```python
# Importing required Libraries.

import pandas as pd
from datetime import date
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

# Import Data Set.

import io
%cd "C:\Users\Hp\Desktop\Data Science and Analytics\Data Science Projects\Walmart Analysis\Data-Science-with-Python-Walmart-Stores-Sales-Prediction-Project-main"
```

```
C:\Users\Hp\Desktop\Data Science and Analytics\Data Science Projects\
Walmart Analysis\Data-Science-with-Python-Walmart-Stores-Sales-
Prediction-Project-main
```

```python
# Read the CSV file.

boschsales=pd.read_csv("Bosch_Store_sales.csv")

# Understand dataset.

boschsales.head(10)
```

```
   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
5      1  12-03-2010    1439541.59             0        57.79
2.667
6      1  19-03-2010    1472515.79             0        54.58
2.720
7      1  26-03-2010    1404429.92             0        51.45
2.732
8      1  02-04-2010    1594968.28             0        62.27
2.719
9      1  09-04-2010    1545418.53             0        65.86
2.770
```

```
           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  211.380643         8.106
6  211.215635         8.106
7  211.018042         8.106
8  210.820450         7.808
9  210.622857         7.808
```

```python
# Basic information about our dataset.

boschsales.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
```

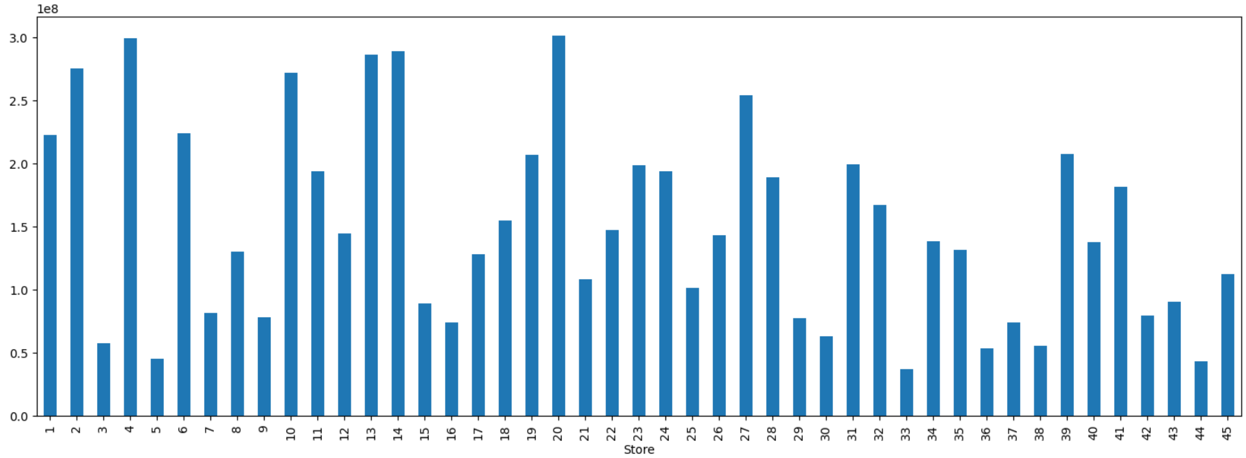
```python
#Maximum value in each column.

boschsales.max()
```

```
Store                    45
Date             31-12-2010
Weekly_Sales     3818686.45
Holiday_Flag              1
Temperature          100.14
Fuel_Price            4.468
CPI              227.232807
Unemployment         14.313
dtype: object
```

```python
boschsales.describe()
```

```
             Store  Weekly_Sales  Holiday_Flag  Temperature
Fuel_Price  \
count  6435.000000  6.435000e+03   6435.000000  6435.000000
```

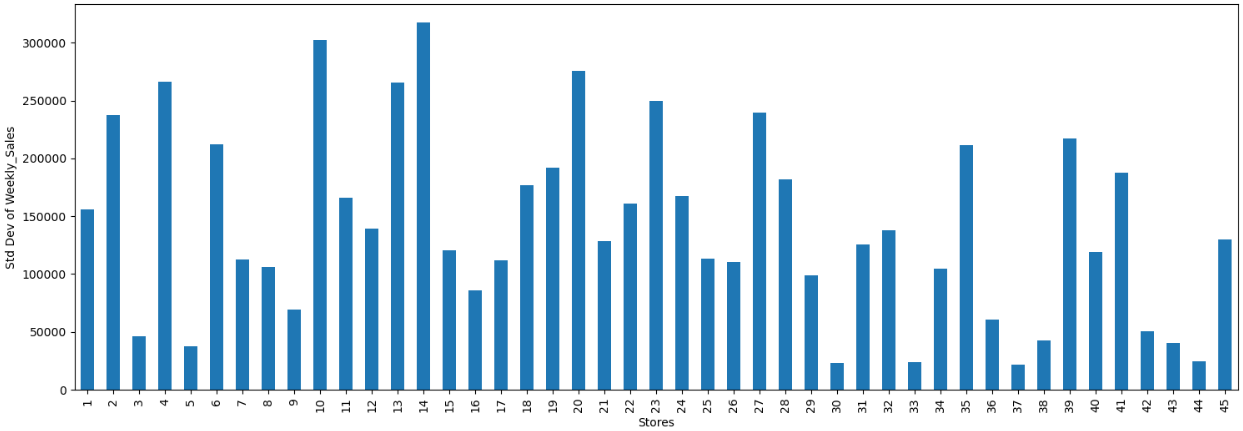
```
6435.000000
mean      23.000000  1.046965e+06      0.069930    60.663782
3.358607
std       12.988182  5.643666e+05      0.255049    18.444933
0.459020
min        1.000000  2.099862e+05      0.000000    -2.060000
2.472000
25%       12.000000  5.533501e+05      0.000000    47.460000
2.933000
50%       23.000000  9.607460e+05      0.000000    62.670000
3.445000
75%       34.000000  1.420159e+06      0.000000    74.940000
3.735000
max       45.000000  3.818686e+06      1.000000   100.140000
4.468000

               CPI  Unemployment
count  6435.000000   6435.000000
mean    171.578394      7.999151
std      39.356712      1.875885
min     126.064000      3.879000
25%     131.735000      6.891000
50%     182.616521      7.874000
75%     212.743293      8.622000
max     227.232807     14.313000

# store having maximum weekly sales.

sales_list= pd.DataFrame(boschsales.groupby(['Store'])
['Weekly_Sales'].sum())
sales_list.reset_index()
max_sales=sales_list.loc[sales_list['Weekly_Sales'] ==
sales_list['Weekly_Sales'].max()]
max_sales

# We can see that store 20 has maximum weekly sales.

       Weekly_Sales
Store
20     3.013978e+08

# Plot showing weekly sales against stores.

plt.figure(figsize=(18,6))
boschsales.groupby(['Store'])['Weekly_Sales'].sum().plot(kind='bar')
plt.show()
```



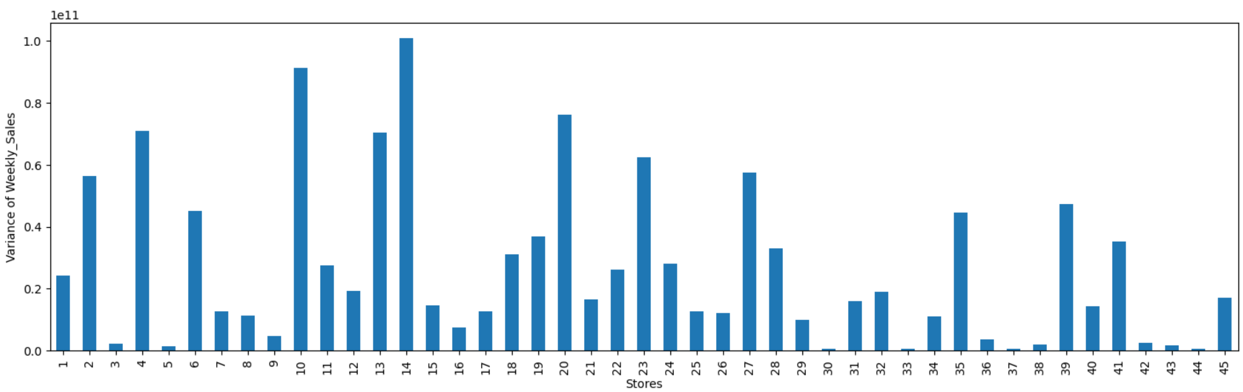

```
# store having maximum standard deviation i.e., the sales vary a lot.
Also, finding out the coefficient of variance (C0V)

maxstd=pd.DataFrame(boschsales.groupby('Store').agg({'Weekly_Sales':
['std','mean','var']}))
maxstd = maxstd.reset_index()

maxstd['CoV']
=(maxstd[('Weekly_Sales','std')]/maxstd[('Weekly_Sales','mean')]) *100

# Finding the store with maximum standard deviation.

maxstd.loc[maxstd[('Weekly_Sales','std')]==maxstd[('Weekly_Sales','std
')].max()]

# store with maximum standard deviation of 317569.949476 is 14.
```

	Store	Weekly_Sales			CoV
		std	mean	var	
13	14	317569.949476	2.020978e+06	1.008507e+11	15.713674

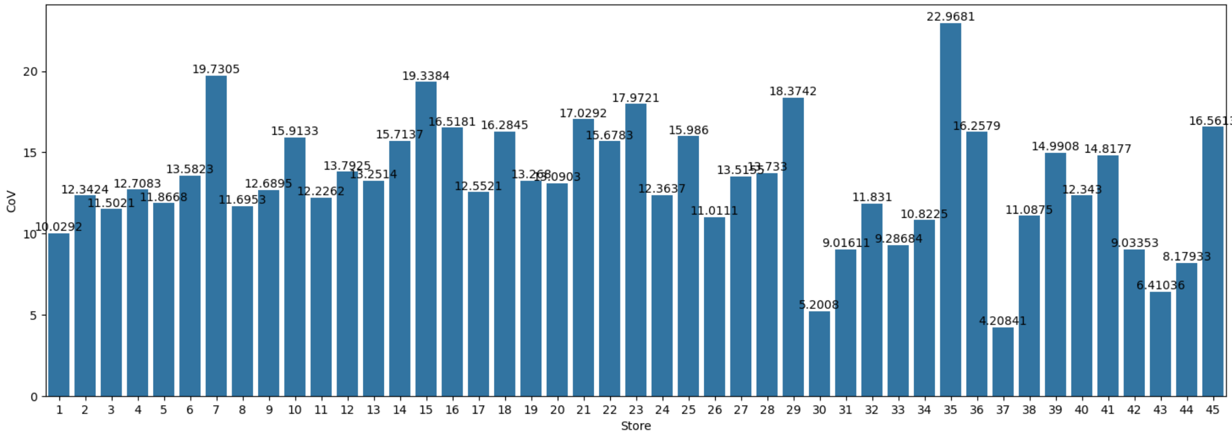
```
# Bar plot showing "Std Dev of Weekly_Sales" agianst "Stores"

plt.figure(figsize=(18,6))
boschsales.Weekly_Sales.groupby(boschsales.Store).std().plot(kind='bar
')
plt.xlabel("Stores")
plt.ylabel("Std Dev of Weekly_Sales")
plt.show()
```




```python
# Bar plot showing "var" agianst "Stores"

plt.figure(figsize=(18,5))
boschsales.Weekly_Sales.groupby(boschsales.Store).var().plot(kind='bar
')
plt.xlabel("Stores")
plt.ylabel("Variance of Weekly_Sales")
plt.show()
```




```python
# Coefficient of mean to standard deviation

# Bar plot showing "CoV" agianst "Stores"

plt.figure(figsize=(18,6))
storeax=sns.barplot(x='Store',y='CoV',data=maxstd)
storeax.bar_label(storeax.containers[0]);
plt.show()
```



Store/s having good quarterly growth rate in Q3’2012.

```
# Extracting Year, Month and Week from date column

boschsales['Date'] = pd.to_datetime(boschsales.Date,format='%d-%m-%Y')

boschsales['Year'], boschsales['Month'], boschsales['Week'] =
boschsales['Date'].dt.year, boschsales['Date'].dt.month,
boschsales['Date'].dt.isocalendar().week
boschsales

      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
...     ...         ...           ...           ...          ...
...
6430     45 2012-09-28     713173.95             0        64.88
3.997
6431     45 2012-10-05     733455.07             0        64.89
3.985
6432     45 2012-10-12     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  Year  Month  Week
0     211.096358         8.106  2010      2     5
1     211.242170         8.106  2010      2     6
2     211.289143         8.106  2010      2     7
3     211.319643         8.106  2010      2     8
4     211.350143         8.106  2010      3     9
...          ...           ...   ...    ...   ...
6430  192.013558         8.684  2012      9    39
6431  192.170412         8.667  2012     10    40
6432  192.327265         8.667  2012     10    41
6433  192.330854         8.667  2012     10    42
6434  192.308899         8.667  2012     10    43

[6435 rows x 11 columns]
```

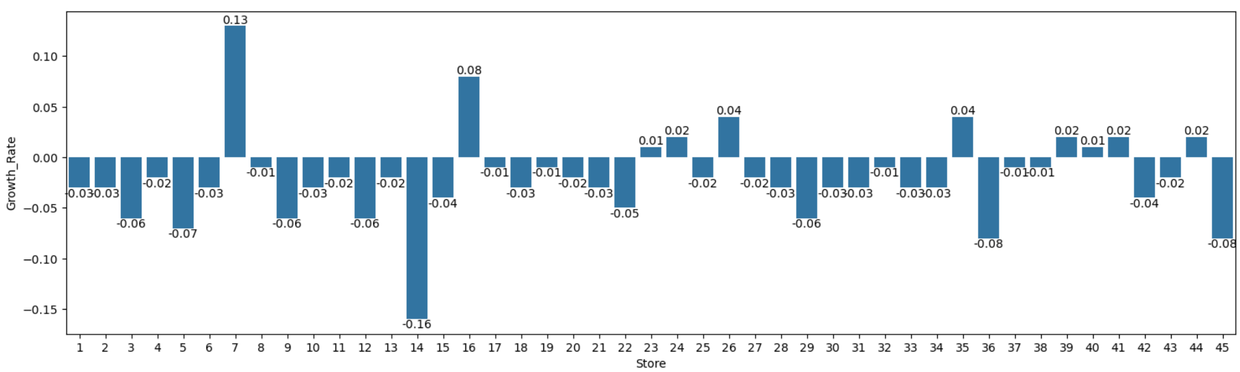
```python
# Defining the start and end date of Q3 and Q2 ( Recent 2 quarters)

Q3_date_from = pd.Timestamp(date(2012,7,1))
Q3_date_to = pd.Timestamp(date(2012,9,30))

Q2_date_from = pd.Timestamp(date(2012,4,1))
Q2_date_to = pd.Timestamp(date(2012,6,30))

# Collecting the data of Q3 and Q2 from original dataset.

Q3data=boschsales[(boschsales['Date'] >= Q3_date_from) &
(boschsales['Date'] <= Q3_date_to)]
Q2data=boschsales[(boschsales['Date'] >= Q2_date_from) &
(boschsales['Date'] <= Q2_date_to)]

# Finding the sum weekly sales of each store in Q3

Q3 = pd.DataFrame(Q3data.groupby('Store')['Weekly_Sales'].sum())
Q3.reset_index(inplace=True)
Q3.rename(columns={'Weekly_Sales': 'Q3_Weekly_Sales'},inplace=True)

# Finding the sum weekly sales of each store in Q2

Q2 = pd.DataFrame(Q2data.groupby('Store')['Weekly_Sales'].sum())
Q2.reset_index(inplace=True)
Q2.rename(columns={'Weekly_Sales': 'Q2_Weekly_Sales'},inplace=True)

# Mergeing Q2 and Q3 data on Store as a common column

Q3_Growth= Q2.merge(Q3,how='inner',on='Store')

Q3_Growth.head(3)
```

	Store	Q2_Weekly_Sales	Q3_Weekly_Sales
0	1	20978760.12	20253947.78
1	2	25083604.88	24303354.86
2	3	5620316.49	5298005.47

```
# Calculating Growth rate of each Store and collecting it into a
dataframe

# Growth rate = ((Present value – Past value )/Past value )*100

Q3_Growth['Growth_Rate'] =(Q3_Growth['Q3_Weekly_Sales'] -
Q3_Growth['Q2_Weekly_Sales'])/Q3_Growth['Q2_Weekly_Sales']
Q3_Growth['Growth_Rate']=round(Q3_Growth['Growth_Rate'],2)
Q3_Growth.head()
```

	Store	Q2_Weekly_Sales	Q3_Weekly_Sales	Growth_Rate
0	1	20978760.12	20253947.78	-0.03
1	2	25083604.88	24303354.86	-0.03
2	3	5620316.49	5298005.47	-0.06
3	4	28454363.67	27796792.46	-0.02
4	5	4466363.69	4163790.99	-0.07

```
# Bar plot showing "Growth_Rate" agianst "Stores"

plt.figure(figsize=(18,5))
storebx=sns.barplot(x='Store',y='Growth_Rate',data=Q3_Growth)
storebx.bar_label(storebx.containers[0]);
plt.show()
```




```
# Finding the store with highest Growth_Rate.

Q3_Growth.sort_values('Growth_Rate',ascending=False).head(1)

# Store 7 has made the highest growth.
```

	Store	Q2_Weekly_Sales	Q3_Weekly_Sales	Growth_Rate
6	7	7290859.27	8262787.39	0.13

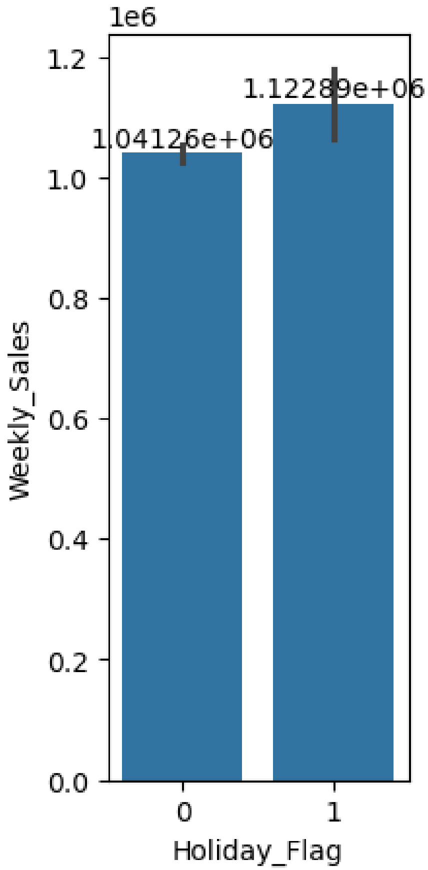
```
# Finding the store with lowest Growth_Rate.

Q3_Growth.sort_values('Growth_Rate',ascending=True).head(1)

# Store 14 has made the lowest growth.
```

```
    Store  Q2_Weekly_Sales  Q3_Weekly_Sales  Growth_Rate
13     14      25155535.41      21187560.65        -0.16
```

```
# Finding the mean sales of non holiday and holiday.

boschsales.groupby('Holiday_Flag')['Weekly_Sales'].mean()
```

```
Holiday_Flag
0    1.041256e+06
1    1.122888e+06
Name: Weekly_Sales, dtype: float64
```

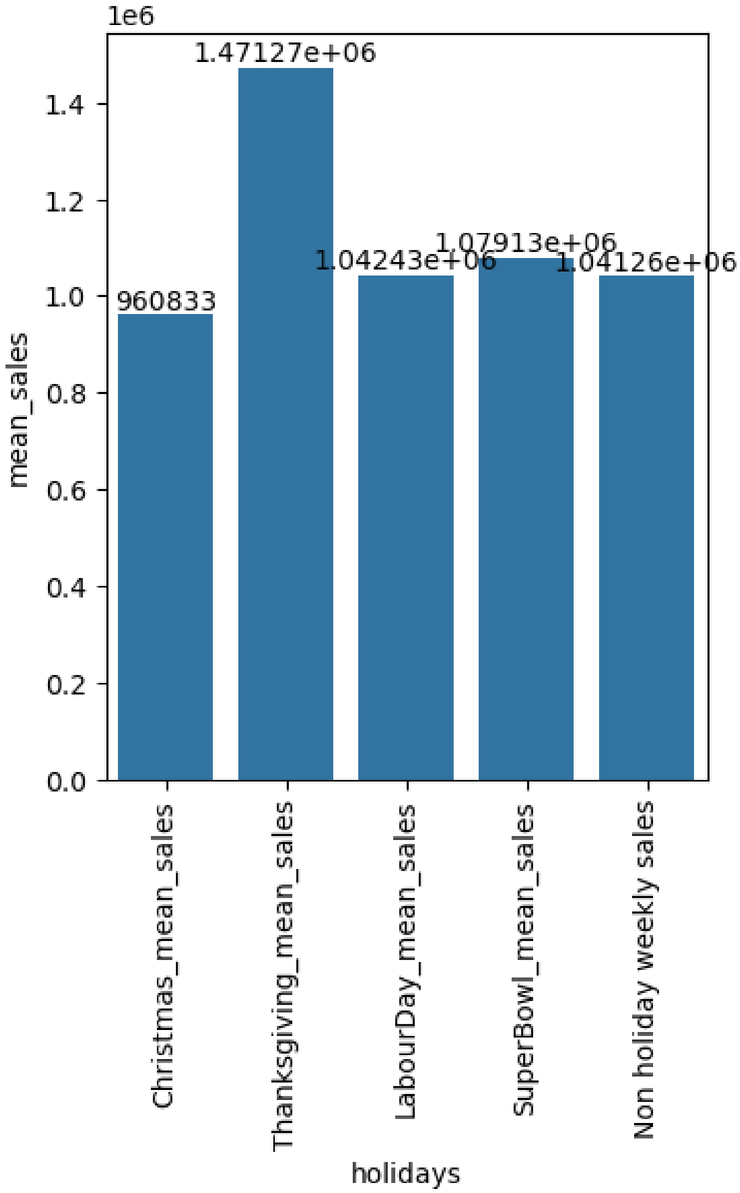
```
# Bar plot showing "Weekly_Sales" agianst "Holiday_Flag"

plt.figure(figsize=(2,5))
storecx=sns.barplot(x='Holiday_Flag',y='Weekly_Sales',data=boschsales)
storecx.bar_label(storecx.containers[0]);
plt.show()
```




```
# Marking the holiday dates.

Christmas1 = pd.Timestamp(date(2010,12,31))
Christmas2 = pd.Timestamp(date(2011,12,30))
Christmas3 = pd.Timestamp(date(2012,12,28))
Christmas4 = pd.Timestamp(date(2013,12,27))

Thanksgiving1=pd.Timestamp(date(2010,11,26))
Thanksgiving2=pd.Timestamp(date(2011,11,25))
Thanksgiving3=pd.Timestamp(date(2012,11,23))
Thanksgiving4=pd.Timestamp(date(2013,11,29))

LabourDay1=pd.Timestamp(date(2010,9,10))
LabourDay2=pd.Timestamp(date(2011,9,9))
LabourDay3=pd.Timestamp(date(2012,9,7))
LabourDay4=pd.Timestamp(date(2013,9,6))

SuperBowl1=pd.Timestamp(date(2010,2,12))
SuperBowl2=pd.Timestamp(date(2011,2,11))
SuperBowl3=pd.Timestamp(date(2012,2,10))
SuperBowl4=pd.Timestamp(date(2013,2,8))
```

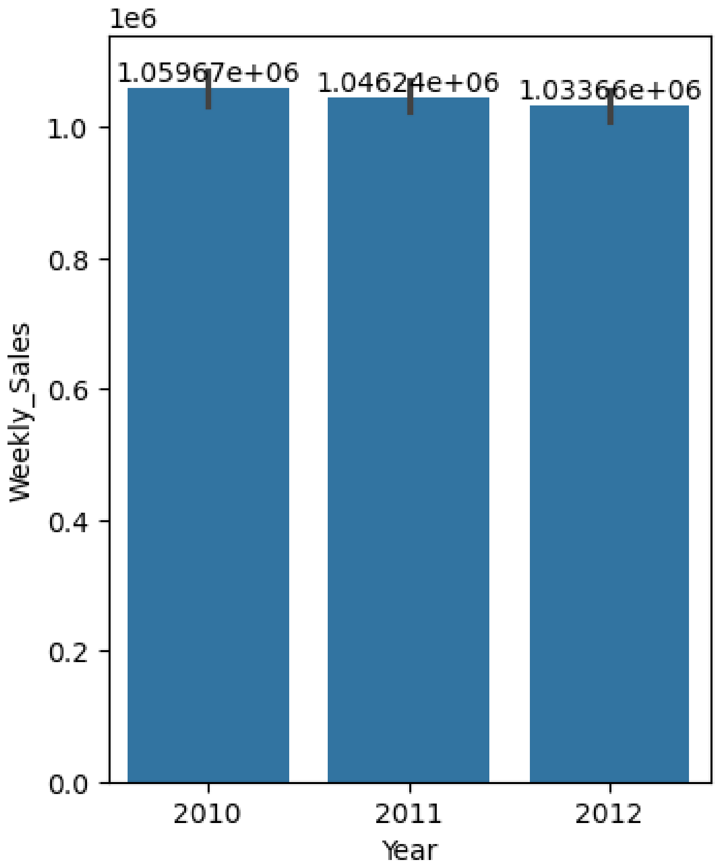
```
# Calculating the mean sales during the holidays.

Christmas_mean_sales=boschsales[(boschsales['Date'] == Christmas1) |
(boschsales['Date'] == Christmas2) | (boschsales['Date'] ==
Christmas3) | (boschsales['Date'] == Christmas4)]
Thanksgiving_mean_sales=boschsales[(boschsales['Date'] ==
Thanksgiving1) | (boschsales['Date'] == Thanksgiving2) |
(boschsales['Date'] == Thanksgiving3) | (boschsales['Date'] ==
Thanksgiving4)]
LabourDay_mean_sales=boschsales[(boschsales['Date'] == LabourDay1) |
(boschsales['Date'] == LabourDay2) | (boschsales['Date'] ==
LabourDay3) | (boschsales['Date'] == LabourDay4)]
SuperBowl_mean_sales=boschsales[(boschsales['Date'] == SuperBowl1) |
(boschsales['Date'] == SuperBowl2) | (boschsales['Date'] ==
SuperBowl3) | (boschsales['Date'] == SuperBowl4)]

dict_of_mean_sales = {'Christmas_mean_sales' :
round(Christmas_mean_sales['Weekly_Sales'].mean(),2),
'Thanksgiving_mean_sales':
round(Thanksgiving_mean_sales['Weekly_Sales'].mean(),2),
'LabourDay_mean_sales' :
round(LabourDay_mean_sales['Weekly_Sales'].mean(),2),
'SuperBowl_mean_sales':round(SuperBowl_mean_sales['Weekly_Sales'].mean
(),2),
'Non holiday weekly sales' : boschsales[boschsales['Holiday_Flag'] ==
0 ]['Weekly_Sales'].mean()}

dict_of_mean_sales # List of mean sales during the holidays and mean
sales during the Non holidays.

# We can see that during Thanksgiving, mean sales are high than the
mean sales during Non holidays.

{'Christmas_mean_sales': 960833.11,
 'Thanksgiving_mean_sales': 1471273.43,
 'LabourDay_mean_sales': 1042427.29,
 'SuperBowl_mean_sales': 1079127.99,
 'Non holiday weekly sales': 1041256.3802088555}

mean_sales_during_holidays_Nonholidays=pd.DataFrame(list(dict_of_mean_
sales.items()),columns = ['holidays','mean_sales'])

mean_sales_during_holidays_Nonholidays

                   holidays    mean_sales
0      Christmas_mean_sales  9.608331e+05
1   Thanksgiving_mean_sales  1.471273e+06
2      LabourDay_mean_sales  1.042427e+06
3      SuperBowl_mean_sales  1.079128e+06
4  Non holiday weekly sales  1.041256e+06
```

```python
# Bar plot showing mean sales during Holidays and Non Holidays.

plt.figure(figsize=(4,5))
storedx=sns.barplot(x='holidays',y='mean_sales',data=mean_sales_during
_holidays_Nonholidays)
plt.xticks(rotation=90)
storedx.bar_label(storedx.containers[0]);
plt.show()
```

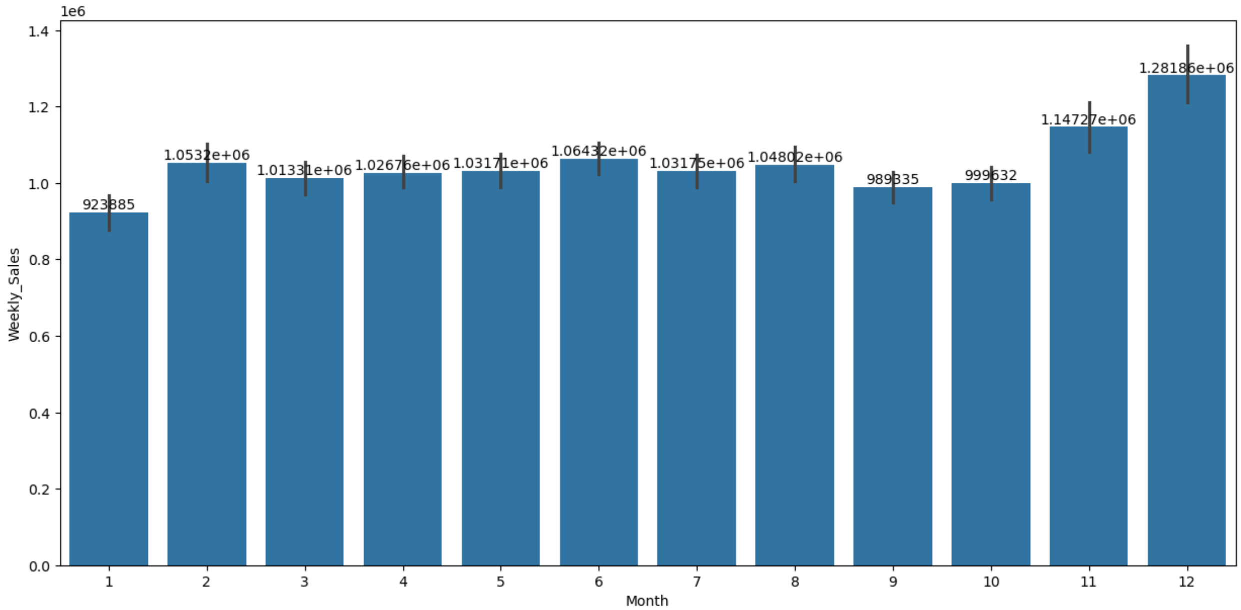



```python
plt.figure(figsize=(4,5))
store_ex=sns.barplot(x='Year', y='Weekly_Sales', data=boschsales); #
Year wise average Weekly_Sales
```

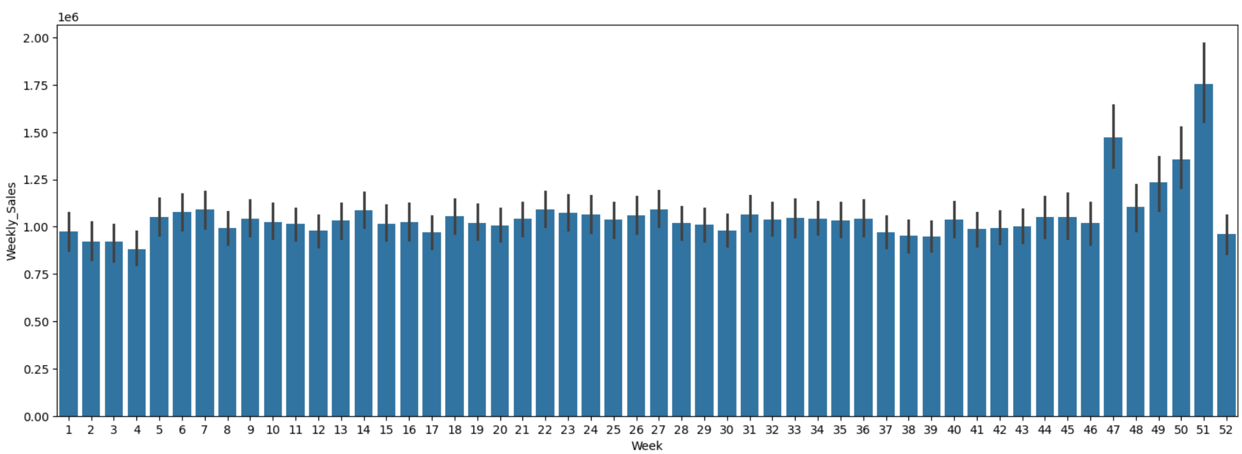
```
store_ex.bar_label(store_ex.containers[0]);
plt.show()
```



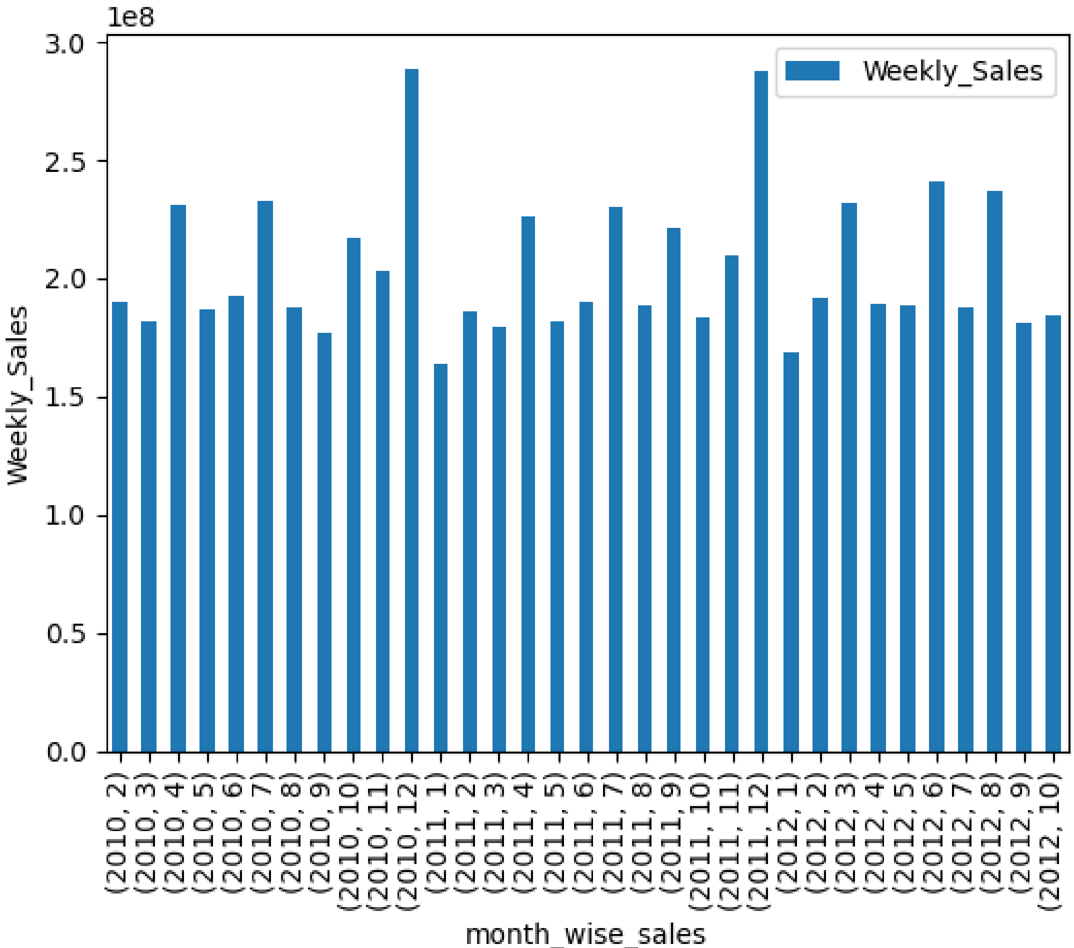

```
plt.figure(figsize=(15,7))
storefx=sns.barplot(x='Month', y='Weekly_Sales', data=boschsales); # Month wise average Weekly_Sales
storefx.bar_label(storefx.containers[0]);
plt.show()
```



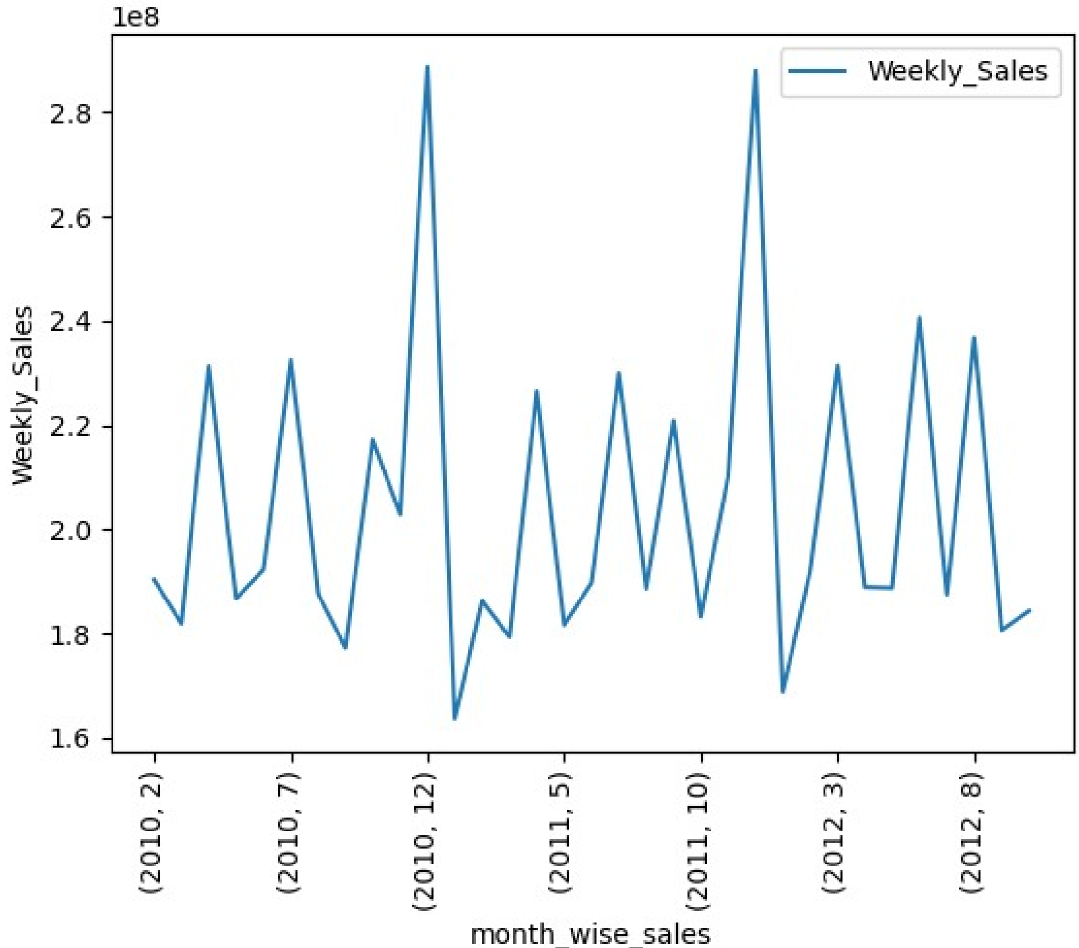

```
plt.figure(figsize=(18,6))
sns.barplot(x='Week', y='Weekly_Sales', data=boschsales); # Week wise
average Weekly_Sales
plt.show()
```




```
# Monthly sales.

Monthly_sales = boschsales.groupby(['Year','Month']) \
.agg(Weekly_Sales = ('Weekly_Sales', 'sum')).plot(kind='bar')

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



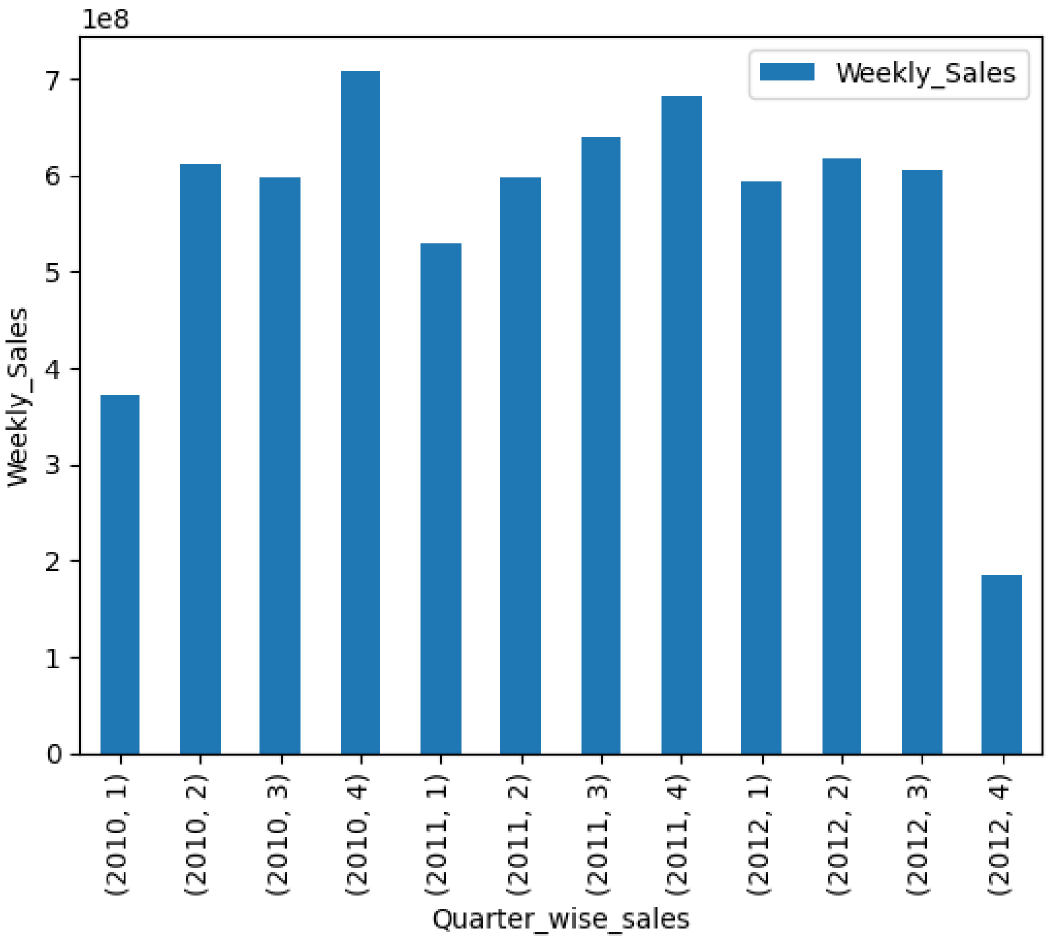

```
# Monthly sales.

Monthly_sales = boschsales.groupby(['Year','Month']) \
.agg(Weekly_Sales = ('Weekly_Sales', 'sum')).plot(kind='line')

plt.xlabel("month_wise_sales")
plt.xticks(rotation=90)
plt.ylabel("Weekly_Sales")
plt.show()

# We can observe from the Monthly Sales Graph that highest sum of
sales is recorded in end of Dec-2010.
```




```
# using the to_period function
#boschsales['quarter'] = boschsales['Date'].dt.to_period('Q')
boschsales['quarter'] = boschsales['Date'].dt.quarter

boschsales.head(5)
```

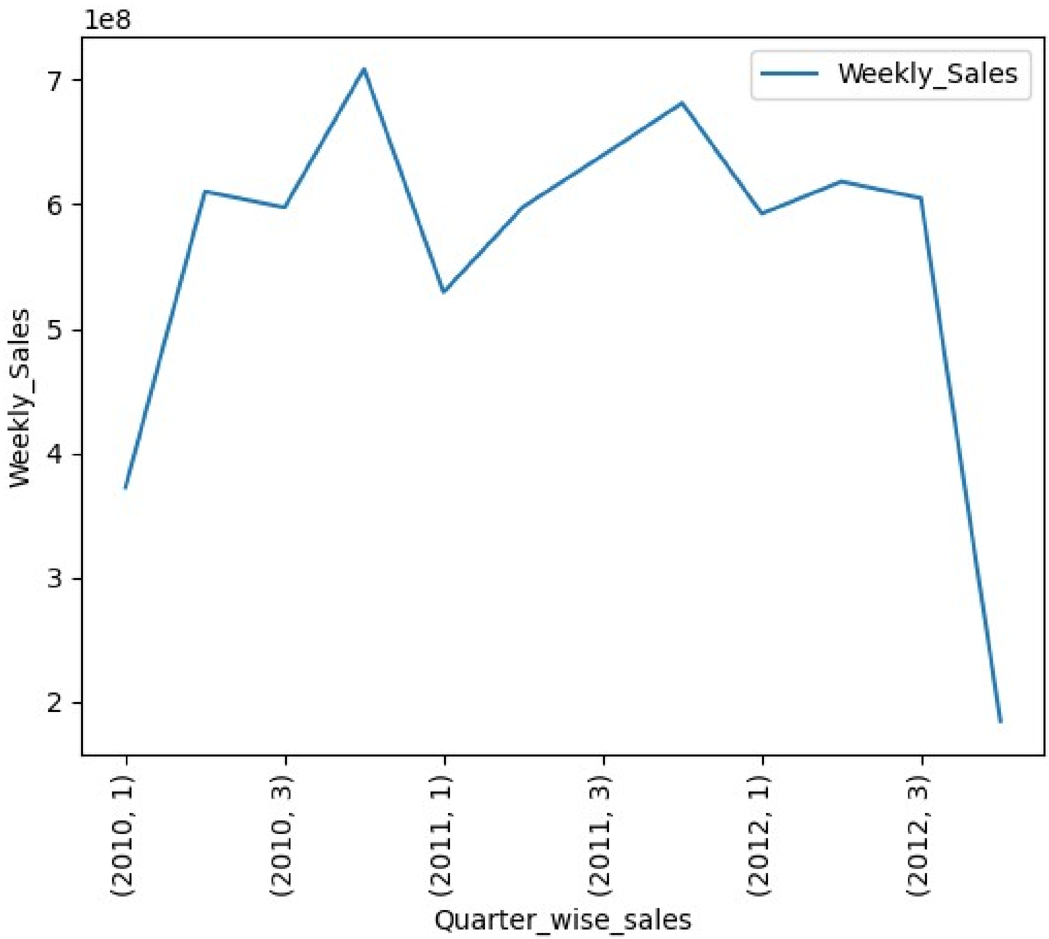
```
   Store       Date  Weekly_Sales  Holiday_Flag  Temperature
Fuel_Price  \
0      1 2010-02-05    1643690.90             0        42.31
2.572
1      1 2010-02-12    1641957.44             1        38.51
2.548
2      1 2010-02-19    1611968.17             0        39.93
2.514
3      1 2010-02-26 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

          CPI  Unemployment  Year  Month  Week  quarter
```

```
0  211.096358          8.106  2010       2     5         1
1  211.242170          8.106  2010       2     6         1
2  211.289143          8.106  2010       2     7         1
3  211.319643          8.106  2010       2     8         1
4  211.350143          8.106  2010       3     9         1

# Quarterly sales.

Quarter_sales = boschsales.groupby(['Year','quarter']) \
.agg(Weekly_Sales = ('Weekly_Sales', 'sum')).plot(kind='bar')

plt.xlabel("Quarter_wise_sales")
plt.xticks(rotation=90)
plt.ylabel("Weekly_Sales")
plt.show()
```



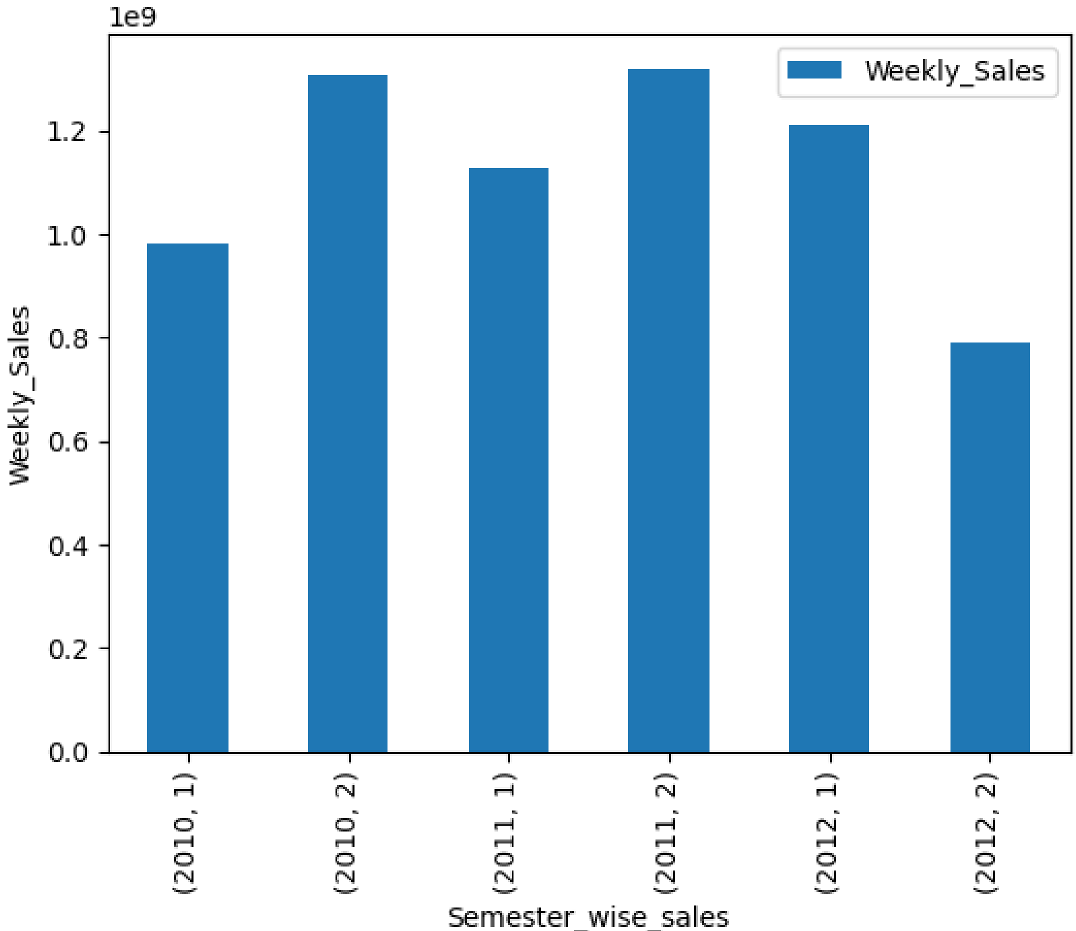

```
# Quarterly sales.

Quarter_sales = boschsales.groupby(['Year','quarter']) \
.agg(Weekly_Sales = ('Weekly_Sales', 'sum')).plot(kind='line')
```

```
plt.xlabel("Quarter_wise_sales")
plt.xticks(rotation=90)
plt.ylabel("Weekly_Sales")
plt.show()

# We can observe from the Quarterly Sales Graph that higest sum of
sales is recorded in end of Q4'2010.
```

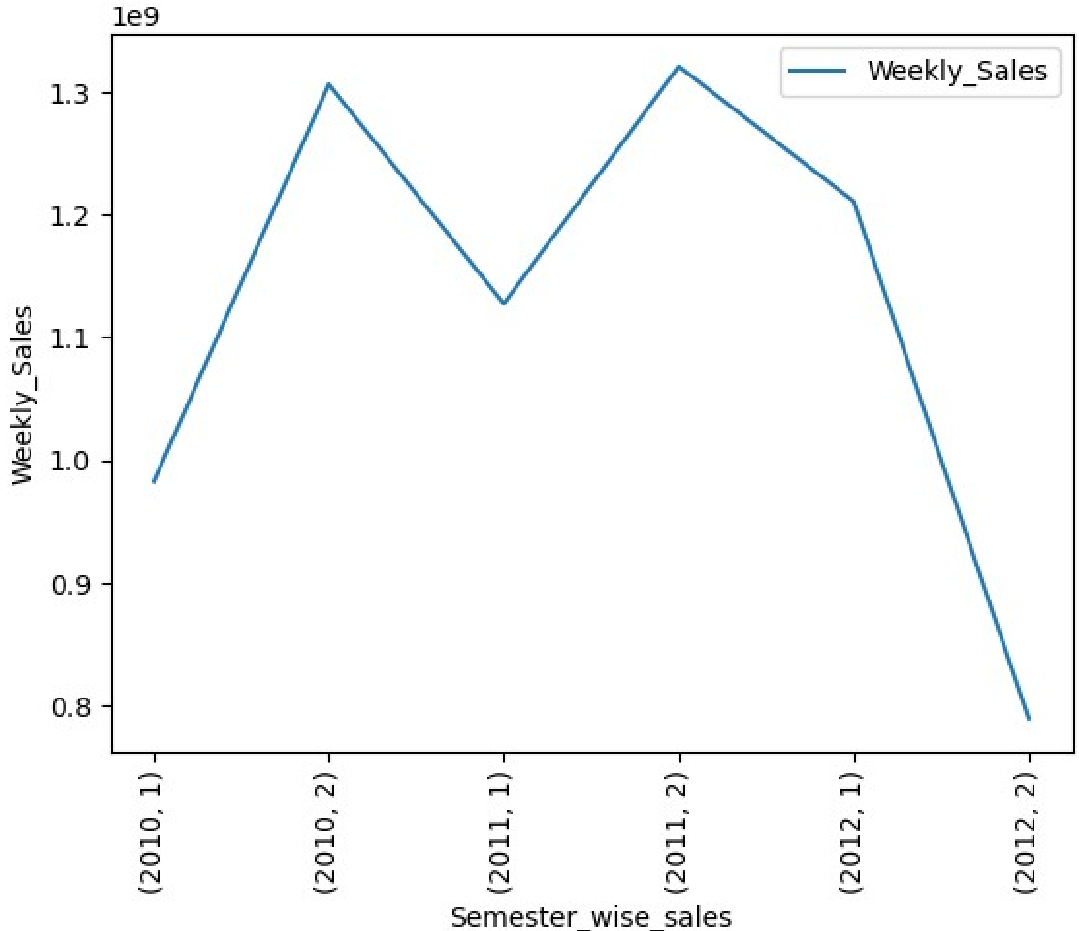



```
# using the to_period function
#boschsales['semester']= boschsales.Date.dt.year.astype(str) + 'S'+
np.where(boschsales.Date.dt.quarter.gt(2),2,1).astype(str)
boschsales['semester']=
np.where(boschsales.Date.dt.quarter.gt(2),2,1).astype(str)

boschsales.head(5)

   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  Year  Month  Week  quarter semester
0  211.096358         8.106  2010      2     5        1        1
1  211.242170         8.106  2010      2     6        1        1
2  211.289143         8.106  2010      2     7        1        1
3  211.319643         8.106  2010      2     8        1        1
4  211.350143         8.106  2010      3     9        1        1

# Semester sales.

Semester_sales = boschsales.groupby(['Year','semester']) \
.agg(Weekly_Sales = ('Weekly_Sales', 'sum')).plot(kind='bar')

plt.xlabel("Semester_wise_sales")
plt.xticks(rotation=90)
plt.ylabel("Weekly_Sales")
plt.show()
```




```
# Semester sales.

Semester_sales = boschsales.groupby(['Year','semester']) \
.agg(Weekly_Sales = ('Weekly_Sales', 'sum')).plot(kind='line')

plt.xlabel("Semester_wise_sales")
plt.xticks(rotation=90)
plt.ylabel("Weekly_Sales")
plt.show()

# We can Observe from Semester graph that at end of 2nd sem of 2011
sales are Highest.
```




```
boschsales.head()

   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  Year  Month  Week  quarter semester
0  211.096358         8.106  2010      2     5        1        1
1  211.242170         8.106  2010      2     6        1        1
2  211.289143         8.106  2010      2     7        1        1
3  211.319643         8.106  2010      2     8        1        1
4  211.350143         8.106  2010      3     9        1        1
```

Hypothesis of Factors like CPI, Unemployment and Fuel_price on Weekly_Sales, Creating a Day Column.

Statistical Modelling For Store 1

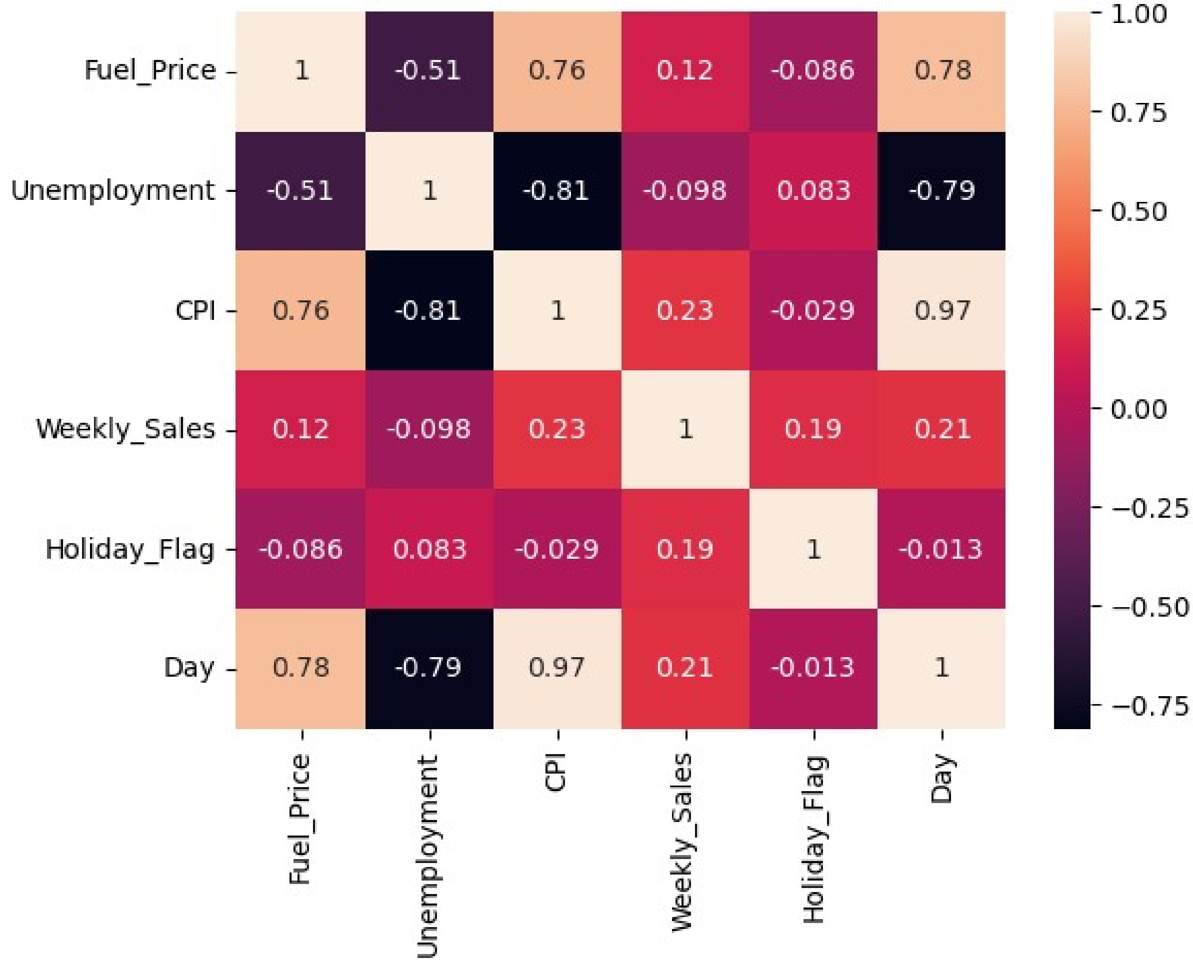
```
# Group the DataFrame by 'Store' and select specific columns
hypothesis = boschsales.groupby('Store')[['Fuel_Price',
'Unemployment', 'CPI', 'Weekly_Sales', 'Holiday_Flag']]
hypothesis.head()
```

```
      Fuel_Price  Unemployment         CPI  Weekly_Sales  Holiday_Flag
0          2.572         8.106  211.096358    1643690.90             0
1          2.548         8.106  211.242170    1641957.44             1
2          2.514         8.106  211.289143    1611968.17             0
3          2.561         8.106  211.319643    1409727.59             0
4          2.625         8.106  211.350143    1554806.68             0
...          ...           ...         ...           ...           ...
6292       2.784         8.992  181.871190     890689.51             0
6293       2.773         8.992  181.982317     656988.64             1
6294       2.745         8.992  182.034782     841264.04             0
6295       2.754         8.992  182.077469     741891.65             0
6296       2.777         8.992  182.120157     777951.22             0

[225 rows x 5 columns]
```

```
# Group the DataFrame by 'Store' and select specific columns
hypothesis = boschsales.groupby('Store')[['Fuel_Price',
'Unemployment', 'CPI', 'Weekly_Sales', 'Holiday_Flag']]

# Get the group for Store 1 and ensure it is a copy (not a view)
factors = hypothesis.get_group(1).copy()

# Create the 'day_arr' list with the starting day as 1
day_arr = [1]
for i in range(1, len(factors)):
    day_arr.append(i * 7)

# Now modify the 'Day' column safely using .loc[]
factors.loc[:, 'Day'] = day_arr.copy()

factors.head()
```

```
   Fuel_Price  Unemployment         CPI  Weekly_Sales  Holiday_Flag
Day
0       2.572         8.106  211.096358    1643690.90             0
```

```
1
1        2.548          8.106  211.242170    1641957.44             1
7
2        2.514          8.106  211.289143    1611968.17             0
14
3        2.561          8.106  211.319643    1409727.59             0
21
4        2.625          8.106  211.350143    1554806.68             0
28

sns.heatmap(factors.corr(), annot = True)
plt.show()
```




```
# By looking at the heatmap we can conclude that CPI and Holiday_Flag
is fairly strongly correlated to Weekly_Sales.
```

Hypothesis of CPI, FuelPrice, Unemployment with Weekly_Sales.

```
# Hypothesis Testing - CPI

from scipy import stats
ttest,pval = stats.ttest_rel(factors['Weekly_Sales'],factors['CPI'])

print(pval)
if pval<0.05:
    print("reject null hypothesis")
else:
    print("accept null hypothesis")
```

```
3.106725927640744e-144
reject null hypothesis
```

```
# Hypothesis Testing - Fuel_Price

ttest,pval =
stats.ttest_rel(factors['Weekly_Sales'],factors['Fuel_Price'])

print(pval)
if pval<0.05:
    print("reject null hypothesis")
else:
    print("accept null hypothesis")
```

```
3.050079726743709e-144
reject null hypothesis
```

```
# Hypothesis Testing - Uneployment

ttest,pval =
stats.ttest_rel(factors['Weekly_Sales'],factors['Unemployment'])

print(pval)
if pval<0.05:
    print("reject null hypothesis")
else:
    print("accept null hypothesis")
```

```
3.0515405336011733e-144
reject null hypothesis
```

```
# Hypothesis Testing - Uneployment

ttest,pval =
stats.ttest_rel(factors['Weekly_Sales'],factors['Holiday_Flag'])
```

```
print(pval)
if pval<0.05:
    print("reject null hypothesis")
else:
    print("accept null hypothesis")
```

```
3.049220543209507e-144
reject null hypothesis
```

Linear Regression Model

```
# 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
```

```
factors
```

```
     Fuel_Price  Unemployment         CPI  Weekly_Sales  Holiday_Flag
Day
0         2.572         8.106  211.096358    1643690.90             0
1
1         2.548         8.106  211.242170    1641957.44             1
7
2         2.514         8.106  211.289143    1611968.17             0
14
3         2.561         8.106  211.319643    1409727.59             0
21
4         2.625         8.106  211.350143    1554806.68             0
28
..          ...           ...         ...           ...           ...
...
138       3.666         6.908  222.981658    1437059.26             0
966
139       3.617         6.573  223.181477    1670785.97             0
973
140       3.601         6.573  223.381296    1573072.81             0
980
141       3.594         6.573  223.425723    1508068.77             0
987
142       3.506         6.573  223.444251    1493659.74             0
994

[143 rows x 6 columns]
```

```
boschsales
```

```
      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
...     ...        ...           ...           ...          ...
...
6430     45 2012-09-28     713173.95             0        64.88
3.997
6431     45 2012-10-05     733455.07             0        64.89
3.985
6432     45 2012-10-12     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  Year  Month  Week  quarter semester
0     211.096358         8.106  2010      2     5        1        1
1     211.242170         8.106  2010      2     6        1        1
2     211.289143         8.106  2010      2     7        1        1
3     211.319643         8.106  2010      2     8        1        1
4     211.350143         8.106  2010      3     9        1        1
...          ...           ...   ...    ...   ...      ...      ...
6430  192.013558         8.684  2012      9    39        3        2
6431  192.170412         8.667  2012     10    40        4        2
6432  192.327265         8.667  2012     10    41        4        2
6433  192.330854         8.667  2012     10    42        4        2
6434  192.308899         8.667  2012     10    43        4        2

[6435 rows x 13 columns]
```

```
# For Store 1

boschsales['Day']=factors['Day']
boschsales_1=boschsales[(boschsales.Store == 1)]
boschsales_1
```

```
     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
..     ...        ...           ...           ...          ...
...
138      1 2012-09-28    1437059.26             0        76.08
3.666
139      1 2012-10-05    1670785.97             0        68.55
3.617
140      1 2012-10-12    1573072.81             0        62.99
3.601
141      1 2012-10-19    1508068.77             0        67.97
3.594
142      1 2012-10-26    1493659.74             0        69.16
3.506

            CPI  Unemployment  Year  Month  Week  quarter semester
Day
0    211.096358         8.106  2010      2     5        1        1
1.0
1    211.242170         8.106  2010      2     6        1        1
7.0
2    211.289143         8.106  2010      2     7        1        1
14.0
3    211.319643         8.106  2010      2     8        1        1
21.0
4    211.350143         8.106  2010      3     9        1        1
28.0
..          ...           ...   ...    ...   ...      ...      ...
...
138  222.981658         6.908  2012      9    39        3        2
966.0
139  223.181477         6.573  2012     10    40        4        2
973.0
140  223.381296         6.573  2012     10    41        4        2
980.0
141  223.425723         6.573  2012     10    42        4        2
987.0
142  223.444251         6.573  2012     10    43        4        2
994.0

[143 rows x 14 columns]

# Remove extra added columns
```

```
boschsales_1 =
boschsales_1.drop(['Year','Month','Week','quarter','semester'],
axis=1)
boschsales_1.head(3)
```

```
   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

          CPI  Unemployment   Day
0  211.096358         8.106   1.0
1  211.242170         8.106   7.0
2  211.289143         8.106  14.0
```

```
# Setup data
X = boschsales_1.drop(['Weekly_Sales', 'Date'], axis=1)
y = boschsales_1['Weekly_Sales']

## Split dataset into training and test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=12)

# Fitting data to multiple Linear Regression
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

```
LinearRegression()
```

```
## Check out the score
regressor.score(X_test, y_test)
```

```
0.051433013580196474
```

```
X_test
```

```
     Store  Holiday_Flag  Temperature  Fuel_Price         CPI
Unemployment  \
57       1             0        53.56       3.459  214.111056
7.742
64       1             0        72.03       3.810  215.627954
7.682
98       1             0        47.96       3.112  219.357722
7.866
21       1             0        80.91       2.669  211.223533
```

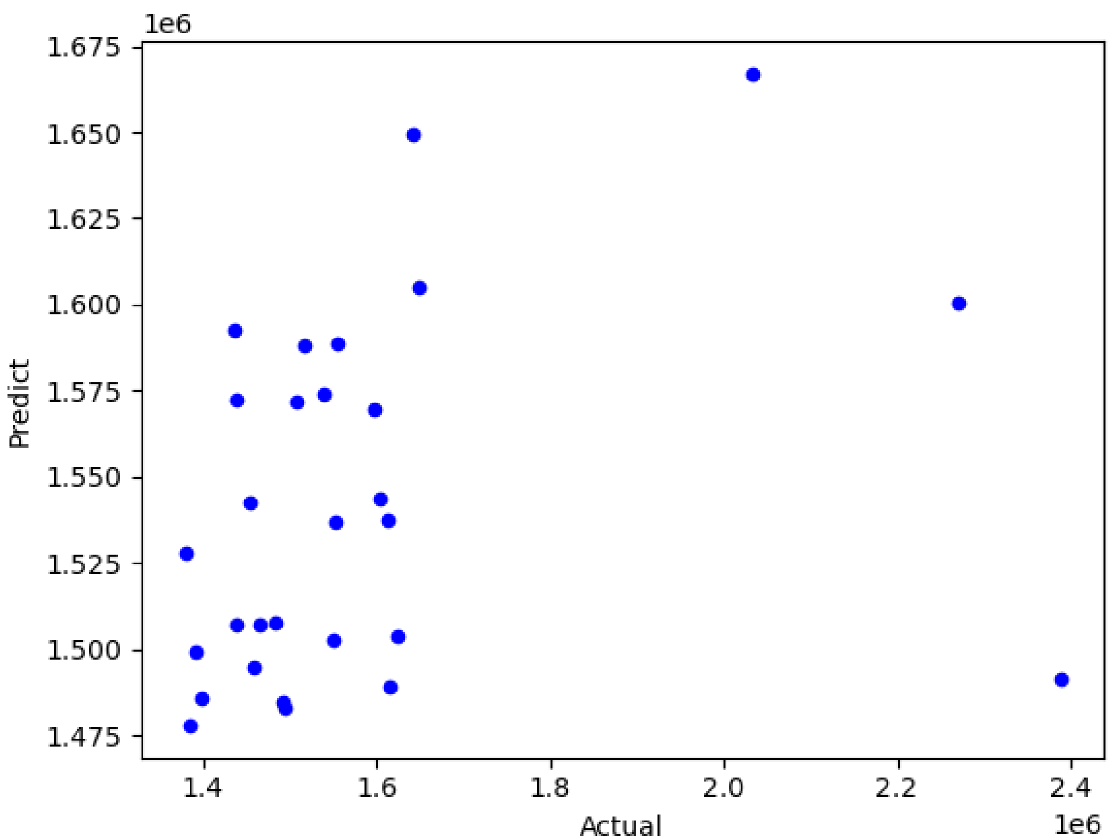
```
7.787
81          1           0           87.96       3.523   215.733226
7.962
31          1           1           78.69       2.565   211.495190
7.787
85          1           0           75.80       3.467   216.375825
7.962
36          1           0           67.18       2.720   211.813744
7.838
41          1           0           51.41       2.771   211.889674
7.838
120         1           0           77.22       3.561   221.744944
7.143
46          1           0           52.33       2.886   211.405122
7.838
112         1           0           67.61       3.845   221.361012
7.348
66          1           0           75.64       3.899   215.964053
7.682
72          1           0           83.58       3.594   215.091098
7.682
125         1           0           84.88       3.286   221.843400
7.143
129         1           0           82.66       3.407   221.941295
6.908
94          1           1           60.14       3.236   218.467621
7.866
132         1           0           84.85       3.571   222.038411
6.908
78          1           0           91.65       3.684   215.544618
7.962
11          1           0           64.84       2.795   210.439123
7.808
17          1           0           80.69       2.705   211.176428
7.808
138         1           0           76.08       3.666   222.981658
6.908
1           1           1           38.51       2.548   211.242170
8.106
136         1           0           74.97       3.717   222.582019
6.908
15          1           0           76.44       2.826   210.617093
7.808
39          1           0           58.74       2.689   211.956394
7.838
14          1           0           74.78       2.854   210.337426
7.808
24          1           0           83.36       2.608   211.235144
7.787
```

```
61       1              0        67.84       3.622  215.074394
7.682

       Day
57   399.0
64   448.0
98   686.0
21   147.0
81   567.0
31   217.0
85   595.0
36   252.0
41   287.0
120  840.0
46   322.0
112  784.0
66   462.0
72   504.0
125  875.0
129  903.0
94   658.0
132  924.0
78   546.0
11    77.0
17   119.0
138  966.0
1      7.0
136  952.0
15   105.0
39   273.0
14    98.0
24   168.0
61   427.0

# Predict test result
y_pred = regressor.predict(X_test)
y_pred

array([1537030.77549694, 1542313.74108229, 1600504.4168272 ,
       1484449.68714448, 1506869.33257533, 1571809.11025818,
       1528110.97658201, 1494492.47724498, 1507666.7674199 ,
       1588580.83361967, 1491621.87947827, 1605106.75546803,
       1543691.82729157, 1507153.71929303, 1573895.00153055,
       1572351.08992789, 1666951.35128518, 1569776.91859298,
       1503942.15612531, 1499041.16158551, 1489032.99809491,
       1592436.55087211, 1649282.41614805, 1588225.59188751,
       1485542.30433995, 1502761.62125991, 1483010.89160763,
       1477888.90990767, 1537421.69997719])
```

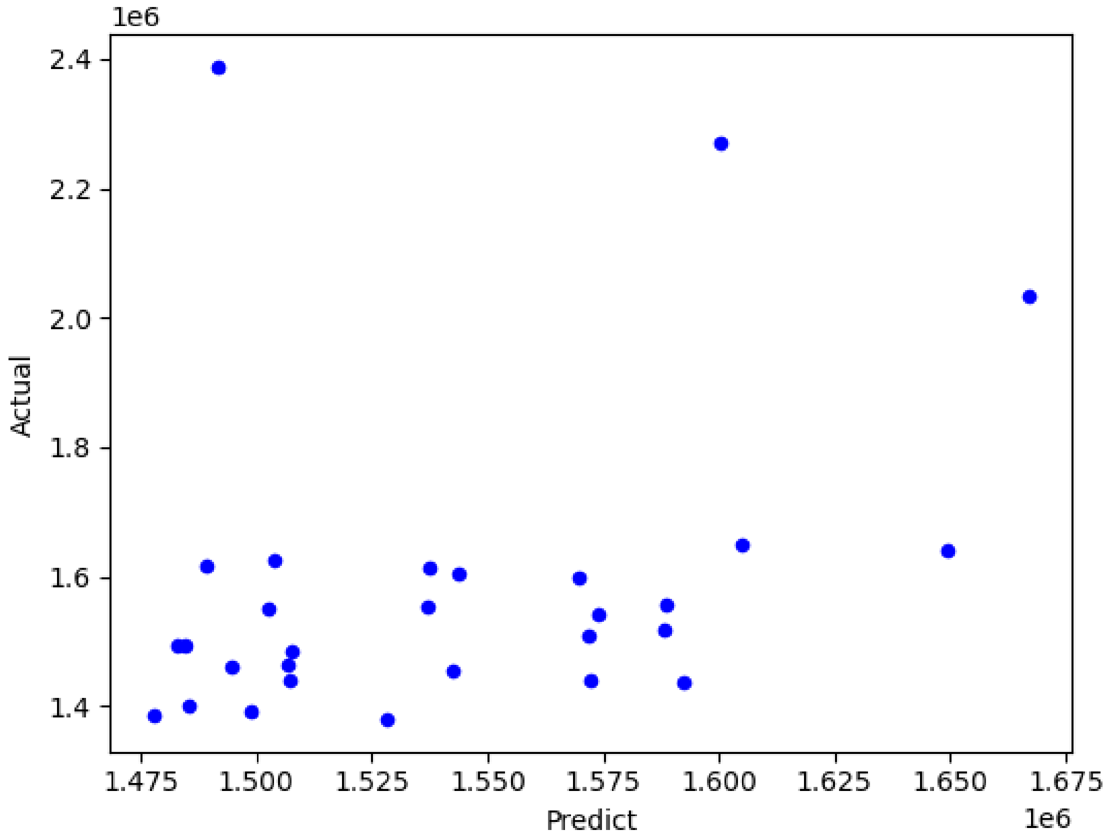
```
## Function to check out the accuracy of the model
def mean_absolute_percentage_error(y_test, y_pred):
    y_test, y_pred = np.array(y_test), np.array(y_pred)
    errors = np.abs(y_test - y_pred)
    mape = np.mean(100 * (errors / y_test))
    print('Mean Absolute Percentage Error:', round(mape, 2), '%.')
    accuracy = 100 - mape
    print('Accuracy:', round(accuracy, 2), '%.')

## Check out the accuracy of the model
mean_absolute_percentage_error(y_test, y_pred)
```

```
Mean Absolute Percentage Error: 6.95 %.
Accuracy: 93.05 %.
```

```
# Plot the Actual vs predicted values
y_test_pred_df = pd.DataFrame(list(zip(y_test, y_pred)), columns
=['Actual', 'Predict'])
y_test_pred_df
y_test_pred_df.plot(x="Actual", y="Predict", kind="scatter",
color="blue");
plt.show()
```



```python
# Plot the predicted vs actual values
y_test_pred_df.plot(x="Predict", y="Actual", kind="scatter",
color="blue");
plt.show()
```




```python
y_test_pred_df
```

	Actual	Predict
0	1553191.63	1.537031e+06
1	1455090.69	1.542314e+06
2	2270188.99	1.600504e+06
3	1492418.14	1.484450e+06
4	1464693.46	1.506869e+06
5	1507460.69	1.571809e+06
6	1380020.27	1.528111e+06
7	1459409.10	1.494492e+06
8	1483784.18	1.507667e+06
9	1555444.55	1.588581e+06
10	2387950.20	1.491622e+06
11	1649604.63	1.605107e+06
12	1604775.58	1.543692e+06
13	1438830.15	1.507154e+06
14	1540421.49	1.573895e+06

15	1439123.71	1.572351e+06
16	2033320.66	1.666951e+06
17	1597868.05	1.569777e+06
18	1624383.75	1.503942e+06
19	1391256.12	1.499041e+06
20	1615524.71	1.489033e+06
21	1437059.26	1.592437e+06
22	1641957.44	1.649282e+06
23	1517428.87	1.588226e+06
24	1399662.07	1.485542e+06
25	1551659.28	1.502762e+06
26	1494251.50	1.483011e+06
27	1385065.20	1.477889e+06
28	1614259.35	1.537422e+06