424286	57.085712	55.014286	55.790001	48.921928	1.136200e+07
25%	85.882858	86.717858	85.056427	86.202145	75.056679	2.758565e+07
50%	113.050003	114.190002	111.870003	113.050003	105.222908	4.346900e+07
75%	165.190002	167.409996	163.424995	165.245002	160.047111	7.471030e+07
max	291.119995	293.970001	288.119995	291.519989	289.522614	3.765300e+08

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2011 entries, 0 to 2010
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       2011 non-null   object
 1   Open       2011 non-null   float64
 2   High       2011 non-null   float64
 3   Low        2011 non-null   float64
 4   Close      2011 non-null   float64
 5   Adj Close  2011 non-null   float64
 6   Volume     2011 non-null   int64
dtypes: float64(5), int64(1), object(1)
memory usage: 110.1+ KB
```

Saved successfully!

```
pe(data['Date'][0]))
print("Open column data type: ", type(data['Open'][0]))
print("Close column data type: ", type(data['Close'][0]))
print("High column data type: ", type(data['High'][0]))
print("Low column data type: ", type(data['Low'][0]))
```

```
Date column data type:  <class 'str'>
Open column data type:  <class 'numpy.float64'>
Close column data type:  <class 'numpy.float64'>
High column data type:  <class 'numpy.float64'>
Low column data type:  <class 'numpy.float64'>
```

```
data['Date']
```

```
0       2012-01-03
1       2012-01-04
2       2012-01-05
3       2012-01-06
4       2012-01-09
           ...
2006    2019-12-23
2007    2019-12-24
2008    2019-12-26
2009    2019-12-27
2010    2019-12-30
Name: Date, Length: 2011, dtype: object
```

```
data['Date'] = pd.to_datetime(data['Date'],format='%Y-%m-%d')
```

```
##Making Date as Index
data.set_index('Date',inplace=True)
```

```
data['Date'] =  data.index
```

```
data.head()
```

	Open	High	Low	Close	Adj Close	Volume	Date
Date							

```
data.isnull().sum()
```

```
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
Date         0
dtype: int64
```

```
data.dropna(inplace = True)
```

```
print("Starting date: ",data.iloc[0][0])
print("Ending date: ", data.iloc[-1][0])
print("Duration: ", data.iloc[-1][0]-data.iloc[0][0])
```

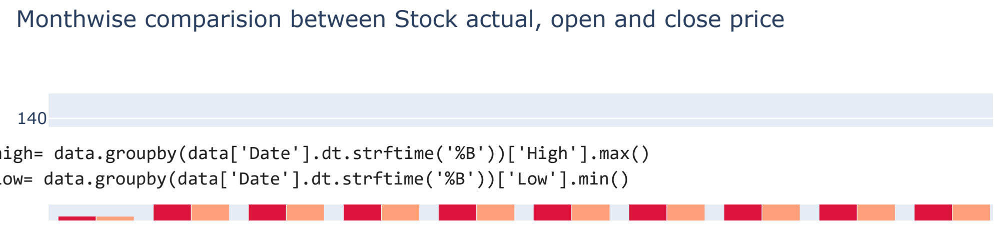
```
Starting date:  58.485714
Ending date:  289.459991
Duration:  230.974277
```

```
monthvise= data.groupby(data['Date'].dt.strftime('%B'))[['Open','Close']].mean().sort_values(by='Close')
monthvise.head()
```

Saved successfully!

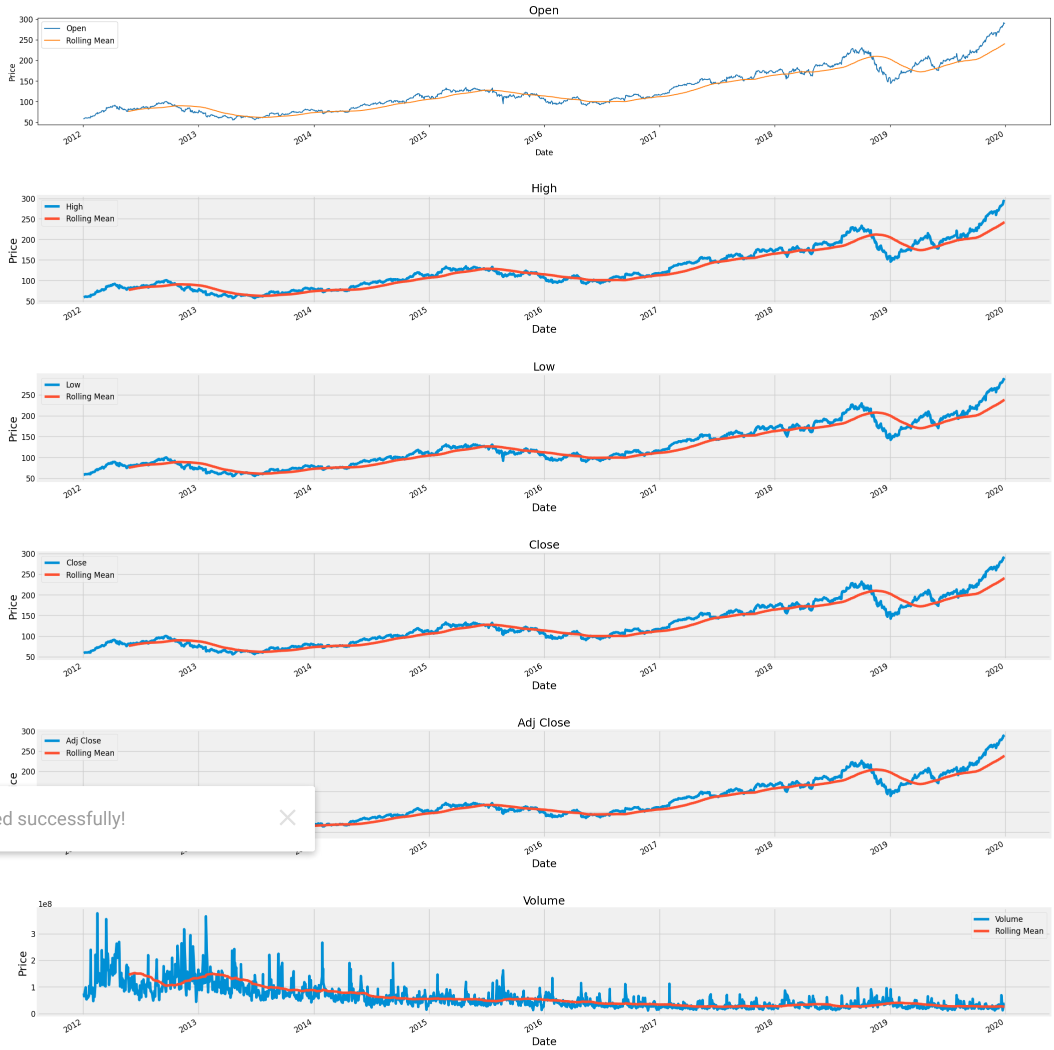
	Open	Close
Date		
[illegible]	[illegible]	[illegible]4
February	112.602078	112.840974
March	119.156412	119.128547
April	120.974871	120.968503
May	123.059776	123.232276

```
fig = go.Figure()

fig.add_trace(go.Bar(
    x=monthvise.index,
    y=monthvise['Open'],
    name='Stock Open Price',
    marker_color='crimson'
))
fig.add_trace(go.Bar(
    x=monthvise.index,
    y=monthvise['Close'],
    name='Stock Close Price',
    marker_color='lightsalmon'
))

fig.update_layout(barmode='group', xaxis_tickangle=-45,
                  title='Monthwise comparision between Stock actual, open and close price')
fig.show()
```

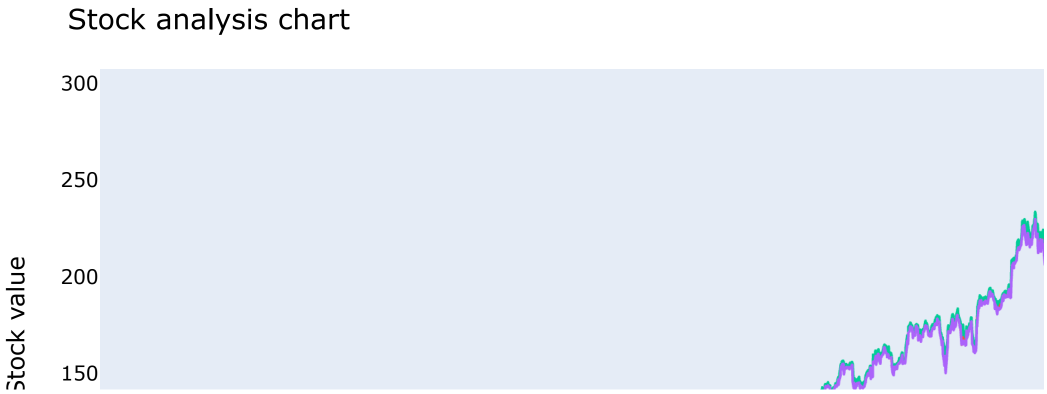



```
monthvise_high= data.groupby(data['Date'].dt.strftime('%B'))['High'].max()
monthvise_low= data.groupby(data['Date'].dt.strftime('%B'))['Low'].min()

fig = go.Figure()
fig.add_trace(go.Bar(
    x=monthvise_high.index,
    y=monthvise_high,
    name='Stock high Price',
    marker_color='rgb(0, 153, 204)'
))
fig.add_trace(go.Bar(
    x=monthvise_low.index,
    y=monthvise_low,
    name='Stock low Price',
    marker_color='rgb(255, 128, 0)'
))

fig.update_layout(barmode='group',
                  title=' Monthwise High and Low stock price')
fig.show()
```

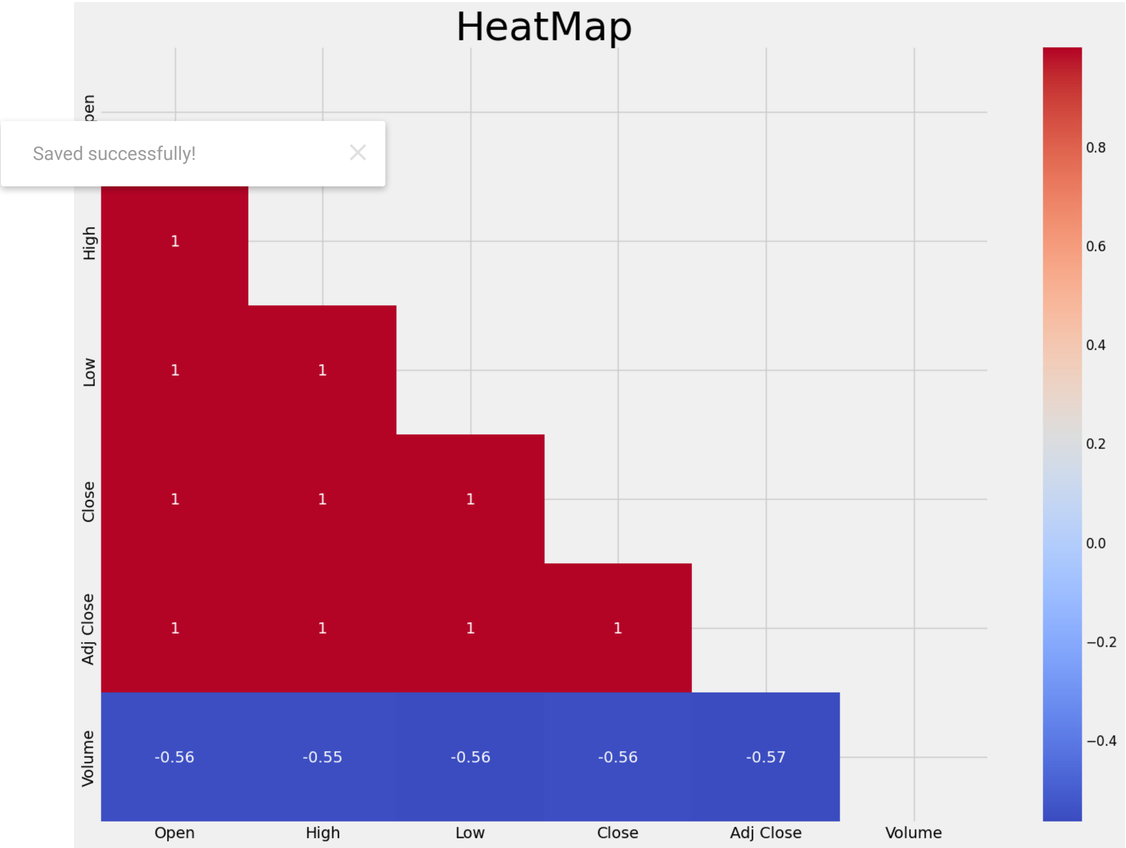

```
##visualizing


col_names = data.columns

fig = plt.figure(figsize=(24, 24))
for i in range(6):
  ax = fig.add_subplot(6,1,i+1)
  ax.plot(data.iloc[:,i],label=col_names[i])
  data.iloc[:,i].rolling(100).mean().plot(label='Rolling Mean')
  ax.set_title(col_names[i],fontsize=18)
  ax.set_xlabel('Date')
  ax.set_ylabel('Price')
  ax.patch.set_edgecolor('black')
  plt.style.context('fivethirtyeight')
  plt.legend(prop={'size': 12})
  plt.style.use('fivethirtyeight')

fig.tight_layout(pad=3.0)

plt.show()
```




```
names = cycle(['Stock Open Price','Stock Close Price','Stock High Price','Stock Low Price'])

fig = px.line(data, x=data.Date, y=[data['Open'], data['Close'],
                                    data['High'], data['Low']],
             labels={'date': 'Date','value':'Stock value'})
fig.update_layout(title_text='Stock analysis chart', font_size=15, font_color='black',legend_title_text='Stock Parameters')
fig.for_each_trace(lambda t:  t.update(name = next(names)))
fig.update_xaxes(showgrid=False)
fig.update_yaxes(showgrid=False)

fig.show()
```




```
##HeatMap to Verify Multicollinearity between Features
fig = plt.figure(figsize=(16,12))
matrix = np.triu(data.corr())
ax = sns.heatmap(data.corr(),annot=True,annot_kws={"size":14},mask=matrix,cmap='coolwarm')
ax.tick_params(labelsize=14)
sns.set(font_scale=3)
ax.set_title('HeatMap')
plt.style.use('fivethirtyeight')
plt.show()
```




```
##Data after feature selection
data_feature_selected = data.drop(axis=1,labels=['Open','High','Low','Close','Volume'])
```

```
col_order = ['Date','Adj Close']
data_feature_selected = data_feature_selected.reindex(columns=col_order)
data_feature_selected
```

	Date	Adj Close
Date		
2012-01-03	2012-01-03	50.765709
2012-01-04	2012-01-04	51.038536
2012-01-05	2012-01-05	51.605175
2012-01-06	2012-01-06	52.144630
2012-01-09	2012-01-09	52.061932
...	...	...
2019-12-23	2019-12-23	282.054138
2019-12-24	2019-12-24	282.322266
2019-12-26	2019-12-26	287.923645
2019-12-27	2019-12-27	287.814392
2019-12-30	2019-12-30	289.522614

2011 rows × 2 columns

```
##Resample Data to Monthly instead of Daily by Aggregating Using Mean
monthly_mean = data_feature_selected['Adj Close'].resample('M').mean()
```

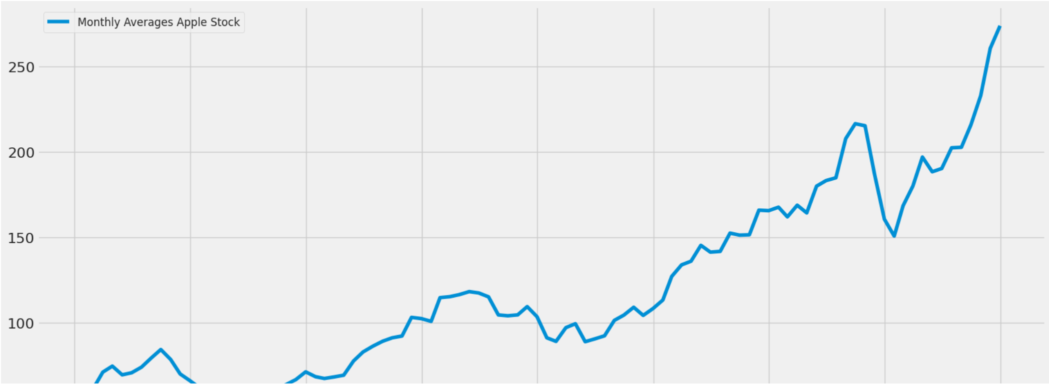
Saved successfully!

```
monthly_data = monthly_mean.to_frame()
monthly_data
```

	Adj Close
Date	
2012-01-31	52.907298
2012-02-29	61.424381
2012-03-31	71.292448
2012-04-30	74.810151
2012-05-31	69.708045
...	...
2019-08-31	202.738817
2019-09-30	215.853332
2019-10-31	232.974974
2019-11-30	260.569057
2019-12-31	273.780717

96 rows × 1 columns

```
##Monthly Stock Price
fig = plt.figure(figsize=(18,8))
plt.plot(monthly_data['Adj Close'],label='Monthly Averages Apple Stock')
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
ax.set_title('Monthly Resampled Data')
plt.style.use('fivethirtyeight')
plt.legend(prop={'size': 12})
plt.show()
```



##EDA

```
closedf = data[['Date','Close']]
print("Shape of close dataframe:", closedf.shape)
```

    Shape of close dataframe: (2011, 2)

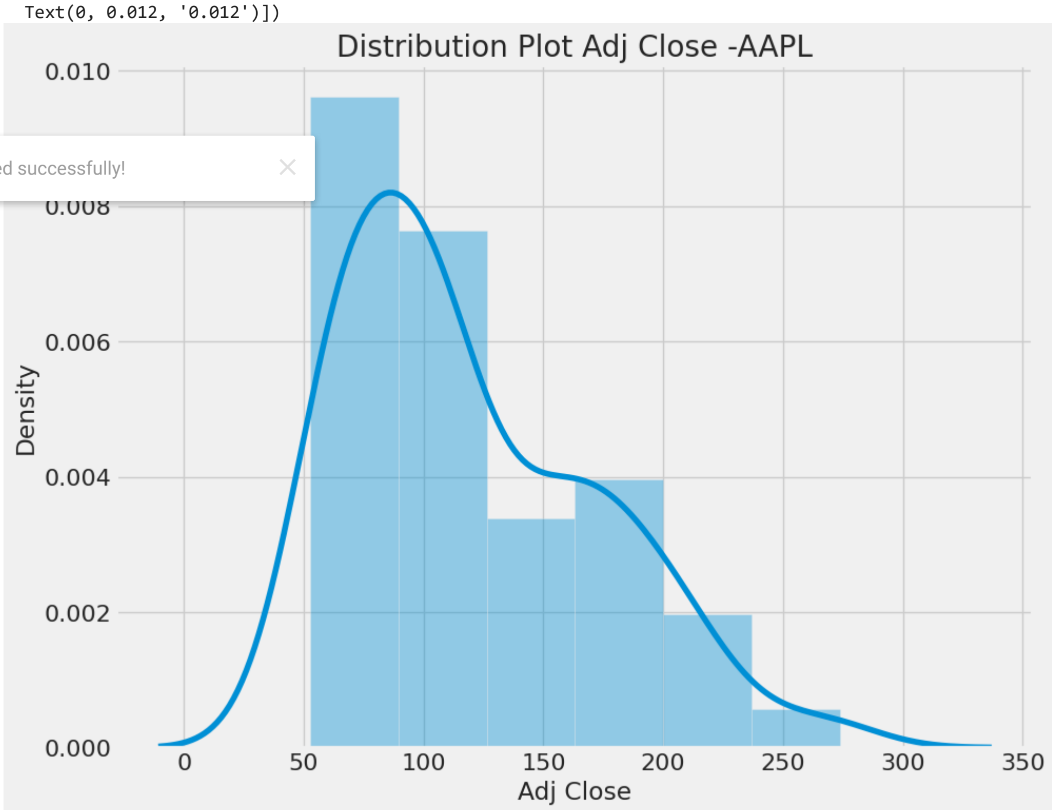
```
fig = px.line(closedf, x=closedf.Date, y=closedf.Close,labels={'date':'Date','close':'Close Stock'})
fig.update_traces(marker_line_width=2, opacity=0.6)
fig.update_layout(title_text='Stock close price chart', plot_bgcolor='white', font_size=15, font_color='black')
fig.update_xaxes(showgrid=False)
fig.update_yaxes(showgrid=False)
fig.show()
```


```
monthly_data['Year'] = monthly_data.index.year
monthly_data['Month'] = monthly_data.index.strftime('%B')
monthly_data['dayofweek'] = monthly_data.index.strftime('%A')
monthly_data['quarter'] = monthly_data.index.quarter
monthly_data
```

Date	Adj Close	Year	Month	dayofweek	quarter
2012-01-31	52.907298	2012	January	Tuesday	1
2012-02-29	61.424381	2012	February	Wednesday	1
2012-03-31	71.292448	2012	March	Saturday	1

```
##Checking Distribution of Our Data
fig = plt.figure(figsize=(10,8))
sns.distplot(monthly_data['Adj Close']).set_title("Distribution Plot Adj Close -AAPL")
ax.tick_params(labelsize=12)
sns.set(font_scale=1)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
```

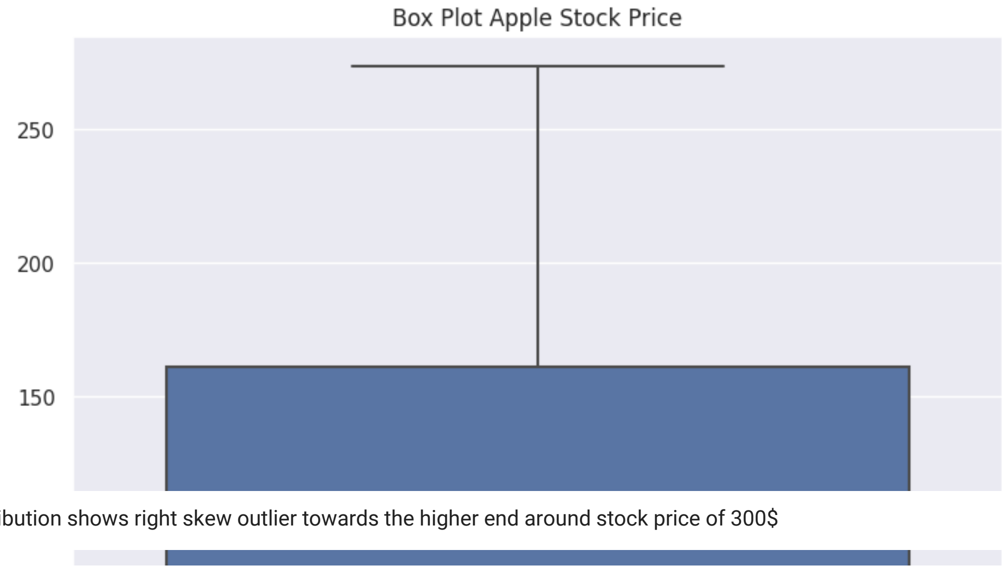
```
(array([0.   , 0.002, 0.004, 0.006, 0.008, 0.01 , 0.012]),
 [Text(0, 0.0, '0.000'),
  Text(0, 0.002, '0.002'),
  Text(0, 0.004, '0.004'),
  Text(0, 0.006, '0.006'),
  Text(0, 0.008, '0.008'),
  Text(0, 0.01, '0.010'),
  Text(0, 0.012, '0.012')])
```



Saved successfully!

```
fig = plt.figure(figsize=(8,6))
sns.boxplot(monthly_data['Adj Close']).set_title('Box Plot Apple Stock Price')
plt.style.context('fivethirtyeight')
```

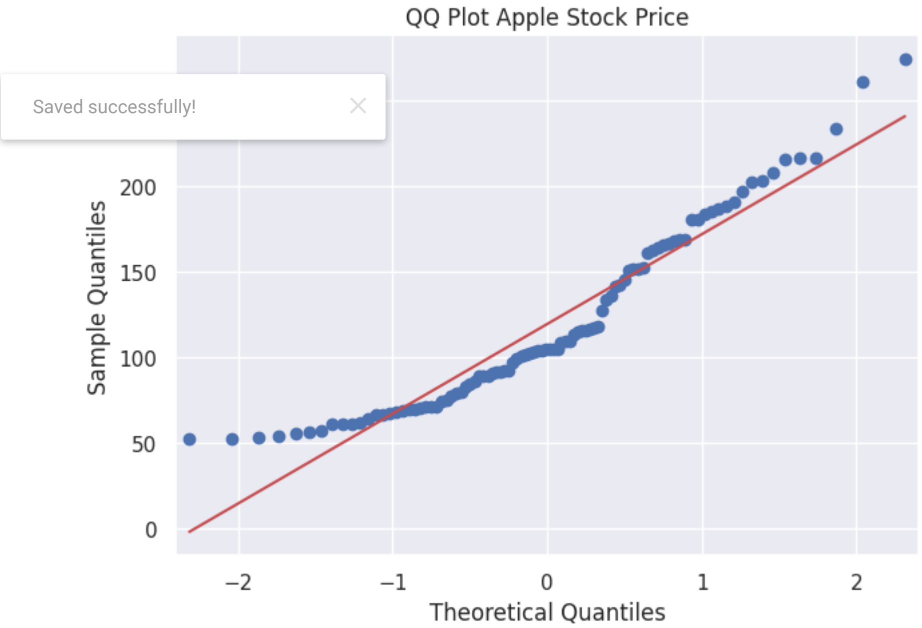
```
<contextlib._GeneratorContextManager at 0x7f0489cba4d0>
```



distribution shows right skew outlier towards the higher end around stock price of 300$

```
qq_plot = qq(monthly_data['Adj Close'],line='s')
plt.title('QQ Plot Apple Stock Price')
```

```
Text(0.5, 1.0, 'QQ Plot Apple Stock Price')
```



both right and left skews not following gaussian normal distribution

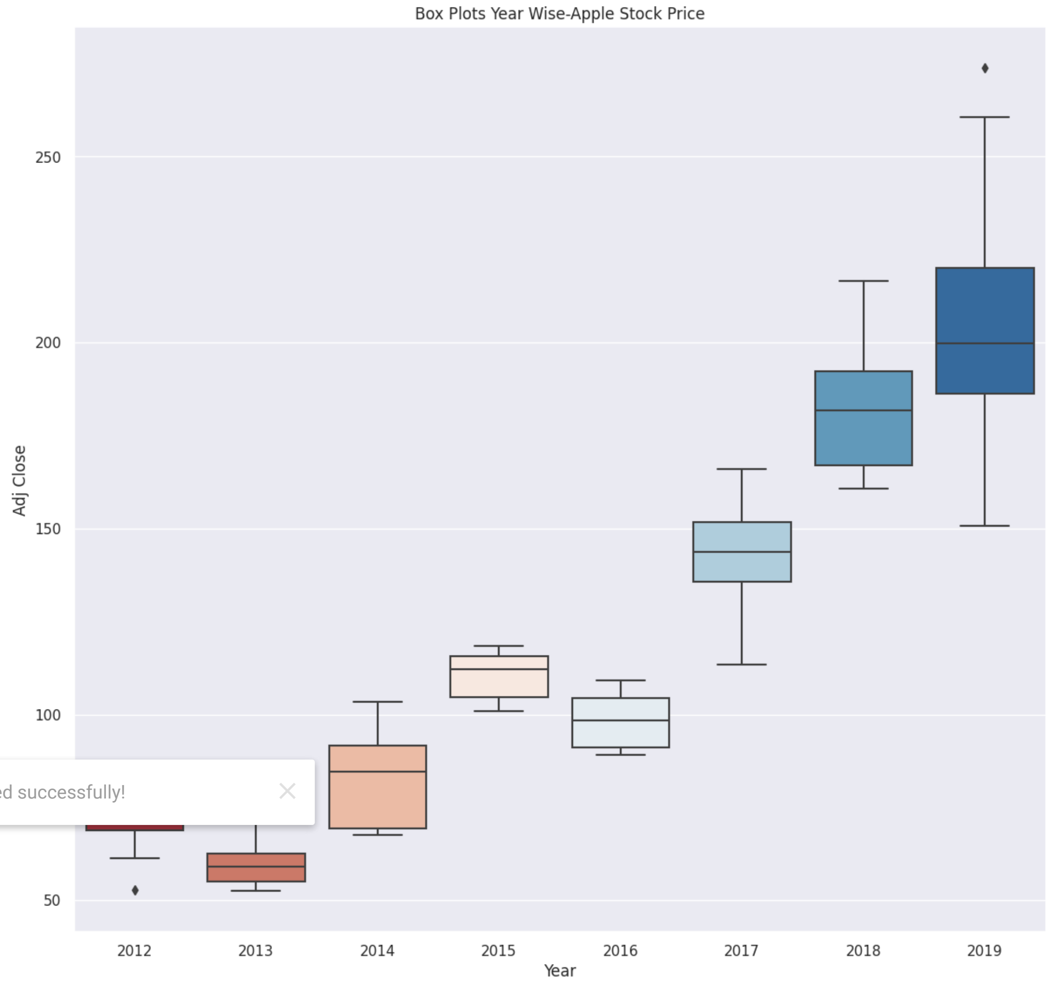
```
print('Skewness of Distribution is ',monthly_data['Adj Close'].skew())
print('Kurtosis of Distribution is ',monthly_data['Adj Close'].kurtosis())
```

```
Skewness of Distribution is  0.8054131572723979
Kurtosis of Distribution is  -0.11205074257880643
```

```
#stock price is heavily skewed-right tailed skewness
```

```
plt.figure(figsize=(12,12))
ax = sns.boxplot(x=monthly_data['Year'],y=monthly_data['Adj Close'],palette='RdBu')
ax.set_title('Box Plots Year Wise-Apple Stock Price')
plt.style.context('fivethirtyeight')
```

```
<contextlib._GeneratorContextManager at 0x7f04e63e90c0>
```




```
# ->Outliers Present in Year 2012 and 2019

# ->Lot of Variability in Years 2014, 2017-19

# ->2019 most volatile year among all years

# ->Upward Rising Trend is shown
```

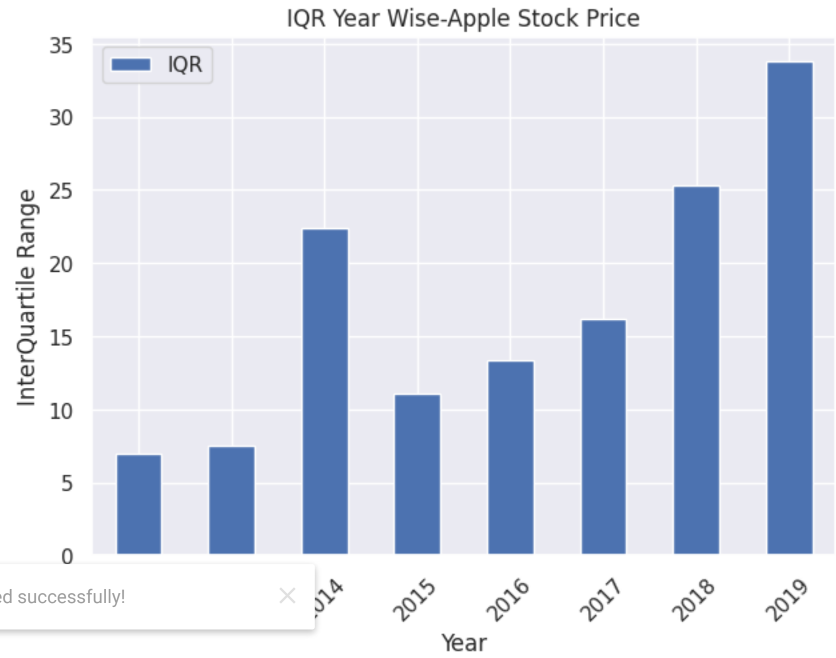
```
group_by_yr = []
list_years = monthly_data['Year'].unique()
dict_IQR = {}
for yr in list_years:
  group_by_yr.append('df' + str(yr))

for enum,yr in enumerate(list_years):
   group_by_yr[enum] = monthly_data[str(yr)]['Adj Close']
   dict_IQR[str(yr)] = stats.iqr(group_by_yr[enum])
```

```
##Interquartile Range(IQR) Year Wise for Stock Price
dict_IQR
```

```
{'2012': 6.933146515313851,
 '2013': 7.476562772903726,
 '2014': 22.34296344824017,
 '2015': 11.10740590584416,
 '2016': 13.310573720864653,
 '2017': 16.22455365139379,
 '2018': 25.26202036594205,
 '2019': 33.78399483999857}
```

```
IQR_df = pd.DataFrame(dict_IQR.items(),columns=['Year','IQR'])
IQR_df.index = IQR_df['Year']
IQR_df.plot(kind='bar')
plt.xticks(rotation=45)
plt.style.context('fivethirtyeight')
plt.title('IQR Year Wise-Apple Stock Price')
plt.ylabel('InterQuartile Range')
```

```
Text(0, 0.5, 'InterQuartile Range')
```

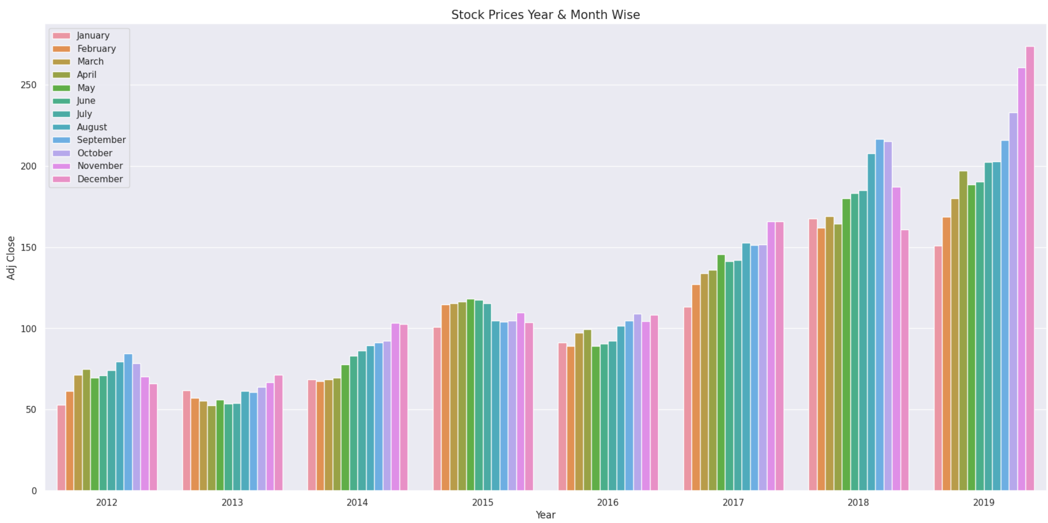


Saved successfully!

->When Data is Not Normal Inter-Quartile Range(IQR) is Better Variability Metric than Standard Deviation as IQR is not affected by outliers.

->As observed with BoxPlot 2014 and 2019 are the most volatile Years for Apple Stock

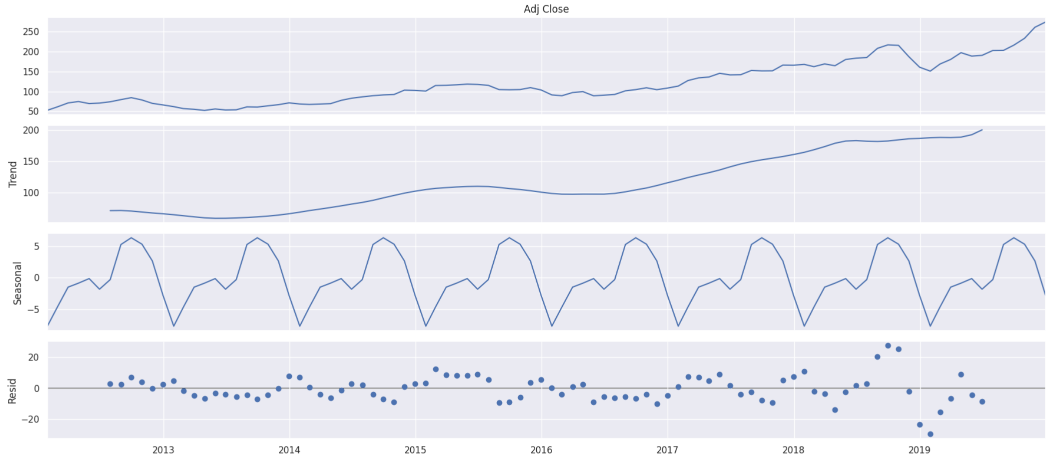
```
fig, ax = plt.subplots(figsize=(20,10))
palette = sns.color_palette("mako_r", 4)
a = sns.barplot(x="Year", y="Adj Close",hue = 'Month',data=monthly_data)
a.set_title("Stock Prices Year & Month Wise",fontsize=15)
plt.legend(loc='upper left')
plt.show()
```



Above figure shows that the Period from July-September seems to push stock price above in comparision to other months.

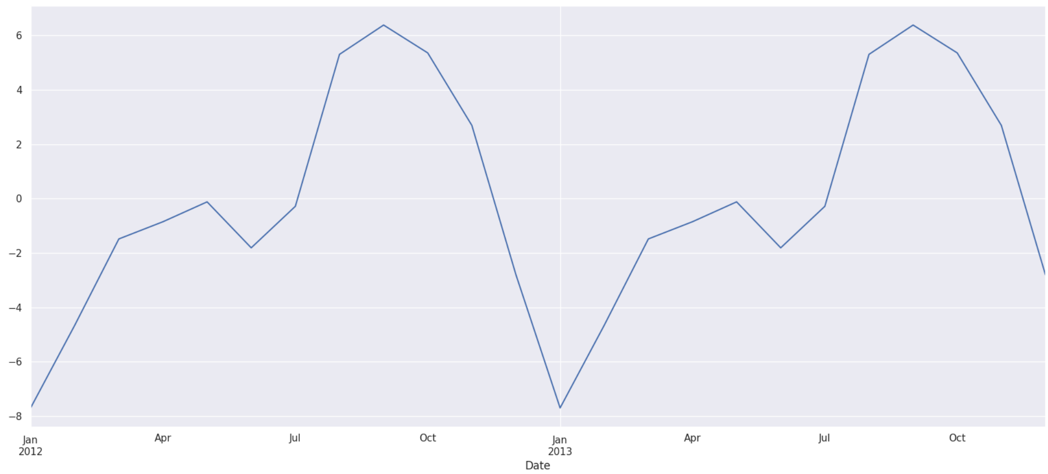
```
#Decomposition of Time Series


rcParams['figure.figsize'] = 18, 8
plt.figure(figsize=(20,16))
decomposed_series = sd(monthly_data['Adj Close'],model='additive')
decomposed_series.plot()
plt.show()
```

<Figure size 2000x1600 with 0 Axes>



Saved successfully!

```
##Drilling Down and Observing Seasonality
decomposed_series.seasonal['2012':'2013'].plot()
fig = plt.figure(figsize=(8,8))
```



<Figure size 800x800 with 0 Axes>

Stationarity of Time Series Stationarity Test of Time Series

Using Augmented Dickey-Fuller(ADF) Test

Null Hypothesis : Time series has a unit root -It is non-stationary

Alternate Hypothesis : Time series does not have a unit root -It is stationary

Time Series is Stationary if we have constant mean,constant variance and No Trend and Seasonality.

```
##ADF Test-Statsmodels Library
```

```
def ad_fuller_func(X):
  result_ad_fuller = adfuller(X)
  print('ADF Statistic: %f' % result_ad_fuller[0])
  print('p-value: %f' %result_ad_fuller[1])
  print('Critical Values:')
  for key, value in result_ad_fuller[4].items():
      print('\t%s: %.3f' % (key, value))

  if result_ad_fuller[0] < result_ad_fuller[4]['5%']:
    print('Reject Null Hypothesis(Ho)-Time Series is Stationary')
  else:
    print('Failed to Reject Ho-Time Series is Non-Stationary')
```

```
ad_fuller_func(monthly_data['Adj Close'])
```

```
ADF Statistic: 1.339253
p-value: 0.996820
Critical Values:
        1%: -3.504
        5%: -2.894
        10%: -2.584
Failed to Reject Ho-Time Series is Non-Stationary
```

Time Series is Not Stationary as observed earlier also by Decomposition(Trend and Seasonality Present)

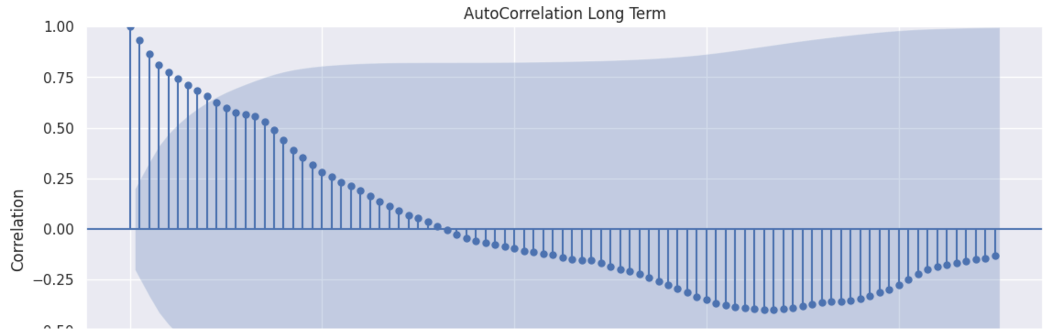
Statistically verified by ADF Test

AutoCorrelation Function(ACF)

Saved successfully!

```
ize=(12,12))
ose'],lags=90,ax=ax1)
 Term')
acf = plot_acf(monthly_data['Adj Close'],lags=30,ax=ax2)
ax2.set_title('AutoCorrelation Short Term')
ax1.set_ylabel('Correlation')
ax1.set_xlabel('Lags')
ax2.set_ylabel('Correlation')
ax2.set_xlabel('Lags')
```

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



Interpreting ACF Plot :-

->Slow Decay of correlation values indicates that the future values are heavily dependent on the lagged values . This shows that the series is not random and good for time series modelling .

->Also tells us series is Non-stationary

->It indicates a MA(1) process

Interpreting PACF Plot :-

->Sudden Decay at Lag-1

->Order of series seems AR(1)

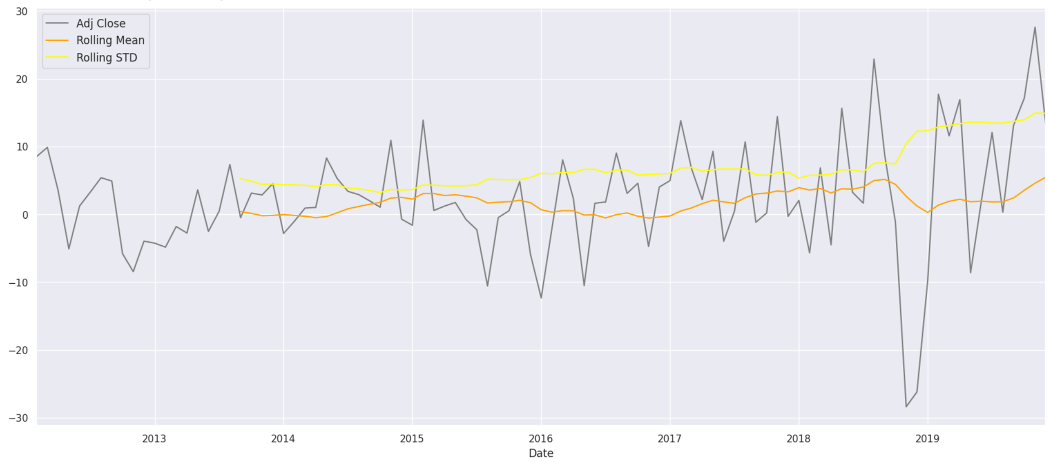
onary

```
##Differencing By 1
monthly_diff = monthly_data['Adj Close'] - monthly_data['Adj Close'].shift(1)
```

0 5 10 15 20 25 30

```
monthly_diff[1:].plot(c='grey')
monthly_diff[1:].rolling(20).mean().plot(label='Rolling Mean',c='orange')
monthly_diff[1:].rolling(20).std().plot(label='Rolling STD',c='yellow')
plt.legend(prop={'size': 12})
```

```
<matplotlib.legend.Legend at 0x7f0489696650>
```

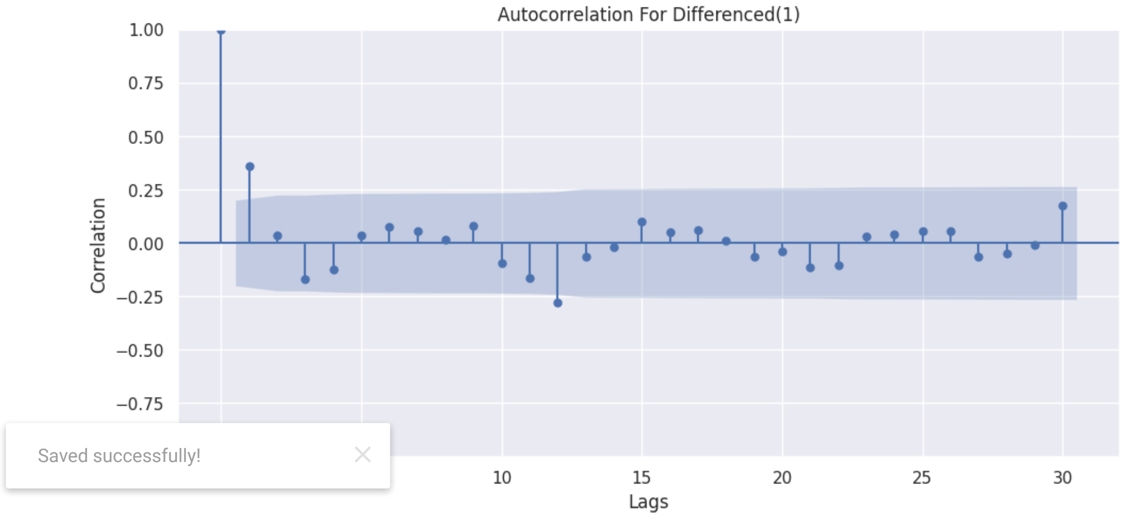


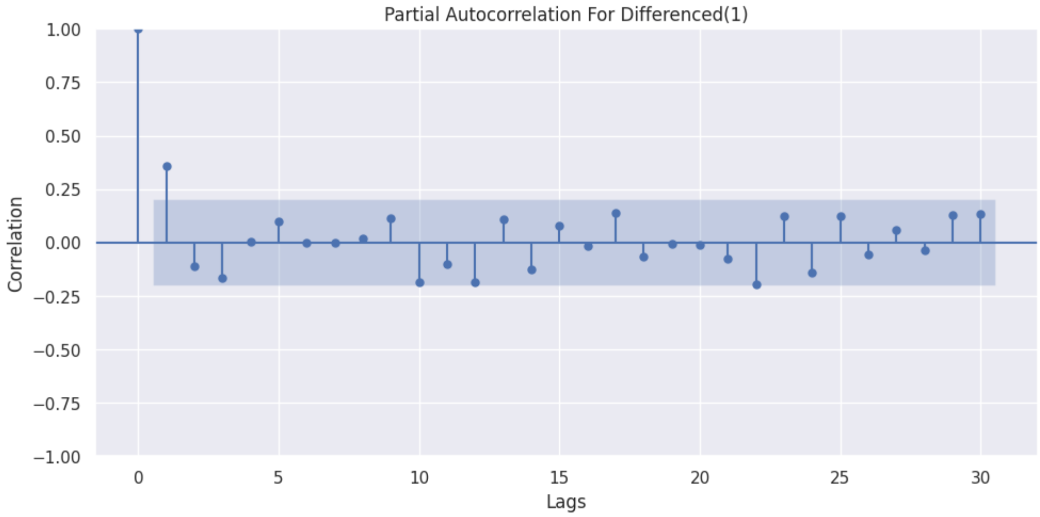

```
##Checking if Time Series is Stationary by Running ADF Test
ad_fuller_func(monthly_diff[1:])
```

```
ADF Statistic: -6.501865
p-value: 0.000000
Critical Values:
        1%: -3.502
        5%: -2.893
```

```
       10%: -2.583
Reject Null Hypothesis(Ho)-Time Series is Stationary
```

```
fig,(ax1,ax2) = plt.subplots(2,figsize=(10,10))
acf = plot_acf(monthly_diff[1:],lags=30,ax=ax1)
pacf = plot_pacf(monthly_diff[1:],lags=30,ax=ax2)
ax1.set_title('Autocorrelation For Differenced(1)')
ax1.set_ylabel('Correlation')
ax1.set_xlabel('Lags')
ax2.set_title('Partial Autocorrelation For Differenced(1)')
ax2.set_ylabel('Correlation')
ax2.set_xlabel('Lags')
plt.tight_layout(pad=1)
```





According to the ACF and PACF we can confirm that Differencing once has transformed series into Stationary

Modelling Seasonal ARIMA

```
modelling_series = monthly_data['Adj Close']
modelling_series
```

```
Date
2012-01-31     52.907298
2012-02-29     61.424381
2012-03-31     71.292448
2012-04-30     74.810151
```

```
2012-05-31     69.708045
                  ...
2019-08-31    202.738817
2019-09-30    215.853332
2019-10-31    232.974974
2019-11-30    260.569057
2019-12-31    273.780717
Freq: M, Name: Adj Close, Length: 96, dtype: float64
```

```
train,test = split(modelling_series,train_size=0.6,shuffle=False)
```

```
train.head(2)
```

```
Date
2012-01-31    52.907298
2012-02-29    61.424381
Freq: M, Name: Adj Close, dtype: float64
```

```
test.head(2)
```

```
Date
2016-10-31    109.212791
2016-11-30    104.453936
Freq: M, Name: Adj Close, dtype: float64
```

```
print('Train',len(train))
print('Test',len(test))
```

```
Train 57
```

Saved successfully!

```
p = d = q = range(0, 3)
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]

print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[1]))
```

```
SARIMAX: (0, 0, 1) x (0, 0, 1, 12)
```

```
p = d = q = range(0, 3)
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]

print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[1]))
```

```
SARIMAX: (0, 0, 1) x (0, 0, 1, 12)
```

Forecasting Seasonal ARIMA

```
##Data after feature selection
data_feature_selected = data.drop(axis=1,labels=['Open','High','Low','Close','Volume'])
```

```
col_order = ['Date','Adj Close']
data_feature_selected = data_feature_selected.reindex(columns=col_order)
data_feature_selected
```

	Date	Adj Close
Date		
2012-01-03	2012-01-03	50.765709

```
##Resample Data to Monthly instead of Daily by Aggregating Using Mean
monthly_mean = data_feature_selected['Adj Close'].resample('M').mean()
```

```
monthly_data = monthly_mean.to_frame()
monthly_data
```

	Adj Close
Date	
2012-01-31	52.907298
2012-02-29	61.424381
2012-03-31	71.292448
2012-04-30	74.810151
2012-05-31	69.708045
...	...
2019-08-31	202.738817
2019-09-30	215.853332
2019-12-31	273.780717

Saved successfully!

96 rows × 1 columns

```
##Getting Data Ready for the Model
prophet_data = monthly_data
prophet_data['Date'] = prophet_data.index
prophet_data
```

	Adj Close	Date
Date		
2012-01-31	52.907298	2012-01-31
2012-02-29	61.424381	2012-02-29
2012-03-31	71.292448	2012-03-31
2012-04-30	74.810151	2012-04-30
2012-05-31	69.708045	2012-05-31
...	...	...
2019-08-31	202.738817	2019-08-31
2019-09-30	215.853332	2019-09-30
2019-10-31	232.974974	2019-10-31
2019-11-30	260.569057	2019-11-30
2019-12-31	273.780717	2019-12-31

96 rows × 2 columns

```
prophet_data = prophet_data.reindex(columns=['Date','Adj Close'])
```

```
##Prophet needs two columns in form of ds and y being Date and series
prophet_data.rename(columns={'Date':'ds',
                   'Adj Close':'y'},inplace=True)
```

```
prophet_data
```

	ds	y
Date		
2012-01-31	2012-01-31	52.907298
2012-02-29	2012-02-29	61.424381
2012-03-31	2012-03-31	71.292448
2012-04-30	2012-04-30	74.810151
2012-05-31	2012-05-31	69.708045
...	...	...
2019-08-31	2019-08-31	202.738817
2019-09-30	2019-09-30	215.853332
2019-10-31	2019-10-31	232.974974
2019-11-30	2019-11-30	260.569057

```
##Spliting Train Test
prophet_train,prophet_test = split(prophet_data,train_size=0.6,shuffle=False)
print('Training Data Size :',len(prophet_train))
print('Testing Data Size :',len(prophet_test))
```

```
Training Data Size : 57
Testing Data Size : 39
```

```
##Model Fitting Basic Model
prophet_model = Prophet(yearly_seasonality=True)
prophet_model.fit(prophet_train)
```

Saved successfully!

```
seasonality. Run prophet with weekly_seasonality=True to override this.
INFO:prophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmphw6jymjy/hvdqkul2.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmphw6jymjy/pkms9tex.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.10/dist-packages/prophet/stan_model/prophet_model.bin', 'random', 'seed=948
02:28:46 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
02:28:47 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
<prophet.forecaster.Prophet at 0x7f0489495480>
```

```
future= prophet_model.make_future_dataframe(periods=39,freq='M')
```

```
future
```

	ds
0	2012-01-31
1	2012-02-29
2	2012-03-31
3	2012-04-30
4	2012-05-31
...	...
91	2019-08-31
92	2019-09-30
93	2019-10-31
94	2019-11-30
95	2019-12-31

96 rows × 1 columns

Forecasting Prophet-Basic Model

```
##Predicting Using Prophet
forecast=prophet_model.predict(future)
forecast.index = prophet_data['y'].index
```

```
prophet_df = pd.concat([forecast['yhat'],prophet_data['y']],axis=1,ignore_index=True)
prophet_df.columns = ['Predicted','Actual']
prophet_df
```

Date	Predicted	Actual
2012-01-31	51.013636	52.907298
2012-02-29	54.127611	61.424381
2012-03-31	62.093606	71.292448
2012-04-30	64.484538	74.810151
2012-05-31	59.239091	69.708045
...	...	...
2019-08-31	137.032218	202.738817
2019-09-30	138.633781	215.853332
2019-10-31	141.063373	232.974974
2019-11-30	151.250768	260.569057
2019-12-31	147.015111	273.780717

96 rows × 2 columns

```
fig = plt.figure(figsize=(12,10))
prophet_df['Predicted'][:57].plot(label='Predicted')
prophet_df['Actual'][:57].plot(label='Actual')
ecasting -Train Data')
plt.legend()
```

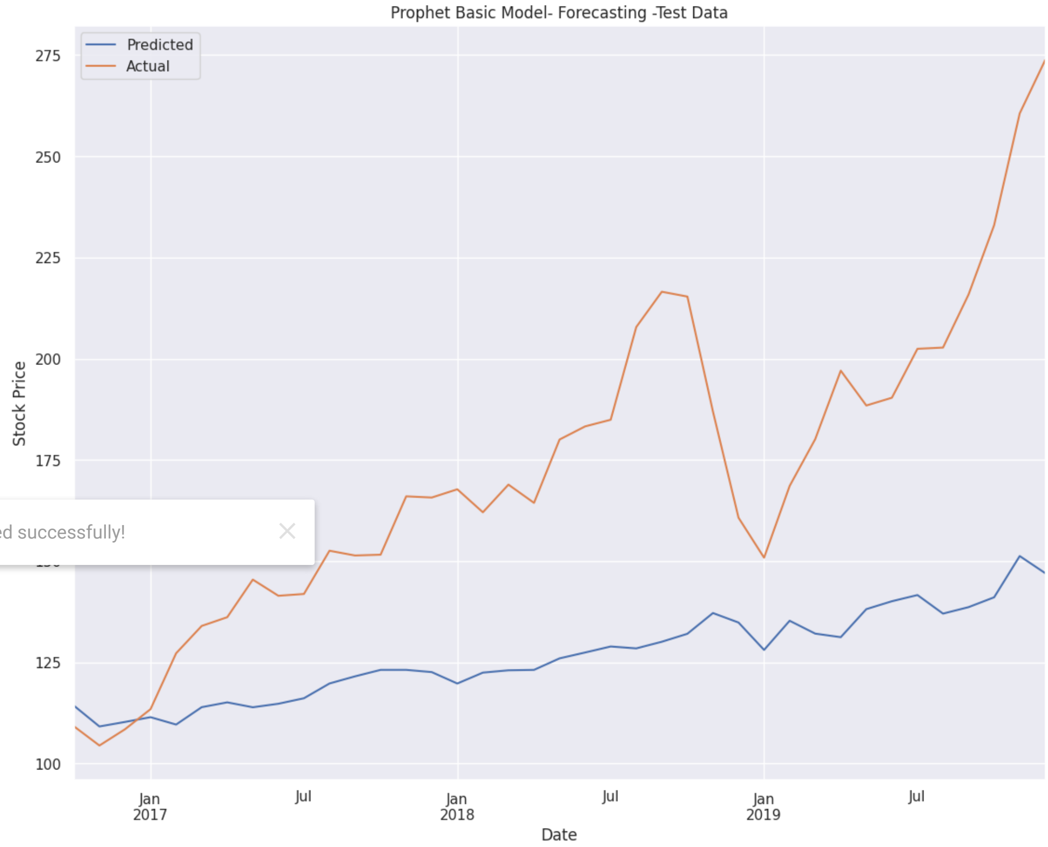
Saved successfully!

```
<matplotlib.legend.Legend at 0x7f0489013eb0>
```

Prophet Basic Model- Forecasting -Train Data

```
fig = plt.figure(figsize=(12,10))
prophet_df['Predicted'][57:].plot(label='Predicted')
prophet_df['Actual'][57:].plot(label='Actual')
plt.title('Prophet Basic Model- Forecasting -Test Data')
plt.ylabel('Stock Price')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f04890b6a40>
```




```
##Function to Calculate Result Metrics
def result_metrics(test_series,forecast_series,model_name):
  print('Result Metrics for {}'.format(model_name))
  print('R2 Score : ',round(r2_score(test_series,forecast_series),3))
  print('Mean Squared Error : ',round(mean_squared_error(test_series,forecast_series),3))
  print('Mean Absolute Error : ',round(mean_absolute_error(test_series,forecast_series),3))
```

```
print(result_metrics(prophet_df['Actual'][:57],prophet_df['Predicted'][:57],'Prophet Basic-Train Data'))
```

```
Result Metrics for Prophet Basic-Train Data
R2 Score :  0.598
Mean Squared Error :  157.648
Mean Absolute Error :  10.794
None
```

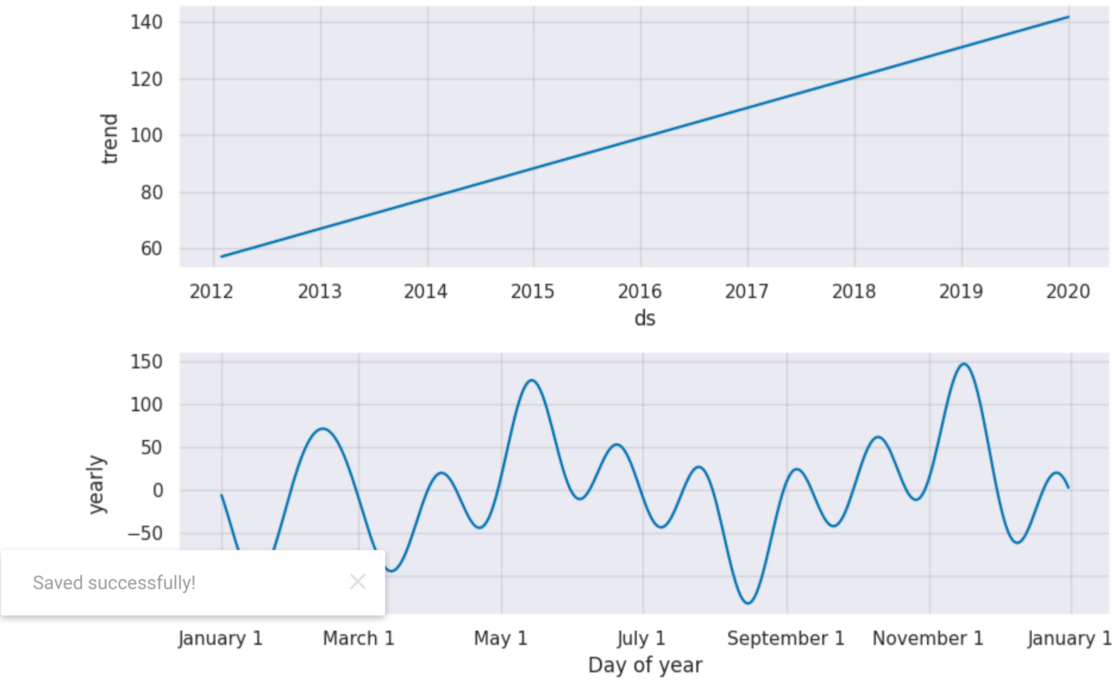
```
print(result_metrics(prophet_df['Actual'][57:],prophet_df['Predicted'][57:],'Prophet Basic-Test Data'))
```

```
Result Metrics for Prophet Basic-Test Data
R2 Score :  -0.973
Mean Squared Error :  2936.428
```

```
Mean Absolute Error :  46.175
None
```

The Basic Prophet Model with default parameters overfits into the model as represented by the Train Test Accuracy differences.

```
fig = prophet_model.plot_components(forecast)
```




```
print('Head',prophet_test.head(1))
print('Tail',prophet_test.tail(1))
```

```
Head                   ds           y
Date
2016-10-31 2016-10-31  109.212791
Tail                   ds           y
Date
2019-12-31 2019-12-31  273.780717
```

Hyper-Tuning for Prophet Model

```
from sklearn.model_selection import ParameterGrid
params_grid = {'seasonality_mode':('multiplicative','additive'),
               'changepoint_prior_scale':[0.3,0.4],
              'holidays_prior_scale':[0.3,0.4],
              'n_changepoints' : [20,50]}
grid = ParameterGrid(params_grid)
cnt = 0
for p in grid:
    cnt = cnt+1

print('Total Possible Models',cnt)
```

```
Total Possible Models 16
```

```
df = prophet_data
```

```
prophet_train_hyper,prophet_test_hyper = split(prophet_data,train_size=0.7,shuffle=False)
```

```
prophet_test_hyper.head(5)
```

	ds	y
Date		
2017-08-31	2017-08-31	152.563906
2017-09-30	2017-09-30	151.386422
2017-10-31	2017-10-31	151.586949

```
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error,mean_absolute_percentage_error, median_absolute_error, mea
```

```
strt='2017-08-31'
end='2019-12-31'
model_parameters = pd.DataFrame(columns = ['MAPE','Parameters'])
for i in grid:
    test = pd.DataFrame()
    print(i)

    train_model =Prophet(changepoint_prior_scale = i['changepoint_prior_scale'],
                         holidays_prior_scale = i['holidays_prior_scale'],
                         n_changepoints = i['n_changepoints'],
                         seasonality_mode = i['seasonality_mode'],
                         weekly_seasonality=False,
                         daily_seasonality = False,
                         yearly_seasonality = True,
                         )

    train_model.fit(prophet_train_hyper)
    train_forecast = train_model.make_future_dataframe(periods=29, freq='M',include_history = False)
    train_forecast = train_model.predict(train_forecast)
    test=train_forecast[['ds','yhat']]
                                (df['ds']<=end)]
                                _error(Actual['y'],abs(test['yhat']))
                                 Error(MAPE)---------------------------------------------------------',MAPE)
    model_parameters = model_parameters.append({'MAPE':MAPE,'Parameters':p},ignore_index=True)
```

Saved successfully!

```
02:38:18 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
Mean Absolute Percentage Error(MAPE)--------------------------------------------------------- 0.12843043117635525
{'changepoint_prior_scale': 0.4, 'holidays_prior_scale': 0.4, 'n_changepoints': 50, 'seasonality_mode': 'additive'}
02:38:23 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
Mean Absolute Percentage Error(MAPE)--------------------------------------------------------- 0.1285595448782009
```

```
parameters = model_parameters.sort_values(by=['MAPE'])
parameters = parameters.reset_index(drop=True)
parameters.head(3)
```

	MAPE	Parameters
0	0.123190	{'changepoint_prior_scale': 0.4, 'holidays_pri...
1	0.123190	{'changepoint_prior_scale': 0.4, 'holidays_pri...
2	0.125918	{'changepoint_prior_scale': 0.4, 'holidays_pri...

```
parameters['Parameters'][0]
```

```
{'changepoint_prior_scale': 0.4,
 'holidays_prior_scale': 0.4,
 'n_changepoints': 50,
 'seasonality_mode': 'additive'}
```

Problem with Prophet is its Overfits quite easily for out dataset. Therefore we try some other hyperparamters with Hit and Trial

Saved successfully!

```
prophet_tuned_model = Prophet(
                      ',
                      ior_scale= 0.001,
                      _scale = 0.02,
                      seasonality_prior_scale=0.3,

                      seasonality_mode = 'additive',
                      weekly_seasonality=False,
                      daily_seasonality = False,
                      yearly_seasonality = True,
                      changepoints=['2017-07-31']
                      )
prophet_tuned_model.add_country_holidays(country_name='US')
prophet_tuned_model.add_seasonality(name='monthly', period=30.5, fourier_order=5, prior_scale=0.02)
prophet_tuned_model.add_seasonality(name='yearly', period=365, fourier_order=20)
prophet_tuned_model.add_country_holidays(country_name='US')
prophet_tuned_model.fit(prophet_train_hyper)
```

```
WARNING:prophet:Changing country holidays from 'US' to 'US'.
DEBUG:cmdstanpy:input tempfile: /tmp/tmphw6jymjy/8nv0gqgh.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmphw6jymjy/ww6xur1q.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.10/dist-packages/prophet/stan_model/prophet_model.bin', 'random', 'seed=3974
02:38:37 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
02:38:37 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
<prophet.forecaster.Prophet at 0x7f0488ff96f0>
```

```
future_hyper= prophet_tuned_model.make_future_dataframe(periods=29,freq='M')
```

```
future_hyper=prophet_tuned_model.predict(future_hyper)
```

```
future_hyper.index = prophet_data['y'].index
```

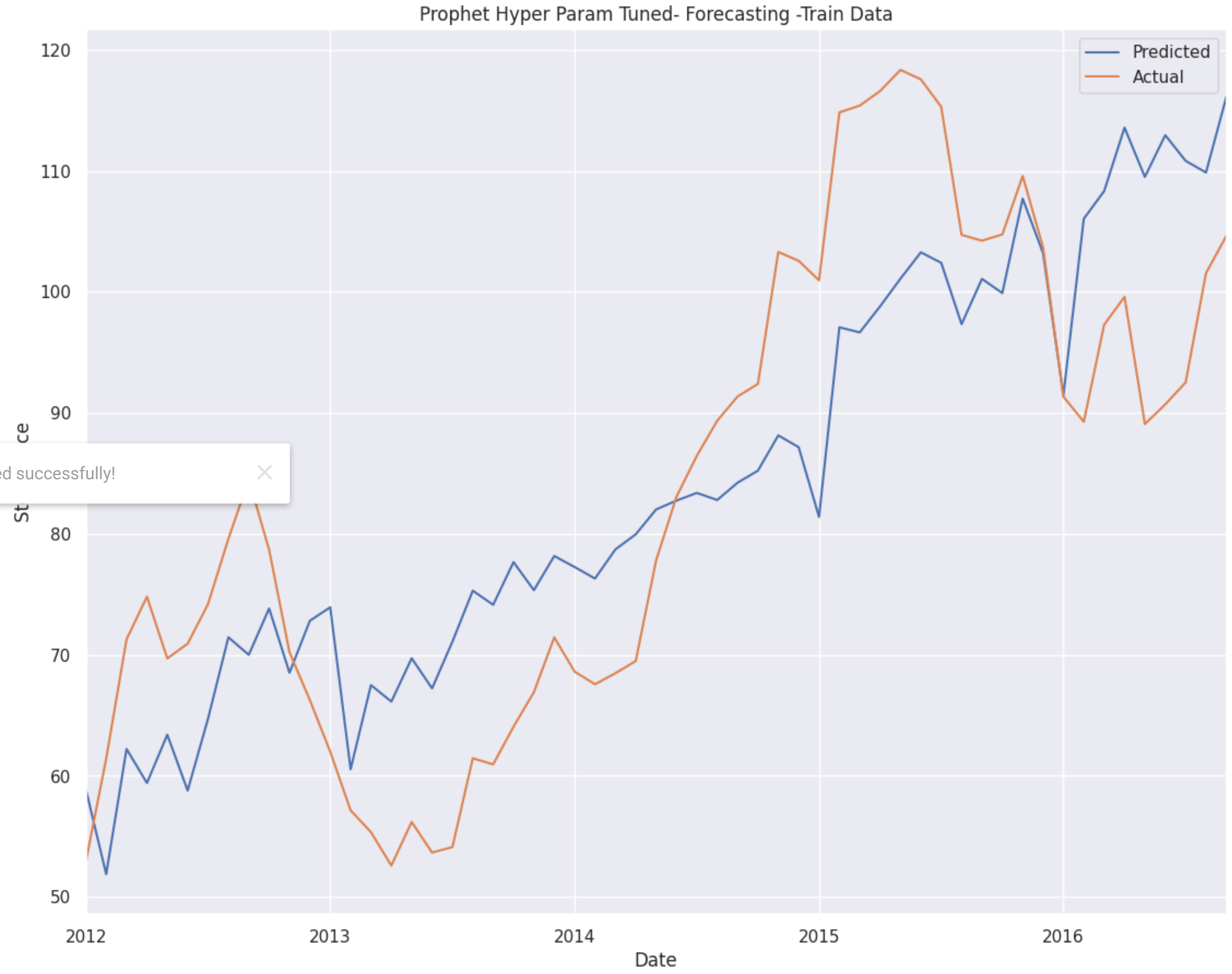
```
prophet_hyper_df = pd.concat([future_hyper['yhat'],prophet_data['y']],axis=1,ignore_index=True)
```

```
prophet_hyper_df.columns = ['Predicted','Actual']
prophet_hyper_df.tail(3)
```

	Predicted	Actual
Date		

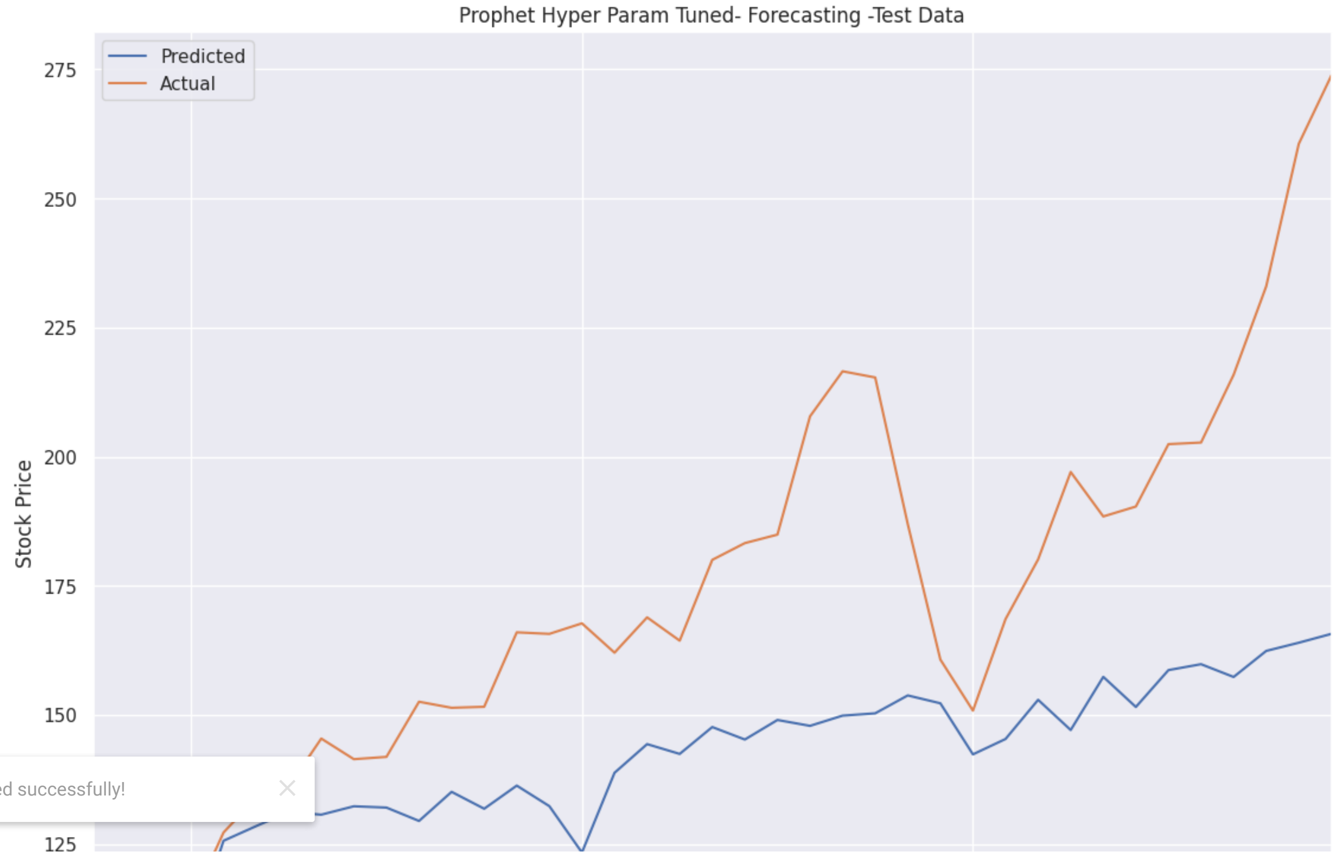
```
fig = plt.figure(figsize=(12,10))
prophet_hyper_df['Predicted'][:57].plot(label='Predicted')
prophet_hyper_df['Actual'][:57].plot(label='Actual')
plt.title('Prophet Hyper Param Tuned- Forecasting -Train Data')
plt.ylabel('Stock Price')
plt.legend()
```

<matplotlib.legend.Legend at 0x7f0488e79ba0>




```
fig = plt.figure(figsize=(12,10))
prophet_hyper_df['Predicted'][57:].plot(label='Predicted')
prophet_hyper_df['Actual'][57:].plot(label='Actual')
plt.title('Prophet Hyper Param Tuned- Forecasting -Test Data')
plt.ylabel('Stock Price')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f0488e950f0>
```




```
result_metrics(prophet_hyper_df['Actual'][:67],prophet_hyper_df['Predicted'][:67],'Hyper-Tuned Prophet Train Data')
```

```
Result Metrics for Hyper-Tuned Prophet Train Data
R2 Score :  0.784
Mean Squared Error :  129.543
Mean Absolute Error :  9.986
```

```
result_metrics(prophet_hyper_df['Actual'][67:],prophet_hyper_df['Predicted'][67:],'Hyper-Tuned Prophet Test Data')
```

```
Result Metrics for Hyper-Tuned Prophet Test Data
R2 Score :  -1.311
Mean Squared Error :  2188.439
Mean Absolute Error :  40.508
```

After Hyper-parameter tuning the model is not able to capture the seasonality and sudden jump in time series in the Year 2017 onwards.

->Prophet is easily overfitted.

->Seasonal ARIMA is superior to Prophet

->Prophet is good at capturing the trend.

->By creating Extra Regressors we can maybe improve the Results in future projects.

Advantages of Prophet includes very easy to implement, fast , and less statistical know-how model .

Actionable Insight Observing the Trend given by the Model.

AAPL IS A BUY.