Capstone Project : Walmart

Problem Statement 1:

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.

1.You are provided with the weekly sales data for their various outlets. Use statistical analysis, EDA, outlier analysis, and handle the missing values to come up with various insights that can give them a clear perspective on the following:

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

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

c. Does temperature affect the weekly sales in any manner?

d. How is the Consumer Price index affecting the weekly sales of various stores?

e. Top performing stores according to the historical data.

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

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

1. Importing Necessary Libraries

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

2. Loading Dataset

In [2]:
```
Data = pd.read_csv("D:/Project/Walmart.csv")
Data.head()
```

Out[2]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
0	1	05-02-2010	1643690.90	0	42.31	2.572	211.096358	8.106
1	1	12-02-2010	1641957.44	1	38.51	2.548	211.242170	8.106
2	1	19-02-2010	1611968.17	0	39.93	2.514	211.289143	8.106
3	1	26-02-2010	1409727.59	0	46.63	2.561	211.319643	8.106
4	1	05-03-2010	1554806.68	0	46.50	2.625	211.350143	8.106

3. Exploratory Data Analysis

In [3]:
```
Data.head()
```

Out[3]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
0	1	05-02-2010	1643690.90	0	42.31	2.572	211.096358	8.106
1	1	12-02-2010	1641957.44	1	38.51	2.548	211.242170	8.106
2	1	19-02-2010	1611968.17	0	39.93	2.514	211.289143	8.106
3	1	26-02-2010	1409727.59	0	46.63	2.561	211.319643	8.106
4	1	05-03-2010	1554806.68	0	46.50	2.625	211.350143	8.106

In [4]:
```
Data.value_counts()
```

Out[4]:

```
Store  Date        Weekly_Sales  Holiday_Flag  Temperature  Fuel_Price  CPI
Unemployment
1      01-04-2011  1495064.75    0             59.17        3.524       214.837166
7.682           1
30     30-09-2011  387001.13     0             78.91        3.355       216.362033
7.852           1
31     02-07-2010  1311704.92    0             82.29        2.669       210.880373
8.099           1
       02-04-2010  1357600.68    0             64.12        2.719       210.479887
8.200           1
       02-03-2012  1427881.22    0             59.30        3.630       220.486689
7.057           1

..
15     30-12-2011  603460.79     1             31.44        3.566       136.643258
7.866           1
       30-09-2011  521297.31     0             64.87        3.858       136.419500
7.806           1
       30-07-2010  619224.06     0             72.04        2.932       132.598387
8.099           1
       30-04-2010  570791.11     0             49.09        3.042       132.064433
8.185           1
45     31-12-2010  679156.20     1             29.67        3.179       182.571448
8.724           1
Length: 6435, dtype: int64
```

In [5]:

```
Data.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 [6]:

```
Data.describe(include='all')
```

Out[6]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Un
count	6435.000000	6435	6.435000e+03	6435.000000	6435.000000	6435.000000	6435.000000	
unique	NaN	143	NaN	NaN	NaN	NaN	NaN	
top	NaN	05-02-2010	NaN	NaN	NaN	NaN	NaN	
freq	NaN	45	NaN	NaN	NaN	NaN	NaN	
mean	23.000000	NaN	1.046965e+06	0.069930	60.663782	3.358607	171.578394	
std	12.988182	NaN	5.643666e+05	0.255049	18.444933	0.459020	39.356712	
min	1.000000	NaN	2.099862e+05	0.000000	-2.060000	2.472000	126.064000	
25%	12.000000	NaN	5.533501e+05	0.000000	47.460000	2.933000	131.735000	
50%	23.000000	NaN	9.607460e+05	0.000000	62.670000	3.445000	182.616521	
75%	34.000000	NaN	1.420159e+06	0.000000	74.940000	3.735000	212.743293	
max	45.000000	NaN	3.818686e+06	1.000000	100.140000	4.468000	227.232807	

In [51]:

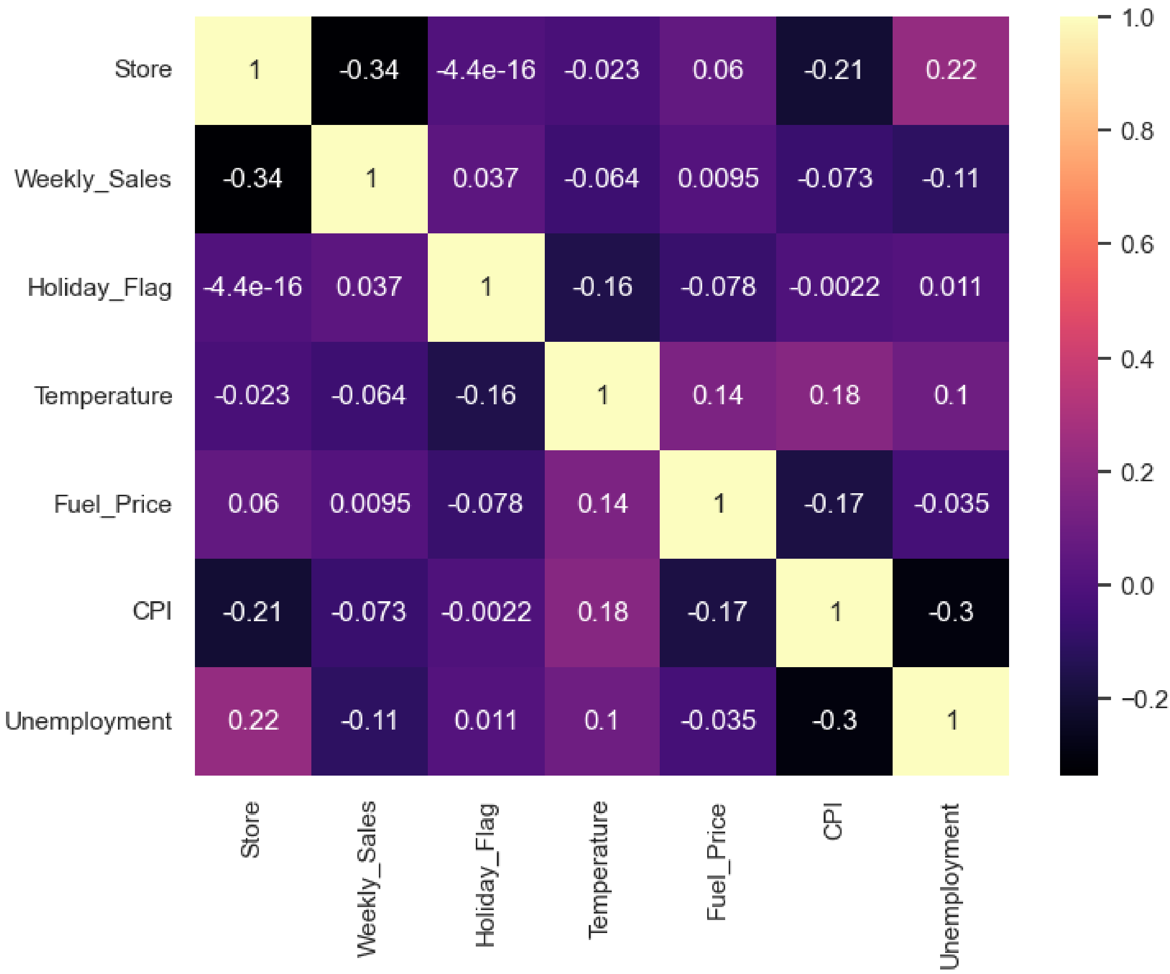
```
# Check for missing values.
Data.isna().sum()
```

Out[51]:

```
index           0
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
dtype: int64
```

In [8]:

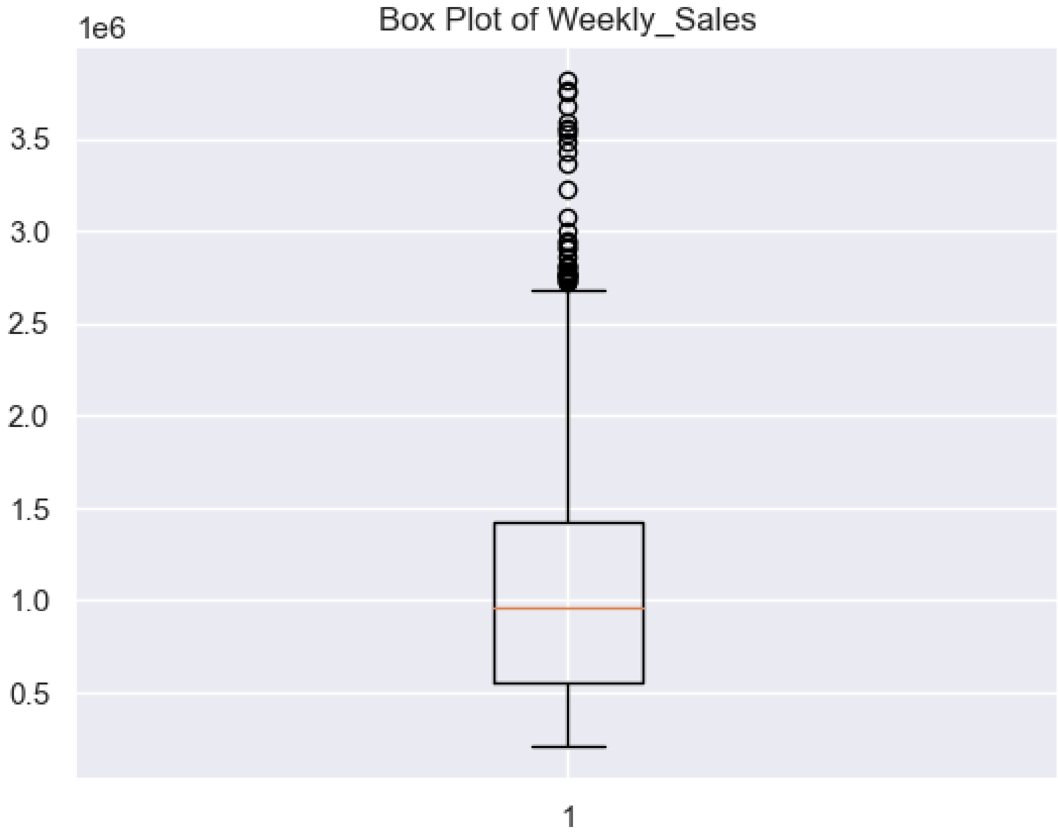
```
Data1 = Data.drop(columns=['Date'])
sns.set()
plt.figure(figsize=(8, 6))
sns.heatmap(Data1.corr(), annot=True, cmap='magma')
plt.show()
```

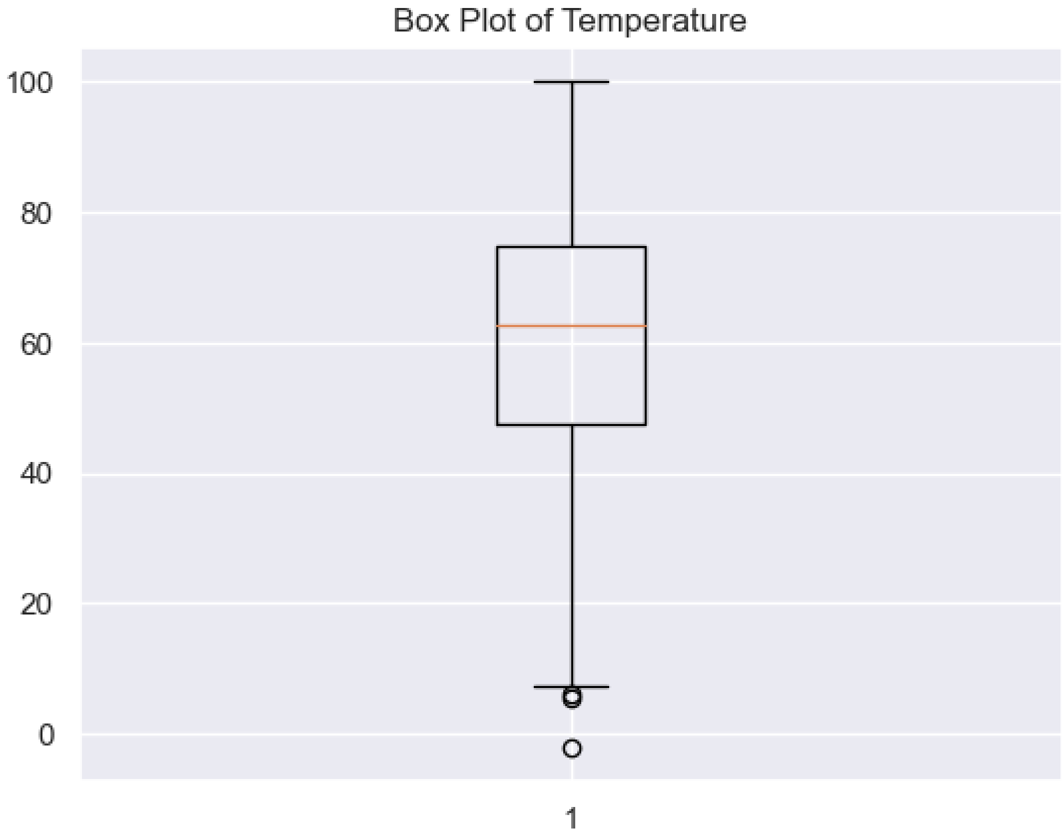


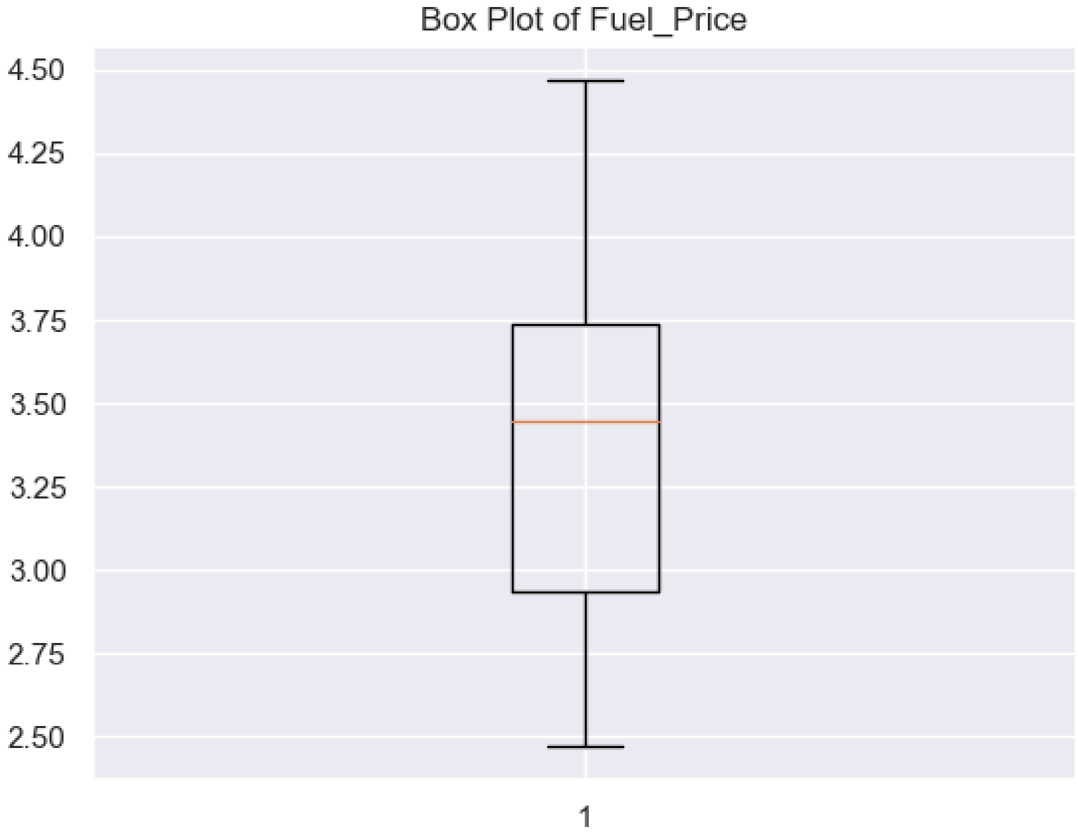
In [10]:
```
Data.columns
```

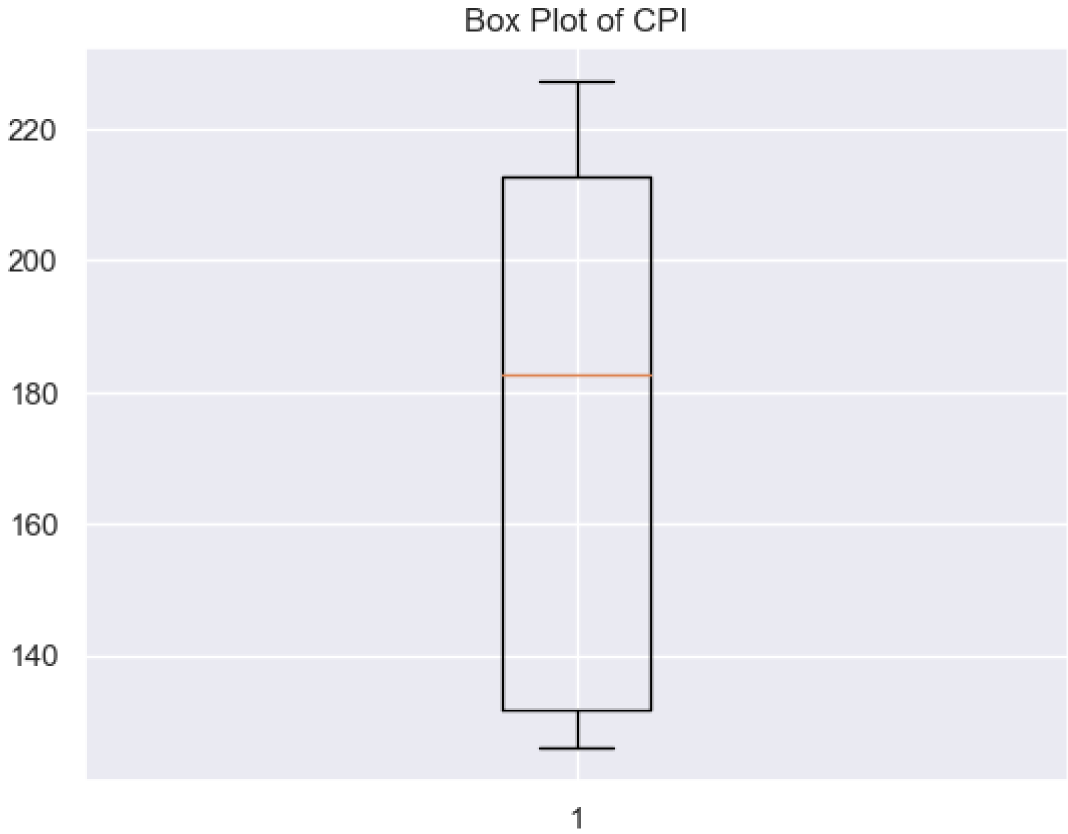
Out[10]:
```
Index(['Store', 'Date', 'Weekly_Sales', 'Holiday_Flag', 'Temperature',
       'Fuel_Price', 'CPI', 'Unemployment'],
      dtype='object')
```

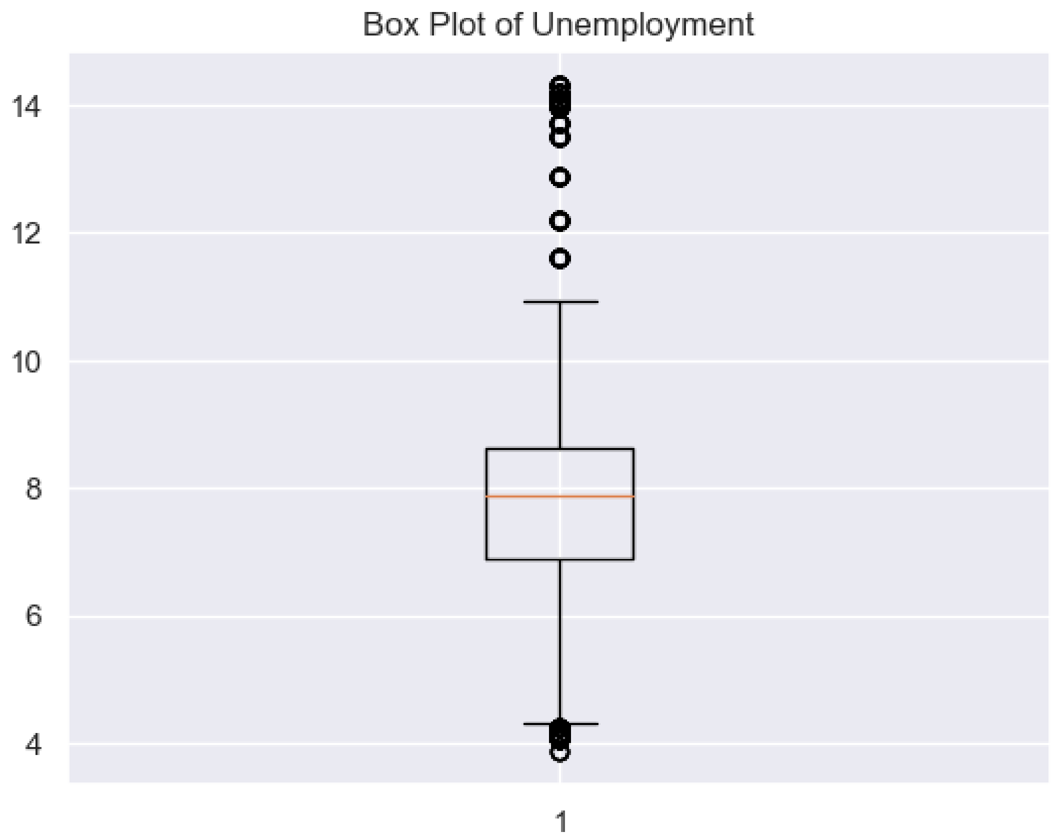
In [11]:
```
columns = ['Weekly_Sales', 'Temperature', 'Fuel_Price', 'CPI', 'Unemployment']

# Create box plots for each column using a for loop
for col in columns:
    plt.figure()  # Create a new figure for each column
    plt.boxplot(Data[col])  # Create the box plot
    plt.title(f'Box Plot of {col}')  # Set the title
    plt.show()  # Display the plot
```


Box Plot of Weekly_Sales
1e6
3.5
3.0
2.5
2.0
1.5
1.0
0.5
1


Box Plot of Temperature
100
80
60
40
20
0
1


Box Plot of Fuel_Price
4.50
4.25
4.00
3.75
3.50
3.25
3.00
2.75
2.50
1


Box Plot of CPI
220
200
180
160
140
1



In [12]:
```
Data.sample(3)
```

Out[12]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemploymen
638	5	13-05-2011	290930.01	0	77.38	3.899	216.534361	6.48
850	6	07-09-2012	1608077.01	1	86.33	3.730	224.056008	5.66
3411	24	08-06-2012	1406313.13	0	59.93	3.871	138.117419	8.98

In [13]:
```
Data['Store'].unique()
```

Out[13]:
```
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 [14]:
```
len(Data['Store'].unique())
```

Out[14]:
```
45
```

Part 1. a. If the weekly sales are affected by the unemployment rate, if yes - which stores are suffering the most?

Let just pick those who have less Weekly Sales. As it will be too lenghty to analyze 45 stores.

We will pick those stores for which weekly sales is less than 10 percentile.

In [15]:
```
# round() function is used to round the value returned by Data['Weekly_Sales'].quant

a1 = Data['Weekly_Sales'].quantile(0.1).round(2)
```

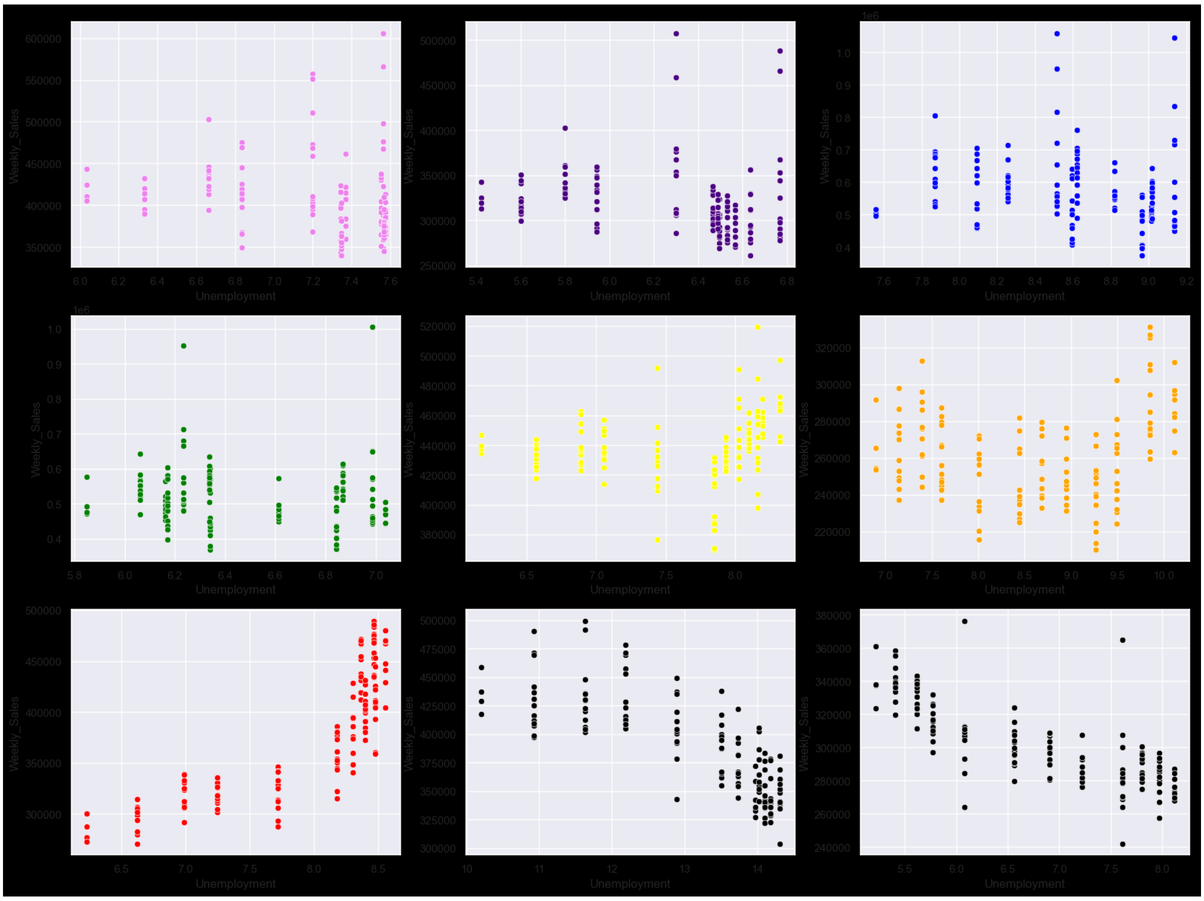
In [16]:
```
# the variable 'less_weekly_sales' contains an array or list of unique store numbers
# are below the threshold 'a1'.(Here a1 contains no of stores where weekly_sales are

less_weekly_sales = Data.loc[Data['Weekly_Sales'] < a1, 'Store'].unique()
less_weekly_sales
```

Out[16]:
```
array([ 3,  5,  7, 16, 30, 33, 36, 38, 44], dtype=int64)
```

Lets check if low value of sales are anyhow affected by unemployment rate.

In [17]:
```
plt.figure(figsize=(20,15),facecolor='black')

#data= is a parameter within the sns.scatterplot() function call,
# and it specifies the DataFrame that contains the data to be plotted.

plt.subplot(3,3,1)
sns.scatterplot(data=Data[Data['Store'] == 3], x='Unemployment', y='Weekly_Sales',co

plt.subplot(3,3,2)
sns.scatterplot(data=Data[Data['Store'] == 5], x='Unemployment', y='Weekly_Sales',co


plt.subplot(3,3,3)
sns.scatterplot(data=Data[Data['Store'] == 7], x='Unemployment', y='Weekly_Sales',co

plt.subplot(3,3,4)
sns.scatterplot(data=Data[Data['Store'] == 16], x='Unemployment',y='Weekly_Sales',co


plt.subplot(3,3,5)
sns.scatterplot(data=Data[Data['Store'] == 30], x='Unemployment',y='Weekly_Sales',co


plt.subplot(3,3,6)
sns.scatterplot(data=Data[Data['Store'] == 33], x='Unemployment',y='Weekly_Sales',co
plt.title='Store33'

plt.subplot(3,3,7)
sns.scatterplot(data=Data[Data['Store'] == 36], x='Unemployment',y='Weekly_Sales',co


plt.subplot(3,3,8)
sns.scatterplot(data=Data[Data['Store'] == 38], x='Unemployment', y='Weekly_Sales',c


plt.subplot(3,3,9)
sns.scatterplot(data=Data[Data['Store'] == 44], x='Unemployment',y='Weekly_Sales',co
```

Out[17]:
```
<AxesSubplot:xlabel='Unemployment', ylabel='Weekly_Sales'>
```



Clearly we can see that in Store number 5 although average of weekly sales is not impacted by unemployement rate, but more density is higher on the higher side of unemployment rate.

There are two Stores we can identify in which weekly sales reduces as the unemployment rate increases. Those stores are Store number 38 and 44

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

In [18]:
```
Data['Date'] = pd.to_datetime(Data['Date'], format='%d-%m-%Y')
```

In [19]:
```
Sales_date = Data[['Date','Weekly_Sales']]
```

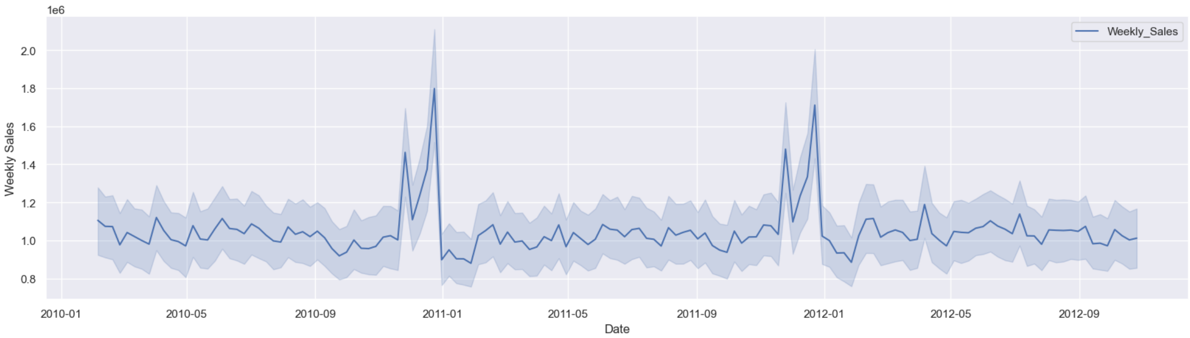
In [20]:
```
Sales_date.set_index('Date',inplace=True)
```

In [21]:
```
Sales_date.head()
```

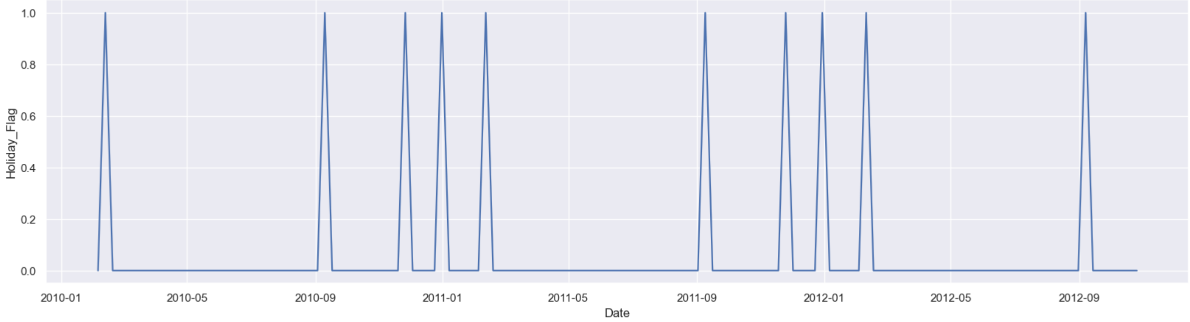
Out[21]:

	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

In [22]:
```
plt.figure(figsize=(20,5))
sns.lineplot(data=Sales_date)
plt.xlabel('Date')
plt.ylabel('Weekly Sales')

plt.show()
```



In [23]:
```
plt.figure(figsize=(20,5))
sns.lineplot(data=Data,x='Date',y='Holiday_Flag')

plt.show()
```



We can clearly see there is a seasonality component in weekly sales. Whole year sales is average. But at the end of the year there is an exponential hike in the sales.

The Major Reason is during this time of the year, the holiday season begins.

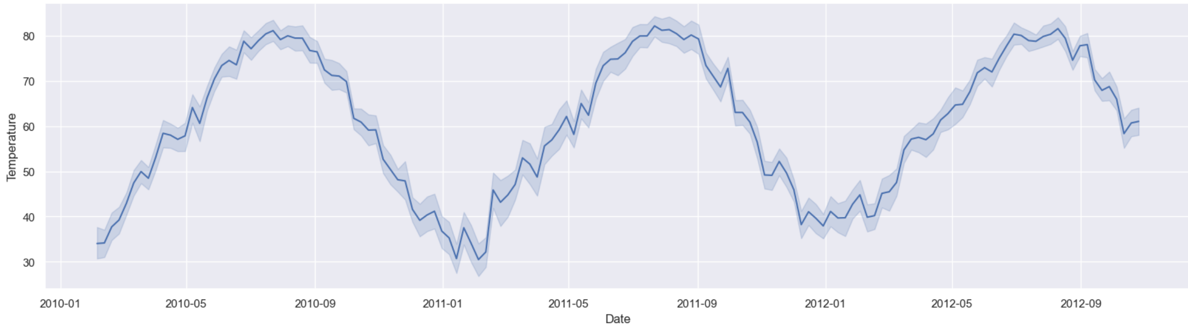
So, the spike in the sales overlaps with the holiday season.

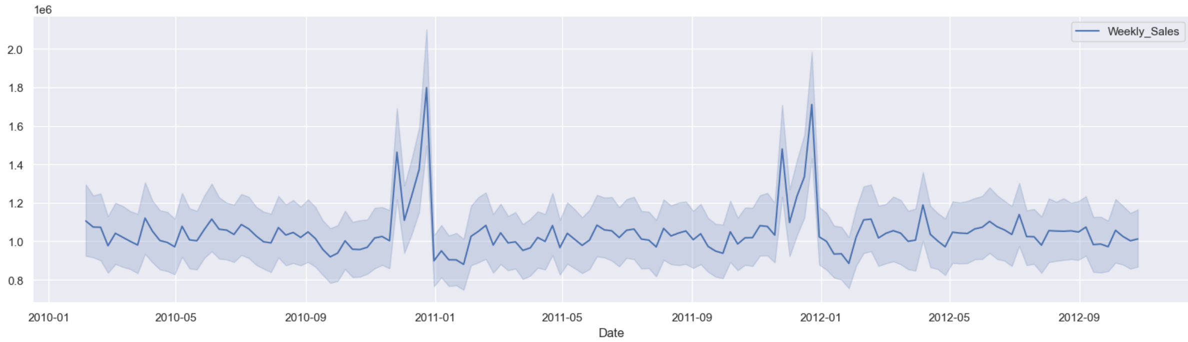
As we know Walmart is very famous in USA, and there is a holiday season during christmans and new year, there might be a lot of offers being given by brands in holiday season. This explains the sudden spike in the sales at the end of the year.

c. Does temperature affect the weekly sales in any manner?

In [24]:
```
plt.figure(figsize=(20,5))
sns.lineplot(data=Data, x='Date', y='Temperature')

plt.figure(figsize=(20,5))
sns.lineplot(data=Sales_date)
```

Out[24]:
```
<AxesSubplot:xlabel='Date'>
```





The only noted effect that can be seen is again of the holiday season. Holiday season are marked with winters and snow, that increases the needed clothing and stuff. Other than this there is no such clear trend of shopping related with temprature.

d. How is the Consumer Price index affecting the weekly sales of various stores?

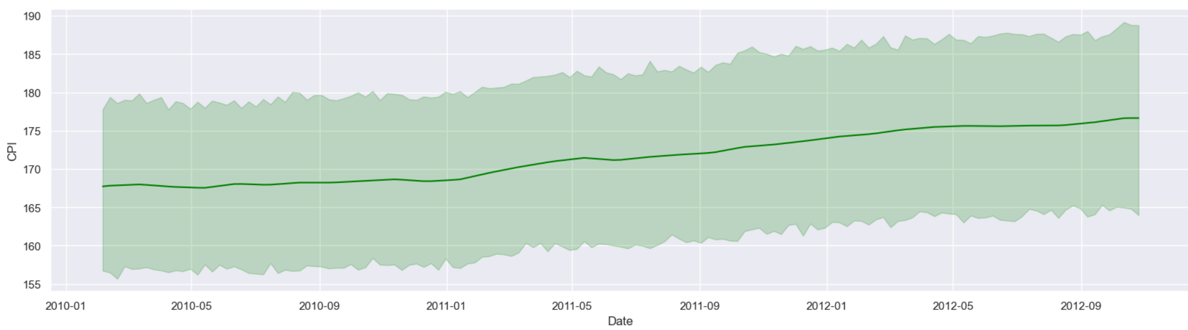
In [25]:
```
Data.head(3)
```

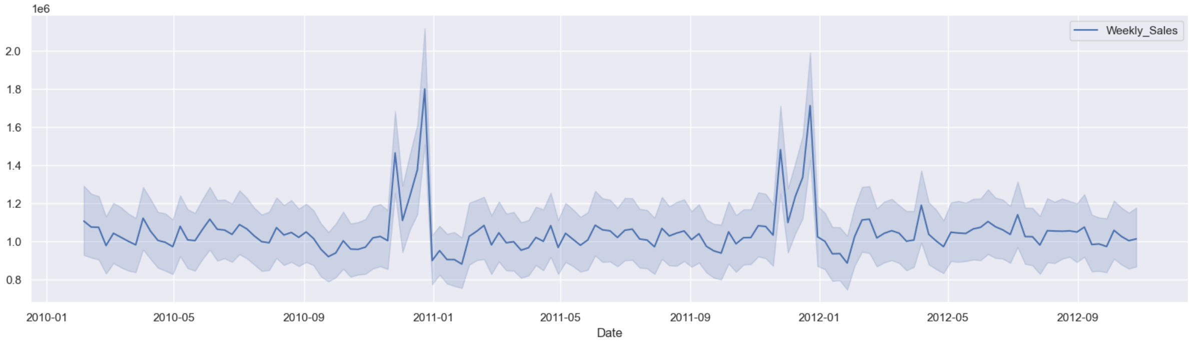
Out[25]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
0	1	2010-02-05	1643690.90	0	42.31	2.572	211.096358	8.106
1	1	2010-02-12	1641957.44	1	38.51	2.548	211.242170	8.106
2	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106

In [26]:
```
plt.figure(figsize=(20,5))
sns.lineplot(data=Data,x='Date',y='CPI',color='green')

plt.figure(figsize=(20,5))
sns.lineplot(data=Sales_date)
```

Out[26]: <AxesSubplot:xlabel='Date'>





Although there is inflation over time represented by increasing CPI over the time period. There is no upward or downward trend followed by weekly sales.

e. Top performing stores according to the historical data.

Lets check the store with maximum average sales over the given period.

In [27]:
```
average_store_sales = Data.groupby('Store')['Weekly_Sales'].agg('mean')
```

In [28]:
```
average_store_sales
```

Out[28]:
```
Store
1     1.555264e+06
2     1.925751e+06
3     4.027044e+05
4     2.094713e+06
5     3.180118e+05
6     1.564728e+06
7     5.706173e+05
8     9.087495e+05
9     5.439806e+05
10    1.899425e+06
11    1.356383e+06
12    1.009002e+06
13    2.003620e+06
14    2.020978e+06
15    6.233125e+05
16    5.192477e+05
17    8.935814e+05
18    1.084718e+06
19    1.444999e+06
20    2.107677e+06
21    7.560691e+05
22    1.028501e+06
23    1.389864e+06
24    1.356755e+06
25    7.067215e+05
26    1.002912e+06
27    1.775216e+06
28    1.323522e+06
29    5.394514e+05
30    4.385796e+05
31    1.395901e+06
32    1.166568e+06
33    2.598617e+05
34    9.667816e+05
35    9.197250e+05
36    3.735120e+05
37    5.189003e+05
38    3.857317e+05
39    1.450668e+06
40    9.641280e+05
41    1.268125e+06
42    5.564039e+05
43    6.333247e+05
44    3.027489e+05
45    7.859814e+05
Name: Weekly_Sales, dtype: float64
```

In [29]:
```
avg_sales=pd.DataFrame(average_store_sales)
```

In [30]:
```
avg_sales
```

Out[30]:

Store	Weekly_Sales
1	1.555264e+06
2	1.925751e+06
3	4.027044e+05
4	2.094713e+06
5	3.180118e+05
6	1.564728e+06
7	5.706173e+05
8	9.087495e+05
9	5.439806e+05
10	1.899425e+06
11	1.356383e+06
12	1.009002e+06
13	2.003620e+06
14	2.020978e+06
15	6.233125e+05
16	5.192477e+05
17	8.935814e+05
18	1.084718e+06
19	1.444999e+06
20	2.107677e+06
21	7.560691e+05
22	1.028501e+06
23	1.389864e+06
24	1.356755e+06
25	7.067215e+05
26	1.002912e+06
27	1.775216e+06
28	1.323522e+06
29	5.394514e+05
30	4.385796e+05
31	1.395901e+06
32	1.166568e+06
33	2.598617e+05
34	9.667816e+05
35	9.197250e+05

	Weekly_Sales
Store	
36	3.735120e+05
37	5.189003e+05
38	3.857317e+05
39	1.450668e+06
40	9.641280e+05
41	1.268125e+06
42	5.564039e+05
43	6.333247e+05
44	3.027489e+05
45	7.859814e+05

In [31]:
```
avg_sales['Weekly_Sales']=avg_sales['Weekly_Sales']/(avg_sales['Weekly_Sales'].max()
```

In [32]:
```
avg_sales
```

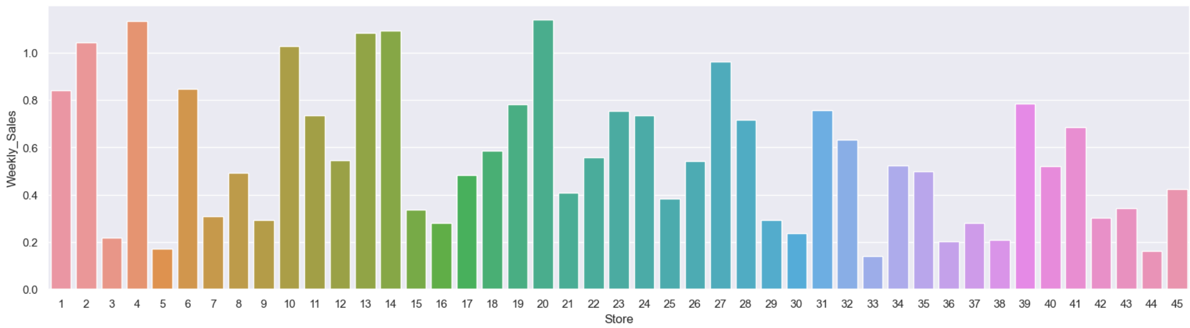
Out[32]:

Store	Weekly_Sales
1	0.841677
2	1.042177
3	0.217935
4	1.133616
5	0.172102
6	0.846799
7	0.308806
8	0.491797
9	0.294391
10	1.027930
11	0.734047
12	0.546051
13	1.084319
14	1.093712
15	0.337324
16	0.281006
17	0.483588
18	0.587028
19	0.782004
20	1.140632
21	0.409169
22	0.556604
23	0.752166
24	0.734248
25	0.382463
26	0.542755
27	0.960711
28	0.716263
29	0.291940
30	0.237350
31	0.755433
32	0.631323
33	0.140632
34	0.523203
35	0.497736

Store	Weekly_Sales
36	0.202137
37	0.280818
38	0.208750
39	0.785072
40	0.521766
41	0.686284
42	0.301114
43	0.342742
44	0.163842
45	0.425357

In [33]:
```
plt.figure(figsize=(20,5))
sns.barplot(data=avg_sales,x=avg_sales.index,y='Weekly_Sales')
```

Out[33]: <AxesSubplot:xlabel='Store', ylabel='Weekly_Sales'>



In [34]:
```
avg_sales.sort_values('Weekly_Sales',ascending=False).head(10)
```

Out[34]:

Store	Weekly_Sales
20	1.140632
4	1.133616
14	1.093712
13	1.084319
2	1.042177
10	1.027930
27	0.960711
6	0.846799
1	0.841677
39	0.785072

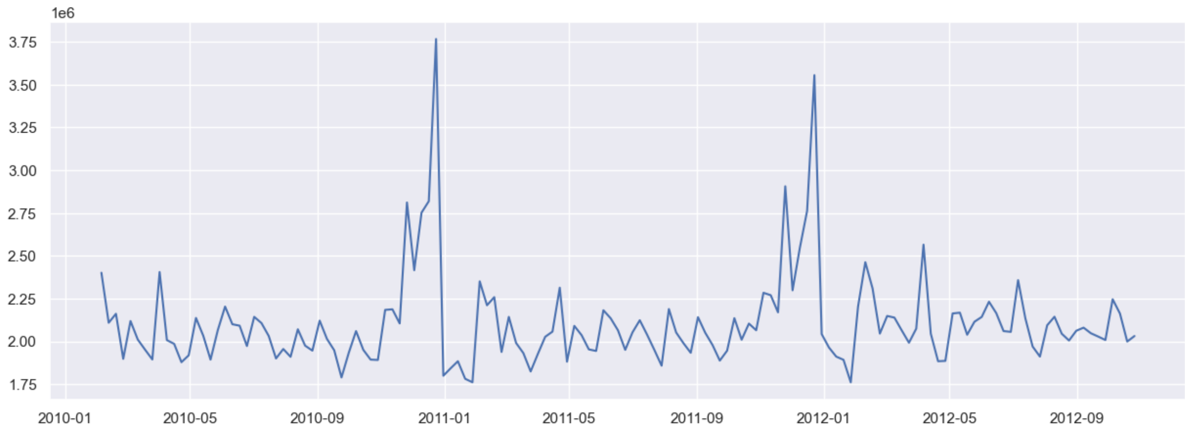
Top performing stores are --> store number 20, 4, 14, 13, 2, 10

In [36]:
```
Store_20 = avg_sales[avg_sales.index == 20]
Store_20
```

Out[36]:

Store	Weekly_Sales
20	1.140632

In [52]:
```
store20 = Data[Data['Store']==20]
plt.figure(figsize=(15,5))
plt.plot(store20['Date'],store20['Weekly_Sales'])
plt.show()
```



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

In [35]:
```
avg_sales.sort_values('Weekly_Sales',ascending=True).head(10)
```

Out[35]:

Store	Weekly_Sales
33	0.140632
44	0.163842
5	0.172102
36	0.202137
38	0.208750
3	0.217935
30	0.237350
37	0.280818
16	0.281006
29	0.291940

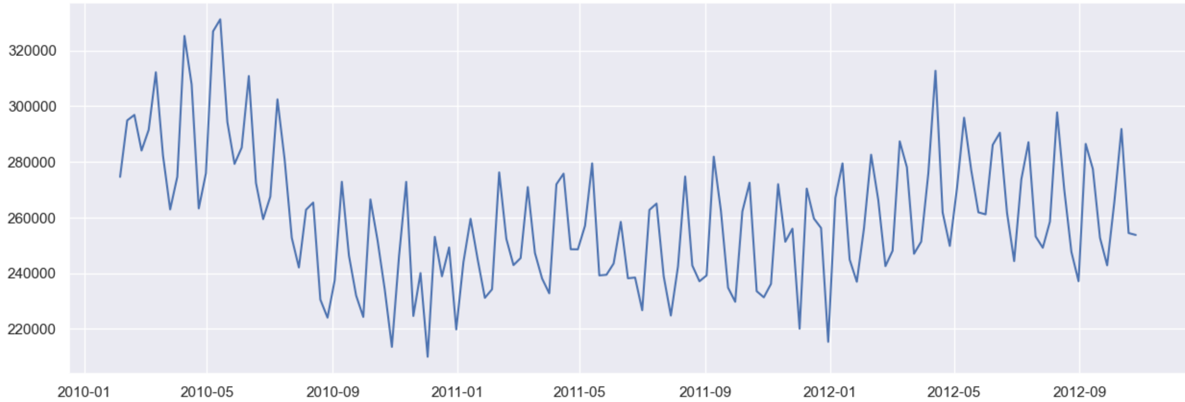
Worst performing stores are 33, 44, 5, 36, 38, 3.

In [37]:
```
Store_33 = avg_sales[avg_sales.index == 33]
Store_33
```

Out[37]:

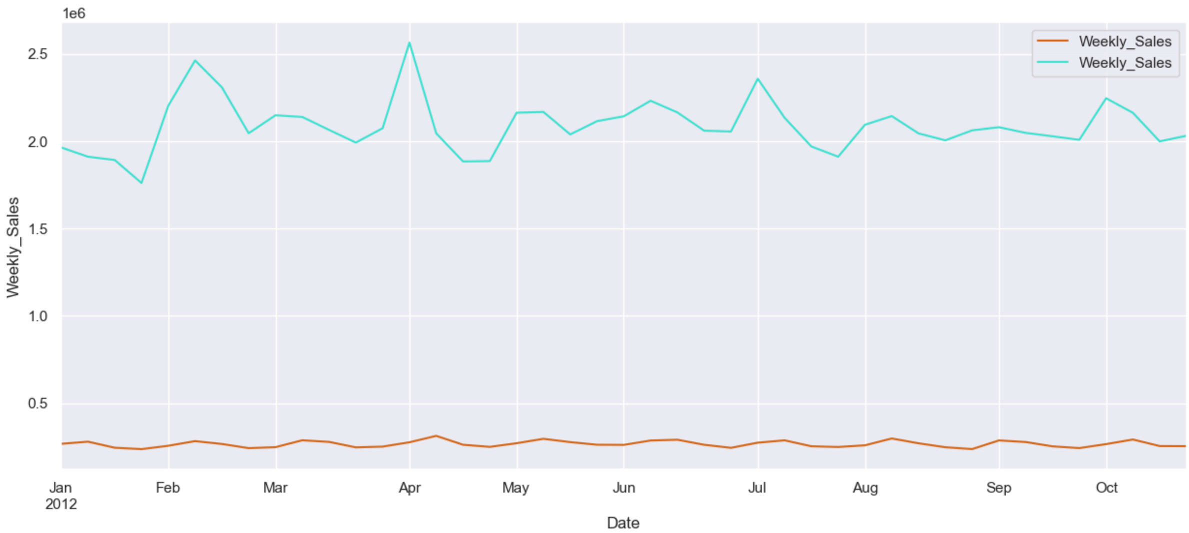
	Weekly_Sales
Store	
33	0.140632

In [38]:
```
store33=Data[Data['Store']==33]
plt.figure(figsize=(15,5))
plt.plot(store33['Date'],store33['Weekly_Sales'])
plt.show()
```



In [39]:
```
sales_20 = Data[(Data['Store'] == 20) & (Data['Date'].dt.year == 2012)]
sales_33 = Data[(Data['Store'] == 33) & (Data['Date'].dt.year == 2012)]

sales_20.set_index('Date',inplace = True)
sales_33.set_index('Date',inplace = True)

y1=sales_33.Weekly_Sales
y2=sales_20.Weekly_Sales
```

In [40]:
```
y1['2012'].plot(figsize=(15, 6), legend=True, color='chocolate')
y2['2012'].plot(figsize=(15, 6), legend=True, color='turquoise')

plt.ylabel("Weekly_Sales")
plt.show()
```



In [41]:
```
avg_sales_2=pd.DataFrame(average_store_sales)
```

In [42]:
```
avg_sales_2
```

Out[42]:

	Weekly_Sales
Store	
1	1.555264e+06
2	1.925751e+06
3	4.027044e+05
4	2.094713e+06
5	3.180118e+05
6	1.564728e+06
7	5.706173e+05
8	9.087495e+05
9	5.439806e+05
10	1.899425e+06
11	1.356383e+06
12	1.009002e+06
13	2.003620e+06
14	2.020978e+06
15	6.233125e+05
16	5.192477e+05
17	8.935814e+05
18	1.084718e+06
19	1.444999e+06
20	2.107677e+06
21	7.560691e+05
22	1.028501e+06
23	1.389864e+06
24	1.356755e+06
25	7.067215e+05
26	1.002912e+06
27	1.775216e+06
28	1.323522e+06
29	5.394514e+05
30	4.385796e+05
31	1.395901e+06
32	1.166568e+06
33	2.598617e+05
34	9.667816e+05
35	9.197250e+05

	Weekly_Sales
Store	
36	3.735120e+05
37	5.189003e+05
38	3.857317e+05
39	1.450668e+06
40	9.641280e+05
41	1.268125e+06
42	5.564039e+05
43	6.333247e+05
44	3.027489e+05
45	7.859814e+05

In [43]:
```
(avg_sales_2.loc[33][0]/avg_sales_2.loc[20][0])*100
```

Out[43]:
```
12.329294669579147
```

Lowest performing store's sales only accounts for 12% of sales done by top performing store on average.

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

In [44]:
```
!pip install prophet
```

```
Requirement already satisfied: prophet in c:\users\admin\anaconda3\lib\site-package
s (1.1.5)
Requirement already satisfied: pandas>=1.0.4 in c:\users\admin\anaconda3\lib\site-p
ackages (from prophet) (1.4.4)
Requirement already satisfied: tqdm>=4.36.1 in c:\users\admin\anaconda3\lib\site-pa
ckages (from prophet) (4.64.1)
Requirement already satisfied: holidays>=0.25 in c:\users\admin\anaconda3\lib\site-
packages (from prophet) (0.42)
Requirement already satisfied: numpy>=1.15.4 in c:\users\admin\anaconda3\lib\site-p
ackages (from prophet) (1.24.3)
Requirement already satisfied: cmdstanpy>=1.0.4 in c:\users\admin\anaconda3\lib\sit
e-packages (from prophet) (1.2.1)
Requirement already satisfied: matplotlib>=2.0.0 in c:\users\admin\anaconda3\lib\si
te-packages (from prophet) (3.5.2)
Requirement already satisfied: importlib-resources in c:\users\admin\anaconda3\lib
\site-packages (from prophet) (6.1.1)
Requirement already satisfied: stanio~=0.3.0 in c:\users\admin\anaconda3\lib\site-p
ackages (from cmdstanpy>=1.0.4->prophet) (0.3.0)
Requirement already satisfied: python-dateutil in c:\users\admin\anaconda3\lib\site
-packages (from holidays>=0.25->prophet) (2.8.2)
Requirement already satisfied: packaging>=20.0 in c:\users\admin\anaconda3\lib\site
-packages (from matplotlib>=2.0.0->prophet) (21.3)
Requirement already satisfied: pillow>=6.2.0 in c:\users\admin\anaconda3\lib\site-p
ackages (from matplotlib>=2.0.0->prophet) (9.2.0)
Requirement already satisfied: cycler>=0.10 in c:\users\admin\anaconda3\lib\site-pa
ckages (from matplotlib>=2.0.0->prophet) (0.11.0)
Requirement already satisfied: pyparsing>=2.2.1 in c:\users\admin\anaconda3\lib\sit
e-packages (from matplotlib>=2.0.0->prophet) (3.0.9)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\admin\anaconda3\lib\si
te-packages (from matplotlib>=2.0.0->prophet) (1.4.2)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\admin\anaconda3\lib\si
te-packages (from matplotlib>=2.0.0->prophet) (4.25.0)
Requirement already satisfied: pytz>=2020.1 in c:\users\admin\anaconda3\lib\site-pa
ckages (from pandas>=1.0.4->prophet) (2022.1)
Requirement already satisfied: colorama in c:\users\admin\anaconda3\lib\site-packag
es (from tqdm>=4.36.1->prophet) (0.4.5)
Requirement already satisfied: zipp>=3.1.0 in c:\users\admin\anaconda3\lib\site-pac
kages (from importlib-resources->prophet) (3.8.0)
Requirement already satisfied: six>=1.5 in c:\users\admin\anaconda3\lib\site-packag
es (from python-dateutil->holidays>=0.25->prophet) (1.16.0)
```

In [45]:

```
from plotly import graph_objs as go
from prophet import Prophet
from prophet.plot import plot_plotly
```

In [46]:

```
Data = Data.reset_index()
Data
```

Out[46]:

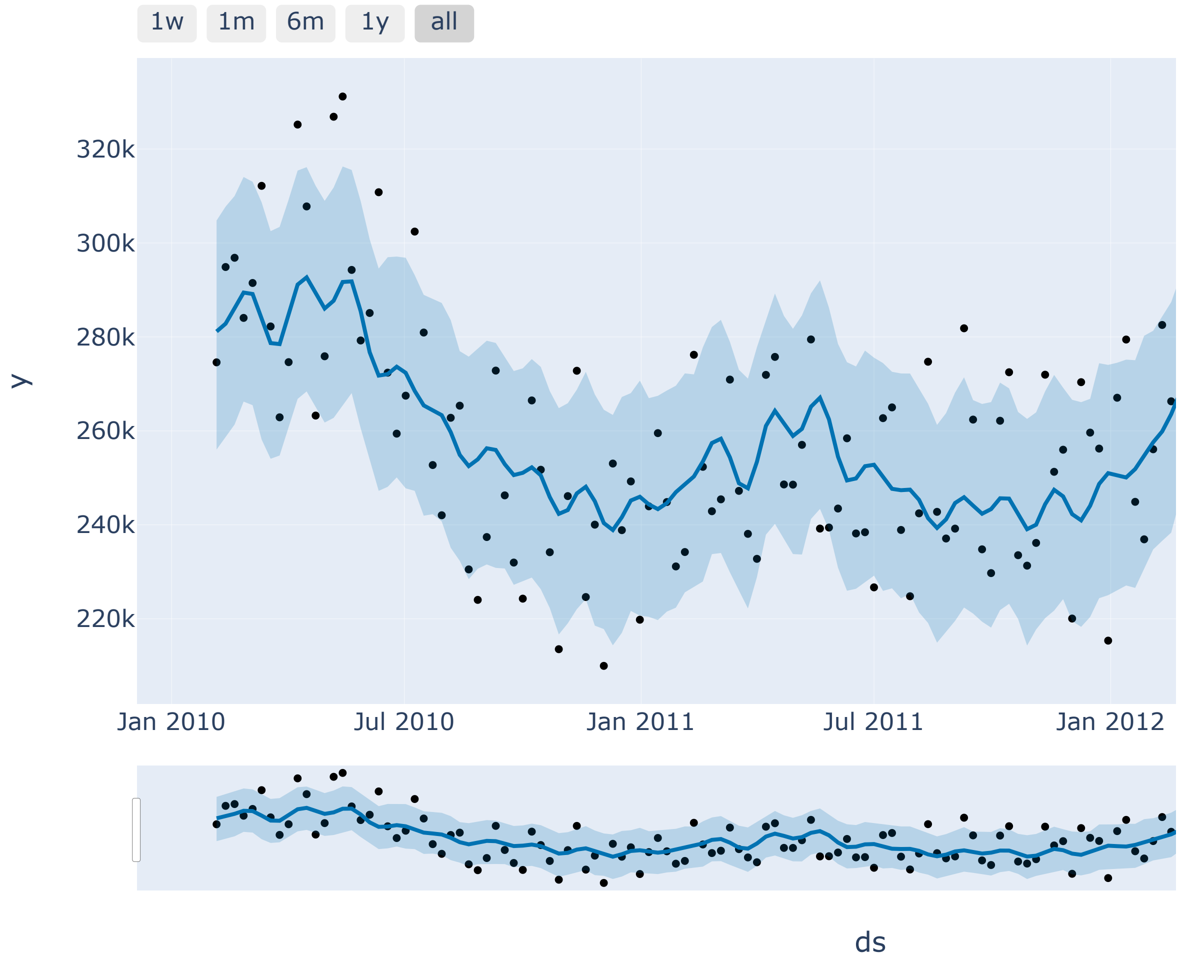
	index	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unem
0	0	1	2010-02-05	1643690.90	0	42.31	2.572	211.096358	
1	1	1	2010-02-12	1641957.44	1	38.51	2.548	211.242170	
2	2	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	
3	3	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	
4	4	1	2010-03-05	1554806.68	0	46.50	2.625	211.350143	
...	...	...	...	...	...	...	...	...	
6430	6430	45	2012-09-28	713173.95	0	64.88	3.997	192.013558	
6431	6431	45	2012-10-05	733455.07	0	64.89	3.985	192.170412	
6432	6432	45	2012-10-12	734464.36	0	54.47	4.000	192.327265	
6433	6433	45	2012-10-19	718125.53	0	56.47	3.969	192.330854	
6434	6434	45	2012-10-26	760281.43	0	58.85	3.882	192.308899	

6435 rows × 9 columns

In [47]:

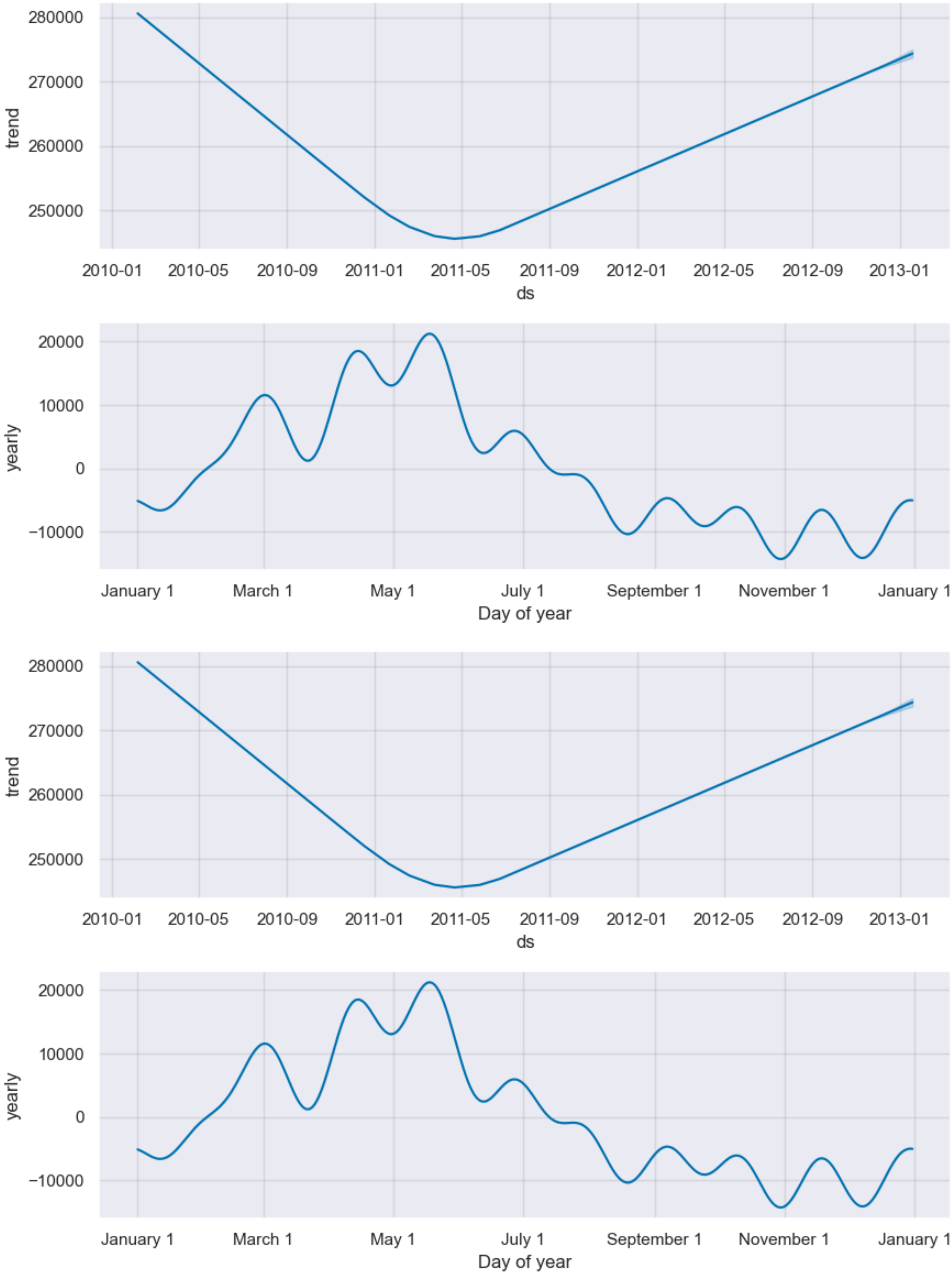
```
store_number = int(input('Enter store number:'))

df1 = Data[Data['Store']==store_number]

Data_train = df1[['Date', 'Weekly_Sales']]

Data_train = Data_train.rename(columns={'Date': 'ds', 'Weekly_Sales': 'y'})

model = Prophet()

model.fit(Data_train)

future = model.make_future_dataframe(periods=84) # 12 weeks

forecast = model.predict(future)

plot_plotly(model, forecast)
```

```
Enter store number:33
19:13:39 - cmdstanpy - INFO - Chain [1] start processing
19:13:39 - cmdstanpy - INFO - Chain [1] done processing
```



In [48]:
```
model.plot_components(forecast)
```

Out[48]:


280000
270000
260000
250000
trend
2010-01
2010-05
2010-09
2011-01
2011-05
2011-09
2012-01
2012-05
2012-09
2013-01
ds
20000
10000
0
−10000
yearly
January 1
March 1
May 1
July 1
September 1
November 1
January 1
Day of year
280000
270000
260000
250000
trend
2010-01
2010-05
2010-09
2011-01
2011-05
2011-09
2012-01
2012-05
2012-09
2013-01
ds
20000
10000
0
−10000
yearly
January 1
March 1
May 1
July 1
September 1
November 1
January 1
Day of year