```python
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
from sklearn.preprocessing import OrdinalEncoder
import statsmodels.api as sm

import warnings
warnings.filterwarnings('ignore')

# import dataset
walmat_df = pd.read_csv('Walmart_Store_sales.csv')
walmat_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
```

```python
walmat_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
```

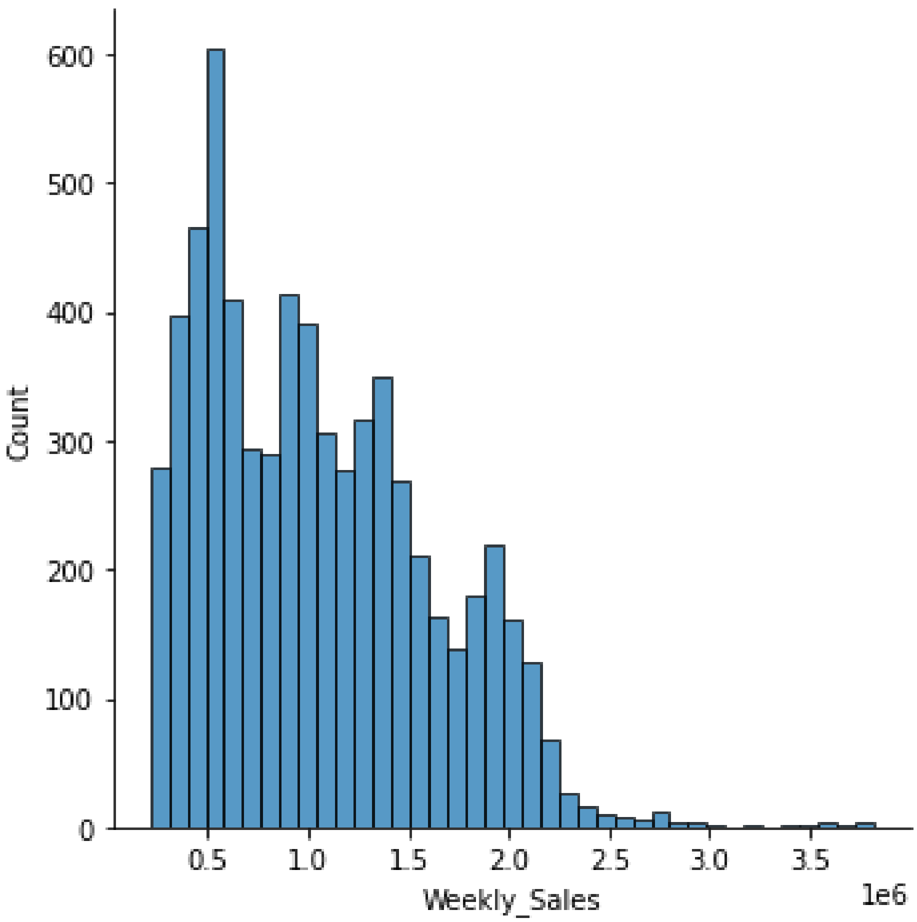
```
dtypes: float64(5), int64(2), object(1)
memory usage: 402.3+ KB
```

Now we can check the uniqueness of categorical values and distribution of continuous values.

```
walmat_df['Store'].nunique()
```

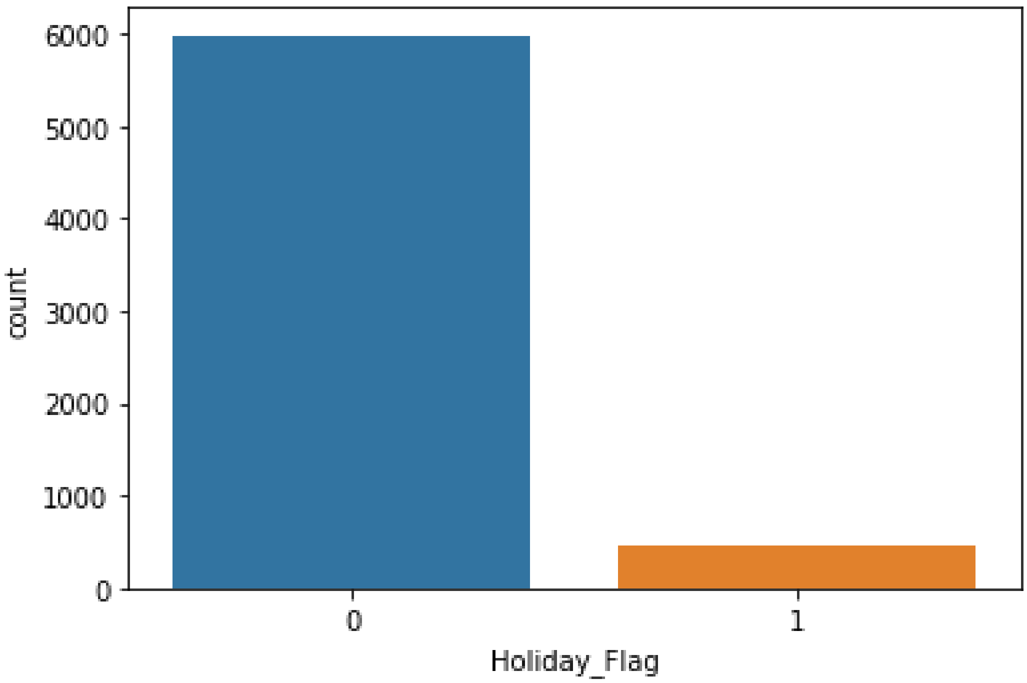
```
45
```

```
sns.displot(walmat_df['Weekly_Sales'])
plt.show()
```

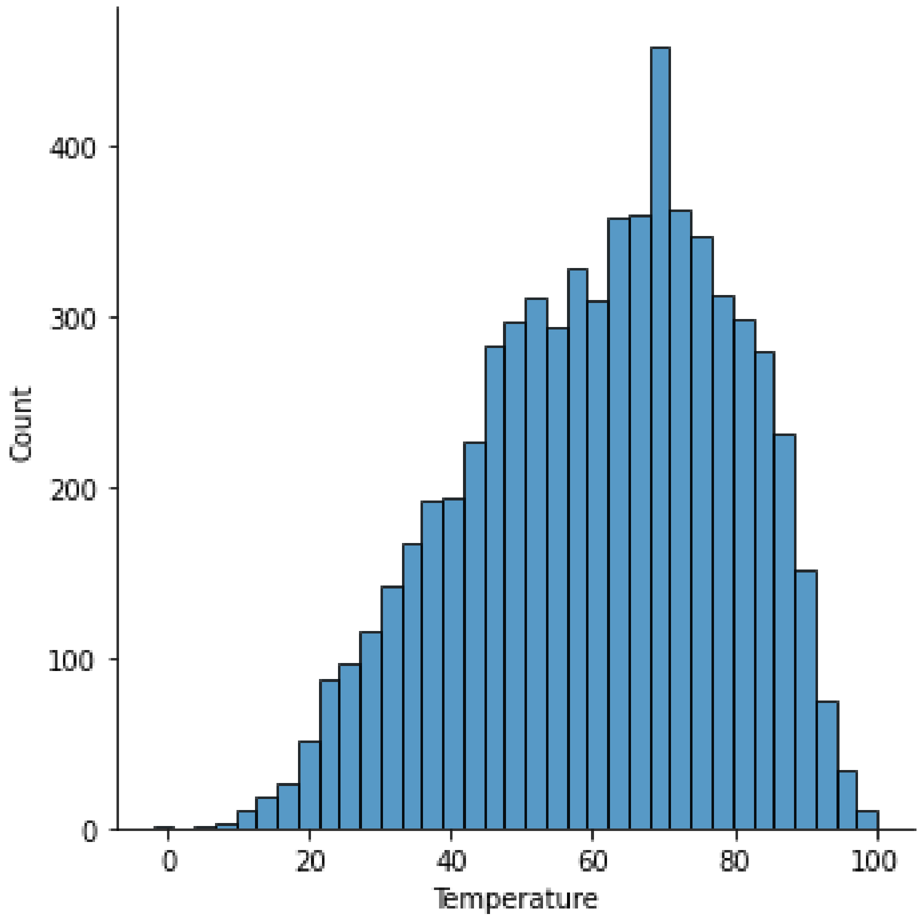


It seems reasonable.

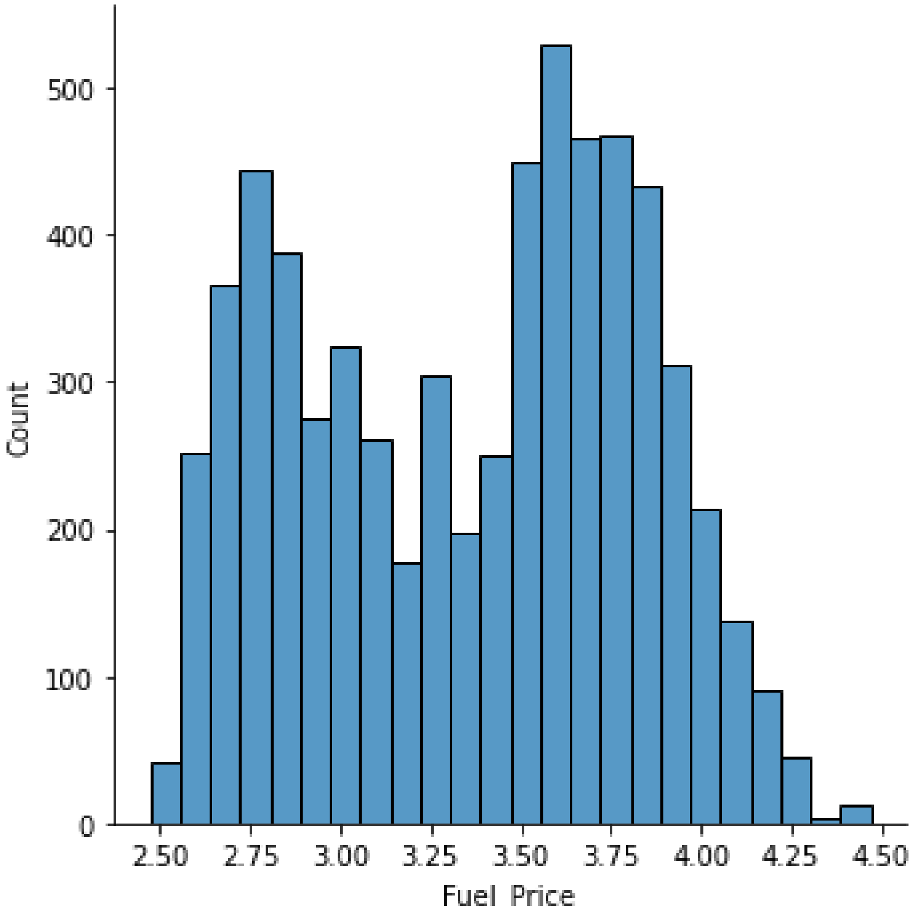
```
sns.countplot(walmat_df['Holiday_Flag'])
plt.show()
```



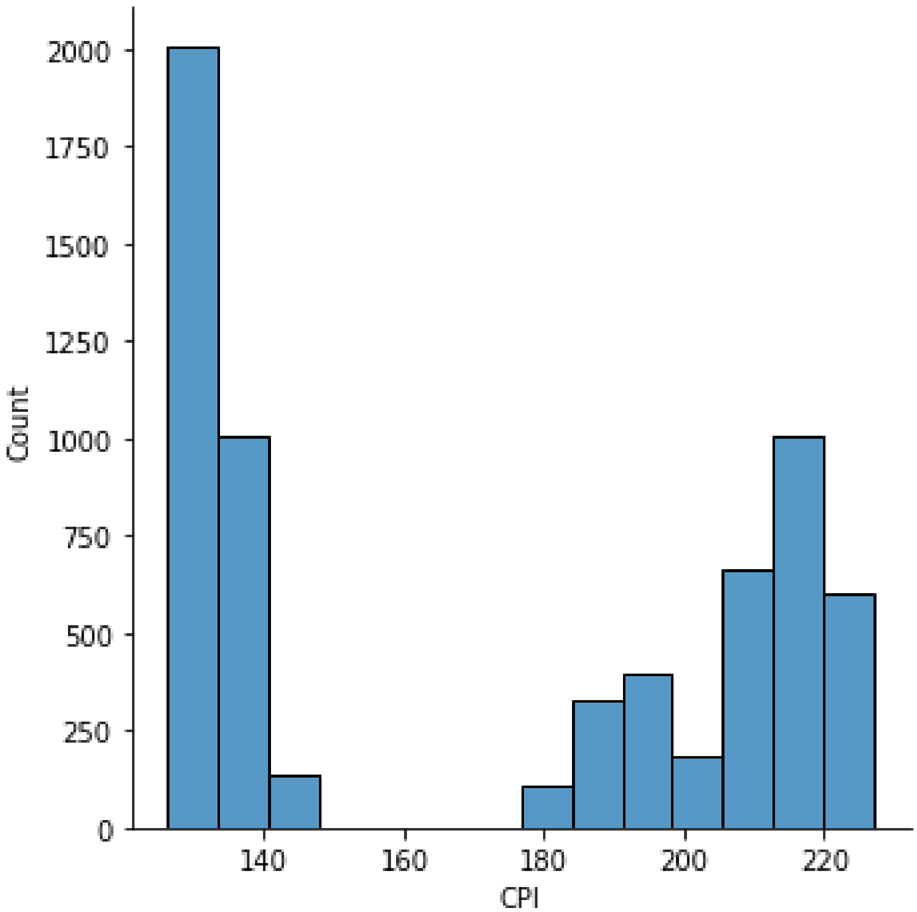

```
sns.displot(walmat_df['Temperature'])
plt.show()
```



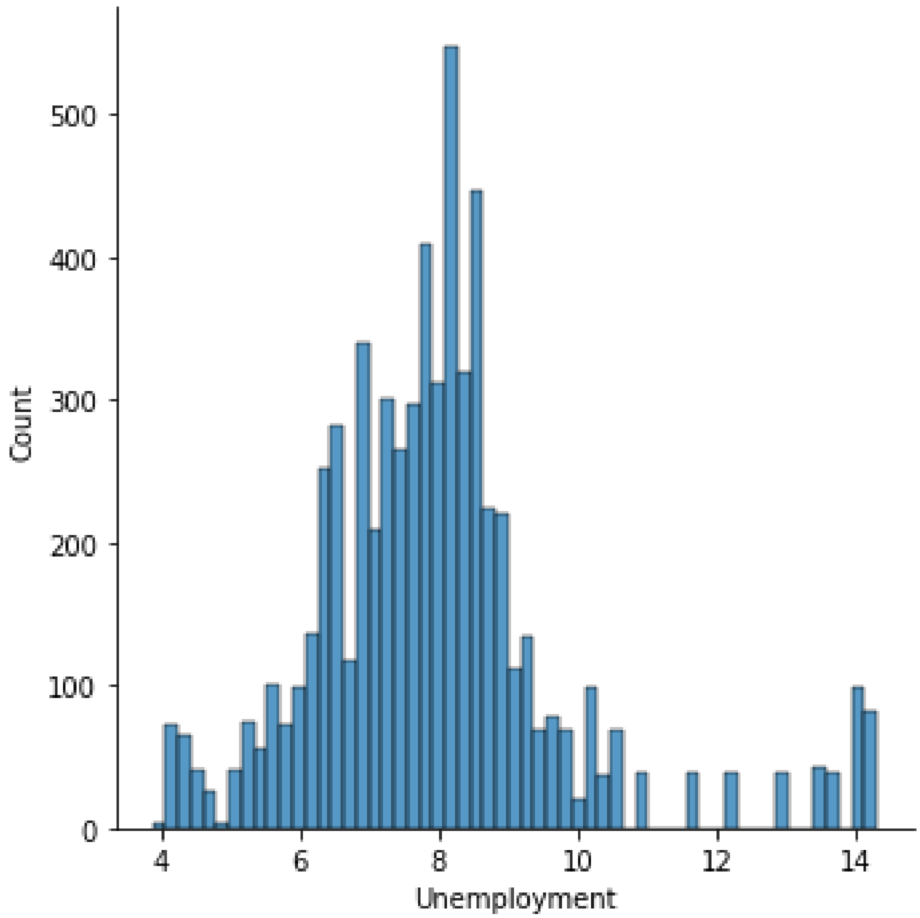

```
sns.displot(walmat_df['Fuel_Price'])
plt.show()
```




```
sns.displot(walmat_df['CPI'])
plt.show()
```

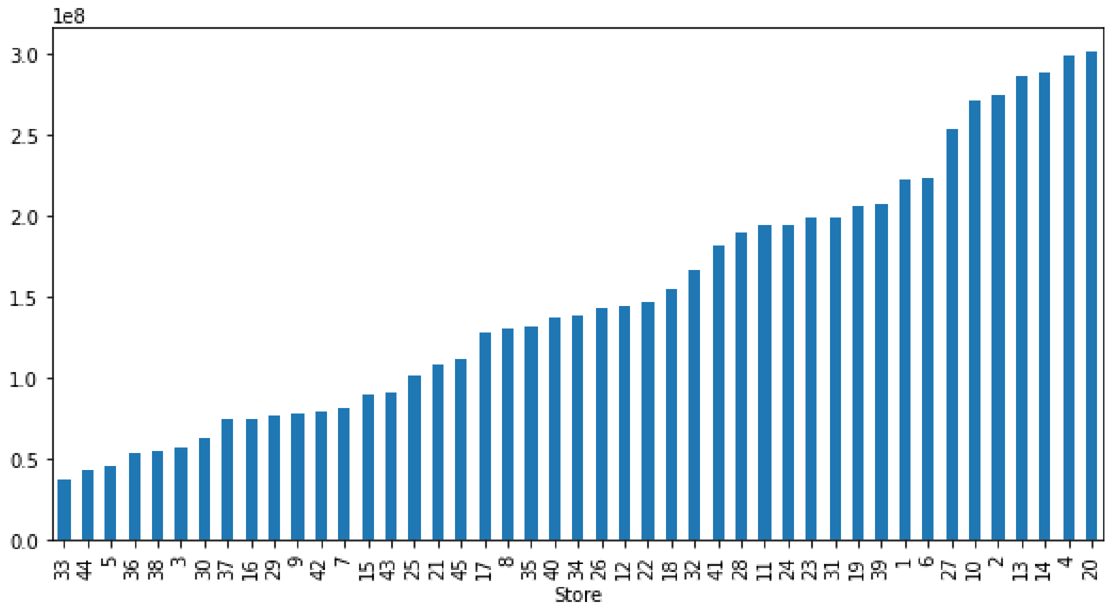



```
sns.displot(walmat_df['Unemployment'])
plt.show()
```



Everything seems fine from the plots.

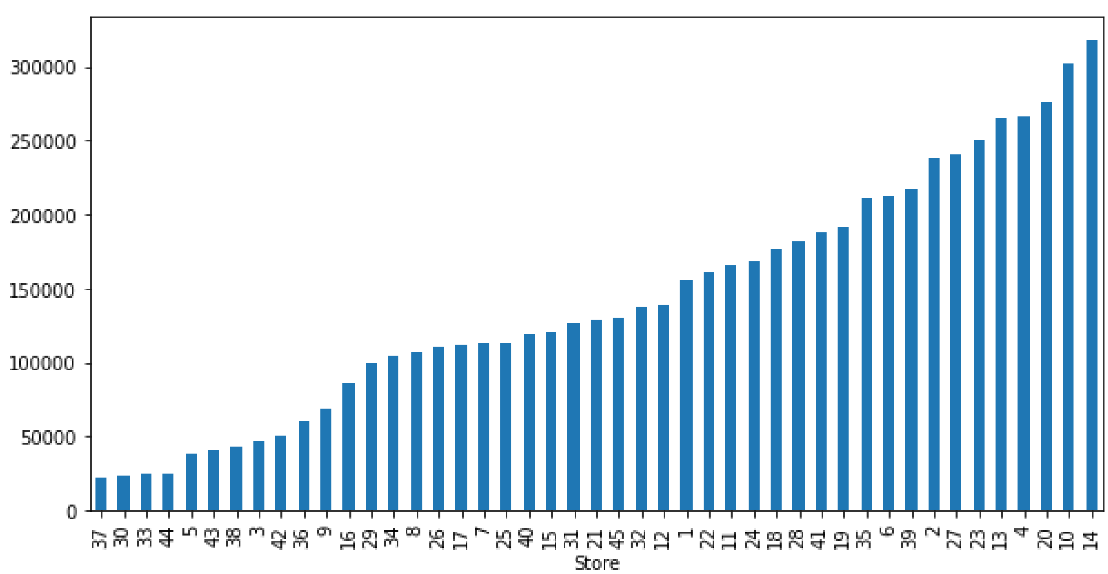
```
# Store with maximum sale

store_sales = walmat_df.groupby('Store')
['Weekly_Sales'].sum().sort_values()

store_sales.plot(kind='bar', figsize=(10,5))
plt.show()
```




```
print('Store {} has highest
sales.'.format(store_sales.index[np.argmax(store_sales.values)]))
```

```
Store 20 has highest sales.
```

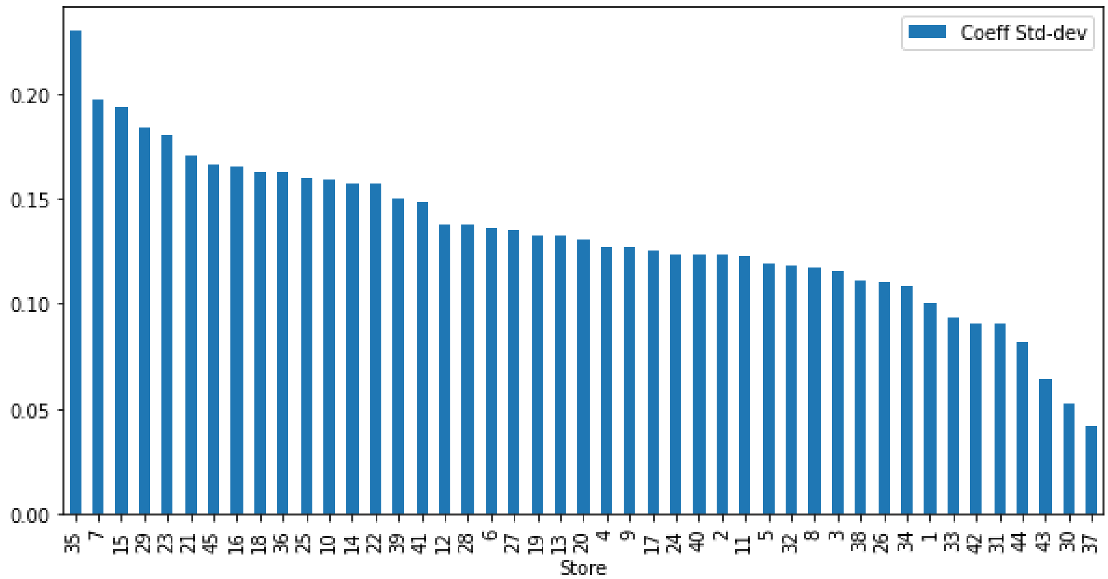
```
# Store with maximum std-dev
store_sales_std = walmat_df.groupby('Store')
['Weekly_Sales'].std().sort_values()

store_sales_std.plot(kind='bar', figsize=(10,5))
plt.show()
```




```
print('Store with highest std of sales:
{}'.format(store_sales_std.index[np.argmax(store_sales_std.values)]))
```

```
Store with highest std of sales: 14
```

```
# coefficient of std-dev
coeff_std = pd.DataFrame(walmat_df.groupby('Store')
['Weekly_Sales'].std() / walmat_df.groupby('Store')
['Weekly_Sales'].mean())
coeff_std.rename(columns={'Weekly_Sales': 'Coeff Std-dev'},
inplace=True)
coeff_std.sort_values('Coeff Std-dev', ascending=False, inplace=True)

coeff_std.plot(kind='bar', figsize=(10,5))
plt.show()
```



Store 35 has highest coefficient of std-dev.

We need the store that has highest quaterly growth in 3rd quester. So can check the difference between the total sales in Q2 and Q3. if difference is +ve, then there is growth in 3rd Q.

```
sales_2Q = walmat_df[['Store', 'Weekly_Sales']][(walmat_df['Month']
>=4) & (walmat_df['Month'] <=6)].groupby('Store').sum()
sales_3Q = walmat_df[['Store', 'Weekly_Sales']][(walmat_df['Month']
>=7) & (walmat_df['Month'] <=9)].groupby('Store').sum()

sales_2Q.rename(columns={'Weekly_Sales': '2ndQ_Sales'}, inplace=True)
sales_3Q.rename(columns={'Weekly_Sales': '3rdQ_Sales'}, inplace=True)

sales_2Q_3Q = pd.concat([sales_2Q, sales_3Q], axis=1)
sales_2Q_3Q.head()
```

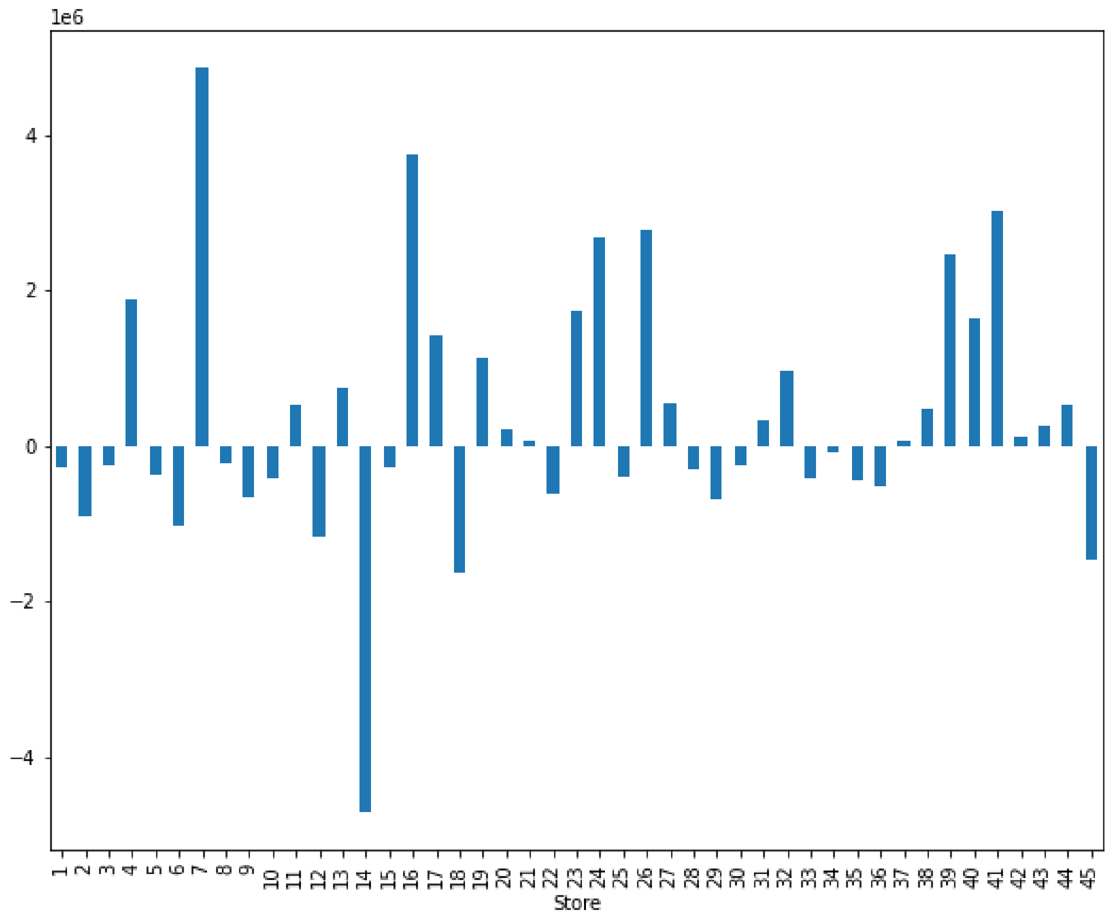
```
        2ndQ_Sales   3rdQ_Sales
Store
1      60428109.28  60156360.07
2      74356863.71  73449989.13
```

```
3       15459189.58  15218138.65
4       79302988.73  81194592.89
5       12523263.09  12166295.19
```

```
sales_2Q_3Q['Diff'] = sales_2Q_3Q['3rdQ_Sales'] -
sales_2Q_3Q['2ndQ_Sales']
sales_2Q_3Q.head()
```

```
        2ndQ_Sales   3rdQ_Sales        Diff
Store
1       60428109.28  60156360.07  -271749.21
2       74356863.71  73449989.13  -906874.58
3       15459189.58  15218138.65  -241050.93
4       79302988.73  81194592.89  1891604.16
5       12523263.09  12166295.19  -356967.90
```

```
sales_2Q_3Q['Diff'].plot(kind='bar', figsize=(10,8))
plt.show()
```



Store 7 has seen the highest growth in 3rd Quater, where as store 14 faced a huge fall in sales. But most of the stores have good sale growth in Q3.

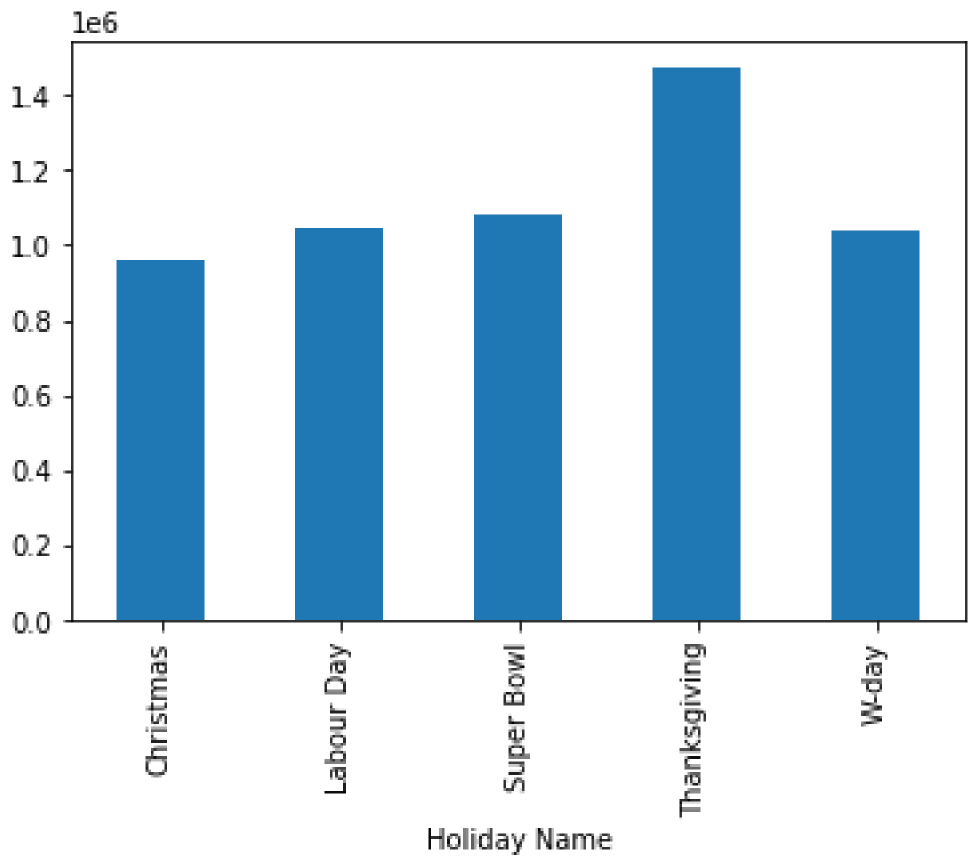
```
walmat_df['Date'] = pd.to_datetime(walmat_df['Date'], format='%d-%m-
%Y')
walmat_df['Day'] = walmat_df['Date'].apply(lambda x: x.day)
walmat_df['Month'] = walmat_df['Date'].apply(lambda x: x.month)
walmat_df['Year'] = walmat_df['Date'].apply(lambda x: x.year)

walmat_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  Day  Month  Year
0  211.096358         8.106    5      2  2010
1  211.242170         8.106   12      2  2010
2  211.289143         8.106   19      2  2010
3  211.319643         8.106   26      2  2010
4  211.350143         8.106    5      3  2010

def getHoliday(x):
    if (x['Day'] in [8,10,11,12] and x['Month'] == 2):
        return 'Super Bowl'
    elif (x['Day'] in [6,7,9,10] and x['Month'] == 9):
        return 'Labour Day'
    elif (x['Day'] in [23,25,26,29] and x['Month'] == 11):
        return 'Thanksgiving'
    elif (x['Day'] in [27,28,30,31] and x['Month'] == 12):
        return 'Christmas'
    else:
        return 'W-day'

holiday_data = walmat_df.copy()
holiday_data['Holiday Name'] = holiday_data.apply(getHoliday, axis=1)
holiday_data.drop(['Temperature', 'Fuel_Price', 'CPI',
'Unemployment'], axis=1, inplace=True)
holiday_data.head()

   Store       Date  Weekly_Sales  Holiday_Flag  Day  Month  Year
Holiday Name
0      1 2010-02-05    1643690.90             0    5      2  2010
W-day
1      1 2010-02-12    1641957.44             1   12      2  2010
```

```
Super Bowl
2      1 2010-02-19    1611968.17             0   19      2  2010
W-day
3      1 2010-02-26    1409727.59             0   26      2  2010
W-day
4      1 2010-03-05    1554806.68             0    5      3  2010
W-day
```

```
# Get avg sales i each holiday and working days

holiday_means = holiday_data.groupby('Holiday Name')
['Weekly_Sales'].mean()
holiday_means
```

```
Holiday Name
Christmas       9.608331e+05
Labour Day      1.042427e+06
Super Bowl      1.079128e+06
Thanksgiving    1.471273e+06
W-day           1.041256e+06
Name: Weekly_Sales, dtype: float64
```

```
holiday_means.plot.bar()
plt.show()
```



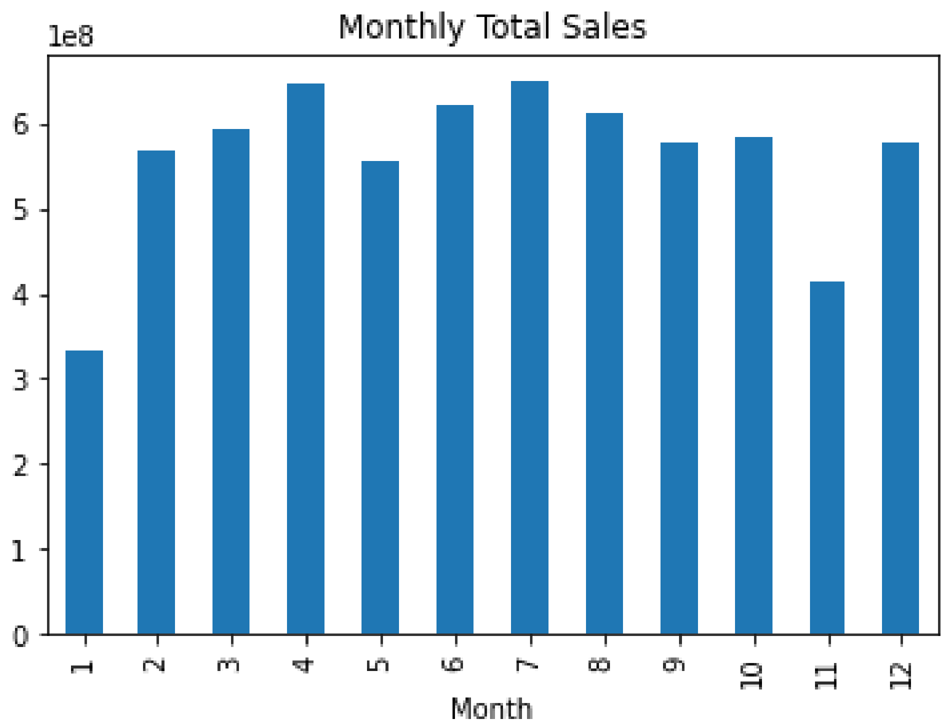
```
# Holidays having mean sales more than that of non-holiday

holiday_means[holiday_means > holiday_means['W-day']]
```

```
Holiday Name
Labour Day      1.042427e+06
Super Bowl      1.079128e+06
Thanksgiving    1.471273e+06
Name: Weekly_Sales, dtype: float64
```

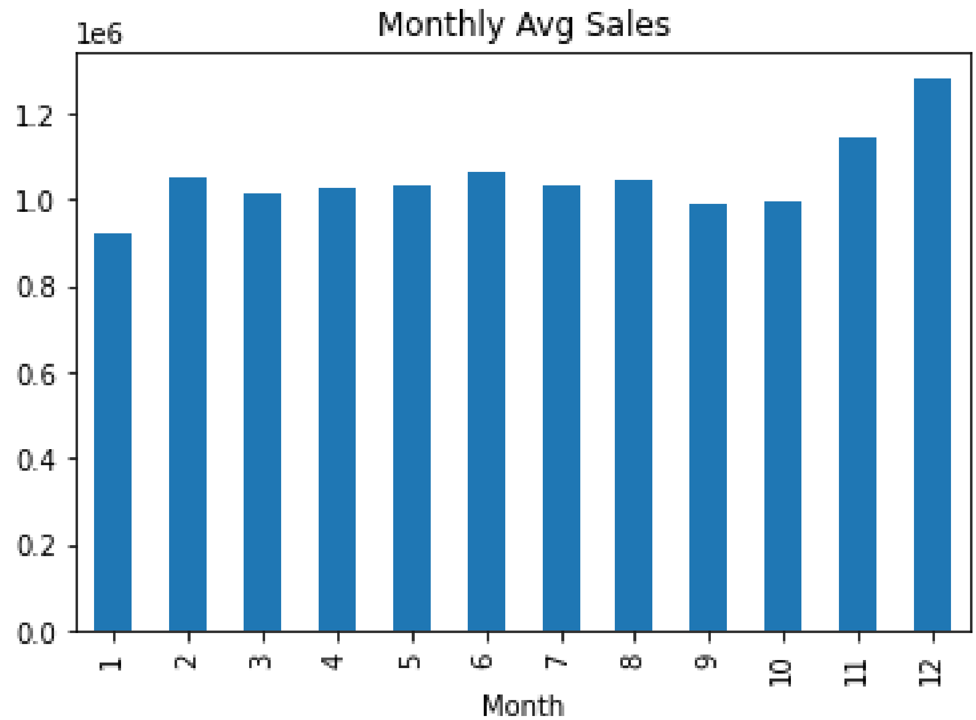
Labour Day, Super Bowl and Thanksgiving holidays have more sales than non-holidays.

Now we can plot the monthly trend for total and avg sales.

```
monthly_total = walmat_df.groupby('Month')['Weekly_Sales'].sum()
monthly_total.plot.bar()
plt.title('Monthly Total Sales')
plt.show()
```




```
monthly_avg = walmat_df.groupby('Month')['Weekly_Sales'].mean()
monthly_avg.plot.bar()
plt.title('Monthly Avg Sales')
plt.show()
```



Store 4 and 7 have highest total sales where as store 11 and 12 have highest avg sales. (Monthly)

```
sem1_data = walmat_df[['Store', 'Weekly_Sales']][(walmat_df['Month']
>=1) & (walmat_df['Month'] <=6)]
sem2_data = walmat_df[['Store', 'Weekly_Sales']][(walmat_df['Month']
>=1) & (walmat_df['Month'] <=6)]

sem1_data.rename(columns={'Weekly_Sales': 'Sem1'}, inplace=True)
sem2_data.rename(columns={'Weekly_Sales': 'Sem2'}, inplace=True)
sem_data = pd.merge(sem1_data, sem2_data, on='Store')
sem_data = sem_data.groupby('Store').sum()
sem_data.head()
```

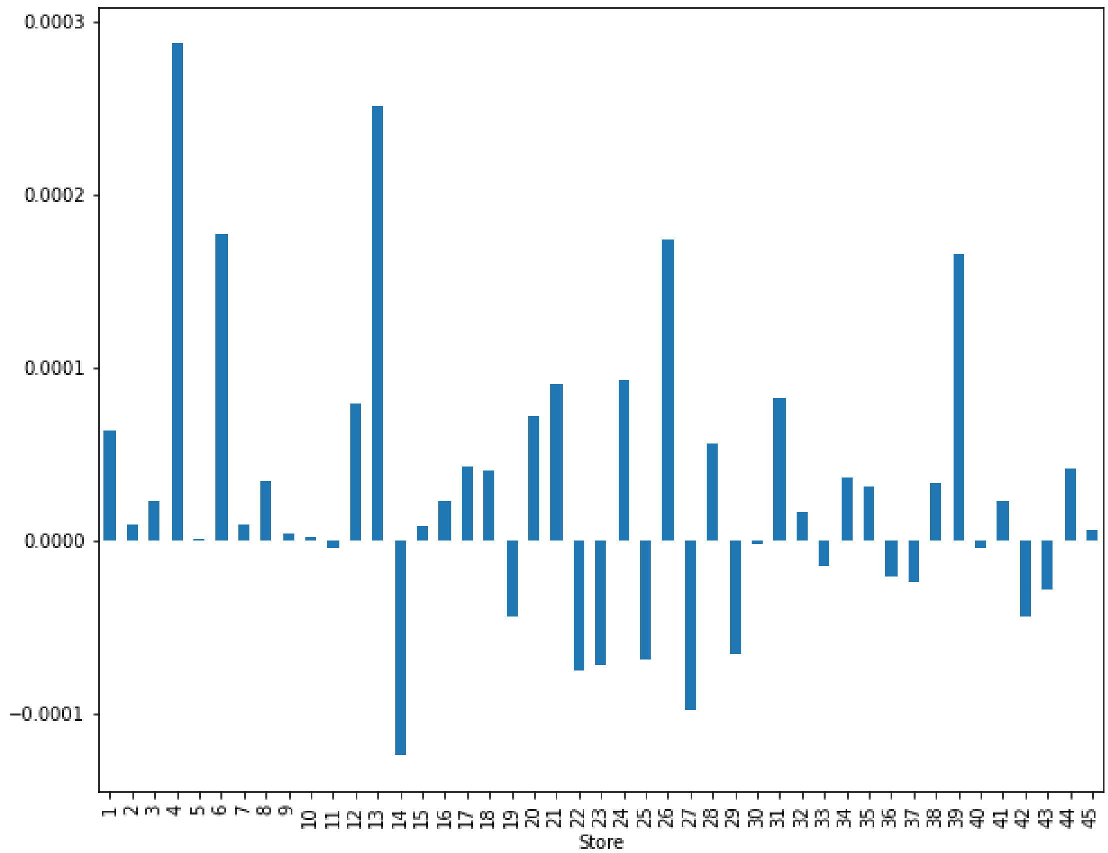
```
               Sem1          Sem2
Store
1      8.029283e+09  8.029283e+09
2      9.886854e+09  9.886854e+09
3      2.081923e+09  2.081923e+09
4      1.061221e+10  1.061221e+10
5      1.636375e+09  1.636375e+09
```

```
sem_data['Diff'] = sem_data['Sem2'] - sem_data['Sem1']
sem_data.head()
```

```
               Sem1          Sem2      Diff
Store
1      8.029283e+09  8.029283e+09  0.000064
```

```
2      9.886854e+09  9.886854e+09  0.000010
3      2.081923e+09  2.081923e+09  0.000023
4      1.061221e+10  1.061221e+10  0.000288
5      1.636375e+09  1.636375e+09  0.000001
```

```
sem_data['Diff'].plot(kind='bar', figsize=(10,8))
plt.show()
```



Most of the stores have growth in 2nd sem compared to 1st.

Now we need to check the impact of features on sales and check linear relationship.

```
# Use data for store 1

walmat_store_1 = walmat_df[walmat_df['Store'] == 1]
walmat_store_1.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
```

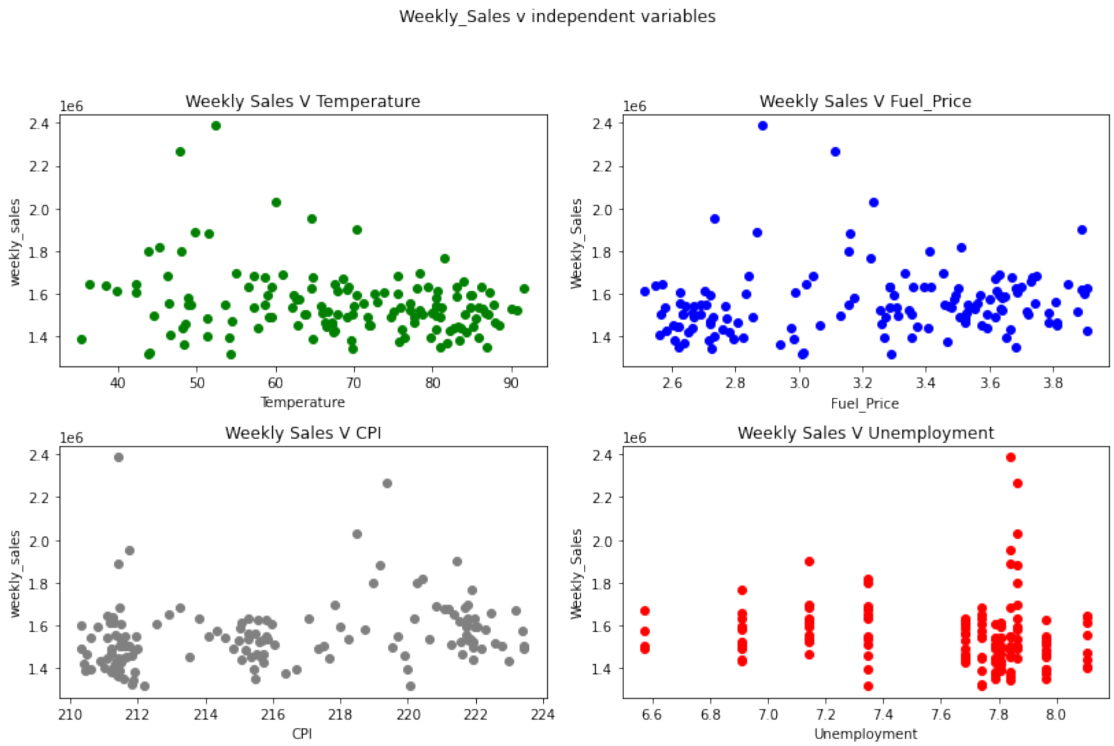
```
3      1 2010-02-26    1409727.59             0        46.63
2.561
4      1 2010-03-05    1554806.68             0        46.50
2.625

          CPI  Unemployment  Day  Month  Year
0  211.096358         8.106    5      2  2010
1  211.242170         8.106   12      2  2010
2  211.289143         8.106   19      2  2010
3  211.319643         8.106   26      2  2010
4  211.350143         8.106    5      3  2010
```

```
walmat_store_1.sort_values('Date', inplace=True)

oc = OrdinalEncoder()
walmat_store_1['Date_Number'] =
oc.fit_transform(walmat_store_1[['Date']])
walmat_store_1['Date_Number'] =
walmat_store_1['Date_Number'].astype('int64')
walmat_store_1.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  Day  Month  Year  Date_Number
0  211.096358         8.106    5      2  2010            0
1  211.242170         8.106   12      2  2010            1
2  211.289143         8.106   19      2  2010            2
3  211.319643         8.106   26      2  2010            3
4  211.350143         8.106    5      3  2010            4
```

```
fig, axs = plt.subplots(2, 2, figsize=(12, 8))
axs[0, 0].scatter(walmat_store_1['Temperature'],
walmat_store_1['Weekly_Sales'],color='green')
axs[0, 0].set(title='Weekly Sales V Temperature',
xlabel='Temperature', ylabel='weekly_sales')
axs[0, 1].scatter(walmat_store_1['Fuel_Price'],
walmat_store_1['Weekly_Sales'],color='blue')
axs[0, 1].set(title='Weekly Sales V Fuel_Price', xlabel='Fuel_Price',
ylabel='Weekly_Sales')
axs[1, 0].scatter(walmat_store_1['CPI'],
```

```
walmat_store_1['Weekly_Sales'],color='grey')
axs[1, 0].set(title='Weekly Sales V CPI', xlabel='CPI',
ylabel='weekly_sales')
axs[1, 1].scatter(walmat_store_1['Unemployment'],
walmat_store_1['Weekly_Sales'],color='red')
axs[1, 1].set(title='Weekly Sales V Unemployment',
xlabel='Unemployment', ylabel='Weekly_Sales')
plt.suptitle('Weekly_Sales v independent variables')
plt.tight_layout(pad=3, w_pad=1.0, h_pad=1.0)
plt.show()
```



From the plots, we dont see linear relationship with sales.

We can use correlation among the attributes.

```
walmat_store_1.corr()
```

```
                Store  Weekly_Sales  Holiday_Flag  Temperature
Fuel_Price  \
Store             NaN           NaN           NaN          NaN
NaN
Weekly_Sales      NaN      1.000000      0.194905    -0.222701
0.124592
Holiday_Flag      NaN      0.194905      1.000000    -0.200543   -
0.085903
Temperature       NaN     -0.222701     -0.200543     1.000000
0.228493
Fuel_Price        NaN      0.124592     -0.085903     0.228493
```

```
1.000000
CPI              NaN      0.225408     -0.028919     0.118503
0.755259
Unemployment     NaN     -0.097955      0.082949    -0.180695   -
0.513944
Day              NaN     -0.271685      0.044526     0.051077
0.030806
Month            NaN      0.202188      0.122996     0.246417   -
0.101256
Year             NaN      0.152396     -0.056783     0.068843
0.809769
Date_Number      NaN      0.214539     -0.013285     0.154069
0.781789

                   CPI  Unemployment       Day     Month      Year  \
Store              NaN           NaN       NaN       NaN       NaN
Weekly_Sales  0.225408     -0.097955 -0.271685  0.202188  0.152396
Holiday_Flag -0.028919      0.082949  0.044526  0.122996 -0.056783
Temperature   0.118503     -0.180695  0.051077  0.246417  0.068843
Fuel_Price    0.755259     -0.513944  0.030806 -0.101256  0.809769
CPI           1.000000     -0.813471  0.033588  0.050952  0.948141
Unemployment -0.813471      1.000000 -0.018342  0.040821 -0.798149
Day           0.033588     -0.018342  1.000000  0.015192  0.006406
Month         0.050952      0.040821  0.015192  1.000000 -0.194465
Year          0.948141     -0.798149  0.006406 -0.194465  1.000000
Date_Number   0.973943     -0.791222  0.041930  0.145651  0.941668

              Date_Number
Store                 NaN
Weekly_Sales     0.214539
Holiday_Flag    -0.013285
Temperature      0.154069
Fuel_Price       0.781789
CPI              0.973943
Unemployment    -0.791222
Day              0.041930
Month            0.145651
Year             0.941668
Date_Number      1.000000
```

There is not much coorelation of attributes with weekly sales.

There are high correlation with temperature, CPI, date.

CPI and unemployeement are -ve correlated.

We can use a pairplot to check further.

```
sns.pairplot(walmat_store_1[['Temperature', 'Fuel_Price', 'CPI',
'Unemployment', 'Holiday_Flag', 'Weekly_Sales']])
plt.show()
```

We dont get much insight from the plot.

Now we can go for linear regression check after selecting few columns.

```
walmat_store_1_selected = walmat_store_1[['Holiday_Flag',
'Temperature', 'Fuel_Price', 'CPI', 'Unemployment', 'Weekly_Sales']]

x = walmat_store_1_selected.drop('Weekly_Sales', axis=1)
y = walmat_store_1_selected['Weekly_Sales']

print(x.shape)
print(y.shape)

(143, 5)
(143,)

# Hypothesis testing OLS (H0: There is no relation between the
features and the target)
```

```
x = sm.add_constant(x)
result = sm.OLS(y, x).fit()
print(result.tvalues)
print(result.summary())
```

```
const          -1.385005
Holiday_Flag    1.811488
Temperature    -2.343076
Fuel_Price     -0.514139
CPI             2.450835
Unemployment    1.365813
dtype: float64
                            OLS Regression Results

======================================================================
========
Dep. Variable:           Weekly_Sales   R-squared:
0.149
Model:                            OLS   Adj. R-squared:
0.118
Method:                 Least Squares   F-statistic:
4.815
Date:                Mon, 23 May 2022   Prob (F-statistic):
0.000436
Time:                        14:18:10   Log-Likelihood:
-1900.8
No. Observations:                 143   AIC:
3814.
Df Residuals:                     137   BIC:
3831.
Df Model:                           5

Covariance Type:            nonrobust

======================================================================
==========
                   coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
----------
const        -2.428e+06   1.75e+06     -1.385      0.168   -5.89e+06
1.04e+06
Holiday_Flag  8.938e+04   4.93e+04      1.811      0.072   -8187.359
1.87e+05
Temperature  -2160.4183    922.044     -2.343      0.021   -3983.696
-337.141
Fuel_Price   -2.434e+04   4.73e+04     -0.514      0.608   -1.18e+05
6.93e+04
CPI           1.663e+04   6786.094      2.451      0.016    3212.560
```

```
3.01e+04
Unemployment  8.021e+04   5.87e+04      1.366      0.174   -3.59e+04
1.96e+05
======================================================================
========
Omnibus:                     87.674   Durbin-Watson:
1.724
Prob(Omnibus):                0.000   Jarque-Bera (JB):
645.562
Skew:                         2.069   Prob(JB):
6.58e-141
Kurtosis:                    12.551   Cond. No.
3.25e+04
======================================================================
========

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 3.25e+04. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

We can see,Holiday_Flag, Fuel_Price, Unemployment has p-value more than 0.05. Fuel price has highest p-value score.

In next model, we can try removing the fuel price and test again.

```
walmat_store_1_selected = walmat_store_1[['Holiday_Flag',
'Temperature', 'CPI', 'Unemployment', 'Weekly_Sales']]
x = walmat_store_1_selected.drop('Weekly_Sales', axis=1)
y = walmat_store_1_selected['Weekly_Sales']

print(x.shape)
print(y.shape)
```

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

```
# 2nd test

x = sm.add_constant(x)
result = sm.OLS(y, x).fit()
print(result.tvalues)
print(result.summary())
```

```
const           -1.339394
Holiday_Flag     1.867002
Temperature     -2.554918
CPI              2.923462
Unemployment     1.272270
```

```
dtype: float64
                            OLS Regression Results
==============================================================================
========
Dep. Variable:           Weekly_Sales   R-squared:
0.148
Model:                            OLS   Adj. R-squared:
0.123
Method:                 Least Squares   F-statistic:
5.985
Date:                Mon, 23 May 2022   Prob (F-statistic):
0.000180
Time:                        14:22:49   Log-Likelihood:
-1900.9
No. Observations:                 143   AIC:
3812.
Df Residuals:                     138   BIC:
3827.
Df Model:                           4

Covariance Type:            nonrobust

==============================================================================
==========
                   coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
----------
const        -1.902e+06   1.42e+06     -1.339      0.183   -4.71e+06
9.06e+05
Holiday_Flag  9.154e+04    4.9e+04      1.867      0.064   -5407.839
1.88e+05
Temperature  -2277.1351    891.275     -2.555      0.012   -4039.457
-514.813
CPI            1.42e+04   4858.072      2.923      0.004    4596.507
2.38e+04
Unemployment  7.083e+04   5.57e+04      1.272      0.205   -3.93e+04
1.81e+05
==============================================================================
========
Omnibus:                       88.044   Durbin-Watson:
1.724
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
647.282
Skew:                           2.082   Prob(JB):
2.78e-141
Kurtosis:                      12.555   Cond. No.
2.64e+04
==============================================================================
```

```
========

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.64e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Holiday_Flag and Unemployment has p-value more than 0.05.

So null hypothesis H0 cant be rejected. We can say, there is no relationship between the weekly sale and the selected features with high p-values.