```
### Time Series Experis
```

```
###! pip install kaggle
```

```
###!pip install pandas-datareader
```

```
import pandas_datareader as pdr
import pandas as pd
from datetime import datetime
```

```
#!pip install pycryptodome pycryptodomex
#!pip uninstall pandas-datareader
#!pip install git+https://github.com/raphi6/pandas-datareader.git@ea66d6b981554f9d0262038aef2106
```

```
import datetime as dt
import yfinance as yf

company = 'MAN'

# Define a start date and End Date
start = dt.datetime(2015,1,1)
end =  dt.datetime(2023,4,4)
```

```
# Read Stock Price Data
data = yf.download(company, start , end ,ignore_tz=True)

data.tail(10)
```

```
[*********************100%***********************]  1 of 1 completed
```

Date	Open	High	Low	Close	Adj Close	Volume
2023-03-21	81.180000	81.519997	80.300003	81.050003	81.050003	265700
2023-03-22	81.230003	81.230003	77.349998	77.410004	77.410004	347700
2023-03-23	77.519997	79.730003	77.389999	77.919998	77.919998	399300
2023-03-24	77.080002	78.419998	76.620003	78.040001	78.040001	287700
2023-03-27	79.120003	79.430000	78.349998	78.900002	78.900002	190000
2023-03-28	78.559998	79.720001	78.160004	79.360001	79.360001	160800
2023-03-29	80.199997	81.430000	80.199997	81.209999	81.209999	313700
2023-03-30	82.139999	82.430000	81.000000	81.209999	81.209999	193200
2023-03-31	81.830002	82.540001	81.529999	82.529999	82.529999	242500
2023-04-03	82.440002	82.629997	81.349998	81.650002	81.650002	298000

```
data.shape
```

```
(2077, 6)
```

```
####! pip install tensorflow
```

```
import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn import preprocessing
import matplotlib.pyplot as plt
```

```
tf.random.set_seed(123)
np.random.seed(123)
```

```
import pandas as pd
#import fbprophet
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
```

```
data.to_csv("/content/manpower.csv")
```

```
df=pd.read_csv('/content/manpower.csv', parse_dates=['Date'], index_col ="Date")
df.head(3)
```

Date	Open	High	Low	Close	Adj Close	Volume
2015-01-02	68.550003	68.809998	66.709999	67.470001	56.032032	346800
2015-01-05	66.919998	67.120003	64.949997	65.879997	54.711567	587400
2015-01-06	66.190002	66.459999	63.980000	65.320000	54.246513	791700

```
df.columns
```

```
Index(['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume'], dtype='object')
```

```
df.describe()
```

	Open	High	Low	Close	Adj Close	Volume
count	2077.000000	2077.000000	2077.000000	2077.000000	2077.000000	2.077000e+03
mean	90.385373	91.442585	89.308508	90.377843	81.765518	5.764965e+05
std	16.201886	16.193432	16.147705	16.164064	15.453887	3.428974e+05
min	50.919998	54.820000	49.570000	51.669998	47.568707	5.200000e+04
25%	78.470001	79.570000	77.610001	78.599998	70.108559	3.643000e+05
50%	88.489998	89.599998	87.320000	88.550003	79.809998	5.069000e+05
75%	98.050003	98.989998	97.089996	98.050003	89.770180	7.019000e+05
max	135.460007	136.929993	134.350006	136.020004	119.406136	5.424100e+06

```
# Basic packages
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import random as rd # generating random numbers
import datetime # manipulating date formats
# Viz
import matplotlib.pyplot as plt # basic plotting
import seaborn as sns # for prettier plots
# TIME SERIES
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from pandas.plotting import autocorrelation_plot
from statsmodels.tsa.stattools import adfuller, acf, pacf,arma_order_select_ic
import statsmodels.formula.api as smf
import statsmodels.tsa.api as smt
import statsmodels.api as sm
import scipy.stats as scs
# settings
```

```
import warnings
warnings.filterwarnings("ignore")
```

```
monthly_high = df["High"].resample('M').sum()
```

```
monthly_open = df["Open"].resample('M').sum()
```

```
monthly_Close = df["Close"].resample('M').sum()
```

```
monthly_Volume = df["Volume"].resample('M').sum()
```

```
monthly_high = pd.DataFrame(monthly_high)
```

```
monthly_high = monthly_high.reset_index()
```

```
monthly_high['weekday'] = monthly_high['Date'].apply(lambda x: x.weekday())
monthly_high.head()
```

	Date	High	weekday
0	2015-01-31	1350.159988	5
1	2015-02-28	1483.560005	5
2	2015-03-31	1858.719994	1
3	2015-04-30	1798.799995	3
4	2015-05-31	1718.530006	6

```
monthly_high['month']=monthly_high['Date'].dt.month
monthly_high.head()
```

	Date	High	weekday	month
0	2015-01-31	1350.159988	5	1
1	2015-02-28	1483.560005	5	2
2	2015-03-31	1858.719994	1	3
3	2015-04-30	1798.799995	3	4
4	2015-05-31	1718.530006	6	5

```
monthly_high['day']=monthly_high['Date'].dt.day
monthly_high.head()
```

	Date	High	weekday	month	day
0	2015-01-31	1350.159988	5	1	31
1	2015-02-28	1483.560005	5	2	28
2	2015-03-31	1858.719994	1	3	31
3	2015-04-30	1798.799995	3	4	30
4	2015-05-31	1718.530006	6	5	31

```
train_month = monthly_high.groupby(["month", "weekday"])['High'].mean().reset_index()
```

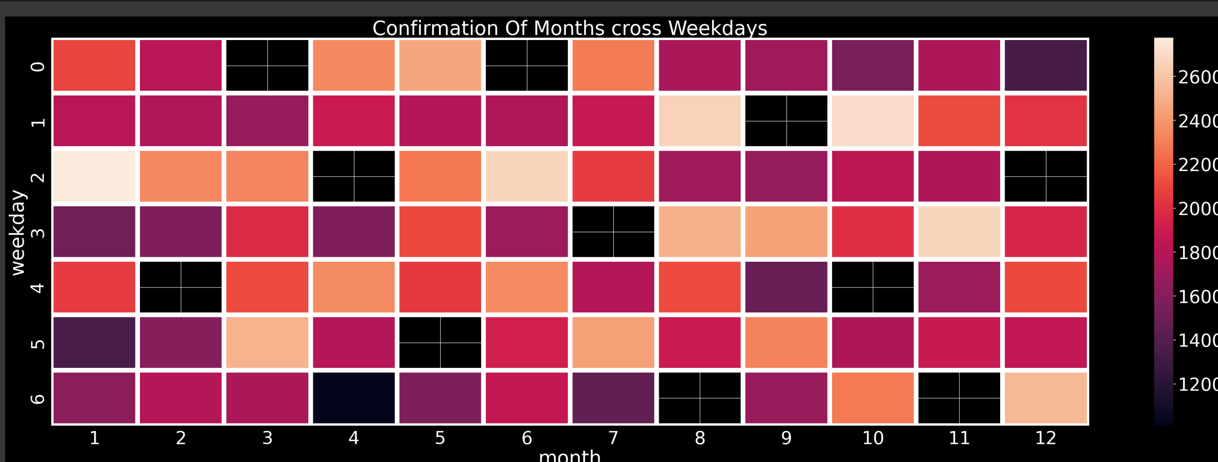
```
train_month = train_month.pivot('weekday','month','High')
train_month.sort_index(inplace=True)
```

```
train_month.head()
```

month	1	2	3	4	5	
weekday						
0	2092.819992	1811.975010	NaN	2347.570000	2463.720001	Na
1	1814.695004	1773.924999	1675.875000	1887.850006	1791.190010	1778.29999
2	2775.989990	2338.260010	2326.969994	NaN	2275.499992	2677.87999
3	1514.550018	1580.399986	1986.600010	1581.979998	2101.100006	1692.99999
4	2053.360008	NaN	2111.730007	2356.179993	2044.250023	2353.63998

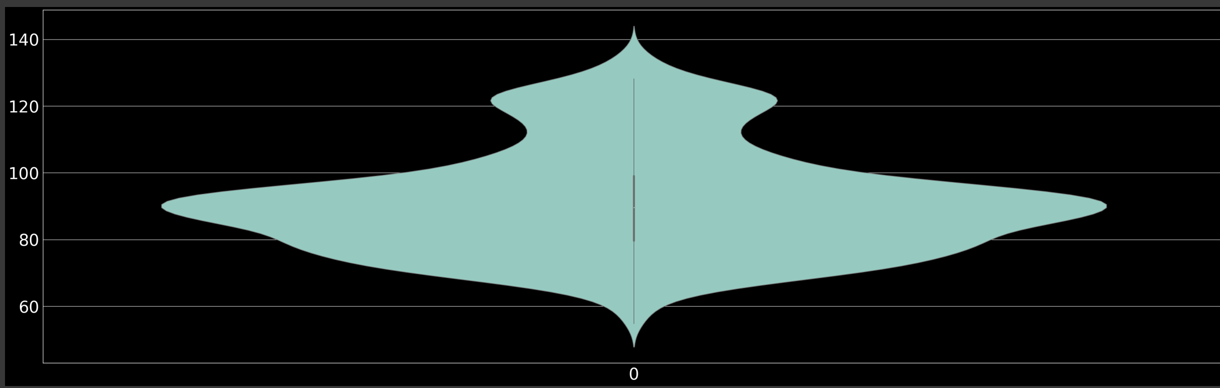
```
import seaborn as sns

sns.set(font_scale=3.5)
plt.style.use('dark_background')
# Draw a heatmap with the numeric values in each cell
f, ax = plt.subplots(figsize=(50, 15))
sns.heatmap(train_month, annot=False, ax=ax, fmt="d", linewidths=10)
plt.title('Confirmation Of Months cross Weekdays')
plt.show()
```




```
plt.figure(figsize=(50,15))
plt.style.use('dark_background')
sns.violinplot(df['High'])
```

<Axes: >




```
monthly_high.head(10)
```

	Date	High	weekday	month	day
0	2015-01-31	1350.159988	5	1	31
1	2015-02-28	1483.560005	5	2	28
2	2015-03-31	1858.719994	1	3	31
3	2015-04-30	1798.799995	3	4	30
4	2015-05-31	1718.530006	6	5	31
5	2015-06-30	1959.079987	1	6	30
6	2015-07-31	2019.840012	4	7	31
7	2015-08-31	1927.259995	0	8	31
8	2015-09-30	1817.609978	2	9	30
9	2015-10-31	1903.770004	5	10	31

```
train_days = monthly_high.groupby(["month", "day"])['High'].mean().reset_index()
train_days = train_days.pivot('day','month','High')
train_days.sort_index(inplace=True)
train_days.dropna(inplace=True)
```

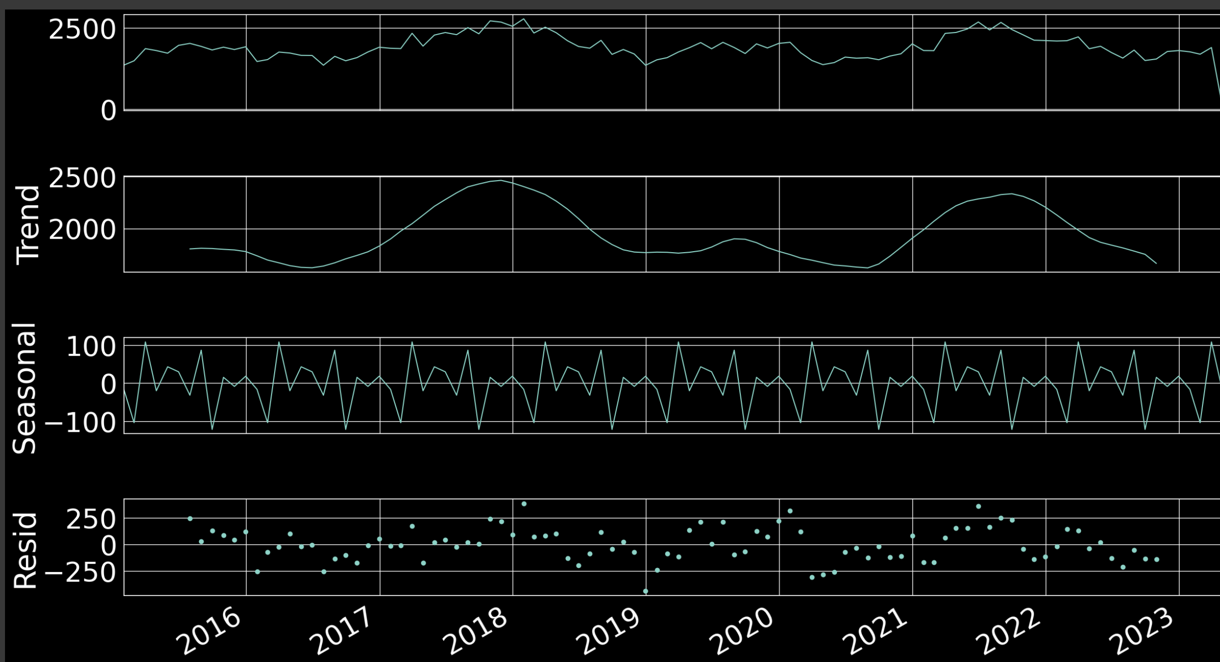
```
import statsmodels.api as sm
from statsmodels.tsa.seasonal import seasonal_decompose
```

```
###! pip install plotly
```

```
import plotly
# plotly.tools.set_credentials_file()
```

```
# Show Rolling mean, Rolling Std and Test for the stationnarity
df_date_index = monthly_high[['Date','High']].set_index('Date')
df_date_index.head()
```

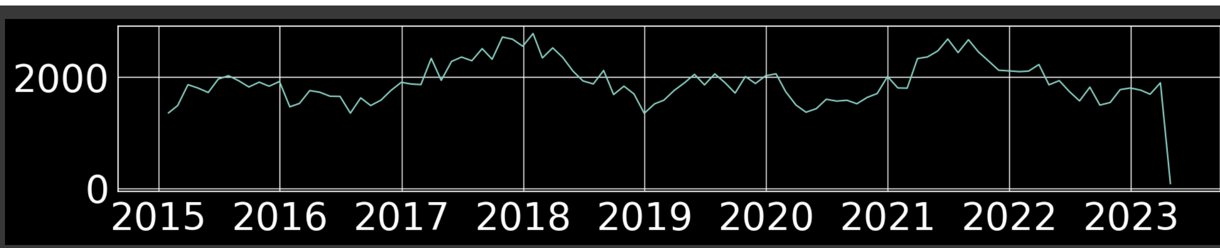
```
from pylab import rcParams
rcParams['figure.figsize'] = 25, 15
decomposition = sm.tsa.seasonal_decompose(df_date_index, model='additive')
fig = decomposition.plot()
fig.autofmt_xdate()
plt.show()
```



Stationarity

A Time Series is said to be stationary if its statistical properties such as mean, variance remain constant over time. Most of the Time Series models work on the assumption that the TS is stationary. Major reason for this is that there are many ways in which a series can be non-stationary, but only one way for stationarity.
Intuitively, we can say that if a Time Series has a particular behaviour over time, there is a very high probability that it will follow the same in the future.
Also, the theories related to stationary series are more mature and easier to implement as compared to non-stationary series.

```
import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = (20,3)
plt.plot(df_date_index)
fig.autofmt_xdate()
```




```
### Testing For Stationarity

from statsmodels.tsa.stattools import adfuller

def adf_test(dataset):
  dftest = adfuller(dataset, autolag = 'AIC')
  print("1. ADF : ",dftest[0])
  print("2. P-Value : ", dftest[1])
  print("3. Num Of Lags : ", dftest[2])
  print("4. Num Of Observations Used For ADF Regression and Critical Values Calculation :", dfte
  print("5. Critical Values :")
  for key, val in dftest[4].items():
      print("\t",key, ": ", val)
```

AD FULLER TEST

```
df_date_index.columns
```

```
Index(['High'], dtype='object')
```

```
adf_test(df_date_index['High'])
```

```
1. ADF :  -2.346440561085355
2. P-Value :  0.15742692227189314
3. Num Of Lags :  10
4. Num Of Observations Used For ADF Regression and Critical Values Calculation : 89
5. Critical Values :
	 1% :  -3.506057133647011
	 5% :  -2.8946066061911946
	 10% :  -2.5844100201994697
```

```
df_date_index['High_First_Order_Differencing'] = df_date_index['High'] - df_date_index['High'].s
```

```
adf_test(df_date_index['High_First_Order_Differencing'].dropna())
```

```
1. ADF :  -3.8042896313506604
2. P-Value :  0.0028637301187774055
3. Num Of Lags :  2
4. Num Of Observations Used For ADF Regression and Critical Values Calculation : 96
5. Critical Values :
	 1% :  -3.5003788874873405
	 5% :  -2.8921519665075235
	 10% :  -2.5830997960069446
```

```
df_date_index['High_Second_Order_Differencing'] = df_date_index['High_First_Order_Differencing']
```

```
adf_test(df_date_index['High_Second_Order_Differencing'].dropna())
```

```
1. ADF :  -5.662340539235939
2. P-Value :  9.317942839696368e-07
3. Num Of Lags :  5
4. Num Of Observations Used For ADF Regression and Critical Values Calculation : 92
5. Critical Values :
	 1% :  -3.503514579651927
```

```
            5% :  -2.893507960466837
            10% :  -2.583823615311909
```

```
def adfuller_test(confirmed):

    result=adfuller(confirmed)

    labels = ['ADF Test Statistic','p-value','#Lags Used','Number of Observations Used']

    for value,label in zip(result,labels):
        print(label+' : '+str(value) )

    if result[1] <= 0.05:

        print("strong evidence against the null hypothesis(Ho), reject the null hypothesis. Data
    else:
        print("weak evidence against null hypothesis, time series has a unit root, indicating it
```

```
adfuller_test(df_date_index['High'].dropna())
```

```
ADF Test Statistic : -2.346440561085355
p-value : 0.15742692227189314
#Lags Used : 10
Number of Observations Used : 89
weak evidence against null hypothesis, time series has a unit root, indicating it is non-st
```

```
adfuller_test(df_date_index['High_First_Order_Differencing'].dropna())
```

```
ADF Test Statistic : -3.8042896313506604
p-value : 0.0028637301187774055
#Lags Used : 2
Number of Observations Used : 96
strong evidence against the null hypothesis(Ho), reject the null hypothesis. Data has no un
```

Plotting ACF and PACF

Autocorrelation and Partial Autocorrelation Functions

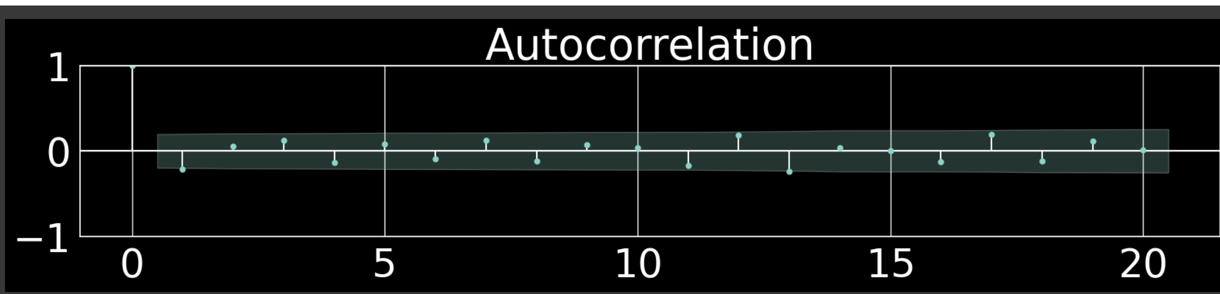
• Autocorrelation is simply the correlation of a series with its own lags. If a series is significantly autocorrelated, that means, the previous values of the series (lags) may be helpful in predicting the current value.
• Partial Autocorrelation also conveys similar information but it conveys the pure correlation of a series and its lag, excluding the correlation contributions from the intermediate lags.

```
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
```

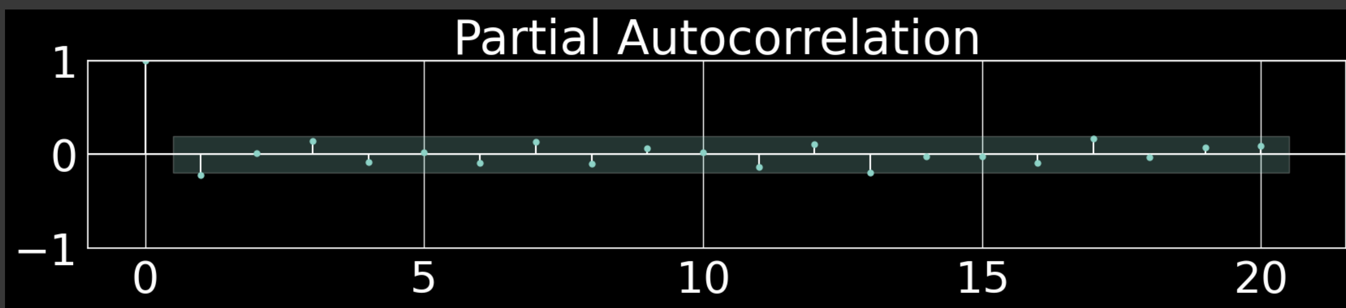
```
df_date_index.columns
```

```
Index(['High', 'High_First_Order_Differencing',
       'High_Second_Order_Differencing'],
      dtype='object')
```

```
acf2 = plot_acf(df_date_index['High_First_Order_Differencing'].dropna())
```




```
result1 = plot_pacf(df_date_index["High_First_Order_Differencing"].dropna())
```




```
print(df_date_index.shape)
train=df_date_index.iloc[:-30]
test=df_date_index.iloc[-30:]
print(train.shape,test.shape)
### print(test.iloc[0],test.iloc[-1])
```

```
(100, 3)
(70, 3) (30, 3)
```

```
train.columns
```

```
Index(['High', 'High_First_Order_Differencing',
       'High_Second_Order_Differencing'],
      dtype='object')
```

```
from statsmodels.tsa.arima.model   import ARIMA
model_ARIMA=ARIMA(train['High_First_Order_Differencing'],order=(0,2,0))
```

```
model_Arima_fit=model_ARIMA.fit()
```

```
model_Arima_fit.summary()
```

SARIMAX Results

Dep. Variable:	High_First_Order_Differencing	**No. Observations:**	70
Model:	ARIMA(0, 2, 0)	**Log Likelihood**	-533.564
Date:	Sat, 15 Apr 2023	**AIC**	1069.128
Time:	17:09:33	**BIC**	1071.347
Sample:	01-31-2015	**HQIC**	1070.007

```
##prediction
pred_start_date=test.index[0]
pred_end_date=test.index[-1]
print(pred_start_date)
print(pred_end_date)
```

```
2020-11-30 00:00:00
2023-04-30 00:00:00
```

```
pred=model_Arima_fit.predict(start=pred_start_date,end=pred_end_date)
```

```
test.columns
```

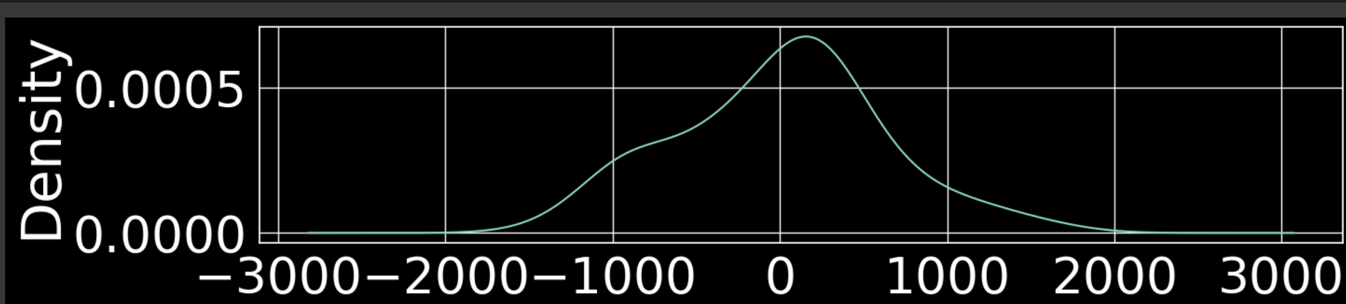
```
Index(['High', 'High_First_Order_Differencing',
       'High_Second_Order_Differencing'],
      dtype='object')
```

```
residuals=test['High_First_Order_Differencing']- pred
```

```
residuals.head(3)
```

```
Date
2020-11-30   -221.269974
2020-12-31   -162.259956
2021-01-31   -848.669914
dtype: float64
```

```
plt.figure(figsize=[15, 3])
model_Arima_fit.resid.plot(kind='kde')
plt.show()
```




```
test['Predicted_ARIMA']=pred
```

```
test.columns
```

```
Index(['High', 'High_First_Order_Differencing',
       'High_Second_Order_Differencing', 'Predicted_ARIMA'],
      dtype='object')
```

```
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error, median_absolute_e
```

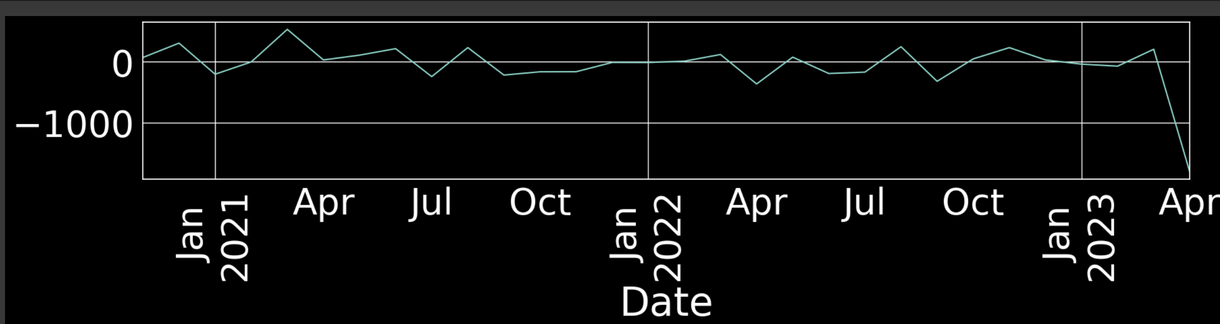
```
from math import sqrt
```

```
# report performance
mse = mean_squared_error(test["High_First_Order_Differencing"], test["Predicted_ARIMA"])
rmse = sqrt(mse)
print('ARIMA RMSE: {}, MSE:{}'.format(rmse,mse))

##plt.title('RMSE: %.4f'% rmse)
```

```
ARIMA RMSE: 3362.314513971152, MSE:11305158.890861062
```

```
start=len(train)
end=len(train)+len(test)-1
#plt.figure(figsize=[10,2])
#if the predicted values dont have date values as index, you will have to uncomment the followin
#index_future_dates=pd.date_range(start='2018-12-01',end='2018-12-30')
pred=model_Arima_fit.predict(start=start,end=end,typ='levels').rename('ARIMA predictions')
#pred.index=index_future_dates
#pred.plot(legend=True)
test['High_First_Order_Differencing'].plot(legend=False)
plt.xticks(rotation="vertical")
plt.show()
```




```
df.columns
```

```
Index(['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume'], dtype='object')
```

```
df.head(2)
```

Date	Open	High	Low	Close	Adj Close	Volume
2015-01-02	68.550003	68.809998	66.709999	67.470001	56.032032	346800
2015-01-05	66.919998	67.120003	64.949997	65.879997	54.711567	587400

```
df = df.reset_index()
```

```
final = df[["Date","High"]]
```

```
final.columns
```

```
Index(['Date', 'High'], dtype='object')
```

```
y = pd.Series(data=final['High'].values, index=final['Date'])
```

```
y.head(3)
```

```
Date
2015-01-02    68.809998
2015-01-05    67.120003
2015-01-06    66.459999
dtype: float64
```

```
import itertools
# Define the p, d and q parameters to take any value between 0 and 3
p = d = q = range(0, 2)

# Generate all different combinations of p, q and q triplets
pdq = list(itertools.product(p, d, q))

# Generate all different combinations of seasonal p, q and q triplets
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]
```

```
warnings.filterwarnings("ignore") # specify to ignore warning messages

best_result = [0, 0, 1000]
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            mod = sm.tsa.statespace.SARIMAX(y,
                                            order=param,
                                            seasonal_order=param_seasonal,
                                            enforce_stationarity=False,
                                            enforce_invertibility=False)

            results = mod.fit()

            print('ARIMA{} x {} - AIC: {}'.format(param, param_seasonal, results.aic))

            if results.aic < best_result[2]:
                best_result = [param, param_seasonal, results.aic]
        except:
            continue

print('\nBest Result:', best_result)
```

```
ARIMA(0, 0, 0) x (0, 0, 0, 12) - AIC: 24707.190736524728
ARIMA(0, 0, 0) x (0, 0, 1, 12) - AIC: 21948.666100502563
ARIMA(0, 0, 0) x (0, 1, 0, 12) - AIC: 13110.239466298432
ARIMA(0, 0, 0) x (0, 1, 1, 12) - AIC: 13033.434345146932
ARIMA(0, 0, 0) x (1, 0, 0, 12) - AIC: 13116.806256104233
ARIMA(0, 0, 0) x (1, 0, 1, 12) - AIC: 13113.258094298659
ARIMA(0, 0, 0) x (1, 1, 0, 12) - AIC: 13041.079532238662
ARIMA(0, 0, 0) x (1, 1, 1, 12) - AIC: 13035.434241935138
ARIMA(0, 0, 1) x (0, 0, 0, 12) - AIC: 21871.200524319884
ARIMA(0, 0, 1) x (0, 0, 1, 12) - AIC: 19191.153241130018
ARIMA(0, 0, 1) x (0, 1, 0, 12) - AIC: 11155.345257022378
ARIMA(0, 0, 1) x (0, 1, 1, 12) - AIC: 11062.265601203919
ARIMA(0, 0, 1) x (1, 0, 0, 12) - AIC: 11166.026293768886
ARIMA(0, 0, 1) x (1, 0, 1, 12) - AIC: 11194.236702465
ARIMA(0, 0, 1) x (1, 1, 0, 12) - AIC: 11075.811898147342
ARIMA(0, 0, 1) x (1, 1, 1, 12) - AIC: 11056.199123698241
ARIMA(0, 1, 0) x (0, 0, 0, 12) - AIC: 7776.3326008990625
ARIMA(0, 1, 0) x (0, 0, 1, 12) - AIC: 7736.097980633494
ARIMA(0, 1, 0) x (0, 1, 0, 12) - AIC: 9166.75432443722
ARIMA(0, 1, 0) x (0, 1, 1, 12) - AIC: 7729.404996802428
ARIMA(0, 1, 0) x (1, 0, 0, 12) - AIC: 7739.9988428945635
ARIMA(0, 1, 0) x (1, 0, 1, 12) - AIC: 7735.105647093213
ARIMA(0, 1, 0) x (1, 1, 0, 12) - AIC: 8473.954099133976
ARIMA(0, 1, 0) x (1, 1, 1, 12) - AIC: 7731.405024142728
```

```
ARIMA(0, 1, 1) x (0, 0, 0, 12) - AIC: 7758.428239725769
ARIMA(0, 1, 1) x (0, 0, 1, 12) - AIC: 7718.159684940403
ARIMA(0, 1, 1) x (0, 1, 0, 12) - AIC: 9149.746674553799
ARIMA(0, 1, 1) x (0, 1, 1, 12) - AIC: 7711.507250223382
ARIMA(0, 1, 1) x (1, 0, 0, 12) - AIC: 7724.847664807259
ARIMA(0, 1, 1) x (1, 0, 1, 12) - AIC: 7716.280565028431
ARIMA(0, 1, 1) x (1, 1, 0, 12) - AIC: 8452.38037854022
ARIMA(0, 1, 1) x (1, 1, 1, 12) - AIC: 7713.5072821919985
ARIMA(1, 0, 0) x (0, 0, 0, 12) - AIC: 7782.177655136049
ARIMA(1, 0, 0) x (0, 0, 1, 12) - AIC: 7744.448001430698
ARIMA(1, 0, 0) x (0, 1, 0, 12) - AIC: 9096.476685557855
ARIMA(1, 0, 0) x (0, 1, 1, 12) - AIC: 7729.001194129281
ARIMA(1, 0, 0) x (1, 0, 0, 12) - AIC: 7741.953209657726
ARIMA(1, 0, 0) x (1, 0, 1, 12) - AIC: 7742.189287766511
ARIMA(1, 0, 0) x (1, 1, 0, 12) - AIC: 8430.973858837962
ARIMA(1, 0, 0) x (1, 1, 1, 12) - AIC: 7731.001034536441
ARIMA(1, 0, 1) x (0, 0, 0, 12) - AIC: 7763.284166879464
ARIMA(1, 0, 1) x (0, 0, 1, 12) - AIC: 7726.67716671868
ARIMA(1, 0, 1) x (0, 1, 0, 12) - AIC: 9061.689599411708
ARIMA(1, 0, 1) x (0, 1, 1, 12) - AIC: 7711.3574960442365
ARIMA(1, 0, 1) x (1, 0, 0, 12) - AIC: 7726.895054603076
ARIMA(1, 0, 1) x (1, 0, 1, 12) - AIC: 7721.089549000614
ARIMA(1, 0, 1) x (1, 1, 0, 12) - AIC: 8399.32994472601
ARIMA(1, 0, 1) x (1, 1, 1, 12) - AIC: 7713.357371132874
ARIMA(1, 1, 0) x (0, 0, 0, 12) - AIC: 7761.401340044908
ARIMA(1, 1, 0) x (0, 0, 1, 12) - AIC: 7721.160757877467
ARIMA(1, 1, 0) x (0, 1, 0, 12) - AIC: 9153.026585627493
ARIMA(1, 1, 0) x (0, 1, 1, 12) - AIC: 7716.074701197872
ARIMA(1, 1, 0) x (1, 0, 0, 12) - AIC: 7721.175761737937
ARIMA(1, 1, 0) x (1, 0, 1, 12) - AIC: 7719.315485936635
ARIMA(1, 1, 0) x (1, 1, 0, 12) - AIC: 8449.842337316484
ARIMA(1, 1, 0) x (1, 1, 1, 12) - AIC: 7718.074651715036
ARIMA(1, 1, 1) x (0, 0, 0, 12) - AIC: 7760.424681591092
ARIMA(1, 1, 1) x (0, 0, 1, 12) - AIC: 7720.146505461582
```

```
train.columns
```

```
Index(['High', 'High_First_Order_Differencing',
       'High_Second_Order_Differencing'],
      dtype='object')
```

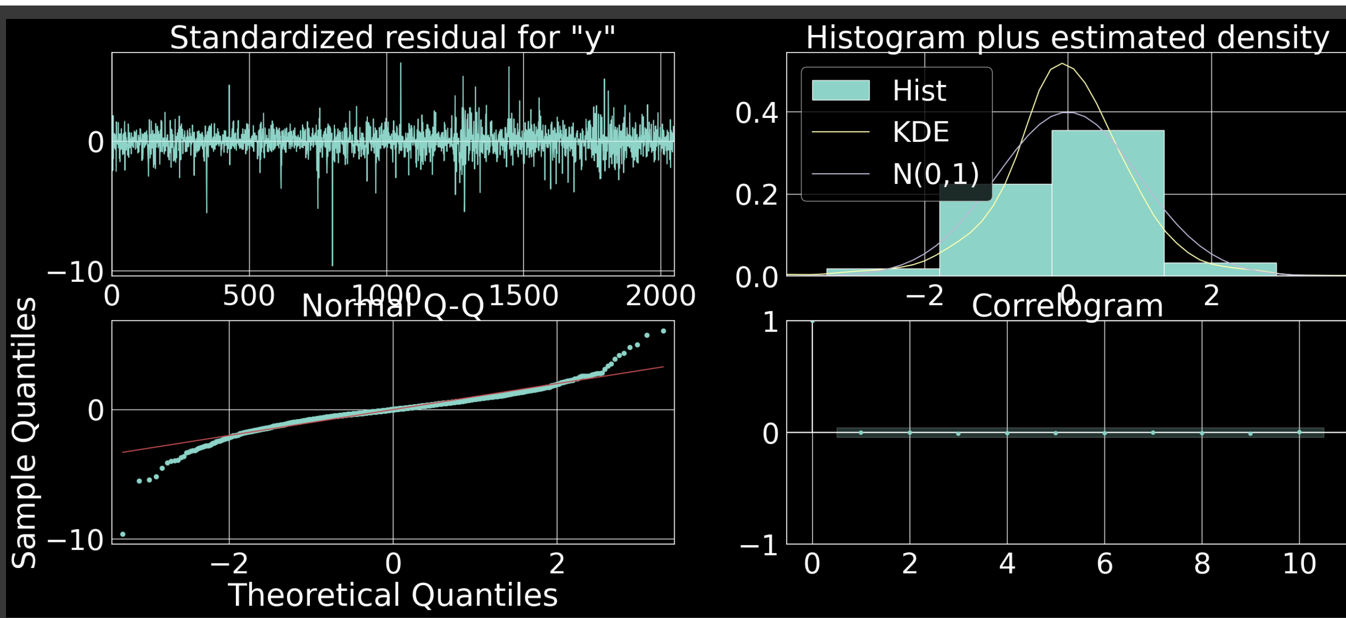
SARIMAX

The implementation is called SARIMAX instead of SARIMA because the “X” addition to the method name means that the implementation also supports exogenous variables. Exogenous variables are optional can be specified via the “exog” argument.
model = SARIMAX(data, exog=other_data, ...)
Examples of exogenous variables: Population, holidays, number of airline companies, major events

```
# SARIMA example
from statsmodels.tsa.statespace.sarimax import SARIMAX

# fit model
model = SARIMAX(train["High_First_Order_Differencing"], order=(1, 1, 0), seasonal_order=(0, 1, 1
model_fit = model.fit(disp=False)
```

```
results.plot_diagnostics(figsize=(30, 12))
plt.show()
```




```
print(train.shape, test.shape)
```

```
(70, 3) (30, 4)
```

```
start_index = test.index.min()
end_index = test.index.max()

#Predictions
predictions = model_fit.predict(start=start_index, end=end_index)
```

```
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error, median_absolute_e
```

```
from math import sqrt
```

```
predictions.head(3)
```

```
2020-11-30   -22.555516
2020-12-31   -76.343957
2021-01-31    52.336261
Freq: M, Name: predicted_mean, dtype: float64
```

```
test.columns
```

```
Index(['High', 'High_First_Order_Differencing',
       'High_Second_Order_Differencing', 'Predicted_ARIMA'],
      dtype='object')
```

```
test2 = test["High_First_Order_Differencing"]
```

```
test2.head(3)
```

```
Date
2020-11-30     69.399994
2020-12-31    305.009987
2021-01-31   -204.799995
Name: High_First_Order_Differencing, dtype: float64
```

```
train2 = train["High_First_Order_Differencing"]
```

```
train2.head(3)
```

```
Date
2015-01-31           NaN
2015-02-28    133.400017
2015-03-31    375.159988
Name: High_First_Order_Differencing, dtype: float64
```

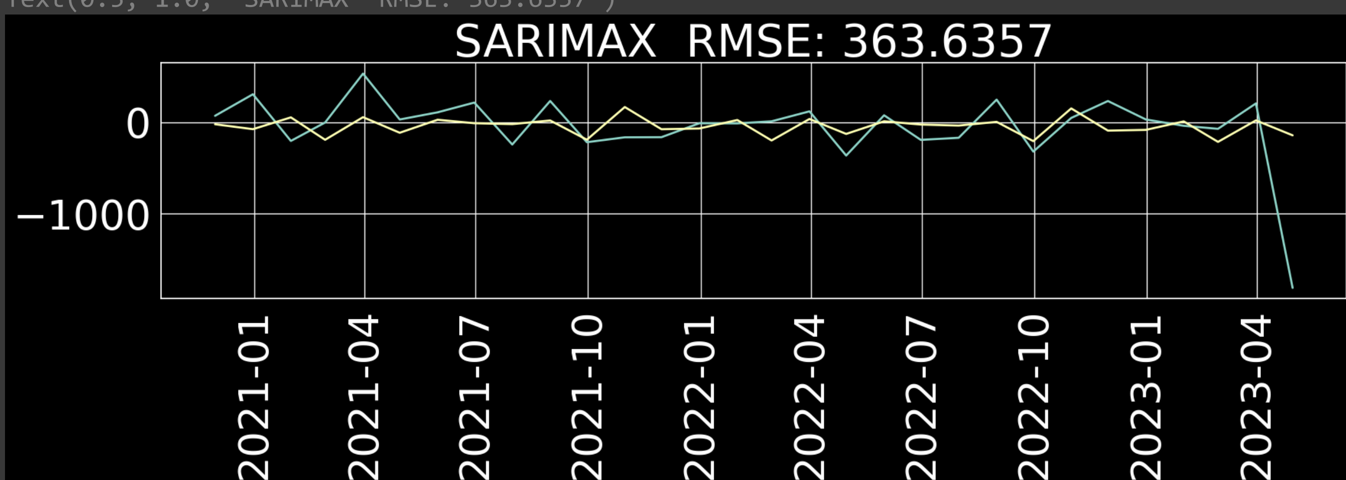
```
# report performance
mse = mean_squared_error(test2[start_index:end_index], predictions)
rmse = sqrt(mse)
print('RMSE: {}, MSE:{}'.format(rmse,mse))
```

```
RMSE: 363.63574666894795, MSE:132230.95625548327
```

```
import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = (20,4)

plt.plot(test2, linewidth=2)
plt.plot(predictions, linewidth=2)
plt.xticks(rotation ='vertical')
plt.title('SARIMAX  RMSE: %.4f'% rmse)
```

```
Text(0.5, 1.0, 'SARIMAX  RMSE: 363.6357')
```




```
####!pip install pmdarima
```

```
test.head(3)
```

Date	High	High_First_Order_Differencing	High_Second_Order_Differencing
2020-11-30	1699.959999	69.399994	-44.669998
2020-12-31	2004.969986	305.009987	235.609993

```
from pmdarima.arima import auto_arima
from pmdarima.arima import ADFTest
```

```
model=auto_arima(train["High_First_Order_Differencing"].dropna(),start_p=0,d=1,start_q=0,
          max_p=5,max_d=5,max_q=5, start_P=0,
          D=1, start_Q=0, max_P=5,max_D=5,
          max_Q=5, m=12, seasonal=True,
          error_action='warn',trace=True,
          supress_warnings=True,stepwise=True,
          random_state=20,n_fits=50)
```

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,1,0)[12]             : AIC=827.562, Time=0.02 sec
 ARIMA(1,1,0)(1,1,0)[12]             : AIC=801.307, Time=0.13 sec
 ARIMA(0,1,1)(0,1,1)[12]             : AIC=inf, Time=0.19 sec
 ARIMA(1,1,0)(0,1,0)[12]             : AIC=807.276, Time=0.03 sec
 ARIMA(1,1,0)(2,1,0)[12]             : AIC=801.459, Time=0.28 sec
 ARIMA(1,1,0)(1,1,1)[12]             : AIC=inf, Time=0.43 sec
 ARIMA(1,1,0)(0,1,1)[12]             : AIC=798.066, Time=0.20 sec
 ARIMA(1,1,0)(0,1,2)[12]             : AIC=inf, Time=0.57 sec
 ARIMA(1,1,0)(1,1,2)[12]             : AIC=inf, Time=0.92 sec
 ARIMA(0,1,0)(0,1,1)[12]             : AIC=819.357, Time=0.14 sec
 ARIMA(2,1,0)(0,1,1)[12]             : AIC=inf, Time=0.43 sec
 ARIMA(1,1,1)(0,1,1)[12]             : AIC=inf, Time=0.30 sec
 ARIMA(2,1,1)(0,1,1)[12]             : AIC=inf, Time=0.52 sec
 ARIMA(1,1,0)(0,1,1)[12] intercept   : AIC=800.035, Time=0.27 sec

Best model:  ARIMA(1,1,0)(0,1,1)[12]
Total fit time: 4.442 seconds
```

```
# SARIMA example
from statsmodels.tsa.statespace.sarimax import SARIMAX

# fit model
model_auto = SARIMAX(train["High_First_Order_Differencing"], order=(1, 1, 0), seasonal_order=(0,
model_auto_fit = model_auto.fit(disp=False)
```

```
model_auto_fit.summary()
```

SARIMAX Results

Dep. Variable:	High_First_Order_Differencing	**No. Observations:**	70
Model:	SARIMAX(1, 1, 0)x(0, 1, [1], 12)	**Log Likelihood**	-403.677
Date:	Sat, 15 Apr 2023	**AIC**	813.354
Time:	17:15:09	**BIC**	819.483
Sample:	01-31-2015 - 10-31-2020	**HQIC**	815.736
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.5859	0.119	-4.917	0.000	-0.819	-0.352
ma.S.L12	-0.6374	0.188	-3.392	0.001	-1.006	-0.269
sigma2	7.387e+04	2.02e+04	3.662	0.000	3.43e+04	1.13e+05

Ljung-Box (L1) (Q):	5.81	**Jarque-Bera (JB):**	2.21
Prob(Q):	0.02	**Prob(JB):**	0.33
Heteroskedasticity (H):	1.40	**Skew:**	0.16
Prob(H) (two-sided):	0.47	**Kurtosis:**	2.09

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

```
print(train.shape, test.shape)
```

```
(70, 3) (30, 4)
```

```
start_index = test.index.min()
end_index = test.index.max()

#Predictions
## pred = model_auto_fit.get_prediction(start=start_index,end=end_index, dynamic=False)
```

```
print(start_index)
print(end_index)
```

```
2020-11-30 00:00:00
2023-04-30 00:00:00
```

```
predictions2 = model_auto_fit.predict(start=start_index, end=end_index)
```

```
print(predictions2.shape, test.shape)
```

```
(30,) (30, 4)
```

```
test.columns
```

```
Index(['High', 'High_First_Order_Differencing',
       'High_Second_Order_Differencing', 'Predicted_ARIMA'],
      dtype='object')
```

```
test3 = test["High_First_Order_Differencing"]
```

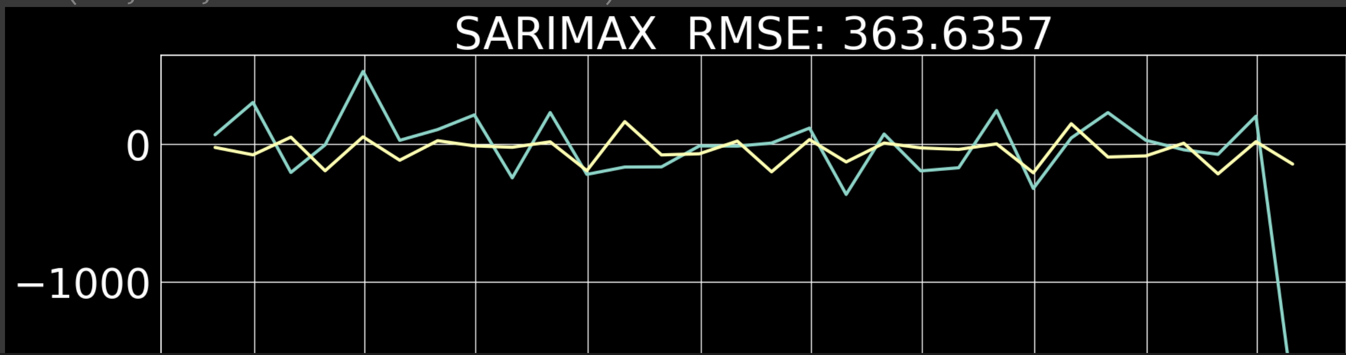
```
# report performance
mse = mean_squared_error(test3[start_index:end_index], predictions2)
rmse = sqrt(mse)
print('RMSE: {}, MSE:{}'.format(rmse,mse))
```

```
RMSE: 363.63574666894795, MSE:132230.95625548327
```

```
import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = (20,6)

plt.plot(test3, linewidth=3)
plt.plot(predictions2, linewidth=3)
plt.xticks(rotation ='vertical')
plt.title('SARIMAX  RMSE: %.4f'% rmse)
```

```
Text(0.5, 1.0, 'SARIMAX  RMSE: 363.6357')
```




```
test.columns
```

```
Index(['High', 'High_First_Order_Differencing',
       'High_Second_Order_Differencing', 'Predicted_ARIMA'],
      dtype='object')
```

```
plt.rcParams["figure.figsize"] = (20,6)
#test['forecast']=model_auto_fit.predict(start=90,end=103,dynamic=True)
#test[['High_First_Order_Differencing','forecast']].plot(figsize=(16,5))

plt.plot(test["forecast"], linewidth=5)
plt.plot(test["High_First_Order_Differencing"], linewidth=5)
plt.xticks(rotation ='vertical')

plt.show()
```