Project_05_Retail_Analysis_with_Walmart_Data

April 6, 2021

1 Project 5 - Retail Analysis with Walmart Data

[1]:
```
import pandas as pd
import numpy as np
import zipfile
from scipy.stats import variation
import scipy.stats as stats
import datetime as dt
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn import preprocessing
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.stats.multicomp import pairwise_tukeyhsd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
```

1.0.1 Import the Dataset

[2]:
```
with zipfile.ZipFile('1577429980_walmart_store_sales.zip','r') as zip_ref:
    zip_ref.extractall('Project 05 - Retail Analysis with Walmart Data')
```

[3]:
```
dateparse = lambda x: pd.datetime.strptime(x,'%d-%m-%Y')
walmart = pd.read_csv('Project 05 - Retail Analysis with Walmart Data/
 ↪Walmart_Store_sales.csv',parse_dates=['Date'],date_parser=dateparse)
walmart.shape
```

```
<ipython-input-3-ac80791f74b5>:1: FutureWarning: The pandas.datetime class is
deprecated and will be removed from pandas in a future version. Import from
datetime module instead.
  dateparse = lambda x: pd.datetime.strptime(x,'%d-%m-%Y')
```

[3]:
```
(6435, 8)
```

[4]:
```
walmart.head()
```

[4]:
```
   Store       Date  Weekly_Sales  Holiday_Flag  Temperature  Fuel_Price  \
0      1 2010-02-05    1643690.90             0        42.31       2.572
1      1 2010-02-12    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 2010-03-05    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
```

[5]:
```
walmart.isnull().sum()
```

[5]:
```
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
dtype: int64
```

[6]:
```
walmart.dtypes
```

[6]:
```
Store                    int64
Date            datetime64[ns]
Weekly_Sales           float64
Holiday_Flag             int64
Temperature            float64
Fuel_Price             float64
CPI                    float64
Unemployment           float64
dtype: object
```

1.1 Task 1 - Which store has maximum sales

[7]:
```
weekly_sales = pd.DataFrame(walmart.groupby(['Store'])['Weekly_Sales'].max().
 ↪sort_values(ascending=False)).reset_index()
weekly_sales['Weekly_Sales'] = weekly_sales['Weekly_Sales'].astype(float)
weekly_sales.head()
```

[7]:
```
   Store  Weekly_Sales
0     14    3818686.45
1     20    3766687.43
```

```
2      10    3749057.69
3       4    3676388.98
4      13    3595903.20
```

According to the above table, it would appear that the store 14 has maximum sales at 3818686.45

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

[8]:
```
weekly_sales = pd.DataFrame(walmart.groupby(['Store'])['Weekly_Sales'].std().
 ↪sort_values(ascending=False)).reset_index()
weekly_sales['Weekly_Sales'] = round(weekly_sales['Weekly_Sales'].
 ↪astype(float),2)
weekly_sales.head()
```

[8]:
```
   Store  Weekly_Sales
0     14     317569.95
1     10     302262.06
2     20     275900.56
3      4     266201.44
4     13     265507.00
```

According to the above table, it would appear that the store 14 has maximum standard deviation of sales at 317569.95

[9]:
```
print("Mean = {}\nStandard Deviation = {}\nCoefficient of Variation = {}".
 ↪format(round(walmart['Weekly_Sales'].mean(),2),round(walmart['Weekly_Sales'].
 ↪std(),2),round(variation(walmart['Weekly_Sales'])*100,2)))
```

```
Mean = 1046964.88
Standard Deviation = 564366.62
Coefficient of Variation = 53.9
```

The Coefficient of Variation was found to be 53.90

1.3 Task 3 - Which stores have good quarterly growth rate in Q3'2012

[10]:
```
walmart['Quarter'] = walmart['Date'].dt.quarter
walmart['Year'] = walmart['Date'].dt.year
walmart_sort = walmart.sort_values(by=['Store','Date'])
walmart['Growth'] = pd.DataFrame.pct_change(walmart_sort['Weekly_Sales'])
walmart_growth = pd.DataFrame(walmart.
 ↪groupby(['Store','Quarter','Year'])['Weekly_Sales','Growth'].sum().
 ↪sort_values(ascending=True,by='Growth')).reset_index()
qtr_growth_2012 = walmart_growth[walmart_growth['Year']==2012]
qtr_growth_2012_q3 = qtr_growth_2012[qtr_growth_2012['Quarter']==3]
qtr_growth_2012_q3.head()
```

```
<ipython-input-10-7e34f7372c4e>:5: FutureWarning: Indexing with multiple keys
(implicitly converted to a tuple of keys) will be deprecated, use a list
instead.
  walmart_growth = pd.DataFrame(walmart.groupby(['Store','Quarter','Year'])['Wee
kly_Sales','Growth'].sum().sort_values(ascending=True,by='Growth')).reset_index(
)
```

[10]:

	Store	Quarter	Year	Weekly_Sales	Growth
19	7	3	2012	8262787.39	-0.264080
36	16	3	2012	7121541.64	-0.166426
39	6	3	2012	20167312.24	-0.144897
46	27	3	2012	22307711.41	-0.136554
58	15	3	2012	7612081.03	-0.097343

According to the above table, it would appear that store 7 has a good quarterly growth in Q3'2012

1.4 Task 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

[11]:
```python
walmart_holiday = walmart[walmart['Holiday_Flag']==1].reset_index()
walmart_holiday = walmart_holiday[['Store','Date','Weekly_Sales']]
walmart_holiday['Month'] = walmart_holiday['Date'].dt.month
walmart_holiday.head()
```

[11]:

	Store	Date	Weekly_Sales	Month
0	1	2010-02-12	1641957.44	2
1	1	2010-09-10	1507460.69	9
2	1	2010-11-26	1955624.11	11
3	1	2010-12-31	1367320.01	12
4	1	2011-02-11	1649614.93	2

[12]:
```python
walmart_non_holiday = walmart[walmart['Holiday_Flag']==0].reset_index()
walmart_non_holiday = walmart_non_holiday[['Store','Date','Weekly_Sales']]
walmart_non_holiday_mean = round(walmart_non_holiday['Weekly_Sales'].mean(),2)
print("The mean sales in non-holiday season for all stores together was found␣
 ↪to be",walmart_non_holiday_mean)
```

```
The mean sales in non-holiday season for all stores together was found to be
1041256.38
```

[13]:
```python
walmart_sales_gt_mean =␣
 ↪walmart_holiday[walmart_holiday['Weekly_Sales']>walmart_non_holiday_mean]
walmart_sales_gt_mean['Date'].value_counts()
```

[13]:
```
2011-11-25    31
2010-11-26    30
2012-09-07    22
2012-02-10    22
```

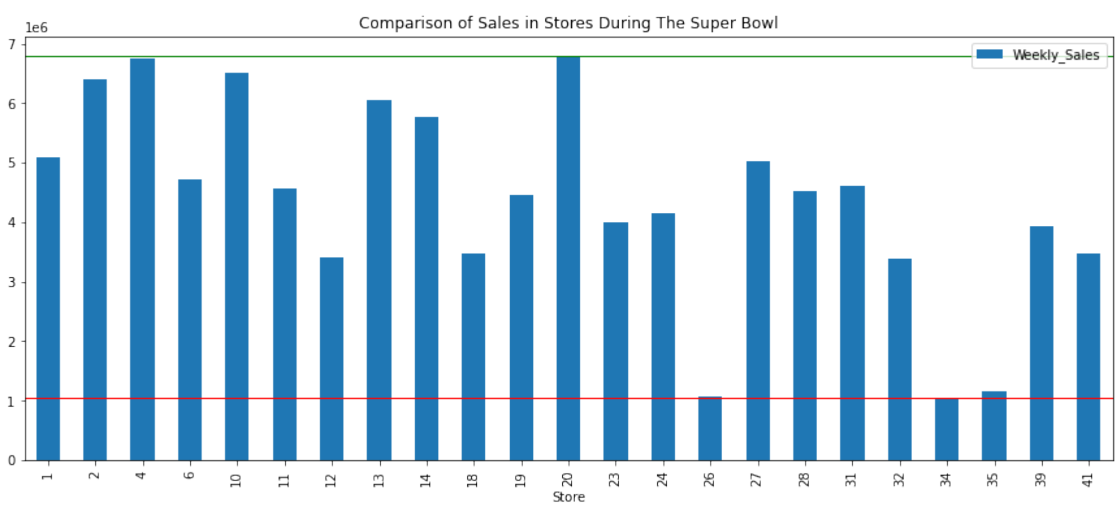
```
2010-02-12    21
2011-09-09    20
2011-02-11    20
2010-09-10    19
2011-12-30    19
2010-12-31    16
Name: Date, dtype: int64
```

[14]:
```python
Event = {2:'Super Bowl',9:'Labour Day',11:'Thanksgiving',12:'Christmas'}
walmart_sales_gt_mean = walmart_sales_gt_mean.replace({'Month': Event})
walmart_sales_gt_mean.rename(columns={'Month':'Event'}, inplace = True)
walmart_sales_eventwise = pd.DataFrame(walmart_sales_gt_mean.groupby(['Event','Store'])['Weekly_Sales'].sum().reset_index())
walmart_sales_eventwise.head()
```

[14]:

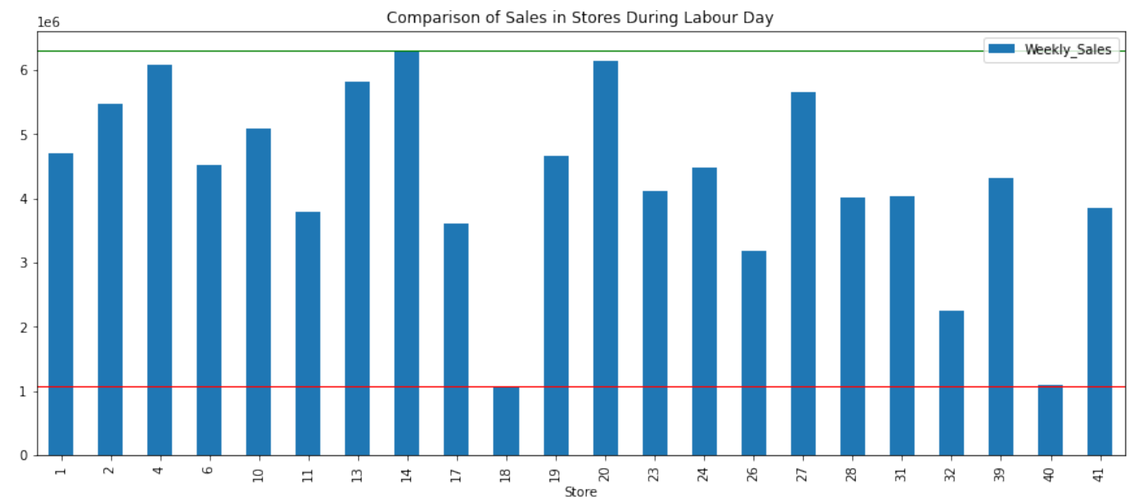
	Event	Store	Weekly_Sales
0	Christmas	1	2864782.73
1	Christmas	2	3624661.07
2	Christmas	4	3801974.60
3	Christmas	6	3062130.54
4	Christmas	10	3637988.51

[15]:
```python
superbowl = walmart_sales_eventwise[walmart_sales_eventwise['Event']=='Super Bowl'].set_index(['Store'])
superbowl.plot(kind='bar',figsize=(15,6),title='Comparison of Sales in Stores During The Super Bowl')
plt.axhline(y=superbowl['Weekly_Sales'].max(),linewidth=1, color='green')
plt.axhline(y=superbowl['Weekly_Sales'].min(),linewidth=1, color='red')
plt.show()
```



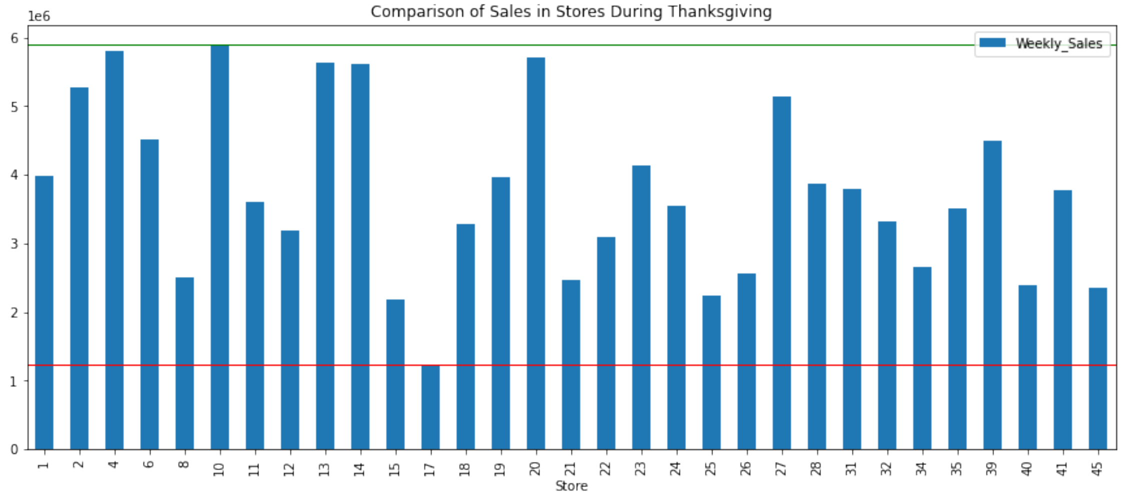
From the figure above, store 20 seems to have maximum sales during The Super Bowl, while store 34 seems to have minimum sales.

[16]:
```python
labourday = walmart_sales_eventwise[walmart_sales_eventwise['Event']=='Labour Day'].set_index(['Store'])
labourday.plot(kind='bar',figsize=(15,6),title='Comparison of Sales in Stores During Labour Day')
plt.axhline(y=labourday['Weekly_Sales'].max(),linewidth=1, color='green')
plt.axhline(y=labourday['Weekly_Sales'].min(),linewidth=1, color='red')
plt.show()
```



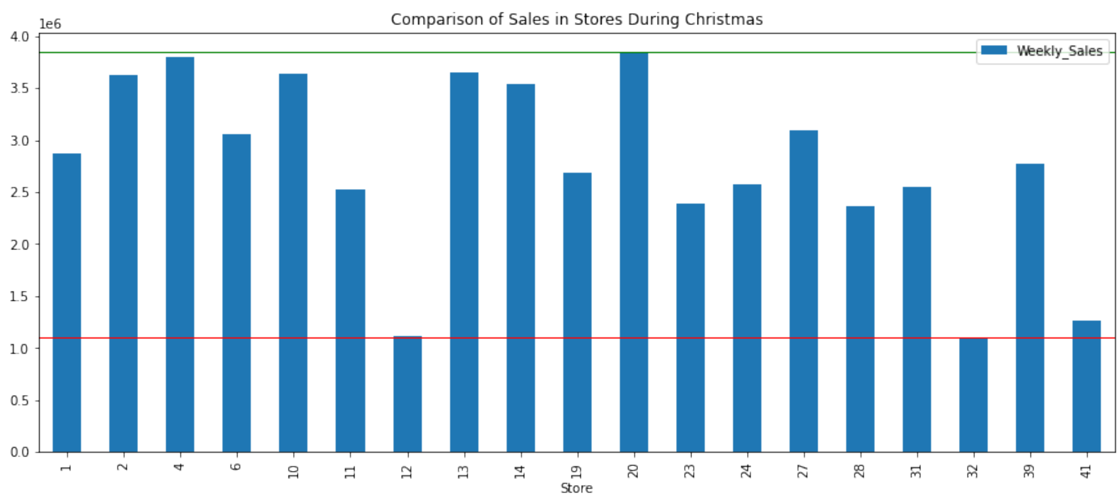
From the figure above, store 14 seems to have maximum sales during Labour Day, while store 18 seems to have minimum sales.

[17]:
```python
thanksgiving = walmart_sales_eventwise[walmart_sales_eventwise['Event']=='Thanksgiving'].set_index(['Store'])
thanksgiving.plot(kind='bar',figsize=(15,6),title='Comparison of Sales in Stores During Thanksgiving')
plt.axhline(y=thanksgiving['Weekly_Sales'].max(),linewidth=1, color='green')
plt.axhline(y=thanksgiving['Weekly_Sales'].min(),linewidth=1, color='red')
plt.show()
```



From the figure above, store 10 seems to have maximum sales during Thanksgiving, while store 17 seems to have minimum sales.

[18]:
```
christmas =␣
↪walmart_sales_eventwise[walmart_sales_eventwise['Event']=='Christmas'].
↪set_index(['Store'])
christmas.plot(kind='bar',figsize=(15,6),title='Comparison of Sales in Stores␣
↪During Christmas')
plt.axhline(y=christmas['Weekly_Sales'].max(),linewidth=1, color='green')
plt.axhline(y=christmas['Weekly_Sales'].min(),linewidth=1, color='red')
plt.show()
```



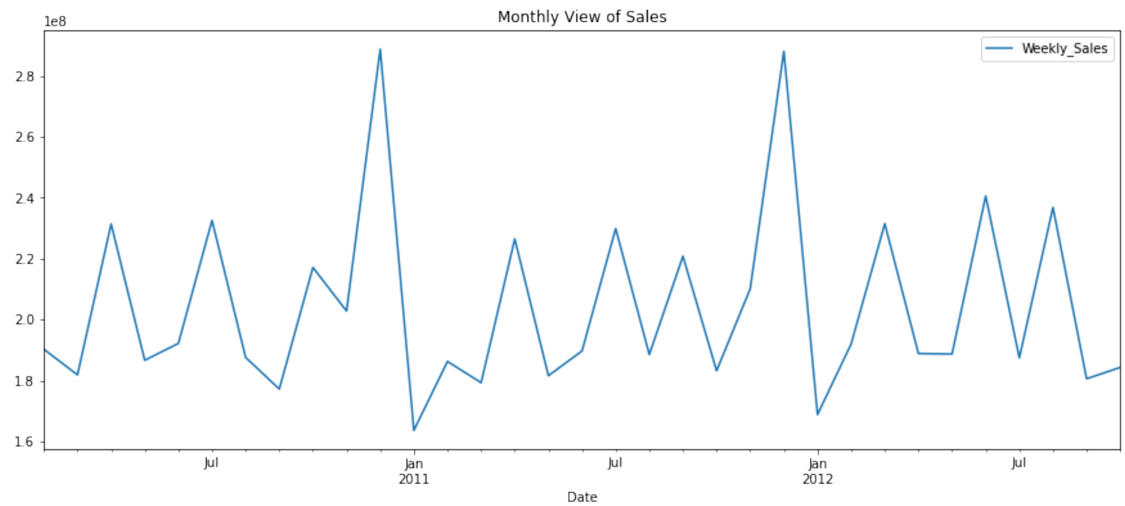
From the figure above, store 20 seems to have maximum sales during Christmas, while store 32 seems to have minimum sales.

1.5 Task 5 - Provide a monthly and semester view of sales in units and give insights

[19]:
```
walmart_sales=walmart[['Date','Weekly_Sales']]
walmart_sales.Date = pd.to_datetime(walmart_sales.Date)
walmart_sales.set_index('Date', inplace=True)
walmart_sales.resample('MS').sum().plot(figsize=(15,6),title='Monthly View of␣
↪Sales')
plt.show()
```

```
c:\users\jude\appdata\local\programs\python\python39\lib\site-
packages\pandas\core\generic.py:5491: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[name] = value
```

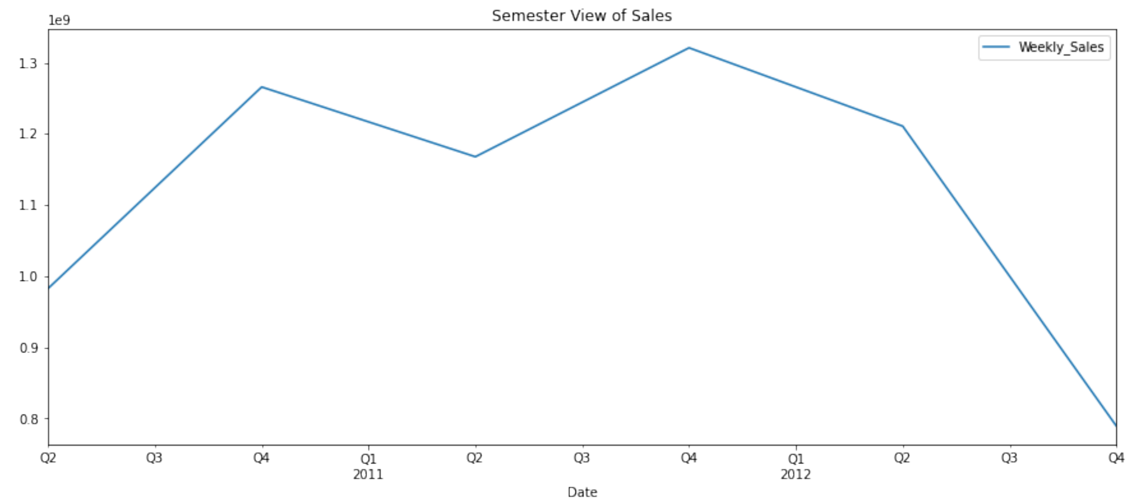


From the above graph, it would appear that the sales increased and decreased alternately but irregularly, with peaks in December and valleys in January.

[20]:
```
walmart_sales=walmart[['Date','Weekly_Sales']]
walmart_sales.Date = pd.to_datetime(walmart_sales.Date)
walmart_sales.set_index('Date', inplace=True)
walmart_sales.resample('2Q',closed='left').sum().
↪plot(figsize=(15,6),title='Semester View of Sales')#QS
plt.show()
```

```
c:\users\jude\appdata\local\programs\python\python39\lib\site-
packages\pandas\core\generic.py:5491: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[name] = value
```



From the above graph, it would appear that the sales increased and decreased alternately, with peaks in July in 2010 & 2011. The sales hit a valley in January 2011 & July 2012.

1.6 Task 6 - Statistical Model For Store 1 – Build prediction models to forecast demand

[21]:
```
walmart_first = walmart[walmart['Store']==1].
 ↪drop(['Quarter','Year','Growth'],axis=1)
walmart_first.head()
```

[21]:
```
   Store        Date  Weekly_Sales  Holiday_Flag  Temperature  Fuel_Price  \
0      1  2010-02-05    1643690.90             0        42.31       2.572
1      1  2010-02-12    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  2010-03-05    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
```

[22]:
```
walmart_first['Store'].value_counts()
```

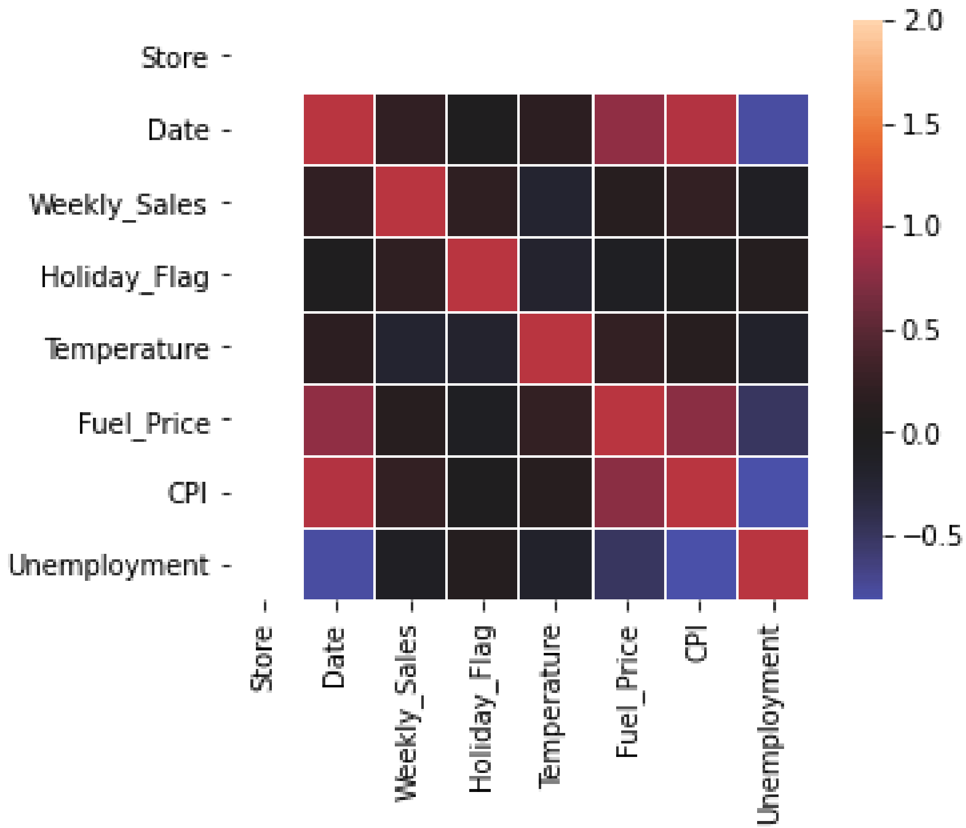
[22]:
```
1    143
Name: Store, dtype: int64
```

1.6.1 Task 6 Subtask 1 - Linear Regression – Utilize variables like date and restructure dates as 1 for 5 Feb 2010 (starting from the earliest date in order).

[23]:
```
label_encoder = preprocessing.LabelEncoder()
walmart_first['Date'] = label_encoder.fit_transform(walmart_first['Date'])
walmart_first['Date'].unique()
```

[23]:
```
array([  0,   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,  46,  47,  48,  49,  50,  51,
        52,  53,  54,  55,  56,  57,  58,  59,  60,  61,  62,  63,  64,
        65,  66,  67,  68,  69,  70,  71,  72,  73,  74,  75,  76,  77,
        78,  79,  80,  81,  82,  83,  84,  85,  86,  87,  88,  89,  90,
        91,  92,  93,  94,  95,  96,  97,  98,  99, 100, 101, 102, 103,
       104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116,
       117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129,
       130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142],
      dtype=int64)
```

[24]:
```
sns.heatmap(walmart_first.corr(),vmax=2,center=0,square=True,linewidths=.5)
plt.show()
```

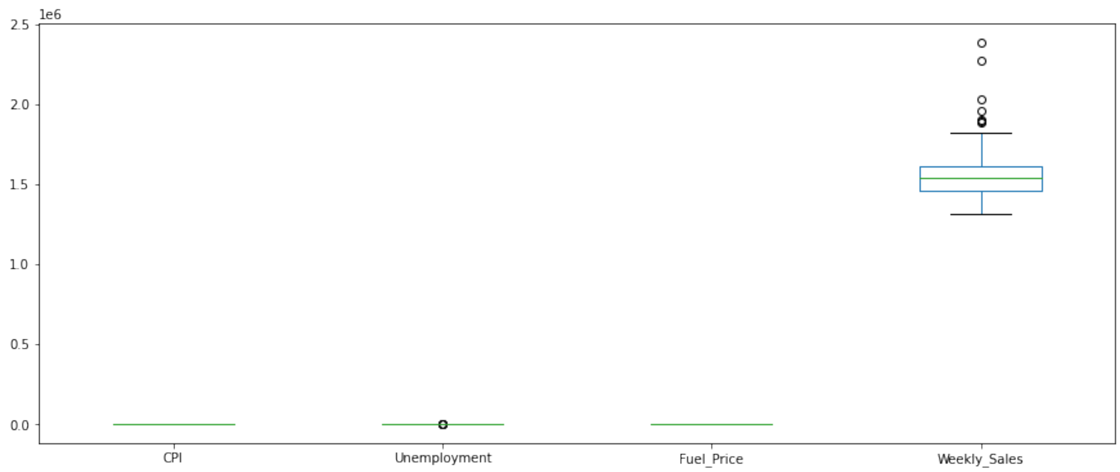


1.6.2 Task 6 Subtask 2 - Hypothesize if CPI, unemployment, and fuel price have any impact on sales. One Way ANOVA

1. Null Hypothesis : CPI, unemployment, and fuel price have no impact on sales
2. Alternate Hypothesis : CPI, unemployment, and fuel price have an impact on sales

[25]:
```
walmart_first.
 ↪boxplot(column=['CPI','Unemployment','Fuel_Price','Weekly_Sales'],figsize=(15,6),grid=False
```

[25]:
```
<AxesSubplot:>
```



[26]:
```
f_value,p_value = stats.
 ↪f_oneway(walmart_first['CPI'],walmart_first['Unemployment'],walmart_first['Fuel_Price'],walm
print("F-value = {}\np-value = {}".format(f_value,p_value))
```

```
F-value = 14215.435538539019
p-value = 0.0
```

[27]:
```
walmart_first_melt = pd.melt(walmart_first.
 ↪reset_index(),id_vars=['index'],value_vars=['CPI','Unemployment','Fuel_Price','Weekly_Sales
walmart_first_melt.columns = ['index','treatments','value']
model = ols('value ~ C(treatments)', data=walmart_first_melt).fit()
anova_table = sm.stats.anova_lm(model, typ=2)
anova_table
```

[27]:

	sum_sq	df	F	PR(>F)
C(treatments)	2.593962e+14	3.0	14215.435539	0.0
Residual	3.454860e+12	568.0	NaN	NaN

The P-value obtained from ANOVA analysis is significant (P<0.05), hence null hypothesis is rejected. CPI, unemployment, and fuel price have an impact on sales.

Post-hoc comparison

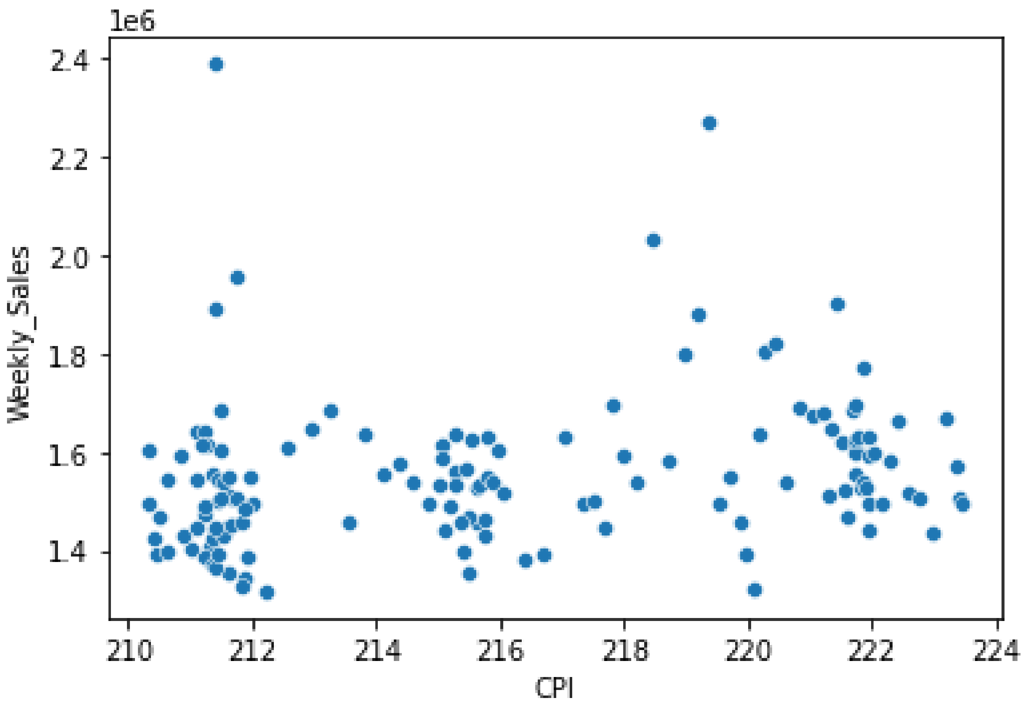
[28]:
```
m_comp =␣
 ↪pairwise_tukeyhsd(endog=walmart_first_melt['value'],groups=walmart_first_melt['treatments']
 ↪05)
print(m_comp)
```

```
             Multiple Comparison of Means - Tukey HSD, FWER=0.05
==============================================================================
   group1       group2      meandiff    p-adj     lower         upper     reject
------------------------------------------------------------------------------
         CPI    Fuel_Price    -212.7772    0.9  -23978.5693    23553.015   False
```

```
         CPI Unemployment    -208.3865   0.9  -23974.1786   23557.4057  False
         CPI Weekly_Sales 1555048.4007 0.001 1531282.6085 1578814.1928   True
  Fuel_Price Unemployment       4.3907   0.9  -23761.4014   23770.1829  False
  Fuel_Price Weekly_Sales 1555261.1779 0.001 1531495.3857   1579026.97   True
Unemployment Weekly_Sales 1555256.7871 0.001  1531490.995 1579022.5793   True
-----------------------------------------------------------------------------
```

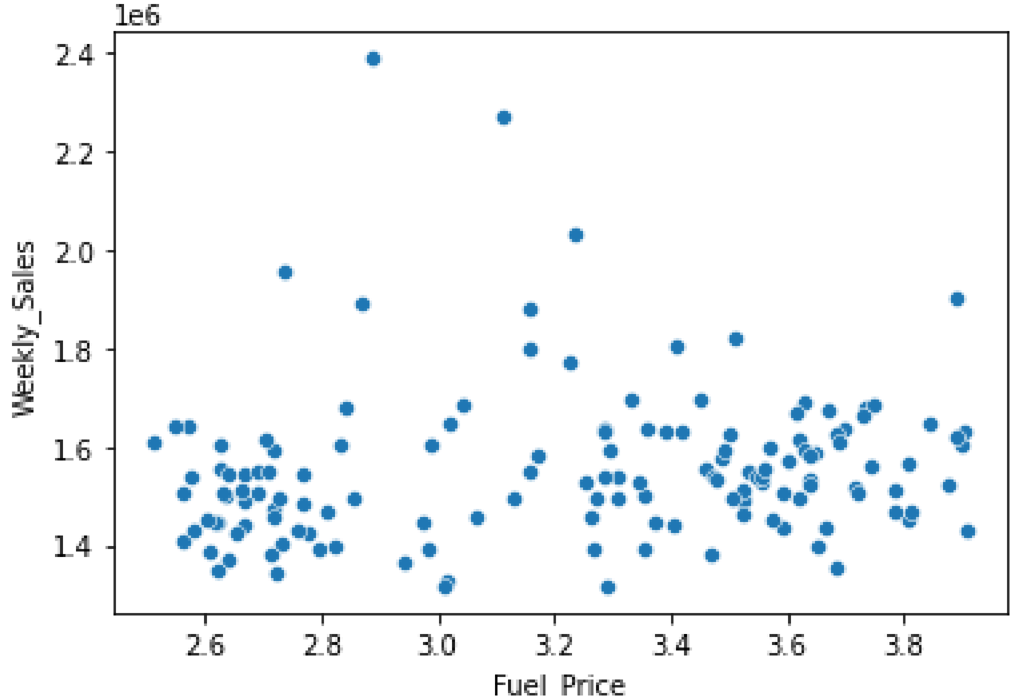
[29]:
```
sns.scatterplot(x=walmart_first['CPI'],y=walmart_first['Weekly_Sales'])
```

[29]: <AxesSubplot:xlabel='CPI', ylabel='Weekly_Sales'>



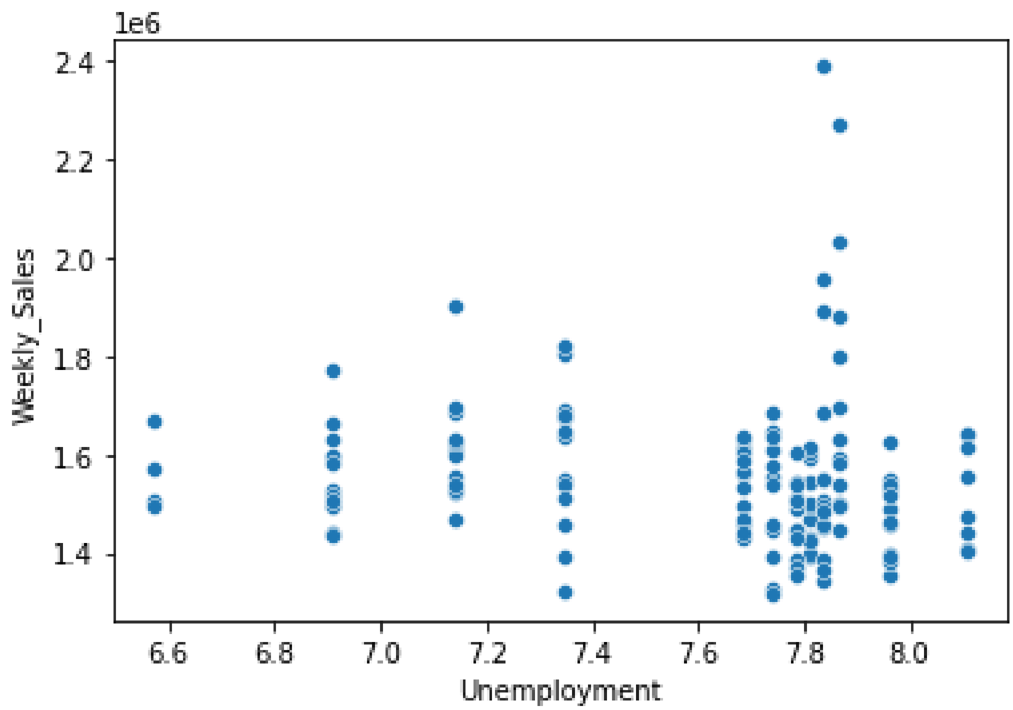
[30]:
```
sns.scatterplot(x=walmart_first['Fuel_Price'],y=walmart_first['Weekly_Sales'])
```

[30]: <AxesSubplot:xlabel='Fuel_Price', ylabel='Weekly_Sales'>



[31]:
```
sns.scatterplot(x=walmart_first['Unemployment'],y=walmart_first['Weekly_Sales'])
```

[31]: <AxesSubplot:xlabel='Unemployment', ylabel='Weekly_Sales'>



1.7 Task 7 - Change dates into days by creating new variable. Select the model which gives best accuracy.

1.7.1 Task 7 Subtask 1 - Post Processing

[32]:
```
features=walmart_first.drop(['Store','Weekly_Sales'],axis=1)
label=walmart_first['Weekly_Sales']
features.shape,label.shape
```

[32]:
```
((143, 6), (143,))
```

[33]:
```
x_train,x_test,y_train,y_test = train_test_split(features,label,test_size=0.
 ↪3,random_state=42)
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(100, 6)
(43, 6)
(100,)
(43,)
```

Model 1 - Linear Regression

[34]:
```
lin_reg = LinearRegression(normalize=True)
lin_reg.fit(x_train,y_train)
```

[34]:
```
LinearRegression(normalize=True)
```

[35]:
```
y_pred=lin_reg.predict(x_test)
acc_lin_reg = round(lin_reg.score(x_train,y_train)*100,2)
acc_lin_reg
```

[35]:
```
10.17
```

Model 2 - KNN Regression

[36]:
```
knn_reg = KNeighborsRegressor()
knn_reg.fit(x_train,y_train)
```

[36]:
```
KNeighborsRegressor()
```

[37]:
```
y_pred=knn_reg.predict(x_test)
acc_knn_reg = round(knn_reg.score(x_train,y_train)*100,2)
acc_knn_reg
```

[37]: 15.05

Model 3 - Random Forest Regression

[38]:
```
rf_reg = RandomForestRegressor()
rf_reg.fit(x_train,y_train)
```

[38]: RandomForestRegressor()

[39]:
```
y_pred=rf_reg.predict(x_test)
acc_rf_reg = round(rf_reg.score(x_train,y_train)*100,2)
acc_rf_reg
```

[39]: 86.76

Model Results

[40]:
```
models = pd.DataFrame({'Model':['Linear Regression','KNN Regression','Random␣
↪Forest Regression'],'Score':[acc_lin_reg,acc_knn_reg,acc_rf_reg]})
models.sort_values(by='Score',ascending=False)
```

[40]:

	Model	Score
2	Random Forest Regression	86.76
1	KNN Regression	15.05
0	Linear Regression	10.17

[41]:
```
print('The best model was found to be {} scoring at {} % on testing data.'.
↪format(models['Model'].loc[models['Score'].idxmax()],max(models['Score'])))
```

```
The best model was found to be Random Forest Regression scoring at 86.76 % on
testing data.
```

2 —X—