Retail Analysis with Walmart Data

March 9, 2024

[2]:
```
# Import necessary libraries
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import dates
from datetime import datetime
```

0.0.1 Data Understanding

There are sales data available for 45 stores of Walmart in Kaggle. This is the data that covers sales from 2010-02-05 to 2012-11-01.

The data contains these features: - Store - the store number - Date - the week of sales - Weekly_Sales - sales for the given store - Holiday_Flag - whether the week is a special holiday week 1 – Holiday week 0 – Non-holiday week - Temperature - Temperature on the day of sale - Fuel_Price - Cost of fuel in the region - CPI – Prevailing consumer price index - Unemployment - Prevailing unemployment rate

[3]:
```
# Load dataset
data = pd.read_csv('Walmart_Store_sales.csv')
data
```

[3]:
```
      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
…       …         …           …           …          …           …
6430     45  28-09-2012     713173.95             0        64.88       3.997
6431     45  05-10-2012     733455.07             0        64.89       3.985
6432     45  12-10-2012     734464.36             0        54.47       4.000
6433     45  19-10-2012     718125.53             0        56.47       3.969
6434     45  26-10-2012     760281.43             0        58.85       3.882

             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
…          …          …
6430  192.013558         8.684
6431  192.170412         8.667
6432  192.327265         8.667
6433  192.330854         8.667
6434  192.308899         8.667

[6435 rows x 8 columns]
```

0.0.2 Data Preparation

[4]:

```
# Convert date to datetime format and show dataset information
data['Date'] =  pd.to_datetime(data['Date'])
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6435 entries, 0 to 6434
Data columns (total 8 columns):
Store           6435 non-null int64
Date            6435 non-null datetime64[ns]
Weekly_Sales    6435 non-null float64
Holiday_Flag    6435 non-null int64
Temperature     6435 non-null float64
Fuel_Price      6435 non-null float64
CPI             6435 non-null float64
Unemployment    6435 non-null float64
dtypes: datetime64[ns](1), float64(5), int64(2)
memory usage: 402.3 KB
```

[5]:

```
# checking for missing values
data.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]:

```
# Splitting Date and create new columns (Day, Month, and Year)
data["Day"]= pd.DatetimeIndex(data['Date']).day
data['Month'] = pd.DatetimeIndex(data['Date']).month
```

```
data['Year'] = pd.DatetimeIndex(data['Date']).year
data
```

[6]:

```
      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]
```

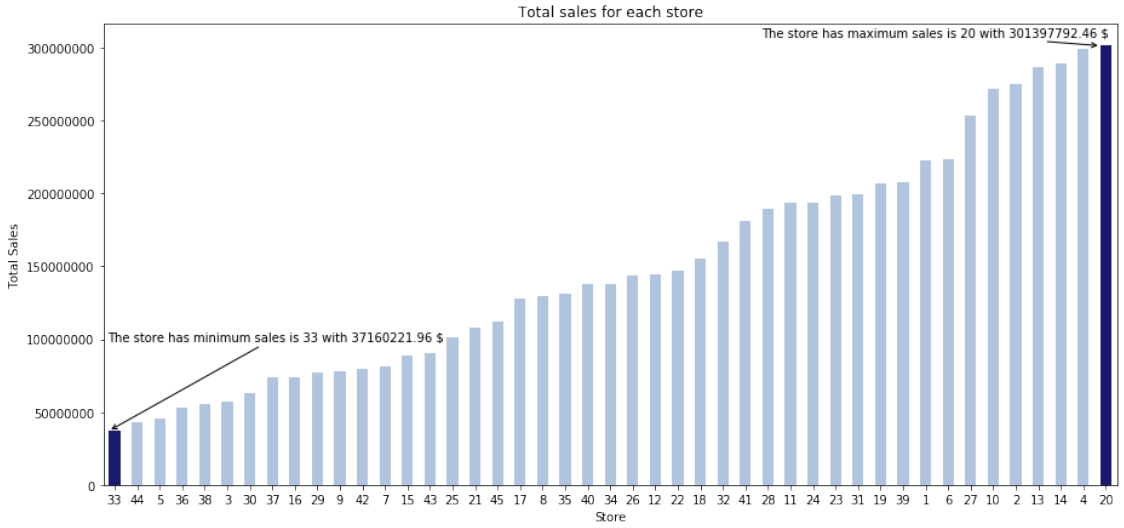
0.0.3 Q1: Which store has minimum and maximum sales?

[7]:

```
plt.figure(figsize=(15,7))

# Sum Weekly_Sales for each store, then sortded by total sales
total_sales_for_each_store = data.groupby('Store')['Weekly_Sales'].sum().
 ↪sort_values()
total_sales_for_each_store_array = np.array(total_sales_for_each_store) #␣
 ↪convert to array

# Assigning a specific color for the stores have the lowest and highest sales
clrs = ['lightsteelblue' if ((x < max(total_sales_for_each_store_array)) and (x␣
 ↪> min(total_sales_for_each_store_array))) else 'midnightblue' for x in␣
 ↪total_sales_for_each_store_array]
```

```python
ax = total_sales_for_each_store.plot(kind='bar',color=clrs);

# store have minimum sales
p = ax.patches[0]
print(type(p.get_height()))
ax.annotate("The store has minimum sales is 33 with {0:.2f} $".format((p.get_height())), xy=(p.get_x(), p.get_height()), xycoords='data',
            xytext=(0.17, 0.32), textcoords='axes fraction',
            arrowprops=dict(arrowstyle="->", connectionstyle="arc3"),
            horizontalalignment='center', verticalalignment='center')


# store have maximum sales
p = ax.patches[44]
ax.annotate("The store has maximum sales is 20 with {0:.2f} $".format((p.get_height())), xy=(p.get_x(), p.get_height()), xycoords='data',
            xytext=(0.82, 0.98), textcoords='axes fraction',
            arrowprops=dict(arrowstyle="->", connectionstyle="arc3"),
            horizontalalignment='center', verticalalignment='center')


# plot properties
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');
```

```
<class 'numpy.float64'>
```



0.0.4 Q2: Which store has maximum standard deviation i.e., the sales vary a lot. Also, find out the coefficient of mean to standard deviation?

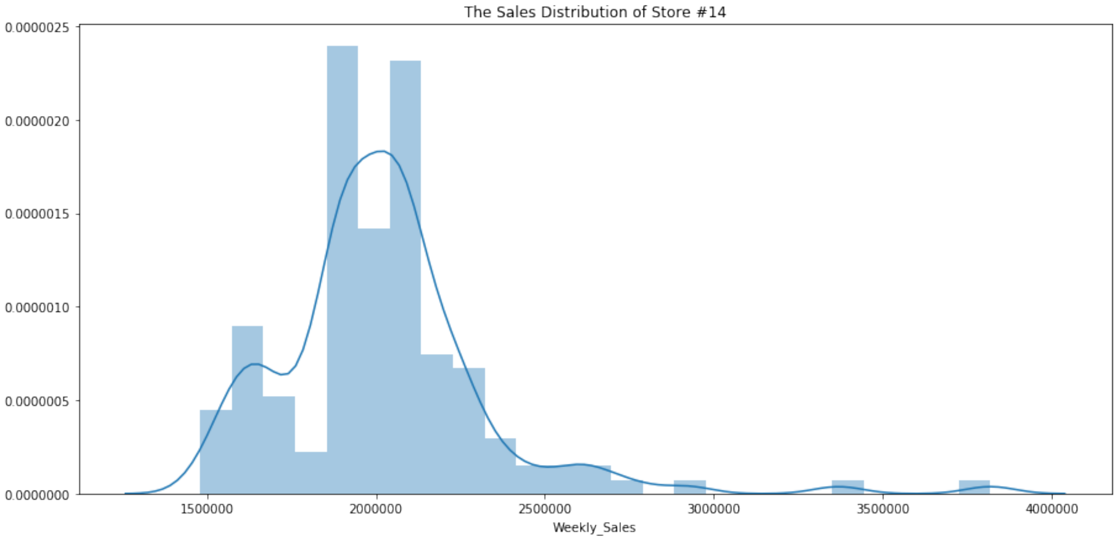
[8]:

```
# Which store has maximum standard deviation
data_std = pd.DataFrame(data.groupby('Store')['Weekly_Sales'].std().
 ↪sort_values(ascending=False))
print("The store has maximum standard deviation is "+str(data_std.head(1).
 ↪index[0])+" with {0:.0f} $".format(data_std.head(1).Weekly_Sales[data_std.
 ↪head(1).index[0]]))
```

```
The store has maximum standard deviation is 14 with 317570 $
```

[9]:

```
# Distribution of store has maximum standard deviation
plt.figure(figsize=(15,7))
sns.distplot(data[data['Store'] == data_std.head(1).index[0]]['Weekly_Sales'])
plt.title('The Sales Distribution of Store #'+ str(data_std.head(1).index[0]));
```



[10]:

```
# Coefficient of mean to standard deviation
coef_mean_std = pd.DataFrame(data.groupby('Store')['Weekly_Sales'].std() / data.
 ↪groupby('Store')['Weekly_Sales'].mean())
coef_mean_std = coef_mean_std.rename(columns={'Weekly_Sales':'Coefficient of␣
 ↪mean to standard deviation'})
coef_mean_std
```

[10]:

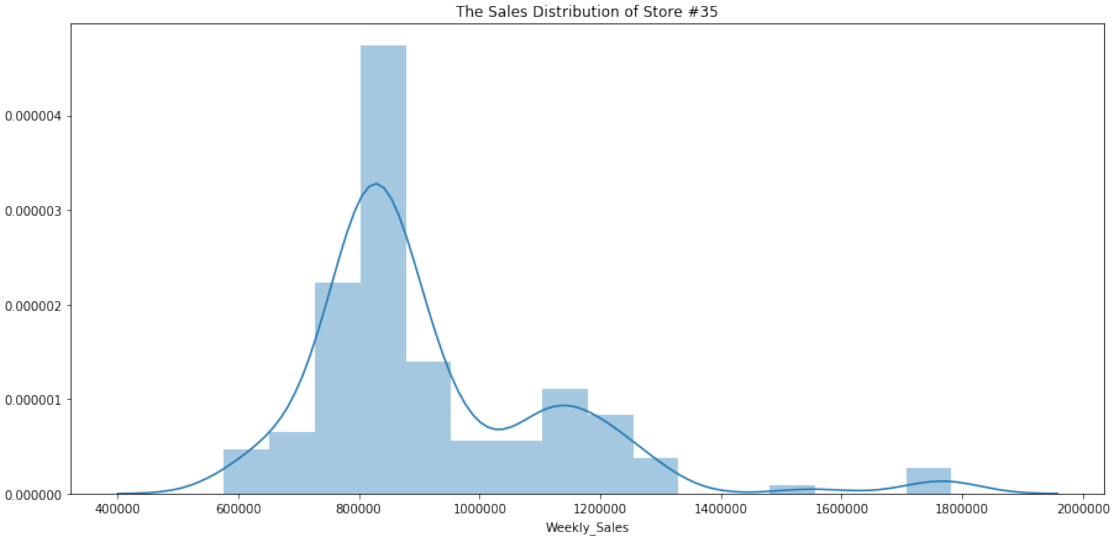
```
       Coefficient of mean to standard deviation
Store
1                                       0.100292
2                                       0.123424
3                                       0.115021
```

```
4                                         0.127083
5                                         0.118668
6                                         0.135823
7                                         0.197305
8                                         0.116953
9                                         0.126895
10                                        0.159133
11                                        0.122262
12                                        0.137925
13                                        0.132514
14                                        0.157137
15                                        0.193384
16                                        0.165181
17                                        0.125521
18                                        0.162845
19                                        0.132680
20                                        0.130903
21                                        0.170292
22                                        0.156783
23                                        0.179721
24                                        0.123637
25                                        0.159860
26                                        0.110111
27                                        0.135155
28                                        0.137330
29                                        0.183742
30                                        0.052008
31                                        0.090161
32                                        0.118310
33                                        0.092868
34                                        0.108225
35                                        0.229681
36                                        0.162579
37                                        0.042084
38                                        0.110875
39                                        0.149908
40                                        0.123430
41                                        0.148177
42                                        0.090335
43                                        0.064104
44                                        0.081793
45                                        0.165613
```

[11]:

```
# Distribution of store has maximum coefficient of mean to standard deviation
coef_mean_std_max = coef_mean_std.sort_values(by='Coefficient of mean to␣
 ↪standard deviation')
plt.figure(figsize=(15,7))
```

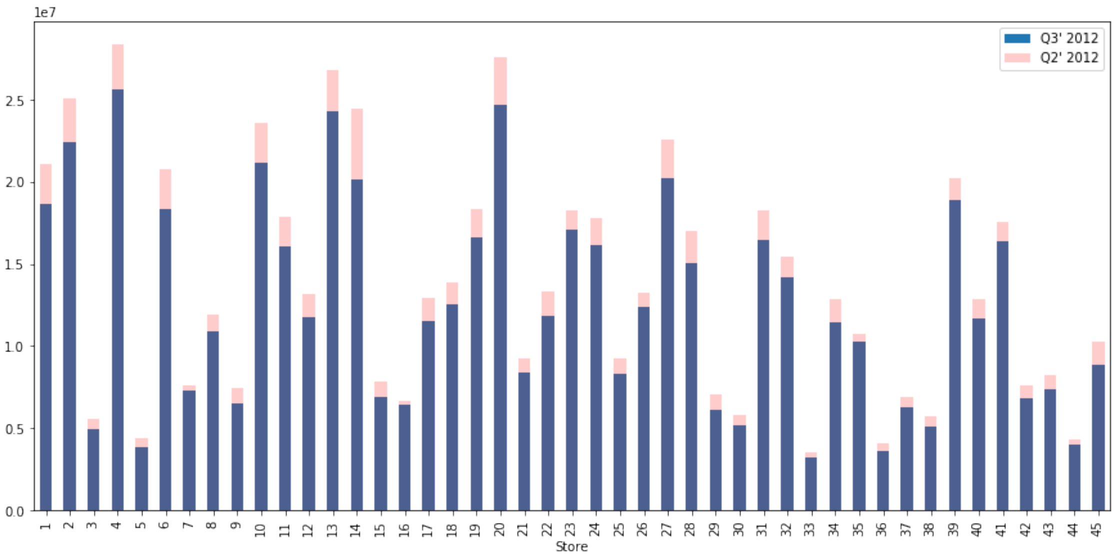
```
sns.distplot(data[data['Store'] == coef_mean_std_max.tail(1).
 ↪index[0]]['Weekly_Sales'])
plt.title('The Sales Distribution of Store #'+str(coef_mean_std_max.tail(1).
 ↪index[0]));
```



0.0.5 Q3: Which store/s has good quarterly growth rate in Q3'2012

[12]:
```
plt.figure(figsize=(15,7))

# Sales for third quarterly in 2012
Q3 = data[(data['Date'] > '2012-07-01') & (data['Date'] < '2012-09-30')].
 ↪groupby('Store')['Weekly_Sales'].sum()

# Sales for second quarterly in 2012
Q2 = data[(data['Date'] > '2012-04-01') & (data['Date'] < '2012-06-30')].
 ↪groupby('Store')['Weekly_Sales'].sum()

# Plotting the difference between sales for second and third quarterly
Q2.plot(ax=Q3.plot('bar',legend=True),kind='bar',color='r',alpha=0.
 ↪2,legend=True);
plt.legend(["Q3' 2012", "Q2' 2012"]);
```

```
C:\Users\Zaraah\Anaconda3\lib\site-packages\ipykernel_launcher.py:10:
FutureWarning: `Series.plot()` should not be called with positional arguments,
only keyword arguments. The order of positional arguments will change in the
future. Use `Series.plot(kind='bar')` instead of `Series.plot('bar',)`.
  # Remove the CWD from sys.path while we load stuff.
```



[13]:
```
#  store/s has good quarterly growth rate in Q3'2012 - .
↪sort_values(by='Weekly_Sales')
print('Store have good quarterly growth rate in Q3'2012 is Store '+str(Q3.
↪idxmax())+' With '+str(Q3.max())+' $')
```

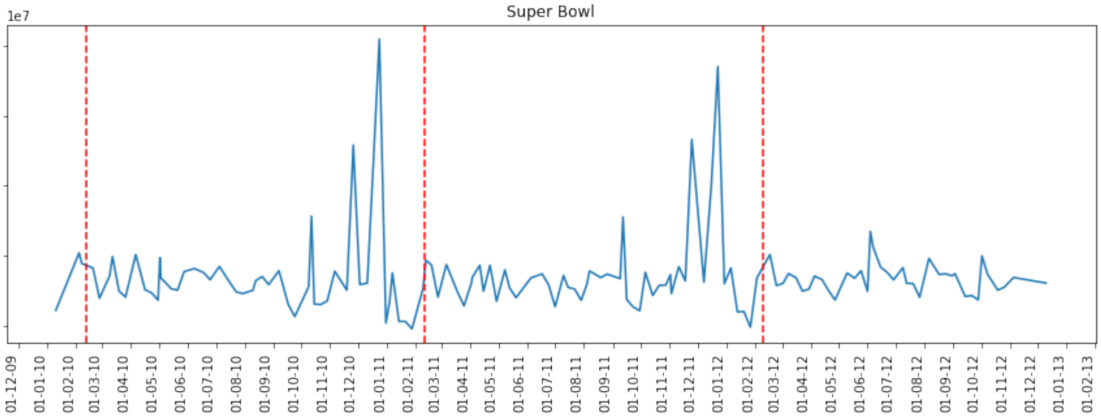
```
Store have good quarterly growth rate in Q3'2012 is Store 4 With 25652119.35 $
```

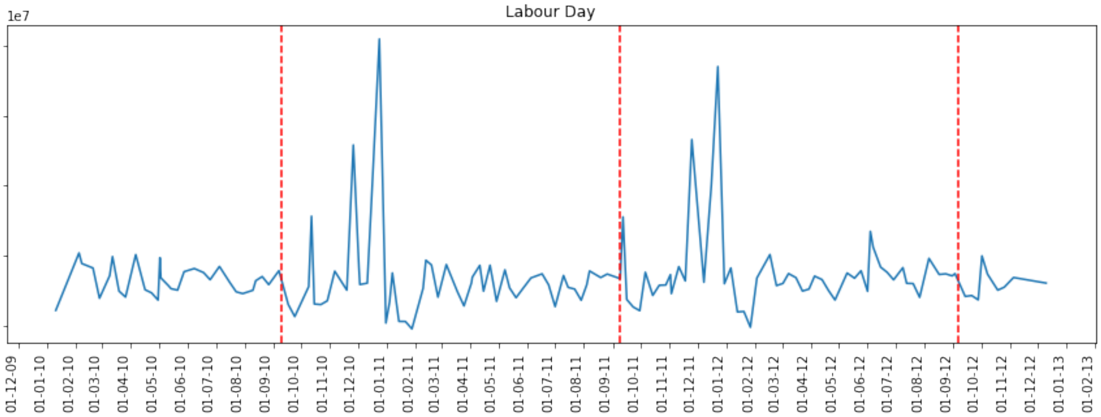
0.0.6 Q4: Some holidays have a negative impact on sales. Find out holidays which have higher sales than the mean sales in non-holiday season for all stores together

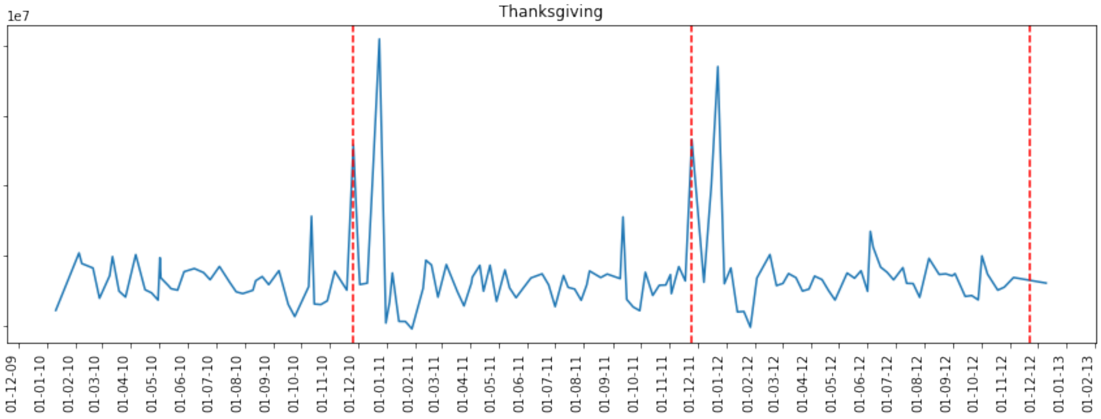
Holiday Events:

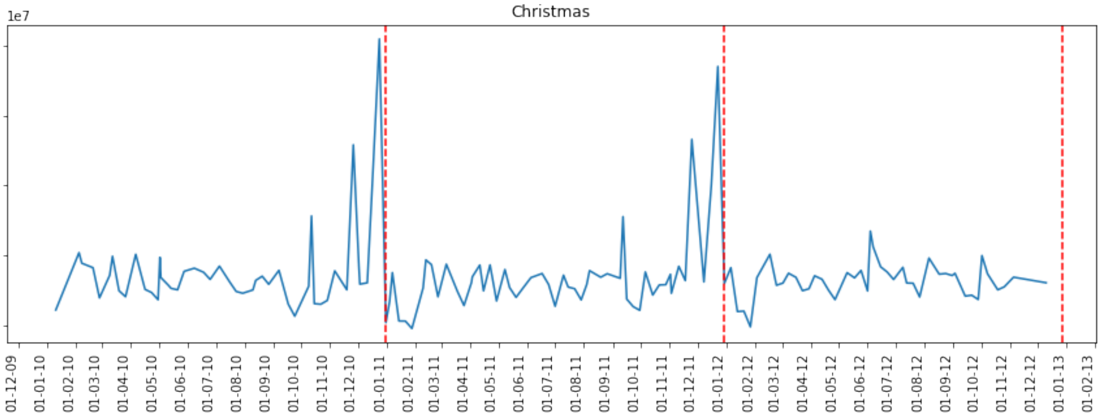
- Super Bowl: 12-Feb-10, 11-Feb-11, 10-Feb-12, 8-Feb-13
- Labour Day: 10-Sep-10, 9-Sep-11, 7-Sep-12, 6-Sep-13
- Thanksgiving: 26-Nov-10, 25-Nov-11, 23-Nov-12, 29-Nov-13
- Christmas: 31-Dec-10, 30-Dec-11, 28-Dec-12, 27-Dec-13

[18]:
```
def plot_line(df,holiday_dates,holiday_label):
    fig, ax = plt.subplots(figsize = (15,5))
    ax.plot(df['Date'],df['Weekly_Sales'],label=holiday_label)

    for day in holiday_dates:
        day = datetime.strptime(day, '%d-%m-%Y')
        plt.axvline(x=day, linestyle='--', c='r')


    plt.title(holiday_label)
    x_dates = df['Date'].dt.strftime('%Y-%m-%d').sort_values().unique()
    xfmt = dates.DateFormatter('%d-%m-%y')
    ax.xaxis.set_major_formatter(xfmt)
    ax.xaxis.set_major_locator(dates.DayLocator(1))
    plt.gcf().autofmt_xdate(rotation=90)
    plt.show()


total_sales = data.groupby('Date')['Weekly_Sales'].sum().reset_index()
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']

plot_line(total_sales,Super_Bowl,'Super Bowl')
plot_line(total_sales,Labour_Day,'Labour Day')
plot_line(total_sales,Thanksgiving,'Thanksgiving')
plot_line(total_sales,Christmas,'Christmas')
```









The sales increased during thanksgiving. And the sales decreased during christmas.

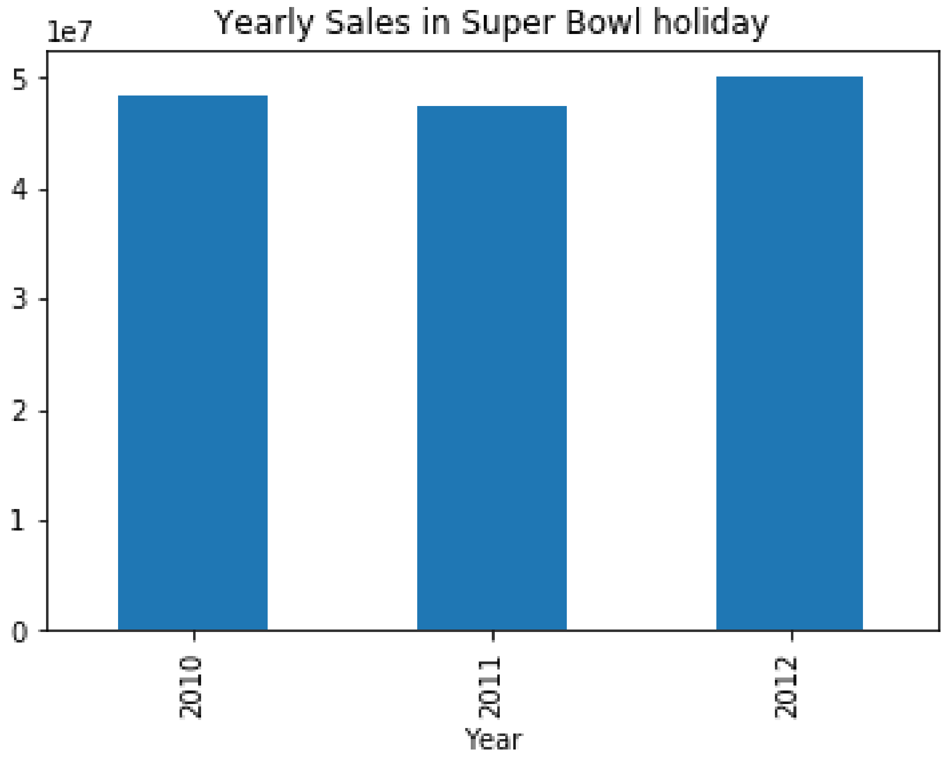
[19]:
```
data.loc[data.Date.isin(Super_Bowl)]
```

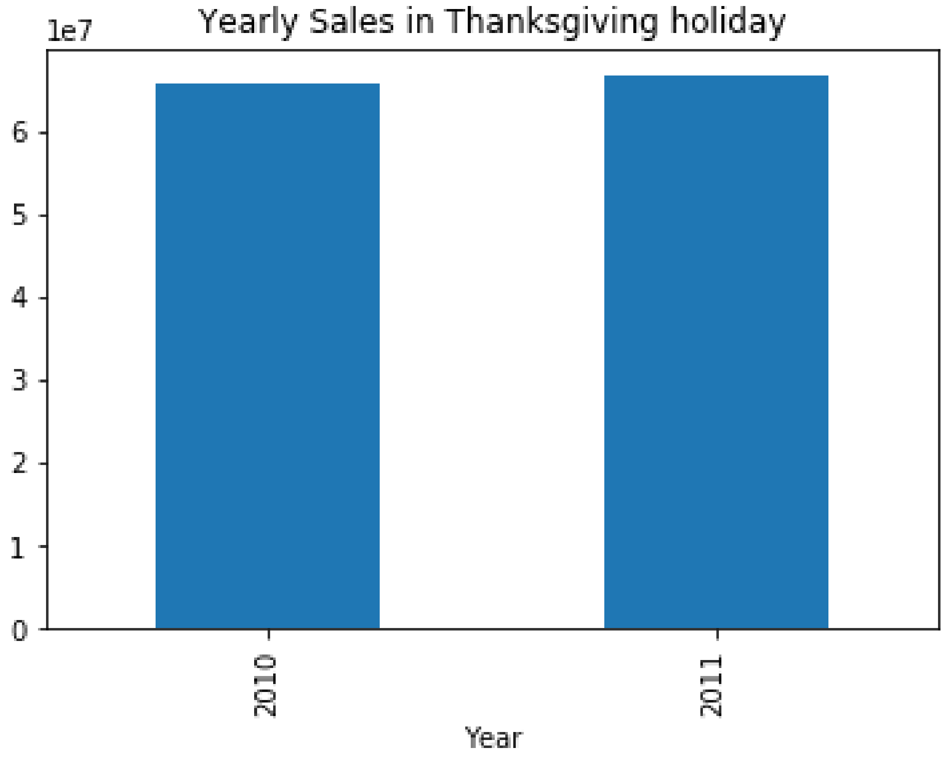
[19]:
```
      Store       Date  Weekly_Sales  Holiday_Flag  Temperature  Fuel_Price  \
1         1 2010-12-02    1641957.44             1        38.51       2.548
53        1 2011-11-02    1649614.93             1        36.39       3.022
105       1 2012-10-02    1802477.43             1        48.02       3.409
144       2 2010-12-02    2137809.50             1        38.49       2.548
196       2 2011-11-02    2168041.61             1        33.19       3.022
…       …        …            …             …          …           …
6202     44 2011-11-02     307486.73             1        30.83       3.034
6254     44 2012-10-02     325377.97             1        33.73       3.116
6293     45 2010-12-02     656988.64             1        27.73       2.773
6345     45 2011-11-02     766456.00             1        30.30       3.239
6397     45 2012-10-02     803657.12             1        37.00       3.640
```

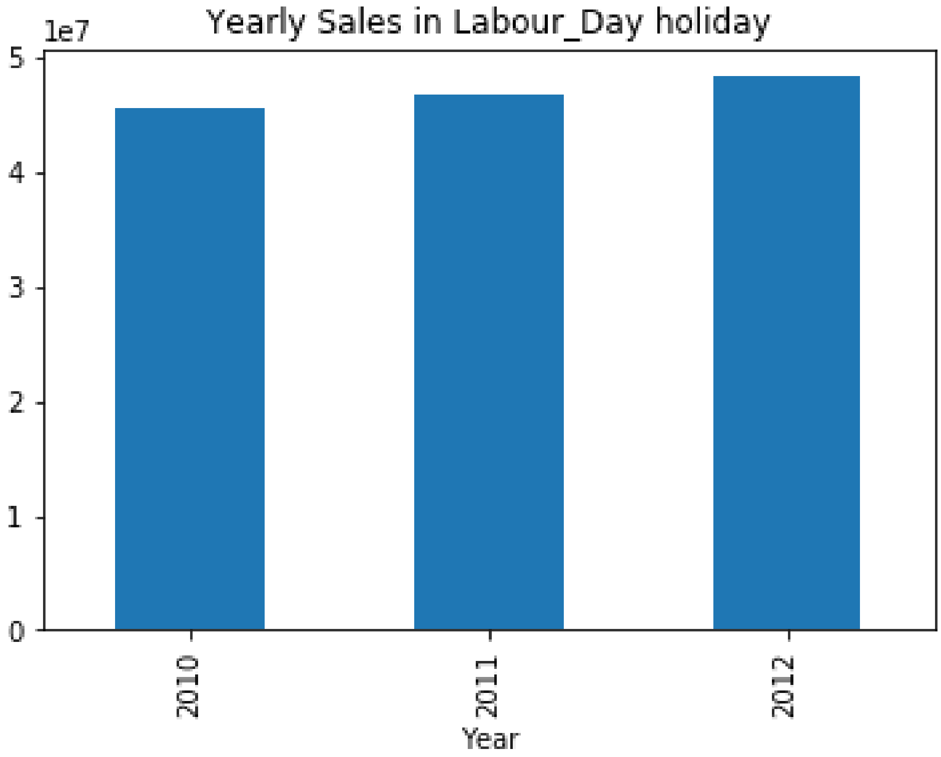
```
             CPI  Unemployment  Day  Month  Year
1     211.242170         8.106    2     12  2010
53    212.936705         7.742    2     11  2011
105   220.265178         7.348    2     10  2012
144   210.897994         8.324    2     12  2010
196   212.592862         8.028    2     11  2011
…            …             …   …      …    …
6202  127.859129         7.224    2     11  2011
6254  130.384903         5.774    2     10  2012
6293  181.982317         8.992    2     12  2010
6345  183.701613         8.549    2     11  2011
6397  189.707605         8.424    2     10  2012

[135 rows x 11 columns]
```

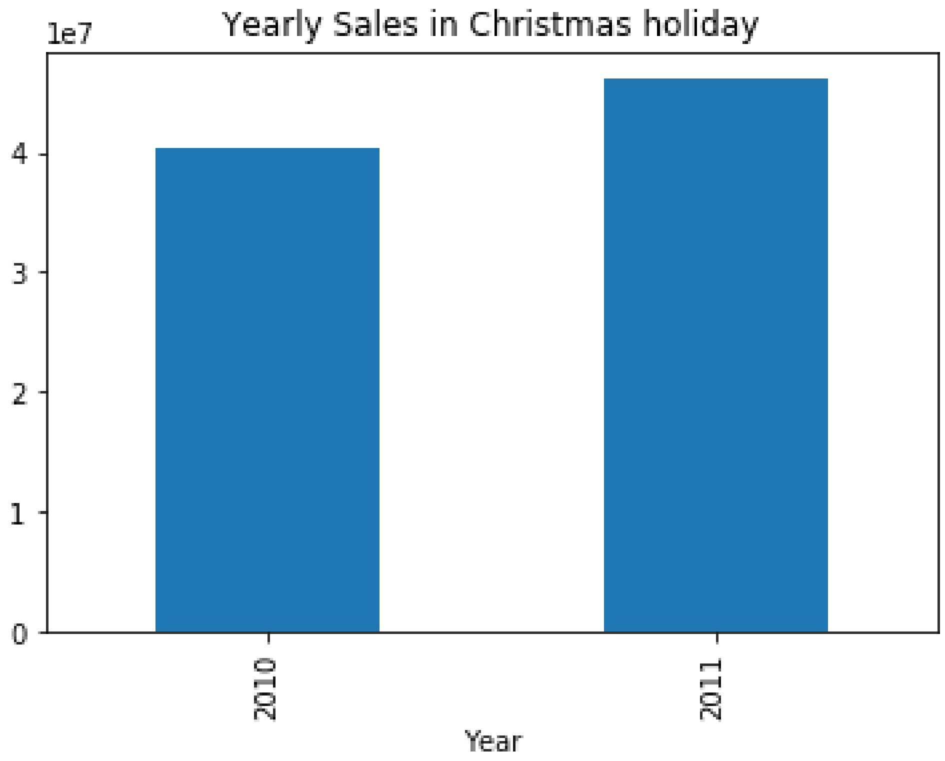
[90]:
```
# Yearly Sales in holidays
Super_Bowl_df = pd.DataFrame(data.loc[data.Date.isin(Super_Bowl)].
 ↪groupby('Year')['Weekly_Sales'].sum())
Thanksgiving_df = pd.DataFrame(data.loc[data.Date.isin(Thanksgiving)].
 ↪groupby('Year')['Weekly_Sales'].sum())
Labour_Day_df = pd.DataFrame(data.loc[data.Date.isin(Labour_Day)].
 ↪groupby('Year')['Weekly_Sales'].sum())
Christmas_df = pd.DataFrame(data.loc[data.Date.isin(Christmas)].
 ↪groupby('Year')['Weekly_Sales'].sum())

Super_Bowl_df.plot(kind='bar',legend=False,title='Yearly Sales in Super Bowl␣
 ↪holiday')
Thanksgiving_df.plot(kind='bar',legend=False,title='Yearly Sales in␣
 ↪Thanksgiving holiday')
Labour_Day_df.plot(kind='bar',legend=False,title='Yearly Sales in Labour_Day␣
 ↪holiday')
Christmas_df.plot(kind='bar',legend=False,title='Yearly Sales in Christmas␣
 ↪holiday')
```

[90]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1b42cb1a08>
```


Yearly Sales in Super Bowl holiday
1e7
5
4
3
2
1
0
2010
2011
2012
Year


Yearly Sales in Thanksgiving holiday
1e7
6
5
4
3
2
1
0
2010
2011
Year

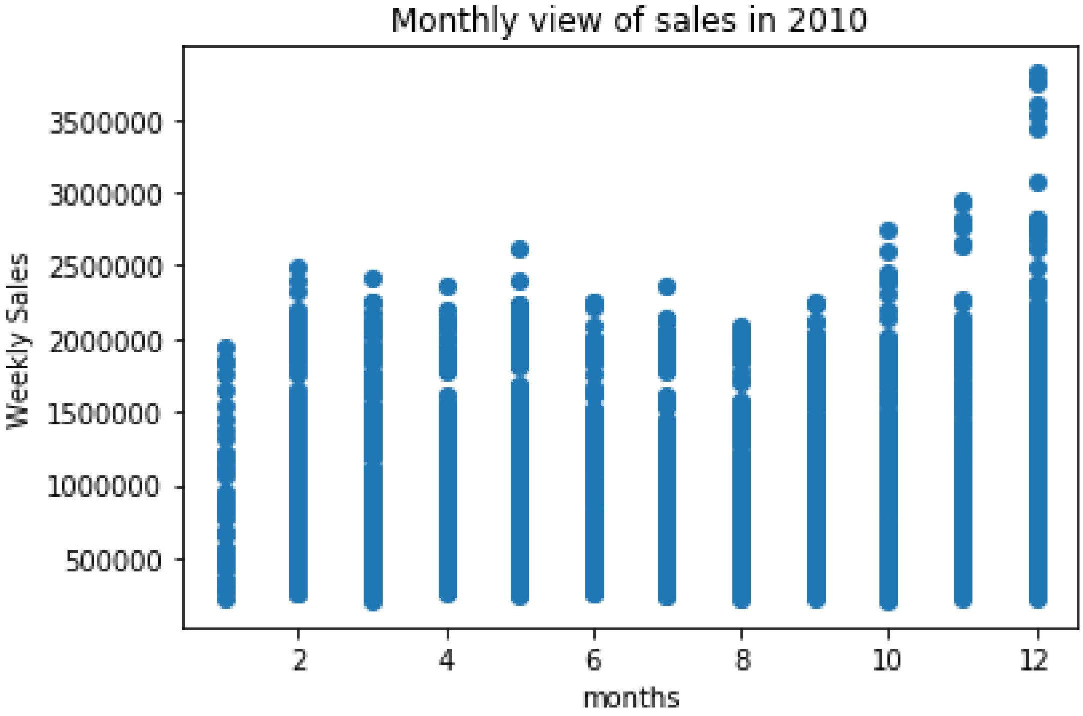

Yearly Sales in Labour_Day holiday
1e7
5
4
3
2
1
0
2010
2011
2012
Year

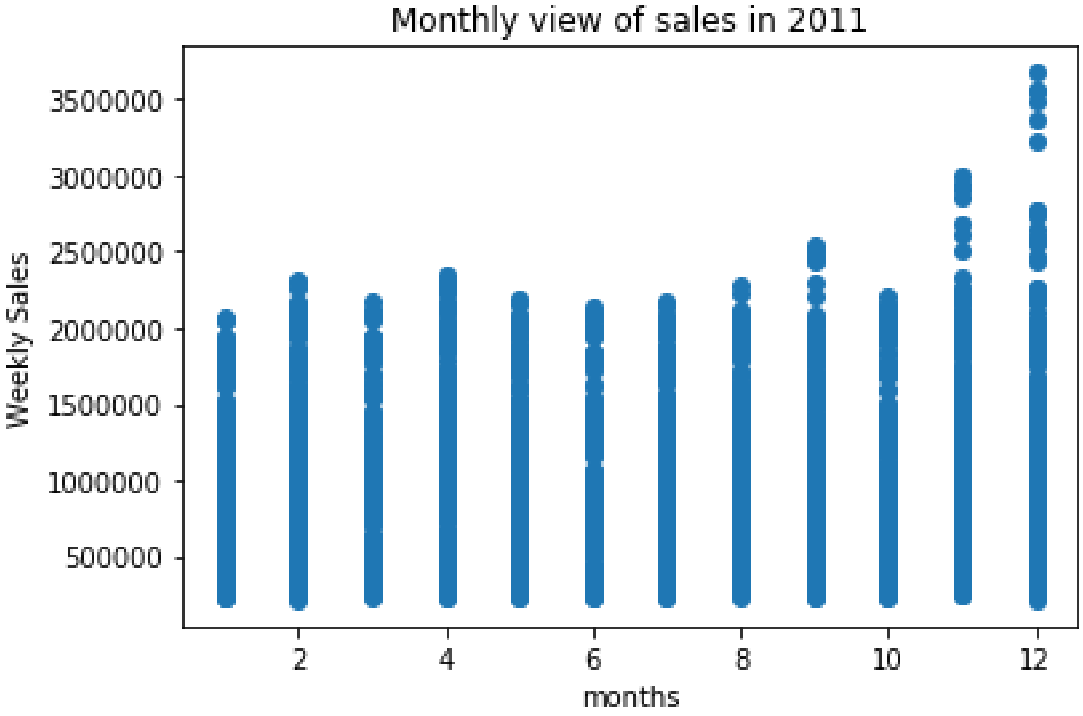


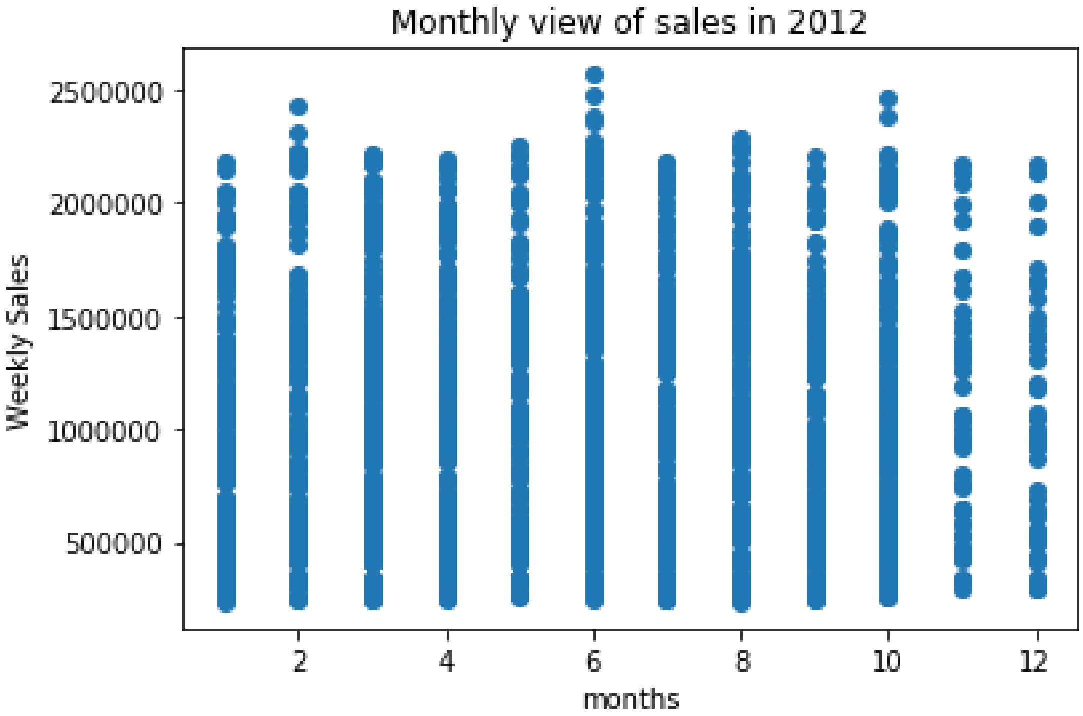
0.0.7 Q5: Provide a monthly and semester view of sales in units and give insights

[101]:

```
# Monthly view of sales for each years
plt.scatter(data[data.Year==2010]["Month"],data[data.
 ↪Year==2010]["Weekly_Sales"])
plt.xlabel("months")
plt.ylabel("Weekly Sales")
plt.title("Monthly view of sales in 2010")
plt.show()

plt.scatter(data[data.Year==2011]["Month"],data[data.
 ↪Year==2011]["Weekly_Sales"])
plt.xlabel("months")
plt.ylabel("Weekly Sales")
plt.title("Monthly view of sales in 2011")
plt.show()

plt.scatter(data[data.Year==2012]["Month"],data[data.
 ↪Year==2012]["Weekly_Sales"])
plt.xlabel("months")
plt.ylabel("Weekly Sales")
plt.title("Monthly view of sales in 2012")
plt.show()
```

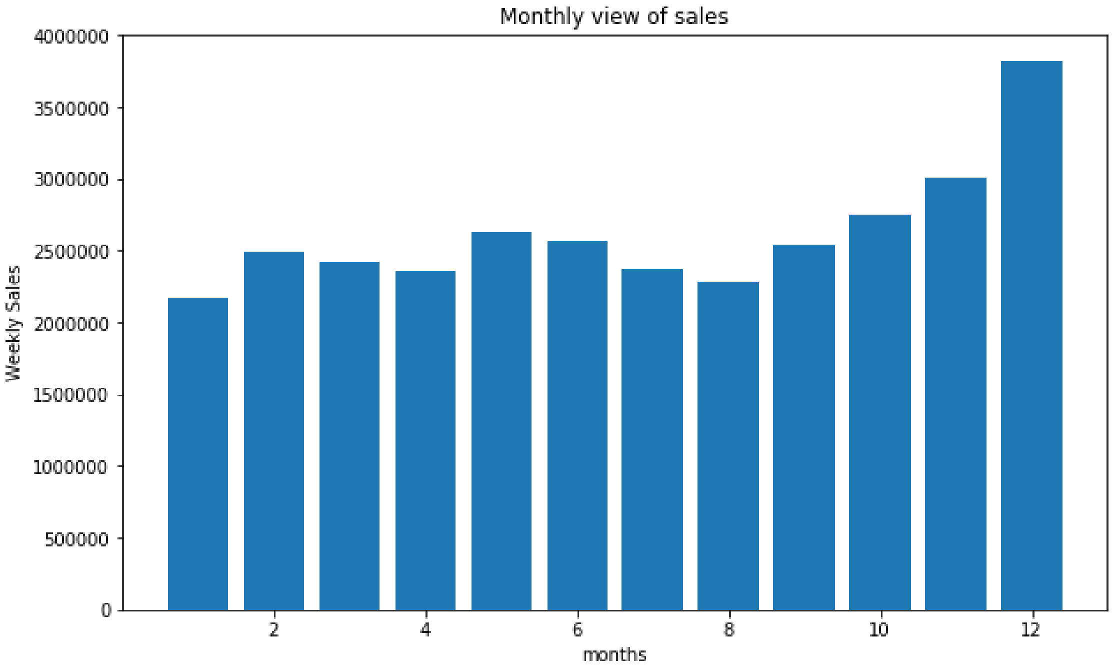

Monthly view of sales in 2010
Weekly Sales
3500000
3000000
2500000
2000000
1500000
1000000
500000
2
4
6
8
10
12
months


Monthly view of sales in 2011
Weekly Sales
3500000
3000000
2500000
2000000
1500000
1000000
500000
2
4
6
8
10
12
months



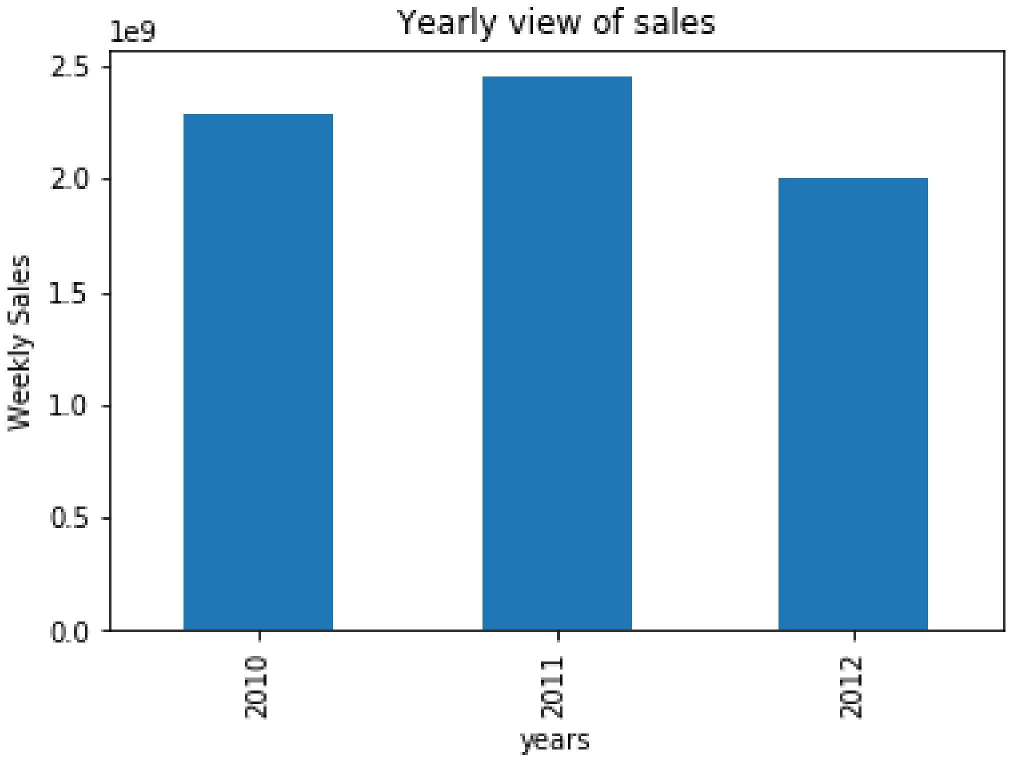
```
[102]: # Monthly view of sales for all years
       plt.figure(figsize=(10,6))
       plt.bar(data["Month"],data["Weekly_Sales"])
       plt.xlabel("months")
       plt.ylabel("Weekly Sales")
       plt.title("Monthly view of sales")
```

```
[102]: Text(0.5, 1.0, 'Monthly view of sales')
```



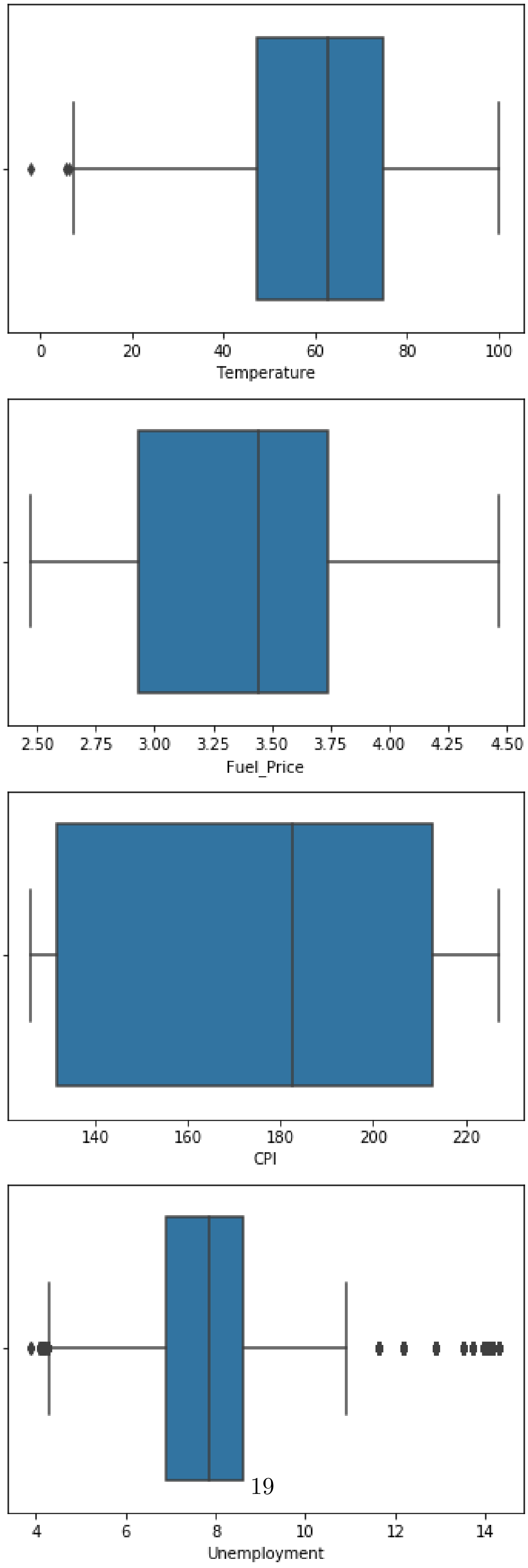
```
[110]: # Yearly view of sales
       plt.figure(figsize=(10,6))
       data.groupby("Year")[["Weekly_Sales"]].sum().plot(kind='bar',legend=False)
       plt.xlabel("years")
       plt.ylabel("Weekly Sales")
       plt.title("Yearly view of sales");
```

```
<Figure size 720x432 with 0 Axes>
```



0.1 Build prediction models to forecast demand (Modeling)

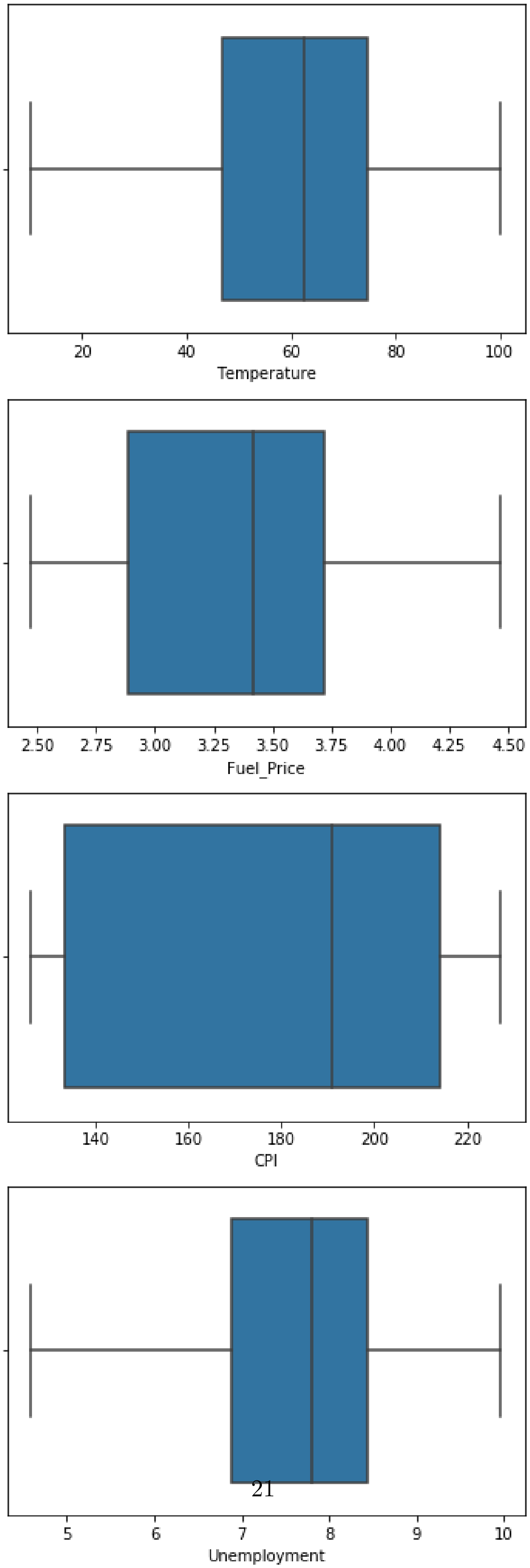
[111]:
```
# find outliers
fig, axs = plt.subplots(4,figsize=(6,18))
X = data[['Temperature','Fuel_Price','CPI','Unemployment']]
for i,column in enumerate(X):
    sns.boxplot(data[column], ax=axs[i])
```


0
20
40
60
80
100
Temperature
2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25
4.50
Fuel_Price
140
160
180
200
220
CPI
4
6
8
10
12
14
Unemployment

[112]:
```
# drop the outliers
data_new = data[(data['Unemployment']<10) & (data['Unemployment']>4.5) &␣
 ↪(data['Temperature']>10)]
data_new
```

[112]:
```
      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]
```

[113]:
```
# check outliers
fig, axs = plt.subplots(4,figsize=(6,18))
X = data_new[['Temperature','Fuel_Price','CPI','Unemployment']]
for i,column in enumerate(X):
    sns.boxplot(data_new[column], ax=axs[i])
```


20
40
60
80
100
Temperature
2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25
4.50
Fuel_Price
140
160
180
200
220
CPI
5
6
7
8
9
10
Unemployment

0.1.1 Build Model

[121]:

```
# Import sklearn
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.linear_model import LinearRegression
```

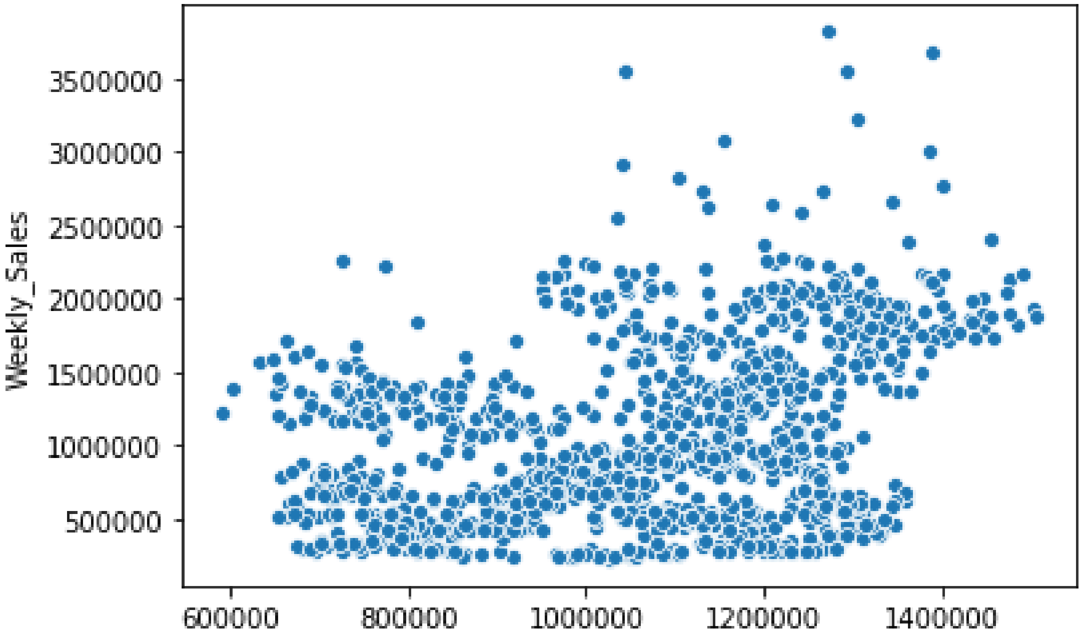
[122]:

```
# Select features and target
X = data_new[['Store','Fuel_Price','CPI','Unemployment','Day','Month','Year']]
y = data_new['Weekly_Sales']

# Split data to train and test (0.80:0.20)
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2)
```

[128]:

```
# Linear Regression model
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);
```

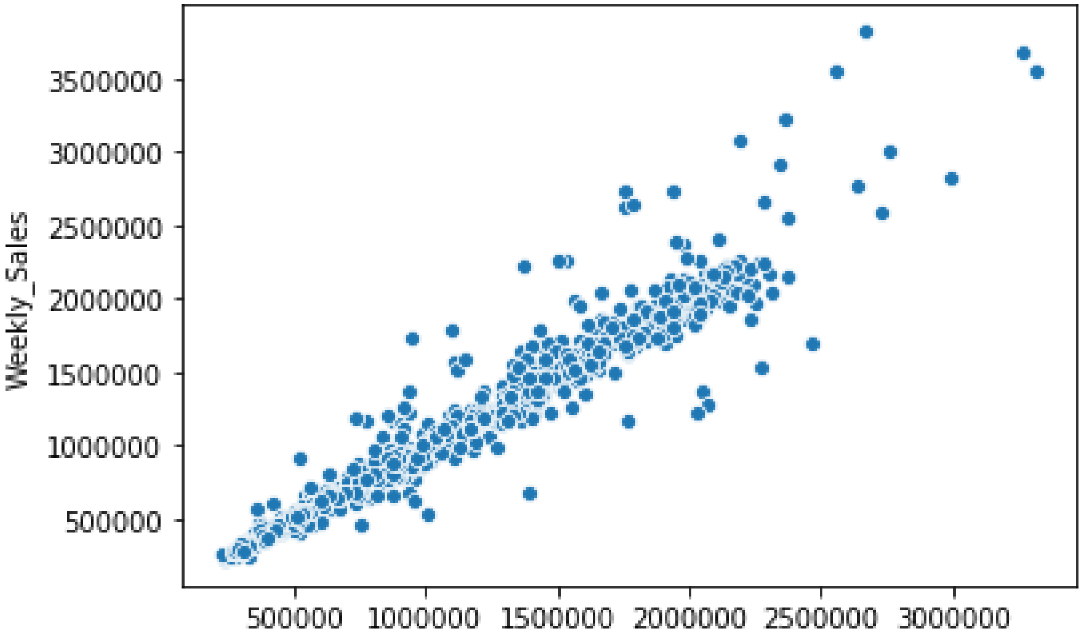
```
Linear Regression:

Accuracy: 12.998176857826893
Mean Absolute Error: 469135.83811432385
Mean Squared Error: 323485572250.08075
Root Mean Squared Error: 568757.9206042591
```



[129]:

```
# Random Forest Regressor
print('Random Forest Regressor:')
print()
rfr = RandomForestRegressor(n_estimators = 400,max_depth=15,n_jobs=5)
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: 94.36923602346438
Mean Absolute Error: 72405.98337255421
Mean Squared Error: 20817040949.867416
Root Mean Squared Error: 144281.11778700433
```


Weekly_Sales
3500000
3000000
2500000
2000000
1500000
1000000
500000
500000
1000000
1500000
2000000
2500000
3000000

```
[ ]:
```

```
[ ]:
```