walmart

March 1, 2024

0.1 RETAIL ANALYSIS WITH WALMART DATA

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[2]:
```
df=pd.read_csv('Walmart_Store_sales.csv')
```

[3]:
```
df.head(2)
```

[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

          CPI  Unemployment
0  211.096358         8.106
1  211.242170         8.106
```

[4]:
```
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   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
```

[5]:
```python
#changing the data type of the 'Date' column because it is an object type
from datetime import datetime
df['Date'] = pd.to_datetime(df['Date'])
```

```
/tmp/ipykernel_297/601733599.py:3: UserWarning: Parsing dates in DD/MM/YYYY
format when dayfirst=False (the default) was specified. This may lead to
inconsistently parsed dates! Specify a format to ensure consistent parsing.
  df['Date'] = pd.to_datetime(df['Date'])
```

[6]:
```python
df.dtypes
```

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

Basic Statistics tasks

- **Which store has maximum sales**

[7]:
```python
total_sales=df.groupby('Store')['Weekly_Sales'].sum().round().
↪sort_values(ascending=False)
```

[8]:
```python
pd.DataFrame(total_sales).head()
```

[8]:
```
       Weekly_Sales
Store
20      301397792.0
4       299543953.0
14      288999911.0
13      286517704.0
2       275382441.0
```

store 20 has maximum sales with weekly sales 301397792.0

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

[9]:
```python
df_std=df.groupby('Store')['Weekly_Sales'].std().round().
↪sort_values(ascending=False)
```

[10]:
```python
pd.DataFrame(df_std).head()
```

[10]:

	Weekly_Sales
Store	
14	317570.0
10	302262.0
20	275901.0
4	266201.0
13	265507.0

Store 14 has maximum Standard Deviation of 317570.0

[11]:
```
#Coefficient of mean to standard deviation
```

[12]:
```
store14=df[df.Store==14].Weekly_Sales
```

[13]:
```
mean_to_stddev=store14.std()/store14.mean()*100
```

[14]:
```
print(mean_to_stddev,'%')
```

```
15.713673600948338 %
```

Coefficient of mean to standard deviation is 15.71 %

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

[15]:
```
#Finding the Q2 sales then Q3 sales,then taking out the difference to get the␣
↪growth rate.
```

[16]:
```
q2_sales=df[(df['Date']>='2012-04-01') & (df['Date']<='2012-06-30')].
↪groupby('Store')['Weekly_Sales'].sum().round()
```

[17]:
```
q3_sales=df[(df['Date']>='2012-07-01') & (df['Date']<='2012-09-30')].
↪groupby('Store')['Weekly_Sales'].sum().round()
```

[18]:
```
#Growth rate = ((present-past)/past)*100
```

[19]:
```
df_2012=pd.DataFrame({'Q2 Sales':q2_sales,'Q3 Sales':q3_sales,'Difference':
↪(q3_sales-q2_sales),'Growth Rate %':(q3_sales-q2_sales)/q2_sales*100}).
↪sort_values(by='Growth Rate %',ascending=False).head()
```

[20]:
```
df_2012
```

[20]:

	Q2 Sales	Q3 Sales	Difference	Growth Rate %
Store				
16	6626133.0	6441311.0	-184822.0	-2.789289
7	7613594.0	7322394.0	-291200.0	-3.824738
35	10753571.0	10252123.0	-501448.0	-4.663084
26	13218290.0	12417575.0	-800715.0	-6.057629
39	20191586.0	18899955.0	-1291631.0	-6.396877

```
[21]: max_sales_2012Q3=df_2012.groupby('Store')['Growth Rate %'].sum()
      max_sales_2012Q3.idxmax()
```

```
[21]: 16
```

No store shown quaterly growth rate in Q3'2012, although store 16 has maximum growth rate as compared to others

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

We have 4 Holiday Events,

(1) Super Bowl: 12-Feb-10, 11-Feb-11, 10-Feb-12, 8-Feb-13,

(2) Labour Day: 10-Sep-10, 9-Sep-11, 7-Sep-12, 6-Sep-13,

(3) Thanksgiving: 26-Nov-10, 25-Nov-11, 23-Nov-12, 29-Nov-13,

(4) Christmas: 31-Dec-10, 30-Dec-11, 28-Dec-12, 27-Dec-13.

```
[22]: #Calculating the holiday event sales of each of the events and then find the␣
       ↪non-holiday sales.
```

```
[23]: #Holiday events
      Super_Bowl=['12-02-2010','11-02-2011','10-02-2012','08-02-2013']
      Labour_Day=['2010-09-10','2011-09-09','2012-09-07','2013-09-06']
      Thanksgiving=['2010-11-26','2011-11-25','2012-11-23','2013-11-29']
      Christmas=['2010-12-31','2011-12-30','2012-12-28','2013-12-27']
```

```
[24]: Super_Bowl_Sales =round(df[df.Date.isin(Super_Bowl)]['Weekly_Sales'].mean(),2)
      Labour_Day_Sales =round(df[df.Date.isin(Labour_Day)]['Weekly_Sales'].mean(),2)
      Thanksgiving_Sales =round(df[df.Date.isin(Thanksgiving)]['Weekly_Sales'].
       ↪mean(),2)
      Christmas_Sales =round(df[df.Date.isin(Christmas)]['Weekly_Sales'].mean(),2)
```

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

```
[25]: (1079127.99, 1039182.83, 1471273.43, 960833.11)
```

```
[26]: #Calculating Non-holiday Sales and Comparision
```

```
[27]: non_holiday_sales=round(df[df['Holiday_Flag']==0]['Weekly_Sales'].mean(),2)
      non_holiday_sales
```

```
[27]: 1041256.38
```

```
[28]:  pd.DataFrame([{'Super Bowl Sales':Super_Bowl_Sales,'Labour day Sales':
       ↪Labour_Day_Sales,'Thanksgiving Sales':Thanksgiving_Sales,'Christmas Sales':
       ↪Christmas_Sales,'non holiday Sales':non_holiday_sales}]).T
```

[28]:
```
                              0
Super Bowl Sales     1079127.99
Labour day Sales     1039182.83
Thanksgiving Sales   1471273.43
Christmas Sales       960833.11
non holiday Sales    1041256.38
```

Thanksgiving has the highest sales (1,471,273.43) than non-holiday sales (1,041,256.38)

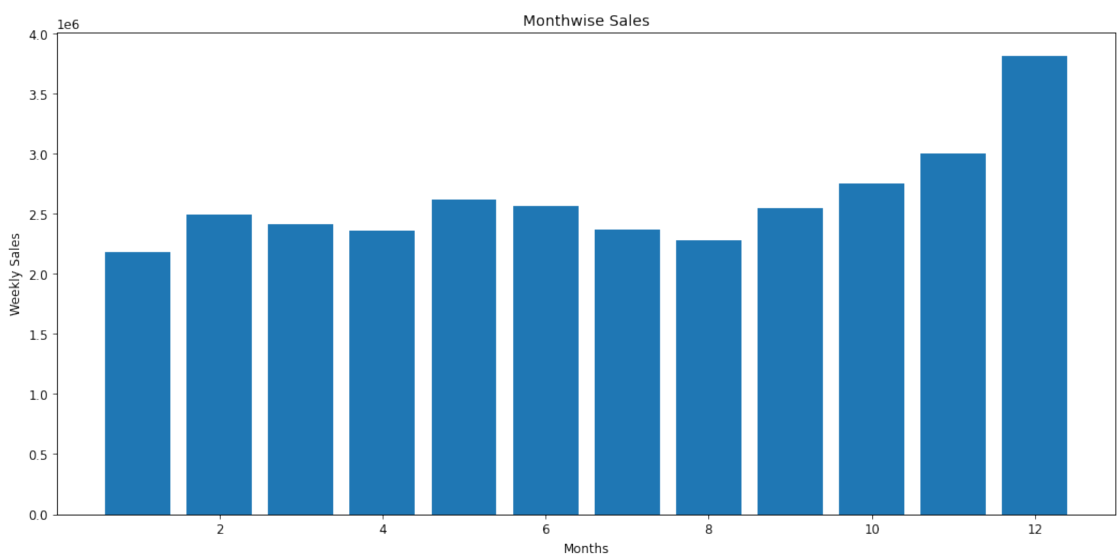
- **Provide a monthly and semester view of sales in units and give insights**

Plotting a month-wise bar graph for weekly sales to get an idea about which month has the maximum sales, then will plot the semester-wise bar graph for weekly sales to get some insights about the semester's weekly sales.

[29]:
```
df['year'] = pd.DatetimeIndex(df['Date']).year
df['month'] = pd.DatetimeIndex(df['Date']).month
df['day'] = pd.DatetimeIndex(df['Date']).day
```

[30]:
```
plt.figure(figsize=(15,7), dpi=85)
plt.bar(df['month'],df['Weekly_Sales'])
plt.xlabel('Months')
plt.ylabel('Weekly Sales')
plt.title('Monthwise Sales')
```

[30]: `Text(0.5, 1.0, 'Monthwise Sales')`



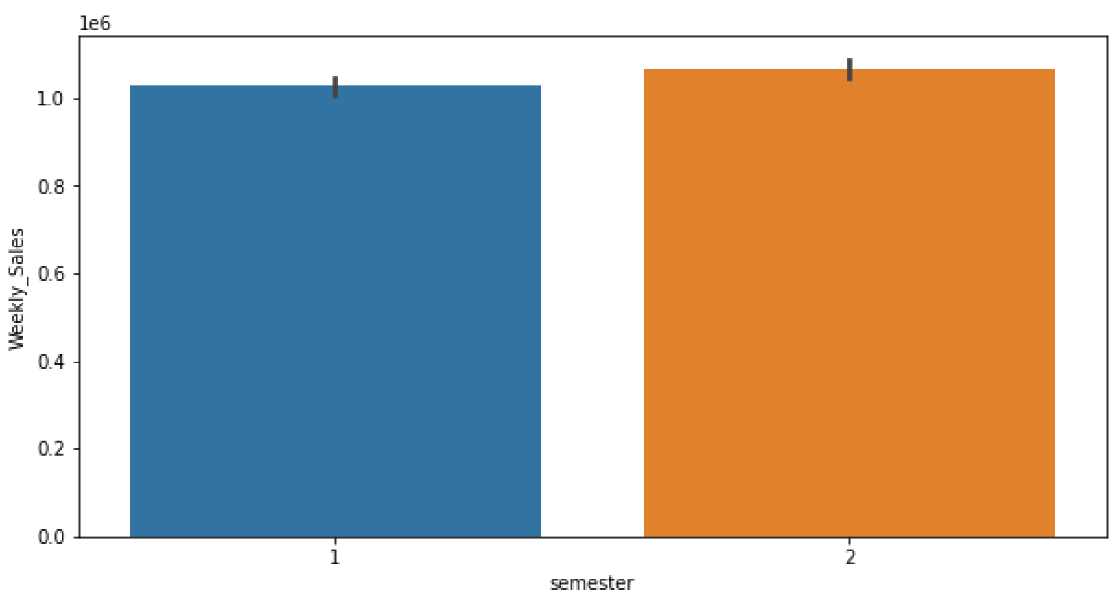
[31]:
```
#Semesterwise Sales
df['semester'] = np.where(df['month']< 7, 1, 2)
```

[32]:
```
df.head(10)
```

[32]:
```
   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
5      1  2010-12-03    1439541.59             0        57.79       2.667
6      1  2010-03-19    1472515.79             0        54.58       2.720
7      1  2010-03-26    1404429.92             0        51.45       2.732
8      1  2010-02-04    1594968.28             0        62.27       2.719
9      1  2010-09-04    1545418.53             0        65.86       2.770

          CPI  Unemployment  year  month  day  semester
0  211.096358         8.106  2010      5    2         1
1  211.242170         8.106  2010     12    2         2
2  211.289143         8.106  2010      2   19         1
3  211.319643         8.106  2010      2   26         1
4  211.350143         8.106  2010      5    3         1
5  211.380643         8.106  2010     12    3         2
6  211.215635         8.106  2010      3   19         1
7  211.018042         8.106  2010      3   26         1
8  210.820450         7.808  2010      2    4         1
9  210.622857         7.808  2010      9    4         2
```

[33]:
```
plt.figure(figsize =(10,5))
semester=sns.barplot(x='semester',y='Weekly_Sales',data=df)
```



Insights drawn-

(1)December month has the highest weekly sales.

(2) Semester 2 has the highest weekly sales.

0.1.1 Statistical Model

Model Building-

First, define dependent and independent variables. Here, store, fuel price, CPI, unemployment, day, month, and year are the independent variables and weekly sales is the dependent variable. Now, it's time to train the model. Import train_test_spit from sklearn.model_selection and train 80% of the data and test on the rest 20% of the data.

[34]:
```
#Define independent and dependent variable
# Select features and target
x=df[['Store','Fuel_Price','CPI','Unemployment','day','month','year']]
y=df['Weekly_Sales']
```

[35]:
```
from sklearn.model_selection import train_test_split
# 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)
```

[36]:
```
from sklearn.preprocessing import StandardScaler
sc= StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.fit_transform(x_test)
```

[37]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
```

[38]:
```
# 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)))
```

```
Linear Regression:

Accuracy: 14.454824024262736
Mean Absolute Error: 434376.40881607507
Mean Squared Error: 278133286094.229
Root Mean Squared Error: 527383.4336554657
```

[39]:
```
# 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)))
```

```
Random Forest Regressor:

Accuracy: 93.28819973374563
Mean Absolute Error: 82418.58630269894
Mean Squared Error: 21828686033.791904
Root Mean Squared Error: 147745.34183449543
```

Here, we have used 2 different algorithms to know which model to use to predict the weekly sales. Linear Regression is not an appropriate model to use as accuracy is very low. However, Random Forest Regression gives an accuracy of almost 91%. so, it is the best model to forecast weekly sales.

Change dates into days by creating new variable.

[40]:
```
df['day'] = pd.to_datetime(df['Date']).dt.day_name()
df.head()
```

[40]:

	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

	CPI	Unemployment	year	month	day	semester
0	211.096358	8.106	2010	5	Sunday	1
1	211.242170	8.106	2010	12	Thursday	2
2	211.289143	8.106	2010	2	Friday	1
3	211.319643	8.106	2010	2	Friday	1
4	211.350143	8.106	2010	5	Monday	1

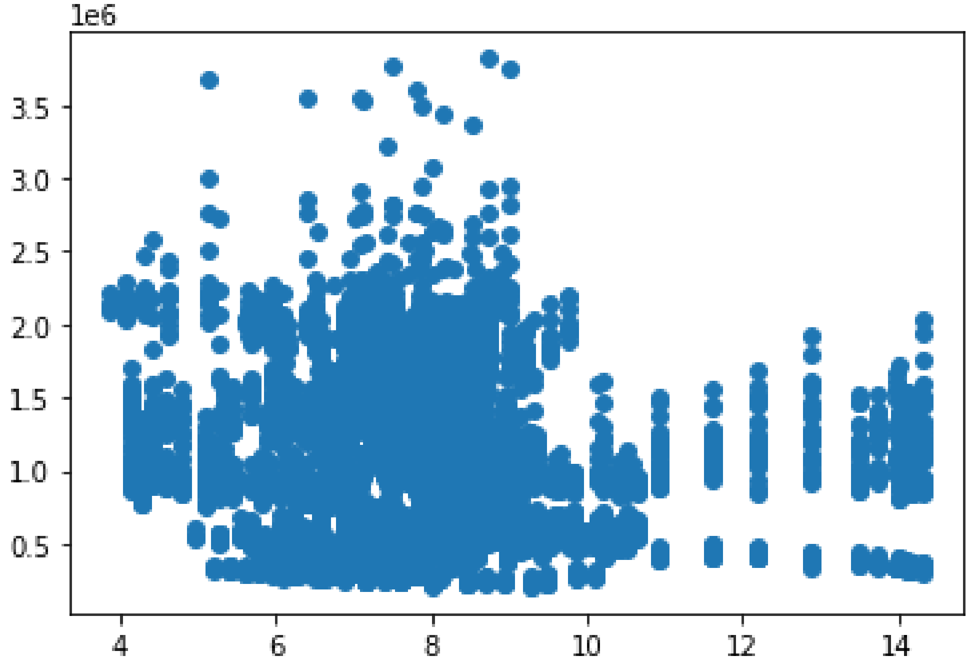
[41]:
```
experiment_day_start=5
df['Date'] = pd.to_datetime(df['Date'], dayfirst=True)
df['exp_day'] = (df['Date']-df['Date'].min()).dt.days + experiment_day_start
```

[42]:
```
df.head()
```

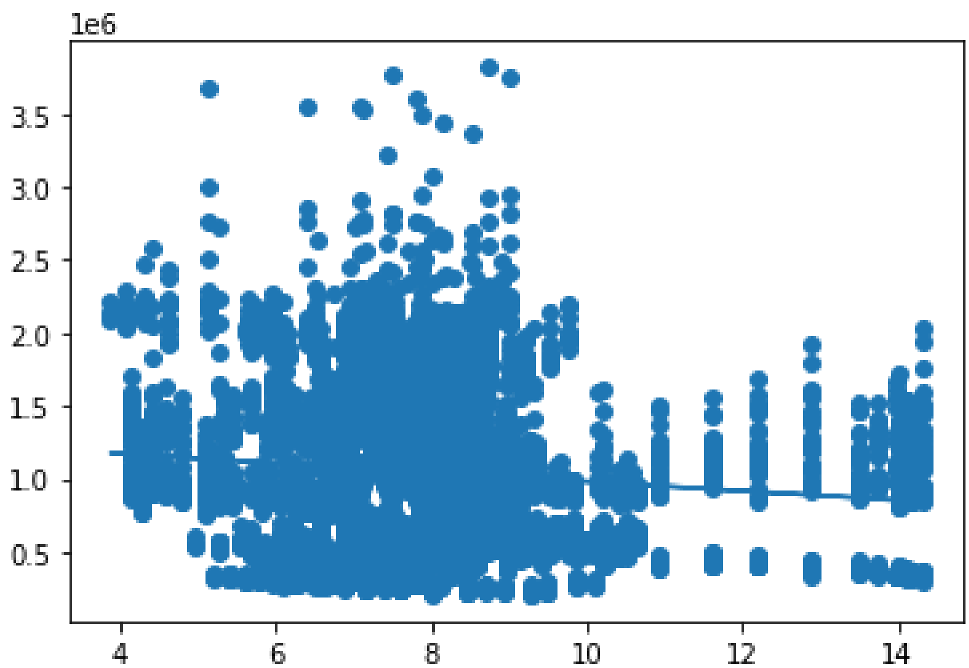
[42]:
```
   Store       Date  Weekly_Sales  Holiday_Flag  Temperature  Fuel_Price  \
0      1 2010-05-02    1643690.90             0        42.31       2.572
1      1 2010-12-02    1641957.44             1        38.51       2.548
2      1 2010-02-19    1611968.17             0        39.93       2.514
3      1 2010-02-26    1409727.59             0        46.63       2.561
4      1 2010-05-03    1554806.68             0        46.50       2.625

          CPI  Unemployment  year  month       day  semester  exp_day
0  211.096358         8.106  2010      5    Sunday         1      117
1  211.242170         8.106  2010     12  Thursday         2      331
2  211.289143         8.106  2010      2    Friday         1       45
3  211.319643         8.106  2010      2    Friday         1       52
4  211.350143         8.106  2010      5    Monday         1      118
```

[43]:
```
from sklearn.linear_model import LinearRegression
from scipy import stats
#Weekly sales vs Unemployment
x = df['Unemployment']
y = df['Weekly_Sales']
plt.scatter(x, y)
plt.show()
slope, intercept, r, p, std_err = stats.linregress(x, y)
print(r)# r should be between -1 to 1
def myfunc(x):
  return slope * x + intercept
mymodel = list(map(myfunc, x))
plt.scatter(x, y)
plt.plot(x, mymodel)
plt.show()
```

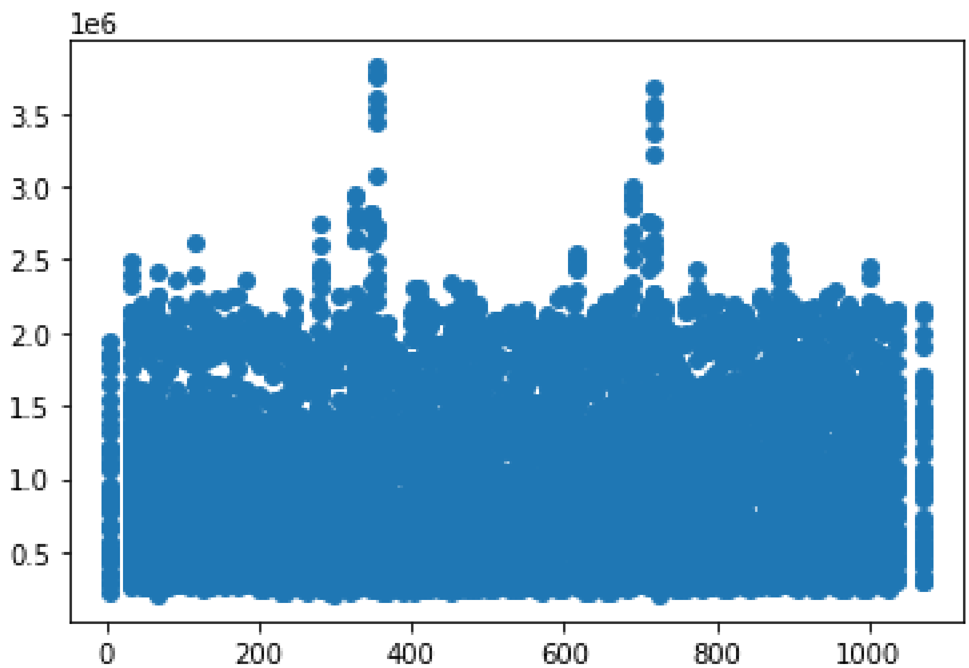


-0.10617608965795412

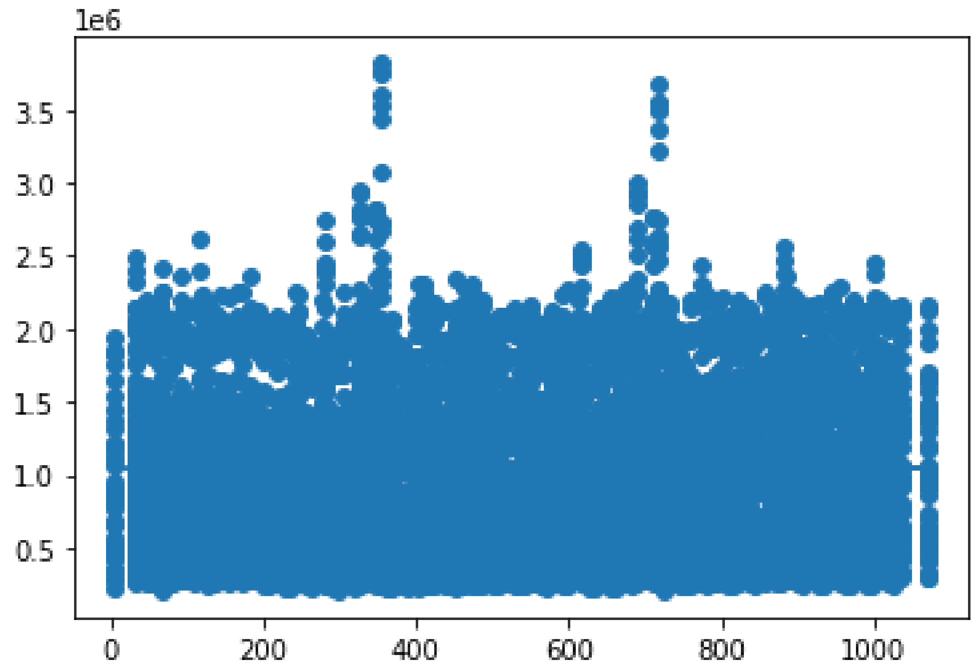


[44]:

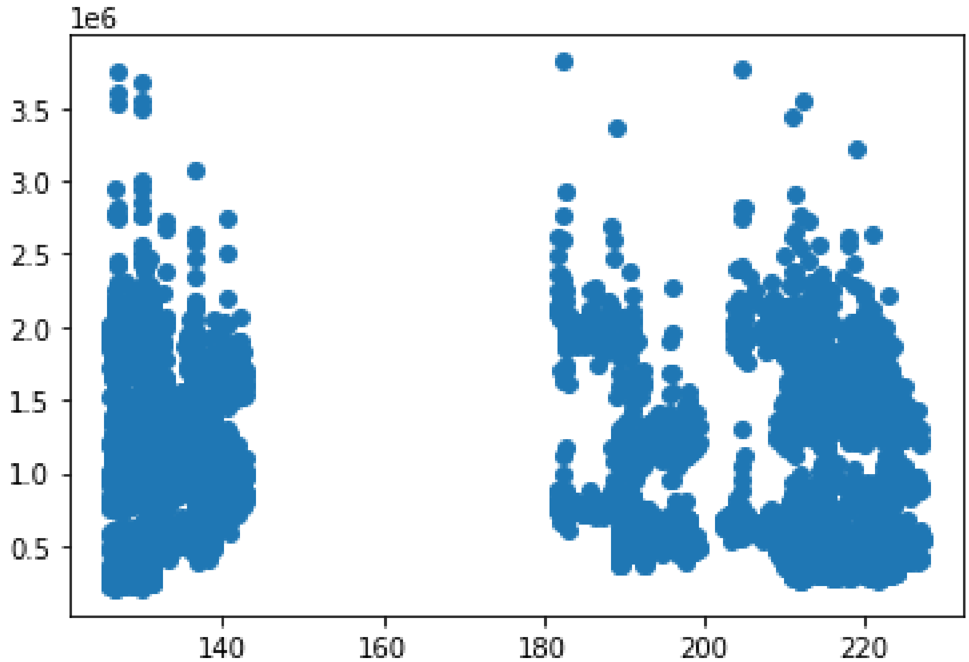
```
# Weekly_Sales vs exp_day
x = df['exp_day']
y = df['Weekly_Sales']
plt.scatter(x, y)
plt.show()
slope, intercept, r, p, std_err = stats.linregress(x, y)
print(r)# r should be between -1 to 1
def myfunc(x):
  return slope * x + intercept
mymodel = list(map(myfunc, x))
plt.scatter(x, y)
plt.plot(x, mymodel)
plt.show()
```



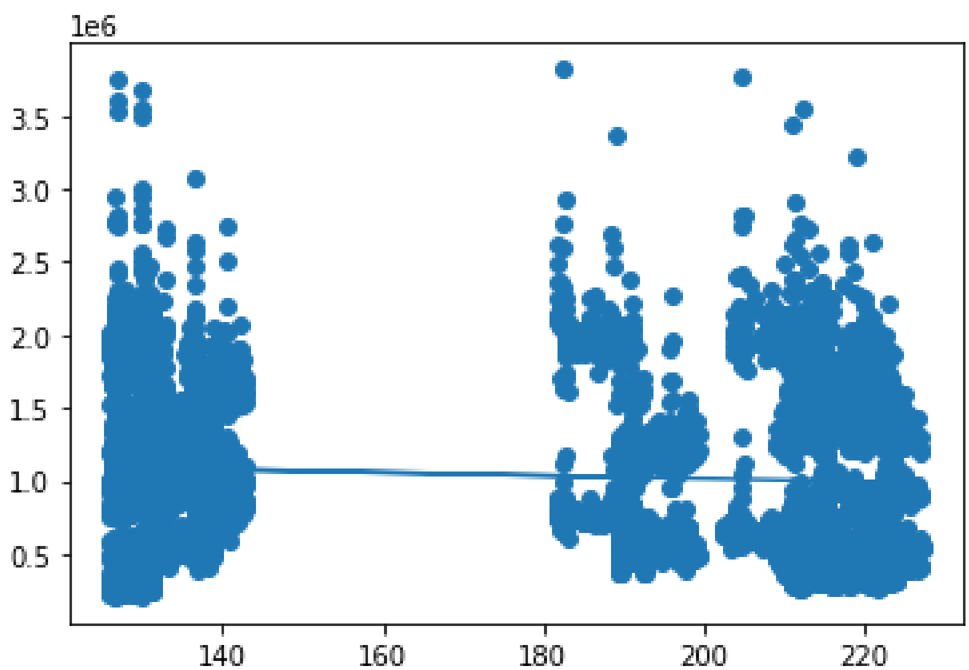

```
0.004591803306455429
```



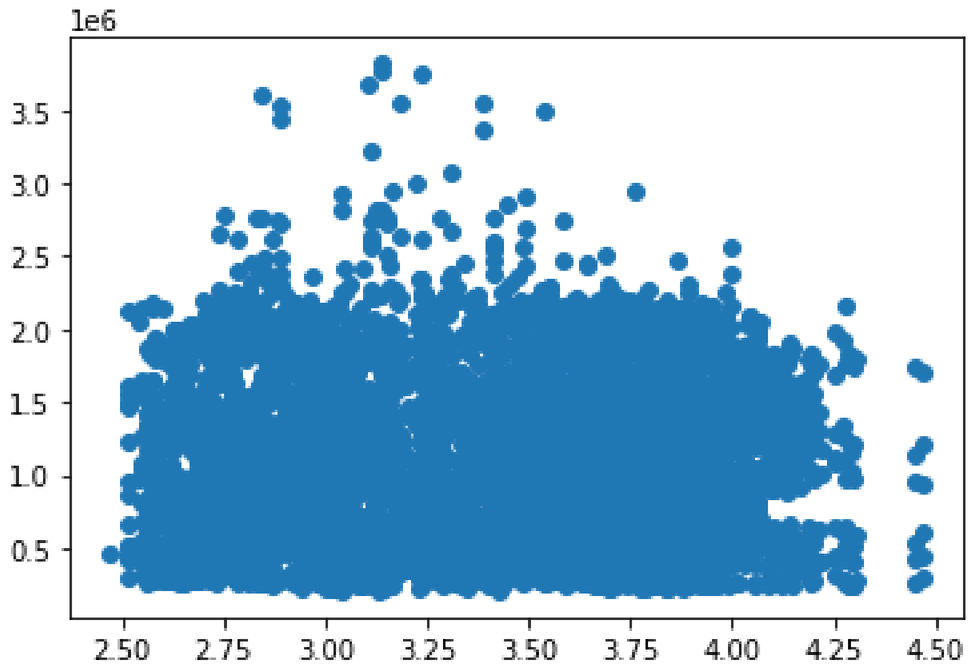
[45]:
```python
#Weekly sales vs CPI
x = df['CPI']
y = df['Weekly_Sales']
plt.scatter(x, y)
plt.show()
slope, intercept, r, p, std_err = stats.linregress(x, y)
print(r)# r should be between -1 to 1
def myfunc(x):
  return slope * x + intercept
mymodel = list(map(myfunc, x))
plt.scatter(x, y)
plt.plot(x, mymodel)
plt.show()
```



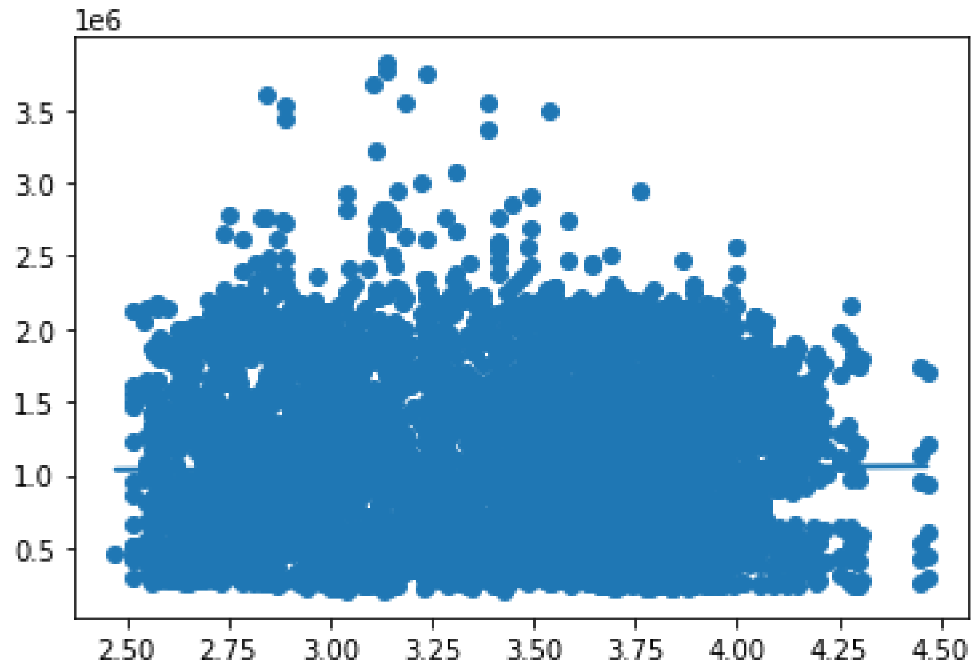
-0.07263416204017624



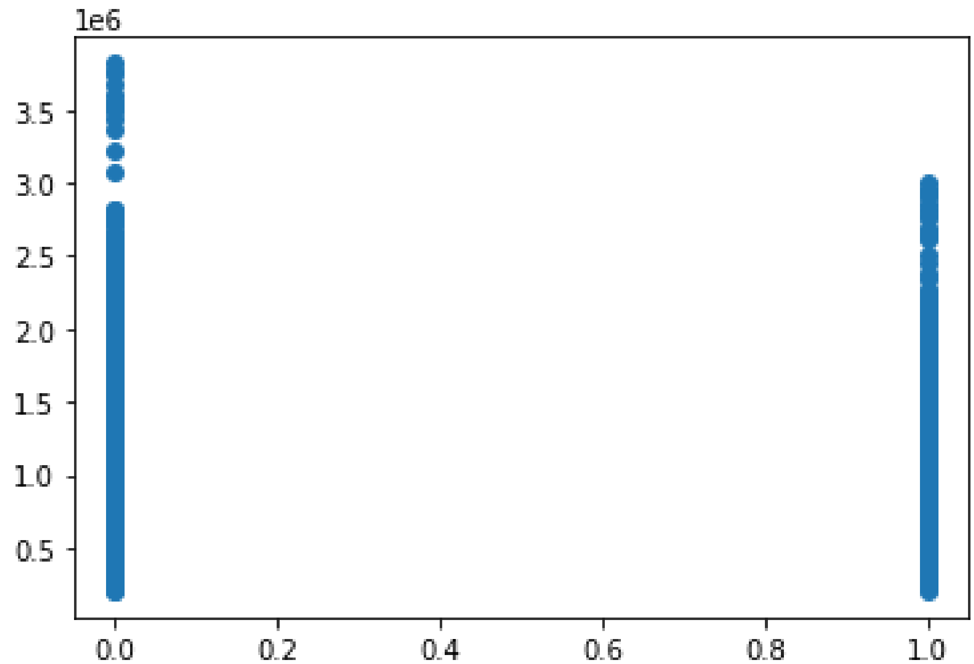
[46]:
```
#Weekly sales vs Fuel price
x = df['Fuel_Price']
y = df['Weekly_Sales']
plt.scatter(x, y)
plt.show()
slope, intercept, r, p, std_err = stats.linregress(x, y)
print(r)# r should be between -1 to 1
def myfunc(x):
  return slope * x + intercept
mymodel = list(map(myfunc, x))
plt.scatter(x, y)
plt.plot(x, mymodel)
plt.show()
```



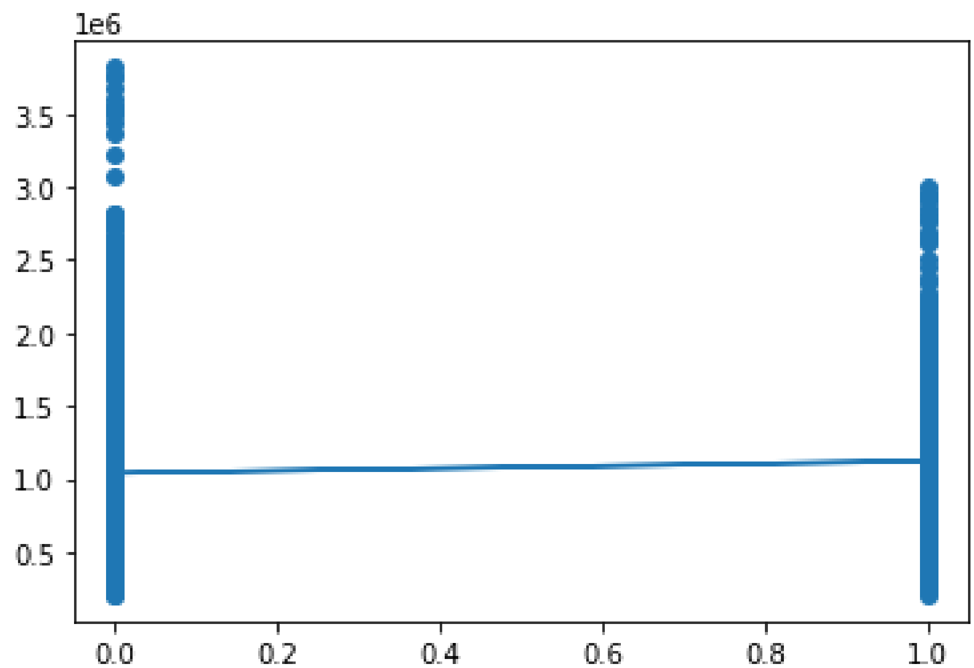

```
0.009463786314475135
```



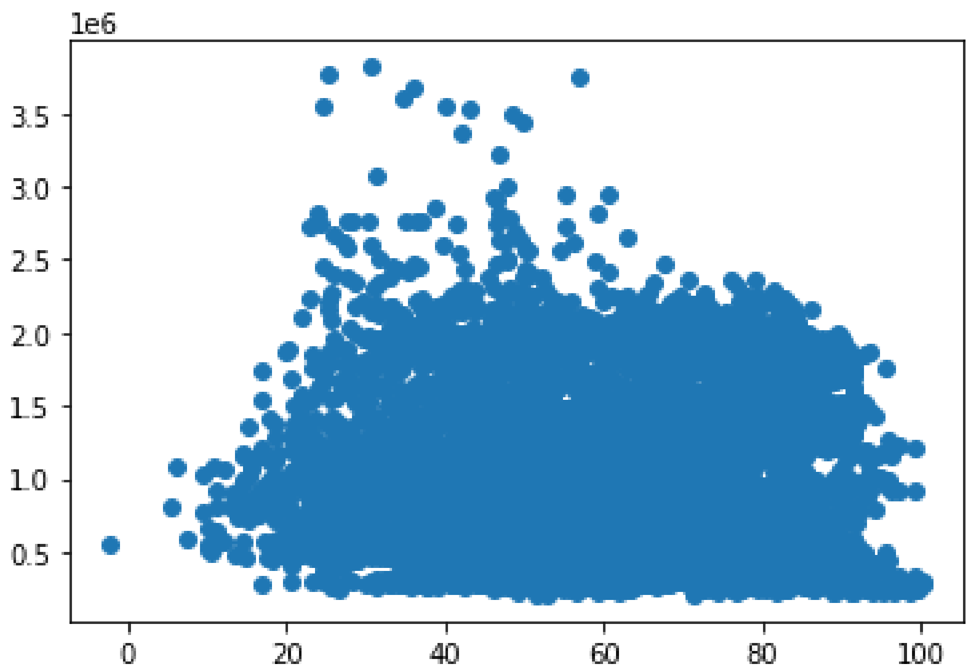
[47]:
```
#Weekly sales vs Holidays
x = df['Holiday_Flag']
y = df['Weekly_Sales']
plt.scatter(x, y)
plt.show()
slope, intercept, r, p, std_err = stats.linregress(x, y)
print(r)# r should be between -1 to 1
def myfunc(x):
  return slope * x + intercept
mymodel = list(map(myfunc, x))
plt.scatter(x, y)
plt.plot(x, mymodel)
plt.show()
```



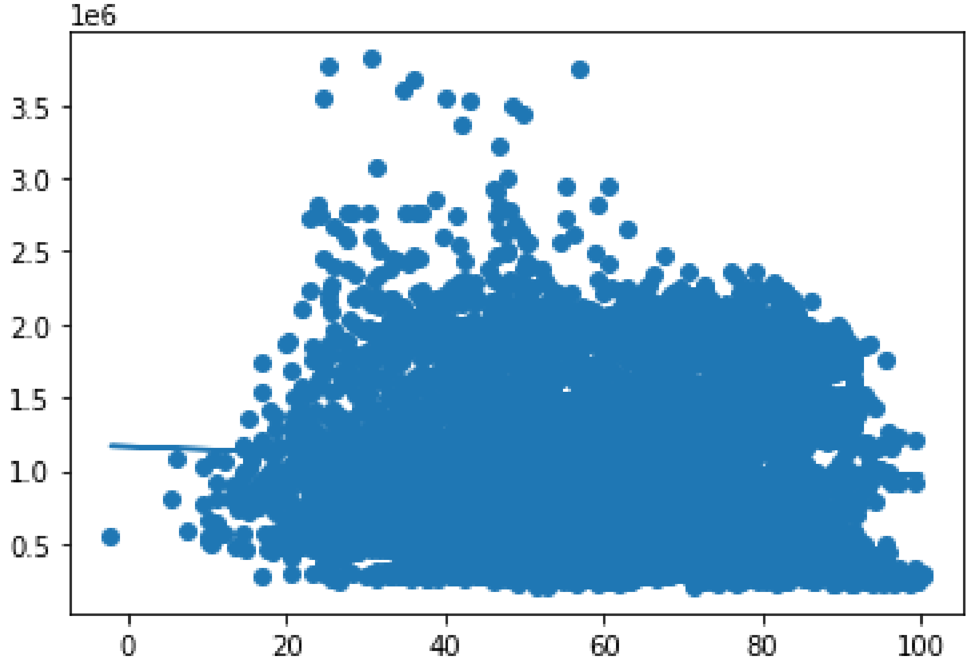
0.03689096801041455



[48]:
```
#Weekly sales vs Temperature
x = df['Temperature']
y = df['Weekly_Sales']
plt.scatter(x, y)
plt.show()
slope, intercept, r, p, std_err = stats.linregress(x, y)
print(r)# r should be between -1 to 1
def myfunc(x):
  return slope * x + intercept
mymodel = list(map(myfunc, x))
plt.scatter(x, y)
plt.plot(x, mymodel)
plt.show()
```




```
-0.06381001317946958
```


1e6
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0
20
40
60
80
100

```
[ ]:
```