Data Preparation :

Loading required libraries :

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

Importing the dataset :

In [2]:
```
walmart_data = pd.read_csv("../input/walmart-dataset-retail/Walmart_Store_sales.csv")
walmart_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

Viewing Data Information :

In [3]:
```
# Convert date to datetime format
walmart_data['Date'] =  pd.to_datetime(walmart_data['Date'])
walmart_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   datetime64[ns]
 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: datetime64[ns](1), float64(5), int64(2)
memory usage: 402.3 KB
```

Checking for missing values :

In [4]:
```
walmart_data.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
```

Splitting date column into day, month and year :

In [5]:
```
walmart_data["Day"]= pd.DatetimeIndex(walmart_data['Date']).day
walmart_data['Month'] = pd.DatetimeIndex(walmart_data['Date']).month
walmart_data['Year'] = pd.DatetimeIndex(walmart_data['Date']).year
walmart_data
```

Out[5]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Day	Month	Year
0	1	2010-05-02	1643690.90	0	42.31	2.572	211.096358	8.106	2	5	2010
1	1	2010-12-02	1641957.44	1	38.51	2.548	211.242170	8.106	2	12	2010
2	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106	19	2	2010
3	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	8.106	26	2	2010
4	1	2010-05-03	1554806.68	0	46.50	2.625	211.350143	8.106	3	5	2010
...	...	...	...	...	...	...	...	...	...	...	...
6430	45	2012-09-28	713173.95	0	64.88	3.997	192.013558	8.684	28	9	2012
6431	45	2012-05-10	733455.07	0	64.89	3.985	192.170412	8.667	10	5	2012
6432	45	2012-12-10	734464.36	0	54.47	4.000	192.327265	8.667	10	12	2012
6433	45	2012-10-19	718125.53	0	56.47	3.969	192.330854	8.667	19	10	2012
6434	45	2012-10-26	760281.43	0	58.85	3.882	192.308899	8.667	26	10	2012

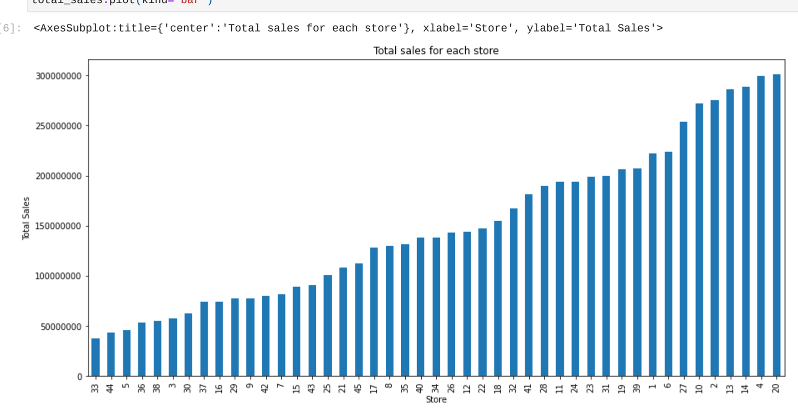
6435 rows × 11 columns

Analysis:

1) Which store has maximum sales ?

In [6]:
```
total_sales= walmart_data.groupby('Store')['Weekly_Sales'].sum().sort_values()
total_sales_array = np.array(total_sales)
plt.figure(figsize=(15,7))
plt.xticks(rotation=0)
plt.ticklabel_format(useOffset=False, style='plain', axis='y')
plt.title('Total sales for each store')
plt.xlabel('Store')
plt.ylabel('Total Sales')
total_sales.plot(kind='bar')
```

Out[6]:
```
<AxesSubplot:title={'center':'Total sales for each store'}, xlabel='Store', ylabel='Total Sales'>
```



Clearly, from the above graph, it is visible that the store which has maximum sales is store number 20 and the store which has minimum sales is the store number 33.

---

2) Which store has maximum standard deviation? i.e. the sales vary a lot. Also, find out the coefficient of mean to standard deviation.

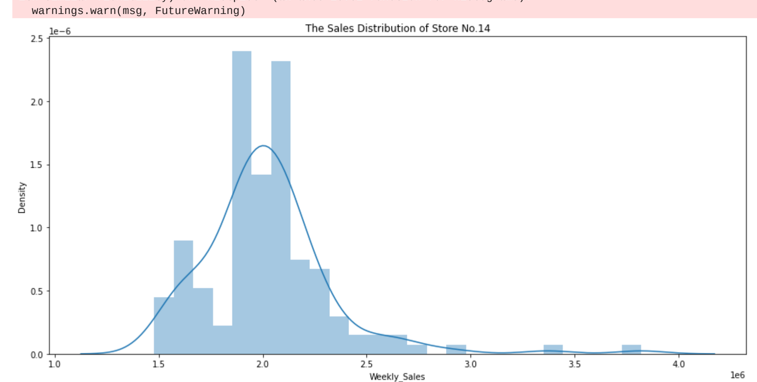
In [7]:
```
walmart_data_std = pd.DataFrame(walmart_data.groupby('Store')['Weekly_Sales'].std().sort_values(ascending=False))
walmart_data_std.head(1).index[0] , walmart_data_std.head(1).Weekly_Sales[walmart_data_std.head(1).index[0]]
```

Out[7]:
```
(14, 317569.9494755081)
```

Thus, the store which has maximum standard deviation is store number 14.

In [8]:
```
# Extracting the sales data for store number 14 and plotting its distribution
plt.figure(figsize=(15,7))
sns.distplot(walmart_data[walmart_data['Store'] == walmart_data_std.head(1).index[0]]['Weekly_Sales'])
plt.title('The Sales Distribution of Store No.'+ str(walmart_data_std.head(1).index[0]))
import warnings
warnings.filterwarnings('ignore')
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function w
ith similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



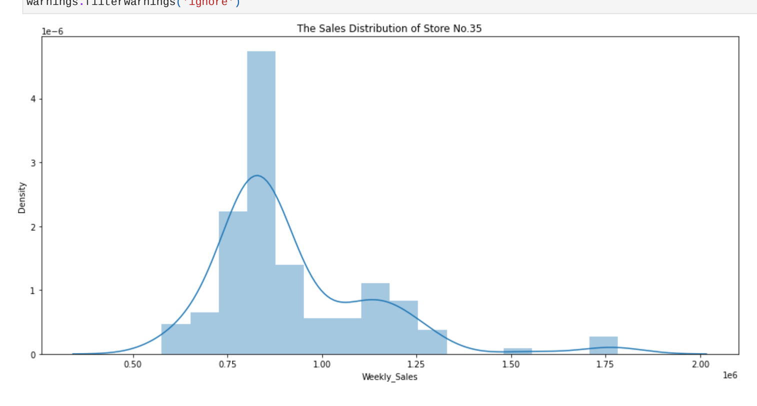
In [9]:
```
#Calculating the coefficient of mean to standard deviation
coef = pd.DataFrame(walmart_data.groupby('Store')['Weekly_Sales'].std() / walmart_data.groupby('Store')['Weekly_Sales'].mean())
coef = coef.rename(columns={'Weekly_Sales':'Coefficient of mean to standard deviation'})
coef_max = coef.sort_values(by='Coefficient of mean to standard deviation',ascending=False)
coef_max.head(7)
```

Out[9]:

Store	Coefficient of mean to standard deviation
35	0.229681
7	0.197305
15	0.193384
29	0.183742
23	0.179721
21	0.170292
45	0.165613

Thus, the store which has maximum coefficient of mean to standard deviation is store number 35.

In [10]:
```
# Distribution of store 35 has maximum coefficient of mean to standard deviation
plt.figure(figsize=(15,7))
sns.distplot(walmart_data[walmart_data['Store'] == coef_max.head(1).index[0]]['Weekly_Sales'])
plt.title('The Sales Distribution of Store No.'+str(coef_max.head(1).index[0]))
import warnings
warnings.filterwarnings('ignore')
```

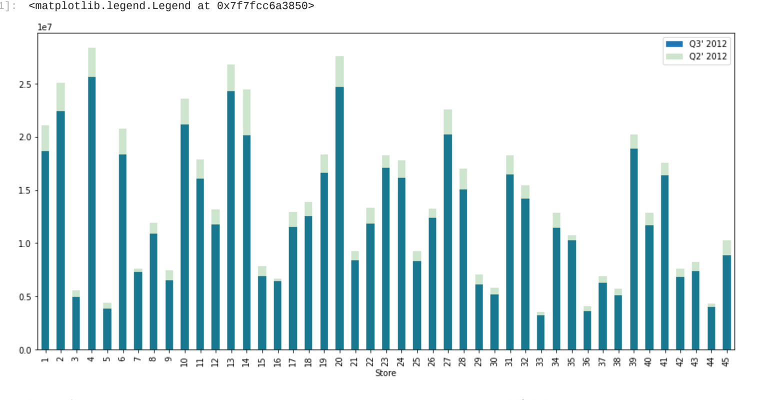


---

3) Which store/s has good quarterly growth rate in Q3'2012 ?

In [11]:
```
# Sales for second and third quarter in 2012
quarter_2_sales = walmart_data[(walmart_data['Date'] >= '2012-04-01') & (walmart_data['Date'] <= '2012-06-30')].groupby('Store')['Weekly_Sales'].sum()
quarter_3_sales= walmart_data[(walmart_data['Date'] >= '2012-07-01') & (walmart_data['Date'] <= '2012-09-30')].groupby('Store')['Weekly_Sales'].sum()

# Plotting the difference between sales for second and third quarterly
plt.figure(figsize=(15,7))
quarter_2_sales.plot(ax=quarter_3_sales.plot(kind ='bar'),kind='bar',color='g',alpha=0.2,legend=True)
plt.legend(["Q3' 2012", "Q2' 2012"])
```

Out[11]:
```
<matplotlib.legend.Legend at 0x7f7fcc6a3850>
```



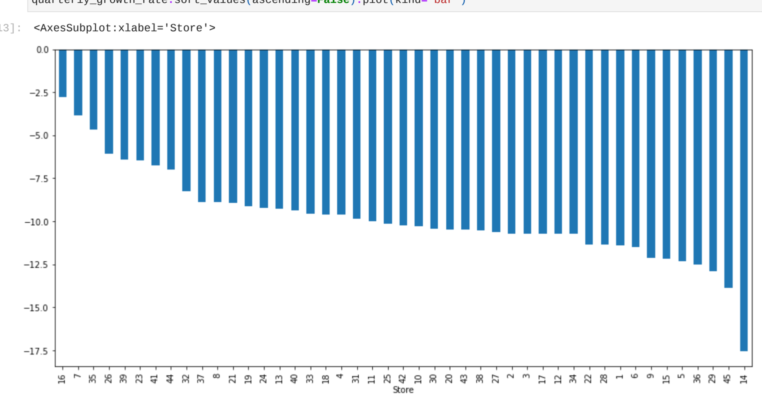
Clearly, from the above graph, it is evident that the store which has good quarterly sales in Q3'2012 is store no. 4.

In [12]:
```
#Calculating Growth rate in Q3'2012
quarter_2_sales= walmart_data[(walmart_data['Date'] >= '2012-04-01') & (walmart_data['Date'] <= '2012-06-30')].groupby('Store')['Weekly_Sales'].sum()
quarter_3_sales= walmart_data[(walmart_data['Date'] >= '2012-07-01') & (walmart_data['Date'] <= '2012-09-30')].groupby('Store')['Weekly_Sales'].sum()
quarterly_growth_rate = ((quarter_3_sales - quarter_2_sales )/quarter_2_sales)*100
quarterly_growth_rate.sort_values(ascending=False).head()
```

Out[12]:
```
Store
16   -2.789294
7    -3.824738
35   -4.663086
26   -6.057624
39   -6.396875
Name: Weekly_Sales, dtype: float64
```

In [13]:
```
plt.figure(figsize=(15,7))
quarterly_growth_rate.sort_values(ascending=False).plot(kind='bar')
```

Out[13]:
```
<AxesSubplot:xlabel='Store'>
```



Here, there is no store which has performed better in the 3rd quarter as compared to the 2nd quarter.

---

4) Some holidays have a negative impact on sales. Find out holidays which have higher sales than the mean sales in non-holiday season for all stores together.

Holiday Events:

- Super Bowl: 12-Feb-10, 11-Feb-11, 10-Feb-12, 8-Feb-13
- Labour Day: 10-Sep-10, 9-Sep-11, 7-Sep-12, 6-Sep-13
- Thanksgiving: 26-Nov-10, 25-Nov-11, 23-Nov-12, 29-Nov-13
- Christmas: 31-Dec-10, 30-Dec-11, 28-Dec-12, 27-Dec-13

In [14]:
```
#Defining holiday dates
Super_Bowl =['12-2-2010', '11-2-2011', '10-2-2012']
Labour_Day =  ['10-9-2010', '9-9-2011', '7-9-2012']
Thanksgiving =  ['26-11-2010', '25-11-2011', '23-11-2012']
Christmas = ['31-12-2010', '30-12-2011', '28-12-2012']
```

In [15]:
```
#Calculating mean sales on holidays :
Super_Bowl_Sales = (pd.DataFrame(walmart_data.loc[walmart_data.Date.isin(Super_Bowl)]))['Weekly_Sales'].mean()
Labour_Day_Sales = (pd.DataFrame(walmart_data.loc[walmart_data.Date.isin(Labour_Day)]))['Weekly_Sales'].mean()
Thanksgiving_Sales = (pd.DataFrame(walmart_data.loc[walmart_data.Date.isin(Thanksgiving)]))['Weekly_Sales'].mean()
Christmas_Sales = (pd.DataFrame(walmart_data.loc[walmart_data.Date.isin(Christmas)]))['Weekly_Sales'].mean()
Super_Bowl_Sales,Labour_Day_Sales,Thanksgiving_Sales,Christmas_Sales
```

Out[15]:
```
(1079127.9877037033, 1042427.2939259257, 1471273.427777778, 960833.1115555551)
```

In [16]:
```
#Calculating mean sales on non-holidays :
Non_Holiday_Sales = walmart_data[walmart_data['Holiday_Flag'] == 0 ]['Weekly_Sales'].mean()
Non_Holiday_Sales
```

Out[16]:
```
1041256.3802088564
```

In [17]:
```
Mean_Sales = {'Super_Bowl_Sales' : Super_Bowl_Sales,
              'Labour_Day_Sales': Labour_Day_Sales,
              'Thanksgiving_Sales':Thanksgiving_Sales,
              'Christmas_Sales': Christmas_Sales,
              'Non_Holiday_Sales': Non_Holiday_Sales}
Mean_Sales
```

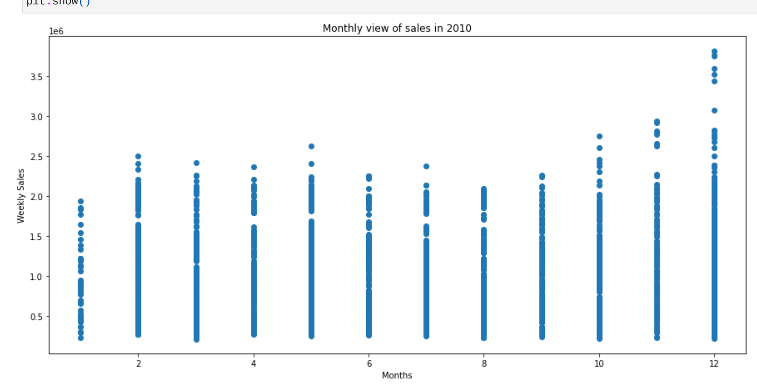
Out[17]:
```
{'Super_Bowl_Sales': 1079127.9877037033,
 'Labour_Day_Sales': 1042427.2939259257,
 'Thanksgiving_Sales': 1471273.427777778,
 'Christmas_Sales': 960833.1115555551,
 'Non_Holiday_Sales': 1041256.3802088564}
```

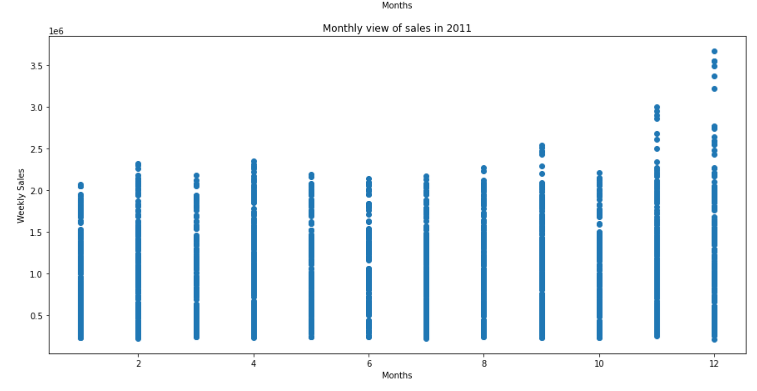
Clearly, Thanksgiving has higher sales than the mean sales on non-holidays.

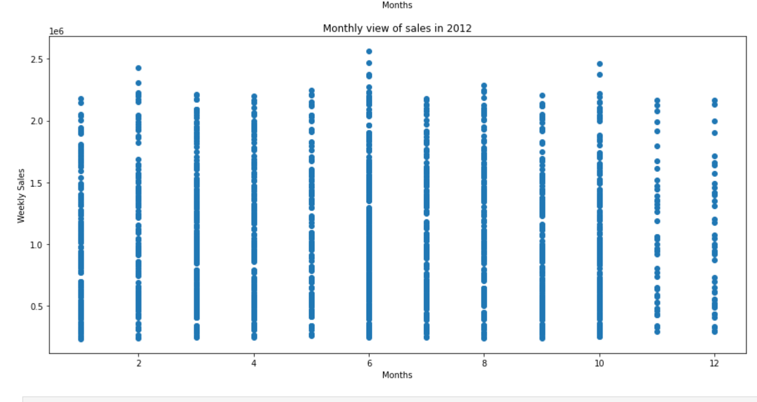
---

5) Provide a monthly and semester view of sales in units and give insights.

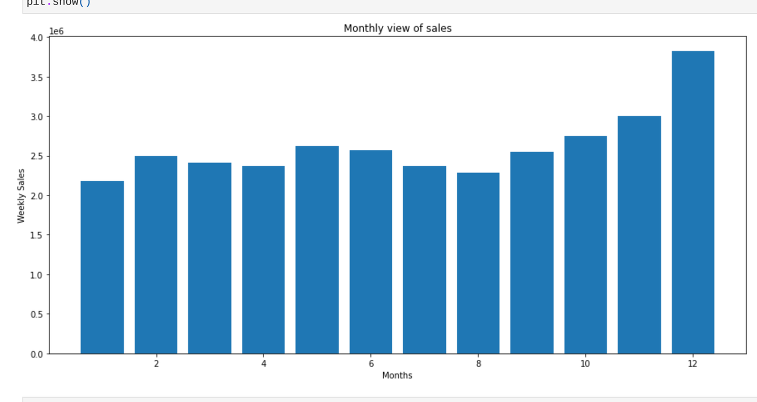
In [18]:
```
#Year-wise Monthly Sales

plt.figure(figsize=(15,7))
plt.scatter(walmart_data[walmart_data.Year==2010]["Month"],walmart_data[walmart_data.Year==2010]["Weekly_Sales"])
plt.xlabel("Months")
plt.ylabel("Weekly Sales")
plt.title("Monthly view of sales in 2010")
plt.show()

plt.figure(figsize=(15,7))
plt.scatter(walmart_data[walmart_data.Year==2011]["Month"],walmart_data[walmart_data.Year==2011]["Weekly_Sales"])
plt.xlabel("Months")
plt.ylabel("Weekly Sales")
plt.title("Monthly view of sales in 2011")
plt.show()

plt.figure(figsize=(15,7))
plt.scatter(walmart_data[walmart_data.Year==2012]["Month"],walmart_data[walmart_data.Year==2012]["Weekly_Sales"])
plt.xlabel("Months")
plt.ylabel("Weekly Sales")
plt.title("Monthly view of sales in 2012")
plt.show()
```





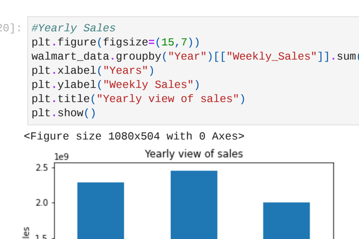


In [19]:
```
#Overall Monthly Sales
plt.figure(figsize=(15,7))
plt.bar(walmart_data["Month"],walmart_data["Weekly_Sales"])
plt.xlabel("Months")
plt.ylabel("Weekly Sales")
plt.title("Monthly view of sales")
plt.show()
```



In [20]:
```
#Yearly Sales
plt.figure(figsize=(15,7))
walmart_data.groupby("Year")[["Weekly_Sales"]].sum().plot(kind='bar',legend=False)
plt.xlabel("Years")
plt.ylabel("Weekly Sales")
plt.title("Yearly view of sales")
plt.show()
```

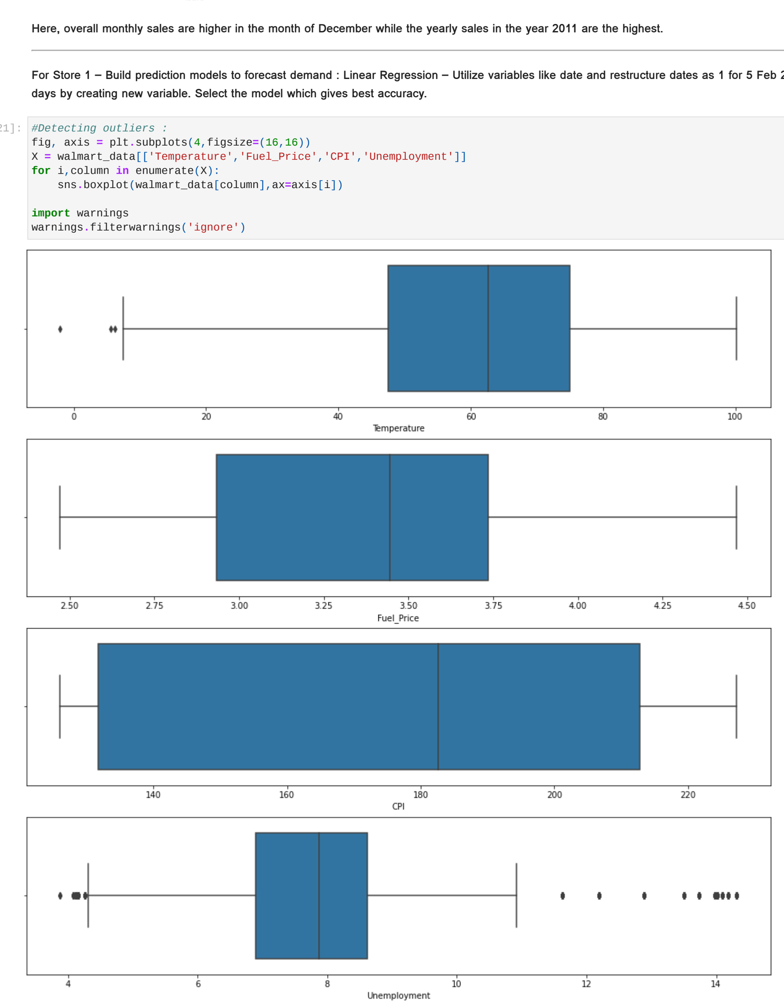
```
<Figure size 1080x504 with 0 Axes>
```



Here, overall monthly sales are higher in the month of December while the yearly sales in the year 2011 are the highest.

For Store 1 – Build prediction models to forecast demand : Linear Regression – Utilize variables like date and restructure dates as 1 for 5 Feb 2010 (starting from the earliest date in order). Hypothesize if CPI, unemployment, and fuel price have any impact on sales. Change dates into days by creating new variable. Select the model which gives best accuracy.

In [21]:
```
#Detecting outliers :
fig, axis = plt.subplots(4,figsize=(16,16))
X = walmart_data[['Temperature','Fuel_Price','CPI','Unemployment']]
for i,column in enumerate(X):
    sns.boxplot(walmart_data[column],ax=axis[i])

import warnings
warnings.filterwarnings('ignore')
```



In [22]:
```
# Dropping outliers
walmart_data_clean = walmart_data[(walmart_data['Unemployment']<10) & (walmart_data['Unemployment']>4.5) & (walmart_data['Temperature']>10)]
walmart_data_clean
```

Out[22]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Day	Month	Year
0	1	2010-05-02	1643690.90	0	42.31	2.572	211.096358	8.106	2	5	2010
1	1	2010-12-02	1641957.44	1	38.51	2.548	211.242170	8.106	2	12	2010
2	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106	19	2	2010
3	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	8.106	26	2	2010
4	1	2010-05-03	1554806.68	0	46.50	2.625	211.350143	8.106	3	5	2010
...	...	...	...	...	...	...	...	...	...	...	...
6430	45	2012-09-28	713173.95	0	64.88	3.997	192.013558	8.684	28	9	2012
6431	45	2012-05-10	733455.07	0	64.89	3.985	192.170412	8.667	10	5	2012
6432	45	2012-12-10	734464.36	0	54.47	4.000	192.327265	8.667	10	12	2012
6433	45	2012-10-19	718125.53	0	56.47	3.969	192.330854	8.667	19	10	2012
6434	45	2012-10-26	760281.43	0	58.85	3.882	192.308899	8.667	26	10	2012

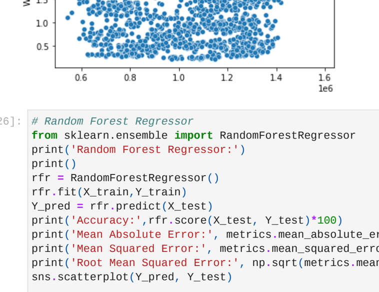
5658 rows × 11 columns

In [23]:
```
#Checking data for outliers
fig, axis = plt.subplots(4,figsize=(16,16))
X = walmart_data_clean[['Temperature','Fuel_Price','CPI','Unemployment']]
for i,column in enumerate(X):
    sns.boxplot(walmart_data_clean[column], ax=axis[i])

import warnings
warnings.filterwarnings('ignore')
```

In [24]:
```
# Linear Regression :
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.linear_model import LinearRegression
X = walmart_data_clean[['Store','Fuel_Price','CPI','Unemployment','Day','Month','Year']]
Y = walmart_data_clean['Weekly_Sales']
X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size=0.2)
```

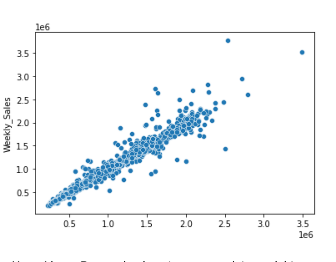
In [25]:
```
print('Linear Regression:')
print()
reg = LinearRegression()
reg.fit(X_train, Y_train)
Y_pred = reg.predict(X_test)
print('Accuracy:',reg.score(X_train, Y_train)*100)
print('Mean Absolute Error:', metrics.mean_absolute_error(Y_test, Y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(Y_test, Y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(Y_test, Y_pred)))
sns.scatterplot(Y_pred, Y_test)

import warnings
warnings.filterwarnings('ignore')
```

```
Linear Regression:

Accuracy: 13.927388936546759
Mean Absolute Error: 459395.4879316832
Mean Squared Error: 302921657729.9133
Root Mean Squared Error: 550383.1917218342
```



In [26]:
```
# Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor
print('Random Forest Regressor:')
print()
rfr = RandomForestRegressor()
rfr.fit(X_train,Y_train)
Y_pred = rfr.predict(X_test)
print('Accuracy:',rfr.score(X_test, Y_test)*100)
print('Mean Absolute Error:', metrics.mean_absolute_error(Y_test, Y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(Y_test, Y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(Y_test, Y_pred)))
sns.scatterplot(Y_pred, Y_test)


import warnings
warnings.filterwarnings('ignore')
```

```
Random Forest Regressor:

Accuracy: 94.58778579379741
Mean Absolute Error: 69566.43963674913
Mean Squared Error: 17901689306.26622
Root Mean Squared Error: 133797.19468758014
```



Here, Linear Regression is not an appropriate model to use which is clear from it's low accuracy. However, Random Forest Regression gives accuracy of over 95% , so, it is the best model to forecast demand.