##Import Libraries

```
import numpy as np
import pandas as pd
from pandas.plotting import lag_plot
from math import sqrt

import matplotlib.pyplot as plt

from itertools import product

from pylab import rcParams

from scipy.stats import boxcox

import statsmodels.api as sm
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.stattools import kpss
from statsmodels.tsa.ar_model import AutoReg
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.metrics import mean_absolute_error
```

###Install External Libraries

```
!pip install pmdarima
```

```
Collecting pmdarima
  Downloading pmdarima-2.0.4-cp310-cp310-
manylinux_2_17_x86_64.manylinux2014_x86_64.manylinux_2_28_x86_64.whl
(2.1 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.1/2.1 MB 21.2 MB/s eta
0:00:00
ent already satisfied: joblib>=0.11 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (1.3.2)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (3.0.5)
Requirement already satisfied: numpy>=1.21.2 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (1.23.5)
Requirement already satisfied: pandas>=0.19 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (1.5.3)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (1.2.2)
```

```
Requirement already satisfied: scipy>=1.3.2 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (1.11.3)
Requirement already satisfied: statsmodels>=0.13.2 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (0.14.0)
Requirement already satisfied: urllib3 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (2.0.7)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (67.7.2)
Requirement already satisfied: packaging>=17.1 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (23.2)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima)
(2023.3.post1)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22-
>pmdarima) (3.2.0)
Requirement already satisfied: patsy>=0.5.2 in
/usr/local/lib/python3.10/dist-packages (from statsmodels>=0.13.2-
>pmdarima) (0.5.3)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-
packages (from patsy>=0.5.2->statsmodels>=0.13.2->pmdarima) (1.16.0)
Installing collected packages: pmdarima
Successfully installed pmdarima-2.0.4
```

```
!pip install tbats
```

```
Collecting tbats
  Downloading tbats-1.1.3-py3-none-any.whl (44 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 44.0/44.0 kB 917.7 kB/s eta
0:00:00
ent already satisfied: numpy in /usr/local/lib/python3.10/dist-
packages (from tbats) (1.23.5)
Requirement already satisfied: scipy in
/usr/local/lib/python3.10/dist-packages (from tbats) (1.11.3)
Requirement already satisfied: pmdarima in
/usr/local/lib/python3.10/dist-packages (from tbats) (2.0.4)
Requirement already satisfied: scikit-learn in
/usr/local/lib/python3.10/dist-packages (from tbats) (1.2.2)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from pmdarima->tbats) (1.3.2)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in
/usr/local/lib/python3.10/dist-packages (from pmdarima->tbats) (3.0.5)
Requirement already satisfied: pandas>=0.19 in
/usr/local/lib/python3.10/dist-packages (from pmdarima->tbats) (1.5.3)
Requirement already satisfied: statsmodels>=0.13.2 in
/usr/local/lib/python3.10/dist-packages (from pmdarima->tbats)
(0.14.0)
```

```
Requirement already satisfied: urllib3 in
/usr/local/lib/python3.10/dist-packages (from pmdarima->tbats) (2.0.7)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in
/usr/local/lib/python3.10/dist-packages (from pmdarima->tbats)
(67.7.2)
Requirement already satisfied: packaging>=17.1 in
/usr/local/lib/python3.10/dist-packages (from pmdarima->tbats) (23.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn->tbats)
(3.2.0)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima-
>tbats) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima-
>tbats) (2023.3.post1)
Requirement already satisfied: patsy>=0.5.2 in
/usr/local/lib/python3.10/dist-packages (from statsmodels>=0.13.2-
>pmdarima->tbats) (0.5.3)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-
packages (from patsy>=0.5.2->statsmodels>=0.13.2->pmdarima->tbats)
(1.16.0)
Installing collected packages: tbats
Successfully installed tbats-1.1.3
```

```
!pip install pystan
##!pip install fbprophet
```

```
Collecting pystan
  Downloading pystan-3.7.0-py3-none-any.whl (13 kB)
Requirement already satisfied: aiohttp<4.0,>=3.6 in
/usr/local/lib/python3.10/dist-packages (from pystan) (3.8.6)
Collecting clikit<0.7,>=0.6 (from pystan)
  Downloading clikit-0.6.2-py2.py3-none-any.whl (91 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 91.8/91.8 kB 2.3 MB/s eta
0:00:00
 pystan)
  Downloading httpstan-4.10.1-cp310-cp310-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (44.4 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 44.4/44.4 MB 10.8 MB/s eta
0:00:00
ent already satisfied: numpy<2.0,>=1.19 in
/usr/local/lib/python3.10/dist-packages (from pystan) (1.23.5)
Collecting pysimdjson<6.0.0,>=5.0.2 (from pystan)
  Downloading pysimdjson-5.0.2-cp310-cp310-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (1.8 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.8/1.8 MB 61.6 MB/s eta
0:00:00
ent already satisfied: setuptools in /usr/local/lib/python3.10/dist-
packages (from pystan) (67.7.2)
```

```
Requirement already satisfied: attrs>=17.3.0 in
/usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.6-
>pystan) (23.1.0)
Requirement already satisfied: charset-normalizer<4.0,>=2.0 in
/usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.6-
>pystan) (3.3.2)
Requirement already satisfied: multidict<7.0,>=4.5 in
/usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.6-
>pystan) (6.0.4)
Requirement already satisfied: async-timeout<5.0,>=4.0.0a3 in
/usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.6-
>pystan) (4.0.3)
Requirement already satisfied: yarl<2.0,>=1.0 in
/usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.6-
>pystan) (1.9.2)
Requirement already satisfied: frozenlist>=1.1.1 in
/usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.6-
>pystan) (1.4.0)
Requirement already satisfied: aiosignal>=1.1.2 in
/usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.6-
>pystan) (1.3.1)
Collecting crashtest<0.4.0,>=0.3.0 (from clikit<0.7,>=0.6->pystan)
  Downloading crashtest-0.3.1-py3-none-any.whl (7.0 kB)
Collecting pastel<0.3.0,>=0.2.0 (from clikit<0.7,>=0.6->pystan)
  Downloading pastel-0.2.1-py2.py3-none-any.whl (6.0 kB)
Collecting pylev<2.0,>=1.3 (from clikit<0.7,>=0.6->pystan)
  Downloading pylev-1.4.0-py2.py3-none-any.whl (6.1 kB)
Requirement already satisfied: appdirs<2.0,>=1.4 in
/usr/local/lib/python3.10/dist-packages (from httpstan<4.11,>=4.10-
>pystan) (1.4.4)
Collecting marshmallow<4.0,>=3.10 (from httpstan<4.11,>=4.10->pystan)
  Downloading marshmallow-3.20.1-py3-none-any.whl (49 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 49.4/49.4 kB 5.4 MB/s eta
0:00:00
 httpstan<4.11,>=4.10->pystan)
  Downloading webargs-8.3.0-py3-none-any.whl (31 kB)
Requirement already satisfied: packaging>=17.0 in
/usr/local/lib/python3.10/dist-packages (from marshmallow<4.0,>=3.10-
>httpstan<4.11,>=4.10->pystan) (23.2)
Requirement already satisfied: idna>=2.0 in
/usr/local/lib/python3.10/dist-packages (from yarl<2.0,>=1.0-
>aiohttp<4.0,>=3.6->pystan) (3.4)
Installing collected packages: pylev, pysimdjson, pastel, marshmallow,
crashtest, webargs, clikit, httpstan, pystan
Successfully installed clikit-0.6.2 crashtest-0.3.1 httpstan-4.10.1
marshmallow-3.20.1 pastel-0.2.1 pylev-1.4.0 pysimdjson-5.0.2 pystan-
3.7.0 webargs-8.3.0
```

```
!pip install prophet
```

```
Requirement already satisfied: prophet in
/usr/local/lib/python3.10/dist-packages (1.1.5)
Requirement already satisfied: cmdstanpy>=1.0.4 in
/usr/local/lib/python3.10/dist-packages (from prophet) (1.2.0)
Requirement already satisfied: numpy>=1.15.4 in
/usr/local/lib/python3.10/dist-packages (from prophet) (1.23.5)
Requirement already satisfied: matplotlib>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from prophet) (3.7.1)
Requirement already satisfied: pandas>=1.0.4 in
/usr/local/lib/python3.10/dist-packages (from prophet) (1.5.3)
Requirement already satisfied: holidays>=0.25 in
/usr/local/lib/python3.10/dist-packages (from prophet) (0.36)
Requirement already satisfied: tqdm>=4.36.1 in
/usr/local/lib/python3.10/dist-packages (from prophet) (4.66.1)
Requirement already satisfied: importlib-resources in
/usr/local/lib/python3.10/dist-packages (from prophet) (6.1.1)
Requirement already satisfied: stanio~=0.3.0 in
/usr/local/lib/python3.10/dist-packages (from cmdstanpy>=1.0.4-
>prophet) (0.3.0)
Requirement already satisfied: python-dateutil in
/usr/local/lib/python3.10/dist-packages (from holidays>=0.25->prophet)
(2.8.2)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=2.0.0-
>prophet) (1.2.0)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=2.0.0-
>prophet) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=2.0.0-
>prophet) (4.44.3)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=2.0.0-
>prophet) (1.4.5)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=2.0.0-
>prophet) (23.2)
Requirement already satisfied: pillow>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=2.0.0-
>prophet) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=2.0.0-
>prophet) (3.1.1)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=1.0.4->prophet)
(2023.3.post1)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil-
>holidays>=0.25->prophet) (1.16.0)
```

###Import Installed

```
from pmdarima import auto_arima

from tbats import TBATS, BATS

from prophet import Prophet
```

##EDA

###Download Dataset

```
!gdown '1_ZZ5H_Yh3xcGtAfJRJunOu6yMwjxKfTp'

Downloading...
From: https://drive.google.com/uc?id=1_ZZ5H_Yh3xcGtAfJRJunOu6yMwjxKfTp
To: /content/1000000 Sales Records.csv
100% 125M/125M [00:03<00:00, 39.0MB/s]
```

###DF and EDA

```
df = pd.read_csv('1000000 Sales Records.csv')
df.head()

                         Region           Country  Item Type Sales
Channel  \
0            Sub-Saharan Africa      South Africa     Fruits
Offline
1  Middle East and North Africa           Morocco    Clothes
Online
2         Australia and Oceania  Papua New Guinea       Meat
Offline
3            Sub-Saharan Africa          Djibouti    Clothes
Offline
4                        Europe          Slovakia  Beverages
Offline

  Order Priority  Order Date   Order ID   Ship Date  Units Sold  Unit
Price  \
0              M   7/27/2012  443368995   7/28/2012        1593
9.33
1              M   9/14/2013  667593514  10/19/2013        4611
109.28
2              M   5/15/2015  940995585    6/4/2015         360
421.89
3              H   5/17/2017  880811536    7/2/2017         562
109.28
4              L  10/26/2016  174590194   12/4/2016        3973
47.45
```

```
   Unit Cost  Total Revenue  Total Cost  Total Profit
0       6.92       14862.69    11023.56       3839.13
1      35.84      503890.08   165258.24     338631.84
2     364.69      151880.40   131288.40      20592.00
3      35.84       61415.36    20142.08      41273.28
4      31.79      188518.85   126301.67      62217.18
```

```
#adding new column as orderdate from existing by converting to
datatime
df['orderdate'] = pd.to_datetime(df['Order Date'])

#adding new column with year and month
df['Order_Month'] = pd.to_datetime(df['orderdate']).dt.to_period('m')

df.head()
```

```
                         Region           Country  Item Type Sales
Channel  \
0            Sub-Saharan Africa      South Africa     Fruits
Offline
1  Middle East and North Africa           Morocco    Clothes
Online
2         Australia and Oceania  Papua New Guinea       Meat
Offline
3            Sub-Saharan Africa          Djibouti    Clothes
Offline
4                        Europe          Slovakia  Beverages
Offline

  Order Priority  Order Date   Order ID   Ship Date  Units Sold  Unit
Price  \
0              M   7/27/2012  443368995   7/28/2012        1593
9.33
1              M   9/14/2013  667593514  10/19/2013        4611
109.28
2              M   5/15/2015  940995585    6/4/2015         360
421.89
3              H   5/17/2017  880811536    7/2/2017         562
109.28
4              L  10/26/2016  174590194   12/4/2016        3973
47.45

   Unit Cost  Total Revenue  Total Cost  Total Profit  orderdate
Order_Month
0       6.92       14862.69    11023.56       3839.13 2012-07-27
2012-07
1      35.84      503890.08   165258.24     338631.84 2013-09-14
2013-09
2     364.69      151880.40   131288.40      20592.00 2015-05-15
2015-05
```

```
3      35.84       61415.36    20142.08      41273.28 2017-05-17
2017-05
4      31.79      188518.85   126301.67      62217.18 2016-10-26
2016-10
```

```
#checking month's unique values in ascending order
sorted(df['Order_Month'].unique())
```

```
[Period('2010-01', 'M'),
 Period('2010-02', 'M'),
 Period('2010-03', 'M'),
 Period('2010-04', 'M'),
 Period('2010-05', 'M'),
 Period('2010-06', 'M'),
 Period('2010-07', 'M'),
 Period('2010-08', 'M'),
 Period('2010-09', 'M'),
 Period('2010-10', 'M'),
 Period('2010-11', 'M'),
 Period('2010-12', 'M'),
 Period('2011-01', 'M'),
 Period('2011-02', 'M'),
 Period('2011-03', 'M'),
 Period('2011-04', 'M'),
 Period('2011-05', 'M'),
 Period('2011-06', 'M'),
 Period('2011-07', 'M'),
 Period('2011-08', 'M'),
 Period('2011-09', 'M'),
 Period('2011-10', 'M'),
 Period('2011-11', 'M'),
 Period('2011-12', 'M'),
 Period('2012-01', 'M'),
 Period('2012-02', 'M'),
 Period('2012-03', 'M'),
 Period('2012-04', 'M'),
 Period('2012-05', 'M'),
 Period('2012-06', 'M'),
 Period('2012-07', 'M'),
 Period('2012-08', 'M'),
 Period('2012-09', 'M'),
 Period('2012-10', 'M'),
 Period('2012-11', 'M'),
 Period('2012-12', 'M'),
 Period('2013-01', 'M'),
 Period('2013-02', 'M'),
 Period('2013-03', 'M'),
 Period('2013-04', 'M'),
 Period('2013-05', 'M'),
 Period('2013-06', 'M'),
```

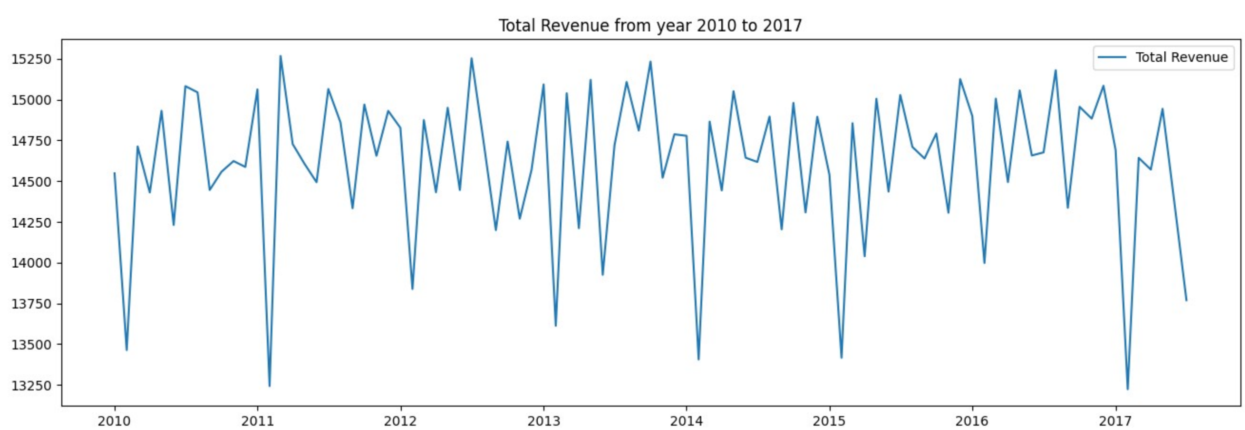
```
 Period('2013-07', 'M'),
 Period('2013-08', 'M'),
 Period('2013-09', 'M'),
 Period('2013-10', 'M'),
 Period('2013-11', 'M'),
 Period('2013-12', 'M'),
 Period('2014-01', 'M'),
 Period('2014-02', 'M'),
 Period('2014-03', 'M'),
 Period('2014-04', 'M'),
 Period('2014-05', 'M'),
 Period('2014-06', 'M'),
 Period('2014-07', 'M'),
 Period('2014-08', 'M'),
 Period('2014-09', 'M'),
 Period('2014-10', 'M'),
 Period('2014-11', 'M'),
 Period('2014-12', 'M'),
 Period('2015-01', 'M'),
 Period('2015-02', 'M'),
 Period('2015-03', 'M'),
 Period('2015-04', 'M'),
 Period('2015-05', 'M'),
 Period('2015-06', 'M'),
 Period('2015-07', 'M'),
 Period('2015-08', 'M'),
 Period('2015-09', 'M'),
 Period('2015-10', 'M'),
 Period('2015-11', 'M'),
 Period('2015-12', 'M'),
 Period('2016-01', 'M'),
 Period('2016-02', 'M'),
 Period('2016-03', 'M'),
 Period('2016-04', 'M'),
 Period('2016-05', 'M'),
 Period('2016-06', 'M'),
 Period('2016-07', 'M'),
 Period('2016-08', 'M'),
 Period('2016-09', 'M'),
 Period('2016-10', 'M'),
 Period('2016-11', 'M'),
 Period('2016-12', 'M'),
 Period('2017-01', 'M'),
 Period('2017-02', 'M'),
 Period('2017-03', 'M'),
 Period('2017-04', 'M'),
 Period('2017-05', 'M'),
 Period('2017-06', 'M'),
 Period('2017-07', 'M')]
```

```
#aggregation over original dataframe on month column using revenue,
cost and profit with sum aggregate function
df_agg = df.groupby(['Order_Month'], as_index=False).agg({'Total
Revenue': "sum", 'Total Cost': "sum", 'Total Profit': "sum"})

#converting value to million
df_agg['Total Revenue'] = df_agg['Total Revenue']/1000000
df_agg['Total Cost'] = df_agg['Total Cost']/1000000
df_agg['Total Profit'] = df_agg['Total Profit']/1000000

df_agg

   Order_Month  Total Revenue    Total Cost  Total Profit
0      2010-01   14547.786773  10259.179775   4288.606999
1      2010-02   13463.186840   9526.252432   3936.934408
2      2010-03   14712.532049  10377.312275   4335.219774
3      2010-04   14429.823464  10190.636550   4239.186914
4      2010-05   14931.168615  10531.010842   4400.157773
..         ...            ...           ...           ...
86     2017-03   14642.602650  10311.719664   4330.882987
87     2017-04   14570.593984  10254.995452   4315.598533
88     2017-05   14943.426668  10559.199632   4384.227036
89     2017-06   14352.098946  10116.164782   4235.934164
90     2017-07   13769.014644   9703.800090   4065.214553

[91 rows x 4 columns]

#using month as an index value
df_agg = df_agg.set_index('Order_Month')
df_agg

             Total Revenue    Total Cost  Total Profit
Order_Month
2010-01       14547.786773  10259.179775   4288.606999
2010-02       13463.186840   9526.252432   3936.934408
2010-03       14712.532049  10377.312275   4335.219774
2010-04       14429.823464  10190.636550   4239.186914
2010-05       14931.168615  10531.010842   4400.157773
...                    ...           ...           ...
2017-03       14642.602650  10311.719664   4330.882987
2017-04       14570.593984  10254.995452   4315.598533
2017-05       14943.426668  10559.199632   4384.227036
2017-06       14352.098946  10116.164782   4235.934164
2017-07       13769.014644   9703.800090   4065.214553

[91 rows x 3 columns]

print(f'data type of index (Order_Month) column:
{df_agg.index.dtype}')

#changing that to timestamp from period
```

```
df_agg.index = df_agg.index.to_timestamp()

print(f'updated data type of index (Order_Month) column:
{df_agg.index.dtype}')

print(f'size of dataframe (number of observations after aggregation):
{len(df_agg)}')
```

```
data type of index (Order_Month) column: period[M]
updated data type of index (Order_Month) column: datetime64[ns]
size of dataframe (number of observations after aggregation): 91
```

```
#plotting function
#def plot_df(df_superstore, x, y, title="", xlabel='Date',
ylabel='Value', dpi=100):
#    plt.figure(figsize=(14,6), dpi=dpi)
#    plt.plot(x, y, color='#F94144')
#    plt.gca().set(title=title, xlabel=xlabel, ylabel=ylabel)
#    plt.show()

#plot_df(df_agg, x=df_agg.index, y=df_agg['Total Profit'],
title='Monthly sales')

#plotting Total Revenue with index as Order_Month
plt.figure(figsize=(16,5))
plt.plot(df_agg.index, df_agg['Total Revenue'], label = "Total
Revenue")
plt.legend(loc='best')
plt.title("Total Revenue from year 2010 to 2017")
plt.show()
```



##Stationarity Check - What & Why

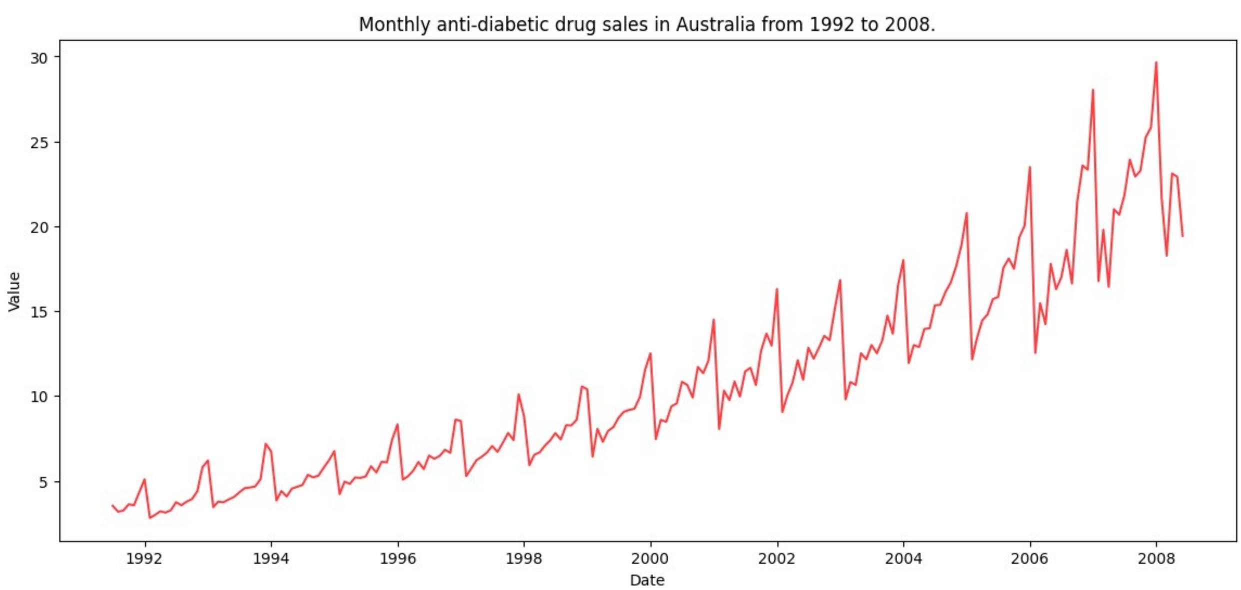
It is important to check as most statistical models support only stationary datasets.

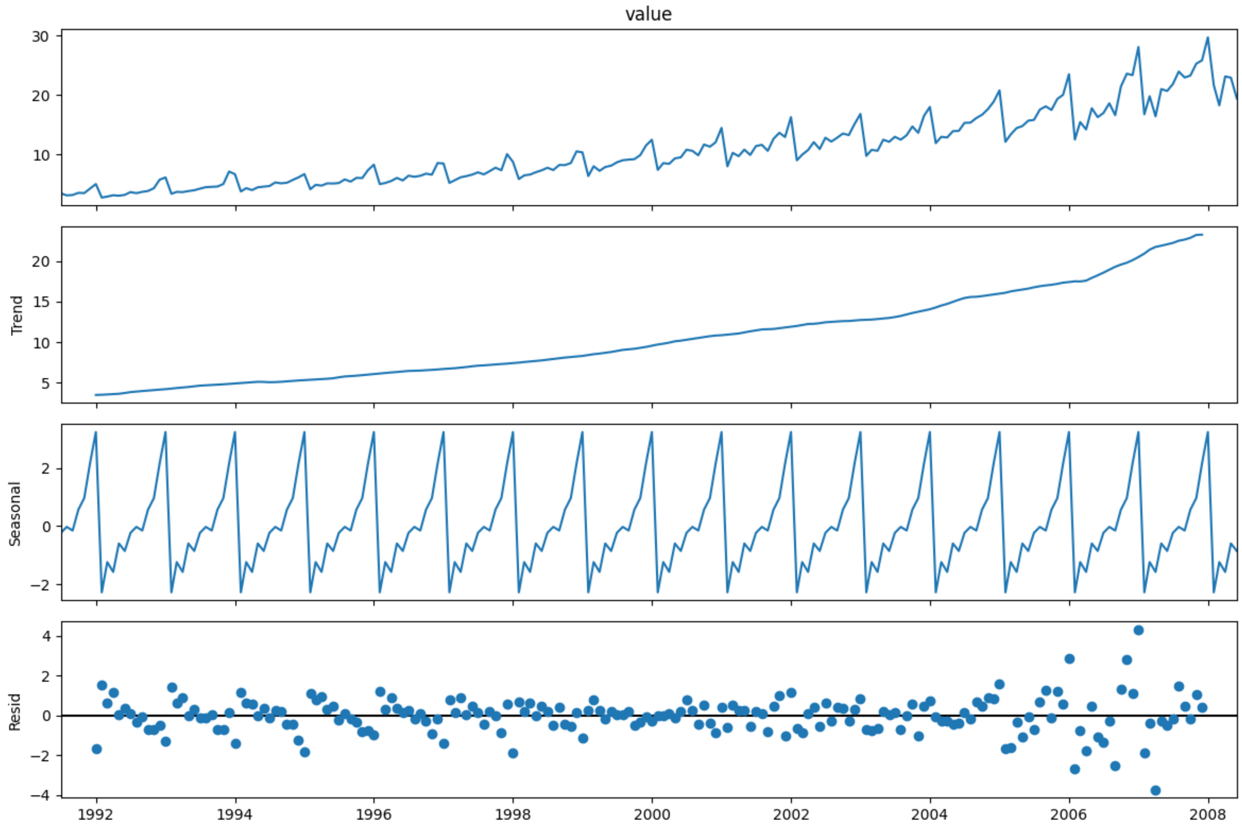
If a dataset doesn't have Trend, Seasonality, Cyclical, and Irregularity components of the time series, then it's Stationary. --Constant mean value; constant variance with time-frame &

If either the mean-variance or covariance (relationship between two variables) is changing with respect to time, the dataset is called non-stationary.

###Decompose Time Series (Check Trend, Season, Cycle, Irregularities (random error))

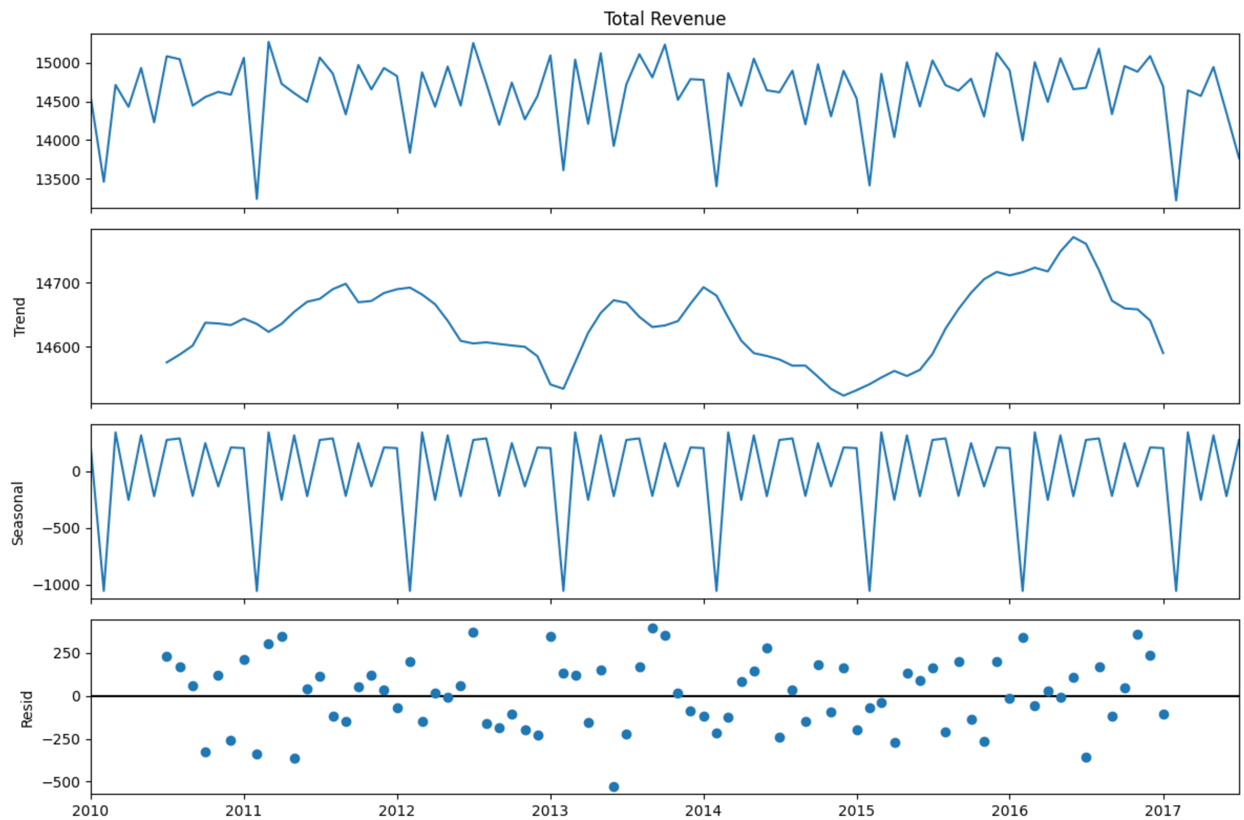
```
#good example to understand mentioned terms - drug dataset

aust_drug_df =
pd.read_csv('https://raw.githubusercontent.com/selva86/datasets/master
/a10.csv', parse_dates=['date'], index_col='date')

# Draw Plot
def plot_df(df, x, y, title="", xlabel='Date', ylabel='Value',
dpi=100):
    plt.figure(figsize=(14,6), dpi=dpi)
    plt.plot(x, y, color='#F94144')
    plt.gca().set(title=title, xlabel=xlabel, ylabel=ylabel)
    plt.show()

plot_df(aust_drug_df, x=aust_drug_df.index, y=aust_drug_df.value,
title='Monthly anti-diabetic drug sales in Australia from 1992 to
2008.')

rcParams['figure.figsize'] = 12, 8
decomposition = sm.tsa.seasonal_decompose(aust_drug_df.value,
model='additive') # additive seasonal index
fig = decomposition.plot()
plt.show()
```





###Decomposing our sales dataset

```
rcParams['figure.figsize'] = 12, 8
decomposition = sm.tsa.seasonal_decompose(df_agg['Total Revenue'],
model='additive') # additive seasonal index
fig = decomposition.plot()
plt.show()
```



###ADF - Augmented Dickey–Fuller test

ADF test is conducted with the following assumptions:

Null Hypothesis (HO): Series is non-stationary, or series has a unit root.

Alternate Hypothesis(HA): Series is stationary, or series has no unit root.

Conditions to Reject Null Hypothesis(HO)

If Test statistic < Critical Value and p-value < 0.05 – Reject Null Hypothesis(HO), i.e., time series does not have a unit root, meaning it is stationary. It does not have a time-dependent structure.

non-stationary p > alpha 0.05 -- failed to reject null hypothesis

```
#defined function for ADF test
def adf_test(datasetSeries):
    print('\nResults of Dickey-Fuller Test (ADF) with AIC as metric:')
    adfullertest = adfuller(datasetSeries, autolag='AIC')
    adfoutput = pd.Series(adfullertest[0:4], index=['Test Statistic',
'p-value', '#Lags Used', 'Number of Observations Used'])
    for key,value in adfullertest[4].items():
      adfoutput['Critical Value (%s)'%key] = value
    print(adfoutput)
```

```
#running this test with the help of above function
adf_test(df_agg['Total Revenue'])


Results of Dickey-Fuller Test (ADF) with AIC as metric:
Test Statistic                  -2.155848
p-value                          0.222658
#Lags Used                      11.000000
Number of Observations Used     79.000000
Critical Value (1%)             -3.515977
Critical Value (5%)             -2.898886
Critical Value (10%)            -2.586694
dtype: float64
```

Observation:

here p-value is > alpha (.05), hence, we failed to reject the null-hypothesis which means the series is non-stationary.

###KPSS - Kwiatkowski–Phillips–Schmidt–Shin test

The KPSS test is conducted with the following assumptions.

Null Hypothesis (HO): Series is trend stationary or series has no unit root.

Alternate Hypothesis(HA): Series is non-stationary, or series has a unit root.

Note: The hypothesis is reversed in the KPSS test compared to ADF Test.

If the null hypothesis is failed to be rejected, this test may provide evidence that the series is trend stationary.

Conditions to Fail to Reject Null Hypothesis(HO)

If the Test Statistic < Critical Value and p-value < 0.05 – Fail to Reject Null Hypothesis(HO), i.e., time series does not have a unit root, meaning it is trend stationary.

p > .05 -- failed to reject null hypothesis

--which means, it is trend stationary

```
#defined function for ADF test
def kpss_test(datasetSeries):
    print ('Results of KPSS Test:')
    kpsstest = kpss(datasetSeries, regression='c', nlags="auto")
    kpss_output = pd.Series(kpsstest[0:3], index=['Test Statistic',
'p-value', '#Lags Used'])
    for key,value in kpsstest[3].items():
      kpss_output['Critical Value (%s)'%key] = value
    print (kpss_output)
```

```
#running this test with the help of above function
kpss_test(df_agg['Total Revenue'])
```

```
Results of KPSS Test:
Test Statistic            0.042469
p-value                   0.100000
#Lags Used                2.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64

<ipython-input-25-d5c9cf2c85a8>:4: InterpolationWarning: The test
statistic is outside of the range of p-values available in the
look-up table. The actual p-value is greater than the p-value
returned.

  kpsstest = kpss(datasetSeries, regression='c', nlags="auto")
```

Note:

The following are the possible outcomes of applying both tests.

Case 1: Both tests conclude that the given series is stationary – The series is stationary

Case 2: Both tests conclude that the given series is non-stationary – The series is non-stationary

Case 3: ADF concludes non-stationary, and KPSS concludes stationary – The series is trend stationary. To make the series strictly stationary, the trend needs to be removed in this case. Then the detrended series is checked for stationarity.

Case 4: ADF concludes stationary, and KPSS concludes non-stationary – The series is difference stationary. Differencing is to be used to make series stationary. Then the differenced series is checked for stationarity.

##Convert time-series from non-stationary to stationary - How

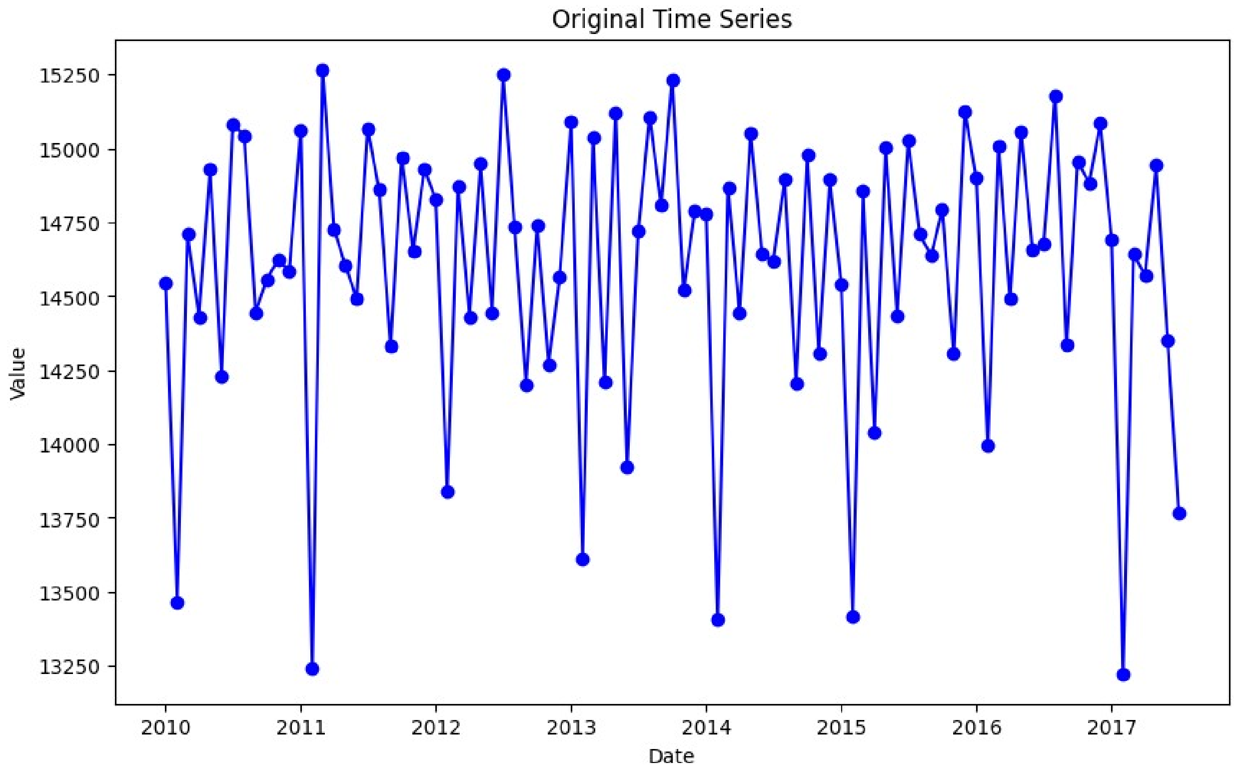
in order to use models for predictions

- Differencing
- Transformation (log, BoxCox)

###Differencing

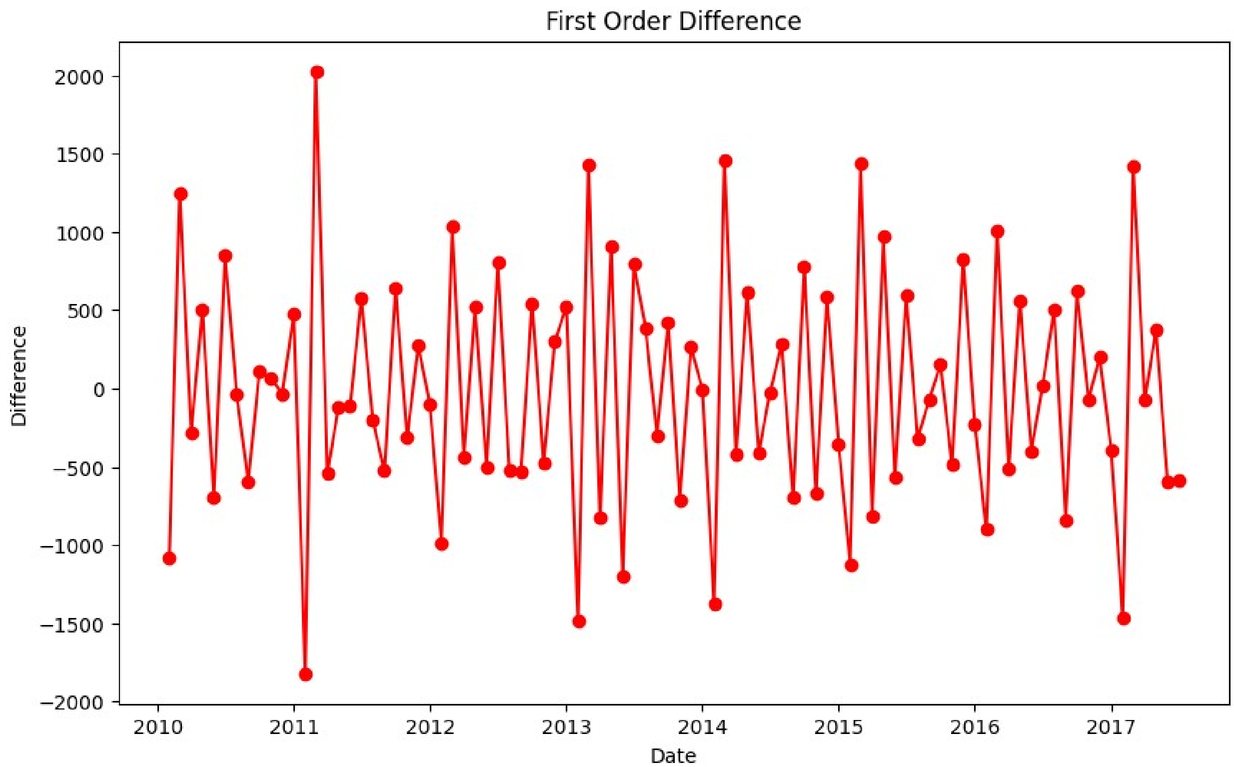
```
#plotting original time series
plt.figure(figsize=(10, 6))
plt.plot(df_agg['Total Revenue'], marker='o', linestyle='-',
color='b')
plt.title('Original Time Series')
plt.xlabel('Date')
```

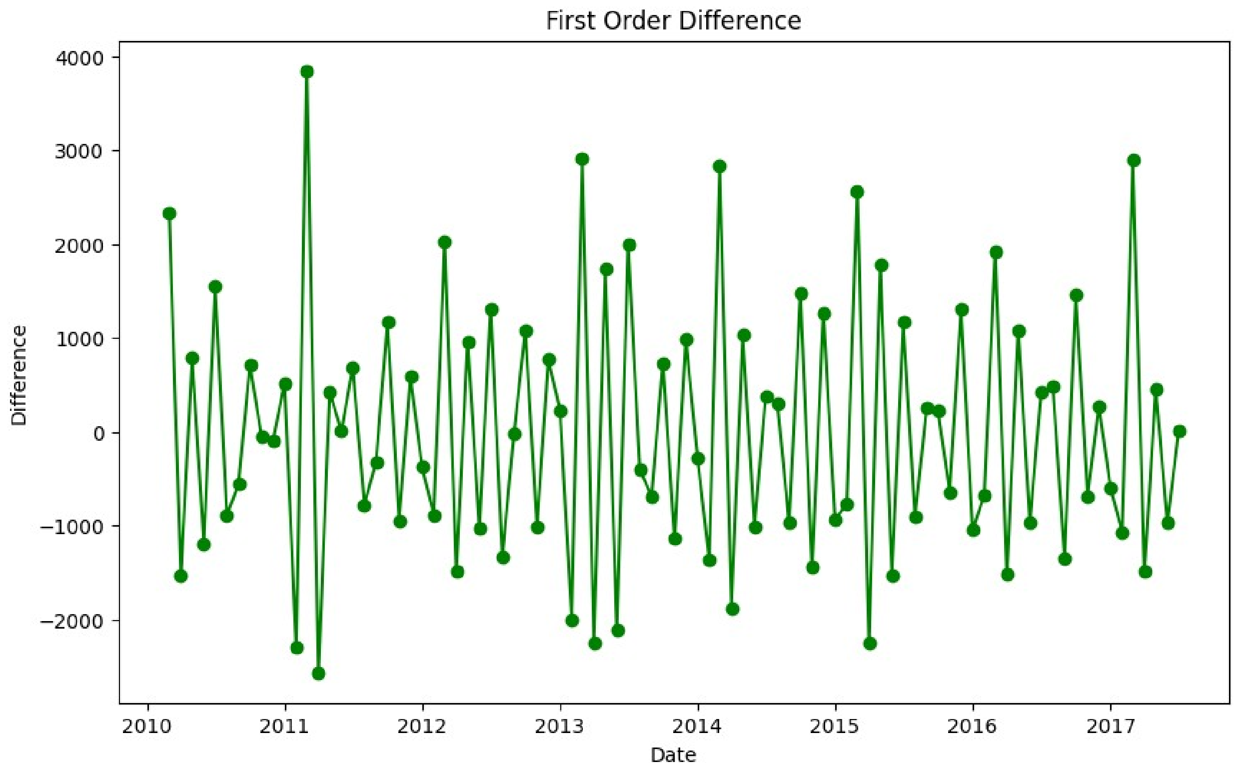
```
plt.ylabel('Value')
plt.show()
```

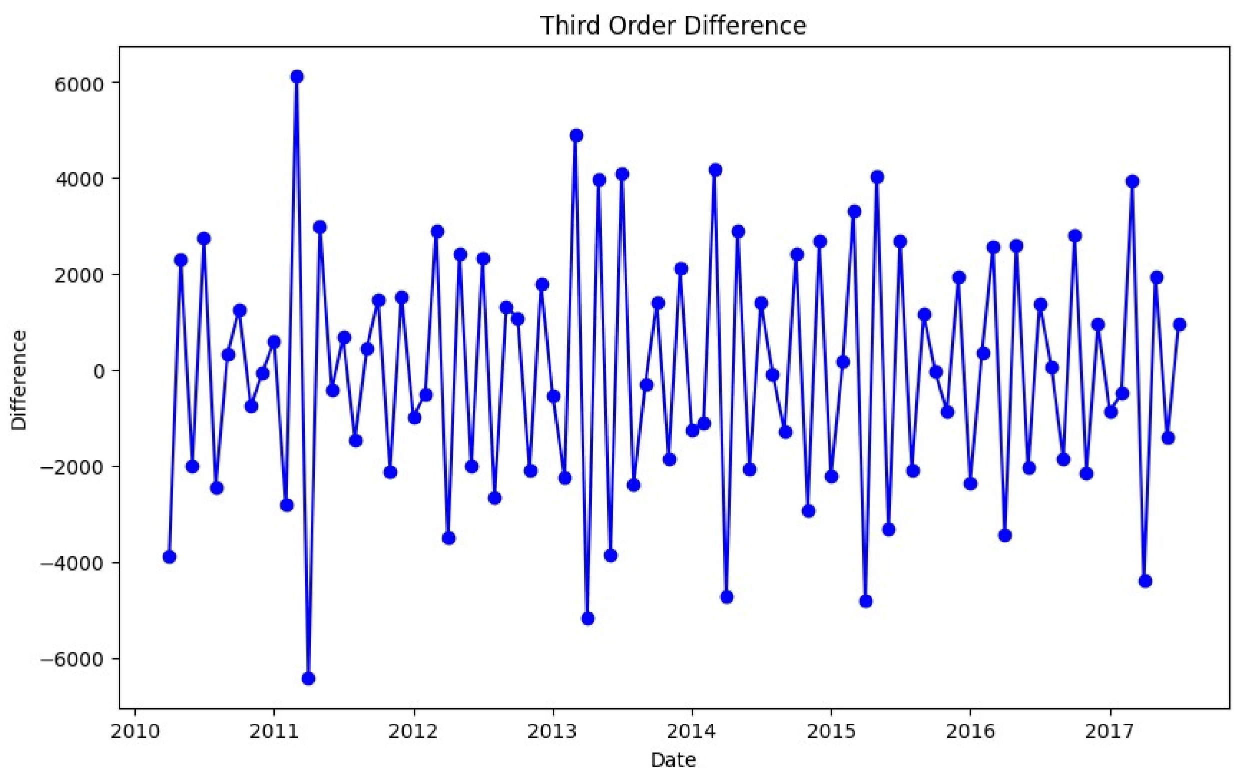



```
#performing differencing once
first_difference = df_agg['Total Revenue'].diff().dropna()

# Perform differencing two times
second_difference = df_agg['Total Revenue'].diff().diff().dropna()

# Perform differencing three times
third_difference = df_agg['Total
Revenue'].diff().diff().diff().dropna()

#plotting first order difference
plt.figure(figsize=(10, 6))
plt.plot(first_difference, marker='o', linestyle='-', color='r')
plt.title('First Order Difference')
plt.xlabel('Date')
plt.ylabel('Difference')
plt.show()

#plotting second order difference
plt.figure(figsize=(10, 6))
plt.plot(second_difference, marker='o', linestyle='-', color='g')
plt.title('First Order Difference')
```

```
plt.xlabel('Date')
plt.ylabel('Difference')
plt.show()

# Plot the third order difference
plt.figure(figsize=(10, 6))
plt.plot(third_difference, marker='o', linestyle='-', color='b')
plt.title('Third Order Difference')
plt.xlabel('Date')
plt.ylabel('Difference')
plt.show()
```





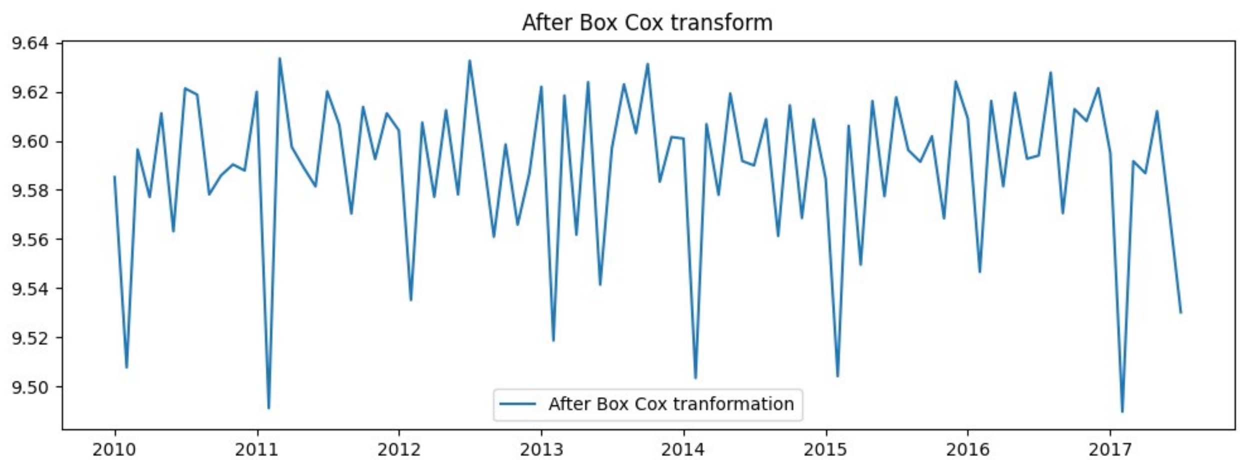



```
#adf_test(df_agg['Total Revenue'])
```

```python
#df_agg['RevenueDiff1'] = df_agg['Total Revenue'].diff().fillna(0)
#df_agg

#adf_test(df_agg['Total Revenue'].diff().dropna())
```

###Transformation - BoxCox

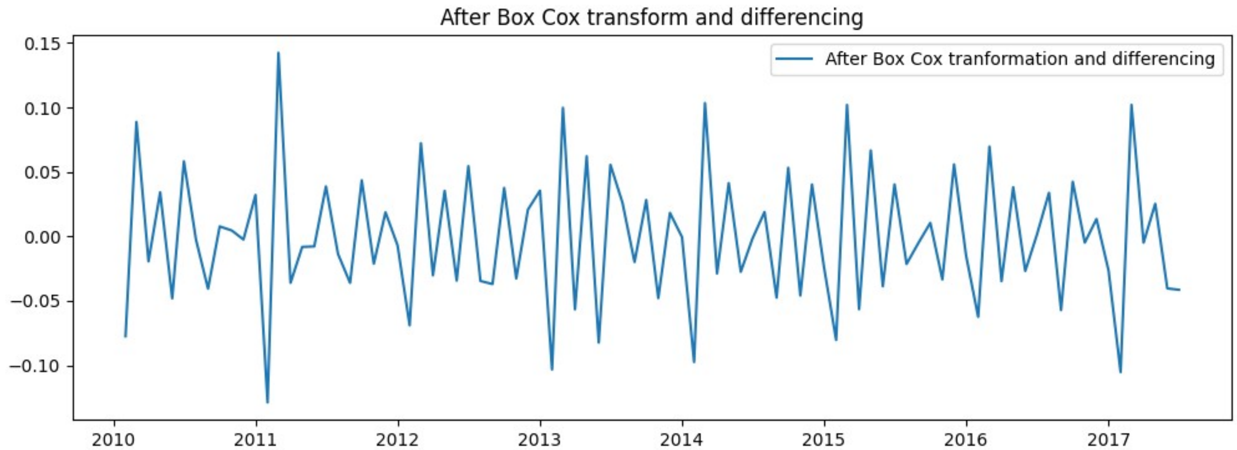
```python
data_boxcox = pd.Series(boxcox(df_agg['Total Revenue'], lmbda=0),
index = df_agg.index)

plt.figure(figsize=(12,4))
plt.plot(data_boxcox, label='After Box Cox tranformation')
plt.legend(loc='best')
plt.title('After Box Cox transform')
plt.show()
```




```python
#adf_test(data_boxcox)
```

###BoxCox with differencing

```python
data_boxcox_diff = pd.Series(data_boxcox - data_boxcox.shift(),
df_agg.index)
plt.figure(figsize=(12,4))
plt.plot(data_boxcox_diff, label='After Box Cox tranformation and
differencing')
plt.legend(loc='best')
plt.title('After Box Cox transform and differencing')
plt.show()

data_boxcox_diff.dropna(inplace=True) # After shifting the data, drop
the first value which is NA

#adf_test(data_boxcox_diff)
```




```
#kpss_test(data_boxcox_diff)
```

###Moving ahead with differencing Checking Stationarity after first order differencing

```
#performing differencing once
df_agg['RevenueDiff1'] = df_agg['Total Revenue'].diff().fillna(0)
df_agg
```

```
              Total Revenue    Total Cost  Total Profit  RevenueDiff1
Order_Month
2010-01-01     14547.786773  10259.179775   4288.606999      0.000000
2010-02-01     13463.186840   9526.252432   3936.934408  -1084.599933
2010-03-01     14712.532049  10377.312275   4335.219774   1249.345209
2010-04-01     14429.823464  10190.636550   4239.186914   -282.708586
2010-05-01     14931.168615  10531.010842   4400.157773    501.345152
...                     ...           ...           ...           ...
2017-03-01     14642.602650  10311.719664   4330.882987   1419.682001
2017-04-01     14570.593984  10254.995452   4315.598533    -72.008666
2017-05-01     14943.426668  10559.199632   4384.227036    372.832684
2017-06-01     14352.098946  10116.164782   4235.934164   -591.327722
2017-07-01     13769.014644   9703.800090   4065.214553   -583.084302

[91 rows x 4 columns]
```

###Checking Stationarity

```
print('Performing ADF Test for both original and differenced data:')
adf_test(df_agg['Total Revenue'])
print()
adf_test(df_agg['RevenueDiff1'])
print('\n\n')
```

```
print('Performing KPSS Test for both original and differenced data:')
kpss_test(df_agg['Total Revenue'])
print()
kpss_test(df_agg['RevenueDiff1'])
```

```
Performing ADF Test for both original and differenced data:

Results of Dickey-Fuller Test (ADF) with AIC as metric:
Test Statistic                  -2.155848
p-value                          0.222658
#Lags Used                      11.000000
Number of Observations Used     79.000000
Critical Value (1%)             -3.515977
Critical Value (5%)             -2.898886
Critical Value (10%)            -2.586694
dtype: float64


Results of Dickey-Fuller Test (ADF) with AIC as metric:
Test Statistic                 -7.252249e+00
p-value                         1.767620e-10
#Lags Used                      1.000000e+01
Number of Observations Used     8.000000e+01
Critical Value (1%)            -3.514869e+00
Critical Value (5%)            -2.898409e+00
Critical Value (10%)           -2.586439e+00
dtype: float64



Performing KPSS Test for both original and differenced data:
Results of KPSS Test:
Test Statistic           0.042469
p-value                  0.100000
#Lags Used               2.000000
Critical Value (10%)     0.347000
Critical Value (5%)      0.463000
Critical Value (2.5%)    0.574000
Critical Value (1%)      0.739000
dtype: float64

Results of KPSS Test:
Test Statistic           0.097339
p-value                  0.100000
#Lags Used               6.000000
Critical Value (10%)     0.347000
Critical Value (5%)      0.463000
Critical Value (2.5%)    0.574000
Critical Value (1%)      0.739000
dtype: float64
```

```
<ipython-input-25-d5c9cf2c85a8>:4: InterpolationWarning: The test
statistic is outside of the range of p-values available in the
look-up table. The actual p-value is greater than the p-value
returned.

  kpsstest = kpss(datasetSeries, regression='c', nlags="auto")
<ipython-input-25-d5c9cf2c85a8>:4: InterpolationWarning: The test
statistic is outside of the range of p-values available in the
look-up table. The actual p-value is greater than the p-value
returned.

  kpsstest = kpss(datasetSeries, regression='c', nlags="auto")
```

Observation:

ADF returned p-value for original data >.05 which means we failed to reject the null hypothesis (series is stationary)

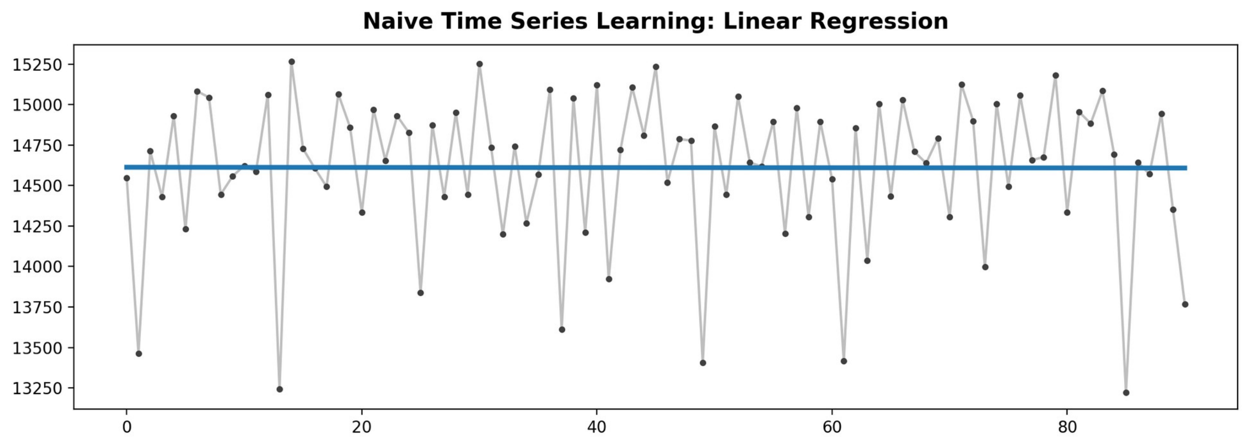
However, after first order differencing, the p-value is <.05 and we can reject the null hypothesis which claims non-stationarity (series is stationary now)

##Modeling

###Linear Regression (naive approach)

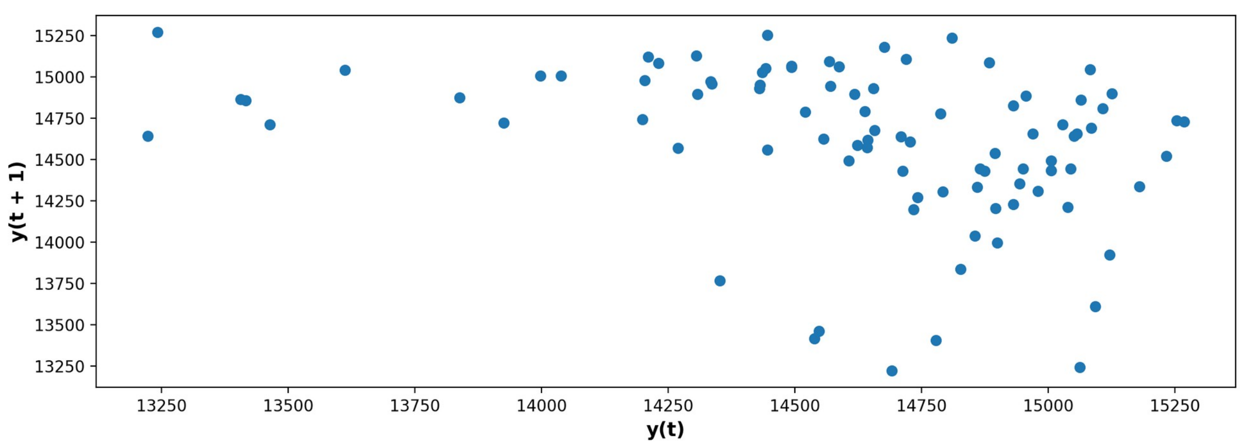
```
#resetting index and adding new column timeseq
df_agg.reset_index(inplace=True)

test_reg_df = df_agg.copy()

test_reg_df['TimeSeq'] = np.arange(len(df_agg.index))

test_reg_df.head()

  Order_Month  Total Revenue    Total Cost  Total Profit  RevenueDiff1
\
0  2010-01-01   14547.786773  10259.179775   4288.606999      0.000000

1  2010-02-01   13463.186840   9526.252432   3936.934408  -1084.599933

2  2010-03-01   14712.532049  10377.312275   4335.219774   1249.345209

3  2010-04-01   14429.823464  10190.636550   4239.186914   -282.708586

4  2010-05-01   14931.168615  10531.010842   4400.157773    501.345152


   TimeSeq
0        0
1        1
2        2
```

```
3        3
4        4

#splitting in train and test
X = test_reg_df.loc[:, ['TimeSeq']]  # features
y = test_reg_df.loc[:, 'Total Revenue']  # target

#model training
model = LinearRegression()
model.fit(X, y)

#model prediction
y_pred = pd.Series(model.predict(X), index=X.index)


#visualizing learnt model regression line
plt.rc("figure", autolayout=True, figsize=(11, 4))
plt.rc(
    "axes",
    labelweight="bold",
    labelsize="large",
    titleweight="bold",
    titlesize=14,
    titlepad=10,
)
plot_params = dict(
    color="0.75",
    style=".-",
    markeredgecolor="0.25",
    markerfacecolor="0.25",
    legend=False,
)
%config InlineBackend.figure_format = 'retina'

ax = y.plot(**plot_params)
ax = y_pred.plot(ax=ax, linewidth=3)
ax.set_title('Naive Time Series Learning: Linear Regression');
```



###Moving to AR - Auto-Regressive Model

```
df_agg.set_index('Order_Month', inplace=True)

lag_plot(df_agg['Total Revenue'])
plt.show()
```

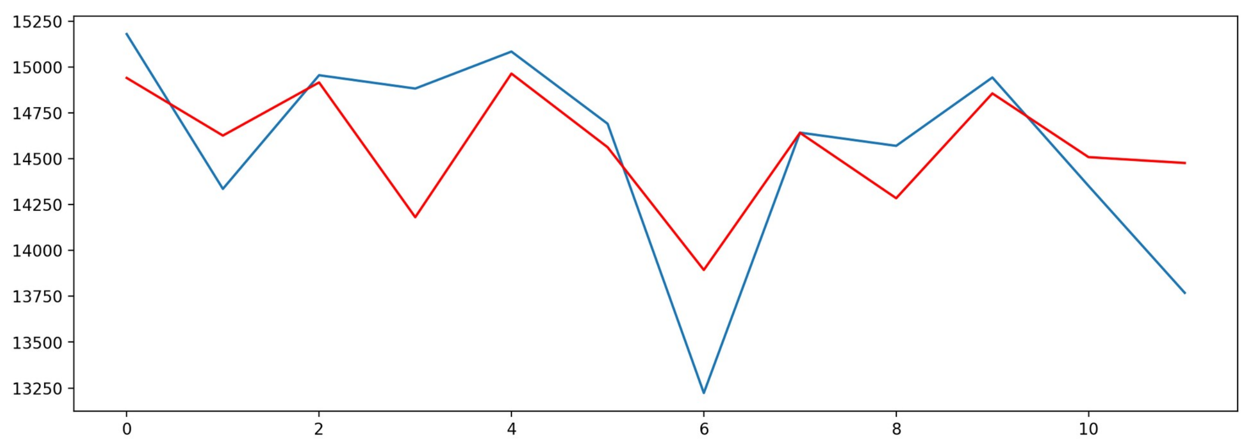


Yes, random values for AR model

```
#split train and test (12 samples to predict)
X = df_agg['Total Revenue'].values
train, test = X[1:len(X)-12], X[len(X)-12:]

#training AR model with 20 lags (p)
model = AutoReg(train, lags=20)
model_fit = model.fit()
##print('Coefficients: %s' % model_fit.params)

#model predictions
predictions = model_fit.predict(start=len(train), end=len(train)
```

```
+len(test)-1, dynamic=False)
for i in range(len(predictions)):
  print('predicted=%f, expected=%f' % (predictions[i], test[i]))

#using rmse as evaluation metrix
rmse = sqrt(mean_squared_error(test, predictions))
print('\nTest RMSE: %.3f\n' % rmse)

#plotting results
plt.plot(test)
plt.plot(predictions, color='red')
plt.show()
```

```
predicted=14940.952495, expected=15180.203861
predicted=14626.611656, expected=14335.875345
predicted=14916.365054, expected=14955.720034
predicted=14181.346272, expected=14883.042133
predicted=14964.573431, expected=15084.654075
predicted=14562.891419, expected=14690.963423
predicted=13893.723641, expected=13222.920650
predicted=14641.730114, expected=14642.602650
predicted=14285.017786, expected=14570.593984
predicted=14856.491630, expected=14943.426668
predicted=14508.968322, expected=14352.098946
predicted=14477.163230, expected=13769.014644

Test RMSE: 379.878
```



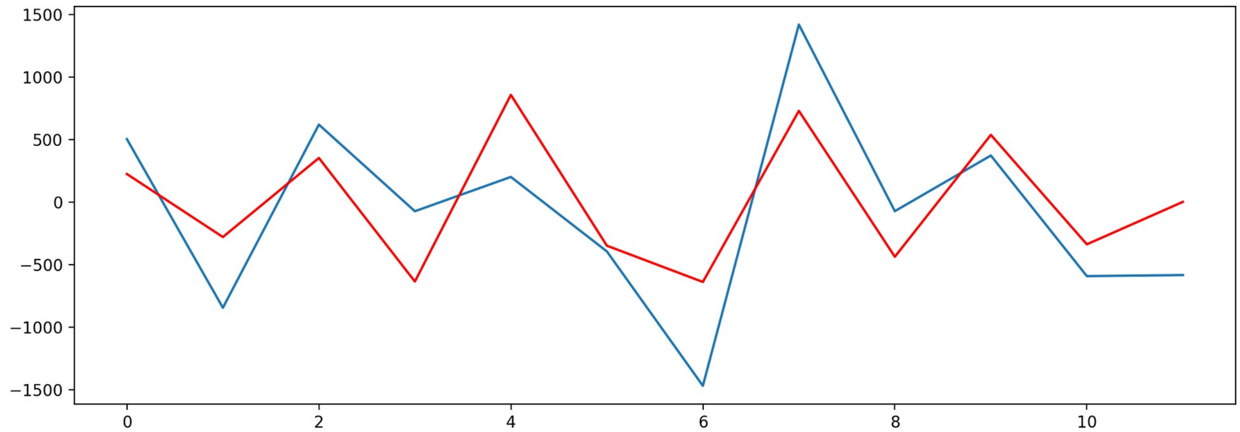
Observation

Expected (blue) Against Predicted (red). The forecast looks good on the 2nd month and the deviation on the 7th and 12th month.

###Auto-Regressive Model with first order differencing

```
#split train and test
X = df_agg['RevenueDiff1'].values
train, test = X[1:len(X)-12], X[len(X)-12:]

#training AR model
model = AutoReg(train, lags=20)
model_fit = model.fit()
#print('Coefficients: %s' % model_fit.params)

#model predictions
predictions = model_fit.predict(start=len(train), end=len(train)
+len(test)-1, dynamic=False)
for i in range(len(predictions)):
    print('predicted=%f, expected=%f' % (predictions[i], test[i]))

rmse = sqrt(mean_squared_error(test, predictions))
print('\nTest RMSE: %.3f\n' % rmse)

#plotting results
plt.plot(test)
plt.plot(predictions, color='red')
plt.show()
```

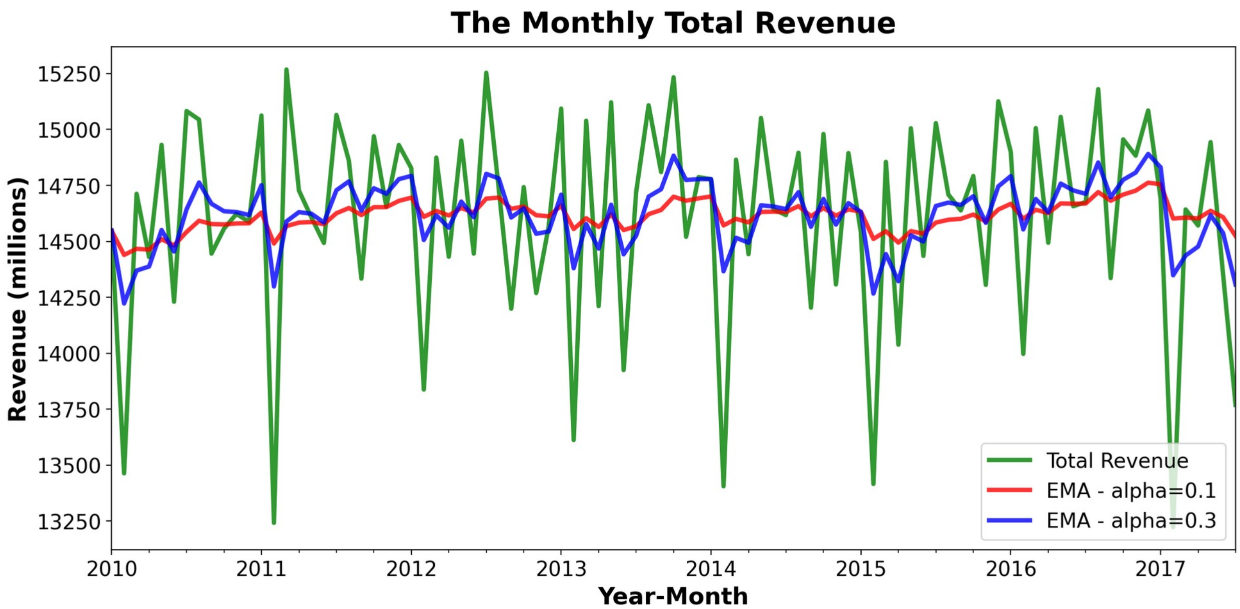
```
predicted=224.867322, expected=504.166831
predicted=-278.867184, expected=-844.328516
predicted=353.017827, expected=619.844689
predicted=-634.652497, expected=-72.677901
predicted=857.492438, expected=201.611942
predicted=-348.030656, expected=-393.690652
predicted=-638.062385, expected=-1468.042773
predicted=729.884283, expected=1419.682001
predicted=-436.653149, expected=-72.008666
predicted=537.981229, expected=372.832684
predicted=-337.192254, expected=-591.327722
predicted=2.036366, expected=-583.084302

Test RMSE: 495.724
```



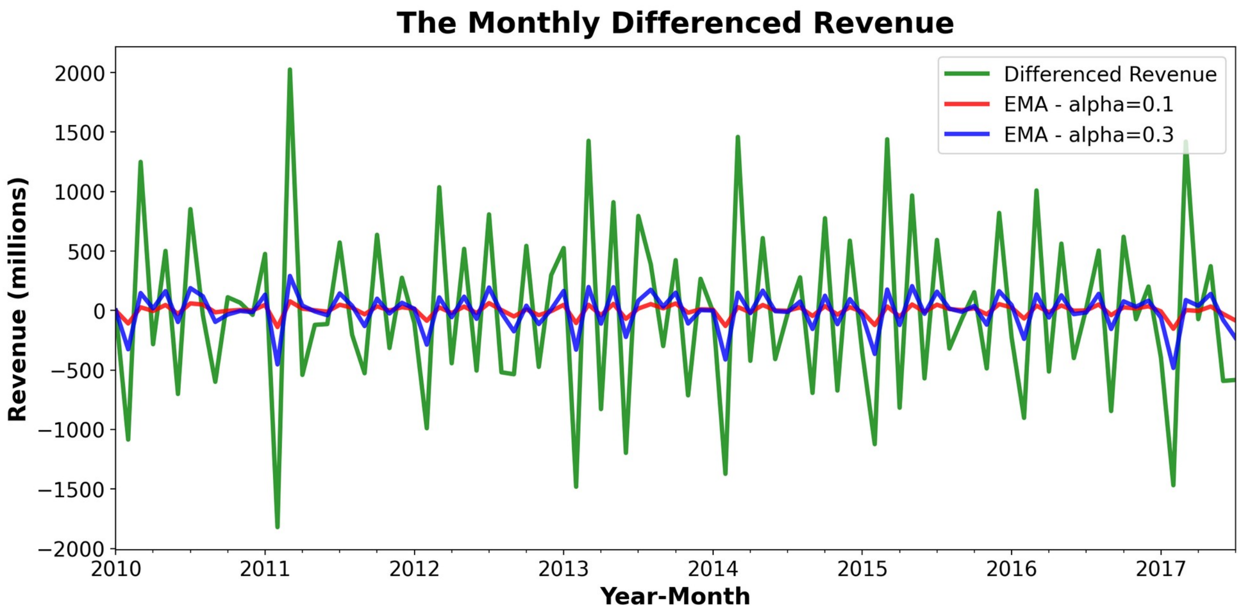
###MA - Moving Average Model

Comparing original and differenced data with exponential moving average

```
#original data points

#exponential moving average smoothing factor - 0.1
df_agg['EMA_0.1'] = df_agg['Total Revenue'].ewm(alpha=0.1,
adjust=False).mean()
#smoothing factor  - 0.3
df_agg['EMA_0.3'] = df_agg['Total Revenue'].ewm(alpha=0.3,
adjust=False).mean()

# green - Original Monthly Revenue, red- smoothing factor - 0.1,
yellow - smoothing factor  - 0.3
colors = ['green', 'red', 'blue']
df_agg[['Total Revenue', 'EMA_0.1', 'EMA_0.3']].plot(color=colors,
linewidth=3, figsize=(12,6), alpha=0.8)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.legend(labels=['Total Revenue', 'EMA - alpha=0.1', 'EMA -
alpha=0.3'], fontsize=14)
plt.title('The Monthly Total Revenue', fontsize=20)
plt.xlabel('Year-Month', fontsize=16)
plt.ylabel('Revenue (millions)', fontsize=16)

Text(0, 0.5, 'Revenue (millions)')
```

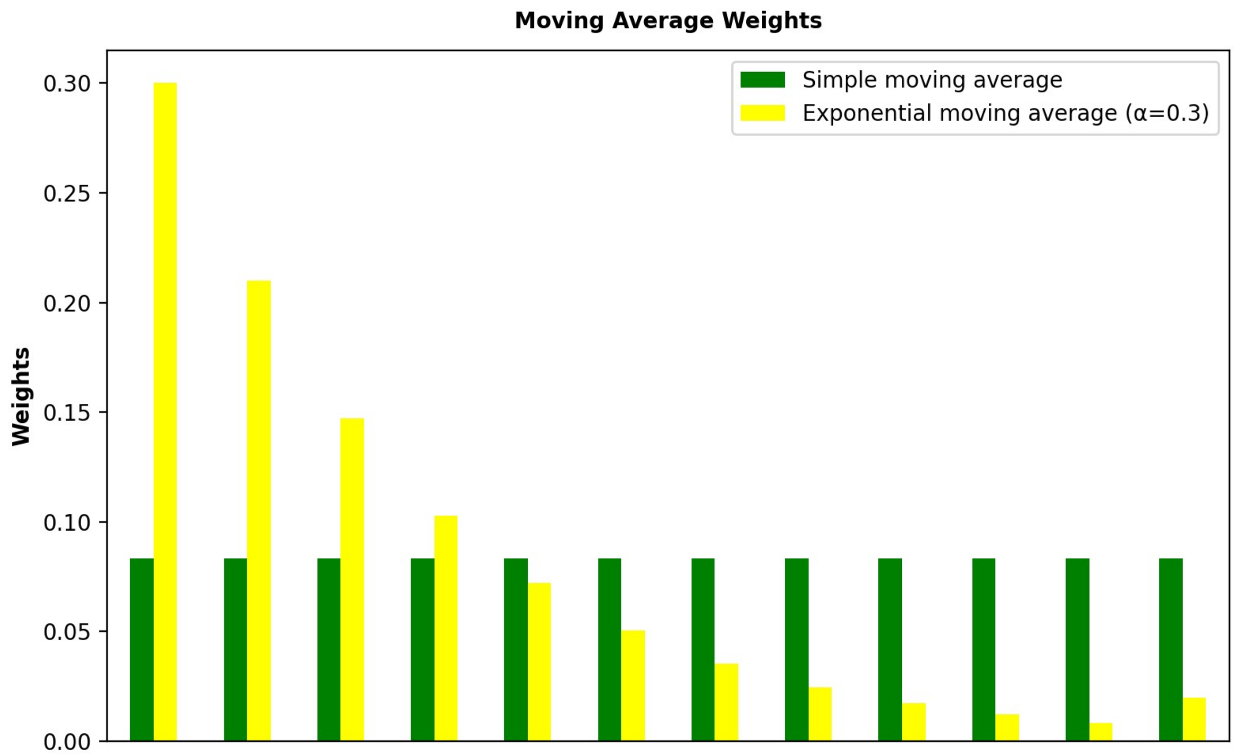



```
#differenced data points

#exponential moving average smoothing factor - 0.1
df_agg['EMA_0.1'] = df_agg['RevenueDiff1'].ewm(alpha=0.1,
adjust=False).mean()
#smoothing factor  - 0.3
df_agg['EMA_0.3'] = df_agg['RevenueDiff1'].ewm(alpha=0.3,
adjust=False).mean()

# green - differenced revenue points, red- smoothing factor - 0.1,
yellow - smoothing factor  - 0.3
colors = ['green', 'red', 'blue']
df_agg[['RevenueDiff1', 'EMA_0.1', 'EMA_0.3']].plot(color=colors,
linewidth=3, figsize=(12,6), alpha=0.8)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.legend(labels=['Differenced Revenue', 'EMA - alpha=0.1', 'EMA -
alpha=0.3'], fontsize=14)
plt.title('The Monthly Differenced Revenue', fontsize=20)
plt.xlabel('Year-Month', fontsize=16)
plt.ylabel('Revenue (millions)', fontsize=16)

Text(0, 0.5, 'Revenue (millions)')
```




```
#Comparing Simple moving average with exponential moving average (with
weights)
alpha= 0.3
n = 12
w_sma = np.repeat(1/n, n)
colors = ['green', 'yellow']

# weights - exponential moving average alpha=0.3 adjust=False
w_ema = [(1-alpha)**i if i==n-1 else alpha*(1-alpha)**i for i in
range(n)]

pd.DataFrame({'w_sma': w_sma, 'w_ema': w_ema}).plot(color=colors,
kind='bar', figsize=(8,5))
plt.xticks([])
plt.yticks(fontsize=10)
plt.legend(labels=['Simple moving average', 'Exponential moving
average (α=0.3)'], fontsize=10)

# title and labels
plt.title('Moving Average Weights', fontsize=10)
plt.ylabel('Weights', fontsize=10)
```

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



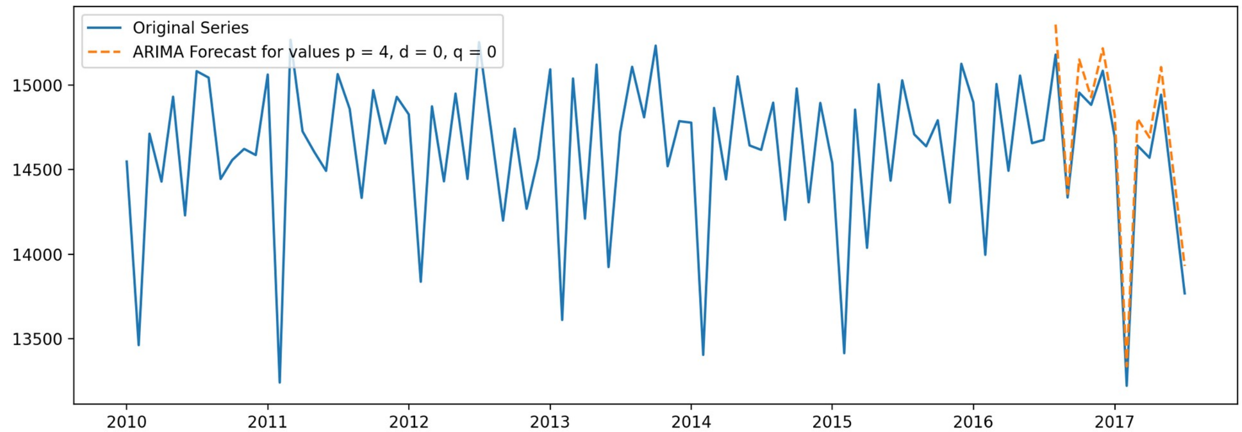
##Function for AR, MA, ARMA & ARIMA

```
def arima_calc_rmse_r2(ip_df, col_name, diff_col_name, train_split,
p_val, d_val, q_val):
  # split dataset for test and training
  X = ip_df[diff_col_name]
  train, test = X[1:len(X)-train_split], X[len(X)-train_split:]

  # Specify the orders (p, d, q) of the ARIMA model
  p = p_val  # Replace with the desired AR order
  q = q_val  # Replace with the desired MA order
  d = d_val

  # Fit the ARIMA model
  arima_model = ARIMA(train, order=(p, d, q))
  arima_results = arima_model.fit()

  ##print(arima_results.summary())

  # Make predictions
  arima_forecast = arima_results.predict(start=len(train),
end=len(train)+len(test)-1)

  rmse = sqrt(mean_squared_error(test, arima_forecast))
  print('Test RMSE: %.3f' % rmse)
  r2s = r2_score(test, arima_forecast)
  print('Test R2: %.3f' % r2s)
```

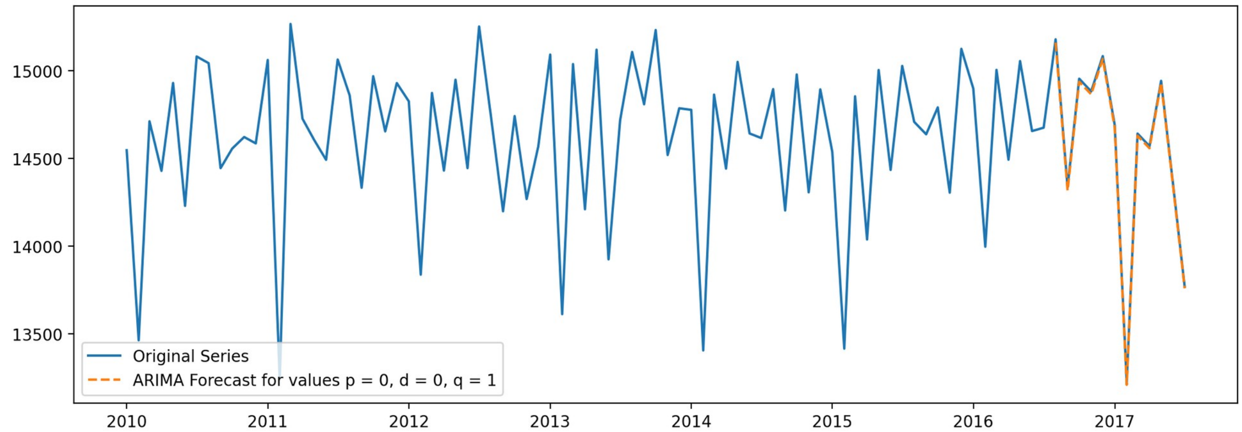
```
  mae = mean_absolute_error(test, arima_forecast)
  print('Test MAE: %.3f' % mae)

  # If differencing was applied, backtransform the forecast to the
original scale
  ##original_forecast = arima_forecast.cumsum() +
data['your_column'].iloc[-1]

  # If differencing was applied, backtransform the forecast to the
original scale
  original_forecast = arima_forecast.cumsum() + ip_df[col_name]

  label_txt = 'ARIMA Forecast for values p = ' + str(p) + ', d = ' +
str(d) + ', q = ' + str(q)

  # Plot the original series, differenced series, and the forecast
  plt.plot(ip_df[col_name], label='Original Series')
  #plt.plot(df_agg[diff_col_name], label='Differenced Series',
linestyle='dashed')
  plt.plot(original_forecast, label=label_txt, linestyle='dashed')
  plt.legend()
  plt.show()

  return rmse, r2s, mae

rmserror = []
r2square = []


print('Calling AR Model:')
ar_rmse, ar_r2s, ar_mae = arima_calc_rmse_r2(df_agg, 'Total Revenue',
'RevenueDiff1', 12, 4, 0, 0)
print('\n\n')

print('Calling MA Model:')
ma_rmse, ma_r2s, ma_mae = arima_calc_rmse_r2(df_agg, 'Total Revenue',
'RevenueDiff1', 12, 0, 0, 1)
print('\n\n')
```

```
Calling AR Model:

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
```

```
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)

Test RMSE: 692.151
Test R2: 0.114
Test MAE: 534.061
```




```
Calling MA Model:
Test RMSE: 740.450
Test R2: -0.014
Test MAE: 597.118

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/statespace/
sarimax.py:978: UserWarning: Non-invertible starting MA parameters
found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
```

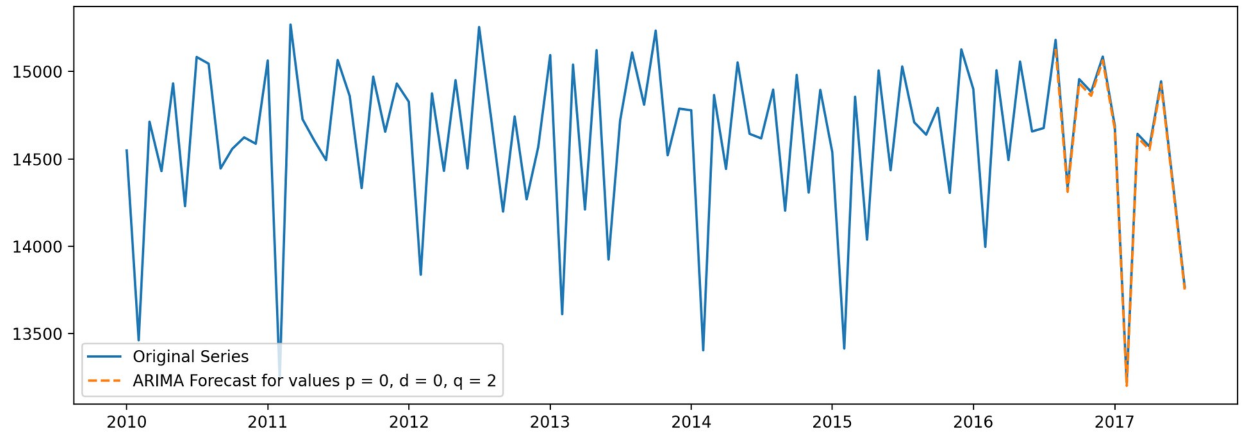


###Only MA from ARIMA

```
print('Calling MA Model with q=2:')
ma_rmse, ma_r2s, ma_mae = arima_calc_rmse_r2(df_agg, 'Total Revenue',
'RevenueDiff1', 12, 0, 0, 2)
```

```
Calling MA Model with q=2:
Test RMSE: 744.987
Test R2: -0.026
Test MAE: 602.027
```

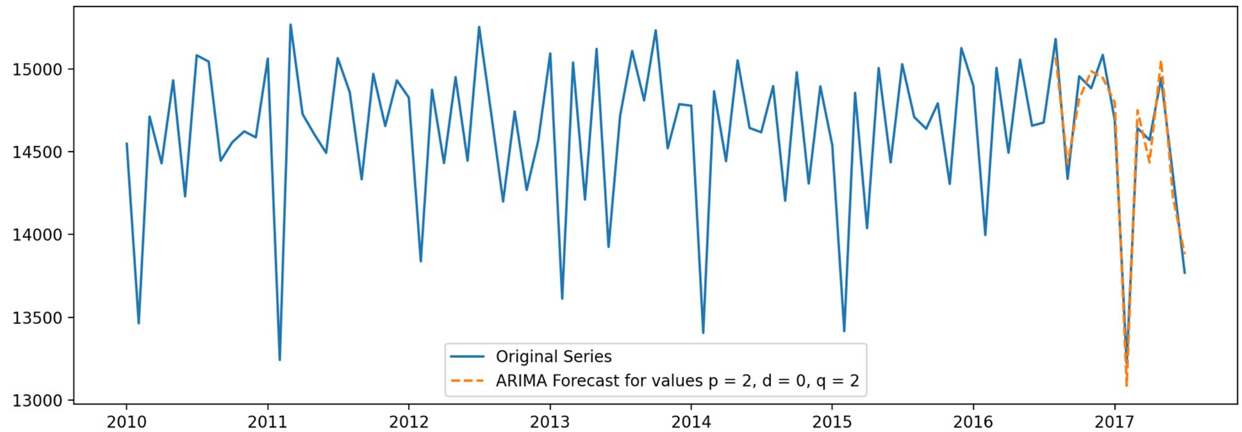
```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
```



###ARMA

```
print('Calling ARMA Model with p=2 and q=2:')
arma_rmse, arma_r2s, arma_mae = arima_calc_rmse_r2(df_agg, 'Total Revenue', 'RevenueDiff1', 12, 2, 0, 2)
```

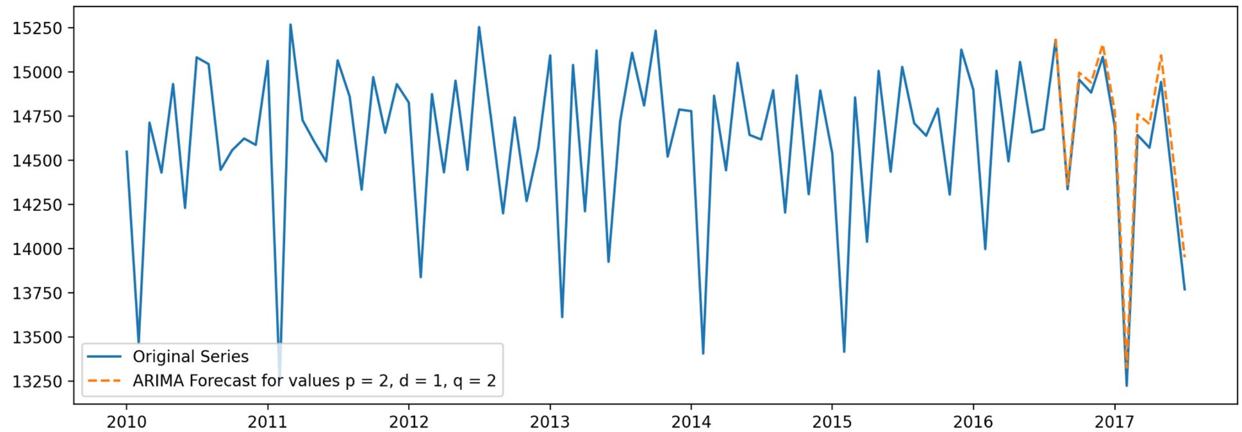
```
Calling ARMA Model with p=2 and q=2:

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/statespace/sarimax.py:966: UserWarning: Non-stationary starting autoregressive parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/statespace/sarimax.py:978: UserWarning: Non-invertible starting MA parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'

Test RMSE: 743.016
Test R2: -0.021
Test MAE: 648.108
```



###ARIMA

```
print('Calling ARIMA Model with p=2, d=1 and q=2:')
arima_rmse, arima_r2s, arima_mae = arima_calc_rmse_r2(df_agg, 'Total Revenue', 'RevenueDiff1', 12, 2, 1, 2)
```

```
Calling ARIMA Model with p=2, d=1 and q=2:

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/statespace/sarimax.py:978: UserWarning: Non-invertible starting MA parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'

Test RMSE: 741.809
Test R2: -0.018
Test MAE: 599.068
```



###SARIMA

```
#split dataset for test and training for differenced data points
X = df_agg['RevenueDiff1']
train, test = X[1:len(X)-12], X[len(X)-12:]

differenced_series = df_agg['RevenueDiff1']


# Specify the orders (p, d, q) and seasonal orders (P, D, Q, S) of the
SARIMA model
p = 2  # Replace with the desired AR order
d = 1  # Replace with the desired differencing order
q = 2  # Replace with the desired MA order
P = 1  # Replace with the desired seasonal AR order
D = 1  # Replace with the desired seasonal differencing order
Q = 1  # Replace with the desired seasonal MA order
S = 12  # Replace with the length of the seasonal cycle (e.g., 12 for
monthly data)

# Fit the SARIMA model
sarima_model = SARIMAX(train, order=(p, d, q), seasonal_order=(P, D,
Q, S))
sarima_results = sarima_model.fit()

#print(sarima_results.summary())

sarima_forecast = sarima_results.predict(start=len(train),
end=len(train)+len(test)-1,)

rmse = sqrt(mean_squared_error(test, sarima_forecast))
print('Test RMSE: %.3f' % rmse)
r2s = r2_score(test, sarima_forecast)
print('Test R2: %.3f' % r2s)
```

```
mae = mean_absolute_error(test, sarima_forecast)
print('Test MAE: %.3f' % mae)

#as differencing was applied, need to back transform the forecast to
the original scale
original_forecast = sarima_forecast.cumsum() + df_agg['Total Revenue']


# Plot the original series and the forecast
plt.plot(df_agg['Total Revenue'], label='Original Series')
#plt.plot(df_agg['RevenueDiff1'], label='Differenced Series',
linestyle='dashed')
plt.plot(original_forecast, label='SARIMA Forecast',
linestyle='dashed')
plt.legend()
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/statespace/
sarimax.py:966: UserWarning: Non-stationary starting autoregressive
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  warn('Non-stationary starting autoregressive parameters'
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/statespace/
sarimax.py:978: UserWarning: Non-invertible starting MA parameters
found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py:607:
ConvergenceWarning: Maximum Likelihood optimization failed to
converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "

Test RMSE: 431.838
Test R2: 0.655
Test MAE: 333.449
```

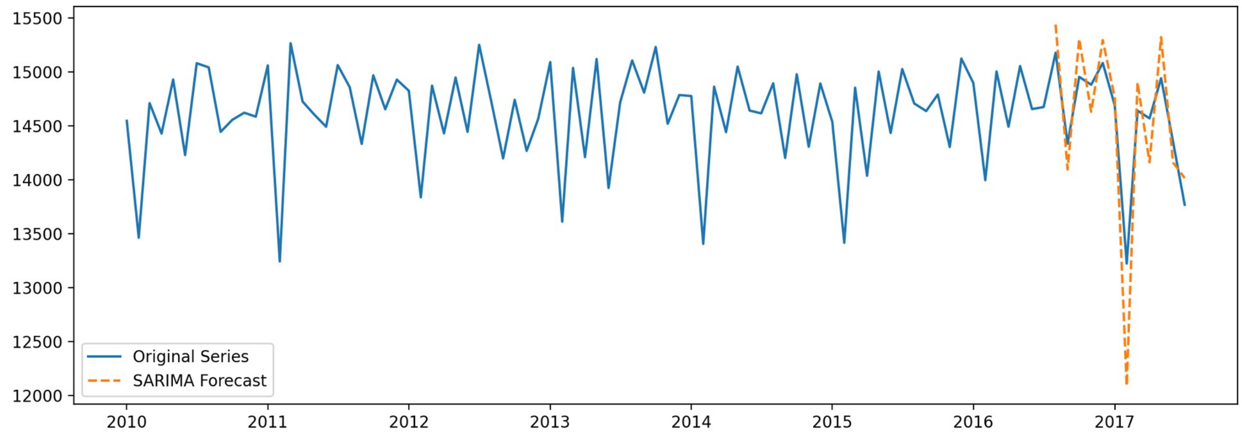

##Hyperparameter Tuning

###Manual way

```
#define the range of values for p, d, and q
p_values = range(0, 3)
d_values = range(0, 2)
q_values = range(0, 3)

#generate all possible combinations of p, d, and q
combinations = product(p_values, d_values, q_values)

#initialize variables to store the best model and its performance
best_model = None
best_aic = np.inf  # AIC (Akaike Information Criterion) is used for
model comparison

#perform grid search (trying all combinations)
for order in combinations:
    try:
        #fit the ARIMA model
        arima_model = ARIMA(df_agg['RevenueDiff1'], order=order)
        arima_results = arima_model.fit()

        #calculate AIC
        aic = arima_results.aic

        #update best model if the current one has a lower AIC
        if aic < best_aic:
            best_aic = aic
            best_model = arima_results

    except Exception as e:
        #handle exceptions, e.g., if the model does not converge for
certain parameters
        print(f"Error for order {order}: {e}")
```

```python
#print the best model summary
print(best_model.summary())
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
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  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
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/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
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inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
```

```
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
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  warn('Non-invertible starting MA parameters found.'
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  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
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inferred frequency MS will be used.
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/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
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inferred frequency MS will be used.
  self._init_dates(dates, freq)
```

```
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/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
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  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
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/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
```

```
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.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/statespace/
sarimax.py:978: UserWarning: Non-invertible starting MA parameters
found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
```

```
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)

                               SARIMAX Results

======================================================================
========
Dep. Variable:           RevenueDiff1   No. Observations:
91
Model:                 ARIMA(1, 1, 2)   Log Likelihood
-682.294
Date:                Sat, 25 Nov 2023   AIC
1372.589
Time:                        21:50:44   BIC
1382.588
Sample:                    01-01-2010   HQIC
1376.621
                         - 07-01-2017

Covariance Type:                  opg

======================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
----------------------------------------------------------------------
--------
ar.L1         -0.3162      0.153     -2.062      0.039      -0.617
-0.016
ma.L1         -1.9971      0.115    -17.428      0.000      -2.222
```

```
-1.772
ma.L2          0.9993      0.113      8.834      0.000       0.778
1.221
sigma2      1.938e+05   1.17e-06   1.65e+11      0.000    1.94e+05
1.94e+05
======================================================================
=============
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):
26.33
Prob(Q):                              0.97   Prob(JB):
0.00
Heteroskedasticity (H):               1.36   Skew:
-1.13
Prob(H) (two-sided):                  0.41   Kurtosis:
4.37
======================================================================
=============

Warnings:
[1] Covariance matrix calculated using the outer product of gradients
(complex-step).
[2] Covariance matrix is singular or near-singular, with condition
number 1.15e+26. Standard errors may be unstable.

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/statespace/
sarimax.py:978: UserWarning: Non-invertible starting MA parameters
found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
```

###Using auto_arima from pmdarima library - with seasonal component False

```
#seasonal False - fit stepwise auto-ARIMA
arima_model = auto_arima(df_agg['RevenueDiff1'], start_p=1, start_q=1,
                         test='adf',
                         max_p=4, max_q=4, m=12,
                         start_P=0, seasonal=False,
                         d=None, D=1, trace=True,
```

```
                            error_action='ignore',
                            suppress_warnings=True,
                            stepwise=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(1,0,1)(0,0,0)[0]             : AIC=inf, Time=0.14 sec

/usr/local/lib/python3.10/dist-packages/pmdarima/arima/
_validation.py:62: UserWarning: m (12) set for non-seasonal fit.
Setting to 0
  warnings.warn("m (%i) set for non-seasonal fit. Setting to 0" % m)

 ARIMA(0,0,0)(0,0,0)[0]             : AIC=1463.284, Time=0.03 sec
 ARIMA(1,0,0)(0,0,0)[0]             : AIC=1411.072, Time=0.06 sec
 ARIMA(0,0,1)(0,0,0)[0]             : AIC=inf, Time=0.05 sec
 ARIMA(2,0,0)(0,0,0)[0]             : AIC=1400.378, Time=0.03 sec
 ARIMA(3,0,0)(0,0,0)[0]             : AIC=1398.131, Time=0.04 sec
 ARIMA(4,0,0)(0,0,0)[0]             : AIC=1383.516, Time=0.07 sec
 ARIMA(4,0,1)(0,0,0)[0]             : AIC=inf, Time=0.27 sec
 ARIMA(3,0,1)(0,0,0)[0]             : AIC=inf, Time=0.19 sec
 ARIMA(4,0,0)(0,0,0)[0] intercept   : AIC=1385.514, Time=0.08 sec

Best model:  ARIMA(4,0,0)(0,0,0)[0]
Total fit time: 0.984 seconds
```

###Using auto_arima from pmdarima library - with seasonal component True

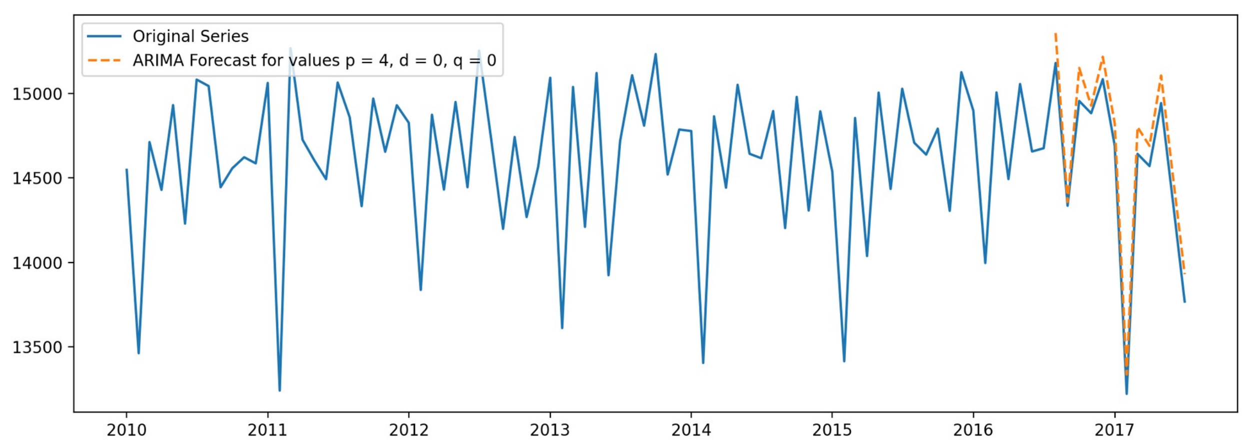
```
#seasonal True - fit stepwise auto-ARIMA
arima_model = auto_arima(df_agg['RevenueDiff1'], start_p=1, start_q=1,
                         test='adf',
                         max_p=4, max_q=4, m=12,
                         start_P=0, seasonal=True,
                         d=None, D=1, trace=True,
                         error_action='ignore',
                         suppress_warnings=True,
                         stepwise=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(1,0,1)(0,1,1)[12] intercept   : AIC=1134.159, Time=1.06 sec
 ARIMA(0,0,0)(0,1,0)[12] intercept   : AIC=1195.781, Time=0.03 sec
 ARIMA(1,0,0)(1,1,0)[12] intercept   : AIC=1156.231, Time=0.37 sec
 ARIMA(0,0,1)(0,1,1)[12] intercept   : AIC=inf, Time=0.60 sec
 ARIMA(0,0,0)(0,1,0)[12]             : AIC=1193.835, Time=0.03 sec
 ARIMA(1,0,1)(0,1,0)[12] intercept   : AIC=inf, Time=0.35 sec
 ARIMA(1,0,1)(1,1,1)[12] intercept   : AIC=inf, Time=0.91 sec
 ARIMA(1,0,1)(0,1,2)[12] intercept   : AIC=inf, Time=1.78 sec
 ARIMA(1,0,1)(1,1,0)[12] intercept   : AIC=inf, Time=0.71 sec
 ARIMA(1,0,1)(1,1,2)[12] intercept   : AIC=inf, Time=2.96 sec
 ARIMA(1,0,0)(0,1,1)[12] intercept   : AIC=1147.409, Time=1.25 sec
 ARIMA(2,0,1)(0,1,1)[12] intercept   : AIC=inf, Time=2.60 sec
```

```
 ARIMA(1,0,2)(0,1,1)[12] intercept   : AIC=inf, Time=3.49 sec
 ARIMA(0,0,0)(0,1,1)[12] intercept   : AIC=1169.217, Time=0.34 sec
 ARIMA(0,0,2)(0,1,1)[12] intercept   : AIC=inf, Time=0.86 sec
 ARIMA(2,0,0)(0,1,1)[12] intercept   : AIC=1146.963, Time=0.66 sec
 ARIMA(2,0,2)(0,1,1)[12] intercept   : AIC=inf, Time=1.19 sec
 ARIMA(1,0,1)(0,1,1)[12]             : AIC=inf, Time=0.46 sec

Best model:  ARIMA(1,0,1)(0,1,1)[12] intercept
Total fit time: 19.699 seconds
```

##Compare results with best hyperparameters from tuning for ARIMA and SARIMA

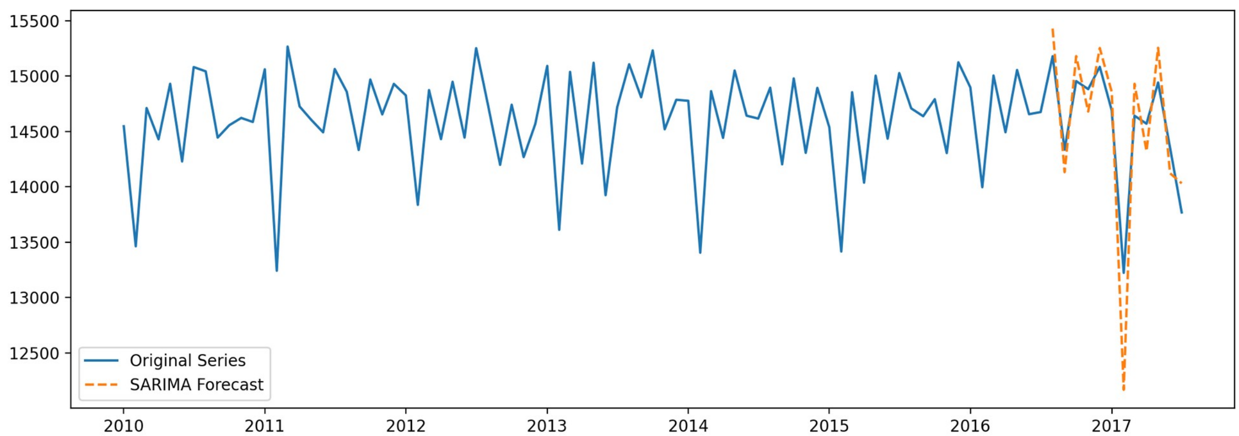
```
#Best model:  ARIMA(4,0,0)(0,0,0)[0]
print('Calling ARIMA Model:')
arima_rmse, arima_r2s, arima_mae = arima_calc_rmse_r2(df_agg, 'Total
Revenue', 'RevenueDiff1', 12, 4, 0, 0)

Calling ARIMA Model:

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)

Test RMSE: 692.151
Test R2: 0.114
Test MAE: 534.061
```



SARIMA

```
#Best model:  ARIMA(1,0,1)(0,1,1)[12] intercept

#split dataset for test and training
X = df_agg['RevenueDiff1']
train, test = X[1:len(X)-12], X[len(X)-12:]

differenced_series = df_agg['RevenueDiff1']


# Specify the orders (p, d, q) and seasonal orders (P, D, Q, S) of the
SARIMA model
p = 1  # Replace with the desired AR order
d = 0  # Replace with the desired differencing order
q = 1  # Replace with the desired MA order
P = 0  # Replace with the desired seasonal AR order
D = 1  # Replace with the desired seasonal differencing order
Q = 1  # Replace with the desired seasonal MA order
S = 12  # Replace with the length of the seasonal cycle (e.g., 12 for
monthly data)

# Fit the SARIMA model
sarima_model = SARIMAX(train, order=(p, d, q), seasonal_order=(P, D,
Q, S))
sarima_results = sarima_model.fit()

#print(sarima_results.summary())

sarima_forecast = sarima_results.predict(start=len(train),
end=len(train)+len(test)-1,)

rmse = sqrt(mean_squared_error(test, sarima_forecast))
print('Test RMSE: %.3f' % rmse)
r2s = r2_score(test, sarima_forecast)
print('Test R2: %.3f' % r2s)
mae = mean_absolute_error(test, sarima_forecast)
print('Test MAE: %.3f' % mae)

#as differencing was applied, need to back transform the forecast to
the original scale
original_forecast = sarima_forecast.cumsum() + df_agg['Total Revenue']


# Plot the original series and the forecast
plt.plot(df_agg['Total Revenue'], label='Original Series')
plt.plot(original_forecast, label='SARIMA Forecast',
linestyle='dashed')
plt.legend()
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)

Test RMSE: 412.061
Test R2: 0.686
Test MAE: 320.800
```



#Exploring new Libraries

##TBATS

```
X = df_agg['Total Revenue']
train, test = X[1:len(X)-12], X[len(X)-12:]

estimator = TBATS(seasonal_periods=(12,))

model_tbats = estimator.fit(train)

y_forecast = model_tbats.forecast(steps=12)


# Summarize fitted model
print('Model Summary:')
print(model_tbats.summary())
print('\n\n')

# Time series analysis
#print('Model Summary:')
```

```
#print(model_tbats.y_hat) # in sample prediction
#print('\n\n')
#print(model_tbats.resid) # in sample residuals
#print('\n\n')
#print(model_tbats.aic)
#print('\n\n')

# Reading model parameters
print('Param alpha')
print(model_tbats.params.alpha)

print('\nParam beta')
print(model_tbats.params.beta)

print('\nParam x0')
print(model_tbats.params.x0)

print('\nParam box_cox required')
print(model_tbats.params.components.use_box_cox)

print('\nParam seasonal_harmonics')
print(model_tbats.params.components.seasonal_harmonics)
```

```
Model Summary:
Use Box-Cox: True
Use trend: False
Use damped trend: False
Seasonal periods: [12.]
Seasonal harmonics [5]
ARMA errors (p, q): (1, 1)
Box-Cox Lambda 1.000000
Smoothing (Alpha): 0.010317
Seasonal Parameters (Gamma): [-0.00673328  0.01924612]
AR coefficients [0.01924612]
MA coefficients [-0.23723979]
Seed vector [ 1.45973091e+04 -1.64991396e+02 -1.00655847e+02 -
2.12415846e+02
 -1.60105135e+02 -2.95707960e+02  3.78700260e+00 -4.84908017e+01
  1.13056243e+01 -6.56572031e+01  2.74279022e+02  0.00000000e+00
  0.00000000e+00]

AIC 1222.360158



Param alpha
0.01031709710684131

Param beta
None
```

```
Param x0
[ 1.45973091e+04 -1.64991396e+02 -1.00655847e+02 -2.12415846e+02
 -1.60105135e+02 -2.95707960e+02  3.78700260e+00 -4.84908017e+01
  1.13056243e+01 -6.56572031e+01  2.74279022e+02  0.00000000e+00
  0.00000000e+00]

Param box_cox required
True

Param seasonal_harmonics
[5]
```

```
#with differenced data points

X = df_agg['RevenueDiff1']
train, test = X[1:len(X)-12], X[len(X)-12:]

estimator = TBATS(seasonal_periods=(12,))

model_tbats = estimator.fit(train)

y_forecast = model_tbats.forecast(steps=12)


# Summarize fitted model
print(model_tbats.summary())

# Time series analysis
#print(model_tbats.y_hat) # in sample prediction
#print(model_tbats.resid) # in sample residuals
#print(model_tbats.aic)

# Reading model parameters
print('Param alpha')
print(model_tbats.params.alpha)

print('\nParam beta')
print(model_tbats.params.beta)

print('\nParam x0')
print(model_tbats.params.x0)

print('\nParam box_cox required')
print(model_tbats.params.components.use_box_cox)

print('\nParam seasonal_harmonics')
print(model_tbats.params.components.seasonal_harmonics)
```

```
Use Box-Cox: False
Use trend: False
Use damped trend: False
```

```
Seasonal periods: [12.]
Seasonal harmonics [5]
ARMA errors (p, q): (5, 3)
Smoothing (Alpha): 0.017869
Seasonal Parameters (Gamma): [-6.54788656e-05 -3.48052384e-06]
AR coefficients [-3.48052384e-06  5.51987861e-01 -2.48648607e-01
7.30197270e-03
 -9.47510262e-02]
MA coefficients [-0.34055473 -0.29759187  0.1765482 ]
Seed vector [  11.56833157  -12.35889955  -93.67812    -193.31821582 -
298.37447141
 -406.87140391   83.18381187   62.29581034  223.78606978   39.95953963
  659.74321802    0.            0.            0.            0.
    0.            0.            0.            0.        ]

AIC 1272.726164
Param alpha
0.017868666000039383

Param beta
None

Param x0
[  11.56833157  -12.35889955  -93.67812    -193.31821582 -298.37447141
 -406.87140391   83.18381187   62.29581034  223.78606978   39.95953963
  659.74321802    0.            0.            0.            0.
    0.            0.            0.            0.        ]

Param box_cox required
False

Param seasonal_harmonics
[5]
```

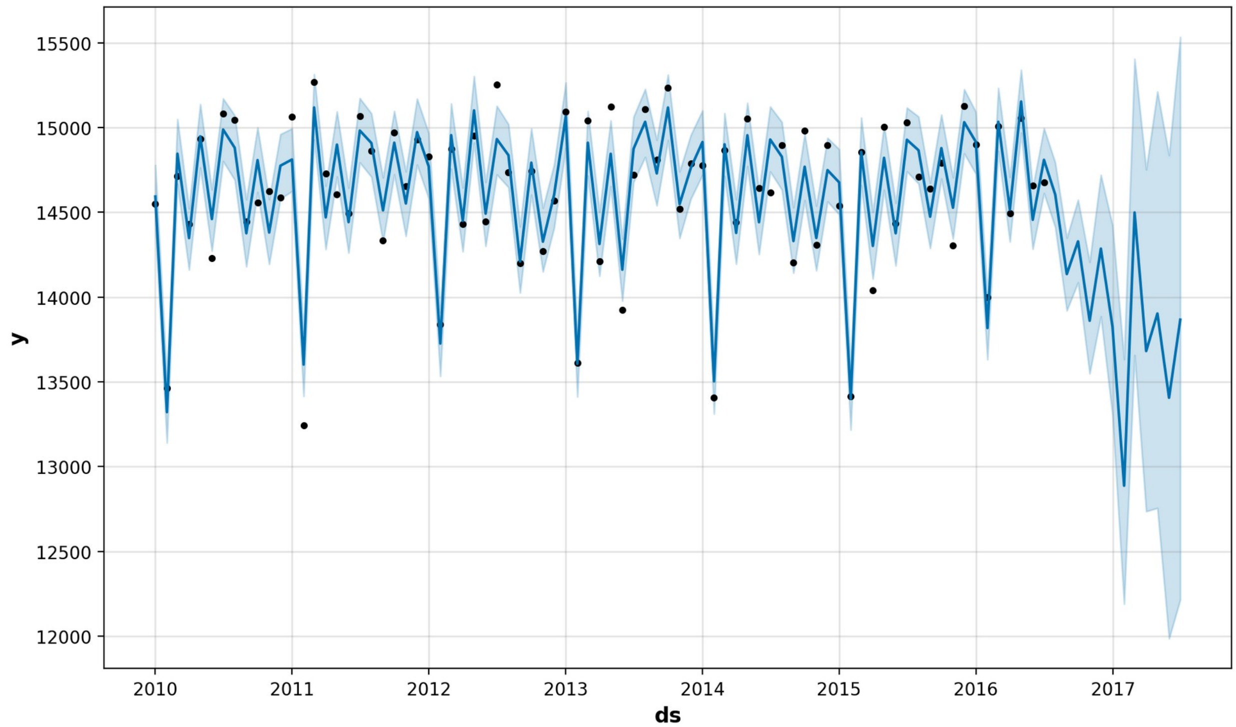
##FB Prophet

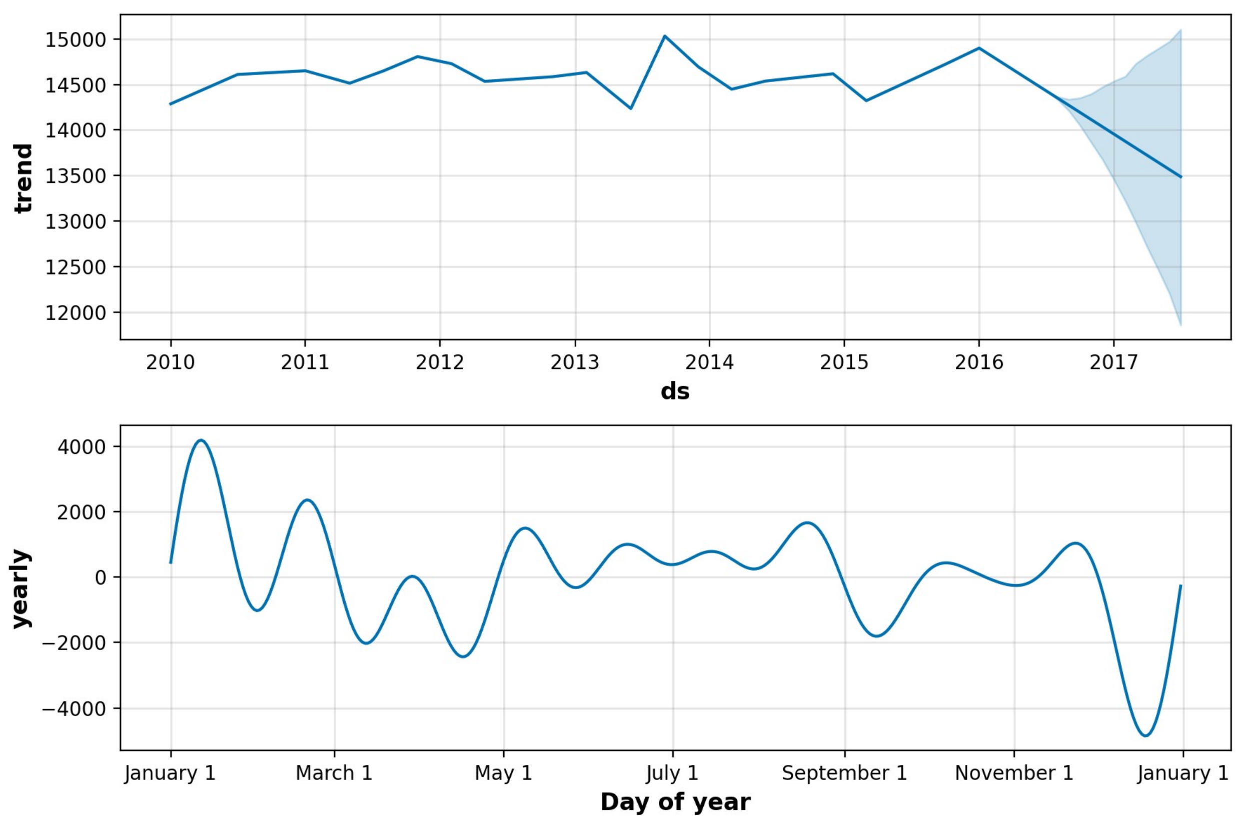
```
ts = pd.DataFrame({'ds':df_agg.index,'y':df_agg['Total Revenue']})
ts

                    ds             y
Order_Month
2010-01-01  2010-01-01  14547.786773
2010-02-01  2010-02-01  13463.186840
2010-03-01  2010-03-01  14712.532049
2010-04-01  2010-04-01  14429.823464
2010-05-01  2010-05-01  14931.168615
...                ...           ...
2017-03-01  2017-03-01  14642.602650
2017-04-01  2017-04-01  14570.593984
2017-05-01  2017-05-01  14943.426668
```

```
2017-06-01  2017-06-01  14352.098946
2017-07-01  2017-07-01  13769.014644

[91 rows x 2 columns]
```

```
#train test split (last 12 data points for 1 year)
ts_test = ts.iloc[-12:,:]
ts_train = ts.iloc[:-12,:]

#instantiate the model and fit the time-series
m = Prophet(yearly_seasonality=True,
changepoint_range=1,changepoint_prior_scale=1)
m.fit(ts_train)

future = m.make_future_dataframe(periods=12 * 1, freq='M')
forecast = m.predict(future)

forecast[['ds','yhat','yhat_lower','yhat_upper']].tail()

#plotting outcome
fig1 = m.plot(forecast)
fig2 = m.plot_components(forecast)
```

```
INFO:prophet:Disabling weekly 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/tmpuu_jbtp0/2r2h70ou.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpuu_jbtp0/ny7mxpbr.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=98809', 'data', 'file=/tmp/tmpuu_jbtp0/2r2h70ou.json',
'init=/tmp/tmpuu_jbtp0/ny7mxpbr.json', 'output',
'file=/tmp/tmpuu_jbtp0/prophet_modelcnt4ky5t/prophet_model-
20231125215438.csv', 'method=optimize', 'algorithm=newton',
'iter=10000']
21:54:38 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
21:54:38 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```

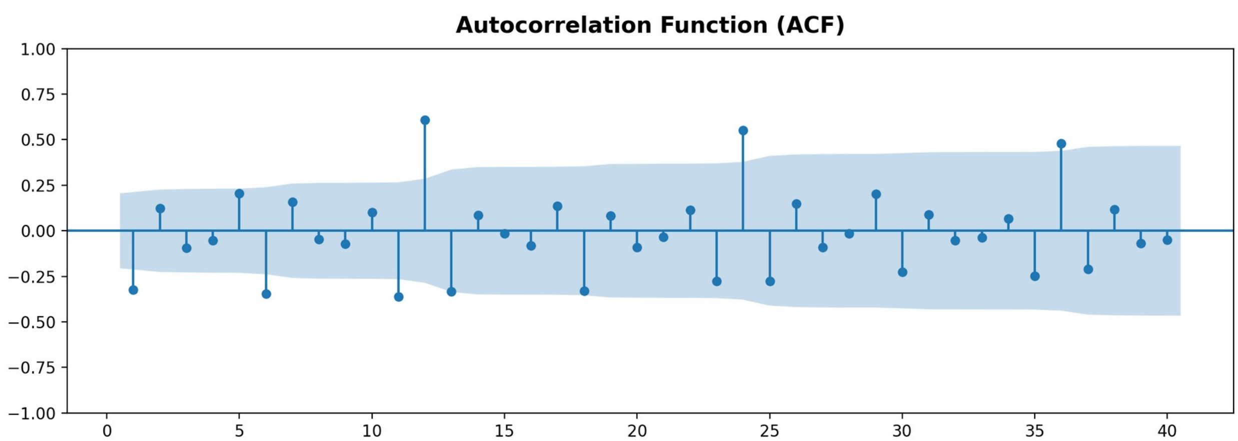

y
15500
15000
14500
14000
13500
13000
12500
12000
2010
2011
2012
2013
2014
2015
2016
2017
ds


trend
15000
14500
14000
13500
13000
12500
12000
2010
2011
2012
2013
2014
2015
2016
2017
ds
yearly
4000
2000
0
−2000
−4000
January 1
March 1
May 1
July 1
September 1
November 1
January 1
Day of year

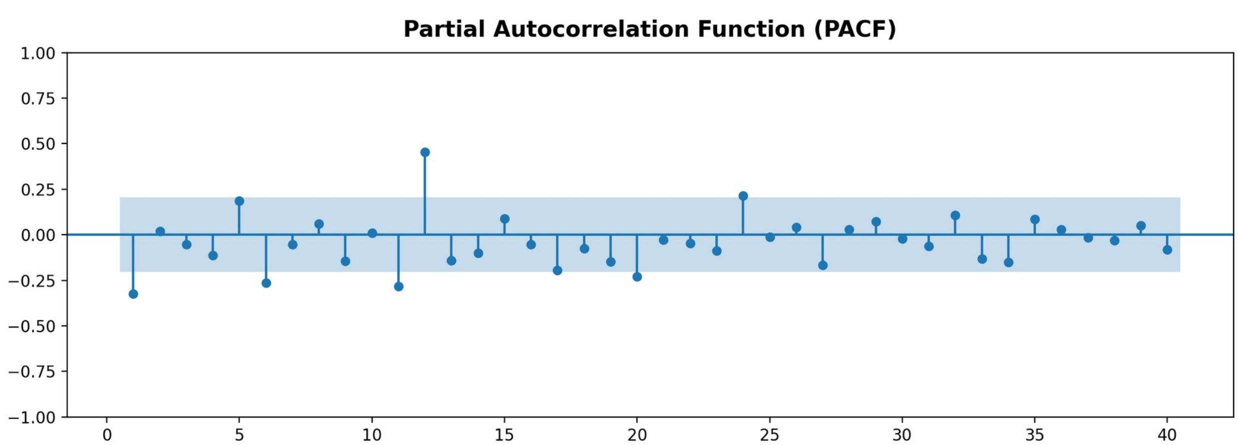
##ACF & PACF

```
# Plot ACF
plt.figure(figsize=(12, 4))
plot_acf(df_agg['Total Revenue'], lags=40, zero=False)  # Adjust
'lags' as needed
plt.title('Autocorrelation Function (ACF)')
plt.show()

# Plot PACF
plt.figure(figsize=(12, 4))
plot_pacf(df_agg['Total Revenue'], lags=40, zero=False)  # Adjust
'lags' as needed
plt.title('Partial Autocorrelation Function (PACF)')
plt.show()
```

```
<Figure size 1200x400 with 0 Axes>
```




```
<Figure size 1200x400 with 0 Axes>
```



#Conclusion

After running both ARIMA and SARIMA using the best hyperparameters (from tuning) we can conclude that SARIMA produced better results as seasonal component is present in our dataset (annual frequency).

The final results from evaluation metrics, RMSE and MAE both produce a lower error for SARIMA, mentioned below:

ARIMA

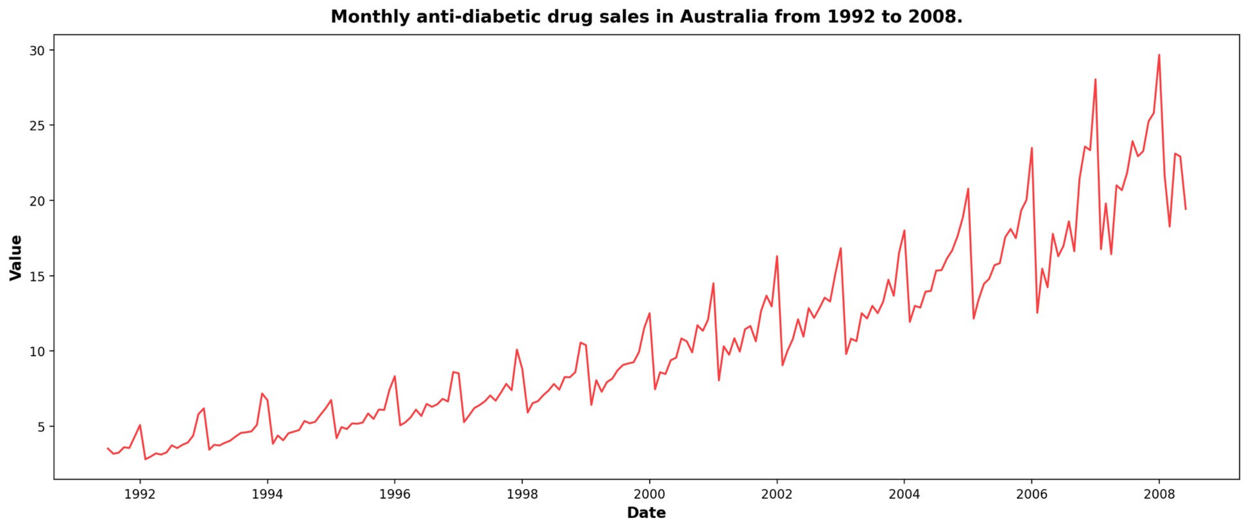
- RMSE: 692.151
- MAE: 534.061

SARIMA

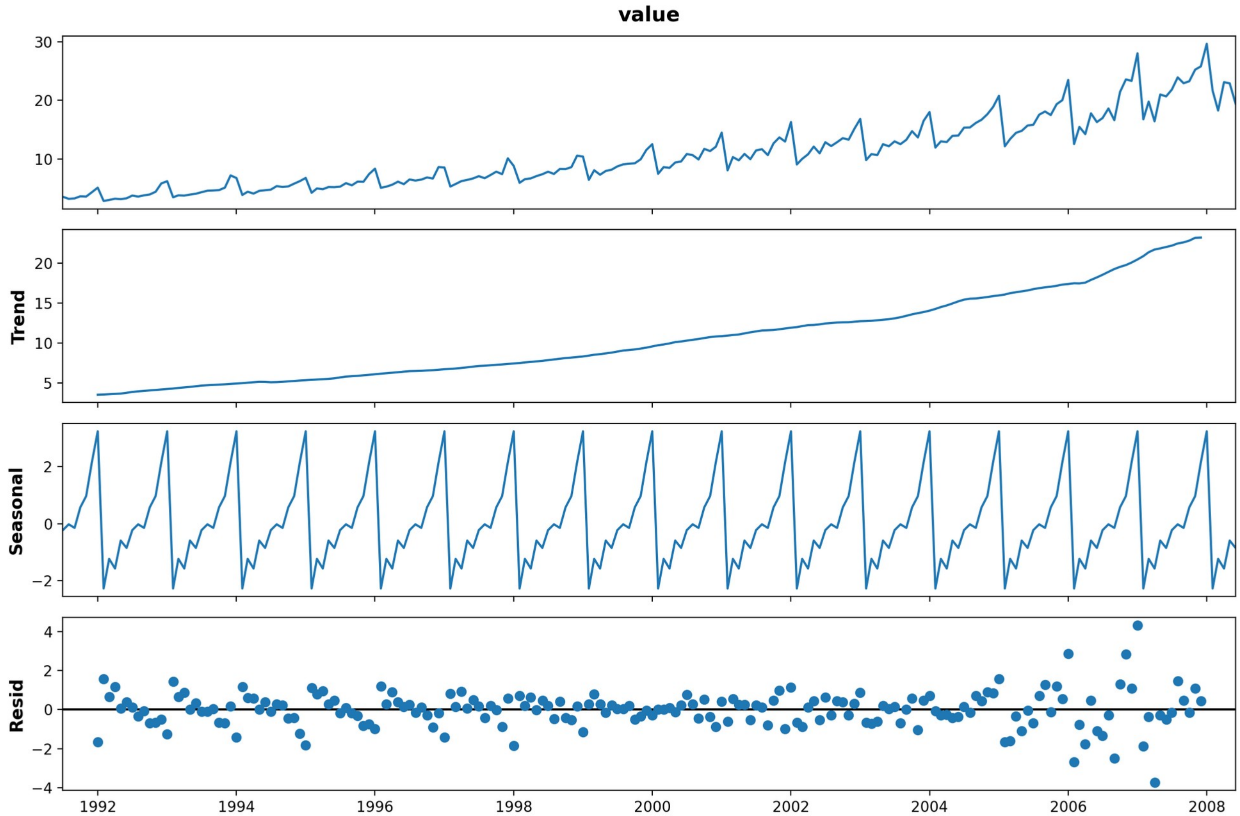
- RMSE: 412.061
- MAE: 320.800

#Another Simpler Example for understanding

```
# Time series data source

aust_drug_df =
pd.read_csv('https://raw.githubusercontent.com/selva86/datasets/master
/a10.csv', parse_dates=['date'], index_col='date')

# Draw Plot
def plot_df(df, x, y, title="", xlabel='Date', ylabel='Value',
dpi=100):
    plt.figure(figsize=(14,6), dpi=dpi)
    plt.plot(x, y, color='#F94144')
    plt.gca().set(title=title, xlabel=xlabel, ylabel=ylabel)
    plt.show()

plot_df(aust_drug_df, x=aust_drug_df.index, y=aust_drug_df.value,
title='Monthly anti-diabetic drug sales in Australia from 1992 to
2008.')
```




```
aust_drug_df['RevenueDiff1'] = aust_drug_df['value'].diff().fillna(0)
aust_drug_df

                value  RevenueDiff1
date
1991-07-01   3.526591      0.000000
1991-08-01   3.180891     -0.345700
1991-09-01   3.252221      0.071330
1991-10-01   3.611003      0.358782
1991-11-01   3.565869     -0.045134
...               ...           ...
2008-02-01  21.654285     -8.011071
2008-03-01  18.264945     -3.389340
2008-04-01  23.107677      4.842732
2008-05-01  22.912510     -0.195167
2008-06-01  19.431740     -3.480770

[204 rows x 2 columns]


rcParams['figure.figsize'] = 12, 8
decomposition = sm.tsa.seasonal_decompose(aust_drug_df.value, 
model='additive') # additive seasonal index
fig = decomposition.plot()
plt.show()
```




```
#seasonal False - fit stepwise auto-ARIMA
arima_model = auto_arima(aust_drug_df['RevenueDiff1'], start_p=1,
start_q=1,
                         test='adf',
                         max_p=4, max_q=4, m=12,
                         start_P=0, seasonal=False,
                         d=None, D=1, trace=True,
                         error_action='ignore',
                         suppress_warnings=True,
                         stepwise=True)
```

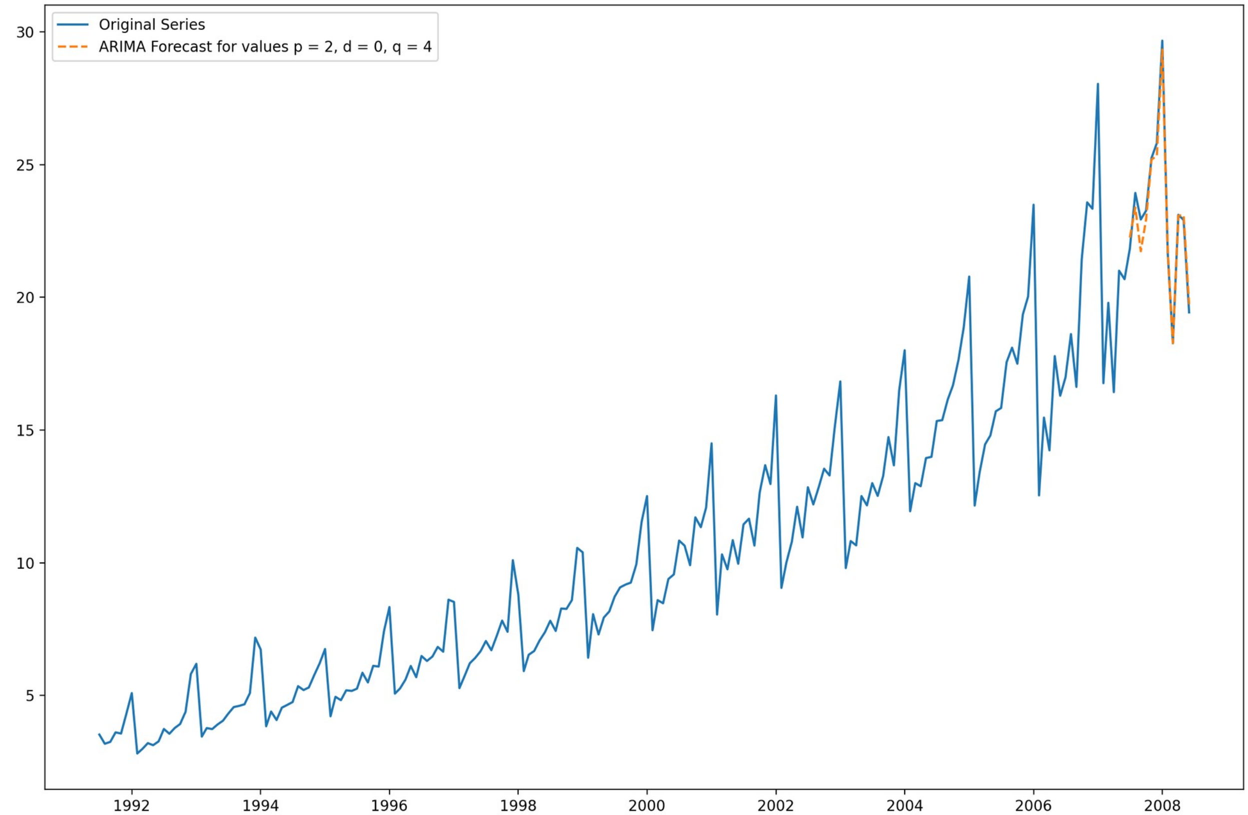
```
/usr/local/lib/python3.10/dist-packages/pmdarima/arima/
_validation.py:62: UserWarning: m (12) set for non-seasonal fit.
Setting to 0
  warnings.warn("m (%i) set for non-seasonal fit. Setting to 0" % m)

Performing stepwise search to minimize aic
 ARIMA(1,0,1)(0,0,0)[0]             : AIC=858.703, Time=0.31 sec
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=908.586, Time=0.11 sec
 ARIMA(1,0,0)(0,0,0)[0]             : AIC=881.504, Time=0.12 sec
 ARIMA(0,0,1)(0,0,0)[0]             : AIC=867.517, Time=0.20 sec
 ARIMA(2,0,1)(0,0,0)[0]             : AIC=860.043, Time=0.40 sec
 ARIMA(1,0,2)(0,0,0)[0]             : AIC=860.318, Time=0.39 sec
 ARIMA(0,0,2)(0,0,0)[0]             : AIC=861.393, Time=0.23 sec
 ARIMA(2,0,0)(0,0,0)[0]             : AIC=879.107, Time=0.18 sec
```

```
 ARIMA(2,0,2)(0,0,0)[0]             : AIC=851.128, Time=1.36 sec
 ARIMA(3,0,2)(0,0,0)[0]             : AIC=853.045, Time=0.83 sec
 ARIMA(2,0,3)(0,0,0)[0]             : AIC=862.585, Time=0.55 sec
 ARIMA(1,0,3)(0,0,0)[0]             : AIC=860.673, Time=0.30 sec
 ARIMA(3,0,1)(0,0,0)[0]             : AIC=860.352, Time=0.36 sec
 ARIMA(3,0,3)(0,0,0)[0]             : AIC=848.186, Time=2.09 sec
 ARIMA(4,0,3)(0,0,0)[0]             : AIC=inf, Time=2.27 sec
 ARIMA(3,0,4)(0,0,0)[0]             : AIC=inf, Time=2.88 sec
 ARIMA(2,0,4)(0,0,0)[0]             : AIC=845.074, Time=0.87 sec
 ARIMA(1,0,4)(0,0,0)[0]             : AIC=862.636, Time=0.67 sec
 ARIMA(2,0,4)(0,0,0)[0] intercept   : AIC=833.588, Time=2.75 sec
 ARIMA(1,0,4)(0,0,0)[0] intercept   : AIC=850.866, Time=0.96 sec
 ARIMA(2,0,3)(0,0,0)[0] intercept   : AIC=836.481, Time=2.51 sec
 ARIMA(3,0,4)(0,0,0)[0] intercept   : AIC=inf, Time=2.49 sec
 ARIMA(1,0,3)(0,0,0)[0] intercept   : AIC=848.915, Time=0.86 sec
 ARIMA(3,0,3)(0,0,0)[0] intercept   : AIC=836.350, Time=2.37 sec

Best model:  ARIMA(2,0,4)(0,0,0)[0] intercept
Total fit time: 26.168 seconds
```

```
print('Calling ARIMA Model:')
arima_rmse, arima_r2s, arima_mae = arima_calc_rmse_r2(aust_drug_df,
'value', 'RevenueDiff1', 12, 2, 0, 4)
```

```
Calling ARIMA Model:

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/statespace/
sarimax.py:966: UserWarning: Non-stationary starting autoregressive
parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/statespace/
sarimax.py:978: UserWarning: Non-invertible starting MA parameters
found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py:607:
ConvergenceWarning: Maximum Likelihood optimization failed to
converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

```
Test RMSE: 3.496
Test R2: -0.069
Test MAE: 2.644
```



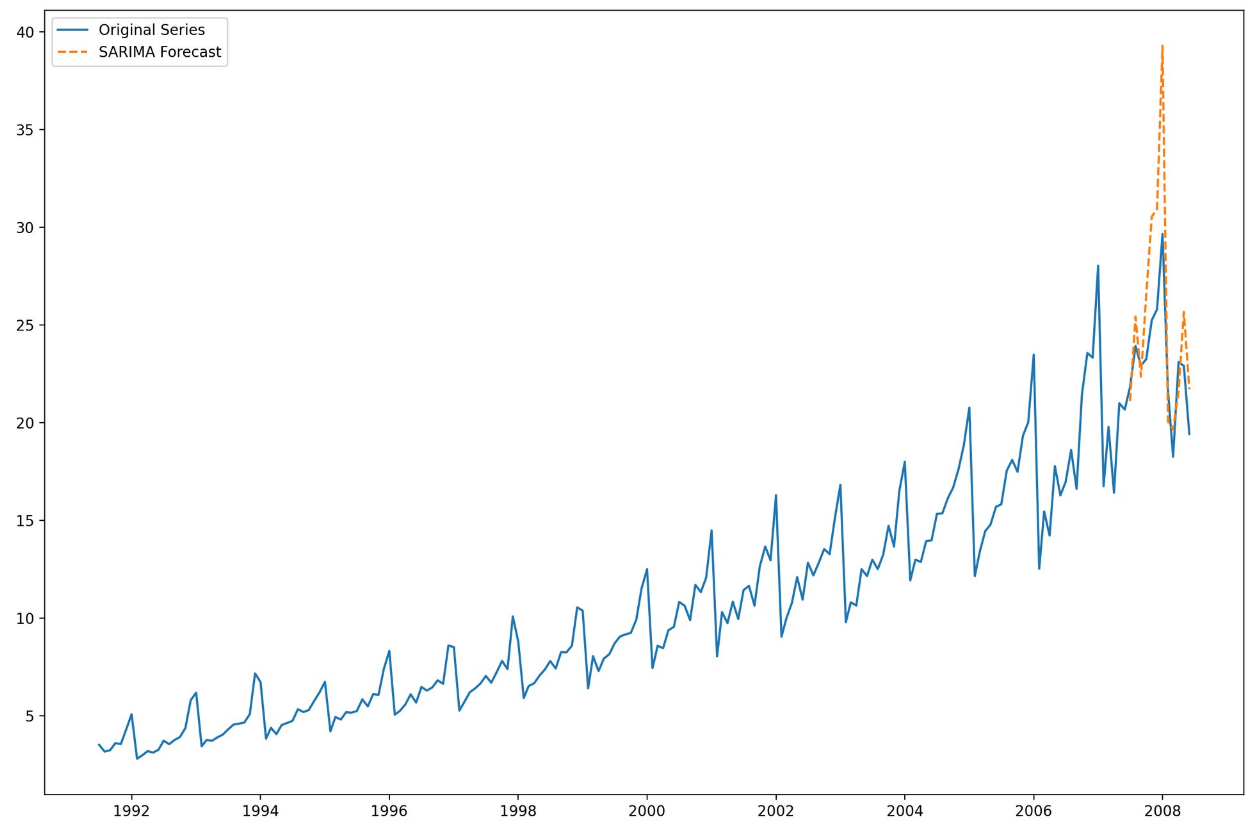

```
#seasonal True - fit stepwise auto-ARIMA
arima_model = auto_arima(aust_drug_df['RevenueDiff1'], start_p=1,
start_q=1,
                         test='adf',
                         max_p=4, max_q=4, m=12,
                         start_P=0, seasonal=True,
                         d=None, D=1, trace=True,
                         error_action='ignore',
                         suppress_warnings=True,
                         stepwise=True)

Performing stepwise search to minimize aic
 ARIMA(1,0,1)(0,1,1)[12] intercept   : AIC=529.065, Time=0.80 sec
 ARIMA(0,0,0)(0,1,0)[12] intercept   : AIC=663.801, Time=0.06 sec
 ARIMA(1,0,0)(1,1,0)[12] intercept   : AIC=564.758, Time=0.39 sec
 ARIMA(0,0,1)(0,1,1)[12] intercept   : AIC=531.871, Time=0.69 sec
 ARIMA(0,0,0)(0,1,0)[12]             : AIC=661.803, Time=0.05 sec
 ARIMA(1,0,1)(0,1,0)[12] intercept   : AIC=559.091, Time=0.23 sec
 ARIMA(1,0,1)(1,1,1)[12] intercept   : AIC=530.520, Time=1.32 sec
 ARIMA(1,0,1)(0,1,2)[12] intercept   : AIC=530.109, Time=5.54 sec
```

```
 ARIMA(1,0,1)(1,1,0)[12] intercept   : AIC=534.753, Time=1.68 sec
 ARIMA(1,0,1)(1,1,2)[12] intercept   : AIC=532.511, Time=7.50 sec
 ARIMA(1,0,0)(0,1,1)[12] intercept   : AIC=557.195, Time=0.79 sec
 ARIMA(2,0,1)(0,1,1)[12] intercept   : AIC=533.629, Time=1.74 sec
 ARIMA(1,0,2)(0,1,1)[12] intercept   : AIC=530.938, Time=5.21 sec
 ARIMA(0,0,0)(0,1,1)[12] intercept   : AIC=639.224, Time=0.79 sec
 ARIMA(0,0,2)(0,1,1)[12] intercept   : AIC=530.339, Time=4.27 sec
 ARIMA(2,0,0)(0,1,1)[12] intercept   : AIC=531.942, Time=0.94 sec
 ARIMA(2,0,2)(0,1,1)[12] intercept   : AIC=529.067, Time=3.37 sec
 ARIMA(1,0,1)(0,1,1)[12]             : AIC=528.118, Time=0.69 sec
 ARIMA(1,0,1)(0,1,0)[12]             : AIC=557.250, Time=0.25 sec
 ARIMA(1,0,1)(1,1,1)[12]             : AIC=529.612, Time=1.00 sec
 ARIMA(1,0,1)(0,1,2)[12]             : AIC=529.228, Time=2.31 sec
 ARIMA(1,0,1)(1,1,0)[12]             : AIC=533.501, Time=0.62 sec
 ARIMA(1,0,1)(1,1,2)[12]             : AIC=531.606, Time=4.55 sec
 ARIMA(0,0,1)(0,1,1)[12]             : AIC=531.975, Time=0.66 sec
 ARIMA(1,0,0)(0,1,1)[12]             : AIC=555.262, Time=0.62 sec
 ARIMA(2,0,1)(0,1,1)[12]             : AIC=531.902, Time=0.96 sec
 ARIMA(1,0,2)(0,1,1)[12]             : AIC=530.056, Time=0.94 sec
 ARIMA(0,0,0)(0,1,1)[12]             : AIC=637.231, Time=0.22 sec
 ARIMA(0,0,2)(0,1,1)[12]             : AIC=529.437, Time=0.42 sec
 ARIMA(2,0,0)(0,1,1)[12]             : AIC=530.262, Time=0.34 sec
 ARIMA(2,0,2)(0,1,1)[12]             : AIC=527.787, Time=1.33 sec
 ARIMA(2,0,2)(0,1,0)[12]             : AIC=554.271, Time=0.39 sec
 ARIMA(2,0,2)(1,1,1)[12]             : AIC=529.277, Time=1.69 sec
 ARIMA(2,0,2)(0,1,2)[12]             : AIC=528.817, Time=2.73 sec
 ARIMA(2,0,2)(1,1,0)[12]             : AIC=532.676, Time=0.95 sec
 ARIMA(2,0,2)(1,1,2)[12]             : AIC=531.177, Time=8.82 sec
 ARIMA(3,0,2)(0,1,1)[12]             : AIC=522.787, Time=1.12 sec
 ARIMA(3,0,2)(0,1,0)[12]             : AIC=547.366, Time=0.50 sec
 ARIMA(3,0,2)(1,1,1)[12]             : AIC=524.448, Time=1.53 sec
 ARIMA(3,0,2)(0,1,2)[12]             : AIC=524.137, Time=2.65 sec
 ARIMA(3,0,2)(1,1,0)[12]             : AIC=528.512, Time=1.13 sec
 ARIMA(3,0,2)(1,1,2)[12]             : AIC=525.989, Time=6.81 sec
 ARIMA(3,0,1)(0,1,1)[12]             : AIC=525.973, Time=1.71 sec
 ARIMA(4,0,2)(0,1,1)[12]             : AIC=524.605, Time=3.02 sec
 ARIMA(3,0,3)(0,1,1)[12]             : AIC=524.686, Time=1.28 sec
 ARIMA(2,0,3)(0,1,1)[12]             : AIC=525.964, Time=1.34 sec
 ARIMA(4,0,1)(0,1,1)[12]             : AIC=522.674, Time=0.86 sec
 ARIMA(4,0,1)(0,1,0)[12]             : AIC=552.927, Time=0.23 sec
 ARIMA(4,0,1)(1,1,1)[12]             : AIC=524.150, Time=1.88 sec
 ARIMA(4,0,1)(0,1,2)[12]             : AIC=523.609, Time=2.08 sec
 ARIMA(4,0,1)(1,1,0)[12]             : AIC=529.653, Time=0.97 sec
 ARIMA(4,0,1)(1,1,2)[12]             : AIC=525.609, Time=8.14 sec
 ARIMA(4,0,0)(0,1,1)[12]             : AIC=527.148, Time=1.01 sec
 ARIMA(3,0,0)(0,1,1)[12]             : AIC=532.223, Time=0.87 sec
 ARIMA(4,0,1)(0,1,1)[12] intercept   : AIC=522.396, Time=4.91 sec
 ARIMA(4,0,1)(0,1,0)[12] intercept   : AIC=554.734, Time=0.45 sec
 ARIMA(4,0,1)(1,1,1)[12] intercept   : AIC=523.839, Time=2.77 sec
```

```
 ARIMA(4,0,1)(0,1,2)[12] intercept   : AIC=523.286, Time=5.34 sec
 ARIMA(4,0,1)(1,1,0)[12] intercept   : AIC=529.716, Time=4.43 sec
 ARIMA(4,0,1)(1,1,2)[12] intercept   : AIC=525.473, Time=8.97 sec
 ARIMA(3,0,1)(0,1,1)[12] intercept   : AIC=inf, Time=3.01 sec
 ARIMA(4,0,0)(0,1,1)[12] intercept   : AIC=528.653, Time=0.65 sec
 ARIMA(4,0,2)(0,1,1)[12] intercept   : AIC=523.080, Time=5.72 sec
 ARIMA(3,0,0)(0,1,1)[12] intercept   : AIC=533.911, Time=1.18 sec
 ARIMA(3,0,2)(0,1,1)[12] intercept   : AIC=521.080, Time=5.23 sec
 ARIMA(3,0,2)(0,1,0)[12] intercept   : AIC=inf, Time=1.53 sec
 ARIMA(3,0,2)(1,1,1)[12] intercept   : AIC=522.929, Time=3.90 sec
 ARIMA(3,0,2)(0,1,2)[12] intercept   : AIC=522.731, Time=10.93 sec
 ARIMA(3,0,2)(1,1,0)[12] intercept   : AIC=527.486, Time=3.36 sec
 ARIMA(3,0,2)(1,1,2)[12] intercept   : AIC=524.157, Time=10.53 sec
 ARIMA(3,0,3)(0,1,1)[12] intercept   : AIC=523.207, Time=5.31 sec
 ARIMA(2,0,3)(0,1,1)[12] intercept   : AIC=526.886, Time=1.92 sec
 ARIMA(4,0,3)(0,1,1)[12] intercept   : AIC=525.078, Time=3.98 sec

Best model:  ARIMA(3,0,2)(0,1,1)[12] intercept
Total fit time: 186.320 seconds

#split dataset for test and training
X = aust_drug_df['RevenueDiff1']
train, test = X[1:len(X)-12], X[len(X)-12:]

differenced_series = aust_drug_df['RevenueDiff1']


# Specify the orders (p, d, q) and seasonal orders (P, D, Q, S) of the
SARIMA model
p = 3  # Replace with the desired AR order
d = 0  # Replace with the desired differencing order
q = 2  # Replace with the desired MA order
P = 0  # Replace with the desired seasonal AR order
D = 1  # Replace with the desired seasonal differencing order
Q = 1  # Replace with the desired seasonal MA order
S = 12  # Replace with the length of the seasonal cycle (e.g., 12 for
monthly data)

# Fit the SARIMA model
sarima_model = SARIMAX(train, order=(p, d, q), seasonal_order=(P, D,
Q, S))
sarima_results = sarima_model.fit()

#print(sarima_results.summary())

sarima_forecast = sarima_results.predict(start=len(train),
end=len(train)+len(test)-1,)

rmse = sqrt(mean_squared_error(test, sarima_forecast))
print('Test RMSE: %.3f' % rmse)
```

```python
r2s = r2_score(test, sarima_forecast)
print('Test R2: %.3f' % r2s)
mae = mean_absolute_error(test, sarima_forecast)
print('Test MAE: %.3f' % mae)

# If differencing was applied, backtransform the forecast to the
original scale
original_forecast = sarima_forecast.cumsum() + aust_drug_df['value']


# Plot the original series and the forecast
plt.plot(aust_drug_df['value'], label='Original Series')
plt.plot(original_forecast, label='SARIMA Forecast',
linestyle='dashed')
plt.legend()
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency MS will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: No frequency information was provided, so
inferred frequency MS will be used.
  self._init_dates(dates, freq)

Test RMSE: 3.626
Test R2: -0.150
Test MAE: 2.726
```



#References:

https://www.analyticsvidhya.com/blog/2021/10/a-comprehensive-guide-to-time-series-analysis/#Converting_Non-Stationary_Into_Stationary

https://towardsdatascience.com/time-series-analysis-with-facebook-prophet-how-it-works-and-how-to-use-it-f15ecf2c0e3a

https://www.analyticsvidhya.com/blog/2021/06/statistical-tests-to-check-stationarity-in-time-series-part-1/#:~:text=There%20are%20various%20statistical%20tests,unit%20root%20in%20the%20data.

https://towardsdatascience.com/time-series-forecasting-based-on-the-trend-and-seasonal-components-26b92866e548

https://www.geeksforgeeks.org/time-series-analysis-using-facebook-prophet/

https://towardsdatascience.com/time-series-analysis-with-facebook-prophet-how-it-works-and-how-to-use-it-f15ecf2c0e3a

https://medium.com/analytics-vidhya/time-series-forecasting-using-tbats-model-ce8c429442a9

https://www.influxdata.com/blog/forecasting-with-fb-prophet-and-influxdb/