```python
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
import seaborn as sns

import statsmodels.api as sm

import math

import datetime

import warnings
warnings.filterwarnings('ignore')

from math import sqrt

from scipy import stats

df = pd.read_csv("/content/WalmartDataSet.csv")

df.shape
```

```
(6435, 8)
```

```python
df.columns
```

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

```python
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
```

```python
# Change Store column to categorical type
df['Store'] = df.Store.astype('category')
```

```
# Change Holiday_Flag column to boolean type
df['Holiday_Flag'] = df['Holiday_Flag'].astype(bool)

# Change Date columns to datetime type
df["Date"] = pd.to_datetime(df["Date"])

df['Year'] =df['Date'].dt.year
df['Month'] =df['Date'].dt.month
df['Week'] =df['Date'].dt.week

df.head()

  Store       Date  Weekly_Sales  Holiday_Flag  Temperature
Fuel_Price  \
0     1 2010-05-02    1643690.90         False        42.31
2.572
1     1 2010-12-02    1641957.44          True        38.51
2.548
2     1 2010-02-19    1611968.17         False        39.93
2.514
3     1 2010-02-26    1409727.59         False        46.63
2.561
4     1 2010-05-03    1554806.68         False        46.50
2.625

          CPI  Unemployment  Year  Month  Week
0  211.096358         8.106  2010      5    17
1  211.242170         8.106  2010     12    48
2  211.289143         8.106  2010      2     7
3  211.319643         8.106  2010      2     8
4  211.350143         8.106  2010      5    18

df.tail()

     Store       Date  Weekly_Sales  Holiday_Flag  Temperature
Fuel_Price  \
6430    45 2012-09-28     713173.95         False        64.88
3.997
6431    45 2012-05-10     733455.07         False        64.89
3.985
6432    45 2012-12-10     734464.36         False        54.47
4.000
6433    45 2012-10-19     718125.53         False        56.47
3.969
6434    45 2012-10-26     760281.43         False        58.85
3.882

             CPI  Unemployment  Year  Month  Week
6430  192.013558         8.684  2012      9    39
6431  192.170412         8.667  2012      5    19
6432  192.327265         8.667  2012     12    50
```

```
6433  192.330854         8.667  2012     10    42
6434  192.308899         8.667  2012     10    43

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6435 entries, 0 to 6434
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Store         6435 non-null   category
 1   Date          6435 non-null   datetime64[ns]
 2   Weekly_Sales  6435 non-null   float64
 3   Holiday_Flag  6435 non-null   bool
 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
 8   Year          6435 non-null   int64
 9   Month         6435 non-null   int64
 10  Week          6435 non-null   int64
dtypes: bool(1), category(1), datetime64[ns](1), float64(5), int64(3)
memory usage: 466.6 KB

df.isnull().sum()

Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
Year            0
Month           0
Week            0
dtype: int64

df.isnull()

      Store   Date  Weekly_Sales  Holiday_Flag  Temperature
Fuel_Price  \
0     False  False         False         False        False
False
1     False  False         False         False        False
False
2     False  False         False         False        False
False
3     False  False         False         False        False
False
```

```
4     False  False         False         False        False
False
...     ...    ...           ...           ...          ...          ..
.
6430  False  False         False         False        False
False
6431  False  False         False         False        False
False
6432  False  False         False         False        False
False
6433  False  False         False         False        False
False
6434  False  False         False         False        False
False

        CPI  Unemployment   Year  Month   Week
0     False         False  False  False  False
1     False         False  False  False  False
2     False         False  False  False  False
3     False         False  False  False  False
4     False         False  False  False  False
...     ...           ...    ...    ...    ...
6430  False         False  False  False  False
6431  False         False  False  False  False
6432  False         False  False  False  False
6433  False         False  False  False  False
6434  False         False  False  False  False

[6435 rows x 11 columns]
```

```
# Exclude datetime column(s) from mean imputation
mean_imputation_cols = df.columns.drop(['Date'])

# Fill missing values with mean imputation
df.fillna(df.mean(), inplace=True)

# Check the number of missing values in each column
df.isnull().sum()
```

```
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
Year            0
Month           0
```

```
Week            0
dtype: int64
```

```
# Check for duplicate rows
df.duplicated().sum()  # Count the number of duplicate rows
```

```
0
```

```
# Remove duplicate rows
df.drop_duplicates(inplace=True)

# Check for duplicate columns
df.columns.duplicated().sum()  # Count the number of duplicate columns
```

```
0
```

```
# Remove duplicate columns, if any
df = df.loc[:, ~df.columns.duplicated()]

Q1 = df['Weekly_Sales'].quantile(0.25)
Q3 = df['Weekly_Sales'].quantile(0.75)
IQR = Q3 - Q1
outlier_threshold = 1.5 * IQR

df = df[(df['Weekly_Sales'] >= Q1 - outlier_threshold) &
(df['Weekly_Sales'] <= Q3 + outlier_threshold)]
```

EDA

```
df.describe()
```

```
       Weekly_Sales  Temperature   Fuel_Price          CPI
Unemployment  \
count  6.401000e+03  6401.000000  6401.000000  6401.000000
6401.000000
mean   1.036130e+06    60.772042     3.359634   171.642219
8.002298
std    5.451961e+05    18.417068     0.459696    39.359852
1.878705
min    2.099862e+05    -2.060000     2.472000   126.064000
3.879000
25%    5.517431e+05    47.660000     2.933000   131.784000
6.891000
50%    9.572983e+05    62.860000     3.452000   182.658578
7.874000
75%    1.414565e+06    75.000000     3.737000   212.833640
8.622000
max    2.685352e+06   100.140000     4.468000   227.232807
14.313000
```

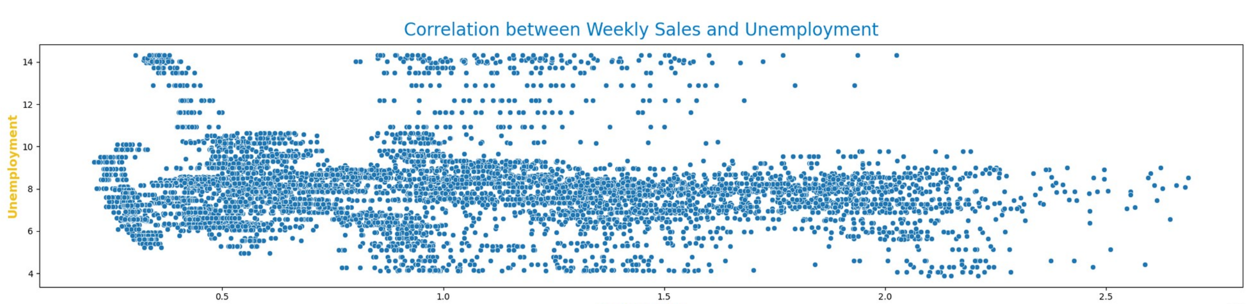
```
              Year        Month         Week
count  6401.000000  6401.000000  6401.000000
mean   2010.967974     6.447899    25.875644
std       0.797304     3.308627    14.448448
min    2010.000000     1.000000     1.000000
25%    2010.000000     4.000000    14.000000
50%    2011.000000     6.000000    26.000000
75%    2012.000000     9.000000    38.000000
max    2012.000000    12.000000    52.000000
```

Min Date & Max Date

```
print('Min Date in Data is - {}'.format(df['Date'].min()))
print('Max Date in Data is - {}'.format(df['Date'].max()))
```

```
Min Date in Data is - 2010-01-10 00:00:00
Max Date in Data is - 2012-12-10 00:00:00
```

```
# Scatter plot to explore the relationship between weekly sales and
unemployment rate
plt.figure(figsize=(20, 5))
sns.scatterplot(x='Weekly_Sales', y='Unemployment', data=df)

# Set the title
plt.title('Correlation between Weekly Sales and Unemployment',
color='#007DC6', fontsize=20, pad=10)

# Set the x and y axis labels
plt.xlabel('Weekly Sales', color='#F1C21B',  fontweight='bold',
fontsize=14)
plt.ylabel('Unemployment', color='#F1C21B',  fontweight='bold',
fontsize=14)

# Adjust plot layout
plt.tight_layout()

# Display the plot
plt.show()
```



```python
# Calculate the correlation coefficient between weekly sales and unemployment rate
correlation_coefficient = df['Weekly_Sales'].corr(df['Unemployment'])
print("Correlation Coefficient Between Weekly Sales and Unemployment Rate:", correlation_coefficient)
```

```
Correlation Coefficient Between Weekly Sales and Unemployment Rate: -0.10429750912578388
```

```python
# Calculate the correlation between each store's weekly sales and unemployment rate
store_correlation = df.groupby('Store')['Weekly_Sales', 'Unemployment'].corr().unstack()

# Find stores with the highest negative correlation
stores_with_highest_negative_correlation = store_correlation['Weekly_Sales']['Unemployment'].idxmin()

print("Stores with the Highest Negative Correlation with Unemployment Rate:", stores_with_highest_negative_correlation)
```

```
Stores with the Highest Negative Correlation with Unemployment Rate:
38
```

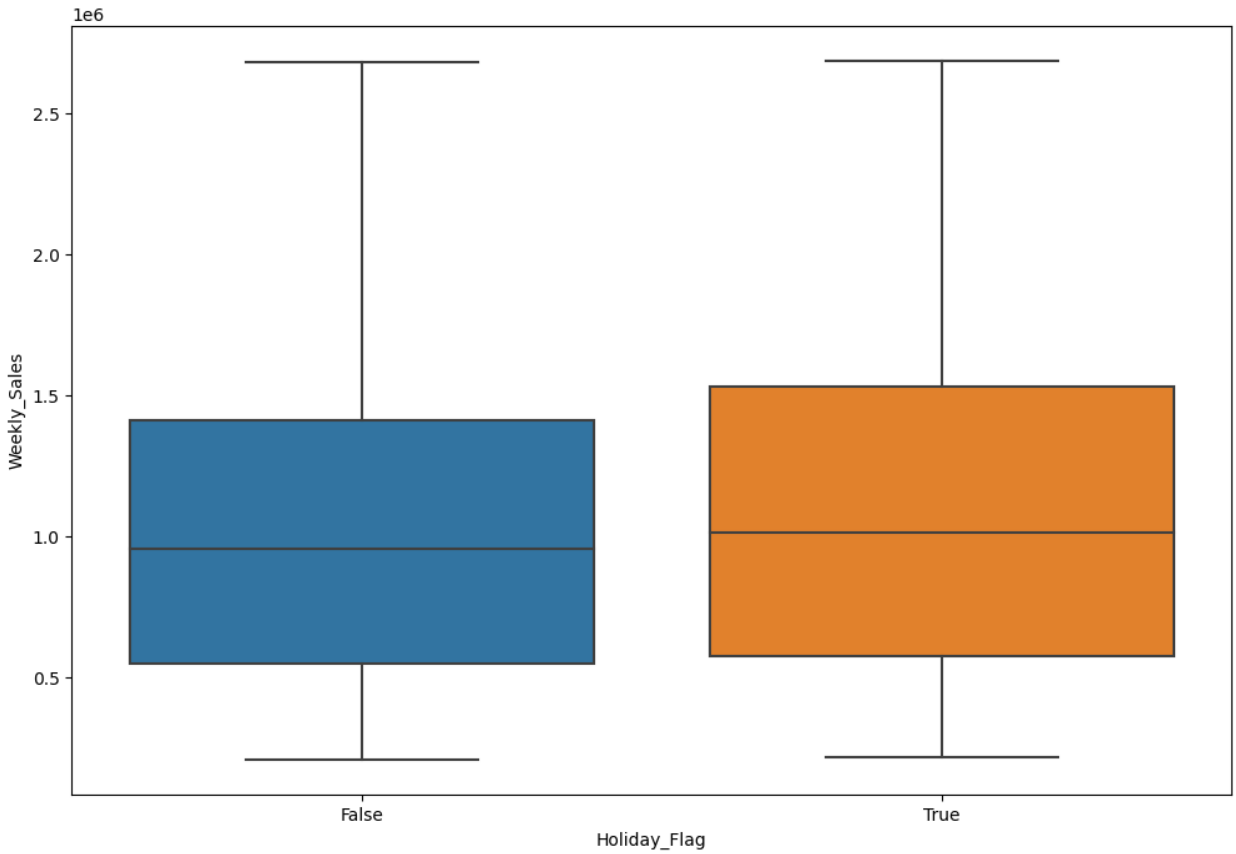
```python
# Find the top N number of stores with the highest negative correlation
n = 10  # specify the number of stores to display, you can modify this value

print("Top", n, "Stores with the Highest Negative Correlation with Unemployment Rate:")

print()

top_negative_corr_stores = store_correlation['Weekly_Sales']['Unemployment'].sort_values().head(n)

# Create a dataframe
top_negative_corr_stores_df = pd.DataFrame({'Store': top_negative_corr_stores.index, 'Negative_Correlation': top_negative_corr_stores.values})

# Set the index to start from 1
top_negative_corr_stores_df.index = top_negative_corr_stores_df.index + 1

print(top_negative_corr_stores_df.to_string(index=False))
```

```
Top 10 Stores with the Highest Negative Correlation with Unemployment Rate:
```

Store	Negative_Correlation
38	-0.785290
44	-0.780076
4	-0.639563
13	-0.400254
39	-0.384681
42	-0.356355
41	-0.350630
17	-0.263600
3	-0.230413
37	-0.221287

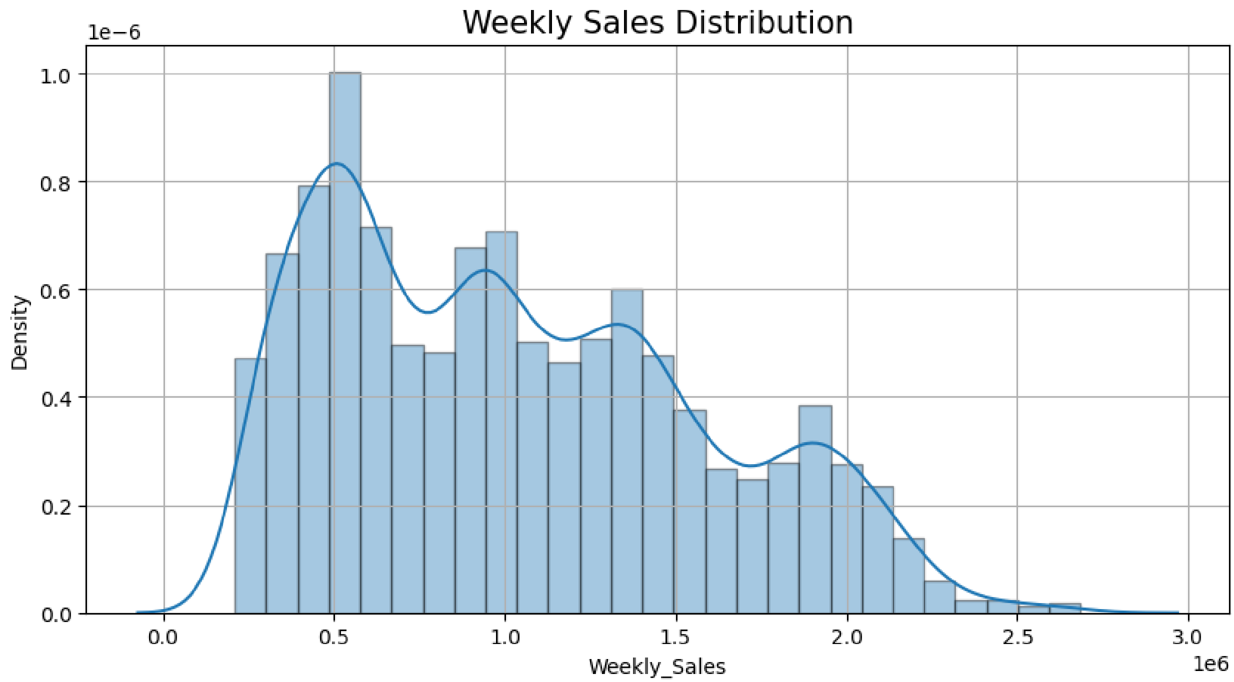
How Holidays affect the sales of each store.

```
# impact of holidays on weekly sales
plt.figure(figsize = (12,8))
sns.boxplot(x = 'Holiday_Flag', y ='Weekly_Sales', data = df,
showfliers = False)

# Mapping 0 to False and 1 to True in x-axis labels
plt.xticks([0, 1], ['False', 'True'])

plt.show()
```



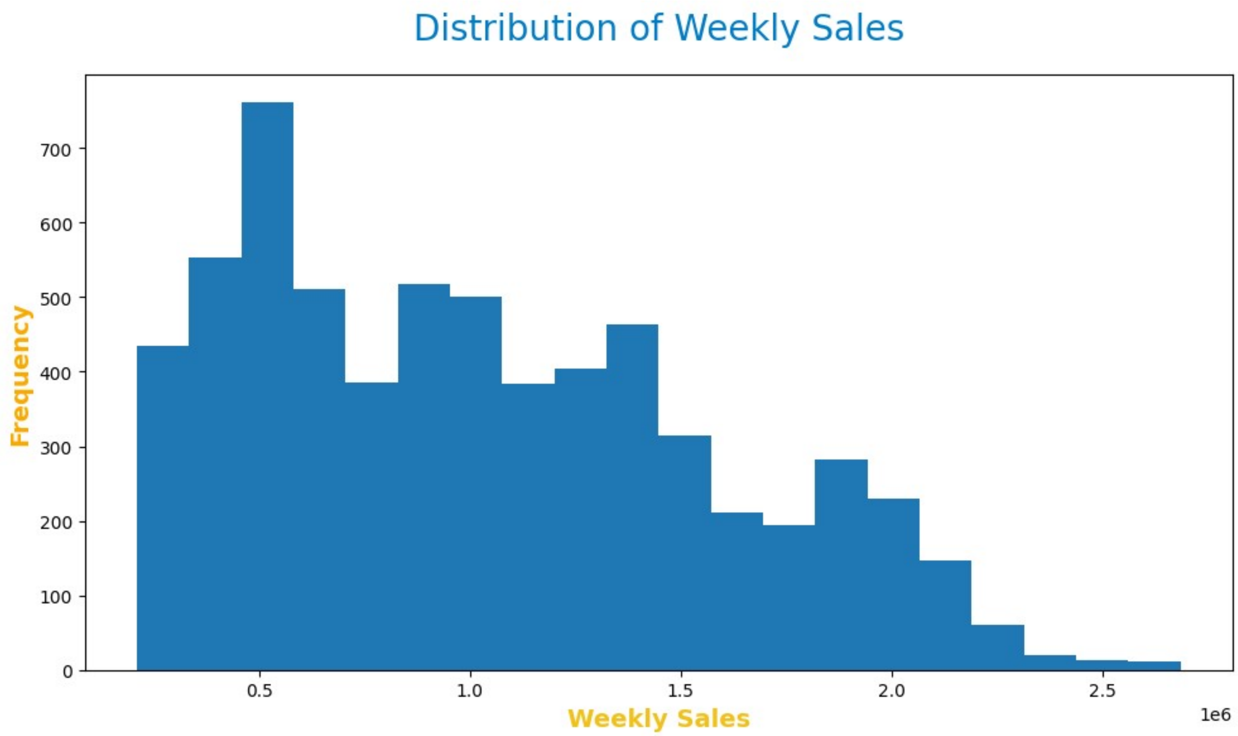
Data Visualization

```
# Analyzing the distribution of target variable
plt.figure(figsize = (10, 5))
sns.distplot(df['Weekly_Sales'], hist_kws=dict(edgecolor="black"))
plt.title('Weekly Sales Distribution', fontsize= 15)
plt.grid()
plt.show()
```



Histogram of Weekly Sales

```
# Set the size of the graph
plt.figure(figsize=(10, 6))

# Plot a histogram of the 'Weekly_Sales' column from the DataFrame
plt.hist(df['Weekly_Sales'], bins=20)

# Set the x and y labels with specified colors, font weight, and font
size
plt.xlabel('Weekly Sales', color='#F1C21B', fontweight='bold',
fontsize=14)
plt.ylabel('Frequency', color='#F9AB00', fontweight='bold',
fontsize=14)

# Set the title with specified color, font style, font size, and
padding
plt.title('Distribution of Weekly Sales', color='#007DC6',
fontsize=20, pad=20)

# Adjust plot appearance and layout
plt.tight_layout()

# Display the plot
plt.show()
```




```
df.groupby('Month')['Weekly_Sales'].mean()

Month
1     9.476139e+05
2     1.054597e+06
3     1.024975e+06
4     1.024324e+06
5     1.035379e+06
6     1.064848e+06
7     1.014212e+06
8     1.044874e+06
9     1.009457e+06
10    1.027683e+06
11    1.093977e+06
12    1.110051e+06
Name: Weekly_Sales, dtype: float64

df.groupby('Year')['Weekly_Sales'].mean()

Year
2010    1.040919e+06
2011    1.033780e+06
2012    1.033660e+06
Name: Weekly_Sales, dtype: float64

df['Holiday_Flag'].value_counts()
```

```
False    5960
True      441
Name: Holiday_Flag, dtype: int64
```

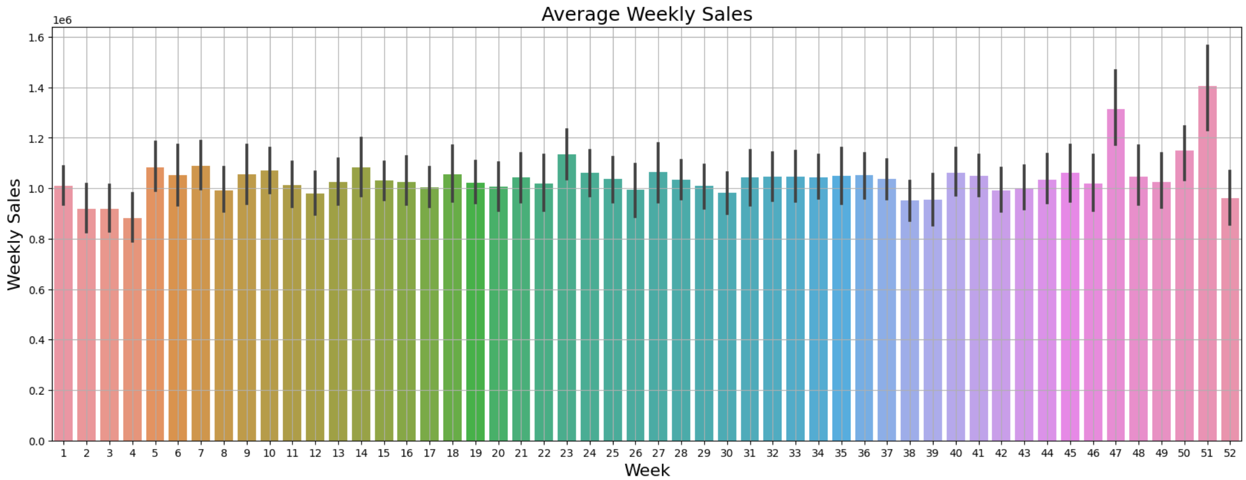
Relation between a categorized feature and the Weekly_Sales

```
def graph_relation_to_weekly_sale(col_relation, df, x='Week',
palette=None):
    cmap = sns.diverging_palette(220, 20, as_cmap=True)

    sns.relplot(
        x=x,
        y='Weekly_Sales',
        hue=col_relation,
        data=df,
        kind='line',
        height=5,
        aspect=2,
        palette=palette
    )
    plt.show()

graph_relation_to_weekly_sale('Year', df, x='Date', palette='Set2')
```

Average Weekly Sales

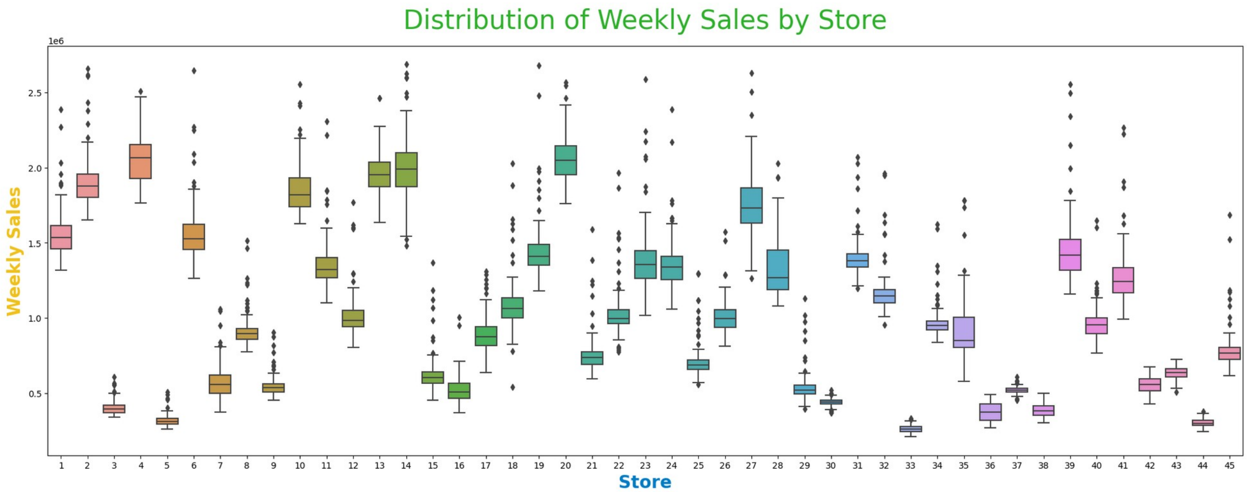
```
plt.figure(figsize=(20, 7))
sns.barplot(x='Week', y='Weekly_Sales', data=df)
plt.title('Average Weekly Sales', fontsize=18)
plt.ylabel('Weekly Sales', fontsize=16)
plt.xlabel('Week', fontsize=16)
```

```
plt.grid()
plt.show()
```



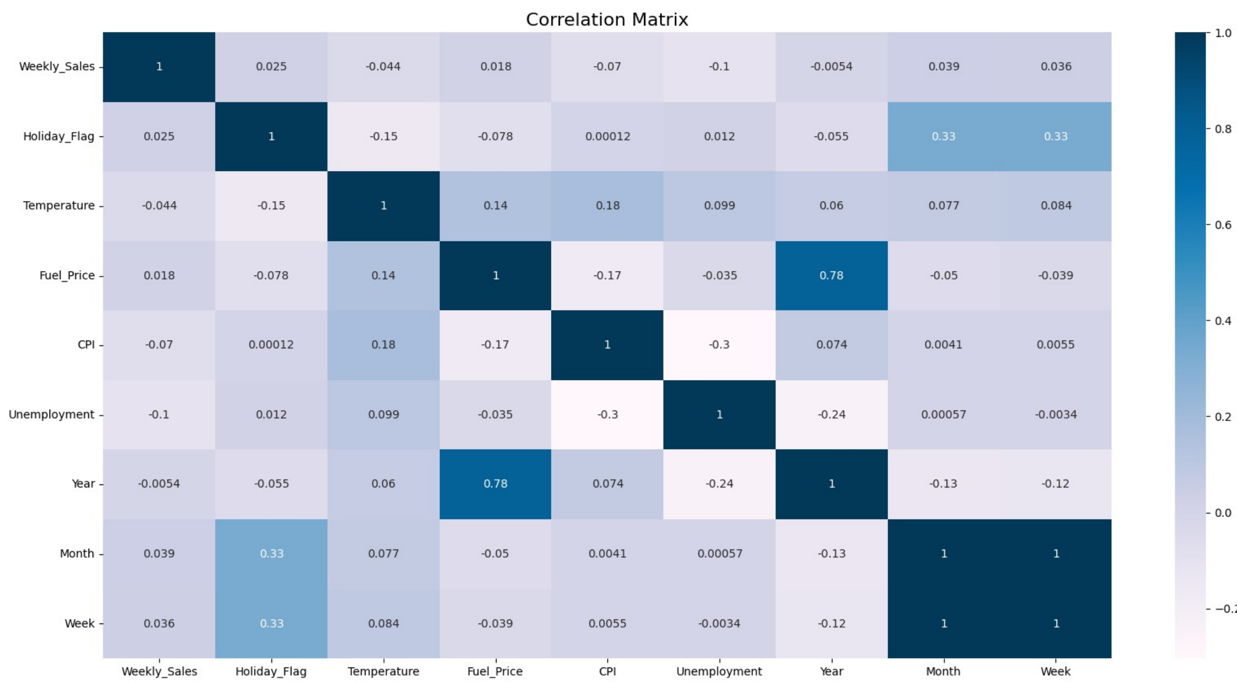
Box plot of Weekly Sales by Store

```
plt.figure(figsize=(20, 8))

# Plot the boxplot
sns.boxplot(x='Store', y='Weekly_Sales', data=df)

# Set the x and y labels with Walmart font colors
plt.xlabel('Store', color='#007DC6', fontweight='bold', fontsize=20)
plt.ylabel('Weekly Sales', color='#F1C21B', fontweight='bold',
fontsize=20)

# Set the title with Walmart font colors
plt.title('Distribution of Weekly Sales by Store', color='#2FB12C',
fontsize=30, pad=20)

# Set the font size for x-axis labels
plt.xticks(fontsize=10)

# Adjust plot layout
plt.tight_layout()

# Display the plot
plt.show()
```



Heatmap

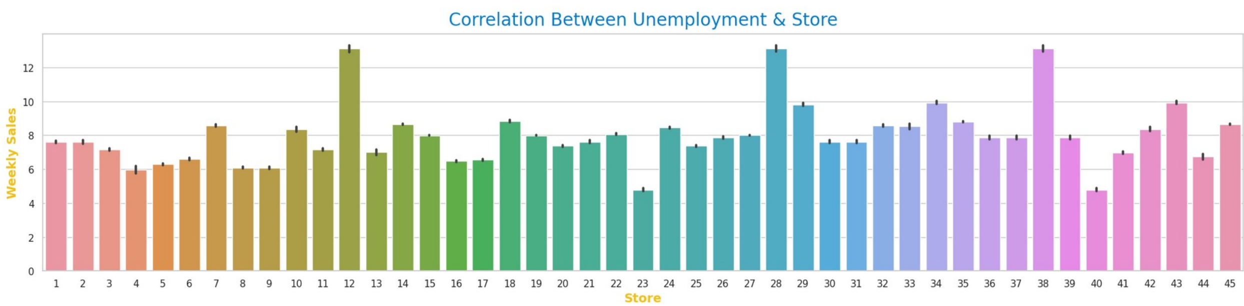
```python
plt.figure(figsize=(20, 10))
sns.heatmap(df.corr(), cmap='PuBu', annot=True)
plt.title('Correlation Matrix',fontsize=16)
plt.show()
```



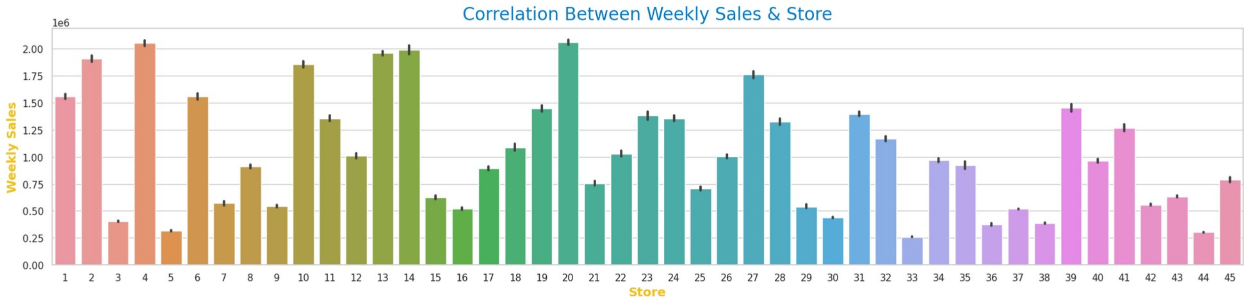
Correlation Graph

```python
# Correlation between Unemployment & Store
plt.figure(figsize=(20, 5))
sns.set_theme(style="whitegrid")
```

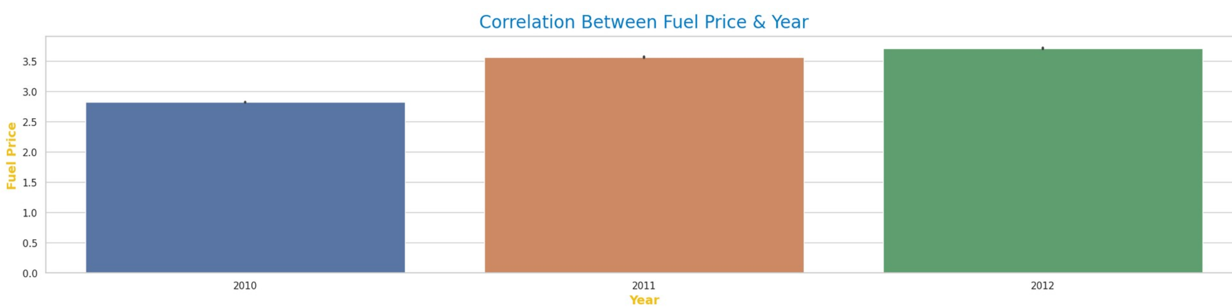
```
ax = sns.barplot(x='Store', y="Unemployment", data=df)

# Set the title
plt.title('Correlation Between Unemployment & Store', color='#007DC6',
fontsize=20, pad=10)

# Set the x and y axis labels
plt.xlabel('Store', color='#F1C21B',  fontweight='bold', fontsize=14)
plt.ylabel('Weekly Sales', color='#F1C21B',  fontweight='bold',
fontsize=14)

# Adjust plot layout
plt.tight_layout()

# Display the plot
plt.show()
```




```
# Correlation between Weekly Sales & Store
plt.figure(figsize=(20, 5))
sns.set_theme(style="whitegrid")
ax = sns.barplot(x='Store', y="Weekly_Sales", data=df)

# Set the title
plt.title('Correlation Between Weekly Sales & Store', color='#007DC6',
fontsize=20, pad=10)

# Set the x and y axis labels
plt.xlabel('Store', color='#F1C21B',  fontweight='bold', fontsize=14)
plt.ylabel('Weekly Sales', color='#F1C21B',  fontweight='bold',
fontsize=14)

# Adjust plot layout
plt.tight_layout()

# Display the plot
plt.show()
```



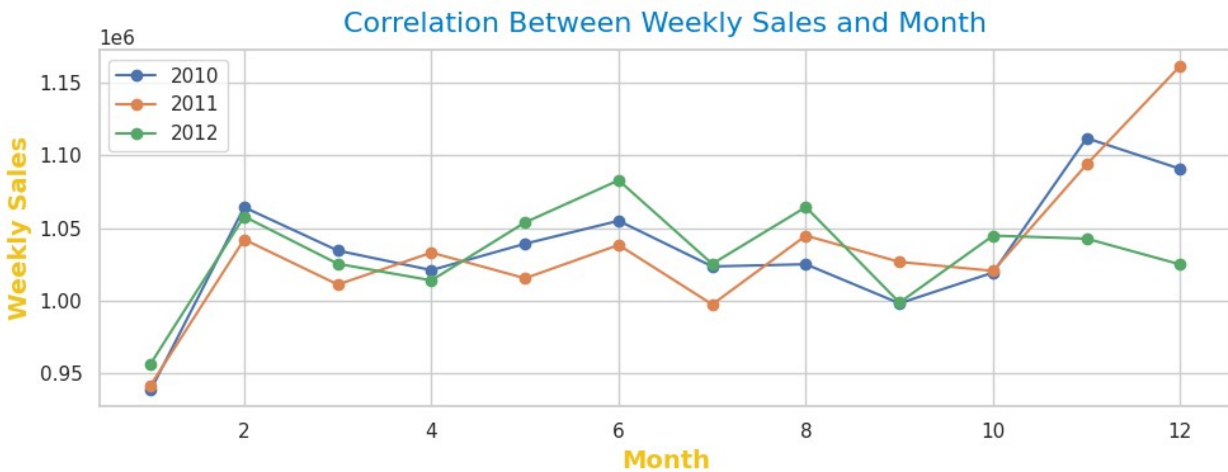

```
# Correlation b/w Fuel_Price & Year
plt.figure(figsize=(20, 5))
sns.set_theme(style="whitegrid")
ax = sns.barplot(x="Year", y="Fuel_Price", data=df)
sns.set(rc = {'figure.figsize': (10,4)})

# Set the title
plt.title('Correlation Between Fuel Price & Year', color='#007DC6',
fontsize=20, pad=10)

# Set the x and y axis labels
plt.xlabel('Year', color='#F1C21B',  fontweight='bold', fontsize=14)
plt.ylabel('Fuel Price', color='#F1C21B',
fontweight='bold',fontsize=14)

# Adjust plot layout
plt.tight_layout()

# Display the plot
plt.show()
```




```
# Correlation between Weekly Sales & Month
plt.figure(figsize=(20, 5))
sns.set_theme(style="whitegrid")
month_wise_sales = df.pivot_table(values="Weekly_Sales",
columns="Year", index="Month")
month_wise_sales.plot(marker='o')

# Set the title with Walmart font colors
plt.title('Correlation Between Weekly Sales and Month',
```

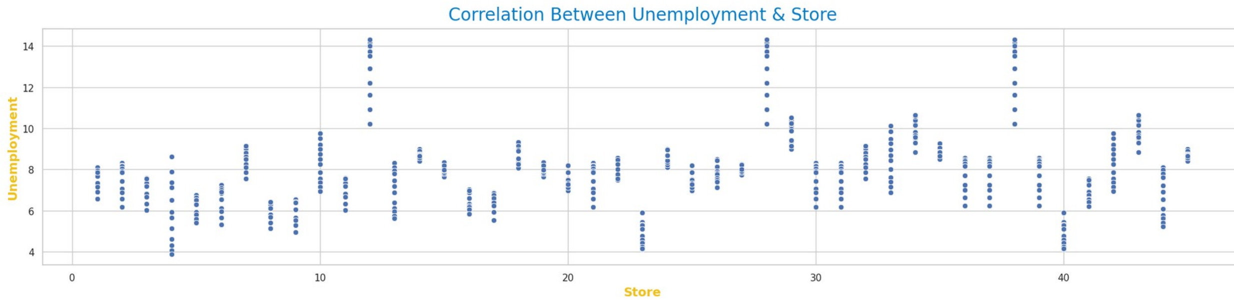
```
color='#007DC6', fontsize=16, pad=10)

# Set the x and y labels with Walmart font colors
plt.xlabel('Month', color='#F1C21B',  fontweight='bold', fontsize=14)
plt.ylabel('Weekly Sales', color='#F1C21B',  fontweight='bold',
fontsize=14)

# Adjust plot layout
plt.legend(loc='upper left')
plt.tight_layout()

# Display the plot
plt.show()
```

```
<Figure size 2000x500 with 0 Axes>
```

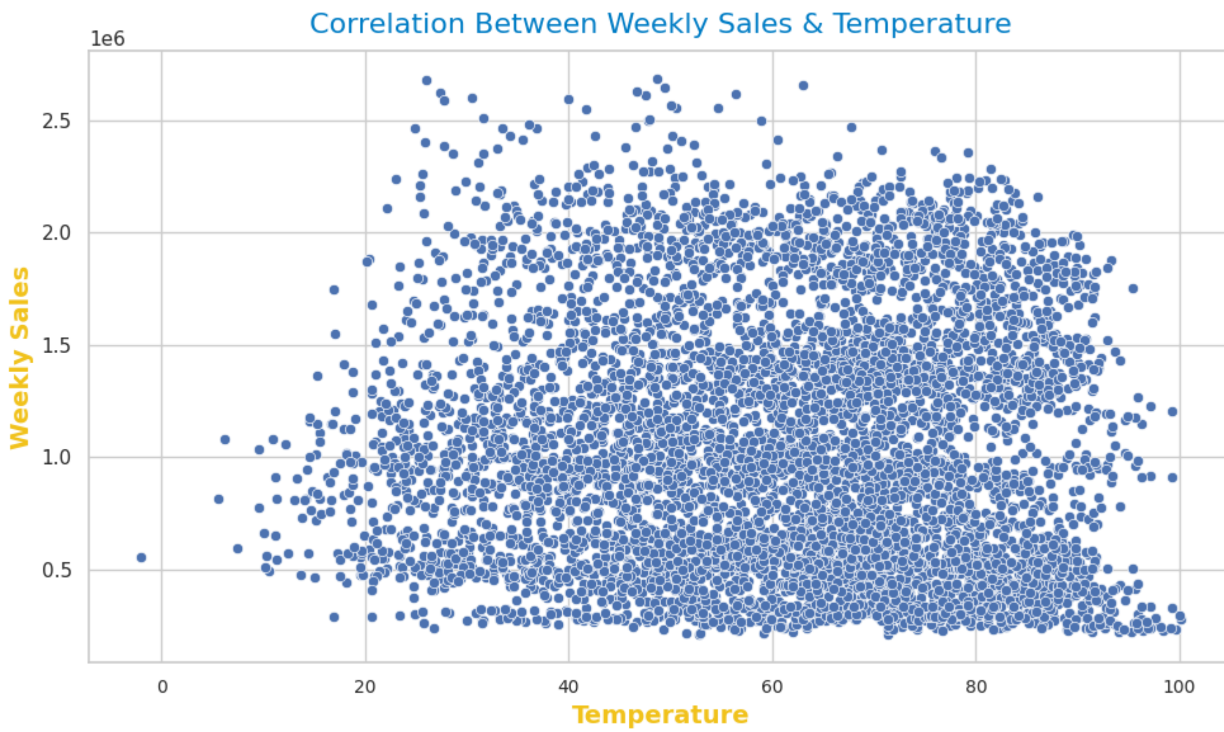



```
# Correlation between Unemployment & Store
plt.figure(figsize=(20, 5))
sns.set_theme(style="whitegrid")

# Draw Scatterplot
sns.scatterplot(x="Store", y="Unemployment", data=df)

# Set the title
plt.title('Correlation Between Unemployment & Store', color='#007DC6',
fontsize=20, pad=10)

# Set the x and y axis labels
plt.xlabel('Store', color='#F1C21B',  fontweight='bold', fontsize=14)
plt.ylabel('Unemployment', color='#F1C21B',  fontweight='bold',
fontsize=14)

# Adjust plot layout
plt.tight_layout()
```

```
# Display the plot
plt.show()
```




```
# Scatter plot of Weekly Sales vs. Temperature
plt.figure(figsize=(10, 6))

# Plot the scatter plot
sns.scatterplot(x="Temperature", y="Weekly_Sales", data=df)

# Set the title with Walmart font colors
plt.title('Correlation Between Weekly Sales & Temperature',
color='#007DC6', fontsize=16, pad=10)

# Set the x and y labels with Walmart font colors
plt.xlabel('Temperature', color='#F1C21B',  fontweight='bold',
fontsize=14)
plt.ylabel('Weekly Sales', color='#F1C21B',  fontweight='bold',
fontsize=14)

# Set the font size for x-axis labels
plt.xticks(fontsize=10)

# Adjust plot layout
plt.tight_layout()

# Display the plot
plt.show()
```



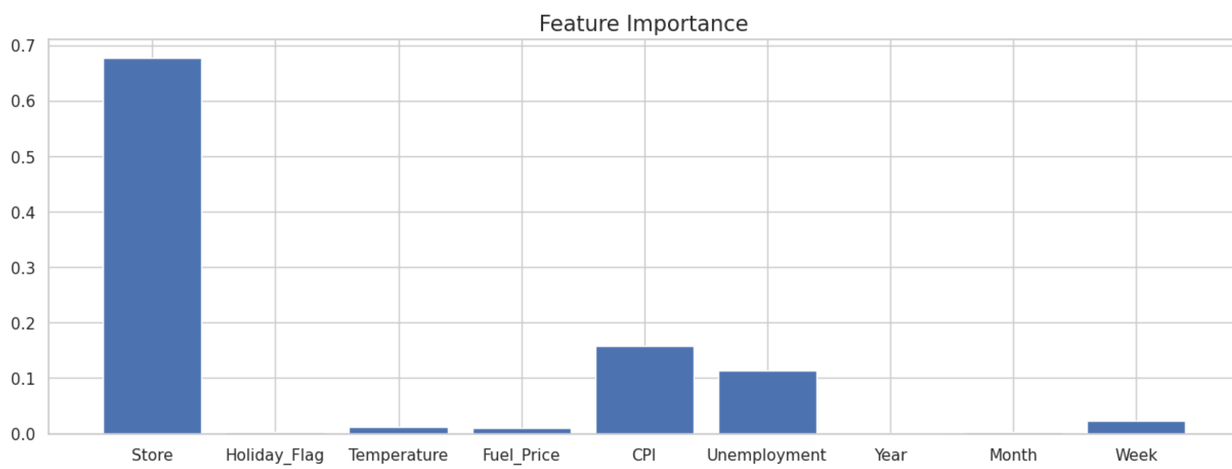

```
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf

from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor

from xgboost import XGBRegressor

from sklearn import tree
from sklearn.preprocessing import OneHotEncoder

from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.model_selection import train_test_split

from sklearn.metrics import *
from sklearn import metrics
```

```
df.columns
```

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

```
x = df.drop(['Date','Weekly_Sales'], axis=1)

x

      Store  Holiday_Flag  Temperature  Fuel_Price         CPI
Unemployment  \
0         1         False        42.31       2.572  211.096358
8.106
1         1          True        38.51       2.548  211.242170
8.106
2         1         False        39.93       2.514  211.289143
8.106
3         1         False        46.63       2.561  211.319643
8.106
4         1         False        46.50       2.625  211.350143
8.106
...     ...           ...          ...         ...         ...
...
6430     45         False        64.88       3.997  192.013558
8.684
6431     45         False        64.89       3.985  192.170412
8.667
6432     45         False        54.47       4.000  192.327265
8.667
6433     45         False        56.47       3.969  192.330854
8.667
6434     45         False        58.85       3.882  192.308899
8.667

      Year  Month  Week
0     2010      5    17
1     2010     12    48
2     2010      2     7
3     2010      2     8
4     2010      5    18
...    ...    ...   ...
6430  2012      9    39
6431  2012      5    19
6432  2012     12    50
6433  2012     10    42
6434  2012     10    43

[6401 rows x 9 columns]

x.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 6401 entries, 0 to 6434
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
```

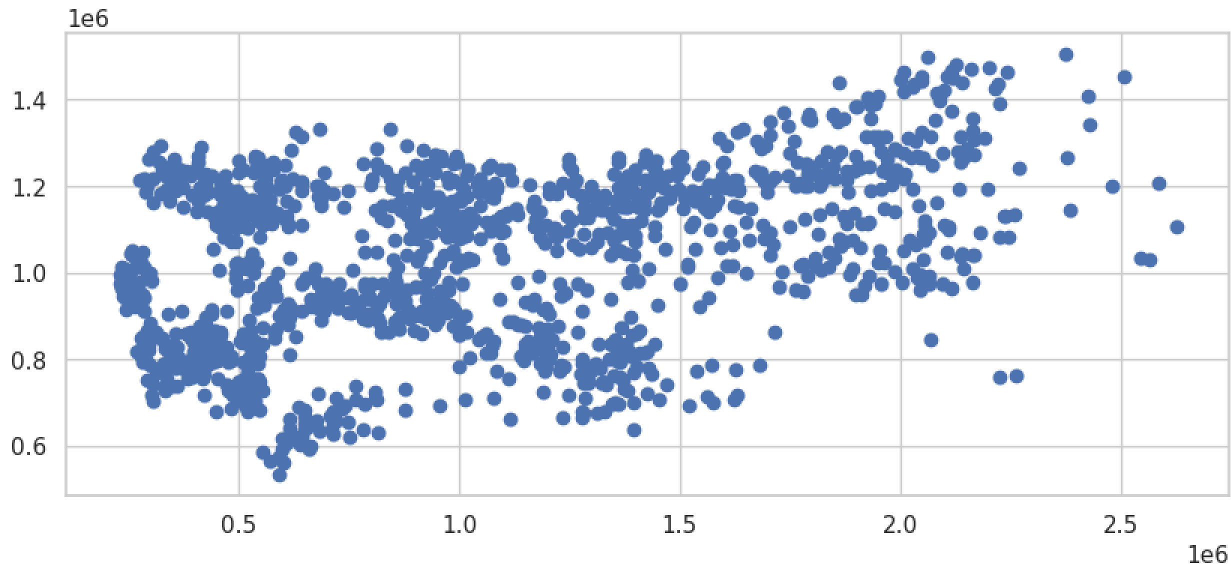
```
---  ------        --------------  -----
 0   Store         6401 non-null   category
 1   Holiday_Flag  6401 non-null   bool
 2   Temperature   6401 non-null   float64
 3   Fuel_Price    6401 non-null   float64
 4   CPI           6401 non-null   float64
 5   Unemployment  6401 non-null   float64
 6   Year          6401 non-null   int64
 7   Month         6401 non-null   int64
 8   Week          6401 non-null   int64
dtypes: bool(1), category(1), float64(4), int64(3)
memory usage: 672.0 KB

y = df['Weekly_Sales']

rf = RandomForestRegressor(n_estimators = 100)
rf.fit(x, y)
RandomForestRegressor()
# checking the feature importance

plt.figure(figsize = (15, 5))
plt.bar(x.columns, rf.feature_importances_)
plt.title("Feature Importance", fontsize = 15)
plt.show()
```




```
x_train, x_test, y_train, y_test = train_test_split(x, y, train_size =
0.8, random_state = 0)

#Linear Regression
lr = LinearRegression()
lr.fit(x_train, y_train)
LinearRegression()
y_pred = lr.predict(x_test)
plt.scatter(y_test, y_pred)
```

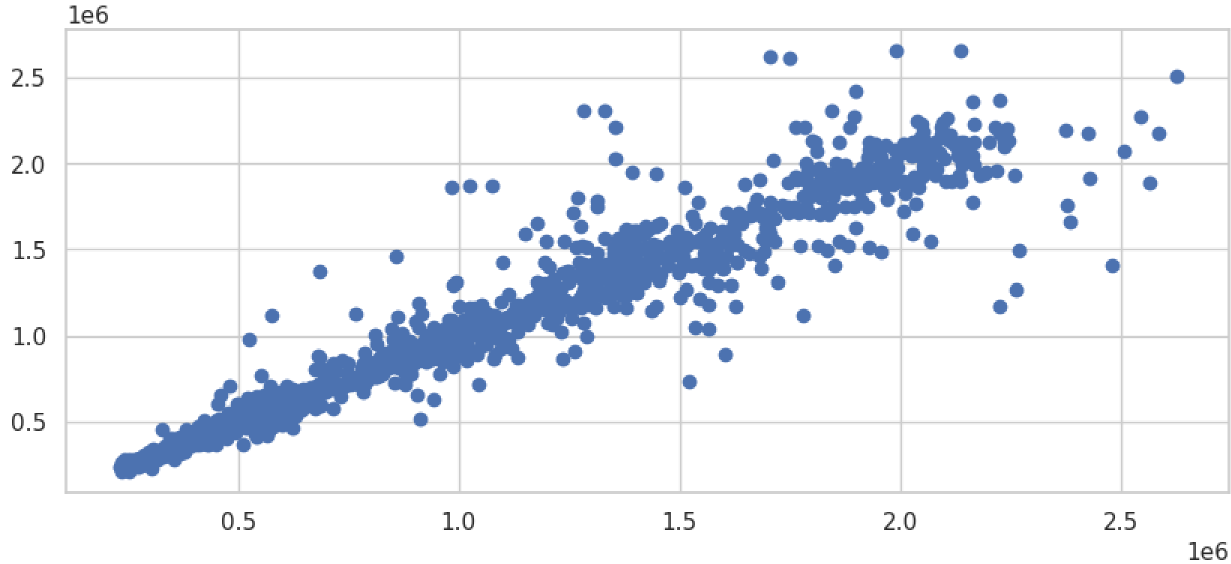
```
print("R2 Score: ", r2_score(y_test, y_pred))
print("MSE Score: ", mean_squared_error(y_test, y_pred))
print("RMSE : ", sqrt(mean_squared_error(y_test, y_pred)))
```

```
R2 Score:  0.1640905885815509
MSE Score:  270519048713.93335
RMSE :  520114.4573206299
```



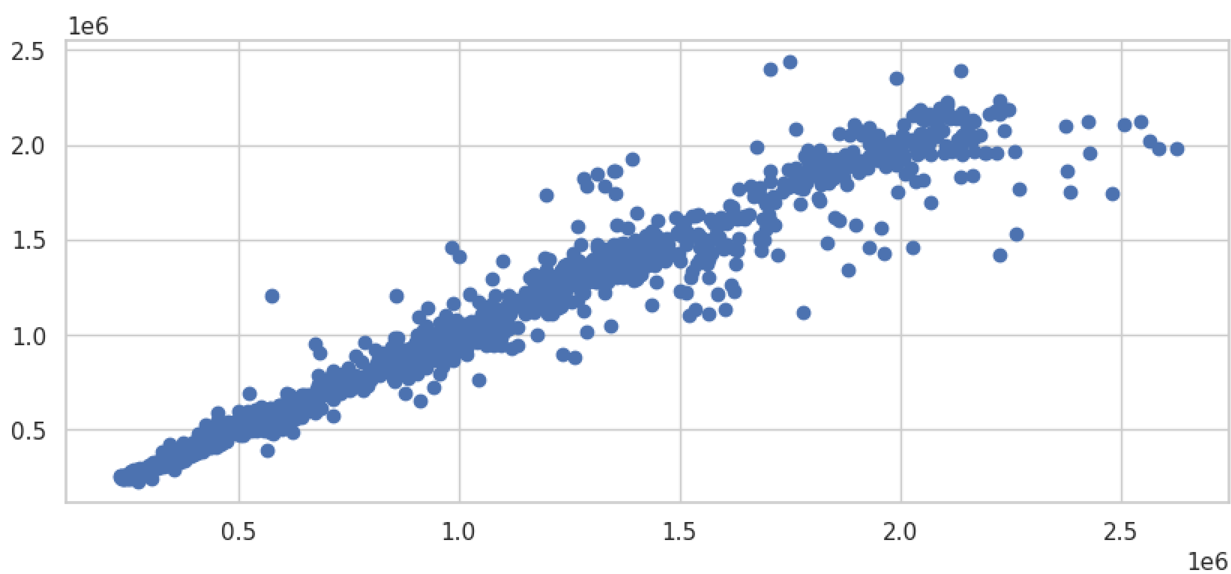

```
#Decision Tree
dtree = DecisionTreeRegressor()
dtree.fit(x_train, y_train)
DecisionTreeRegressor()
y_pred1 = dtree.predict(x_test)
plt.scatter(y_test, y_pred1)

print("R2 Score: ", r2_score(y_test, y_pred1))
print("MSE Score: ", mean_squared_error(y_test, y_pred1))
print("RMSE : ", sqrt(mean_squared_error(y_test, y_pred1)))
```

```
R2 Score:  0.9203742962187489
MSE Score:  25768665056.097343
RMSE :  160526.21298746613
```



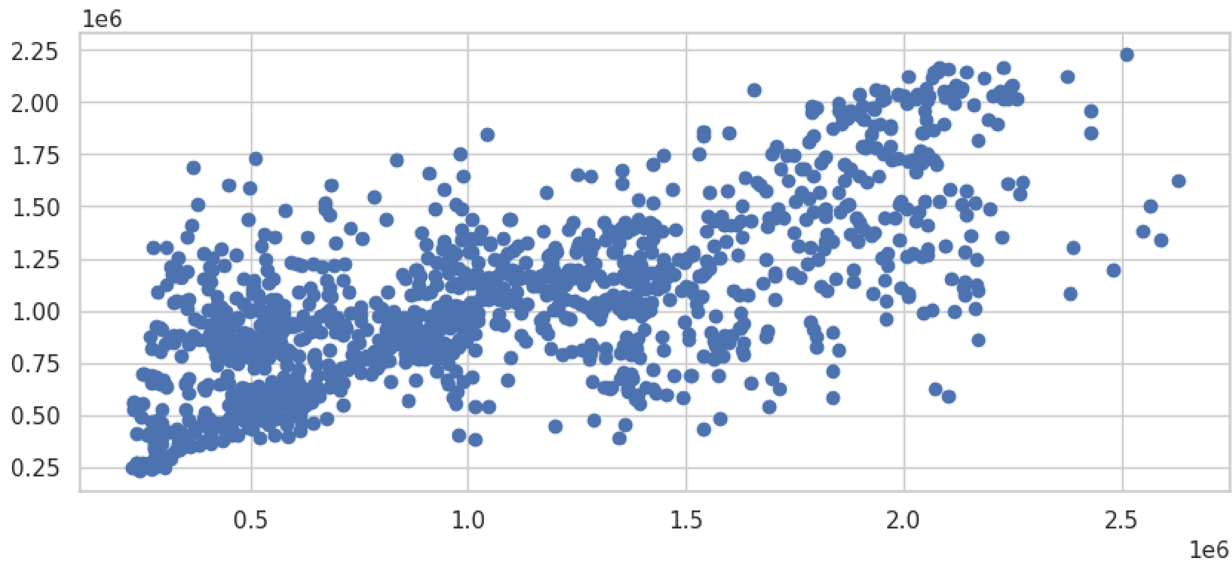

```
#Random Forest
rf1 = RandomForestRegressor(n_estimators = 100)
rf1.fit(x_train, y_train)
RandomForestRegressor()
y_pred2 = rf1.predict(x_test)
plt.scatter(y_test, y_pred2)

print("R2 Score: ", r2_score(y_test, y_pred2))
print("MSE Score: ", mean_squared_error(y_test, y_pred2))
print("RMSE : ", sqrt(mean_squared_error(y_test, y_pred2)))
```

```
R2 Score:  0.9530368529163145
MSE Score:  15198328551.096323
RMSE :  123281.50125260612
```



```
#KNN
knn = KNeighborsRegressor()
knn.fit(x_train, y_train)
KNeighborsRegressor()
y_pred3 = knn.predict(x_test)
plt.scatter(y_test, y_pred3)

print("R2 Score: ", r2_score(y_test, y_pred3))
print("MSE Score: ", mean_squared_error(y_test, y_pred3))
print("RMSE : ", sqrt(mean_squared_error(y_test, y_pred3)))
```

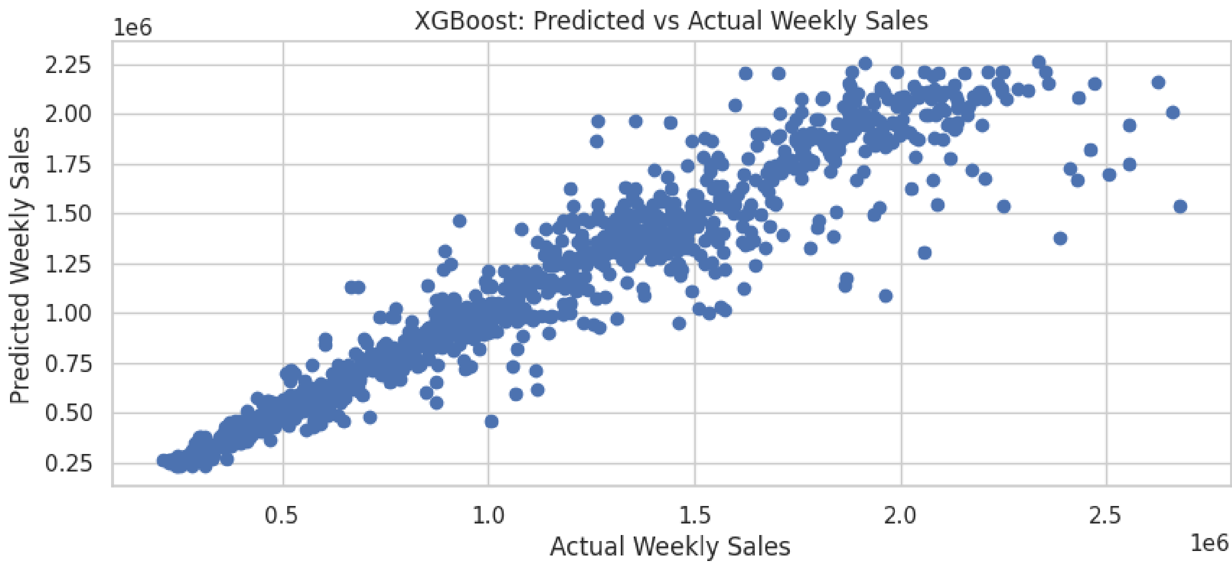
```
R2 Score:  0.4890754165027007
MSE Score:  165346663650.68936
RMSE :  406628.4097928837
```




```
#XGBoost

# Specify the features and target variable
features = ['Store', 'Year', 'Month']
target = 'Weekly_Sales'

# Split the data into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(df[features],
df[target], test_size=0.2, random_state=42)

# Create and train the XGBoost model with enable_categorical=True
xg = XGBRegressor(n_estimators=100, random_state=42,
enable_categorical=True)
xg.fit(x_train, y_train)
```

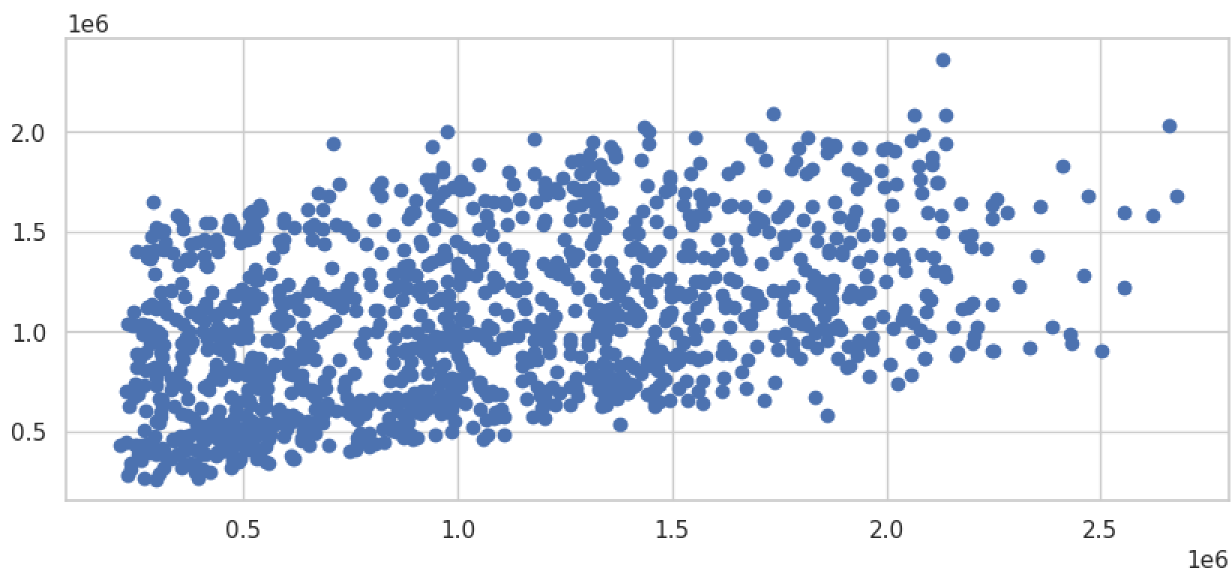
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
```

```
             colsample_bytree=None, device=None,
early_stopping_rounds=None,
             enable_categorical=True, eval_metric=None,
feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None,
max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan,
monotone_constraints=None,
             multi_strategy=None, n_estimators=100, n_jobs=None,
             num_parallel_tree=None, random_state=42, ...)

# Make predictions on the test set
y_pred4 = xg.predict(x_test)

# Evaluate the model
r2 = r2_score(y_test, y_pred4)
mse = mean_squared_error(y_test, y_pred4)
rmse = np.sqrt(mse)

print("R2 Score: ", r2)
print("MSE Score: ", mse)
print("RMSE Score: ", rmse)

# Plot predicted vs actual values
plt.scatter(y_test, y_pred4)
plt.xlabel("Actual Weekly Sales")
plt.ylabel("Predicted Weekly Sales")
plt.title("XGBoost: Predicted vs Actual Weekly Sales")
plt.show()

R2 Score:  0.9248258065451529
MSE Score:  23872625335.60029
RMSE Score:  154507.68697899886
```




```python
# Getting Average of Best Models
y_pred_final = (y_pred1 + y_pred2  + y_pred4)/3.0
plt.scatter(y_test, y_pred_final)

print("R2 Score: ", r2_score(y_test, y_pred_final))
print("MSE Score: ", mean_squared_error(y_test, y_pred_final))
print("RMSE : ", sqrt(mean_squared_error(y_test, y_pred_final)))
```

```
R2 Score:  0.08903920858824954
MSE Score:  289288446863.84094
RMSE :  537855.4144599094
```



```
# Calculate summary statistics
summary_stats = df.describe()

# Perform statistical tests or correlations
# Example: Calculate correlation between Weekly Sales and Unemployment
Rate
correlation = df['Weekly_Sales'].corr(df['Unemployment'])

# Additional statistical tests
# Example: t-test comparing Weekly Sales between two groups (Group_A
and Group_B)
group_a_sales = df[df['Holiday_Flag'] == 0]['Weekly_Sales']
group_b_sales = df[df['Holiday_Flag'] == 1]['Weekly_Sales']
t_stat, p_value = stats.ttest_ind(group_a_sales, group_b_sales)
```

Perform t-test

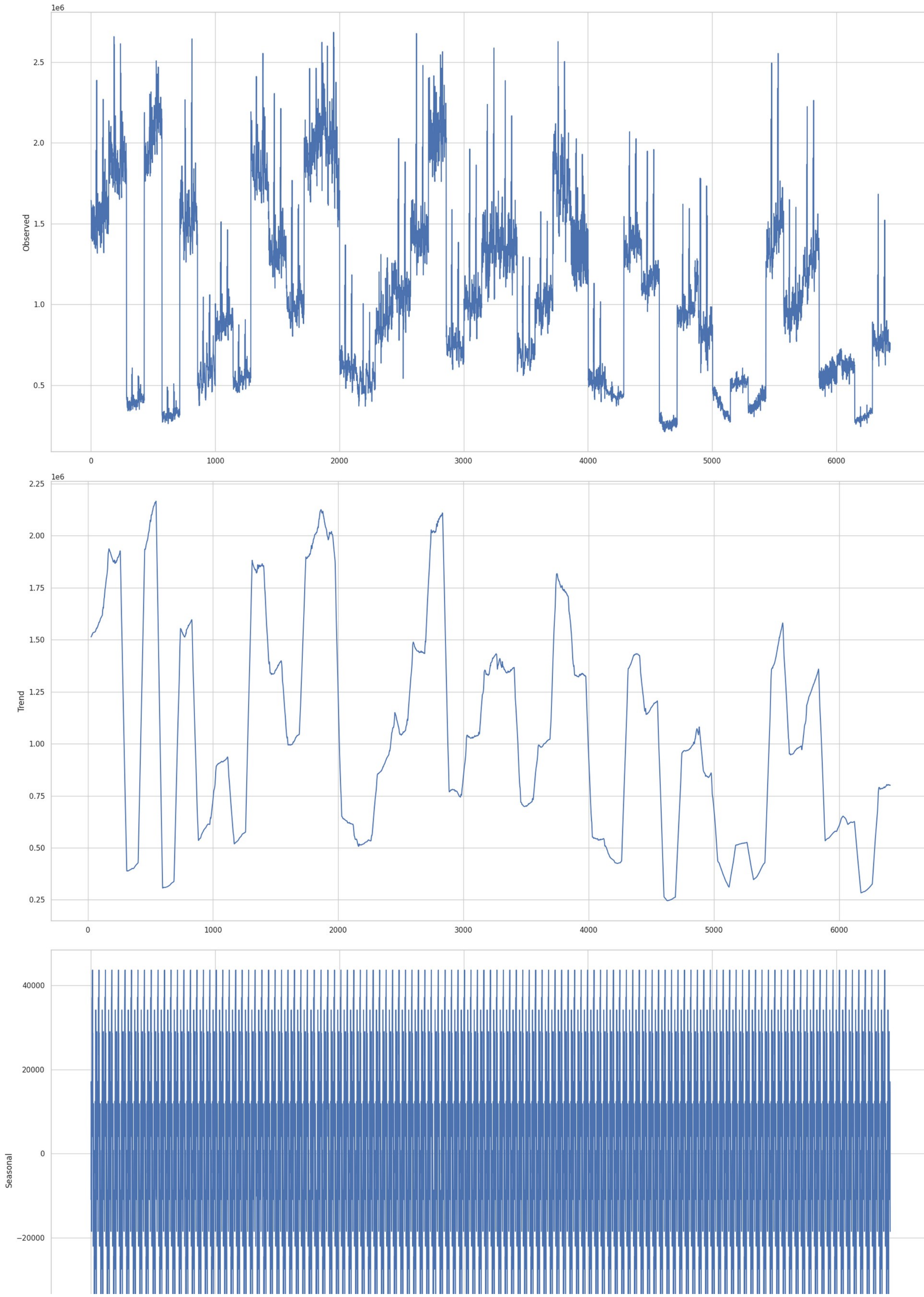
```
# Perform t-test
t_stat, p_value = stats.ttest_ind(group_a_sales, group_b_sales)

# Print the results
print("T-Statistic:", t_stat)
print("P-Value:", p_value)
```

```
T-Statistic: -2.029118506966506
P-Value: 0.042487534639960314
```

#OR

```
# Perform t-test
#t_stat, p_value = stats.ttest_ind(group_a_sales, group_b_sales)

# Create a DataFrame to display the results
#results_df = pd.DataFrame({'T-Statistic': [t_stat], 'P-Value':
[p_value]})

# Display the results
#display(results_df)

#3. Apply time series analysis to identify seasonal trends:

# Use seasonal decomposition to identify seasonal, trend, and residual
components
result = sm.tsa.seasonal_decompose(df['Weekly_Sales'],
model='additive', period=52)

# Plot the decomposed components
fig, ax = plt.subplots(4, 1, figsize=(20, 40))
result.observed.plot(ax=ax[0])
ax[0].set_ylabel('Observed')
```

```
result.trend.plot(ax=ax[1])
ax[1].set_ylabel('Trend')
result.seasonal.plot(ax=ax[2])
ax[2].set_ylabel('Seasonal')
result.resid.plot(ax=ax[3])
ax[3].set_ylabel('Residual')

plt.tight_layout()
plt.show()
```

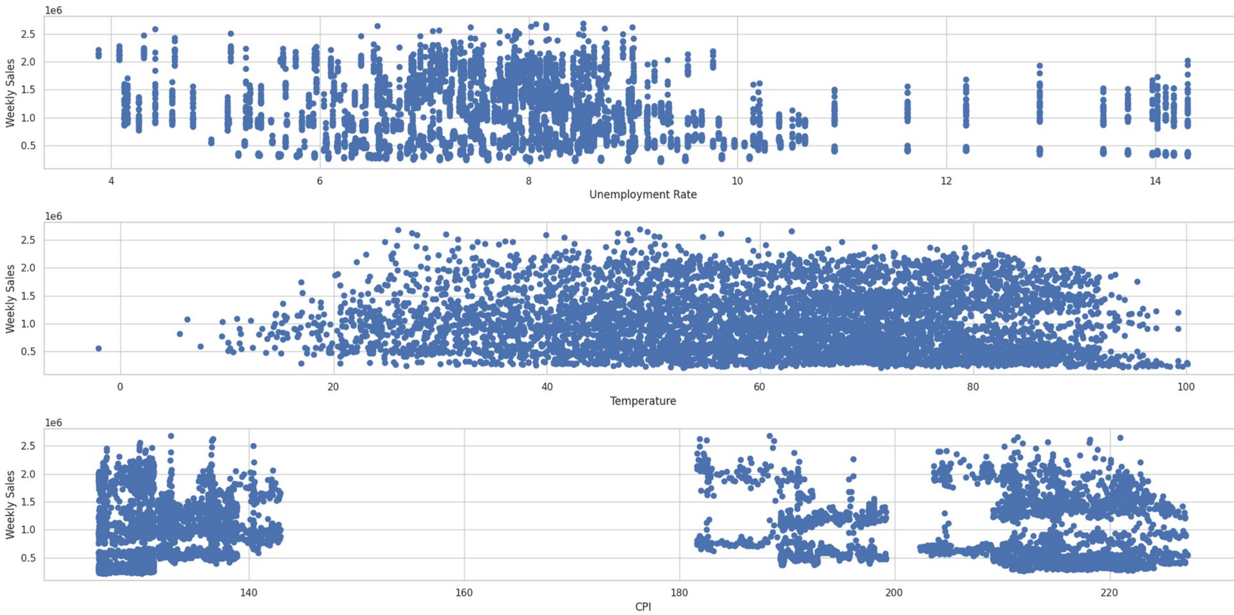


1e6
Observed
2.5
2.0
1.5
1.0
0.5
0
1000
2000
3000
4000
5000
6000
1e6
Trend
2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0
1000
2000
3000
4000
5000
6000
Seasonal
40000
20000
0
−20000

```python
#4. Analyze the impact of variables on weekly sales:

# Assuming you have additional variables (unemployment rate,
temperature, and CPI) in your dataset

# Create a matrix of independent variables
X = df[['Unemployment', 'Temperature', 'CPI']]

# Add constant to the matrix
X = sm.add_constant(X)

# Fit the multiple linear regression model
model = sm.OLS(df['Weekly_Sales'], X)
results = model.fit()

# Print the model summary
print(results.summary())
```

```
                            OLS Regression Results

======================================================================
========
Dep. Variable:           Weekly_Sales   R-squared:
0.022
Model:                            OLS   Adj. R-squared:
0.022
Method:                 Least Squares   F-statistic:
48.68
Date:                Tue, 21 Nov 2023   Prob (F-statistic):
4.22e-31
Time:                        10:31:55   Log-Likelihood:
-93560.
No. Observations:                6401   AIC:
1.871e+05
Df Residuals:                    6397   BIC:
1.872e+05
Df Model:                           3

Covariance Type:            nonrobust

======================================================================
==========
                   coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
----------
const         1.633e+06   5.09e+04     32.065      0.000    1.53e+06
1.73e+06
Unemployment -3.956e+04   3817.156    -10.363      0.000    -4.7e+04
-3.21e+04
```

```
Temperature   -342.2836    376.853     -0.908      0.364   -1081.041
396.474
CPI          -1510.3415    184.191     -8.200      0.000   -1871.417
-1149.266
======================================================================
========
Omnibus:                      554.908   Durbin-Watson:
0.090
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
371.066
Skew:                           0.474   Prob(JB):
2.65e-81
Kurtosis:                       2.299   Cond. No.
1.41e+03
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.41e+03. This might indicate that
there are
strong multicollinearity or other numerical problems.

#5. Visualize relationships using appropriate plots:

# Scatter plots of the variables against weekly sales
fig, axs = plt.subplots(3, 1, figsize=(20, 10))
axs[0].scatter(df['Unemployment'], df['Weekly_Sales'])
axs[0].set_xlabel('Unemployment Rate')
axs[0].set_ylabel('Weekly Sales')
axs[1].scatter(df['Temperature'], df['Weekly_Sales'])
axs[1].set_xlabel('Temperature')
axs[1].set_ylabel('Weekly Sales')
axs[2].scatter(df['CPI'], df['Weekly_Sales'])
axs[2].set_xlabel('CPI')
axs[2].set_ylabel('Weekly Sales')

plt.tight_layout()
plt.show()
```




```python
#2. Aggregate the weekly sales data by store and calculate total
sales:

# Assuming you have already loaded and preprocessed the Walmart
dataset

# Group the dataset by store
df_by_store = df.groupby('Store')['Weekly_Sales'].sum().reset_index()

# Sort the stores based on total sales
df_by_store_sorted = df_by_store.sort_values('Weekly_Sales',
ascending=False)

# Print the top 5 best performing stores
print("Top 5 Best Performing Stores:")
print(df_by_store_sorted.head())

# Print Empty Row
print("")

# Print the worst performing stores
print("Top 5 Worst Performing Store:")
print(df_by_store_sorted.tail(5))
```

```
Top 5 Best Performing Stores:
    Store  Weekly_Sales
3       4  2.810352e+08
19     20  2.800237e+08
13     14  2.761276e+08
1       2  2.687221e+08
12     13  2.682025e+08
```

```
Top 5 Worst Performing Store:
    Store  Weekly_Sales
37     38   55159626.42
35     36   53412214.97
4       5   45475688.90
43     44   43293087.84
32     33   37160221.96
```

```
#3. Rank the stores based on their historical sales data to identify
the top performing stores:

# Add a rank column based on total sales
df_by_store_sorted['Rank'] = np.arange(1, len(df_by_store_sorted) + 1)

# Print the ranked stores
print("Ranked Stores:")
print(df_by_store_sorted)
```

```
Ranked Stores:
    Store  Weekly_Sales  Rank
3       4  2.810352e+08     1
19     20  2.800237e+08     2
13     14  2.761276e+08     3
1       2  2.687221e+08     4
12     13  2.682025e+08     5
9      10  2.556789e+08     6
26     27  2.480387e+08     7
0       1  2.224028e+08     8
5       6  2.210286e+08     9
38     39  2.074455e+08    10
18     19  2.066349e+08    11
30     31  1.996139e+08    12
22     23  1.960163e+08    13
23     24  1.940160e+08    14
10     11  1.939628e+08    15
27     28  1.892637e+08    16
40     41  1.813419e+08    17
31     32  1.668192e+08    18
17     18  1.551147e+08    19
21     22  1.470756e+08    20
11     12  1.442872e+08    21
25     26  1.434164e+08    22
33     34  1.382498e+08    23
39     40  1.378703e+08    24
34     35  1.315207e+08    25
7       8  1.299512e+08    26
16     17  1.277821e+08    27
44     45  1.123953e+08    28
20     21  1.081179e+08    29
```

```
24    25  1.010612e+08    30
42    43  9.056544e+07    31
14    15  8.913368e+07    32
6      7  8.159828e+07    33
41    42  7.956575e+07    34
8      9  7.778922e+07    35
28    29  7.714155e+07    36
15    16  7.425243e+07    37
36    37  7.420274e+07    38
29    30  6.271689e+07    39
2      3  5.758674e+07    40
37    38  5.515963e+07    41
35    36  5.341221e+07    42
4      5  4.547569e+07    43
43    44  4.329309e+07    44
32    33  3.716022e+07    45

# Create a new column 'Date' based on the index
df['Date'] = df.index

# If the index is not in the correct date format, convert it to
datetime format
df['Date'] = pd.to_datetime(df['Date'])

# Reset the index since we now have the 'Date' column
df.reset_index(drop=True, inplace=True)

# Now, the 'Date' column should be restored in your DataFrame
print(df.head())

  Store                          Date  Weekly_Sales  Holiday_Flag  \
0     1 1970-01-01 00:00:00.000000000    1643690.90         False
1     1 1970-01-01 00:00:00.000000001    1641957.44          True
2     1 1970-01-01 00:00:00.000000002    1611968.17         False
3     1 1970-01-01 00:00:00.000000003    1409727.59         False
4     1 1970-01-01 00:00:00.000000004    1554806.68         False

   Temperature  Fuel_Price         CPI  Unemployment  Year  Month
Week
0        42.31       2.572  211.096358         8.106  2010      5
17
1        38.51       2.548  211.242170         8.106  2010     12
48
2        39.93       2.514  211.289143         8.106  2010      2
7
3        46.63       2.561  211.319643         8.106  2010      2
8
4        46.50       2.625  211.350143         8.106  2010      5
18
```

```
df.columns
```

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

```
#2. Load the dataset and preprocess the data:

# Convert the 'Date' column to datetime
df['Date'] = pd.to_datetime(df['Date'])

# Set the 'Date' column as the index
df.set_index('Date', inplace=True)

#3. Split the dataset into training and testing sets:

# Split the dataset into 80% train and 20% test
train_size = int(len(df) * 0.8)
train_data, test_data = df[:train_size], df[train_size:]

#4. Choose a predictive modeling technique:
#- For linear regression:

model = RandomForestRegressor()

#- For time series forecasting, you may use SARIMAX from the
statsmodels library. However, this requires additional preprocessing
and stationarity checks for the time series.

#5. Implement and train the model:

# Assuming you have selected the predictive modeling technique (e.g.,
Random Forest)

# Separate the target variable from the features
X_train, y_train = train_data.drop('Weekly_Sales', axis=1),
train_data['Weekly_Sales']
X_test, y_test = test_data.drop('Weekly_Sales', axis=1),
test_data['Weekly_Sales']

# Fit the model on the training data
model.fit(X_train, y_train)
```

```
RandomForestRegressor()
```

```
#6. Evaluate the model's performance:

plt.figure(figsize=(20, 8))

# Make predictions on the test set
y_pred = model.predict(X_test)
```

```python
# Evaluate the model using mean squared error (MSE)
mse = mean_squared_error(y_test, y_pred)
print("Mean Squared Error:", mse)

# Visualize the actual vs. predicted values
plt.plot(y_test.index, y_test.values, label='Actual')
plt.plot(y_test.index, y_pred, label='Predicted')
plt.xlabel('Date')
plt.ylabel('Weekly Sales')
plt.title('Actual vs. Predicted Weekly Sales')
plt.legend()
plt.show()
```

```
Mean Squared Error: 303464742634.45807
```