Importing Necessary Packages

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import acf
from statsmodels.tsa.stattools import pacf
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf
import statsmodels.api as sm
from statsmodels.tsa.statespace.sarimax import SARIMAX, SARIMAXResults
```

Data Preprocessing

```
df=pd.read_csv(r"C:\Users\Arigala.Adarsh\Downloads\
re1386870regardingcapstoneproject\Walmart (1).csv")

df
```

```
      Store        Date  Weekly_Sales  Holiday_Flag  Temperature
Fuel_Price  \
0         1  05-02-2010    1643690.90             0        42.31
2.572
1         1  12-02-2010    1641957.44             1        38.51
2.548
2         1  19-02-2010    1611968.17             0        39.93
2.514
3         1  26-02-2010    1409727.59             0        46.63
2.561
4         1  05-03-2010    1554806.68             0        46.50
2.625
...     ...         ...           ...           ...          ...
...
6430     45  28-09-2012     713173.95             0        64.88
3.997
6431     45  05-10-2012     733455.07             0        64.89
3.985
6432     45  12-10-2012     734464.36             0        54.47
4.000
6433     45  19-10-2012     718125.53             0        56.47
3.969
6434     45  26-10-2012     760281.43             0        58.85
3.882
```

```
              CPI  Unemployment
0      211.096358         8.106
1      211.242170         8.106
2      211.289143         8.106
3      211.319643         8.106
4      211.350143         8.106
...           ...           ...
6430   192.013558         8.684
6431   192.170412         8.667
6432   192.327265         8.667
6433   192.330854         8.667
6434   192.308899         8.667

[6435 rows x 8 columns]
```

Feature Name & Description

- **Store** : Store number
- **Date** : Week of Sales
- **Weekly_Sales** : Sales for the given store in that week
- **Holiday_Flag** : If it is a holiday week
- **Temperature** : Temperature on the day of the sale
- **Fuel_Price** : Cost of the fuel in the region
- **CPI Consumer** : Price Index
- **Unemployment** : Unemployment Rate

Exploratory Data Analysis(EDA)

```
df.shape
```

```
(6435, 8)
```

```
df.columns
```

```
Index(['Store', 'Date', 'Weekly_Sales', 'Holiday_Flag', 'Temperature',
       'Fuel_Price', 'CPI', 'Unemployment'],
      dtype='object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6435 entries, 0 to 6434
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Store         6435 non-null   int64
```

```
 1   Date          6435 non-null   object
 2   Weekly_Sales  6435 non-null   float64
 3   Holiday_Flag  6435 non-null   int64
 4   Temperature   6435 non-null   float64
 5   Fuel_Price    6435 non-null   float64
 6   CPI           6435 non-null   float64
 7   Unemployment  6435 non-null   float64
dtypes: float64(5), int64(2), object(1)
memory usage: 402.3+ KB
```

```
df.describe()
```

```
              Store  Weekly_Sales  Holiday_Flag  Temperature
Fuel_Price  \
count  6435.000000  6.435000e+03   6435.000000  6435.000000
6435.000000
mean     23.000000  1.046965e+06      0.069930    60.663782
3.358607
std      12.988182  5.643666e+05      0.255049    18.444933
0.459020
min       1.000000  2.099862e+05      0.000000    -2.060000
2.472000
25%      12.000000  5.533501e+05      0.000000    47.460000
2.933000
50%      23.000000  9.607460e+05      0.000000    62.670000
3.445000
75%      34.000000  1.420159e+06      0.000000    74.940000
3.735000
max      45.000000  3.818686e+06      1.000000   100.140000
4.468000

                CPI  Unemployment
count  6435.000000   6435.000000
mean    171.578394      7.999151
std      39.356712      1.875885
min     126.064000      3.879000
25%     131.735000      6.891000
50%     182.616521      7.874000
75%     212.743293      8.622000
max     227.232807     14.313000
```

```
df.isnull().sum()
```

```
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
```

```
Unemployment    0
dtype: int64
```

```
df.duplicated()
```

```
0       False
1       False
2       False
3       False
4       False
        ...
6430    False
6431    False
6432    False
6433    False
6434    False
Length: 6435, dtype: bool
```

```
df.duplicated().sum()
```

```
0
```

```
df.dtypes
```

```
Store             int64
Date             object
Weekly_Sales    float64
Holiday_Flag      int64
Temperature     float64
Fuel_Price      float64
CPI             float64
Unemployment    float64
dtype: object
```

```
df.Store.unique()
```

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
17,
       18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
34,
       35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45], dtype=int64)
```

```
df.Store.nunique()
```

```
45
```

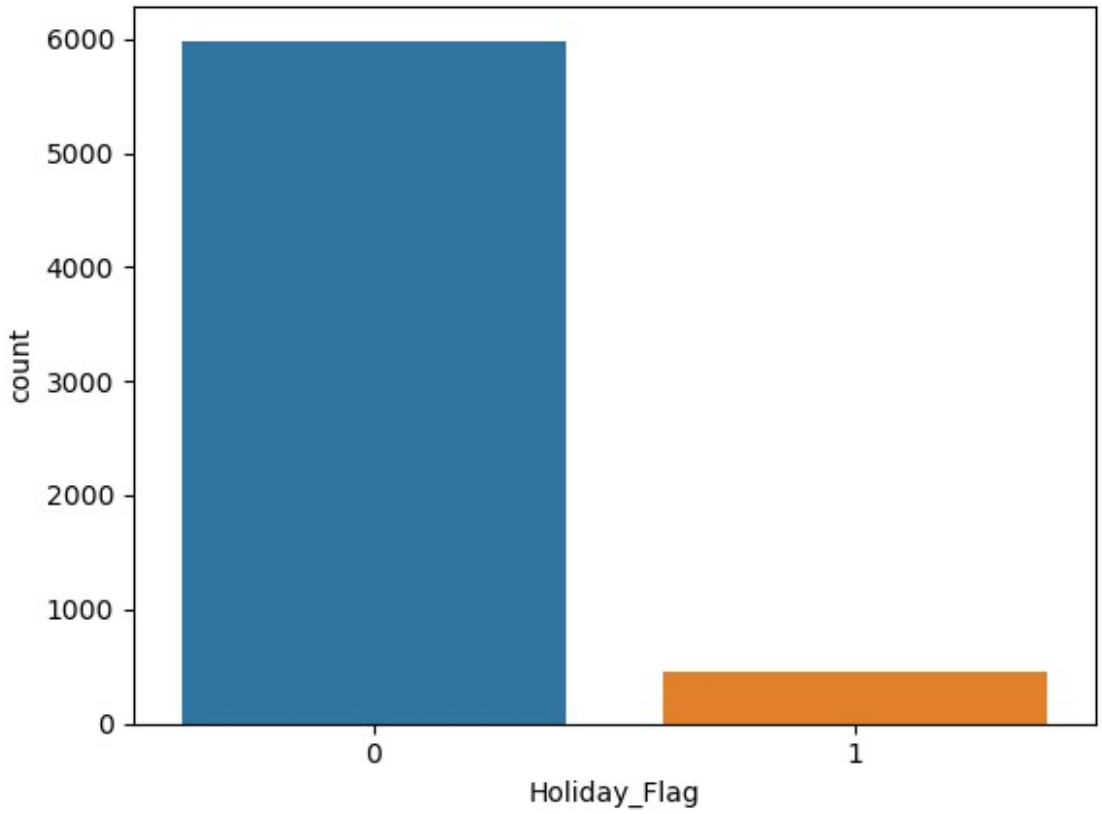
```
df.Holiday_Flag.unique()
```

```
array([0, 1], dtype=int64)
```

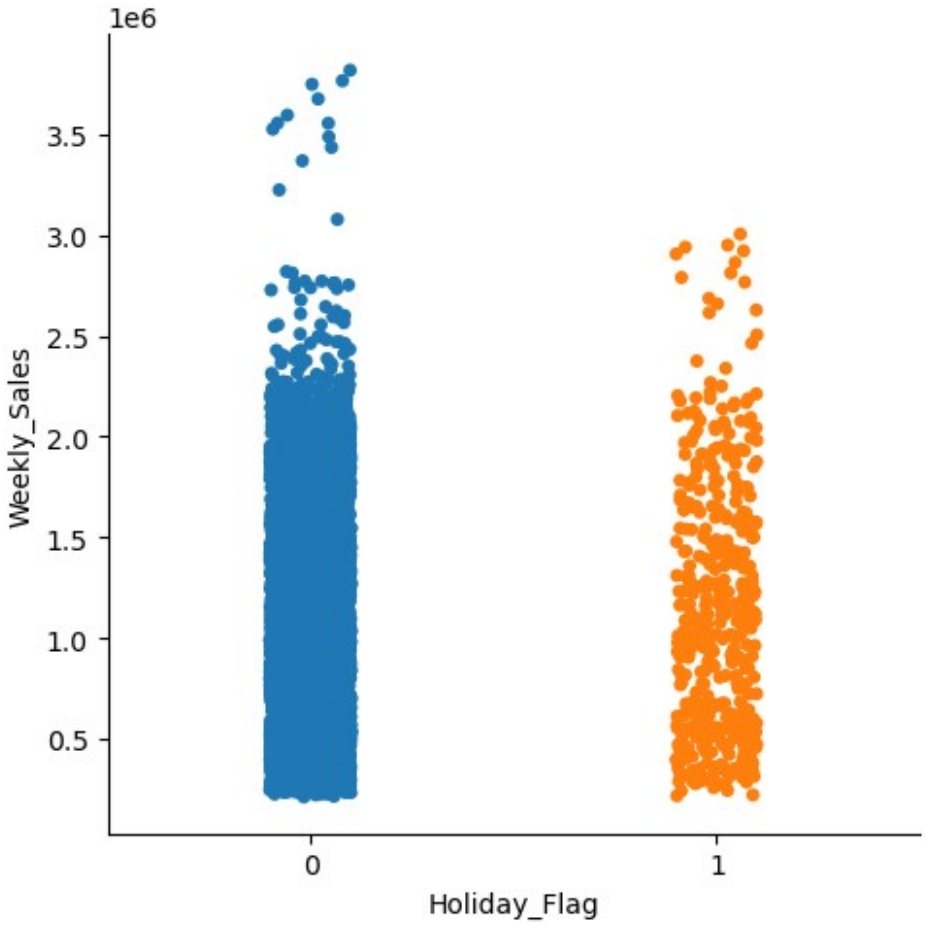
Analzing Data by using visualization

```
sns.countplot(df.Holiday_Flag)
plt.show()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
```

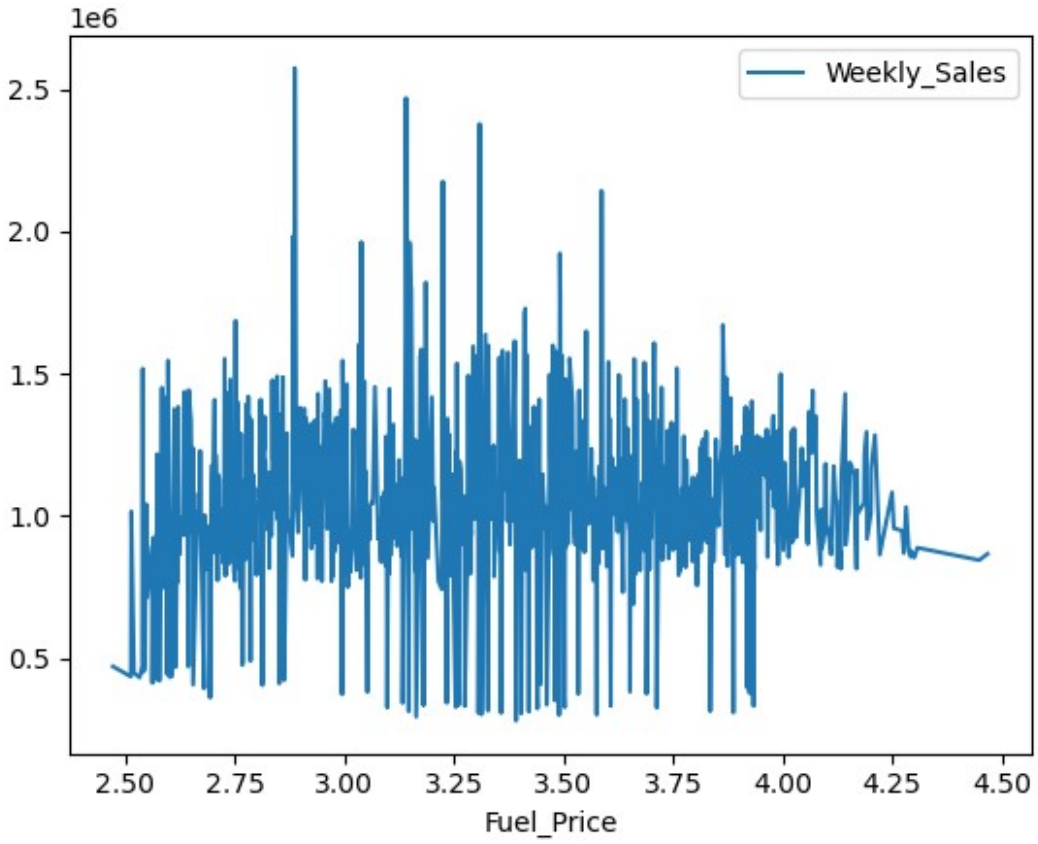



```
sns.catplot(x='Holiday_Flag', y='Weekly_Sales', data=df)
plt.show()
```



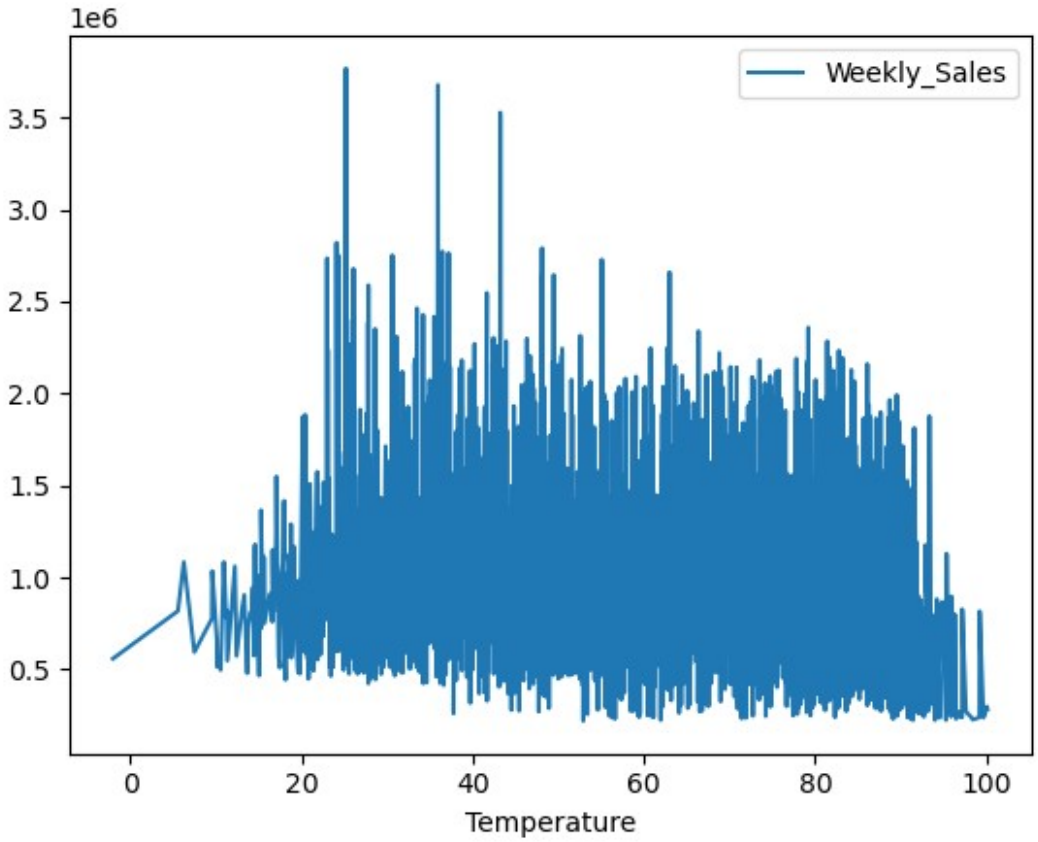

```
fuel_price = pd.pivot_table(df, values = "Weekly_Sales", index=
"Fuel_Price")
fuel_price.plot()
```

```
<AxesSubplot:xlabel='Fuel_Price'>
```



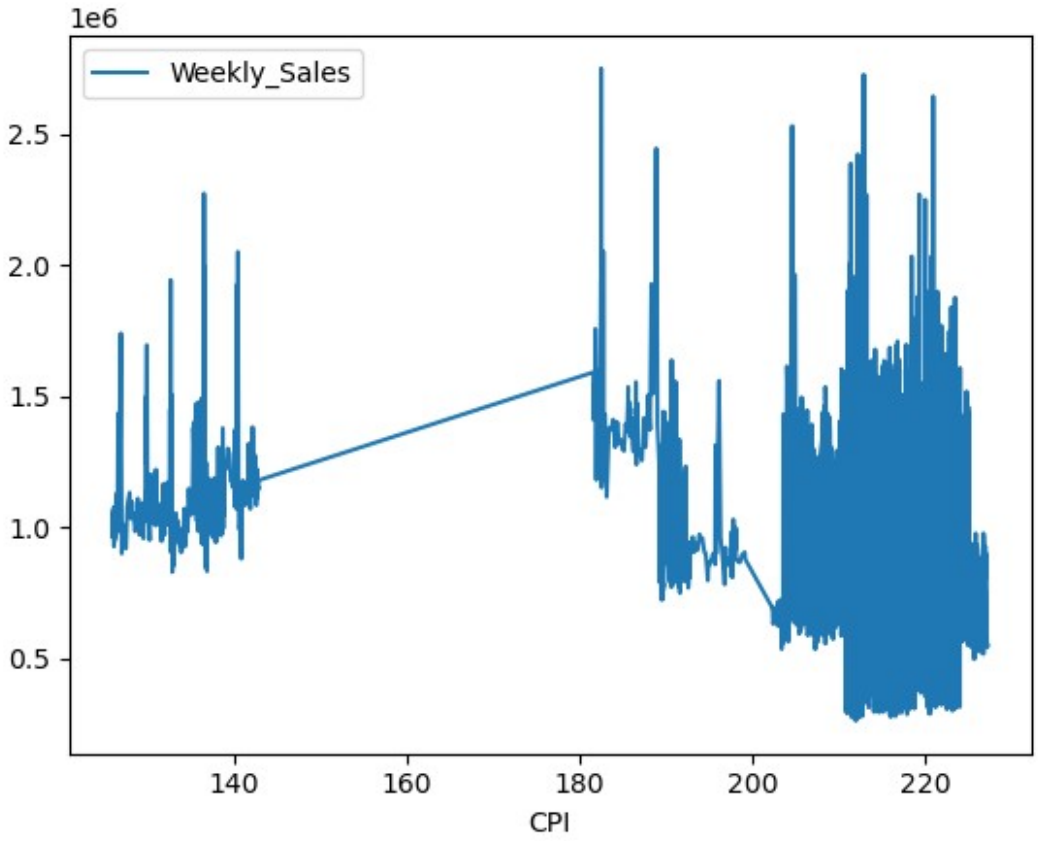

```
Temperature = pd.pivot_table(df, values = "Weekly_Sales", index=
"Temperature")
Temperature.plot()
```

```
<AxesSubplot:xlabel='Temperature'>
```



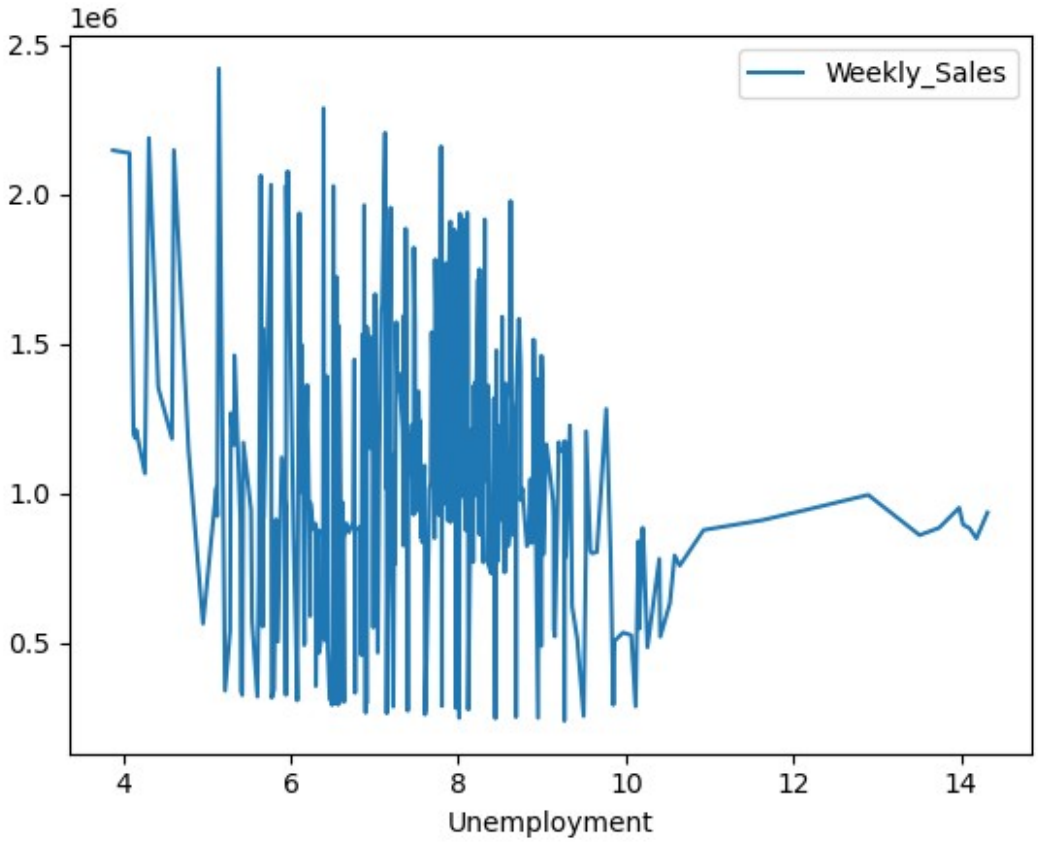

```
CPI = pd.pivot_table(df, values = "Weekly_Sales", index= "CPI")
CPI.plot()
```

```
<AxesSubplot:xlabel='CPI'>
```



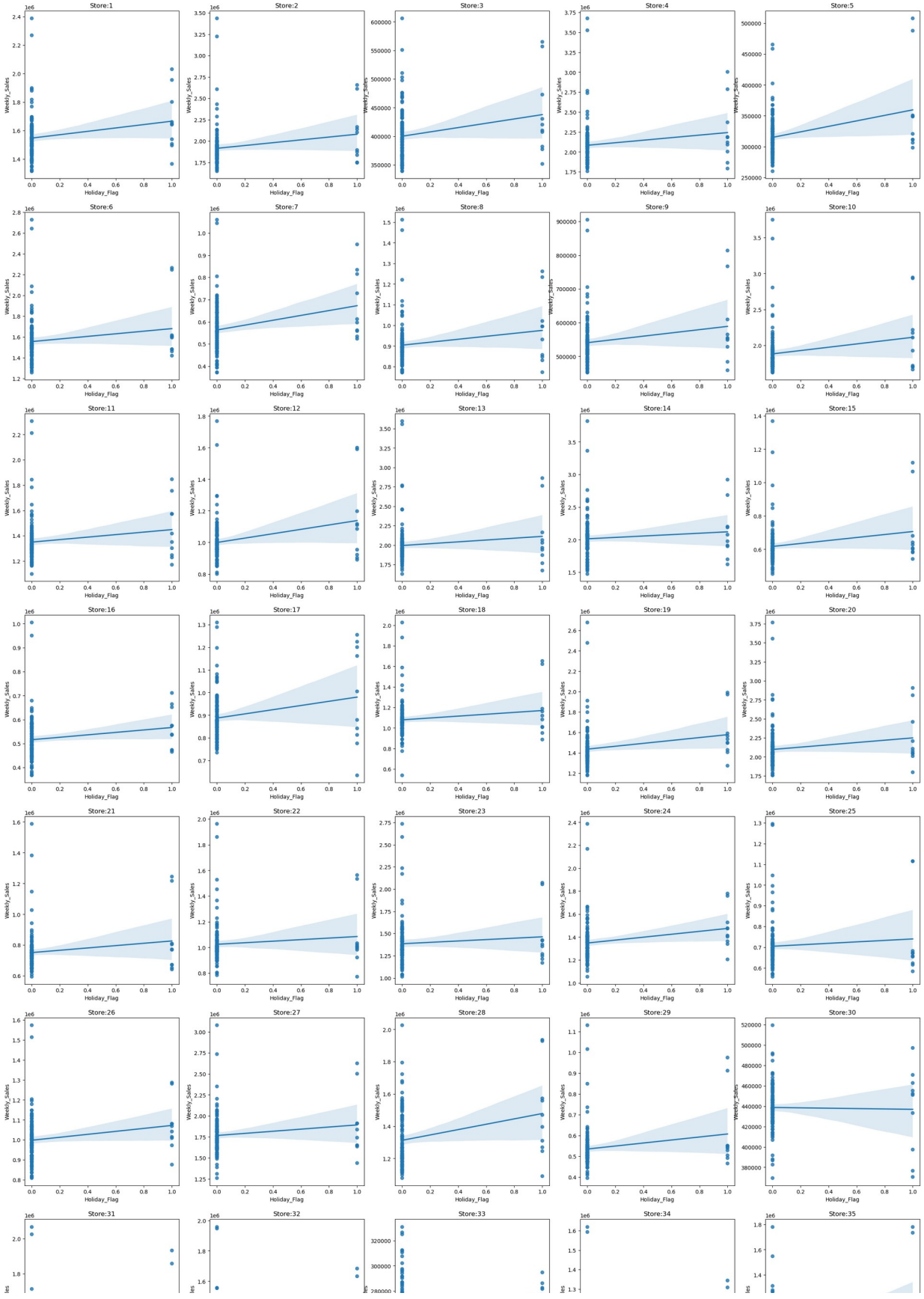

```
Unemployment=pd.pivot_table(values="Weekly_Sales",index="Unemployment"
,data=df)
Unemployment.plot()
```

```
<AxesSubplot:xlabel='Unemployment'>
```



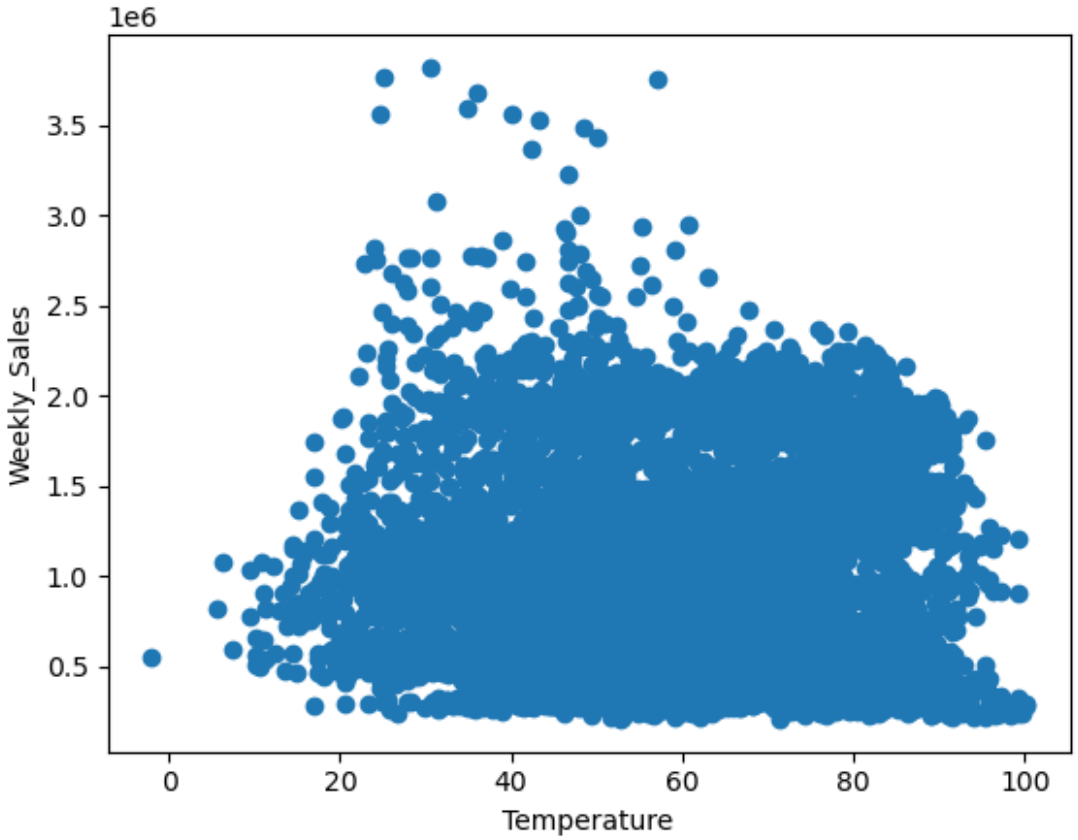
Holiday Vs Weekly Sales of all 45 stores

```
plt.subplots(9,5, figsize=(30,60))
for i in range (1,46):
    plt.subplot(9,5,i)
    sns.regplot(x='Holiday_Flag',
y='Weekly_Sales',data=df[df['Store']==i])
    plt.title(f'Store:{i}')
```

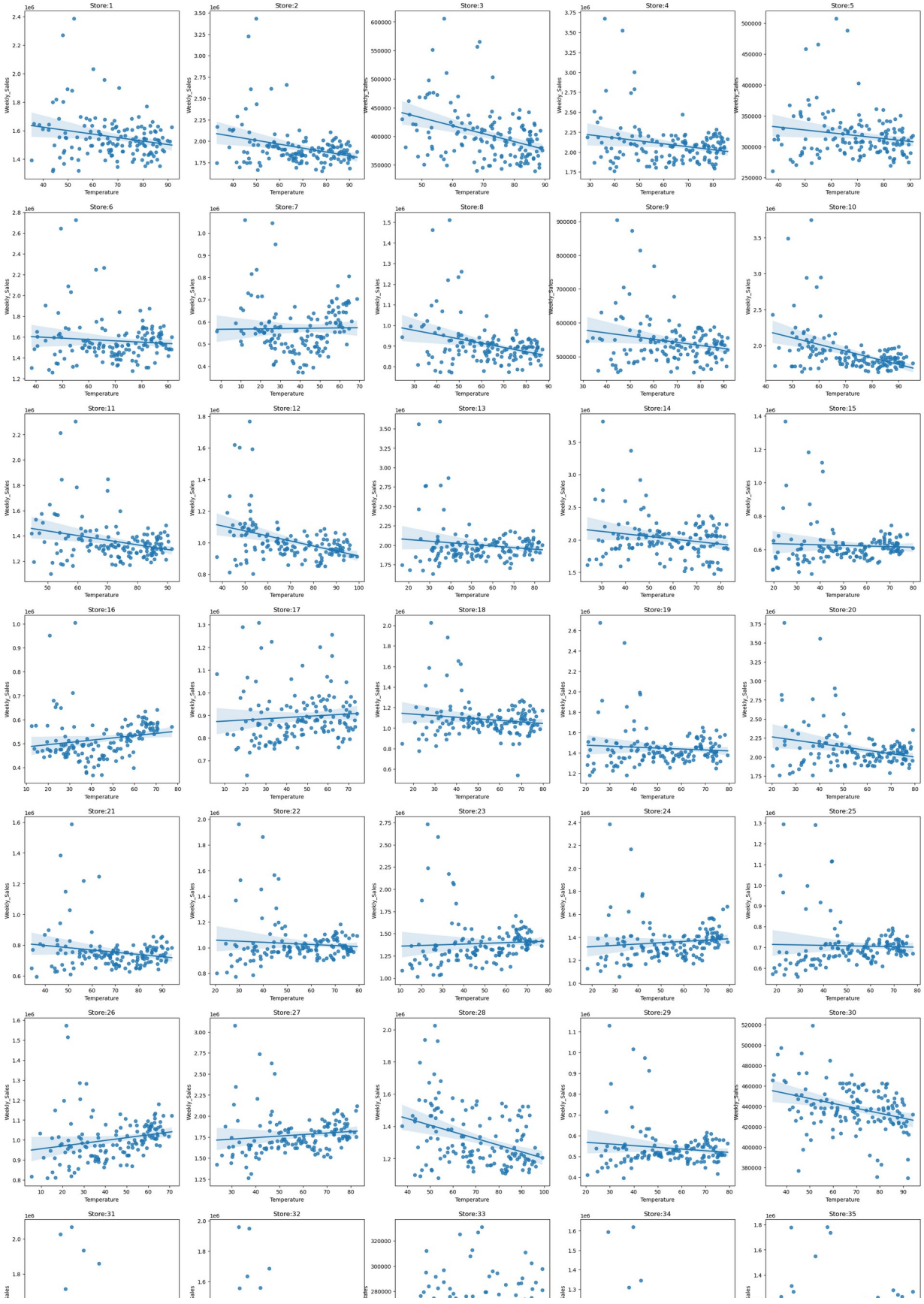

Store:1
Store:2
Store:3
Store:4
Store:5
Store:6
Store:7
Store:8
Store:9
Store:10
Store:11
Store:12
Store:13
Store:14
Store:15
Store:16
Store:17
Store:18
Store:19
Store:20
Store:21
Store:22
Store:23
Store:24
Store:25
Store:26
Store:27
Store:28
Store:29
Store:30
Store:31
Store:32
Store:33
Store:34
Store:35
Weekly_Sales
Holiday_Flag
1e6

Temperature Vs Weekly Sales of all 45 stores

```
plt.scatter(df['Temperature'],df['Weekly_Sales'])
plt.xlabel('Temperature')
plt.ylabel("Weekly_Sales")
plt.show()
```

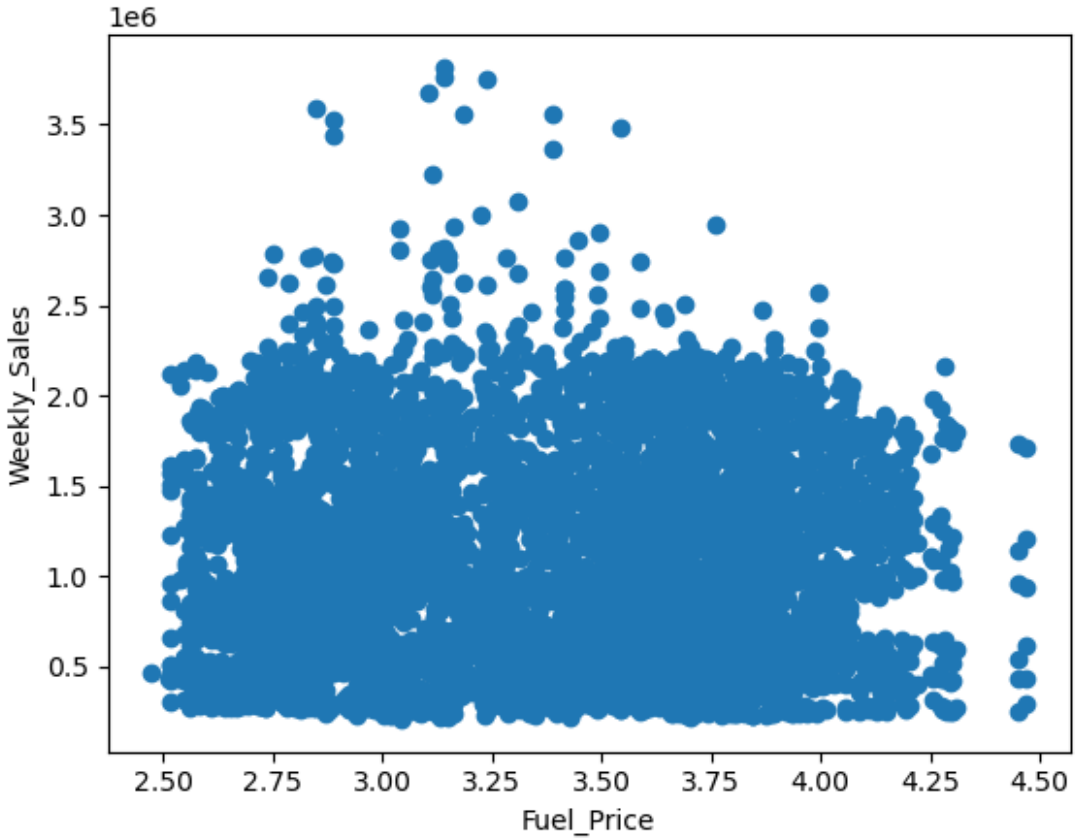



```
plt.subplots(9,5, figsize=(30,60))
for i in range (1,46):
    plt.subplot(9,5,i)
    sns.regplot(x='Temperature', y='Weekly_Sales',
data=df[df['Store']==i])
    plt.title(f'Store:{i}')
```

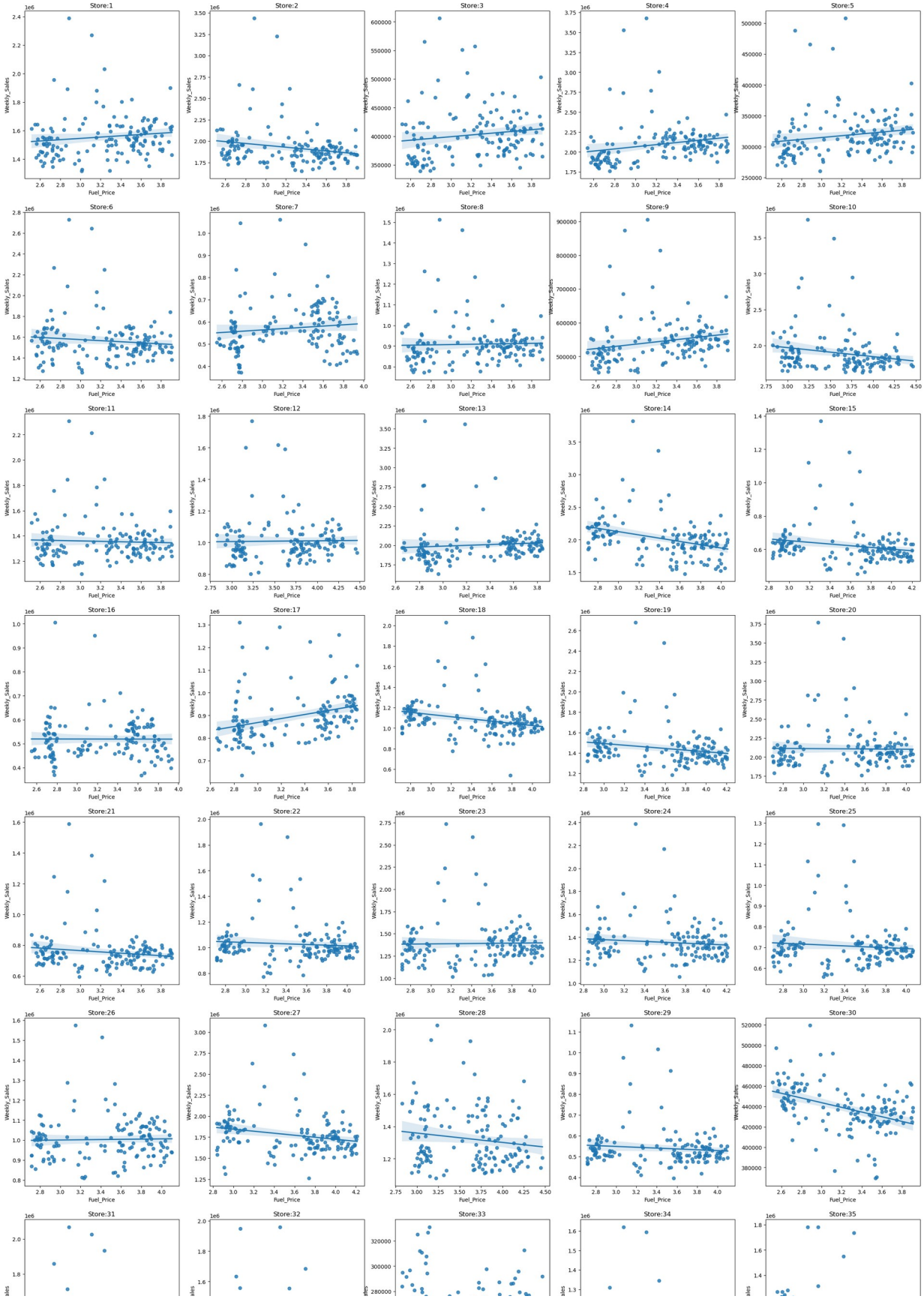

Store:1
Store:2
Store:3
Store:4
Store:5
Store:6
Store:7
Store:8
Store:9
Store:10
Store:11
Store:12
Store:13
Store:14
Store:15
Store:16
Store:17
Store:18
Store:19
Store:20
Store:21
Store:22
Store:23
Store:24
Store:25
Store:26
Store:27
Store:28
Store:29
Store:30
Store:31
Store:32
Store:33
Store:34
Store:35
Weekly_Sales
Temperature

Fuel Vs Weekly Sales of all 45 stores

```
plt.scatter(df['Fuel_Price'],df['Weekly_Sales'])
plt.xlabel('Fuel_Price')
plt.ylabel("Weekly_Sales")
plt.show()
```

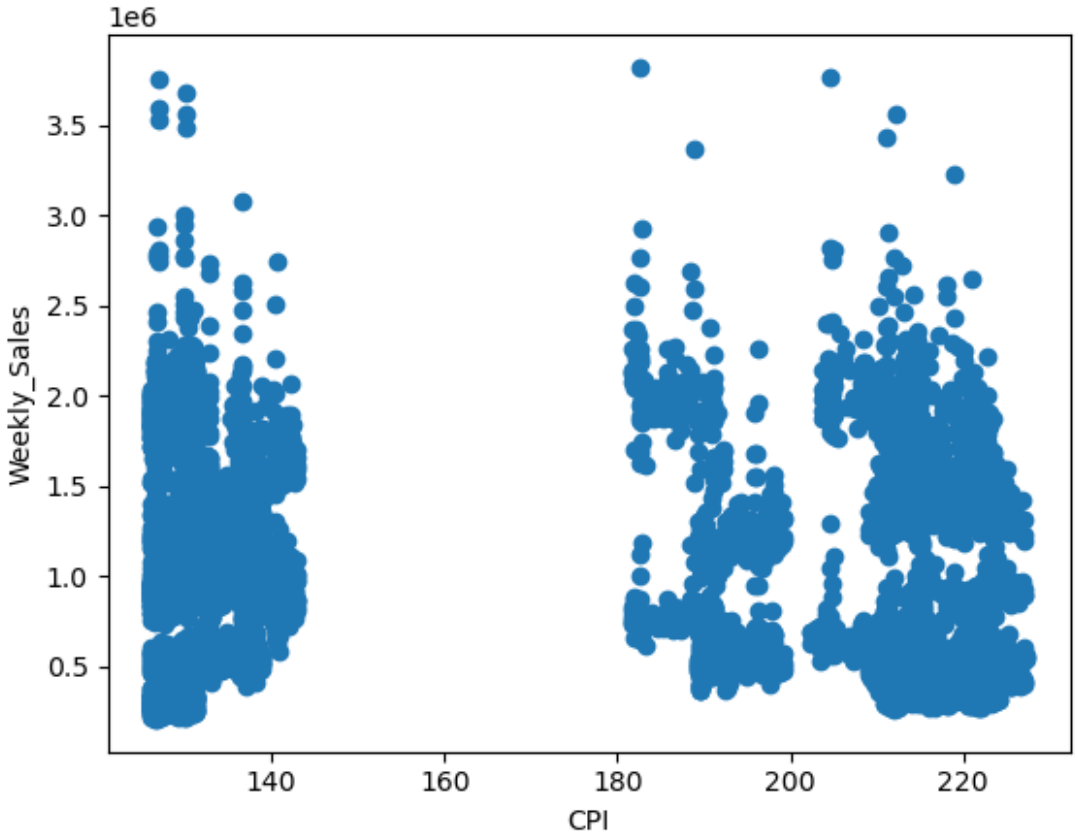



```
plt.subplots(9,5, figsize=(30,60))
for i in range (1,46):
    plt.subplot(9,5,i)
    sns.regplot(x='Fuel_Price', y='Weekly_Sales',
data=df[df['Store']==i])
    plt.title(f'Store:{i}')
```

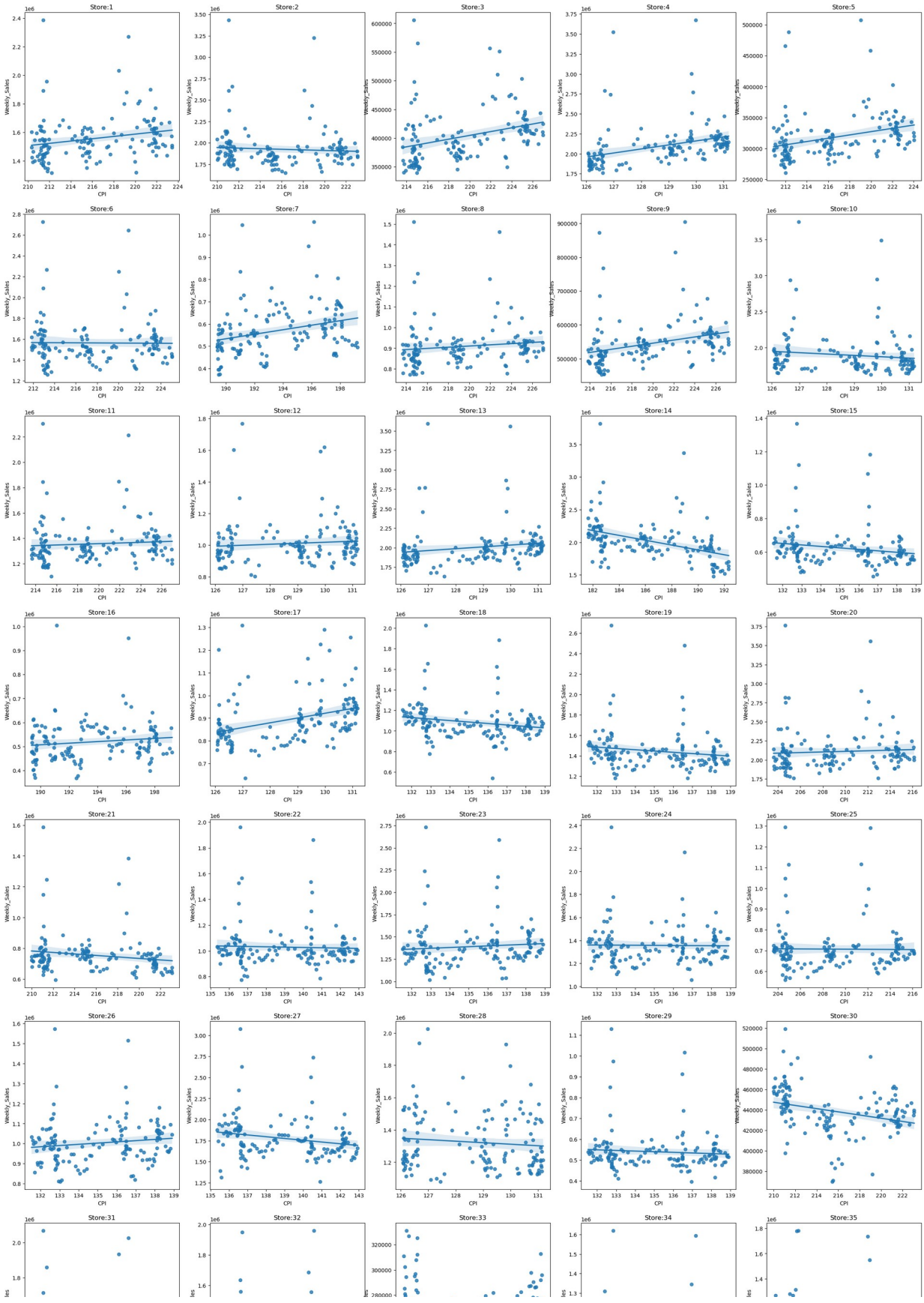

Store:1
Store:2
Store:3
Store:4
Store:5
Store:6
Store:7
Store:8
Store:9
Store:10
Store:11
Store:12
Store:13
Store:14
Store:15
Store:16
Store:17
Store:18
Store:19
Store:20
Store:21
Store:22
Store:23
Store:24
Store:25
Store:26
Store:27
Store:28
Store:29
Store:30
Store:31
Store:32
Store:33
Store:34
Store:35
Weekly_Sales
Fuel_Price
1e6

CPI Vs Weekly Sales of all 45 stores

```
plt.scatter(df["CPI"],df['Weekly_Sales'])
plt.xlabel('CPI')
plt.ylabel("Weekly_Sales")
plt.show()
```

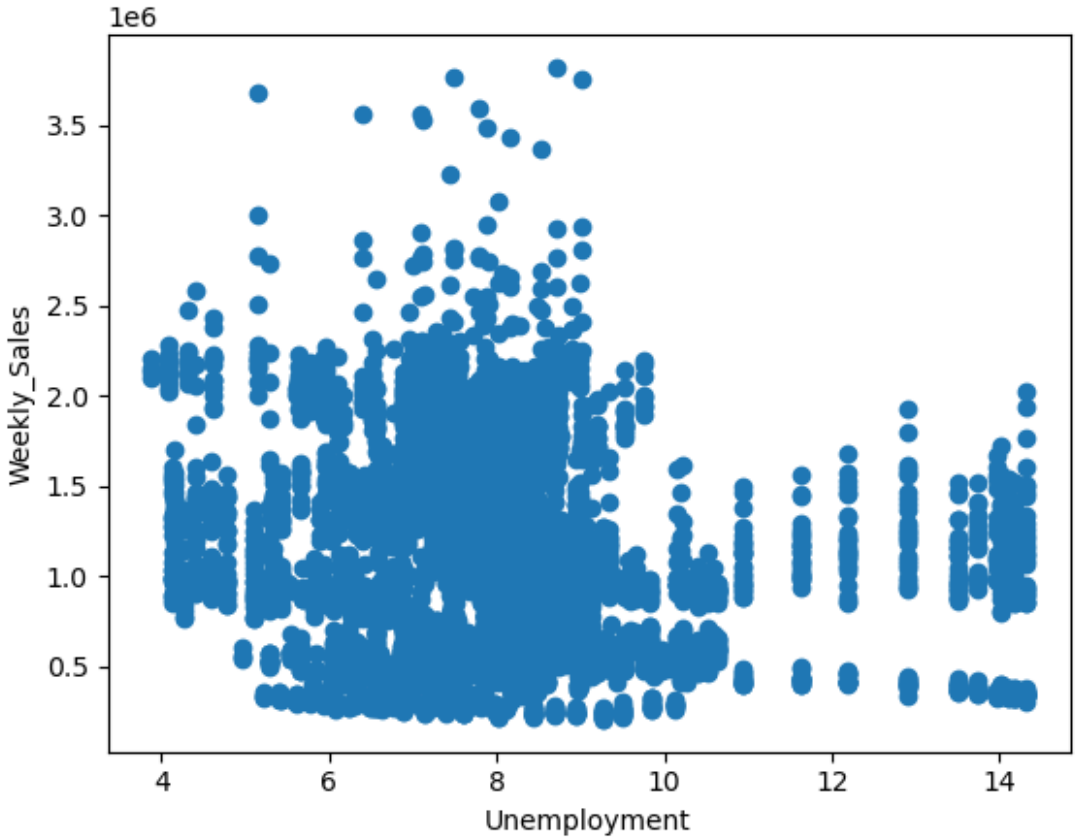



```
plt.subplots(9,5, figsize=(30,60))
for i in range (1,46):
    plt.subplot(9,5,i)
    sns.regplot(x='CPI', y='Weekly_Sales', data=df[df['Store']==i])
    plt.title(f'Store:{i}')
```

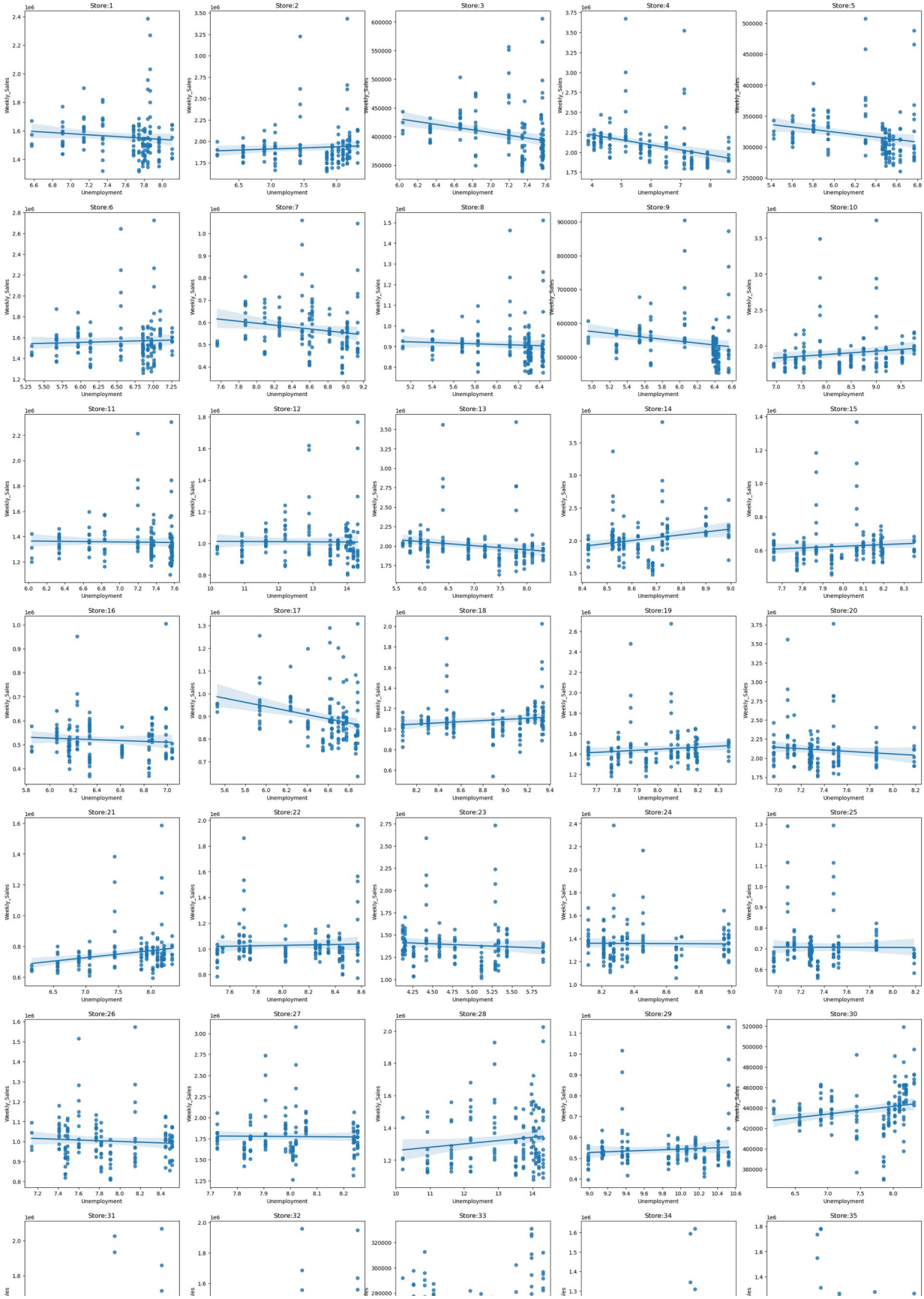

Store:1
Store:2
Store:3
Store:4
Store:5
Store:6
Store:7
Store:8
Store:9
Store:10
Store:11
Store:12
Store:13
Store:14
Store:15
Store:16
Store:17
Store:18
Store:19
Store:20
Store:21
Store:22
Store:23
Store:24
Store:25
Store:26
Store:27
Store:28
Store:29
Store:30
Store:31
Store:32
Store:33
Store:34
Store:35
Weekly_Sales
CPI

Unemployment Vs Weekly Sales of all 45 stores

```
plt.scatter(df['Unemployment'],df['Weekly_Sales'])
plt.xlabel('Unemployment')
plt.ylabel("Weekly_Sales")
plt.show()
```




```
plt.subplots(9,5, figsize=(30,60))
for i in range (1,46):
    plt.subplot(9,5,i)
    sns.regplot(x='Unemployment', y='Weekly_Sales',
data=df[df['Store']==i])
    plt.title(f'Store:{i}')
```


Store:1
Store:2
Store:3
Store:4
Store:5
Store:6
Store:7
Store:8
Store:9
Store:10
Store:11
Store:12
Store:13
Store:14
Store:15
Store:16
Store:17
Store:18
Store:19
Store:20
Store:21
Store:22
Store:23
Store:24
Store:25
Store:26
Store:27
Store:28
Store:29
Store:30
Store:31
Store:32
Store:33
Store:34
Store:35
Weekly_Sales
Unemployment

```
plt.figure(figsize=(20,8))
sns.heatmap(df.corr(),annot=True)
plt.show()
```

Insights on Walmart Dataset

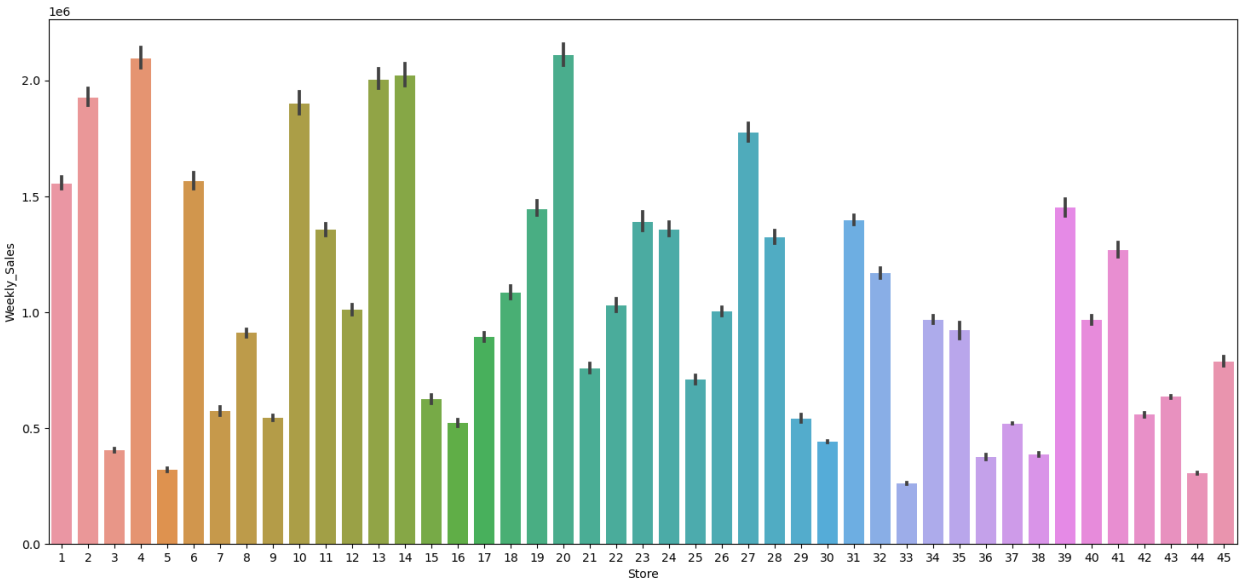
A) If the weekly sales are affected by the unemployment rate, if yes - which stores are suffering the most?

```
plt.figure(figsize=(18,8))
sns.scatterplot(df['Weekly_Sales'],df['Unemployment'])
plt.show()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variables as
keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

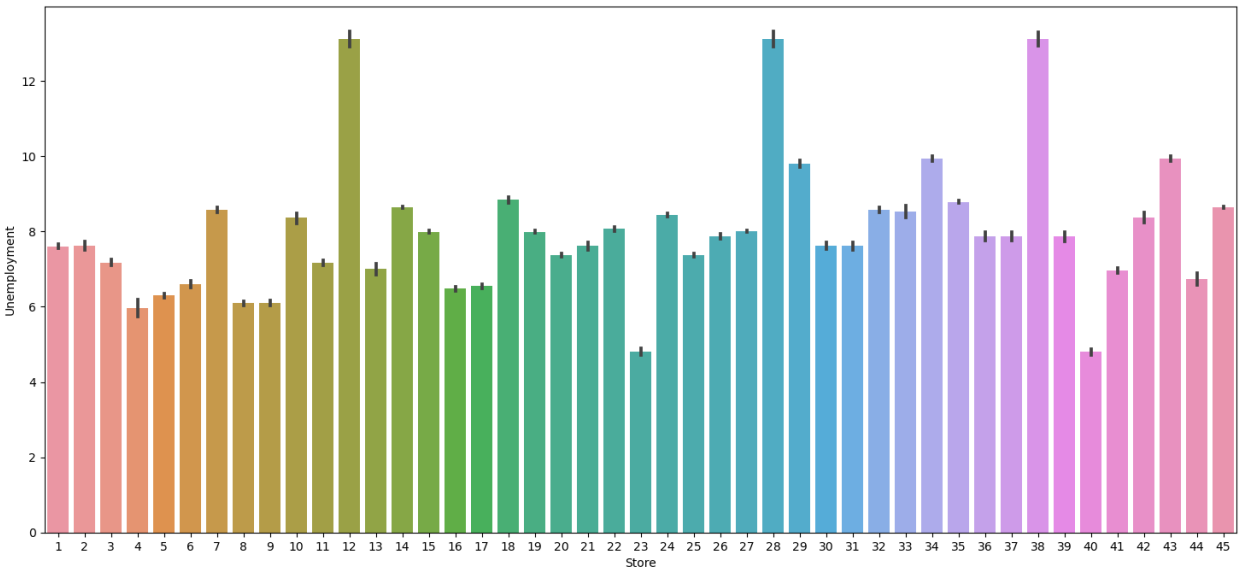

```
plt.figure(figsize=(18,8))
sns.barplot(df['Store'],df['Weekly_Sales'])
plt.show()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variables as
keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



```
plt.figure(figsize=(18,8))
sns.barplot(df['Store'],df['Unemployment'])
plt.show()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variables as
keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```




```
Total_by_store = df.groupby('Store').agg({'Weekly_Sales': 'sum',
'Unemployment': 'sum'})
Total_by_store
```

Store	Weekly_Sales	Unemployment
1	2.224028e+08	1088.290
2	2.753824e+08	1090.210
3	5.758674e+07	1026.309
4	2.995440e+08	852.951
5	4.547569e+07	900.243
6	2.237561e+08	944.787
7	8.159828e+07	1227.760
8	1.299512e+08	871.134
9	7.778922e+07	872.283
10	2.716177e+08	1195.904
11	1.939628e+08	1026.309
12	1.442872e+08	1875.657
13	2.865177e+08	1001.261
14	2.889999e+08	1236.771

```
15     8.913368e+07      1143.464
16     7.425243e+07       926.353
17     1.277821e+08       936.565
18     1.551147e+08      1263.877
19     2.066349e+08      1143.464
20     3.013978e+08      1054.112
21     1.081179e+08      1090.210
22     1.470756e+08      1153.920
23     1.987506e+08       685.830
24     1.940160e+08      1207.923
25     1.010612e+08      1054.112
26     1.434164e+08      1125.706
27     2.538559e+08      1144.250
28     1.892637e+08      1875.657
29     7.714155e+07      1402.313
30     6.271689e+07      1090.210
31     1.996139e+08      1090.210
32     1.668192e+08      1227.760
33     3.716022e+07      1220.241
34     1.382498e+08      1420.677
35     1.315207e+08      1256.766
36     5.341221e+07      1125.274
37     7.420274e+07      1125.274
38     5.515963e+07      1875.657
39     2.074455e+08      1125.274
40     1.378703e+08       685.830
41     1.813419e+08       997.193
42     7.956575e+07      1195.904
43     9.056544e+07      1420.677
44     4.329309e+07       963.194
45     1.123953e+08      1236.771
```

```
store_correlation=df.groupby('Store')
['Weekly_Sales','Unemployment'].corr()['Unemployment']
print(store_correlation.idxmin())
```

```
(38, 'Weekly_Sales')
```

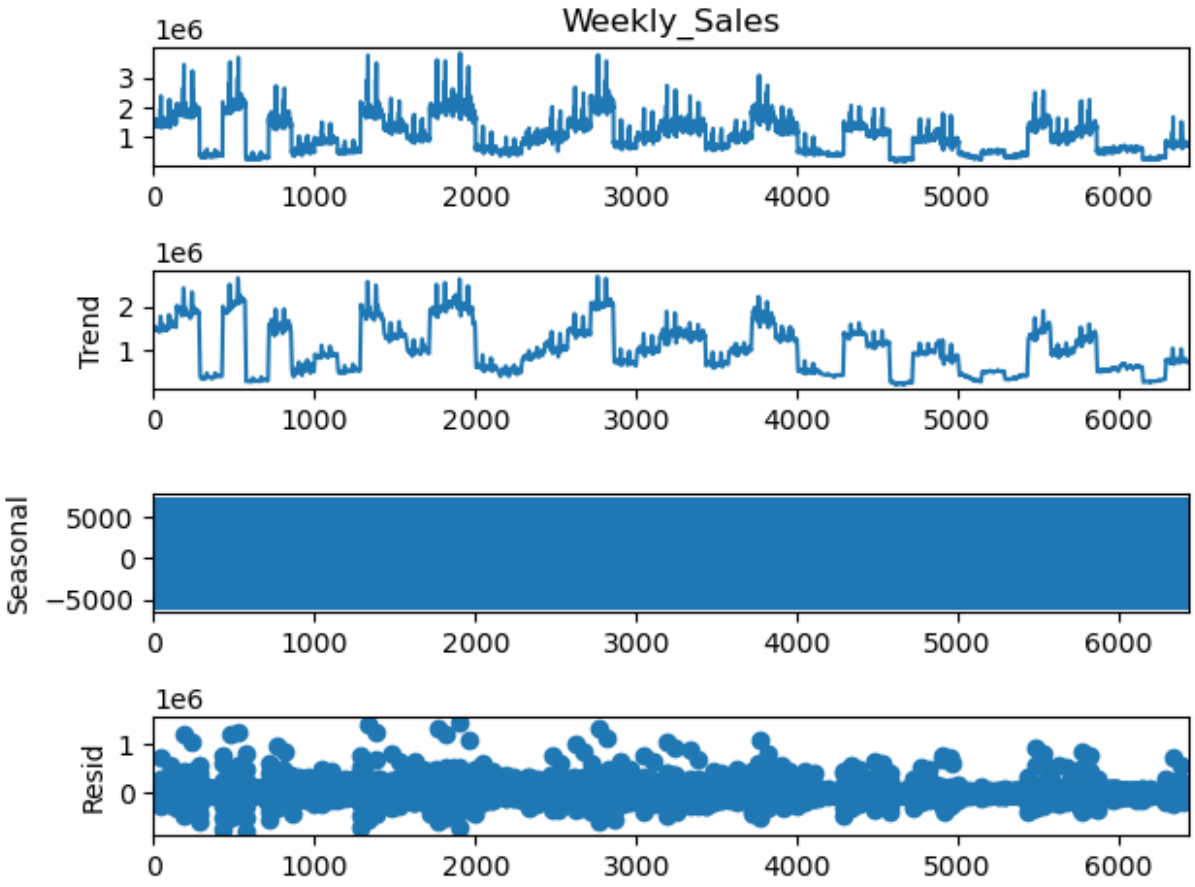
```
C:\Users\Arigala.Adarsh\AppData\Local\Temp\
ipykernel_24176\532463401.py:1: FutureWarning: Indexing with multiple
keys (implicitly converted to a tuple of keys) will be deprecated, use
a list instead.
  store_correlation=df.groupby('Store')
['Weekly_Sales','Unemployment'].corr()['Unemployment']
```

- Store **12,28,38** has more unempoloyment i.e 1875.657.
- Unemployment effect is showing more on Store **38**.

B) If the weekly sales show a seasonal trend, when and what could be the reason?

```
#seasonal Decompose
result=seasonal_decompose(df['Weekly_Sales'],model='additive',
period=7)

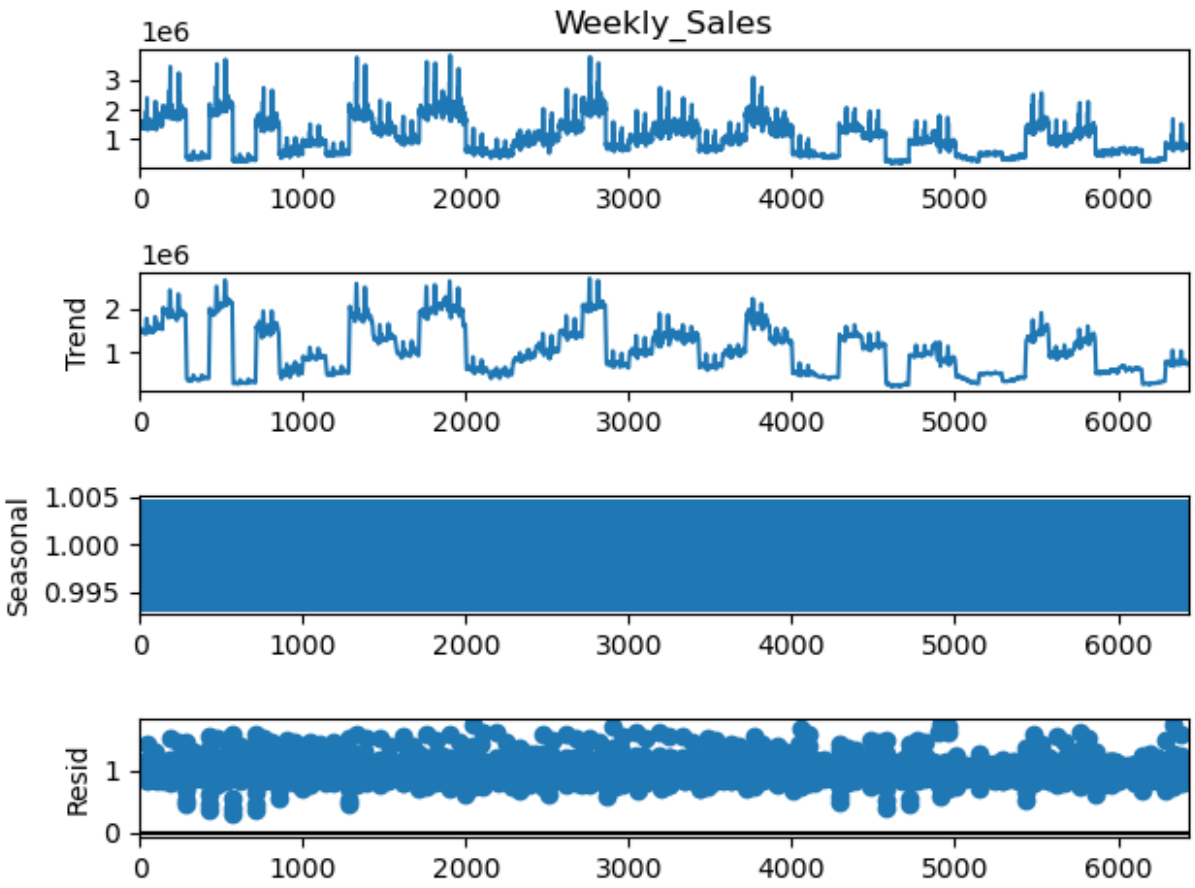
result.plot()
plt.show()
```




```
#Addictive
new_df_add=pd.concat([result.seasonal,result.trend,result.resid,result
.observed],axis=1)
new_df_add.columns=["seasonality","trend","residual","actual_values"]
new_df_add.head(5)
```

	seasonality	trend	residual	actual_values
0	-3978.147451	NaN	NaN	1643690.90
1	7215.473014	NaN	NaN	1641957.44
2	5479.430196	NaN	NaN	1611968.17
3	1547.439597	1.539173e+06	-130992.443883	1409727.59
4	-1440.045828	1.504992e+06	51254.271542	1554806.68

```
result=seasonal_decompose(df['Weekly_Sales'],model='multiplicative',
period=7)
result.plot()
plt.show()
```



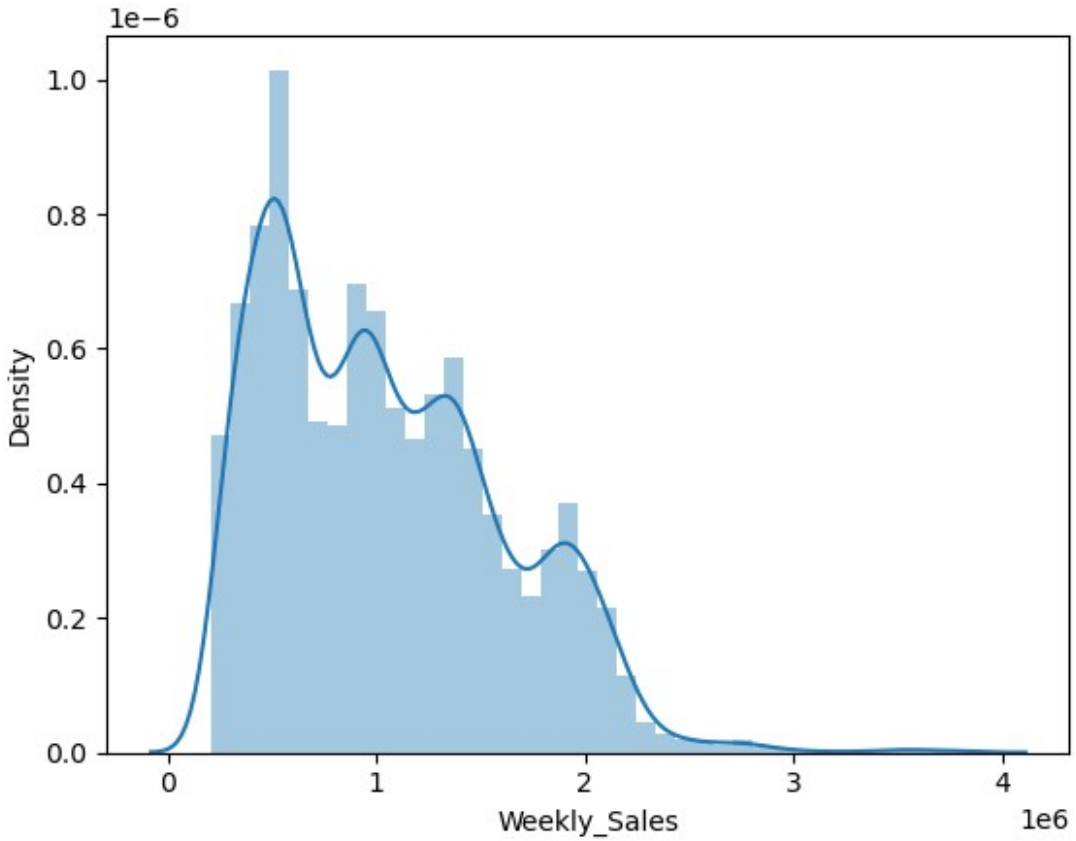

```
#Addictive
new_df_mul=pd.concat([result.seasonal,result.trend,result.resid,result
.observed],axis=1)
new_df_mul.columns=["seasonality","trend","residual","actual_values"]
new_df_mul.head(5)
```

	seasonality	trend	residual	actual_values
0	0.998500	NaN	NaN	1643690.90
1	1.003554	NaN	NaN	1641957.44
2	1.004503	NaN	NaN	1611968.17
3	1.003575	1.539173e+06	0.912637	1409727.59
4	0.998428	1.504992e+06	1.034726	1554806.68

```
sns.distplot(df['Weekly_Sales'],hist=True)
plt.plot()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\seaborn\
distributions.py:2619: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)

[]
```



- Weekly sales show a seasonal trend...

```
df.Holiday_Flag.value_counts()

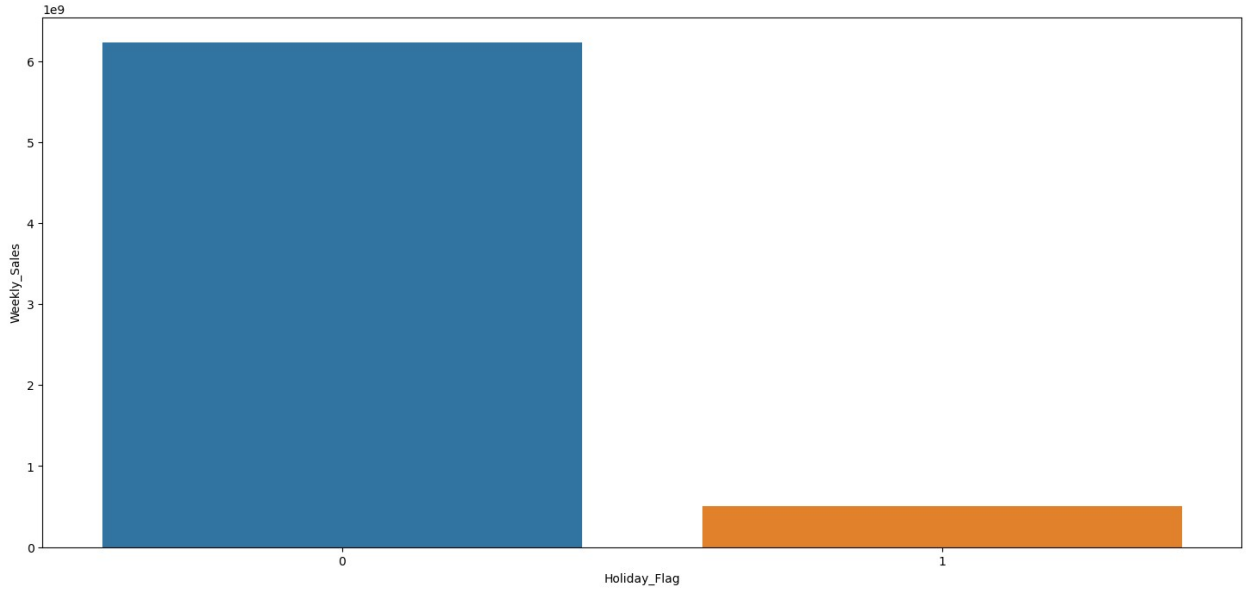
0    5985
1     450
Name: Holiday_Flag, dtype: int64

Total_by_store =
df.groupby(['Holiday_Flag'],as_index=False).agg({'Weekly_Sales':
'sum'})
Total_by_store
```

```
   Holiday_Flag  Weekly_Sales
0             0  6.231919e+09
1             1  5.052996e+08
```

```
plt.figure(figsize=(18,8))
sns.barplot(Total_by_store['Holiday_Flag'],Total_by_store['Weekly_Sales'])
plt.show()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



- Here we can observe that on Non Holiday Week -Sales is more than the Holiday Week

```
Total_by_store = df.groupby(['Store','Holiday_Flag'],as_index=False).agg({'Weekly_Sales': 'sum','Temperature':"mean"})
Total_by_store
```

```
    Store  Holiday_Flag  Weekly_Sales  Temperature
0       1             0  2.057453e+08    69.087669
1       1             1  1.665748e+07    57.921000
2       2             0  2.545898e+08    69.025263
3       2             1  2.079267e+07    57.458000
4       3             0  5.320862e+07    72.076617
..    ...           ...           ...          ...
85     43             1  6.359463e+06    58.168000
86     44             0  4.033273e+07    54.503459
```

```
87     44             1  2.960356e+06    42.973000
88     45             0  1.040324e+08    58.561729
89     45             1  8.362937e+06    47.540000

[90 rows x 4 columns]
```

```
Total_by_store[Total_by_store["Weekly_Sales"]==Total_by_store["Weekly_
Sales"].max()]
```

```
    Store  Holiday_Flag  Weekly_Sales  Temperature
38     20             0  2.789074e+08    56.242256
```

```
Total_by_store[Total_by_store["Weekly_Sales"]==Total_by_store["Weekly_
Sales"].min()]
```

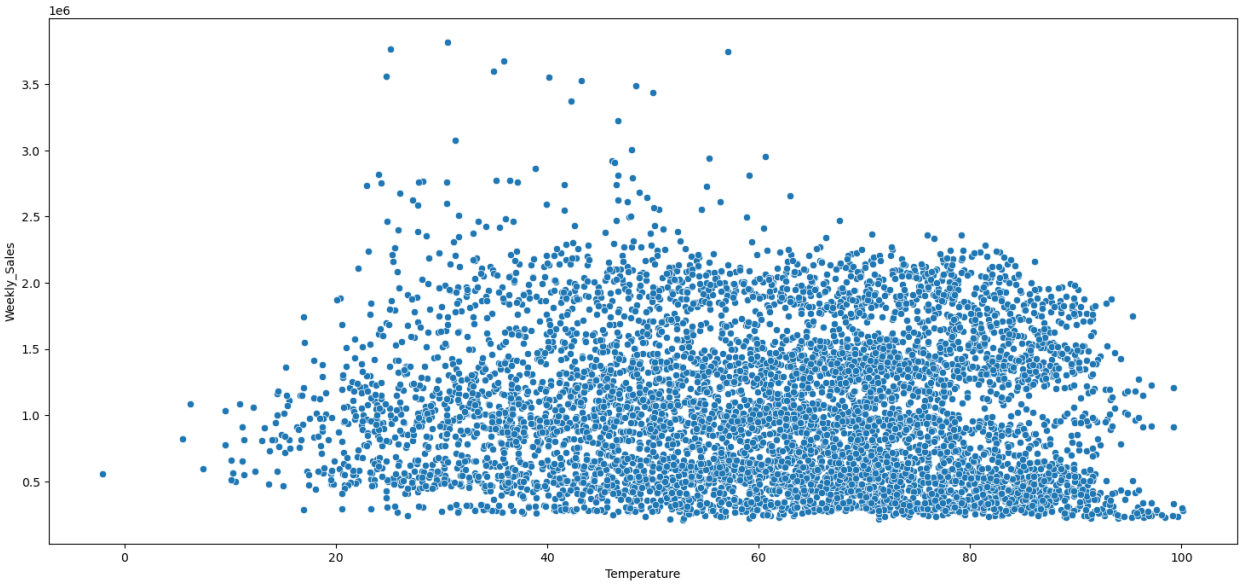
```
    Store  Holiday_Flag  Weekly_Sales  Temperature
65     33             1    2625945.19        67.25
```

-We can observe that on Sotre 20 Non Holiday Weekday sales is more and temperature is less - On Holiday Weekday Sales is less and Temperature is More.

C) Does temperature affect the weekly sales in any manner?

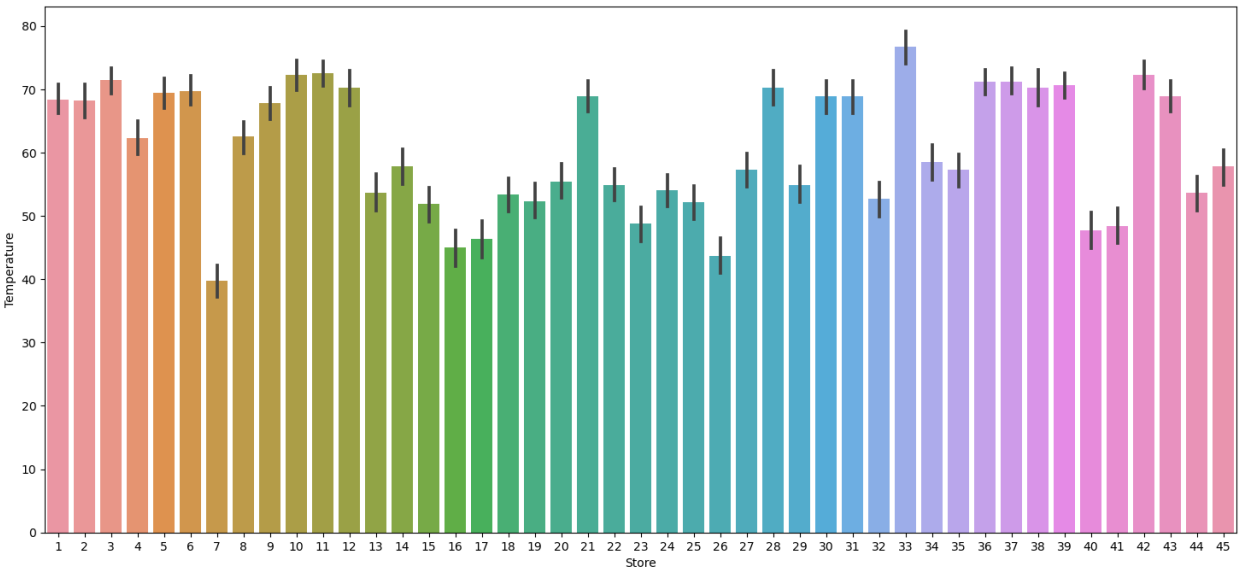
```
plt.figure(figsize=(18,8))
sns.scatterplot(df['Temperature'],df['Weekly_Sales'])
plt.show()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variables as
keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



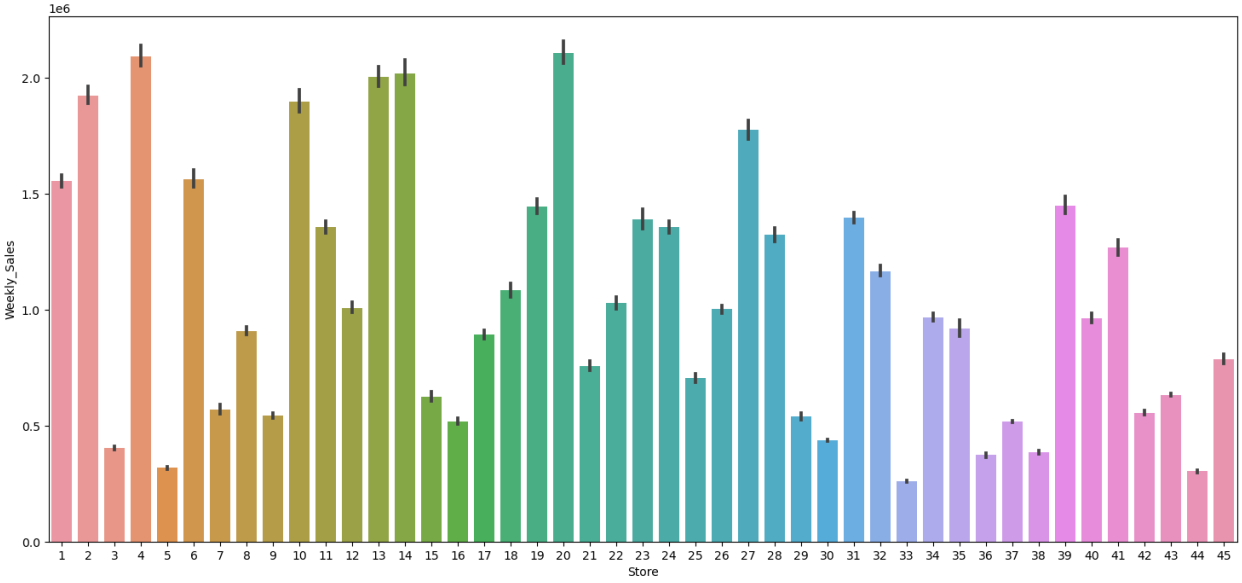

```
plt.figure(figsize=(18,8))
sns.barplot(df['Store'],df['Temperature'])
plt.show()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variables as
keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

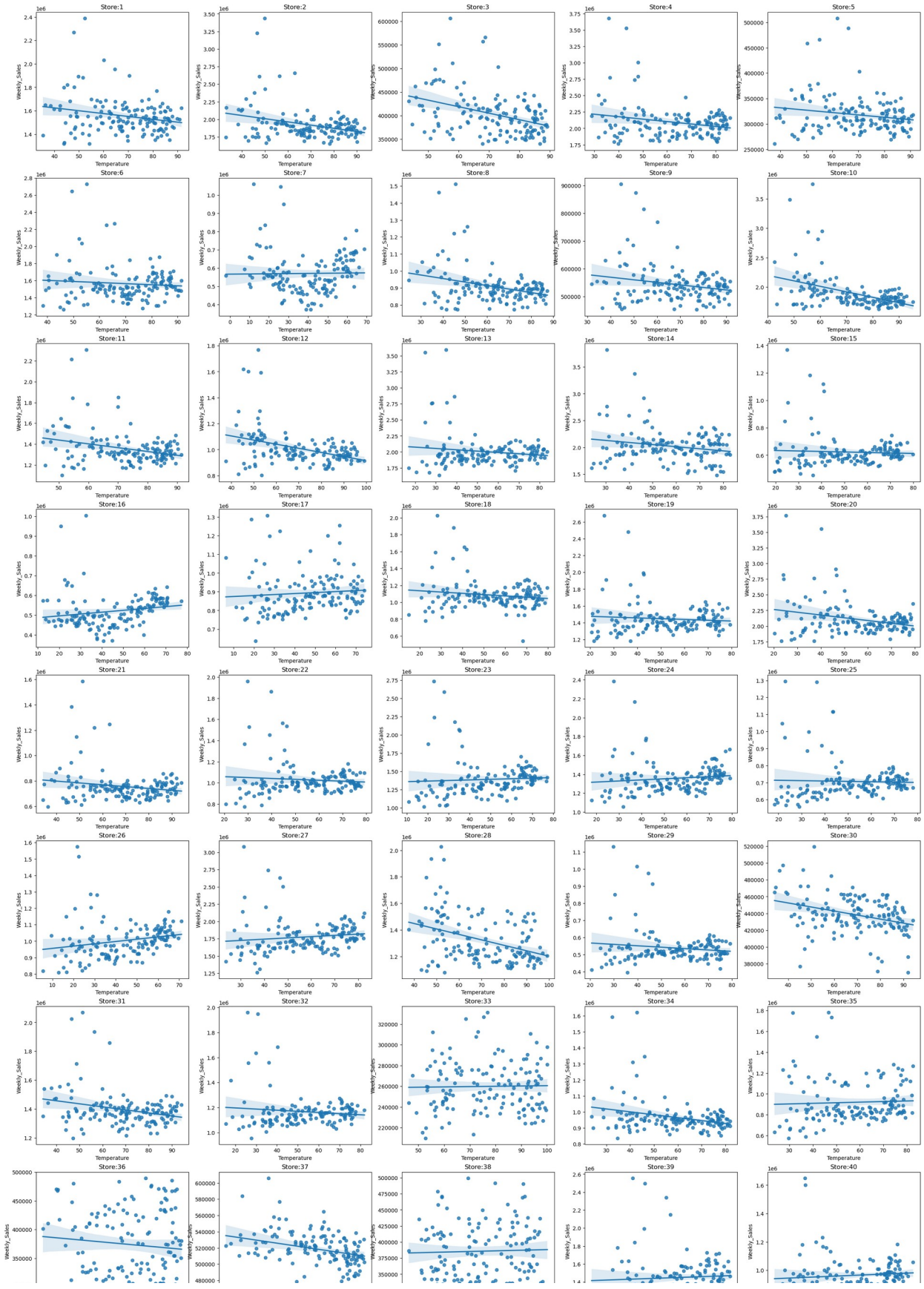


```
plt.figure(figsize=(18,8))
sns.barplot(df['Store'],df['Weekly_Sales'])
plt.show()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variables as
keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```




```
plt.subplots(9,5, figsize=(30,50))
for i in range (1,46):
    plt.subplot(9,5,i)
    sns.regplot(x='Temperature', y='Weekly_Sales',
data=df[df['Store']==i])
    plt.title(f'Store:{i}')
```

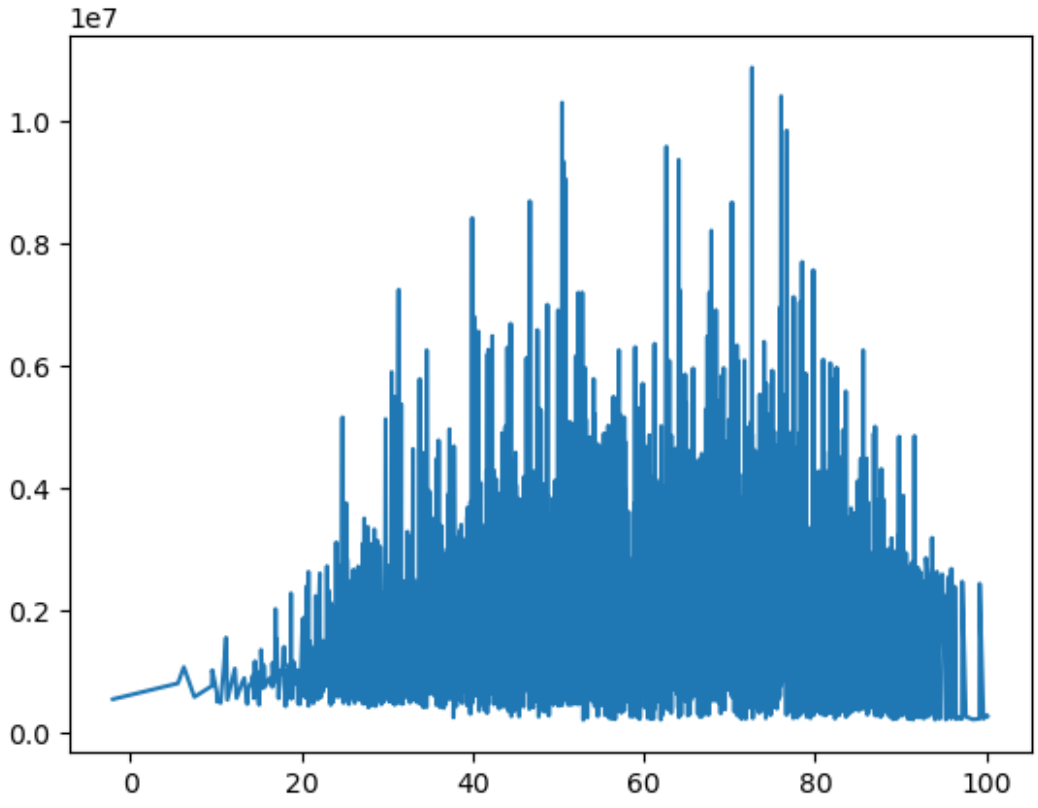

Store:1
Store:2
Store:3
Store:4
Store:5
Store:6
Store:7
Store:8
Store:9
Store:10
Store:11
Store:12
Store:13
Store:14
Store:15
Store:16
Store:17
Store:18
Store:19
Store:20
Store:21
Store:22
Store:23
Store:24
Store:25
Store:26
Store:27
Store:28
Store:29
Store:30
Store:31
Store:32
Store:33
Store:34
Store:35
Store:36
Store:37
Store:38
Store:39
Store:40
Weekly_Sales
Temperature

```
Total_by_temp =
df.groupby('Temperature',as_index=False).agg({'Weekly_Sales': 'sum'})
Total_by_temp
```

	Temperature	Weekly_Sales
0	-2.06	558027.77
1	5.54	817485.14
2	6.23	1083071.14
3	7.46	593875.46
4	9.51	775910.43
...	...	...
3523	99.20	239198.36
3524	99.22	2446625.50
3525	99.66	237095.82
3526	100.07	297753.49
3527	100.14	280937.84

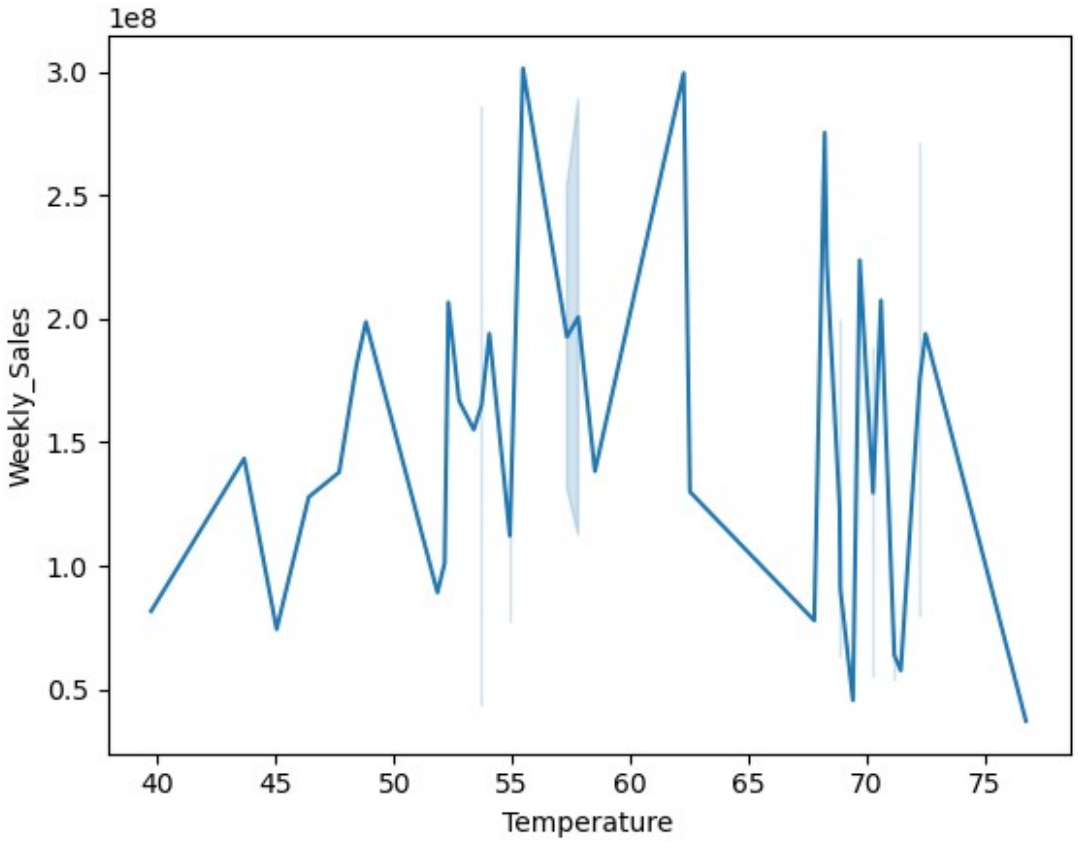
[3528 rows x 2 columns]

```
plt.plot(Total_by_temp['Temperature'],Total_by_temp['Weekly_Sales'])
plt.show()
```



```
Total_by_store = df.groupby(['Store'],
as_index=False).agg({'Weekly_Sales': 'sum', 'Temperature': 'mean'})
sns.lineplot(x='Temperature', y='Weekly_Sales', data=Total_by_store)
```

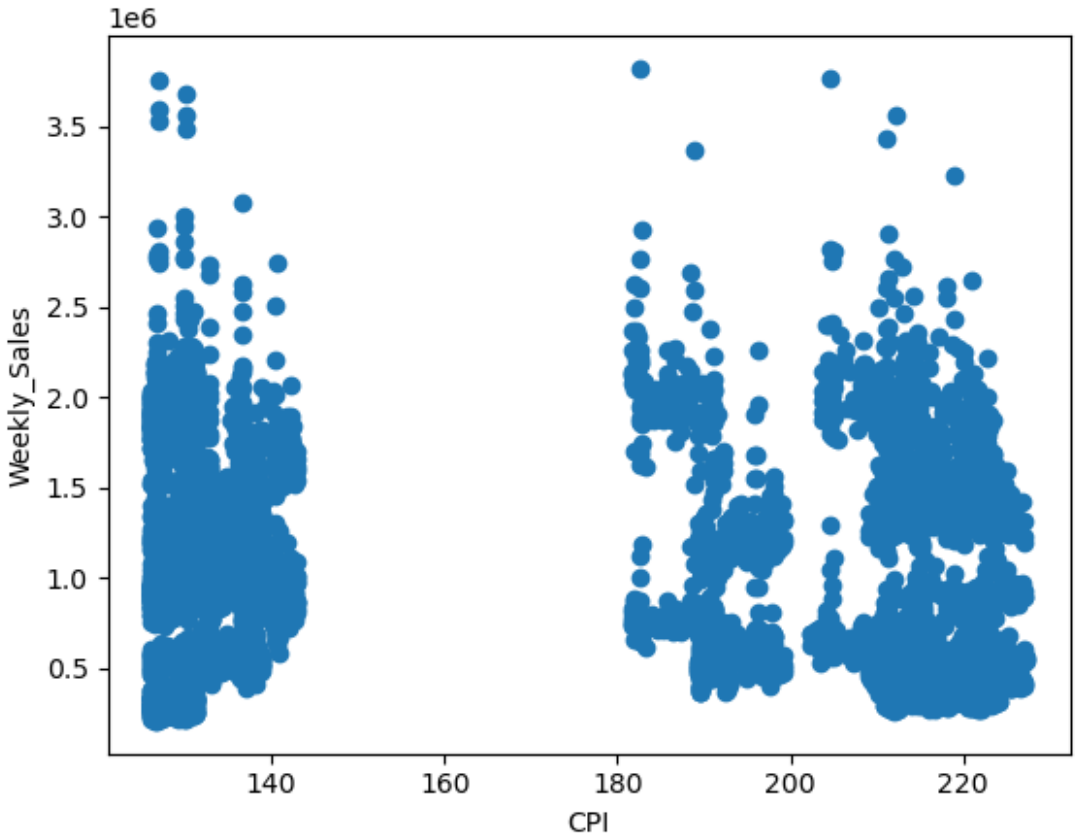
```
<AxesSubplot:xlabel='Temperature', ylabel='Weekly_Sales'>
```



- Temperature affects we can observer above visualization at High Weekly Sales at lower temperature
- At Low Weekly Sales at higher temperature

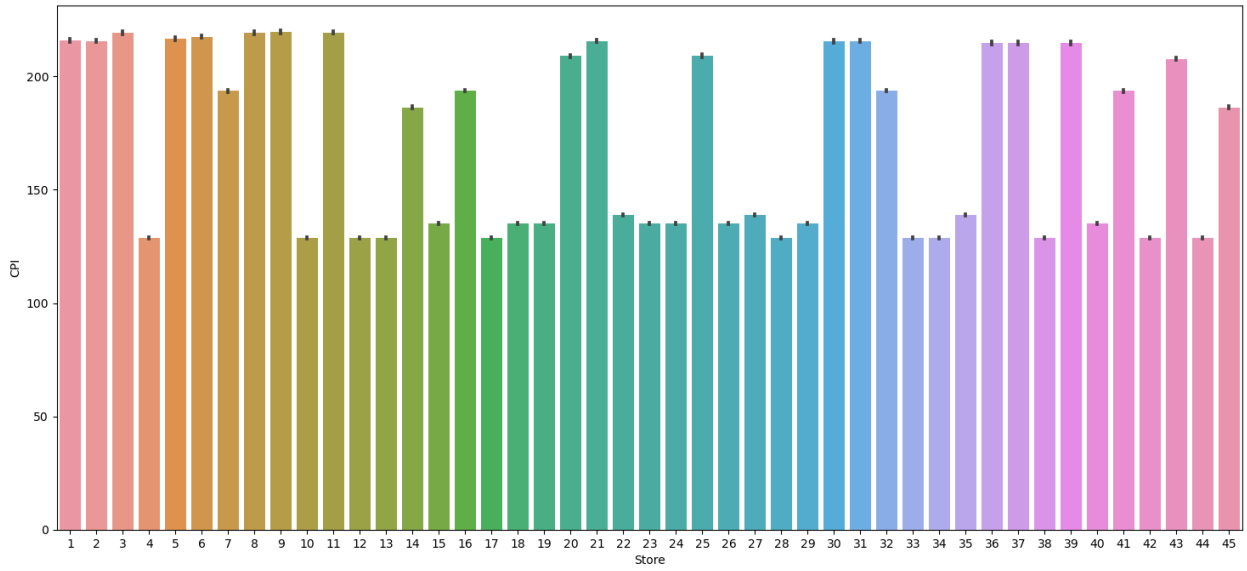
D) How is the Consumer Price index affecting the weekly sales of various stores?

```
plt.scatter(df["CPI"],df['Weekly_Sales'])
plt.xlabel('CPI')
plt.ylabel("Weekly_Sales")
plt.show()
```



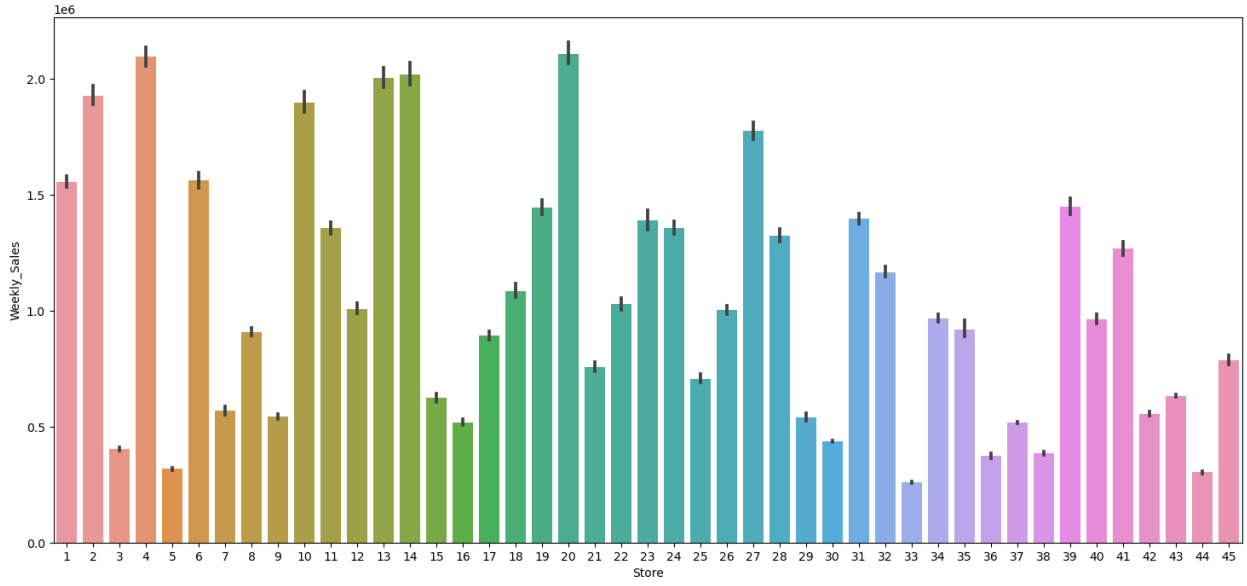

```
plt.figure(figsize=(18,8))
sns.barplot(df['Store'],df['CPI'])
plt.show()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variables as
keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```




```
plt.figure(figsize=(18,8))
sns.barplot(df['Store'],df['Weekly_Sales'])
plt.show()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\seaborn\
_decorators.py:36: FutureWarning: Pass the following variables as
keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



```
Total_by_store = df.groupby('Store').agg({'Weekly_Sales': 'sum',
'CPI': 'sum'})
Total_by_store
```

Store	Weekly_Sales	CPI
1	2.224028e+08	30887.555523
2	2.753824e+08	30837.422420
3	5.758674e+07	31372.988971
4	2.995440e+08	18401.192733
5	4.547569e+07	30968.878137
6	2.237561e+08	31110.107182
7	8.159828e+07	27693.986741
8	1.299512e+08	31379.780750
9	7.778922e+07	31406.616557
10	2.716177e+08	18401.192733
11	1.939628e+08	31372.988971
12	1.442872e+08	18401.192733
13	2.865177e+08	18401.192733
14	2.889999e+08	26638.851959
15	8.913368e+07	19318.242848
16	7.425243e+07	27693.986741
17	1.277821e+08	18401.192733
18	1.551147e+08	19318.242848
19	2.066349e+08	19318.242848
20	3.013978e+08	29892.452680
21	1.081179e+08	30837.422420
22	1.470756e+08	19878.613542
23	1.987506e+08	19318.242848
24	1.940160e+08	19318.242848
25	1.010612e+08	29892.452680
26	1.434164e+08	19318.242848
27	2.538559e+08	19878.613542
28	1.892637e+08	18401.192733
29	7.714155e+07	19318.242848
30	6.271689e+07	30837.422420
31	1.996139e+08	30837.422420
32	1.668192e+08	27693.986741
33	3.716022e+07	18401.192733
34	1.382498e+08	18401.192733
35	1.315207e+08	19878.613542
36	5.341221e+07	30706.256907
37	7.420274e+07	30706.256907
38	5.515963e+07	18401.192733
39	2.074455e+08	30706.256907
40	1.378703e+08	19318.242848
41	1.813419e+08	27693.986741
42	7.956575e+07	18401.192733
43	9.056544e+07	29706.128216

```
44     4.329309e+07  18401.192733
45     1.123953e+08  26638.851959
```

```
Total_by_store[Total_by_store.CPI==Total_by_store.CPI.max()]
```

```
       Weekly_Sales           CPI
Store
9       77789218.99  31406.616557
```

```
Total_by_store[Total_by_store.CPI==Total_by_store.CPI.min()]
```

```
       Weekly_Sales           CPI
Store
4      2.995440e+08  18401.192733
10     2.716177e+08  18401.192733
12     1.442872e+08  18401.192733
13     2.865177e+08  18401.192733
17     1.277821e+08  18401.192733
28     1.892637e+08  18401.192733
33     3.716022e+07  18401.192733
34     1.382498e+08  18401.192733
38     5.515963e+07  18401.192733
42     7.956575e+07  18401.192733
44     4.329309e+07  18401.192733
```

- Consumer Index(CPI) affects we can observer above visualization at High Weekly Sales CPI is low.
- At Low Weekly Sales CPI is high.

E) Top performing stores according to the historical data.

```
Total_data_by_store=df.groupby('Store',as_index=False).agg({"Weekly_Sales":"sum"})
Top_sales_store=Total_data_by_store.sort_values(by='Weekly_Sales',ascending=False)
Top_sales_store
```

```
    Store  Weekly_Sales
19     20  3.013978e+08
3       4  2.995440e+08
13     14  2.889999e+08
12     13  2.865177e+08
1       2  2.753824e+08
9      10  2.716177e+08
26     27  2.538559e+08
5       6  2.237561e+08
0       1  2.224028e+08
38     39  2.074455e+08
18     19  2.066349e+08
30     31  1.996139e+08
```

```
22     23  1.987506e+08
23     24  1.940160e+08
10     11  1.939628e+08
27     28  1.892637e+08
40     41  1.813419e+08
31     32  1.668192e+08
17     18  1.551147e+08
21     22  1.470756e+08
11     12  1.442872e+08
25     26  1.434164e+08
33     34  1.382498e+08
39     40  1.378703e+08
34     35  1.315207e+08
7       8  1.299512e+08
16     17  1.277821e+08
44     45  1.123953e+08
20     21  1.081179e+08
24     25  1.010612e+08
42     43  9.056544e+07
14     15  8.913368e+07
6       7  8.159828e+07
41     42  7.956575e+07
8       9  7.778922e+07
28     29  7.714155e+07
15     16  7.425243e+07
36     37  7.420274e+07
29     30  6.271689e+07
2       3  5.758674e+07
37     38  5.515963e+07
35     36  5.341221e+07
4       5  4.547569e+07
43     44  4.329309e+07
32     33  3.716022e+07
```

```
top_5_stores=Top_sales_store.head()
top_5_stores.reset_index(drop=True)
```

```
   Store  Weekly_Sales
0     20  3.013978e+08
1      4  2.995440e+08
2     14  2.889999e+08
3     13  2.865177e+08
4      2  2.753824e+08
```

- From above result we can observe the top performing stores.

F) The worst performing store, and how significant is the difference between the highest and lowest performing stores.

```
Total_data_by_store=df.groupby('Store',as_index=False).agg({"Weekly_Sales":"sum","Temperature":"mean","CPI":"sum","Unemployment":"mean"})
Total_data_by_store
```

	Store	Weekly_Sales	Temperature	CPI	Unemployment
0	1	2.224028e+08	68.306783	30887.555523	7.610420
1	2	2.753824e+08	68.216364	30837.422420	7.623846
2	3	5.758674e+07	71.434196	31372.988971	7.176986
3	4	2.995440e+08	62.253357	18401.192733	5.964692
4	5	4.547569e+07	69.410140	30968.878137	6.295406
5	6	2.237561e+08	69.700000	31110.107182	6.606902
6	7	8.159828e+07	39.720280	27693.986741	8.585734
7	8	1.299512e+08	62.513986	31379.780750	6.091846
8	9	7.778922e+07	67.775175	31406.616557	6.099881
9	10	2.716177e+08	72.241189	18401.192733	8.362965
10	11	1.939628e+08	72.480769	31372.988971	7.176986
11	12	1.442872e+08	70.262797	18401.192733	13.116483
12	13	2.865177e+08	53.697133	18401.192733	7.001825
13	14	2.889999e+08	57.790979	26638.851959	8.648748
14	15	8.913368e+07	51.833846	19318.242848	7.996252
15	16	7.425243e+07	45.030070	27693.986741	6.477993
16	17	1.277821e+08	46.387203	18401.192733	6.549406
17	18	1.551147e+08	53.371259	19318.242848	8.838301
18	19	2.066349e+08	52.295035	19318.242848	7.996252
19	20	3.013978e+08	55.451399	29892.452680	7.371413
20	21	1.081179e+08	68.847622	30837.422420	7.623846
21	22	1.470756e+08	54.897133	19878.613542	8.069371
22	23	1.987506e+08	48.805105	19318.242848	4.796014
23	24	1.940160e+08	54.030000	19318.242848	8.447014
24	25	1.010612e+08	52.138392	29892.452680	7.371413
25	26	1.434164e+08	43.658252	19318.242848	7.872070
26	27	2.538559e+08	57.311119	19878.613542	8.001748
27	28	1.892637e+08	70.262797	18401.192733	13.116483
28	29	7.714155e+07	54.897133	19318.242848	9.806385
29	30	6.271689e+07	68.847622	30837.422420	7.623846
30	31	1.996139e+08	68.847622	30837.422420	7.623846
31	32	1.668192e+08	52.747552	27693.986741	8.585734
32	33	3.716022e+07	76.728182	18401.192733	8.533154
33	34	1.382498e+08	58.495874	18401.192733	9.934804
34	35	1.315207e+08	57.311119	19878.613542	8.788573
35	36	5.341221e+07	71.160350	30706.256907	7.869049
36	37	7.420274e+07	71.160350	30706.256907	7.869049
37	38	5.515963e+07	70.262797	18401.192733	13.116483
38	39	2.074455e+08	70.597343	30706.256907	7.869049
39	40	1.378703e+08	47.674545	19318.242848	4.796014
40	41	1.813419e+08	48.410350	27693.986741	6.973378
41	42	7.956575e+07	72.241189	18401.192733	8.362965

```
42     43  9.056544e+07    68.877692  29706.128216      9.934804
43     44  4.329309e+07    53.697133  18401.192733      6.735622
44     45  1.123953e+08    57.790979  26638.851959      8.648748
```

```
Lowest_Store=Total_data_by_store.loc[(Total_data_by_store.Weekly_Sales
==Total_data_by_store.Weekly_Sales.min())]
Lowest_Store
```

```
    Store  Weekly_Sales  Temperature          CPI  Unemployment
32     33   37160221.96    76.728182  18401.192733      8.533154
```

```
Highest_Store=Total_data_by_store.loc[(Total_data_by_store.Weekly_Sale
s==Total_data_by_store.Weekly_Sales.max())]
Highest_Store
```

```
    Store  Weekly_Sales  Temperature          CPI  Unemployment
19     20  3.013978e+08    55.451399  29892.45268      7.371413
```

-- From above analysis Temperatue & Unemployement on lowest store is high that effects the sales

```
# Extract the 'Weekly_Sales' values for the lowest and highest stores
lowest_sales = Lowest_Store['Weekly_Sales'].values[0]
highest_sales = Highest_Store['Weekly_Sales'].values[0]

# Calculate the difference
difference = highest_sales - lowest_sales

print("Worst Performing Store:", Lowest_Store['Store'].values[0])
print("Best Performing Store:",Highest_Store['Store'].values[0])
print("Difference between the highest and lowest store sales:",
difference)
```

```
Worst Performing Store: 33
Best Performing Store: 20
Difference between the highest and lowest store sales:
264237570.49999997
```

```
#two sample t-test for unequal variances
from scipy.stats import ttest_ind

t_stat_2, p_val_2 =
ttest_ind(Highest_Store['Store'].values[0],Lowest_Store['Store'].value
s[0], equal_var=False)
print(t_stat_2, p_val_2)
```

```
nan nan
```

```
C:\Users\Arigala.Adarsh\AppData\Local\Temp\
ipykernel_24176\3270785390.py:4: RuntimeWarning: Precision loss
occurred in moment calculation due to catastrophic cancellation. This
```

```
occurs when the data are nearly identical. Results may be unreliable.
  t_stat_2, p_val_2 =
ttest_ind(Highest_Store['Store'].values[0],Lowest_Store['Store'].value
s[0], equal_var=False)
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\scipy\stats\
_stats_py.py:1250: RuntimeWarning: divide by zero encountered in
divide
  var *= np.divide(n, n-ddof)  # to avoid error on division by zero
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\scipy\stats\
_stats_py.py:1250: RuntimeWarning: invalid value encountered in
double_scalars
  var *= np.divide(n, n-ddof)  # to avoid error on division by zero
```

```
df.dtypes
```

```
Store             int64
Date             object
Weekly_Sales    float64
Holiday_Flag      int64
Temperature     float64
Fuel_Price      float64
CPI             float64
Unemployment    float64
dtype: object
```

Converting Date data_type(object) to datetime(datetime64) data_types

```
df.Date=pd.to_datetime(df.Date,format="%d-%m-%Y")

df.Date.dtypes

dtype('<M8[ns]')

df=df.set_index("Date")

df
```

Date	Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price
2010-02-05	1	1643690.90	0	42.31	2.572
2010-02-12	1	1641957.44	1	38.51	2.548
2010-02-19	1	1611968.17	0	39.93	2.514
2010-02-26	1	1409727.59	0	46.63	2.561
2010-03-05	1	1554806.68	0	46.50	2.625
...	...	...	...	...	...

```
2012-09-28     45     713173.95             0         64.88        3.997

2012-10-05     45     733455.07             0         64.89        3.985

2012-10-12     45     734464.36             0         54.47        4.000

2012-10-19     45     718125.53             0         56.47        3.969

2012-10-26     45     760281.43             0         58.85        3.882
```

```
                    CPI  Unemployment
Date
2010-02-05  211.096358         8.106
2010-02-12  211.242170         8.106
2010-02-19  211.289143         8.106
2010-02-26  211.319643         8.106
2010-03-05  211.350143         8.106
...                ...           ...
2012-09-28  192.013558         8.684
2012-10-05  192.170412         8.667
2012-10-12  192.327265         8.667
2012-10-19  192.330854         8.667
2012-10-26  192.308899         8.667

[6435 rows x 7 columns]
```

```
df.shape
```

```
(6435, 7)
```

Time Series Analysis

```
df_target=df.loc[:,['Store',"Weekly_Sales"]]
```

```
df_target
```

```
             Store  Weekly_Sales
Date
2010-02-05       1    1643690.90
2010-02-12       1    1641957.44
2010-02-19       1    1611968.17
2010-02-26       1    1409727.59
2010-03-05       1    1554806.68
...            ...           ...
2012-09-28      45     713173.95
2012-10-05      45     733455.07
2012-10-12      45     734464.36
```

```
2012-10-19     45     718125.53
2012-10-26     45     760281.43

[6435 rows x 2 columns]
```

```
df_target.dtypes
```

```
Store             int64
Weekly_Sales    float64
dtype: object
```

```
from pmdarima import auto_arima
model = auto_arima(df["Weekly_Sales"], seasonal=True, stepwise=True,
trace=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=173103.554, Time=1.98 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=174457.419, Time=0.11 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=173626.224, Time=0.37 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=173359.721, Time=0.36 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=174455.423, Time=0.08 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=173301.748, Time=1.26 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=173266.524, Time=1.39 sec
 ARIMA(3,1,2)(0,0,0)[0] intercept   : AIC=172741.309, Time=2.43 sec
 ARIMA(3,1,1)(0,0,0)[0] intercept   : AIC=172905.020, Time=2.07 sec
 ARIMA(4,1,2)(0,0,0)[0] intercept   : AIC=172730.428, Time=5.52 sec
 ARIMA(4,1,1)(0,0,0)[0] intercept   : AIC=172847.176, Time=1.76 sec
 ARIMA(5,1,2)(0,0,0)[0] intercept   : AIC=172588.751, Time=10.03 sec
 ARIMA(5,1,1)(0,0,0)[0] intercept   : AIC=172597.113, Time=2.62 sec
 ARIMA(5,1,3)(0,0,0)[0] intercept   : AIC=172572.018, Time=5.79 sec
 ARIMA(4,1,3)(0,0,0)[0] intercept   : AIC=172609.343, Time=7.86 sec
 ARIMA(5,1,4)(0,0,0)[0] intercept   : AIC=172568.730, Time=6.89 sec
 ARIMA(4,1,4)(0,0,0)[0] intercept   : AIC=172608.399, Time=5.48 sec
 ARIMA(5,1,5)(0,0,0)[0] intercept   : AIC=172515.273, Time=9.59 sec
 ARIMA(4,1,5)(0,0,0)[0] intercept   : AIC=172515.184, Time=5.78 sec
 ARIMA(3,1,5)(0,0,0)[0] intercept   : AIC=172520.188, Time=5.01 sec
 ARIMA(3,1,4)(0,0,0)[0] intercept   : AIC=172730.332, Time=5.61 sec
 ARIMA(4,1,5)(0,0,0)[0]             : AIC=172513.152, Time=5.20 sec
 ARIMA(3,1,5)(0,0,0)[0]             : AIC=172518.165, Time=4.59 sec
 ARIMA(4,1,4)(0,0,0)[0]             : AIC=172606.296, Time=5.30 sec
 ARIMA(5,1,5)(0,0,0)[0]             : AIC=172513.236, Time=8.90 sec
 ARIMA(3,1,4)(0,0,0)[0]             : AIC=172728.335, Time=5.16 sec
 ARIMA(5,1,4)(0,0,0)[0]             : AIC=172566.624, Time=6.81 sec

Best model:  ARIMA(4,1,5)(0,0,0)[0]
Total fit time: 117.957 seconds
```

Store_1 Dataset

```
result=adfuller(df_target[df_target['Store']==1]['Weekly_Sales'])
result
```

```
(-5.102186145192286,
 1.3877788330759535e-05,
 4,
 138,
 {'1%': -3.47864788917503,
  '5%': -2.882721765644168,
  '10%': -2.578065326612056},
 3412.7325502876756)
```

From the above, we see that that p value is close to 0 and we can conclude that the data is stationary

```
p_value=result[1]
p_value
if p_value <=0.05:
    print('Stationarity is present')
else:
    print('NO Stationarity is present')
```

```
Stationarity is present
```

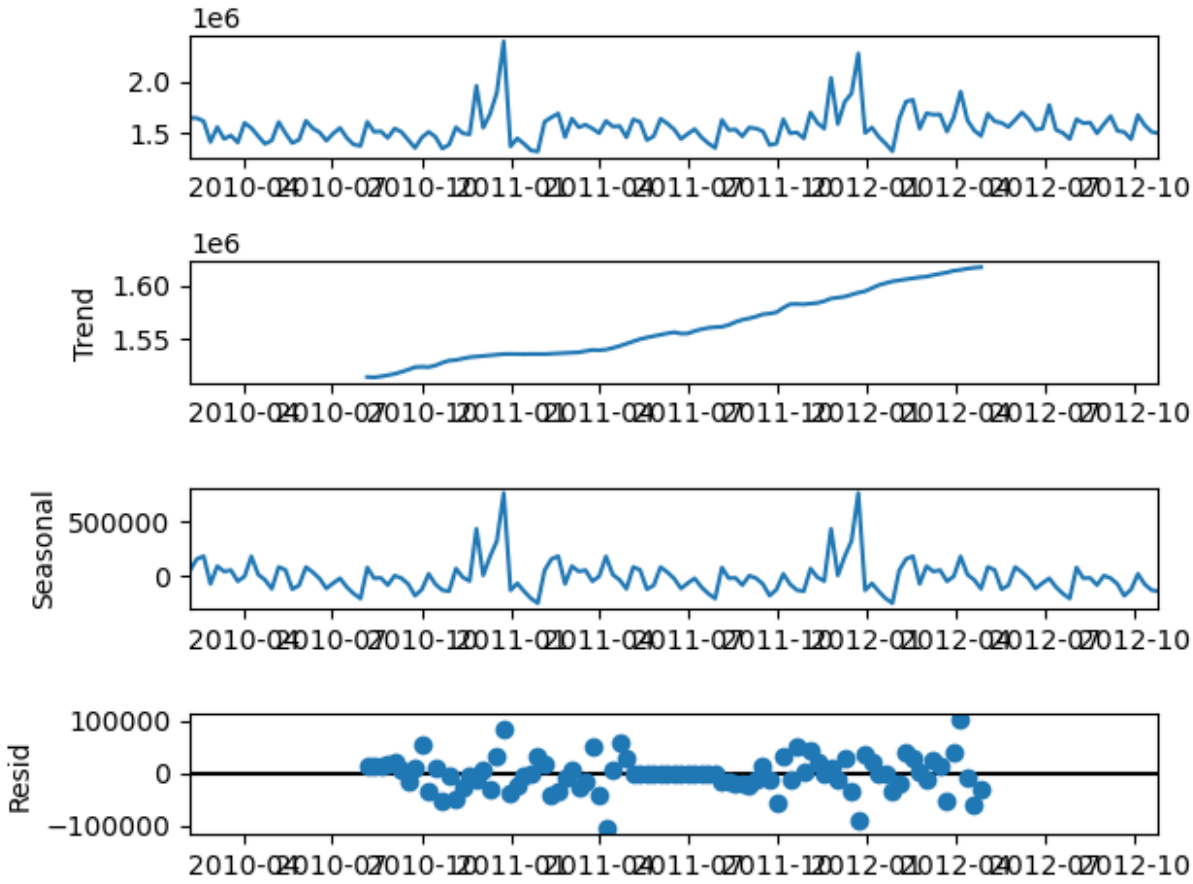
```
store1=pd.DataFrame(df_target[df_target['Store']==1]['Weekly_Sales'])
store1=store1.sort_index()
store1
```

```
            Weekly_Sales
Date
2010-02-05    1643690.90
2010-02-12    1641957.44
2010-02-19    1611968.17
2010-02-26    1409727.59
2010-03-05    1554806.68
...                  ...
2012-09-28    1437059.26
2012-10-05    1670785.97
2012-10-12    1573072.81
2012-10-19    1508068.77
2012-10-26    1493659.74

[143 rows x 1 columns]
```

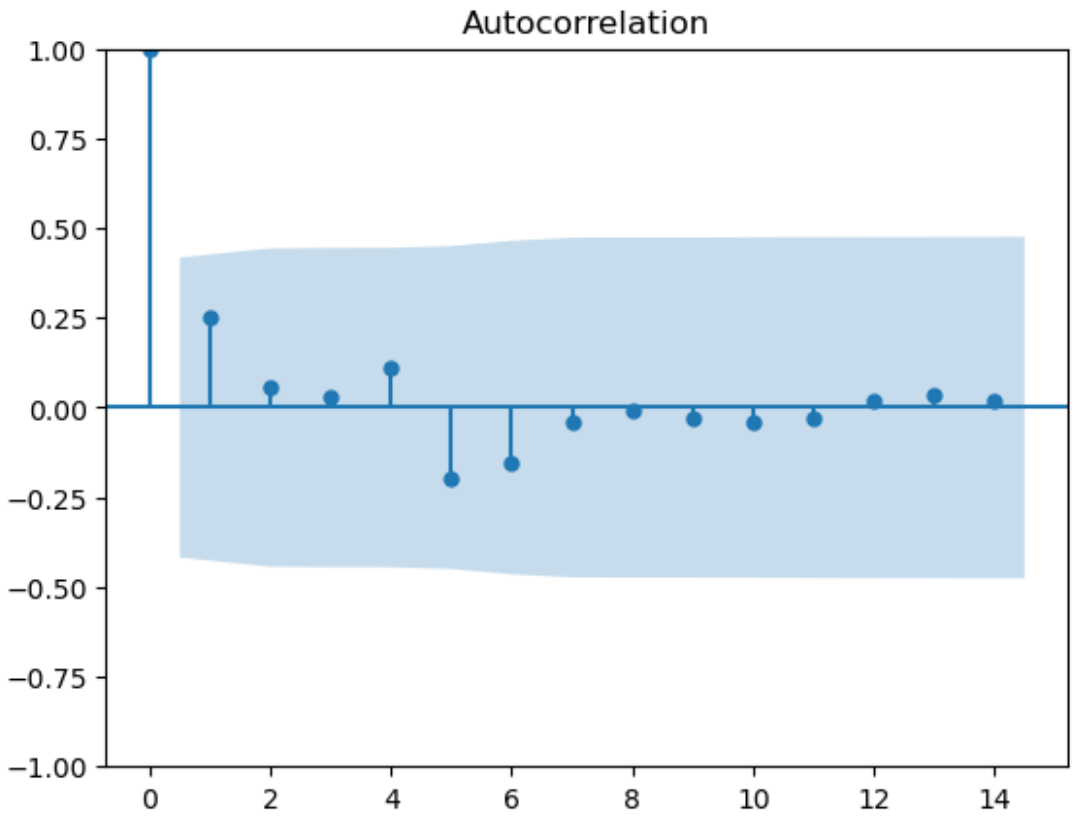
Visualizing Seasonality

```
decompose=seasonal_decompose(store1.dropna())
decompose_plot=decompose.plot()
```



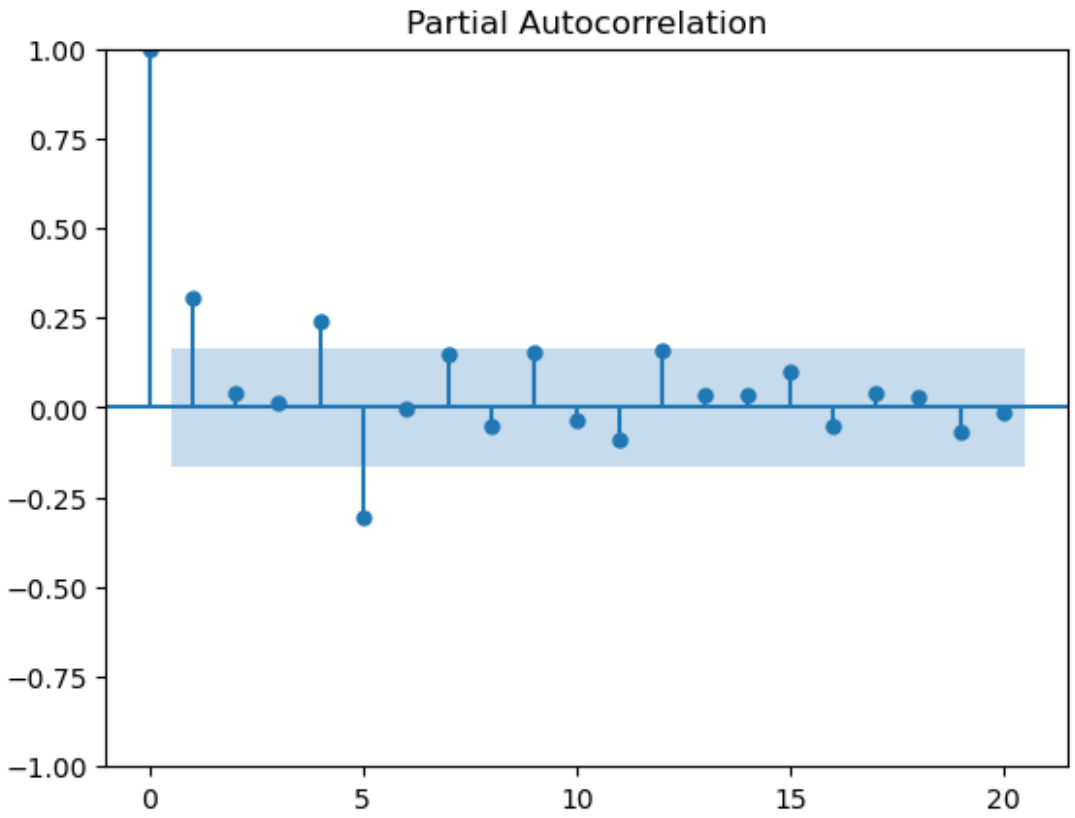

```
acf_plot=acf(store1["Weekly_Sales"])

plot_acf(acf_plot)
plt.show()
```




```
plot_pacf(store1["Weekly_Sales"],lags=20)
plt.show()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\
graphics\tsaplots.py:348: FutureWarning: The default method 'yw' can
produce PACF values outside of the [-1,1] interval. After 0.13, the
default will change tounadjusted Yule-Walker ('ywm'). You can use this
method now by setting method='ywm'.
  warnings.warn(
```

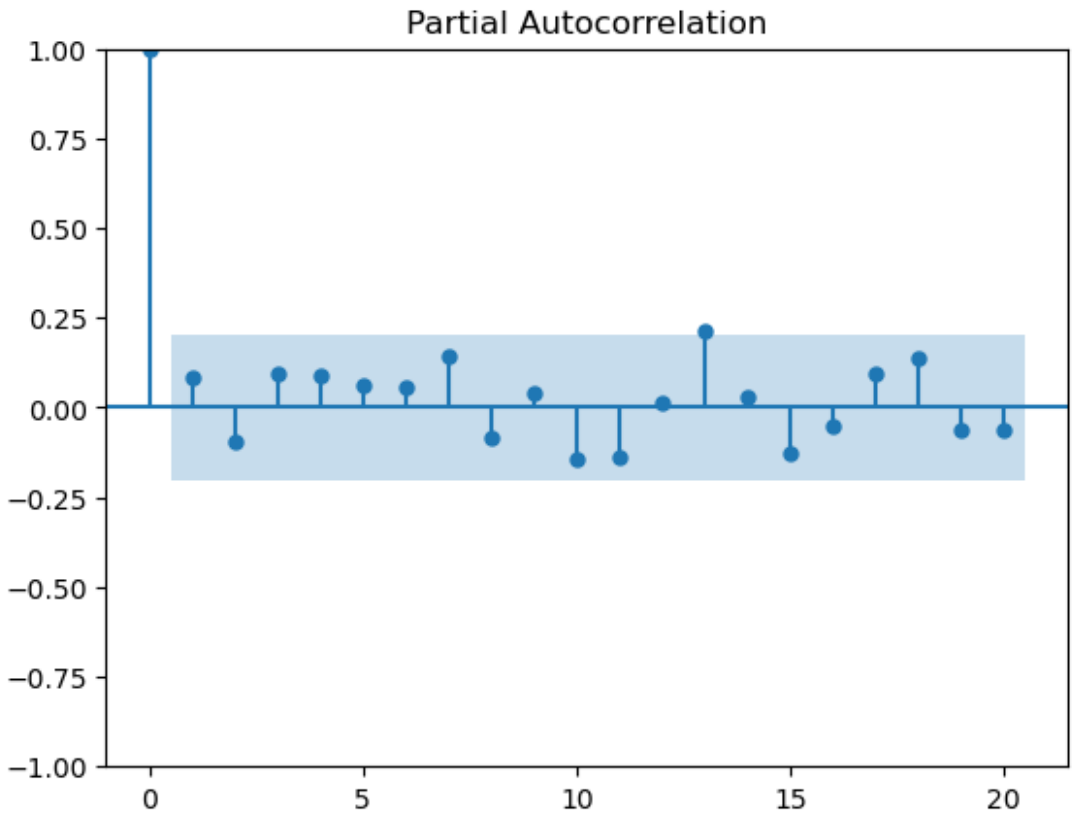



```
store1['lag1']=store1['Weekly_Sales'].diff()

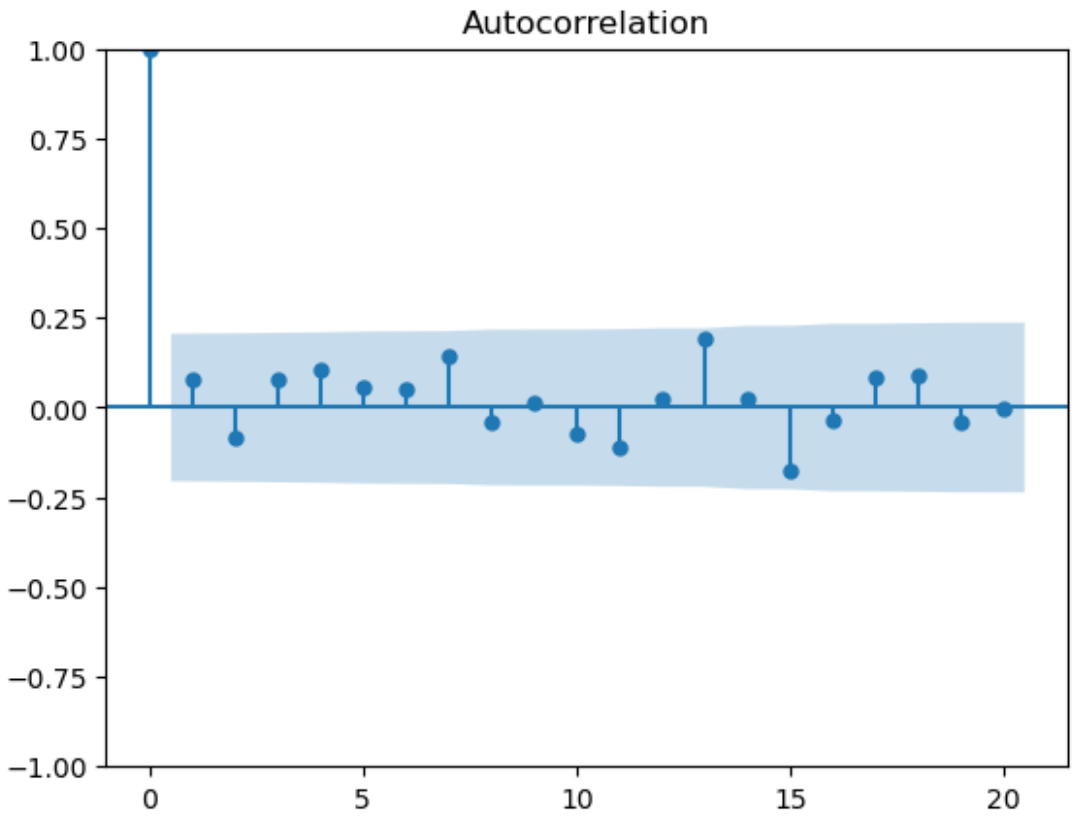
store1['lag52']=store1['Weekly_Sales'].diff(52)

pacf_values=plot_pacf(store1['lag52'].dropna(),lags=20)
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\
graphics\tsaplots.py:348: FutureWarning: The default method 'yw' can
produce PACF values outside of the [-1,1] interval. After 0.13, the
default will change tounadjusted Yule-Walker ('ywm'). You can use this
method now by setting method='ywm'.
  warnings.warn(
```




```
acf_values=plot_acf(store1['lag52'].dropna(),lags=20)
```




```
# From the above, pacf(p) ,acf(q) value is 0
pacf_values=sm.tsa.pacf(store1['Weekly_Sales'],nlags=20)
pacf_values
```

```
array([ 1.        ,  0.30375985,  0.04021628,  0.01219543,
0.23927843,
       -0.30788835, -0.0014493 ,  0.14798536, -0.05206473,
0.1547872 ,
       -0.03652748, -0.08797706,  0.16184013,  0.03250986,
0.03380417,
        0.10062548, -0.04966531,  0.04265725,  0.02866535, -
0.0672978 ,
       -0.0144685 ])
```

- p[1]=0.30 value will be near to zero then p=0

```
train = store1.iloc[:116]['Weekly_Sales']
test = store1.iloc[117:]['Weekly_Sales']
```

Training the Model

```
model=SARIMAX(train,order=(0,1,0),seasonal_order=(0,1,0,52))
model_fit = model.fit()
model_fit.summary()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\tsa\
base\tsa_model.py:471: ValueWarning: No frequency information was
provided, so inferred frequency W-FRI will be used.
  self._init_dates(dates, freq)
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\tsa\
base\tsa_model.py:471: ValueWarning: No frequency information was
provided, so inferred frequency W-FRI will be used.
  self._init_dates(dates, freq)

<class 'statsmodels.iolib.summary.Summary'>
"""
                                     SARIMAX Results

==========================================================================
====================
Dep. Variable:                          Weekly_Sales   No. Observations:
116
Model:              SARIMAX(0, 1, 0)x(0, 1, 0, 52)   Log Likelihood
-814.081
Date:                               Thu, 21 Dec 2023   AIC
1630.161
Time:                                       21:14:30   BIC
1632.305
Sample:                                   02-05-2010   HQIC
1631.004
                                        - 04-20-2012

Covariance Type:                                 opg

==========================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------
--------
sigma2      4.227e+09   3.26e+08     12.964      0.000    3.59e+09
4.87e+09
==========================================================================
==============
Ljung-Box (L1) (Q):                   7.14   Jarque-Bera (JB):
2.40
Prob(Q):                              0.01   Prob(JB):
0.30
Heteroskedasticity (H):               1.86   Skew:
0.09
Prob(H) (two-sided):                  0.16   Kurtosis:
3.94
==========================================================================
==============
```

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

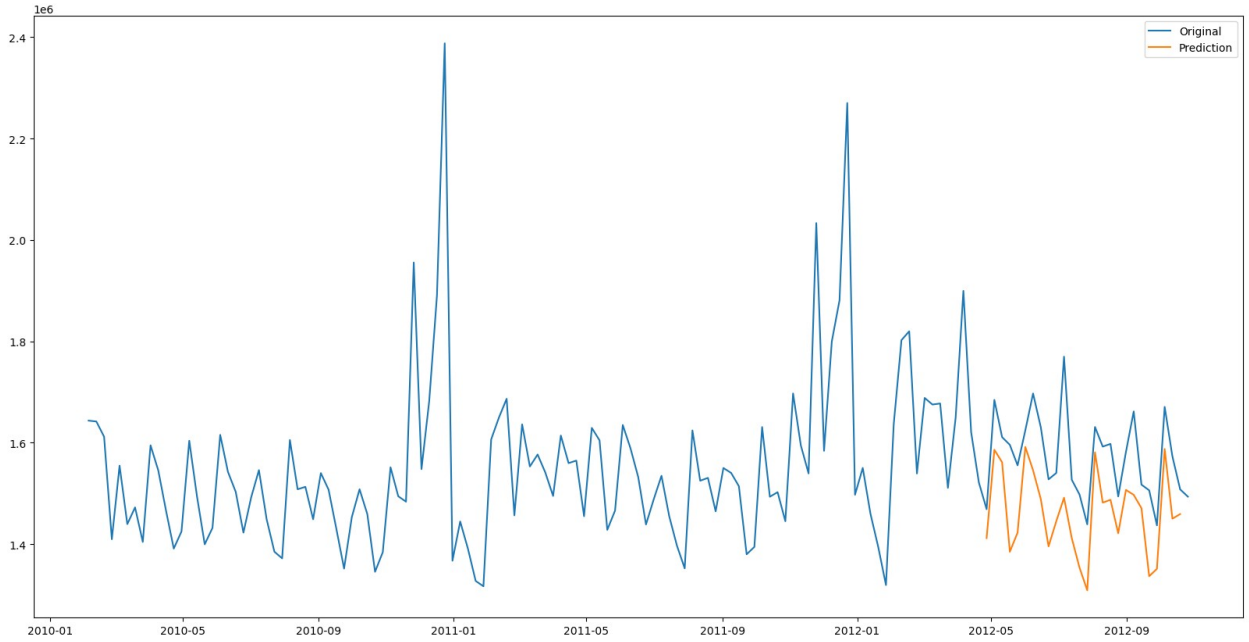
Testing the Model

```
pred = model_fit.predict(start= len(train),end=len(train)+len(test)-
1,dynamic=True)


pred


2012-04-27    1411848.75
2012-05-04    1586149.34
2012-05-11    1561533.64
2012-05-18    1384976.33
2012-05-25    1422804.73
2012-06-01    1591836.47
2012-06-08    1545706.38
2012-06-15    1488872.92
2012-06-22    1395588.21
2012-06-29    1445296.15
2012-07-06    1491607.70
2012-07-13    1411878.03
2012-07-20    1353684.88
2012-07-27    1308977.85
2012-08-03    1581141.81
2012-08-10    1481905.15
2012-08-17    1487519.49
2012-08-24    1421451.52
2012-08-31    1506987.28
2012-09-07    1497229.30
2012-09-14    1471017.84
2012-09-21    1336778.33
2012-09-28    1351319.89
2012-10-05    1587748.01
2012-10-12    1450283.99
2012-10-19    1459320.84
Freq: W-FRI, Name: predicted_mean, dtype: float64

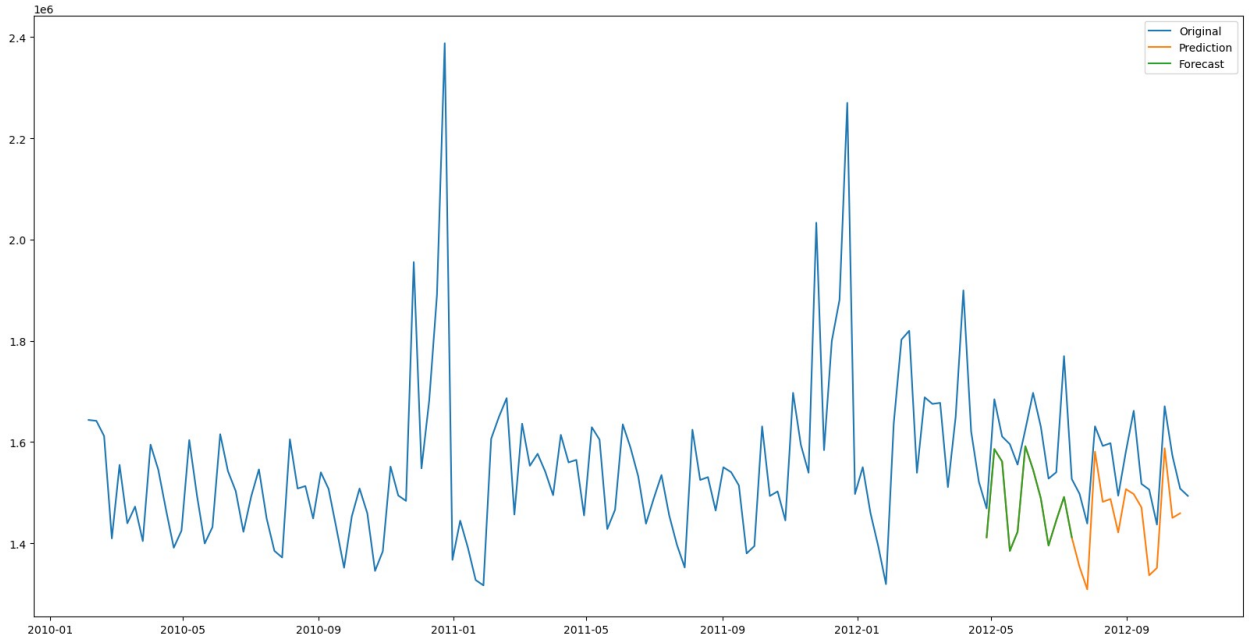
plt.figure(figsize=(20,10))
plt.plot(store1['Weekly_Sales'],label="Original")
plt.plot(pred,label="Prediction")
plt.legend()
plt.show()
```



Forecasting for Next 12 Weekly_Sales

```
forecast=model_fit.forecast(steps=12)

plt.figure(figsize=(20,10))
plt.plot(store1['Weekly_Sales'],label="Original")
plt.plot(pred,label="Prediction")
plt.plot(forecast,label="Forecast")
plt.legend()
plt.show()
```



```
# Assuming 'test' contains the actual values from your test dataset
comparison = pd.DataFrame({'Actual': test, 'Predicted': pred})
comparison.dropna(inplace=True)

from sklearn.metrics import mean_absolute_error, mean_squared_error

mae = mean_absolute_error(comparison['Actual'],
comparison['Predicted'])
mse = mean_squared_error(comparison['Actual'],
comparison['Predicted'])
rmse = np.sqrt(mse)
print(f'Mean Absolute Error (MAE): {mae}')
print(f'Mean Squared Error (MSE): {mse}')
print(f'Root Mean Squared Error (RMSE): {rmse}')
```

```
Mean Absolute Error (MAE): 114072.18199999996
Mean Squared Error (MSE): 16028529961.942461
Root Mean Squared Error (RMSE): 126603.83075540196
```

```
### Store_2 Dataset

result=adfuller(df_target[df_target['Store']==2]['Weekly_Sales'])
result
```

```
(-3.7088625726189157,
 0.003990207089066268,
 6,
 136,
 {'1%': -3.4793722137854926,
  '5%': -2.8830370378332995,
  '10%': -2.578233635380623},
 3512.243755386891)
```

```
#### From the above, we see that that p value is close to 0 and we can
conclude that the data is stationary

p_value=result[1]
p_value
if p_value <=0.05:
    print('Stationarity is present')
else:
    print('NO Stationarity is present')
```

```
Stationarity is present
```

```
store2=pd.DataFrame(df_target[df_target['Store']==2]['Weekly_Sales'])
store2=store2.sort_index()
store2
```

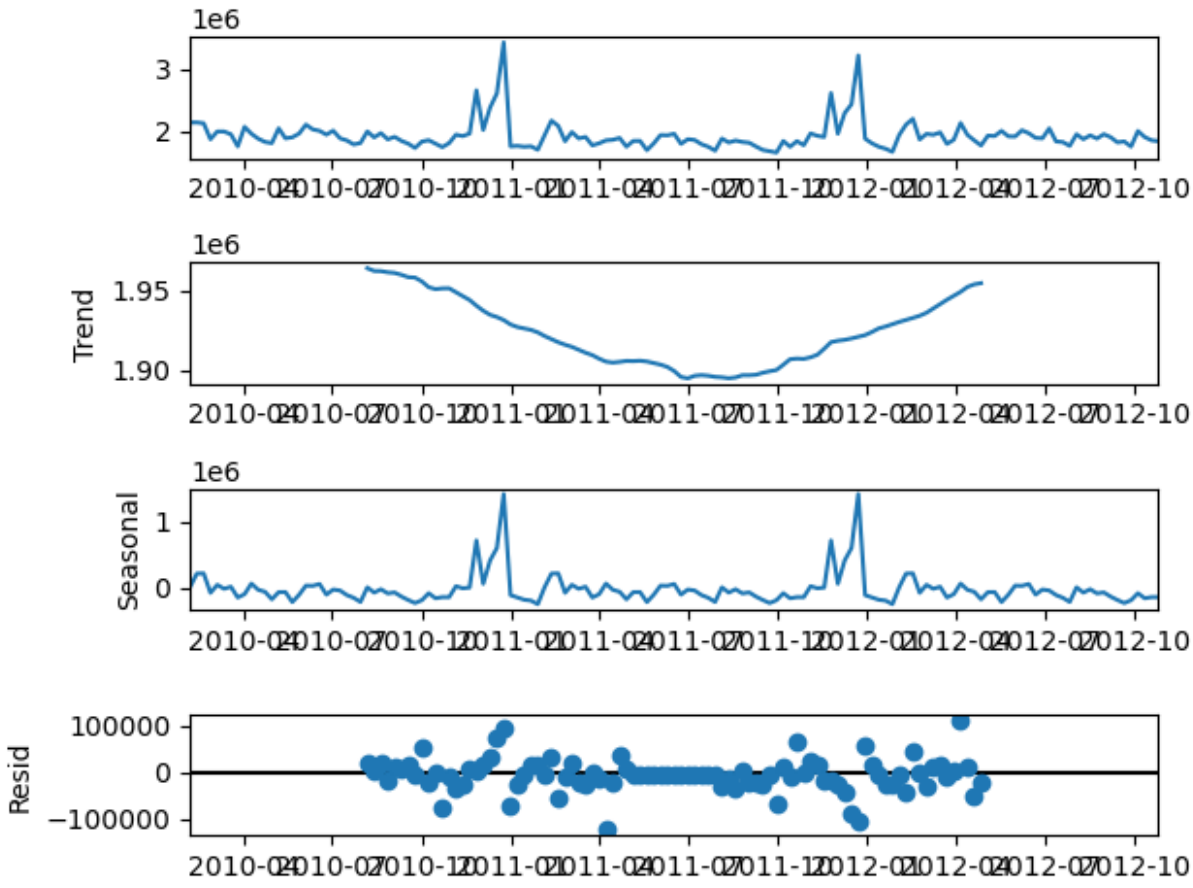
```
            Weekly_Sales
Date
2010-02-05    2136989.46
```

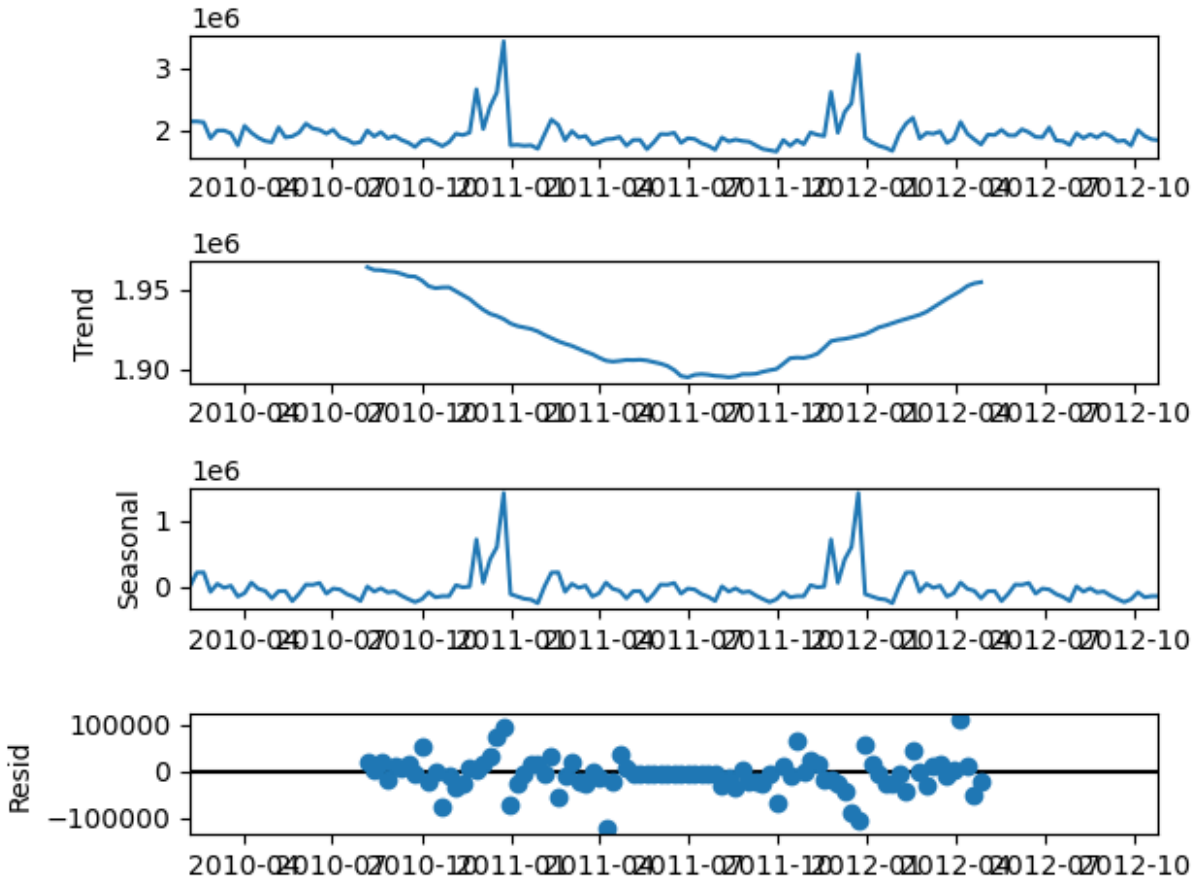
```
2010-02-12    2137809.50
2010-02-19    2124451.54
2010-02-26    1865097.27
2010-03-05    1991013.13
...                  ...
2012-09-28    1746470.56
2012-10-05    1998321.04
2012-10-12    1900745.13
2012-10-19    1847990.41
2012-10-26    1834458.35

[143 rows x 1 columns]
```

Visualizing Seasonality

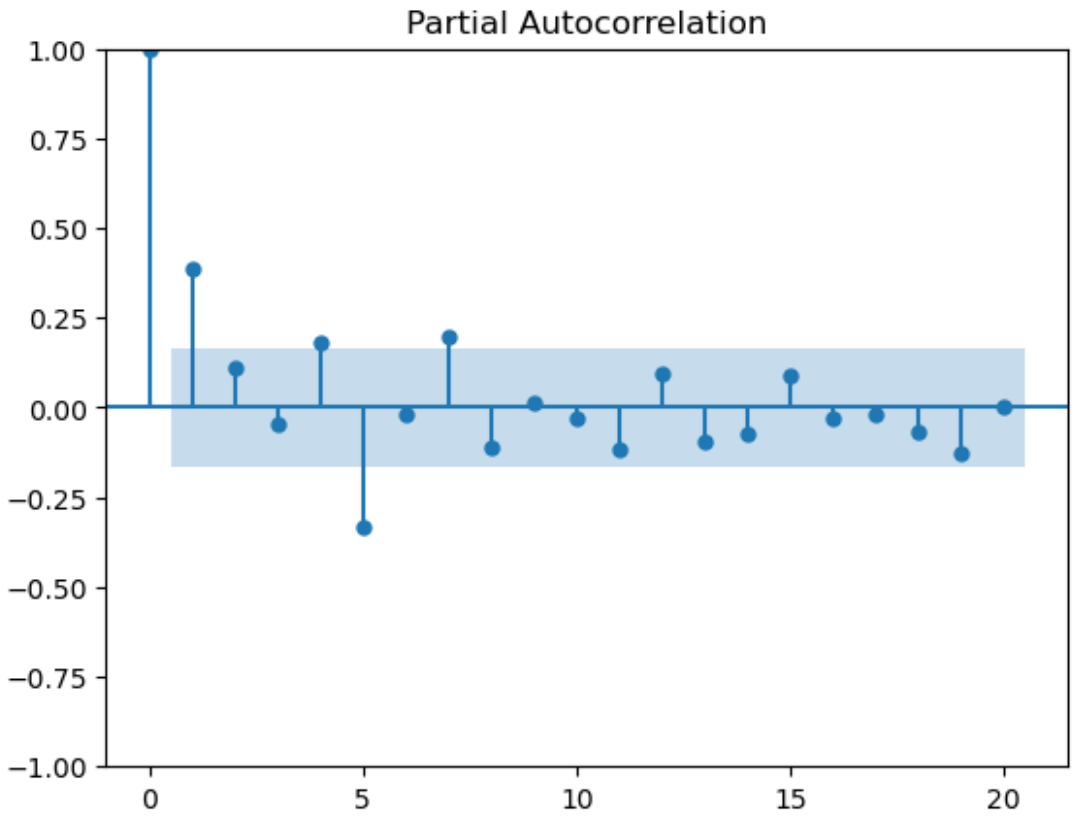
```
decompose=seasonal_decompose(store2.dropna())
decompose.plot()
```






```
plot_pacf(store2["Weekly_Sales"],lags=20)
plt.show()
```

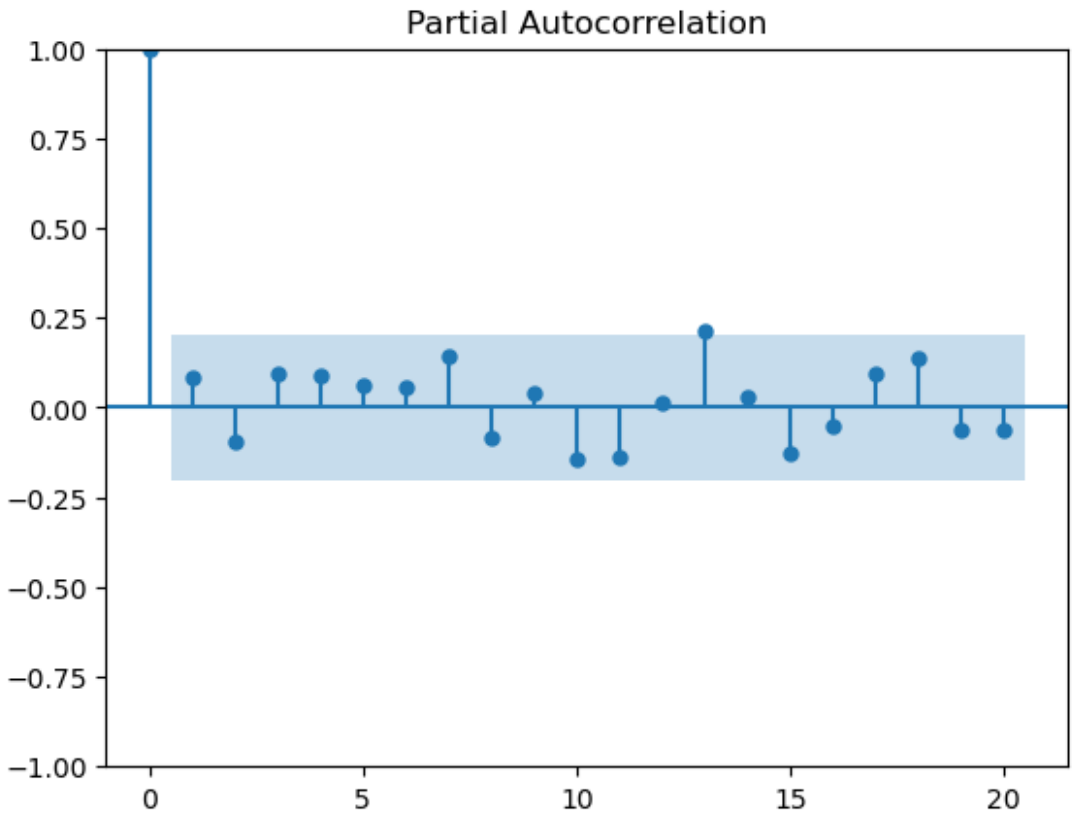
```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\
graphics\tsaplots.py:348: FutureWarning: The default method 'yw' can
produce PACF values outside of the [-1,1] interval. After 0.13, the
default will change tounadjusted Yule-Walker ('ywm'). You can use this
method now by setting method='ywm'.
  warnings.warn(
```




```
store2['lag1']=store1['Weekly_Sales'].diff()
store2['lag52']=store1['Weekly_Sales'].diff(52)

pacf_values=plot_pacf(store1['lag52'].dropna(),lags=20)
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\
graphics\tsaplots.py:348: FutureWarning: The default method 'yw' can
produce PACF values outside of the [-1,1] interval. After 0.13, the
default will change tounadjusted Yule-Walker ('ywm'). You can use this
method now by setting method='ywm'.
  warnings.warn(
```



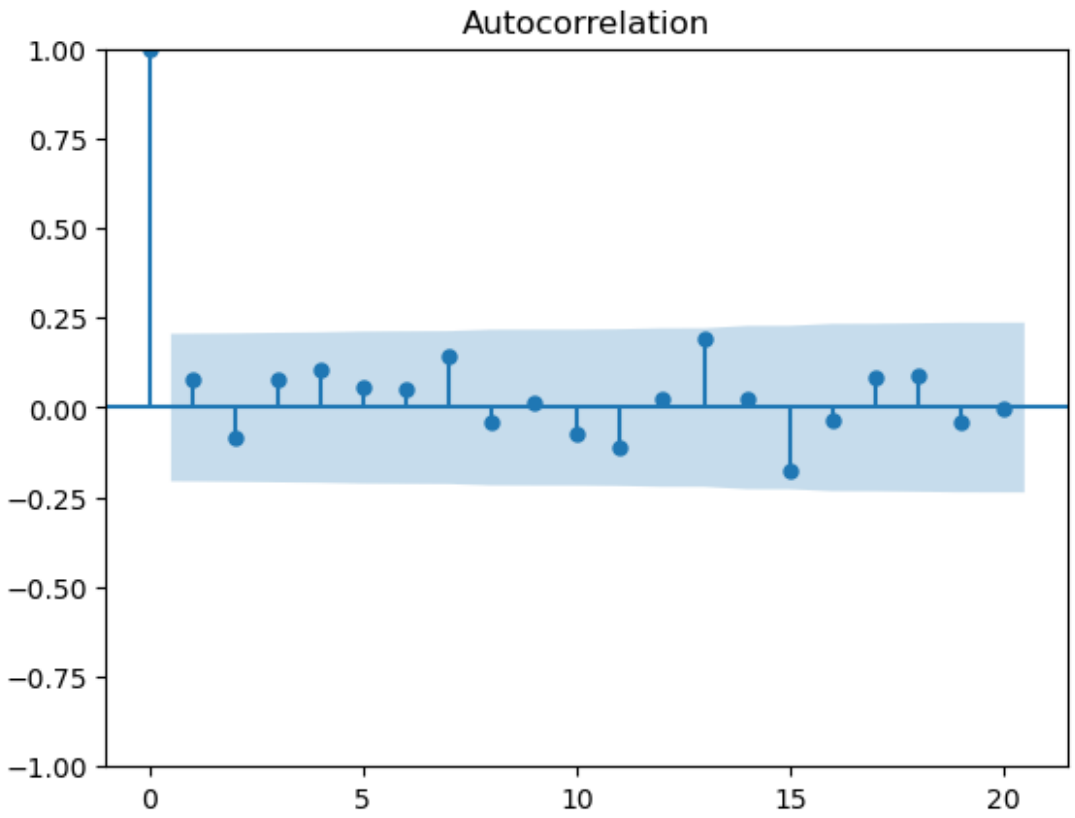

```
pacf_values=sm.tsa.pacf(store2['Weekly_Sales'],nlags=20)
pacf_values
```

```
array([ 1.        ,  0.38587372,  0.10823551, -0.04658177,
0.17916511,
       -0.33086122, -0.0192553 ,  0.20004553, -0.10931221,
0.01105632,
       -0.03023624, -0.11649167,  0.09603219, -0.0947752 , -
0.07070914,
        0.09128467, -0.03215824, -0.01709414, -0.07026318, -
0.12648523,
        0.00434761])
```

- p[1]=0.38 value will be near to zero then p=0

```
# From the above, pacf(p) ,acf(q) value is 0

acf_values=plot_acf(store2['lag52'].dropna(),lags=20)
```




```
train = store2.iloc[:round(len(store2)*0.7)]['Weekly_Sales']
```

Training the Model

```
model=SARIMAX(train,order=(0,1,0),seasonal_order=(0,1,0,52))
model_fit = model.fit()
model_fit.summary()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\tsa\
base\tsa_model.py:471: ValueWarning: No frequency information was
provided, so inferred frequency W-FRI will be used.
  self._init_dates(dates, freq)
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\tsa\
base\tsa_model.py:471: ValueWarning: No frequency information was
provided, so inferred frequency W-FRI will be used.
  self._init_dates(dates, freq)
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                      SARIMAX Results

==============================================================================
====================
```

```
Dep. Variable:                        Weekly_Sales   No. Observations:
100
Model:             SARIMAX(0, 1, 0)x(0, 1, 0, 52)   Log Likelihood
-620.580
Date:                            Thu, 21 Dec 2023   AIC
1243.161
Time:                                    21:14:32   BIC
1245.011
Sample:                                02-05-2010   HQIC
1243.857
                                     - 12-30-2011

Covariance Type:                               opg

==============================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
--------
sigma2      5.578e+09   4.13e+08     13.503      0.000    4.77e+09
6.39e+09
==============================================================================
=============
Ljung-Box (L1) (Q):                   6.61   Jarque-Bera (JB):
3.07
Prob(Q):                              0.01   Prob(JB):
0.22
Heteroskedasticity (H):               0.73   Skew:
0.32
Prob(H) (two-sided):                  0.53   Kurtosis:
4.07
==============================================================================
=============

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

Testing the Model

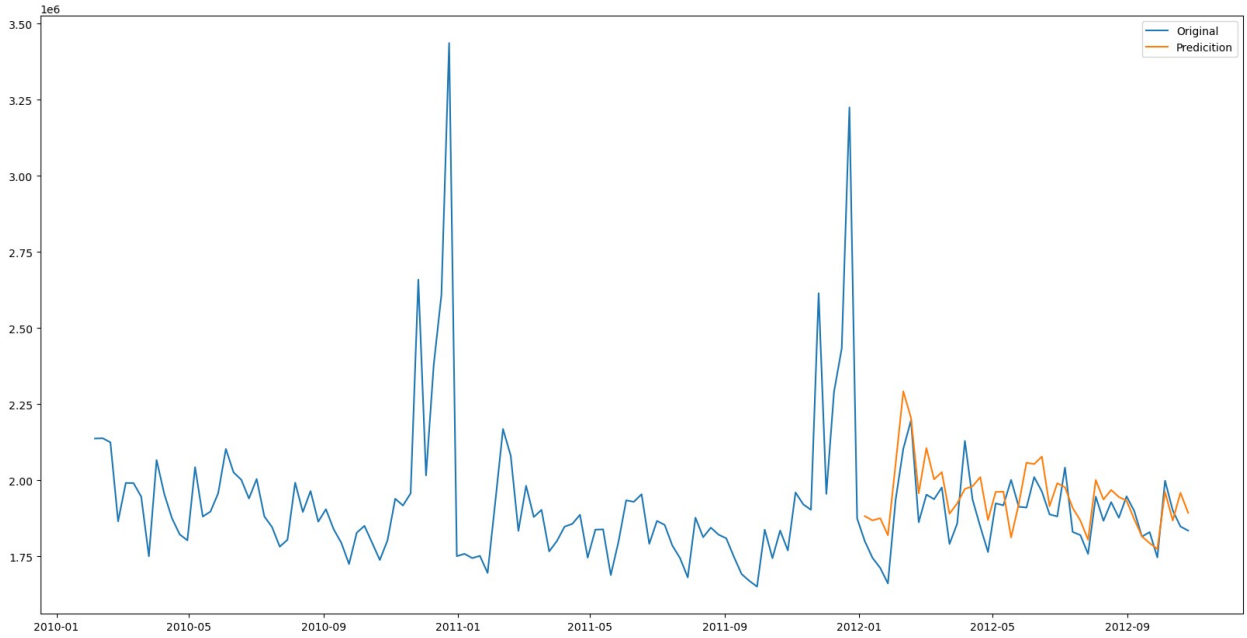
```
pred = model_fit.predict(start= len(train),end=len(store2)-
1,dynamic=True)


pred

2012-01-06    1881842.76
2012-01-13    1867985.55
```

```
2012-01-20    1875176.87
2012-01-27    1819163.65
2012-02-03    2053138.20
2012-02-10    2291833.58
2012-02-17    2204676.79
2012-02-24    1957303.05
2012-03-02    2105399.75
2012-03-09    2002899.28
2012-03-16    2026349.63
2012-03-23    1889954.02
2012-03-30    1923963.33
2012-04-06    1971344.58
2012-04-13    1980259.81
2012-04-20    2010131.57
2012-04-27    1869337.25
2012-05-04    1961535.57
2012-05-11    1962305.04
2012-05-18    1812073.83
2012-05-25    1921524.53
2012-06-01    2057548.18
2012-06-08    2052945.13
2012-06-15    2077563.96
2012-06-22    1914717.77
2012-06-29    1990034.97
2012-07-06    1976953.96
2012-07-13    1908979.26
2012-07-20    1867608.38
2012-07-27    1804485.03
2012-08-03    2000496.23
2012-08-10    1936560.23
2012-08-17    1967886.56
2012-08-24    1944931.88
2012-08-31    1932911.67
2012-09-07    1871792.62
2012-09-14    1815231.49
2012-09-21    1793091.75
2012-09-28    1774186.41
2012-10-05    1961345.40
2012-10-12    1867674.16
2012-10-19    1958472.22
2012-10-26    1893088.22
Freq: W-FRI, Name: predicted_mean, dtype: float64
```

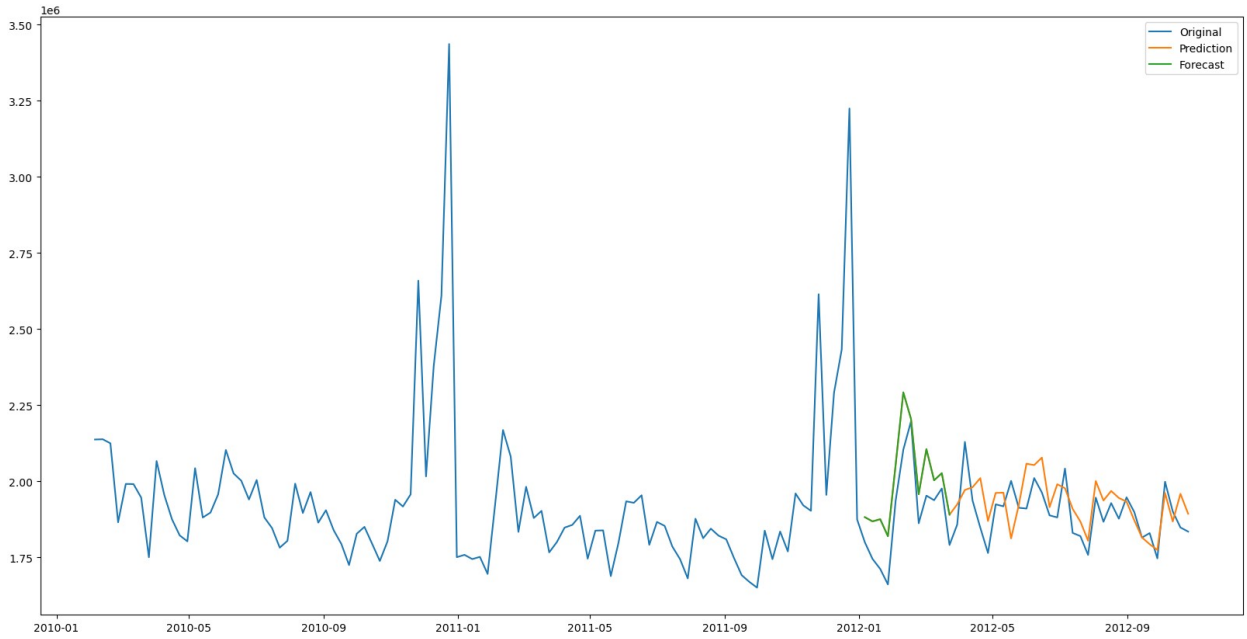
```
plt.figure(figsize=(20,10))
plt.plot(store2['Weekly_Sales'],label="Original")
plt.plot(pred,label="Predicition")
plt.legend(loc="best")
plt.show()
```



Forecasting for Next 12 Weekly_Sales

```
forecast=model_fit.forecast(steps=12)

plt.figure(figsize=(20,10))
plt.plot(store2['Weekly_Sales'],label="Original")
plt.plot(pred,label="Prediction")
plt.plot(forecast,label="Forecast")
plt.legend()
plt.show()
```



```
### Store_3 Dataset

result=adfuller(df_target[df_target["Store"]==3]['Weekly_Sales'])
result
```

```
(-2.9638677455113234,
 0.03840926179831252,
 6,
 136,
 {'1%': -3.4793722137854926,
  '5%': -2.8830370378332995,
  '10%': -2.578233635380623},
 3064.8688740270827)
```

```
#### From the above, we see that that p value is close to 0 and we can conclude that the data is stationary

if(result[1]<0.05):
    print("Stationary is present")
else:
    print("Not Stationary is present")
```

```
Stationary is present
```

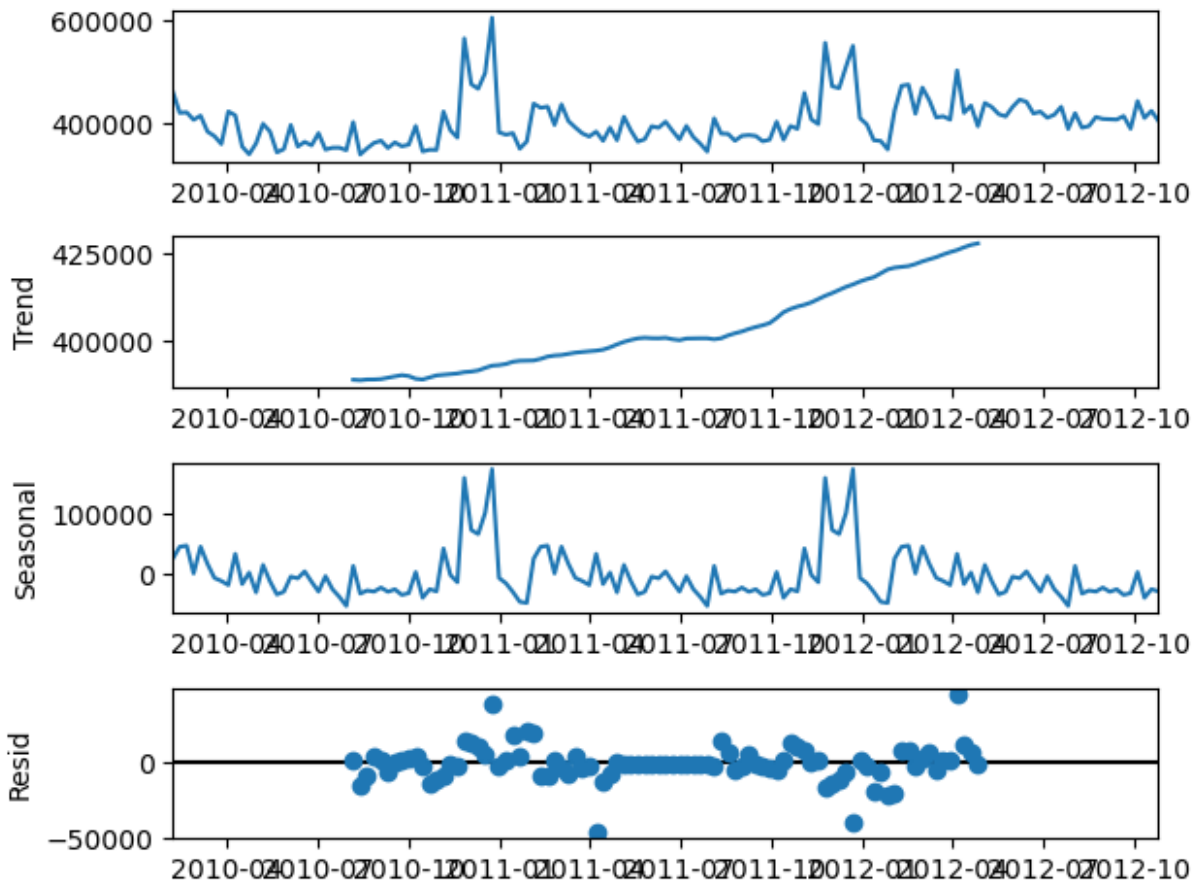
```
store3=pd.DataFrame(df_target[df_target["Store"]==3]["Weekly_Sales"])
store3
```

```
            Weekly_Sales
Date
2010-02-05     461622.22
2010-02-12     420728.96
2010-02-19     421642.19
2010-02-26     407204.86
2010-03-05     415202.04
...                  ...
2012-09-28     389813.02
2012-10-05     443557.65
2012-10-12     410804.39
2012-10-19     424513.08
2012-10-26     405432.70

[143 rows x 1 columns]
```

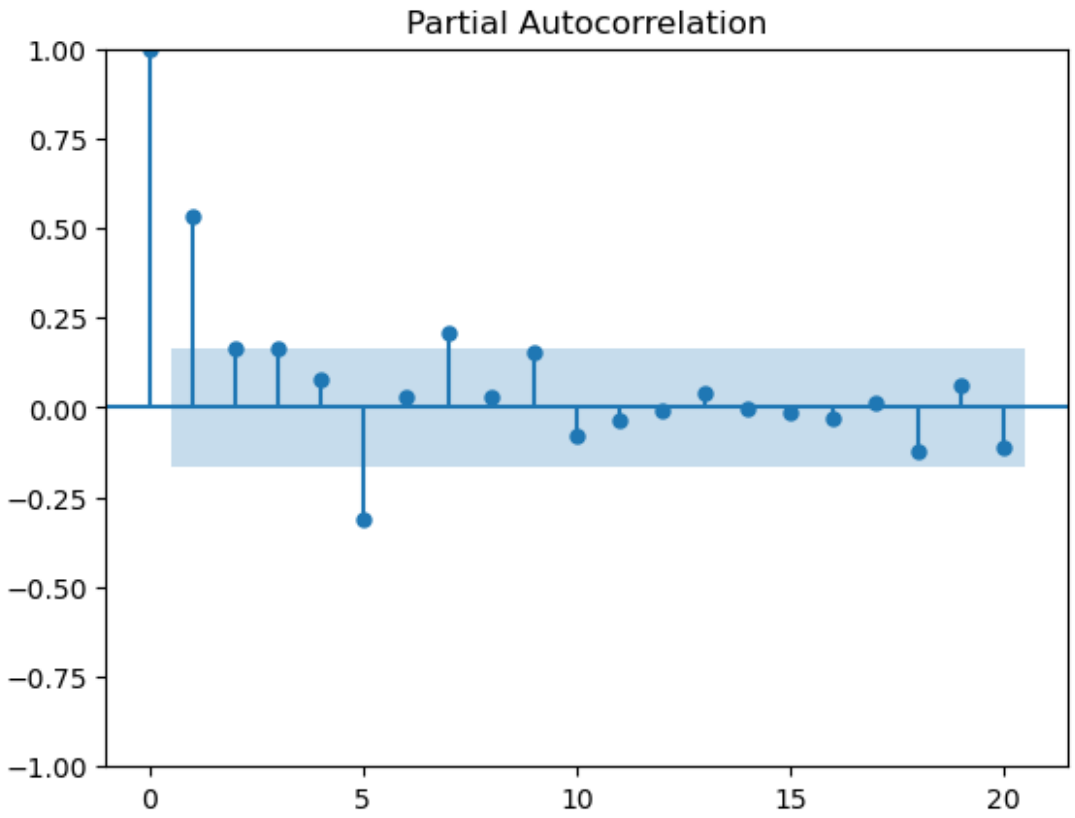
Visualizing Seasonality

```
decompose=seasonal_decompose(store3.dropna())
decompose_plot=decompose.plot()
```




```
plot_pacf=plot_pacf(store3,lags=20)
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\
graphics\tsaplots.py:348: FutureWarning: The default method 'yw' can
produce PACF values outside of the [-1,1] interval. After 0.13, the
default will change tounadjusted Yule-Walker ('ywm'). You can use this
method now by setting method='ywm'.
  warnings.warn(
```




```
pacf_values=sm.tsa.pacf(store3)
pacf_values

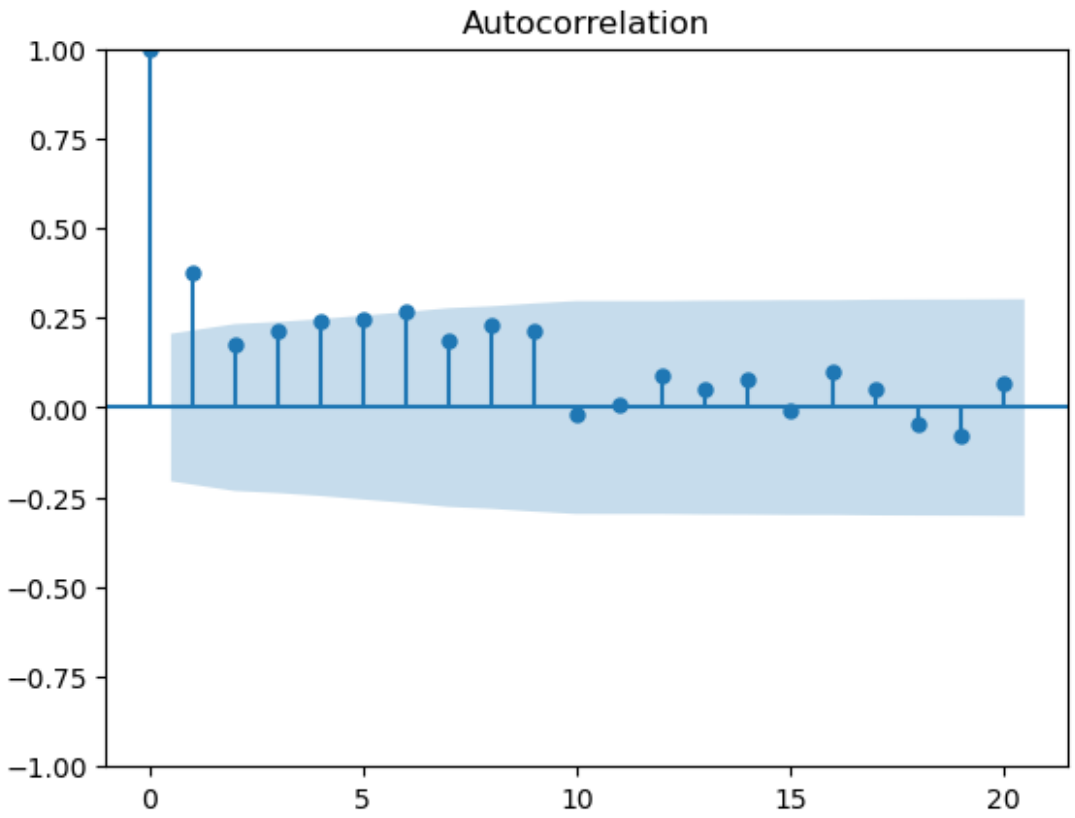
array([ 1.        ,  0.53042557,  0.16668644,  0.16412365,
0.07607959,
       -0.30861064,  0.03206715,  0.20732115,  0.03058033,
0.15655645,
       -0.07733061, -0.03305565, -0.00670322,  0.04113646, -
0.00272844,
       -0.01149093, -0.02874185,  0.01255839, -0.12058603,
0.05944455,
       -0.10975721, -0.10468814])
```

- p[1]=0.53 value will be near to zero then p=0

```
store3['lag1']=store3['Weekly_Sales'].diff()
store3['lag52']=store3['Weekly_Sales'].diff(52)

# From the above, pacf(p) ,acf(q) value is 0

acf_values = plot_acf(store3['lag52'].dropna(), lags=20)
```




```
train = store3.iloc[:round(len(store2)*0.7)]['Weekly_Sales']
```

Training the Model

```
model=SARIMAX(train,order=(0,1,0),seasonal_order=(0,1,0,52))
model_fit=model.fit()
model_fit.summary()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\tsa\
base\tsa_model.py:471: ValueWarning: No frequency information was
provided, so inferred frequency W-FRI will be used.
  self._init_dates(dates, freq)
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\tsa\
base\tsa_model.py:471: ValueWarning: No frequency information was
provided, so inferred frequency W-FRI will be used.
  self._init_dates(dates, freq)
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                      SARIMAX Results

==============================================================================
====================
```

```
Dep. Variable:                        Weekly_Sales   No. Observations:
100
Model:             SARIMAX(0, 1, 0)x(0, 1, 0, 52)   Log Likelihood
-550.102
Date:                            Thu, 21 Dec 2023   AIC
1102.205
Time:                                    21:14:34   BIC
1104.055
Sample:                                02-05-2010   HQIC
1102.901
                                     - 12-30-2011

Covariance Type:                               opg

==============================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
--------
sigma2      5.882e+08   7.07e+07      8.320      0.000     4.5e+08
7.27e+08
==============================================================================
=============
Ljung-Box (L1) (Q):                   5.22   Jarque-Bera (JB):
2.07
Prob(Q):                              0.02   Prob(JB):
0.35
Heteroskedasticity (H):               1.01   Skew:
0.07
Prob(H) (two-sided):                  0.98   Kurtosis:
4.02
==============================================================================
=============

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

Testing the Model

```
pred=model_fit.predict(start=len(train),end=len(store3)-
1,dynamic=True)

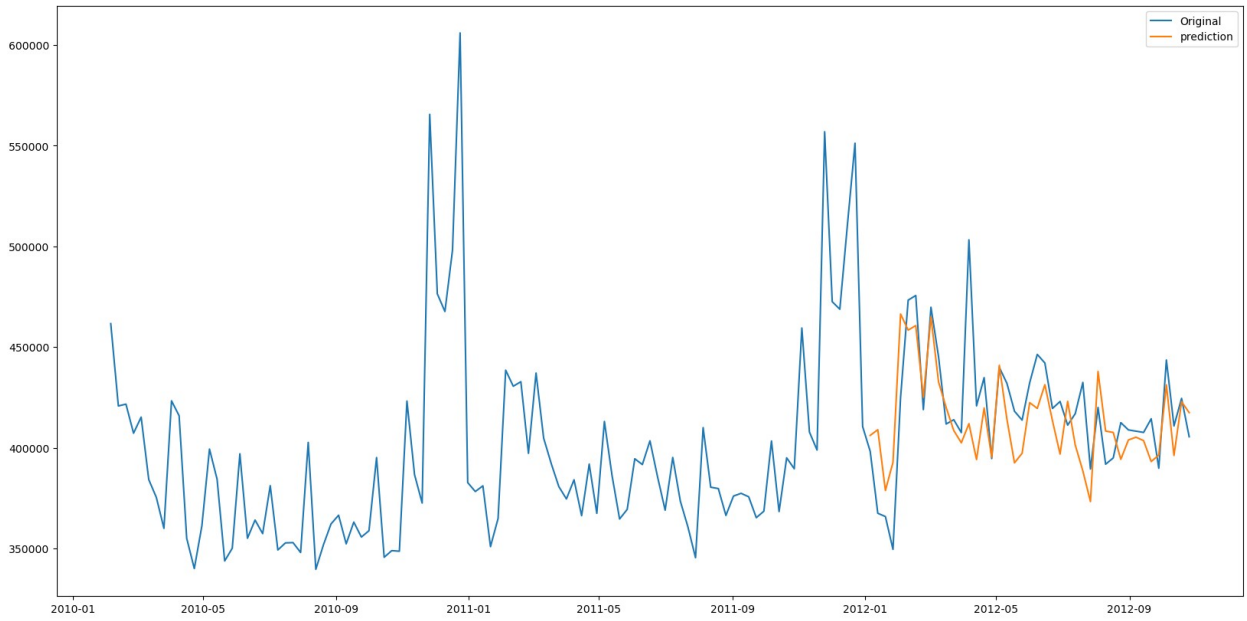
pred

2012-01-06    406117.46
2012-01-13    408937.22
2012-01-20    378752.82
```

```
2012-01-27    392742.36
2012-02-03    466392.65
2012-02-10    458402.33
2012-02-17    460658.22
2012-02-24    425087.31
2012-03-02    464960.63
2012-03-09    432629.42
2012-03-16    419985.63
2012-03-23    408559.79
2012-03-30    402432.20
2012-04-06    411951.43
2012-04-13    394126.81
2012-04-20    419736.16
2012-04-27    395281.52
2012-05-04    440918.24
2012-05-11    414188.80
2012-05-18    392479.25
2012-05-25    397226.72
2012-06-01    422383.96
2012-06-08    419514.87
2012-06-15    431299.46
2012-06-22    413396.83
2012-06-29    396838.84
2012-07-06    423022.36
2012-07-13    401330.45
2012-07-20    388493.49
2012-07-27    373257.41
2012-08-03    437857.37
2012-08-10    408252.97
2012-08-17    407593.03
2012-08-24    394243.67
2012-08-31    403864.81
2012-09-07    405223.61
2012-09-14    403505.63
2012-09-21    393125.06
2012-09-28    396354.05
2012-10-05    431218.52
2012-10-12    396158.69
2012-10-19    422852.48
2012-10-26    417416.74
Freq: W-FRI, Name: predicted_mean, dtype: float64
```

```
plt.figure(figsize=(20,10))
plt.plot(store3['Weekly_Sales'],label="Original")
plt.plot(pred,label="prediction")
plt.legend()
plt.plot()
```

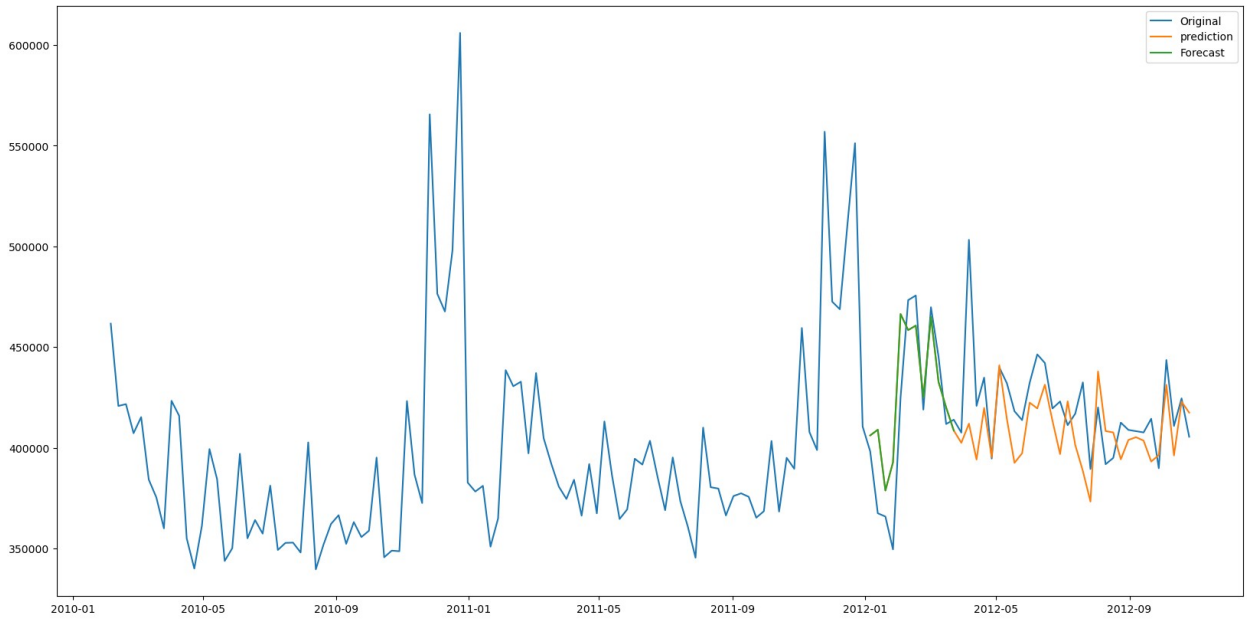
```
[]
```



Forecasting for Next 12 Weekly_Sales

```
forecast=model_fit.forecast(steps=12)

plt.figure(figsize=(20,10))
plt.plot(store3['Weekly_Sales'],label="Original")
plt.plot(pred,label="prediction")
plt.plot(forecast,label="Forecast")
plt.legend()
plt.show()
```




```
### Store_4 Dataset
```

```
result=adfuller(df_target[df_target["Store"]==3]['Weekly_Sales'])
result
```

```
(-2.9638677455113234,
 0.03840926179831252,
 6,
 136,
 {'1%': -3.4793722137854926,
  '5%': -2.8830370378332995,
  '10%': -2.578233635380623},
 3064.8688740270827)
```

```
#### From the above, we see that that p value is close to 0 and we can conclude that the data is stationary

if(result[1]<0.05):
    print("Stationary is present")
else:
    print("Not Stationary is present")
```

```
Stationary is present
```

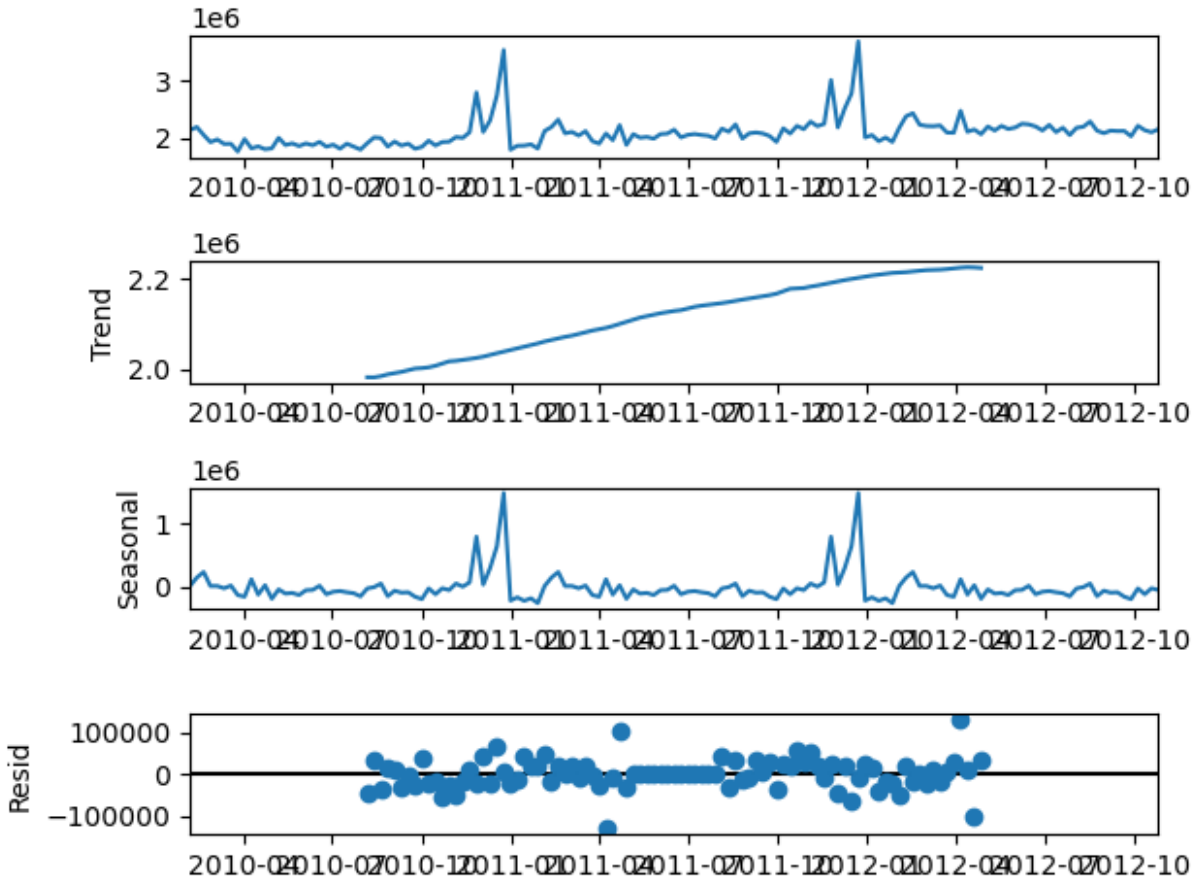
```
store4=pd.DataFrame(df_target[df_target["Store"]==4]["Weekly_Sales"])
store4
```

```
            Weekly_Sales
Date
2010-02-05    2135143.87
2010-02-12    2188307.39
2010-02-19    2049860.26
2010-02-26    1925728.84
2010-03-05    1971057.44
...                  ...
2012-09-28    2027620.23
2012-10-05    2209835.43
2012-10-12    2133026.07
2012-10-19    2097266.85
2012-10-26    2149594.46

[143 rows x 1 columns]
```

Visualizing Seasonality

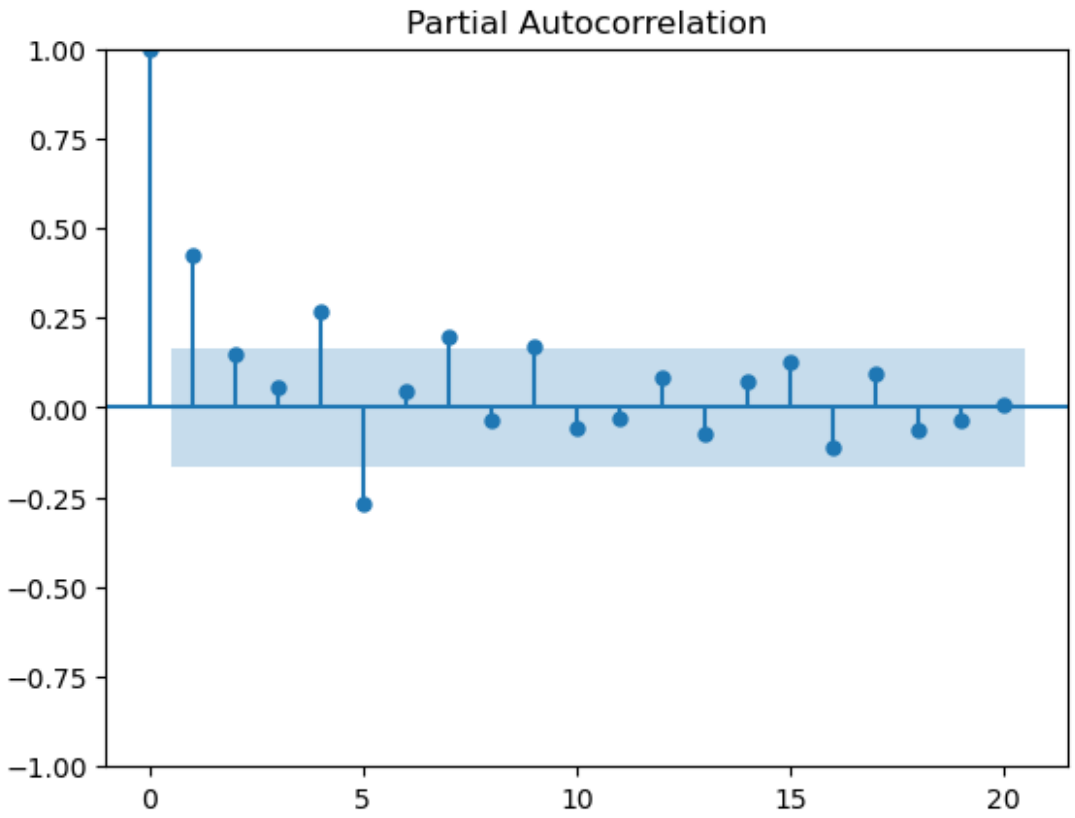
```
decompose=seasonal_decompose(store4.dropna())
decompose_plot=decompose.plot()
```




```
from statsmodels.graphics.tsaplots import plot_pacf  # Import the
plot_pacf function
store4["lag1"] = store4["Weekly_Sales"].diff()
store4["lag52"] = store4["Weekly_Sales"].diff(52)

# Assign the result to a different variable, e.g., pacf_values
pacf_values = plot_pacf(store4["Weekly_Sales"].dropna(), lags=20)
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\
graphics\tsaplots.py:348: FutureWarning: The default method 'yw' can
produce PACF values outside of the [-1,1] interval. After 0.13, the
default will change tounadjusted Yule-Walker ('ywm'). You can use this
method now by setting method='ywm'.
  warnings.warn(
```



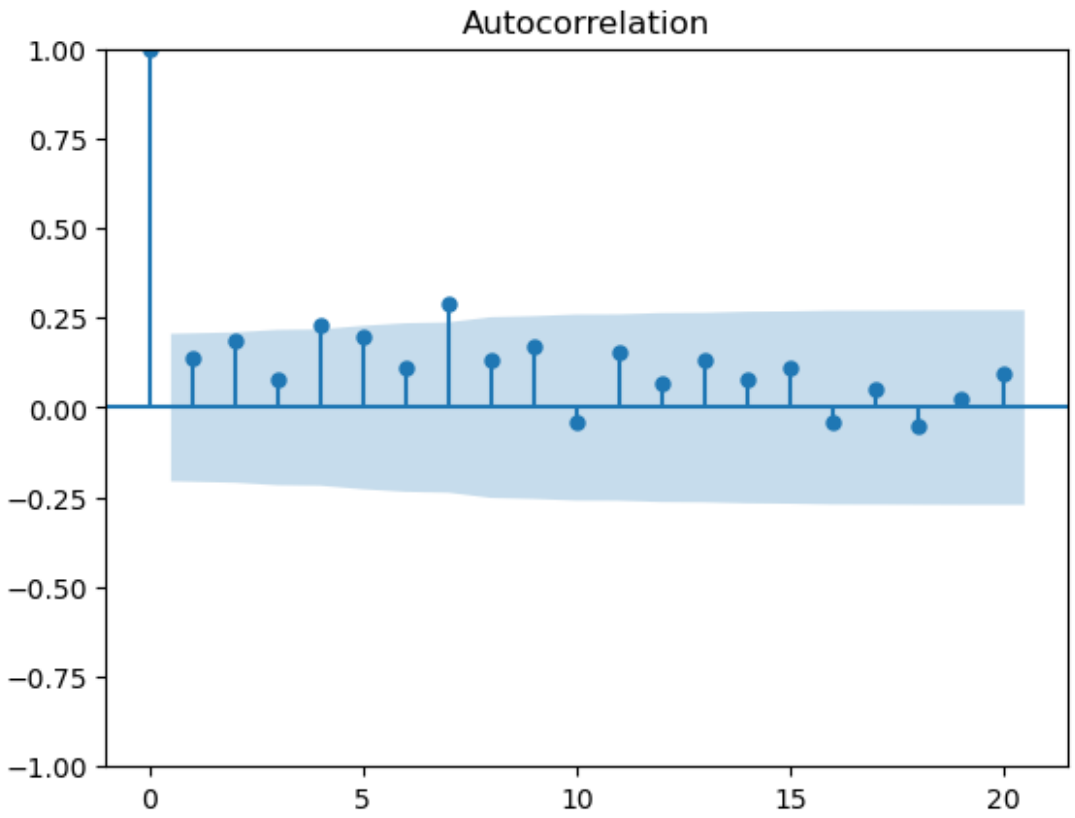

```
import statsmodels.api as sm
pacf_values = sm.tsa.pacf(store4['Weekly_Sales'])
pacf_values
```

```
array([ 1.        ,  0.42660057,  0.14997967,  0.05755091,
0.26798839,
       -0.26983153,  0.04846441,  0.19886998, -0.03604879,
0.17085998,
       -0.05515318, -0.02977369,  0.08230812, -0.07078321,
0.07406462,
        0.12552134, -0.10985915,  0.0946333 , -0.05996523, -
0.03564473,
        0.0082363 , -0.104122  ])
```

- p[1]=0.426 value will be near to zero then p=0

```
# From the above, pacf(p) ,acf(q) value is 0

acf_values = plot_acf(store4['lag52'].dropna(), lags=20)
```




```
train = store4.iloc[:round(len(store4)*0.7)]['Weekly_Sales']
```

Training the Model

```
model=SARIMAX(train,order=(0,1,0),seasonal_order=(0,1,0,52))
model.fit=model.fit()
model_fit.summary()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\tsa\
base\tsa_model.py:471: ValueWarning: No frequency information was
provided, so inferred frequency W-FRI will be used.
  self._init_dates(dates, freq)
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\tsa\
base\tsa_model.py:471: ValueWarning: No frequency information was
provided, so inferred frequency W-FRI will be used.
  self._init_dates(dates, freq)
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                      SARIMAX Results

==============================================================================
====================
```

```
Dep. Variable:                        Weekly_Sales   No. Observations:
100
Model:             SARIMAX(0, 1, 0)x(0, 1, 0, 52)   Log Likelihood
-550.102
Date:                            Thu, 21 Dec 2023   AIC
1102.205
Time:                                    21:14:35   BIC
1104.055
Sample:                                02-05-2010   HQIC
1102.901
                                     - 12-30-2011

Covariance Type:                               opg

==============================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
--------
sigma2      5.882e+08   7.07e+07      8.320      0.000     4.5e+08
7.27e+08
==============================================================================
=============
Ljung-Box (L1) (Q):                   5.22   Jarque-Bera (JB):
2.07
Prob(Q):                              0.02   Prob(JB):
0.35
Heteroskedasticity (H):               1.01   Skew:
0.07
Prob(H) (two-sided):                  0.98   Kurtosis:
4.02
==============================================================================
=============

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

Testing the Model

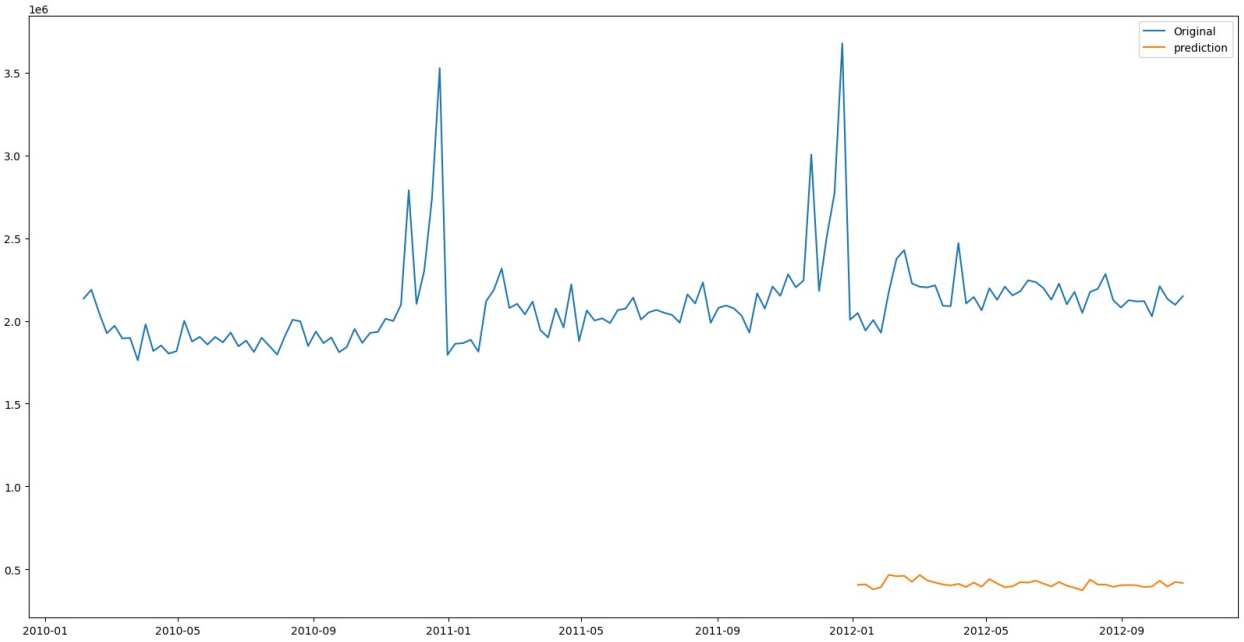
```
pred=model_fit.predict(start=len(train),end=len(store4)-
1,dynamic=True)

pred

2012-01-06    406117.46
2012-01-13    408937.22
2012-01-20    378752.82
```

```
2012-01-27    392742.36
2012-02-03    466392.65
2012-02-10    458402.33
2012-02-17    460658.22
2012-02-24    425087.31
2012-03-02    464960.63
2012-03-09    432629.42
2012-03-16    419985.63
2012-03-23    408559.79
2012-03-30    402432.20
2012-04-06    411951.43
2012-04-13    394126.81
2012-04-20    419736.16
2012-04-27    395281.52
2012-05-04    440918.24
2012-05-11    414188.80
2012-05-18    392479.25
2012-05-25    397226.72
2012-06-01    422383.96
2012-06-08    419514.87
2012-06-15    431299.46
2012-06-22    413396.83
2012-06-29    396838.84
2012-07-06    423022.36
2012-07-13    401330.45
2012-07-20    388493.49
2012-07-27    373257.41
2012-08-03    437857.37
2012-08-10    408252.97
2012-08-17    407593.03
2012-08-24    394243.67
2012-08-31    403864.81
2012-09-07    405223.61
2012-09-14    403505.63
2012-09-21    393125.06
2012-09-28    396354.05
2012-10-05    431218.52
2012-10-12    396158.69
2012-10-19    422852.48
2012-10-26    417416.74
Freq: W-FRI, Name: predicted_mean, dtype: float64
```

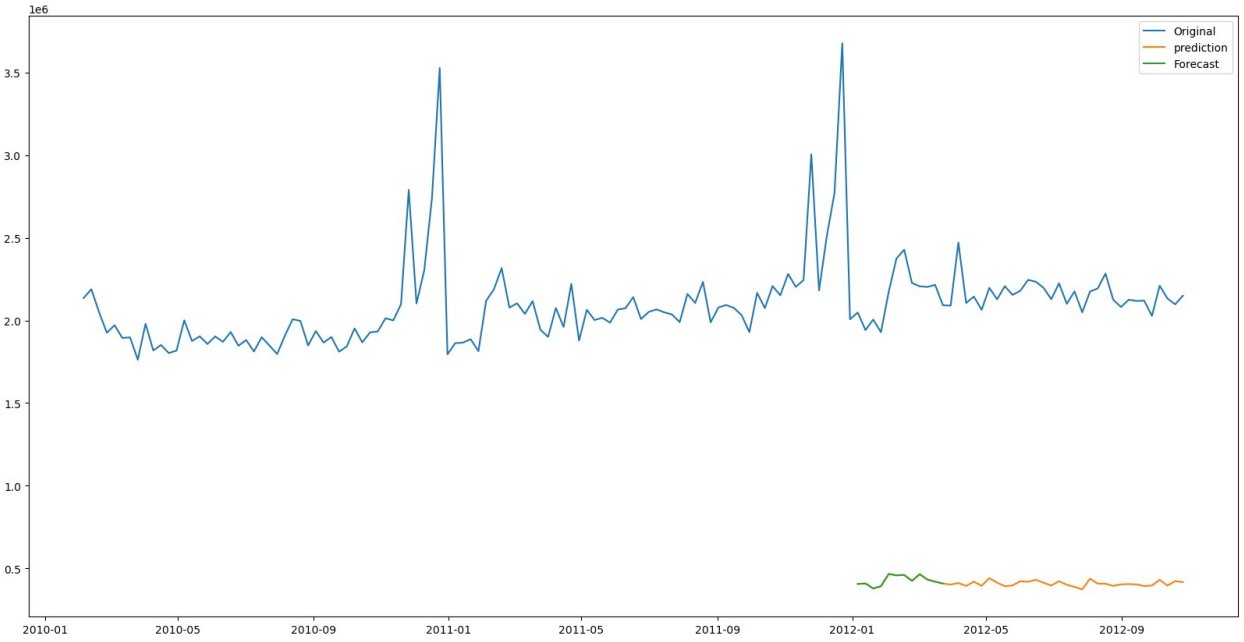
```
plt.figure(figsize=(20,10))
plt.plot(store4['Weekly_Sales'],label="Original")
plt.plot(pred,label="prediction")
plt.legend()
plt.show()
```



Forecasting for Next 12 Weekly_Sales

```
forecast=model_fit.forecast(steps=12)

plt.figure(figsize=(20,10))
plt.plot(store4['Weekly_Sales'],label="Original")
plt.plot(pred,label="prediction")
plt.plot(forecast,label="Forecast")
plt.legend()
plt.show()
```



Foresting Week_Sales for 45 Stores

```
for i in range(1,46):
    new_data=pd.DataFrame(df[df["Store"]==i]["Weekly_Sales"])
    lag52=pd.DataFrame(new_data["Weekly_Sales"].diff(52))

acf_values,confidence_intervals=sm.tsa.acf(lag52.dropna(),nlags=20,alp
ha=0.05)
    pacf_values=sm.tsa.pacf(lag52.dropna(),nlags=20)
    significant_acf = []
    significant_pacf = []
    for lag,acf,confident in
zip(range(len(acf_values)),acf_values,confidence_intervals):
        if(abs(acf)>confident[1]):
            significant_acf.append(acf)
        else:
            break
    for lag,pacf,confident in
zip(range(len(pacf_values)),pacf_values,confidence_intervals):
        if(abs(acf)>confident[1]):
            significant_pacf.append(acf)
        else:
            break
    p=len(significant_acf)
    q=len(significant_pacf)
    train=new_data[:round(len(new_data)*0.7)]
    model=SARIMAX(train,order=(p,1,q),seasonal_order=(p,1,q,52))
    model_fit=model.fit()
    pred=model_fit.predict(start=len(train),end=len(new_data)-
1,dynamic=True)
    forecast=model_fit.forecast(steps=12)
    plt.figure(figsize=(20,10))
    plt.plot(new_data['Weekly_Sales'],label='Given_sales')
    plt.plot(pred,label='Prediction')
    plt.plot(forecast,label="12 weeks forecast")
    plt.legend()
    plt.title(f'store {i}')
    plt.show()
```

```
C:\Users\Arigala.Adarsh\anaconda3\lib\site-packages\statsmodels\tsa\
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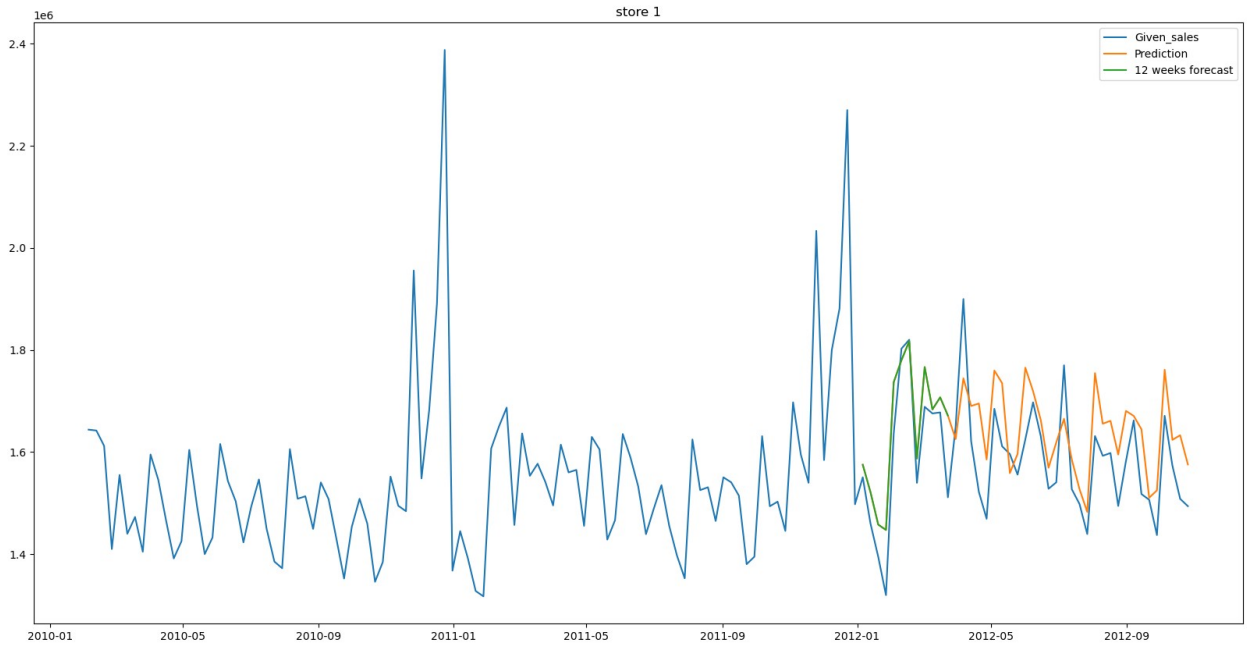


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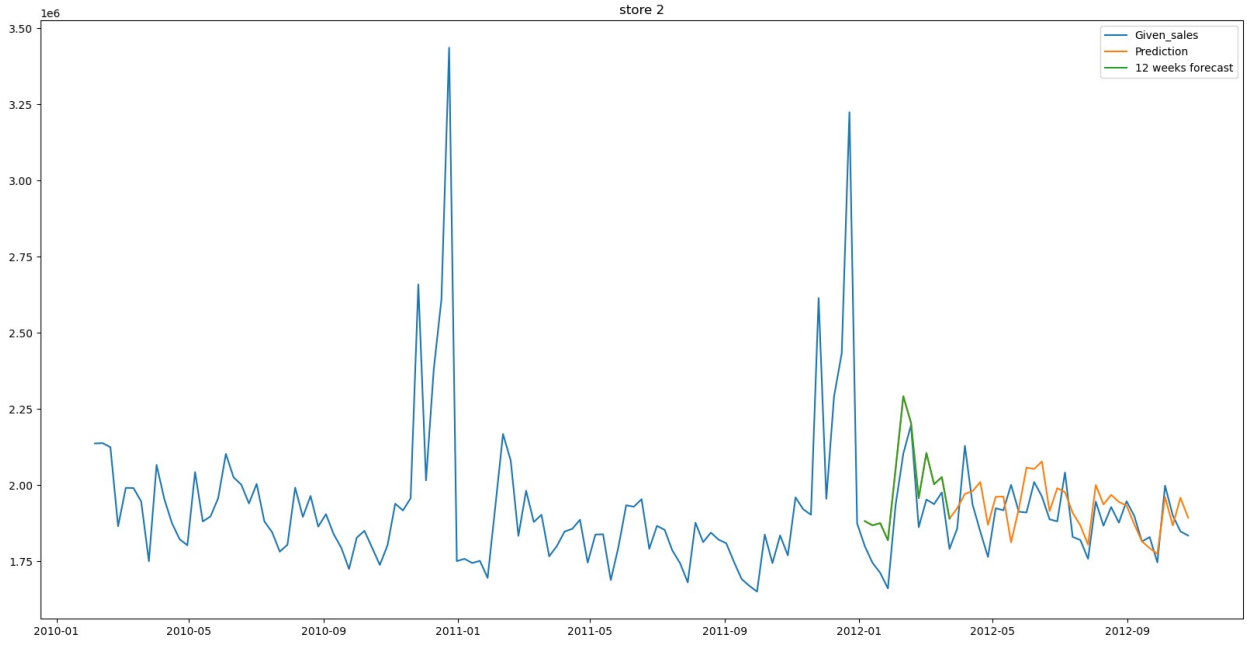

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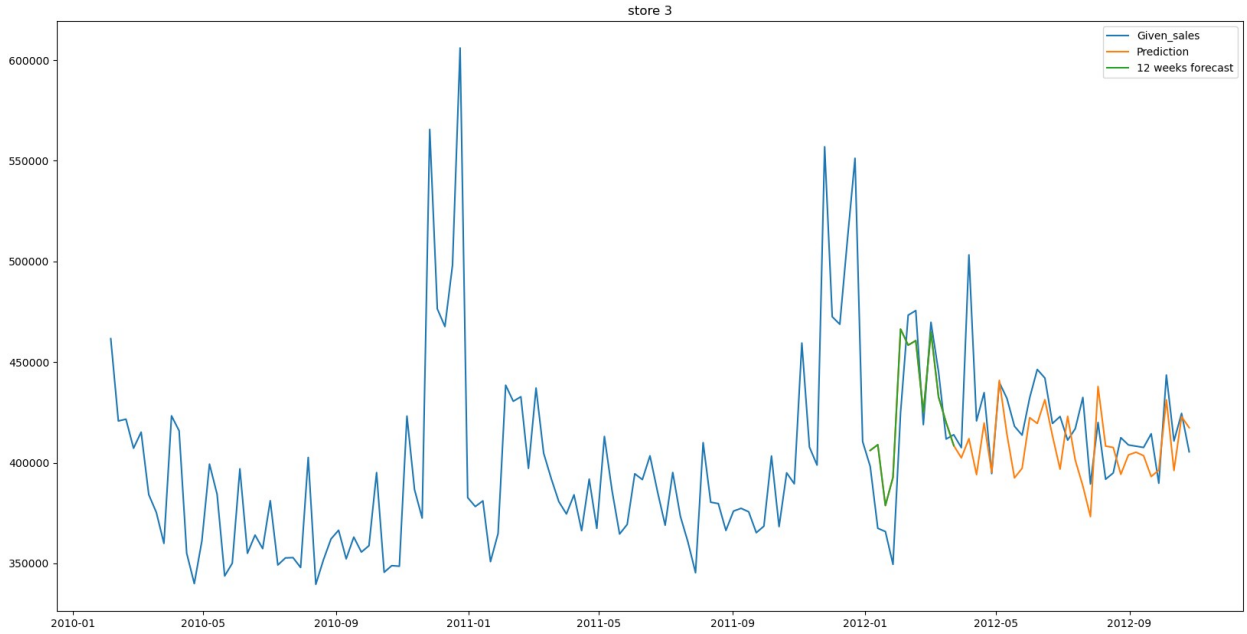


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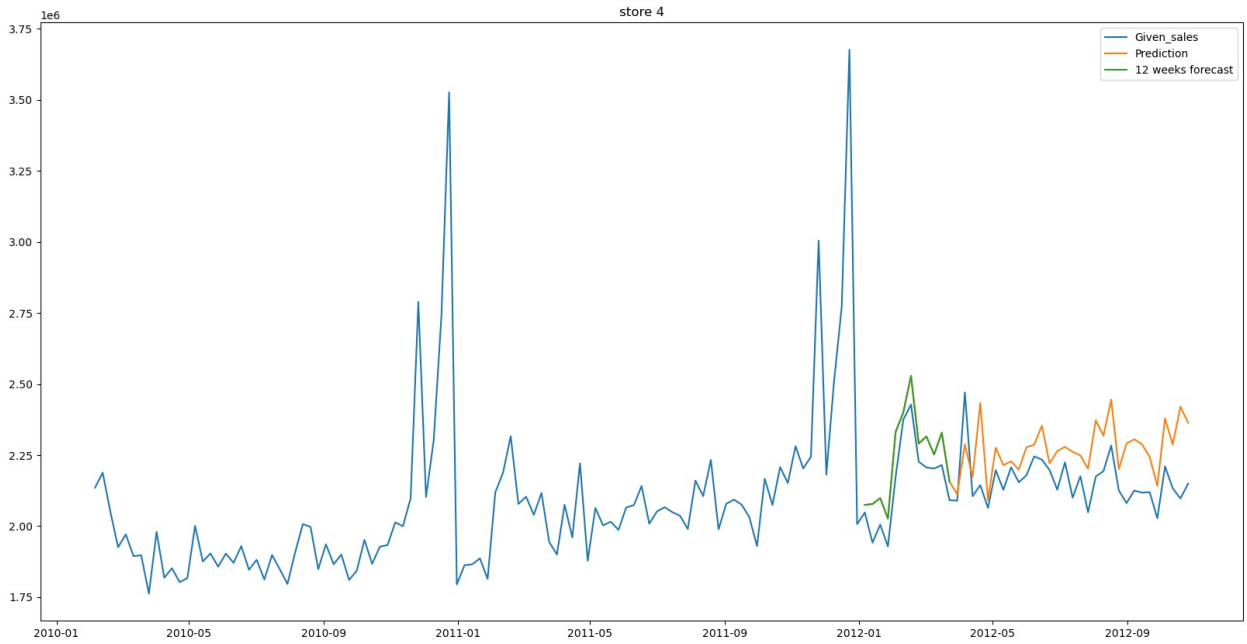


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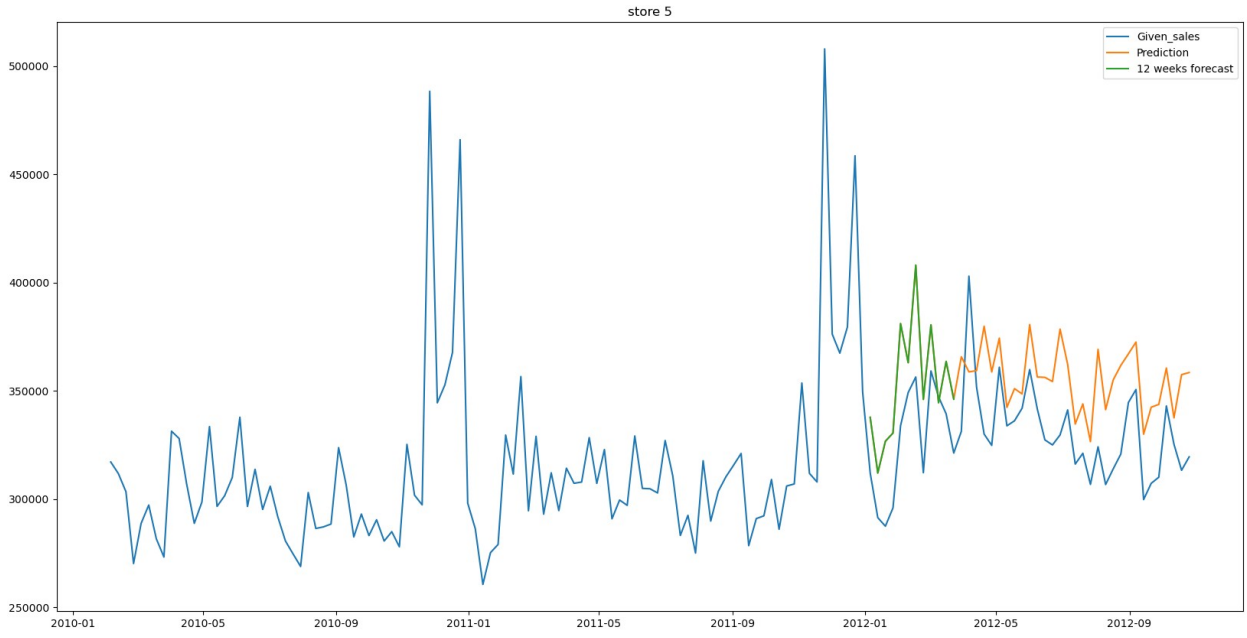

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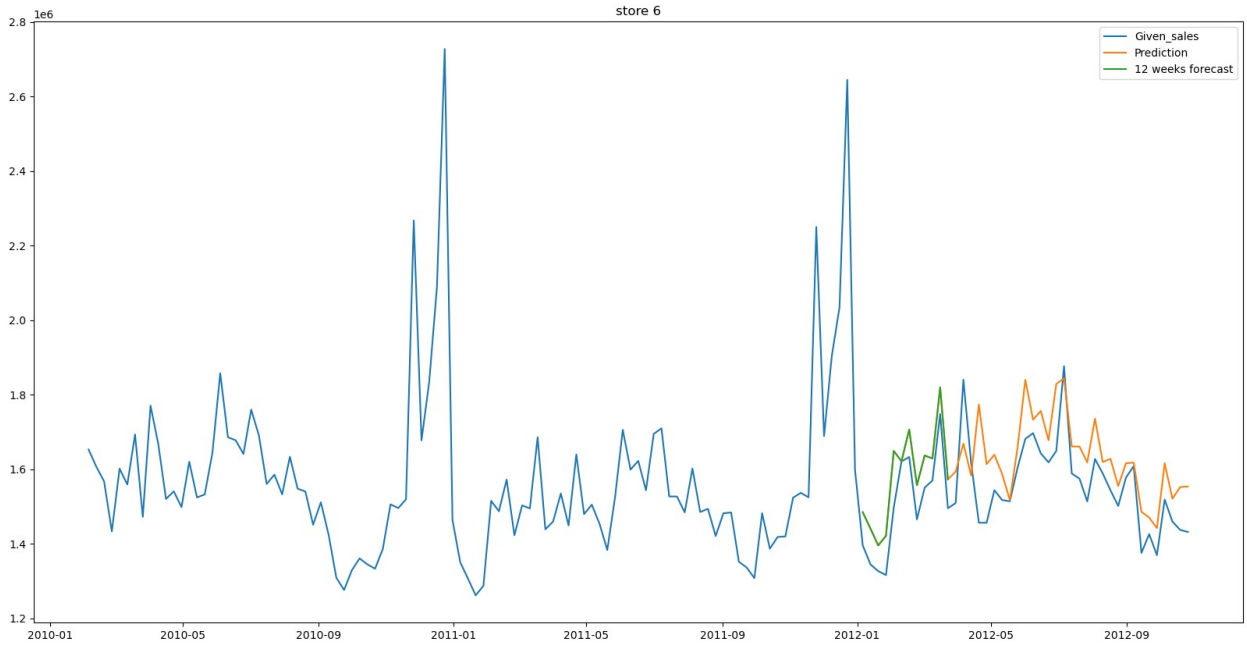


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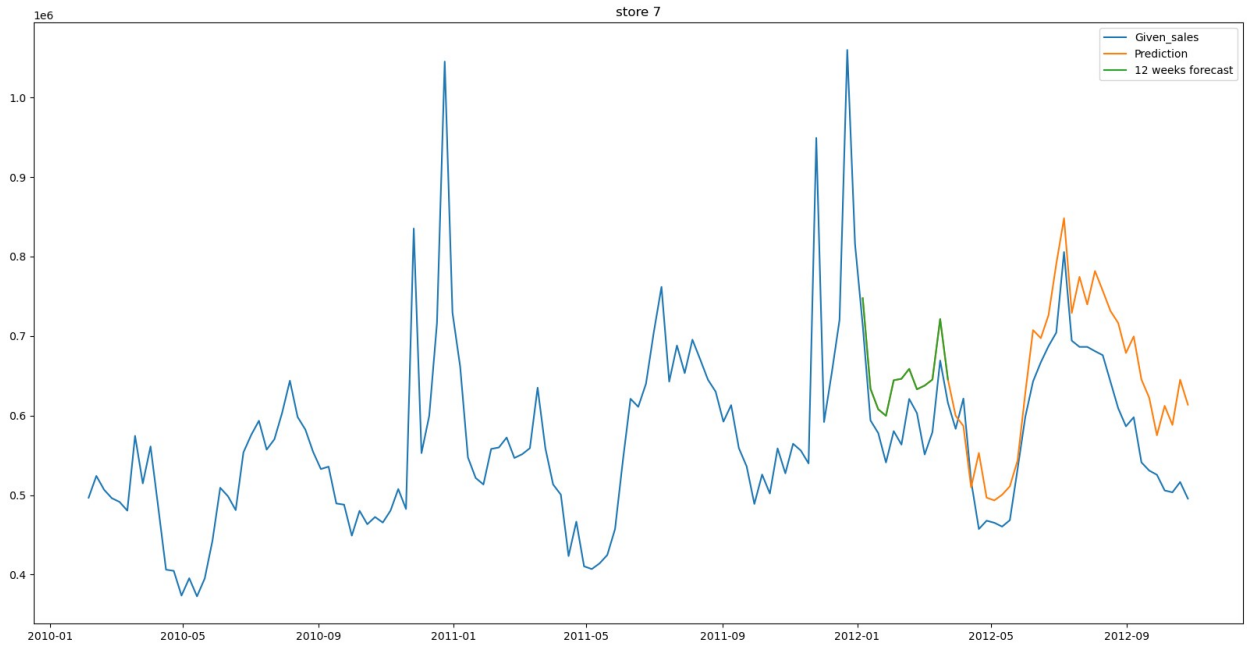


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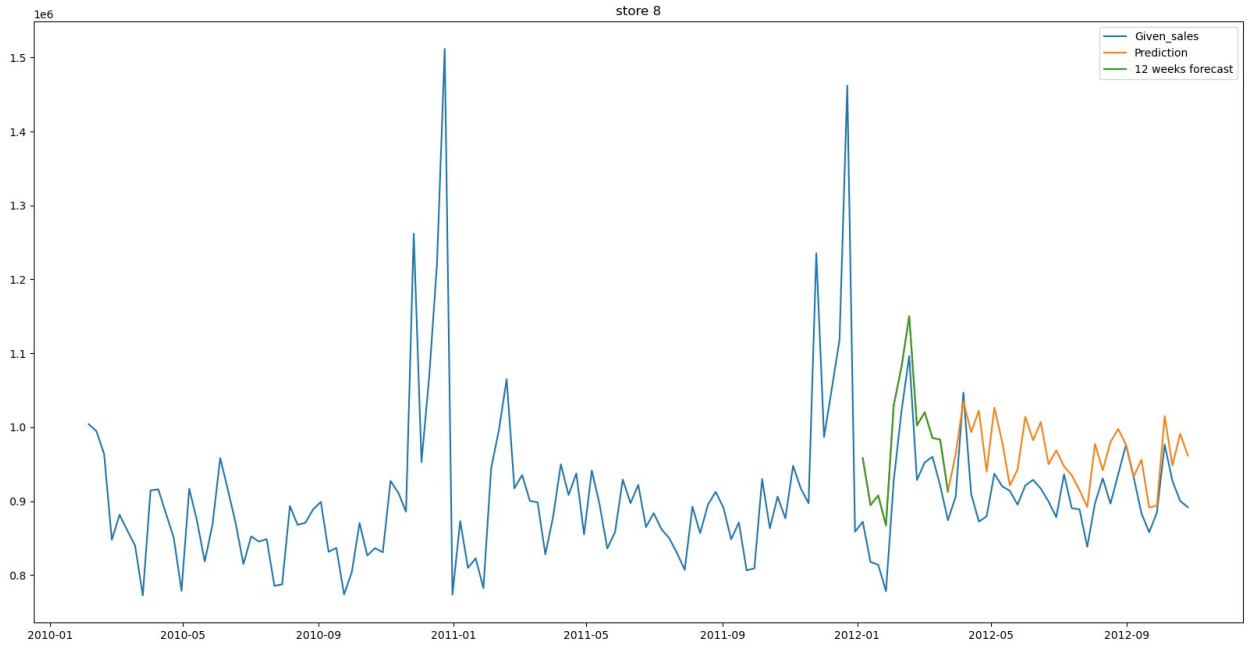

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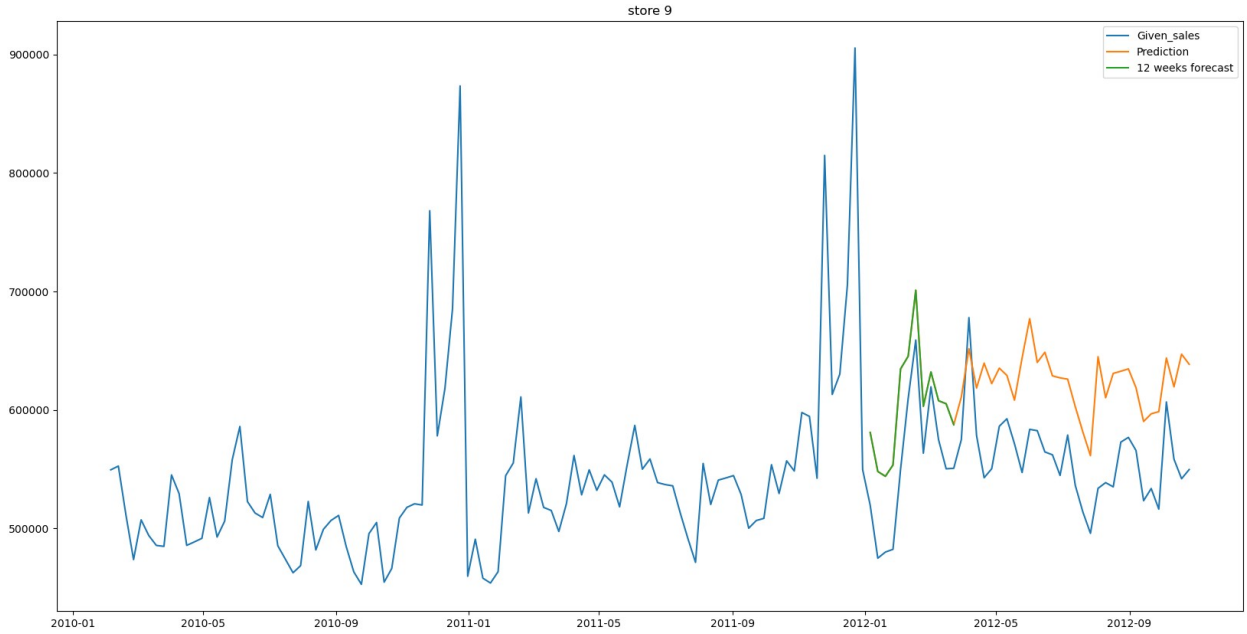


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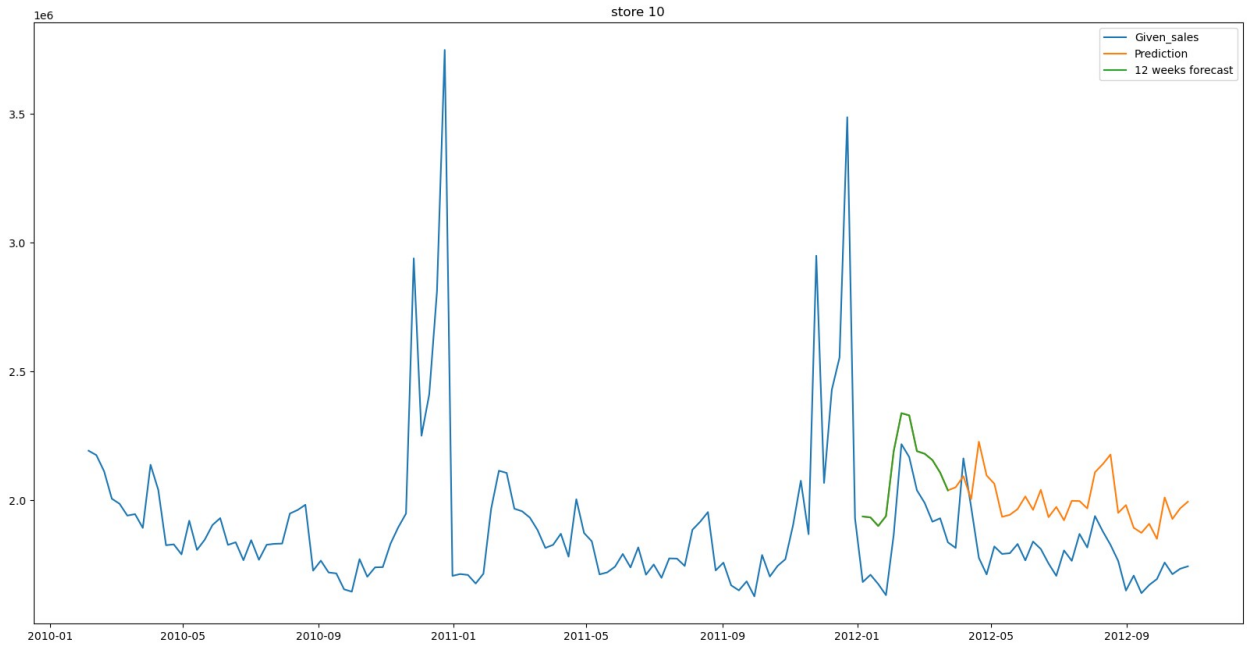


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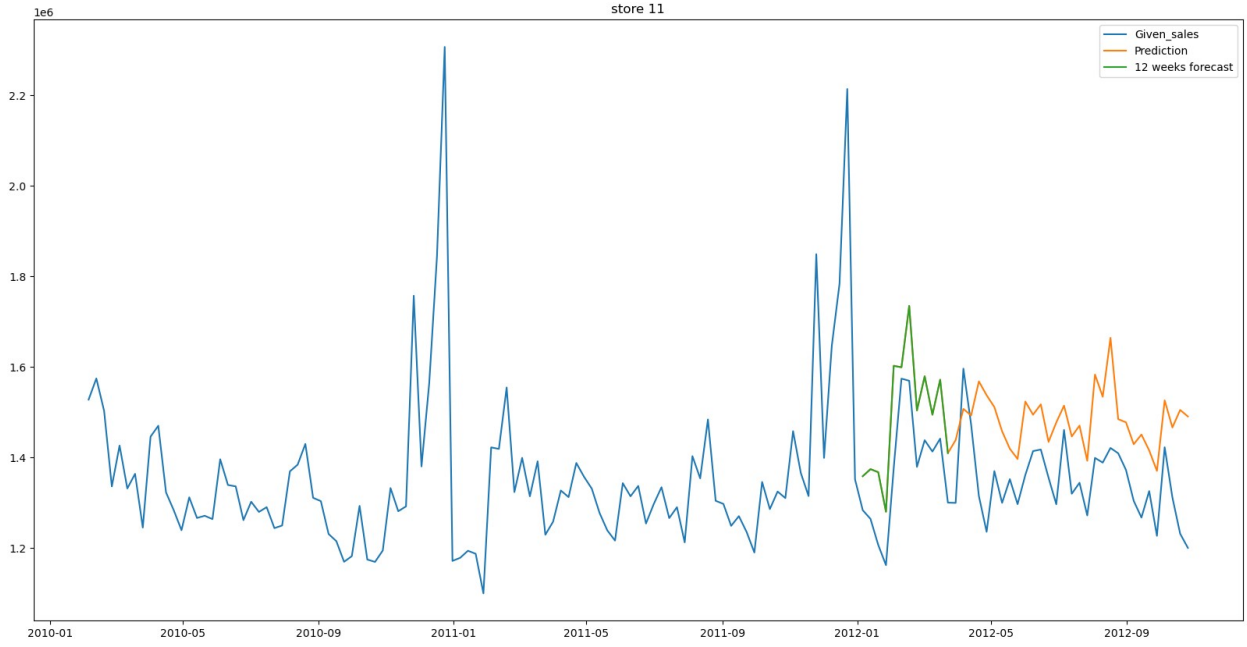

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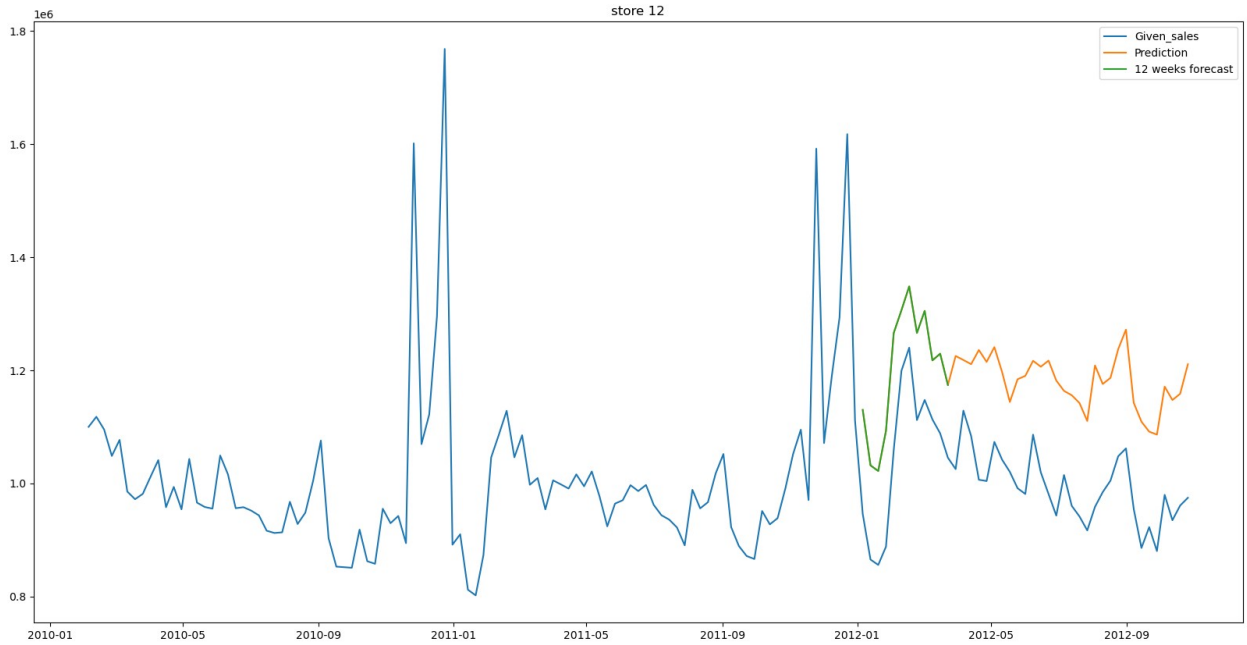


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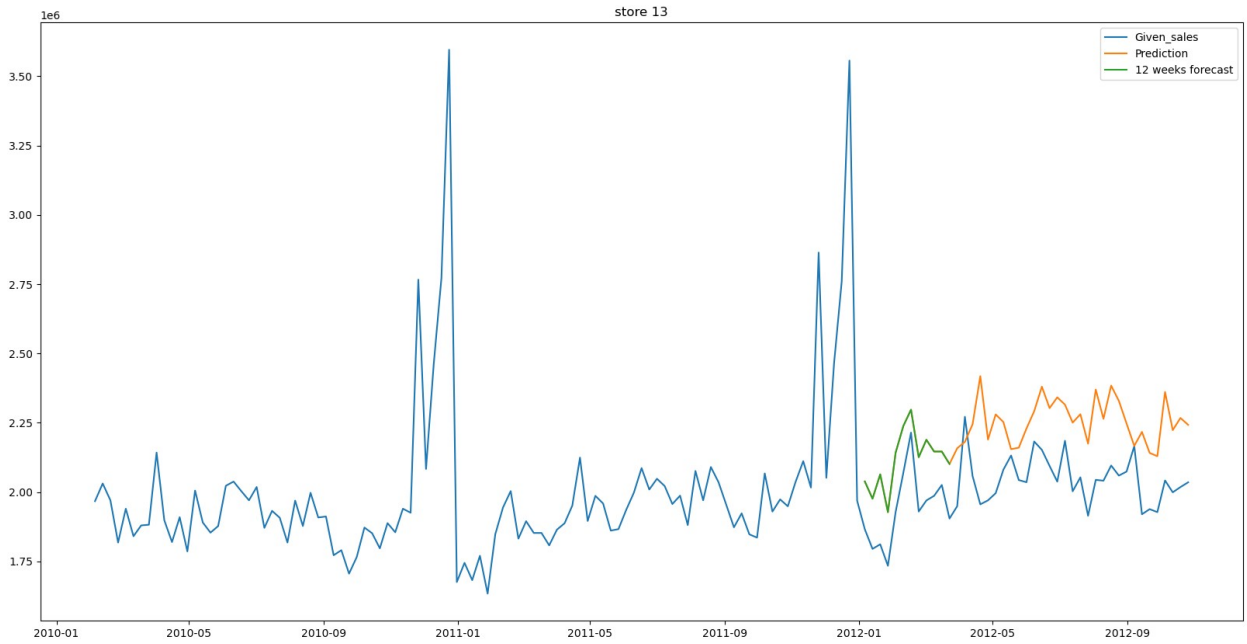


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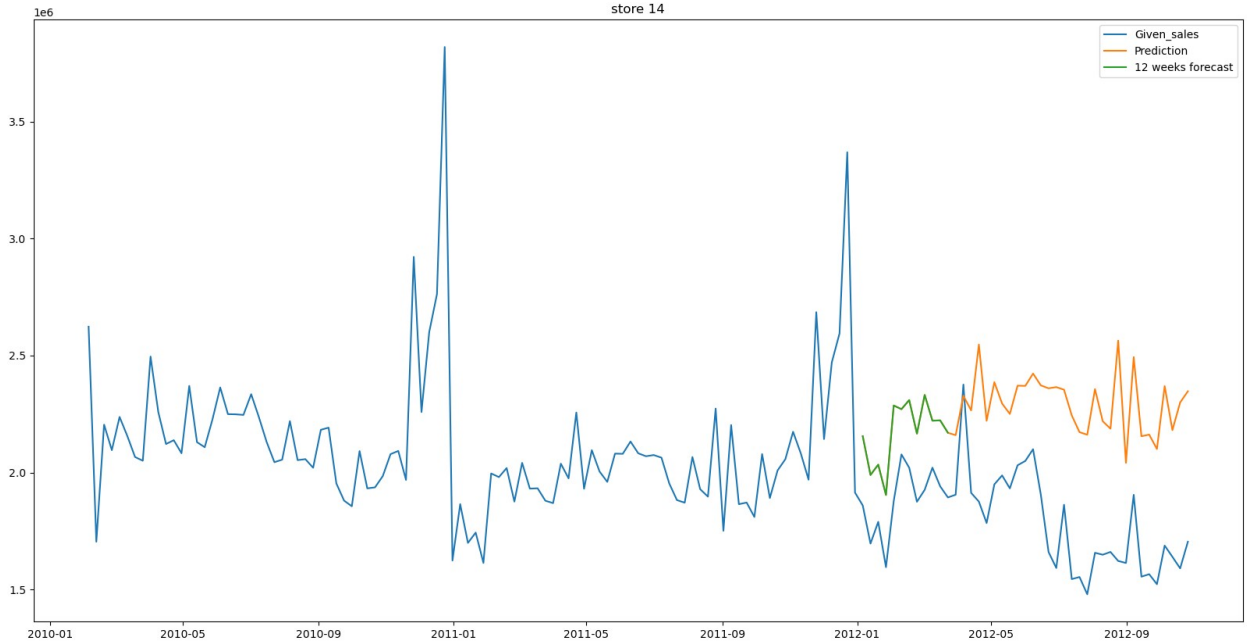

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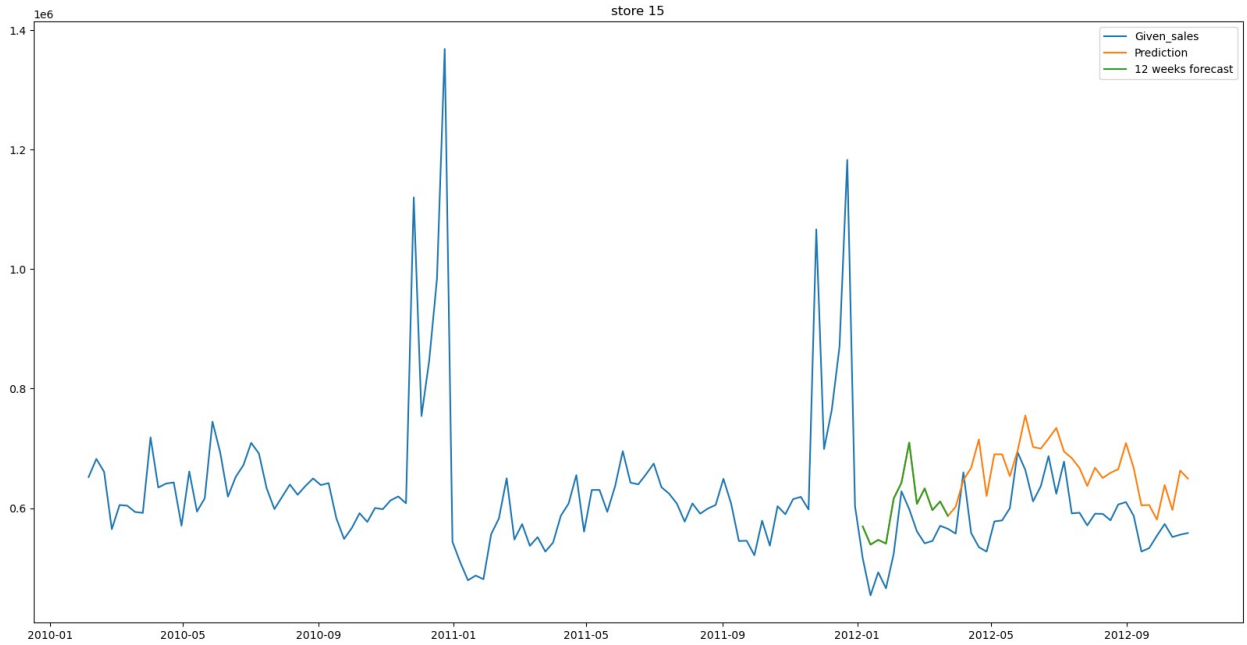


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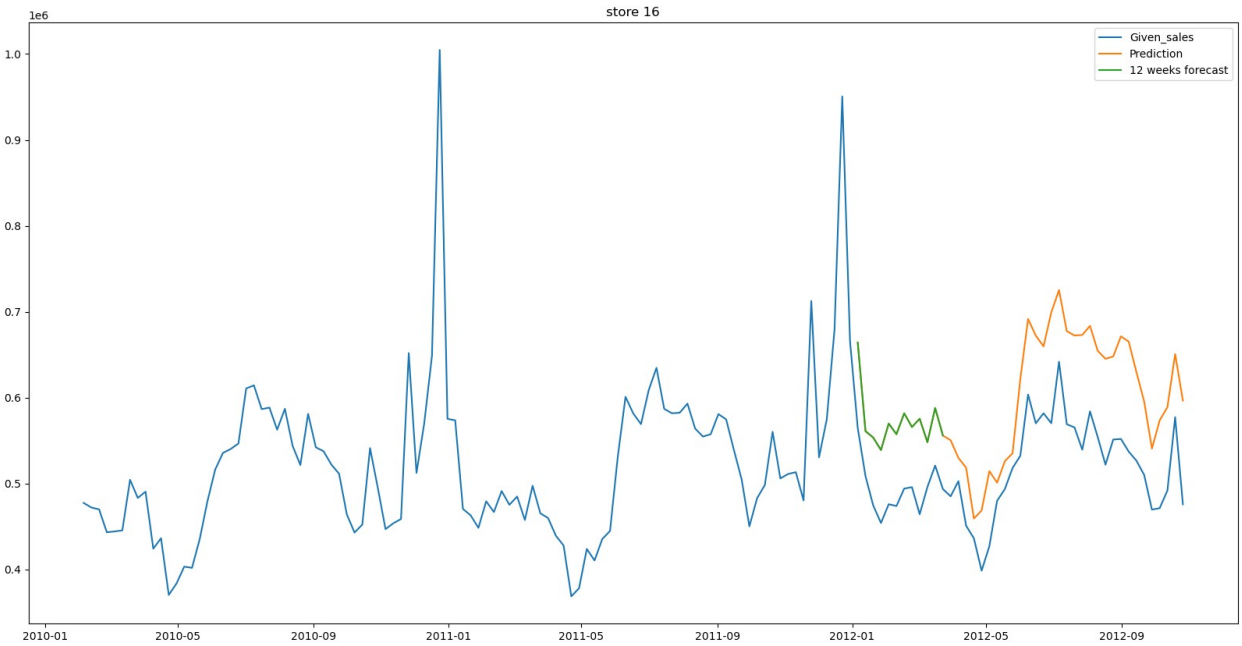


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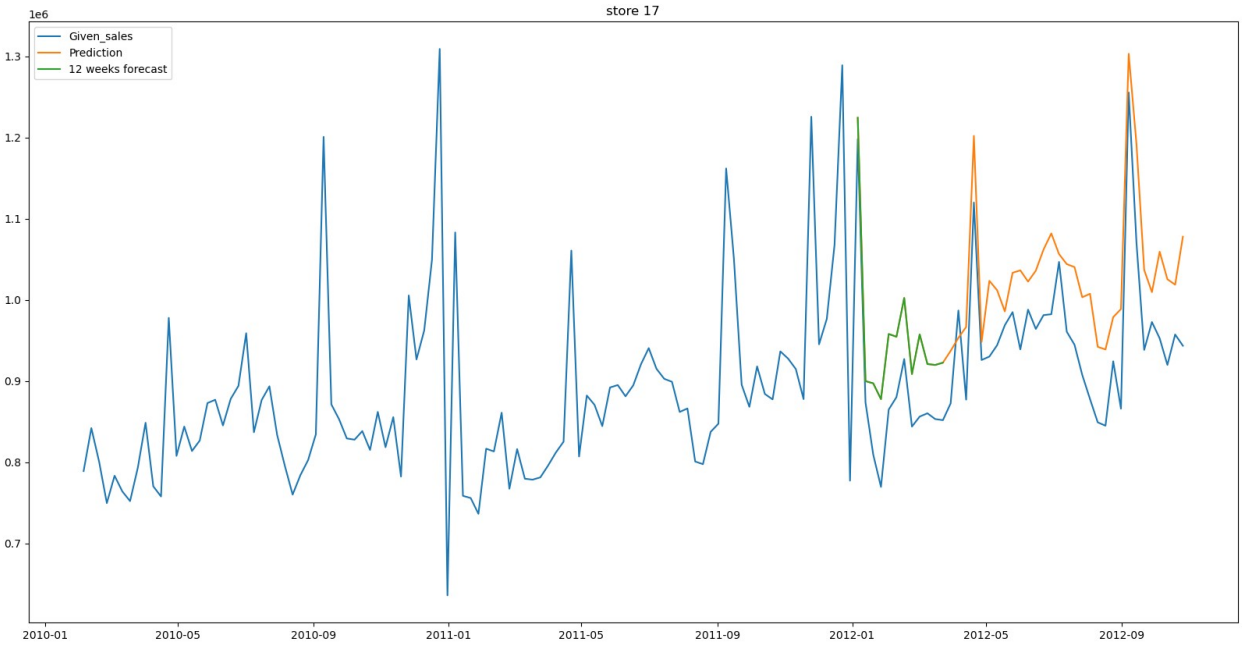

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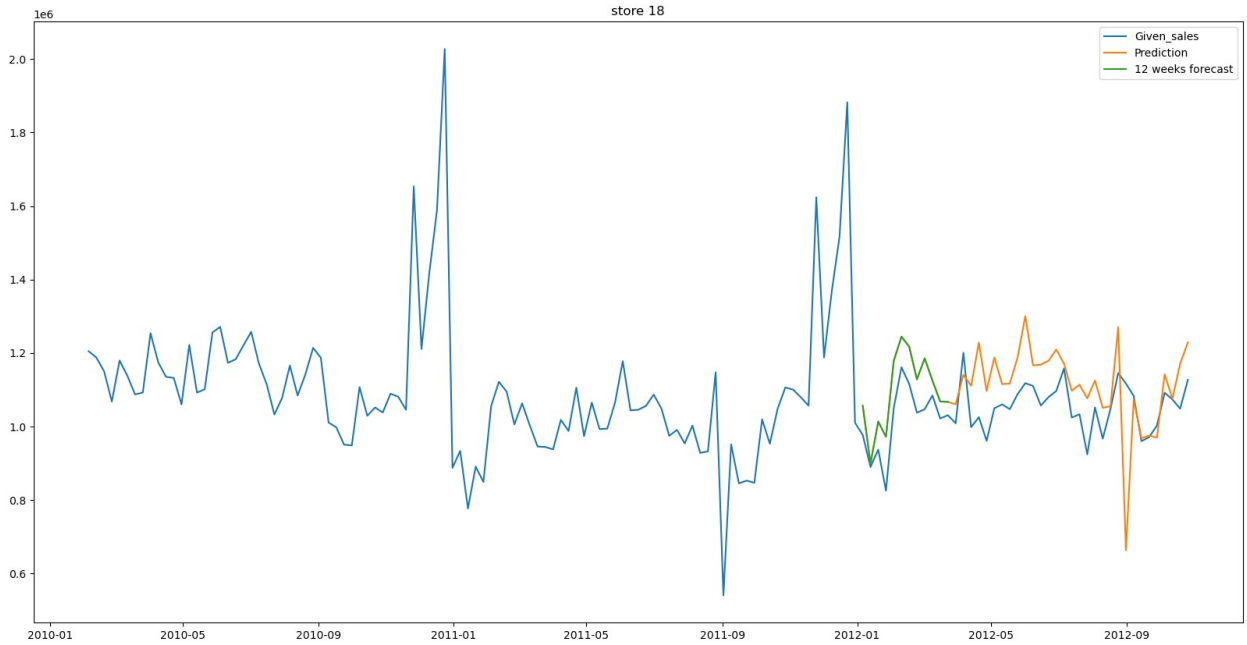


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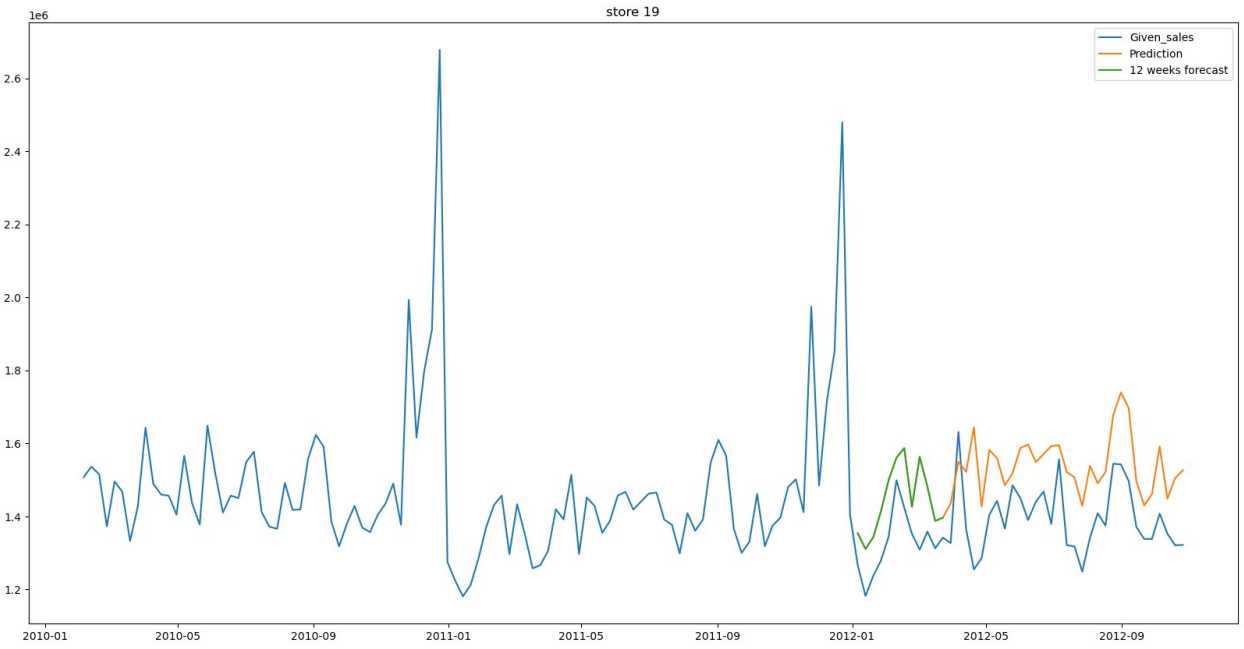


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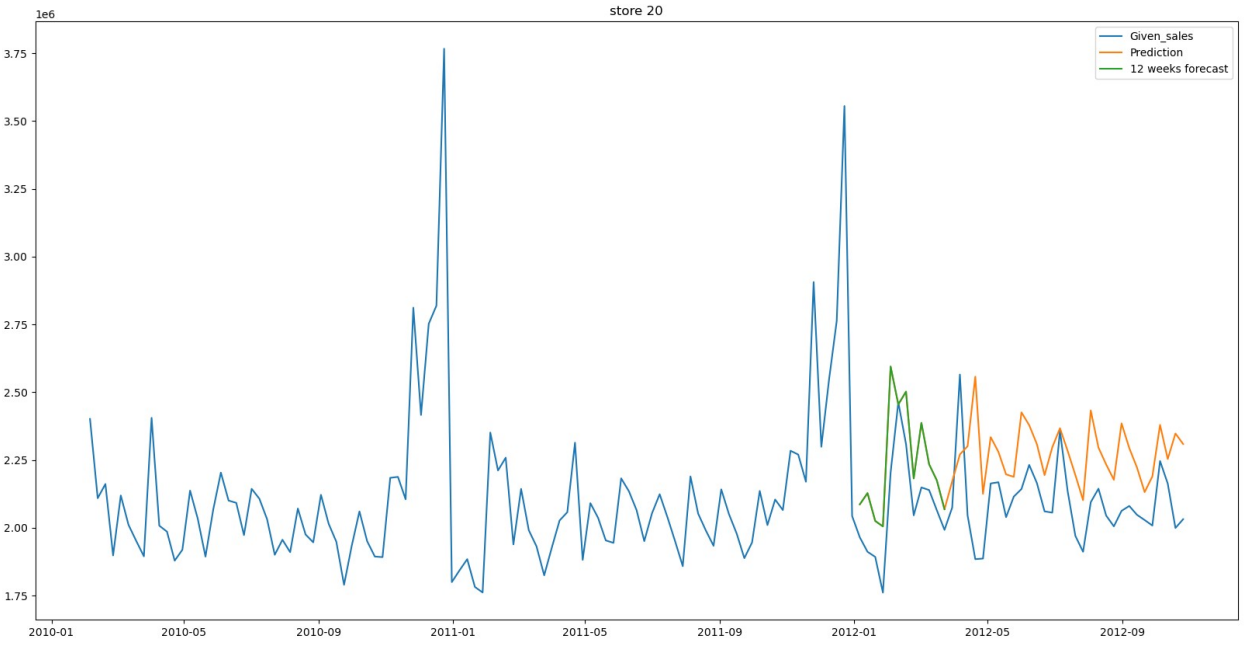

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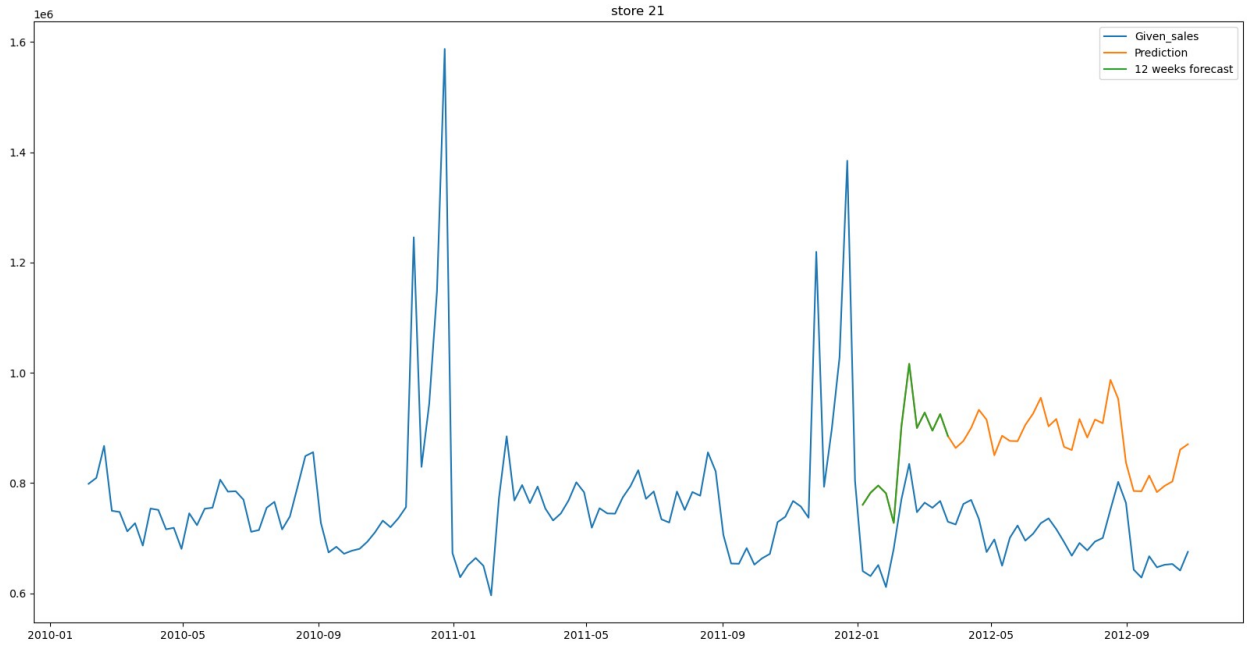


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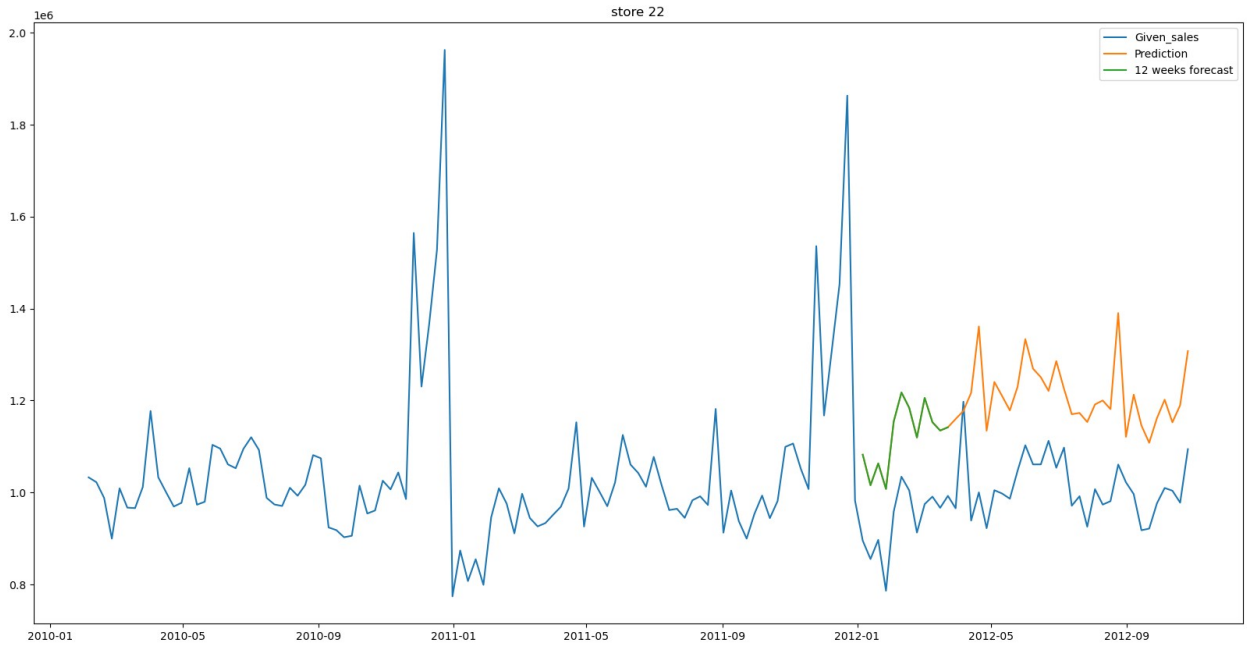


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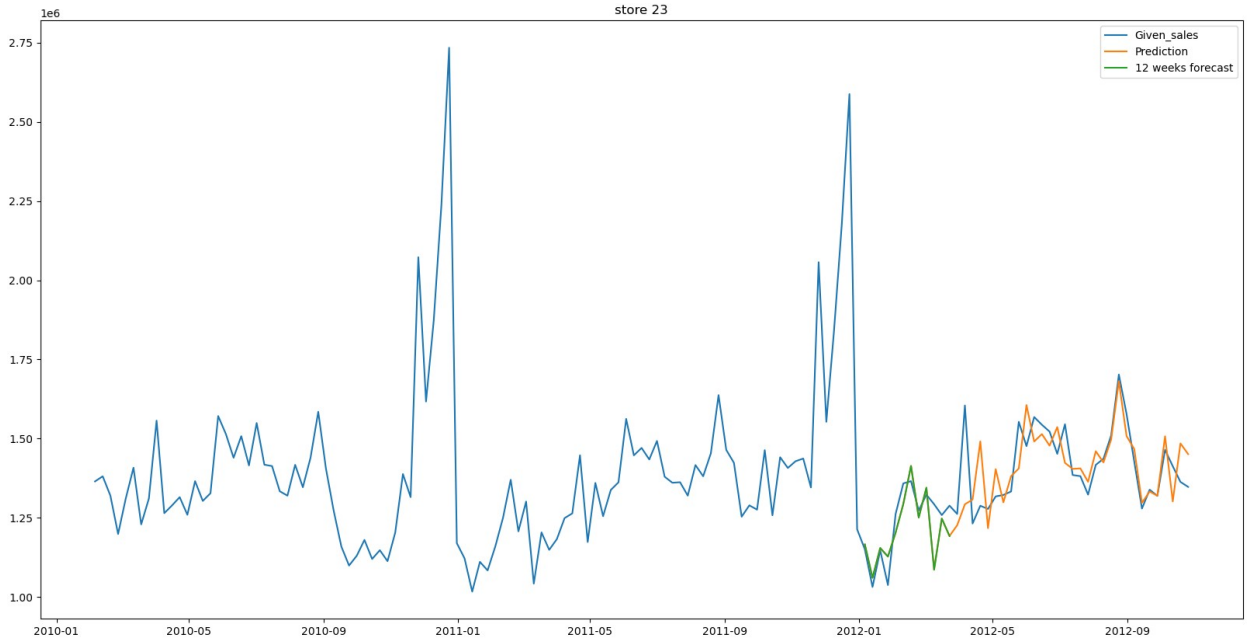

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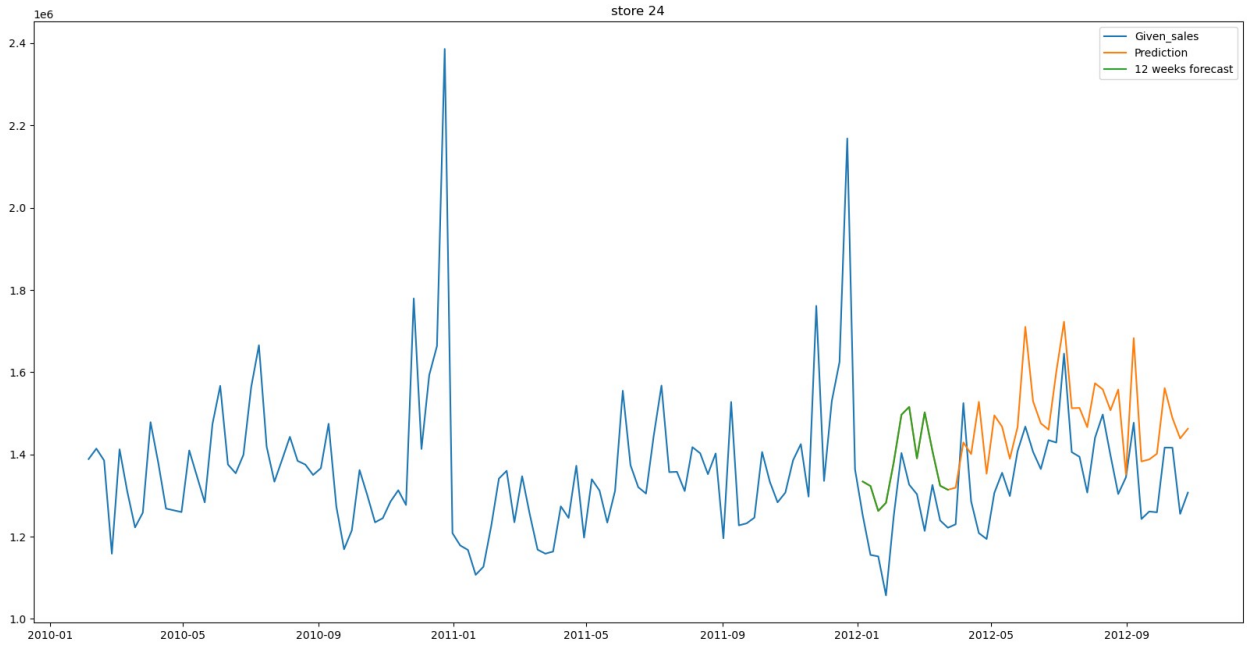


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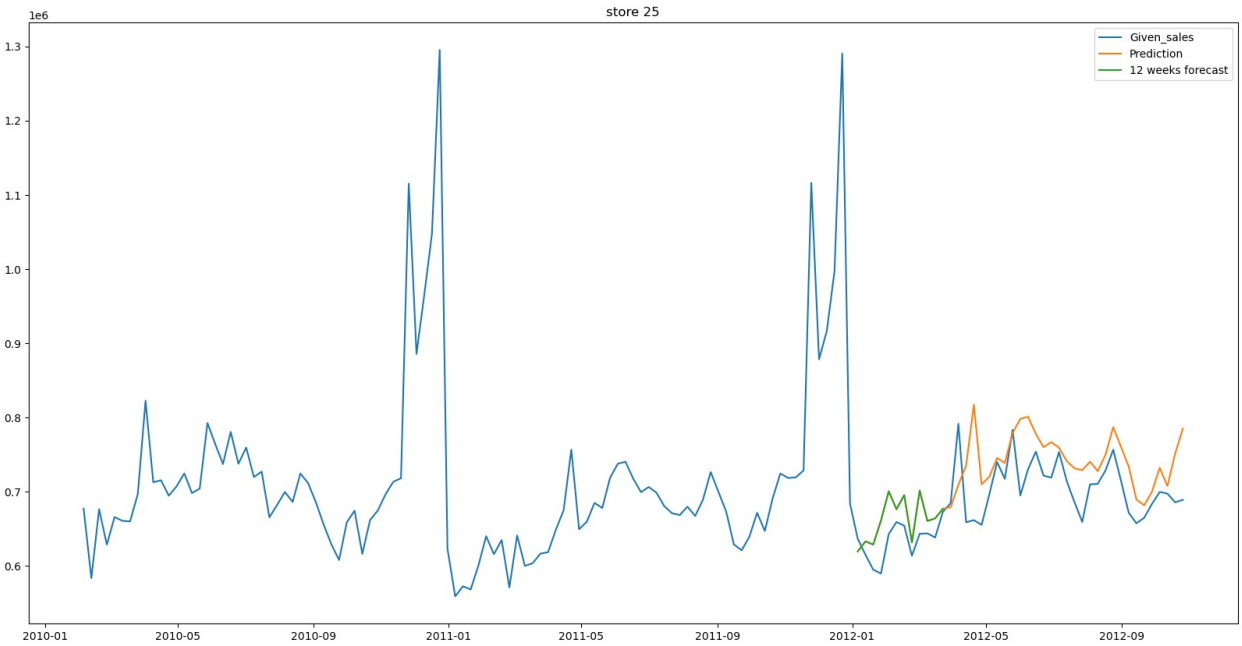


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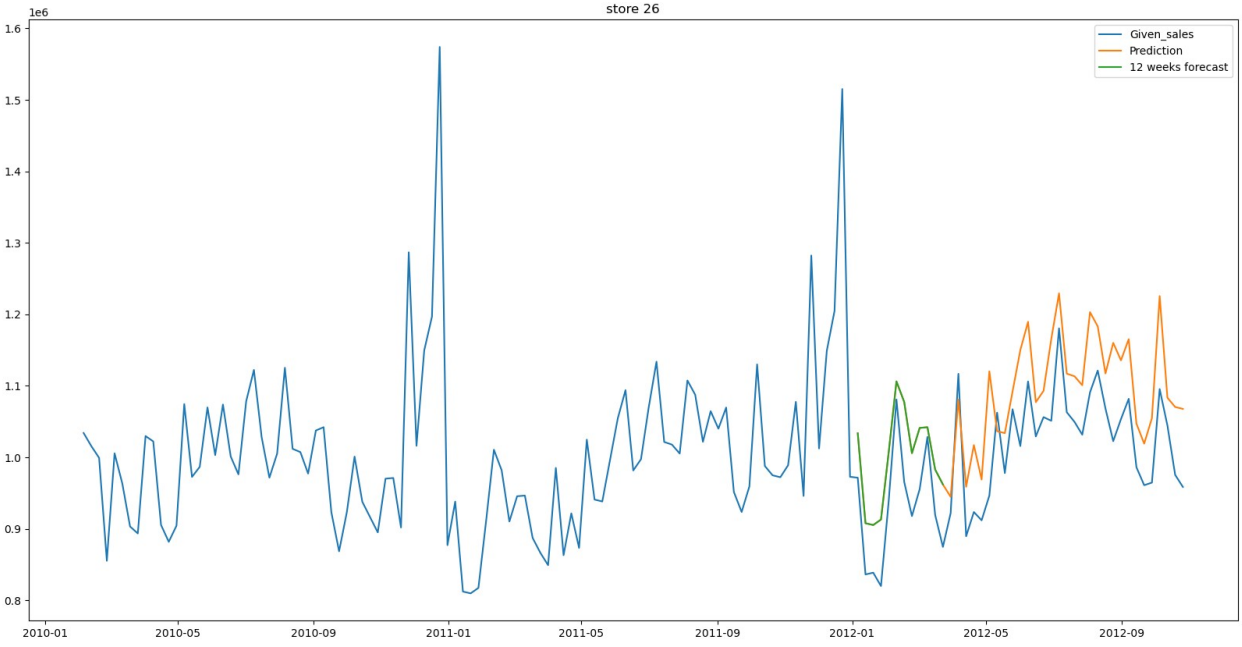

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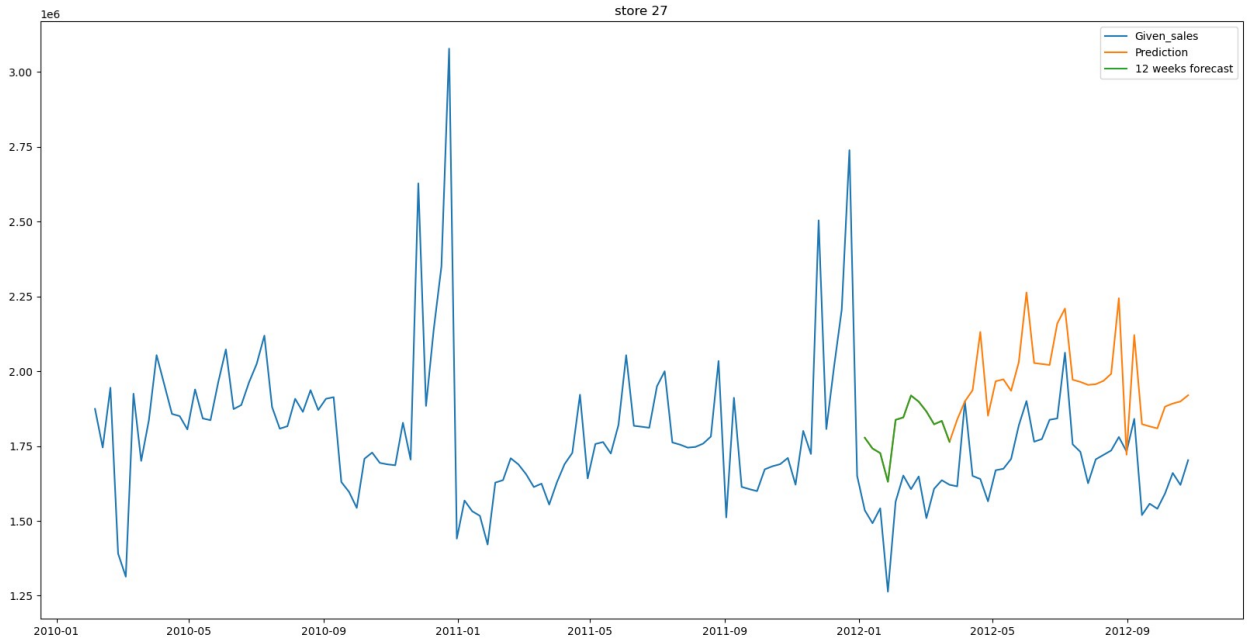


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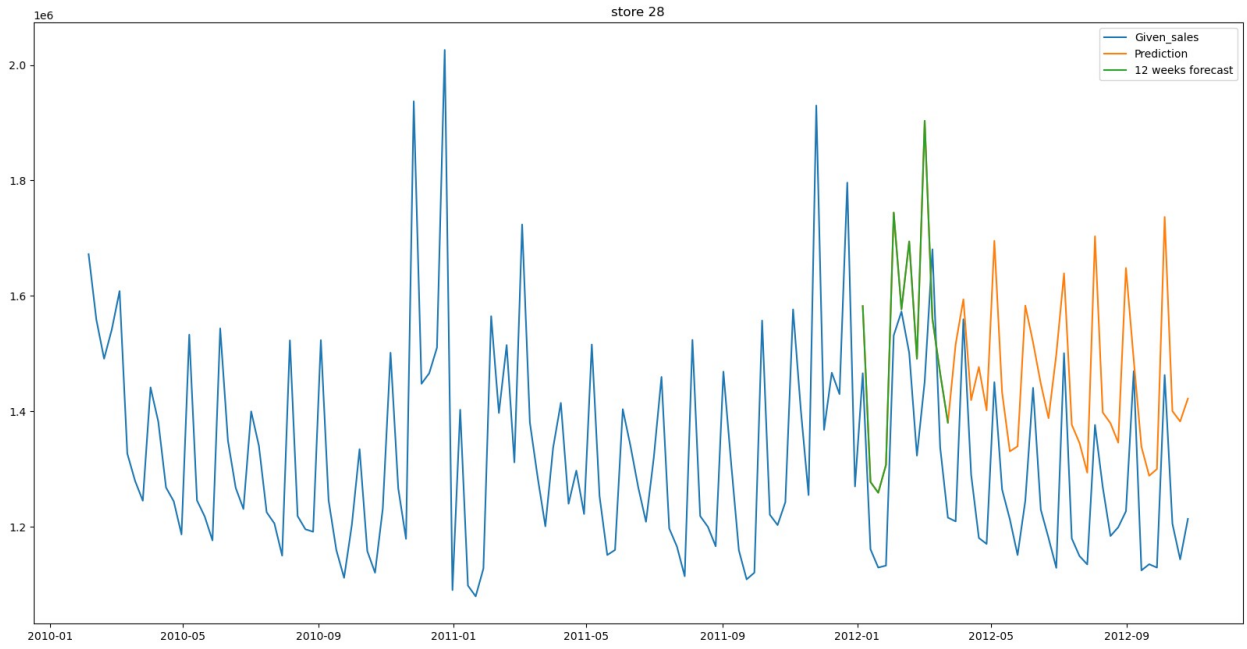


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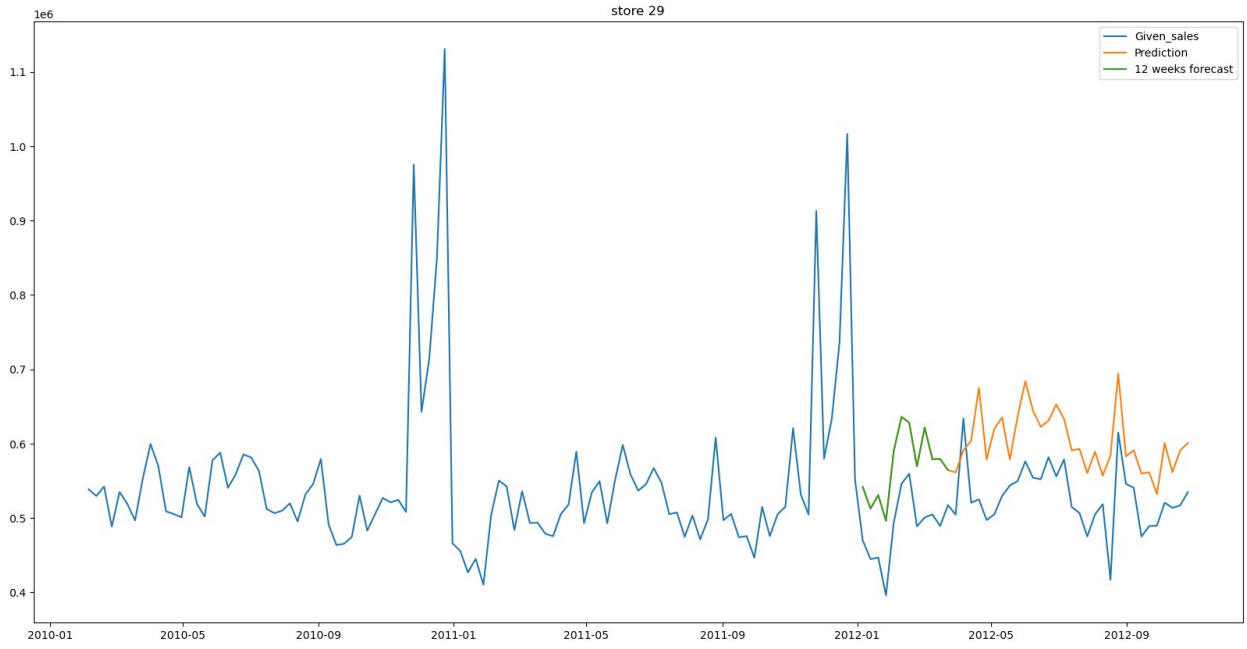

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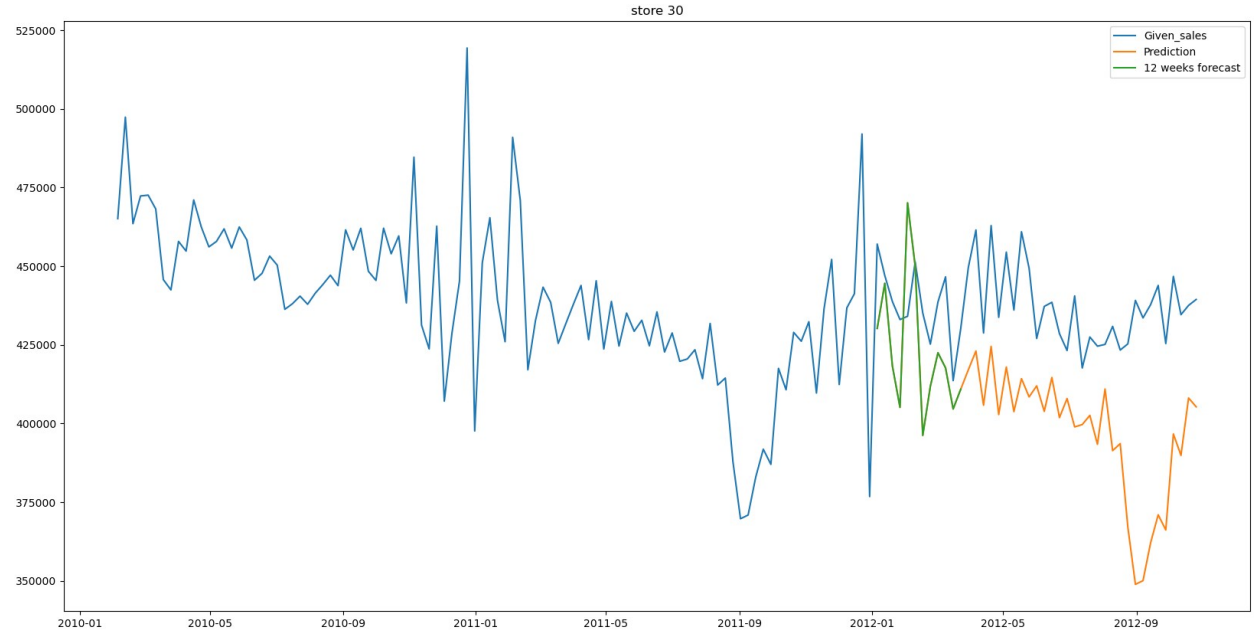


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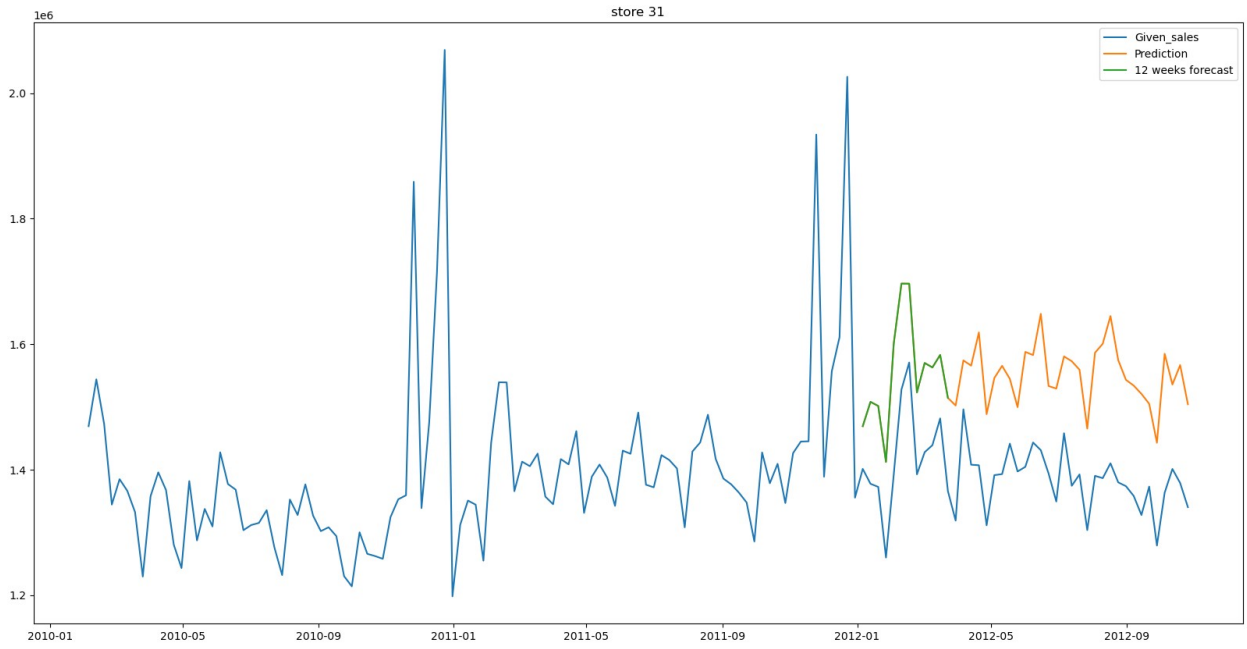


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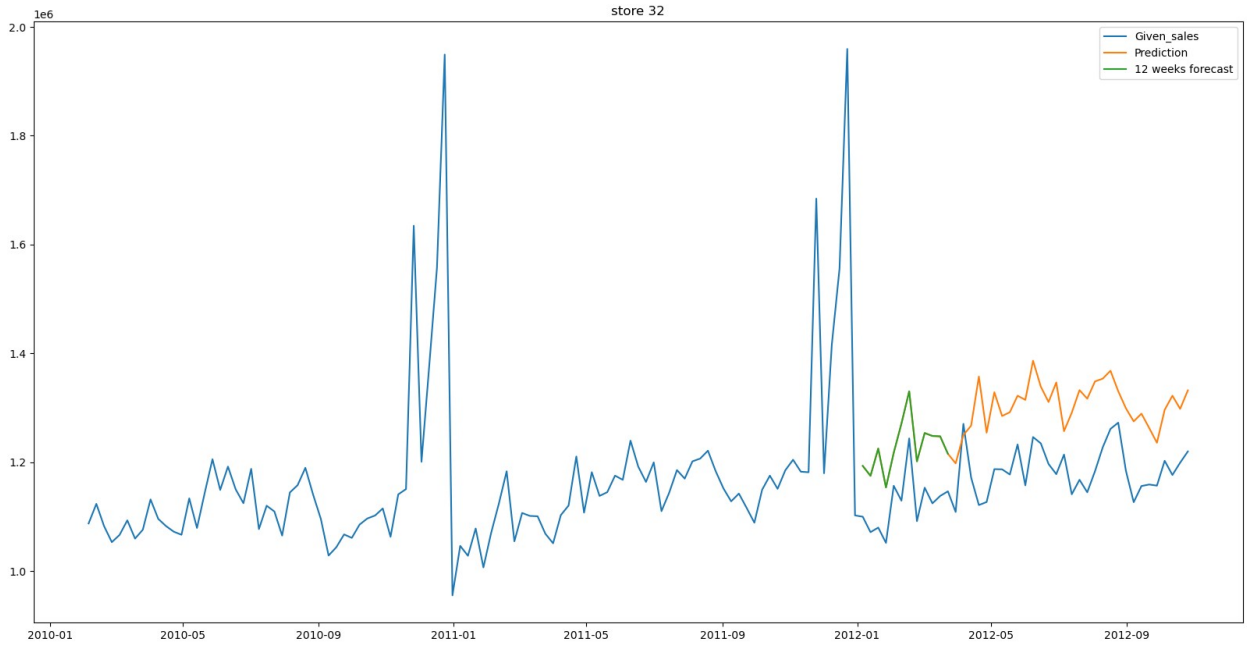

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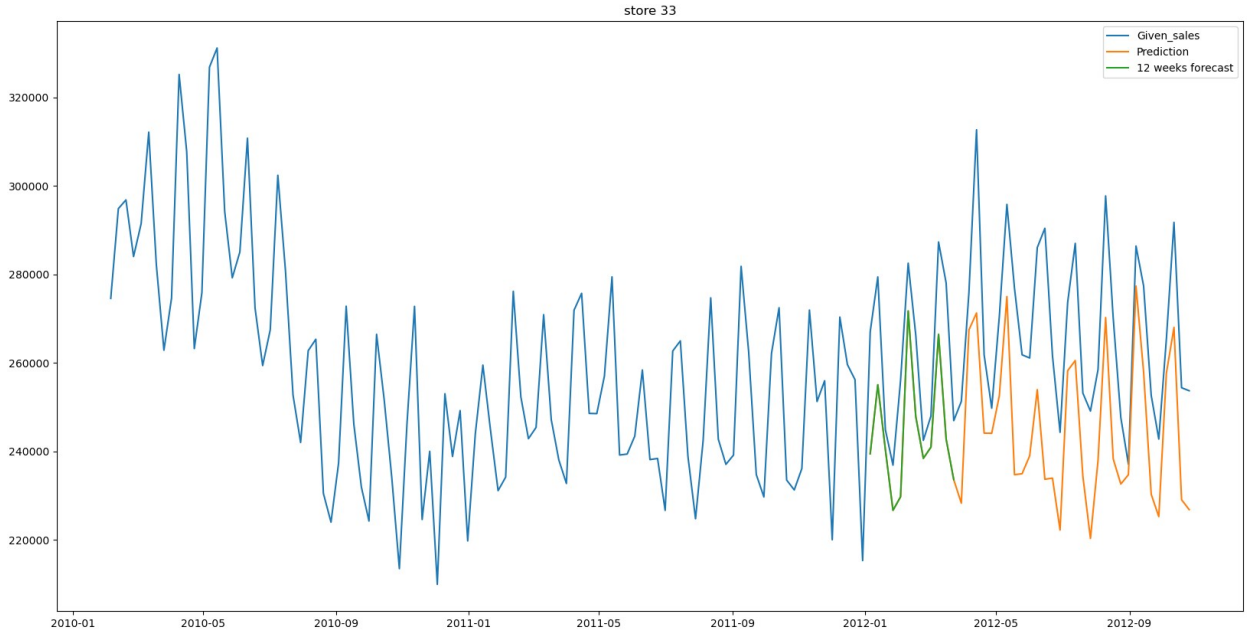


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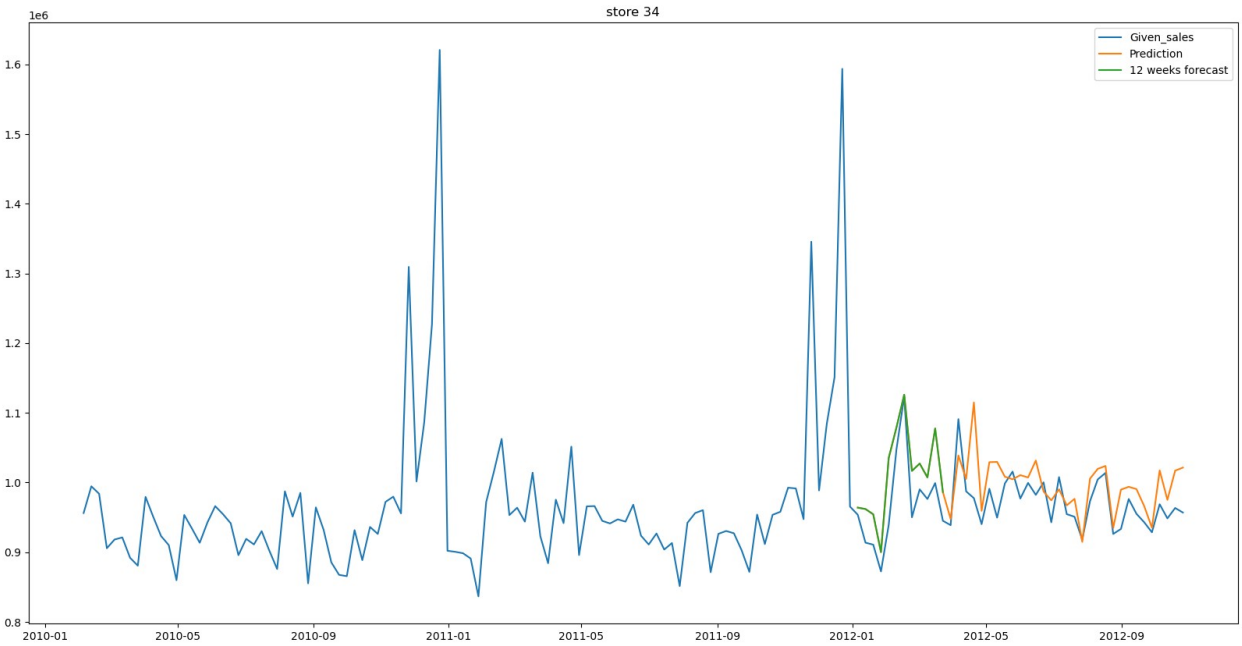


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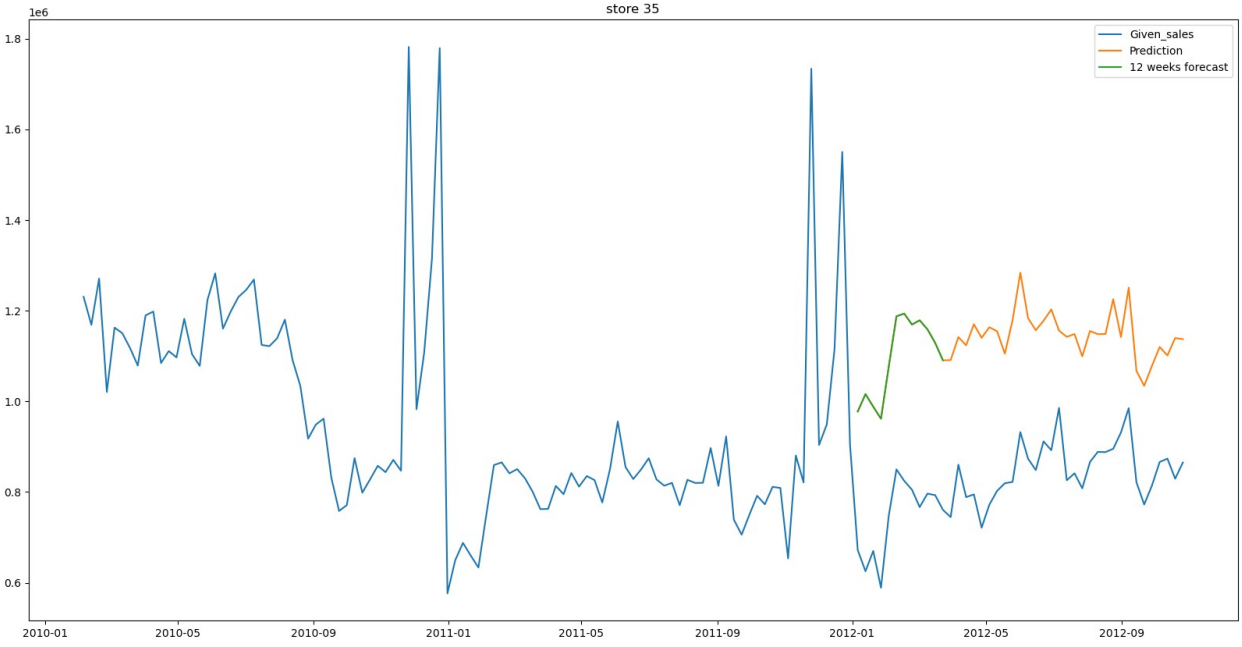

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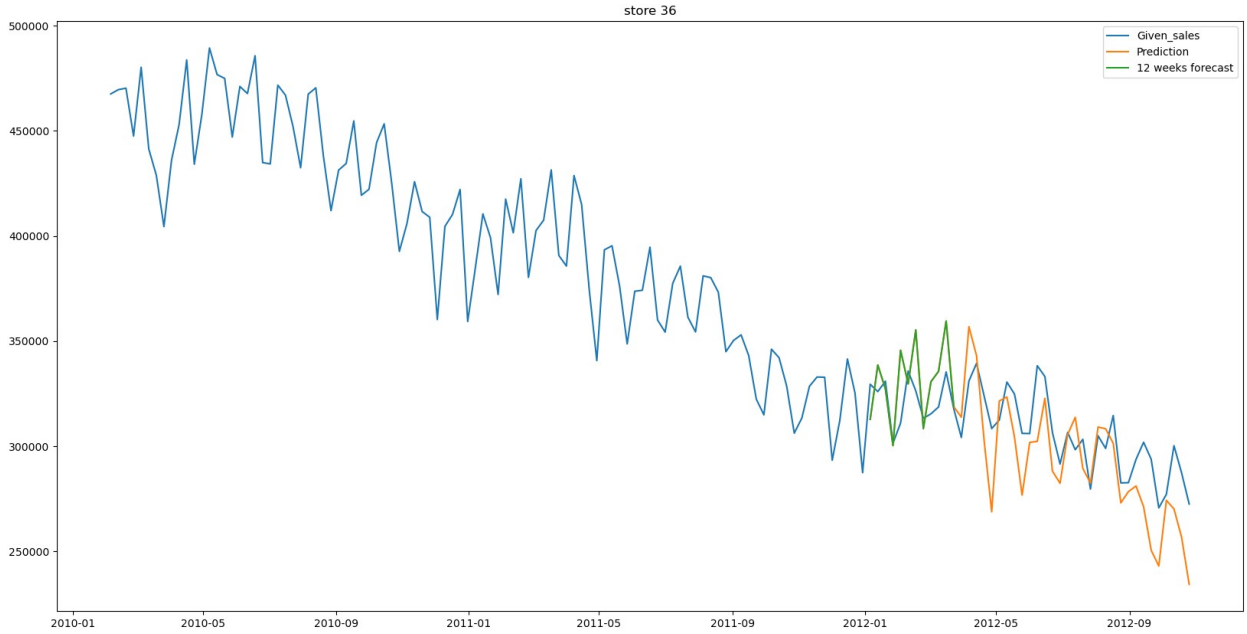


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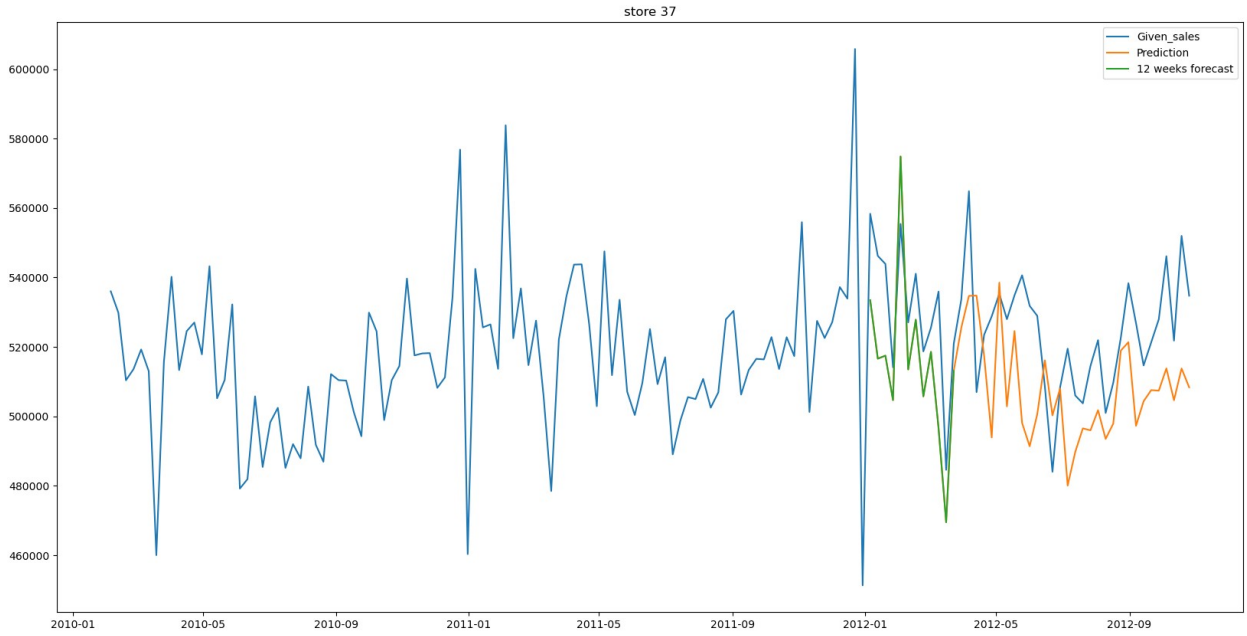


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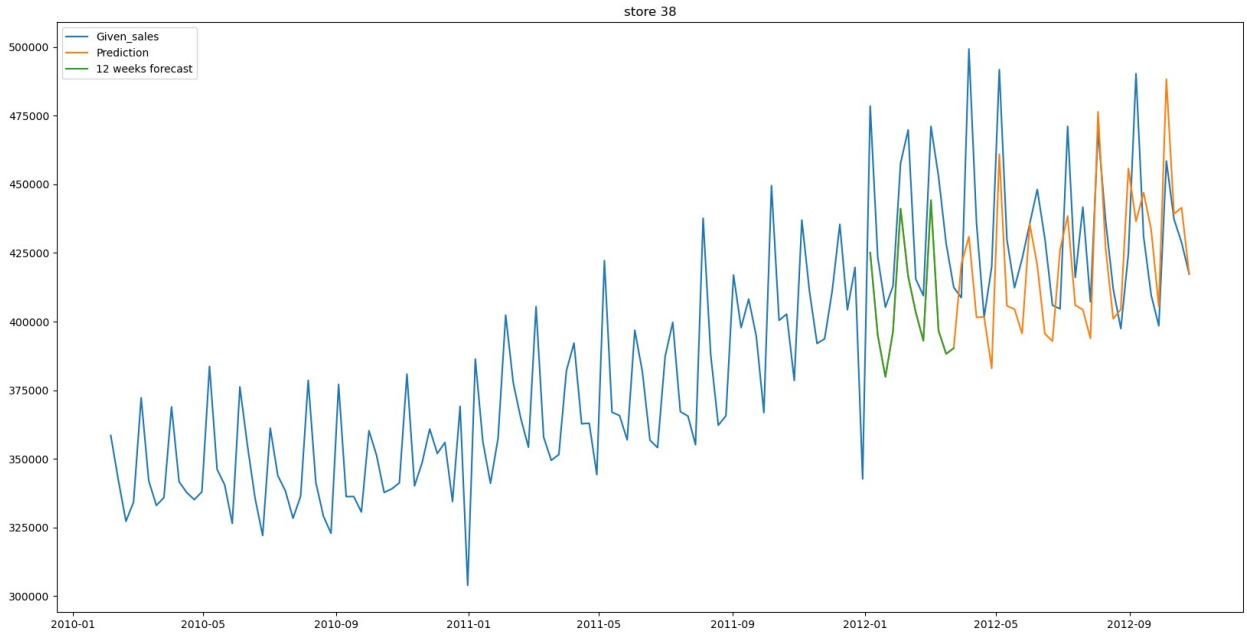

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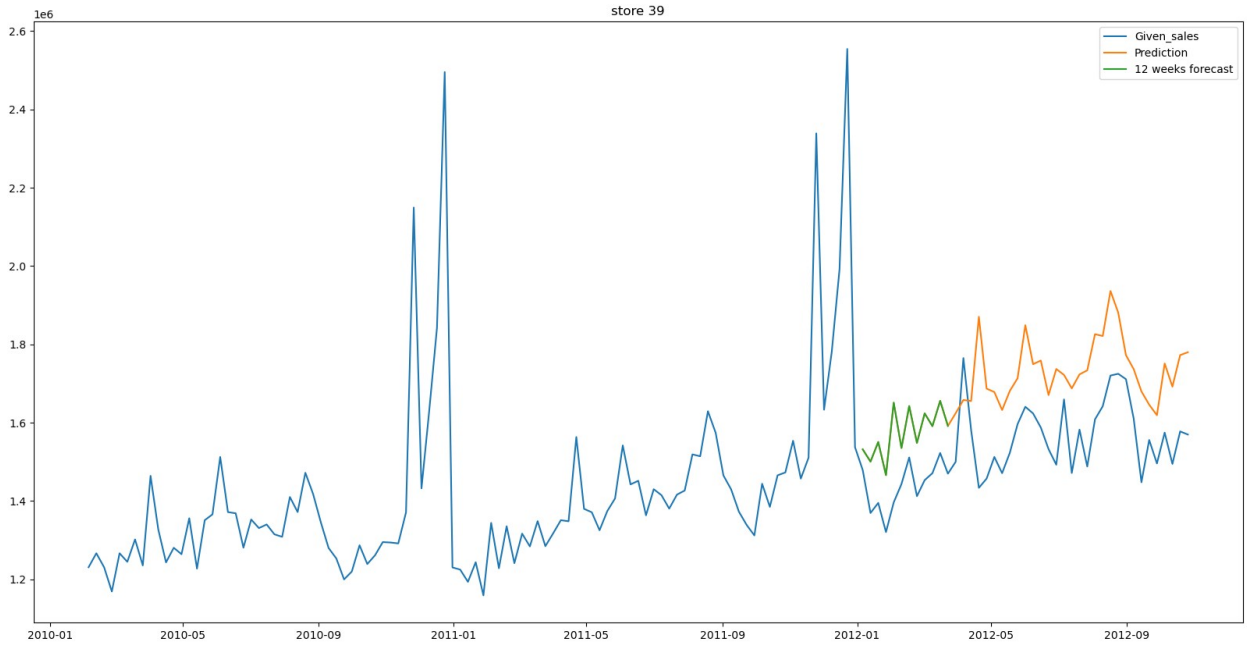


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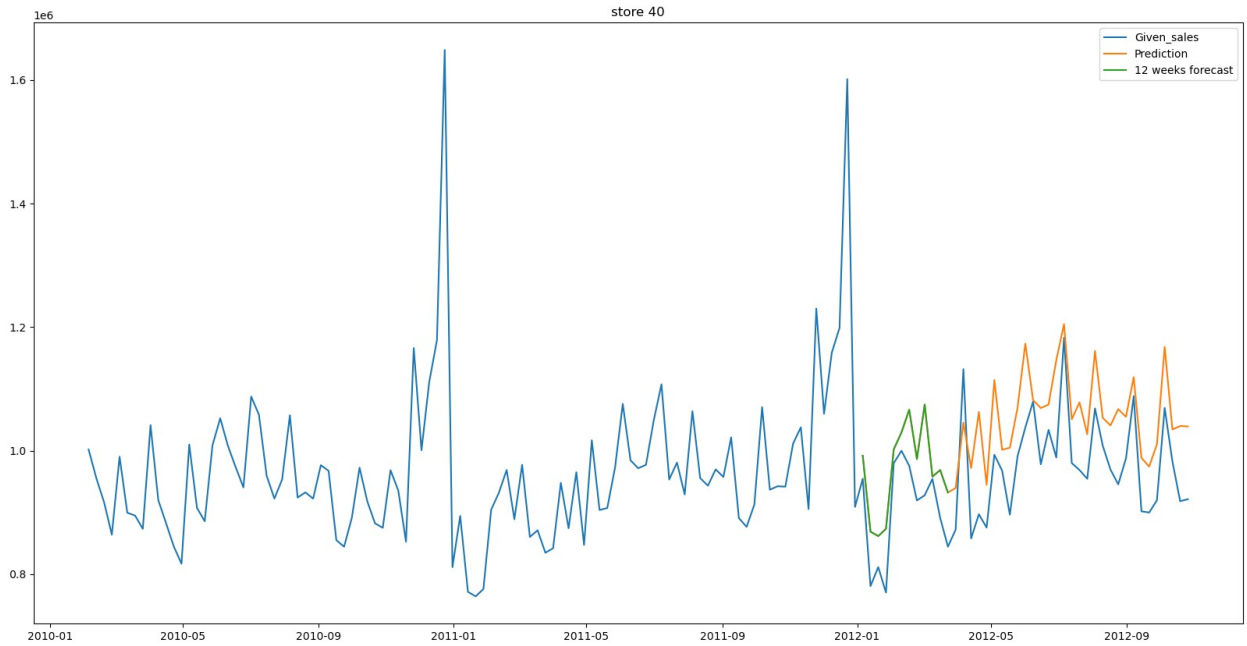


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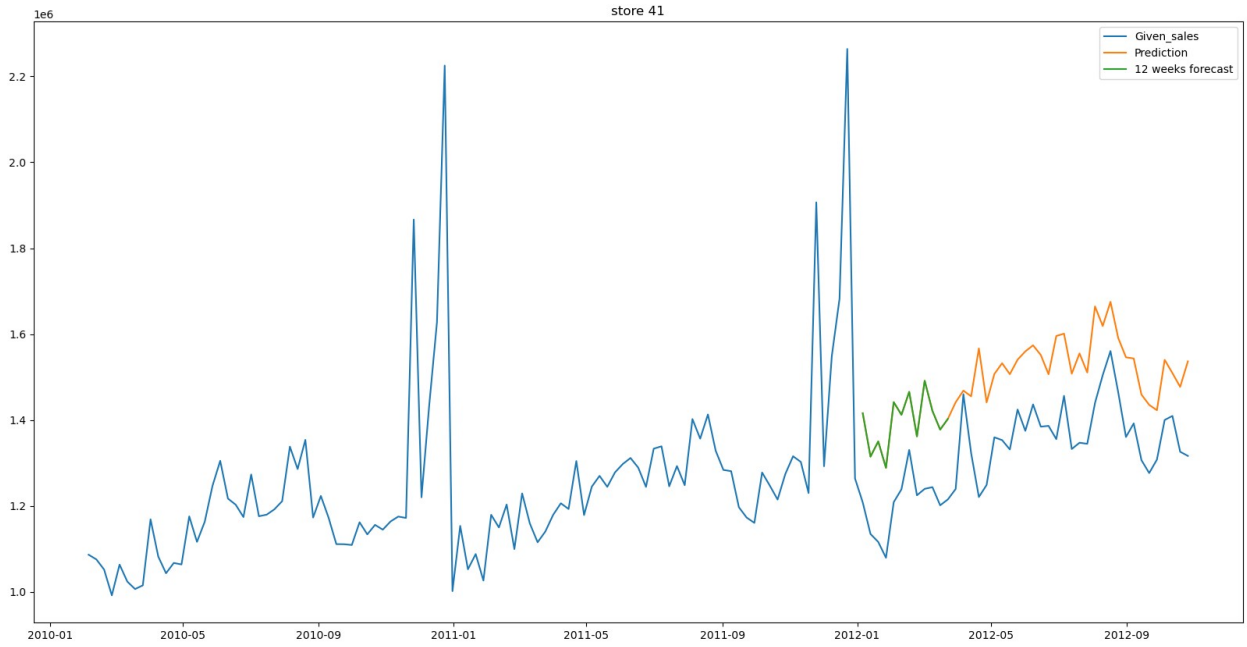

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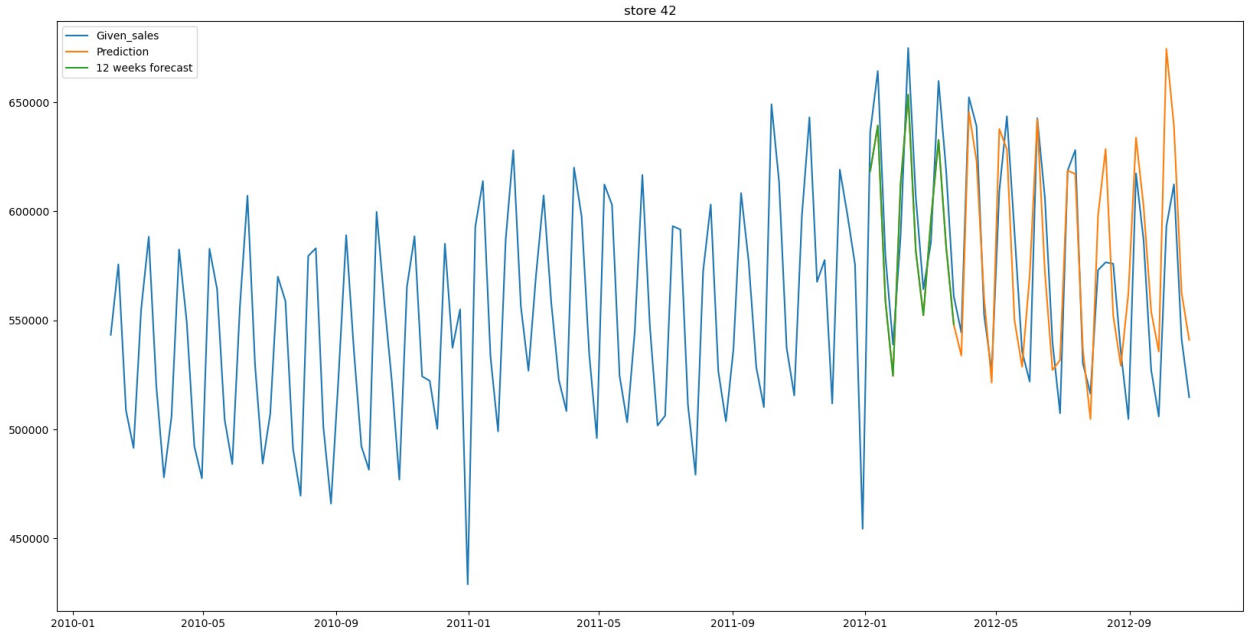


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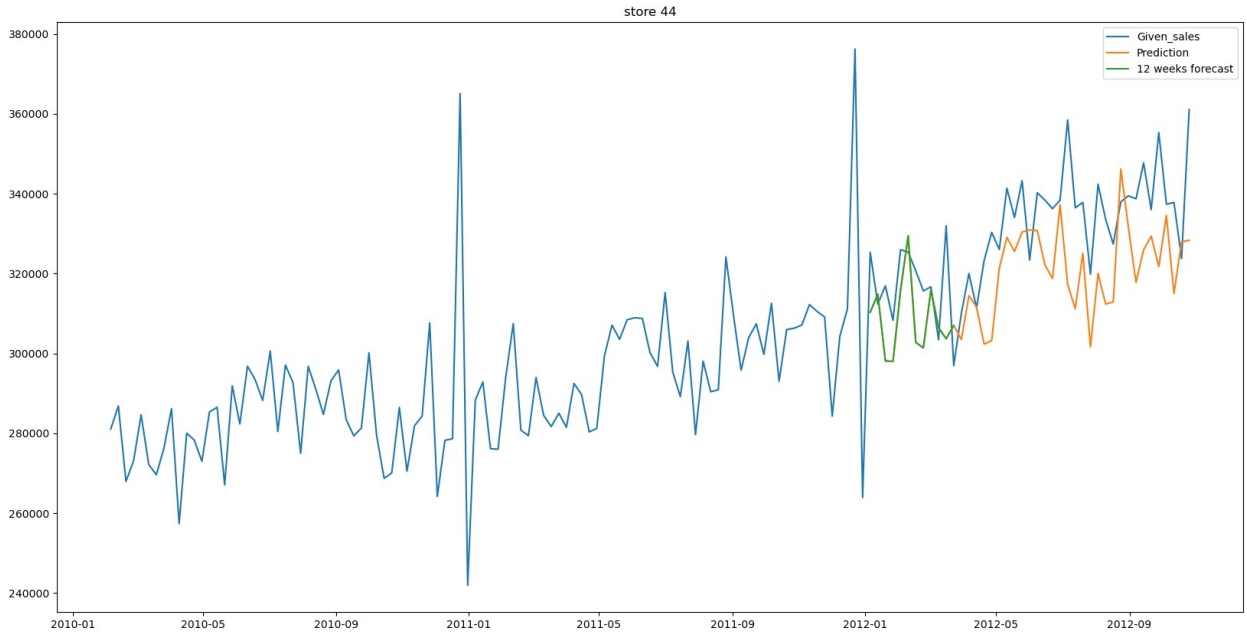

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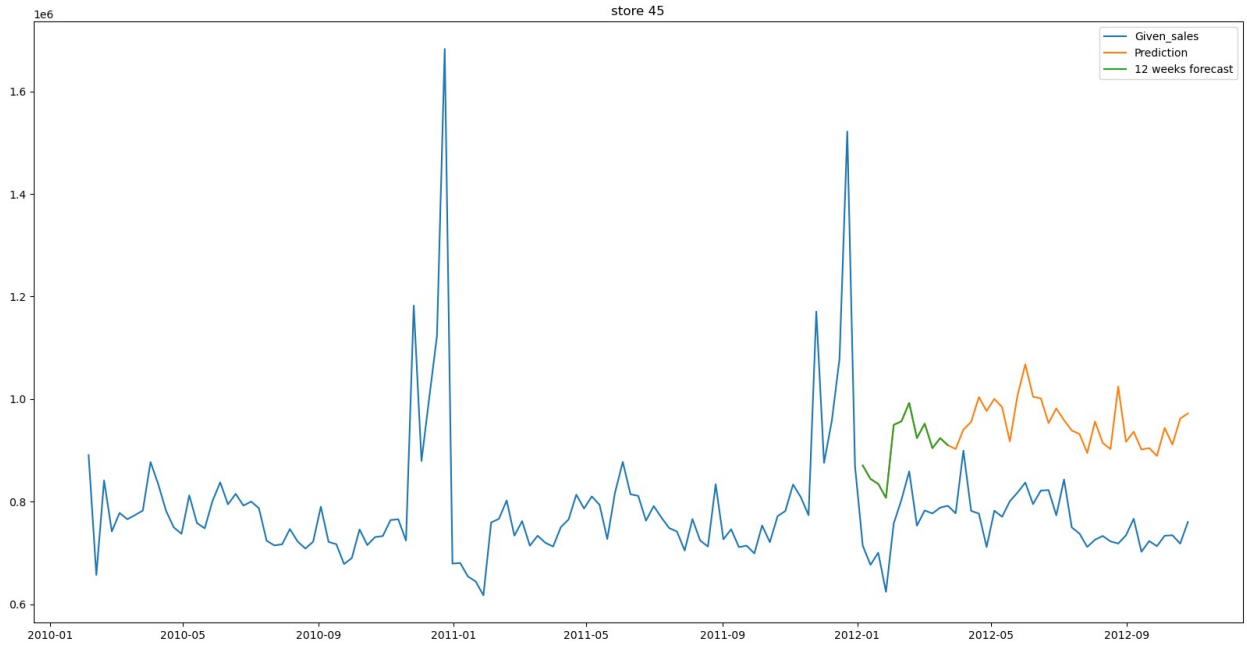

- **From the Above visualization we can observe the next 12 weeks sales of the 45 Stores of Walmart.**