Retail Analysis with Walmart Data

Project 4

DESCRIPTION

One of the leading retail stores in the US, Walmart, would like to predict the sales and demand accurately. There are certain events and holidays which impact sales on each day. There are sales data available for 45 stores of Walmart. The business is facing a challenge due to unforeseen demands and runs out of stock some times, due to the inappropriate machine learning algorithm. An ideal ML algorithm will predict demand accurately and ingest factors like economic conditions including CPI, Unemployment Index, etc.

Walmart runs several promotional markdown events throughout the year. These markdowns precede prominent holidays, the four largest of all, which are the Super Bowl, Labour Day, Thanksgiving, and Christmas. The weeks including these holidays are weighted five times higher in the evaluation than non-holiday weeks. Part of the challenge presented by this competition is modeling the effects of markdowns on these holiday weeks in the absence of complete/ideal historical data. Historical sales data for 45 Walmart stores located in different regions are available.

Dataset Description

This is the historical data that covers sales from 2010-02-05 to 2012-11-01, in the file Walmart_Store_sales. Within this file you will find the following fields:

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

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

Analysis Tasks

Basic Statistics tasks

Which store has maximum sales

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

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

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

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

Statistical Model

For Store 1 – Build prediction models to forecast demand

Linear Regression – Utilize variables like date and restructure dates as 1 for 5 Feb 2010 (starting from the earliest date in order). Hypothesize if CPI, unemployment, and fuel price have any impact on sales.

Change dates into days by creating new variable.

Select the model which gives best accuracy.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import style
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from statsmodels.formula.api import ols
import datetime as dt
import warnings

walmart_df=pd.read_csv('Walmart_Store_sales.csv')
warnings.filterwarnings('ignore')
```

```
# to display first 5 rows
walmart_df.head()
```

```
   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
```

```
# to display last 5 rows
walmart_df.tail()
```

```
      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
```

```
#info() is used to complete description of data
walmart_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
```

```
# to get columns names
walmart_df.columns
```

```
Index(['Store', 'Date', 'Weekly_Sales', 'Holiday_Flag', 'Temperature',
       'Fuel_Price', 'CPI', 'Unemployment'],
      dtype='object')
```

```
# generalising column names by loweringcase
walmart_df.columns=walmart_df.columns.str.lower()
walmart_df.columns
```

```
Index(['store', 'date', 'weekly_sales', 'holiday_flag', 'temperature',
       'fuel_price', 'cpi', 'unemployment'],
      dtype='object')
```

```
# looking for null values in dataset
walmart_df.isnull().sum()
```

```
store           0
date            0
weekly_sales    0
holiday_flag    0
temperature     0
fuel_price      0
cpi             0
unemployment    0
dtype: int64
```

Maximum Sales

```
# groupby stores and get total sales
store_total_weekly_sales=walmart_df.groupby('store')
['weekly_sales'].sum()
store_total_weekly_sales.to_frame()
```

```
       weekly_sales
store
```

```
1      2.224028e+08
2      2.753824e+08
3      5.758674e+07
4      2.995440e+08
5      4.547569e+07
6      2.237561e+08
7      8.159828e+07
8      1.299512e+08
9      7.778922e+07
10     2.716177e+08
11     1.939628e+08
12     1.442872e+08
13     2.865177e+08
14     2.889999e+08
15     8.913368e+07
16     7.425243e+07
17     1.277821e+08
18     1.551147e+08
19     2.066349e+08
20     3.013978e+08
21     1.081179e+08
22     1.470756e+08
23     1.987506e+08
24     1.940160e+08
25     1.010612e+08
26     1.434164e+08
27     2.538559e+08
28     1.892637e+08
29     7.714155e+07
30     6.271689e+07
31     1.996139e+08
32     1.668192e+08
33     3.716022e+07
34     1.382498e+08
35     1.315207e+08
36     5.341221e+07
37     7.420274e+07
38     5.515963e+07
39     2.074455e+08
40     1.378703e+08
41     1.813419e+08
42     7.956575e+07
43     9.056544e+07
44     4.329309e+07
45     1.123953e+08

print("{:.2f}".format(store_total_weekly_sales.max()))
# using argmax to get the std max std.dev store index
print(store_total_weekly_sales.index[store_total_weekly_sales.argmax()
])
```

```
301397792.46
20
```

Store number :20 has the maximum sales of 301397792.46

Maximum Sales Standard Deviation

```
# groupby stores and get std.dev
store_sales_std=walmart_df.groupby('store')['weekly_sales'].std()
store_sales_std.to_frame()
```

store	weekly_sales
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
```

```
print("{:.2f}".format(store_sales_std.max()))
# using argmax to get the max std.dev store index
print(store_sales_std.index[store_sales_std.argmax()])
```

```
317569.95
14
```

Store number : 14 has the maximum sales standard seviation 317569.95

Coeffcient of Mean to Standatd Deviation

```
# groupby stores and get mean values
store_sales_mean=walmart_df.groupby('store')['weekly_sales'].mean()
store_sales_mean.to_frame()
```

```
       weekly_sales
store
1      1.555264e+06
2      1.925751e+06
3      4.027044e+05
4      2.094713e+06
5      3.180118e+05
6      1.564728e+06
7      5.706173e+05
8      9.087495e+05
9      5.439806e+05
10     1.899425e+06
11     1.356383e+06
12     1.009002e+06
13     2.003620e+06
14     2.020978e+06
15     6.233125e+05
16     5.192477e+05
17     8.935814e+05
18     1.084718e+06
19     1.444999e+06
20     2.107677e+06
```

```
21     7.560691e+05
22     1.028501e+06
23     1.389864e+06
24     1.356755e+06
25     7.067215e+05
26     1.002912e+06
27     1.775216e+06
28     1.323522e+06
29     5.394514e+05
30     4.385796e+05
31     1.395901e+06
32     1.166568e+06
33     2.598617e+05
34     9.667816e+05
35     9.197250e+05
36     3.735120e+05
37     5.189003e+05
38     3.857317e+05
39     1.450668e+06
40     9.641280e+05
41     1.268125e+06
42     5.564039e+05
43     6.333247e+05
44     3.027489e+05
45     7.859814e+05
```

```
# cv=(mean/std.dev)*100
covariance_std_mean=(store_sales_std / store_sales_mean)*100
```

Covariance Values (Cv)

```
-Cv less than 10= Very Good
-Cv between 10-20=Good
-Cv between 21-30=Acceptable
-Cv greater than 30=Not Acceptable

covariance_std_mean.to_frame()
```

```
       weekly_sales
store
1         10.029212
2         12.342388
3         11.502141
4         12.708254
5         11.866844
6         13.582286
7         19.730469
8         11.695283
9         12.689547
10        15.913349
```

```
11        12.226183
12        13.792532
13        13.251363
14        15.713674
15        19.338399
16        16.518065
17        12.552067
18        16.284550
19        13.268012
20        13.090269
21        17.029239
22        15.678288
23        17.972115
24        12.363738
25        15.986040
26        11.011066
27        13.515544
28        13.732974
29        18.374247
30         5.200804
31         9.016105
32        11.831049
33         9.286835
34        10.822524
35        22.968111
36        16.257891
37         4.208412
38        11.087545
39        14.990779
40        12.342978
41        14.817711
42         9.033533
43         6.410363
44         8.179331
45        16.561273
```

Store numbers: 30,31,33,37,42,43,44 has very good co-efficients of mean to standard deviation

Good Quarterly growth rate in year 2010

```
# Converting date column from object dtype to datetime dtype
walmart_df['date']=walmart_df['date'].apply(lambda
x:dt.datetime.strptime(x,"%d-%m-%Y"))

# Using datetimeindex to get year/month/day from dataset
walmart_df['year']=pd.DatetimeIndex(walmart_df['date']).year
```

```
walmart_df['month']=pd.DatetimeIndex(walmart_df['date']).month
walmart_df['day']=pd.DatetimeIndex(walmart_df['date']).day

walmart_df.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  day
0  211.096358         8.106  2010      2    5
1  211.242170         8.106  2010      2   12
2  211.289143         8.106  2010      2   19
3  211.319643         8.106  2010      2   26
4  211.350143         8.106  2010      3    5
```

```
# Converting date back to string with our desired format
walmart_df['date']=walmart_df['date'].apply(lambda
x:dt.datetime.strptime(x,"%d-%m-%Y"))

month_dict={1:"Jan",2:"Feb",3:"Mar",4:"Apr",5:"May",6:"Jun",7:"Jul",8:
"Aug",9:"Sep",10:"Oct",11:"Nov",12:"Dec"}
# Converrting month int values to corresponding month names using
apply functin and dictionary
walmart_df['month']=walmart_df['month'].apply(lambda x: month_dict[x])

walmart_df.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  day
```

```
0  211.096358         8.106  2010   Feb    5
1  211.242170         8.106  2010   Feb   12
2  211.289143         8.106  2010   Feb   19
3  211.319643         8.106  2010   Feb   26
4  211.350143         8.106  2010   Mar    5
```

```
# grouping data by years
Yearly_walmartdata=walmart_df.groupby('year')
Yearly_walmartdata.ngroups
```

```
3
```

```
# getting groups of different years(2010,2011,2012)
stores_2012_sales =Yearly_walmartdata.get_group(2012)
stores_2011_sales =Yearly_walmartdata.get_group(2011)
stores_2010_sales =Yearly_walmartdata.get_group(2010)
```

```
stores_2012_sales.head()
```

```
     store       date  weekly_sales  holiday_flag  temperature
fuel_price  \
100      1 2012-01-06    1550369.92             0        49.01
3.157
101      1 2012-01-13    1459601.17             0        48.53
3.261
102      1 2012-01-20    1394393.84             0        54.11
3.268
103      1 2012-01-27    1319325.59             0        54.26
3.290
104      1 2012-02-03    1636339.65             0        56.55
3.360

            cpi  unemployment  year month  day
100  219.714258         7.348  2012   Jan    6
101  219.892526         7.348  2012   Jan   13
102  219.985689         7.348  2012   Jan   20
103  220.078852         7.348  2012   Jan   27
104  220.172015         7.348  2012   Feb    3
```

```
# adding new column to find and store quartile values
stores_2012_sales['quartile']=0
stores_2012_sales.head()
```

```
     store       date  weekly_sales  holiday_flag  temperature
fuel_price  \
100      1 2012-01-06    1550369.92             0        49.01
3.157
101      1 2012-01-13    1459601.17             0        48.53
3.261
102      1 2012-01-20    1394393.84             0        54.11
3.268
103      1 2012-01-27    1319325.59             0        54.26
```

```
3.290
104      1 2012-02-03    1636339.65             0        56.55
3.360

            cpi  unemployment  year month  day  quartile
100  219.714258         7.348  2012   Jan    6         0
101  219.892526         7.348  2012   Jan   13         0
102  219.985689         7.348  2012   Jan   20         0
103  220.078852         7.348  2012   Jan   27         0
104  220.172015         7.348  2012   Feb    3         0

stores_2012_sales['month'].unique()

array(['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep',
       'Oct'], dtype=object)

# using python code to split month into quartiles
for i in stores_2012_sales['month']:
    if i in ['Jan','Feb','Mar']:
        stores_2012_sales['quartile']
[stores_2012_sales[stores_2012_sales['month']==i].index]='Q1'
    elif i in ['Apr','May','Jun']:
        stores_2012_sales['quartile']
[stores_2012_sales[stores_2012_sales['month']==i].index]='Q2'
    elif i in ['Jul','Aug','Sep']:
        stores_2012_sales['quartile']
[stores_2012_sales[stores_2012_sales['month']==i].index]='Q3'
    elif i in ['Oct','Nov','Dec']:
        stores_2012_sales['quartile']
[stores_2012_sales[stores_2012_sales['month']==i].index]='Q4'

stores_2012_sales

      store       date  weekly_sales  holiday_flag  temperature
fuel_price  \
100       1 2012-01-06    1550369.92             0        49.01
3.157
101       1 2012-01-13    1459601.17             0        48.53
3.261
102       1 2012-01-20    1394393.84             0        54.11
3.268
103       1 2012-01-27    1319325.59             0        54.26
3.290
104       1 2012-02-03    1636339.65             0        56.55
3.360
...     ...        ...           ...           ...          ...
...
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  day quartile
100   219.714258         7.348  2012   Jan    6       Q1
101   219.892526         7.348  2012   Jan   13       Q1
102   219.985689         7.348  2012   Jan   20       Q1
103   220.078852         7.348  2012   Jan   27       Q1
104   220.172015         7.348  2012   Feb    3       Q1
...          ...           ...   ...   ...  ...      ...
6430  192.013558         8.684  2012   Sep   28       Q3
6431  192.170412         8.667  2012   Oct    5       Q4
6432  192.327265         8.667  2012   Oct   12       Q4
6433  192.330854         8.667  2012   Oct   19       Q4
6434  192.308899         8.667  2012   Oct   26       Q4

[1935 rows x 12 columns]
```

```
# grouping data by quartilesabs
stores_2012sales=stores_2012_sales.groupby('quartile')
stores_2012sales.ngroups
```

```
4
```

```
# get individual quartile groups (Q1,Q2,Q3,Q4)
q1_data =stores_2012sales.get_group('Q1')
q2_data =stores_2012sales.get_group('Q2')
q3_data =stores_2012sales.get_group('Q3')
q4_data =stores_2012sales.get_group('Q4')
```

```
# getting total sales of all stores in each quarters
q1_sales =q1_data.groupby('store')['weekly_sales'].sum()
q2_sales =q2_data.groupby('store')['weekly_sales'].sum()
q3_sales =q3_data.groupby('store')['weekly_sales'].sum()
q4_sales =q4_data.groupby('store')['weekly_sales'].sum()
```

```
q2_sales.head(3)
```

```
store
1    20978760.12
2    25083604.88
3     5620316.49
Name: weekly_sales, dtype: float64
```

```
q3_sales.head(3)
```

```
store
1    20253947.78
```

```
2    24303354.86
3     5298005.47
Name: weekly_sales, dtype: float64
```

```
# finding the Q3 growth rate for each store
q3_salesgrowth  =q3_sales-q2_sales
q3_salesgrowth.to_frame()
```

store	weekly_sales
1	-724812.34
2	-780250.02
3	-322311.02
4	-657571.21
5	-302572.70
6	-666597.68
7	971928.12
8	-170678.25
9	-462785.55
10	-713110.41
11	-271290.51
12	-826064.21
13	-587947.84
14	-3967974.76
15	-343162.04
16	557205.66
17	-132947.88
18	-406429.38
19	-163745.39
20	-632670.34
21	-266997.03
22	-642754.35
23	152606.33
24	292158.81
25	-213930.25
26	520356.34
27	-436301.34
28	-426188.16
29	-454073.36
30	-147612.43
31	-460524.05
32	-92742.10
33	-115380.03
34	-367622.08
35	484108.12
36	-320299.94
37	-96481.13
38	-32436.44
39	500987.77
40	145457.84
41	433901.28

```
42       -271479.93
43       -168264.19
44        104845.38
45       -809499.45
```

```
# Using argmax to find the store that has maximm sales growth in
quarter 3
print(q3_salesgrowth.index[q3_salesgrowth.argmax()])
print('{:.2f}'.format(q3_salesgrowth.max()))
```

```
7
971928.12
```

Store number : 7 has good quarterly 3 sales growth than other stores

Holiday and Non-Holiday Sales

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

```
# finding mean sales on superbowl for all stores each year
superbowl_sales=walmart_df[(walmart_df['date']=='12-Feb-10')+
(walmart_df['date']=='11-Feb-11')+(walmart_df['date']=='10-Feb-12')+
(walmart_df['date']=='8-Feb-13')]
print('{:.2f}'.format(superbowl_sales['weekly_sales'].mean()))
```

```
1079127.99
```

```
# finding mean sales on Labour Day for all stores each year
Labourday_sales=walmart_df[(walmart_df['date']=='10-Sep-10')+
(walmart_df['date']=='09-Sep-11')+(walmart_df['date']=='07-Sep-12')+
(walmart_df['date']=='06-Sep-13')]
print('{:.2f}'.format(Labourday_sales['weekly_sales'].mean()))
```

```
1042427.29
```

```
# finding mean sales on Thanksgiving for all stores each year
Thanksgiving_sales=walmart_df[(walmart_df['date']=='26-Nov-10')+
(walmart_df['date']=='25-Nov-11')+(walmart_df['date']=='23-Nov-12')+
(walmart_df['date']=='29-Nov-13')]
print('{:.2f}'.format(Thanksgiving_sales['weekly_sales'].mean()))
```

```
1471273.43
```

```
# finding mean sales on Thanksgiving for all stores each year
Christmas_sales=walmart_df[(walmart_df['date']=='31-Dec-10')+
(walmart_df['date']=='30-Dec-11')+(walmart_df['date']=='28-Dec-12')+
```

```
(walmart_df['date']=='27-Dec-13')]
print('{:.2f}'.format(Christmas_sales['weekly_sales'].mean()))
```

```
960833.11
```

Thanks giving Holiday have mean sales than any other Holiday sales

Holiday and Non-Holiday data

```
# grouping dataset by holidayflag
holidaysdf=walmart_df.groupby('holiday_flag')

# getting only hoilday data
holiday_sales=holidaysdf.get_group(1)
print("{:.2f}".format(holiday_sales['weekly_sales'].mean()))
```

```
1122887.89
```

```
# getting only hoilday data
nonholiday_sales=holidaysdf.get_group(0)
print("{:.2f}".format(nonholiday_sales['weekly_sales'].mean()))
```

```
1041256.38
```

Holiday have higher sales mean than non-holiday sales mean

```
# Each holiday vs Non-holiday mean sales

print("{:.2f}".format(superbowl_sales['weekly_sales'].mean()))
print("{:.2f}".format(Labourday_sales['weekly_sales'].mean()))
print("{:.2f}".format(Thanksgiving_sales['weekly_sales'].mean()))
print("{:.2f}".format(Christmas_sales['weekly_sales'].mean()))
```

```
1079127.99
1042427.29
1471273.43
960833.11
```

```
print("{:.2f}".format(nonholiday_sales['weekly_sales'].mean()))
```

```
1041256.38
```

Christmas holiday sales has a negative impact on sales than other holiday when compared to Non- holiday sales mean

Monthly and Semester view of Sales(Year-wise)

```
# grouping by month for all years
totalmonthly_sales=walmart_df.groupby('month')
totalmonthly_sales.ngroups
```

```
12
```

```
totalmonthly_sales['weekly_sales'].describe()
```

```
       count          mean            std        min          25%  \
month
Apr    630.0  1.026762e+06  543864.624192  232769.09  534583.5075
Aug    585.0  1.048017e+06  542653.059046  224031.19  575997.7800
Dec    450.0  1.281864e+06  774037.720767  209986.25  616295.8450
Feb    540.0  1.053200e+06  564207.057354  234218.03  554628.6350
Jan    360.0  9.238846e+05  472616.460339  231155.90  521051.0125
Jul    630.0  1.031748e+06  531141.778886  224806.96  577830.8550
Jun    585.0  1.064325e+06  548683.953608  238172.66  581745.7200
Mar    585.0  1.013309e+06  529805.743801  238084.08  544408.1400
May    540.0  1.031714e+06  536589.412470  239206.26  543588.2225
Nov    360.0  1.147266e+06  648832.347036  224639.76  585869.0500
Oct    585.0  9.996321e+05  517186.653614  213538.32  534738.4300
Sep    585.0  9.893353e+05  510532.949375  229731.98  533161.6400

                50%          75%         max
month
Apr     948789.575  1402726.700  2565259.92
Aug     969387.480  1442819.280  2283540.30
Dec    1154880.920  1714442.515  3818686.45
Feb     980765.180  1431376.635  2623469.95
Jan     830944.935  1256202.130  2047766.07
Jul     953770.830  1396269.865  2358055.30
Jun     984336.040  1442092.080  2363601.47
Mar     943951.670  1365824.970  2237544.75
May     969562.080  1388603.735  2370116.52
Nov    1044710.505  1542527.595  3004702.33
Oct     937956.890  1363365.050  2246411.89
Sep     922440.640  1345167.610  2202742.90
```

```
# grouping by month for year 2010
monthlysales_2010=stores_2010_sales.groupby('month')
monthlysales_2010['weekly_sales'].describe()
```

```
       count          mean            std        min          25%  \
month
Apr    225.0  1.028499e+06  545424.247706  257361.30  527019.7800
Aug    180.0  1.042445e+06  539322.149800  224031.19  573235.4675
Dec    225.0  1.283380e+06  793498.247838  209986.25  599730.0700
Feb    180.0  1.057405e+06  571029.268079  267956.30  534468.2225
Jul    225.0  1.033689e+06  534340.296029  242047.03  570231.2100
Jun    180.0  1.068034e+06  556849.016817  259419.91  551924.8925
```

```
Mar    180.0  1.010666e+06  531192.529079  262893.76  519202.3825
May    180.0  1.037283e+06  542985.021379  267065.35  530713.0675
Nov    180.0  1.126963e+06  642755.592239  224639.76  558963.6550
Oct    225.0  9.651637e+05  496358.362753  213538.32  514485.9000
Sep    180.0  9.848216e+05  508207.747513  231976.84  530738.3025

                50%           75%         max
month
Apr      969594.470  1.391256e+06  2495630.51
Aug      981237.730  1.418366e+06  2219813.50
Dec     1149612.040  1.707298e+06  3818686.45
Feb      997074.975  1.470286e+06  2623469.95
Jul      959229.090  1.371987e+06  2334788.42
Jun     1002244.665  1.423940e+06  2363601.47
Mar      964763.590  1.340757e+06  2237544.75
May      973124.460  1.368593e+06  2370116.52
Nov      995672.600  1.508792e+06  2939946.38
Oct      891152.330  1.286599e+06  2091663.20
Sep      910702.500  1.304980e+06  2191767.76
```

```
semester1_2010=stores_2010_sales[stores_2010_sales['month'].isin(['Jan
','Feb','Mar','Apr','May','Jun'])]
semester1_2010.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  day
0  211.096358         8.106  2010   Feb    5
1  211.242170         8.106  2010   Feb   12
2  211.289143         8.106  2010   Feb   19
3  211.319643         8.106  2010   Feb   26
4  211.350143         8.106  2010   Mar    5
```

```
semester2_2010=stores_2010_sales[stores_2010_sales['month'].isin(['Jul
','Aug','Sep','Oct','Nov','Dec'])]
semester2_2010.head()
```

```
    store       date  weekly_sales  holiday_flag  temperature
fuel_price  \
21      1 2010-07-02    1492418.14             0        80.91
```

```
2.669
22      1 2010-07-09    1546074.18             0        80.48
2.642
23      1 2010-07-16    1448938.92             0        83.15
2.623
24      1 2010-07-23    1385065.20             0        83.36
2.608
25      1 2010-07-30    1371986.60             0        81.84
2.640

           cpi  unemployment  year month  day
21  211.223533         7.787  2010   Jul    2
22  211.108414         7.787  2010   Jul    9
23  211.100385         7.787  2010   Jul   16
24  211.235144         7.787  2010   Jul   23
25  211.369903         7.787  2010   Jul   30
```

```
# grouping by month for year 2011
monthlysales_2011=stores_2011_sales.groupby('month')
monthlysales_2011['weekly_sales'].describe()
```

```
       count          mean            std        min          25%  \
month
Apr    225.0  1.006784e+06  532258.833292  232769.09  534578.7800
Aug    180.0  1.047774e+06  549887.085283  237095.82  570423.6150
Dec    225.0  1.280347e+06  755843.504954  215359.21  630327.2800
Feb    180.0  1.035174e+06  552442.387986  234218.03  556183.5800
Jan    180.0  9.094665e+05  466122.257495  231155.90  513597.3125
Jul    225.0  1.021828e+06  526841.700020  224806.96  582381.9500
Jun    180.0  1.054297e+06  543819.984741  238172.66  585639.7750
Mar    180.0  9.964247e+05  522341.244321  238084.08  536784.3775
May    180.0  1.009156e+06  523438.331445  239206.26  543719.8250
Nov    180.0  1.167569e+06  656014.430247  236157.12  597808.1050
Oct    180.0  1.018118e+06  533282.121588  231319.96  537294.8075
Sep    225.0  9.815455e+05  511836.769295  229731.98  537124.7600

               50%           75%         max
month
Apr     937473.130  1.372485e+06  2313861.81
Aug     955710.315  1.445838e+06  2273470.62
Dec    1158708.980  1.781529e+06  3676388.98
Feb     961012.950  1.420064e+06  2351143.07
Jan     812167.545  1.215770e+06  1886393.94
Jul     936001.980  1.396927e+06  2123787.79
Jun     974263.155  1.441112e+06  2182246.69
Mar     929977.755  1.352847e+06  2143424.61
May     943238.085  1.371667e+06  2095599.93
Nov    1061735.140  1.559386e+06  3004702.33
Oct     943328.485  1.406234e+06  2207742.13
Sep     899834.750  1.347608e+06  2202742.90
```

```
semester1_2011=stores_2011_sales[stores_2011_sales['month'].isin(['Jan
','Feb','Mar','Apr','May','Jun'])]
semester1_2011.head()
```

```
    store       date  weekly_sales  holiday_flag  temperature
fuel_price  \
48      1 2011-01-07    1444732.28             0        48.27
2.976
49      1 2011-01-14    1391013.96             0        35.40
2.983
50      1 2011-01-21    1327405.42             0        44.04
3.016
51      1 2011-01-28    1316899.31             0        43.83
3.010
52      1 2011-02-04    1606629.58             0        42.27
2.989

           cpi  unemployment  year month  day
48  211.404742         7.742  2011   Jan    7
49  211.457411         7.742  2011   Jan   14
50  211.827234         7.742  2011   Jan   21
51  212.197058         7.742  2011   Jan   28
52  212.566881         7.742  2011   Feb    4
```

```
semester2_2011=stores_2011_sales[stores_2011_sales['month'].isin(['Jul
','Aug','Sep','Oct','Nov','Dec'])]
semester2_2011.head()
```

```
    store       date  weekly_sales  holiday_flag  temperature
fuel_price  \
73      1 2011-07-01    1488538.09             0        85.55
3.524
74      1 2011-07-08    1534849.64             0        85.83
3.480
75      1 2011-07-15    1455119.97             0        88.54
3.575
76      1 2011-07-22    1396926.82             0        85.77
3.651
77      1 2011-07-29    1352219.79             0        86.83
3.682

           cpi  unemployment  year month  day
73  215.184137         7.962  2011   Jul    1
74  215.277175         7.962  2011   Jul    8
75  215.361109         7.962  2011   Jul   15
76  215.422278         7.962  2011   Jul   22
77  215.483448         7.962  2011   Jul   29
```

```
# grouping by month for year 2012
monthlysales_2012=stores_2012_sales.groupby('month')
monthlysales_2012['weekly_sales'].describe()
```

```
       count          mean            std        min          25%
50%  \
month

Apr    180.0  1.049561e+06  558183.253234  249798.75  548516.0000
950743.050
Aug    225.0  1.052670e+06  541866.268723  237129.81  576620.3100
976137.730
Feb    180.0  1.067020e+06  571613.468771  242526.70  564122.8100
970644.815
Jan    180.0  9.383026e+05  479887.956347  236920.49  540523.1525
855680.105
Jul    180.0  1.041719e+06  535223.017499  249134.32  577204.6500
960529.395
Jun    225.0  1.069379e+06  548322.510590  244338.31  583648.5900
988764.840
Mar    225.0  1.028932e+06  536489.204740  246970.97  557547.2500
952264.910
May    180.0  1.048703e+06  545296.384619  261851.74  549055.7525
988833.255
Oct    180.0  1.024232e+06  526815.738642  253731.13  548829.2100
962230.855
Sep    180.0  1.003586e+06  513766.298200  242813.51  532581.7925
949096.910

                75%         max
month
Apr    1.456415e+06  2565259.92
Aug    1.497055e+06  2283540.30
Feb    1.448538e+06  2462978.28
Jan    1.269834e+06  2047766.07
Jul    1.456741e+06  2358055.30
Jun    1.451782e+06  2245257.18
Mar    1.427881e+06  2214967.44
May    1.428744e+06  2207214.81
Oct    1.413769e+06  2246411.89
Sep    1.371256e+06  2165796.31
```

```
semester1_2012=stores_2012_sales[stores_2012_sales['month'].isin(['Jan
','Feb','Mar','Apr','May','Jun'])]
semester1_2012.head()
```

```
     store       date  weekly_sales  holiday_flag  temperature
fuel_price  \
100      1 2012-01-06    1550369.92             0        49.01
3.157
101      1 2012-01-13    1459601.17             0        48.53
3.261
102      1 2012-01-20    1394393.84             0        54.11
3.268
```

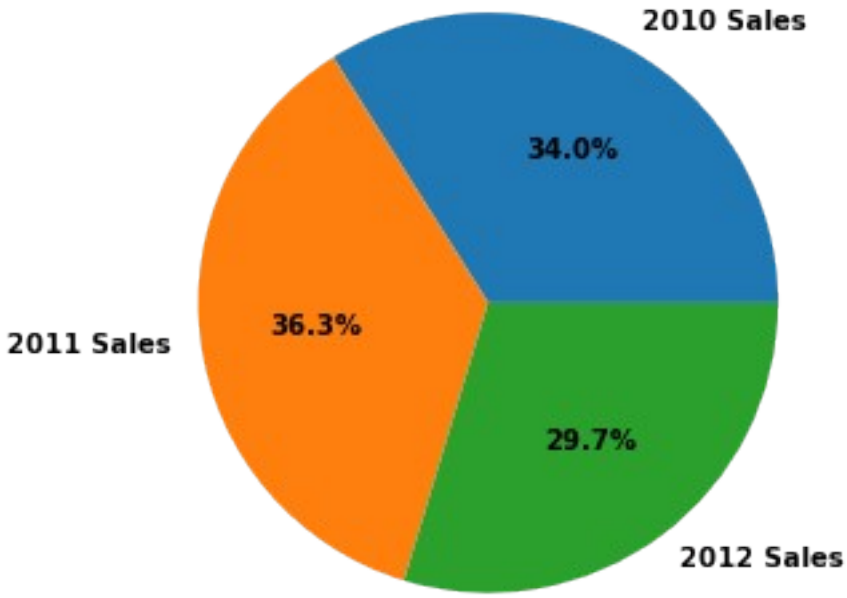
```
103      1 2012-01-27    1319325.59             0        54.26
3.290
104      1 2012-02-03    1636339.65             0        56.55
3.360

            cpi  unemployment  year month  day quartile
100  219.714258         7.348  2012   Jan    6       Q1
101  219.892526         7.348  2012   Jan   13       Q1
102  219.985689         7.348  2012   Jan   20       Q1
103  220.078852         7.348  2012   Jan   27       Q1
104  220.172015         7.348  2012   Feb    3       Q1
```

```
semester2_2012=stores_2012_sales[stores_2012_sales['month'].isin(['Jul
','Aug','Sep','Oct','Nov','Dec'])]
semester2_2012.head()
```

```
     store       date  weekly_sales  holiday_flag  temperature
fuel_price  \
126      1 2012-07-06    1769854.16             0        81.57
3.227
127      1 2012-07-13    1527014.04             0        77.12
3.256
128      1 2012-07-20    1497954.76             0        80.42
3.311
129      1 2012-07-27    1439123.71             0        82.66
3.407
130      1 2012-08-03    1631135.79             0        86.11
3.417

            cpi  unemployment  year month  day quartile
126  221.883779         6.908  2012   Jul    6       Q3
127  221.924158         6.908  2012   Jul   13       Q3
128  221.932727         6.908  2012   Jul   20       Q3
129  221.941295         6.908  2012   Jul   27       Q3
130  221.949864         6.908  2012   Aug    3       Q3
```

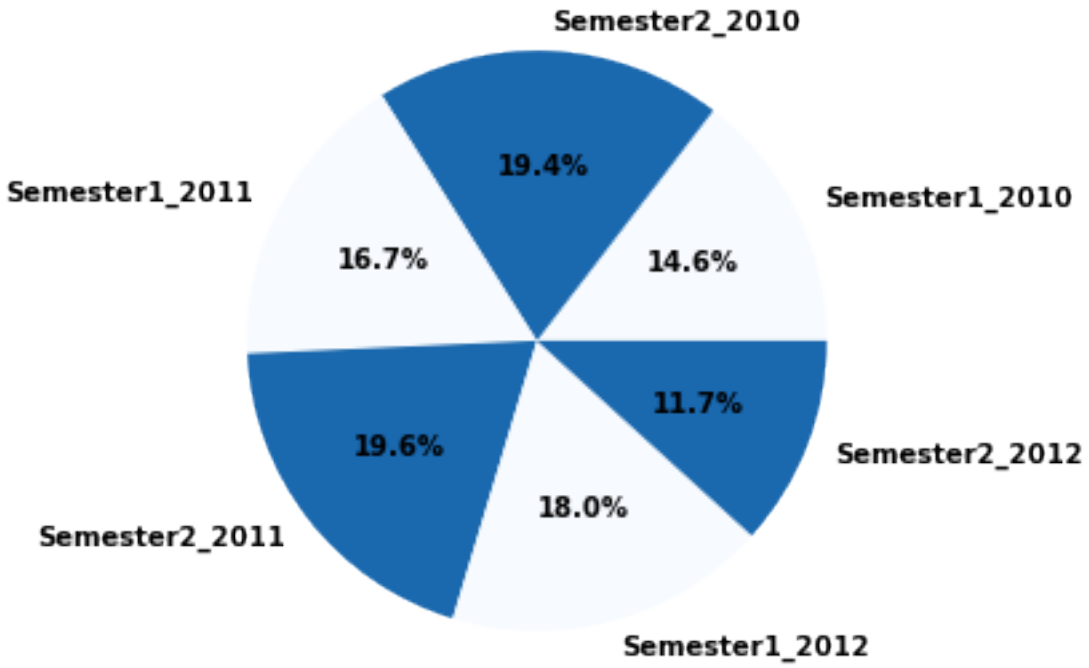
Visualization

```
# Visualization total sales percentage for each year
list1=[stores_2010_sales['weekly_sales'].sum(),stores_2011_sales['week
ly_sales'].sum(),stores_2012_sales['weekly_sales'].sum()]
labels='2010 Sales','2011 Sales','2012 Sales'
# cmap=plt.get_cmap('YlGnBu')
# colors=cmap(np.arange(3)*95)
txt={'weight':'bold'}
plt.figure(figsize=(15,5))
plt.pie(list1,labels=labels,autopct='%.1f%%',textprops=txt)
plt.show()
```



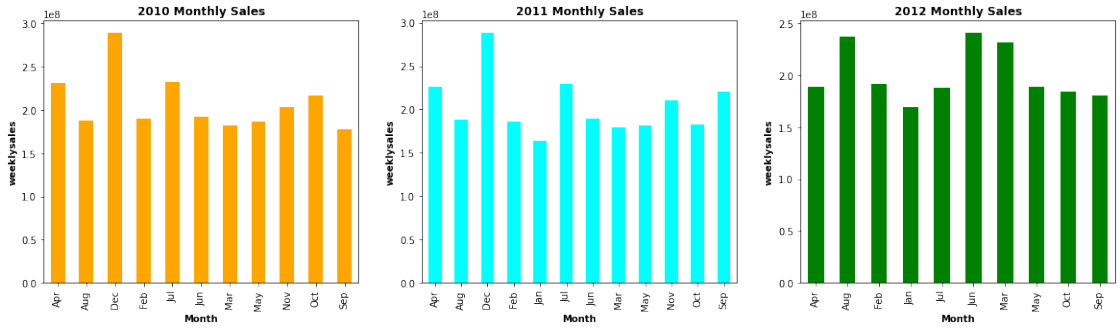
The sales was maximum in the year 2011

```
# Visualizing total sales percentage semester wise for defferent years
list1=[semester1_2010['weekly_sales'].sum(),semester2_2010['weekly_sal
es'].sum(),

semester1_2011['weekly_sales'].sum(),semester2_2011['weekly_sales'].su
m(),

semester1_2012['weekly_sales'].sum(),semester2_2012['weekly_sales'].su
m()]

labels='Semester1_2010','Semester2_2010','Semester1_2011','Semester2_2
011','Semester1_2012','Semester2_2012'
cmap=plt.get_cmap('Blues')
colors=cmap(np.arange(2)*200)
txt={'weight':'bold'}
plt.figure(figsize=(15,5))
plt.pie(list1,labels=labels,autopct='%.1f%
%',colors=colors,textprops=txt)
plt.show()
```



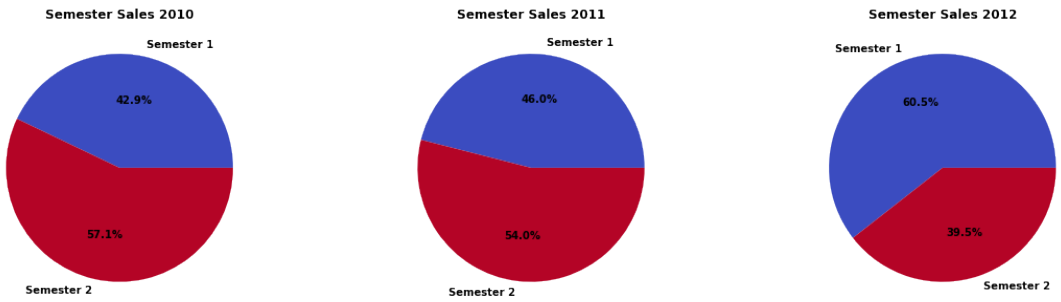
The sale was maximum in the 2nd semester of the year 2011

```
# Visualization Monthly sales for each year
plt.figure(figsize=(20,5))
plt.subplots_adjust(hspace=.25)
txt={'weight':'bold'}
plt.subplot(1,3,1)
plt.title('2010 Monthly Sales',fontdict=txt)
monthlysales_2010['weekly_sales'].sum().plot.bar(color='orange')
plt.xlabel('Month',fontdict=txt)
plt.ylabel('weeklysales',fontdict=txt)
plt.subplot(1,3,2)
plt.title('2011 Monthly Sales',fontdict=txt)
monthlysales_2011['weekly_sales'].sum().plot.bar(color='cyan')
plt.xlabel('Month',fontdict=txt)
plt.ylabel('weeklysales',fontdict=txt)
plt.subplot(1,3,3)
plt.title('2012 Monthly Sales',fontdict=txt)
monthlysales_2012['weekly_sales'].sum().plot.bar(color='green')
plt.xlabel('Month',fontdict=txt)
plt.ylabel('weeklysales',fontdict=txt)
plt.show()
```



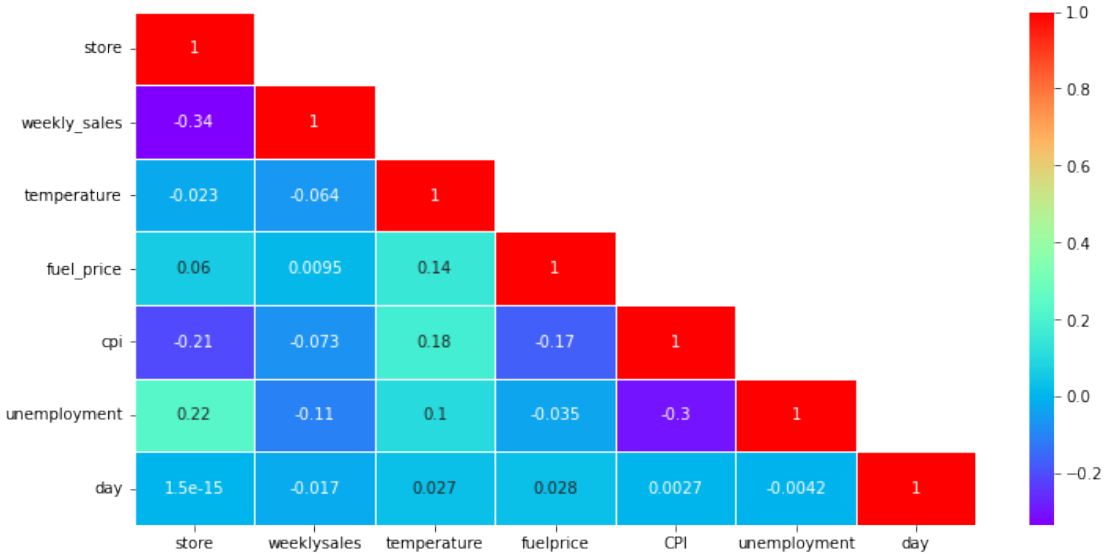
There Bar-graphs show monthly sales for each year

```
# Visualizing semester-wise sales percentage for each years
list1=[semester1_2010['weekly_sales'].sum(),semester2_2010['weekly_sal
es'].sum()]
list2=[semester1_2011['weekly_sales'].sum(),semester2_2011['weekly_sal
es'].sum()]
list3=[semester1_2012['weekly_sales'].sum(),semester2_2012['weekly_sal
es'].sum()]

label='Semester 1','Semester 2'
cmap=plt.get_cmap('coolwarm')
colors=cmap(np.arange(2)*1010)
txt={'weight':'bold'}
plt.figure(figsize=(20,5))
plt.subplots_adjust(hspace=.25)

plt.subplot(1,3,1)
plt.title("Semester Sales 2010",fontdict=txt)
plt.pie(list1,labels=label,autopct='%.1f%
%',colors=colors,textprops=txt)

plt.subplot(1,3,2)
plt.title("Semester Sales 2011",fontdict=txt)
plt.pie(list2,labels=label,autopct='%.1f%
%',colors=colors,textprops=txt)

plt.subplot(1,3,3)
plt.title("Semester Sales 2012",fontdict=txt)
plt.pie(list3,labels=label,autopct='%.1f%
%',colors=colors,textprops=txt)
plt.show()
```



There Pie-charts show semester wise sales percentage for each year

```
# Heat Map
m=np.ones_like(walmart_df.drop(columns=['holiday_flag','year']).corr()
)
m[np.tril_indices_from(m)]=0
labels=['store','weeklysales','temperature','fuelprice','CPI','unemplo
yment','day']
plt.figure(figsize=(12,6))
sns.heatmap(walmart_df.drop(columns=['holiday_flag','year']).corr(),an
not=True,mask=m,cmap='rainbow',linewidths=.5,xticklabels=labels)
plt.show()
```



CPI, Unemployment and fule price does not have any significant import on

Statistical Model

For Store 1- Build prediction models to forecast demand

```
# getting data for store 1
store_data=walmart_df.groupby('store')
```

```
store1_dataset=store_data.get_group(1)
store1_dataset['strdate']=pd.to_datetime(store1_dataset['date'])
store1_dataset['month']=store1_dataset['strdate'].dt.month
store1_dataset.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  day    strdate
0  211.096358         8.106  2010      2    5 2010-02-05
1  211.242170         8.106  2010      2   12 2010-02-12
2  211.289143         8.106  2010      2   19 2010-02-19
3  211.319643         8.106  2010      2   26 2010-02-26
4  211.350143         8.106  2010      3    5 2010-03-05
```

Restructuring dates as 1 for 5th Feb 2010 and so on

```
# Restructuring dates to number to use them in model as categoricl
data cannot be used in liner model 1.
dummy =[]
for i in range (1,144):
    dummy.append(i)
store1_dataset['dummy_date']=dummy

store1_dataset.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  day    strdate  dummy_date
0  211.096358         8.106  2010      2    5 2010-02-05           1
1  211.242170         8.106  2010      2   12 2010-02-12           2
```

```
2  211.289143         8.106  2010      2   19 2010-02-19           3
3  211.319643         8.106  2010      2   26 2010-02-26           4
4  211.350143         8.106  2010      3    5 2010-03-05           5
```

LinearRegression Model

```
model_dataset=store1_dataset[['store','holiday_flag','temperature','fu
el_price','cpi','unemployment',

'year','month','day','dummy_date','weekly_sales']]
model_dataset.head()
```

```
   store  holiday_flag  temperature  fuel_price         cpi
unemployment  \
0      1             0        42.31       2.572  211.096358
8.106
1      1             1        38.51       2.548  211.242170
8.106
2      1             0        39.93       2.514  211.289143
8.106
3      1             0        46.63       2.561  211.319643
8.106
4      1             0        46.50       2.625  211.350143
8.106
```

```
   year  month  day  dummy_date  weekly_sales
0  2010      2    5           1    1643690.90
1  2010      2   12           2    1641957.44
2  2010      2   19           3    1611968.17
3  2010      2   26           4    1409727.59
4  2010      3    5           5    1554806.68
```

```
# Splitting date into train and test for the linear model
train,test=train_test_split(model_dataset,test_size=0.20,random_state=
0)
lr=LinearRegression()
x_train= train.drop(columns=['weekly_sales'])
x_test= test.drop(columns=['weekly_sales'])
y_train= train['weekly_sales']
y_test= test['weekly_sales']

# Fitting the model
lr.fit(x_train,y_train)

LinearRegression()

lr.intercept_

-2364627031.702815

# Predicting the weekly_sales using the test data
y_pred=lr.predict(x_test)
y_pred.shape, y_test.shape
```

```
((29,), (29,))
```

```
# Finding R2 score
print("Test Score={:.2f}".format(lr.score(x_train,y_train)))
```

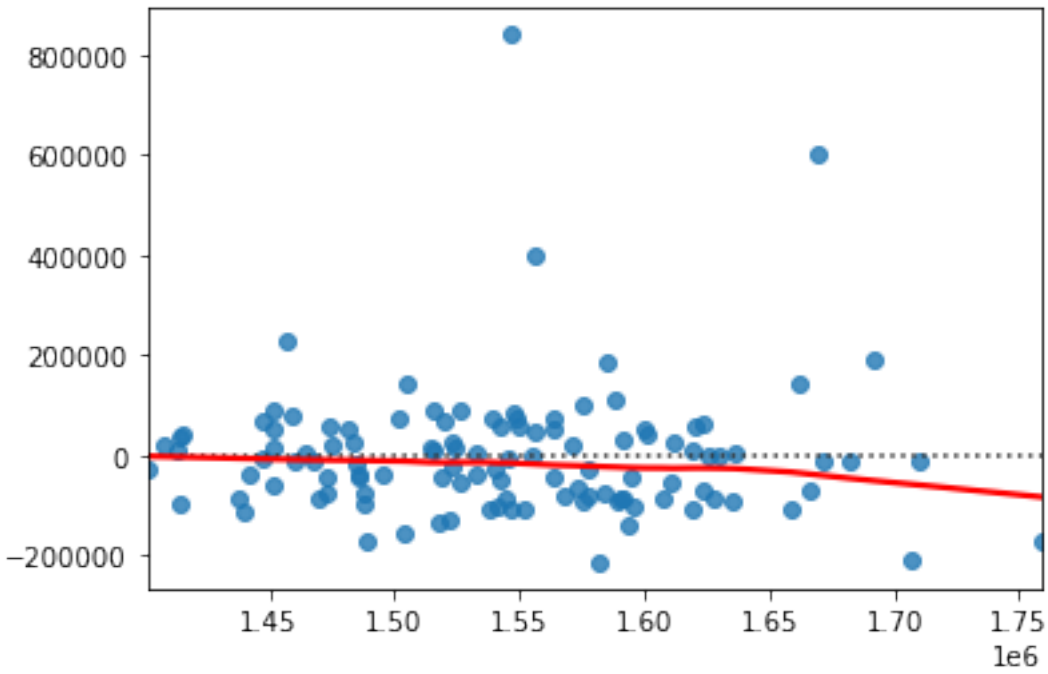
```
Test Score=0.24
```

Using Ordinary Least Square Method

```
# Performing Ordinary Least Square method
fts='+'.join(train.drop(columns=['weekly_sales']).columns)
linearmodel=ols('weekly_sales ~'+fts,data=train).fit()
linearmodel.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

==============================================================================
========
Dep. Variable:           weekly_sales   R-squared:
0.237
Model:                            OLS   Adj. R-squared:
0.171
Method:                 Least Squares   F-statistic:
3.585
Date:                Sat, 25 Dec 2021   Prob (F-statistic):
0.000644
Time:                        12:12:11   Log-Likelihood:
-1506.8
No. Observations:                 114   AIC:
3034.
Df Residuals:                     104   BIC:
3061.
Df Model:                           9

Covariance Type:            nonrobust

==============================================================================
==========
                    coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
----------
Intercept    -1.182e+09   1.02e+10     -0.116      0.908   -2.14e+10
1.9e+10
store        -1.182e+09   1.02e+10     -0.116      0.908   -2.14e+10
1.9e+10
holiday_flag  5.748e+04   5.19e+04      1.107      0.271   -4.55e+04
1.6e+05
temperature  -2791.4208   1171.719     -2.382      0.019   -5114.984
-467.857
```

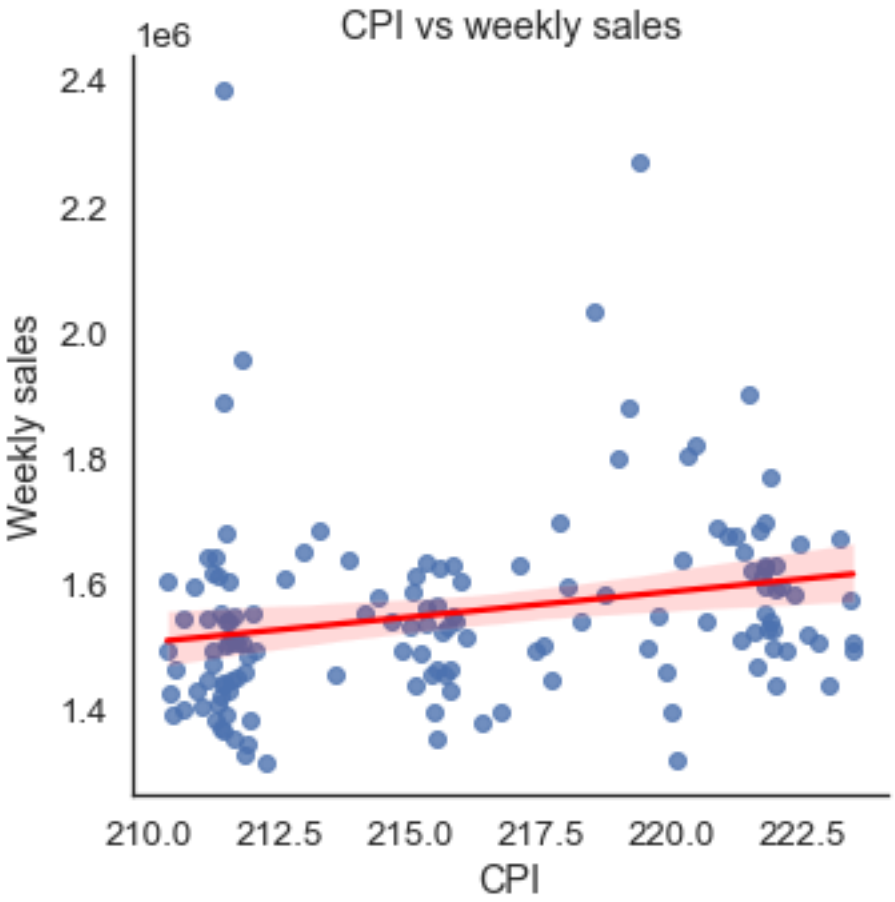
```
fuel_price    4.154e+04   7.15e+04      0.581      0.562      -1e+05
1.83e+05
cpi           2.514e+04   1.46e+04      1.717      0.089   -3892.399
5.42e+04
unemployment  1.591e+04   6.82e+04      0.233      0.816   -1.19e+05
1.51e+05
year          1.174e+06   1.01e+07      0.116      0.908   -1.89e+07
2.13e+07
month         1.114e+05   8.44e+05      0.132      0.895   -1.56e+06
1.78e+06
day          -1522.8776   2.77e+04     -0.055      0.956   -5.65e+04
5.34e+04
dummy_date   -2.452e+04   1.94e+05     -0.127      0.900   -4.09e+05
3.6e+05
==============================================================================
========
Omnibus:                      107.827   Durbin-Watson:
2.041
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
1379.530
Skew:                           3.169   Prob(JB):
2.75e-300
Kurtosis:                      18.819   Cond. No.
1.50e+19
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The smallest eigenvalue is 2.07e-30. This might indicate that
there are
strong multicollinearity problems or that the design matrix is
singular.
"""

# Residual plot
fitted=linearmodel.fittedvalues
residuals=linearmodel.resid
sns.residplot(fitted,residuals,lowess=True,line_kws={'color':'red'})
plt.show()
```



CPI, Unemployment index and Fual price vs Weekly Sales

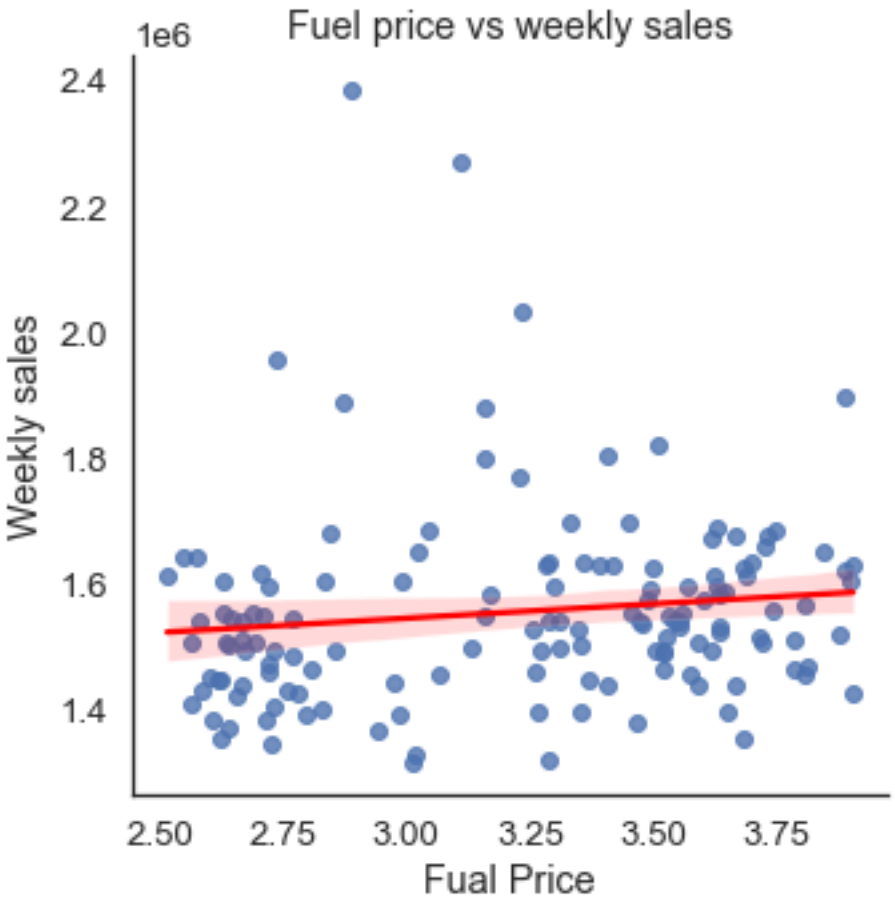
```
plt.figure(figsize=(6,3))
sns.set(font_scale=1.2,style='white')
sns.lmplot(x='cpi',y='weekly_sales',data=store1_dataset,line_kws={'col
or':'red'})
plt.title('CPI vs weekly sales')
plt.xlabel('CPI')
plt.ylabel('Weekly sales')
plt.show()
```

```
<Figure size 432x216 with 0 Axes>
```




```
# Visualizing weekly sales and fuel price using a line plot
plt.figure(figsize=(16,10))
sns.set(font_scale=1.2,style='white')
sns.lmplot(x='fuel_price',y='weekly_sales',data=store1_dataset,line_kw
s={'color':'red'})
plt.title('Fuel price vs weekly sales')
plt.xlabel('Fual Price')
plt.ylabel('Weekly sales')
plt.show()
```

```
<Figure size 1152x720 with 0 Axes>
```




```
# Visualizing weekly sales and unemployment index usinga line plot
plt.figure(figsize=(6,3))
sns.set(font_scale=1.2,style='white')
sns.lmplot(x='unemployment',y='weekly_sales',data=store1_dataset,line_
kws={'color':'red'})
plt.title('unemployment vs weekly sales')
plt.xlabel('Fual Price')
plt.ylabel('Weekly sales')
plt.show()
```

```
<Figure size 432x216 with 0 Axes>
```

Changing date to day of the week

```
# Converting string object to datetime object
walmart_df['date']=pd.to_datetime(walmart_df['date'])

# Converting string object to datetime object
walmart_df['dayofweek']=walmart_df['date'].dt.day_name()

walmart_df.head(10)
```

```
   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
5      1 2010-03-12    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 2010-04-02    1594968.28             0        62.27
2.719
9      1 2010-04-09    1545418.53             0        65.86
2.770
```

	cpi	unemployment	year	month	day	dayofweek
0	211.096358	8.106	2010	Feb	5	Friday
1	211.242170	8.106	2010	Feb	12	Friday
2	211.289143	8.106	2010	Feb	19	Friday
3	211.319643	8.106	2010	Feb	26	Friday
4	211.350143	8.106	2010	Mar	5	Friday
5	211.380643	8.106	2010	Mar	12	Friday
6	211.215635	8.106	2010	Mar	19	Friday
7	211.018042	8.106	2010	Mar	26	Friday
8	210.820450	7.808	2010	Apr	2	Friday
9	210.622857	7.808	2010	Apr	9	Friday