Walmart

Capstone Project

🛒 Walmart-Capstone Project 🛒

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[💠 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.

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[💠 Project Objective 💠]

🛒 To come up with useful insights using the data and make

prediction models to forecast the sales for 12 number of weeks.

[💠 Data Description 💠]

▶The walmart.csv 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
►CPI Consumer   Price Index
►Unemployment   Unemployment Rate
```

[💠 Data Pre-processing Steps 💠]

▶Checking Shape and rows of Data Frame

▶Checking Dtype of columns

▶Checking for NULL values

▶Checking for Duplicate records

▶Correcting Dtype of columns and creating necessary columns

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

In [2]:
```
df=pd.read_csv('Walmart.csv')
print('____________________________________________________________________________________________________________')
print('**** Sahpe of dataframe ',df.shape,' ****')
print('____________________________________________________________________________________________________________')
df.head()
```

```
____________________________________________________________________________________________________________
**** Sahpe of dataframe  (6435, 8)  ****
____________________________________________________________________________________________________________
```

Out[2]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemploy
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	

In [3]:
```
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
```

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
dtype: int64
```

In [5]:
```
print('______________________________________________________________________
print(f'Number of duplicate records in the dataframe {df.duplicated().sum(
print('______________________________________________________________________
```

```
_________________________________________________________________________
_______

Number of duplicate records in the dataframe 0
_________________________________________________________________________
_______
```

In [6]:
```
df['Date']=pd.to_datetime(df['Date'])

df['year']=df['Date'].dt.year
df['Month']=df['Date'].dt.month
df['Week']=df['Date'].dt.week

df.head()
```

```
C:\Users\MAYUR\AppData\Local\Temp\ipykernel_18800\234875604.py:1: UserWar
ning: Parsing dates in DD/MM/YYYY format when dayfirst=False (the defaul
t) was specified. This may lead to inconsistently parsed dates! Specify a
format to ensure consistent parsing.
  df['Date']=pd.to_datetime(df['Date'])
C:\Users\MAYUR\AppData\Local\Temp\ipykernel_18800\234875604.py:5: FutureW
arning: Series.dt.weekofyear and Series.dt.week have been deprecated. Ple
ase use Series.dt.isocalendar().week instead.
  df['Week']=df['Date'].dt.week
```

Out[6]:

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

[💠 Analysing the DataFrame 💠][EDA]

▶Average Weekly_Sales analysis

▶Top N best and worst performing stores

▶Trend analysis of stores based on months

▶The effect of Unemployment on Weekly_Sales

▶Effect of Temperature on Weekly_sales

▶Effect of Consumer Price index affecting the weekly sales

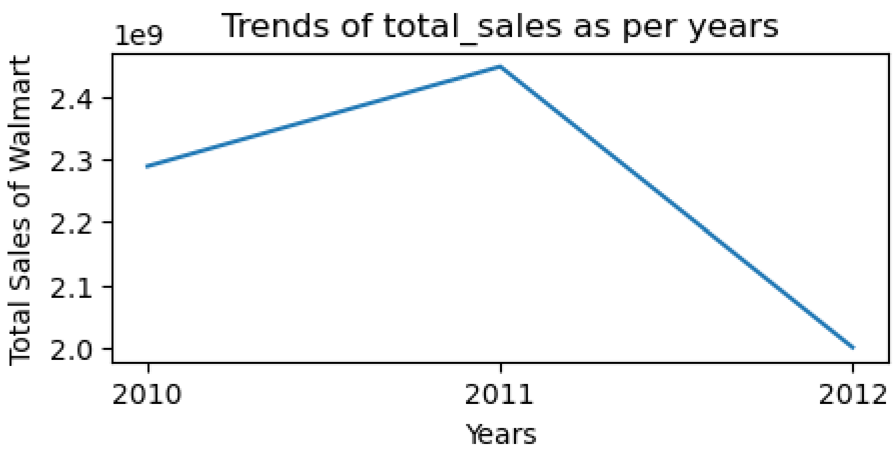
▶Effect of Holiday_Flag on Weekly_Sales

▶Effect of Fuel_Price on Weekly_Sales

--

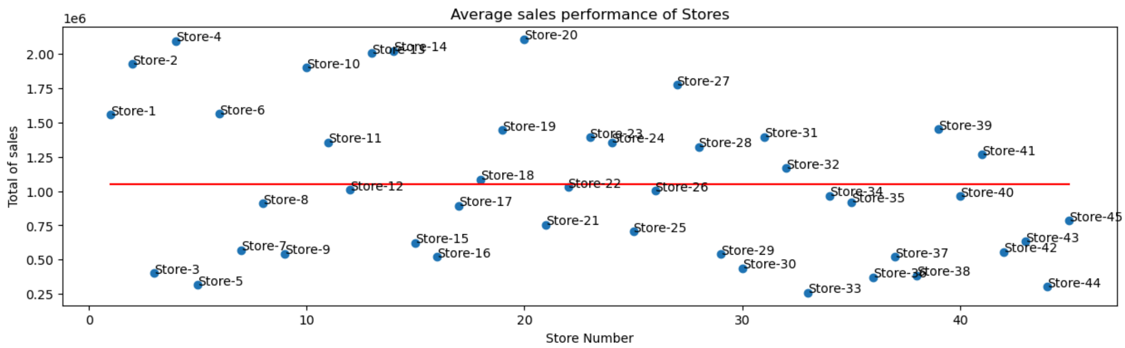
💠 Average Weekly_Sales analysis

In [7]:
```
Year=df.groupby('year')['Weekly_Sales'].sum()

plt.figure(figsize=(5,2))
plt.plot([str(x) for x in Year.index],Year)
plt.title('Trends of total_sales as per years')
plt.ylabel('Total Sales of Walmart')
plt.xlabel('Years')
plt.show()

del Year
```



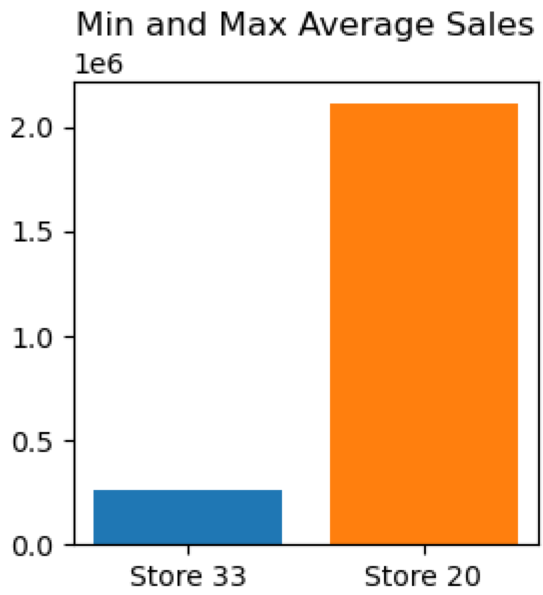
In [8]:
```
Avg_sales=pd.DataFrame(df.groupby('Store')['Weekly_Sales'].mean())
Avg_sales['AVG']=Avg_sales.mean()[0]

Store=['Store-'+str(i) for i in range(1,46)]
x=list(Avg_sales.index)
y=list(Avg_sales['Weekly_Sales'])

Above_avg=[i+1 for i in range(0,45) if y[i]>=Avg_sales['AVG'][1]]
Below_avg=[i+1 for i in range(0,45) if y[i]<Avg_sales['AVG'][1]]

print('______________________________________________________________________
print('*** Stores with sales below average sales are ',Below_avg)
print('*** Stores with sales above average sales are ',Above_avg)
print('______________________________________________________________________


plt.figure(figsize=(15,4))
plt.scatter(x,y)

for i,t in enumerate(Store):
    plt.annotate(t,(x[i],y[i]))

plt.plot(x,Avg_sales['AVG'],color='red')
plt.annotate('Average sales =',(0,Avg_sales['AVG'][1]+1800000),fontsize=12
plt.annotate(int(Avg_sales['AVG'][1]),(1,Avg_sales['AVG'][1]-19000000),fon

plt.xlabel('Store Number')
plt.ylabel('Total of sales')
plt.title('Average sales performance of Stores')
plt.show()
```

```
__________________________________________________________________________
____________________________________________
*** Stores with sales below average sales are  [3, 5, 7, 8, 9, 12, 15, 1
6, 17, 21, 22, 25, 26, 29, 30, 33, 34, 35, 36, 37, 38, 40, 42, 43, 44, 4
5]
*** Stores with sales above average sales are  [1, 2, 4, 6, 10, 11, 13, 1
4, 18, 19, 20, 23, 24, 27, 28, 31, 32, 39, 41]
__________________________________________________________________________
____________________________________________
```



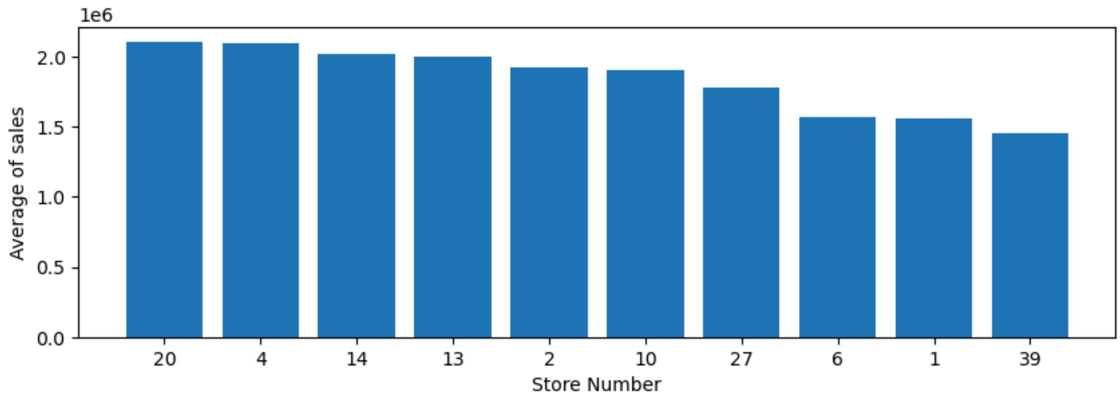
In [9]:
```
Avg_sales=pd.DataFrame(df.groupby('Store')['Weekly_Sales'].mean().sort_valu

print('_______________________________________________________________________
print(f'Store-{Avg_sales.index[0]} has minimum average sales ',Avg_sales.il
print(f'Store-{Avg_sales.index[-1]} has maximum average sales ',Avg_sales.i
print('The difference between performance of best and worst performing stor
print('_______________________________________________________________________

plt.figure(figsize=(3,3))
plt.bar(x='Store '+str(Avg_sales.index[0]),height=Avg_sales.iloc[0][0])
plt.bar(x='Store '+str(Avg_sales.index[-1]),height=Avg_sales.iloc[-1][0])


plt.title('Min and Max Average Sales')
plt.show()

del Avg_sales
```

```
_________________________________________________________________________
________________________
Store-33 has minimum average sales  259861.69202797202
Store-20 has maximum average sales  2107676.8703496503
The difference between performance of best and worst performing store 184
7815.1783216782
_________________________________________________________________________
________________________
```



🔹 Top N best and worst performing stores

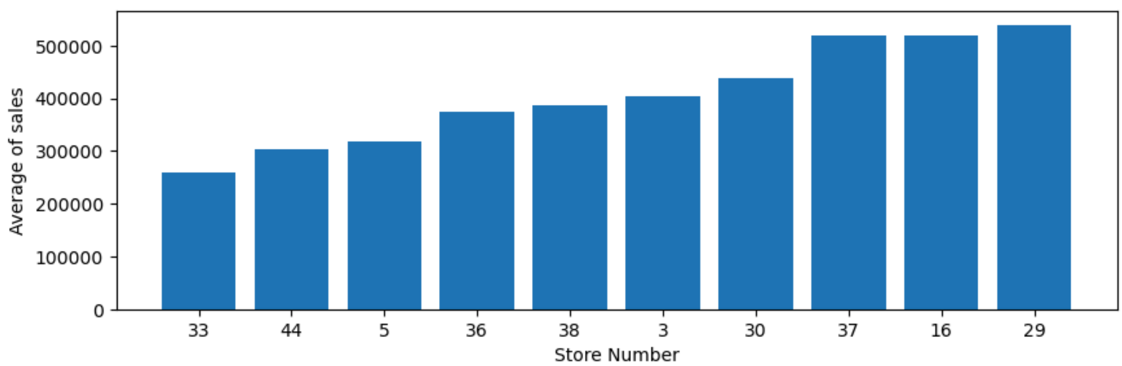
In [10]:
```
def top_N(n=10,bottom=False):
    Avg_sales=pd.DataFrame(df.groupby('Store')['Weekly_Sales'].mean().sort_
    Avg_sales=Avg_sales.iloc[:n]

    plt.figure(figsize=(10,3))
    plt.bar(x=[str(x) for x in Avg_sales.index],height=list(Avg_sales['Weel
    plt.xlabel('Store Number')
    plt.ylabel('Average of sales')
    plt.show()
    return(Avg_sales.transpose())

top_N(10)
```



Out[10]:

Store	20	4	14	13	2
Weekly_Sales	2.107677e+06	2.094713e+06	2.020978e+06	2.003620e+06	1.925751e+06	1.899

In [11]:
```
top_N(10,bottom=True)
```



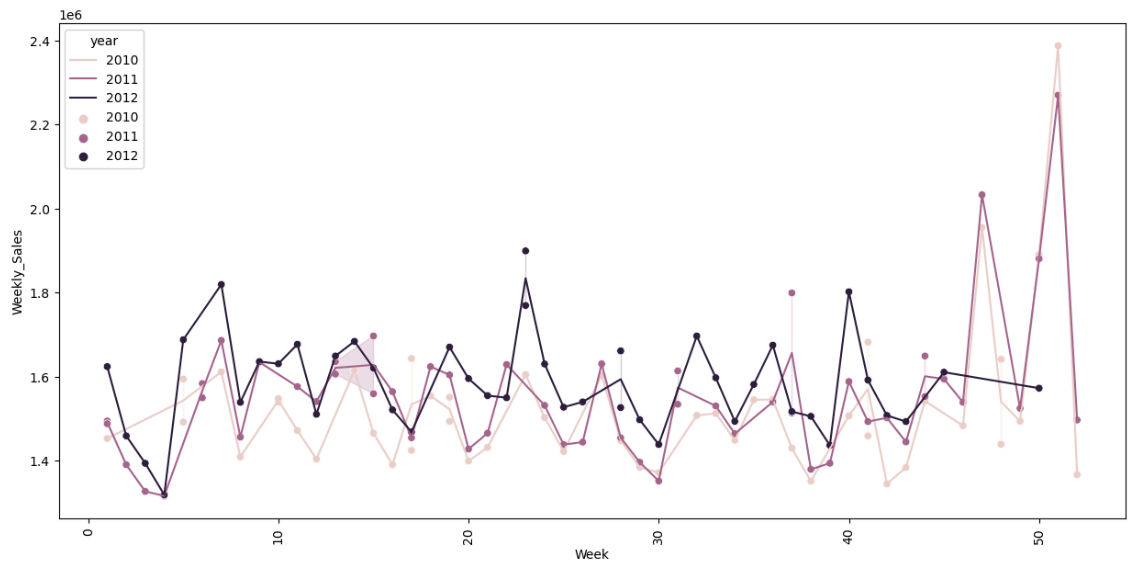
Out[11]:

Store	33	44	5	36	38
Weekly_Sales	259861.692028	302748.866014	318011.81049	373511.992797	385731.653287	4

💠 Trend analysis of stores based on months

After analysing the store sales data using the function 'sales_trend_visual' it can be inferred that, graph shows a spike in the month of mid November to December as these are months of festive season.

In [12]:
```
def sales_trend_visual(n):
    data=df[df['Store']==n]

    plt.figure(figsize=(15,7))
    sns.lineplot(data=data,x=data['Week'],y=data['Weekly_Sales'],hue=data[
    sns.scatterplot(data=data,x=data['Week'],y=data['Weekly_Sales'],hue=da

    plt.xticks(rotation=90)
    plt.show()


sales_trend_visual(1)
```



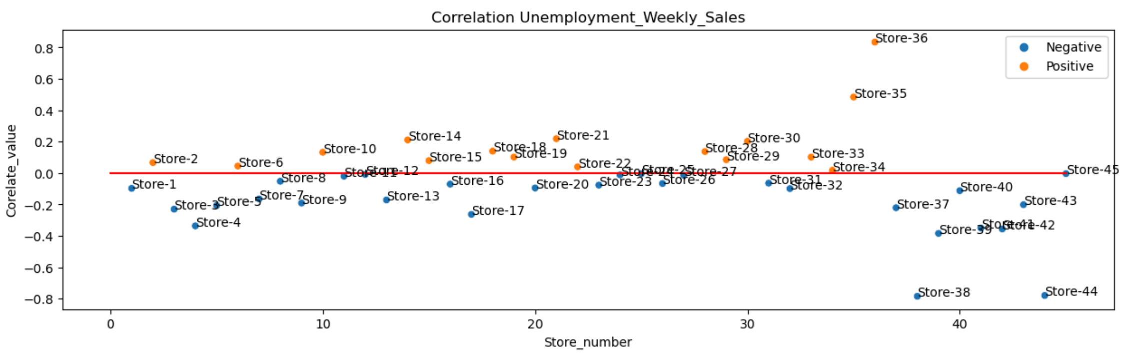
💠 The effect of Unemployment on Weekly_Sales

The Unemployment rate shows weak inverse relation with sales

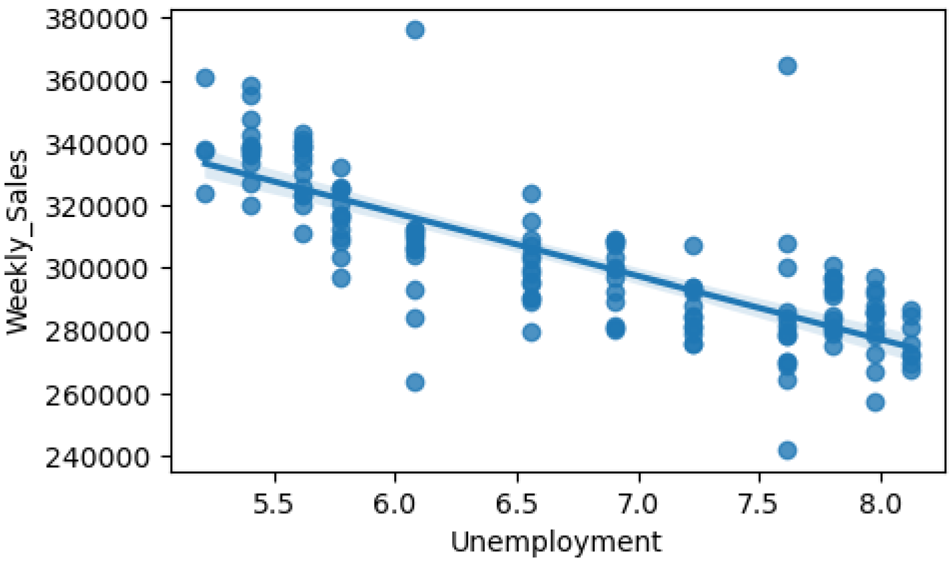
In [13]:

```
Corelate_value=[df[df['Store']==n][['Unemployment','Weekly_Sales']].corr()
Rel_type=['Positive'  if i>0   else 'Negative' for i in Corelate_value]
Store_number=[n for n in range(1,46)]
Store=['Store-'+str(i) for i in range(1,46)]

Unemployment_Weekly_Sales={'Corelate_value':Corelate_value,'Store_number':S
Unemployment_Weekly_Sales=pd.DataFrame(Unemployment_Weekly_Sales).set_inde

print('__________________________________________________________________________
print('***** The Unemployment shows weak inverse relation with sales *****
print('From the below mentioned plot it can be seen that store No[38,44] ar
print('__________________________________________________________________________

plt.figure(figsize=(15,4))
plt.plot([0 for i in range(46) ],color='red')
sns.scatterplot(data=Unemployment_Weekly_Sales,x=Unemployment_Weekly_Sales
                hue=Rel_type)

plt.title('Correlation Unemployment_Weekly_Sales')
for i,t in enumerate(Store):
    plt.annotate(t,(Store_number[i],Corelate_value[i]))
plt.show()
```

```
_________________________________________________________________________________________________________________
***** The Unemployment shows weak inverse relation with sales *****
From the below mentioned plot it can be seen that store No[38,44] are aff
ected the most inversly by the Unemployment
_________________________________________________________________________________________________________________
```



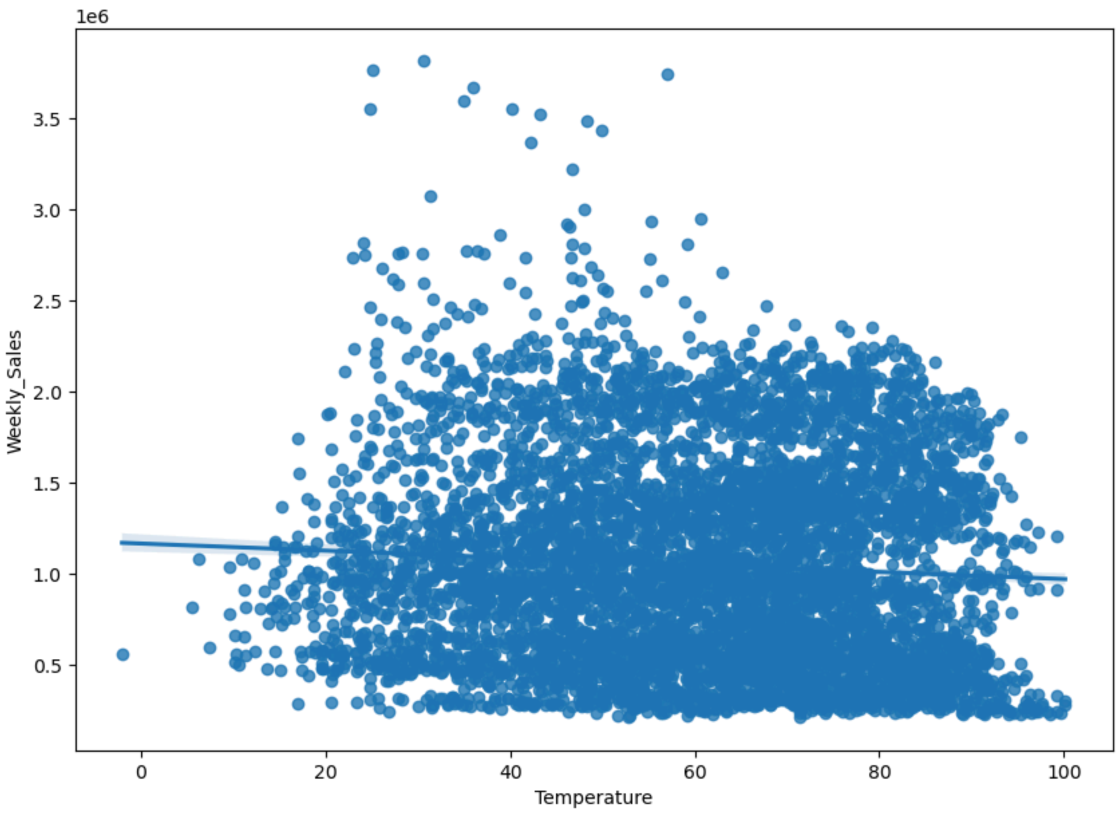
In [14]:
```
def reg_unemployment_Store(n):                                        #This functio
    dt=df[df['Store']==n]
    plt.figure(figsize=(5,3))
    sns.regplot(x='Unemployment',y='Weekly_Sales',data=dt)
    plt.show()



reg_unemployment_Store(44)
```



💠 Effect of Temperature on Weekly_sales

In [15]:
```
print('________________________________________________________________________
print('As we can infer from the graph below the weekly sales has a very wea
print('________________________________________________________________________

plt.figure(figsize=(10,7))
sns.regplot(x='Temperature',y='Weekly_Sales',data=df)
plt.show()
```

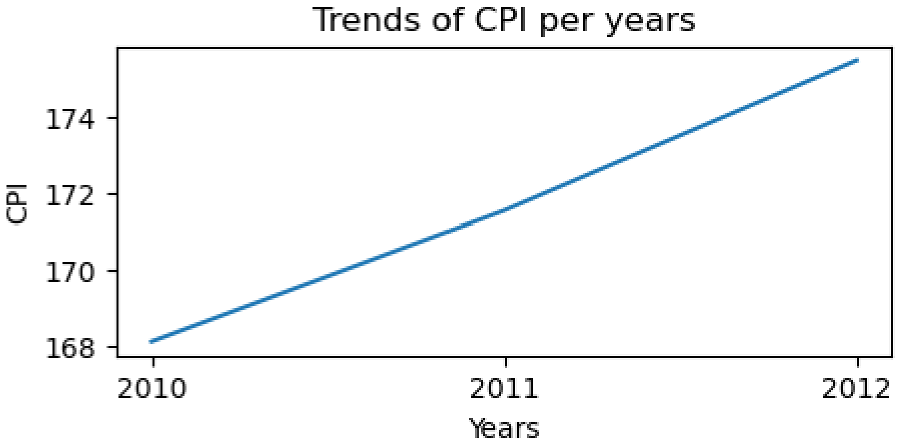
```
________________________________________________________________________
______________________________________________
As we can infer from the graph below the weekly sales has a very weak inv
erse relation with the temperature(-0.063810).
________________________________________________________________________
______________________________________________
```



💠 Effect of Consumer Price index affecting the weekly sales

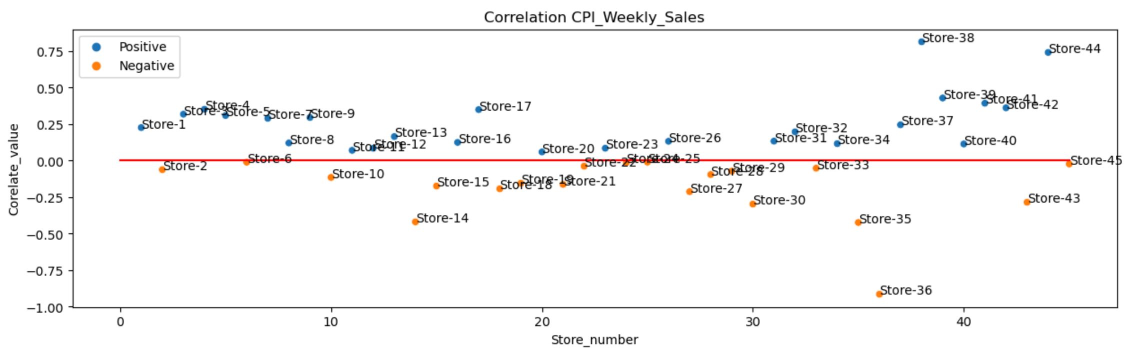
The CPI rate shows weak inverse relation with sales

In [16]:
```
Year=df.groupby('year')['CPI'].mean()

plt.figure(figsize=(5,2))
plt.plot([str(x) for x in Year.index],Year)
plt.title('Trends of CPI per years')
plt.ylabel('CPI')
plt.xlabel('Years')
plt.show()
```



In [17]:
```
Corelate_value=[df[df['Store']==n][['CPI','Weekly_Sales']].corr().iloc[1,0]
Rel_type=['Positive'  if i>0   else 'Negative' for i in Corelate_value]
Store_number=[n for n in range(1,46)]
Store=['Store-'+str(i) for i in range(1,46)]

CPI_Weekly_Sales={'Corelate_value':Corelate_value,'Store_number':Store_numb
CPI_Weekly_Sales=pd.DataFrame(CPI_Weekly_Sales).set_index('Store_number')

print('____________________________________________________________________________
print('***** The CPI shows weak inverse relation with sales *****'   )
print('From the below mentioned plot it can be seen that store No[36] are a
print('____________________________________________________________________________

plt.figure(figsize=(15,4))
plt.plot([0 for i in range(46) ],color='red')
sns.scatterplot(data=CPI_Weekly_Sales,x=CPI_Weekly_Sales.index,y=CPI_Weekly
                hue=Rel_type)

plt.title('Correlation CPI_Weekly_Sales')
for i,t in enumerate(Store):
    plt.annotate(t,(Store_number[i],Corelate_value[i]))
plt.show()
```

```
__________________________________________________________________________
______________________________________________
***** The CPI shows weak inverse relation with sales *****
From the below mentioned plot it can be seen that store No[36] are affect
ed the most inversly by the CPI
__________________________________________________________________________
______________________________________________
```



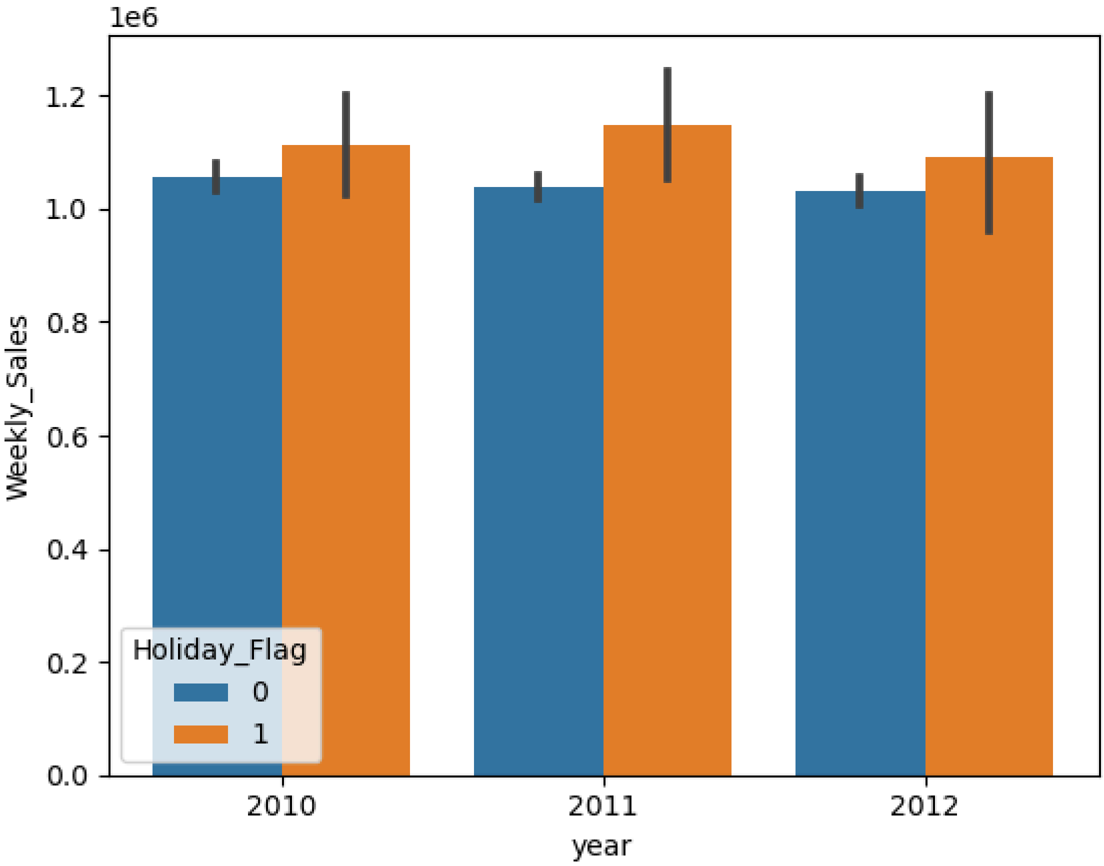
🔷 Effect of Holiday_Flag on Weekly_Sales

From the plot it is clear that the sales is slightly hight on holidays which is about 7.83% more than sales on working days. Which indicates Holiday_Flag has very weak positive relation with Weekly_Sales. This sales occures in the late second half of year.

In [18]:
```
print('___________________________________________________________________________
print('From the plot it is clear that the sales is slightly hight on holida
print('___________________________________________________________________________

sns.barplot(data=df,x='year',y='Weekly_Sales',hue='Holiday_Flag')
plt.plot()
```

```
_________________________________________________________________________
_
From the plot it is clear that the sales is slightly hight on holidays
_________________________________________________________________________
_
```

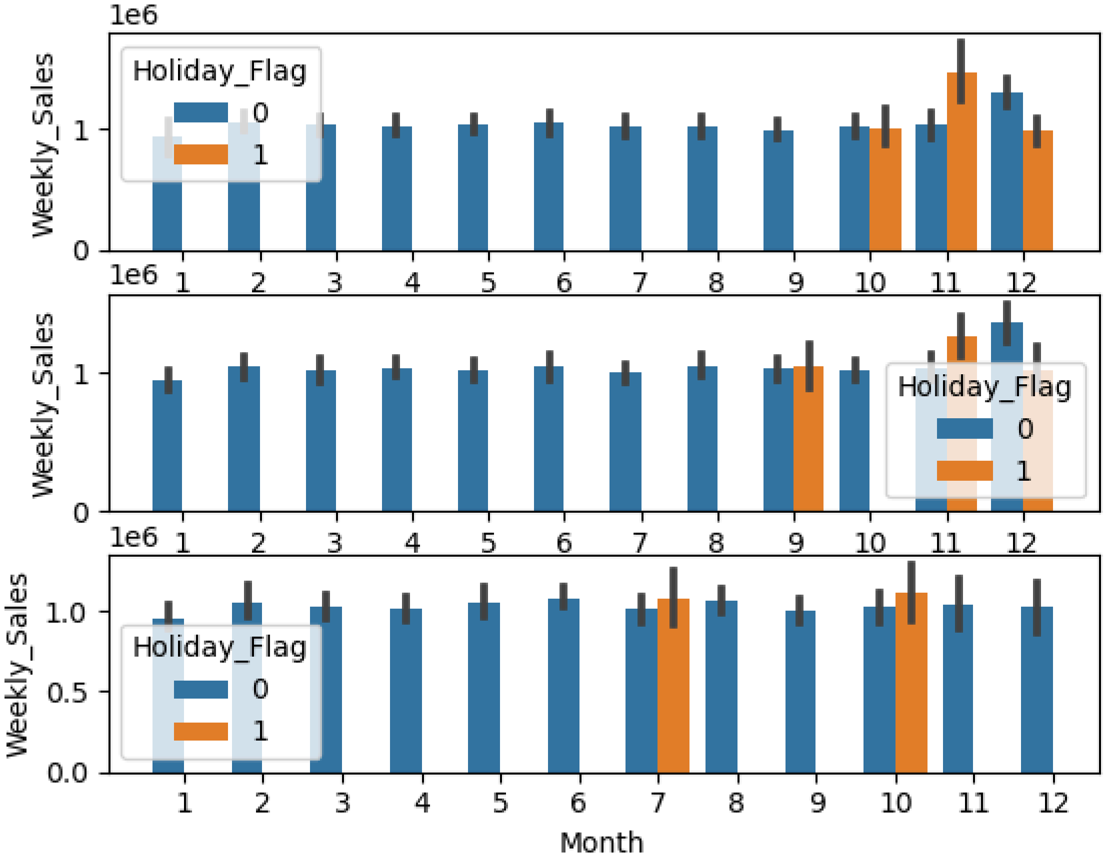
Out[18]: []



In [19]:
```
HS=df.groupby('Holiday_Flag')['Weekly_Sales'].mean()
print(HS)
percent=int((HS[1]-HS[0])/HS[0]*10000)/100

print('___________________________________________________________________________
print(f'*** On an average the sales is {percent}% more on Holidays ***')
```

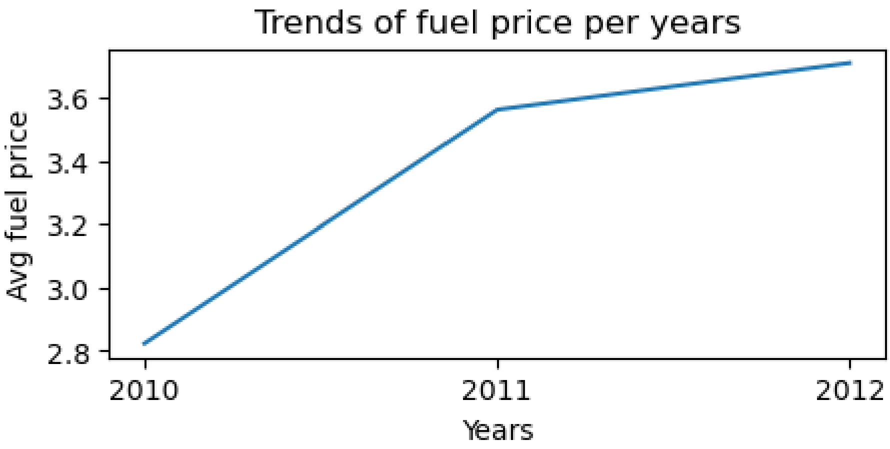
```
Holiday_Flag
0    1.041256e+06
1    1.122888e+06
Name: Weekly_Sales, dtype: float64
_________________________________________________________________________
_
*** On an average the sales is 7.83% more on Holidays ***
```

In [20]:
```
years=list(df['year'].unique())
for i,j in enumerate(years):
    dt=df[df['year']==j]
    plt.subplot(3,1,i+1)
    sns.barplot(data=dt,x='Month',y='Weekly_Sales',hue='Holiday_Flag')
    plt.plot()
```



🔷 Effect of Fuel_Price on Weekly_Sales

In [21]:
```
Year=df.groupby('year')['Fuel_Price'].mean()

plt.figure(figsize=(5,2))
plt.plot([str(x) for x in Year.index],Year)
plt.title('Trends of fuel price per years')
plt.ylabel('Avg fuel price')
plt.xlabel('Years')
plt.show()
```



In [22]:
```
co_rel=df[['Fuel_Price','Weekly_Sales']].corr().iloc[1,0]
print(f'There is no corelation between Fuel_Price and Weekly_Sales {co_rel]
```

```
There is no corelation between Fuel_Price and Weekly_Sales 0.009463786314
475482 as the corelation factor is too small
```

[💠 Choosing the Algorithm For the Project 💠]

🛒 Considering the complexity of the data and very low correlation between the Dependent and Independent variables, Random forest and XGboost can be more reliable than the traditional linear models.

💠 Model building & Prediction

In [23]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, r2_score
from xgboost import XGBRegressor
```

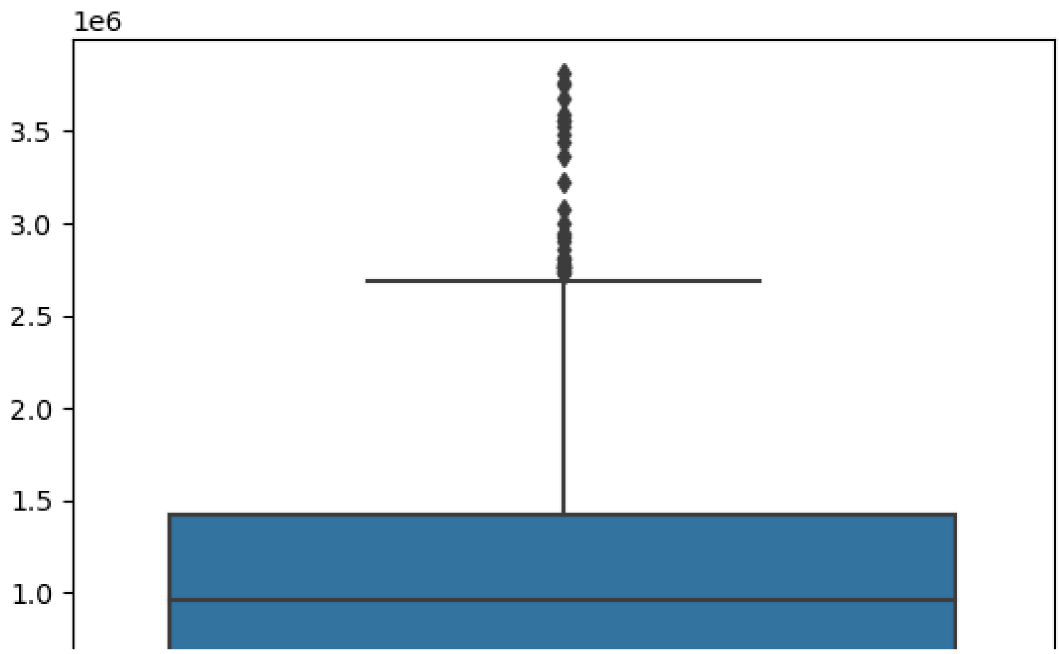
In [24]:
```
df['Date'] = pd.to_datetime(df['Date'])
df=df.sort_values(by='Date')
df=df.set_index('Date')

df.head()
```

Out[24]:

	Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployme
Date							
2010-01-10	5	283178.12	0	71.10	2.603	212.226946	6.7
2010-01-10	15	566945.95	0	59.69	2.840	132.756800	8.0
2010-01-10	42	481523.93	0	86.01	3.001	126.234600	9.0
2010-01-10	33	224294.39	0	91.45	3.001	126.234600	9.2
2010-01-10	36	422169.47	0	74.66	2.567	210.440443	8.4

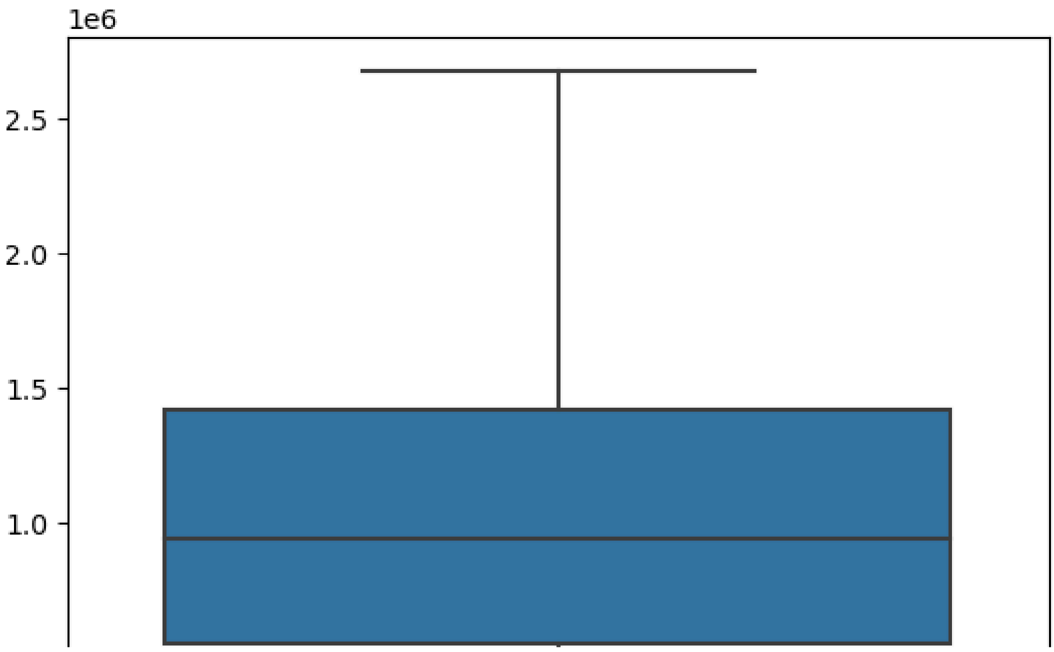
🔹 Outlier treatment

In [25]:
```
col=['Weekly_Sales','Temperature','Fuel_Price', 'CPI', 'Unemployment']

for i in col:
    sns.boxplot(df[i])
    plt.xlabel(i)
    plt.show()
```



In [26]:
```
Q1=df.quantile(0.25)
Q3=df.quantile(0.75)
IQR=Q3-Q1

df = df[~((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).any(axis=1)]
```

In [27]:
```
for i in col:
    sns.boxplot(df[i])
    plt.xlabel(i)
    plt.show()
```

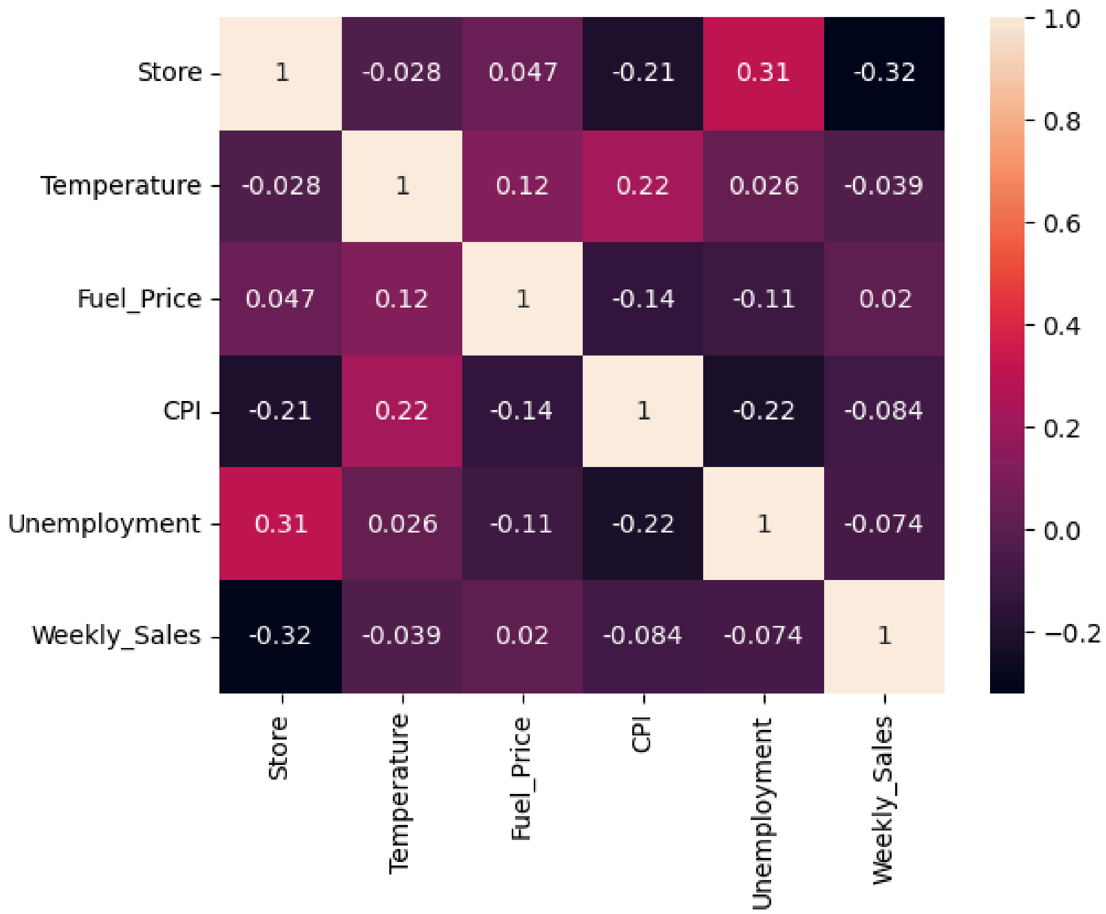


In [28]:
```
df.columns
```

Out[28]:
```
Index(['Store', 'Weekly_Sales', 'Holiday_Flag', 'Temperature', 'Fuel_Pric
e',
       'CPI', 'Unemployment', 'year', 'Month', 'Week'],
      dtype='object')
```

In [29]:
```
sns.heatmap(df[['Store', 'Temperature', 'Fuel_Price','CPI', 'Unemployment'
```

Out[29]: <Axes: >



RandomForestRegressor

In [30]:
```
X = df[['Store','Week','Month','year']][:4406]
x = df[['Store','Week','Month','year']][4406:]
Y = df['Weekly_Sales'][:4406]
y = df['Weekly_Sales'][4406:]
```

In [31]:
```
regressor = RandomForestRegressor(n_estimators=1000,max_depth=10)
regressor.fit(X,Y)
```

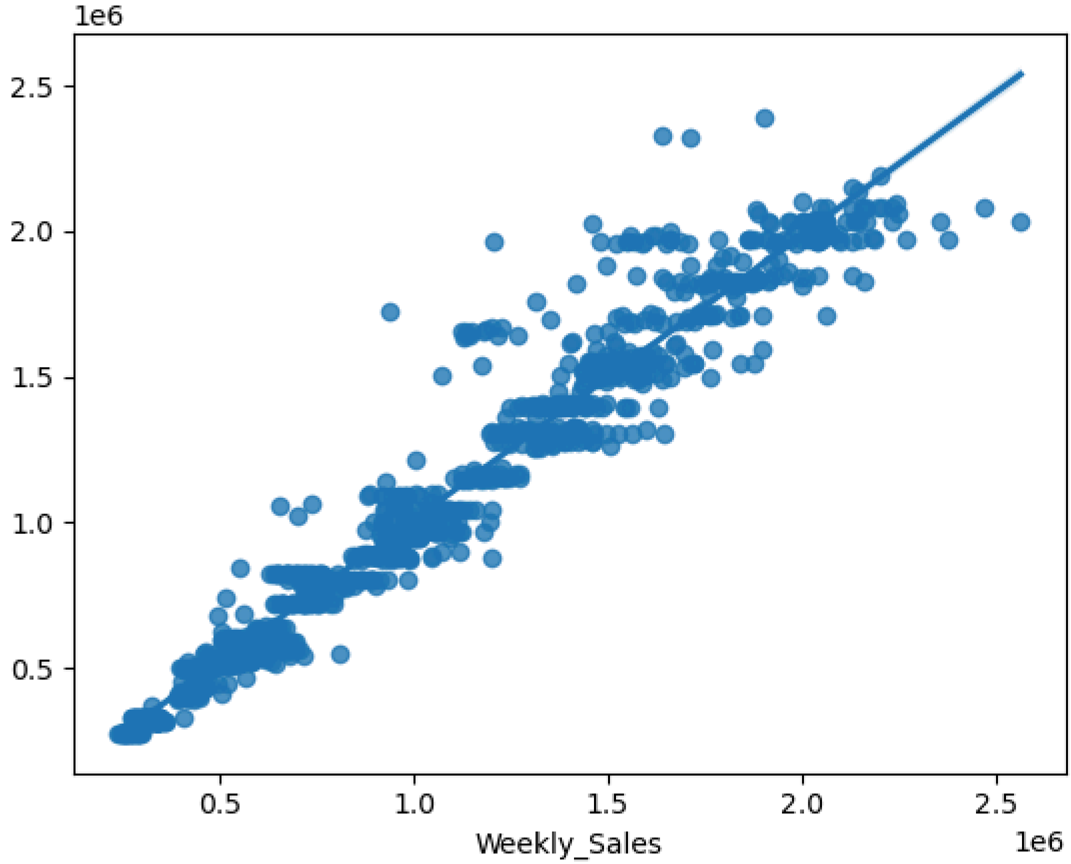
Out[31]: `RandomForestRegressor(max_depth=10, n_estimators=1000)`

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

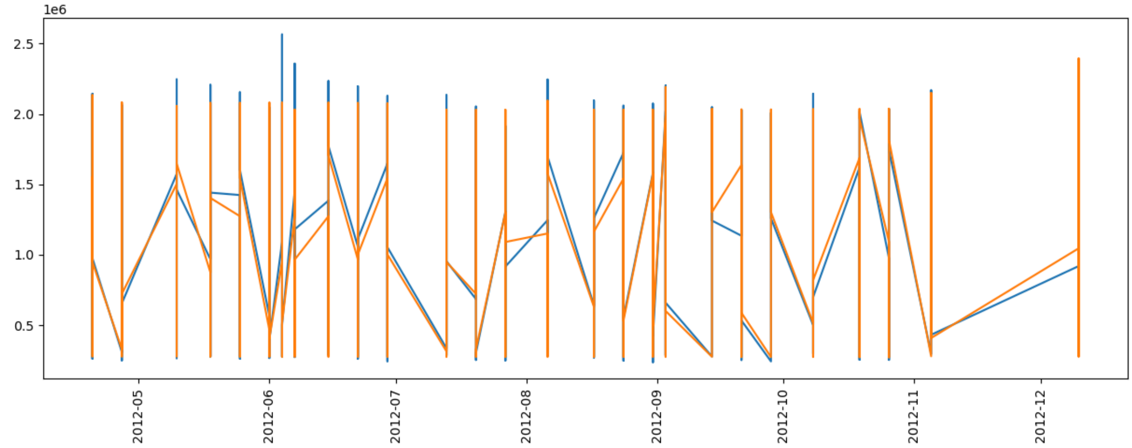
In [32]:
```
Y_pred = regressor.predict(x)

print('r2 score of Randomforest : ',r2_score(y,Y_pred))
print('mean_absolute_error of Randomforest : ',mean_absolute_error(y,Y_pre(
```

```
r2 score of Randomforest :  0.9476013468101423
mean_absolute_error of Randomforest :  74728.2507054864
```

In [33]:
```
sns.regplot(x=y,y=Y_pred)
plt.show()
```



In [34]:
```
y=pd.DataFrame(y)
predict=list(Y_pred)

y['Predict']=predict

plt.figure(figsize=(15,5))
plt.plot(df['Weekly_Sales'][4406:])
plt.plot(y['Predict'])
plt.xticks(rotation=90)
plt.show()
```



XGBRegressor

In [35]:
```
X = df[['Store','Week','Month','year']][:4406]
x = df[['Store','Week','Month','year']][4406:]
Y = df['Weekly_Sales'][:4406]
y = df['Weekly_Sales'][4406:]
```

In [36]:
```
Model_xgb=XGBRegressor(n_estimators=1000,max_depth=10)
Model_xgb.fit(X,Y)
```

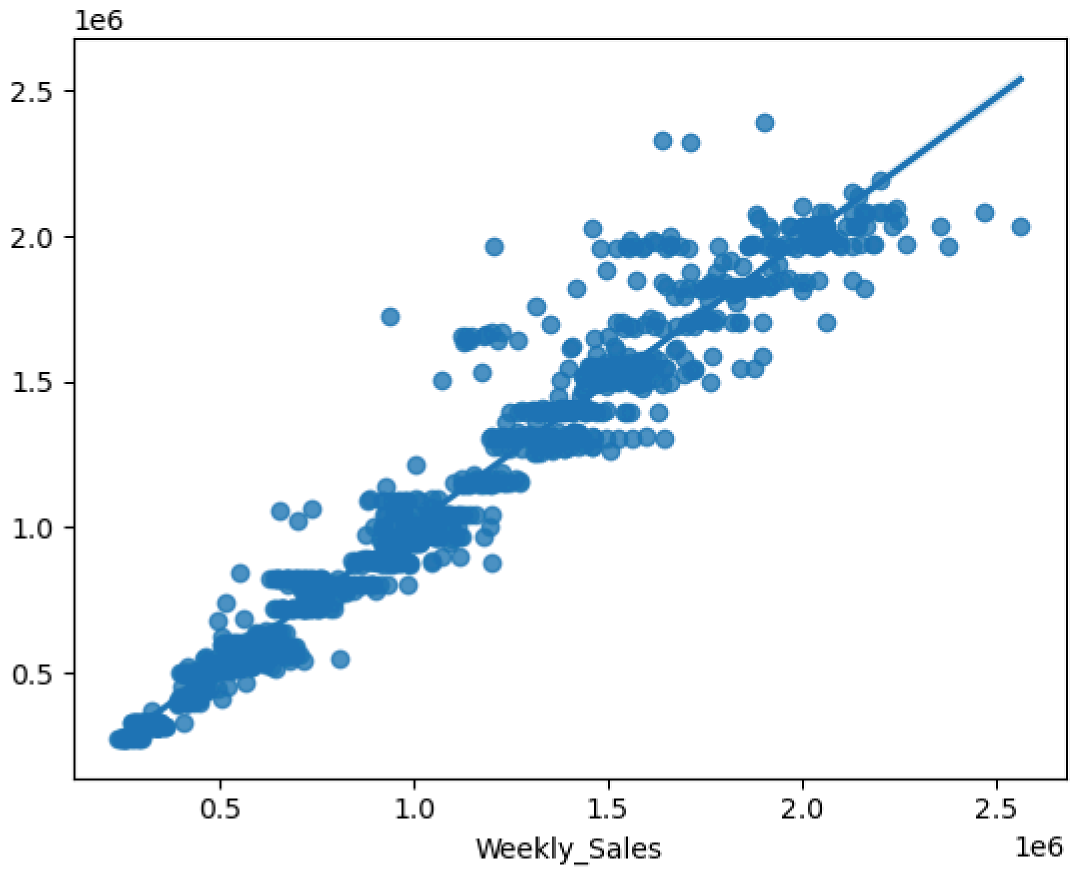
Out[36]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=No
ne,
             enable_categorical=False, eval_metric=None, feature_types=No
ne,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None, max_bin=No
ne,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=10, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=Non
e,
             multi_strategy=None, n_estimators=1000, n_jobs=None,
             num_parallel_tree=None, random_state=None, ...)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [37]:
```
y_pred=Model_xgb.predict(x)
print("r2 score of XGBoost: ",r2_score(y,y_pred))
print("mean_absolute_error of XGBoost: ",mean_absolute_error(y,y_pred))
```

```
r2 score of XGBoost:  0.942767628806841
mean_absolute_error of XGBoost:  81709.9449506579
```

In [38]:
```
sns.regplot(x=y,y=Y_pred)
plt.show()
```



[💠 Model Evaluation and Techniques 💠]

🛒 I have chosen two Model Evaluation Techniques

▶`r2_score`
▶`mean_absolute_error`

--

In [39]:
```
Model_Evaluation={'MODEL':['RandomForestRegressor','XGBRegressor'],
                  'r2_score':[0.94,0.94],'mean_absolute_error':[74826.78,8
pd.DataFrame(Model_Evaluation)
```

Out[39]:

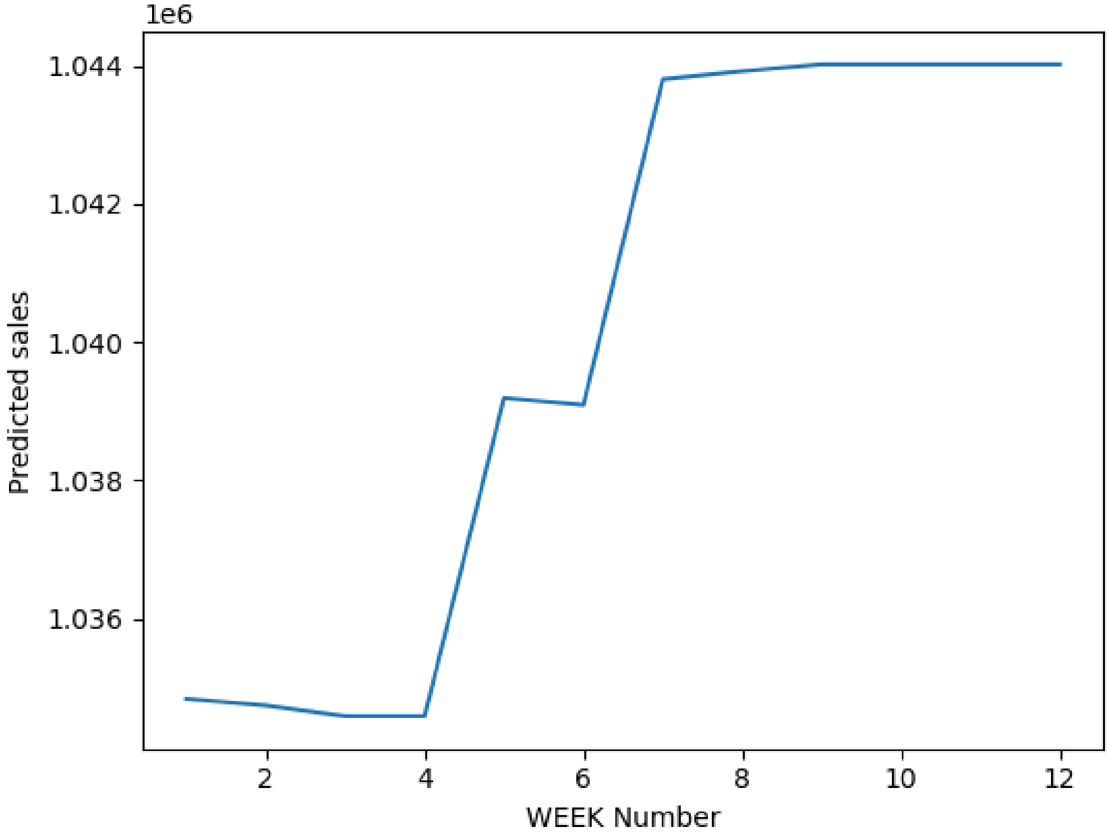
	MODEL	r2_score	mean_absolute_error
0	RandomForestRegressor	0.94	74826.78
1	XGBRegressor	0.94	81709.94

[💠 Predictions of 12 weeks of each store: Using RandomForest 💠]

In [40]:
```
import calendar
import datetime

def Sales_predict_per_store(Store_num,year,M=[]):

    DF={'Store':[],'Week':[],'Month':[],'year':[]}
    for i in M:
        for j in range(len(calendar.monthcalendar(year,i))-1):
            DF['Store'].append(Store_num)
            DF['Month'].append(i)
            DF['year'].append(year)
        for k in range(len(calendar.monthcalendar(year,i))-1):
            day=calendar.monthcalendar(year,i)[k][-1]
            DF['Week'].append(datetime.date(year,i,day).isocalendar()[1])

    DF=pd.DataFrame(DF)

    Sales_predict=regressor.predict(DF)
    DF['Sales_predict']=Sales_predict
    print(DF)

    plt.plot(DF["Week"],DF['Sales_predict'])
    plt.xlabel('WEEK Number')
    plt.ylabel('Predicted sales')
    plt.show()
```

In [41]:
```
Sales_predict_per_store(18,2013,[1,2,3])
```

```
    Store  Week  Month  year  Sales_predict
0      18     1      1  2013   1.034835e+06
1      18     2      1  2013   1.034737e+06
2      18     3      1  2013   1.034585e+06
3      18     4      1  2013   1.034585e+06
4      18     5      2  2013   1.039189e+06
5      18     6      2  2013   1.039088e+06
6      18     7      2  2013   1.043803e+06
7      18     8      2  2013   1.043918e+06
8      18     9      3  2013   1.044019e+06
9      18    10      3  2013   1.044019e+06
10     18    11      3  2013   1.044019e+06
11     18    12      3  2013   1.044019e+06
```



In [42]:
```
def Sales_predict(Store_num,year,M=[]):

    DF={'Store':[],'Week':[],'Month':[],'year':[]}
    for i in M:
        for j in range(len(calendar.monthcalendar(year,i))-1):
            DF['Store'].append(Store_num)
            DF['Month'].append(i)
            DF['year'].append(year)
        for k in range(len(calendar.monthcalendar(year,i))-1):
            day=calendar.monthcalendar(year,i)[k][-1]
            DF['Week'].append(datetime.date(year,i,day).isocalendar()[1])

    DF=pd.DataFrame(DF)

    Sales_predict=regressor.predict(DF)
    DF['Sales_predict']=Sales_predict
    return(DF['Sales_predict'])


Prediction_values={'Week':[1,2,3,4,5,6,7,8,9,10,11,12]}
for i in range(1,max(df['Store'])+1):

    Prediction_values[f'Store- {i}']=list(Sales_predict(i,2013,[1,2,3]).va


Prediction_values=pd.DataFrame(Prediction_values).set_index('Week')
Prediction_values
```

Out[42]:

	Store- 1	Store- 2	Store- 3	Store- 4	Store- 5	Store-
Week						
1	1.568031e+06	1.875882e+06	407549.284629	2.103027e+06	328654.434512	1.527642e+0
2	1.472367e+06	1.764209e+06	384503.434224	1.989765e+06	307319.834566	1.382872e+0
3	1.401833e+06	1.727138e+06	367647.267666	1.979909e+06	299052.123970	1.368756e+0
4	1.362995e+06	1.685974e+06	362536.833121	1.952080e+06	300772.700063	1.369444e+0
5	1.661221e+06	1.930034e+06	446402.394627	2.169977e+06	336695.270566	1.581575e+0
6	1.683178e+06	1.937659e+06	454651.894611	2.210481e+06	340580.918317	1.571747e+0
7	1.741728e+06	2.116719e+06	453916.672334	2.321941e+06	338714.334621	1.563722e+0
8	1.610547e+06	1.910948e+06	427442.711335	2.210392e+06	330661.188004	1.562175e+0
9	1.621618e+06	1.922526e+06	419202.374724	2.163785e+06	329951.451373	1.564459e+0
10	1.625901e+06	1.925518e+06	420699.504725	2.160105e+06	330014.737744	1.565043e+0
11	1.631727e+06	1.924270e+06	414024.746800	2.156584e+06	329837.648256	1.567900e+0
12	1.584368e+06	1.851414e+06	412919.485809	2.125031e+06	329524.877499	1.552759e+0

12 rows × 45 columns

[💠 Predictions of 12 weeks of each store: Using SARIMAX 💠]

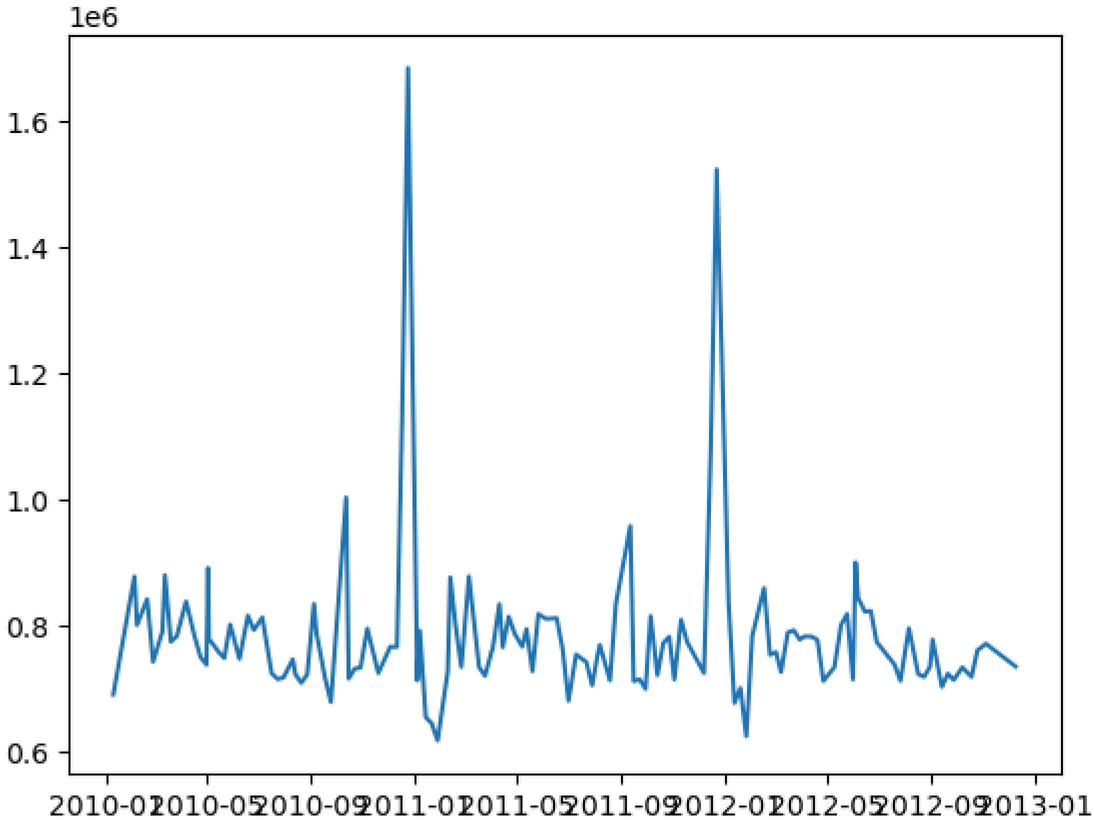
In [43]:
```
df.head()                                    #This data is pre-processed in abo
```

Out[43]:

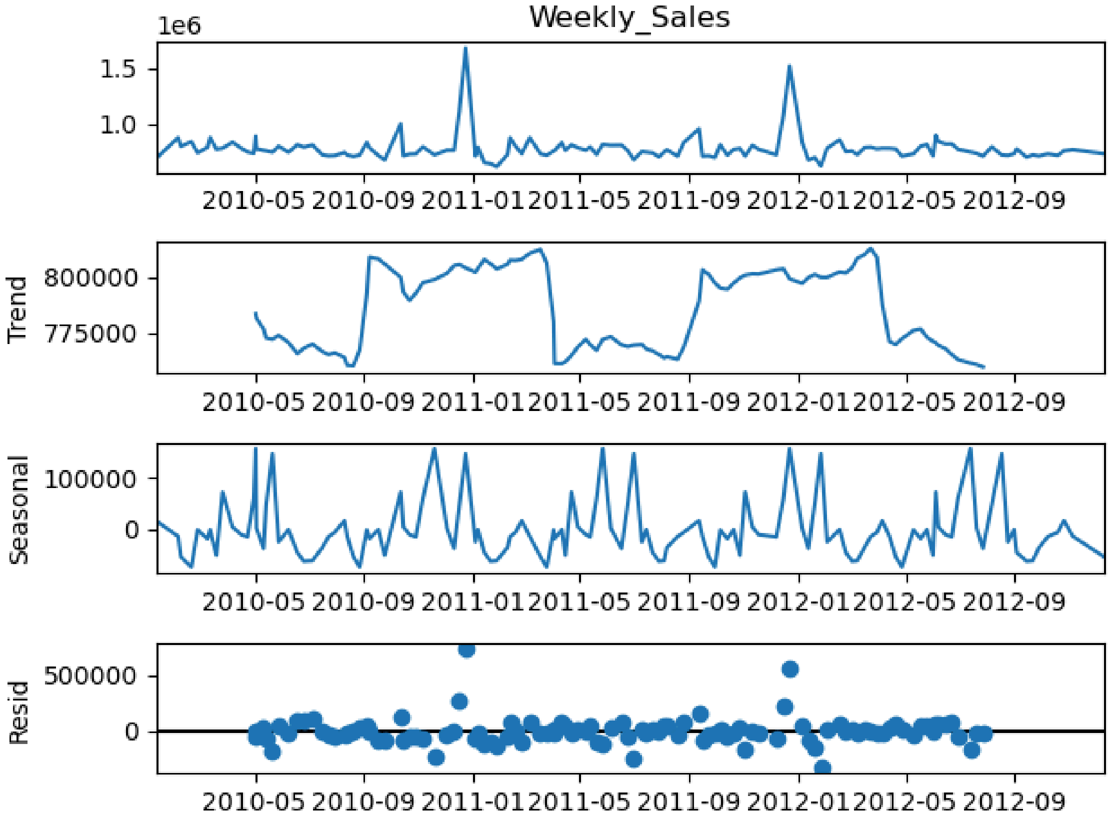
	Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployme
Date							
2010-01-10	5	283178.12	0	71.10	2.603	212.226946	6.7
2010-01-10	15	566945.95	0	59.69	2.840	132.756800	8.0
2010-01-10	42	481523.93	0	86.01	3.001	126.234600	9.0
2010-01-10	33	224294.39	0	91.45	3.001	126.234600	9.2
2010-01-10	36	422169.47	0	74.66	2.567	210.440443	8.4

💠 Testing and analysing data for parameters of SARIMAX time-series

In [44]:
```
Store=df[df['Store']==45]['Weekly_Sales']
plt.plot(Store)
plt.show()
```



In [45]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
result=seasonal_decompose(Store,period=26)
result.plot()
plt.show()
```

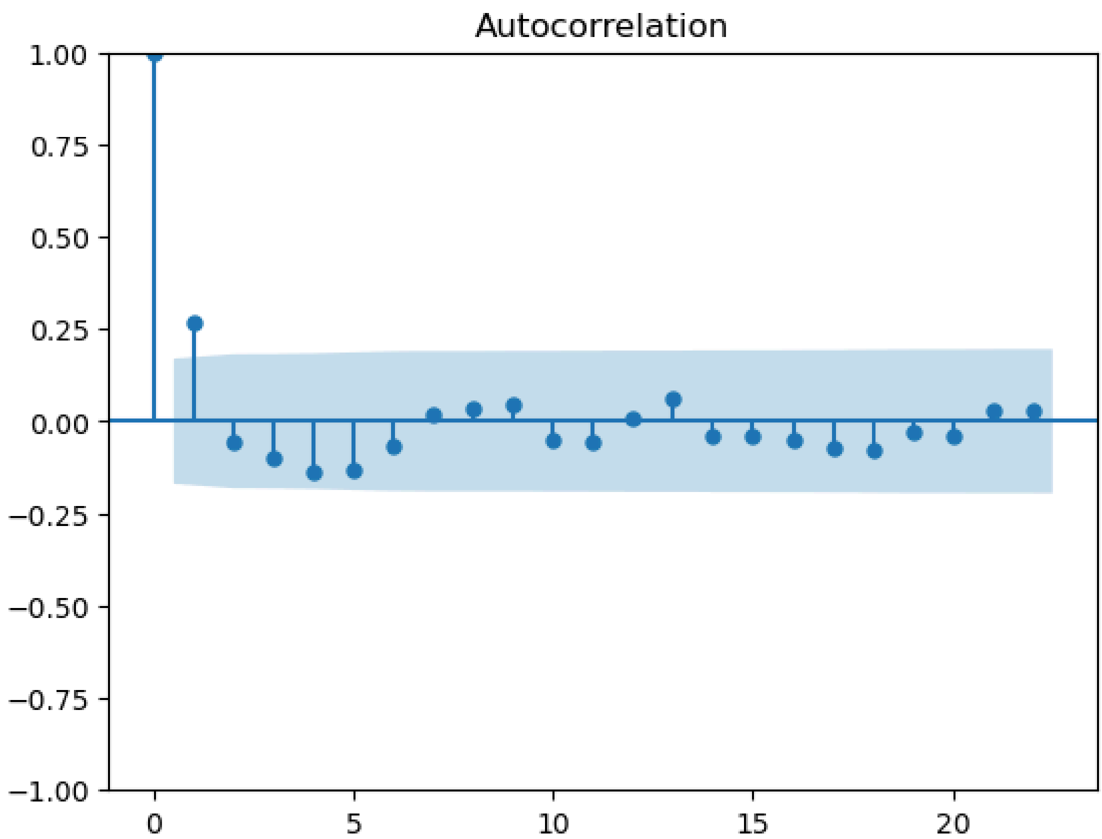


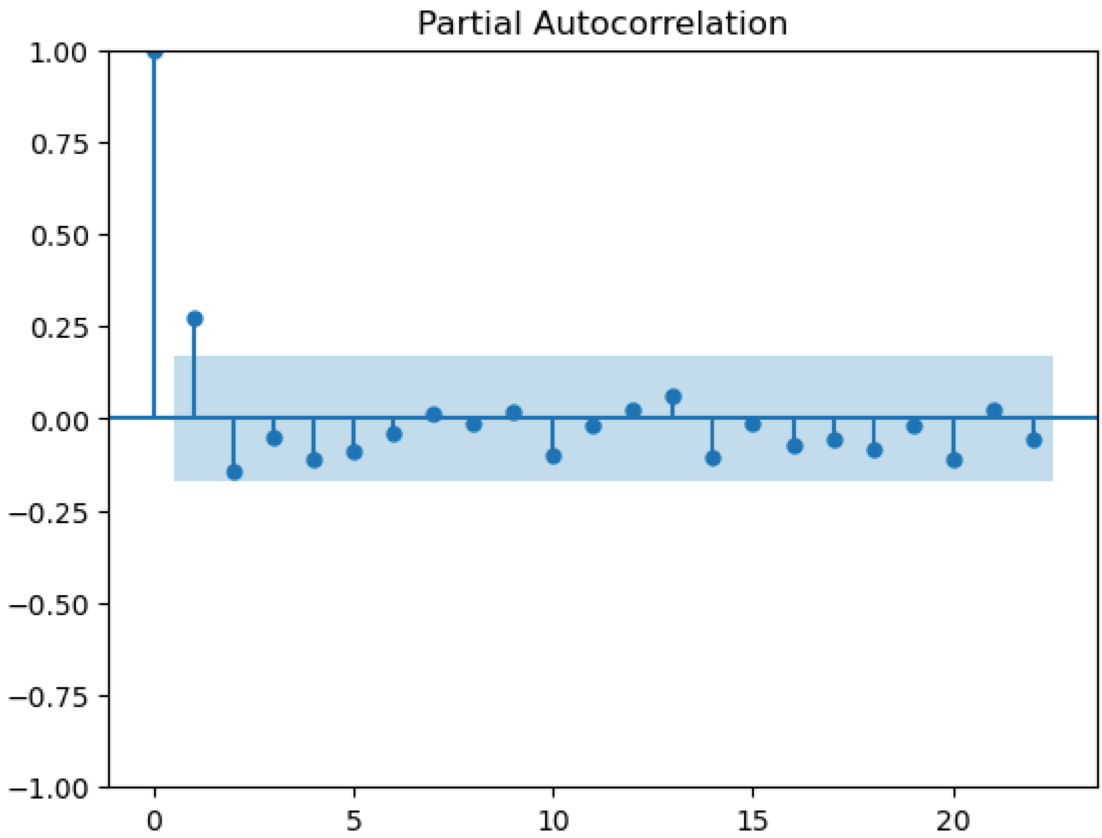
In [46]:
```
from statsmodels.tsa.stattools import adfuller

result=adfuller(Store)
print('Stationary series' if result[1]<0.05 else 'Non-Stationary series')

train=Store[:len(Store)-12]
test=Store[len(Store)-12:]
```

```
Stationary series
```

In [47]:
```
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf

plot_acf(Store)

plot_pacf(Store)

plt.show()
```

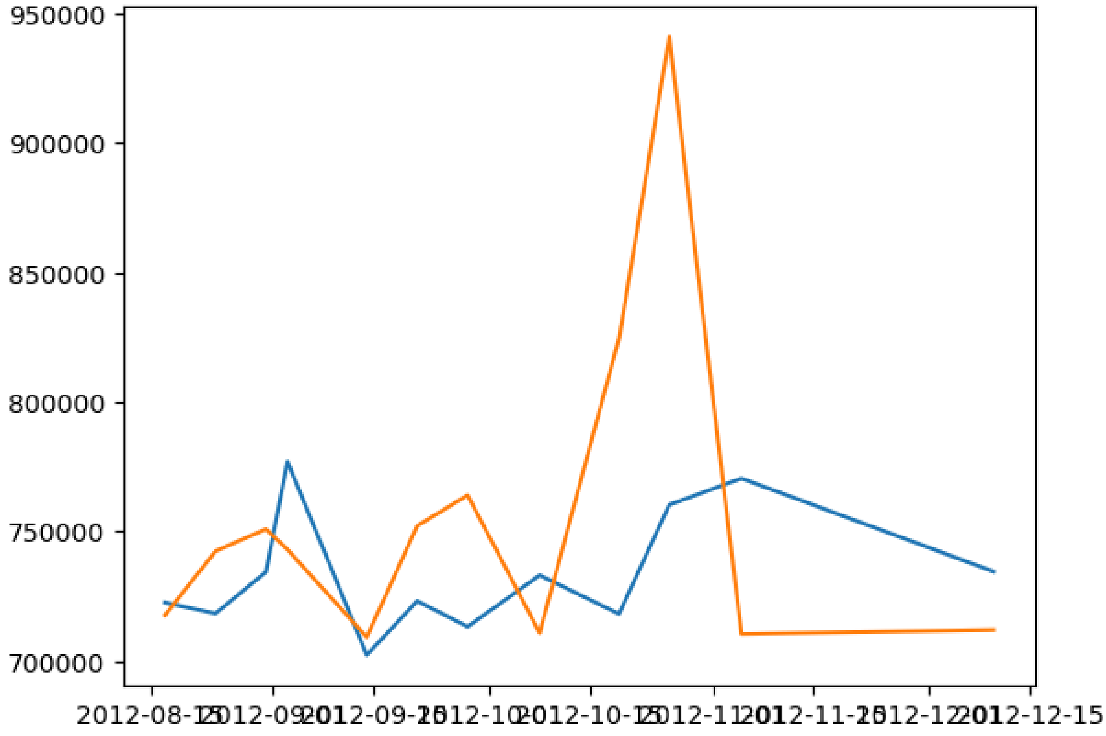
```
C:\Users\MAYUR\anaconda3\Lib\site-packages\statsmodels\graphics\tsaplots.
py:348: FutureWarning: The default method 'yw' can produce PACF values ou
tside of the [-1,1] interval. After 0.13, the default will change tounadj
usted Yule-Walker ('ywm'). You can use this method now by setting method
='ywm'.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



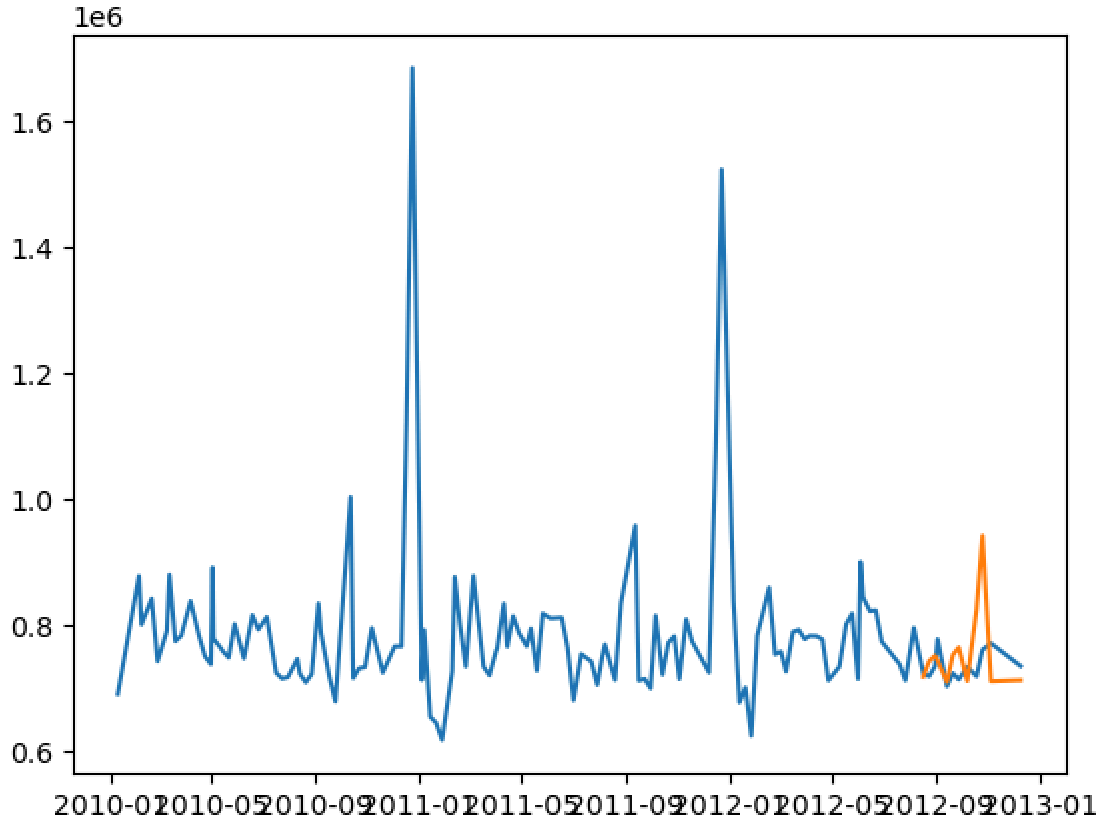

Partial Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20

In [48]:
```
import statsmodels.api as sm
from sklearn.metrics import mean_absolute_error,mean_squared_error

model = sm.tsa.SARIMAX(train, order=(1,0,1), seasonal_order=(1,1,1,52))
results = model.fit()

forecast = results.get_forecast(steps=12)
forecast_mean = forecast.predicted_mean
forecast_mean=pd.DataFrame(forecast_mean).set_index(test.index)


print('Mean_absolute_error ',mean_absolute_error(test,forecast_mean))
print('Root_Mean_absolute_error ',np.sqrt(mean_squared_error(test,forecast_
plt.plot(test)
plt.plot(forecast_mean)
plt.show()
```

```
C:\Users\MAYUR\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_mode
l.py:471: ValueWarning: A date index has been provided, but it has no ass
ociated frequency information and so will be ignored when e.g. forecastin
g.
  self._init_dates(dates, freq)
C:\Users\MAYUR\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_mode
l.py:471: ValueWarning: A date index has been provided, but it has no ass
ociated frequency information and so will be ignored when e.g. forecastin
g.
  self._init_dates(dates, freq)
C:\Users\MAYUR\anaconda3\Lib\site-packages\statsmodels\tsa\statespace\sar
imax.py:866: UserWarning: Too few observations to estimate starting param
eters for seasonal ARMA. All parameters except for variances will be set
to zeros.
  warn('Too few observations to estimate starting parameters%s.'
C:\Users\MAYUR\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_mode
l.py:834: ValueWarning: No supported index is available. Prediction resul
ts will be given with an integer index beginning at `start`.
  return get_prediction_index(

Mean_absolute_error  46535.57878264931
Root_Mean_absolute_error  67172.50462638694
```



In [49]:
```
plt.plot(Store)
plt.plot(forecast_mean)
plt.show()
```



💠 Predicting sales for 12 weeks for all the stores

In [50]:
```
import warnings
warnings.filterwarnings('ignore')

SARIMAX_pred={'Week':[x for x in range(1,13)]}

for i in range(1,max(df['Store'].unique())):
    S=df[df['Store']==i]['Weekly_Sales']
    model = sm.tsa.SARIMAX(S, order=(1,0,1), seasonal_order=(1,1,1,52))
    results = model.fit()
    forecast = results.get_forecast(steps=12)
    forecast_mean = forecast.predicted_mean
    SARIMAX_pred['Store'+str(i)]=list(forecast_mean)

SARIMAX_pred
```

Out[50]:
```
{'Week': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12],
 'Store1': [1412760.9981626882,
  1614331.0228198054,
  1515918.4445315055,
  1525662.519328615,
  1467279.477189733,
  1576903.474230957,
  1619307.6890464788,
  1563025.0626175066,
  1548457.1402390092,
  1909957.7653290508,
  2304985.894145947,
  1649312.6793549284],
 'Store2': [1727498.8037285097,
  1705073.6091885425,
  1964951.7010873626,
  1793002.3731032955,
  1875382.4155128142,
  1807299.727947292,
```

Note : There is very insufficient data for Store-38

In [53]:
```
SARIMAX_pred=pd.DataFrame(SARIMAX_pred).set_index(SARIMAX_pred['Week'])
SARIMAX_pred.head()
```

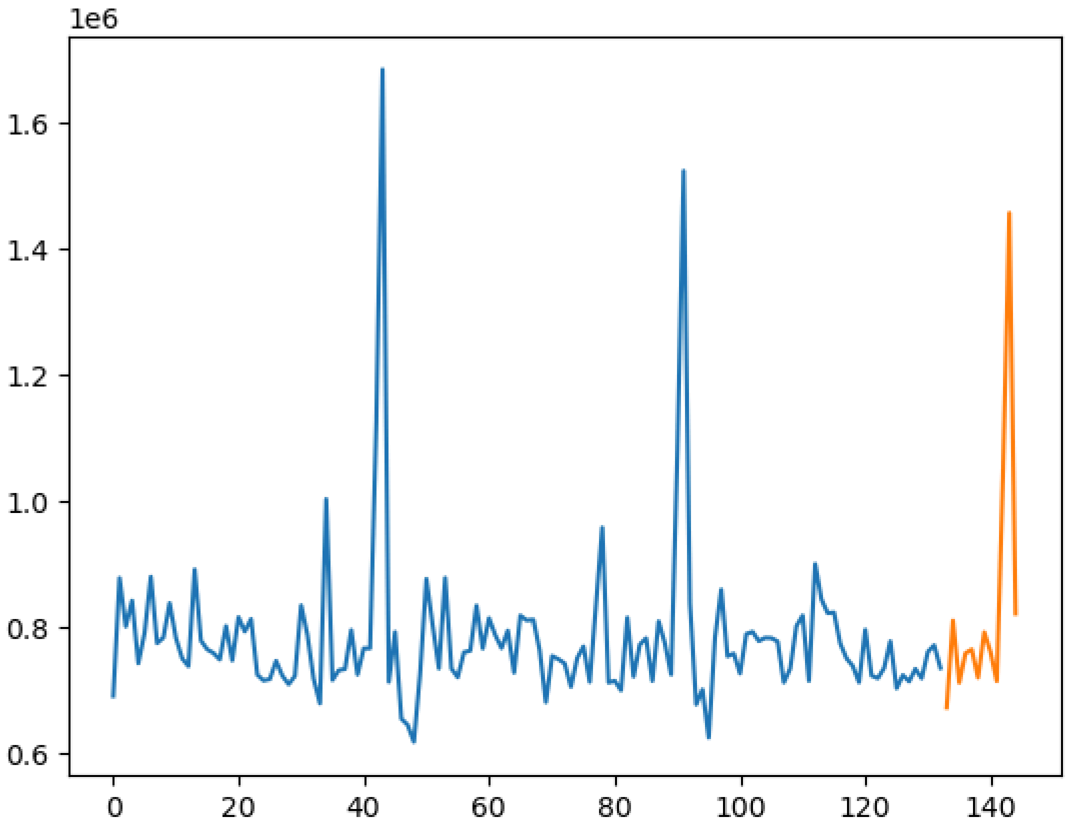
Out[53]:

	Week	Store1	Store2	Store3	Store4	Store5	
Week							
1	1	1.412761e+06	1.727499e+06	364296.124731	2.107245e+06	296548.800425	1.33
2	2	1.614331e+06	1.705074e+06	407267.949388	2.122591e+06	314271.815323	1.60
3	3	1.515918e+06	1.964952e+06	376708.988847	2.092587e+06	293495.668274	1.40
4	4	1.525663e+06	1.793002e+06	406398.130541	2.175040e+06	314408.814140	1.43
5	5	1.467279e+06	1.875382e+06	400040.715882	2.251063e+06	315274.429091	1.42

5 rows × 45 columns

In [56]:
```
def Prediction_visual(Store_no):
        S=df[df['Store']==Store_no]['Weekly_Sales']
        model = sm.tsa.SARIMAX(S, order=(1,0,1), seasonal_order=(1,1,1,52))
        results = model.fit()
        forecast = results.get_forecast(steps=12)
        forecast_mean = forecast.predicted_mean
        print(forecast_mean)
        plt.plot(list(S))
        plt.plot(forecast_mean)
        plt.show()

Prediction_visual(45)
```

```
133    6.717618e+05
134    8.097461e+05
135    7.112587e+05
136    7.579282e+05
137    7.638963e+05
138    7.191444e+05
139    7.912565e+05
140    7.595992e+05
141    7.137143e+05
142    1.047051e+06
143    1.455273e+06
144    8.205898e+05
Name: predicted_mean, dtype: float64
```



In [ ]:

[💠 Inferences from Analysis 💠]

▶Top 10 best performing stores: [Store 20, 4, 14, 13, 2, 10, 27, 6, 1, 39]

▶Top 10 worst performing stores: [Store 33, 44, 5, 36, 38, 3, 30, 37, 16, 29]

▶Store-33 has minimum average sales 259861.69202797202, Store-20 has maximum average sales 2107676.8703496503

The difference between performance of best and worst performing store 1847815.17832167

▶After analysing the store sales data using the function 'sales_trend_visual' it can be inferred that, graph shows a spike in the month of mid November to December as these are months of festive season.

▶From the above analysis it can be seen that store No[38,44] are affected the most inversly by the Unemployment

▶As we can infer from the above analysis the weekly sales has a very weak inverse relation with the temperature(-0.063810).

▶From the analysis it is clear that the sales is slightly hight on holidays which is about 7.83% more than sales on working days. Which indicates Holiday_Flag has very weak positive relation with Weekly_Sales. This sales occures in the late second half of year.

▶The fuel price does not affects the weekly sales

[💠 Future Possibilities of the Project 💠]

▶Intigrating more features based on location of store, population density, standard of living of population can increase the accuracy of the model which ultimately leads to increment in sales.

▶Informative features about promotional campaign,nearby competative stores, discount sales can be helpful for improving performance of stores with less than average sales.

▶Although Randomforest,XGBoost gives satisfactory results, more efficient techniques such as Timeseries, Neural Networks along with the improved features will give more effective insights for the development and growth of indiviual store.

[💠 Conclusion 💠]

▶After analysing the given sales data it can be seen that sales of walmart is decreasing and majority of the stores are performing below average, an in depth analysis is required for identification the causes.

[💠 References 💠]

▶Matplotlib. (2024). Matplotlib Documentation. ['https://matplotlib.org/stable/api/pyplot_summary.html] (https://matplotlib.org/stable/api/pyplot_summary.html%5D)

▶Scikit-learn Documentation.(2024). Random Forests ['https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html] (https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html%5D)

▶kaggle. XGBoost : XGBRegressor ['https://www.kaggle.com/code/dansbecker/xgboost'] (https://www.kaggle.com/code/dansbecker/xgboost'%5D)

▶geeksforgeeks: SARIMAX :Complete Guide To SARIMAX in Python https://www.geeksforgeeks.org/complete-guide-to-sarimax-in-python/ (https://www.geeksforgeeks.org/complete-guide-to-sarimax-in-python/)
