```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

#normalization of data
from sklearn.preprocessing import MinMaxScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

#Load data
df=pd.read_csv("D:\\Excel_project\\Walmart Data Analysis and
Forcasting.csv")
print(df)
```

```
      Store        Date  Weekly_Sales  Holiday_Flag  Temperature
Fuel_Price  \
0         1  05-02-2010    1643690.90             0        42.31
2.572
1         1  12-02-2010    1641957.44             1        38.51
2.548
2         1  19-02-2010    1611968.17             0        39.93
2.514
3         1  26-02-2010    1409727.59             0        46.63
2.561
4         1  05-03-2010    1554806.68             0        46.50
2.625
...     ...         ...           ...           ...          ...
...
6430     45  28-09-2012     713173.95             0        64.88
3.997
6431     45  05-10-2012     733455.07             0        64.89
3.985
6432     45  12-10-2012     734464.36             0        54.47
4.000
6433     45  19-10-2012     718125.53             0        56.47
3.969
6434     45  26-10-2012     760281.43             0        58.85
3.882

             CPI  Unemployment
0     211.096358         8.106
1     211.242170         8.106
2     211.289143         8.106
3     211.319643         8.106
4     211.350143         8.106
...          ...           ...
6430  192.013558         8.684
6431  192.170412         8.667
6432  192.327265         8.667
```

```
6433  192.330854         8.667
6434  192.308899         8.667

[6435 rows x 8 columns]
```

```
# Display the shape of the DataFrame
print(f'Shape of the DataFrame: {df.shape}')
```

```
Shape of the DataFrame: (6435, 8)
```

```
# Info about data
print(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
None
```

```
# Display top 5 rows
print(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
```

```
# Check for null values
print('Null values in each column:')
print(df.isnull().sum())
```

```
Null values in each column:
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
dtype: int64
```

```
# Check for duplicates
print(f'Total duplicates: {df.duplicated().sum()}')
```

```
Total duplicates: 0
```

```
# Descriptive statistics
print('Descriptive Statistics:')
print(df.describe(include='all'))
```

```
Descriptive Statistics:
              Store        Date  Weekly_Sales  Holiday_Flag
Temperature  \
count   6435.000000        6435  6.435000e+03   6435.000000
6435.000000
unique          NaN         143           NaN           NaN
NaN
top             NaN  05-02-2010           NaN           NaN
NaN
freq            NaN          45           NaN           NaN
NaN
mean      23.000000         NaN  1.046965e+06      0.069930
60.663782
std       12.988182         NaN  5.643666e+05      0.255049
18.444933
min        1.000000         NaN  2.099862e+05      0.000000    -
2.060000
25%       12.000000         NaN  5.533501e+05      0.000000
47.460000
50%       23.000000         NaN  9.607460e+05      0.000000
62.670000
75%       34.000000         NaN  1.420159e+06      0.000000
74.940000
max       45.000000         NaN  3.818686e+06      1.000000
```

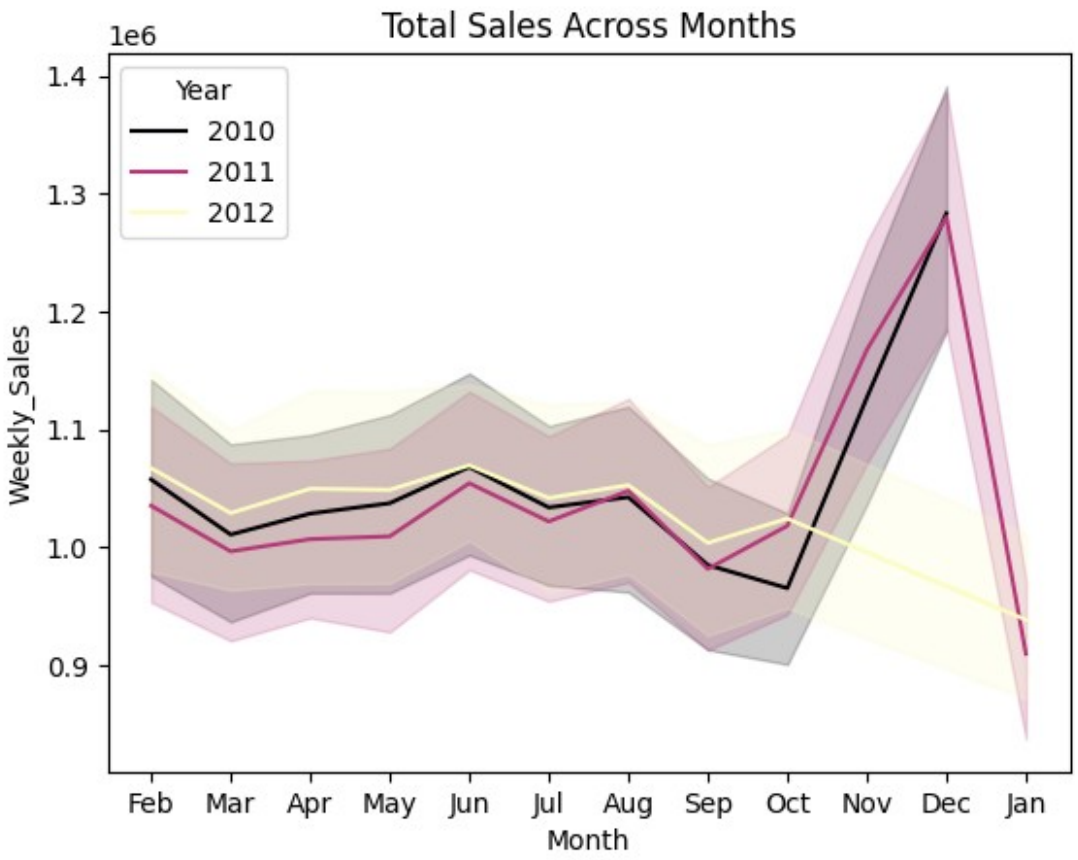
```
100.140000
```

	Fuel_Price	CPI	Unemployment
count	6435.000000	6435.000000	6435.000000
unique	NaN	NaN	NaN
top	NaN	NaN	NaN
freq	NaN	NaN	NaN
mean	3.358607	171.578394	7.999151
std	0.459020	39.356712	1.875885
min	2.472000	126.064000	3.879000
25%	2.933000	131.735000	6.891000
50%	3.445000	182.616521	7.874000
75%	3.735000	212.743293	8.622000
max	4.468000	227.232807	14.313000

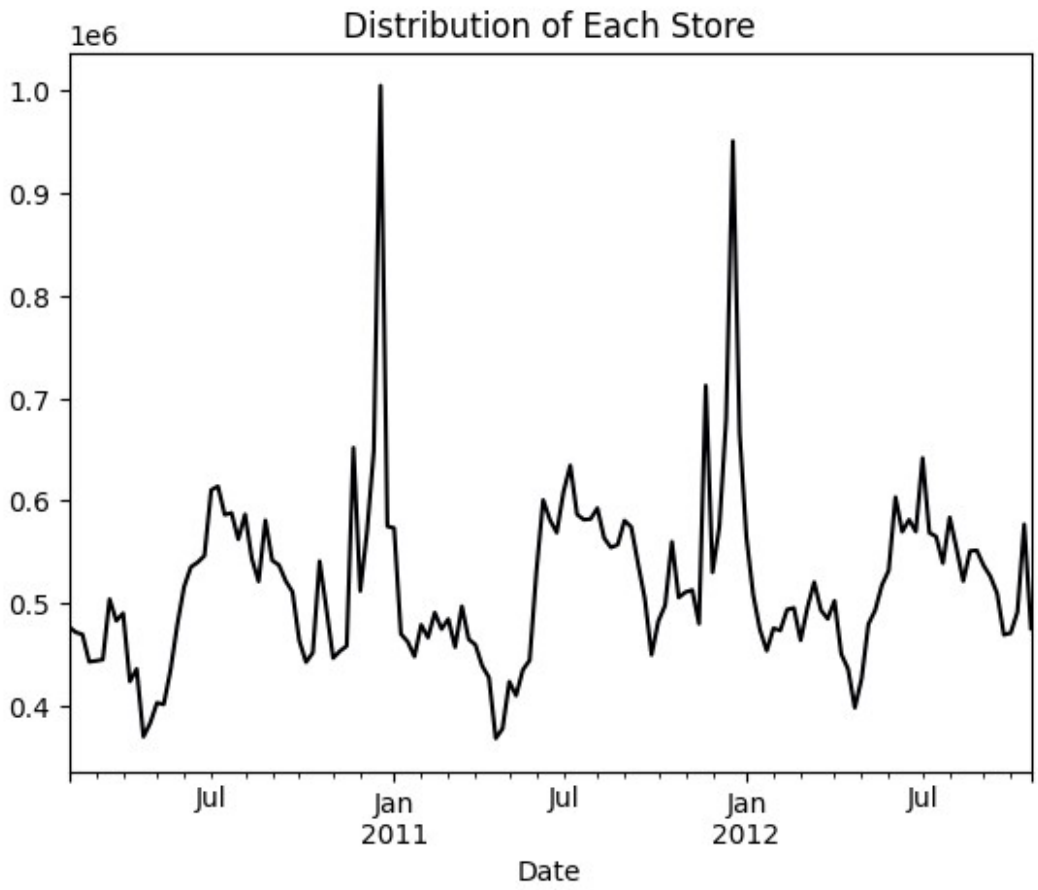
```
# Unique Stores and Weeks
print('Total Unique Stores:', df['Store'].nunique())
print('Total No of Weeks:', df['Date'].nunique())
```

```
Total Unique Stores: 45
Total No of Weeks: 143
```

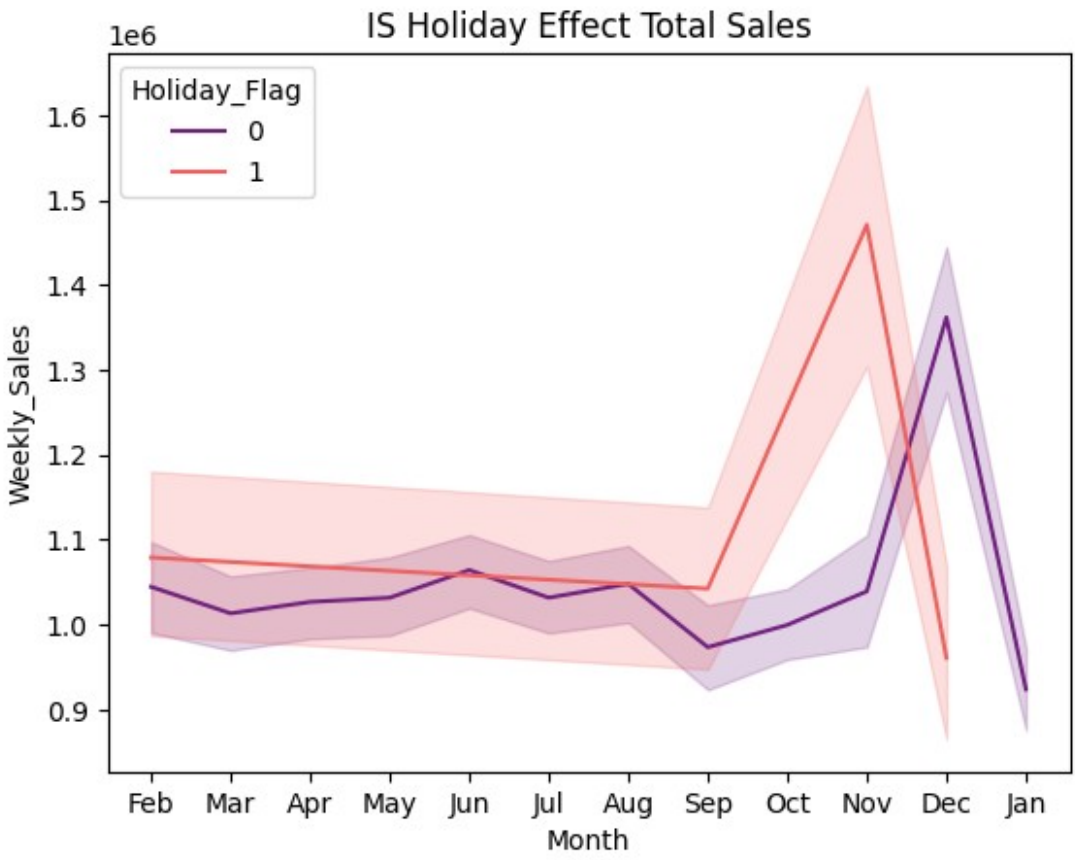
```
# Convert Date column to datetime
df['Date'] = pd.to_datetime(df['Date'], format='%d-%m-%Y')
# Extract Month and Year
df['Month'] = df['Date'].dt.strftime('%b')
df['Year'] = df['Date'].dt.year

#EDA
# Total Sales Across Months
sns.lineplot(x='Month', y='Weekly_Sales', data=df, hue='Year',
palette='magma')
plt.title("Total Sales Across Months")
plt.show()
```



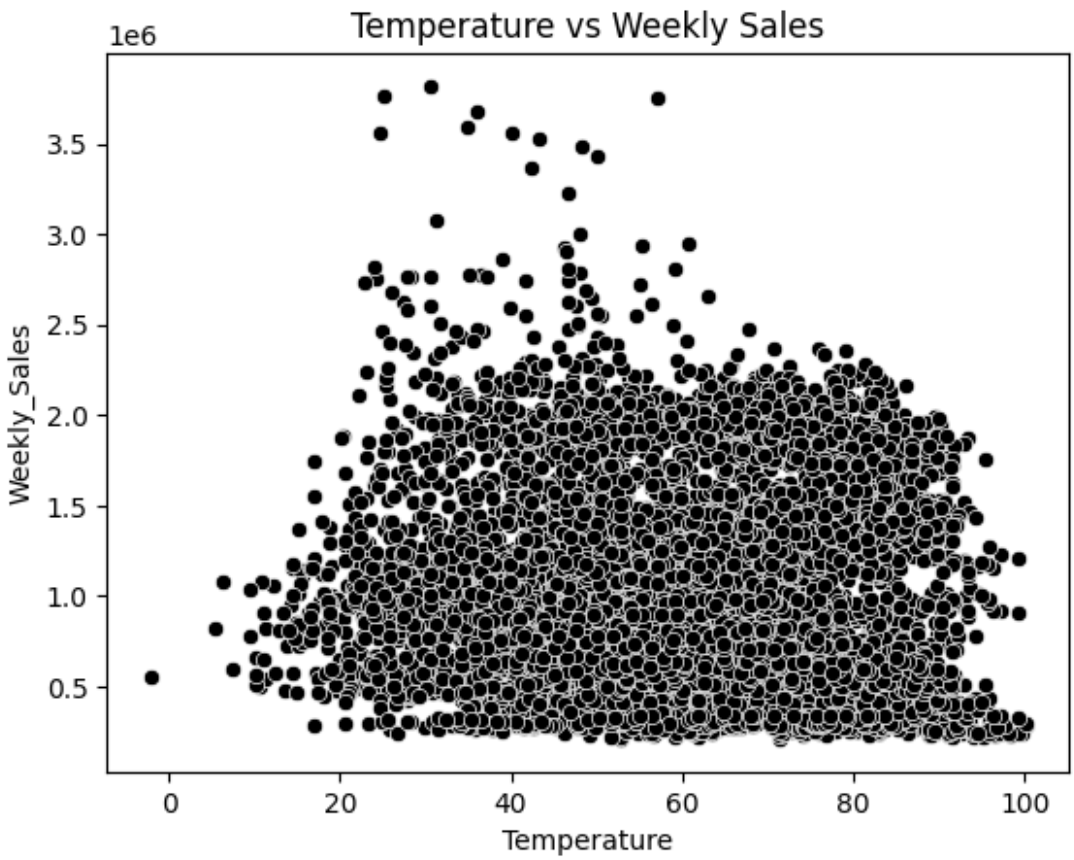

```
# Distribution of Each Store
sales_pivot = df.pivot(index='Date', columns='Store',
values='Weekly_Sales')
sales_pivot[16].plot(kind='line', cmap='magma')
plt.title('Distribution of Each Store')
plt.show()
```



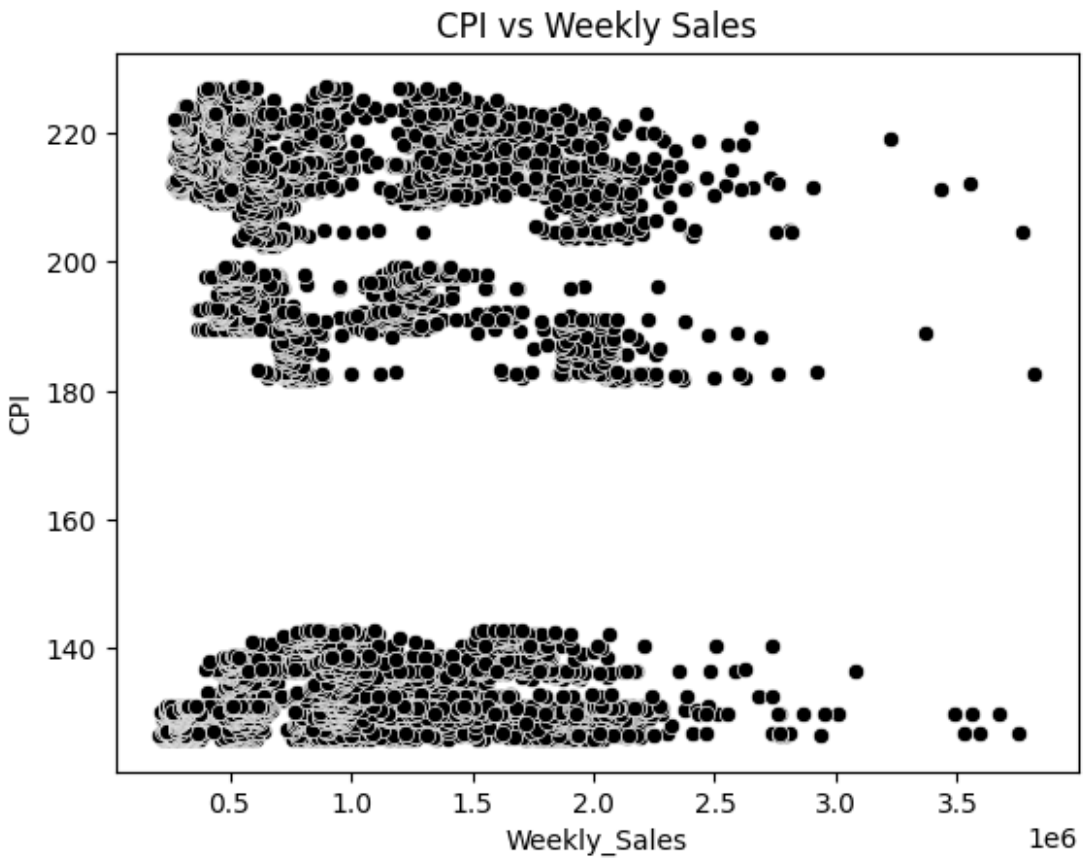

```
# IS Holiday Effect Total Sales
sns.lineplot(x='Month', y='Weekly_Sales', data=df, palette='magma',
hue='Holiday_Flag')
plt.title("IS Holiday Effect Total Sales")
plt.show()
```



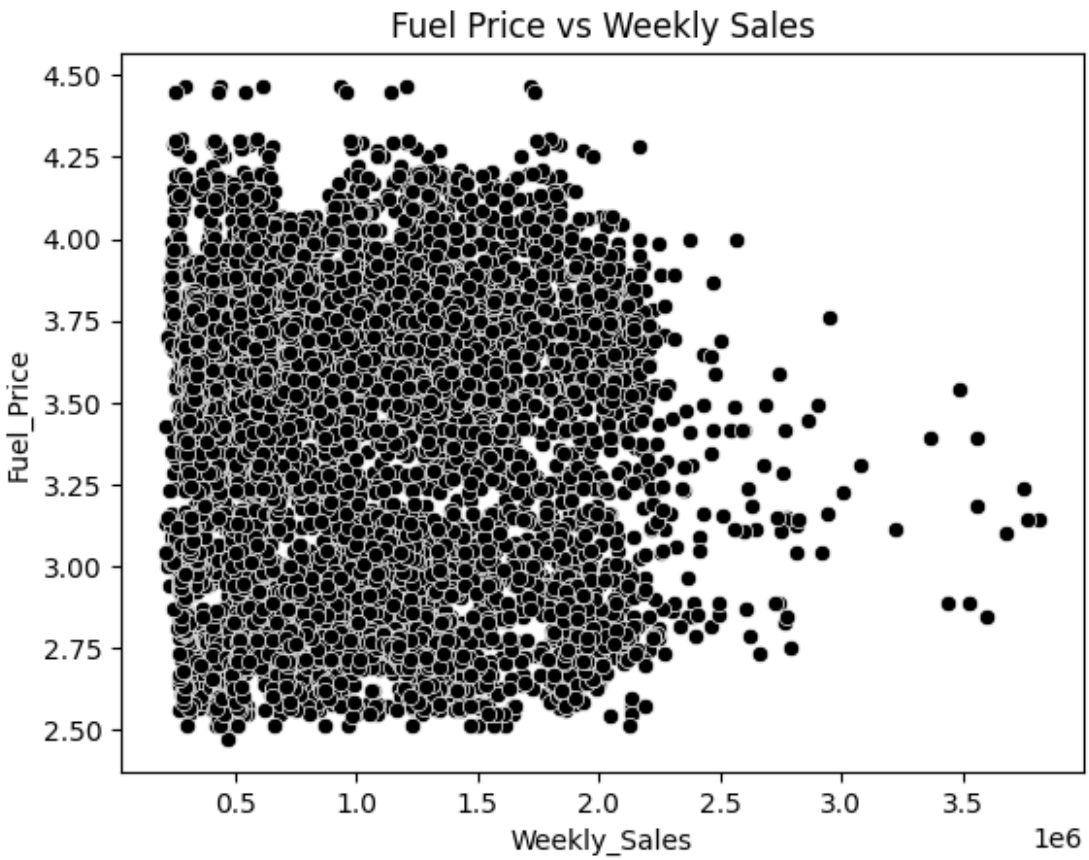

```
# Temperature vs Weekly Sales
sns.scatterplot(y="Weekly_Sales", x='Temperature', data=df,
color='black')
plt.title("Temperature vs Weekly Sales")
plt.show()
```




```
# CPI vs Weekly Sales
sns.scatterplot(y='CPI', x='Weekly_Sales', data=df, color='black')
plt.title("CPI vs Weekly Sales")
plt.show()
```

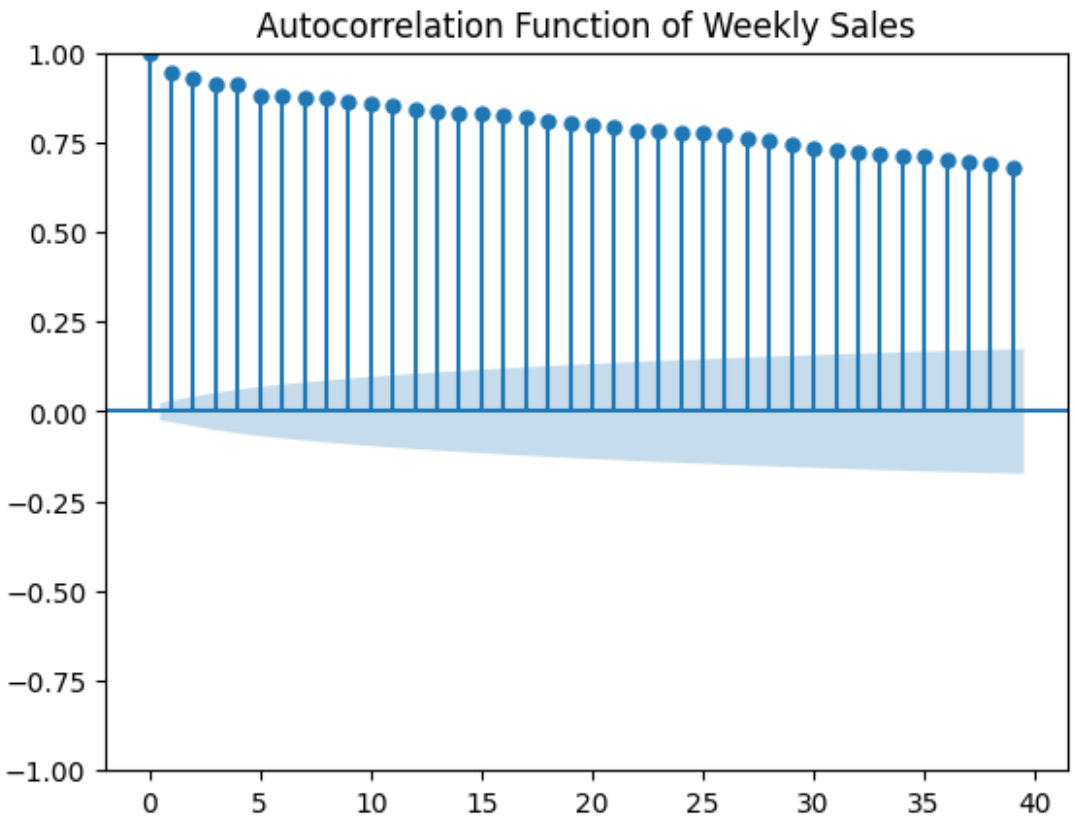



```
# Fuel Price vs Weekly Sales
sns.scatterplot(y='Fuel_Price', x='Weekly_Sales', data=df,
color='black')
plt.title("Fuel Price vs Weekly Sales")
plt.show()
```




```
'''
     Unemployment vs Weakly Sales
'''
sns.scatterplot(y='Unemployment',x='Weekly_Sales',data=df,color='black
')
plt.title(" Unemployment vs Weekly Sales ")
plt.show()
```


```
#Statatical analysis
from statsmodels.graphics.tsaplots import plot_acf
plot_acf(df['Weekly_Sales'])
plt.title("Autocorrelation Function of Weekly Sales")
plt.show()
```




```
# Stationarity Check: ADF Test
result = adfuller(df['Weekly_Sales'])
print('ADF Statistic:', result[0])
print('p-value:', result[1])
print('Critical Values:', result[4])
```

```
ADF Statistic: -4.624149498578303
p-value: 0.0001165586969990124
Critical Values: {'1%': -3.4313721757424656, '5%': -
2.8619917128968813, '10%': -2.5670104435791017}
```

```
# Time Series Forecasting using ARIMA
model = ARIMA(df['Weekly_Sales'], order=(5, 1, 0))
model_fit = model.fit()
print(model_fit.summary())
```

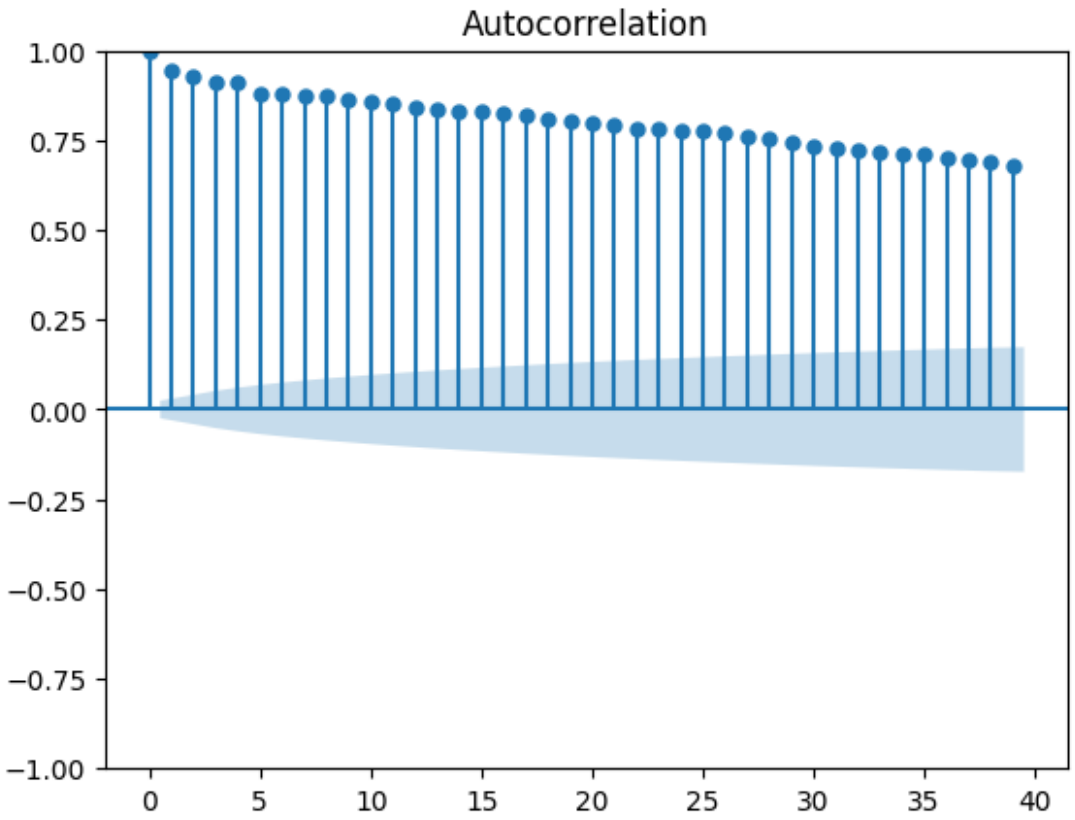
```
                               SARIMAX Results

==============================================================================
========
Dep. Variable:           Weekly_Sales   No. Observations:
6435
Model:                 ARIMA(5, 1, 0)   Log Likelihood                -
86374.457
Date:                Tue, 01 Oct 2024   AIC
```

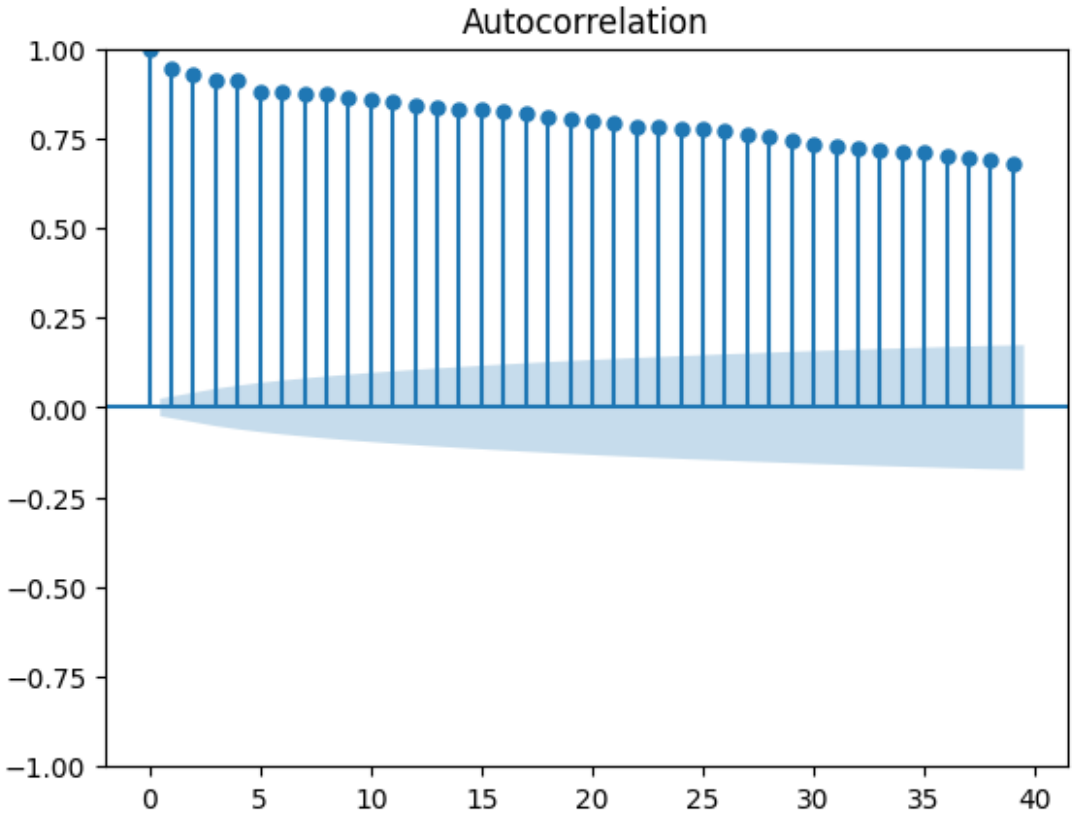
```
172760.914
Time:                        16:22:04   BIC
172801.530
Sample:                             0   HQIC
172774.969
                                - 6435

Covariance Type:                   opg

==============================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
--------
ar.L1         -0.3568      0.006    -61.474      0.000      -0.368
-0.345
ar.L2         -0.2148      0.007    -30.361      0.000      -0.229
-0.201
ar.L3         -0.1943      0.008    -25.386      0.000      -0.209
-0.179
ar.L4          0.1264      0.009     14.291      0.000       0.109
0.144
ar.L5         -0.1401      0.010    -14.591      0.000      -0.159
-0.121
sigma2      2.675e+10   9.21e-14    2.9e+23      0.000    2.67e+10
2.67e+10
==============================================================================
=============
Ljung-Box (L1) (Q):                   4.76   Jarque-Bera (JB):
108825.74
Prob(Q):                              0.03   Prob(JB):
0.00
Heteroskedasticity (H):               0.35   Skew:
-0.23
Prob(H) (two-sided):                  0.00   Kurtosis:
23.14
==============================================================================
=============

Warnings:
[1] Covariance matrix calculated using the outer product of gradients
(complex-step).
[2] Covariance matrix is singular or near-singular, with condition
number 2.76e+38. Standard errors may be unstable.


'''
Stationary Test:-
```

```
When the test statistic is lower than the critical value shown,
you reject the null hypothesis and infer that the time series is
stationary.
'''

result = adfuller(df['Weekly_Sales'])
print('ADF Statistic:', result[0])
print('p-value:', result[1])

for key, value in result[4].items():
    print('Critial Values:')
    print(f'   {key}, {value}')
```

```
ADF Statistic: -4.624149498578303
p-value: 0.0001165586969990124
Critial Values:
   1%, -3.4313721757424656
Critial Values:
   5%, -2.8619917128968813
Critial Values:
   10%, -2.5670104435791017
```

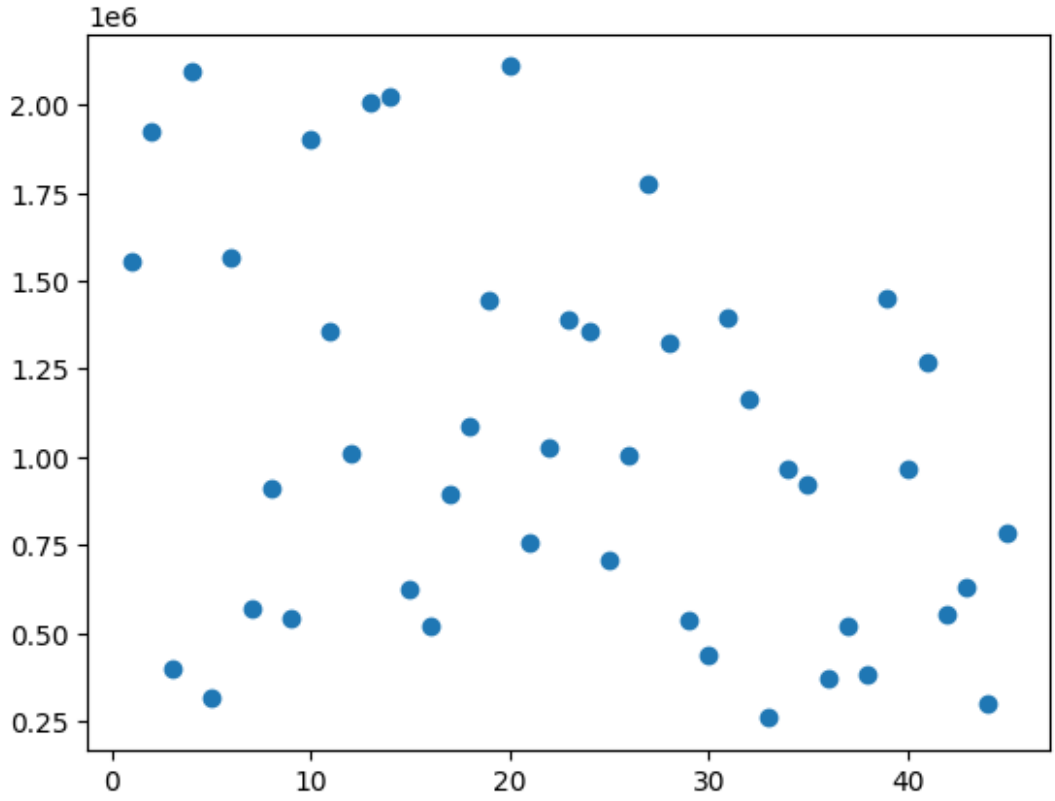
```
#Assuming 'df' is the time series data
plot_acf(df['Weekly_Sales'])
plot_acf(df['Weekly_Sales'])
plt.show()
```


Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30
35
40

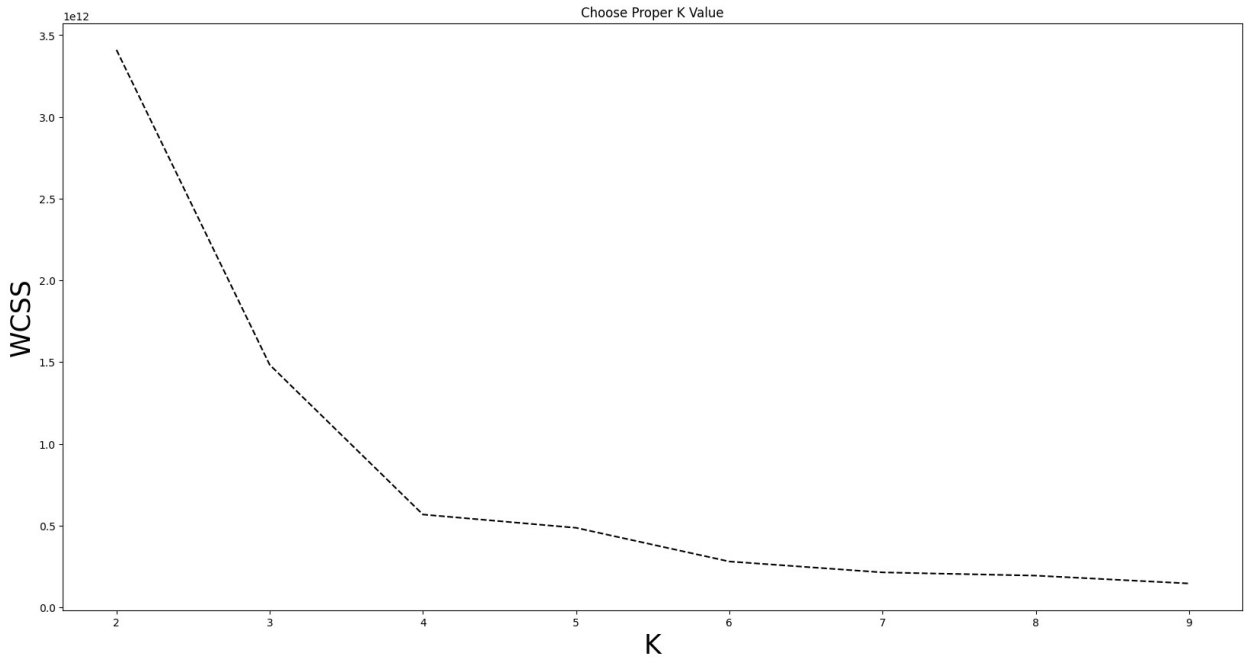

Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30
35
40

```
#Cluster Anlaysis
store_data=df.groupby('Store').agg({'Weekly_Sales':'mean'}).reset_inde
x()
plt.scatter(store_data['Store'],store_data['Weekly_Sales']
            )
```

```
<matplotlib.collections.PathCollection at 0x1a1e1facfe0>
```



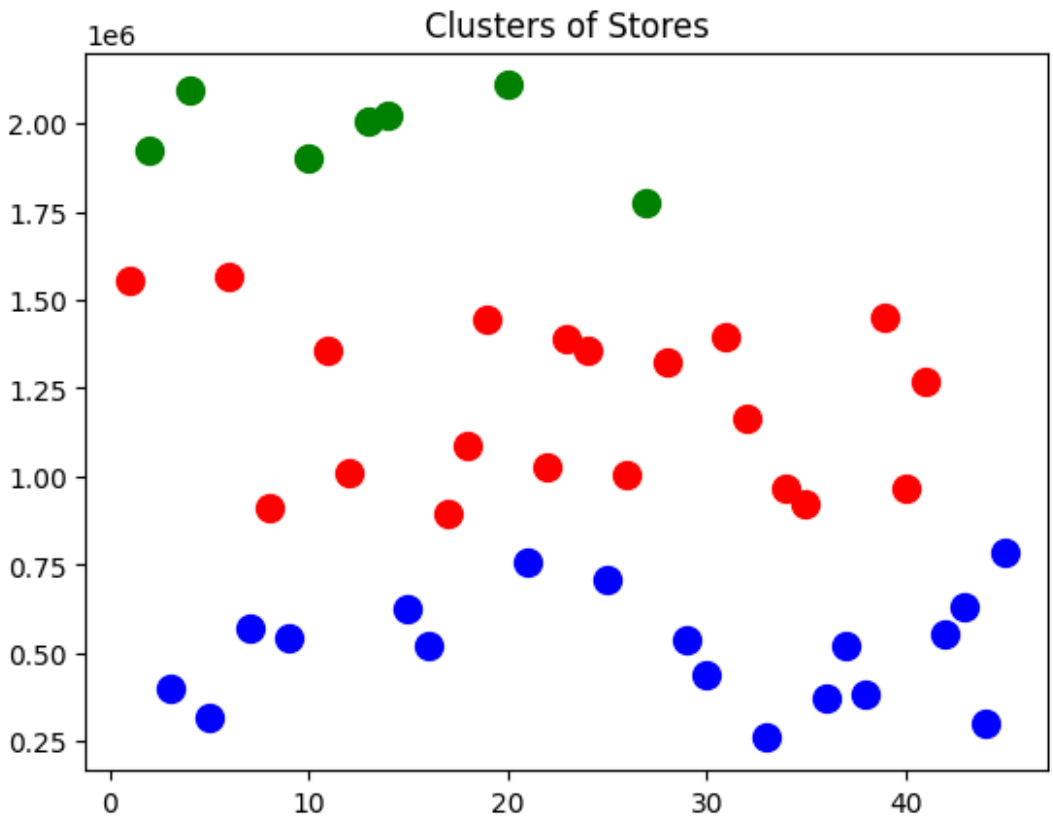

```
from sklearn.cluster import KMeans
X = store_data[['Weekly_Sales']]
wcss=[]
for i in range(2,10):
    model=KMeans(n_clusters=i,init='k-means++',max_iter=100)
    model.fit(X)
    wcss.append(model.inertia_)

plt.figure(figsize=(20,10))
plt.plot(list(range(2,10)),wcss,color='black',linestyle='--')
plt.xlabel('K',fontsize = 25)
plt.ylabel('WCSS',fontsize = 25)
plt.title("Choose Proper K Value")
plt.show()
```




```
model=KMeans(n_clusters=3,init='k-means++',max_iter=100)
model.fit(X)
y_kmeans=model.fit_predict(X)

from sklearn.metrics import silhouette_score
silhouette_score( X,y_kmeans)
```

```
0.6147007510833369
```

```
X=np.array(X)
store_data=np.array(store_data)
plt.scatter(store_data[y_kmeans==0, 0],X[y_kmeans==0, 0], s=100,
c='red', label ='Cluster 1')
plt.scatter(store_data[y_kmeans==1, 0],X[y_kmeans==1, 0] , s=100,
c='blue', label ='Cluster 2')
plt.scatter(store_data[y_kmeans==2, 0],X[y_kmeans==2, 0] , s=100,
c='green', label ='Cluster 3')


plt.title('Clusters of Stores')
plt.show()
```


Clusters of Stores
1e6
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0
10
20
30
40