Walmart project-04

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DOMAIN-RETAIL

PROJECT-Retail Analysis with Walmart Data

OBJECTIVE-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.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
data=pd.read_csv("Walmart_Store_sales.csv")
```

[3]:
```
data.head()
```

[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	
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

[4]:
```
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
```

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

[5]:

	Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
count	6435.000000	6.435000e+03	6435.000000	6435.000000	6435.000000	6435.000000	6435.000000
mean	23.000000	1.046965e+06	0.069930	60.663782	3.358607	171.578394	7.999151
std	12.988182	5.643666e+05	0.255049	18.444933	0.459020	39.356712	1.875885
min	1.000000	2.099862e+05	0.000000	-2.060000	2.472000	126.064000	3.879000
25%	12.000000	5.533501e+05	0.000000	47.460000	2.933000	131.735000	6.891000
50%	23.000000	9.607460e+05	0.000000	62.670000	3.445000	182.616521	7.874000
75%	34.000000	1.420159e+06	0.000000	74.940000	3.735000	212.743293	8.622000
max	45.000000	3.818686e+06	1.000000	100.140000	4.468000	227.232807	14.313000

[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["Date"]=pd.to_datetime(data["Date"])
```

[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   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
```

[9]:
```
data["Date_index"]=data["Date"]
data=data.set_index(data["Date_index"])
```

[10]:
```
data.head()
```

[10]:

Date_index	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Date_index
2010-05-02	1	2010-05-02	1643690.90	0	42.31	2.572	211.096358	8.106	2010-05-02
2010-12-02	1	2010-12-02	1641957.44	1	38.51	2.548	211.242170	8.106	2010-12-02
2010-02-19	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106	2010-02-19
2010-02-26	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	8.106	2010-02-26
2010-05-03	1	2010-05-03	1554806.68	0	46.50	2.625	211.350143	8.106	2010-05-03

Which store has maximum sales?

[11]:
```
data.groupby(["Store"])["Weekly_Sales"].sum().sort_values(ascending=False)[:1]
```

[11]:
```
Store
20    3.013978e+08
Name: Weekly_Sales, dtype: float64
```

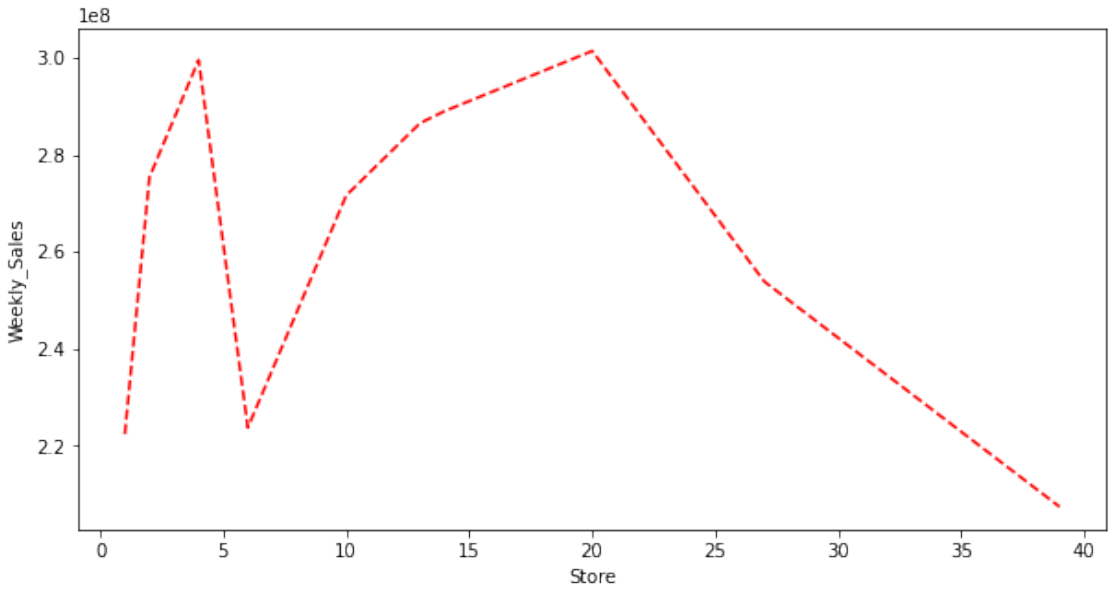
[12]:
```
pd.DataFrame(data.groupby(["Store"])["Weekly_Sales"].sum().
 ↪sort_values(ascending=False))[:1]
```

[12]:

Store	Weekly_Sales
20	3.013978e+08

[13]:
```
data1=data.groupby(["Store"])["Weekly_Sales"].sum().
 ↪sort_values(ascending=False).head(10)
plt.figure(figsize=(10,5))
sns.lineplot(data=data1,color="r",linestyle="--")
```

[13]:
```
<AxesSubplot:xlabel='Store', ylabel='Weekly_Sales'>
```



2 store 20 has maximum sales.

Which store has maximum standard deviation?

[14]:
```
pd.DataFrame(data.groupby(["Store"])["Weekly_Sales"].std().
 ↪sort_values(ascending=False))[:1]
```

[14]:
```
         Weekly_Sales
Store
14     317569.949476
```

3 store 14 has maximum standard deviation i.e., the sales vary a lot.

[15]:
```
mean=data["Weekly_Sales"].mean()
mean
```

[15]:
```
1046964.8775617732
```

[16]:
```
std=data["Weekly_Sales"].std()
std
```

[16]:
```
564366.6220536974
```

[17]:
```
coefficient=mean/std
round(coefficient,3)
```

[17]:
```
1.855
```

4 Coefficient of mean to std is 1.855

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

[18]:
```
data2=data.groupby(["Date","Store"])["Weekly_Sales"].agg(sum).reset_index()
data2.head()
```

[18]:

	Date	Store	Weekly_Sales
0	2010-01-10	1	1453329.50
1	2010-01-10	2	1827440.43
2	2010-01-10	3	358784.10
3	2010-01-10	4	1842821.02
4	2010-01-10	5	283178.12

[19]:
```
data2["Year"]=data2["Date"].dt.year
data2["Quarter"]=data2["Date"].dt.quarter
data2["Month"]=data2["Date"].dt.month
data2["Day"]=data2["Date"].dt.day
```

[20]:
```
data2
```

[20]:

	Date	Store	Weekly_Sales	Year	Quarter	Month	Day
0	2010-01-10	1	1453329.50	2010	1	1	10
1	2010-01-10	2	1827440.43	2010	1	1	10

```
2    2010-01-10      3     358784.10  2010        1      1   10
3    2010-01-10      4    1842821.02  2010        1      1   10
4    2010-01-10      5     283178.12  2010        1      1   10
…           …    …            …    …       …    …  …
6430 2012-12-10     41    1409544.97  2012        4     12   10
6431 2012-12-10     42     612379.90  2012        4     12   10
6432 2012-12-10     43     619369.72  2012        4     12   10
6433 2012-12-10     44     337796.13  2012        4     12   10
6434 2012-12-10     45     734464.36  2012        4     12   10

[6435 rows x 7 columns]
```

[21]:
```
Q3_2012=data2[(data2["Quarter"]==3) & (data2["Year"]==2012)]
```

[22]:
```
Q3_2012
```

[22]:
```
           Date  Store  Weekly_Sales  Year  Quarter  Month  Day
5625 2012-07-09      1    1661767.33  2012        3      7    9
5626 2012-07-09      2    1898777.07  2012        3      7    9
5627 2012-07-09      3     408229.73  2012        3      7    9
5628 2012-07-09      4    2125104.72  2012        3      7    9
5629 2012-07-09      5     350648.91  2012        3      7    9
…           …    …            …    …       …    …  …
6160 2012-09-28     41    1307928.01  2012        3      9   28
6161 2012-09-28     42     505978.46  2012        3      9   28
6162 2012-09-28     43     577792.32  2012        3      9   28
6163 2012-09-28     44     355307.94  2012        3      9   28
6164 2012-09-28     45     713173.95  2012        3      9   28

[540 rows x 7 columns]
```

[59]:
```
pd.DataFrame(Q3_2012.groupby(["Store"])["Weekly_Sales"].sum().
 ↪sort_values(ascending=False))[:3]
```

[59]:
```
       Weekly_Sales
Store
4       25652119.35
20      24665938.11
13      24319994.35
```

5 Stores 4,20 and 13 have good quarterly growth rate in Q3'2012.

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

[24]:
```
a1=data[data["Date"]=="12-02-2010"]["Weekly_Sales"].sum()
b1=data[data["Date"]=="11-02-2011"]["Weekly_Sales"].sum()
c1=data[data["Date"]=="10-02-2012"]['Weekly_Sales'].sum()
d1=data[data["Date"]=="08-02-2013"]['Weekly_Sales'].sum()
super_bowl=a1+b1+c1+d1
super_bowl
```

[24]:
```
145682278.34000003
```

[25]:
```
a2=data[data["Date"]=="10-09-2010"]['Weekly_Sales'].sum()
b2=data[data["Date"]=="09-09-2011"]['Weekly_Sales'].sum()
c2=data[data["Date"]=="07-09-2012"]['Weekly_Sales'].sum()
d2=data[data["Date"]=="06-09-2013"]['Weekly_Sales'].sum()
labour_day=a2+b2+c2+d2
labour_day
```

[25]:
```
140727684.68
```

[26]:
```
a3=data[data["Date"]=="26-11-2010"]['Weekly_Sales'].sum()
b3=data[data["Date"]=="25-11-2011"]['Weekly_Sales'].sum()
c3=data[data["Date"]=="23-11-2012"]['Weekly_Sales'].sum()
d3=data[data["Date"]=="29-11-2013"]['Weekly_Sales'].sum()
thanks_giving=a3+b3+c3+d3
thanks_giving
```

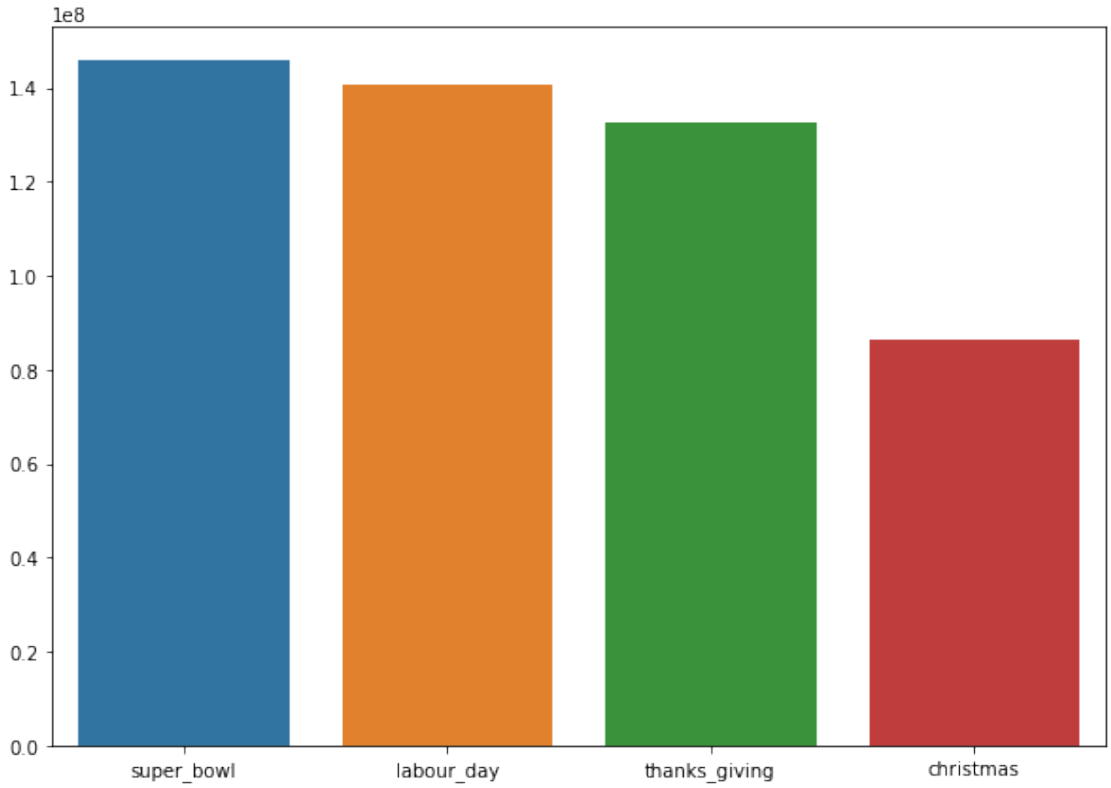
[26]:
```
132414608.5
```

[27]:
```
a4=data[data["Date"]=="31-12-2010"]['Weekly_Sales'].sum()
b4=data[data["Date"]=="30-12-2011"]['Weekly_Sales'].sum()
c4=data[data["Date"]=="28-12-2012"]['Weekly_Sales'].sum()
d4=data[data["Date"]=="27-12-2013"]['Weekly_Sales'].sum()
christmas=a4+b4+c4+d4
christmas
```

[27]:
```
86474980.04
```

[28]:
```
plt.figure(figsize=(10,7))
sns.barplot(x=list(["super_bowl","labour_day","thanks_giving","christmas"])
            ,y=list([super_bowl,labour_day,thanks_giving,christmas])
           )
```

[28]:
```
<AxesSubplot:>
```



6 In Super bowl festival,the sales is high and in christmas,it is low.

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

[29]:
```
data.head()
```

[29]:

Date_index	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Date_index
2010-05-02	1	2010-05-02	1643690.90	0	42.31	2.572	211.096358	8.106	2010-05-02
2010-12-02	1	2010-12-02	1641957.44	1	38.51	2.548	211.242170	8.106	2010-12-02
2010-02-19	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106	2010-02-19
2010-02-26	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	8.106	2010-02-26
2010-05-03	1	2010-05-03	1554806.68	0	46.50	2.625	211.350143	8.106	2010-05-03

[30]:
```
data["Year"]=data["Date"].dt.year
data["Semester"]=(data["Date"].dt.month-1)//6
data["Quarter"]=data["Date"].dt.quarter
data["Month"]=data["Date"].dt.month
```

[31]:
```
data.head()
```

[31]:

Date_index	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Date_index	Year	Semester	Quarter	Month
2010-05-02	1	2010-05-02	1643690.90	0	42.31	2.572	211.096358	8.106	2010-05-02	2010	0	2	5
2010-12-02	1	2010-12-02	1641957.44	1	38.51	2.548	211.242170	8.106	2010-12-02	2010	1	4	12
2010-02-19	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106	2010-02-19	2010	0	1	2
2010-02-26	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	8.106	2010-02-26	2010	0	1	2
2010-05-03	1	2010-05-03	1554806.68	0	46.50	2.625	211.350143	8.106	2010-05-03	2010	0	2	5

[32]:
```
data["Semester"].value_counts()
```

[32]:
```
0    3240
1    3195
Name: Semester, dtype: int64
```

Yearly view of sales in unit

[33]:
```
pd.DataFrame(data.groupby(["Year"])["Weekly_Sales"].agg(sum))
```

[33]:

Year	Weekly_Sales
2010	2.288886e+09
2011	2.448200e+09
2012	2.000133e+09

Semester view of sales in unit

[34]:
```
pd.DataFrame(data.groupby(["Semester"])["Weekly_Sales"].agg(sum))
```

[34]:

Semester	Weekly_Sales
0	3.327977e+09
1	3.409242e+09

Monthly view of sales in unit

[35]:
```
pd.DataFrame(data.groupby(["Month"])["Weekly_Sales"].agg(sum))
```

[35]:

Month	Weekly_Sales
1	4.264263e+08
2	5.220257e+08
3	5.534864e+08
4	6.453239e+08
5	6.056966e+08
6	5.750180e+08
7	5.933139e+08
8	5.642317e+08
9	5.905323e+08
10	6.029189e+08
11	4.591693e+08
12	5.990761e+08

For Store 1 – Build prediction models to forecast demand

[36]:
```
data_store1=data[data["Store"]==1]
data_store1
```

[36]:

Date_index	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	\
2010-05-02	1	2010-05-02	1643690.90	0	42.31	
2010-12-02	1	2010-12-02	1641957.44	1	38.51	
2010-02-19	1	2010-02-19	1611968.17	0	39.93	
2010-02-26	1	2010-02-26	1409727.59	0	46.63	
2010-05-03	1	2010-05-03	1554806.68	0	46.50	
…	…	…	…	…	…	
2012-09-28	1	2012-09-28	1437059.26	0	76.08	
2012-05-10	1	2012-05-10	1670785.97	0	68.55	
2012-12-10	1	2012-12-10	1573072.81	0	62.99	
2012-10-19	1	2012-10-19	1508068.77	0	67.97	
2012-10-26	1	2012-10-26	1493659.74	0	69.16	

Date_index	Fuel_Price	CPI	Unemployment	Date_index	Year	Semester	\
2010-05-02	2.572	211.096358	8.106	2010-05-02	2010	0	

```
2010-12-02       2.548  211.242170         8.106 2010-12-02  2010         1
2010-02-19       2.514  211.289143         8.106 2010-02-19  2010         0
2010-02-26       2.561  211.319643         8.106 2010-02-26  2010         0
2010-05-03       2.625  211.350143         8.106 2010-05-03  2010         0
…                …          …              …         …    …        …
2012-09-28       3.666  222.981658         6.908 2012-09-28  2012         1
2012-05-10       3.617  223.181477         6.573 2012-05-10  2012         0
2012-12-10       3.601  223.381296         6.573 2012-12-10  2012         1
2012-10-19       3.594  223.425723         6.573 2012-10-19  2012         1
2012-10-26       3.506  223.444251         6.573 2012-10-26  2012         1

            Quarter  Month
Date_index
2010-05-02        2      5
2010-12-02        4     12
2010-02-19        1      2
2010-02-26        1      2
2010-05-03        2      5
…               …    …
2012-09-28        3      9
2012-05-10        2      5
2012-12-10        4     12
2012-10-19        4     10
2012-10-26        4     10

[143 rows x 13 columns]
```

[37]:
```
data_store1=data_store1.
 ↪drop(columns=["Date","Date_index","Year","Semester","Quarter","Month"],axis=1)
data_store1
```

[37]:
```
            Store  Weekly_Sales  Holiday_Flag  Temperature  Fuel_Price  \
Date_index
2010-05-02      1    1643690.90             0        42.31       2.572
2010-12-02      1    1641957.44             1        38.51       2.548
2010-02-19      1    1611968.17             0        39.93       2.514
2010-02-26      1    1409727.59             0        46.63       2.561
2010-05-03      1    1554806.68             0        46.50       2.625
…             …           …             …           …          …
2012-09-28      1    1437059.26             0        76.08       3.666
2012-05-10      1    1670785.97             0        68.55       3.617
2012-12-10      1    1573072.81             0        62.99       3.601
2012-10-19      1    1508068.77             0        67.97       3.594
2012-10-26      1    1493659.74             0        69.16       3.506

                 CPI  Unemployment
Date_index
```

```
2010-05-02  211.096358         8.106
2010-12-02  211.242170         8.106
2010-02-19  211.289143         8.106
2010-02-26  211.319643         8.106
2010-05-03  211.350143         8.106
…                 …           …
2012-09-28  222.981658         6.908
2012-05-10  223.181477         6.573
2012-12-10  223.381296         6.573
2012-10-19  223.425723         6.573
2012-10-26  223.444251         6.573

[143 rows x 7 columns]
```

[38]:
```
x=data_store1.drop(columns=["Weekly_Sales"],axis=1)
y=data_store1["Weekly_Sales"]
```

[39]:
```
from sklearn.model_selection import train_test_split
x_train, x_test,y_train, y_test=train_test_split(x,y,train_size=0.
 ↪70,random_state=25)
```

[40]:
```
x_train.shape
```

[40]:
```
(100, 6)
```

[41]:
```
from sklearn.preprocessing import StandardScaler
scaler =StandardScaler()
x_train=scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
```

[42]:
```
from sklearn.linear_model import LinearRegression
model=LinearRegression()
model.fit(x_train,y_train)
```

[42]:
```
LinearRegression()
```

[43]:
```
y_train_pred=model.predict(x_train)
y_train_pred
```

[43]:
```
array([1471636.69286487, 1518034.74286925, 1734596.81107131,
       1578846.65451469, 1582110.34070684, 1486845.01919804,
       1613830.67161552, 1728076.41349178, 1532697.50621254,
       1475983.73969879, 1469962.84156643, 1642437.27730833,
       1646697.58348579, 1539717.57719319, 1557996.34865692,
       1522375.64011688, 1471639.01600054, 1587886.25485918,
       1602187.71966184, 1515204.26610863, 1464900.81409886,
       1548565.87577876, 1495787.6426348 , 1474236.11629783,
```

```
       1552889.64847633, 1741405.80745604, 1508775.6064927 ,
       1531420.76928711, 1515900.88886987, 1504700.76230922,
       1453270.62844704, 1468404.69081356, 1641441.22761588,
       1533010.82922664, 1547220.18329704, 1518557.79649247,
       1616726.48441836, 1451790.19377634, 1567817.29193025,
       1463111.24578713, 1559860.74175954, 1551035.24078906,
       1596337.32116049, 1514234.68723225, 1620475.68778683,
       1446191.13110305, 1465705.55823054, 1527715.11640268,
       1615673.04293637, 1545474.95421723, 1578449.37139168,
       1633865.66527176, 1559844.29571595, 1654841.75457877,
       1478202.02884657, 1466002.07647468, 1572758.30929572,
       1543850.61563192, 1577334.99256493, 1631075.65538366,
       1516762.54702863, 1666730.60332025, 1480643.11156287,
       1745648.82012279, 1590466.47842746, 1666889.51464781,
       1476771.58282041, 1554081.95564284, 1670101.29970282,
       1591378.37655605, 1595774.01136729, 1669855.58440977,
       1582663.47210435, 1535189.57087643, 1474858.74130973,
       1477782.54085642, 1482566.7568932 , 1519995.64335647,
       1583333.35842183, 1540055.0490123 , 1641278.8309632 ,
       1633123.15644702, 1454591.73358299, 1522492.91379901,
       1591146.07863836, 1521221.05456397, 1683563.55117759,
       1540518.09336202, 1559435.42659187, 1555045.13835612,
       1619914.38713482, 1611616.22391838, 1557680.3299684 ,
       1638098.96521054, 1572168.37172067, 1570123.33087003,
       1588693.79292471, 1512476.71120919, 1500470.75237656,
       1542176.92126352])
```

[44]:
```
y_test_pred=model.predict(x_test)
y_test_pred
```

[44]:
```
array([1625516.38640268, 1664247.29265922, 1465956.06588888,
       1513512.08965932, 1515179.00456702, 1462344.92098931,
       1810483.46590538, 1587125.07499827, 1593355.24469718,
       1576752.05314107, 1570440.75266356, 1573451.36025913,
       1495710.60152353, 1512123.62506055, 1461272.48506071,
       1525548.2251959 , 1534344.44384478, 1535569.62855775,
       1557287.37966943, 1719478.98887134, 1543326.59293686,
       1576538.85432819, 1655284.90034381, 1566530.20697397,
       1607812.75996748, 1465042.63042201, 1532990.71187724,
       1721270.59846662, 1502482.38747871, 1668765.25394195,
       1460620.50999408, 1543106.81544014, 1595366.49001142,
       1615465.40326547, 1500772.02724821, 1469844.08524033,
       1592286.223557  , 1578096.6109447 , 1479461.29014204,
       1460283.74693403, 1598647.85454236, 1605760.14753715,
       1578261.3103446 ])
```

[45]:
```
from sklearn.metrics import mean_squared_error,r2_score
```

[46]:
```
mean_squared_error(y_pred=y_train_pred,y_true=y_train)
```

[46]:
```
22405193652.33057
```

[47]:
```
mean_squared_error(y_pred=y_test_pred,y_true=y_test)
```

[47]:
```
17866558742.5383
```

[48]:
```
r2_score(y_pred=y_train_pred,y_true=y_train)
```

[48]:
```
0.18009850399469085
```

[49]:
```
r2_score(y_pred=y_test_pred,y_true=y_test)
```

[49]:
```
-0.06910826627253108
```

[50]:
```
error=y_test-y_test_pred
accurcy=round((y_test_pred-y_test)*100/y_test,2)
error_data=pd.DataFrame(np.array([y_test,y_test_pred,error,accurcy])).T
error_data=error_data.rename(columns={0:'Actual',1:'Predicted',2:'Error',3:
 ↪'Accurcy%'})
error_data
```

[50]:

	Actual	Predicted	Error	Accurcy%
0	1677472.78	1.625516e+06	51956.393597	-3.10
1	1539483.70	1.664247e+06	-124763.592659	8.10
2	1492418.14	1.465956e+06	26462.074111	-1.77
3	1453329.50	1.513512e+06	-60182.589659	4.14
4	1352219.79	1.515179e+06	-162959.214567	12.05
5	1513080.49	1.462345e+06	50735.569011	-3.35
6	1497462.72	1.810483e+06	-313020.745905	20.90
7	1521577.87	1.587125e+06	-65547.204998	4.31
8	1624477.58	1.593355e+06	31122.335303	-1.92
9	1472515.79	1.576752e+06	-104236.263141	7.08
10	1497954.76	1.570441e+06	-72485.992664	4.84
11	1899676.88	1.573451e+06	326225.519741	-17.17
12	1604775.58	1.495711e+06	109064.978476	-6.80
13	1525147.09	1.512124e+06	13023.464939	-0.85
14	1605491.78	1.461272e+06	144219.294939	-8.98
15	1576818.06	1.525548e+06	51269.834804	-3.25
16	1636263.41	1.534344e+06	101918.966155	-6.23
17	1456800.28	1.535570e+06	-78769.348558	5.41
18	1483784.18	1.557287e+06	-73503.199669	4.95
19	1802477.43	1.719479e+06	82998.441129	-4.60
20	1494479.49	1.543327e+06	-48847.102937	3.27
21	1955624.11	1.576539e+06	379085.255672	-19.38
22	1319325.59	1.655285e+06	-335959.310344	25.46

```
23  1606629.58  1.566530e+06   40099.373026     -2.50
24  1554806.68  1.607813e+06  -53006.079967      3.41
25  1422711.60  1.465043e+06  -42331.030422      2.98
26  1508239.93  1.532991e+06  -24750.781877      1.64
27  1584083.95  1.721271e+06 -137186.648467      8.66
28  1455090.69  1.502482e+06  -47391.697479      3.26
29  1550369.92  1.668765e+06 -118395.333942      7.64
30  1448938.92  1.460621e+06  -11681.589994      0.81
31  1686842.78  1.543107e+06  143735.964560     -8.52
32  1540421.49  1.595366e+06  -54945.000011      3.57
33  1643690.90  1.615465e+06   28225.496735     -1.72
34  1594968.28  1.500772e+06   94196.252752     -5.91
35  1371986.60  1.469844e+06  -97857.485240      7.13
36  1468928.37  1.592286e+06 -123357.853557      8.40
37  1684519.99  1.578097e+06  106423.379055     -6.32
38  1351791.03  1.479461e+06 -127670.260142      9.44
39  1508237.76  1.460284e+06   47954.013066     -3.18
40  1630607.00  1.598648e+06   31959.145458     -1.96
41  1527845.81  1.605760e+06  -77914.337537      5.10
42  1404429.92  1.578261e+06 -173831.390345     12.38
```

Correlation among CPI,unemployment,Fuel price and Weekly_sales.

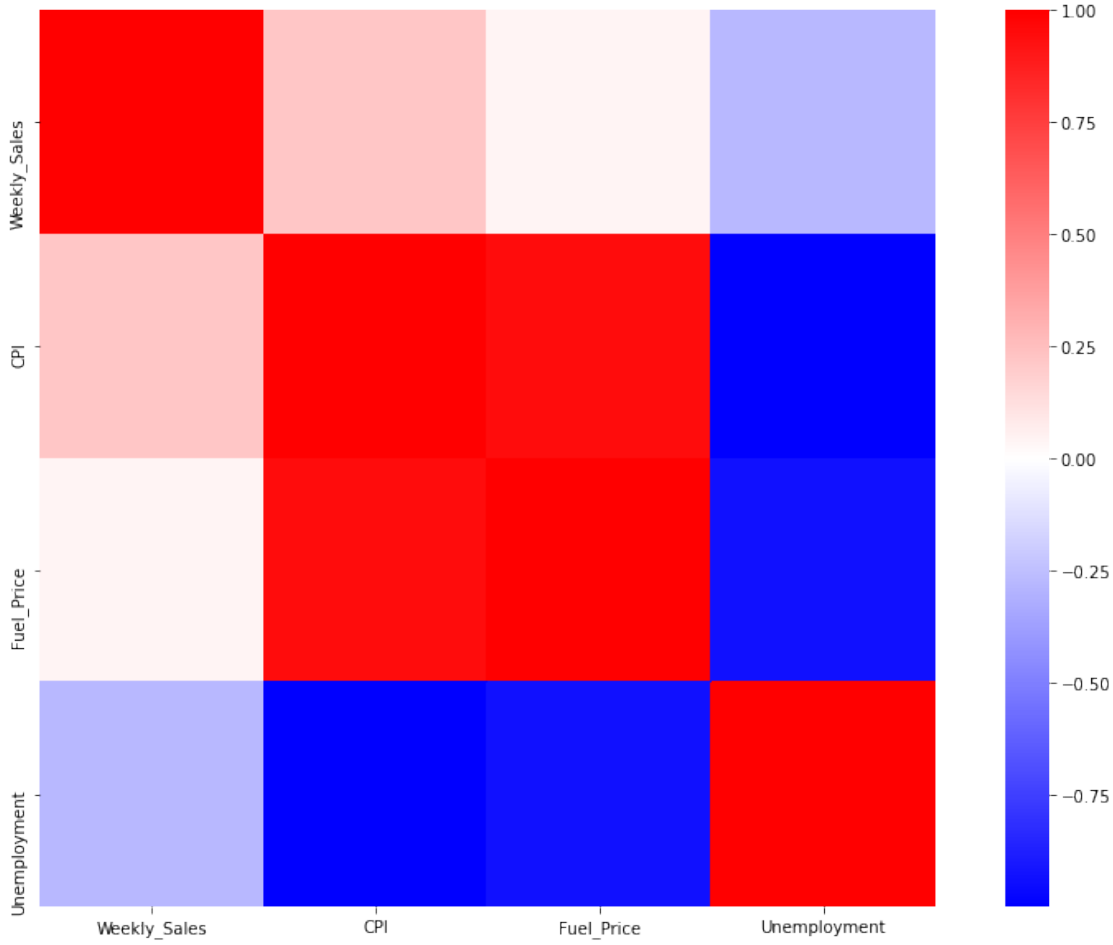
[51]:
```
data3=data_store1[["Weekly_Sales","CPI","Fuel_Price","Unemployment"]].corr()
data3
```

[51]:

	Weekly_Sales	CPI	Fuel_Price	Unemployment
Weekly_Sales	1.000000	0.225408	0.124592	-0.097955
CPI	0.225408	1.000000	0.755259	-0.813471
Fuel_Price	0.124592	0.755259	1.000000	-0.513944
Unemployment	-0.097955	-0.813471	-0.513944	1.000000

[52]:
```
plt.figure(figsize=(15,10))
sns.heatmap(data3.corr(),cmap="bwr",square=True)
```

[52]:
```
<AxesSubplot:>
```



Hypothesize if CPI, unemployment, and fuel price have any impact on sales.

[53]:
```
import statsmodels.formula.api as smf
```

[54]:
```
data4=smf.
 ↪ols(formula="Weekly_Sales~CPI+Unemployment+Fuel_Price",data=data_store1).
 ↪fit()
print(data4.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           Weekly_Sales   R-squared:                       0.085
Model:                            OLS   Adj. R-squared:                  0.065
Method:                 Least Squares   F-statistic:                     4.303
Date:                Mon, 24 Jan 2022   Prob (F-statistic):           0.00616
Time:                        14:36:44   Log-Likelihood:                -1906.0
No. Observations:                 143   AIC:                             3820.
Df Residuals:                     139   BIC:                             3832.
```

```
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept  -3.887e+06   1.74e+06     -2.234      0.027   -7.33e+06   -4.46e+05
CPI          2.179e+04   6785.272      3.212      0.002    8376.030    3.52e+04
Unemployment  1.241e+05   5.88e+04      2.111      0.037    7846.506     2.4e+05
Fuel_Price  -6.484e+04   4.68e+04     -1.384      0.169   -1.57e+05    2.78e+04
==============================================================================
Omnibus:                       93.038   Durbin-Watson:                   1.544
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              655.590
Skew:                           2.267   Prob(JB):                    4.37e-143
Kurtosis:                      12.459   Cond. No.                     2.99e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.99e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

6.1 CPI, unemployment, and fuel price have a low impact on sales i.e. 8.5%.

[55]:
```
from sklearn.metrics import mean_squared_error,r2_score
```

[56]:
```
y_pred=data4.predict()
```

[57]:
```
 mean_squared_error(y_pred=y_pred,y_true=data_store1["Weekly_Sales"])
```

[57]: 22106620866.561615

[58]:
```
r2_score(y_pred=y_pred,y_true=data_store1["Weekly_Sales"])
```

[58]: 0.0849855578999581

7 THANK YOU