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]:
```python
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]:
```python
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	(
Day	6435.0	15.678322	1.0	8.0	16.0	23
Year	6435.0	2010.965035	2010.0	2010.0	2011.0	2012

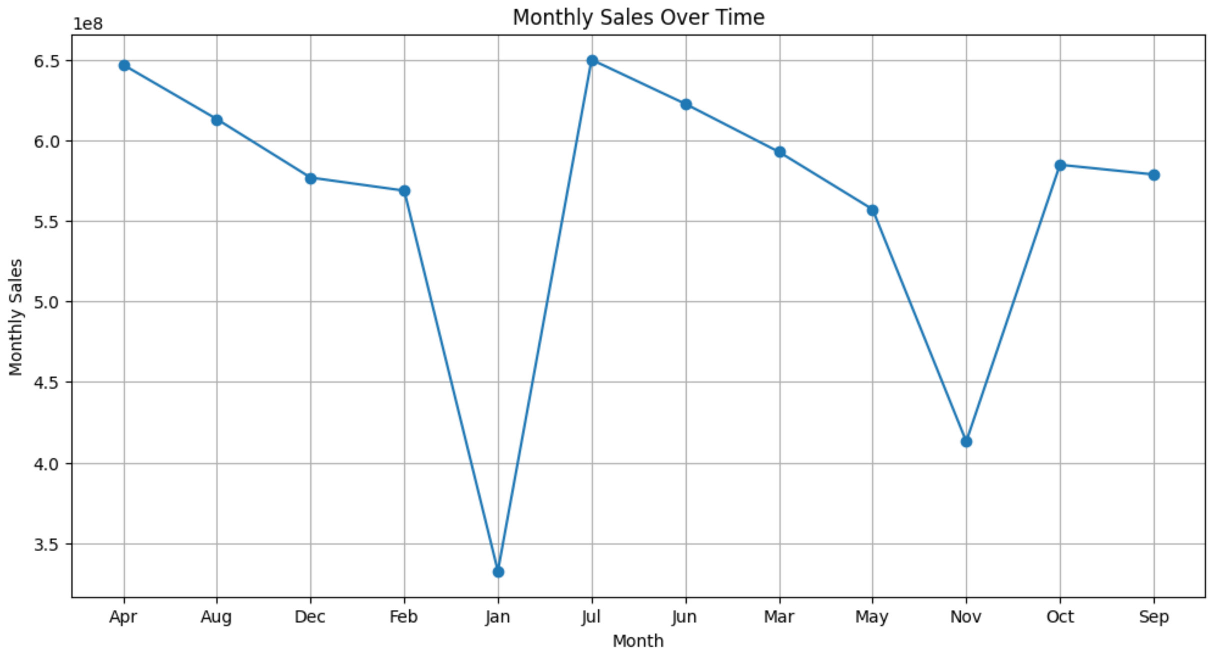
In [15]:
```python
#add a 'week' column to the dataset for further analysis
data['Week'] = data.Date.dt.isocalendar().week
data.dtypes
```

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

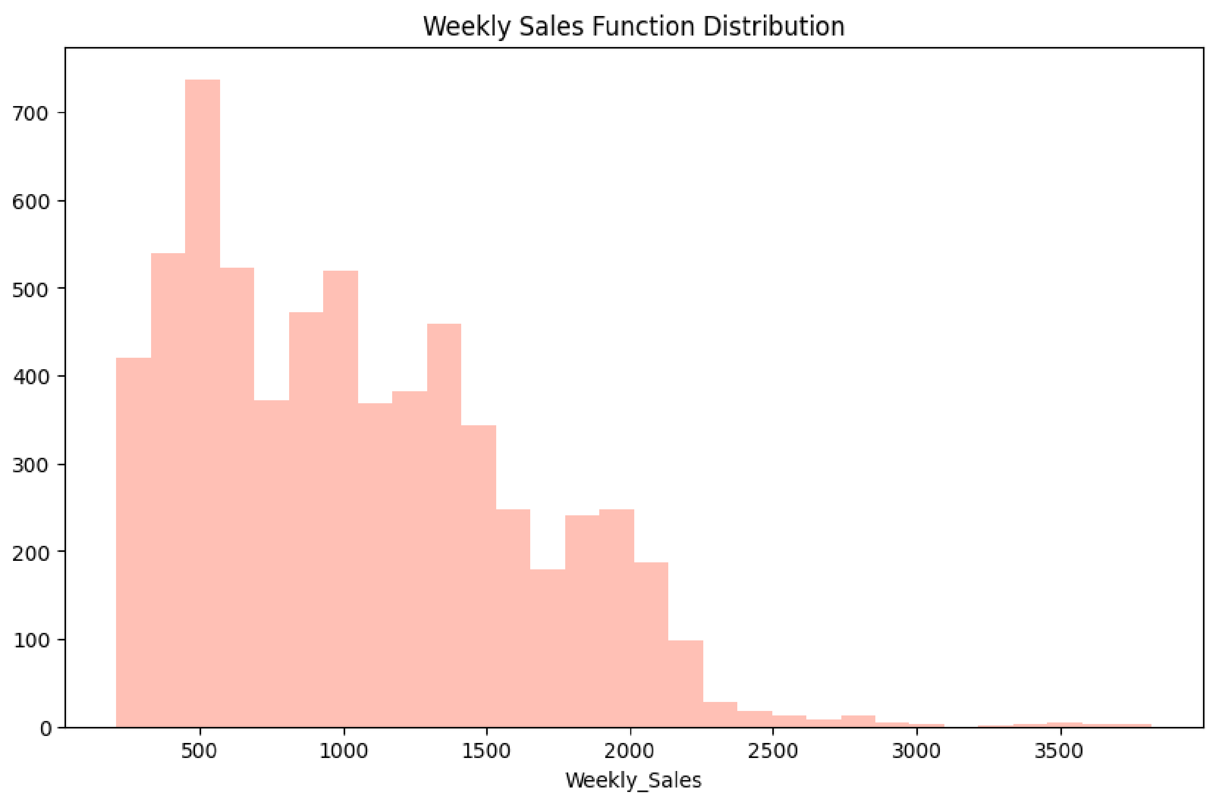
In [16]:
```python
import matplotlib.pyplot as plt

# 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()
```



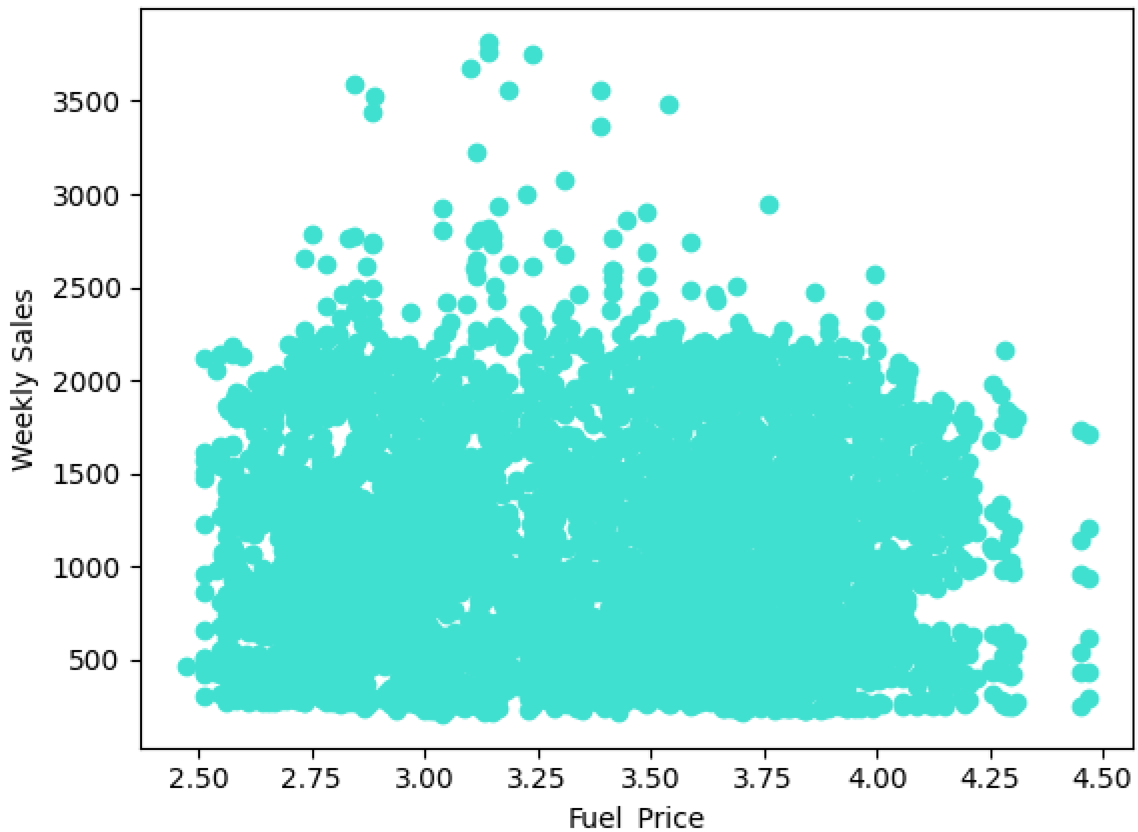
In [17]:
```
df_weeks.dtypes
```

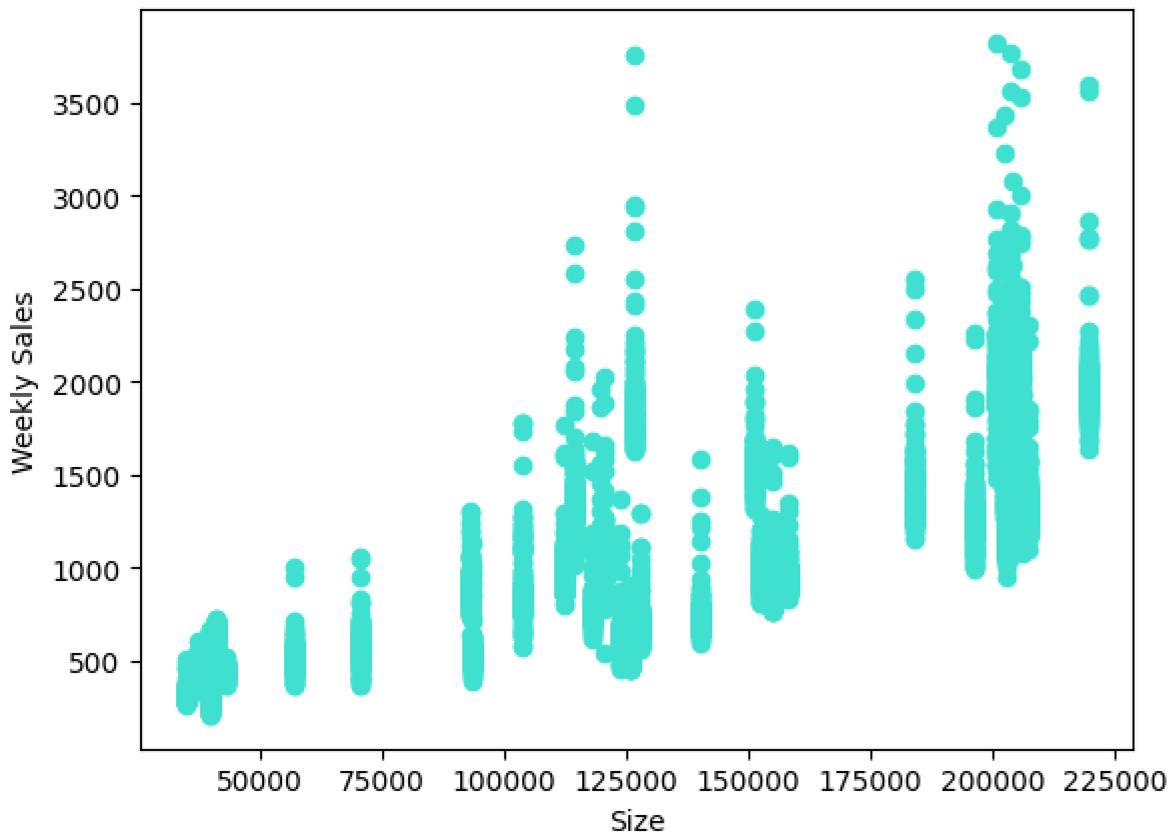
Out[17]:
```
dtype('float64')
```

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()
```

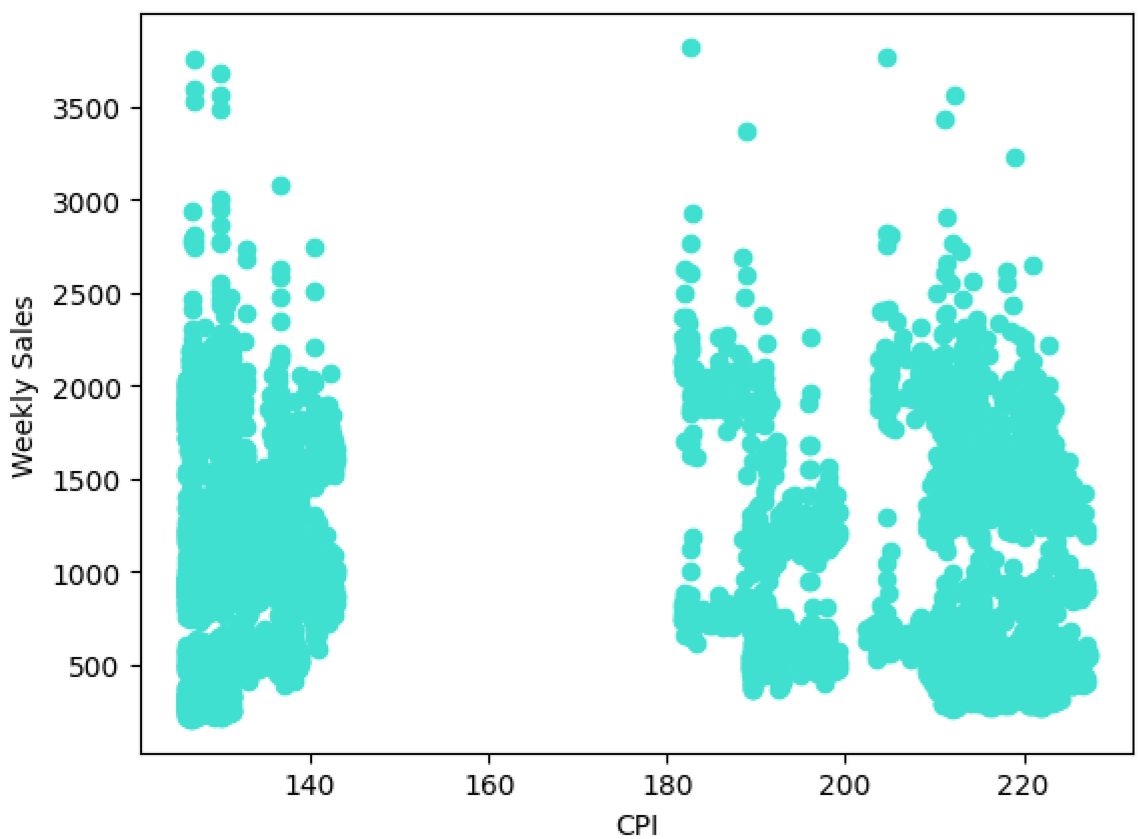


In [19]:
```
def scatter(dataset, column):
    plt.figure()
    plt.scatter(data[column] , data['Weekly_Sales'], color = 'turquoise')
    plt.ylabel('Weekly Sales')
    plt.xlabel(column)
scatter(data, 'Fuel_Price')
scatter(data, 'Size')
scatter(data, 'CPI')
scatter(data, 'Type')
scatter(data, 'IsHoliday')
scatter(data, 'Unemployment')
scatter(data, 'Temperature')
scatter(data, 'Store')
```

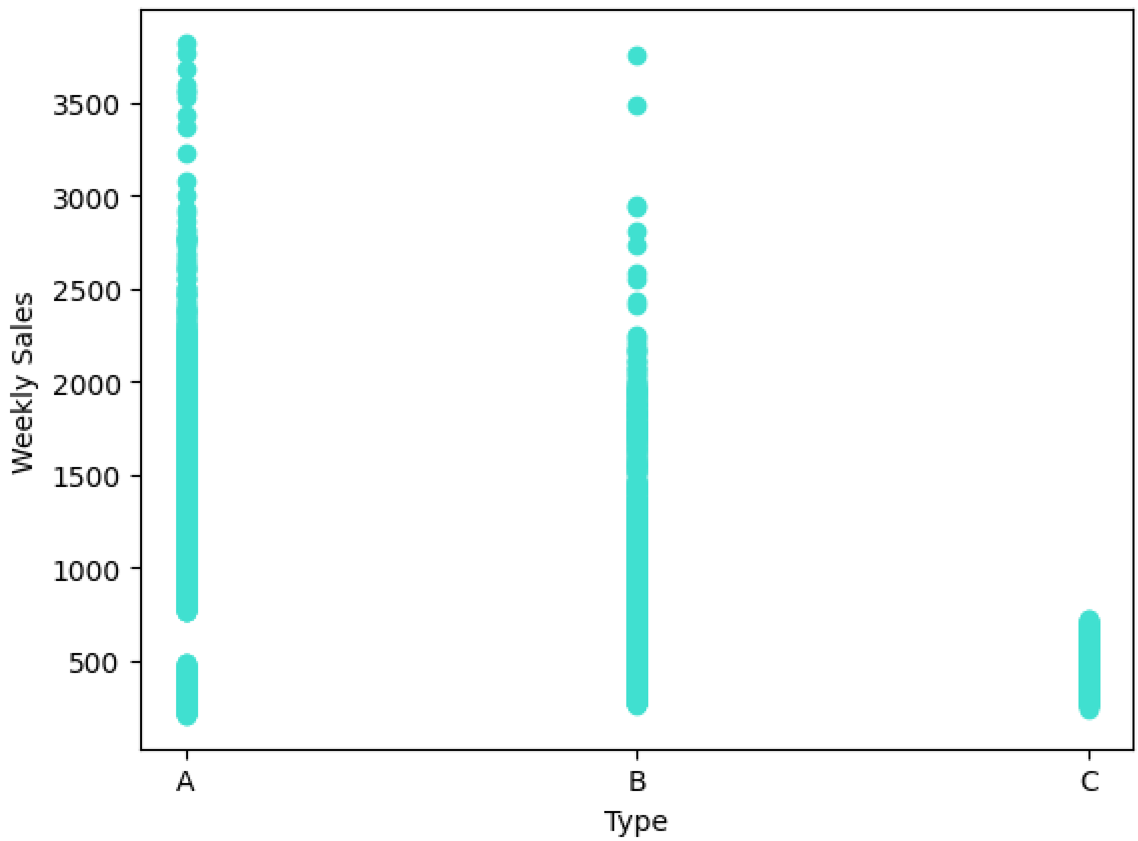


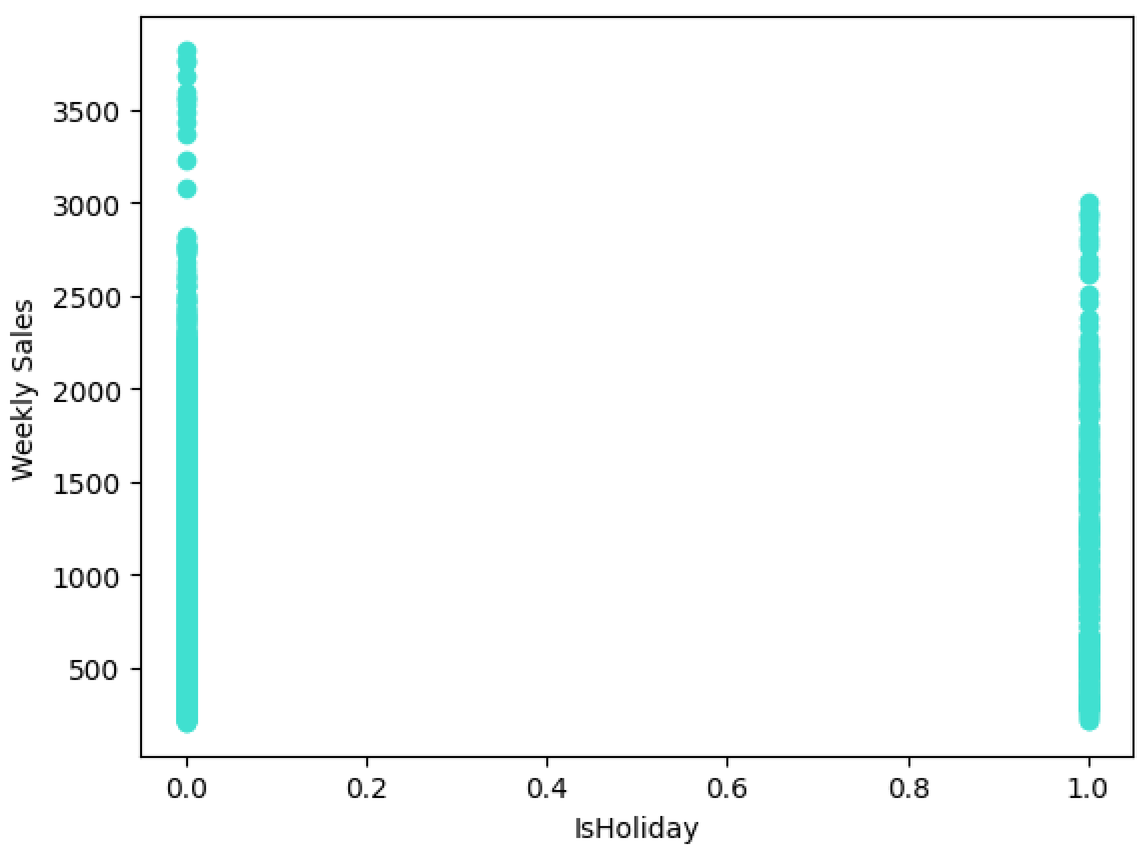


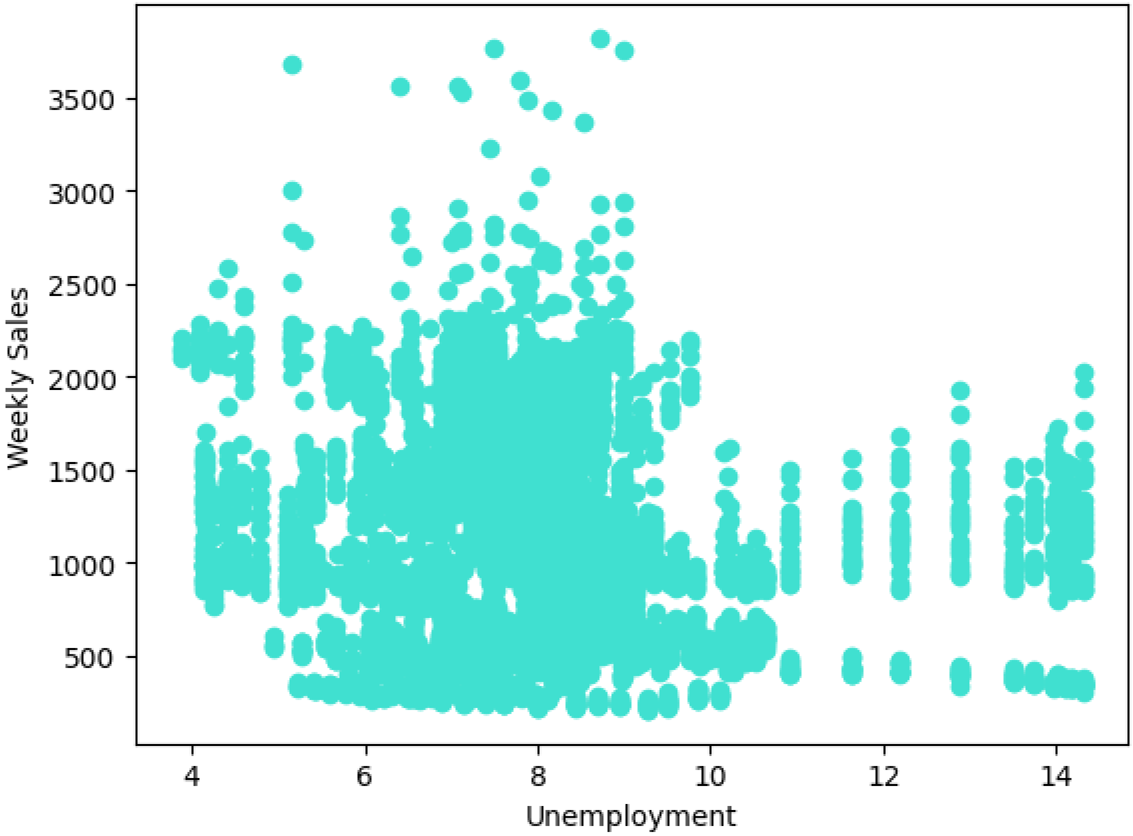
Weekly Sales
Size

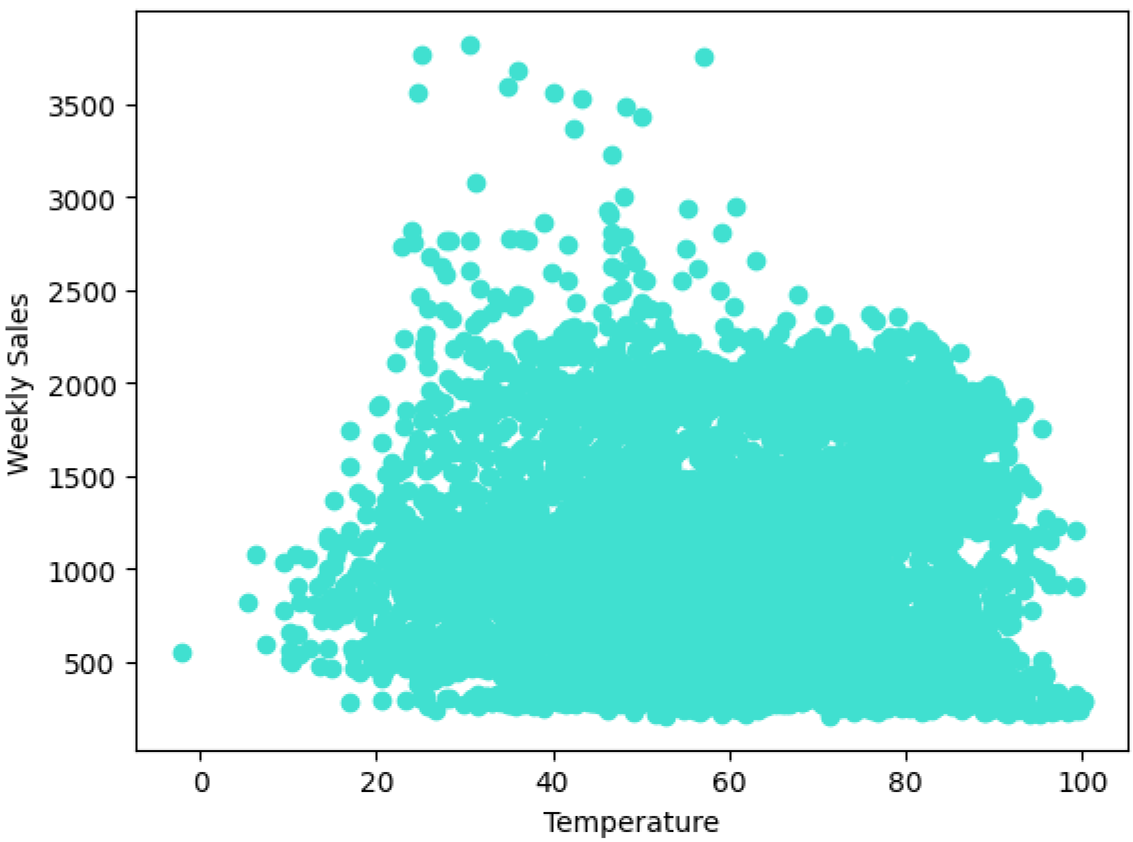


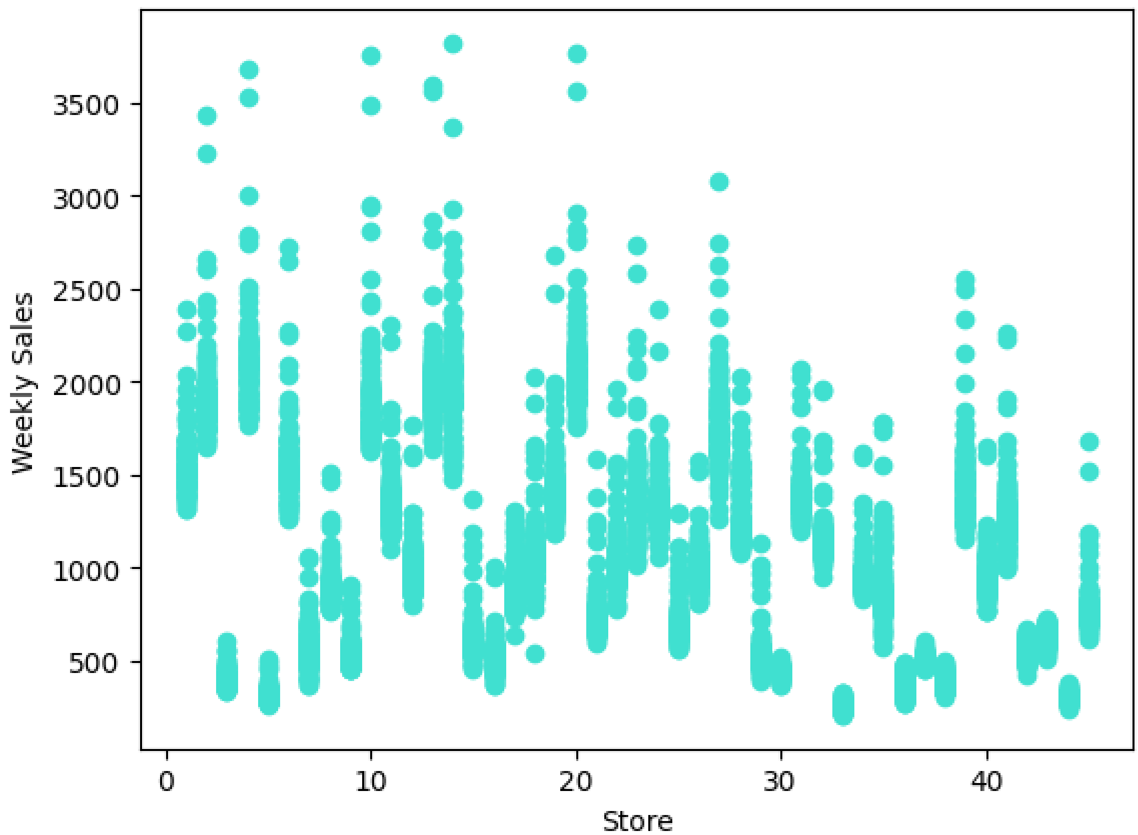
Weekly Sales
CPI


Weekly Sales
3500
3000
2500
2000
1500
1000
500
A
B
C
Type


Weekly Sales
3500
3000
2500
2000
1500
1000
500
0.0
0.2
0.4
0.6
0.8
1.0
IsHoliday


3500
3000
2500
2000
1500
1000
500
Weekly Sales
4
6
8
10
12
14
Unemployment


3500
3000
2500
2000
1500
1000
500
Weekly Sales
0
20
40
60
80
100
Temperature



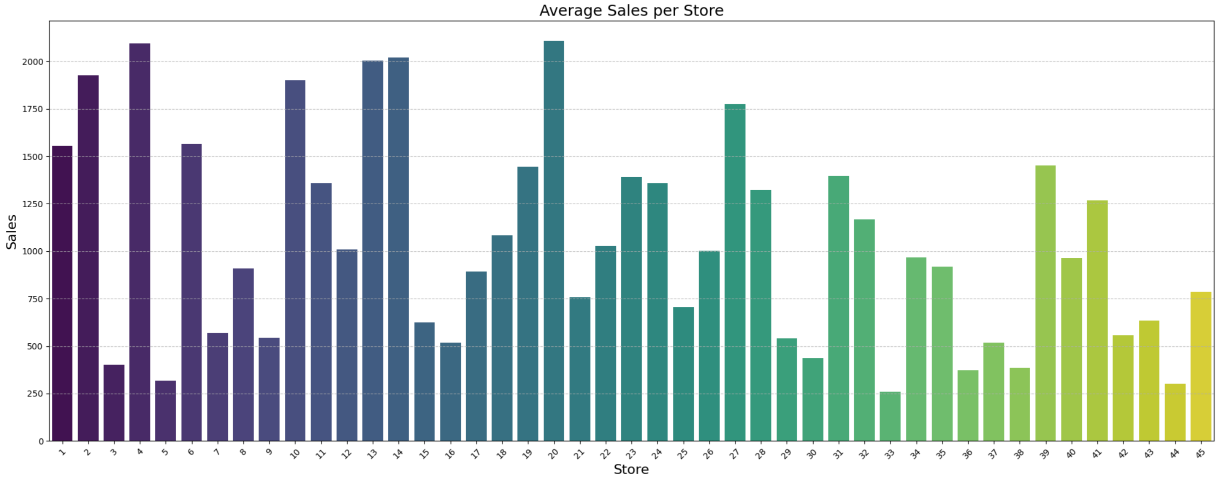
In [23]:
```
import plotly.express as px

# 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
```

```python
fig.update_layout(
    xaxis_title='Week',
    yaxis_title='Sales',
    legend_title='Year',
)

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

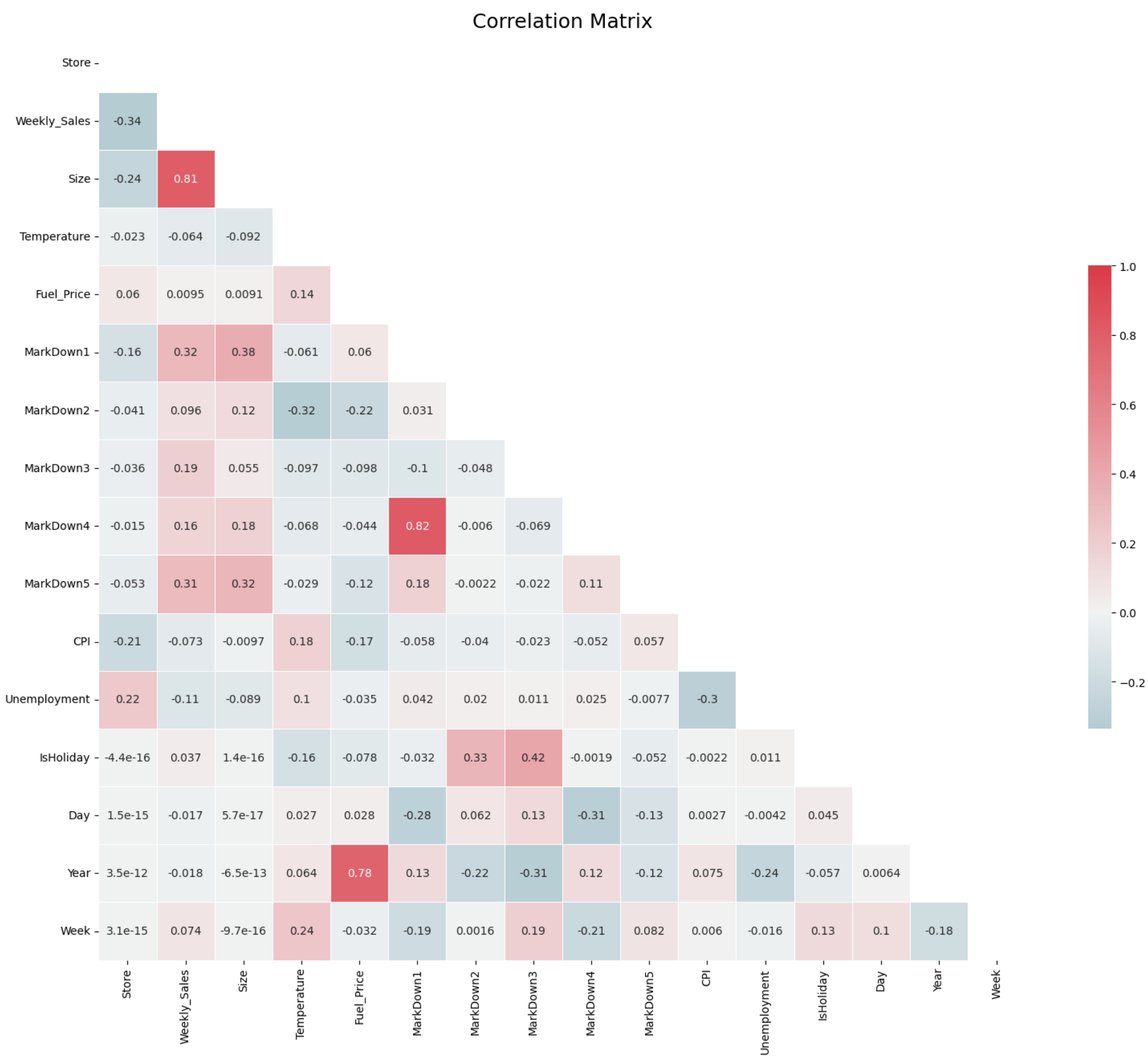
In [20]:

```python
# Calculate the average weekly sales per store
weekly_sales = data.groupby('Store')['Weekly_Sales'].mean()

# Create the bar plot
plt.figure(figsize=(20, 8))
plt.style.use('default')

# Use Seaborn's barplot function
sns.barplot(x=weekly_sales.index, y=weekly_sales.values, palette='viridis')

plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.title('Average Sales per Store', fontsize=18)
plt.ylabel('Sales', fontsize=16)
plt.xlabel('Store', fontsize=16)
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
```

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



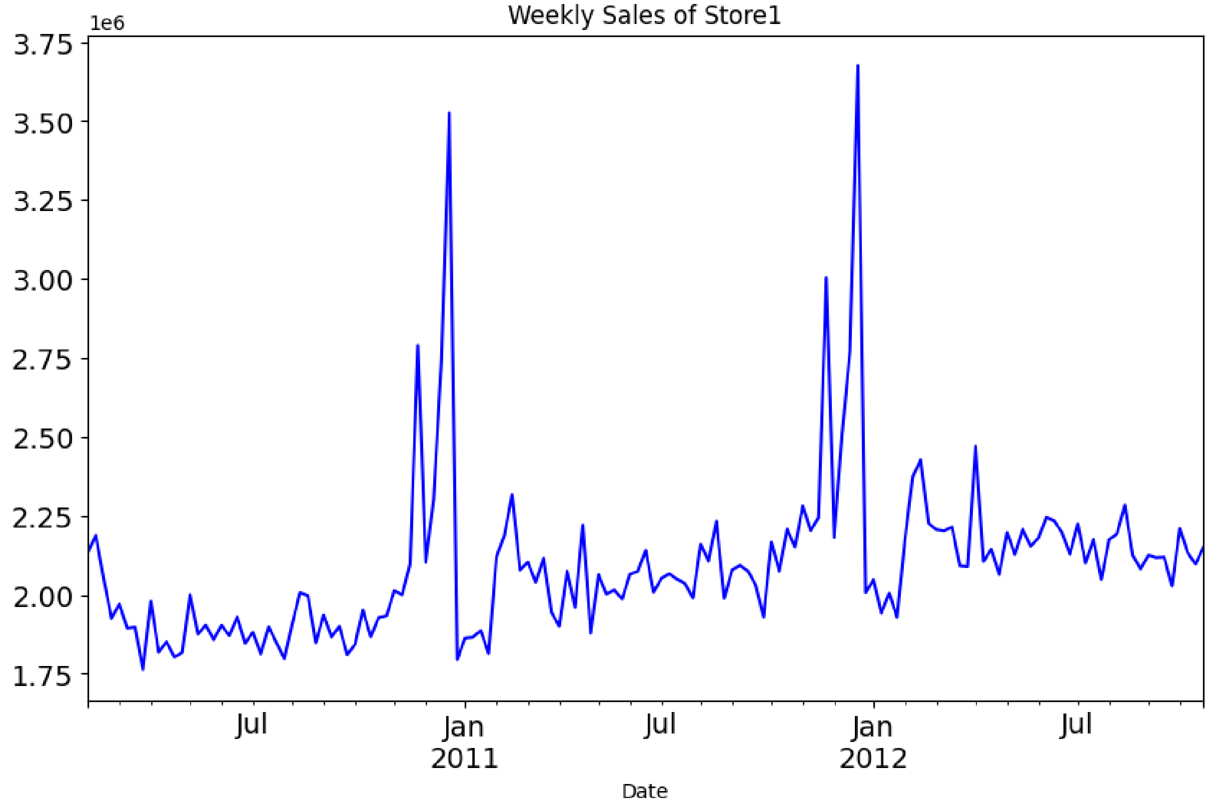
Detailed Time-Series Analysis

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
```

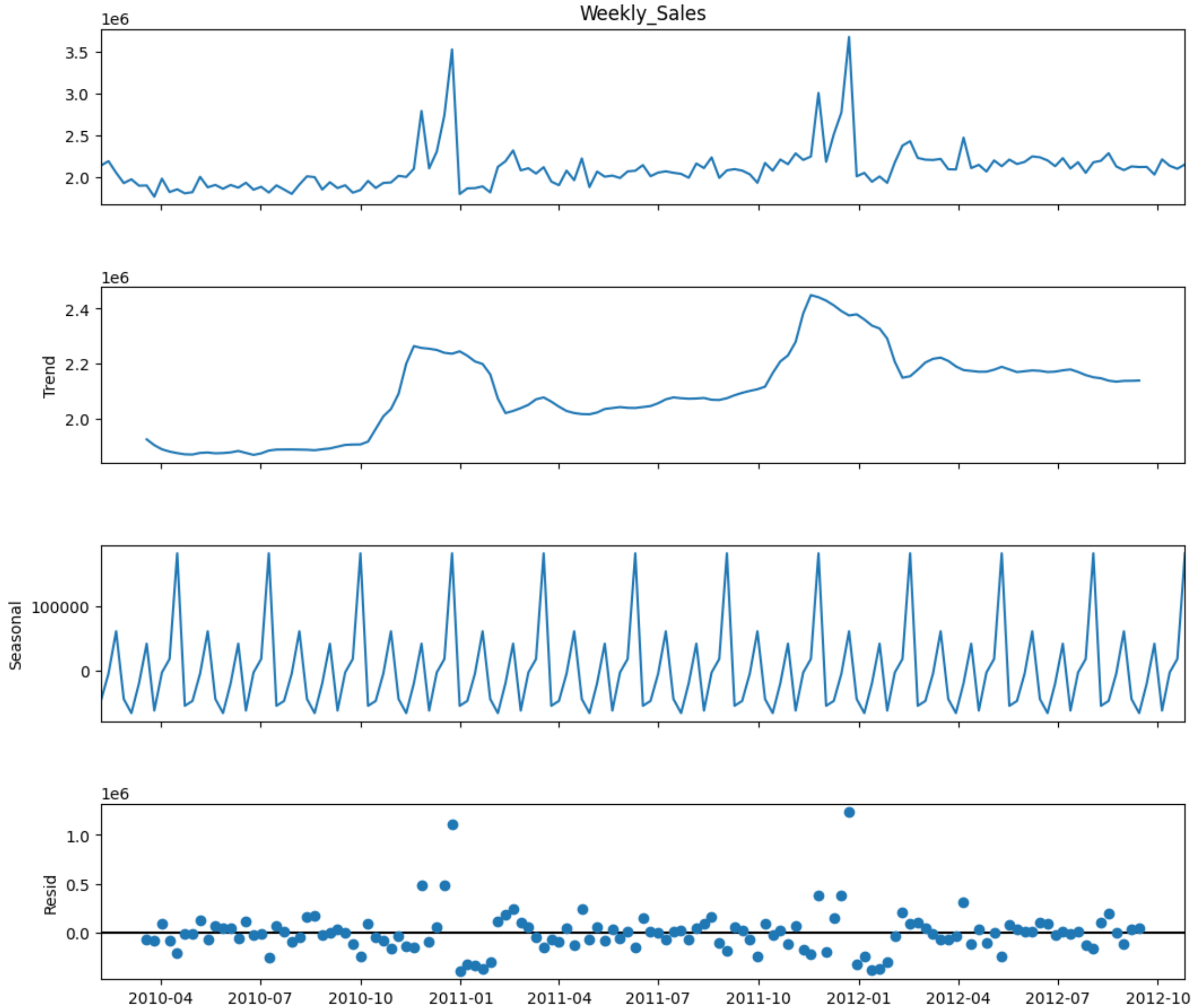
```
#remove date from index to change its dtype because it clearly isnt acceptab
sales4.reset_index(inplace = True)

#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 [21]:
```
sales4.Weekly_Sales.plot(figsize=(10,6), title= 'Weekly Sales of Store1', fo
plt.show()
```



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
0:0000:010:01
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>
```

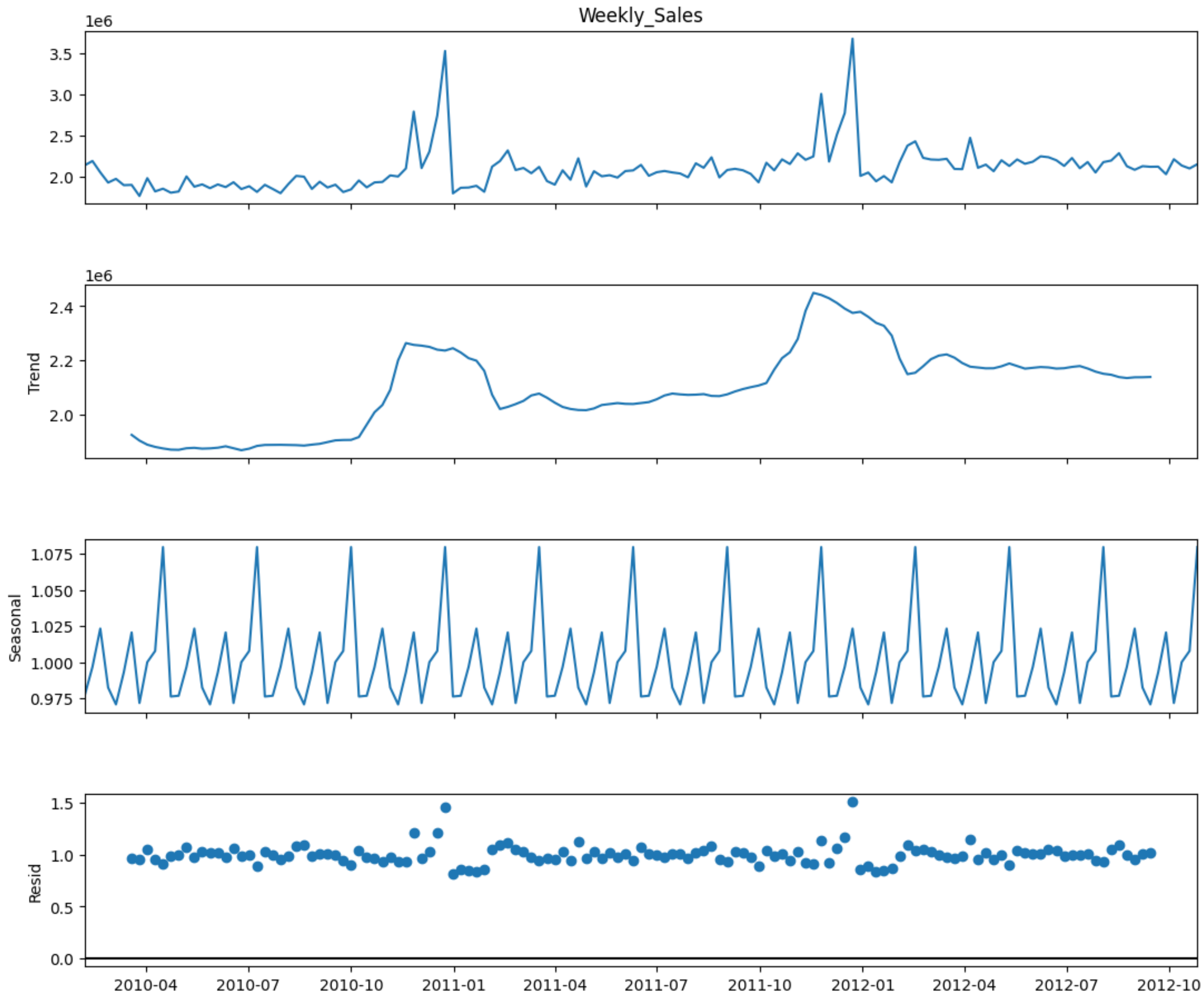


Multiplicative Decomposition

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.

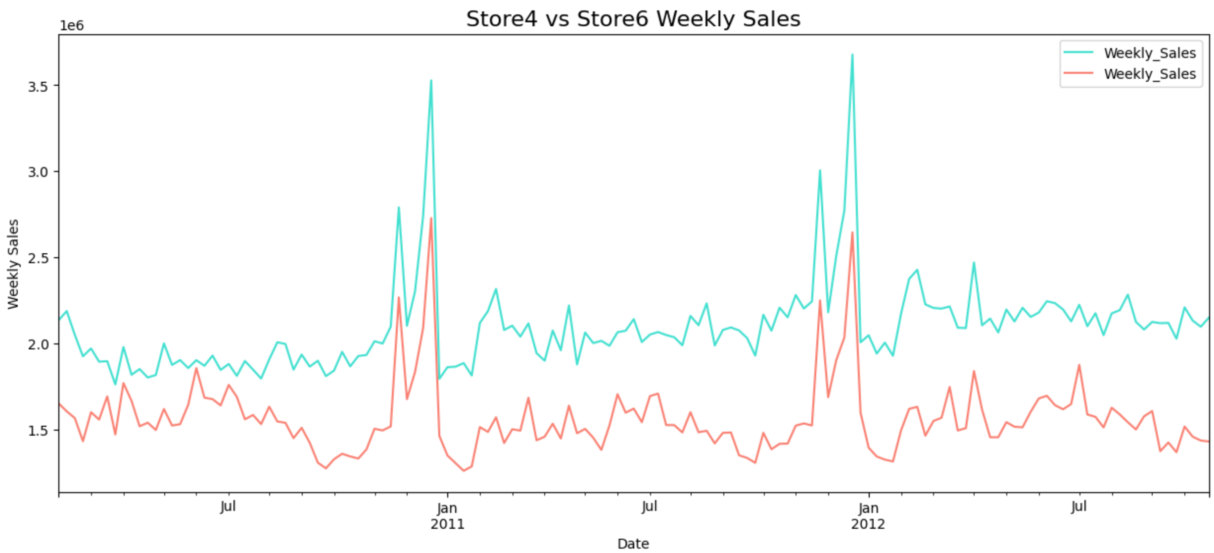
In [23]:
```
decomposition = seasonal_decompose(sales4.Weekly_Sales, model= 'multiplicati
fig = plt.figure()
fig = decomposition.plot()
fig.set_size_inches(12, 10)
plt.show()
```

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



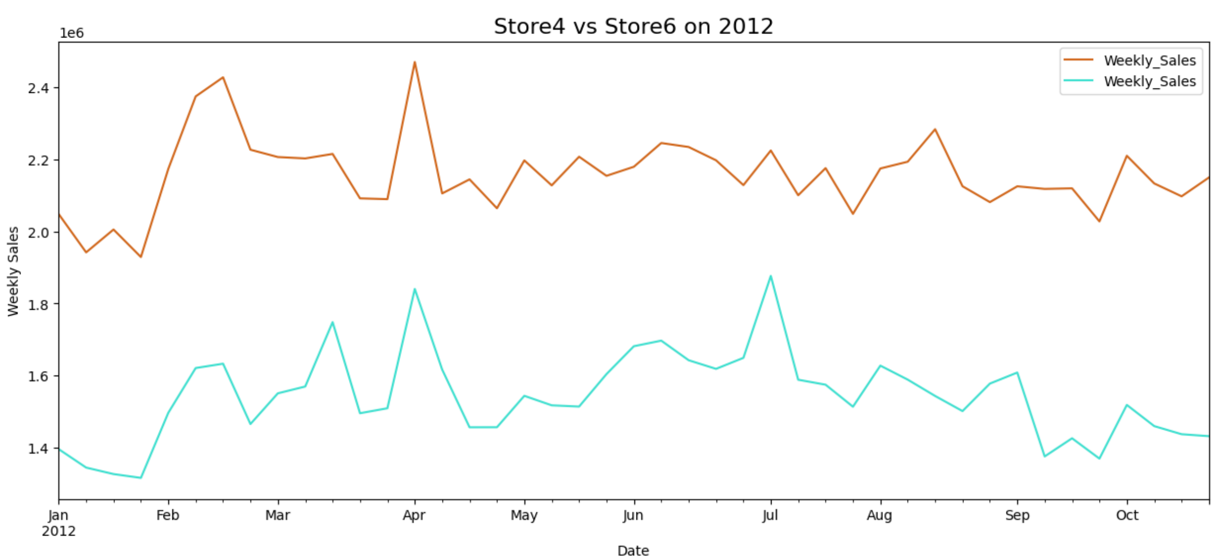
In [24]:
```
#Comparing sales from store 4 and store 6
# Lets take store 6 data for analysis
store6 = data1[data1.Store == 6]
# there are about 45 different stores in this dataset.

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

In [26]:
```
# Lets Look into 2012 data for a better view
y1['2012'].plot(figsize=(15, 6),legend=True, color = 'chocolate')
y2['2012'].plot(figsize=(15, 6), legend=True, color = 'turquoise')
plt.ylabel('Weekly Sales')
plt.title('Store4 vs Store6 on 2012', fontsize = '16')
plt.show()
```



Not quite a trend. Here comes yet another component of timeseries - Irregular component which are other non random sources of variations of series and are mainly the impact of random events such as strikes, earthquakes, and sudden changes in the weather. By their nature, these effects are completely unpredictable.

In [30]:
```
# Define the p, d and q parameters to take any value between 0 and 2
p = d = q = range(0, 5)
```

```python

# Generate all different combinations of p, d and q triplets
pdq = list(itertools.product(p, d, q))

# Generate all different combinations of seasonal p, d and q triplets
seasonal_pdq = [(x[0], x[1], x[2], 52) for x in list(itertools.product(p, d,
```

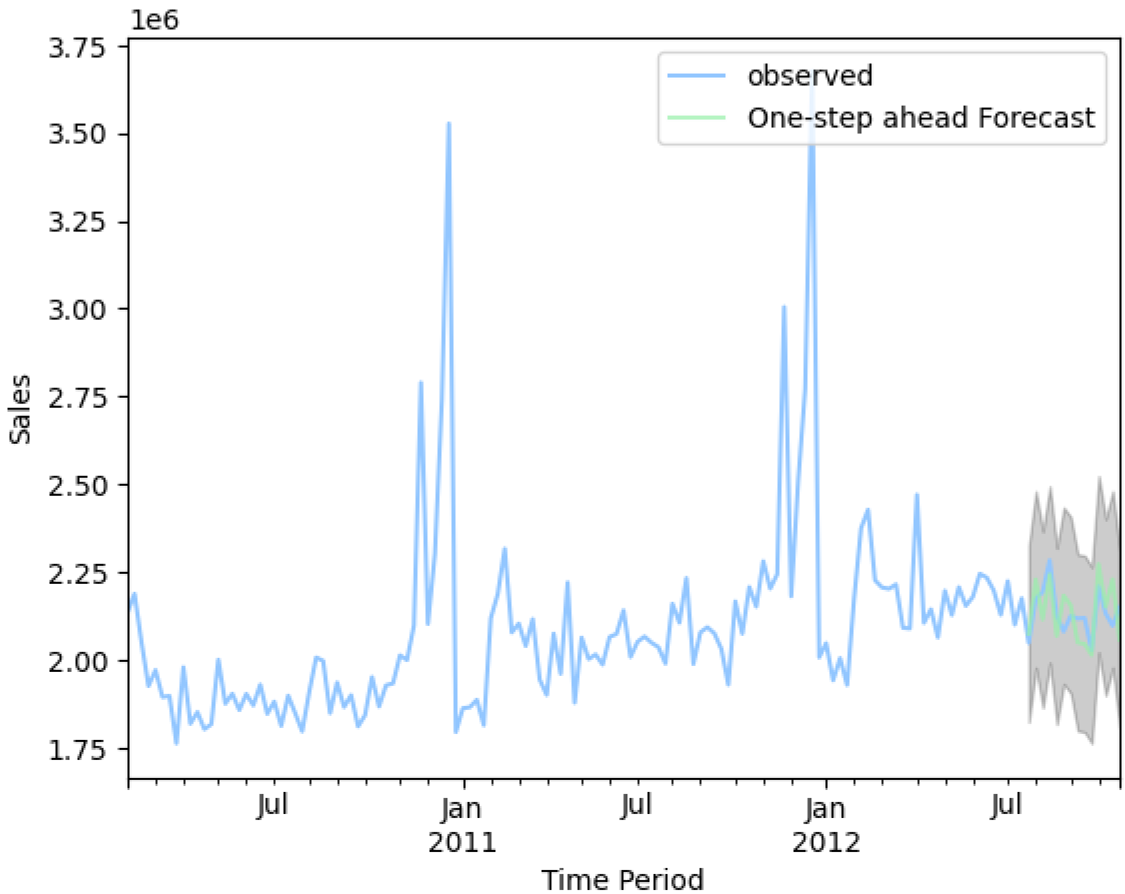
In [ ]:
```python
import statsmodels.api as sm

mod = sm.tsa.statespace.SARIMAX(y1,
                                order=(4, 4, 3),
                                seasonal_order=(1, 1, 0, 52),   #enforce_sta
                                enforce_invertibility=False)

results = mod.fit()

print(results.summary().tables[1])
```

```
This problem is unconstrained.
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            9     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  8.32190D+00    |proj g|=  2.11788D-01

At iterate    5    f=  8.19196D+00    |proj g|=  3.64631D-01

At iterate   10    f=  8.03865D+00    |proj g|=  1.09208D+00

At iterate   15    f=  7.98422D+00    |proj g|=  3.19650D-01

At iterate   20    f=  7.98334D+00    |proj g|=  9.55541D-02

At iterate   25    f=  7.98301D+00    |proj g|=  5.13009D-02

At iterate   30    f=  7.98253D+00    |proj g|=  2.77669D-01

At iterate   35    f=  7.98218D+00    |proj g|=  2.75702D-02

At iterate   40    f=  7.98217D+00    |proj g|=  4.99852D-03

At iterate   45    f=  7.98212D+00    |proj g|=  3.40274D-02
```

In [ ]:
```python
plt.style.use('seaborn-pastel')
results.plot_diagnostics(figsize=(15, 12))
plt.show()
```

In [37]:
```python
# Will predict for last 90 days. So setting the date according to that
pred = results.get_prediction(start=pd.to_datetime('2012-07-27'), dynamic=Fa
pred_ci = pred.conf_int()
```

In [38]:
```
ax = y1['2010':].plot(label='observed')
pred.predicted_mean.plot(ax=ax, label='One-step ahead Forecast', alpha=.7)

ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.2)

ax.set_xlabel('Time Period')
ax.set_ylabel('Sales')
plt.legend()

plt.show()
```



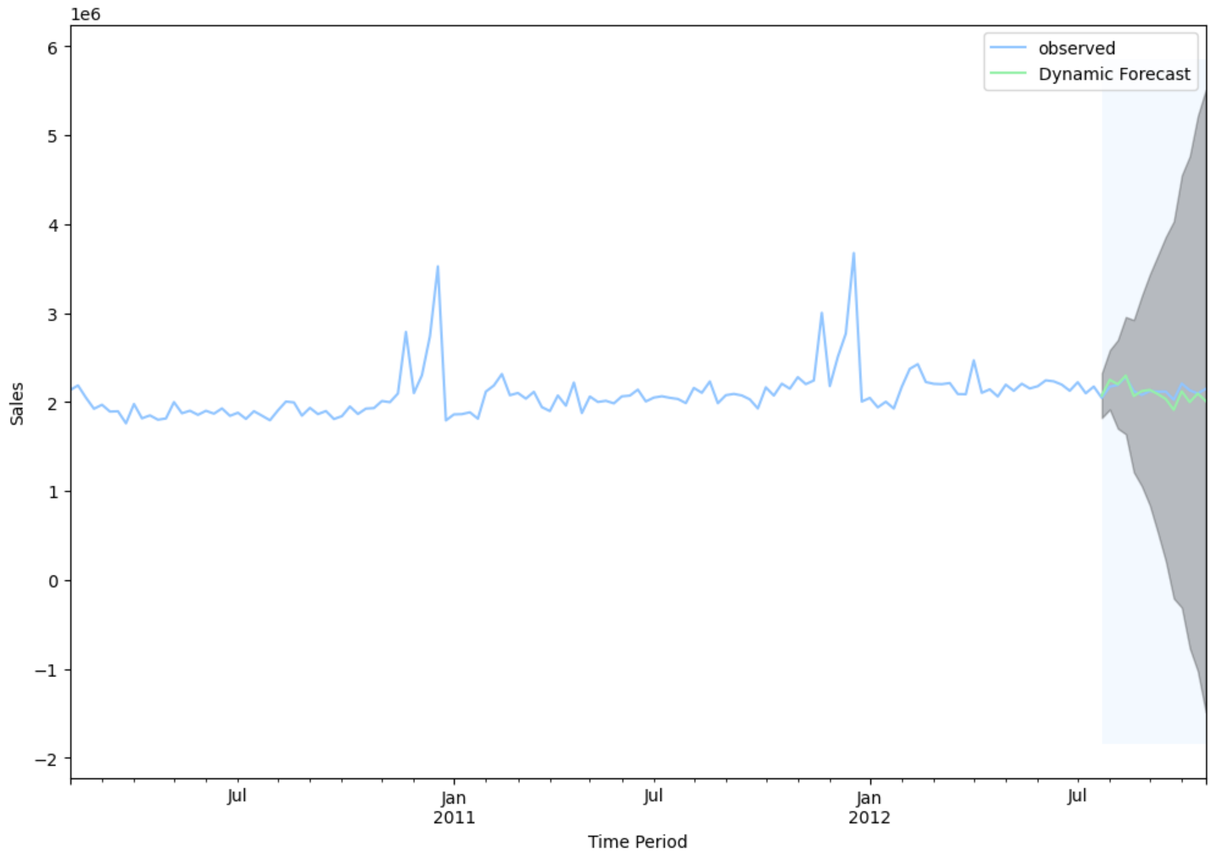
In [39]:
```
y_forecasted = pred.predicted_mean
y_truth = y1['2012-7-27':]

# Compute the mean square error
mse = ((y_forecasted - y_truth) ** 2).mean()
print('The Mean Squared Error of our forecasts is {}'.format(round(mse, 2)))
```

```
The Mean Squared Error of our forecasts is 4732600295.02
```

In [40]:
```
pred_dynamic = results.get_prediction(start=pd.to_datetime('2012-7-27'), dyr
pred_dynamic_ci = pred_dynamic.conf_int()
```

In [41]:
```
ax = y1['2010':].plot(label='observed', figsize=(12, 8))
pred_dynamic.predicted_mean.plot(label='Dynamic Forecast', ax=ax)
```

```
ax.fill_between(pred_dynamic_ci.index,
                pred_dynamic_ci.iloc[:, 0],
                pred_dynamic_ci.iloc[:, 1], color='k', alpha=.25)

ax.fill_betweenx(ax.get_ylim(), pd.to_datetime('2012-7-26'), y1.index[-1],
                 alpha=.1, zorder=-1)

ax.set_xlabel('Time Period')
ax.set_ylabel('Sales')

plt.legend()
plt.show()
```



That looks good. Both the observed and predicted lines go together indicating nearly accurate prediction

In [42]:
```
# Extract the predicted and true values of our time series
y_forecasted = pred_dynamic.predicted_mean

y_truth = y1['2012-7-27':]

# Compute the Root mean square error
rmse = np.sqrt(((y_forecasted - y_truth) ** 2).mean())
print('The Root Mean Squared Error of our forecasts is {}'.format(round(rmse
```

```
The Root Mean Squared Error of our forecasts is 74160.46
```

In [43]:
```
Residual= y_forecasted - y_truth
print("Residual for Store1",np.abs(Residual).sum()))
```

```
  Cell In[43], line 2
    print("Residual for Store1",np.abs(Residual).sum()))
                                                        ^
SyntaxError: unmatched ')'
```

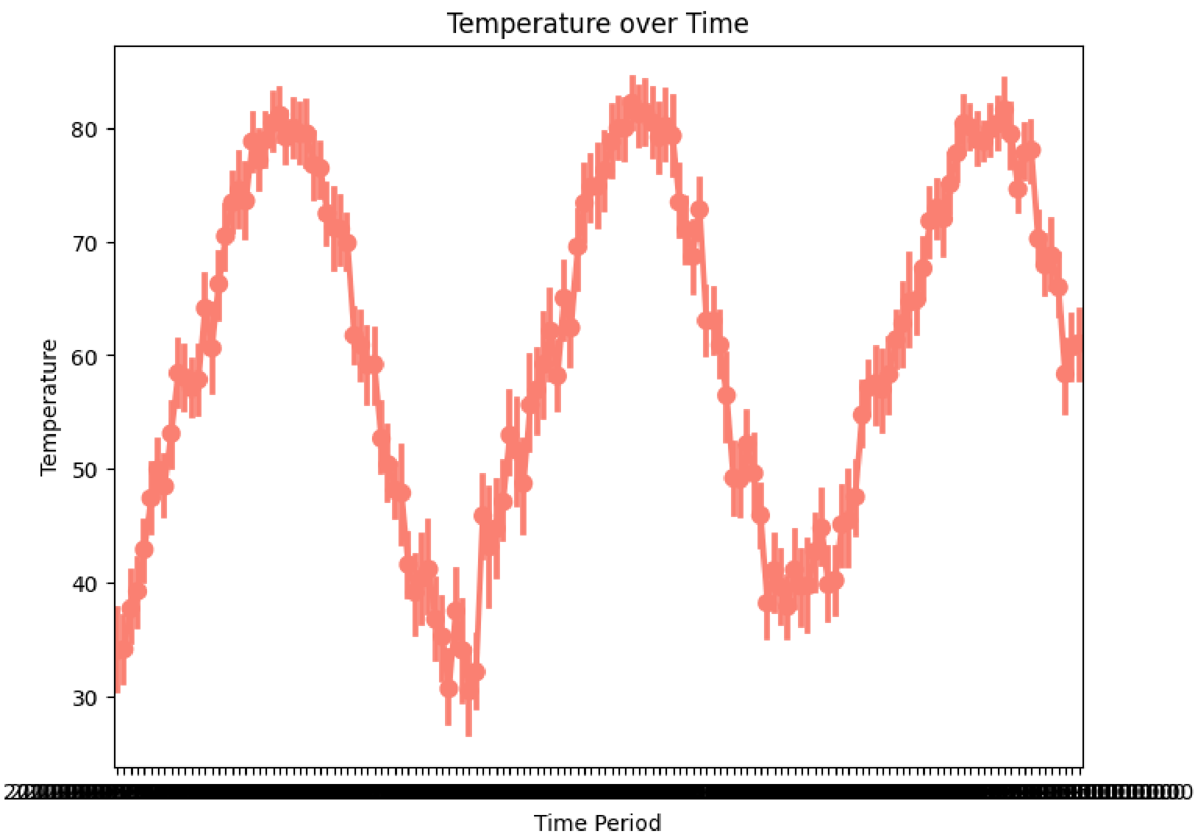
In [ ]:
```
# Get forecast 12 weeks ahead in future
pred_uc = results.get_forecast(steps=12)

# Get confidence intervals of forecasts
pred_ci = pred_uc.conf_int()
```

In [ ]:
```
ax = y1.plot(label='observed', figsize=(12, 8))
pred_uc.predicted_mean.plot(ax=ax, label='Forecast')
ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.25)
ax.set_xlabel('Time Period')
ax.set_ylabel('Sales')

plt.legend()
plt.show()
```

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.

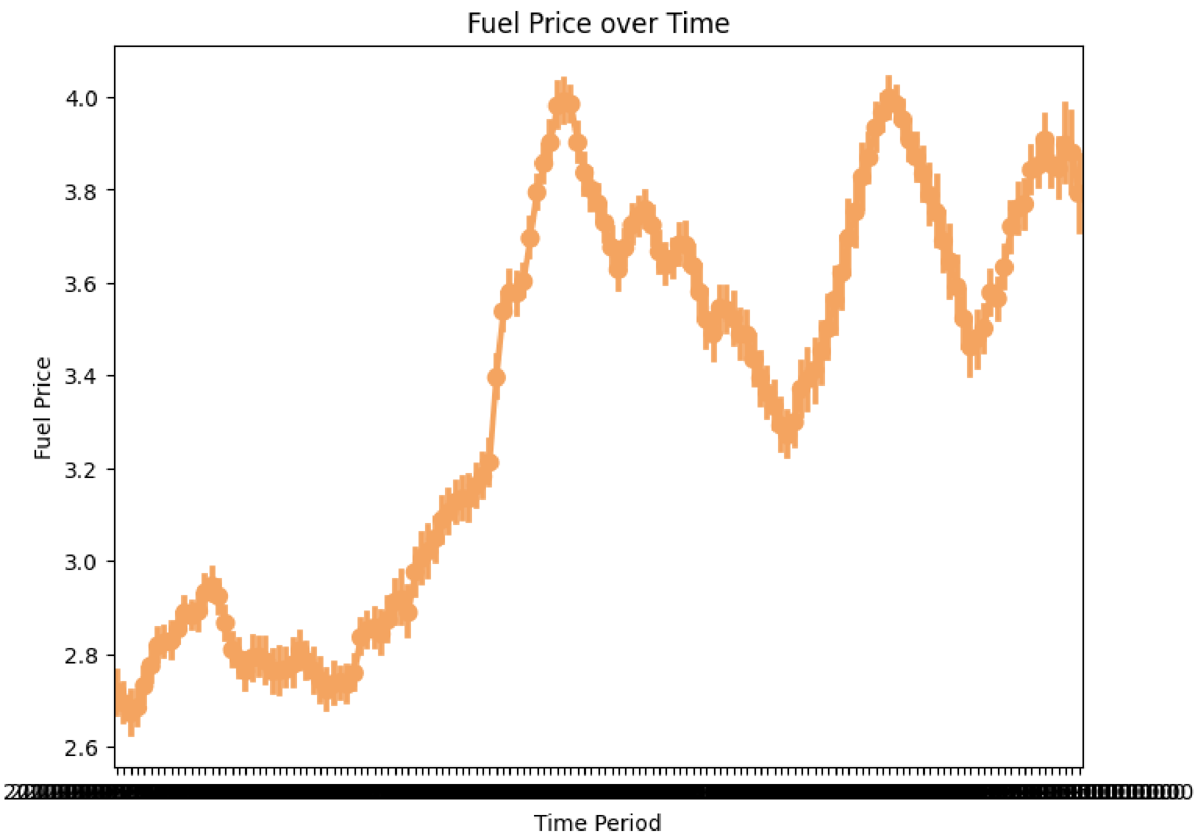
Plotting Data

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()
```



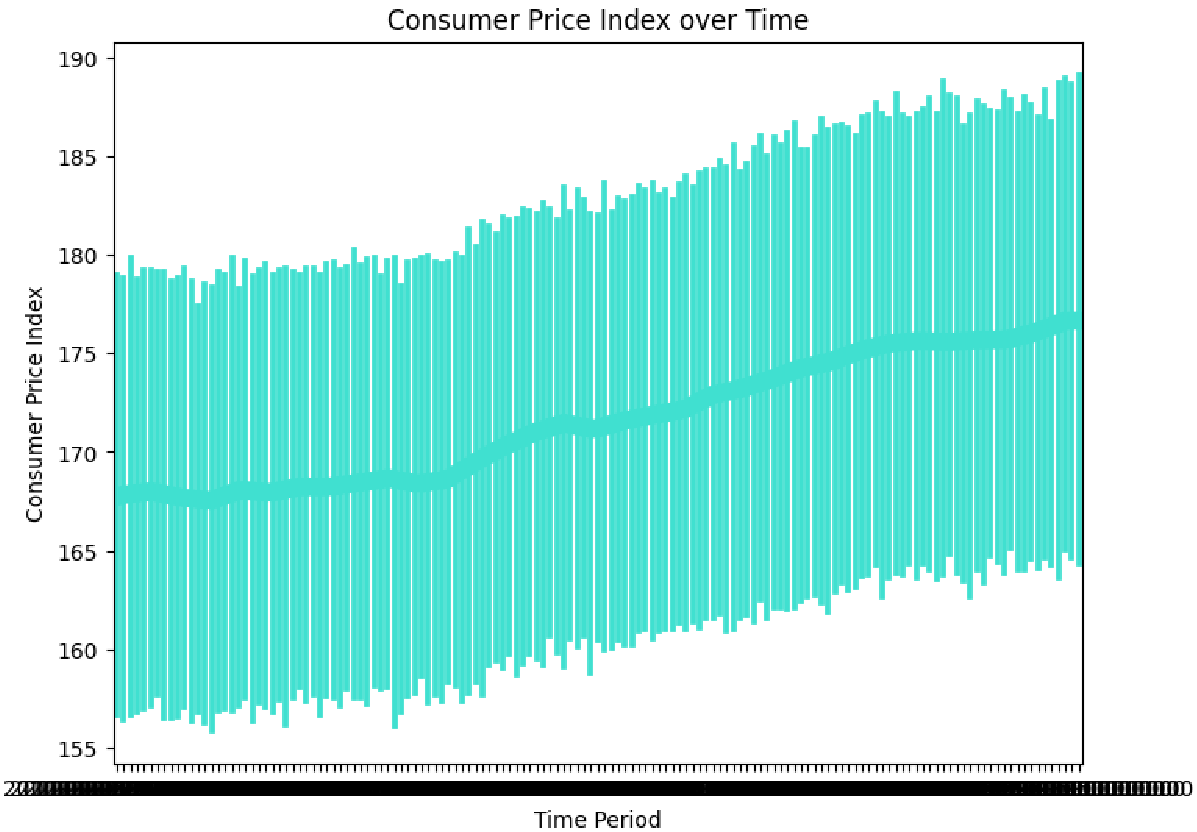
Graph clearly shows Temperature is more of a seasonal and repeated in cycles and this would be an interesting data point that we can use for studies further

In [28]:
```
plt.figure(figsize=(8,6))
sns.pointplot(x="Date", y="Fuel_Price", data=data, color = 'sandybrown')
plt.xlabel('Time Period')
plt.ylabel('Fuel Price')
plt.title('Fuel Price over Time')
plt.show()
```



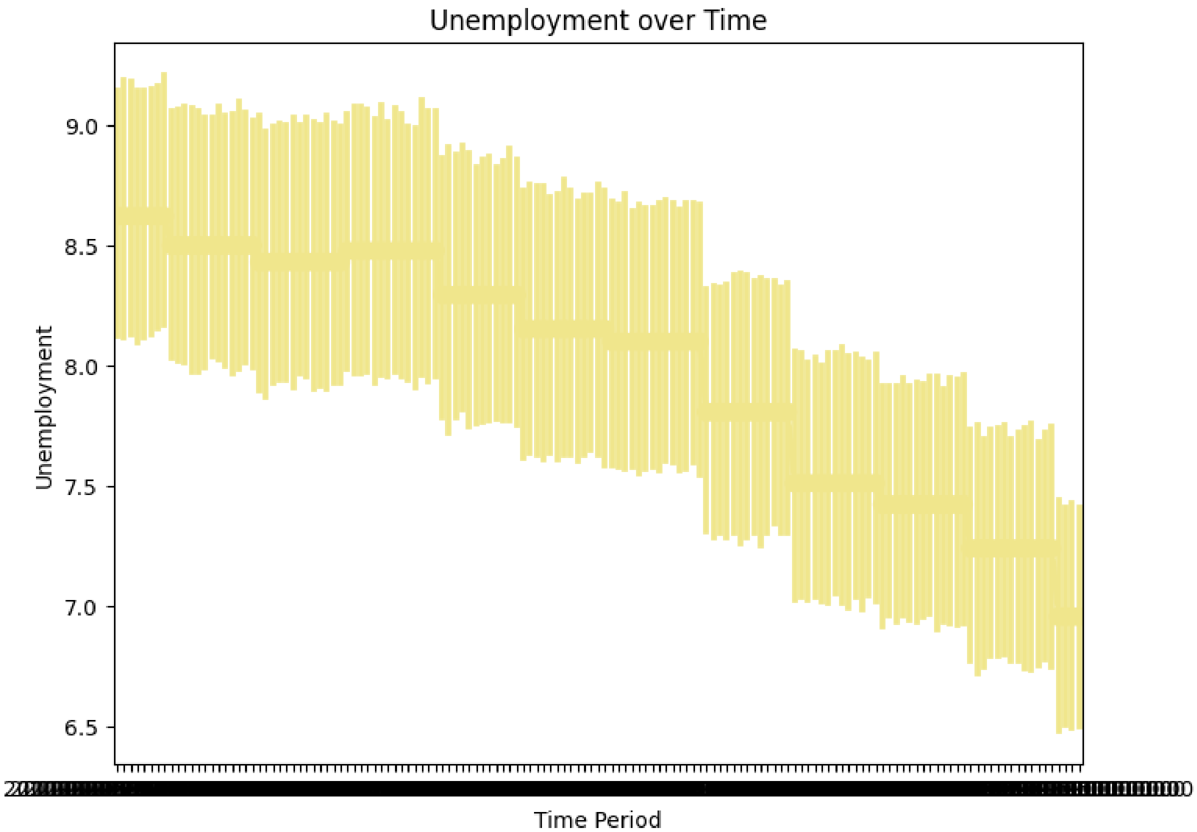
inference: Fuel price varies over time and there are high and lows

In [30]:
```
plt.figure(figsize=(8,6))
sns.pointplot(x="Date", y="CPI", data=data, color = 'turquoise')
plt.xlabel('Time Period')
plt.ylabel('Consumer Price Index')
plt.title('Consumer Price Index over Time')
plt.show()
```



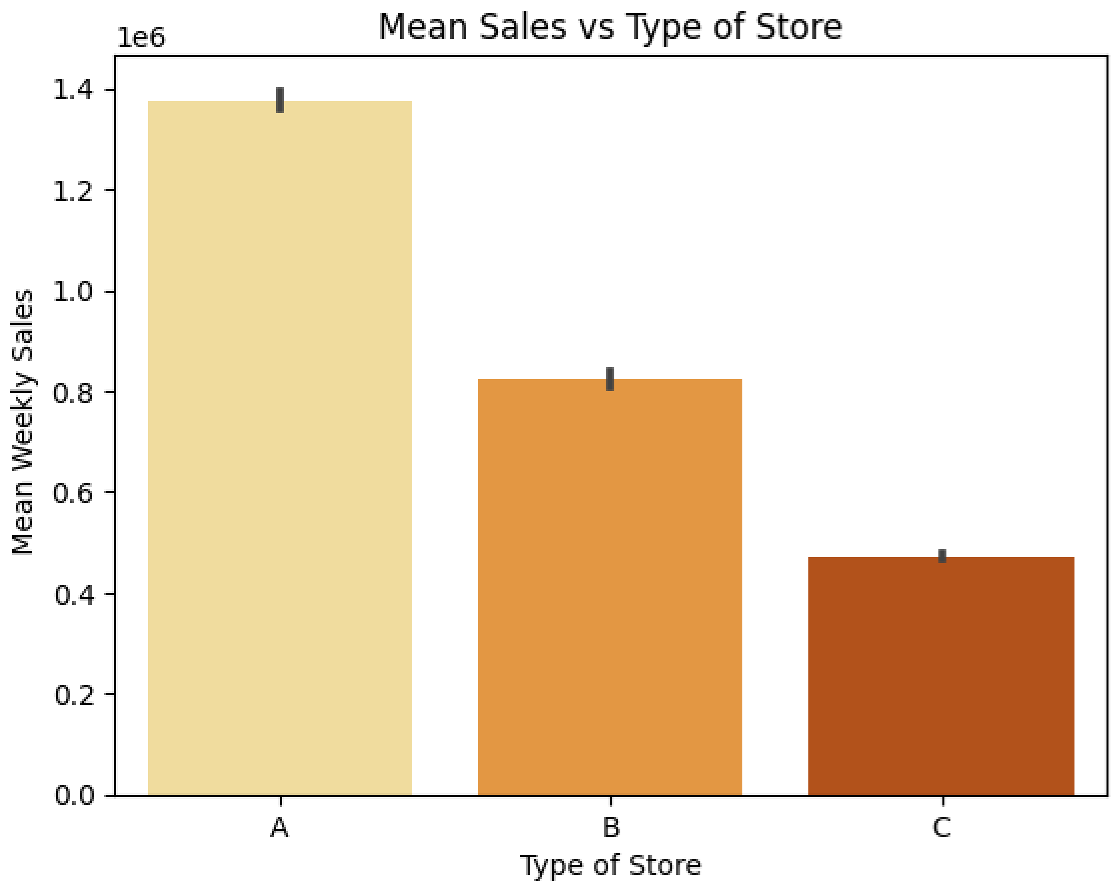
inference: over time CPI have increased. but the change is not much

In [31]:
```
plt.figure(figsize=(8,6))
sns.pointplot(x="Date", y="Unemployment", data=data, color='khaki')
plt.xlabel('Time Period')
plt.ylabel('Unemployment')
plt.title('Unemployment over Time')
plt.show()
```



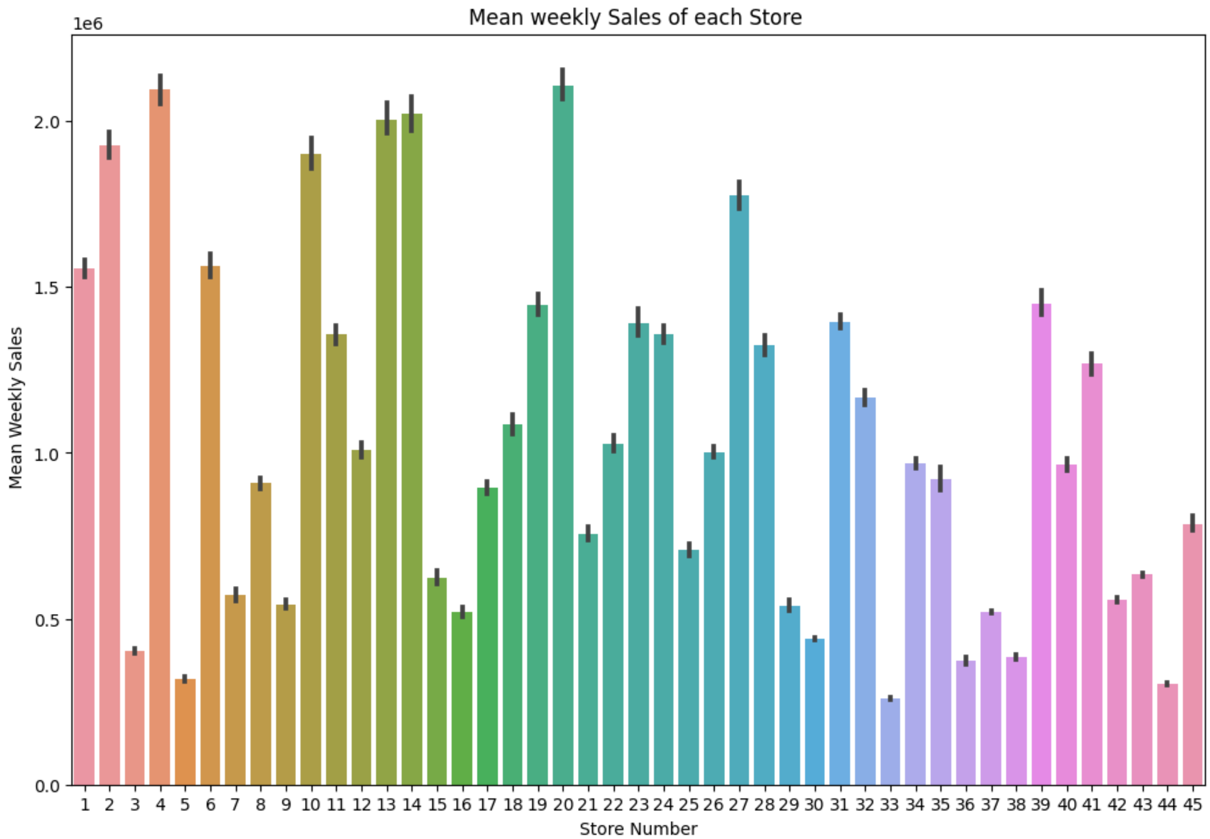
inference: Over time unemployment have came down we can see this factor also whether it have affected the Sales

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()
```



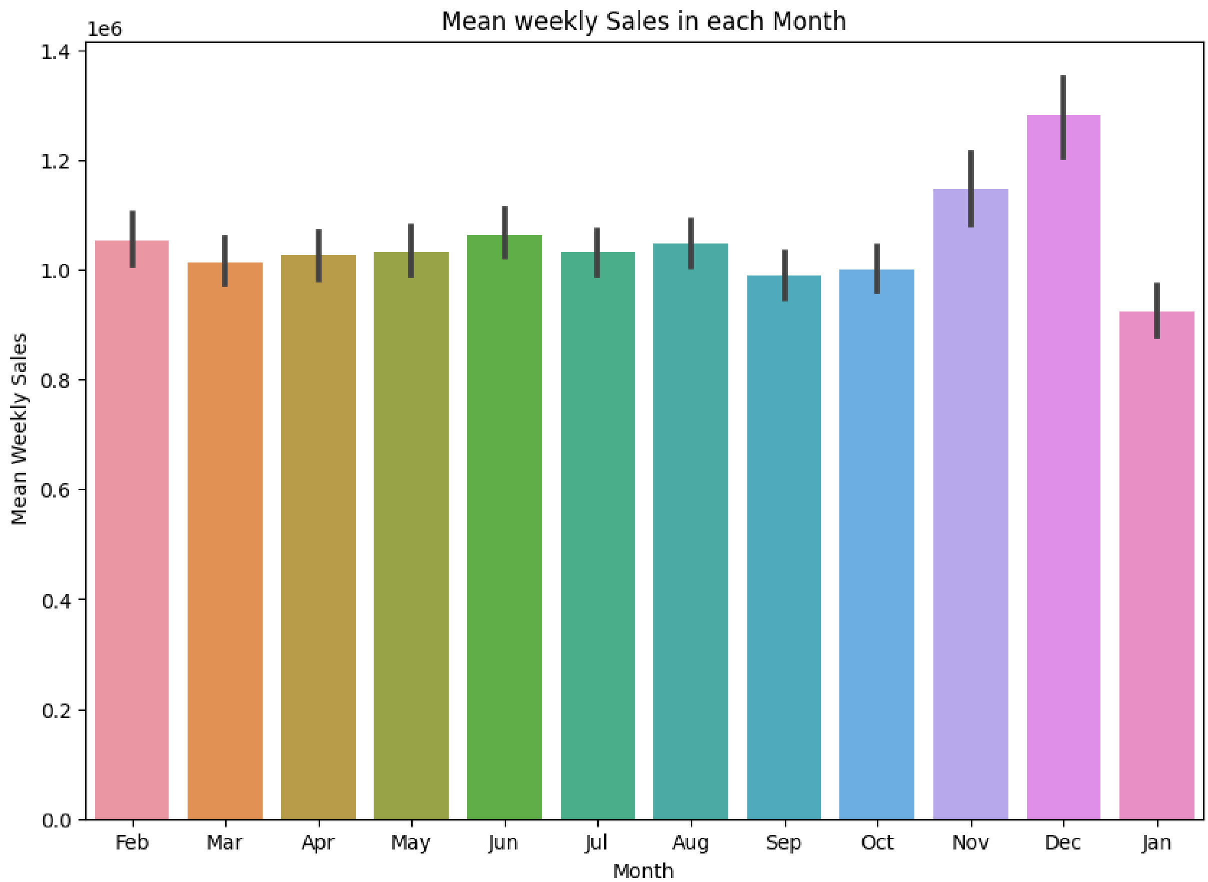
inference: From the graph its clear that Type A > Type B > Type C in mean weekly sales.

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.

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

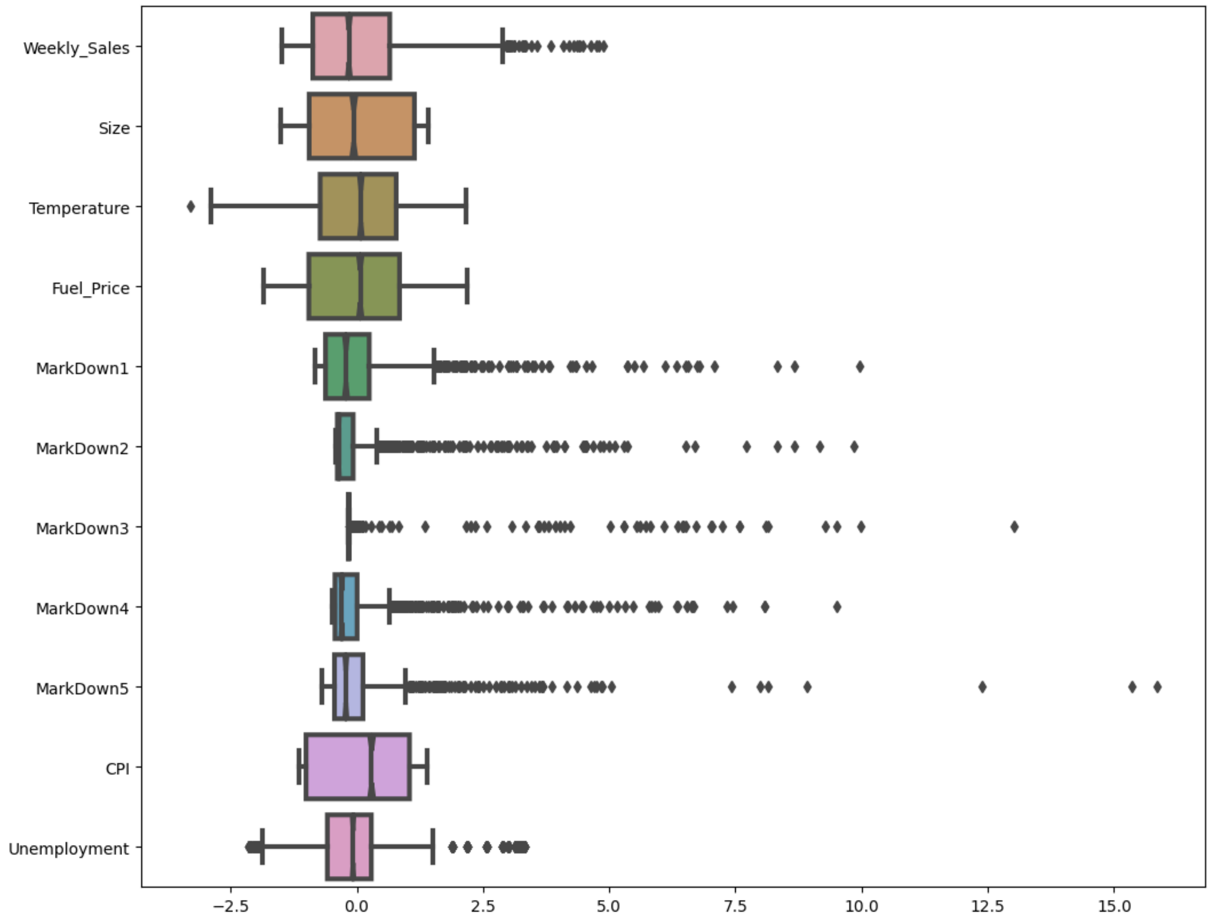
In [22]:
```
data_train = data_train.reindex(np.random.permutation(data.index))## Identif
data_train.columns
```

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
```

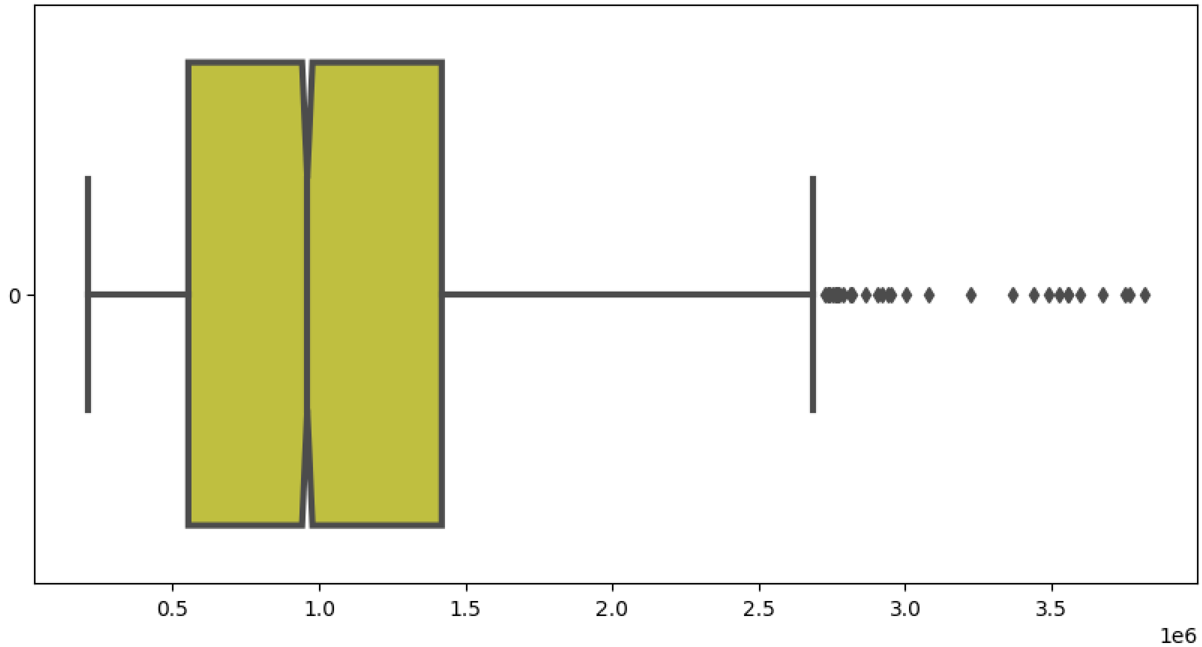
Out[23]:
```
Store                   float64
Date             datetime64[ns]
Weekly_Sales            float64
Type                     object
Size                    float64
Temperature             float64
Fuel_Price              float64
MarkDown1               float64
MarkDown2               float64
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()
```

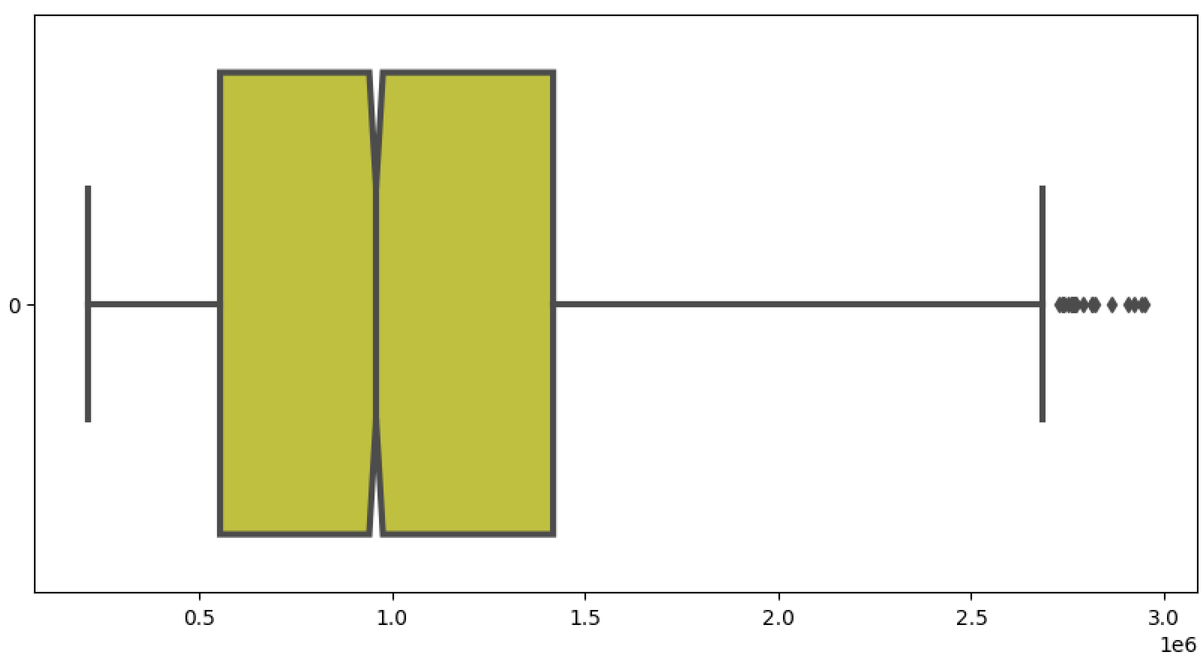


In [57]:
```
# Lets consider 3,000,000 as upper limit
data_train[data_train.Weekly_Sales>3000000].shape
```

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()
```



```
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)
```

```
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
```

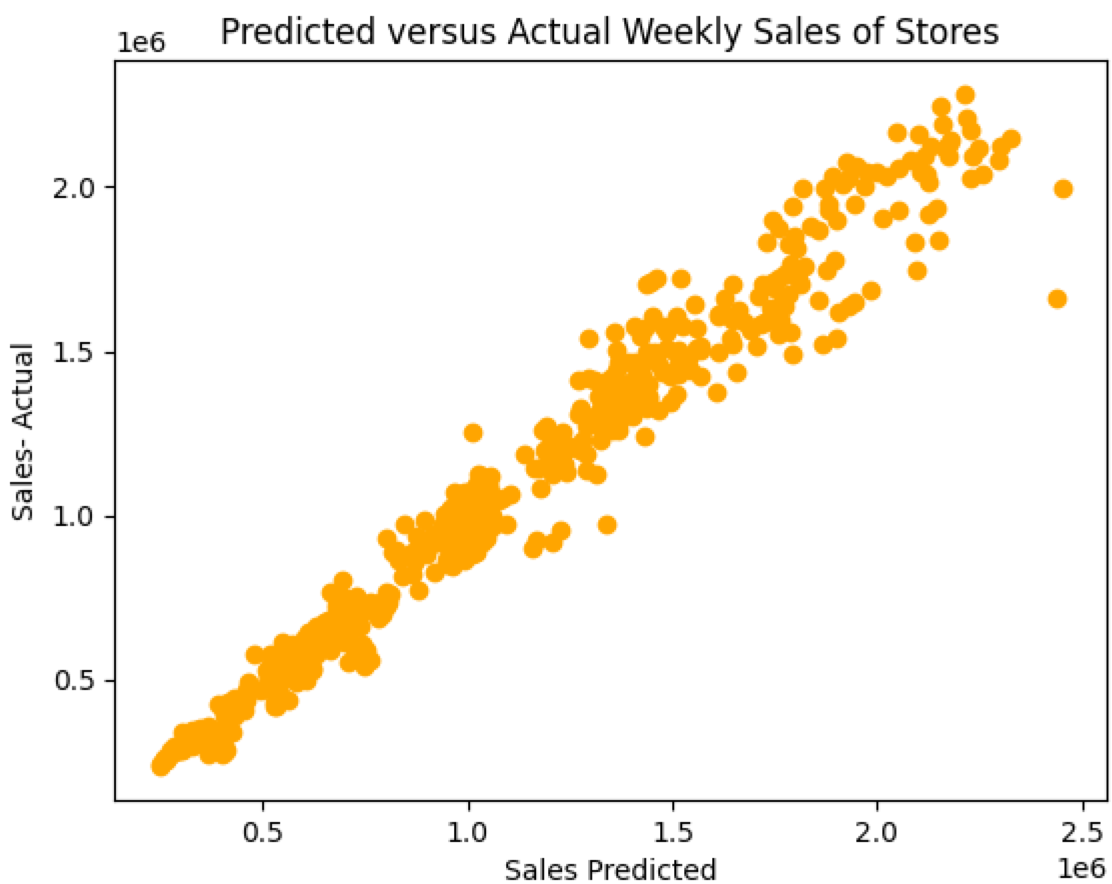
```
In [91]: gb_yhat=gb.predict(X_test_s)
         gb_score=gb.score(X_test_s,y_test)

         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()
```

```python
# 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]:
```python
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()
```



In [93]:
```python
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]:
```python
svr_scores = cross_val_score(svr, X_train_s, y_train, cv=10)
np.mean(svr_scores)
```

Out[94]: 0.5993284400427829

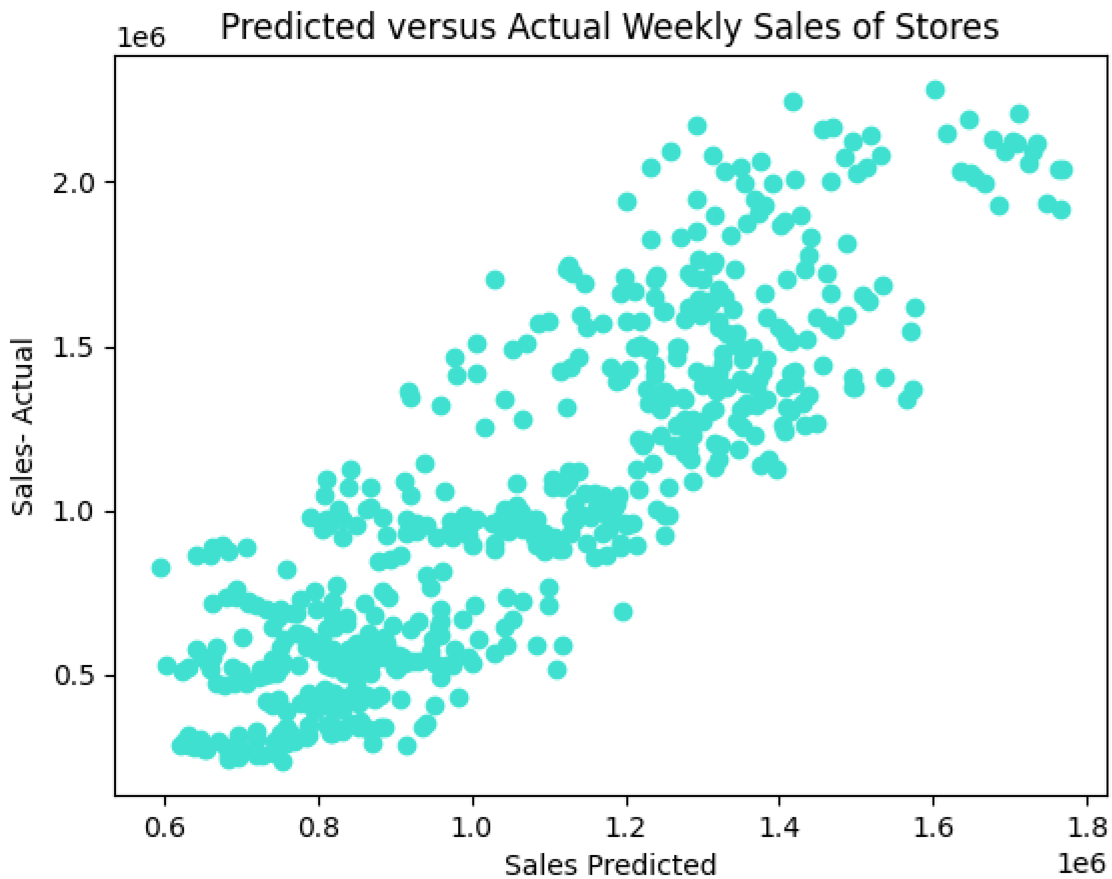
In [95]:
```
svr_yhat=svr.predict(X_test_s)
svr_score=svr.score(X_test_s,y_test)
print("R2: ",svr_score)
svr_adj_r2 = 1 - (len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)*(1-svr_scor
print("Adjusted R2: ",svr_adj_r2)
```

```
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
```

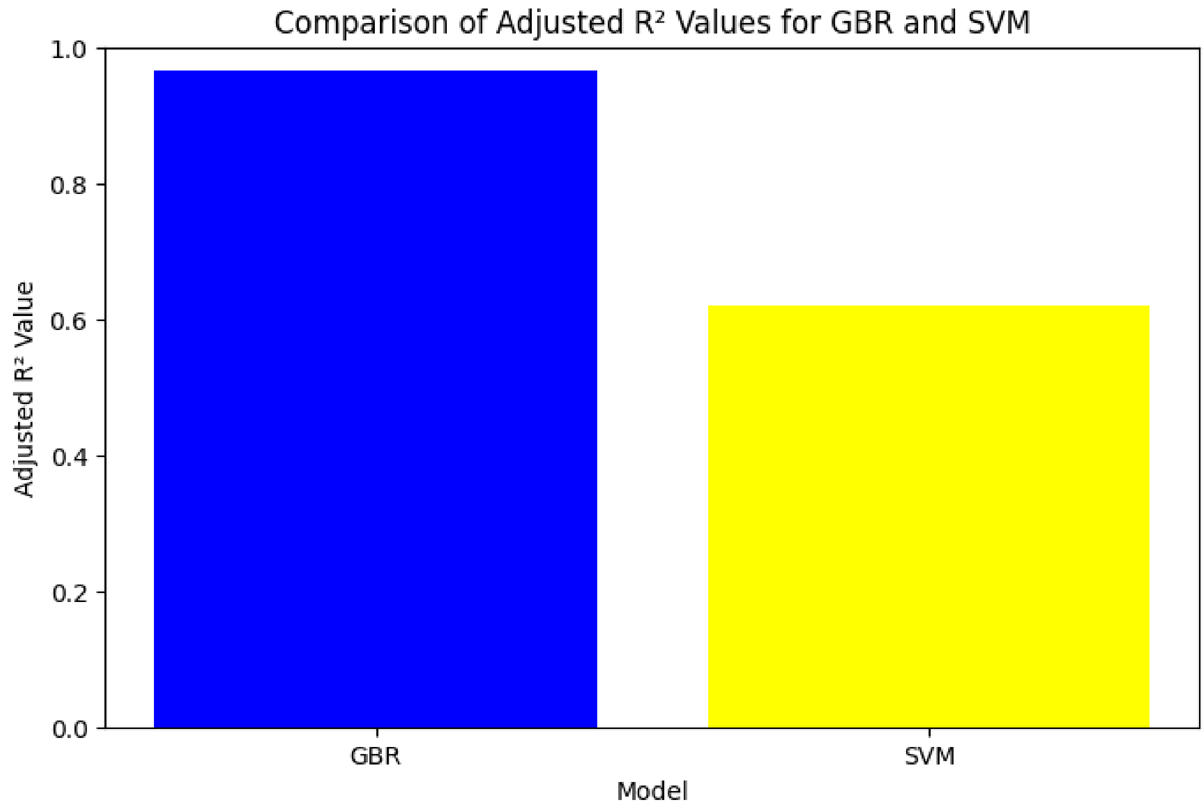
```
Train Residual 1611104539346.1753
Test Residual 157585040874.20804
Residual ratio of Test to Train 0.09781180365748321
```

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()
```



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()
```


Comparison of Adjusted R² Values for GBR and SVM
1.0
0.8
0.6
0.4
0.2
0.0
Adjusted R² Value
GBR
SVM
Model