retail-analysis-with-walmart-data

July 30, 2024

1 Retail Analysis with Walmart Data

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

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

[4]:
```
data.head(5)
```

[4]:
```
   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
```

[5]:
```
data.tail(5)
```

[5]:
```
      Store        Date  Weekly_Sales  Holiday_Flag  Temperature  Fuel_Price  \
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
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
```

[6]:
```
data.isna().sum()
```

[6]:
```
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
dtype: int64
```

[7]:
```
data.shape
```

[7]:
```
(6435, 8)
```

[8]:
```
data.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
```

[9]:
```
data.describe
```

[9]:
```
<bound method NDFrame.describe of       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]>
```

[10]:
```python
from datetime import datetime
data['Date']=pd.to_datetime(data['Date'],format='mixed')
```

[11]:
```python
data.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   datetime64[ns]
 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: datetime64[ns](1), float64(5), int64(2)
memory usage: 402.3 KB
```

1.1 store has maximum sales

[13]:
```
Max_sales = data.groupby('Store')['Weekly_Sales'].sum().round().
↪sort_values(ascending=0)
```

[14]:
```
Max_sales
```

[14]:
```
Store
20    301397792.0
4     299543953.0
14    288999911.0
13    286517704.0
2     275382441.0
10    271617714.0
27    253855917.0
6     223756131.0
1     222402809.0
39    207445542.0
19    206634862.0
31    199613906.0
23    198750618.0
24    194016021.0
11    193962787.0
28    189263681.0
41    181341935.0
32    166819246.0
18    155114734.0
22    147075649.0
12    144287230.0
26    143416394.0
34    138249763.0
40    137870310.0
35    131520672.0
8     129951181.0
17    127782139.0
45    112395341.0
21    108117879.0
25    101061179.0
43     90565435.0
15     89133684.0
7      81598275.0
42     79565752.0
9      77789219.0
29     77141554.0
16     74252425.0
37     74202740.0
30     62716885.0
```

```
3       57586735.0
38      55159626.0
36      53412215.0
5       45475689.0
44      43293088.0
33      37160222.0
Name: Weekly_Sales, dtype: float64
```

[15]:
```
pd.DataFrame(Max_sales).head(1)
```

[15]:
```
       Weekly_Sales
Store
20      301397792.0
```

[16]:
```
pd.DataFrame(Max_sales).tail(1)
```

[16]:
```
       Weekly_Sales
Store
33       37160222.0
```

Observation Store 20 records highest sale of value 301,397,792. And store 33 records lowest sale 37,160,222

1.2 store has maximum standard deviation

[19]:
```
Stddv_sales = data.groupby('Store')['Weekly_Sales'].std().round().
  ↪sort_values(ascending=0)
```

[20]:
```
Stddv_sales
```

[20]:
```
Store
14     317570.0
10     302262.0
20     275901.0
4      266201.0
13     265507.0
23     249788.0
27     239930.0
2      237684.0
39     217466.0
6      212526.0
35     211243.0
19     191723.0
41     187907.0
28     181759.0
18     176642.0
24     167746.0
```

```
11     165834.0
22     161251.0
1      155981.0
12     139167.0
32     138017.0
45     130169.0
21     128753.0
31     125856.0
15     120539.0
40     119002.0
25     112977.0
7      112585.0
17     112163.0
26     110431.0
8      106281.0
34     104630.0
29      99120.0
16      85770.0
9       69029.0
36      60725.0
42      50263.0
3       46320.0
38      42768.0
43      40598.0
5       37738.0
44      24763.0
33      24133.0
30      22810.0
37      21837.0
Name: Weekly_Sales, dtype: float64
```

[21]:
```
pd.DataFrame(Stddv_sales).head(1)
```

[21]:
```
       Weekly_Sales
Store
14         317570.0
```

[22]:
```
pd.DataFrame(Stddv_sales).tail(1)
```

[22]:
```
       Weekly_Sales
Store
37          21837.0
```

[51]:
```
store14 = data[data.Store==14].Weekly_Sales
```

[53]:
```
store14
```

```
[53]: 1859    2623469.95
      1860    1704218.84
      1861    2204556.70
      1862    2095591.63
      1863    2237544.75
                 …
      1997    1522512.20
      1998    1687592.16
      1999    1639585.61
      2000    1590274.72
      2001    1704357.62
      Name: Weekly_Sales, Length: 143, dtype: float64
```

```
[55]: cv_store14=store14.std()/store14.mean()*100
      cv_store14.round(2)
```

```
[55]: 15.71
```

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

```
[58]: Q2_sales=data[(data['Date']>='2012-04-01')&(data['Date']<='2012-06-30')].
       ↪groupby('Store')['Weekly_Sales'].sum().round()
      Q3_sales=data[(data['Date']>='2012-07-01')&(data['Date']<='2012-09-30')].
       ↪groupby('Store')['Weekly_Sales'].sum().round()
```

```
[68]: pd.DataFrame({'Q2_sales':Q2_sales,'Q3_sales':Q3_sales,'Difference':
       ↪(Q3_sales-Q2_sales),
                   'growth_rate':((Q3_sales-Q2_sales)/Q3_sales)*100}).
       ↪sort_values(by=['growth_rate'], ascending=0).head(5)
```

[68]:

Store	Q2_sales	Q3_sales	Difference	growth_rate
16	6626133.0	6441311.0	-184822.0	-2.869323
7	7613594.0	7322394.0	-291200.0	-3.976841
35	10753571.0	10252123.0	-501448.0	-4.891163
26	13218290.0	12417575.0	-800715.0	-6.448240
39	20191586.0	18899955.0	-1291631.0	-6.834043

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

```
[76]: #Holiday Events
      Super_Bowl= ['12-2-2010', '11-2-2011', '10-2-2012', '8-2-2013']
      Labour_Day= ['10-9-2010', '9-9-2011', '7-9-2012', '6-9-2013']
      Thanksgiving= ['26-11-2010', '25-11-2011', '23-11-2012', '29-11-2013']
      Christmas= ['31-12-2010', '30-12-2011', '28-12-2012', '27-11-2013']
```

[78]:
```
Super_Bowl_sales=data.loc[data.Date.isin(Super_Bowl)]['Weekly_Sales'].mean().
  ↪round()
Labour_Day_sales=data.loc[data.Date.isin(Labour_Day)]['Weekly_Sales'].mean().
  ↪round()
Thanksgiving_sales=data.loc[data.Date.isin(Thanksgiving)]['Weekly_Sales'].
  ↪mean().round()
Christmas_sales=data.loc[data.Date.isin(Christmas)]['Weekly_Sales'].mean().
  ↪round()
```

[80]:
```
print(Super_Bowl_sales)
print(Labour_Day_sales)
print(Thanksgiving_sales)
print (Christmas_sales)
```

```
1079128.0
1042427.0
1471273.0
960833.0
```

[82]:
```
non_holiday_sales=data[(data['Holiday_Flag']==0)]['Weekly_Sales'].mean().
  ↪round(2)
non_holiday_sales
```

[82]:
```
1041256.38
```

[84]:
```
difference_holidays=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}])
```

[86]:
```
difference_holidays
```

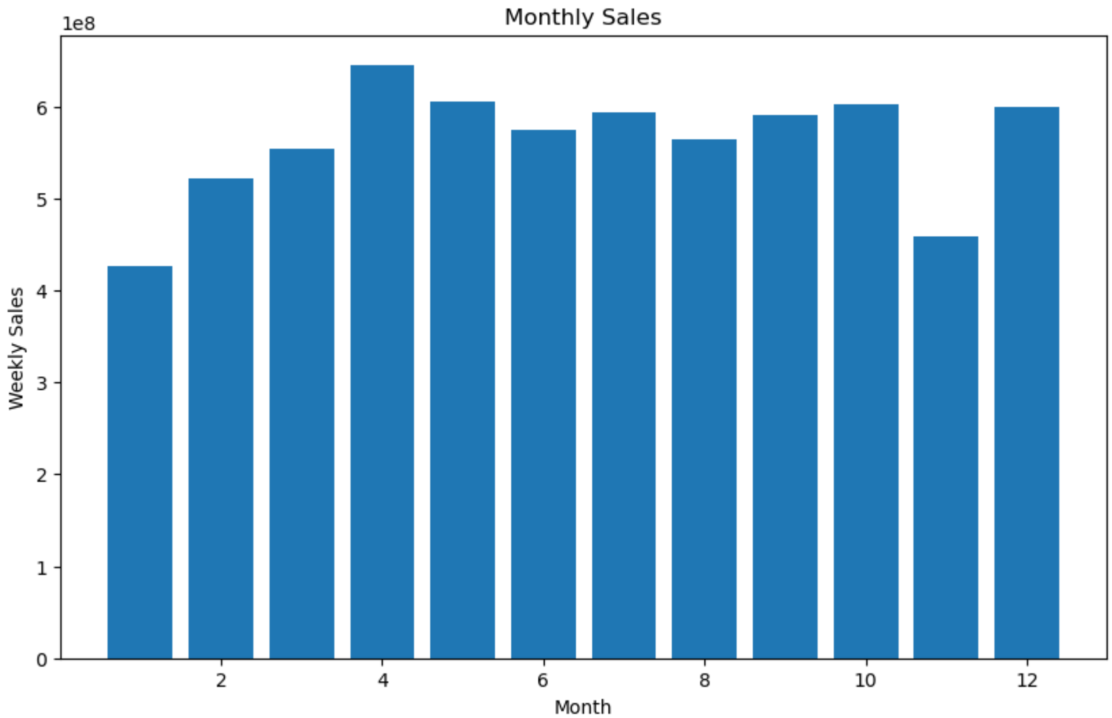
[86]:
```
   Super_Bowl_sales  Labour_Day_sales  Thanksgiving_sales  Christmas_sales  \
0         1079128.0         1042427.0           1471273.0         960833.0

   non_holiday_sales
0         1041256.38
```

1.5 monthly view of sales in units and give insights

[88]:
```
data['Month'] = data['Date'].dt.month
data['Year'] = data['Date'].dt.year
```

[92]:
```
monthly_sales = data.groupby('Month')['Weekly_Sales'].sum().reset_index()
```

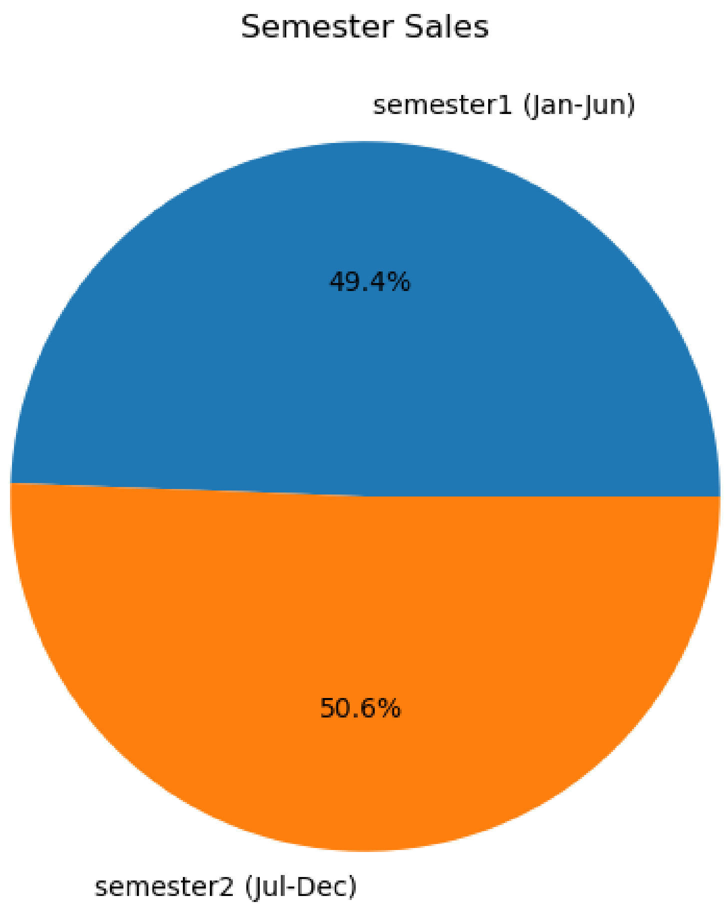
[94]:
```
plt.figure(figsize=(10, 6))
plt.bar(monthly_sales['Month'], monthly_sales['Weekly_Sales'])
plt.xlabel('Month')
plt.ylabel('Weekly Sales')
plt.title('Monthly Sales')
plt.show()
```



1.6 Semester view of sales in units and give insights

[102]:
```
# Group the data by Semester and calculate the total sales
semester1_sales = data[data['Month'].isin([1, 2, 3, 4, 5, 6])]['Weekly_Sales'].
    ↪sum()
semester2_sales = data[data['Month'].isin([7, 8, 9, 10, 11,␣
    ↪12])]['Weekly_Sales'].sum()
```

[106]:
```
plt.figure(figsize=(8, 6))
plt.pie([semester1_sales, semester2_sales], labels=['semester1 (Jan-Jun)',␣
    ↪'semester2 (Jul-Dec)'], autopct='%1.1f%%')
plt.title('Semester Sales')
plt.show()
```



1.7 Build prediction models to forecast demand

[110]:
```
import statsmodels.formula.api as sm
model=sm.ols(formula='Weekly_Sales~CPI+Fuel_Price+Unemployment',data=data).fit()
```

[112]:
```
model.summary()
```

[112]:

Dep. Variable:	Weekly_Sales	**R-squared:**	0.024
Model:	OLS	**Adj. R-squared:**	0.023
Method:	Least Squares	**F-statistic:**	51.75
Date:	Tue, 30 Jul 2024	**Prob (F-statistic):**	4.81e-33
Time:	09:12:00	**Log-Likelihood:**	-94275.
No. Observations:	6435	**AIC:**	1.886e+05
Df Residuals:	6431	**BIC:**	1.886e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P> |t|	[0.025	0.975]
Intercept	1.746e+06	7.96e+04	21.938	0.000	1.59e+06	1.9e+06
CPI	-1696.8760	188.793	-8.988	0.000	-2066.973	-1326.779
Fuel_Price	-1.927e+04	1.54e+04	-1.248	0.212	-4.95e+04	1.1e+04
Unemployment	-4.286e+04	3905.197	-10.975	0.000	-5.05e+04	-3.52e+04

Omnibus:	370.117	**Durbin-Watson:**	0.112
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	436.792
Skew:	0.638	**Prob(JB):**	1.42e-95
Kurtosis:	3.051	**Cond. No.**	2.04e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.04e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

```
[ ]:
```