```
!pip install pmdarima -q
!pip install tensorflow
```

```
Requirement already satisfied: tensorflow in c:\users\rishav raj
singh\anaconda3\lib\site-packages (2.16.1)
Requirement already satisfied: tensorflow-intel==2.16.1 in c:\users\
rishav raj singh\anaconda3\lib\site-packages (from tensorflow)
(2.16.1)
Requirement already satisfied: absl-py>=1.0.0 in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (2.1.0)
Requirement already satisfied: astunparse>=1.6.0 in c:\users\rishav
raj singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=23.5.26 in c:\users\rishav
raj singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (24.3.25)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in
c:\users\rishav raj singh\anaconda3\lib\site-packages (from
tensorflow-intel==2.16.1->tensorflow) (0.5.4)
Requirement already satisfied: google-pasta>=0.1.1 in c:\users\rishav
raj singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (0.2.0)
Requirement already satisfied: h5py>=3.10.0 in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (3.10.0)
Requirement already satisfied: libclang>=13.0.0 in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (18.1.1)
Requirement already satisfied: ml-dtypes~=0.3.1 in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (0.3.2)
Requirement already satisfied: opt-einsum>=2.3.2 in c:\users\rishav
raj singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (3.3.0)
Requirement already satisfied: packaging in c:\users\rishav raj singh\
anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (23.1)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!
=4.21.3,!=4.21.4,!=4.21.5,<5.0.0dev,>=3.20.3 in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (3.20.3)
Requirement already satisfied: requests<3,>=2.21.0 in c:\users\rishav
raj singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (2.31.0)
Requirement already satisfied: setuptools in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (68.2.2)
Requirement already satisfied: six>=1.12.0 in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
```

```
>tensorflow) (1.16.0)
Requirement already satisfied: termcolor>=1.1.0 in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (2.4.0)
Requirement already satisfied: typing-extensions>=3.6.6 in c:\users\
rishav raj singh\anaconda3\lib\site-packages (from tensorflow-
intel==2.16.1->tensorflow) (4.10.0)
Requirement already satisfied: wrapt>=1.11.0 in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (1.14.1)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in c:\users\rishav
raj singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (1.62.1)
Requirement already satisfied: tensorboard<2.17,>=2.16 in c:\users\
rishav raj singh\anaconda3\lib\site-packages (from tensorflow-
intel==2.16.1->tensorflow) (2.16.2)
Requirement already satisfied: keras>=3.0.0 in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (3.1.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in
c:\users\rishav raj singh\anaconda3\lib\site-packages (from
tensorflow-intel==2.16.1->tensorflow) (0.31.0)
Requirement already satisfied: numpy<2.0.0,>=1.23.5 in c:\users\rishav
raj singh\anaconda3\lib\site-packages (from tensorflow-intel==2.16.1-
>tensorflow) (1.26.4)
Requirement already satisfied: wheel<1.0,>=0.23.0 in c:\users\rishav
raj singh\anaconda3\lib\site-packages (from astunparse>=1.6.0-
>tensorflow-intel==2.16.1->tensorflow) (0.41.2)
Requirement already satisfied: rich in c:\users\rishav raj singh\
anaconda3\lib\site-packages (from keras>=3.0.0->tensorflow-
intel==2.16.1->tensorflow) (13.3.5)
Requirement already satisfied: namex in c:\users\rishav raj singh\
anaconda3\lib\site-packages (from keras>=3.0.0->tensorflow-
intel==2.16.1->tensorflow) (0.0.7)
Requirement already satisfied: optree in c:\users\rishav raj singh\
anaconda3\lib\site-packages (from keras>=3.0.0->tensorflow-
intel==2.16.1->tensorflow) (0.11.0)
Requirement already satisfied: charset-normalizer<4,>=2 in c:\users\
rishav raj singh\anaconda3\lib\site-packages (from
requests<3,>=2.21.0->tensorflow-intel==2.16.1->tensorflow) (2.0.4)
Requirement already satisfied: idna<4,>=2.5 in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from requests<3,>=2.21.0-
>tensorflow-intel==2.16.1->tensorflow) (3.4)
Requirement already satisfied: urllib3<3,>=1.21.1 in c:\users\rishav
raj singh\anaconda3\lib\site-packages (from requests<3,>=2.21.0-
>tensorflow-intel==2.16.1->tensorflow) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\rishav
raj singh\anaconda3\lib\site-packages (from requests<3,>=2.21.0-
>tensorflow-intel==2.16.1->tensorflow) (2024.2.2)
```

```
Requirement already satisfied: markdown>=2.6.8 in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from tensorboard<2.17,>=2.16-
>tensorflow-intel==2.16.1->tensorflow) (3.4.1)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0
in c:\users\rishav raj singh\anaconda3\lib\site-packages (from
tensorboard<2.17,>=2.16->tensorflow-intel==2.16.1->tensorflow) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from tensorboard<2.17,>=2.16-
>tensorflow-intel==2.16.1->tensorflow) (2.2.3)
Requirement already satisfied: MarkupSafe>=2.1.1 in c:\users\rishav
raj singh\anaconda3\lib\site-packages (from werkzeug>=1.0.1-
>tensorboard<2.17,>=2.16->tensorflow-intel==2.16.1->tensorflow)
(2.1.3)
Requirement already satisfied: markdown-it-py<3.0.0,>=2.2.0 in c:\
users\rishav raj singh\anaconda3\lib\site-packages (from rich-
>keras>=3.0.0->tensorflow-intel==2.16.1->tensorflow) (2.2.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in c:\users\
rishav raj singh\anaconda3\lib\site-packages (from rich->keras>=3.0.0-
>tensorflow-intel==2.16.1->tensorflow) (2.15.1)
Requirement already satisfied: mdurl~=0.1 in c:\users\rishav raj
singh\anaconda3\lib\site-packages (from markdown-it-py<3.0.0,>=2.2.0-
>rich->keras>=3.0.0->tensorflow-intel==2.16.1->tensorflow) (0.1.0)
```

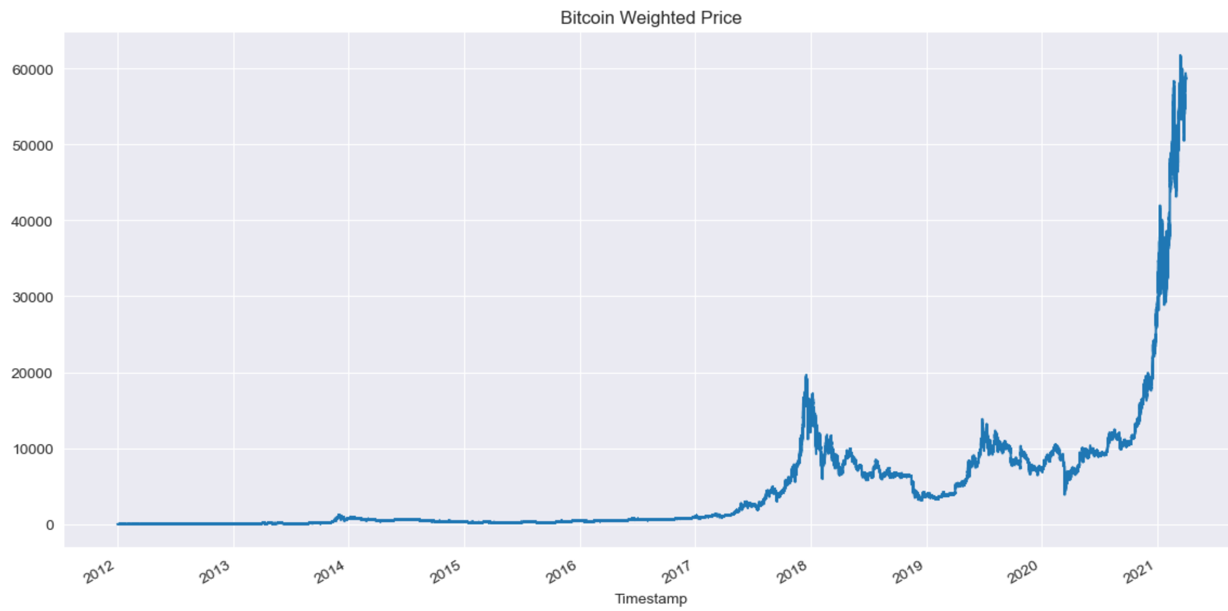
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from datetime import datetime
import seaborn as sns
import plotly.express as px
from itertools import product
import warnings
import statsmodels.api as sm
import statsmodels.api as sm
sns.set_style("darkgrid")
```

```python
BTC_DF = pd.read_csv("bitstampUSD_1-min_data_2012-01-01_to_2021-03-
31.csv")
```

```python
BTC_DF.head()
```

```
    Timestamp  Open  High   Low  Close  Volume_(BTC)
Volume_(Currency)  \
0  1325317920  4.39  4.39  4.39   4.39      0.455581
2.0
1  1325317980   NaN   NaN   NaN    NaN           NaN
NaN
2  1325318040   NaN   NaN   NaN    NaN           NaN
NaN
3  1325318100   NaN   NaN   NaN    NaN           NaN
NaN
```

```
4  1325318160   NaN   NaN   NaN    NaN            NaN
NaN

   Weighted_Price
0            4.39
1             NaN
2             NaN
3             NaN
4             NaN

BTC_DF.head()

    Timestamp  Open  High   Low  Close  Volume_(BTC)
Volume_(Currency)  \
0  1325317920  4.39  4.39  4.39   4.39      0.455581
2.0
1  1325317980   NaN   NaN   NaN    NaN            NaN
NaN
2  1325318040   NaN   NaN   NaN    NaN            NaN
NaN
3  1325318100   NaN   NaN   NaN    NaN            NaN
NaN
4  1325318160   NaN   NaN   NaN    NaN            NaN
NaN

   Weighted_Price
0            4.39
1             NaN
2             NaN
3             NaN
4             NaN

# Converting the Timestamp column from string to datetime
BTC_DF['Timestamp'] = [datetime.fromtimestamp(x) for x in
BTC_DF['Timestamp']]

BTC_DF.shape

(4857377, 8)

BTC_DF.set_index("Timestamp").Weighted_Price.plot(figsize=(14,7),
title="Bitcoin Weighted Price")

<Axes: title={'center': 'Bitcoin Weighted Price'}, xlabel='Timestamp'>
```




```
#calculating missing values in the dataset

missing_values = BTC_DF.isnull().sum()
missing_per = (missing_values/BTC_DF.shape[0])*100
missing_table = pd.concat([missing_values,missing_per], axis=1,
ignore_index=True)
missing_table.rename(columns={0:'Total Missing Values',1:'Missing %'},
inplace=True)
missing_table
```

	Total Missing Values	Missing %
Timestamp	0	0.00000
Open	1243608	25.60246
High	1243608	25.60246
Low	1243608	25.60246
Close	1243608	25.60246
Volume_(BTC)	1243608	25.60246
Volume_(Currency)	1243608	25.60246
Weighted_Price	1243608	25.60246

```
def fill_missing(df):
    ### function to impute missing values using interpolation ###
    df['Open'] = df['Open'].interpolate()
    df['Close'] = df['Close'].interpolate()
    df['Weighted_Price'] = df['Weighted_Price'].interpolate()

    df['Volume_(BTC)'] = df['Volume_(BTC)'].interpolate()
    df['Volume_(Currency)'] = df['Volume_(Currency)'].interpolate()
    df['High'] = df['High'].interpolate()
    df['Low'] = df['Low'].interpolate()
```

```
    print(df.head())
    print(df.isnull().sum())

fill_missing(BTC_DF)

            Timestamp  Open  High   Low  Close  Volume_(BTC)  \
0 2011-12-31 13:22:00  4.39  4.39  4.39   4.39      0.455581
1 2011-12-31 13:23:00  4.39  4.39  4.39   4.39      0.555046
2 2011-12-31 13:24:00  4.39  4.39  4.39   4.39      0.654511
3 2011-12-31 13:25:00  4.39  4.39  4.39   4.39      0.753977
4 2011-12-31 13:26:00  4.39  4.39  4.39   4.39      0.853442

   Volume_(Currency)  Weighted_Price
0           2.000000            4.39
1           2.436653            4.39
2           2.873305            4.39
3           3.309958            4.39
4           3.746611            4.39
Timestamp            0
Open                 0
High                 0
Low                  0
Close                0
Volume_(BTC)         0
Volume_(Currency)    0
Weighted_Price       0
dtype: int64

#created a copy
bitstamp_non_indexed = BTC_DF.copy()

BTC_DF = BTC_DF.set_index('Timestamp')
BTC_DF.head()

                     Open  High   Low  Close  Volume_(BTC)
Volume_(Currency)  \
Timestamp

2011-12-31 13:22:00  4.39  4.39  4.39   4.39      0.455581
2.000000
2011-12-31 13:23:00  4.39  4.39  4.39   4.39      0.555046
2.436653
2011-12-31 13:24:00  4.39  4.39  4.39   4.39      0.654511
2.873305
2011-12-31 13:25:00  4.39  4.39  4.39   4.39      0.753977
3.309958
2011-12-31 13:26:00  4.39  4.39  4.39   4.39      0.853442
3.746611

                     Weighted_Price
Timestamp
```

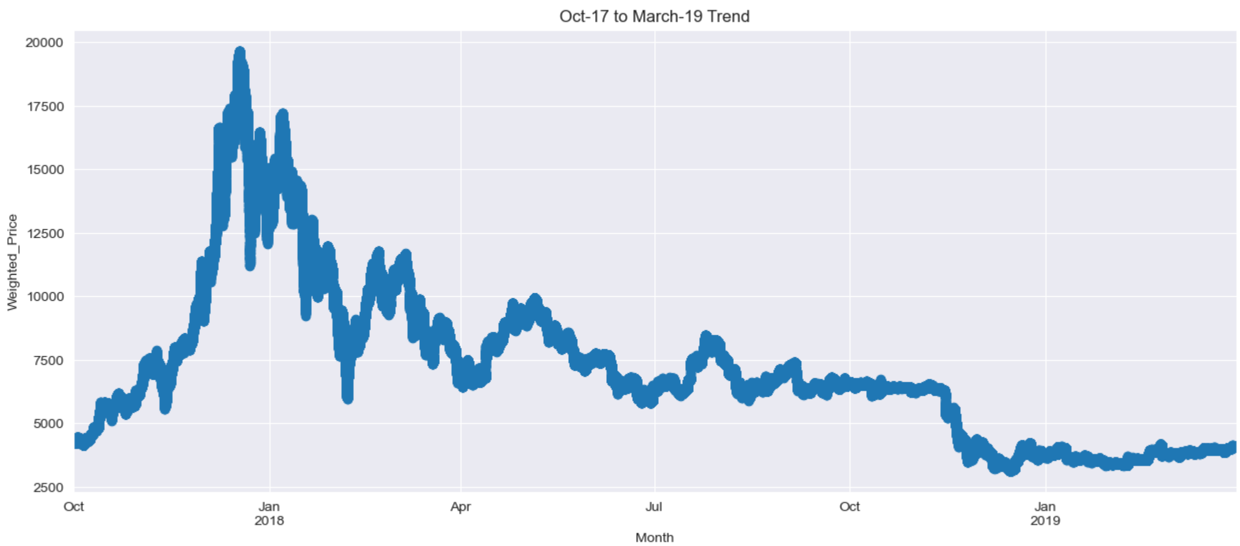
```
2011-12-31 13:22:00          4.39
2011-12-31 13:23:00          4.39
2011-12-31 13:24:00          4.39
2011-12-31 13:25:00          4.39
2011-12-31 13:26:00          4.39
```

```
ax = BTC_DF['Weighted_Price'].plot(title='Bitcoin Prices', grid=True,
figsize=(14,7))
ax.set_xlabel('Year')
ax.set_ylabel('Weighted Price')

ax.axvspan('2018-12-01','2019-01-31',color='red', alpha=0.3)
ax.axhspan(17500,20000, color='green',alpha=0.3)
```

```
<matplotlib.patches.Polygon at 0x2e38d6dd510>
```

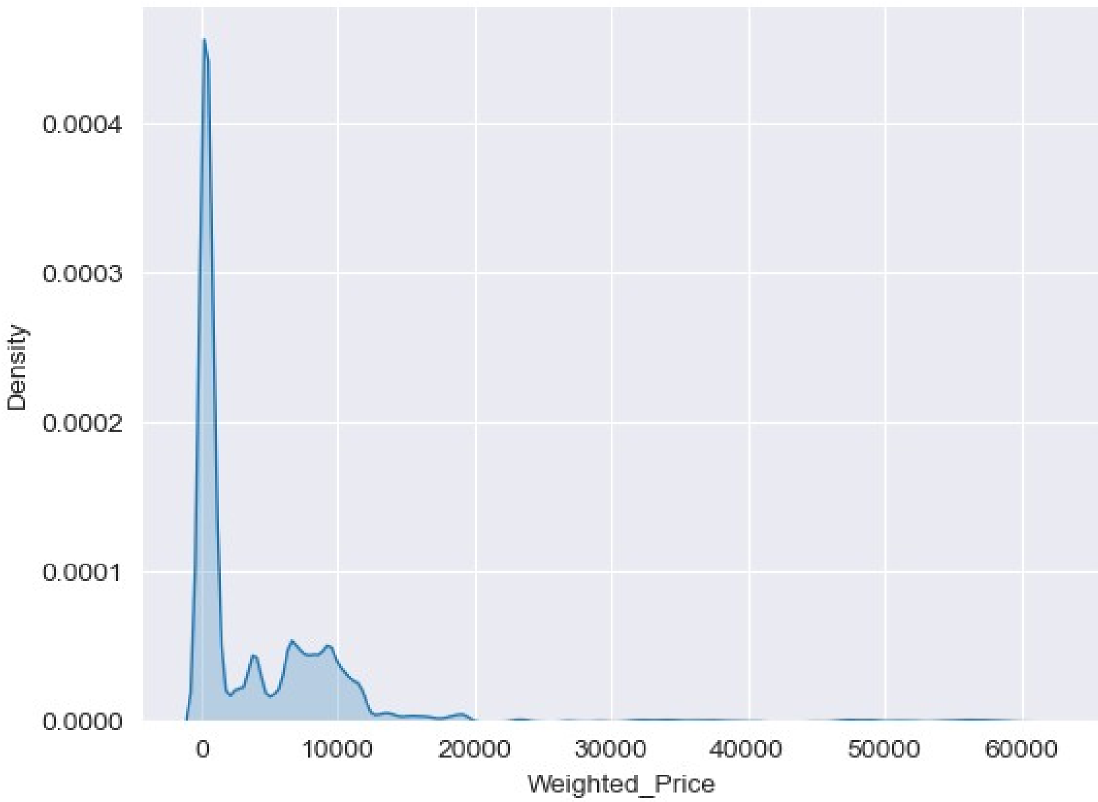

```
#Zooming in

ax = BTC_DF.loc['2017-10':'2019-03','Weighted_Price'].plot(marker='o',
linestyle='-',figsize=(15,6), title="Oct-17 to March-19 Trend",
grid=True)
ax.set_xlabel('Month')
ax.set_ylabel('Weighted_Price')
```

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



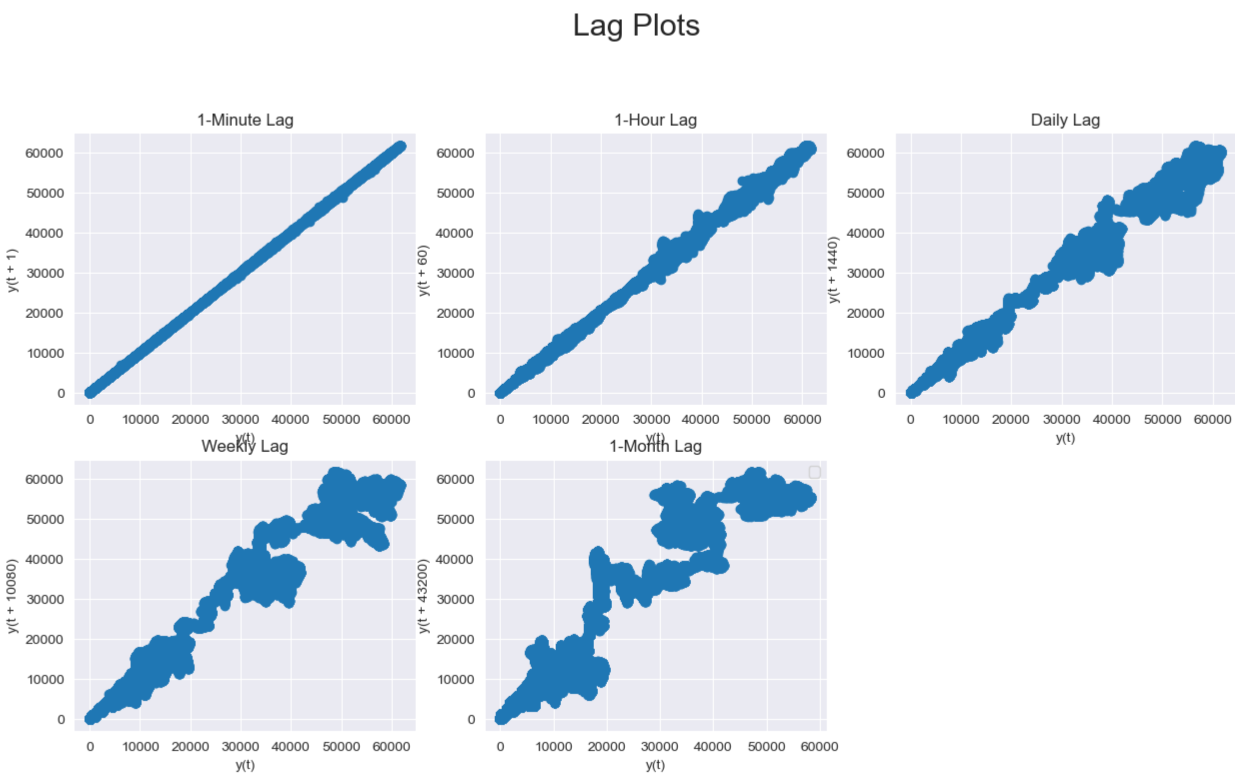

```
sns.kdeplot(BTC_DF['Weighted_Price'], shade=True)
```

```
C:\Users\RISHAV RAJ SINGH\AppData\Local\Temp\
ipykernel_44116\1539549472.py:1: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(BTC_DF['Weighted_Price'], shade=True)
C:\Users\RISHAV RAJ SINGH\anaconda3\Lib\site-packages\seaborn\
_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated
and will be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):

<Axes: xlabel='Weighted_Price', ylabel='Density'>
```




```
plt.figure(figsize=(15,12))
plt.suptitle('Lag Plots', fontsize=22)

plt.subplot(3,3,1)
pd.plotting.lag_plot(BTC_DF['Weighted_Price'], lag=1) #minute lag
plt.title('1-Minute Lag')

plt.subplot(3,3,2)
pd.plotting.lag_plot(BTC_DF['Weighted_Price'], lag=60) #hourley lag
plt.title('1-Hour Lag')

plt.subplot(3,3,3)
pd.plotting.lag_plot(BTC_DF['Weighted_Price'], lag=1440) #Daily lag
plt.title('Daily Lag')

plt.subplot(3,3,4)
pd.plotting.lag_plot(BTC_DF['Weighted_Price'], lag=10080) #weekly lag
plt.title('Weekly Lag')

plt.subplot(3,3,5)
pd.plotting.lag_plot(BTC_DF['Weighted_Price'], lag=43200) #month lag
plt.title('1-Month Lag')

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

```
No artists with labels found to put in legend.  Note that artists whose label start with an underscore are ignored when legend() is called with no argument.
```



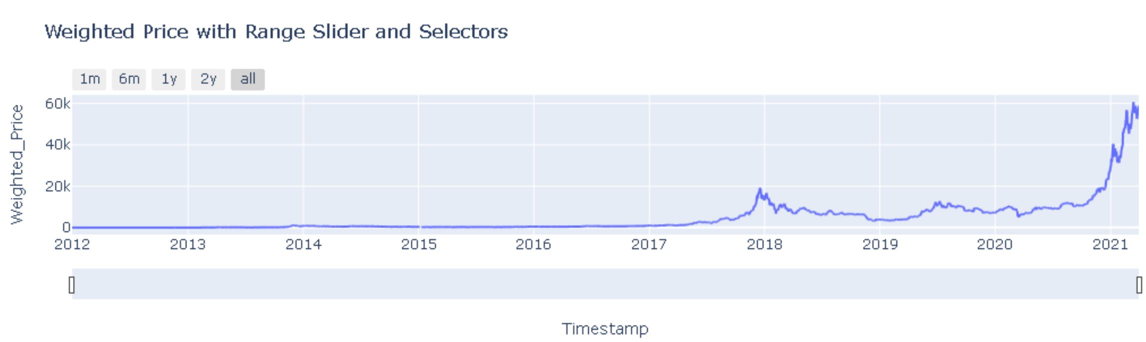

```
hourly_data = BTC_DF.resample('1H').mean()
hourly_data = hourly_data.reset_index()

hourly_data.head()
```

	Timestamp	Open	High	Low	Close	Volume_(BTC)	\
0	2011-12-31 13:00:00	4.39	4.39	4.39	4.39	2.295689	
1	2011-12-31 14:00:00	4.39	4.39	4.39	4.39	7.169489	
2	2011-12-31 15:00:00	4.39	4.39	4.39	4.39	13.137408	
3	2011-12-31 16:00:00	4.39	4.39	4.39	4.39	19.105327	
4	2011-12-31 17:00:00	4.39	4.39	4.39	4.39	25.073246	

	Volume_(Currency)	Weighted_Price
0	10.078075	4.39
1	31.474059	4.39
2	57.673222	4.39
3	83.872385	4.39
4	110.071548	4.39

```
BTC_Price_daily = BTC_DF.resample("24H").mean() #daily resampling
```

```
import plotly.express as px

BTC_Price_daily.reset_index(inplace=True)
fig = px.line(BTC_Price_daily, x='Timestamp', y='Weighted_Price',
title='Weighted Price with Range Slider and Selectors')
fig.update_layout(hovermode="x")

fig.update_xaxes(
    rangeslider_visible=True,
    rangeselector=dict(
        buttons=list([
            dict(count=1, label="1m", step="month",
stepmode="backward"),
            dict(count=6, label="6m", step="month",
stepmode="backward"),
            dict(count=1, label="1y", step="year",
stepmode="backward"),
            dict(count=2, label="2y", step="year",
stepmode="backward"),
            dict(step="all")

        ])
    )
)
fig.show()
```




```
#TIME SERIES DECOMPOSITION AND STATICAL TESTS

from statsmodels.tsa.seasonal import seasonal_decompose

from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

fill_missing(BTC_Price_daily)
```

```
   Timestamp      Open      High       Low     Close  Volume_(BTC)  \
0 2011-12-31  4.422837  4.426677  4.422837  4.426677     24.024874
```

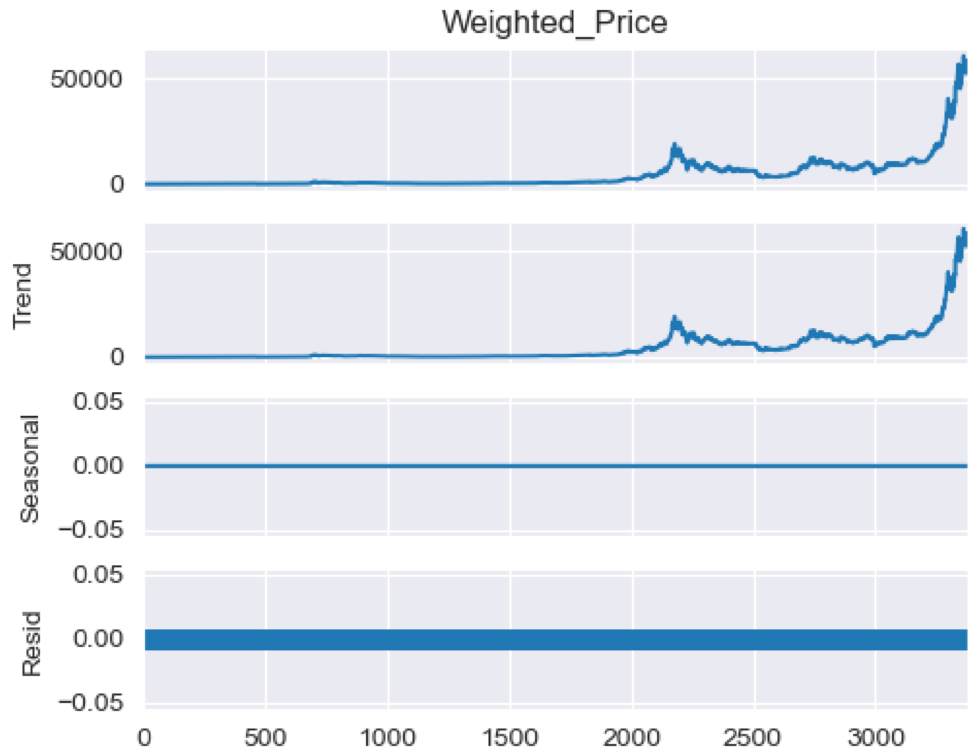
```
1 2012-01-01  4.677625  4.677625  4.677625  4.677625      5.883361
2 2012-01-02  4.991701  4.991701  4.991701  4.991701     13.503075
3 2012-01-03  5.175495  5.175495  5.175495  5.175495     11.136690
4 2012-01-04  5.120500  5.133742  5.120500  5.133742      8.327158

   Volume_(Currency)  Weighted_Price
0         105.980529        4.424286
1          27.923145        4.677625
2          67.432386        4.991701
3          56.749845        5.175495
4          43.510443        5.125202
Timestamp            0
Open                 0
High                 0
Low                  0
Close                0
Volume_(BTC)         0
Volume_(Currency)    0
Weighted_Price       0
dtype: int64
```

```
BTC_Price_daily.Weighted_Price
```

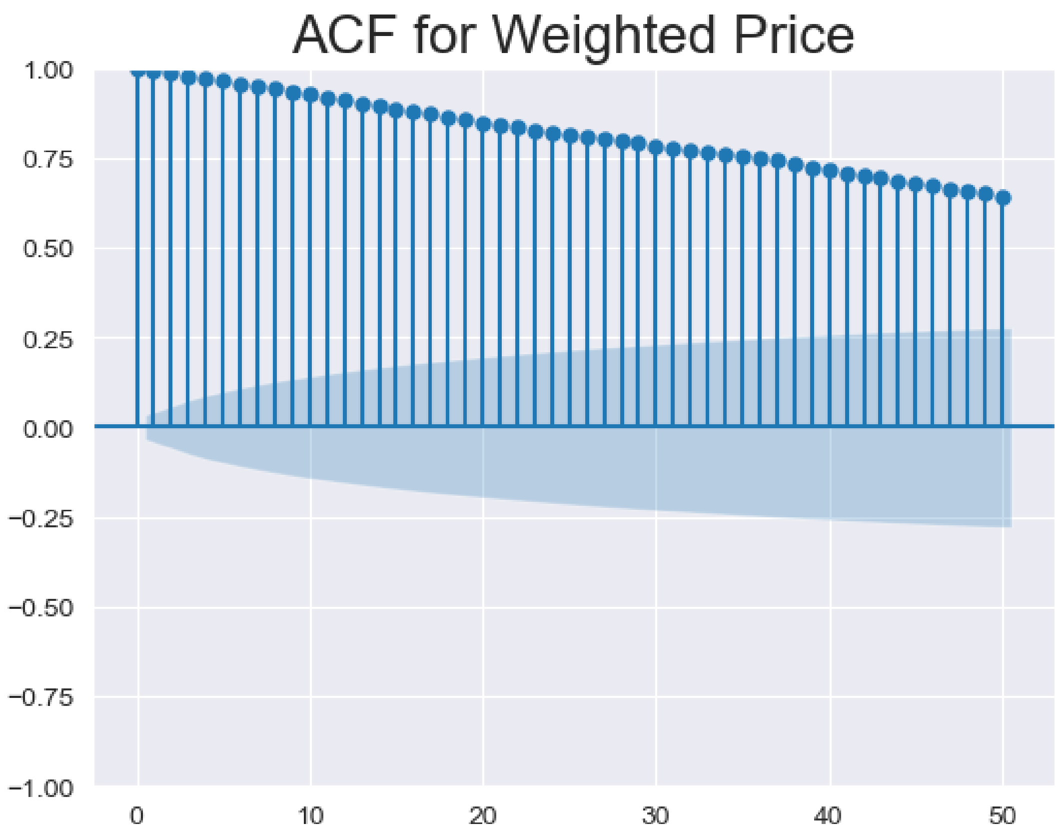
```
0            4.424286
1            4.677625
2            4.991701
3            5.175495
4            5.125202
              ...
3374    54788.954020
3375    56002.734323
3376    56376.937694
3377    58075.416823
3378    58758.891360
Name: Weighted_Price, Length: 3379, dtype: float64
```

```
plt.figure(figsize=(15,12))
series = BTC_Price_daily.Weighted_Price
result = seasonal_decompose(series, model='additive',period=1)
result.plot().set_size_inches(5, 4)
```

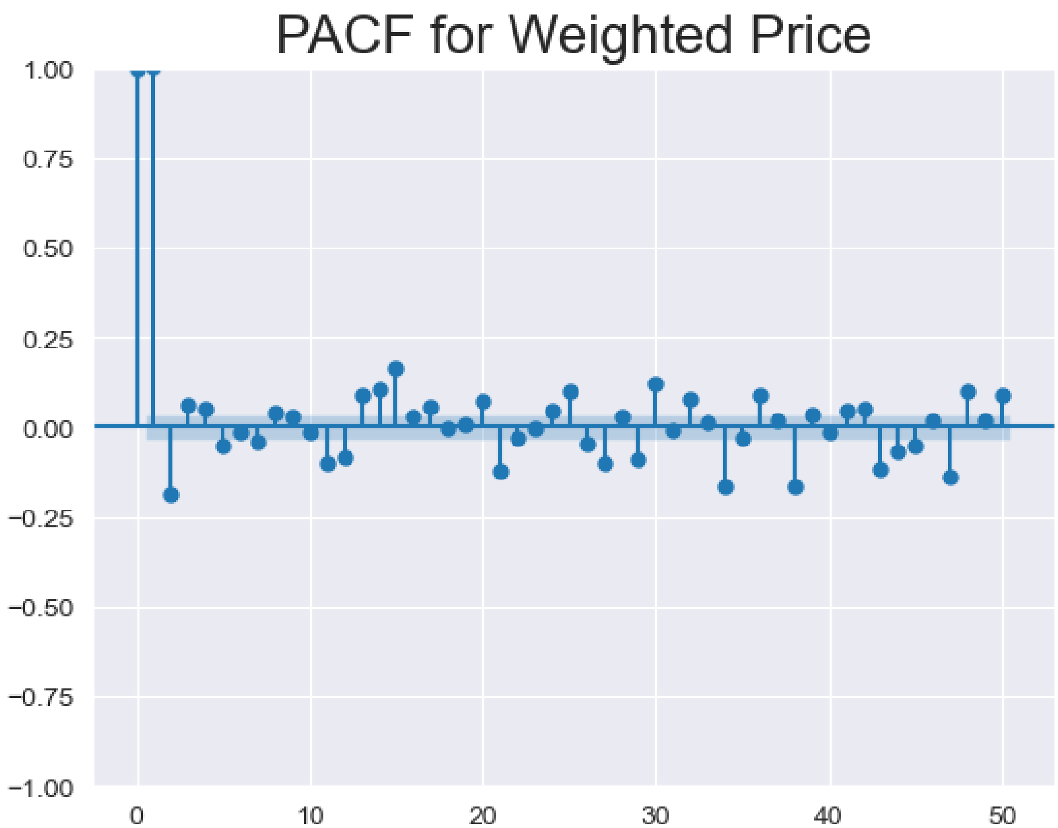
```
<Figure size 1500x1200 with 0 Axes>
```




```
acf = plot_acf(series, lags=50, alpha=0.05)
plt.title("ACF for Weighted Price", size=20,)
plt.show()
```




```
plot_pacf(series, lags=50, alpha=0.05, method='ols')
plt.title("PACF for Weighted Price", size=20)
plt.show()
```




```
#stationary time series

from statsmodels.tsa.stattools import kpss

#adf test
stats, p, lags, critical_values = kpss(series, 'ct')

C:\Users\RISHAV RAJ SINGH\AppData\Local\Temp\
ipykernel_44116\108484339.py:2: InterpolationWarning:

The test statistic is outside of the range of p-values available in
the
look-up table. The actual p-value is smaller than the p-value
returned.



def adf_test(timeseries):
    print ('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries, autolag='AIC')
    print("dftest: ", dftest)
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-
value','#Lags Used','Number of Observations Used'])
    for key,value in dftest[4].items():
       dfoutput['Critical Value (%s)'%key] = value
```

```
    print (dfoutput)

    if p > 0.05:
        print('Series is not Stationary')
    else:
        print('Series is Stationary')

adf_test(series)

Results of Dickey-Fuller Test:
dftest:  (6.302120534312761, 1.0, 29, 3349, {'1%': -3.432304111473485,
'5%': -2.862403412310526, '10%': -2.56722961145352},
48472.31981125205)
Test Statistic                     6.302121
p-value                            1.000000
#Lags Used                        29.000000
Number of Observations Used     3349.000000
Critical Value (1%)               -3.432304
Critical Value (5%)               -2.862403
Critical Value (10%)              -2.567230
dtype: float64
Series is Stationary

#FEATURE ENGINEERING

df = BTC_Price_daily.set_index("Timestamp")

df.reset_index(drop=False, inplace=True)

rolling_features = ["Open", "High", "Low", "Close","Volume_(BTC)"]
window1 = 3
window2 = 7
window3 = 30

# First convert our original df to a rolling df of 3d, 7d  and 30d
df_rolled_3d = df[rolling_features].rolling(window=window1,
min_periods=0)
df_rolled_7d = df[rolling_features].rolling(window=window2,
min_periods=0)
df_rolled_30d = df[rolling_features].rolling(window=window3,
min_periods=0)


# dataframe.shift() function Shift index by desired number of periods.
It takes a scalar parameter called the period,
# which represents the number of shifts to be made over the desired
axis. It defaults to 1 and
# it is shifting values vertically along the axis 0 . NaN will be
filled for missing values introduced as a result of the shifting.
# Very helpful when dealing with time-series data.
```

```python
# https://towardsdatascience.com/all-the-pandas-shift-you-should-know-for-data-analysis-791c1692b5e
df_mean_3d = df_rolled_3d.mean().shift(1).reset_index()
df_mean_7d = df_rolled_7d.mean().shift(1).reset_index()
df_mean_30d = df_rolled_30d.mean().shift(1).reset_index()


# Just print to see the structure of one of them
df_mean_30d
```

```
      index          Open          High           Low         Close  \
0         0           NaN           NaN           NaN           NaN
1         1      4.422837      4.426677      4.422837      4.426677
2         2      4.550231      4.552151      4.550231      4.552151
3         3      4.697388      4.698668      4.697388      4.698668
4         4      4.816915      4.817875      4.816915      4.817875
...     ...           ...           ...           ...           ...
3374   3374  53206.447763  53245.227654  53167.556178  53207.530781
3375   3375  53364.378192  53402.510297  53326.251128  53365.529760
3376   3376  53658.228941  53694.963607  53621.648890  53659.456192
3377   3377  53968.885871  54005.334879  53932.677167  53970.075025
3378   3378  54394.961787  54430.840483  54359.421673  54396.251845

      Volume_(BTC)
0              NaN
1        24.024874
2        14.954117
3        14.470437
4        13.637000
...            ...
3374      3.852066
3375      3.754108
3376      3.594949
3377      3.623054
3378      3.581530

[3379 rows x 6 columns]
```

```python
df_std_3d = df_rolled_3d.std().shift(1).reset_index()
df_std_7d = df_rolled_7d.std().shift(1).reset_index()
df_std_30d = df_rolled_30d.std().shift(1).reset_index()

# Just print to see the structure of one of them
df_std_30d
```

```
      index          Open          High           Low         Close
Volume_(BTC)
0         0           NaN           NaN           NaN           NaN
NaN
1         1           NaN           NaN           NaN           NaN
```

```
NaN
2          2     0.180163     0.177447     0.180163     0.177447
12.827987
3          3     0.284946     0.283099     0.284946     0.283099
9.109362
4          4     0.333581     0.332071     0.333581     0.332071
7.622256
...      ...          ...          ...          ...          ...
...
3374   3374  4435.974803  4434.057878  4437.954547  4436.182696
1.223055
3375   3375  4403.971836  4402.115028  4405.906128  4404.182498
1.250130
3376   3376  4269.649305  4268.898044  4270.343124  4269.817028
1.245602
3377   3377  4108.821654  4108.182451  4109.416624  4109.022442
1.232919
3378   3378  3831.773514  3831.207184  3831.997540  3831.768848
1.238370

[3379 rows x 6 columns]
```

```
for feature in rolling_features:
    df[f"{feature}_mean_lag{window1}"] = df_mean_3d[feature]
    df[f"{feature}_mean_lag{window2}"] = df_mean_7d[feature]
    df[f"{feature}_mean_lag{window3}"] = df_mean_30d[feature]

    df[f"{feature}_std_lag{window1}"] = df_std_3d[feature]
    df[f"{feature}_std_lag{window2}"] = df_std_7d[feature]
    df[f"{feature}_std_lag{window3}"] = df_std_30d[feature]

df.fillna(df.mean(), inplace=True)

df.set_index("Timestamp", drop=False, inplace=True)
df.head()
```

```
            Timestamp      Open      High       Low     Close
Volume_(BTC)  \
Timestamp

2011-12-31 2011-12-31  4.422837  4.426677  4.422837  4.426677
24.024874
2012-01-01 2012-01-01  4.677625  4.677625  4.677625  4.677625
5.883361
2012-01-02 2012-01-02  4.991701  4.991701  4.991701  4.991701
13.503075
2012-01-03 2012-01-03  5.175495  5.175495  5.175495  5.175495
11.136690
2012-01-04 2012-01-04  5.120500  5.133742  5.120500  5.133742
8.327158
```

```
            Volume_(Currency)  Weighted_Price  Open_mean_lag3
Open_mean_lag7  \
Timestamp

2011-12-31         105.980529        4.424286     4564.752758
4532.014863
2012-01-01          27.923145        4.677625        4.422837
4.422837
2012-01-02          67.432386        4.991701        4.550231
4.550231
2012-01-03          56.749845        5.175495        4.697388
4.697388
2012-01-04          43.510443        5.125202        4.948274
4.816915

            ...  Close_mean_lag30  Close_std_lag3  Close_std_lag7  \
Timestamp   ...
2011-12-31  ...       4342.158190      112.850620      186.071830
2012-01-01  ...          4.426677      112.850620      186.071830
2012-01-02  ...          4.552151        0.177447        0.177447
2012-01-03  ...          4.698668        0.283099        0.283099
2012-01-04  ...          4.817875        0.251760        0.332071

            Close_std_lag30  Volume_(BTC)_mean_lag3
Volume_(BTC)_mean_lag7  \
Timestamp

2011-12-31       417.775512                9.565484
9.572699
2012-01-01       417.775512               24.024874
24.024874
2012-01-02         0.177447               14.954117
14.954117
2012-01-03         0.283099               14.470437
14.470437
2012-01-04         0.332071               10.174375
13.637000

            Volume_(BTC)_mean_lag30  Volume_(BTC)_std_lag3  \
Timestamp
2011-12-31                 9.590264               3.369452
2012-01-01                24.024874               3.369452
2012-01-02                14.954117              12.827987
2012-01-03                14.470437               9.109362
2012-01-04                13.637000               3.899942

            Volume_(BTC)_std_lag7  Volume_(BTC)_std_lag30
Timestamp
2011-12-31               4.136303                5.128796
```

```
2012-01-01               4.136303                 5.128796
2012-01-02              12.827987                12.827987
2012-01-03               9.109362                 9.109362
2012-01-04               7.622256                 7.622256

[5 rows x 38 columns]
```

```
df["month"] = df.Timestamp.dt.month
df["week"] = df.Timestamp.dt.isocalendar().week
df["day"] = df.Timestamp.dt.day
df["day_of_week"] = df.Timestamp.dt.dayofweek
df.head()
```

```
            Timestamp      Open      High       Low     Close
Volume_(BTC)  \
Timestamp

2011-12-31 2011-12-31  4.422837  4.426677  4.422837  4.426677
24.024874
2012-01-01 2012-01-01  4.677625  4.677625  4.677625  4.677625
5.883361
2012-01-02 2012-01-02  4.991701  4.991701  4.991701  4.991701
13.503075
2012-01-03 2012-01-03  5.175495  5.175495  5.175495  5.175495
11.136690
2012-01-04 2012-01-04  5.120500  5.133742  5.120500  5.133742
8.327158

            Volume_(Currency)  Weighted_Price  Open_mean_lag3
Open_mean_lag7  \
Timestamp

2011-12-31         105.980529        4.424286     4564.752758
4532.014863
2012-01-01          27.923145        4.677625        4.422837
4.422837
2012-01-02          67.432386        4.991701        4.550231
4.550231
2012-01-03          56.749845        5.175495        4.697388
4.697388
2012-01-04          43.510443        5.125202        4.948274
4.816915

            ...  Volume_(BTC)_mean_lag3  Volume_(BTC)_mean_lag7  \
Timestamp   ...
2011-12-31  ...                9.565484                9.572699
2012-01-01  ...               24.024874               24.024874
2012-01-02  ...               14.954117               14.954117
2012-01-03  ...               14.470437               14.470437
2012-01-04  ...               10.174375               13.637000
```

```
            Volume_(BTC)_mean_lag30  Volume_(BTC)_std_lag3  \
Timestamp
2011-12-31                 9.590264               3.369452
2012-01-01                24.024874               3.369452
2012-01-02                14.954117              12.827987
2012-01-03                14.470437               9.109362
2012-01-04                13.637000               3.899942

            Volume_(BTC)_std_lag7  Volume_(BTC)_std_lag30  month  week
day  \
Timestamp

2011-12-31               4.136303                5.128796     12    52
31
2012-01-01               4.136303                5.128796      1    52
1
2012-01-02              12.827987               12.827987      1     1
2
2012-01-03               9.109362                9.109362      1     1
3
2012-01-04               7.622256                7.622256      1     1
4

            day_of_week
Timestamp
2011-12-31            5
2012-01-01            6
2012-01-02            0
2012-01-03            1
2012-01-04            2

[5 rows x 42 columns]
```

```python
#MODEL BUILDING

df_train = df[df.Timestamp < "2020"]
df_valid = df[df.Timestamp >= "2020"]

print('train shape :', df_train.shape)
print('validation shape :', df_valid.shape)
```

```
train shape : (2923, 42)
validation shape : (456, 42)
```

```python
df_train = df[df.Timestamp < "2020"]
df_valid = df[df.Timestamp >= "2020"]

print('train shape :', df_train.shape)
print('validation shape :', df_valid.shape)
```

```
train shape : (2923, 42)
validation shape : (456, 42)
```

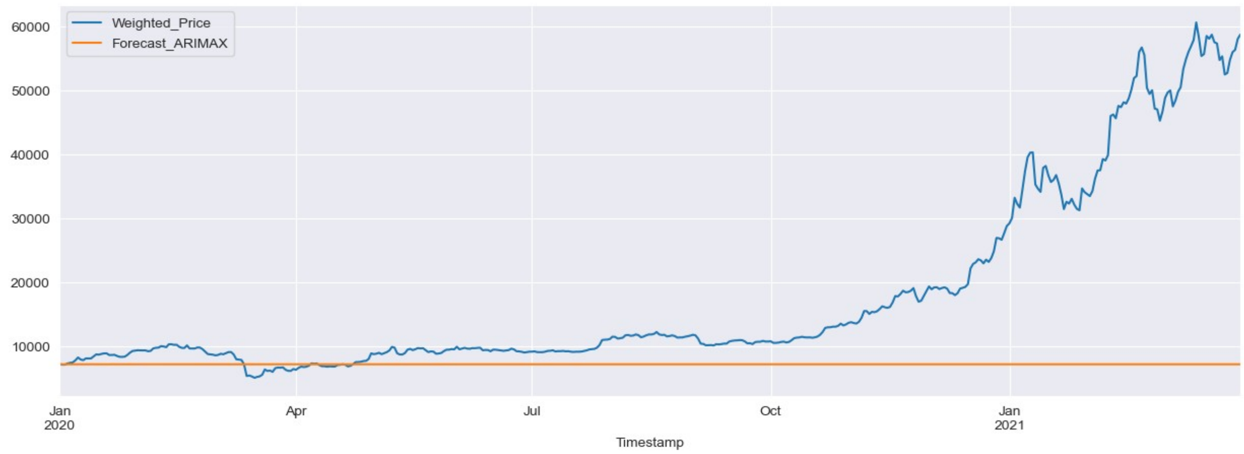
```
#ARIMA

import pmdarima as pm

# From df.columns, I remove all the original 8 columns i.e
# 'Timestamp', 'Open', 'High', 'Low', 'Close', 'Volume_(BTC)',
'Volume_(Currency)', 'Weighted_Price',
# So I will be left with below newly created (engineered) columns
# Also

exogenous_features = ['Open_mean_lag3',
       'Open_mean_lag7', 'Open_mean_lag30', 'Open_std_lag3',
'Open_std_lag7',
       'Open_std_lag30', 'High_mean_lag3', 'High_mean_lag7',
'High_mean_lag30',
       'High_std_lag3', 'High_std_lag7', 'High_std_lag30',
'Low_mean_lag3',
       'Low_mean_lag7', 'Low_mean_lag30', 'Low_std_lag3',
'Low_std_lag7',
       'Low_std_lag30', 'Close_mean_lag3', 'Close_mean_lag7',
       'Close_mean_lag30', 'Close_std_lag3', 'Close_std_lag7',
       'Close_std_lag30', 'Volume_(BTC)_mean_lag3',
'Volume_(BTC)_mean_lag7',
       'Volume_(BTC)_mean_lag30', 'Volume_(BTC)_std_lag3',
       'Volume_(BTC)_std_lag7', 'Volume_(BTC)_std_lag30', 'month',
       'day', 'day_of_week']

# len(exogenous_features1) # 34

model = pm.auto_arima(df_train.Weighted_Price,
exogenous=df_train[exogenous_features], trace=True,
error_action="ignore", suppress_warnings=True)


model.fit(df_train.Weighted_Price,
exogenous=df_train[exogenous_features])

forecast = model.predict(n_periods=len(df_valid),
exogenous=df_valid[exogenous_features])

df_valid["Forecast_ARIMAX"] = forecast
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=38726.548, Time=2.87 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=38854.989, Time=0.12 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=38739.796, Time=0.31 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=38737.063, Time=0.31 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=38853.501, Time=0.07 sec
```

```
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=38728.327, Time=2.10 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=38740.389, Time=0.41 sec
 ARIMA(3,1,2)(0,0,0)[0] intercept   : AIC=38718.014, Time=5.14 sec
 ARIMA(3,1,1)(0,0,0)[0] intercept   : AIC=38742.364, Time=0.63 sec
 ARIMA(4,1,2)(0,0,0)[0] intercept   : AIC=38732.559, Time=2.68 sec
 ARIMA(3,1,3)(0,0,0)[0] intercept   : AIC=38727.437, Time=7.64 sec
 ARIMA(2,1,3)(0,0,0)[0] intercept   : AIC=38725.338, Time=5.87 sec
 ARIMA(4,1,1)(0,0,0)[0] intercept   : AIC=38729.099, Time=1.78 sec
 ARIMA(4,1,3)(0,0,0)[0] intercept   : AIC=38728.781, Time=3.70 sec
 ARIMA(3,1,2)(0,0,0)[0]             : AIC=38716.214, Time=2.57 sec
 ARIMA(2,1,2)(0,0,0)[0]             : AIC=38724.804, Time=1.35 sec
 ARIMA(3,1,1)(0,0,0)[0]             : AIC=38730.459, Time=1.09 sec
 ARIMA(4,1,2)(0,0,0)[0]             : AIC=38730.822, Time=1.04 sec
 ARIMA(3,1,3)(0,0,0)[0]             : AIC=38725.524, Time=3.72 sec
 ARIMA(2,1,1)(0,0,0)[0]             : AIC=38738.753, Time=0.12 sec
 ARIMA(2,1,3)(0,0,0)[0]             : AIC=38730.606, Time=1.11 sec
 ARIMA(4,1,1)(0,0,0)[0]             : AIC=38727.378, Time=1.18 sec
 ARIMA(4,1,3)(0,0,0)[0]             : AIC=38727.060, Time=2.81 sec

Best model:  ARIMA(3,1,2)(0,0,0)[0]
Total fit time: 48.654 seconds

C:\Users\RISHAV RAJ SINGH\AppData\Local\Temp\
ipykernel_44116\183215675.py:8: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
```

```
df_valid[["Weighted_Price", "Forecast_ARIMAX"]].plot(figsize=(15, 5))
```

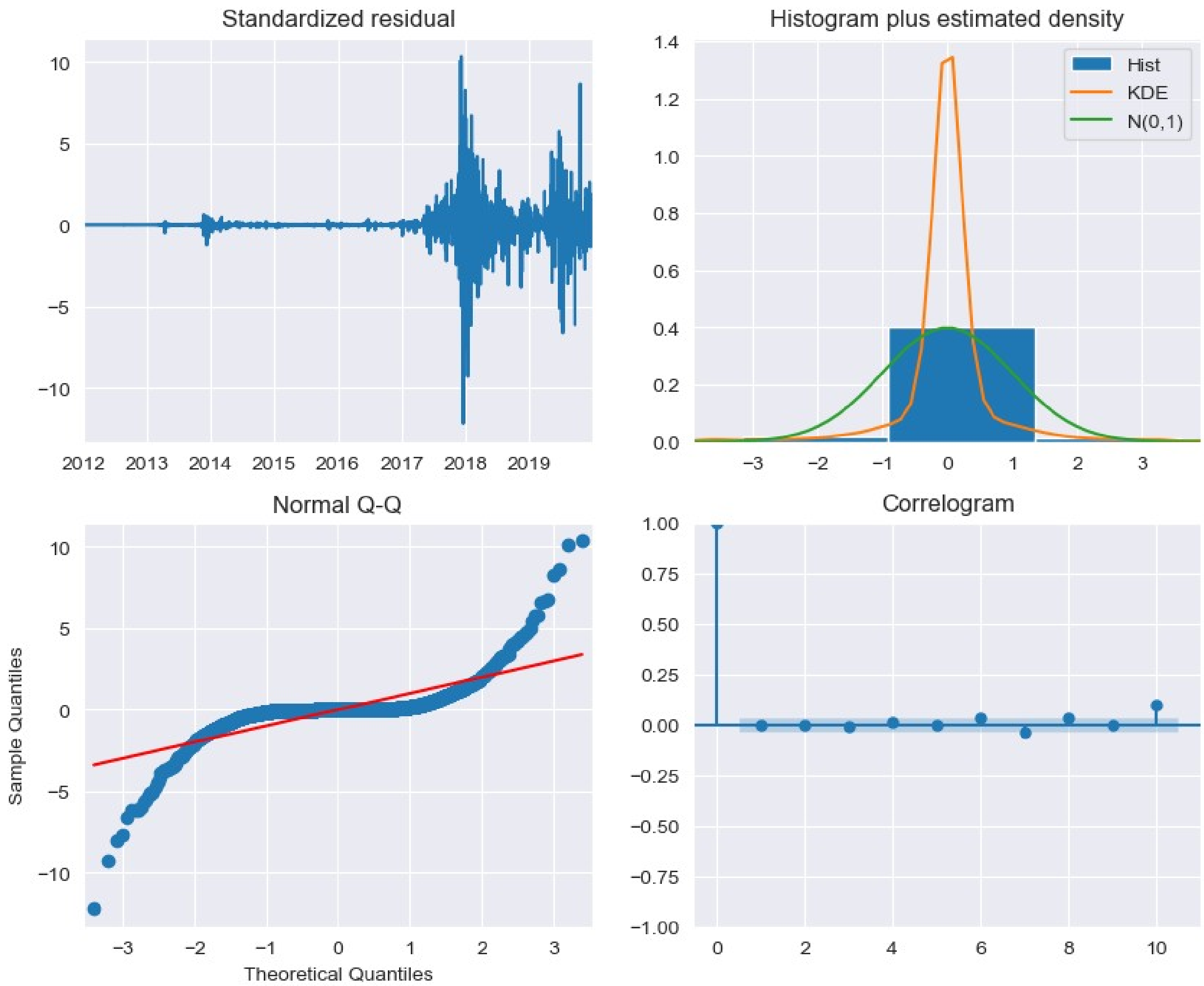
```
<Axes: xlabel='Timestamp'>
```




```
from sklearn.metrics import mean_squared_error, mean_absolute_error

print("RMSE of Auto ARIMAX:",
np.sqrt(mean_squared_error(df_valid.Weighted_Price,
df_valid.Forecast_ARIMAX)))

print("\nMAE of Auto ARIMAX:",
mean_absolute_error(df_valid.Weighted_Price,
df_valid.Forecast_ARIMAX))
```

```
RMSE of Auto ARIMAX: 18052.527118342223

MAE of Auto ARIMAX: 10692.217013361565
```

```
model.plot_diagnostics().set_size_inches(10, 8)  # Adjust the size as
needed
plt.show()
```




```
#LSTM

price_series = BTC_Price_daily.reset_index().Weighted_Price.values
price_series
```

```
array([4.42428590e+00, 4.67762540e+00, 4.99170099e+00, ...,
       5.63769377e+04, 5.80754168e+04, 5.87588914e+04])
```

```
# Lets check what was the split of earlier train and test dataset
df_train.shape # (2923, 43)
```

```
(2923, 42)
```

```
train_data, test_data = price_series[0:2923], price_series[2923:]
```

```
# Feature Scaling
# from sklearn.preprocessing import MinMaxScaler

# scaler = MinMaxScaler(feature_range = (0, 1))
```

```python
# price_series_scaled = scaler.fit_transform(price_series.reshape(-1,1))

from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler(feature_range = (0, 1))

train_data = scaler.fit_transform(train_data.reshape(-1,1))

test_data = scaler.transform(test_data.reshape(-1,1))

# train_data, test_data = price_series_scaled[0:2923], price_series_scaled[2923:]

train_data.shape, test_data.shape
```

```
((2923, 1), (456, 1))
```

```python
def get_window_ds_list_for_lstm(series, time_step):
    # Here, basically for each window, all data upto the last but one data-point
    # will be appended to as X variable and then
    # the last data-point of that window will be the Y variable (i.e. target)
    dataX, dataY = [], []
    for i in range(len(series)- time_step-1):
        a = series[i : (i+time_step), 0]
        dataX.append(a)
        b = series[i + time_step, 0]
        dataY.append(b)

    return np.array(dataX), np.array(dataY)

X_train, y_train = get_window_ds_list_for_lstm(train_data, time_step=100)
X_test, y_test = get_window_ds_list_for_lstm(test_data, time_step=100)


X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

```
((2822, 100), (2822,), (355, 100), (355,))
```

```python
#reshape inputs to be [samples, timesteps, features] which is requred for LSTM

X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)


print(X_train.shape)
print(X_test.shape)
```

```
(2822, 100, 1)
(355, 100, 1)
```

```python
print(y_train.shape)
print(y_test.shape)
```

```
(2822,)
(355,)
```

```python
#Create Stacked LSTM Model

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LSTM
from tensorflow.keras.layers import Dropout

# Initialising the LSTM
regressor = Sequential()

# Adding the first LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True, input_shape =
(X_train.shape[1], 1)))
regressor.add(Dropout(0.2))

# Adding a second LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a third LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))

# Adding a fourth LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50))
regressor.add(Dropout(0.2))

# Adding the output layer
regressor.add(Dense(units = 1))

# Compiling the RNN
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')
```

```
C:\Users\RISHAV RAJ SINGH\anaconda3\Lib\site-packages\keras\src\
layers\rnn\rnn.py:204: UserWarning:

Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the
first layer in the model instead.
```

```python
regressor.summary()
```

```
Model: "sequential"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                          ┃ Output Shape                 ┃ Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━┩
│ lstm (LSTM)                           │ (None, 100, 50)              │ 10,400 │
├───────────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ dropout (Dropout)                     │ (None, 100, 50)              │ 0 │
├───────────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ lstm_1 (LSTM)                         │ (None, 100, 50)              │ 20,200 │
├───────────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ dropout_1 (Dropout)                   │ (None, 100, 50)              │ 0 │
├───────────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ lstm_2 (LSTM)                         │ (None, 100, 50)              │ 20,200 │
├───────────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ dropout_2 (Dropout)                   │ (None, 100, 50)              │ 0 │
├───────────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ lstm_3 (LSTM)                         │ (None, 50)                   │ 20,200 │
├───────────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ dropout_3 (Dropout)                   │ (None, 50)                   │ 0 │
├───────────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ dense (Dense)                         │ (None, 1)                    │ 51 │
└───────────────────────────────────────┴──────────────────────────────┴─────────────────┘

 Total params: 71,051 (277.54 KB)

 Trainable params: 71,051 (277.54 KB)

 Non-trainable params: 0 (0.00 B)
```

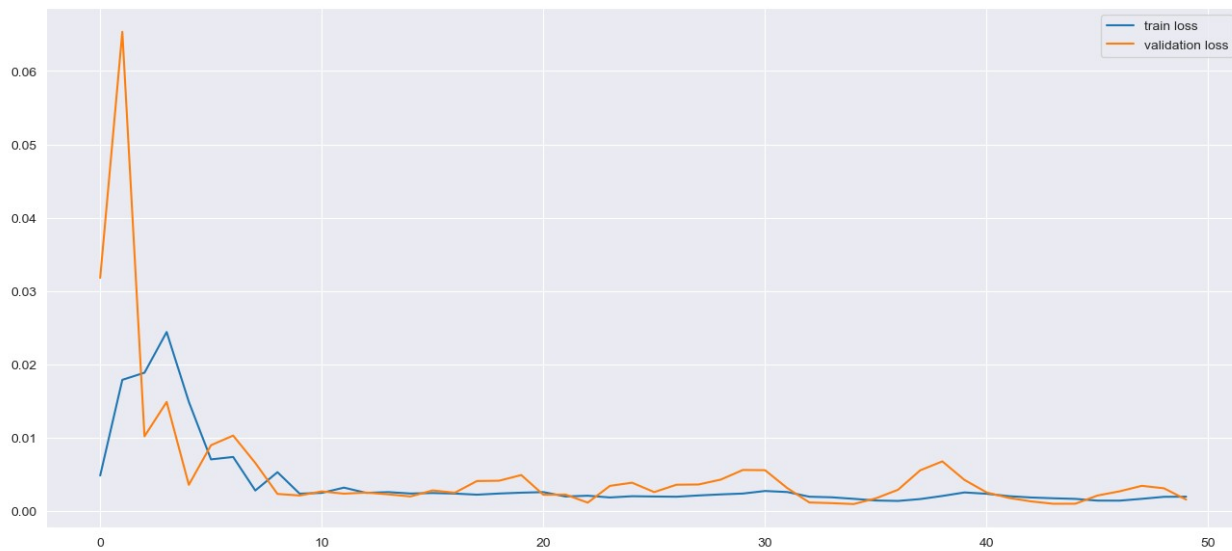
```
# Fitting the RNN to the Training set
history = regressor.fit(X_train, y_train, validation_split=0.1, epochs
= 50, batch_size = 32, verbose=1, shuffle=False)
```

```
Epoch 1/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 21s 168ms/step - loss: 9.4814e-04 -
val_loss: 0.0318
Epoch 2/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 14s 173ms/step - loss: 0.0124 - val_loss:
0.0654
Epoch 3/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 12s 152ms/step - loss: 0.0081 - val_loss:
0.0102
Epoch 4/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 14s 181ms/step - loss: 0.0227 - val_loss:
0.0148
Epoch 5/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 16s 195ms/step - loss: 0.0109 - val_loss:
0.0035
Epoch 6/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 13s 166ms/step - loss: 0.0053 - val_loss:
0.0089
Epoch 7/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 12s 150ms/step - loss: 0.0042 - val_loss:
0.0103
Epoch 8/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 12s 154ms/step - loss: 0.0023 - val_loss:
0.0065
Epoch 9/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 12s 154ms/step - loss: 0.0066 - val_loss:
0.0023
Epoch 10/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 13s 156ms/step - loss: 0.0016 - val_loss:
0.0021
Epoch 11/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 14s 172ms/step - loss: 0.0025 - val_loss:
0.0026
Epoch 12/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 14s 178ms/step - loss: 0.0042 - val_loss:
0.0023
Epoch 13/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 14s 179ms/step - loss: 0.0022 - val_loss:
0.0025
Epoch 14/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 21s 263ms/step - loss: 0.0023 - val_loss:
0.0022
Epoch 15/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 18s 229ms/step - loss: 0.0025 - val_loss:
0.0020
Epoch 16/50
```

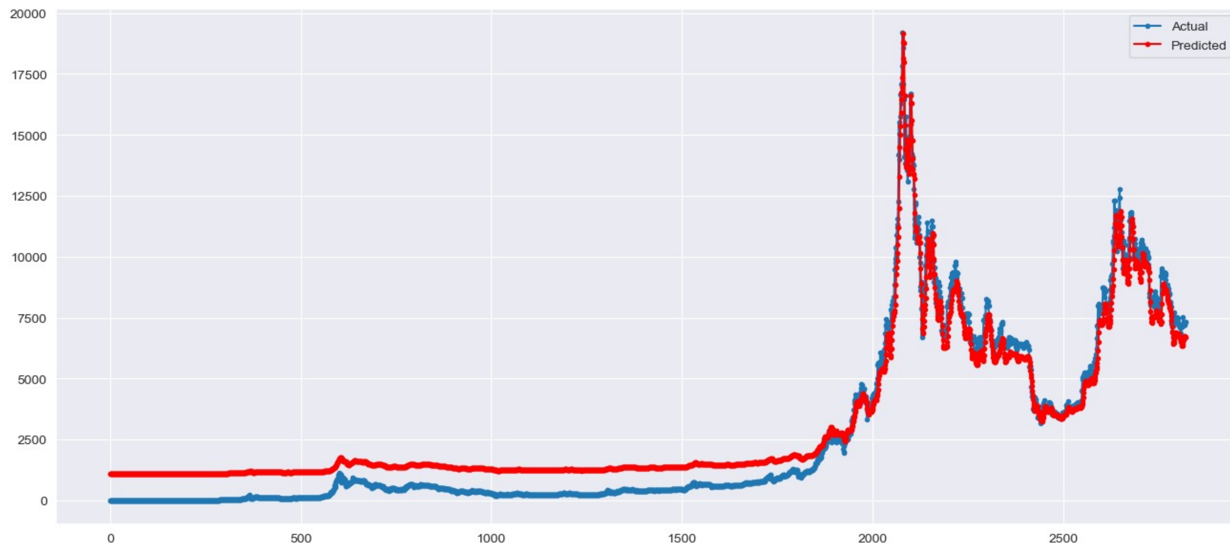
```
80/80 ━━━━━━━━━━━━━━━━━━━━ 20s 253ms/step - loss: 0.0025 - val_loss:
0.0028
Epoch 17/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 21s 256ms/step - loss: 0.0024 - val_loss:
0.0025
Epoch 18/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 19s 242ms/step - loss: 0.0022 - val_loss:
0.0041
Epoch 19/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 19s 238ms/step - loss: 0.0024 - val_loss:
0.0041
Epoch 20/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 19s 239ms/step - loss: 0.0021 - val_loss:
0.0049
Epoch 21/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 19s 224ms/step - loss: 0.0022 - val_loss:
0.0022
Epoch 22/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 19s 238ms/step - loss: 0.0018 - val_loss:
0.0022
Epoch 23/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 18s 225ms/step - loss: 0.0020 - val_loss:
0.0011
Epoch 24/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 18s 228ms/step - loss: 0.0020 - val_loss:
0.0034
Epoch 25/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 18s 224ms/step - loss: 0.0019 - val_loss:
0.0038
Epoch 26/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 18s 227ms/step - loss: 0.0017 - val_loss:
0.0026
Epoch 27/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 18s 223ms/step - loss: 0.0016 - val_loss:
0.0036
Epoch 28/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 8s 104ms/step - loss: 0.0018 - val_loss:
0.0036
Epoch 29/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 7s 89ms/step - loss: 0.0019 - val_loss:
0.0043
Epoch 30/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 7s 88ms/step - loss: 0.0019 - val_loss:
0.0056
Epoch 31/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 7s 87ms/step - loss: 0.0019 - val_loss:
0.0055
Epoch 32/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 7s 90ms/step - loss: 0.0020 - val_loss:
```

```
0.0031
Epoch 33/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 7s 88ms/step - loss: 0.0018 - val_loss:
0.0011
Epoch 34/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 7s 86ms/step - loss: 0.0019 - val_loss:
0.0010
Epoch 35/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 7s 92ms/step - loss: 0.0023 - val_loss:
9.1630e-04
Epoch 36/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 8s 105ms/step - loss: 0.0020 - val_loss:
0.0017
Epoch 37/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 7s 92ms/step - loss: 0.0014 - val_loss:
0.0029
Epoch 38/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 8s 94ms/step - loss: 0.0013 - val_loss:
0.0055
Epoch 39/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 7s 90ms/step - loss: 0.0015 - val_loss:
0.0067
Epoch 40/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 8s 95ms/step - loss: 0.0017 - val_loss:
0.0042
Epoch 41/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 9s 115ms/step - loss: 0.0014 - val_loss:
0.0025
Epoch 42/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 9s 106ms/step - loss: 0.0017 - val_loss:
0.0018
Epoch 43/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 8s 102ms/step - loss: 0.0017 - val_loss:
0.0013
Epoch 44/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 8s 99ms/step - loss: 0.0016 - val_loss:
9.5515e-04
Epoch 45/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 8s 98ms/step - loss: 0.0027 - val_loss:
9.6075e-04
Epoch 46/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 8s 100ms/step - loss: 0.0017 - val_loss:
0.0021
Epoch 47/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 8s 97ms/step - loss: 0.0011 - val_loss:
0.0027
Epoch 48/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 8s 99ms/step - loss: 0.0013 - val_loss:
0.0034
```

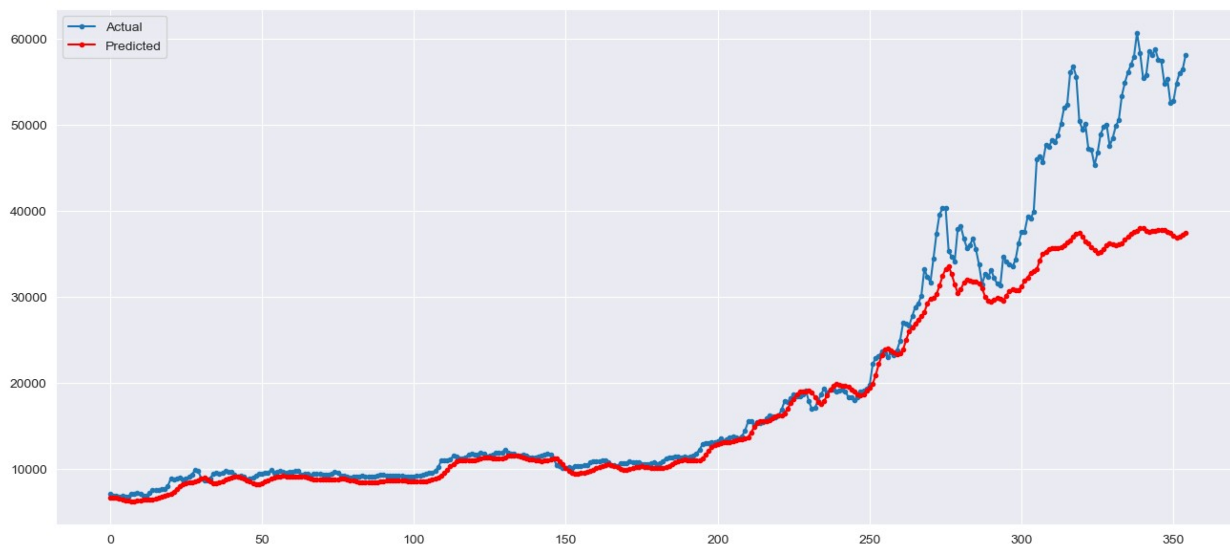
```
Epoch 49/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 8s 97ms/step - loss: 0.0014 - val_loss:
0.0031
Epoch 50/50
80/80 ━━━━━━━━━━━━━━━━━━━━ 8s 101ms/step - loss: 0.0014 - val_loss:
0.0015

plt.figure(figsize=(16,7))
plt.plot(history.history["loss"], label= "train loss")
plt.plot(history.history["val_loss"], label= "validation loss")
plt.legend()

<matplotlib.legend.Legend at 0x2e492f5a9d0>
```




```
train_predict = regressor.predict(X_train)
test_predict = regressor.predict(X_test)

89/89 ━━━━━━━━━━━━━━━━━━━━ 4s 37ms/step
12/12 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step

y_train_inv = scaler.inverse_transform(y_train.reshape(-1, 1))
y_test_inv = scaler.inverse_transform(y_test.reshape(-1, 1))

train_predict_inv = scaler.inverse_transform(train_predict)
test_predict_inv = scaler.inverse_transform(test_predict)

plt.figure(figsize=(16,7))
plt.plot(y_train_inv.flatten(), marker='.', label="Actual")
plt.plot(train_predict_inv.flatten(), 'r', marker='.',
label="Predicted")
plt.legend()

<matplotlib.legend.Legend at 0x2e4932482d0>
```

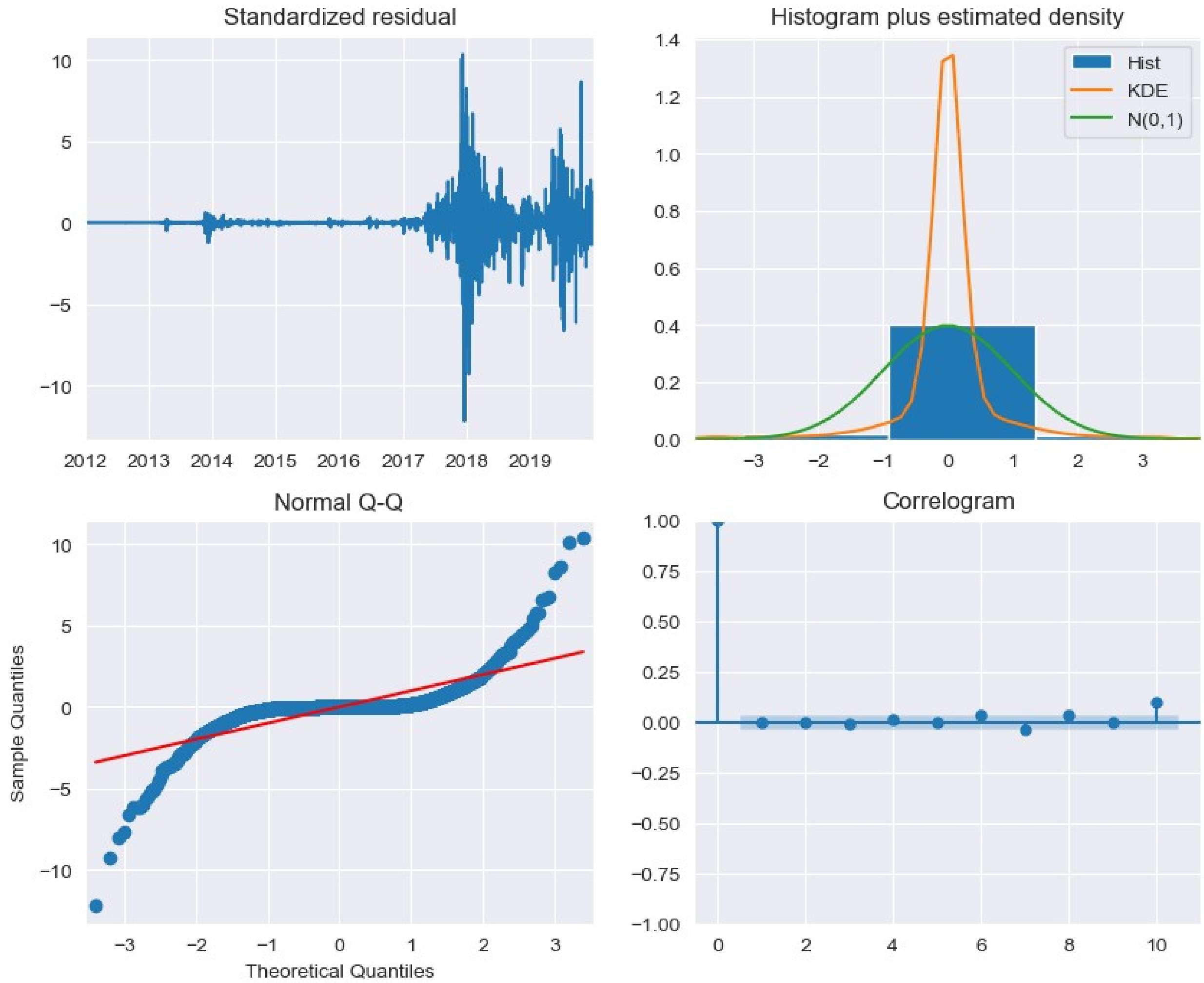



```
plt.figure(figsize=(16,7))
plt.plot(y_test_inv.flatten(), marker='.', label="Actual")
plt.plot(test_predict_inv.flatten(), 'r', marker='.',
label="Predicted")
plt.legend()

<matplotlib.legend.Legend at 0x2e493849b10>
```




```
LSTM_train_RMSE_inverse = np.sqrt(mean_squared_error(y_train_inv,
train_predict_inv))
LSTM_test_RMSE_inverse = np.sqrt(mean_squared_error(y_test_inv,
test_predict_inv))

LSTM_train_MAE_inverse = mean_squared_error(y_train_inv,
train_predict_inv )
```

```
LSTM_test_MAE_inverse = mean_squared_error(y_test_inv,
test_predict_inv )

model.plot_diagnostics().set_size_inches(10, 8)  # Adjust the size as
needed
plt.show()
```




```
#PROPHET

from prophet import Prophet

# Resampling originial data to day level and forward fill the missing
values
daily_data = BTC_DF.resample("24H").mean() #daily resampling
fill_missing(daily_data)
```

```
                Open      High       Low     Close  Volume_(BTC)  \
Timestamp
2011-12-31  4.422837  4.426677  4.422837  4.426677     24.024874
```

```
2012-01-01  4.677625  4.677625  4.677625  4.677625      5.883361
2012-01-02  4.991701  4.991701  4.991701  4.991701     13.503075
2012-01-03  5.175495  5.175495  5.175495  5.175495     11.136690
2012-01-04  5.120500  5.133742  5.120500  5.133742      8.327158

            Volume_(Currency)  Weighted_Price
Timestamp
2011-12-31         105.980529        4.424286
2012-01-01          27.923145        4.677625
2012-01-02          67.432386        4.991701
2012-01-03          56.749845        5.175495
2012-01-04          43.510443        5.125202
Open                    0
High                    0
Low                     0
Close                   0
Volume_(BTC)            0
Volume_(Currency)       0
Weighted_Price          0
dtype: int64
```

```
# Renaming the column names according to Prophet's requirements

daily_data_fb = daily_data.reset_index()
[['Timestamp','Weighted_Price']].rename({'Timestamp':'ds','Weighted_Pr
ice':'y'}, axis=1)
daily_data_fb.head()
```

```
          ds         y
0 2011-12-31  4.424286
1 2012-01-01  4.677625
2 2012-01-02  4.991701
3 2012-01-03  5.175495
4 2012-01-04  5.125202
```

```
split_date = "2020-01-01"
train_split = daily_data_fb['ds'] <= split_date
test_split = daily_data_fb['ds'] > split_date

train_fb = daily_data_fb[train_split]
test_fb = daily_data_fb[test_split]

print("train data shape :", train_fb.shape)
print("test data shape :", test_fb.shape)
```

```
train data shape : (2924, 2)
test data shape : (455, 2)
```

```
model_prophet = Prophet()
for feature in exogenous_features:
    model_prophet.add_regressor(feature)
```

```
model_prophet.fit(df_train[["Timestamp", "Weighted_Price"] +
exogenous_features].rename(columns={"Timestamp": "ds",
"Weighted_Price": "y"}))

forecast = model_prophet.predict(df_valid[["Timestamp",
"Weighted_Price"] + exogenous_features].rename(columns={"Timestamp":
"ds"}))

forecast.head()
```

```
00:00:13 - cmdstanpy - INFO - Chain [1] start processing
00:00:15 - cmdstanpy - INFO - Chain [1] done processing
```

```
          ds        trend   yhat_lower   yhat_upper  trend_lower
trend_upper  \
0 2020-01-01  2702.877325  7072.301253  7700.919906  2702.877325
2702.877325
1 2020-01-02  2702.983911  7019.668240  7651.231829  2702.983911
2702.983911
2 2020-01-03  2703.090497  6874.553688  7501.087476  2703.090497
2703.090497
3 2020-01-04  2703.197083  6788.016202  7456.747590  2703.197083
2703.197083
4 2020-01-05  2703.303669  6881.145692  7508.624325  2703.303669
2703.303669

   Close_mean_lag3  Close_mean_lag3_lower  Close_mean_lag3_upper  \
0      3072.371173            3072.371173            3072.371173
1      3042.349141            3042.349141            3042.349141
2      2997.689186            2997.689186            2997.689186
3      2979.850021            2979.850021            2979.850021
4      3008.359587            3008.359587            3008.359587

   Close_mean_lag30  ...     weekly  weekly_lower  weekly_upper
yearly  \
0         -0.260959  ...   0.726059      0.726059      0.726059  -
55.586668
1         -0.260709  ...  -6.347854     -6.347854     -6.347854  -
72.035715
2         -0.260368  ... -10.520293    -10.520293    -10.520293  -
87.736168
3         -0.260110  ...   7.412343      7.412343      7.412343 -
102.582359
4         -0.260116  ...   5.141867      5.141867      5.141867 -
116.484028

   yearly_lower  yearly_upper  multiplicative_terms  \
0    -55.586668    -55.586668                   0.0
1    -72.035715    -72.035715                   0.0
```

```
2    -87.736168    -87.736168                   0.0
3   -102.582359   -102.582359                   0.0
4   -116.484028   -116.484028                   0.0

   multiplicative_terms_lower  multiplicative_terms_upper         yhat

0                         0.0                         0.0  7390.766672

1                         0.0                         0.0  7330.359539

2                         0.0                         0.0  7197.632892

3                         0.0                         0.0  7133.479597

4                         0.0                         0.0  7189.611819


[5 rows x 121 columns]
```

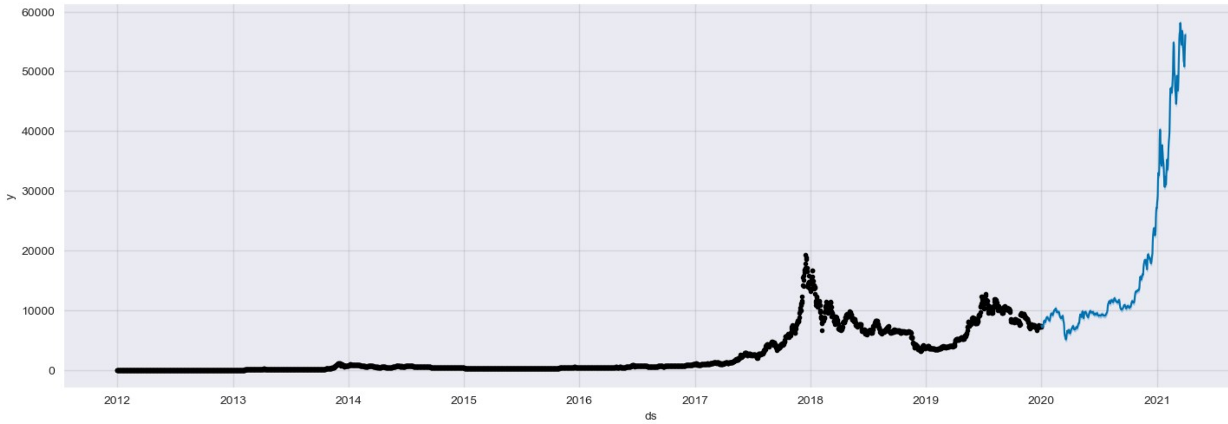
```
df_valid["Forecast_Prophet"] = forecast.yhat.values
```

```
C:\Users\RISHAV RAJ SINGH\AppData\Local\Temp\
ipykernel_44116\3795914625.py:1: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
```

```
# Plot Our Predictions
fig1 = model_prophet.plot(forecast)
fig1.set_size_inches(15, 5)
plt.show()
```

```
C:\Users\RISHAV RAJ SINGH\anaconda3\Lib\site-packages\prophet\
plot.py:72: FutureWarning:

The behavior of DatetimeProperties.to_pydatetime is deprecated, in a
future version this will return a Series containing python datetime
objects instead of an ndarray. To retain the old behavior, call
`np.array` on the result

C:\Users\RISHAV RAJ SINGH\anaconda3\Lib\site-packages\prophet\
plot.py:73: FutureWarning:

The behavior of DatetimeProperties.to_pydatetime is deprecated, in a
future version this will return a Series containing python datetime
objects instead of an ndarray. To retain the old behavior, call
```

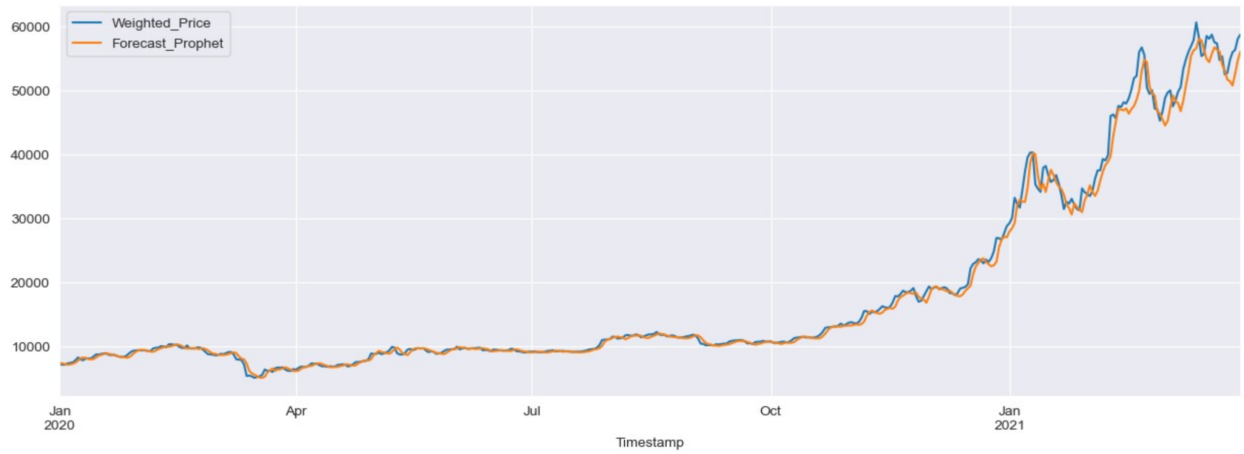
```
`np.array` on the result
```



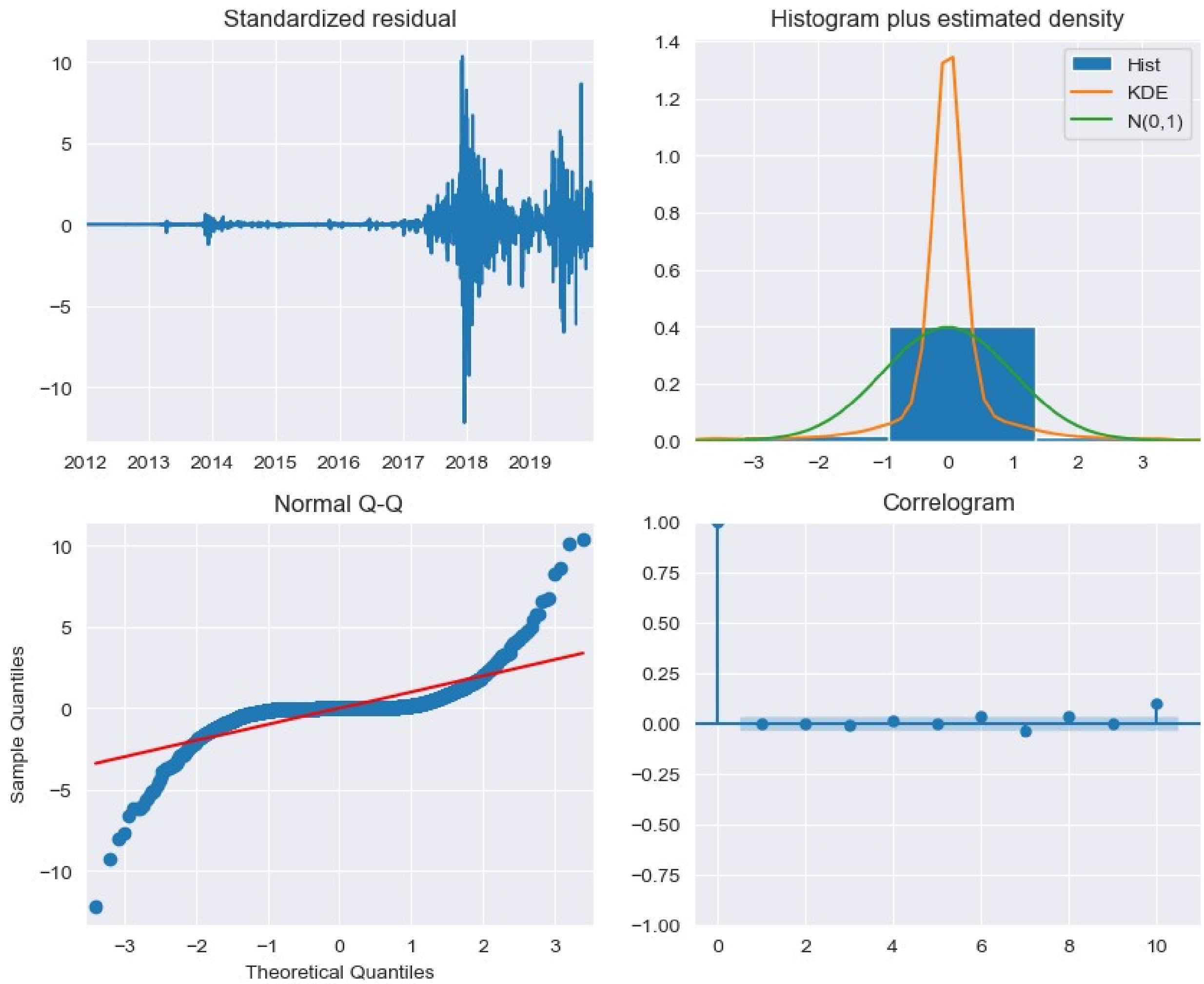

```
# Plotting changepoints
from prophet.plot import add_changepoints_to_plot

fig = model_prophet.plot(forecast)

a = add_changepoints_to_plot(fig.gca(), model_prophet, forecast)
```


```
df_valid[["Weighted_Price", "Forecast_Prophet"]].plot(figsize=(15, 5))
```

```
<Axes: xlabel='Timestamp'>
```




```
test_mae_prophet = mean_absolute_error(df_valid['Weighted_Price'],
df_valid['Forecast_Prophet'])

test_rmse_prophet =
np.sqrt(mean_squared_error(df_valid['Weighted_Price'],
df_valid['Forecast_Prophet']))

print(f"Prophet's Test MAE : {test_mae_prophet}")
print(f"Prophet's Test RMSE : {test_rmse_prophet}")

Prophet's Test MAE : 667.2904494828131
Prophet's Test RMSE : 1250.55220793491

model.plot_diagnostics().set_size_inches(10, 8)  # Adjust the size as
needed
plt.show()
```




```
#xgboost

!pip install xgboost
from sklearn import ensemble
from sklearn import metrics
from sklearn.model_selection import RandomizedSearchCV
import xgboost as xgb
from xgboost import plot_importance, plot_tree
from sklearn.metrics import mean_squared_error, mean_absolute_error
plt.style.use('fivethirtyeight')

from datetime import datetime
```

```
Requirement already satisfied: xgboost in c:\users\rishav raj singh\
anaconda3\lib\site-packages (2.0.3)
Requirement already satisfied: numpy in c:\users\rishav raj singh\
anaconda3\lib\site-packages (from xgboost) (1.26.4)
Requirement already satisfied: scipy in c:\users\rishav raj singh\
anaconda3\lib\site-packages (from xgboost) (1.11.4)
```

```
X_train, y_train = df_train[exogenous_features],
df_train.Weighted_Price
X_test, y_test = df_valid[exogenous_features], df_valid.Weighted_Price

reg = xgb.XGBRegressor()

## Hyper Parameter Optimization Grid

params={
 "learning_rate"    : [0.05, 0.10, 0.15, 0.20, 0.25, 0.30],
 "max_depth"        : [1, 3, 4, 5, 6, 7],
 "n_estimators"     : [int(x) for x in np.linspace(start=100,
stop=2000, num=10)],
 "min_child_weight" : [int(x) for x in np.arange(3, 15, 1)],
 "gamma"            : [ 0.0, 0.1, 0.2 , 0.3, 0.4, 0.5, 0.6, 0.7, 0.8,
0.9, 1],
 "subsample"        : [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9,
1],
 "colsample_bytree" : [0.5, 0.6, 0.7, 0.8, 0.9, 1],
 "colsample_bylevel": [0.5, 0.6, 0.7, 0.8, 0.9, 1],
}

model  = RandomizedSearchCV(
                reg,
                param_distributions=params,
                n_iter=10,
                n_jobs=-1,
                cv=5,
                verbose=3,
)

model.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

RandomizedSearchCV(cv=5,
                   estimator=XGBRegressor(base_score=None,
booster=None,
                                          callbacks=None,
                                          colsample_bylevel=None,
                                          colsample_bynode=None,
                                          colsample_bytree=None,
device=None,
                                          early_stopping_rounds=None,
                                          enable_categorical=False,
                                          eval_metric=None,
feature_types=None,
                                          gamma=None,
grow_policy=None,
                                          importance_type=None,
```

```
interaction_constraints=None,
                                          learning_rate=...
                                                              0.8,
0.9, 1],
                                        'colsample_bytree': [0.5, 0.6,
0.7, 0.8,
                                                             0.9, 1],
                                        'gamma': [0.0, 0.1, 0.2, 0.3,
0.4, 0.5,
                                                  0.6, 0.7, 0.8, 0.9,
1],
                                        'learning_rate': [0.05, 0.1,
0.15, 0.2,
                                                          0.25, 0.3],
                                        'max_depth': [1, 3, 4, 5, 6,
7],
                                        'min_child_weight': [3, 4, 5,
6, 7, 8,
                                                             9, 10,
11, 12, 13,
                                                             14],
                                        'n_estimators': [100, 311,
522, 733,
                                                         944, 1155,
1366, 1577,
                                                         1788, 2000],
                                        'subsample': [0.1, 0.2, 0.3,
0.4, 0.5,
                                                      0.6, 0.7, 0.8,
0.9, 1]},
                   verbose=3)
```

```
print(f"Model Best Score : {model.best_score_}")
print(f"Model Best Parameters : {model.best_estimator_.get_params()}")
```

```
Model Best Score : -3.044758444490456
Model Best Parameters : {'objective': 'reg:squarederror',
'base_score': None, 'booster': None, 'callbacks': None,
'colsample_bylevel': 0.6, 'colsample_bynode': None,
'colsample_bytree': 0.5, 'device': None, 'early_stopping_rounds':
None, 'enable_categorical': False, 'eval_metric': None,
'feature_types': None, 'gamma': 0.3, 'grow_policy': None,
'importance_type': None, 'interaction_constraints': None,
'learning_rate': 0.15, 'max_bin': None, 'max_cat_threshold': None,
'max_cat_to_onehot': None, 'max_delta_step': None, 'max_depth': 6,
'max_leaves': None, 'min_child_weight': 3, 'missing': nan,
'monotone_constraints': None, 'multi_strategy': None, 'n_estimators':
1577, 'n_jobs': None, 'num_parallel_tree': None, 'random_state': None,
'reg_alpha': None, 'reg_lambda': None, 'sampling_method': None,
```

```
'scale_pos_weight': None, 'subsample': 0.9, 'tree_method': None,
'validate_parameters': None, 'verbosity': None}
```

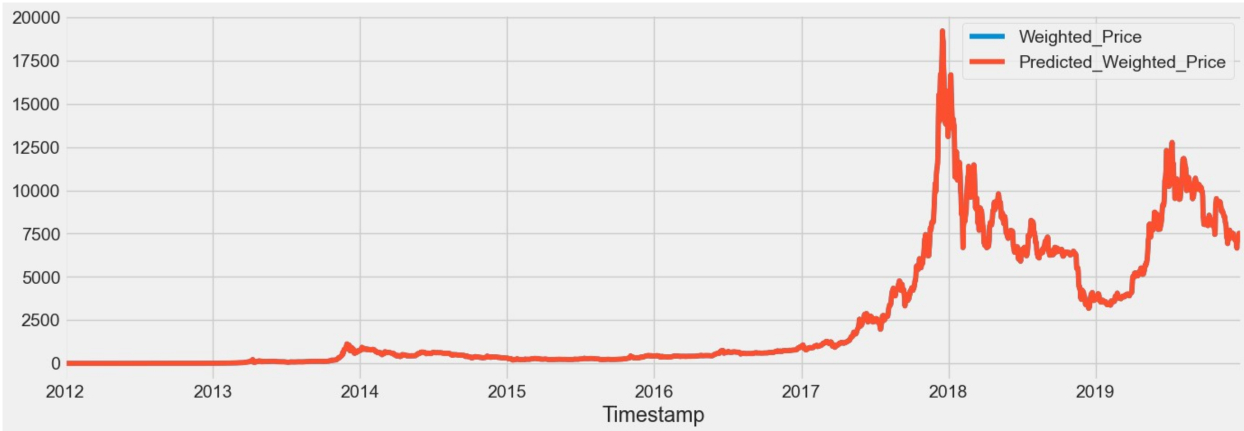
```
model.best_estimator_
```

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=0.6, colsample_bynode=None,
colsample_bytree=0.5,
             device=None, early_stopping_rounds=None,
enable_categorical=False,
             eval_metric=None, feature_types=None, gamma=0.3,
grow_policy=None,
             importance_type=None, interaction_constraints=None,
             learning_rate=0.15, max_bin=None, max_cat_threshold=None,
             max_cat_to_onehot=None, max_delta_step=None, max_depth=6,
             max_leaves=None, min_child_weight=3, missing=nan,
             monotone_constraints=None, multi_strategy=None,
n_estimators=1577,
             n_jobs=None, num_parallel_tree=None,
random_state=None, ...)
```

```
df_train['Predicted_Weighted_Price'] = model.predict(X_train)
```

```
df_train[['Weighted_Price','Predicted_Weighted_Price']].plot(figsize=(
15, 5))
```

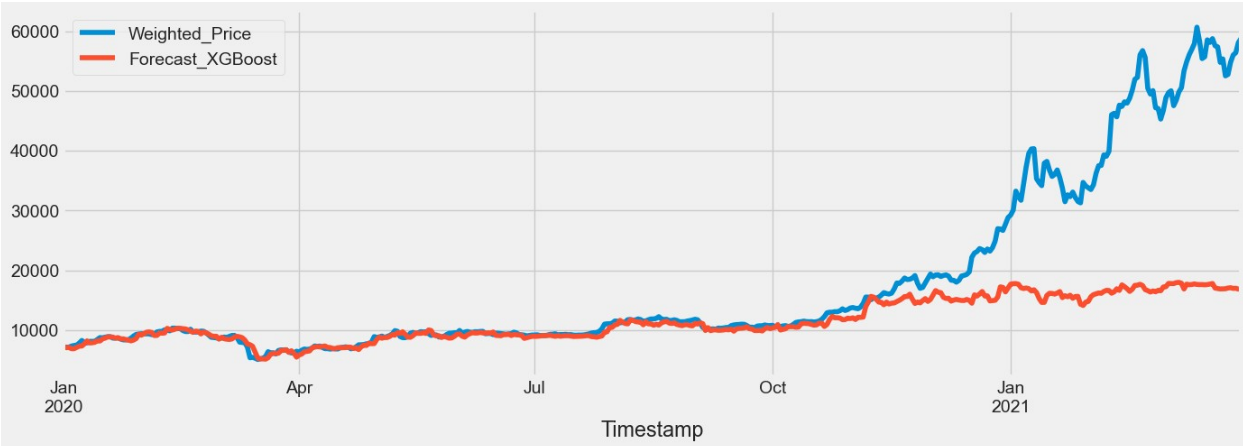
```
C:\Users\RISHAV RAJ SINGH\AppData\Local\Temp\
ipykernel_44116\3944082182.py:1: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy


<Axes: xlabel='Timestamp'>
```




```
df_valid['Forecast_XGBoost'] = model.predict(X_test)

overall_data = pd.concat([df_train, df_valid], sort=False)

C:\Users\RISHAV RAJ SINGH\AppData\Local\Temp\
ipykernel_44116\390820625.py:1: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy


overall_data[['Weighted_Price','Forecast_XGBoost']].plot(figsize=(15,
5))

<Axes: xlabel='Timestamp'>
```


```
df_valid[['Weighted_Price','Forecast_XGBoost']].plot(figsize=(15, 5))
```

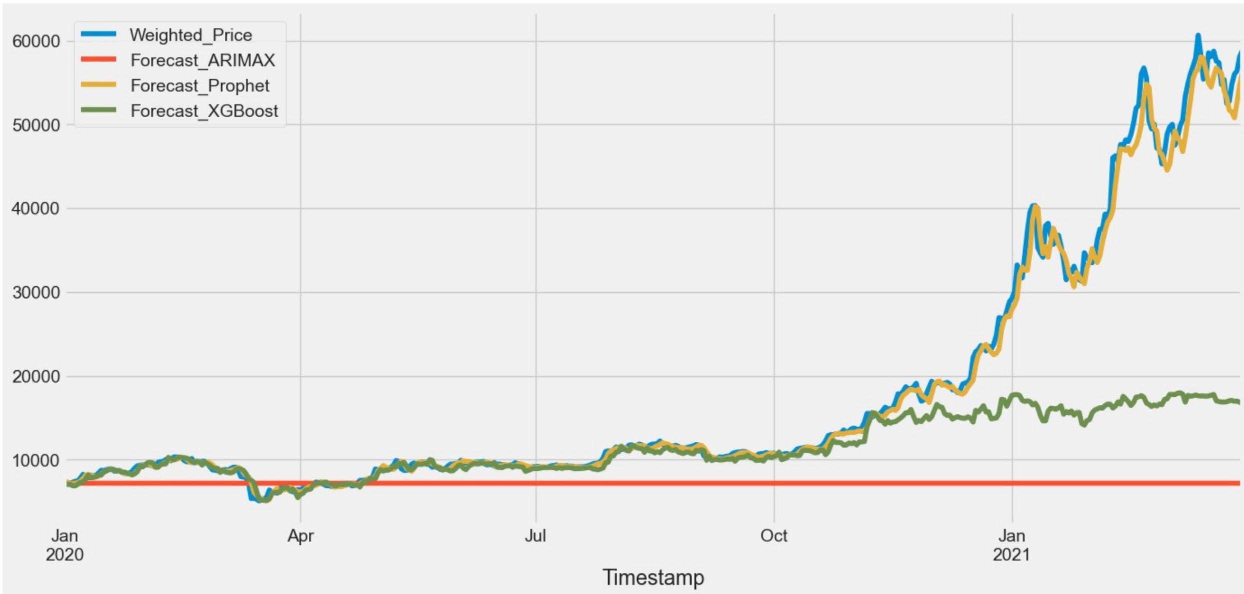
```
<Axes: xlabel='Timestamp'>
```




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

train_mae_xgboost = mean_absolute_error(df_train['Weighted_Price'],
df_train['Predicted_Weighted_Price'])
train_rmse_xgboost =
np.sqrt(mean_squared_error(df_train['Weighted_Price'],
df_train['Predicted_Weighted_Price']))
train_r_square_xgboost = r2_score(df_train['Weighted_Price'],
df_train['Predicted_Weighted_Price'])

print(f"train MAE : {train_mae_xgboost}")
print(f"train RMSE : {train_rmse_xgboost}")
print(f"train R2 : {train_r_square_xgboost}")

train MAE : 0.32486661540843664
train RMSE : 0.4374347732644935
train R2 : 0.999999985179853

test_mae_xgboost = mean_absolute_error(df_valid['Weighted_Price'],
df_valid['Forecast_XGBoost'])
test_rmse_xgboost =
np.sqrt(mean_squared_error(df_valid['Weighted_Price'],
df_valid['Forecast_XGBoost']))
test_r2_xgboost = r2_score(df_valid['Weighted_Price'],
df_valid['Forecast_XGBoost'])

print(f"test MAE XGBOOST : {test_mae_xgboost}")
print(f"test RMSE XGBOOST : {test_rmse_xgboost}")
print(f"test R2 XGBOOST : {test_r2_xgboost}")

test MAE XGBOOST : 6412.765432274534
test RMSE XGBOOST : 13319.975715568999
test R2 XGBOOST : 0.17193759741592907
```

```python
#overall forecast of all model

df_valid[["Weighted_Price", "Forecast_ARIMAX", "Forecast_Prophet",
"Forecast_XGBoost"]].plot(figsize=(15,7))
```

```
<Axes: xlabel='Timestamp'>
```




```python
arimax_rmse = np.sqrt(mean_squared_error(df_valid['Weighted_Price'],
df_valid['Forecast_ARIMAX']))

fbp_rmse = np.sqrt(mean_squared_error(df_valid['Weighted_Price'],
df_valid['Forecast_Prophet']))

xgb_rmse = np.sqrt(mean_squared_error(df_valid['Weighted_Price'],
df_valid['Forecast_XGBoost']))

# MAE

arimax_mae = mean_absolute_error(df_valid['Weighted_Price'],
df_valid['Forecast_ARIMAX'])
fbp_mae = mean_absolute_error(df_valid['Weighted_Price'],
df_valid['Forecast_Prophet'])
xgb_mae = mean_absolute_error(df_valid['Weighted_Price'],
df_valid['Forecast_XGBoost'])

#mae,rmse of all model

print("ARIMAX RMSE :", arimax_rmse)
print("FB Prophet RMSE :", fbp_rmse)
print("XGBoost RMSE :", xgb_rmse)

print("\nARIMAX MAE :", arimax_mae)
```

```python
print("FB Prophet MAE :", fbp_mae)
print("XGBoost MAE :", xgb_mae)
```

```
ARIMAX RMSE : 18052.527118342223
FB Prophet RMSE : 1250.55220793491
XGBoost RMSE : 13319.975715568999

ARIMAX MAE : 10692.217013361565
FB Prophet MAE : 667.2904494828131
XGBoost MAE : 6412.765432274534
```

```python
print(f"Train RMSE Inverse: {LSTM_train_RMSE_inverse}")
print(f"Train MAE Inverse: {LSTM_train_MAE_inverse}")

print(f"Test RMSE Inverse: {LSTM_test_RMSE_inverse}")
print(f"Test MAE Inverse: {LSTM_test_MAE_inverse}")
```

```
Train RMSE Inverse: 879.906222025592
Train MAE Inverse: 774234.9595593504
Test RMSE Inverse: 6348.332969319255
Test MAE Inverse: 40301331.48934583
```