Retail Analysis with Walmart Data

January 30, 2022

Retail Analysis with Walmart Data

[1]:
```
import pandas as pd
import numpy as np
```

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

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

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

[3]:
```
df_wss.shape
```

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

[4]:
```
df_wss.isnull().sum()
```

[4]:
```
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
dtype: int64
```

[5]:
```
df_wss.describe()
```

[5]:
```
             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
```

1 Basic Statistic Task

2 Which store has maximum sales

[6]:
```
#Values of the Total Weekly_Sales for each store
df_groupby = df_wss.groupby('Store')['Weekly_Sales'].sum()
print(df_groupby.shape)
print(df_groupby.head())
```

```
(45,)
Store
1    2.224028e+08
2    2.753824e+08
3    5.758674e+07
4    2.995440e+08
5    4.547569e+07
Name: Weekly_Sales, dtype: float64
```

[7]:
```
#Store with Maximum Sales and Value of the Sales
print( 'Store Number {} has maximum total weekly sales of {}.'.format␣
 ↪(df_groupby.idxmax(),df_groupby.max()))
```

```
Store Number 20 has maximum total weekly sales of 301397792.46000004.
```

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

[8]:
```
#Value of Standard Deviations
df_groupstd = df_wss.groupby('Store')['Weekly_Sales'].std()
print(df_groupstd.shape)
print(df_groupstd)
```

```
(45,)
Store
1      155980.767761
2      237683.694682
3       46319.631557
4      266201.442297
5       37737.965745
6      212525.855862
7      112585.469220
8      106280.829881
9       69028.666585
10     302262.062504
11     165833.887863
12     139166.871880
13     265506.995776
14     317569.949476
15     120538.652043
16      85769.680133
17     112162.936087
18     176641.510839
19     191722.638730
20     275900.562742
21     128752.812853
22     161251.350631
23     249788.038068
24     167745.677567
25     112976.788600
26     110431.288141
27     239930.135688
28     181758.967539
29      99120.136596
30      22809.665590
31     125855.942933
32     138017.252087
33      24132.927322
34     104630.164676
35     211243.457791
```

```
36     60725.173579
37     21837.461190
38     42768.169450
39    217466.454833
40    119002.112858
41    187907.162766
42     50262.925530
43     40598.413260
44     24762.832015
45    130168.526635
Name: Weekly_Sales, dtype: float64
```

[9]:
```
#Store with Maximum Standard Deviation
print( 'Store Number {} has Maximum Standard Deviation of {}.'.format␣
↪(df_groupstd.idxmax(),df_groupstd.max()))
```

```
Store Number 14 has Maximum Standard Deviation of 317569.9494755081.
```

[10]:
```
#Coefficient of mean to standard deviation
df_groupmean = df_wss.groupby('Store')['Weekly_Sales'].mean()
print(df_groupmean.shape)
cms = (df_groupstd.sum()/df_groupmean.sum())*100
print(cms)
```

```
(45,)
13.523458876035265
```

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

5 Store/s that has good quarterly growth rate in Q3'2012(July 1 to September 30)

[11]:
```
df_Q32012=df_wss[(pd.to_datetime(df_wss['Date'])>= pd.
↪to_datetime('01-07-2012'))&(pd.to_datetime(df_wss['Date'])<= pd.
↪to_datetime('30-09-2012'))]
df_wss_growth = df_Q32012.groupby(['Store'])['Weekly_Sales'].sum()
print("Store Number {} has a good Quartely Growth in 3rd Quarter(Q3) of 2012␣
↪{}".format(df_wss_growth.idxmax(),df_wss_growth.max()))
```

```
Store Number 4 has a good Quartely Growth in 3rd Quarter(Q3) of 2012 77516251.42
```

6 Some holidays have a negative impact on sales.

7 Find out holidays which have higher sales than the mean sales in non-holiday season for all stores together

[12]:
```
# Stores Holiday
stores_holiday_sales = df_wss[df_wss['Holiday_Flag'] == 0]
#Store_non_holiday
stores_nonholiday_sales = df_wss[df_wss['Holiday_Flag'] == 1]
```

[13]:
```
stores_holiday_sales_mean = df_wss[(df_wss['Holiday_Flag'] ==␣
↪0)]['Weekly_Sales'].mean()
stores_nonholiday_sales_sum = df_wss[(df_wss['Holiday_Flag'] == 1)].
↪groupby('Date')['Weekly_Sales'].sum()
```

[14]:
```
print(stores_nonholiday_sales_sum>stores_holiday_sales_mean)
```

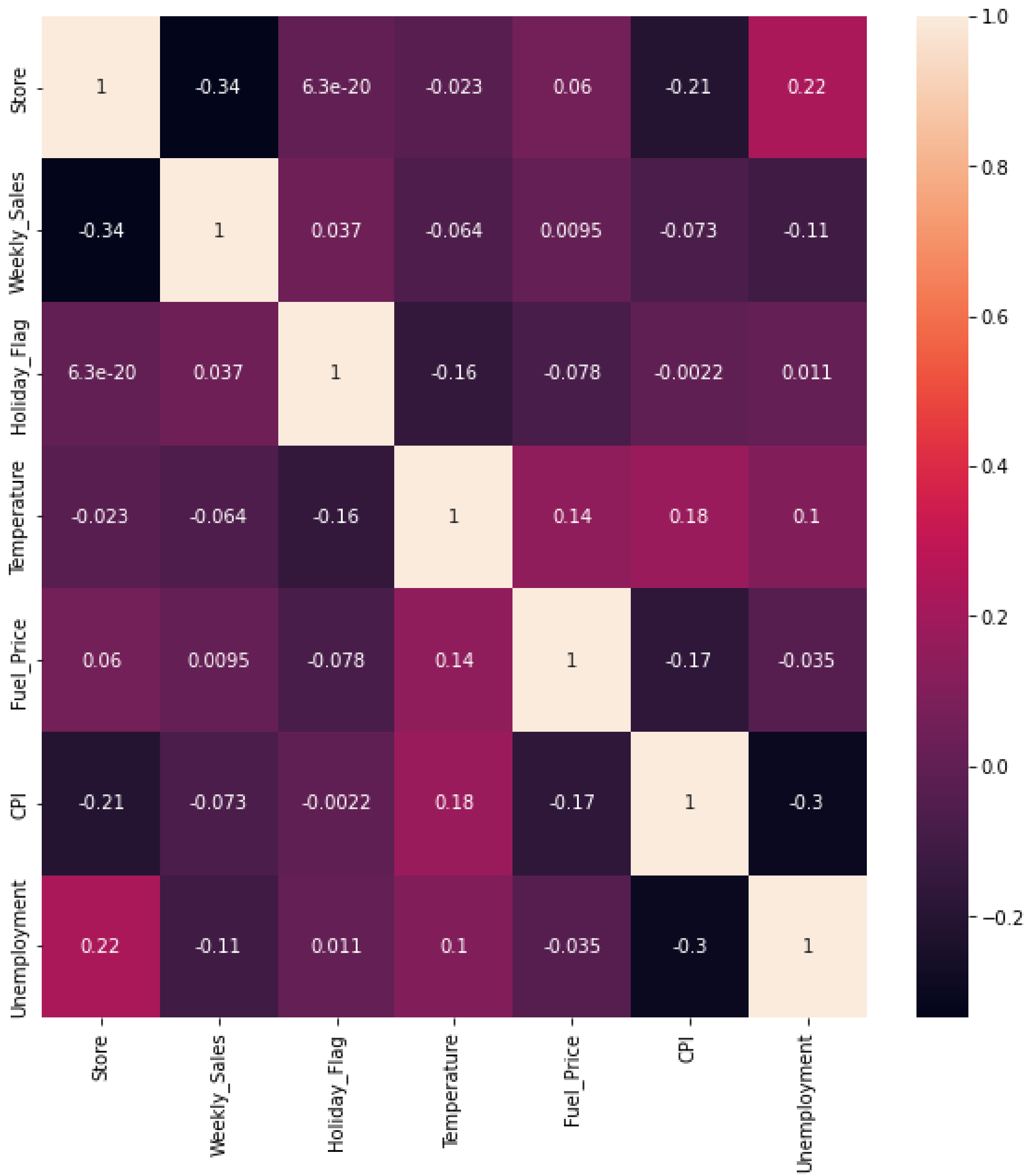
```
Date
07-09-2012    True
09-09-2011    True
10-02-2012    True
10-09-2010    True
11-02-2011    True
12-02-2010    True
25-11-2011    True
26-11-2010    True
30-12-2011    True
31-12-2010    True
Name: Weekly_Sales, dtype: bool
```

8 Correlation Plot using heatmap

[15]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

[16]:
```
corr = df_wss.corr()
plt.figure(figsize=(10,10))
sns.heatmap(corr, annot=True)
plt.plot()
```

[16]: []



[17]:
```python
# Correlation Values
df_wss[['Store','CPI','Fuel_Price','Unemployment','Weekly_Sales']].corr()
```

[17]:

	Store	CPI	Fuel_Price	Unemployment	Weekly_Sales
Store	1.000000	-0.209492	0.060023	0.223531	-0.335332
CPI	-0.209492	1.000000	-0.170642	-0.302020	-0.072634
Fuel_Price	0.060023	-0.170642	1.000000	-0.034684	0.009464
Unemployment	0.223531	-0.302020	-0.034684	1.000000	-0.106176

```
Weekly_Sales -0.335332 -0.072634    0.009464     -0.106176      1.000000
```

[18]:
```
# Change dates into days by creating new variable.
df_wss['Days'] = pd.to_datetime(df_wss['Date']).dt.day_name()
df_wss.head()
```

[18]:
```
   Store        Date  Weekly_Sales  Holiday_Flag  Temperature  Fuel_Price  \
0      1  05-02-2010    1643690.90             0        42.31       2.572
1      1  12-02-2010    1641957.44             1        38.51       2.548
2      1  19-02-2010    1611968.17             0        39.93       2.514
3      1  26-02-2010    1409727.59             0        46.63       2.561
4      1  05-03-2010    1554806.68             0        46.50       2.625

          CPI  Unemployment      Days
0  211.096358         8.106    Sunday
1  211.242170         8.106  Thursday
2  211.289143         8.106    Friday
3  211.319643         8.106    Friday
4  211.350143         8.106    Monday
```

9 Statistical Model

10

11 For Store 1 – Build prediction models to forecast demand

12

13 Linear Regression

14 Utilize variables like date and restructure dates as 1 for 5 Feb 2010 (starting from the earliest date in order).

15

16 SLR

[19]:
```
#import LinearRegression model from sklearn package
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
import numpy as np
```

```
from sklearn import metrics
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
```

[20]:
```
#Feature
X_features = df_wss[df_wss['Store'] ==1][['Store','Date']]
next_date = df_wss[df_wss['Store'] ==1]['Date']
next_date.index +=1
X_features.Date = next_date.index
print(X_features.shape)
print(X_features.head())
```

```
(143, 2)
   Store  Date
0      1     1
1      1     2
2      1     3
3      1     4
4      1     5
```

[21]:
```
#Target
y_targets = df_wss[df_wss['Store']==1][['Store','Weekly_Sales']] #Store 1␣
↪Weekly_Sales is the target
print(y_targets.shape)
print(y_targets.head())
```

```
(143, 2)
   Store  Weekly_Sales
0      1    1643690.90
1      1    1641957.44
2      1    1611968.17
3      1    1409727.59
4      1    1554806.68
```

[22]:
```
#Train and Test split
X_train,X_test,y_train,y_test =␣
↪train_test_split(X_features,y_targets,random_state = 21)
```

[23]:
```
#Calling Linear Regression and fitting the model
lm = LinearRegression()
lm.fit(X_train,y_train)
```

[23]:
```
LinearRegression()
```

[24]:
```
#Intercept and Coefficient Values
print("Intercept: ",lm.intercept_)
print("Coefficient: ",lm.coef_)
```

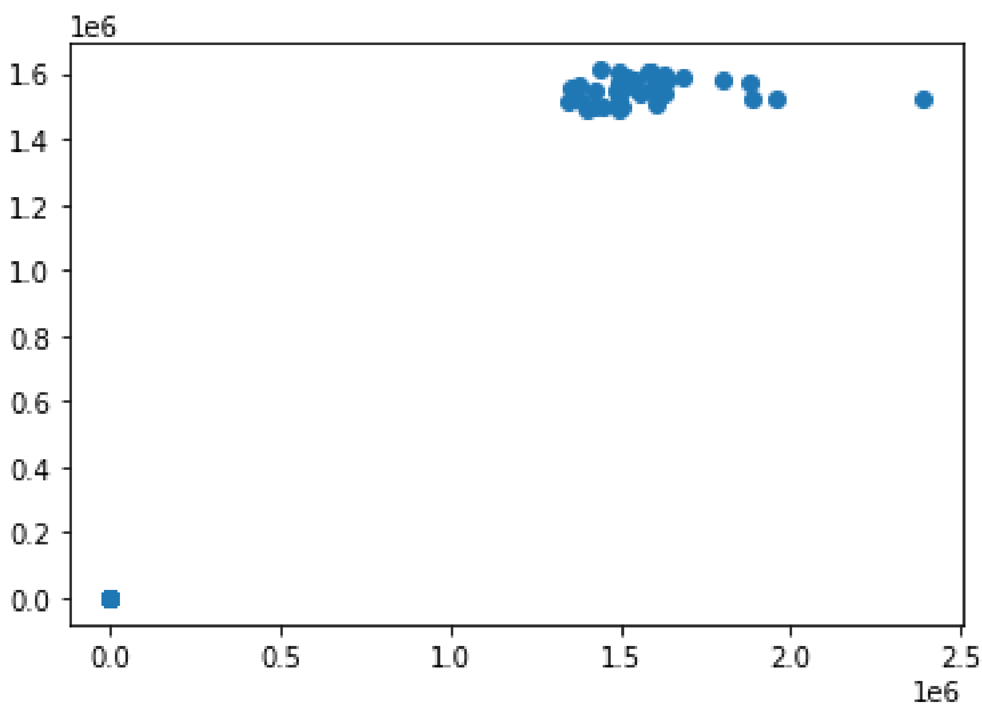
```
Intercept:  [1.00000000e+00 1.48003198e+06]
Coefficient:  [[  0.           0.        ]
 [  0.         944.85378805]]
```

[25]:
```python
#Predicting using the feature test values
y_pred_slr = lm.predict(X_test)
```

[26]:
```python
#Root mean square error value and score(Accuracy) calculation
print("RMSE Value: ",np.sqrt(metrics.mean_squared_error(y_pred_slr,y_test)))
accuracy = metrics.r2_score(y_test,y_pred_slr)
print("Accuracy: ",accuracy)
```

```
RMSE Value:  142629.0580637676
Accuracy:  0.48388547025022033
```

[27]:
```python
#Scatter Plot for predicted values
import matplotlib.pyplot as plt
import seaborn as sns
get_ipython().run_line_magic('matplotlib', 'inline')
plt.scatter(y_test,y_pred_slr)
plt.show()
```



17 MLR

[28]:
```
#Feature
X_feature = df_wss[df_wss['Store'] ==1][['Store','CPI',␣
↪'Unemployment','Fuel_Price']]
print(X_feature.head())
#Target
y_target = df_wss[df_wss['Store']==1][['Store','Weekly_Sales']] #Store 1␣
↪Weekly_Sales is the target
print(y_target.head())
```

```
   Store         CPI  Unemployment  Fuel_Price
0      1  211.096358         8.106       2.572
1      1  211.242170         8.106       2.548
2      1  211.289143         8.106       2.514
3      1  211.319643         8.106       2.561
4      1  211.350143         8.106       2.625
   Store  Weekly_Sales
0      1    1643690.90
1      1    1641957.44
2      1    1611968.17
3      1    1409727.59
4      1    1554806.68
```

[29]:
```
#Train and Test split
X_train,X_test,y_train,y_test =␣
↪train_test_split(X_feature,y_target,random_state = 21)
```

[30]:
```
#Calling Linear Regression and fitting the model
linreg = LinearRegression()
linreg.fit(X_train,y_train)
```

[30]:
```
LinearRegression()
```

[31]:
```
#Predicting using the feature test values
y_pred_mlr = linreg.predict(X_test)
```

[32]:
```
#Intercept and Coefficient Values
print("Intercept: ",linreg.intercept_)
print("Coefficient: ",linreg.coef_)
```

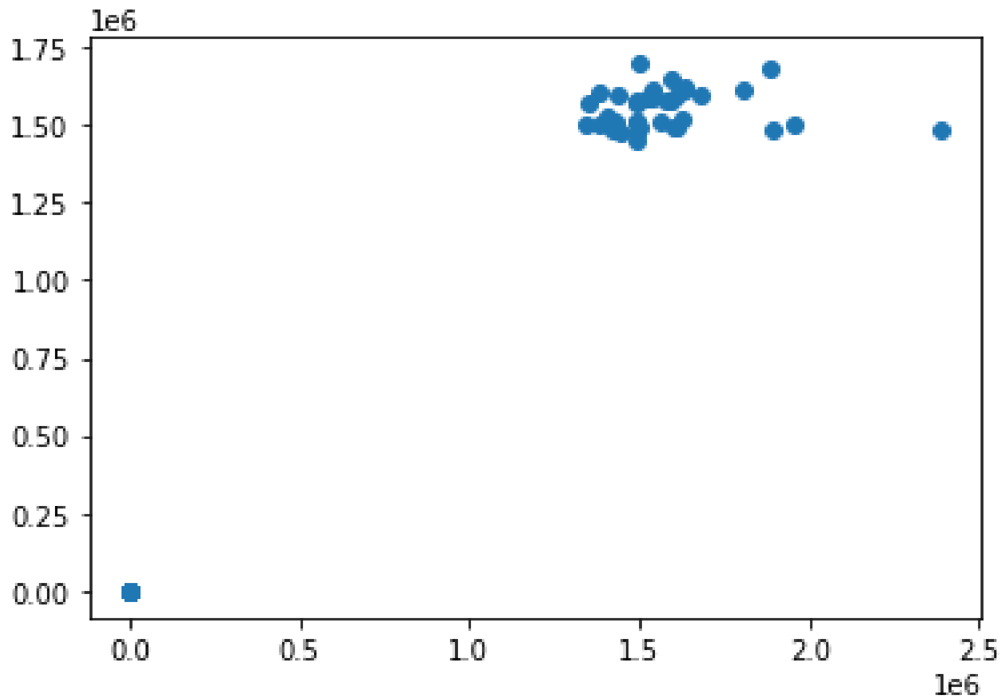
```
Intercept:  [ 1.00000000e+00 -5.58124608e+06]
Coefficient:  [[     0.              0.              0.              0.        ]
 [     0.          27771.28586632 173495.37854177 -58855.15513113]]
```

[33]:
```
#Root mean square error value and r2_score(Accuracy) calculation
print("RMSE Value: ",np.sqrt(metrics.mean_squared_error(y_pred_mlr,y_test)))
```

```
accuracy = metrics.r2_score(y_test,y_pred_mlr)
print("Accuracy: ",accuracy)
```

```
RMSE Value:  148439.4678314597
Accuracy:  0.4409780834834336
```

[34]:
```
#Scatter Plot for predicted values
plt.scatter(y_test,y_pred_mlr)
plt.show()
```



[39]:
```
# Polynomial Regression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
```

[40]:
```
#Degree of polynomial is 3
PolyReg = PolynomialFeatures(degree = 3)
#Transform features for polynomial regression
X_feature_PolyReg = PolyReg.fit_transform(X_feature)
# Pipeline is created by creating a list of tuples including the name of model␣
↪or estimator and its correspondign constructor
#for Polynomial regression
Pip_Input =[('scale',StandardScaler()), ('polynomial',␣
↪PolynomialFeatures(include_bias=False)),('model',LinearRegression())]
```

```
# Pipeline the above input
pipe = Pipeline(Pip_Input)
print(pipe)
```

```
Pipeline(steps=[('scale', StandardScaler()),
                ('polynomial', PolynomialFeatures(include_bias=False)),
                ('model', LinearRegression())])
```

[41]:
```
# Fit the model and predicting the first four 'Weekly_Sales' using Polynomial␣
↪regression
pipe.fit(X_feature_PolyReg,y_target)
```

[41]:
```
Pipeline(steps=[('scale', StandardScaler()),
                ('polynomial', PolynomialFeatures(include_bias=False)),
                ('model', LinearRegression())])
```

[42]:
```
Ypipehat = pipe.predict(X_feature_PolyReg)
print(Ypipehat[0:4])
```

```
[[1.000000e+00 1.674632e+06]
 [1.000000e+00 1.573768e+06]
 [1.000000e+00 1.630344e+06]
 [1.000000e+00 1.440392e+06]]
```

[43]:
```
#shape of features in Polyreg
print(X_feature.shape)
print(X_feature_PolyReg.shape)
```

```
(143, 4)
(143, 35)
```

[44]:
```
from math import sqrt
from sklearn. metrics import r2_score
from sklearn.metrics import mean_squared_error
```

[45]:
```
#Root mean square error value and score(Accuracy) calculation
r_squared = r2_score(y_target, Ypipehat)
print('R-squared :', r_squared)
print('RMSE:' , sqrt(mean_squared_error(y_target,Ypipehat)))
```

```
R-squared : 0.850954407069321
RMSE: 60007.67173079369
```

[46]:
```
# CPI positive impact on sales
#
# Unemployment positive impact on sales
# Fuel_Price negative impact on sales
# Select the model which gives best accuracy.
```

```
# Polynomial Regression with degree 3 gives the best accuracy of 85%
# Simple Linear Regression gives 48% of accuracy and
# Multiple Linear Regression gives 44% of accuracy
```

[ ]:

```

```