Project 5 - Retail Analysis with Walmart Data

December 20, 2022

[170]:
```
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
```

[171]:
```
df=pd.read_csv('Walmart_Store_sales.csv')
```

[172]:
```
df.head()
```

[172]:
```
   Store        Date  Weekly_Sales  Holiday_Flag  Temperature  Fuel_Price  \
0      1  05-02-2010    1643690.90             0        42.31       2.572
1      1  12-02-2010    1641957.44             1        38.51       2.548
2      1  19-02-2010    1611968.17             0        39.93       2.514
3      1  26-02-2010    1409727.59             0        46.63       2.561
4      1  05-03-2010    1554806.68             0        46.50       2.625

          CPI  Unemployment
0  211.096358         8.106
1  211.242170         8.106
2  211.289143         8.106
3  211.319643         8.106
4  211.350143         8.106
```

[173]:
```
df['Date'] =  pd.to_datetime(df['Date'])
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   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
```

[174]:
```
df.isnull().sum()
```

[174]:
```
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
dtype: int64
```

[175]:
```
df["Day"]= pd.DatetimeIndex(df['Date']).day
df['Month'] = pd.DatetimeIndex(df['Date']).month
df['Year'] = pd.DatetimeIndex(df['Date']).year
df
```

[175]:
```
      Store       Date  Weekly_Sales  Holiday_Flag  Temperature  Fuel_Price  \
0         1 2010-05-02    1643690.90             0        42.31       2.572
1         1 2010-12-02    1641957.44             1        38.51       2.548
2         1 2010-02-19    1611968.17             0        39.93       2.514
3         1 2010-02-26    1409727.59             0        46.63       2.561
4         1 2010-05-03    1554806.68             0        46.50       2.625
…       …          …           …           …            …          …
6430     45 2012-09-28     713173.95             0        64.88       3.997
6431     45 2012-05-10     733455.07             0        64.89       3.985
6432     45 2012-12-10     734464.36             0        54.47       4.000
6433     45 2012-10-19     718125.53             0        56.47       3.969
6434     45 2012-10-26     760281.43             0        58.85       3.882

             CPI  Unemployment  Day  Month  Year
0     211.096358         8.106    2      5  2010
1     211.242170         8.106    2     12  2010
2     211.289143         8.106   19      2  2010
3     211.319643         8.106   26      2  2010
4     211.350143         8.106    3      5  2010
…          …               …   …     …    …
6430  192.013558         8.684   28      9  2012
6431  192.170412         8.667   10      5  2012
6432  192.327265         8.667   10     12  2012
```

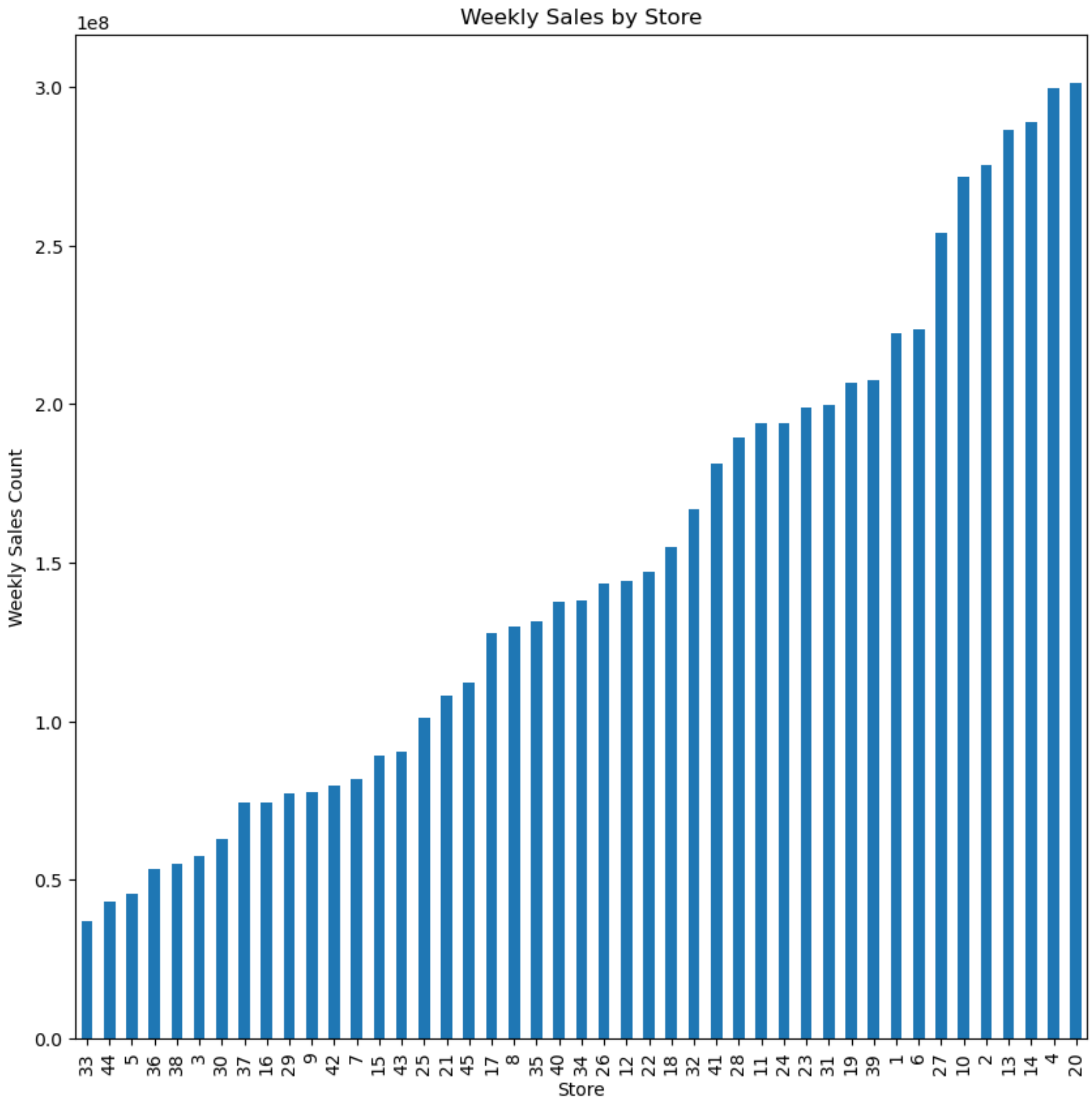
```
6433  192.330854         8.667   19      10  2012
6434  192.308899         8.667   26      10  2012

[6435 rows x 11 columns]
```

[176]:
```
df.shape
```

[176]:
```
(6435, 11)
```

1 1. Which store has maximum sales

[177]:
```
maximumsales = df.groupby('Store')['Weekly_Sales'].sum().sort_values()
plt.figure(figsize=(10,10))
maximumsales.plot(kind='bar')
plt.xlabel('Store')
plt.ylabel('Weekly Sales Count')
plt.title('Weekly Sales by Store')
plt.show()
```



[178]:
```
df.groupby('Store')['Weekly_Sales'].sum().sort_values(ascending=False).head(1)
```

[178]:
```
Store
20    3.013978e+08
Name: Weekly_Sales, dtype: float64
```

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

[179]:
```
maxstd = pd.DataFrame(df.groupby('Store')['Weekly_Sales'].std().
    ↪sort_values(ascending=False).head(1))
```

[180]:
```
maxstd
```

[180]:

	Weekly_Sales
Store	
14	317569.949476

[181]:
```
co_mean = pd.DataFrame(df.groupby('Store')['Weekly_Sales'].std() / df.
    ↪groupby('Store')['Weekly_Sales'].mean())
```

[182]:
```
co_mean = co_mean.rename(columns={'Weekly_Sales':'Coefficient of mean'})
co_mean.sort_values(by='Coefficient of mean',ascending=False)
```

[182]:

	Coefficient of mean
Store	
35	0.229681
7	0.197305
15	0.193384
29	0.183742
23	0.179721
21	0.170292
45	0.165613
16	0.165181
18	0.162845
36	0.162579
25	0.159860
10	0.159133
14	0.157137
22	0.156783
39	0.149908
41	0.148177
12	0.137925
28	0.137330
6	0.135823
27	0.135155
19	0.132680
13	0.132514
20	0.130903
4	0.127083
9	0.126895
17	0.125521

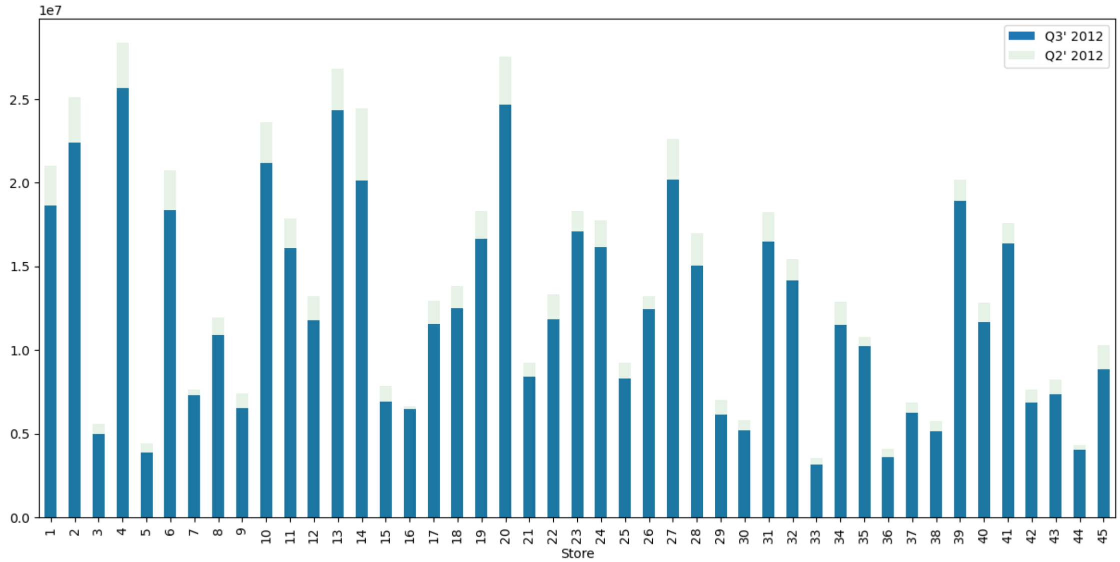
```
24                  0.123637
40                  0.123430
2                   0.123424
11                  0.122262
5                   0.118668
32                  0.118310
8                   0.116953
3                   0.115021
38                  0.110875
26                  0.110111
34                  0.108225
1                   0.100292
33                  0.092868
42                  0.090335
31                  0.090161
44                  0.081793
43                  0.064104
30                  0.052008
37                  0.042084
```

3 3. Which stores has good quarterly growth rate in Q3'2012

[183]:
```
Q2 = df[(df['Date'] >= '2012-04-01') & (df['Date'] <= '2012-06-30')].
 ↪groupby('Store')['Weekly_Sales'].sum()
Q3 = df[(df['Date'] >= '2012-07-01') & (df['Date'] <= '2012-09-30')].
 ↪groupby('Store')['Weekly_Sales'].sum()
```

[184]:
```
plt.figure(figsize=(15,7))
Q2.plot(x=Q3.plot(kind ='bar'),kind='bar',color='g',alpha=0.1,legend=True)
plt.legend(["Q3' 2012", "Q2' 2012"])
```

[184]: <matplotlib.legend.Legend at 0x2374f99e700>



3.0.1 From the above graph, Store 4 has good quarterly growth rate in Q3'2012

4 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

4.0.1 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

[185]:
```
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']
```

[186]:
```
Super_Bowl_Sales = (pd.DataFrame(df.loc[df.Date.
↪isin(Super_Bowl)]))['Weekly_Sales'].mean()
Labour_Day_Sales = (pd.DataFrame(df.loc[df.Date.
↪isin(Labour_Day)]))['Weekly_Sales'].mean()
Thanksgiving_Sales = (pd.DataFrame(df.loc[df.Date.
↪isin(Thanksgiving)]))['Weekly_Sales'].mean()
```

```
Christmas_Sales = (pd.DataFrame(df.loc[df.Date.
 ↪isin(Christmas)]))['Weekly_Sales'].mean()
```

[187]:
```
Super_Bowl_Sales,Labour_Day_Sales,Thanksgiving_Sales,Christmas_Sales
```

[187]: (1079127.9877037033, 1042427.2939259257, 1471273.427777778, 960833.1115555551)

[188]:
```
Non_Holiday_Sales = df[df['Holiday_Flag'] == 0 ]['Weekly_Sales'].mean()
Non_Holiday_Sales
```

[188]: 1041256.3802088564

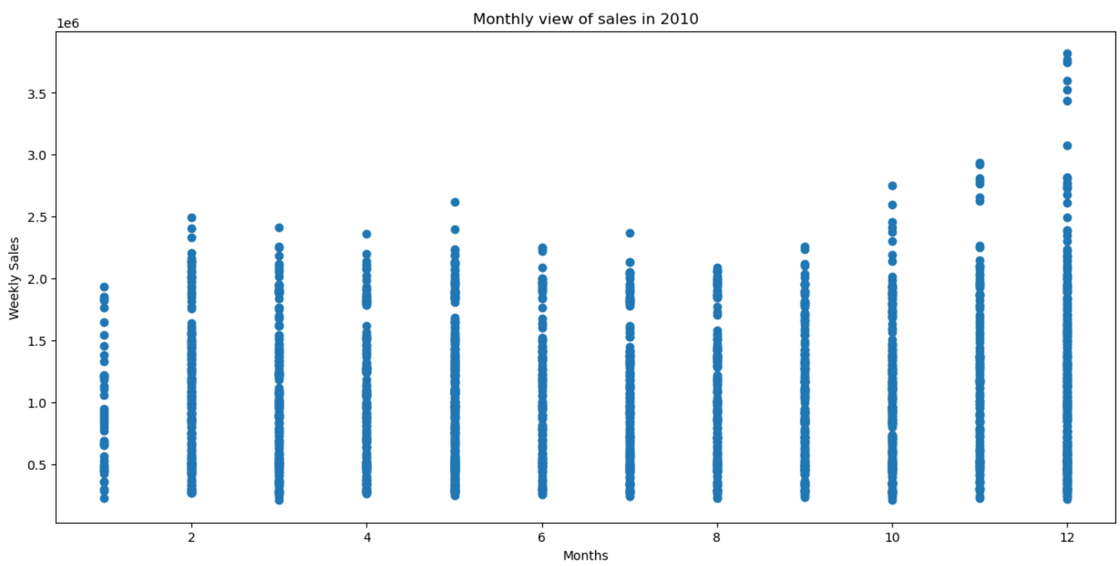
4.0.2 Thank Giving has the highest sales

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

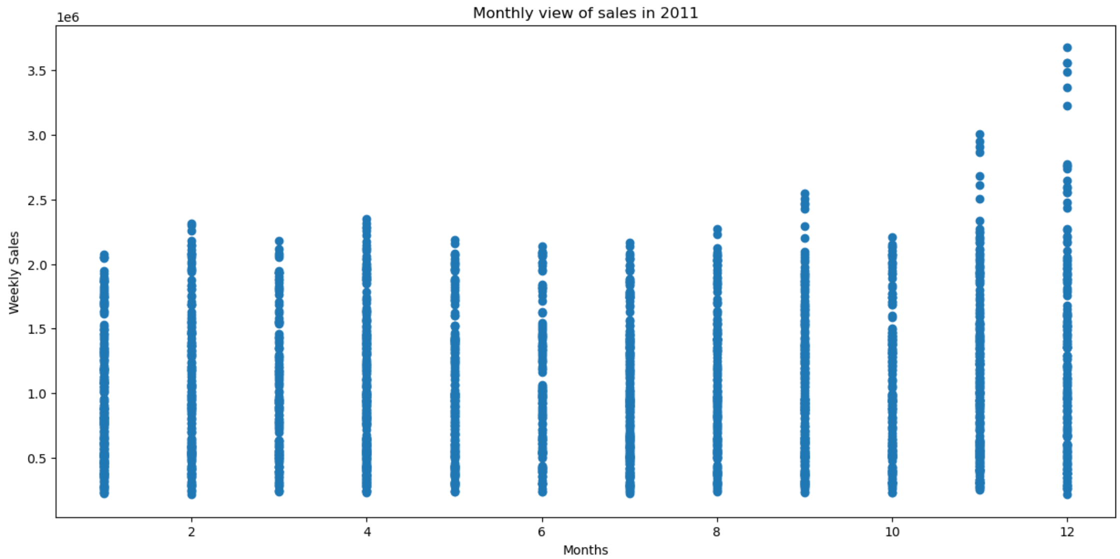
[189]:
```
df['Year'].value_counts()
```

[189]:
```
2011    2340
2010    2160
2012    1935
Name: Year, dtype: int64
```

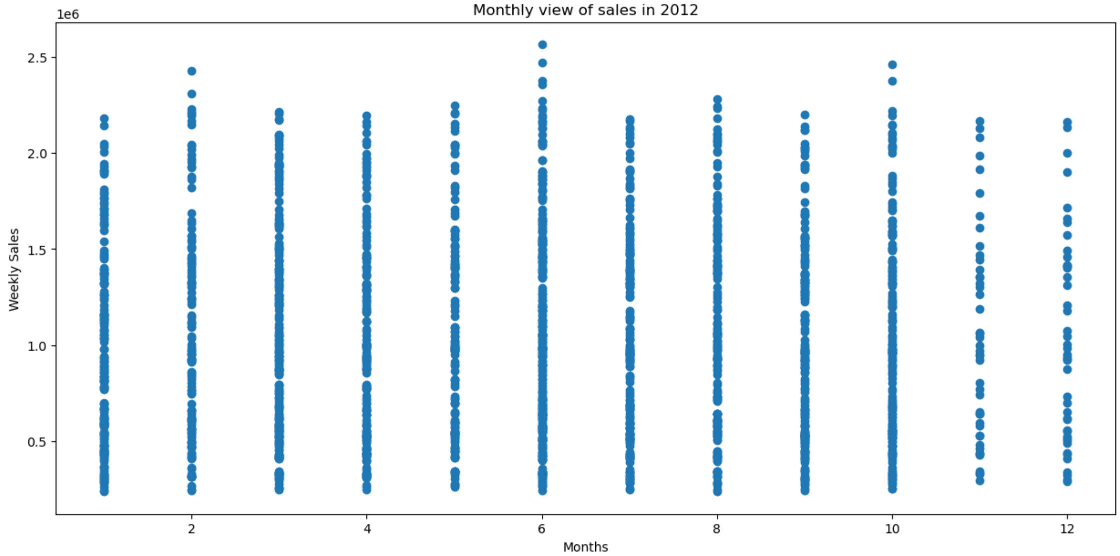
[190]:
```
plt.figure(figsize=(15,7))
plt.scatter(df[df.Year==2010]["Month"],df[df.Year==2010]["Weekly_Sales"])
plt.xlabel("Months")
plt.ylabel("Weekly Sales")
plt.title("Monthly view of sales in 2010")
plt.show()
```



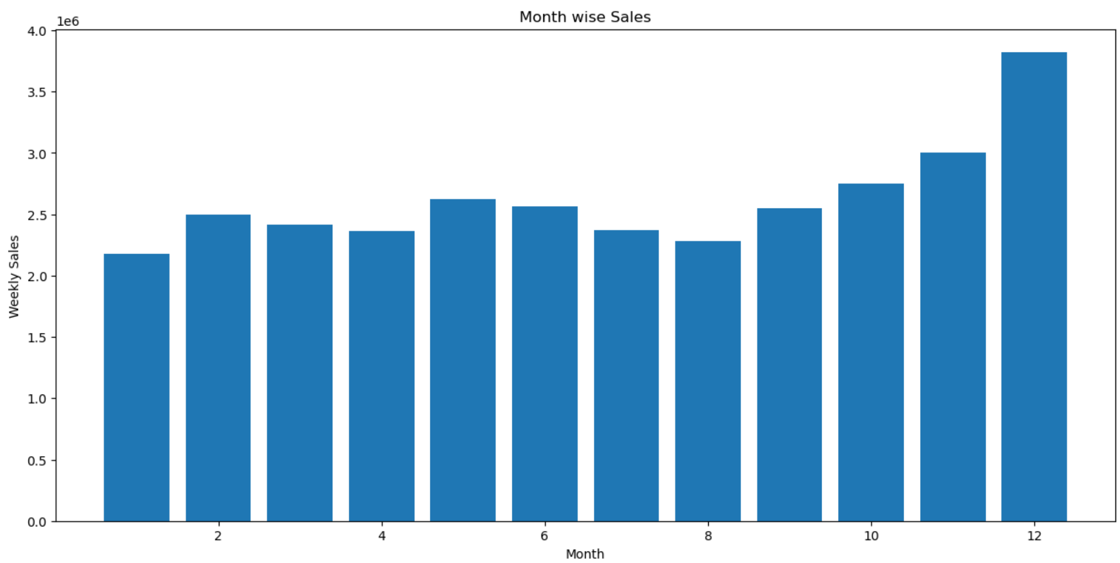
[191]:
```
plt.figure(figsize=(15,7))
plt.scatter(df[df.Year==2011]["Month"],df[df.Year==2011]["Weekly_Sales"])
plt.xlabel("Months")
plt.ylabel("Weekly Sales")
plt.title("Monthly view of sales in 2011")
plt.show()
```



[192]:
```
plt.figure(figsize=(15,7))
plt.scatter(df[df.Year==2012]["Month"],df[df.Year==2012]["Weekly_Sales"])
plt.xlabel("Months")
plt.ylabel("Weekly Sales")
plt.title("Monthly view of sales in 2012")
plt.show()
```

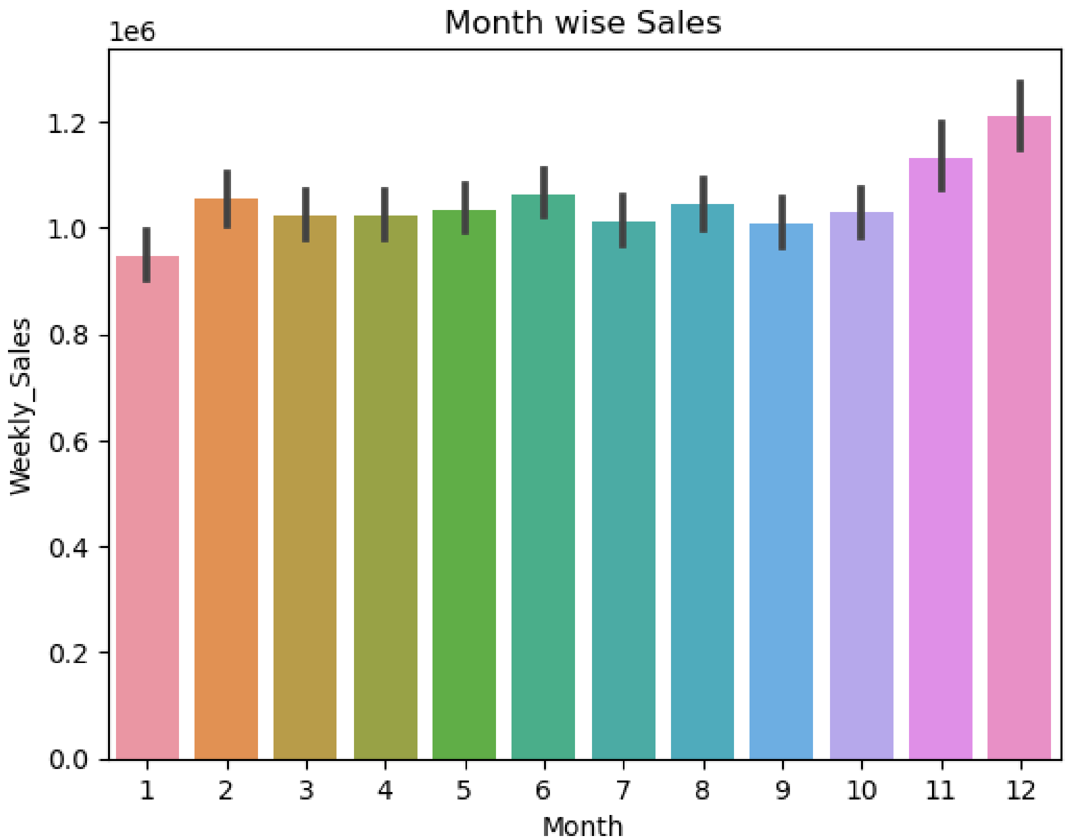


[193]:
```
plt.figure(figsize=(15,7))
plt.bar(df['Month'],df['Weekly_Sales'])
plt.xlabel('Month')
plt.ylabel('Weekly Sales')
plt.title('Month wise Sales')
plt.show()
```



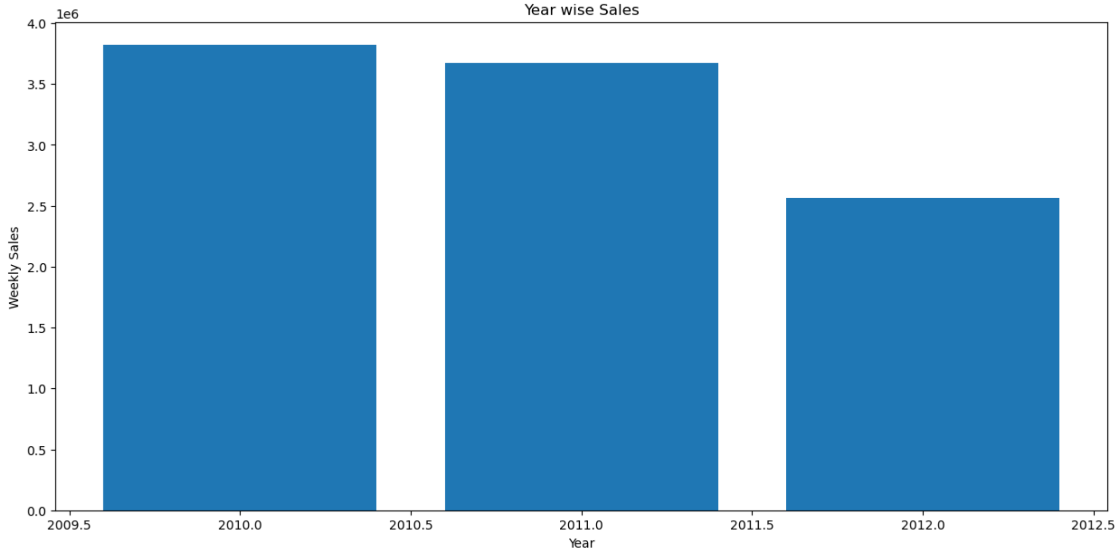
[194]:
```
sns.barplot(x=df['Month'],y=df['Weekly_Sales'])
plt.title('Month wise Sales')
```

```
plt.show()
```

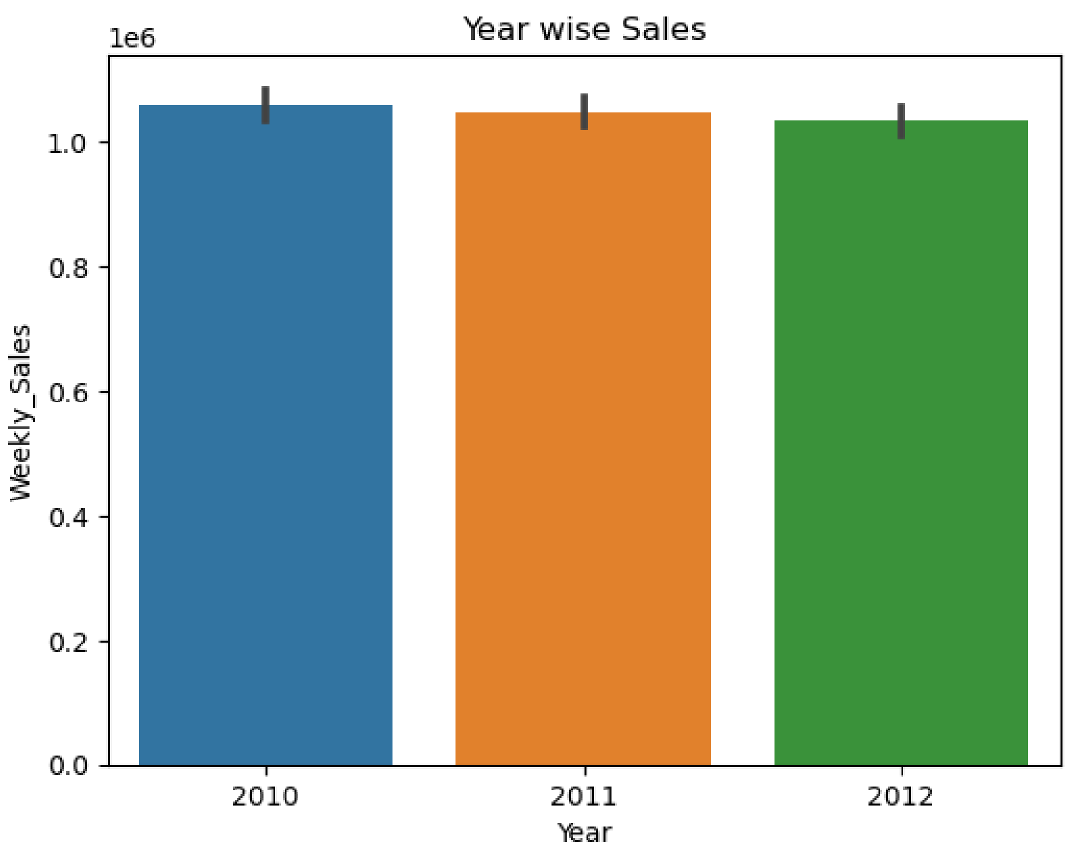


[195]:

```
plt.figure(figsize=(15,7))
plt.bar(df['Year'],df['Weekly_Sales'])
plt.xlabel('Year')
plt.ylabel('Weekly Sales')
plt.title('Year wise Sales')
plt.show()
```



[196]:
```
sns.barplot(x=df['Year'],y=df['Weekly_Sales'])
plt.title('Year wise Sales')
plt.show()
```



6 5. For Store 1 – Build prediction models to forecast demand

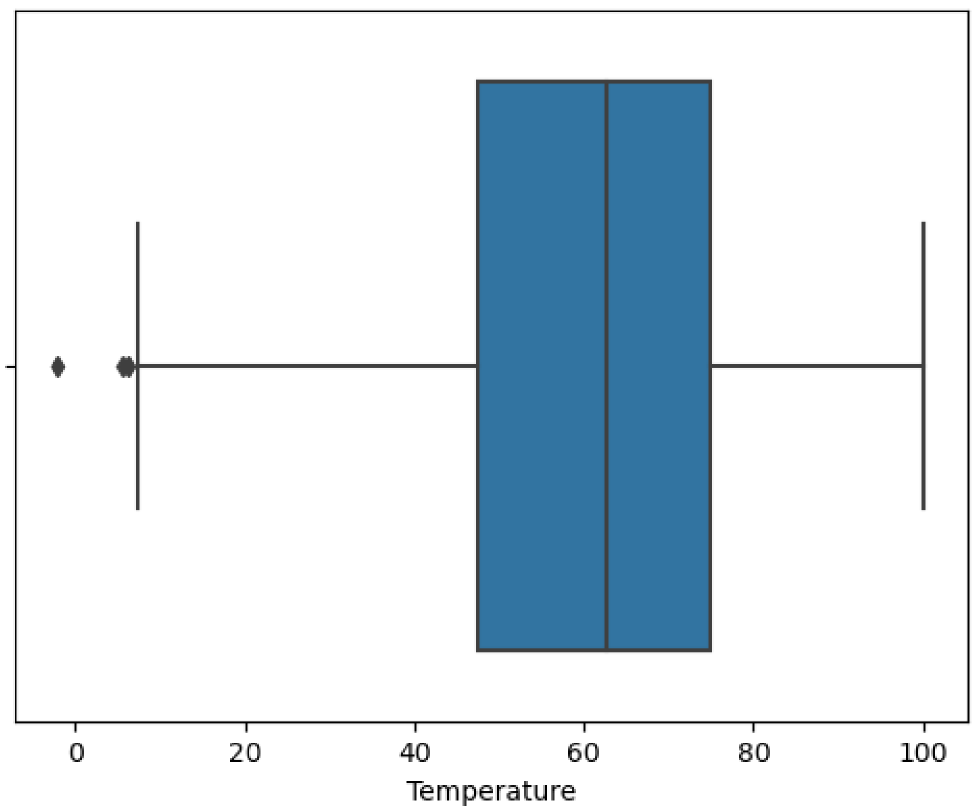
1. Linear Regression – Utilize variables like date and restructure dates as 1 for 5 Feb 2010 (starting from the earliest date in order). Hypothesize if CPI, unemployment, and fuel price have any impact on sales.
2. Change dates into days by creating new variable

6.0.1 5) 1) 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

[197]:
```
x = df[['Temperature','Fuel_Price','CPI','Unemployment']]
```

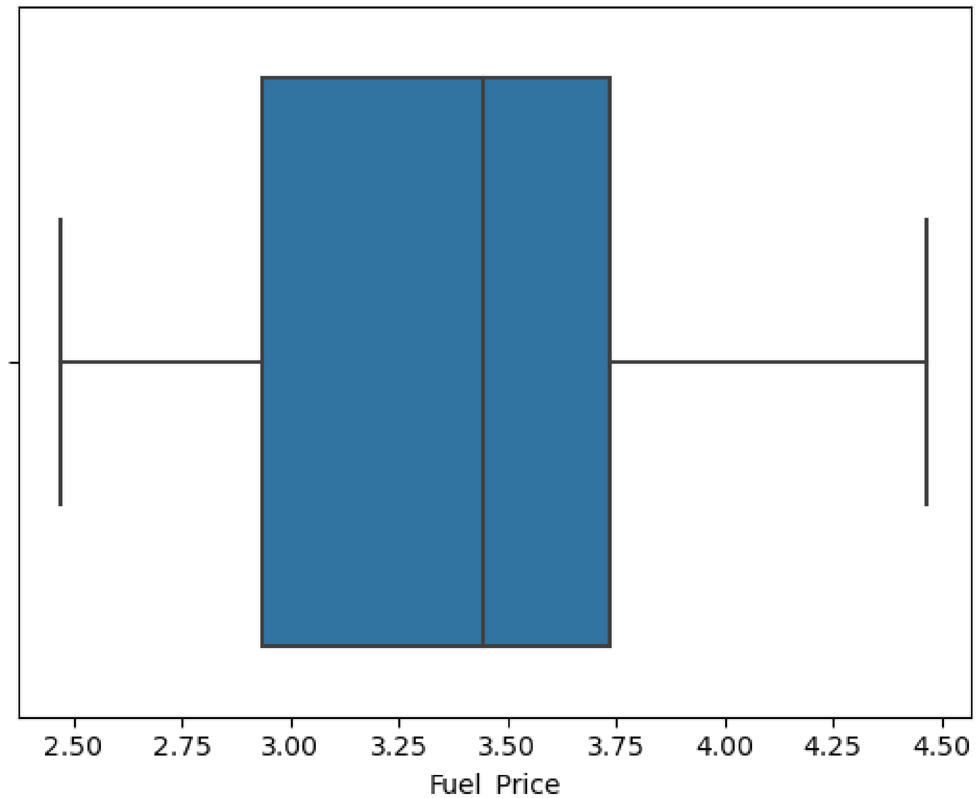
[198]:
```
sns.boxplot(x['Temperature'])
```

[198]: <AxesSubplot:xlabel='Temperature'>



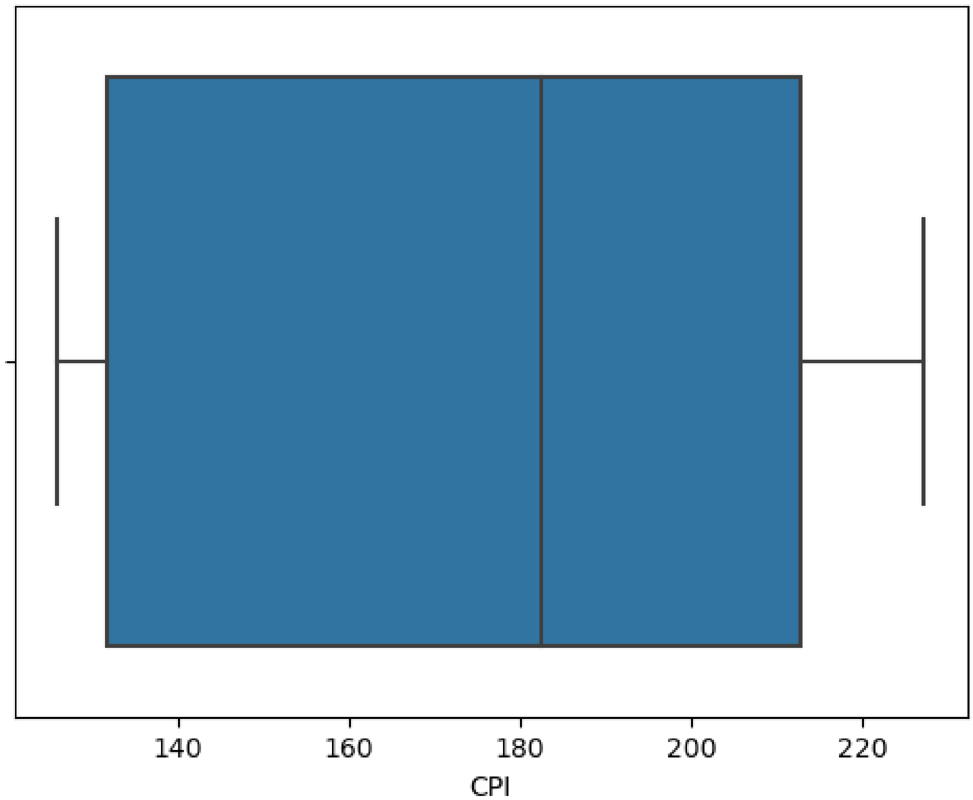
[199]:
```
sns.boxplot(x['Fuel_Price'])
```

[199]: <AxesSubplot:xlabel='Fuel_Price'>



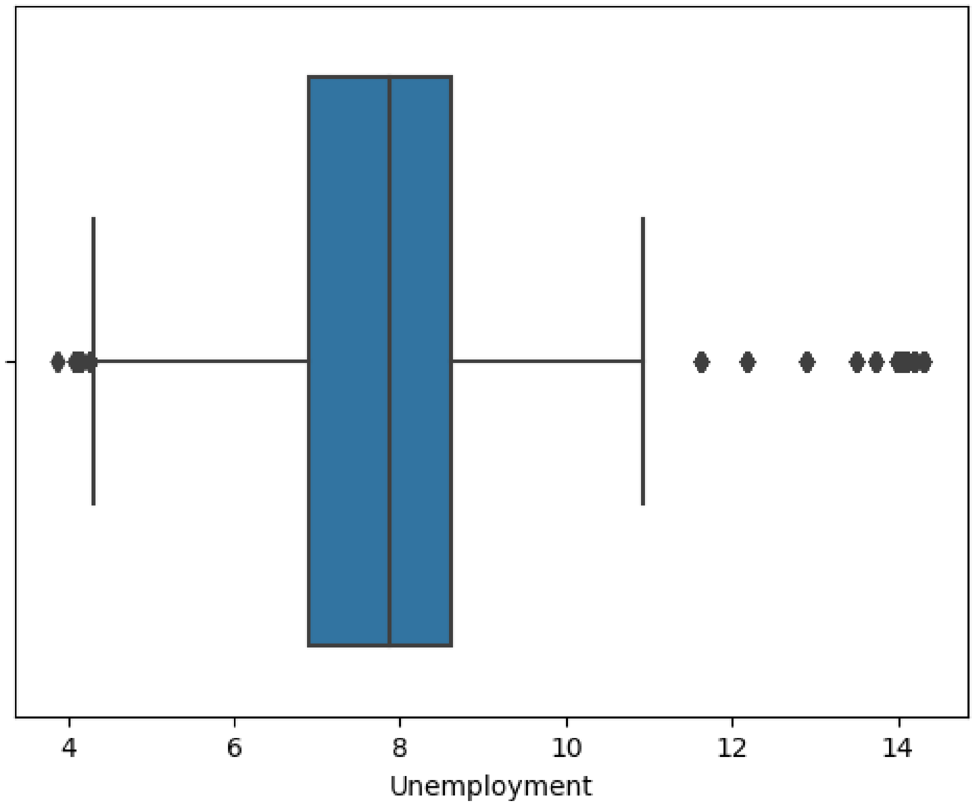
[200]:
```
sns.boxplot(x['CPI'])
```

[200]: <AxesSubplot:xlabel='CPI'>




```
[201]: sns.boxplot(x['Unemployment'])
```

```
[201]: <AxesSubplot:xlabel='Unemployment'>
```



[202]:
```
clean_data = df[(df['Unemployment']>4.5) & (df['Unemployment']<10) &␣
↪(df['Temperature']>10)]
```

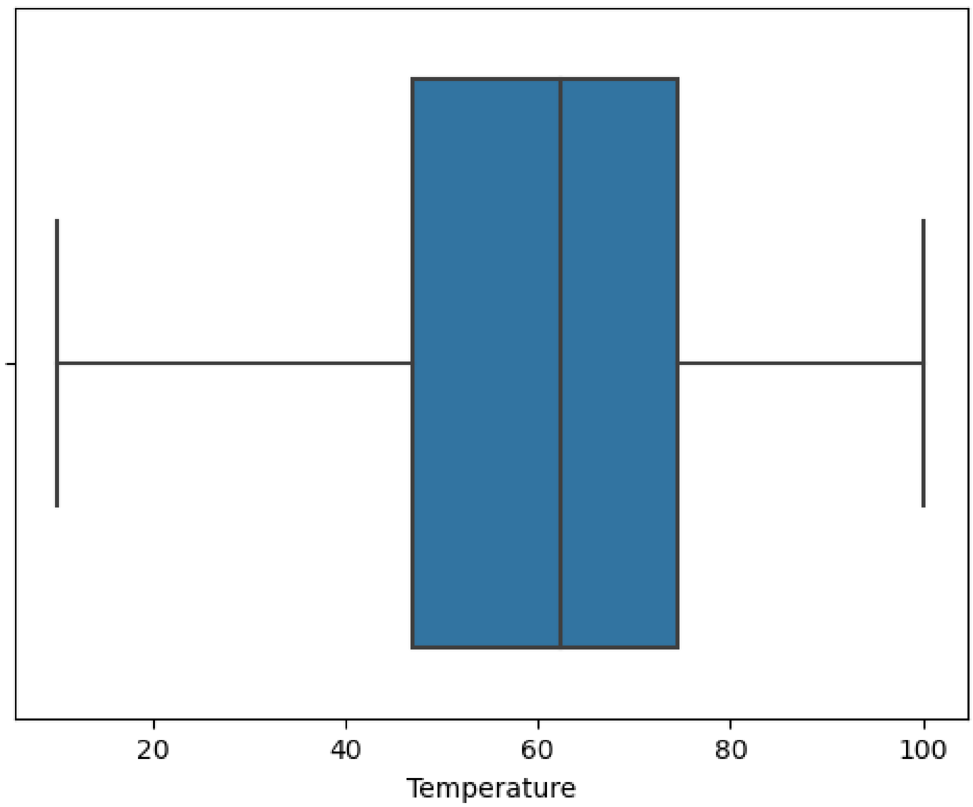
[203]:
```
clean_data
```

[203]:
```
      Store        Date  Weekly_Sales  Holiday_Flag  Temperature  Fuel_Price  \
0         1  2010-05-02    1643690.90             0        42.31       2.572
1         1  2010-12-02    1641957.44             1        38.51       2.548
2         1  2010-02-19    1611968.17             0        39.93       2.514
3         1  2010-02-26    1409727.59             0        46.63       2.561
4         1  2010-05-03    1554806.68             0        46.50       2.625
…       …         …           …           …           …          …
6430     45  2012-09-28     713173.95             0        64.88       3.997
6431     45  2012-05-10     733455.07             0        64.89       3.985
6432     45  2012-12-10     734464.36             0        54.47       4.000
6433     45  2012-10-19     718125.53             0        56.47       3.969
6434     45  2012-10-26     760281.43             0        58.85       3.882

             CPI  Unemployment  Day  Month  Year
0     211.096358         8.106    2      5  2010
1     211.242170         8.106    2     12  2010
```

```
2      211.289143         8.106   19      2  2010
3      211.319643         8.106   26      2  2010
4      211.350143         8.106    3      5  2010
…          …            …   …     …    …
6430   192.013558         8.684   28      9  2012
6431   192.170412         8.667   10      5  2012
6432   192.327265         8.667   10     12  2012
6433   192.330854         8.667   19     10  2012
6434   192.308899         8.667   26     10  2012

[5658 rows x 11 columns]
```

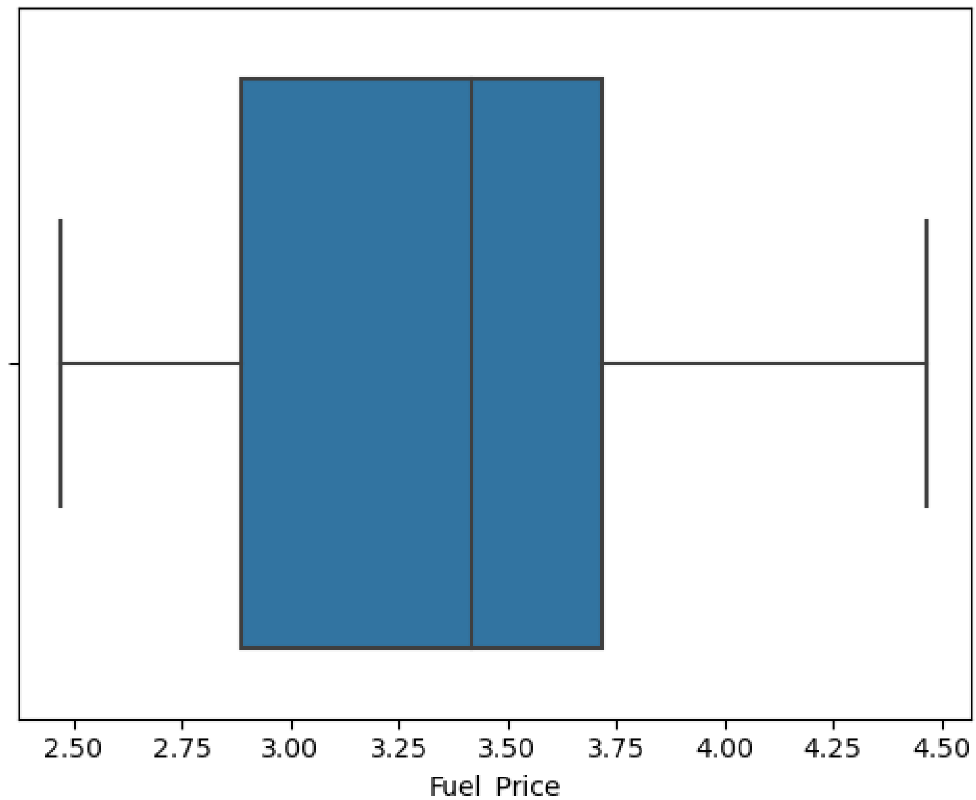
[204]:
```
sns.boxplot(clean_data['Temperature'])
```

[204]: <AxesSubplot:xlabel='Temperature'>



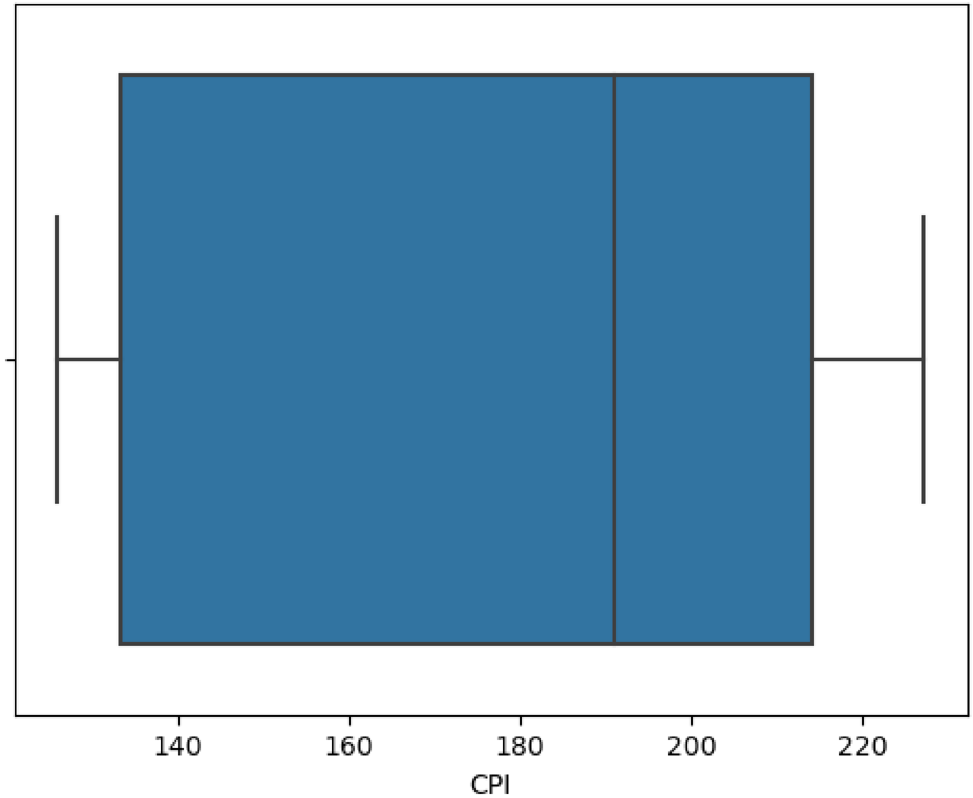
[205]:
```
sns.boxplot(clean_data['Fuel_Price'])
```

[205]: <AxesSubplot:xlabel='Fuel_Price'>



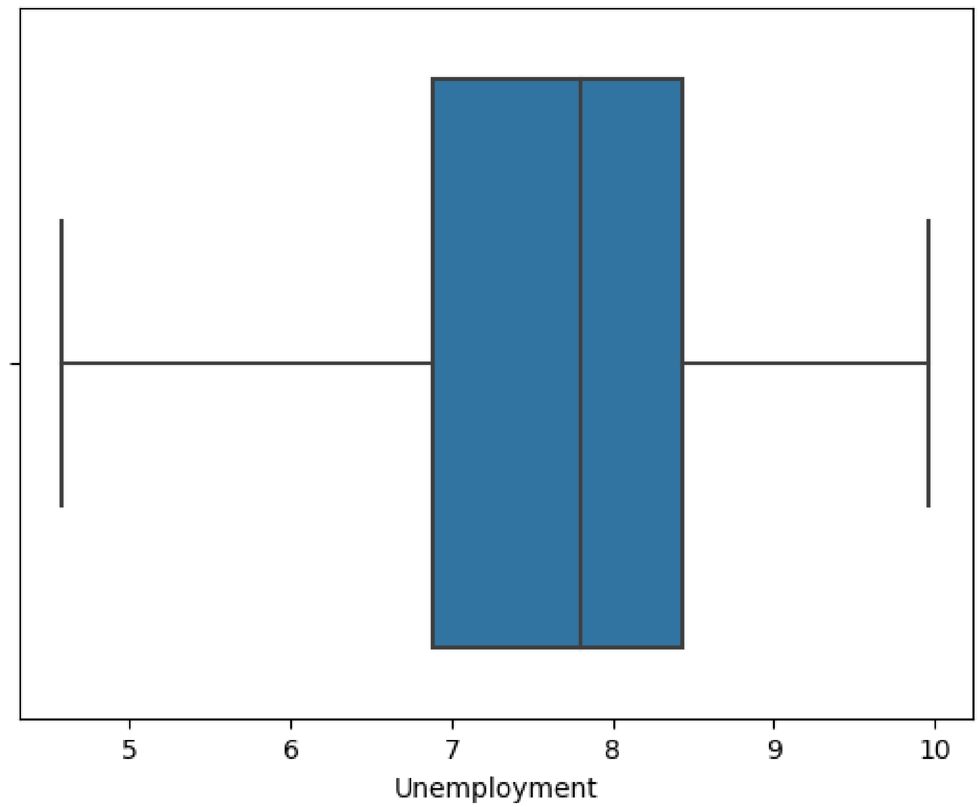
[206]:
```
sns.boxplot(clean_data['CPI'])
```

[206]: <AxesSubplot:xlabel='CPI'>



[207]:
```
sns.boxplot(clean_data['Unemployment'])
```

[207]: <AxesSubplot:xlabel='Unemployment'>



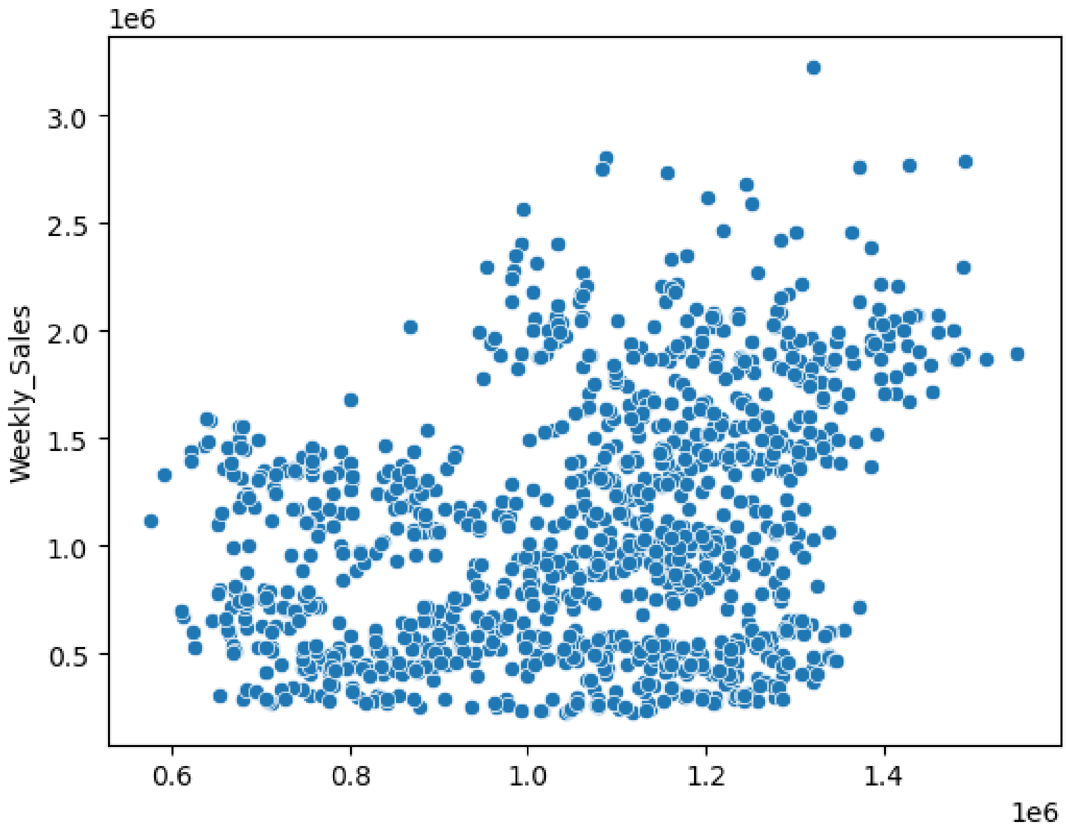
[208]:
```
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.linear_model import LinearRegression
X = clean_data[['Store','Fuel_Price','CPI','Unemployment','Day','Month','Year']]
Y = clean_data['Weekly_Sales']
X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size=0.2)
```

[209]:
```
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)
```

```
Linear Regression:
```

```
Accuracy: 13.211686177931515
Mean Absolute Error: 455020.5977995599
Mean Squared Error: 297972619443.4271
Root Mean Squared Error: 545868.6833327473
```

[209]: <AxesSubplot:ylabel='Weekly_Sales'>

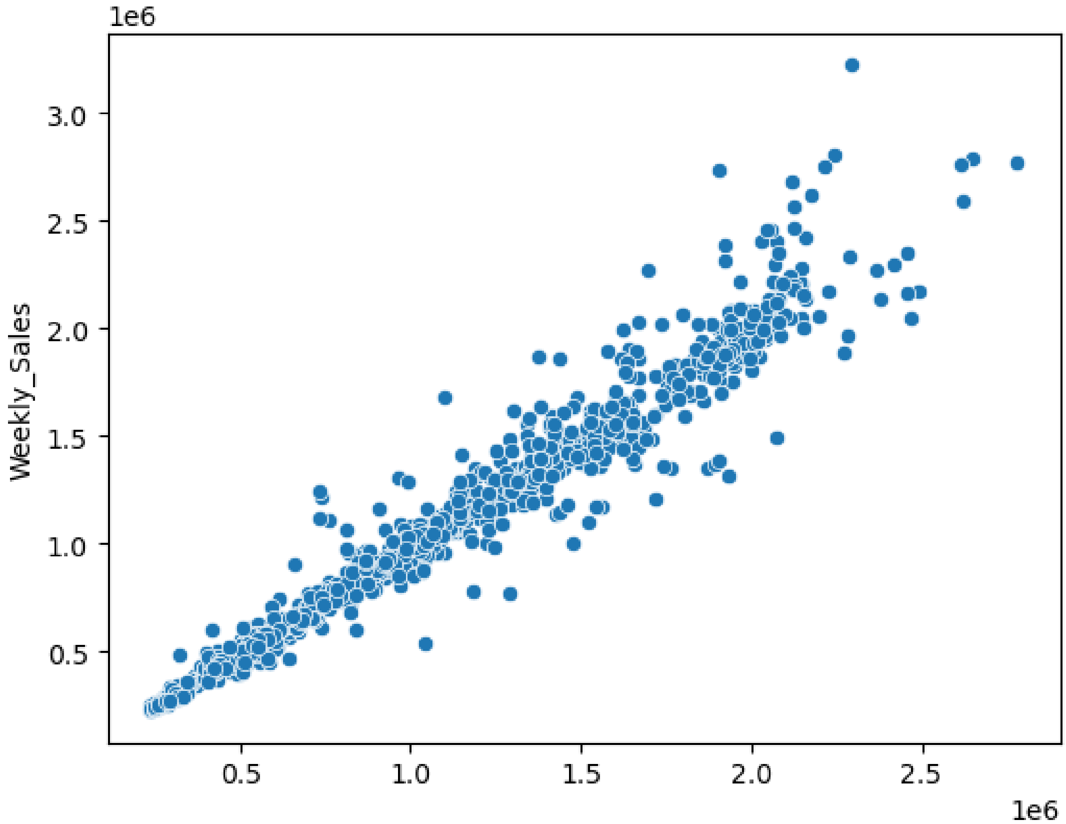


[210]:
```python
from sklearn.ensemble import RandomForestRegressor
print('Random Forest Regressor:')
print()
rfr = RandomForestRegressor()
rfr.fit(X_train,Y_train)
Y_pred = rfr.predict(X_test)
print('Accuracy:',rfr.score(X_test, Y_test)*100)
print('Mean Absolute Error:', metrics.mean_absolute_error(Y_test, 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)
```

```
Random Forest Regressor:
```

```
Accuracy: 95.63354250352644
Mean Absolute Error: 68251.03058136045
Mean Squared Error: 14716278445.261433
Root Mean Squared Error: 121310.66913203237
```

[210]: <AxesSubplot:ylabel='Weekly_Sales'>



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.

[ ]: