Final Report Group 4

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Goals/Objectives

1. Conducting an in-depth time series analysis of Walmart's weekly sales, exploring historical data to uncover nuanced patterns and trends. The focus is on understanding the complex interplay of various determinants, including economic factors, promotions, and seasonal influences.
2. Utilizing the extracted insights as a compass for strategic decision-making. Our analysis seeks to empower Walmart with a roadmap for adaptive and responsive sales strategies, ensuring resilience and growth in the dynamic retail landscape. This approach extends beyond retrospective analysis, providing a forward-looking perspective for sustainable success.

Research Questions

1. What factors influence variations in weekly sales and monthly sales across different stores and time periods?
2. Are there seasonal trends or specific periods (holidays, markdowns) that significantly impact sales?
3. Can certain features be identified as strong indicators affecting sales performance?

Data Sources And Characteristics

- For this project, we have selected the "Walmart Time Series Sales Forecasting" dataset, available on Kaggle. This dataset contains real-world retail sales data from Walmart and is used in an annual competition hosted by the company. The dataset's key attributes include sales data, date-time information, store and department details, temperature, fuel price, and other relevant factors. This dataset comprises more than 4,000 records with a variety of data categories, making it suitable for our analysis.

- The authority of this dataset is derived from its direct source, Walmart, which provides real sales data used in their annual competition. Walmart is a recognized authority in the retail industry, and this dataset aligns perfectly with our project objectives, offering a credible foundation for predictive modeling and analysis.

- While we initially explored open datasets from authoritative sources like the World Bank and the U.S. Federal Government, we concluded that the Walmart dataset from Kaggle is the most suitable due to its alignment with our project goals and the guidelines provided by the instructor. We believe that this dataset will enable us to conduct comprehensive data analysis and generate accurate sales predictions to enhance Walmart's supply chain management.

Characteristics of Dataset

- Rows - 421570 Columns - 15
- Data from 2010 - 2012

3 datasets as follows:

1. Stores:

- Store: The store number. Range from 1–45.
- Type: Three types of stores ‘A’, ‘B’ or ‘C’.
- Size: The size of a Store based on the no. of products available in the particular store ranging from 34,000 to 210,000.

2. Sales:

- Date: The date of the week where this observation was taken. -Weekly_Sales: The sales recorded during that Week.
- Store: The store which observation in recorded 1–45
- Dept: One of 1–99 that shows the department.
- IsHoliday: Boolean value representing a holiday.

3. Features:

- Temperature: Temperature of the region during that week. -Fuel_Price: Fuel Price in that region during that week.
- MarkDown1:5 : Represents the Type of markdown and what quantity was available during that week.
- CPI: Consumer Price Index during that week.
- Unemployment: The unemployment rate during that week in the region of the store.

Analysis Strategy

- Analysis -
    1. Dataset loading and exploration
    2. Exploratory data Analysis
    3. Detailed time series Analysis
- Forecasting -
    1. Handling Missing Values and Outliers
    2. Implementing Gradient Boost and SVM models

Import Libraries

In [1]:
```
pip install scipy
```

```
Collecting scipy
  Downloading scipy-1.11.4-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x8
6_64.whl (36.4 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 36.4/36.4 MB 45.2 MB/s eta 0:0
0:0000:0100:01
Requirement already satisfied: numpy<1.28.0,>=1.21.6 in /opt/conda/lib/python
3.11/site-packages (from scipy) (1.25.1)
Installing collected packages: scipy
Successfully installed scipy-1.11.4
Note: you may need to restart the kernel to use updated packages.
```

In [2]:
```
pip install scikit-learn
```

```
Collecting scikit-learn
  Downloading scikit_learn-1.3.2-cp311-cp311-manylinux_2_17_x86_64.manylinux2
014_x86_64.whl (10.9 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10.9/10.9 MB 84.6 MB/s eta 0:0
0:0000:0100:01
Requirement already satisfied: numpy<2.0,>=1.17.3 in /opt/conda/lib/python3.1
1/site-packages (from scikit-learn) (1.25.1)
Requirement already satisfied: scipy>=1.5.0 in /opt/conda/lib/python3.11/site
-packages (from scikit-learn) (1.11.4)
Collecting joblib>=1.1.1 (from scikit-learn)
  Downloading joblib-1.3.2-py3-none-any.whl (302 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 302.2/302.2 kB 54.9 MB/s eta 0:0
0:00
Collecting threadpoolctl>=2.0.0 (from scikit-learn)
  Downloading threadpoolctl-3.2.0-py3-none-any.whl (15 kB)
Installing collected packages: threadpoolctl, joblib, scikit-learn
Successfully installed joblib-1.3.2 scikit-learn-1.3.2 threadpoolctl-3.2.0
Note: you may need to restart the kernel to use updated packages.
```

In [3]:
```
import warnings
import itertools
import numpy as np
import scipy.stats as stats
import warnings
warnings.filterwarnings("ignore")
```

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
import calendar
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn import metrics
from datetime import timedelta
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_scor
```

load and read the datasets

In [4]:
```
walmart = pd.read_csv('train.csv')

walmart_feature = pd.read_csv('features.csv')

walmart_store = pd.read_csv('stores.csv')
```

In [5]:
```
walmart.head()
```

Out[5]:

	Store	Dept	Date	Weekly_Sales	IsHoliday
0	1	1	2010-02-05	24924.50	False
1	1	1	2010-02-12	46039.49	True
2	1	1	2010-02-19	41595.55	False
3	1	1	2010-02-26	19403.54	False
4	1	1	2010-03-05	21827.90	False

In [6]:
```
walmart.shape
```

Out[6]:
```
(421570, 5)
```

Group by store

In [7]:
```
walmart_store_group=walmart.groupby(["Store","Date"])[["Weekly_Sales"]].sum(
walmart_store_group.reset_index(inplace=True)
```

Merging all the datasets into one place for easier analysis.

In [8]:
```
result = pd.merge(walmart_store_group, walmart_store, how='inner', on='Store
        left_index=False, right_index=False, sort=False,
        suffixes=('_x', '_y'), copy=True, indicator=False)

data = pd.merge(result, walmart_feature, how='inner', on=['Store','Date'], l
        left_index=False, right_index=False, sort=False,
        suffixes=('_x', '_y'), copy=True, indicator=False)
```

In [10]:
```
print(data.shape)
```

```
(6435, 15)
```

Dataframe Walmart with 421570 rows has come down to 6435 rows by doing a group by and merge

Data Cleaning

In [9]:
```
data.head()
```

Out[9]:

	Store	Date	Weekly_Sales	Type	Size	Temperature	Fuel_Price	MarkDown1	M
0	1	2010-02-05	1643690.90	A	151315	42.31	2.572	NaN	
1	1	2010-02-12	1641957.44	A	151315	38.51	2.548	NaN	
2	1	2010-02-19	1611968.17	A	151315	39.93	2.514	NaN	
3	1	2010-02-26	1409727.59	A	151315	46.63	2.561	NaN	
4	1	2010-03-05	1554806.68	A	151315	46.50	2.625	NaN	

In [10]:
```
#Encode the categorical column : IsHoliday

data['IsHoliday'] = data['IsHoliday'].apply(lambda x: 1 if x == True else 0)
```

In [11]:
```
data.dtypes
```

Out[11]:
```
Store             int64
Date             object
Weekly_Sales    float64
Type             object
Size              int64
Temperature     float64
Fuel_Price      float64
MarkDown1       float64
MarkDown2       float64
MarkDown3       float64
MarkDown4       float64
MarkDown5       float64
CPI             float64
Unemployment    float64
IsHoliday         int64
dtype: object
```

In [12]:
```
# Converting "Date"  to date time
data["Date"]=pd.to_datetime(data.Date)

# Extracting details from date given. so that can be used for seasonal check

data["Day"]=data.Date.dt.day
data["Month"]=data.Date.dt.month
data["Year"]=data.Date.dt.year

# Changing the Months value from numbers to real values like Jan, Feb to Dec
data['Month'] = data['Month'].apply(lambda x: calendar.month_abbr[x])
```

In [13]:
```
data.isnull().sum()
```

Out[13]:
```
Store              0
Date               0
Weekly_Sales       0
Type               0
Size               0
Temperature        0
Fuel_Price         0
MarkDown1       4155
MarkDown2       4798
MarkDown3       4389
MarkDown4       4470
MarkDown5       4140
CPI                0
Unemployment       0
IsHoliday          0
Day                0
Month              0
Year               0
dtype: int64
```

In [14]:
```
data.describe().T
```

Out[14]:

	count	mean	min	25%	50%	75
Store	6435.0	23.0	1.0	12.0	23.0	34
Date	6435	2011-06-17 00:00:00	2010-02-05 00:00:00	2010-10-08 00:00:00	2011-06-17 00:00:00	2012-0 00:00:
Weekly_Sales	6435.0	1046964.877562	209986.25	553350.105	960746.04	1420158.
Size	6435.0	130287.6	34875.0	70713.0	126512.0	20230
Temperature	6435.0	60.663782	-2.06	47.46	62.67	74.
Fuel_Price	6435.0	3.358607	2.472	2.933	3.445	3.7
MarkDown1	2280.0	6855.58743	0.27	1679.19	4972.59	8873.58
MarkDown2	1637.0	3218.965504	-265.76	37.2	187.04	1785.
MarkDown3	2046.0	1349.853021	-29.1	4.7	22.7	99.98
MarkDown4	1965.0	3303.858142	0.22	483.27	1419.42	3496.
MarkDown5	2295.0	4435.26224	135.16	1702.565	3186.52	5422.
CPI	6435.0	171.578394	126.064	131.735	182.616521	212.7432
Unemployment	6435.0	7.999151	3.879	6.891	7.874	8.6
IsHoliday	6435.0	0.06993	0.0	0.0	0.0	0
Day	6435.0	15.678322	1.0	8.0	16.0	23
Year	6435.0	2010.965035	2010.0	2010.0	2011.0	2012

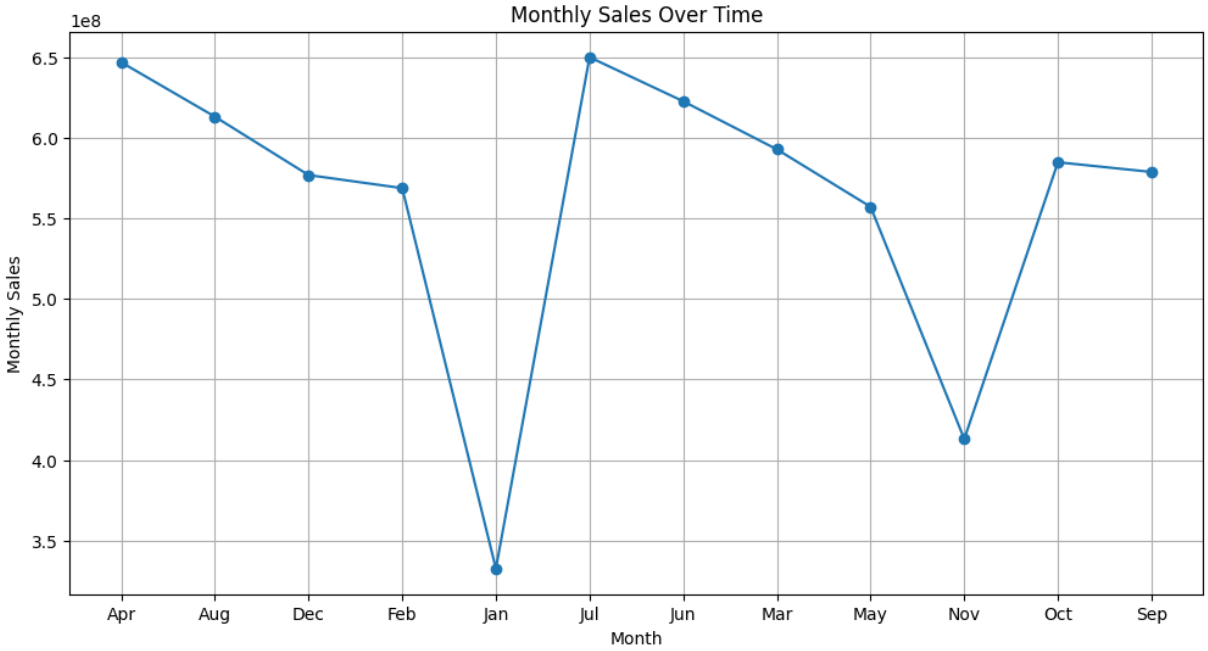
In [15]:
```
#add a 'week' column to the dataset for further analysis
data['Week'] = data.Date.dt.isocalendar().week
data.dtypes
```

Out[15]:
```
Store                    int64
Date            datetime64[ns]
Weekly_Sales           float64
Type                    object
Size                     int64
Temperature            float64
Fuel_Price             float64
MarkDown1              float64
MarkDown2              float64
MarkDown3              float64
MarkDown4              float64
MarkDown5              float64
CPI                    float64
Unemployment           float64
IsHoliday                int64
Day                      int32
Month                   object
Year                     int32
Week                    UInt32
dtype: object
```

Exploratory Data Analysis

Weekly Sales

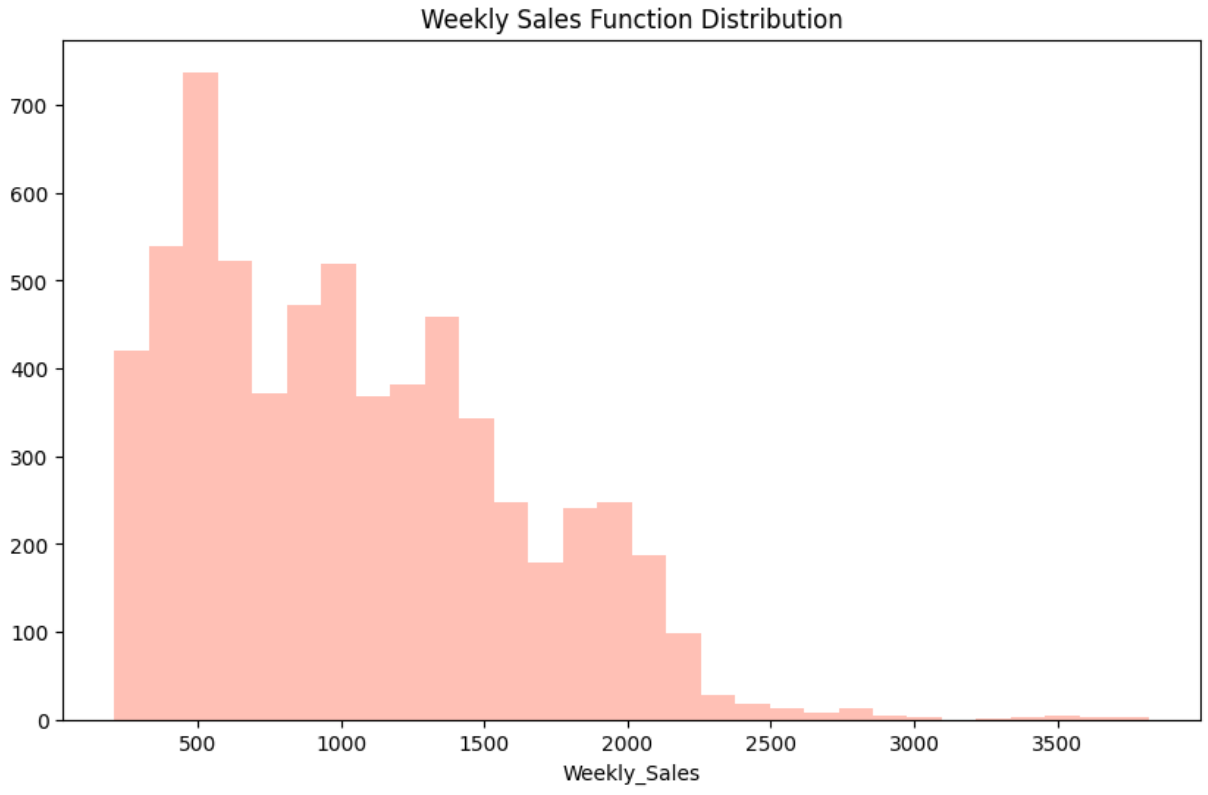
In [16]:
```
import matplotlib.pyplot as plt

# Group the data by Date and calculate the sum of Weekly Sales for each week
df_weeks = data.groupby('Month')['Weekly_Sales'].sum()
# Create a time series plot
plt.figure(figsize=(12, 6))
plt.plot(df_weeks.index, df_weeks.values, marker='o', linestyle='-')
plt.title('Monthly Sales Over Time')
plt.xlabel('Month')
plt.ylabel('Monthly Sales')
plt.grid(True)

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



In [17]:
```
df_weeks.dtypes
```

Out[17]:
```
dtype('float64')
```

In [18]:
```
plt.figure(figsize=(10, 6))
data["Weekly_Sales"]=data.Weekly_Sales/1000

sns.distplot(data.Weekly_Sales, kde=False, bins=30, color = 'tomato')
plt.title('Weekly Sales Function Distribution')
plt.show()
```



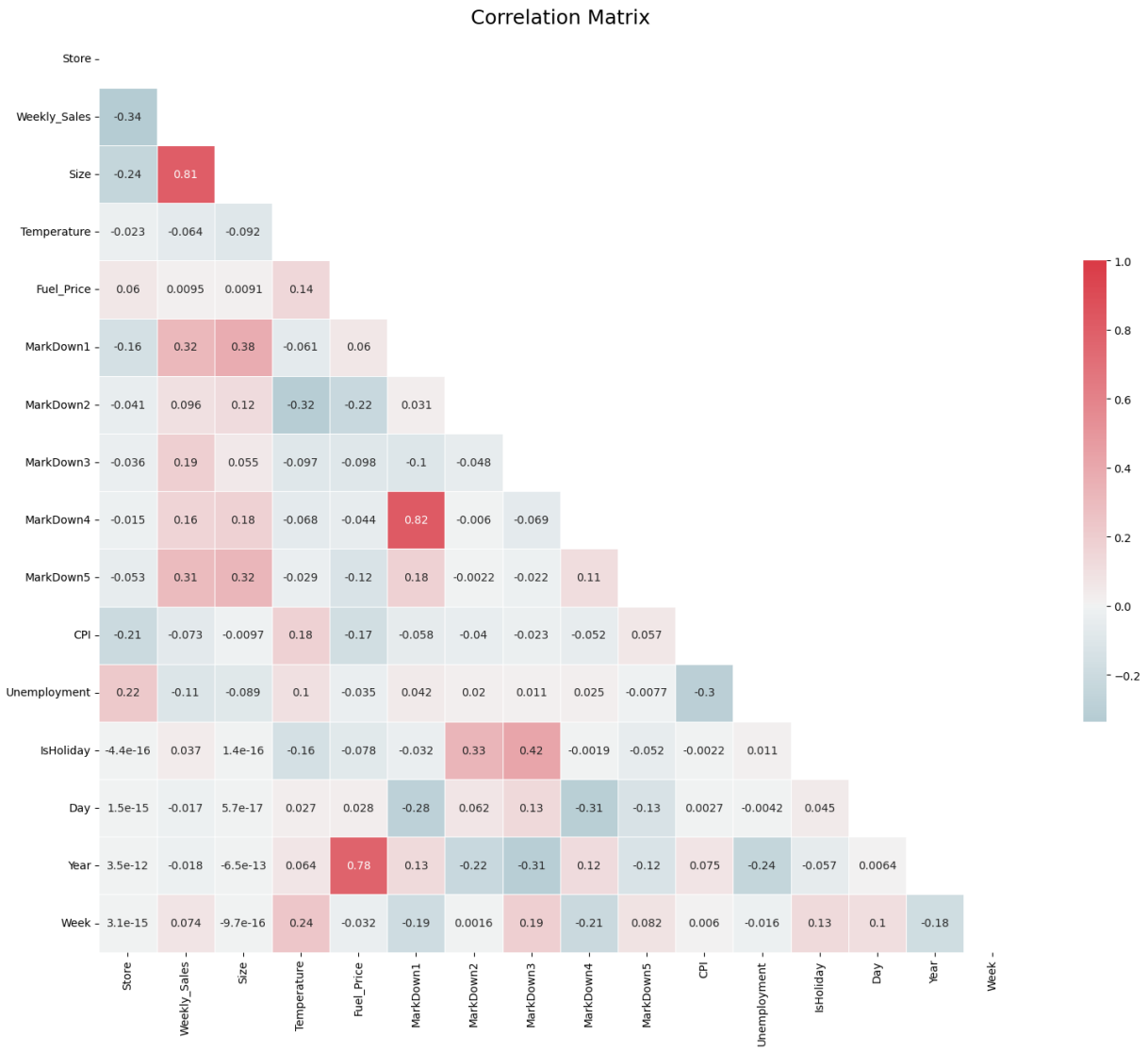
In [23]:

```
import plotly.express as px

# Assuming 'Date' is the date-time column, make sure it's in datetime format
data['Date'] = pd.to_datetime(data['Date'])

# Extract the year and week from the 'Date' column
data['Year'] = data['Date'].dt.year
data['Week'] = data['Date'].dt.isocalendar().week

# Group the data by 'Year' and 'Week' and calculate the mean of 'Weekly_Sale
weekly_sales_yearly = data.groupby(['Year', 'Week'])['Weekly_Sales'].mean().

# Create separate DataFrames for each year
weekly_sales_2010 = weekly_sales_yearly[weekly_sales_yearly['Year'] == 2010]
weekly_sales_2011 = weekly_sales_yearly[weekly_sales_yearly['Year'] == 2011]
weekly_sales_2012 = weekly_sales_yearly[weekly_sales_yearly['Year'] == 2012]

# Create line charts for each year using Plotly Express
fig = px.line(
    title='Average Weekly Sales - Per Year',
    labels={'value': 'Sales', 'variable': 'Year', 'Week': 'Week'},
)

# Add traces for each year's average weekly sales
fig.add_scatter(x=weekly_sales_2010['Week'], y=weekly_sales_2010['Weekly_Sal
fig.add_scatter(x=weekly_sales_2011['Week'], y=weekly_sales_2011['Weekly_Sal
fig.add_scatter(x=weekly_sales_2012['Week'], y=weekly_sales_2012['Weekly_Sal

# Customize the layout
fig.update_layout(
    xaxis_title='Week',
    yaxis_title='Sales',
    legend_title='Year',
)

# Show the chart
fig.show()
```

In [22]:

```
# Exclude non-numeric columns before calculating the correlation matrix
numeric_columns = data.select_dtypes(include=[np.number]).columns.tolist()
numeric_data = data[numeric_columns]

# Calculate the correlation matrix
corr = numeric_data.corr()

# Create a mask for the upper triangle
mask = np.triu(np.ones_like(corr, dtype=bool))

# Set up the matplotlib figure
plt.figure(figsize=(20, 15))

# Define a color palette
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Create the heatmap
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=1, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}, annot=True)

# Set plot title and adjust font size
plt.title('Correlation Matrix', fontsize=18)
```

```
plt.show()
```



Detailed Time-Series Analysis

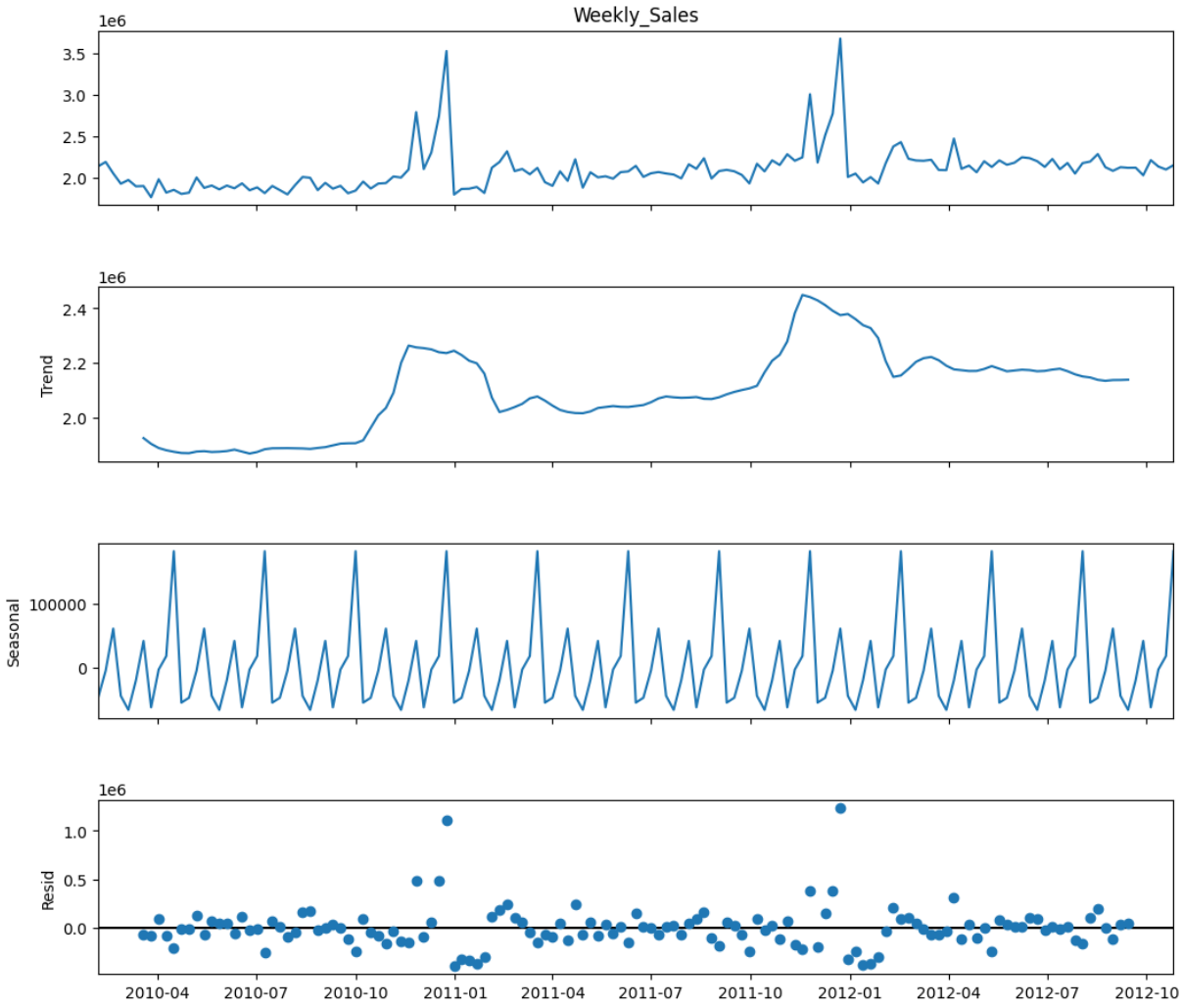
Any data that is recorded with some fixed interval of time, is called as Time Series Data. The data can be at a fixed interval of time, it can be hourly, daily, monthly or yearly. The main objective of Time Series is to understand how change in time can affect the dependent variables and accordingly predict values for the futured time intervals.
For this particular case, we are focusing on one store(store 4) and performing a detailed time-series analysis on it.

In [20]:
```
data1 = pd.read_csv('train.csv')
data1.set_index('Date', inplace=True)

store4 = data1[data1.Store == 4]
# there are about 45 different stores in this dataset.

sales4 = pd.DataFrame(store4.Weekly_Sales.groupby(store4.index).sum())
```

```
sales4.dtypes
sales4.head(20)
# Grouped weekly sales by store 4

#remove date from index to change its dtype because it clearly isnt acceptab
sales4.reset_index(inplace = True)

#converting 'date' column to a datetime type
sales4['Date'] = pd.to_datetime(sales4['Date'])
# resetting date back to the index
sales4.set_index('Date',inplace = True)
```

In [22]:
```
!pip install statsmodels
from statsmodels.tsa.seasonal import seasonal_decompose

decomposition = seasonal_decompose(sales4.Weekly_Sales, period=12)
fig = plt.figure()
fig = decomposition.plot()
fig.set_size_inches(12, 10)
plt.show()
```

```
Collecting statsmodels
  Downloading statsmodels-0.14.0-cp311-cp311-manylinux_2_17_x86_64.manylinux2
014_x86_64.whl (10.1 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10.1/10.1 MB 68.0 MB/s eta 0:0
0:00:010:01
Requirement already satisfied: numpy>=1.18 in /opt/conda/lib/python3.11/site-
packages (from statsmodels) (1.25.1)
Requirement already satisfied: scipy!=1.9.2,>=1.4 in /opt/conda/lib/python3.1
1/site-packages (from statsmodels) (1.11.4)
Requirement already satisfied: pandas>=1.0 in /opt/conda/lib/python3.11/site-
packages (from statsmodels) (2.0.3)
Collecting patsy>=0.5.2 (from statsmodels)
  Downloading patsy-0.5.3-py2.py3-none-any.whl (233 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 233.8/233.8 kB 47.0 MB/s eta 0:0
0:00
Requirement already satisfied: packaging>=21.3 in /opt/conda/lib/python3.11/s
ite-packages (from statsmodels) (23.1)
Requirement already satisfied: python-dateutil>=2.8.2 in /opt/conda/lib/pytho
n3.11/site-packages (from pandas>=1.0->statsmodels) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /opt/conda/lib/python3.11/site
-packages (from pandas>=1.0->statsmodels) (2023.3)
Requirement already satisfied: tzdata>=2022.1 in /opt/conda/lib/python3.11/si
te-packages (from pandas>=1.0->statsmodels) (2023.3)
Requirement already satisfied: six in /opt/conda/lib/python3.11/site-packages
(from patsy>=0.5.2->statsmodels) (1.16.0)
Installing collected packages: patsy, statsmodels
Successfully installed patsy-0.5.3 statsmodels-0.14.0
<Figure size 640x480 with 0 Axes>
```



Multiplicative Decomposition

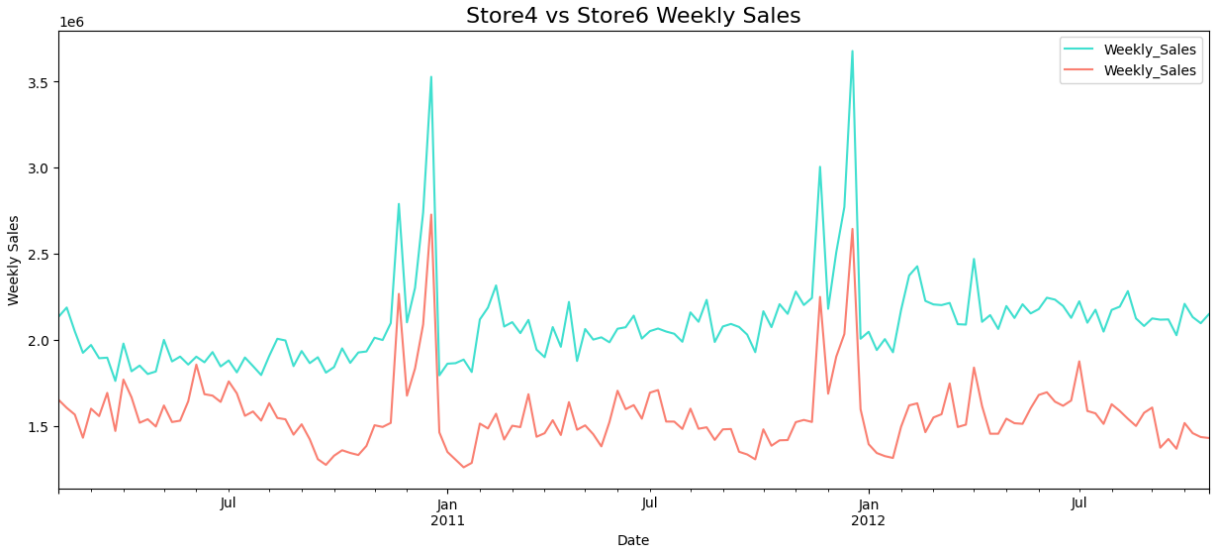
An additive model suggests that the components are multipled together. An additive model is non-linear such as quadratic or exponential. Changes increase or decrease over time. A non-linear seasonality has an increasing or decreasing frequency (width of the cycles) and / or amplitude (height of the cycles) over time.

In [23]:
```
decomposition = seasonal_decompose(sales4.Weekly_Sales, model= 'multiplicati
fig = plt.figure()
fig = decomposition.plot()
fig.set_size_inches(12, 10)
plt.show()
```

```
<Figure size 640x480 with 0 Axes>
```

In [24]:
```
#Comparing sales from store 4 and store 6
# Lets take store 6 data for analysis
store6 = data1[data1.Store == 6]
# there are about 45 different stores in this dataset.

sales6 = pd.DataFrame(store6.Weekly_Sales.groupby(store6.index).sum())
sales6.dtypes
# Grouped weekly sales by store 6

#remove date from index to change its dtype because it clearly isnt acceptab
sales6.reset_index(inplace = True)

#converting 'date' column to a datetime type
sales6['Date'] = pd.to_datetime(sales6['Date'])
# resetting date back to the index
sales6.set_index('Date',inplace = True)
y1=sales4.Weekly_Sales
y2=sales6.Weekly_Sales
```

In [25]:
```
y1.plot(figsize=(15, 6), legend=True, color = 'turquoise')
y2.plot(figsize=(15, 6), legend=True, color = 'salmon')
plt.ylabel('Weekly Sales')
plt.title('Store4 vs Store6 Weekly Sales', fontsize = '16')
plt.show()
```

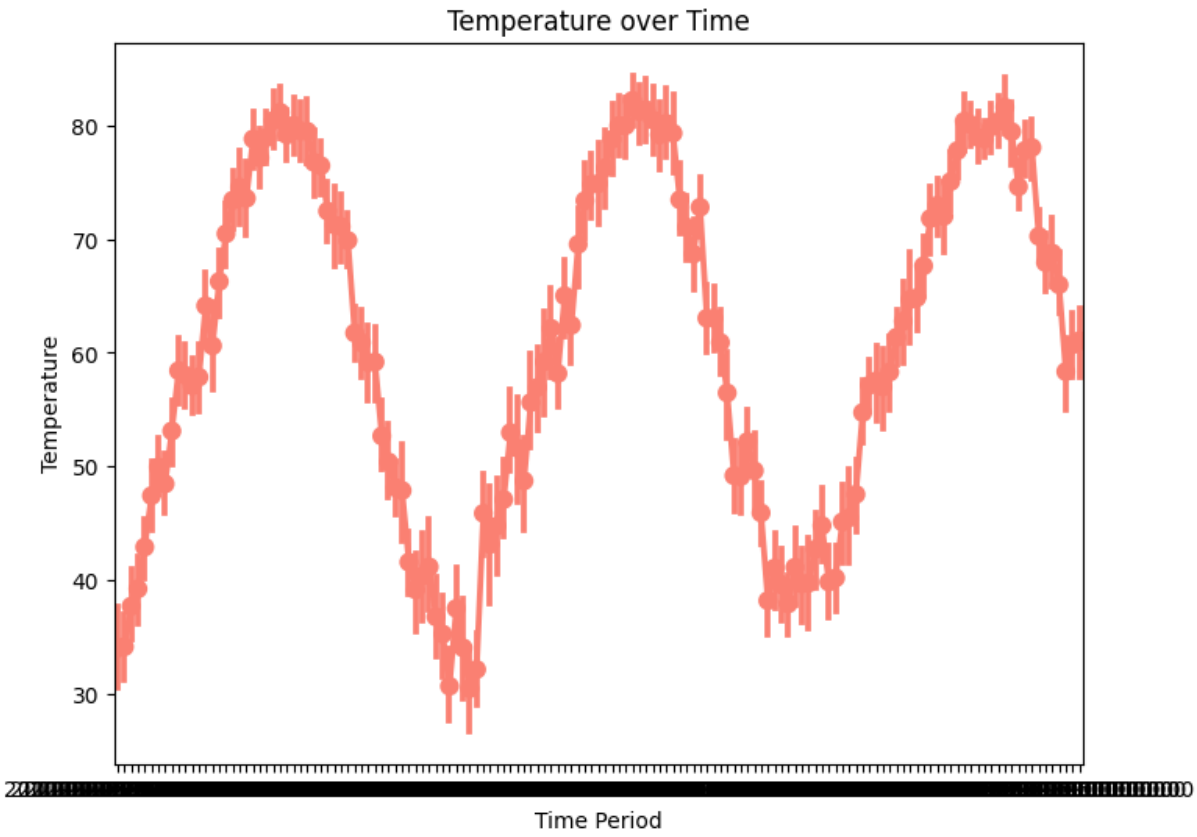


This shows an interesting trend during year ends (during both 2011 & 2012). The best thing is both the stores have almost the same trends and spike just the magnitude is different This clearly tells its a timeseries problem and it will be interesting to look more into it

For future prediction the model is not that great because the error interval is way big. But if we just check the green line prediction this is almost like earlier years. If we look for may be first 2 weeks the prediction is way better and error is also low.

Plotting Data

In [27]:
```
plt.figure(figsize=(8,6))
sns.pointplot(x="Date", y="Temperature", data=data, color = 'salmon')
plt.xlabel('Time Period')
plt.ylabel('Temperature')
plt.title('Temperature over Time')
plt.show()
```

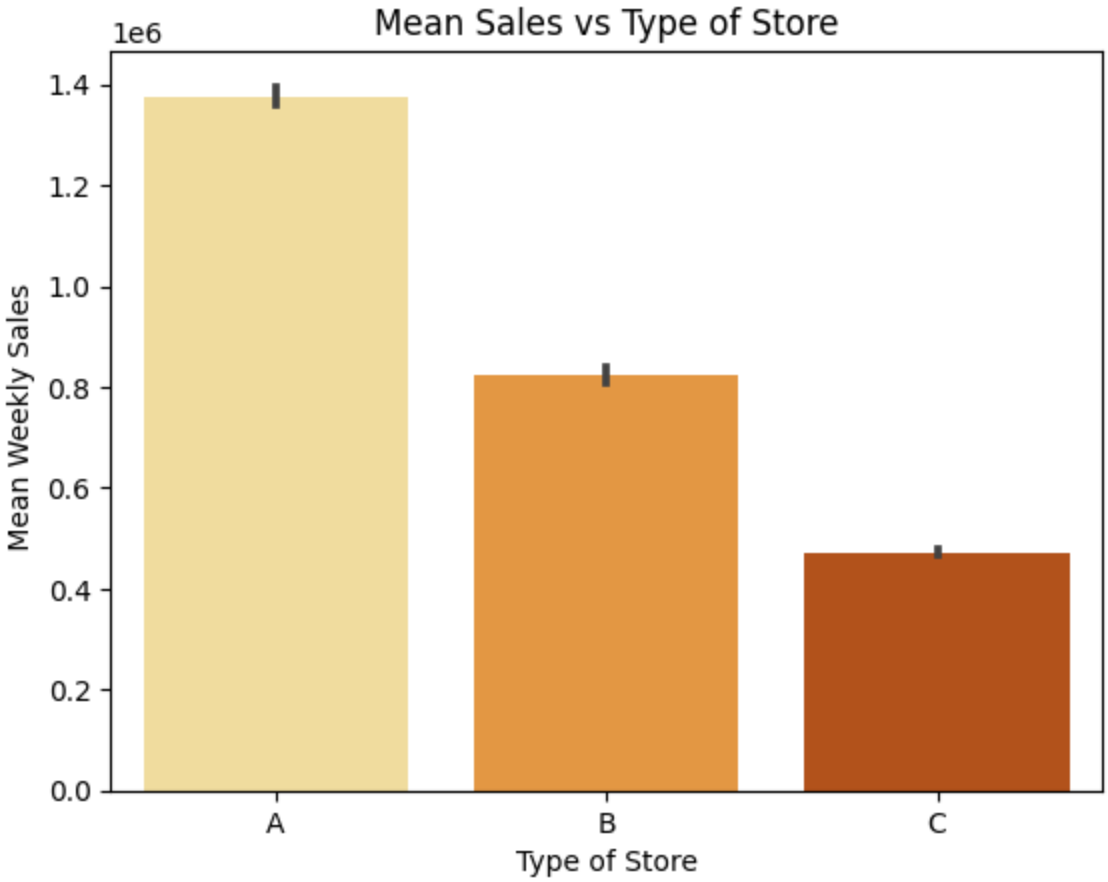


Graph clearly shows Temperature is more of a seasonal and repeated in cycles and this would be an interesting data point that we can use for studies further

inference: Fuel price varies over time and there are high and lows

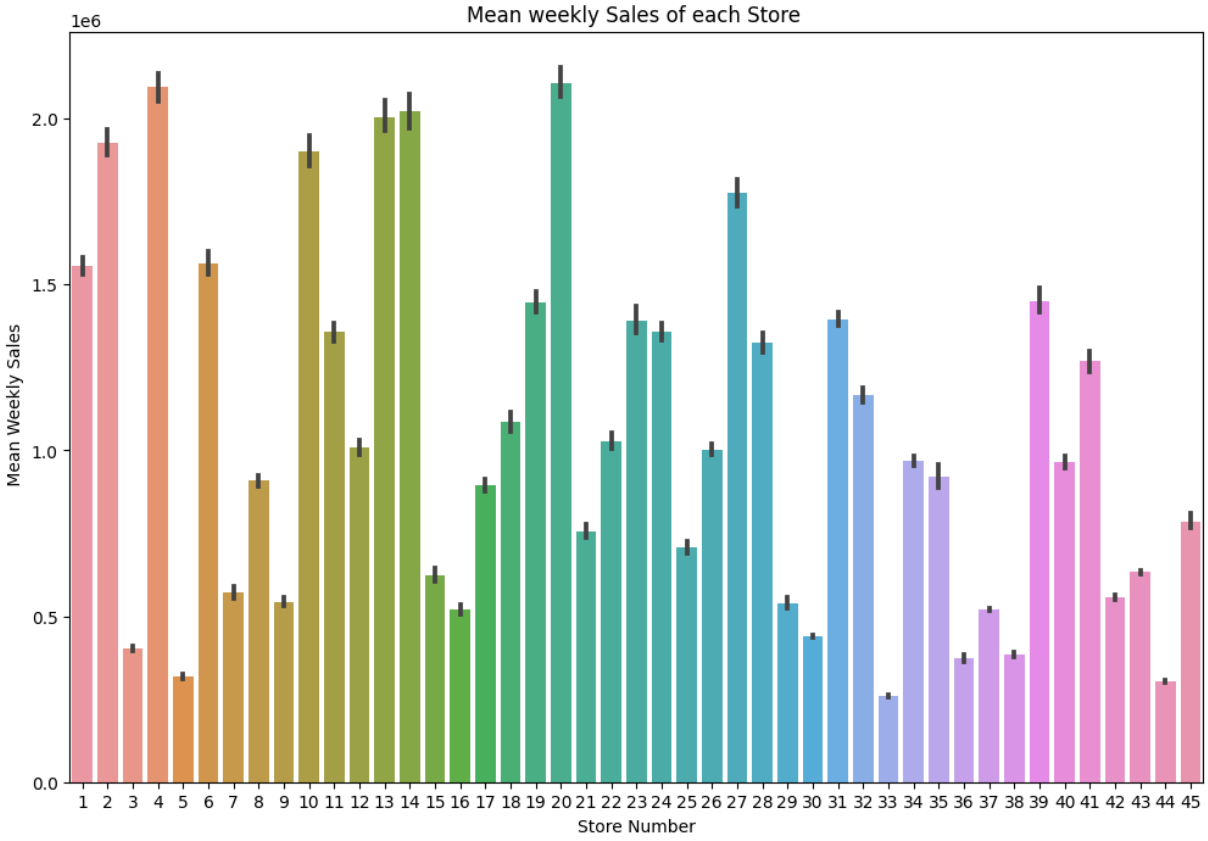
inference: Over time unemployment have came down we can see this factor also whether it have affected the Sales

In [32]:
```
# Checking how the Type of the store have effect on the sales.
col=['coral', 'greenyellow', 'turquoise']
sns.barplot(x="Type", y="Weekly_Sales", data=data,orient='v', palette ='YlOr
plt.xlabel('Type of Store')
plt.ylabel(' Mean Weekly Sales')
plt.title('Mean Sales vs Type of Store')
#plt.savefig('./images/Type_vs_Sales.png')
plt.show()
```



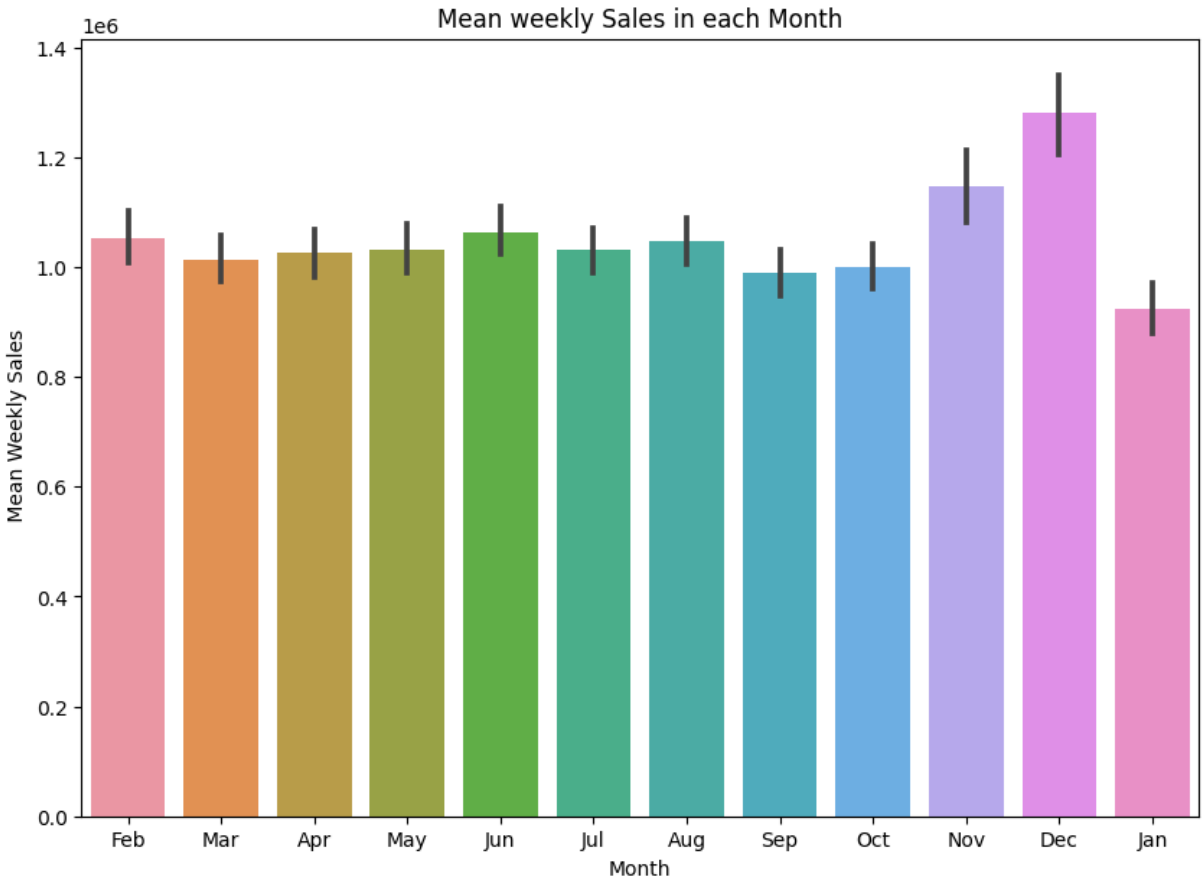
inference: From the graph its clear that Type A > Type B > Type C in mean weekly sales.

In [17]:
```
plt.subplots(figsize=(12,8))
sns.barplot(x="Store", y="Weekly_Sales", data=data,orient='v')
plt.xlabel('Store Number')
plt.ylabel(' Mean Weekly Sales')
plt.title('Mean weekly Sales of each Store ')
#plt.savefig('./images/Mean_Weekly_Sales_vs_Stores.png')
plt.show()
```



inference : From the chart we can see that there are stores that have a weekly sales from $250,000 to $2,200,000

In [35]:
```
plt.subplots(figsize=(10,7))
sns.barplot(x="Month", y="Weekly_Sales", data=data,orient='v')
plt.xlabel('Month')
plt.ylabel(' Mean Weekly Sales')
plt.title('Mean weekly Sales in each Month')
#plt.savefig('./images/Mean_Weekly_Sales_vs_Months.png')
plt.show()
```



Graph shows sales in each month and from this we can see December seems to have a very high sales compared to every other month and January have the least sales.

Handling Missing Values and Outliers

In [38]:
```
for col in ['MarkDown1', 'MarkDown2', 'MarkDown3', 'MarkDown4', 'MarkDown5']
    mean_value = data[col].mean()
    data[col].fillna(mean_value, inplace=True)
```

In [42]:
```
data.isnull().sum()
```

Out[42]:
```
Store           0
Date            0
Weekly_Sales    0
Type            0
Size            0
Temperature     0
Fuel_Price      0
MarkDown1       0
MarkDown2       0
MarkDown3       0
MarkDown4       0
MarkDown5       0
CPI             0
Unemployment    0
IsHoliday       0
Day             0
Month           0
Year            0
Week            0
dtype: int64
```

We will divide our train and test datasets first and then deal with that seperately

In [20]:
```
# Setting the offset to finalize the test data.
offset = timedelta(days=90)
split_date=data.Date.max()-offset
```

In [21]:
```
data_train=data[data.Date < split_date]
data_test=data[data.Date > split_date]
```

Shuffle the dataframe a bit because while we use crossvalidation for regressors it won't take a random sample as test and train, instead it takes section by section. Here my Dataframe have data for each store in order. So if we take section by section model might not have enough data to learn about certain stores and which intern will give terrible answers

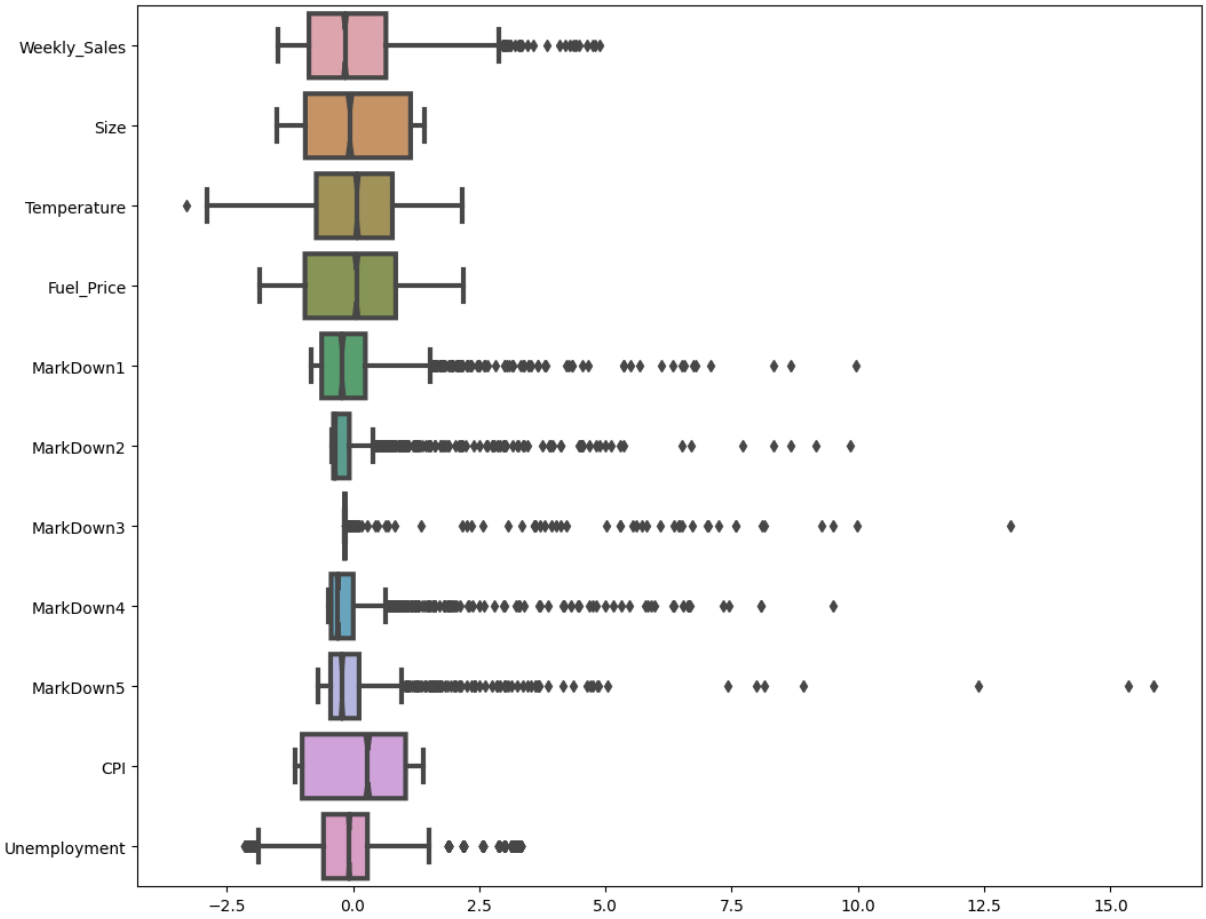
In [22]:
```
data_train = data_train.reindex(np.random.permutation(data.index))## Identif
data_train.columns
```

Out[22]:
```
Index(['Store', 'Date', 'Weekly_Sales', 'Type', 'Size', 'Temperature',
       'Fuel_Price', 'MarkDown1', 'MarkDown2', 'MarkDown3', 'MarkDown4',
       'MarkDown5', 'CPI', 'Unemployment', 'IsHoliday', 'Day', 'Month', 'Ye
ar',
       'Week'],
      dtype='object')
```

In [23]:
```
data_train.dtypes
```

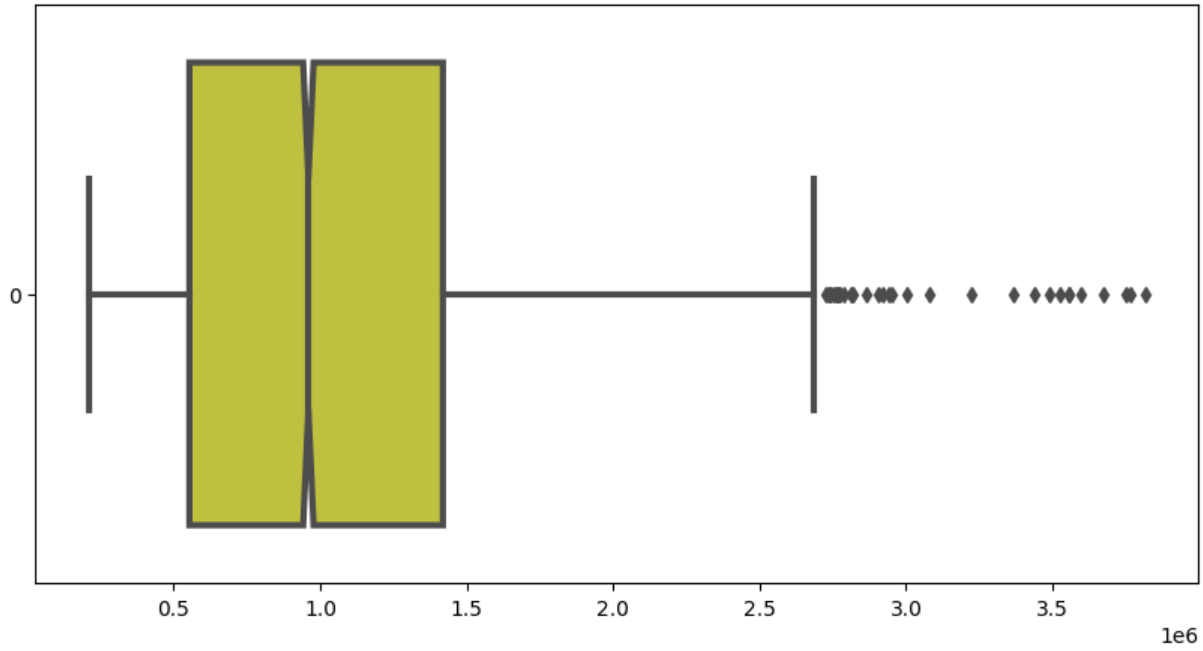
Out[23]:
```
Store                  float64
Date            datetime64[ns]
Weekly_Sales           float64
Type                    object
Size                   float64
Temperature            float64
Fuel_Price             float64
MarkDown1              float64
MarkDown2              float64
MarkDown3              float64
MarkDown4              float64
MarkDown5              float64
CPI                    float64
Unemployment           float64
IsHoliday              float64
Day                    float64
Month                   object
Year                   float64
Week                    UInt32
dtype: object
```

In [24]:
```
data_box=data_train[['Weekly_Sales', 'Size', 'Temperature', 'Fuel_Price',
                     'MarkDown1', 'MarkDown2', 'MarkDown3', 'MarkDown4', '
                     'CPI', 'Unemployment']]
data_norm = (data_box - data_box.mean()) / data_box.std()

fig = plt.figure(figsize=(12, 10))
ax = fig.gca()

ax = sns.boxplot(data=data_norm, orient='h', fliersize=5,
                 linewidth=3, notch=True, saturation=0.5, ax=ax)
plt.show()
```



There are quite a lot of outliers in MarkDown, But Lets first deal the outliers in weekly sales data because we might just drop MarkDowns Later because the percentage of missing values are really high in MarkDowns

In [55]:
```
fig = plt.figure(figsize=(10, 5))
ax = fig.gca()

ax = sns.boxplot(data_train.Weekly_Sales, orient='h', fliersize=5,
                 linewidth=3, notch=True, saturation=0.5, ax=ax, color = 'ye
plt.show()
```

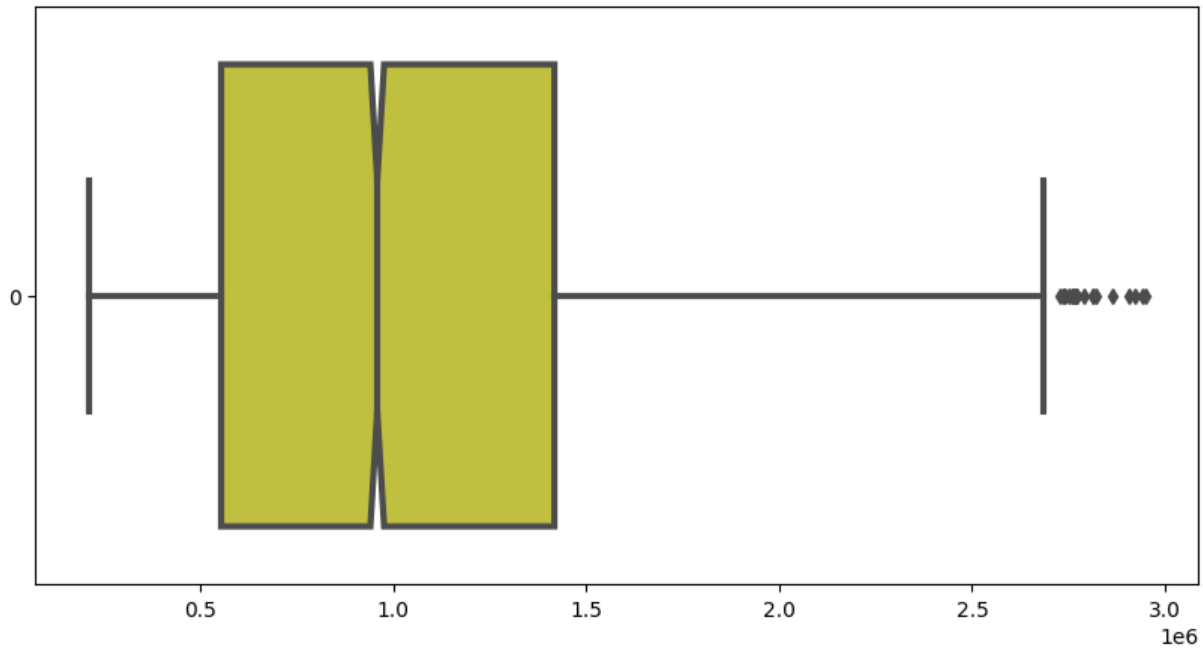


In [57]:
```
# Lets consider 3,000,000 as upper limit
data_train[data_train.Weekly_Sales>3000000].shape
```

Out[57]: (14, 19)

In [58]:
```
# there is only 14 outliers. Lets drop it and proceed.
data_train=data_train[data_train.Weekly_Sales<3000000]
```

In [59]:
```
fig = plt.figure(figsize=(10, 5))
ax = fig.gca()

ax = sns.boxplot(data_train.Weekly_Sales, orient='h', fliersize=5,
                 linewidth=3, notch=True, saturation=0.5, ax=ax, color = 'ye
plt.show()
```



Forecasting Using Gradient Boost Regreessor and Support Vector Regressor

In [77]:
```
# Exclude categorical columns from predictors
predictors = [col for col in data.columns if data[col].dtype in [np.float64,
```

In [84]:
```
from sklearn.preprocessing import OneHotEncoder

# Assuming 'Type' is the only categorical column in predictors
categorical_cols = ['Type']

# One-hot encode the categorical columns
one_hot_encoder = OneHotEncoder()
X_train_encoded = one_hot_encoder.fit_transform(X_train[categorical_cols])
X_test_encoded = one_hot_encoder.transform(X_test[categorical_cols])

# Convert the encoded features into a DataFrame
X_train_encoded_df = pd.DataFrame(X_train_encoded.toarray(), index=X_train.i
X_test_encoded_df = pd.DataFrame(X_test_encoded.toarray(), index=X_test.inde

# Combine the encoded features with the rest of the predictors
X_train_combined = pd.concat([X_train.drop(columns=categorical_cols), X_trai
X_test_combined = pd.concat([X_test.drop(columns=categorical_cols), X_test_e

# Now apply StandardScaler
# Convert feature names to strings
X_train_combined.columns = X_train_combined.columns.astype(str)
X_test_combined.columns = X_test_combined.columns.astype(str)
X_train = data_train[predictors]
y_train = data_train.Weekly_Sales.values

X_test = data_test[predictors]
y_test = data_test.Weekly_Sales.values
# Now apply StandardScaler
ss = StandardScaler()
X_train_s = ss.fit_transform(X_train_combined)
X_test_s = ss.transform(X_test_combined)
```

Gradient Boost Regressor

In [90]:
```
gb = GradientBoostingRegressor(n_estimators=100,max_depth=10,learning_rate=0
gb.fit(X_train_s, y_train)
gb_scores = cross_val_score(gb, X_train_s, y_train, cv=6)
np.mean(gb_scores)
```

Out[90]:
```
0.9498621552677727
```

In [91]:
```
gb_yhat=gb.predict(X_test_s)
gb_score=gb.score(X_test_s,y_test)

print("R2: ",gb_score)
```

```
gb_adj_r2 = 1 - (len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)*(1-gb_score)
print("Adjusted R2: ",gb_adj_r2)
```

```
R2:  0.9659843351144408
Adjusted R2:  0.9652707197671914
```

In [92]:
```
train_resids = y_train*1000 - gb.predict(X_train_s)*1000
test_resids = y_test*1000 - gb_yhat*1000
gb_residue=np.abs(test_resids).sum()
# Let me look at the actual Residuals.
print("Train Residual",np.abs(train_resids).sum())
print("Test Residual",gb_residue)
print("Residual ratio of Test to Train",np.abs(test_resids).sum()/np.abs(tra
```

```
Train Residual 40360206674.11125
Test Residual 37487101822.35924
Residual ratio of Test to Train 0.9288134256855789
```

In [99]:
```
plt.scatter(gb_yhat, y_test, c='orange')
plt.xlabel('Sales Predicted')
plt.ylabel('Sales- Actual')
plt.title('Predicted versus Actual Weekly Sales of Stores')

plt.show()
```

Support Vector Regressor

In [93]:
```
svr=SVR(C=50000.0, max_iter=500)
```

```
svr.fit(X_train_s, y_train)
```

Out[93]:

SVR

SVR(C=50000.0, max_iter=500)

In [94]:
```
svr_scores = cross_val_score(svr, X_train_s, y_train, cv=10)
np.mean(svr_scores)
```

Out[94]: 0.5993284400427829

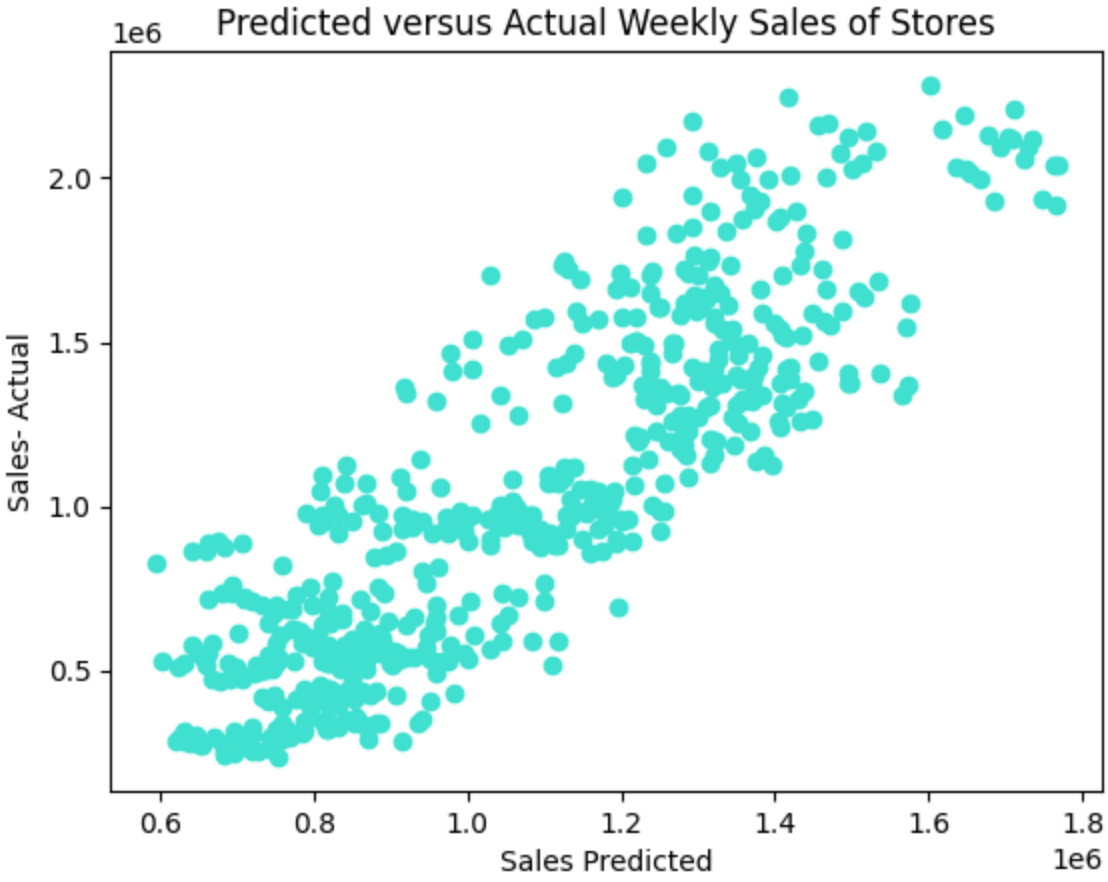
In [95]:
```
svr_yhat=svr.predict(X_test_s)
svr_score=svr.score(X_test_s,y_test)
print("R2: ",svr_score)
svr_adj_r2 = 1 - (len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)*(1-svr_scor
print("Adjusted R2: ",svr_adj_r2)
```

```
R2:  0.6280759901521427
Adjusted R2:  0.6202733885469428
```

In [97]:
```
train_resids = y_train*1000 - svr.predict(X_train_s)*1000
test_resids = y_test*1000 - svr_yhat*1000
svr_residue=np.abs(test_resids).sum()
# Let me look at the actual Residuals.
print("Train Residual", np.abs(train_resids).sum())
print("Test Residual",svr_residue)
print("Residual ratio of Test to Train",np.abs(test_resids).sum()/np.abs(tra
```

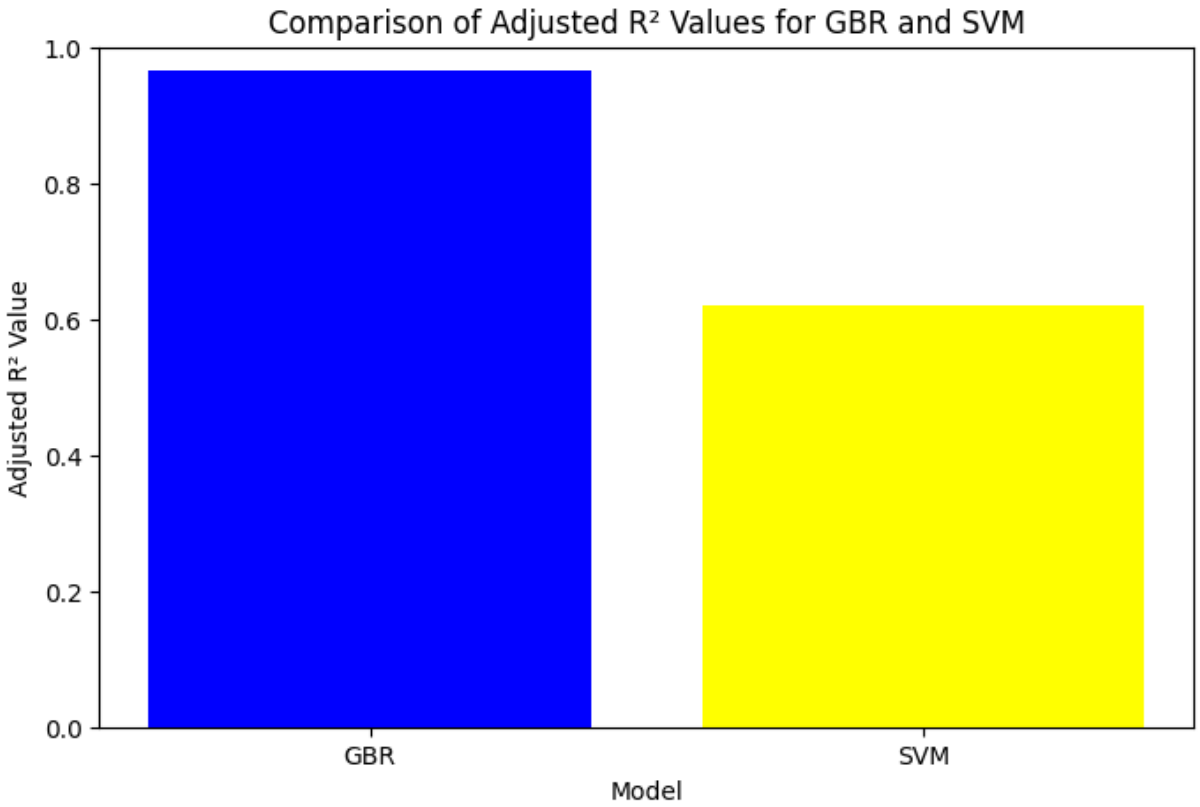
```
Train Residual 1611104539346.1753
Test Residual 157585040874.20804
Residual ratio of Test to Train 0.09781180365748321
```

In [98]:
```
plt.scatter(svr_yhat, y_test, c='turquoise')
plt.xlabel('Sales Predicted')
plt.ylabel('Sales- Actual')
plt.title('Predicted versus Actual Weekly Sales of Stores')

plt.show()
```



Comaprison of GBR And SVR

In [19]:
```
adjusted_r2 = {'GBR': 0.9652707197671914, 'SVM': 0.6202733885469428}

# Names of models
models = list(adjusted_r2.keys())

# Corresponding R2 values
r2_values = list(adjusted_r2.values())

# Creating the bar chart
plt.figure(figsize=(8, 5))
plt.bar(models, r2_values, color=['blue', 'yellow'])

# Adding chart labels and title
plt.xlabel('Model')
plt.ylabel('Adjusted R² Value')
plt.title('Comparison of Adjusted R² Values for GBR and SVM')
plt.ylim(0, 1)  # Setting the y-axis limit for better comparison

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



Findings

1. There is an increase in sales during the holiday season.
2. There is a strong correlation between the size of the store and weekly sales.
3. The data that we used before the time series analysis was not stationary which was converted into stationary data during our analysis for further exploration which means that the statistical properties of the time series data were not a function of time.
4. We also found variations in weekly sales for type of store, month, and store number

Recommendations

1. Get a prediction for each individual store.
2. Adjust the staff in the store according to season.
3. The low-selling stores should look forward to increasing their size and capacity to store more items and consumer products.
4. Special discount coupons can be distributed during low-selling periods to attract more customers.

5. Special offers can be given during the festive season accompanied by suitable marketing to keep the sales high during holidays as well.

6. This data can be further improved, and other models can be used for predicting the sales for business decisions.

Conclusion

The analysis highlighted key factors impacting sales, such as holiday seasons and store size, and transformed non-stationary data to better understand sales variations.

It suggests that strategies like seasonal staffing adjustments, store expansion, and targeted promotions can boost sales and guide business decisions.

In [ ]: