Capstone Project

Problem Statement

A retail store that has multiple outlets across the country are facing issues in managing the inventory - to match the demand with respect to supply. You are a data scientist, who has to come up with useful insights using the data and make prediction models to forecast the sales for X number of months/years.

Dataset Information:

The walmart.csv file contains 6435 rows and 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
СРІ	Consumer Price Index
Unemployment	Unemployment Rate

- 1. Using the above data, come up with useful insights that can be used by each of the stores to improve in various areas.
- 2. Forecast the sales for each store for the next 12 weeks.

```
In [1]: # Importing the Libraries
    import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns

In [2]: # Importing the Dataset
    df= pd.read_csv('Walmart.csv')
In [3]: df.head()
```

Out[3]:		Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	СРІ	Unem
	0	1	05- 02- 2010	1643690.90	0	42.31	2.572	211.096358	
	1	1	12- 02- 2010	1641957.44	1	38.51	2.548	211.242170	
	2	1	19- 02- 2010	1611968.17	0	39.93	2.514	211.289143	
	3	1	26- 02- 2010	1409727.59	0	46.63	2.561	211.319643	
	4	1	05- 03- 2010	1554806.68	0	46.50	2.625	211.350143	
	4								•

Performing EDA

```
In [4]:
       df.shape
Out[4]: (6435, 8)
In [5]:
       df.columns
Out[5]: Index(['Store', 'Date', 'Weekly_Sales', 'Holiday_Flag', 'Temperature',
               'Fuel_Price', 'CPI', 'Unemployment'],
              dtype='object')
In [6]: 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
           Weekly Sales 6435 non-null float64
                                       int64
           Holiday_Flag 6435 non-null
           Temperature 6435 non-null
                                         float64
       5
           Fuel_Price
                         6435 non-null
                                         float64
           CPI
                         6435 non-null
                                         float64
           Unemployment 6435 non-null
                                         float64
       dtypes: float64(5), int64(2), object(1)
       memory usage: 402.3+ KB
In [7]:
       df.describe()
```

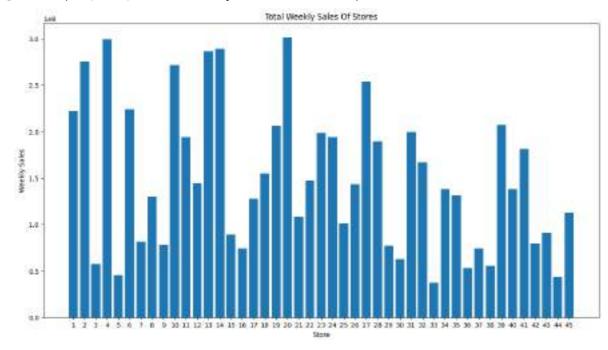
```
Out[7]:
                       Store Weekly_Sales Holiday_Flag
                                                        Temperature
                                                                       Fuel_Price
                                                                                          CPI
          count 6435.000000 6.435000e+03
                                            6435.000000
                                                         6435.000000 6435.000000 6435.000000
                   23.000000
                            1.046965e+06
                                               0.069930
                                                           60.663782
                                                                         3.358607
                                                                                   171.578394
          mean
            std
                   12.988182 5.643666e+05
                                               0.255049
                                                           18.444933
                                                                        0.459020
                                                                                    39.356712
                    1.000000 2.099862e+05
                                               0.000000
                                                                         2.472000
                                                                                   126.064000
           min
                                                           -2.060000
           25%
                   12.000000 5.533501e+05
                                               0.000000
                                                           47.460000
                                                                        2.933000
                                                                                   131.735000
           50%
                   23.000000 9.607460e+05
                                               0.000000
                                                           62.670000
                                                                         3.445000
                                                                                   182.616521
           75%
                   34.000000 1.420159e+06
                                               0.000000
                                                                         3.735000
                                                                                   212.743293
                                                           74.940000
                   45.000000 3.818686e+06
                                               1.000000
                                                          100.140000
                                                                         4.468000
                                                                                   227.232807
           max
 In [8]:
         df.isnull().sum()
                          0
 Out[8]:
          Store
          Date
                          0
          Weekly_Sales
                          0
          Holiday_Flag
                          0
          Temperature
                          0
          Fuel_Price
                          0
          CPI
                          0
          Unemployment
          dtype: int64
 In [9]:
         df.duplicated().sum()
 Out[9]: 0
         df['Store'].unique()
In [10]:
Out[10]: 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)
In [11]: df['Store'].nunique()
Out[11]: 45
In [12]: df['Holiday_Flag'].unique()
Out[12]: array([0, 1], dtype=int64)
In [13]: df['Holiday_Flag'].nunique()
Out[13]: 2
In [14]: df['Date'] = pd.to_datetime(df['Date'], format='%d-%m-%Y')
          df['Day_of_Week'] = df['Date'].dt.dayofweek
          df['Month'] = df['Date'].dt.month
          df['Year'] = df['Date'].dt.year
```

In [15]:	<pre>df.head()</pre>								
Out[15]:	Sto	re	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI Und	er
	0	1	2010- 02-05	1643690.90	0	42.31	2.572 21	1.096358	
	1	1	2010- 02-12	1641957.44	1	38.51	2.548 21	1.242170	
	2	1	2010- 02-19	1611968.17	0	39.93	2.514 21	1.289143	
	3	1	2010- 02-26	1409727.59	0	46.63	2.561 21	1.319643	
	4	1	2010- 03-05	1554806.68	0	46.50	2.625 21	1.350143	
	4							•	,
In [16]:	total_	sale	es_by_	store = df.gr	oupby('Store')['Weekly_Sal	.es'].sum().re	eset_index()	
In [17]:	df.cor	r()							
Out[17]:				Store	Date	Weekly_Sales	Holiday_Flag	Temperature	e
		S	Store	1.000000e+00	1.577299e-13	-0.335332	-4.386841e- 16	-0.022659	-
		ı	Date	1.577299e-13	1.000000e+00	0.006949	-1.328524e- 02	0.145357	7
	Wee	kly_S	Sales	-3.353320e- 01	6.949360e-03	1.000000	3.689097e-02	-0.063810)
	Holi	iday_	Flag	-4.386841e- 16	-1.328524e- 02	0.036891	1.000000e+00	-0.155091	1
	Tem	pera	ature	-2.265908e- 02	1.453566e-01	-0.063810	-1.550913e- 01	1.000000)
	F	uel_l	Price	6.002295e-02	7.714439e-01	0.009464	-7.834652e- 02	0.144982	2
			СРІ	-2.094919e- 01	7.715746e-02	-0.072634	-2.162091e- 03	0.176888	3
	Unemp	oloyn	nent	2.235313e-01	-2.482029e- 01	-0.106176	1.096028e-02	0.101158	3
	Day_	_of_V	Veek	NaN	NaN	NaN	NaN	NaN	1
		M	onth	2.910676e-15	1.456512e-01	0.076143	1.229958e-01	0.235862	2
			Year	3.474318e-12	9.416680e-01	-0.018378	-5.678257e- 02	U Uh4/h)
	4							•	,

Visualization

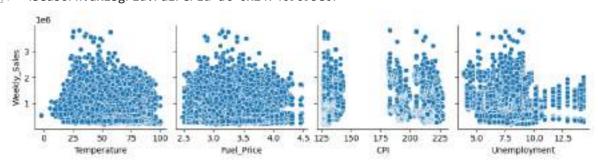
```
In [18]: plt.figure(figsize = (15, 8))
   plt.bar(total_sales_by_store['Store'], total_sales_by_store['Weekly_Sales'])
   plt.xlabel("Store")
   plt.ylabel("Weekly Sales")
   plt.xticks(range(1, 46))
   plt.title("Total Weekly Sales Of Stores")
```

Out[18]: Text(0.5, 1.0, 'Total Weekly Sales Of Stores')

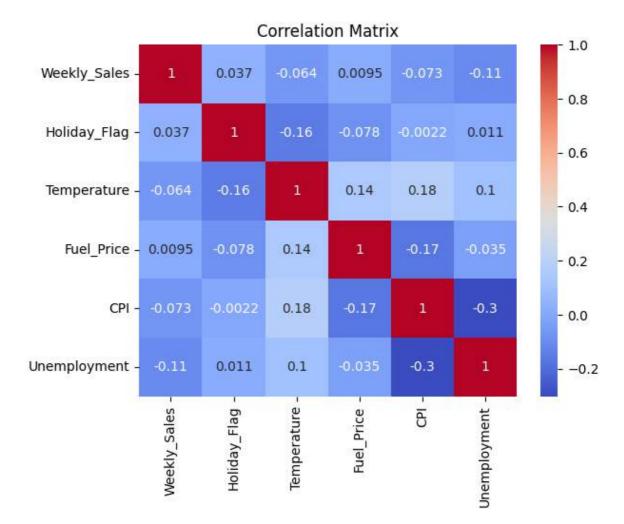


In [19]: sns.pairplot(df,x_vars=['Temperature', 'Fuel_Price', 'CPI', 'Unemployment'], y_v

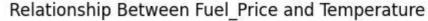
Out[19]: <seaborn.axisgrid.PairGrid at 0x247409695e0>

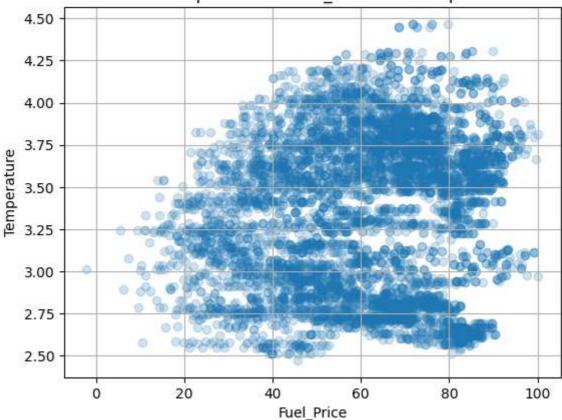


Out[20]: Text(0.5, 1.0, 'Correlation Matrix')



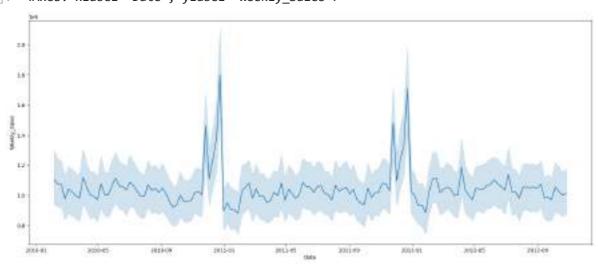
```
In [21]: plt.scatter(df['Temperature'], df['Fuel_Price'], alpha=0.2)
    plt.title('Relationship Between Fuel_Price and Temperature')
    plt.xlabel('Fuel_Price')
    plt.ylabel('Temperature')
    plt.grid(True)
```





```
In [22]: plt.figure(figsize=(20, 8))
sns.lineplot(x='Date', y='Weekly_Sales', data = df)
```



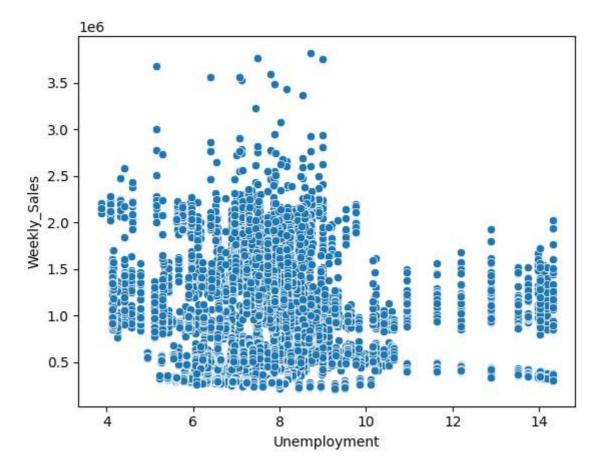


Insights On Walmart Dataset

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

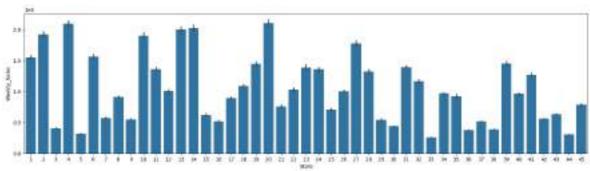
```
In [23]: sns.scatterplot(x=df['Unemployment'], y=df['Weekly_Sales'])
```

Out[23]: <Axes: xlabel='Unemployment', ylabel='Weekly_Sales'>



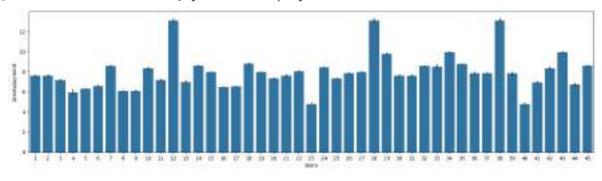
```
In [24]: plt.figure(figsize=(20, 5))
sns.barplot(x=df['Store'], y=df['Weekly_Sales'])
```

Out[24]: <Axes: xlabel='Store', ylabel='Weekly_Sales'>



```
In [25]: plt.figure(figsize=(20, 5))
sns.barplot(x=df['Store'], y=df['Unemployment'])
```

Out[25]: <Axes: xlabel='Store', ylabel='Unemployment'>



```
In [26]: df.groupby(by='Store').agg({'Weekly_Sales':'sum', 'Unemployment':'sum'})
```

Out[26]: Weekly_Sales Unemployment

Store	vveeniy_buies	onemployen
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

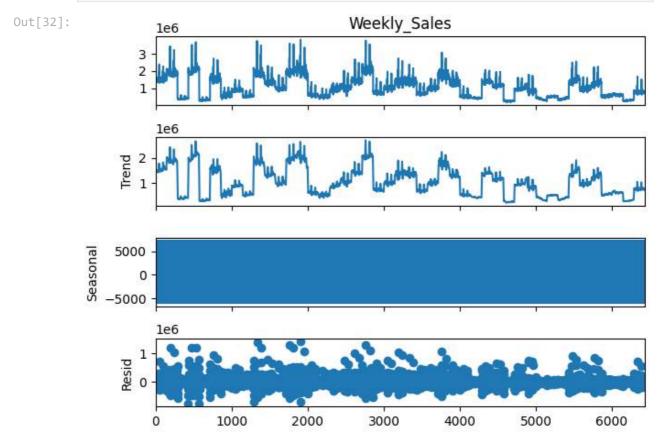
Store

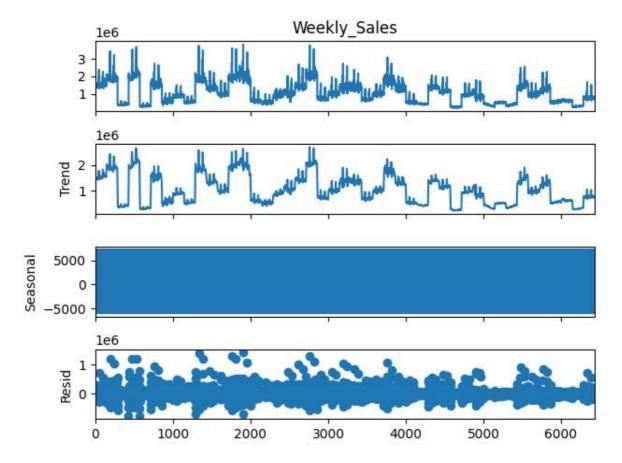
Weekly_Sales Unemployment

_	Store		
	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
[27]: [28]: t[28]:		_correlation=df	
-	1	Weekly_Sales Unemployment	-0.097955 1.000000
	2	Weekly_Sales Unemployment	0.066325 1.000000
	3	Weekly_Sales	-0.230413
	43	Unemployment	1.000000
	44	Weekly_Sales Unemployment	1.000000
	45	Weekly_Sales Unemployment	-0.004041 1.000000
	Name:	Unemployment,	Length: 90, dt
29]:	sorted	l_store_corr =	store_correlat
[30]:	sorted	l_store_corr.he	ad(3)
[30]:	Store 36	0.833734	
	38 44	0.785290 0.780076	
	Name:	Unemployment,	dtype: float64

• Store 36, 38, 44 are more affected by Unemployment

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

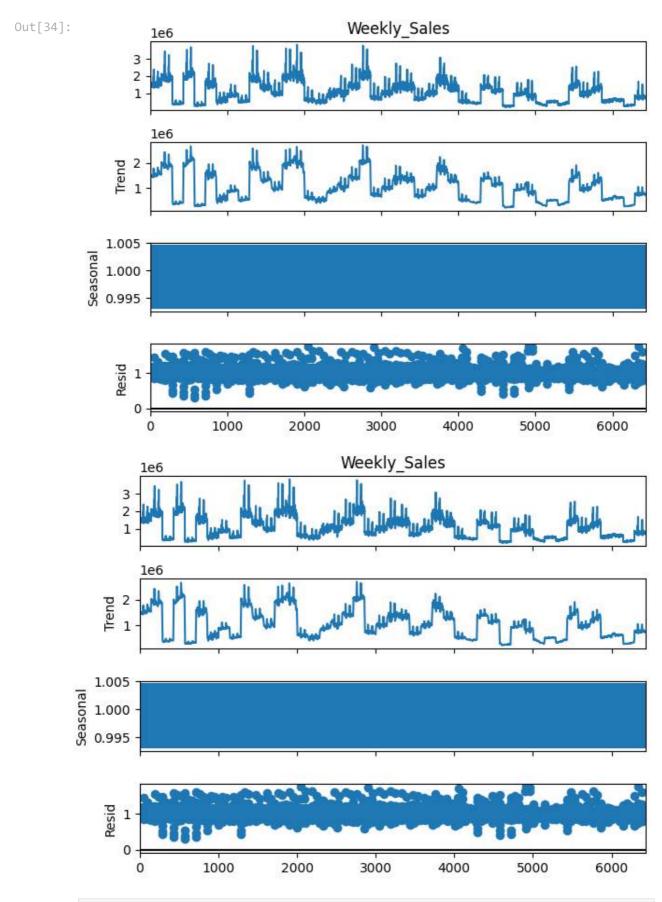




In [33]: new_df_add=pd.concat([result.seasonal,result.trend,result.resid,result
 .observed],axis=1)
 new_df_add.columns=["seasonality","trend","residual","actual_values"]
 new_df_add.head(5)

Out[33]:		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

```
In [34]: result=seasonal_decompose(df['Weekly_Sales'],model='multiplicative',
    period=7)
    result.plot()
```



Out[35]:		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

In [36]: sns.distplot(df['Weekly_Sales'],hist=True)
plt.plot()

C:\Users\zayna\AppData\Local\Temp\ipykernel_5580\642300183.py:1: UserWarning:

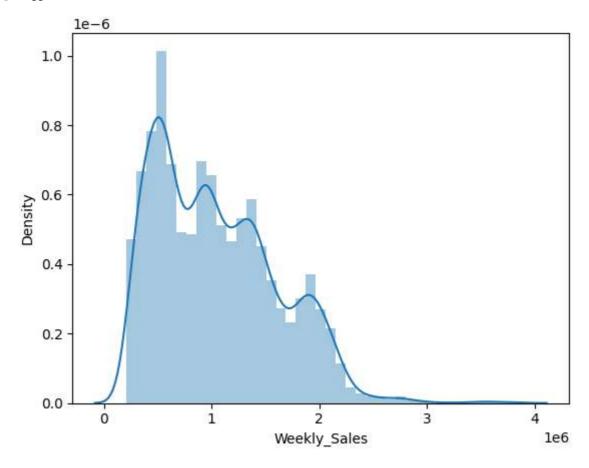
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

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

Out[36]: []



Weekly Sales Show a Seasonal Trend

```
In [37]: df.Holiday_Flag.value_counts()
```

```
Out[37]: Holiday_Flag
0 5985
1 450
```

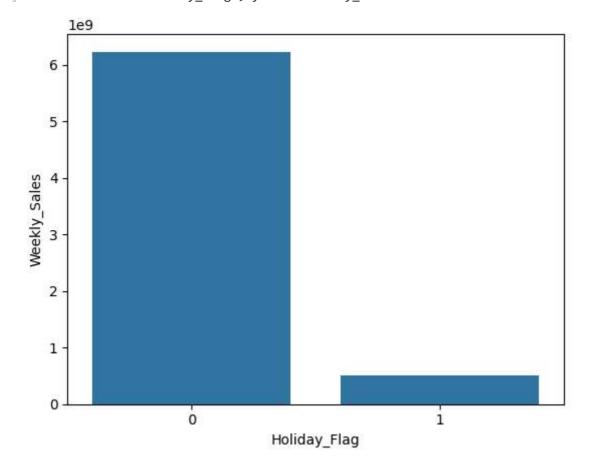
Name: count, dtype: int64

```
In [38]: Total_by_store = df.groupby(['Holiday_Flag'],as_index=False).agg({'Weekly_Sales'
Total_by_store
```

Out[38]:		Holiday_Flag	Weekly_Sales
	0	0	6.231919e+09
	1	1	5.052996e+08

```
In [39]: sns.barplot(x=Total_by_store['Holiday_Flag'],y=Total_by_store['Weekly_Sales'])
```

Out[39]: <Axes: xlabel='Holiday_Flag', ylabel='Weekly_Sales'>



• Average Weekly Sales in Holiday Week are more that that of Non Holiday weeks

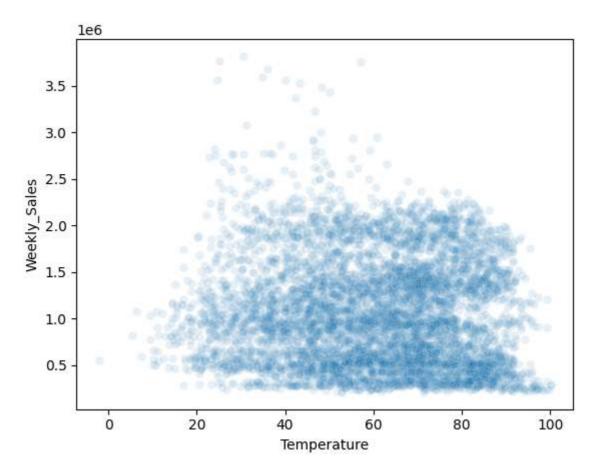
```
In [40]: Total_by_store = df.groupby(['Store','Holiday_Flag'],as_index=False).agg({'Weekl
Total_by_store
```

Out[40]:		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

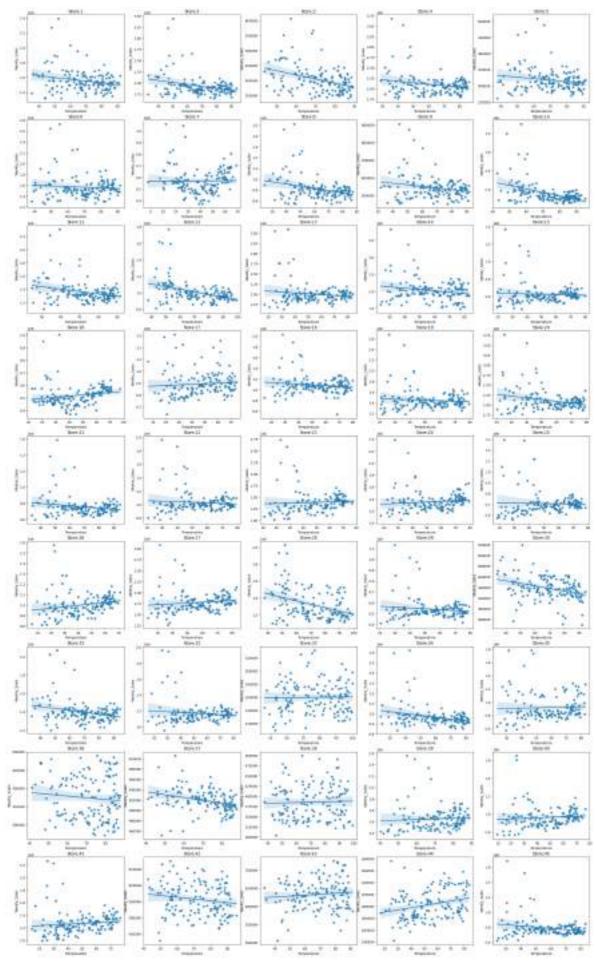
90 rows × 4 columns

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

```
In [43]: sns.scatterplot(x = df['Temperature'],y = df['Weekly_Sales'], alpha=0.1)
Out[43]: <Axes: xlabel='Temperature', ylabel='Weekly_Sales'>
```



```
In [44]: 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}')
```



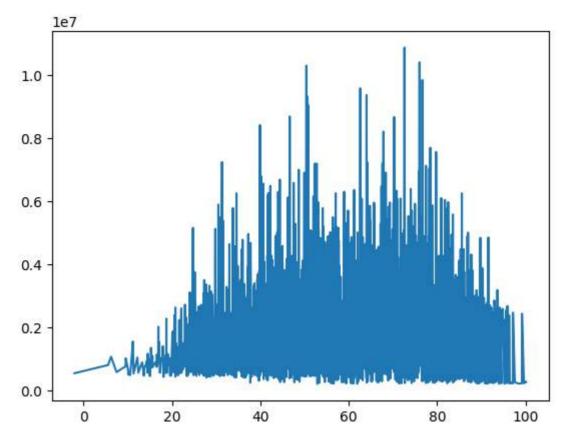
In [45]: Total_by_temp =df.groupby('Temperature',as_index=False).agg({'Weekly_Sales': 'su
Total_by_temp

Out[45]:		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 × 2 columns

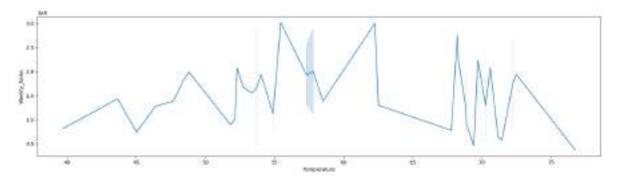
```
In [46]: plt.plot(Total_by_temp['Temperature'],Total_by_temp['Weekly_Sales'])
```

Out[46]: [<matplotlib.lines.Line2D at 0x2474edd9520>]



In [47]: Total_by_store = df.groupby(['Store'], as_index=False).agg({'Weekly_Sales': 'sum
 plt.figure(figsize=(20, 5))
 sns.lineplot(x='Temperature', y='Weekly_Sales', data=Total_by_store)

Out[47]: <Axes: xlabel='Temperature', ylabel='Weekly_Sales'>

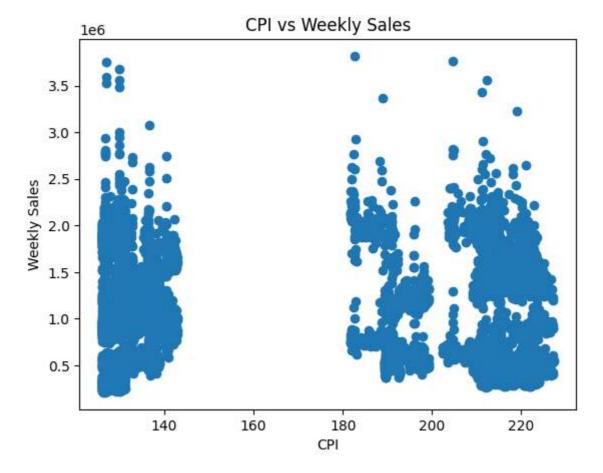


- Temperature affects the weekly sales
- At Low and High Temperatures the weekly sales are lower
- At moderate temperatures the Weekly sales are higher

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

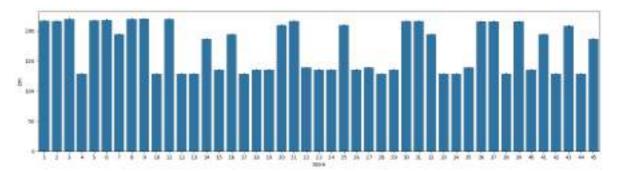
```
In [48]: plt.scatter(df["CPI"],df['Weekly_Sales'])
    plt.xlabel('CPI')
    plt.ylabel('Weekly Sales')
    plt.title("CPI vs Weekly Sales")
```

Out[48]: Text(0.5, 1.0, 'CPI vs Weekly Sales')



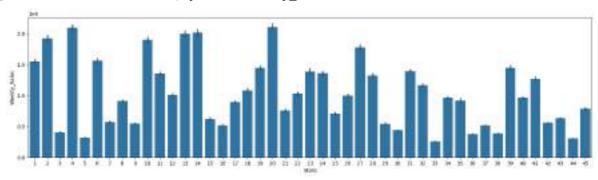
```
In [49]: plt.figure(figsize=(20, 5))
sns.barplot(x = df['Store'], y=df['CPI'])
```

Out[49]: <Axes: xlabel='Store', ylabel='CPI'>



```
In [50]: plt.figure(figsize=(20, 5))
sns.barplot(x = df['Store'], y=df['Weekly_Sales'])
```

Out[50]: <Axes: xlabel='Store', ylabel='Weekly_Sales'>



```
In [51]: Total_by_store = df.groupby('Store').agg({'Weekly_Sales': 'sum', 'CPI': 'sum'})
    Total_by_store
```

Out[51]:

Weekly_Sales CPI	es CPI
------------------	--------

Store		
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

		Weekly_Sales	СРІ
	Store		
	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
		_	
In [52]:	Total_	_by_store[Tota	l_by_store.CP
Out[52]:		Weekly_Sales	СРІ
	Store		
	9	77789218.99	31406.616557
In [53]:	Total_	_by_store[Tota	l_by_store.CP

Out[53]:

	7 =	
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

Weekly_Sales

• When CPI is higher Weekly Sales are Lower

E) Top performing stores according to the historical data

CPI

In [54]: 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=Fals
 Top_sales_store

Out[54]:		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

Store	Weekly_Sales
42	7.956575e+07
9	7.778922e+07
29	7.714155e+07
16	7.425243e+07
37	7.420274e+07
30	6.271689e+07
3	5.758674e+07
38	5.515963e+07
36	5.341221e+07
5	4.547569e+07
44	4.329309e+07
33	3.716022e+07
	42 9 29 16 37 30 3 38 36 5 44

```
In [55]: Top_sales_store.head()
```

Out[55]:		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

• The Top Performing stores are Stor number 20, 4, 14, 13, 2

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

• The Worst Performing store is Store No 33

```
In [57]: Top_sales_store.max()['Weekly_Sales'] - Top_sales_store.min()['Weekly_Sales']
Out[57]: 264237570.49999997
```

• The Difference Between the best and the worst performing store is 264237570.49999997

```
In [58]: df.Date=pd.to_datetime(df.Date,format="%d-%m-%Y")
In [59]: df=df.set_index("Date")
```

2. Use predictive modeling techniques to forecast the sales for each store for the next 12 weeks.

Time Series Analysis

```
In [60]: df_target=df.loc[:,['Store',"Weekly_Sales"]]
In [61]: df_target
Out[61]: 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 × 2 columns

```
In [62]: from pmdarima.arima import auto_arima
model = auto_arima(df["Weekly_Sales"], seasonal=True, stepwise=True, trace=True)
```

```
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
 warnings.warn(
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
 warnings.warn(
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
 warnings.warn(
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce all finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
Performing stepwise search to minimize aic
ARIMA(2,1,2)(0,0,0)[0] intercept : AIC=173103.554, Time=4.29 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(0,1,0)(0,0,0)[0] intercept : AIC=174457.419, Time=0.24 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(1,1,0)(0,0,0)[0] intercept : AIC=173626.224, Time=0.65 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(0,1,1)(0,0,0)[0] intercept : AIC=173359.721, Time=0.83 sec
                                    : AIC=174455.423, Time=0.16 sec
ARIMA(0,1,0)(0,0,0)[0]
```

```
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(1,1,2)(0,0,0)[0] intercept
                                   : AIC=173301.748, Time=2.83 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(2,1,1)(0,0,0)[0] intercept
                                   : AIC=173266.524, Time=3.18 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(3,1,2)(0,0,0)[0] intercept
                                  : AIC=172741.309, Time=4.85 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(3,1,1)(0,0,0)[0] intercept
                                   : AIC=172905.020, Time=4.69 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
                                  : AIC=172730.428, Time=12.92 sec
ARIMA(4,1,2)(0,0,0)[0] intercept
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(4,1,1)(0,0,0)[0] intercept : AIC=172847.176, Time=4.30 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(5,1,2)(0,0,0)[0] intercept
                                   : AIC=172588.751, Time=23.11 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
                                   : AIC=172597.113, Time=6.85 sec
ARIMA(5,1,1)(0,0,0)[0] intercept
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
                                  : AIC=172572.018, Time=13.13 sec
ARIMA(5,1,3)(0,0,0)[0] intercept
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce all finite' was renamed to 'ensure all finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(4,1,3)(0,0,0)[0] intercept : AIC=172609.343, Time=19.04 sec
```

```
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(5,1,4)(0,0,0)[0] intercept : AIC=172568.730, Time=15.32 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(4,1,4)(0,0,0)[0] intercept : AIC=172608.399, Time=12.34 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(5,1,5)(0,0,0)[0] intercept : AIC=172515.273, Time=27.51 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(4,1,5)(0,0,0)[0] intercept : AIC=172515.184, Time=12.83 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(3,1,5)(0,0,0)[0] intercept : AIC=172520.188, Time=11.26 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(3,1,4)(0,0,0)[0] intercept : AIC=172730.332, Time=13.91 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
                                    : AIC=172513.152, Time=12.63 sec
ARIMA(4,1,5)(0,0,0)[0]
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce all finite' was renamed to 'ensure all finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
                                    : AIC=172518.165, Time=9.96 sec
ARIMA(3,1,5)(0,0,0)[0]
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce all finite' was renamed to 'ensure all finite' in 1.6 and will be removed in
1.8.
warnings.warn(
ARIMA(4,1,4)(0,0,0)[0]
                                    : AIC=172606.296, Time=10.99 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
warnings.warn(
ARIMA(5,1,5)(0,0,0)[0]
                                    : AIC=172513.236, Time=21.20 sec
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
1.8.
 warnings.warn(
ARIMA(3,1,4)(0,0,0)[0]
                                    : AIC=172728.335, Time=11.63 sec
```

```
d:\yourenv\Lib\site-packages\sklearn\utils\deprecation.py:151: FutureWarning: 'fo
        rce_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in
        1.8.
          warnings.warn(
         ARIMA(5,1,4)(0,0,0)[0]
                                             : AIC=172566.624, Time=14.47 sec
        Best model: ARIMA(4,1,5)(0,0,0)[0]
        Total fit time: 275.163 seconds
          Store 1 Dataset
In [63]:
         result = adfuller(df_target[df_target['Store']==1]['Weekly_Sales'])
          result
Out[63]: (-5.102186145192289,
           1.3877788330759307e-05,
           4,
           138,
           {'1%': -3.47864788917503,
            '5%': -2.882721765644168,
            '10%': -2.578065326612056},
           3412.7325502876756)
In [64]:
         p_value=result[1]
          p_value
Out[64]: 1.3877788330759307e-05
          p value is close to 0 and we can conclude that the data is stationary
In [65]: store1=pd.DataFrame(df_target[df_target['Store']==1]['Weekly_Sales'])
          store1=store1.sort index()
          store1
```

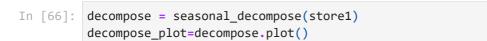
Out[65]:

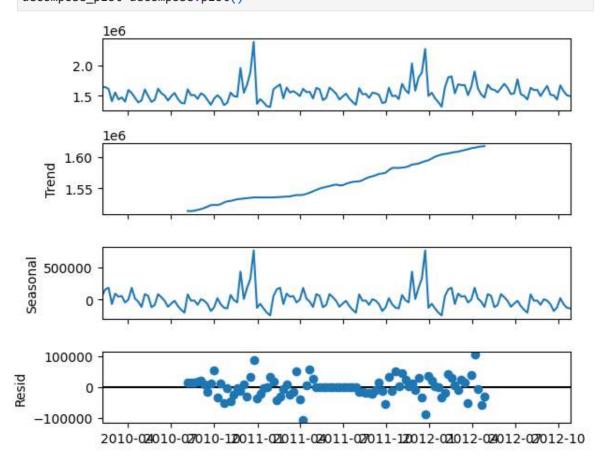
Weekly_Sales

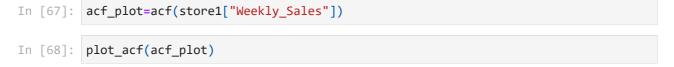
Date	
2010-02-05	1643690.90
2010-02-12	1641957.44
2010-02-19	1611968.17
2010-02-26	1409727.59
2010-03-05	1554806.68
•••	
2012-09-28	1437059.26
2012-10-05	1670785.97
2012-10-12	1573072.81
2012-10-19	1508068.77
2012-10-26	1493659.74

143 rows × 1 columns

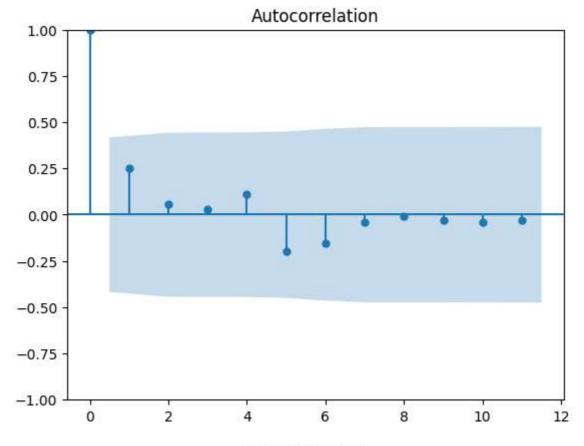
Visualizing Seasonality

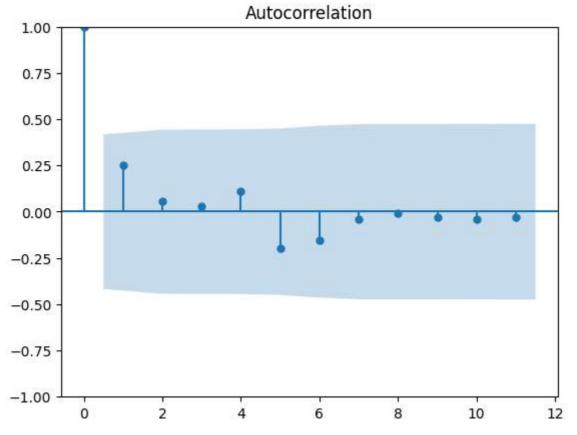




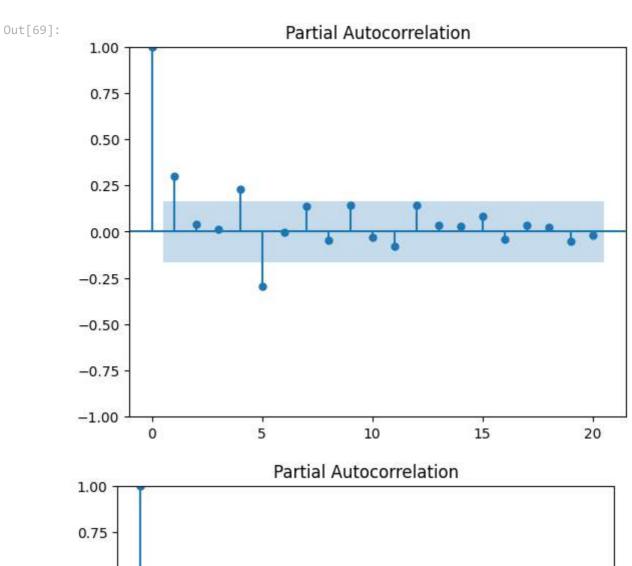


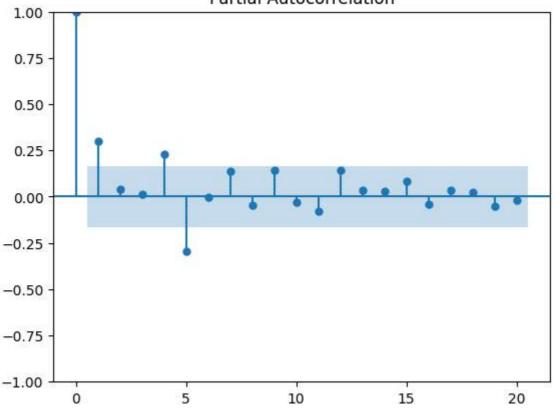




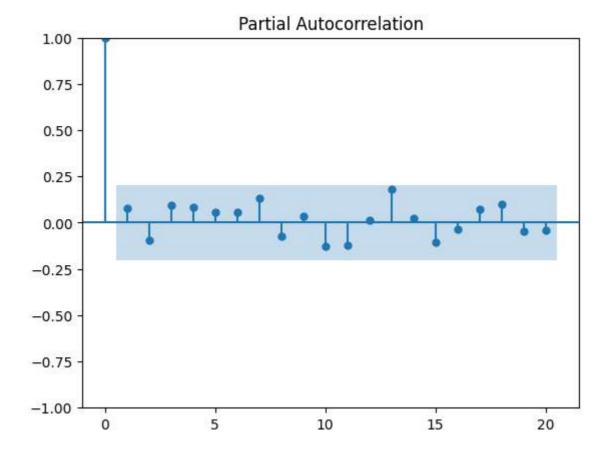


In [69]: plot_pacf(store1["Weekly_Sales"],lags=20)

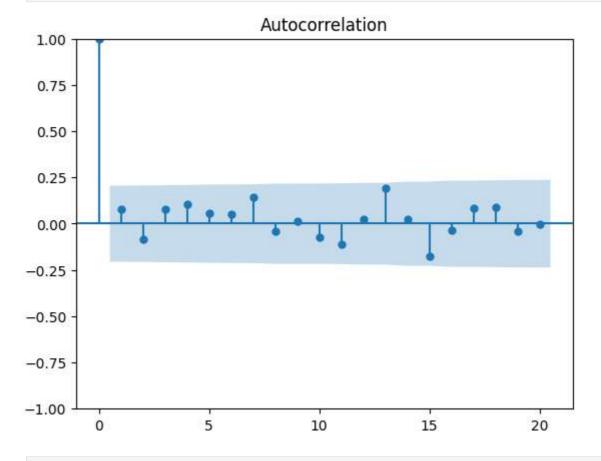




```
In [70]: store1['lag1']=store1['Weekly_Sales'].diff()
In [71]: store1['lag52']=store1['Weekly_Sales'].diff(52)
In [72]: pacf_values=plot_pacf(store1['lag52'].dropna(),lags=20)
```



In [73]: acf_values=plot_acf(store1['lag52'].dropna(),lags=20)



In [74]: # From the above, pacf(p) ,acf(q) value is 0
 pacf_values=sm.tsa.pacf(store1['Weekly_Sales'],nlags=20)
 pacf_values

```
In [75]: train = store1.iloc[:115]['Weekly_Sales']
test = store1.iloc[115:]['Weekly_Sales']

In [76]: # Training The Model
    model=SARIMAX(train,order=(0,1,0),seasonal_order=(0,1,0,52))
    model_fit = model.fit()
    model_fit.summary()

d:\yourenv\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning:
    No frequency information was provided, so inferred frequency W-FRI will be used.
        self._init_dates(dates, freq)
    d:\yourenv\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning:
    No frequency information was provided, so inferred frequency W-FRI will be used.
```

self._init_dates(dates, freq)
Out[76]: SARIMAX Results

Dep. Variable:	Weekly_Sales	No. Observations:	115
Model:	SARIMAX(0, 1, 0)x(0, 1, 0, 52)	Log Likelihood	-801.151
Date:	Mon, 27 Jan 2025	AIC	1604.302
Time:	02:55:27	ВІС	1606.429
Sample:	02-05-2010	HQIC	1605.137
	- 04-13-2012		
Covariance Type:	opg		

	coef	std err	z	P> z	[0.025	0.975]
sigma2	4.169e+09	3.17e+08	13.134	0.000	3.55e+09	4.79e+09

Ljung-Box (L1) (Q):	9.70	Jarque-Bera (JB):	2.72
Prob(Q):	0.00	Prob(JB):	0.26
Heteroskedasticity (H):	1.79	Skew:	0.06
Prob(H) (two-sided):	0.19	Kurtosis:	4.02

Warnings:

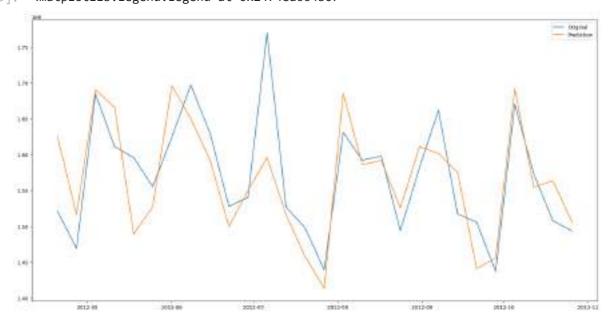
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

Testing The Model

```
In [77]: pred = model_fit.predict(start= len(train),end=len(train)+len(test)- 1,dynamic=T
```

```
In [78]:
          pred
                        1625962.51
Out[78]:
          2012-04-20
                        1516233.39
          2012-04-27
          2012-05-04
                        1690533.98
          2012-05-11
                        1665918.28
          2012-05-18
                        1489360.97
          2012-05-25
                        1527189.37
          2012-06-01
                        1696221.11
          2012-06-08
                        1650091.02
          2012-06-15
                        1593257.56
          2012-06-22
                        1499972.85
          2012-06-29
                        1549680.79
          2012-07-06
                        1595992.34
          2012-07-13
                        1516262.67
          2012-07-20
                        1458069.52
          2012-07-27
                        1413362.49
          2012-08-03
                        1685526.45
          2012-08-10
                        1586289.79
          2012-08-17
                        1591904.13
          2012-08-24
                        1525836.16
          2012-08-31
                        1611371.92
          2012-09-07
                        1601613.94
          2012-09-14
                        1575402.48
          2012-09-21
                        1441162.97
          2012-09-28
                        1455704.53
          2012-10-05
                        1692132.65
          2012-10-12
                        1554668.63
          2012-10-19
                        1563705.48
          2012-10-26
                        1506391.79
          Freq: W-FRI, Name: predicted_mean, dtype: float64
In [79]:
         plt.figure(figsize=(20,10))
          plt.plot(test,label="Original")
          plt.plot(pred,label="Prediction")
          plt.legend()
```

Out[79]: <matplotlib.legend.Legend at 0x2474ea664b0>

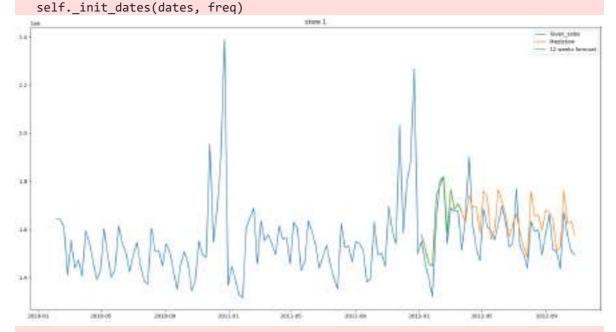


Forecasting for Next 12 Weeks

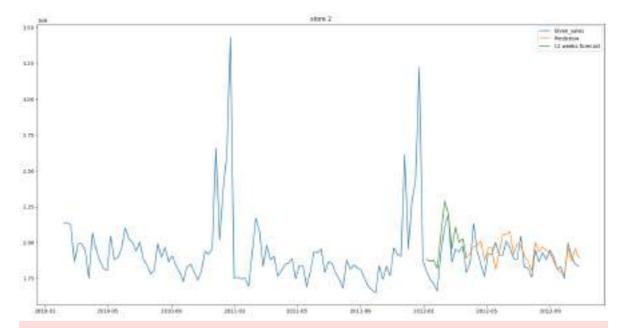
```
In [80]:
         forecast=model fit.forecast(steps=12)
         plt.figure(figsize=(20,10))
In [81]:
         plt.plot(store1['Weekly_Sales'],label="Original")
         plt.plot(pred,label="Prediction")
         plt.plot(forecast, label="Forecast")
         plt.legend()
Out[81]: <matplotlib.legend.Legend at 0x247049c9fd0>
       3.0
                                    2001/01
                                             2057-80
                                                                2012-01
                                                                         2012/01
                                                      3001-09
         comparison = pd.DataFrame({'Actual': test, 'Predicted': pred})
In [82]:
         comparison.dropna(inplace=True)
         from sklearn.metrics import mean_absolute_error, mean_squared_error
In [83]:
         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): 43867.10071428573
        Mean Squared Error (MSE): 3251568436.6039357
        Root Mean Squared Error (RMSE): 57022.525694710646
In [84]: 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,alpha=0.0
             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_in
                  if(abs(acf)>confident[1]):
                      significant_acf.append(acf)
                  else:
                      break
             for lag,pacf,confident in zip(range(len(pacf_values)),pacf_values,confidence
                  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()
```

d:\yourenv\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning:
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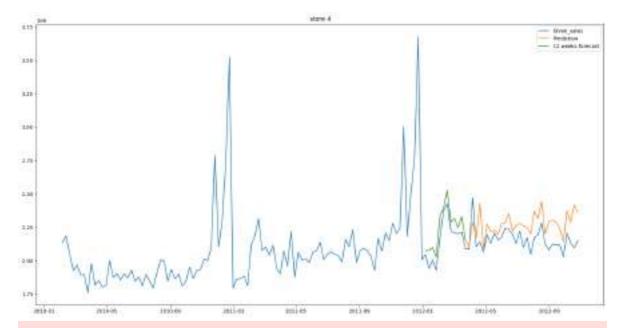


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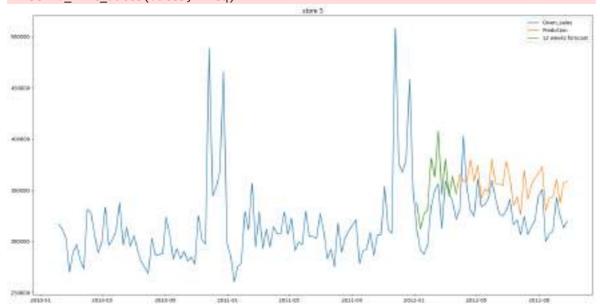


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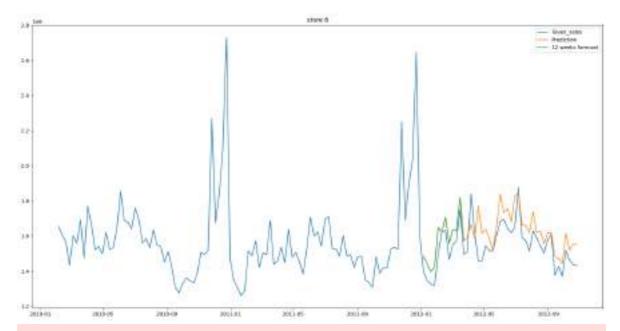


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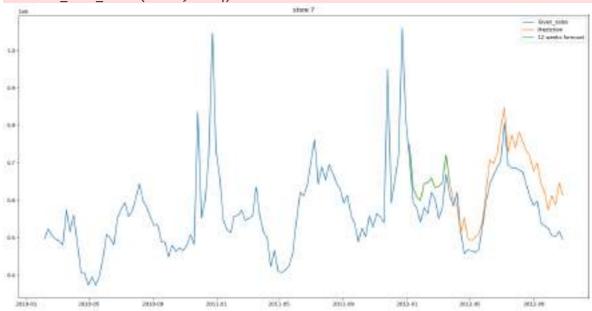


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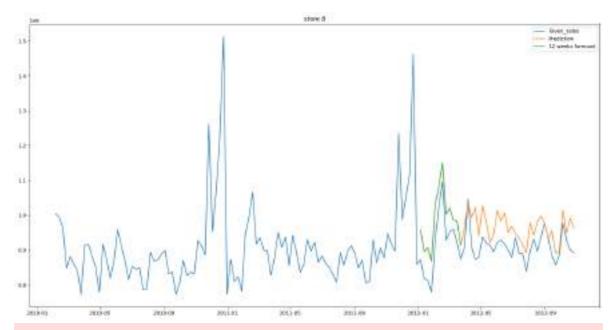


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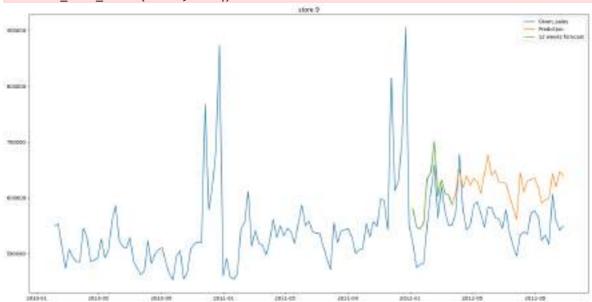
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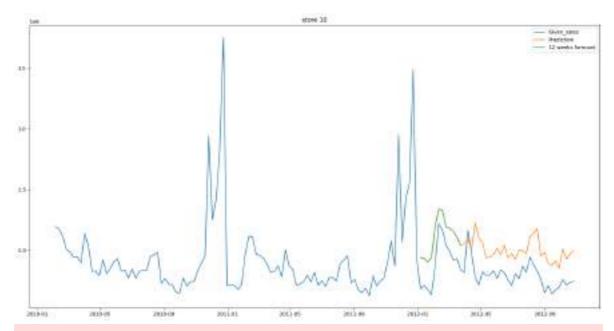
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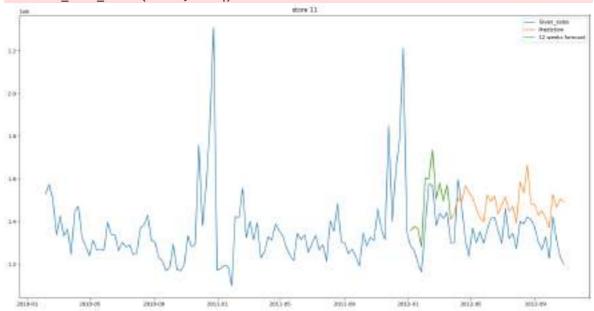
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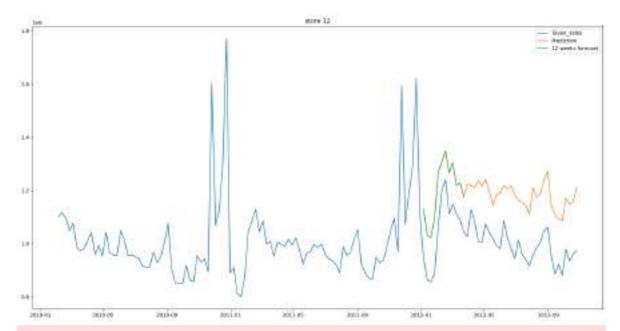
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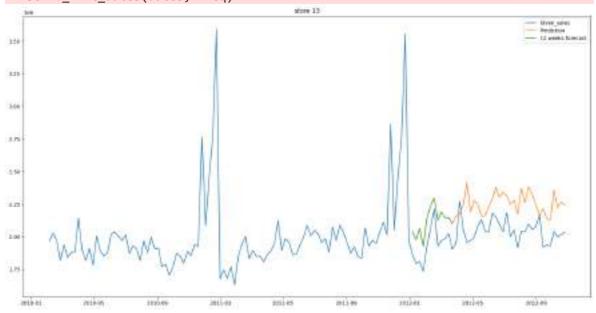
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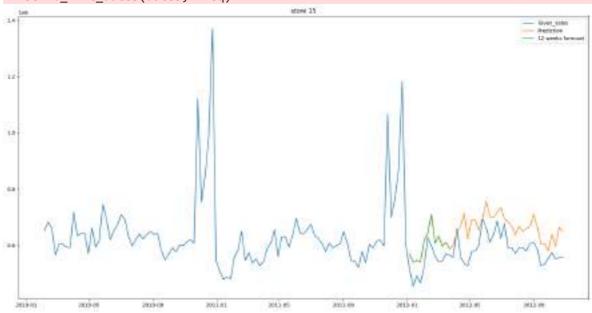
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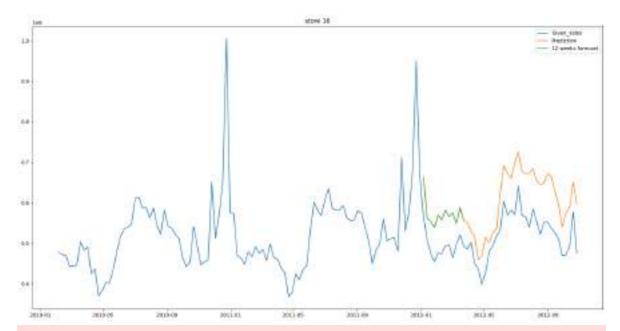
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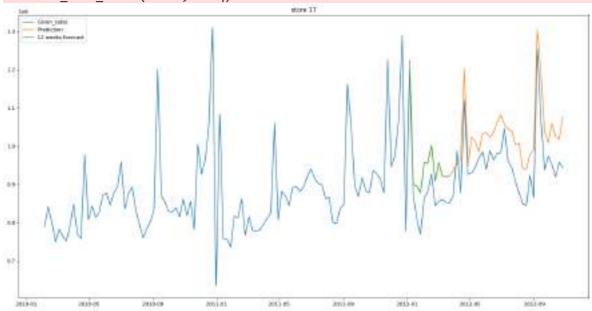
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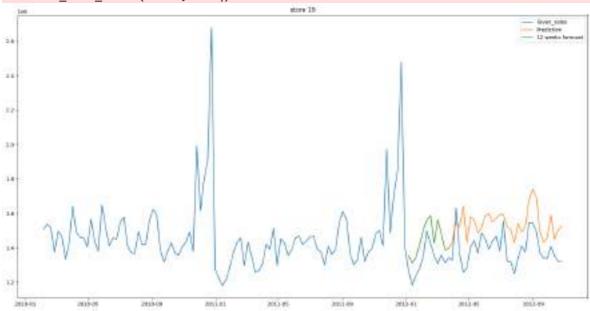
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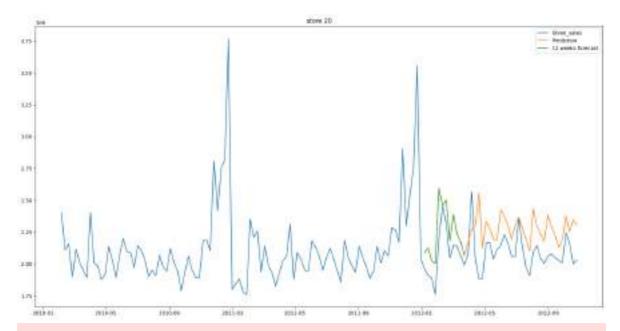
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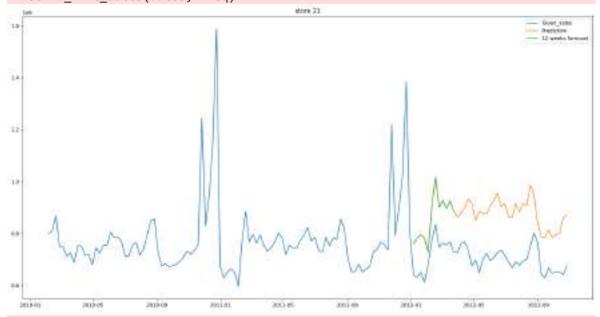
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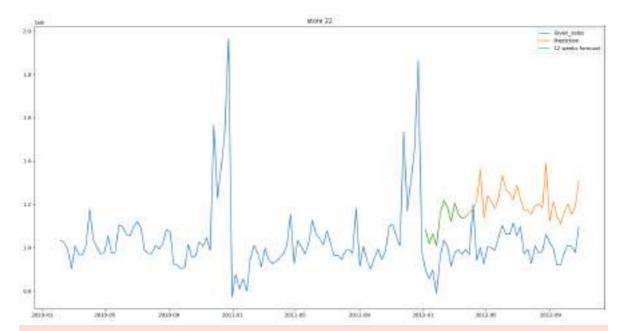
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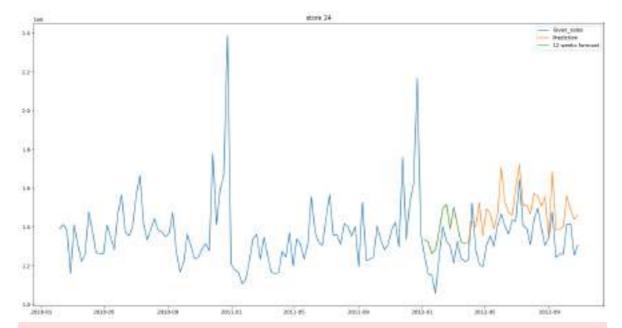


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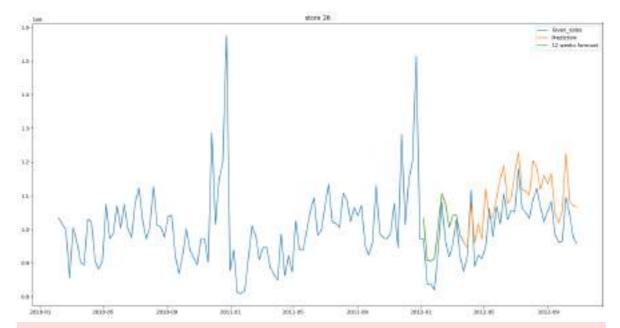
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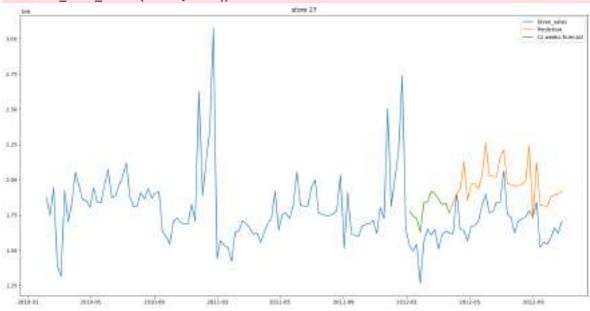
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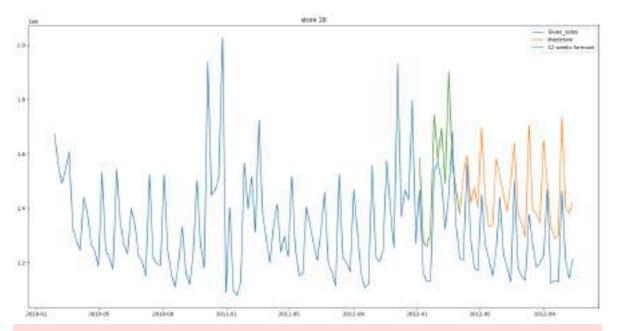
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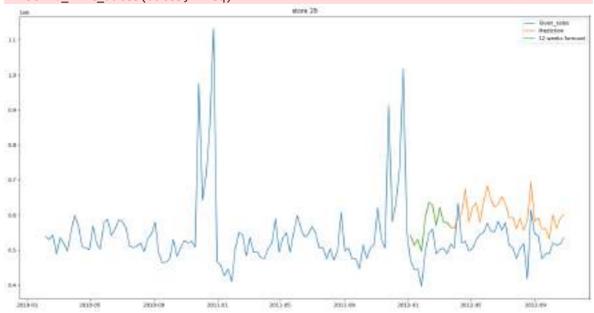
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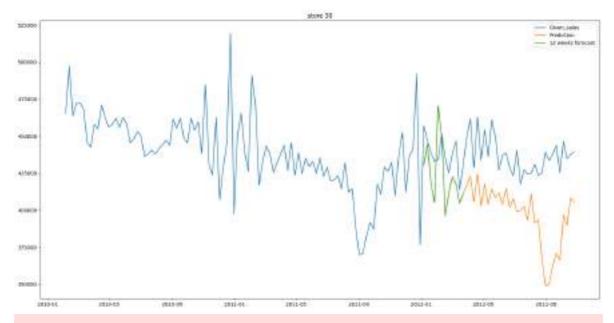
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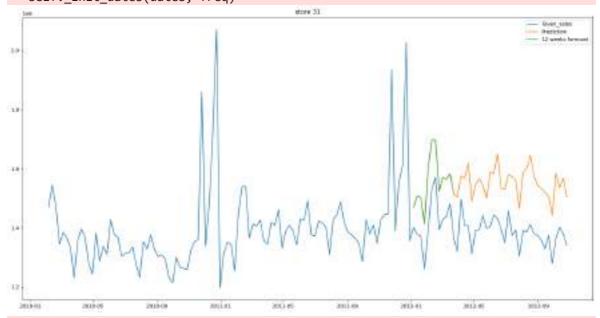
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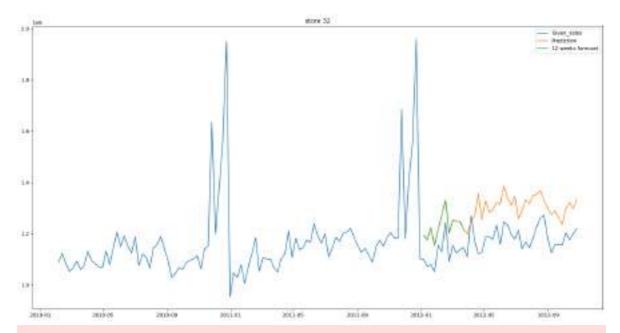
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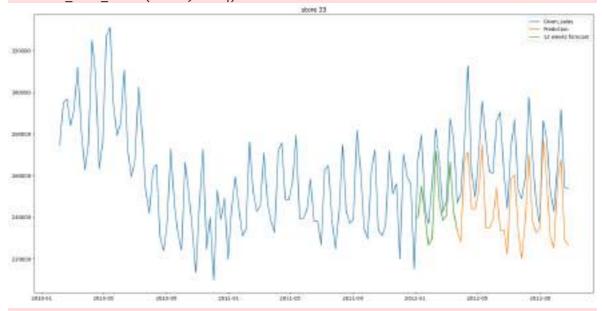
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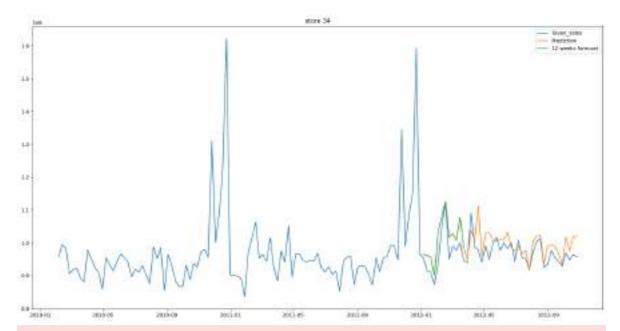
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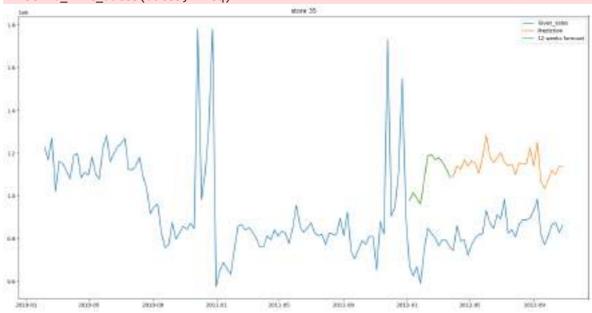
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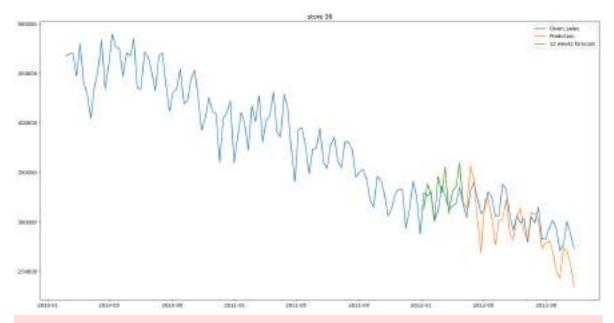
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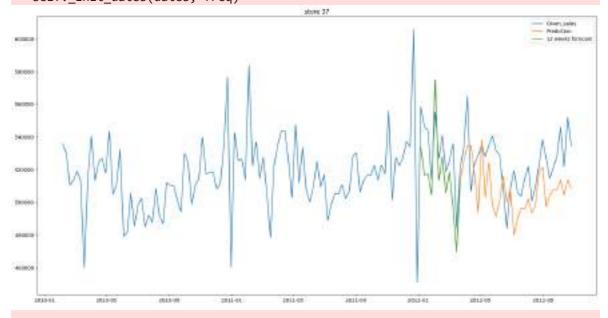
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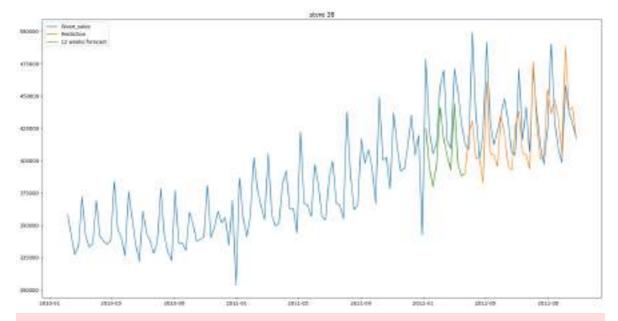
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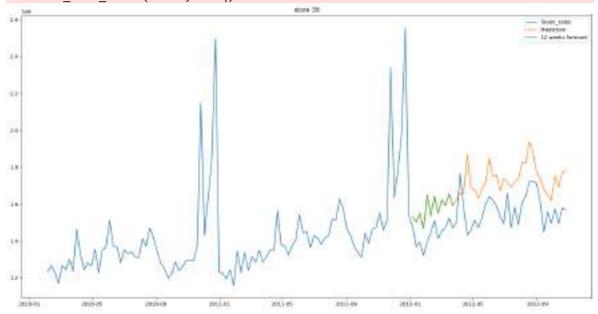
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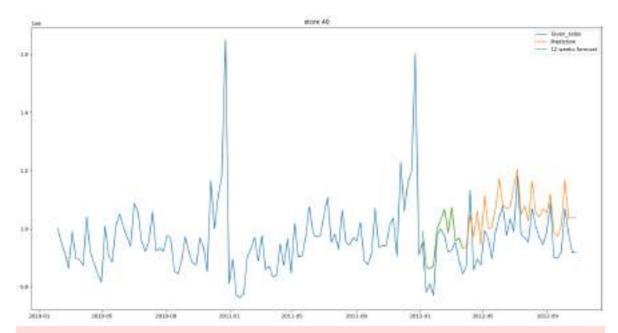
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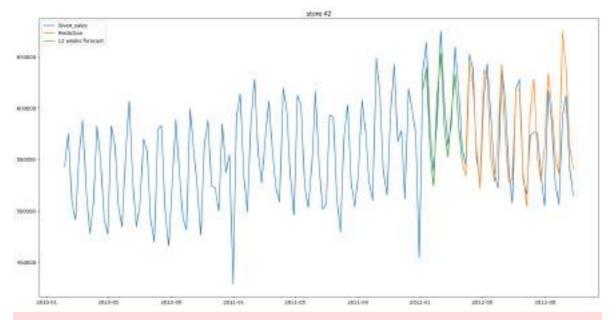
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