Capstone Project

Walmart Sales Forecasting

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1. Problem Statement:

A **Retail Store** that has multiple outlets across the country.

They are facing issues in managing the inventory - to match the demand with respect to supply.

Dataset Information:

You are provided with the Weekly_Sales data for their various outlets.

The **Walmart**.csv contains 6435 rows and 8 columns.

Feature Name	Description
Stores	Store number
Date	Week of Sales
Weekly_Sales	Sales for the given store in that week
Holiday_Flag	Indicates if it is a holiday week
Temperature	Temperature on the day of the sale
Fuel_Price	Cost of fuel in the region

CPI	Consumer Price Index

Unemployment	Unemployment Rate

2. Objectives:

1. Use

> - Handle the missing values
> - Exploratory Data Analysis (EDA)
> - Outlier Analysis
> - Statistical Analysis

To come up with various INSIGHTS that can give them a clear perspective on the following:

> - a. If the Weekly_Sales are affected by the Unemployment Rate,
>   - If YES - which Stores are suffering the most?
> - b. If the Weekly_Sales show a seasonal trend,
>   - When and what could be the reason?
> - c. Does temperature affect the Weekly_Sales in any manner?
> - d. How is the Consumer Price index (CPI) affecting the Weekly_Sales of various Stores?
> - e. TOP Performing Stores according to the historical data.
> - f. The WORST Performing Stores, and
>   - How significant is the difference between the HIGHEST and LOWEST Performing Stores.

2. Use

> - Predictive Modeling Techniques

To FORECAST the Weekly_Sales for each Stores for the NEXT 12 WEEKS.

Importing Libraries

In [8]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import warnings
warnings.filterwarnings('ignore')
import plotly.graph_objects as go
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PowerTransformer, FunctionTransformer
from sklearn.compose import ColumnTransformer
from sklearn.metrics import r2_score
from sklearn.tree import DecisionTreeRegressor
```

```python
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [9]:
```python
df_Walmart = pd.read_csv('Walmart.csv')
```

In [10]:
```python
df_Walmart
```

Out[10]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
0	1	05-02-2010	1643690.90	0	42.31	2.572	211.096358	8.106
1	1	12-02-2010	1641957.44	1	38.51	2.548	211.242170	8.106
2	1	19-02-2010	1611968.17	0	39.93	2.514	211.289143	8.106
3	1	26-02-2010	1409727.59	0	46.63	2.561	211.319643	8.106
4	1	05-03-2010	1554806.68	0	46.50	2.625	211.350143	8.106
...	...	...	...	...	...	...	...	...
6430	45	28-09-2012	713173.95	0	64.88	3.997	192.013558	8.684
6431	45	05-10-2012	733455.07	0	64.89	3.985	192.170412	8.667
6432	45	12-10-2012	734464.36	0	54.47	4.000	192.327265	8.667
6433	45	19-10-2012	718125.53	0	56.47	3.969	192.330854	8.667
6434	45	26-10-2012	760281.43	0	58.85	3.882	192.308899	8.667

6435 rows × 8 columns

Basic EDA and Data Cleaning

Checking basic information of data

In [11]:
```python
df_Walmart.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
```

Changing Data types

In [12]:
```python
#converting Date columns to data
df_Walmart['Date'] = pd.to_datetime(df_Walmart['Date'])
```

In [13]:
```python
#converting  Holiday flag to bool
df_Walmart['Holiday_Flag'] = df_Walmart['Holiday_Flag'].astype('category')
```

In [14]:
```python
#converting Store to category
df_Walmart['Store'] = df_Walmart['Store'].astype('category')
```

In [15]:
```python
# adding year column to
df_Walmart['Year'] = df_Walmart['Date'].dt.year

# adding week column to
df_Walmart['Week'] = df_Walmart['Date'].dt.week

# adding month column to
df_Walmart['Month'] = df_Walmart['Date'].dt.month
df_Walmart.head(5)
```

Out[15]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Year	Week
0	1	2010-05-02	1643690.90	0	42.31	2.572	211.096358	8.106	2010	17
1	1	2010-12-02	1641957.44	1	38.51	2.548	211.242170	8.106	2010	48
2	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106	2010	7
3	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	8.106	2010	8
4	1	2010-05-03	1554806.68	0	46.50	2.625	211.350143	8.106	2010	18

In [16]:
```python
df_Walmart.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   category
 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   Week          6435 non-null   int64
 10  Month         6435 non-null   int64
dtypes: category(2), datetime64[ns](1), float64(5), int64(3)
memory usage: 466.7 KB
```

Checking NULL values

In [17]:
```
df_Walmart.isnull().sum()
```

Out[17]:
```
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
Year            0
Week            0
Month           0
dtype: int64
```

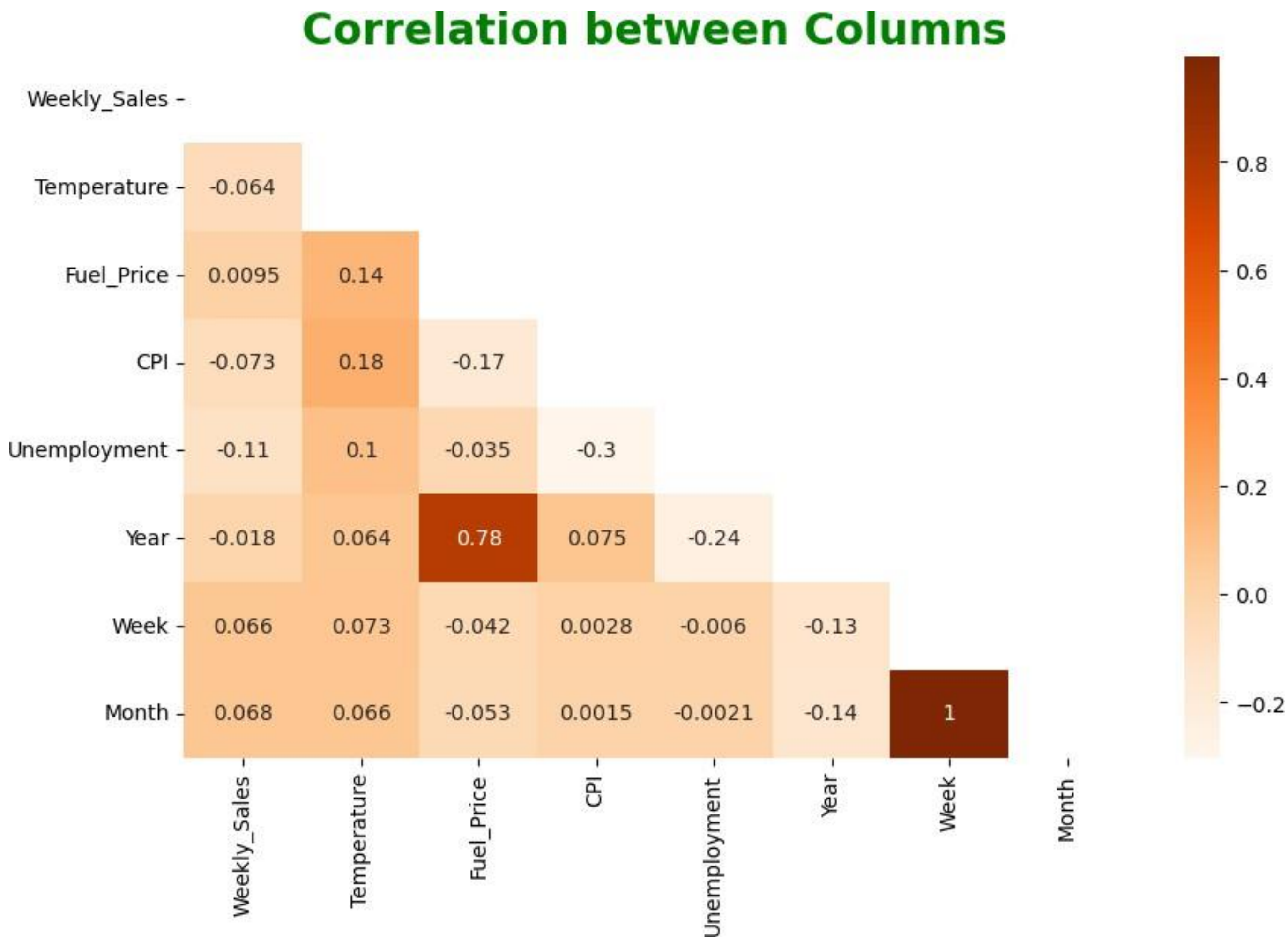
Reading the data for elementary Statistics

In [18]:
```
df_Walmart.describe()
```

Out[18]:

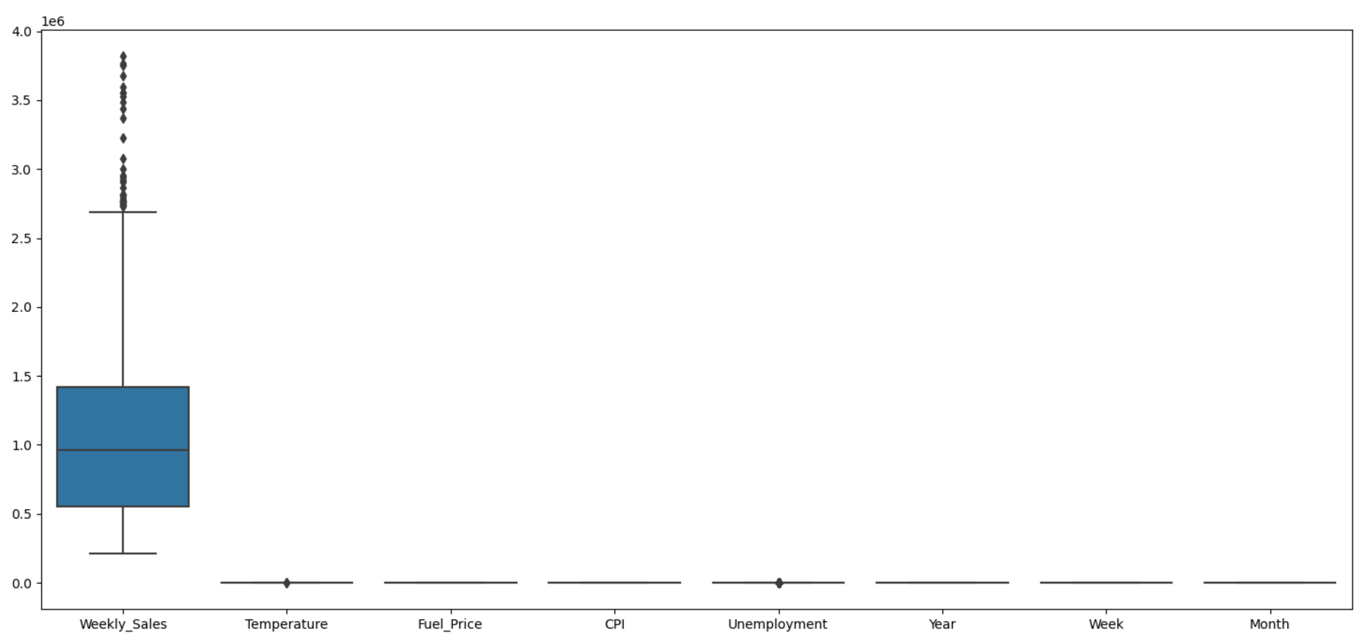
	Weekly_Sales	Temperature	Fuel_Price	CPI	Unemployment	Year	Week	Mo
count	6.435000e+03	6435.000000	6435.000000	6435.000000	6435.000000	6435.000000	6435.000000	6435.000
mean	1.046965e+06	60.663782	3.358607	171.578394	7.999151	2010.965035	26.000000	6.475
std	5.643666e+05	18.444933	0.459020	39.356712	1.875885	0.797019	14.511794	3.321
min	2.099862e+05	-2.060000	2.472000	126.064000	3.879000	2010.000000	1.000000	1.000
25%	5.533501e+05	47.460000	2.933000	131.735000	6.891000	2010.000000	14.000000	4.000
50%	9.607460e+05	62.670000	3.445000	182.616521	7.874000	2011.000000	26.000000	6.000
75%	1.420159e+06	74.940000	3.735000	212.743293	8.622000	2012.000000	38.000000	9.000
max	3.818686e+06	100.140000	4.468000	227.232807	14.313000	2012.000000	52.000000	12.000

In [19]:
```
#looking at correaltion between columns

plt.figure(figsize=(10,6))
heatmap_data  =  df_Walmart.corr()
mask = np.triu(np.ones_like(heatmap_data, dtype=bool))
sns.heatmap(heatmap_data,annot=True,cmap='Oranges',mask  =  mask)
plt.title("Correlation between Columns",fontdict={'fontsize':20,'color':'Green','fontwei
plt.show()
```



Outliers Detection

In [20]:
```python
# Using box plots
plt.figure(figsize=(18,8))
colours = sns.color_palette(n_colors=8)
sns.boxplot(data = df_Walmart,palette=colours)
plt.show()
```



Outliers Treatment

In [21]:
```
Q3  =  df_Walmart['Weekly_Sales'].quantile(0.75)
Q1  =  df_Walmart['Weekly_Sales'].quantile(0.25)
IQR = Q3-Q1
upperLimit  =  Q3+(1.5*IQR)
lowerLimit  =  Q1-(1.5*IQR)
```

In [22]:
```
filt  =  ((df_Walmart['Weekly_Sales']<=  upperLimit)  &  (df_Walmart['Weekly_Sales']>=  lowerL
df_Walmart  =  df_Walmart[filt]
```

In [23]:
```
df_Walmart
```

Out[23]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Year	Wee
0	1	2010-05-02	1643690.90	0	42.31	2.572	211.096358	8.106	2010	1
1	1	2010-12-02	1641957.44	1	38.51	2.548	211.242170	8.106	2010	4
2	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106	2010	
3	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	8.106	2010	
4	1	2010-05-03	1554806.68	0	46.50	2.625	211.350143	8.106	2010	1
...	...	...	...	...	...	...	...	...	...	.
6430	45	2012-09-28	713173.95	0	64.88	3.997	192.013558	8.684	2012	3
6431	45	2012-05-10	733455.07	0	64.89	3.985	192.170412	8.667	2012	1
6432	45	2012-12-10	734464.36	0	54.47	4.000	192.327265	8.667	2012	5
6433	45	2012-10-19	718125.53	0	56.47	3.969	192.330854	8.667	2012	4
6434	45	2012-10-26	760281.43	0	58.85	3.882	192.308899	8.667	2012	4

6401 rows × 11 columns

Checking for duplicate values

In [24]:
```
df_Walmart.duplicated().sum()
```

Out[24]: 0

Insights that will give a clear perspective on the following

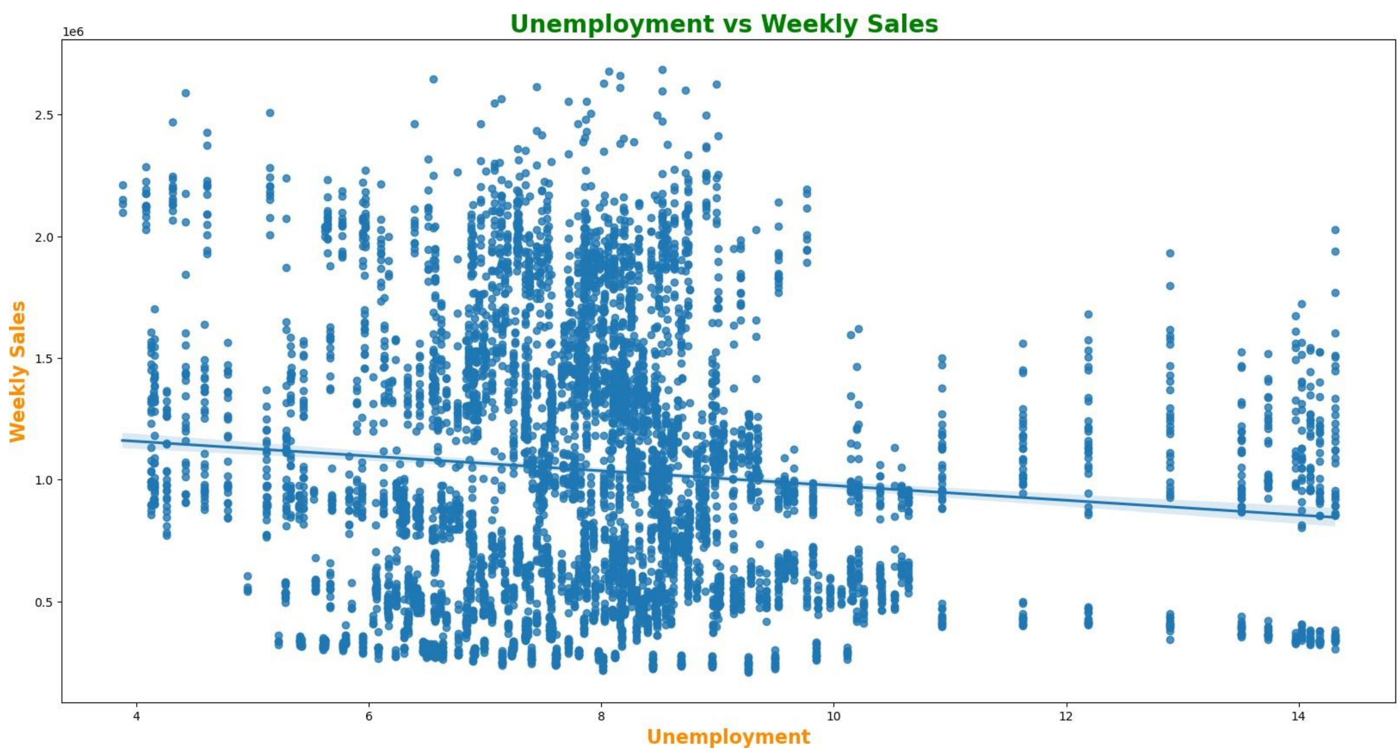
(a).If the Weekly_Sales are affected by the Unemployment Rate

Correlation between Weekly_Sales and Unemployment Rate

In [25]:
```
#checking correaltion between Weekly Sales and Unemployment Rate
correlationCoeff = df_Walmart['Weekly_Sales'].corr(df_Walmart['Unemployment'])
print("The correlation coefficient of Weekly Sales and Unemployment Rate is : ",correlat
```

```
The correlation coefficient of Weekly Sales and Unemployment Rate is :  -0.1042975091257
8391
```

In [26]:
```
#plotting the regression plot

plt.figure(figsize=(20,10))
sns.regplot(data = df_Walmart,x = 'Unemployment',y = 'Weekly_Sales')

# Set the title
plt.title('Unemployment  vs  Weekly  Sales  ',fontdict={'fontsize':20,'color':'Green','fontw

# Set the x and y axis labels
plt.xlabel('Unemployment',  color='#FF8C00',  fontweight='bold',  fontsize=16)
plt.ylabel('Weekly  Sales',  color='#FF8C00',  fontweight='bold',  fontsize=16)

plt.show()
```



(b).Which Stores are suffering the most?

In [ ]:

In [27]:
```
# getting the correaltion between weekly sales and unemployment and sorting it
sortewise_correlation  =  df_Walmart.groupby('Store')['Weekly_Sales',  'Unemployment'].corr

#restting the index
sortewise_correlation.reset_index(inplace  =  True)

#creating filter
```

```
min_corr = sortewise_correlation[('Weekly_Sales','Unemployment')].min()
filt  =  (sortewise_correlation[('Weekly_Sales','Unemployment')]==min_corr)
store = sortewise_correlation.loc[filt, 'Store']
print("Stores with the Highest Negative Correlation with Unemployment Rate:",store[0])
```

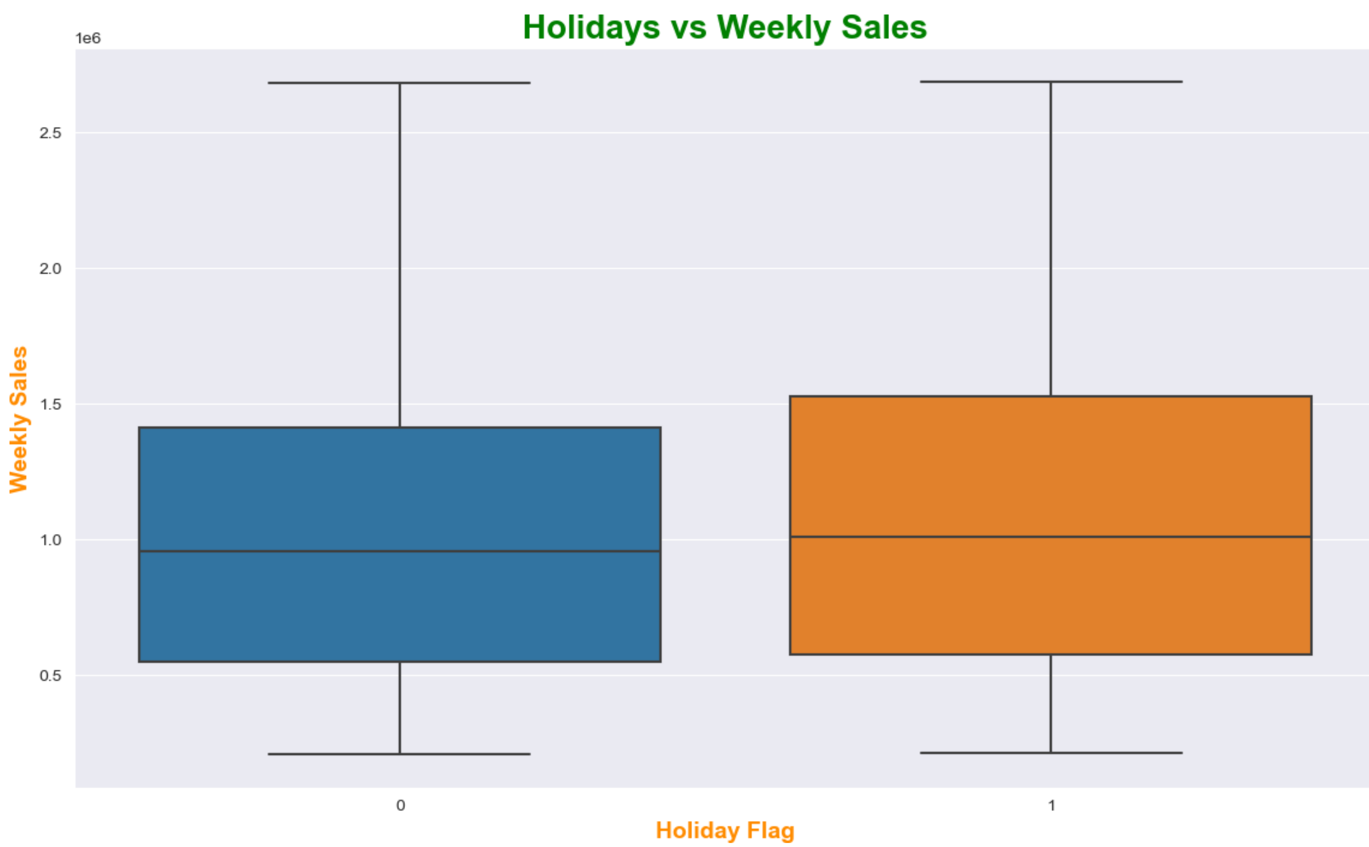
```
Stores with the Highest Negative Correlation with Unemployment Rate: 38
```

(c).If the Weekly_Sales show a seasonal trend?

When and what could be the reason?

In [28]:

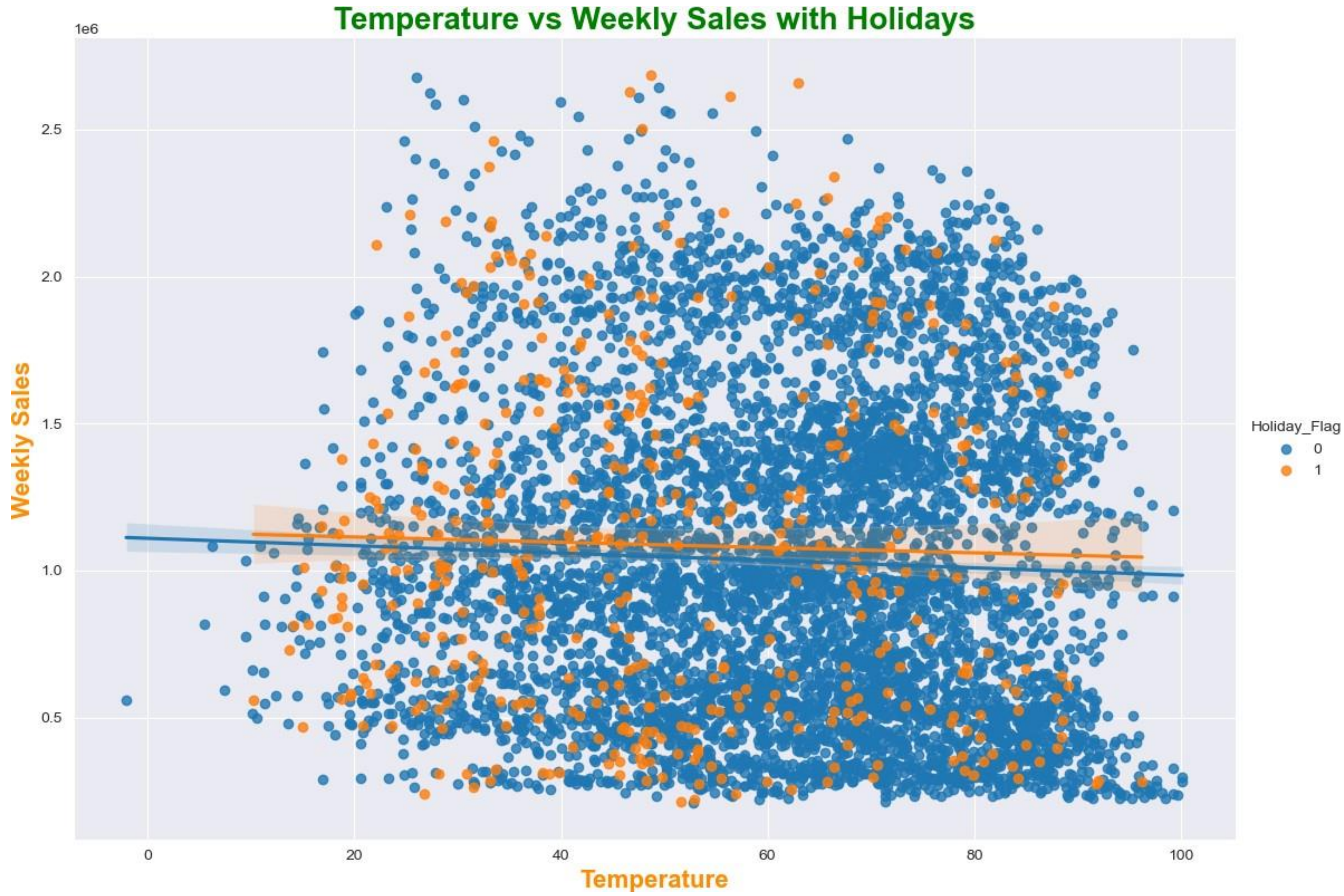
```
# checking for holiday flag and how it affects weekly sales
plt.figure(figsize=(14,8))
sns.set_style('darkgrid')
sns.boxplot(data = df_Walmart,x = 'Holiday_Flag',y = 'Weekly_Sales')
plt.title("Holidays  vs  Weekly  Sales",fontdict={'fontsize':20,'color':'Green','fontweight
plt.xlabel('Holiday Flag', color='#FF8C00', fontweight='bold', fontsize=14)
plt.ylabel('Weekly Sales', color='#FF8C00',  fontweight='bold', fontsize=14)
plt.show()
```



(d).Does temperature affect the Weekly_Sales in any manner?

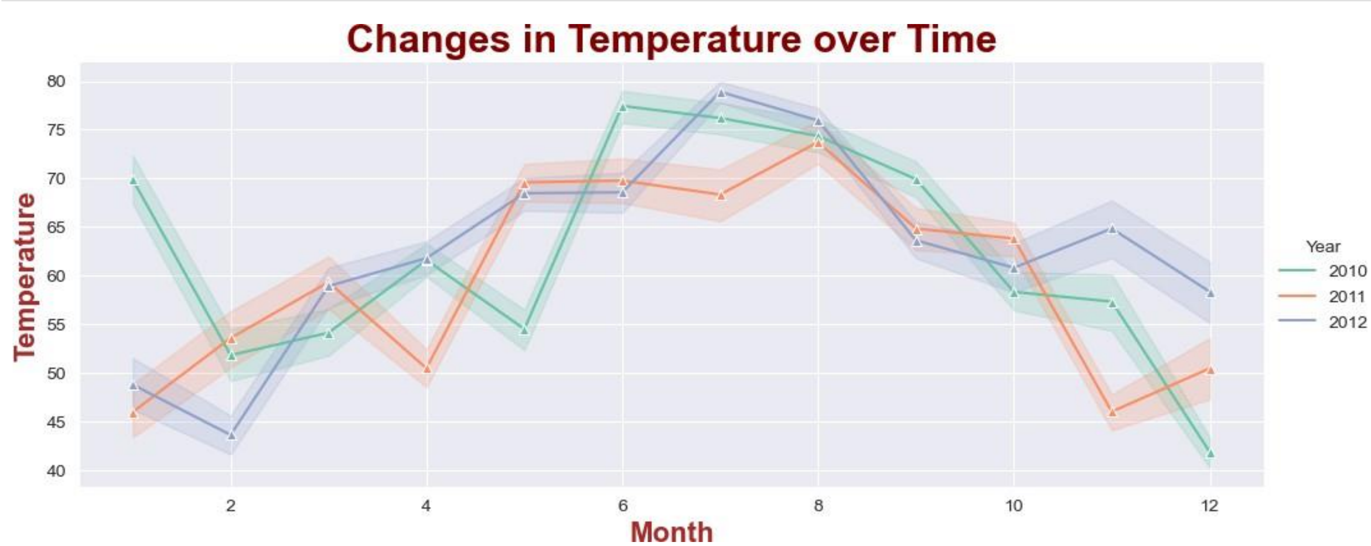
In [29]:

```
# checking fortemperature and how it affects weekly sales with holiday flag
sns.set_style('darkgrid')
sns.lmplot(data = df_Walmart,x =  'Temperature',y =  'Weekly_Sales',hue='Holiday_Flag',hei
plt.title("Temperature  vs  Weekly  Sales  with  Holidays",fontdict={'fontsize':20,'color':'G
plt.xlabel('Temperature', color='#FF8C00', fontweight='bold', fontsize=16)
plt.ylabel('Weekly Sales', color='#FF8C00',  fontweight='bold', fontsize=16)
plt.show()
```



(e).Changes in Temperature over time

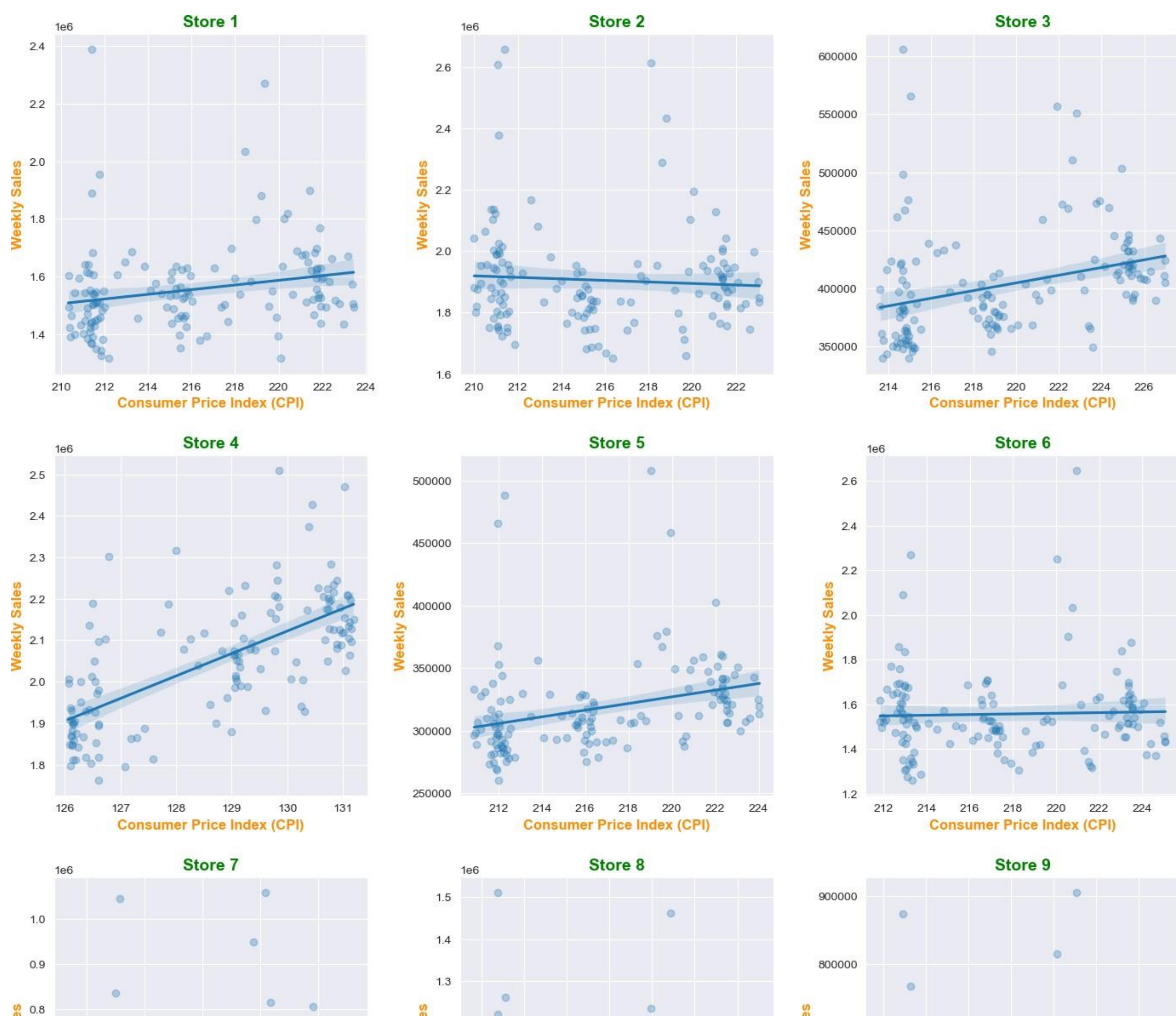
In [30]:
```
sns.set_style('darkgrid')
sns.relplot(data = df_Walmart,x = 'Month',y = 'Temperature',hue='Year',
            kind = 'line',height = 4,aspect=2.5,palette='Set2',
            marker ='^')

# Set the title
plt.title('Changes  in  Temperature  over  Time',  fontdict={'fontsize':22,'color':'Maroon','

# Set the x and y axis labels
plt.xlabel('Month', color='brown',fontweight='bold', fontsize=16)
plt.ylabel('Temperature',  color='brown',fontweight='bold',  fontsize=16)
plt.show()
```

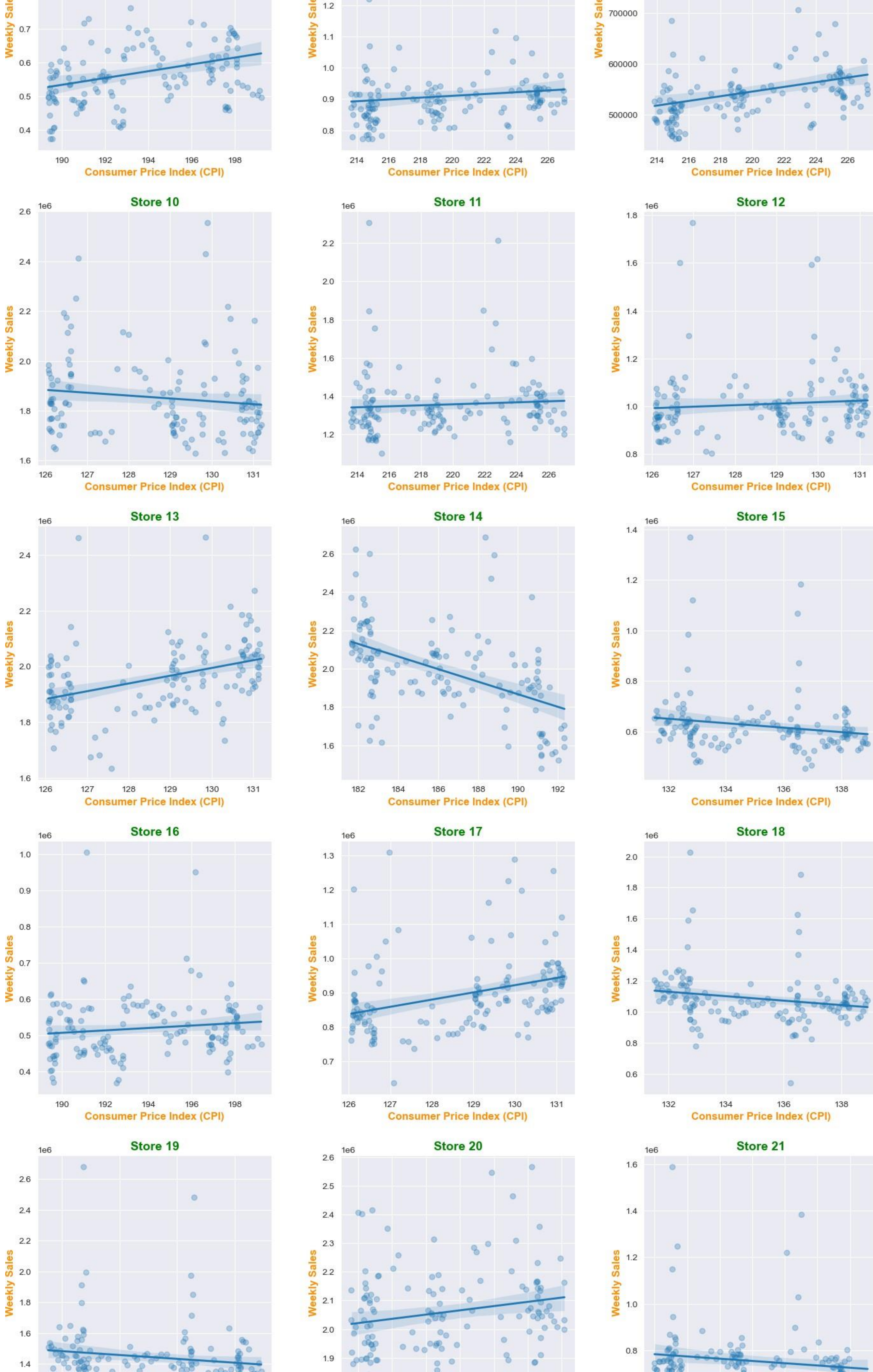


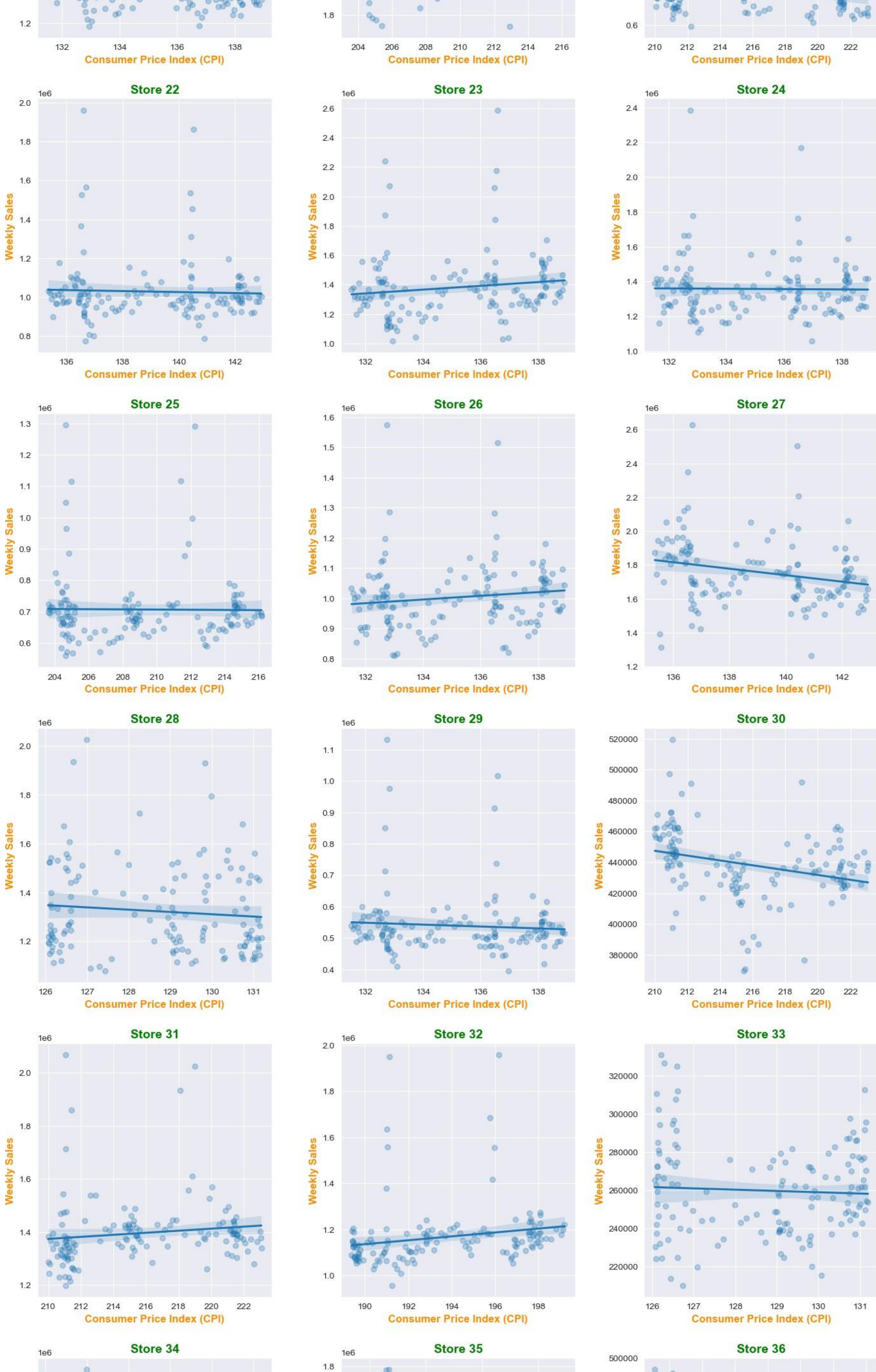
(f).How is the Consumer Price index (CPI) affecting the Weekly_Sales of various Stores?

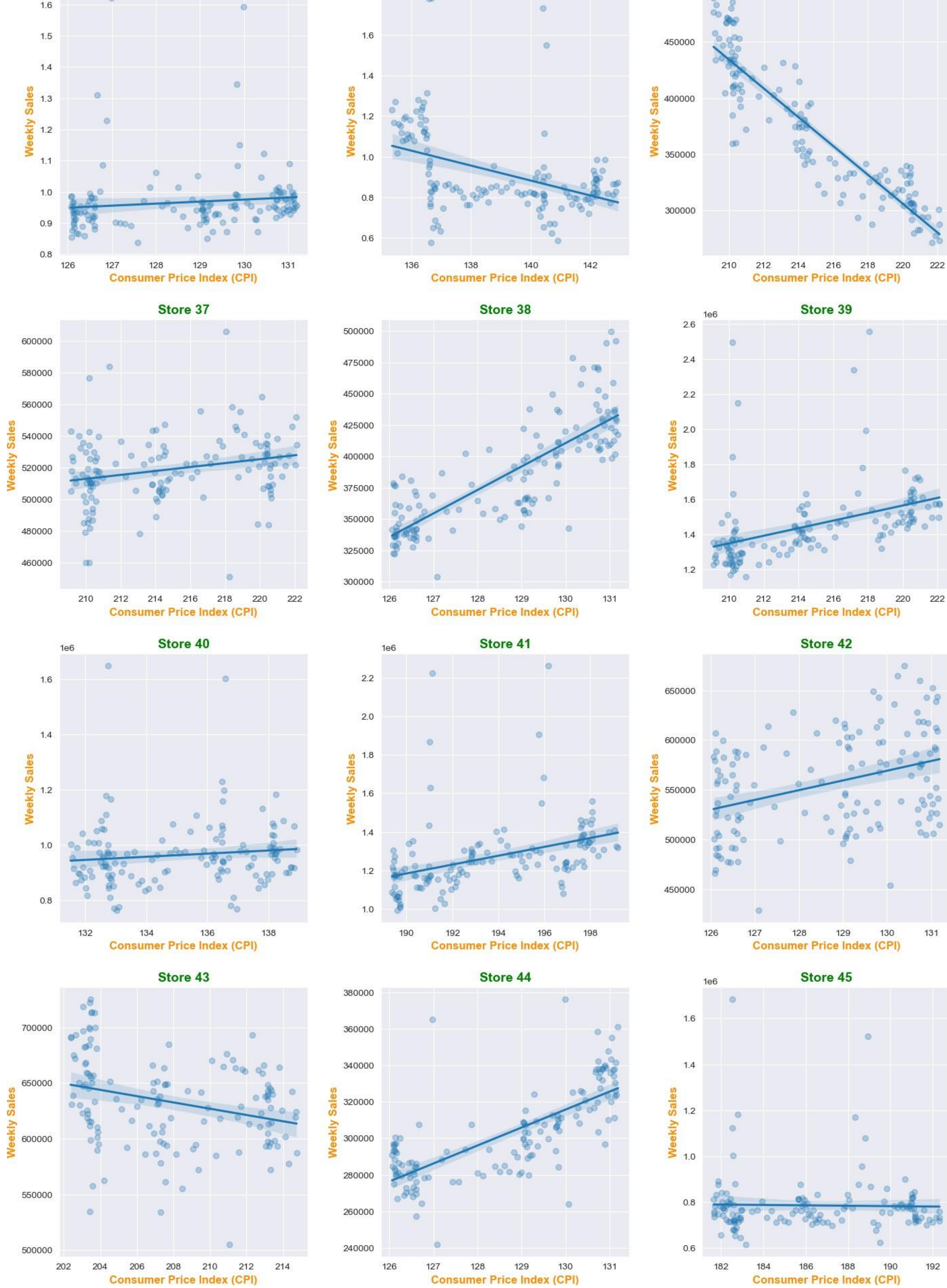
In [31]:

```
# Create a list of unique store numbers
stores = df_Walmart['Store'].unique()

# Set up subplots

fig, axes = plt.subplots(nrows=len(stores)//3, ncols=3, figsize=(15, 5*len(stores)//3))
fig.tight_layout(pad=5.0)

# Iterate over each store and create a scatter plot
for i, store_num in enumerate(stores):
    row = i // 3
    col = i % 3
    ax = axes[row, col]

    # Filter the data for the specific store
    store_data = df_Walmart[df_Walmart['Store'] == store_num]

    # Plot scatter plot with regression line
    sns.set_style('darkgrid')
    sns.regplot(x='CPI', y='Weekly_Sales', data=store_data, ax=ax, scatter_kws={'alpha':

    ax.set_title(f'Store   {store_num}',fontdict={'fontsize':14,'color':'Green','fontweigh
    ax.set_xlabel('Consumer Price Index (CPI)', color='#FF8C00', fontweight='bold', fon
    ax.set_ylabel('Weekly Sales', color='#FF8C00', fontweight='bold', fontsize=12)

plt.show()
```




Weekly Sales
Consumer Price Index (CPI)
Store 10
Store 11
Store 12
Store 13
Store 14
Store 15
Store 16
Store 17
Store 18
Store 19
Store 20
Store 21
1e6

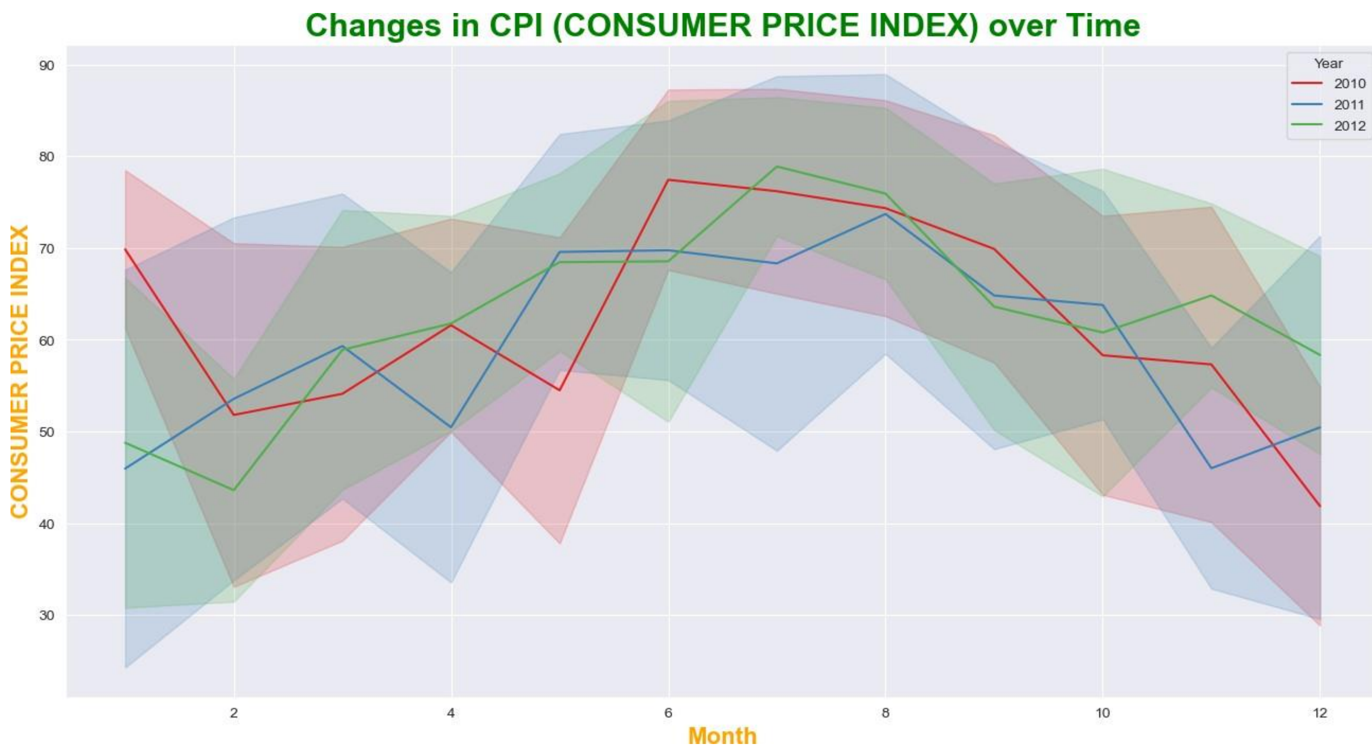

Consumer Price Index (CPI)
Store 22
Store 23
Store 24
Store 25
Store 26
Store 27
Store 28
Store 29
Store 30
Store 31
Store 32
Store 33
Store 34
Store 35
Store 36
Weekly Sales
1e6



(g).Changes in CPI (CONSUMER PRICE INDEX) over time

In [32]:
```
plt.figure(figsize=(16,8))
sns.set_style('darkgrid')
```

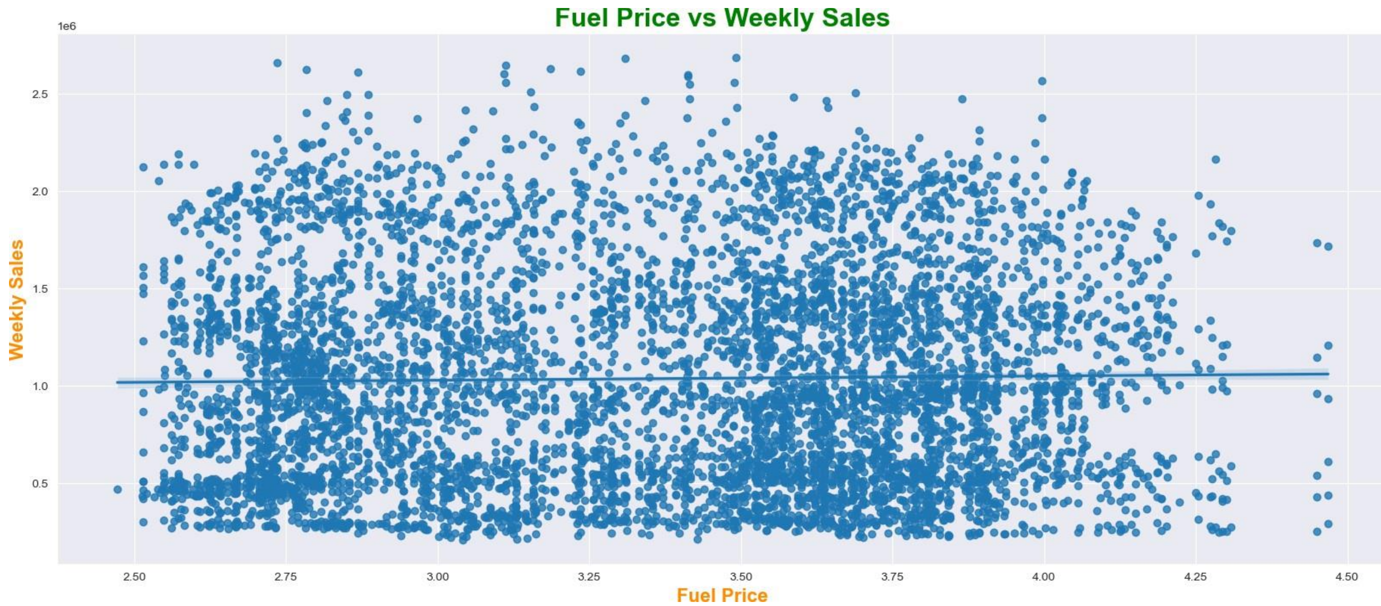
```
sns.lineplot(
    data=df_Walmart,
    x='Month',
    y='Temperature',
    hue='Year',
    ci='sd', # Specify the standard deviation for shading
    err_style='band',  # Use a shaded band for the confidence interval
    palette='Set1'
)

# Set the title
plt.title('Changes in CPI (CONSUMER PRICE INDEX) over Time', fontdict={'fontsize':22,'co

# Set the x and y axis labels
plt.xlabel('Month', color='orange',fontweight='bold', fontsize=16)
plt.ylabel('CONSUMER PRICE INDEX', color='orange',fontweight='bold', fontsize=16)
plt.show()
```



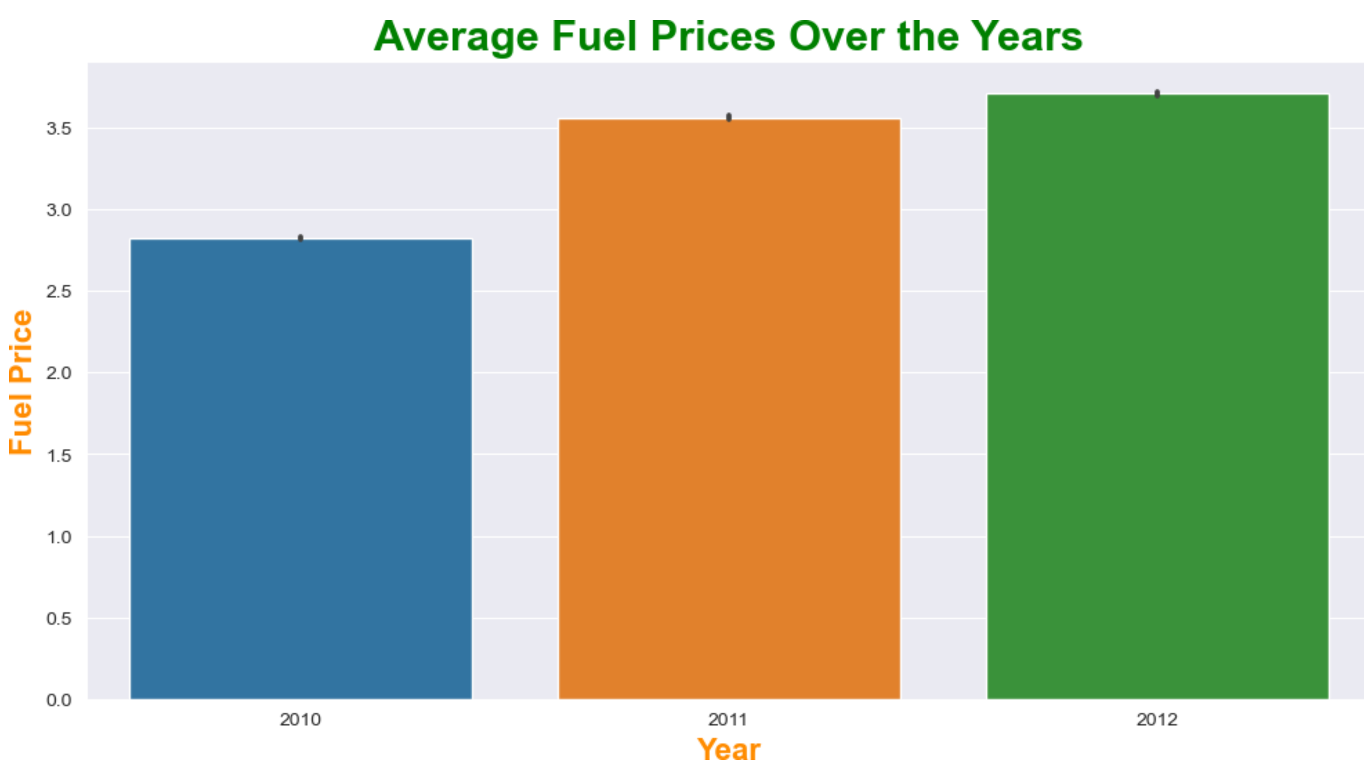
(h).How is the Fuel Prices are affecting the Weekly_Sales of various Stores?

In [33]:

```
sns.set_style('darkgrid')
plt.figure(figsize=(20,8))
sns.regplot(data = df_Walmart,x = 'Fuel_Price',y = 'Weekly_Sales')

# Set the title
plt.title('Fuel Price vs Weekly Sales', fontdict={'fontsize':22,'color':'Green','fontwei

# Set the x and y axis labels
plt.ylabel('Weekly Sales', color='#FF8C00', fontweight='bold', fontsize=16)
plt.xlabel('Fuel Price', color='#FF8C00', fontweight='bold', fontsize=16)

plt.show()
```



In [34]:
```
sns.set_style('darkgrid')
plt.figure(figsize=(12,6))
sns.barplot(data = df_Walmart,x = 'Year',y = 'Fuel_Price')

# Set the title
plt.title('Average Fuel Prices Over the Years', fontdict={'fontsize':22,'color':'Green',

# Set the x and y axis labels
plt.xlabel('Year', color='#FF8C00',fontweight='bold', fontsize=16)
plt.ylabel('Fuel  Price', color='#FF8C00',fontweight='bold',  fontsize=16)

plt.show()
```



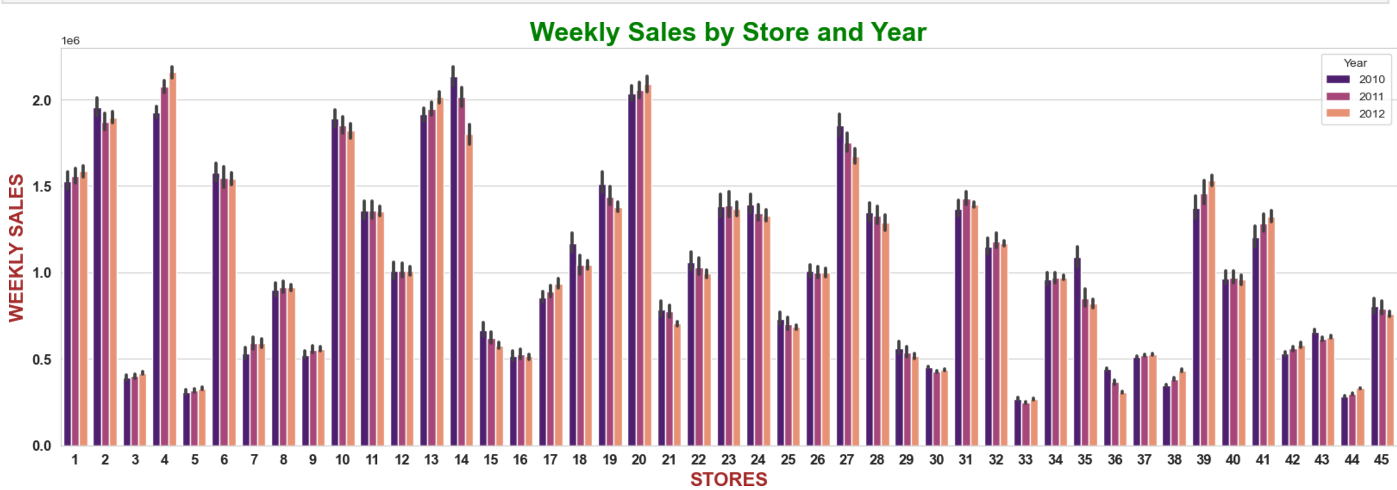
(i).Relation between Date and Weekly Sales

In [35]:
```
sns.set_style('darkgrid')
sns.relplot(data = df_Walmart,x = 'Date',y = 'Weekly_Sales',hue='Year',kind = 'line',hei
```

```
# Set the title
plt.title('Weekly Sales Over Time by Year', fontdict={'fontsize':22,'color':'Green','fon

# Set the x and y axis labels
plt.xlabel('Date', color='#FF8C00',fontweight='bold', fontsize=16)
plt.ylabel('Sales',  color='#FF8C00',fontweight='bold',  fontsize=16)
plt.show()
```

(j).Relation between Store and Weekly Sales

In [36]:
```
plt.figure(figsize=(20,6))
sns.set_style('whitegrid')
sns.barplot(data = df_Walmart,x = 'Store',y = 'Weekly_Sales',hue ='Year',palette='magma'

# Set the title
plt.title('Weekly Sales by Store and Year', fontdict={'fontsize':22,'color':'Green','fon

# Set the x and y axis labels
plt.xlabel('STORES', color='brown',fontweight='bold', fontsize=16)
plt.ylabel('WEEKLY  SALES',  color='brown',fontweight='bold',  fontsize=16)
plt.xticks(fontweight='bold', fontsize=12)
plt.yticks(fontweight='bold', fontsize=12)
plt.show()
```

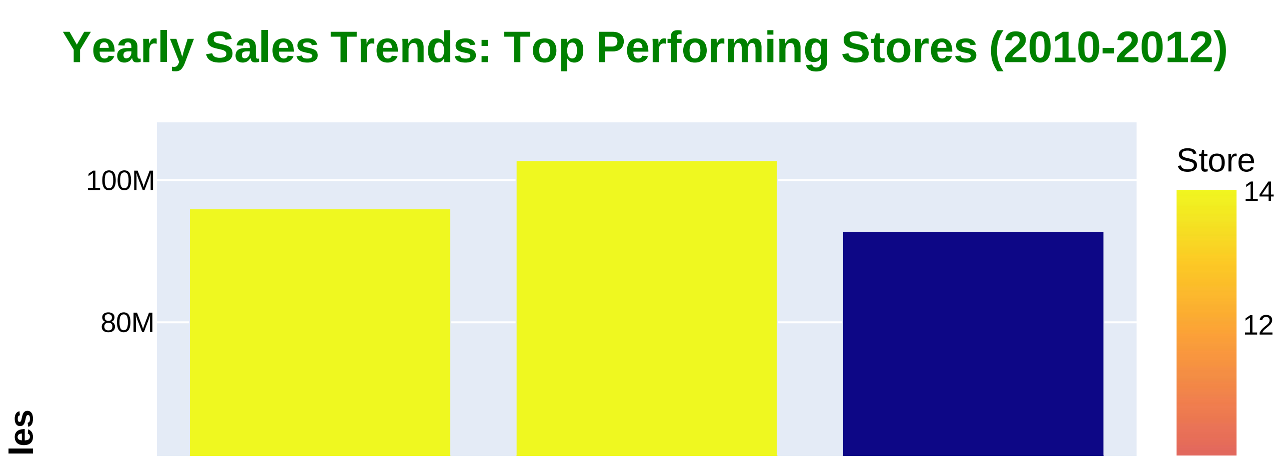


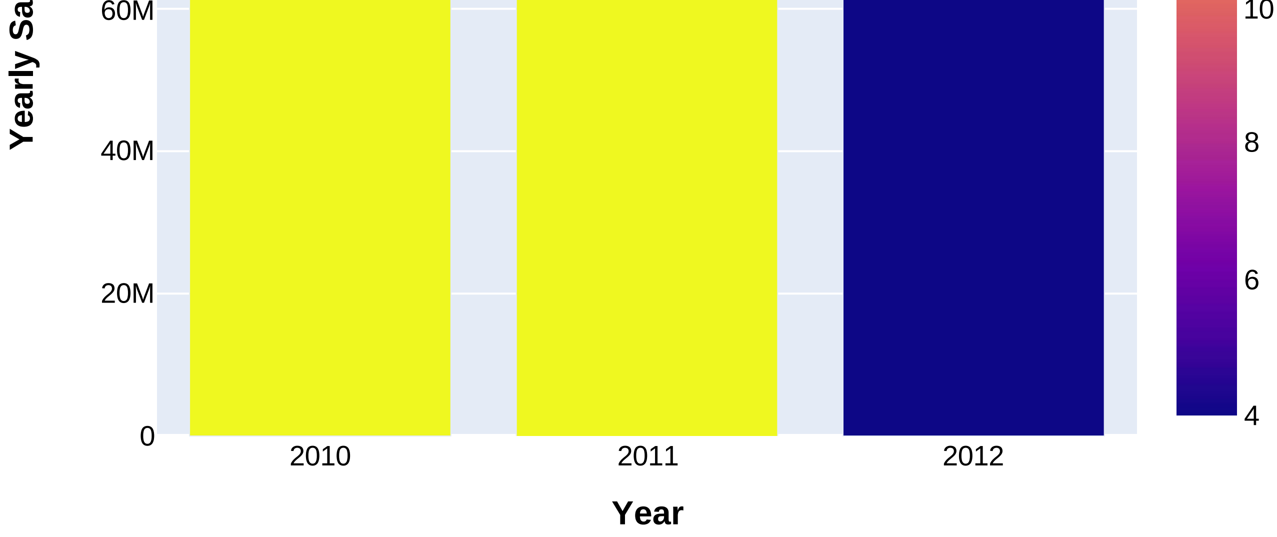
TOP Performing Stores according to the historical data

TOP Performing Stores Year wise according to the historical data

In [37]:

```
#grouping the data Year wsie and then Store wise
performers  =  df_Walmart.groupby(['Year','Store']).agg(Yearly_Sales=('Weekly_Sales','sum'

best_store = pd.DataFrame()
# getting unique values in Year column
year = df_Walmart.Year.unique()
for i in year:
    # Filter the top performers for the current year
    filt = (performers['Year'] == i)
    max_sale  =  performers[filt]['Yearly_Sales'].max()
    mask = (performers['Yearly_Sales']==max_sale)
    best_store  =  pd.concat([best_store,performers[filt][mask]])

best_store.reset_index(drop = True,inplace=True)

#Changing the datatype to int for Store column
best_store['Store']  =  best_store['Store'].astype('int')
unique_years = sorted(best_store['Year'].unique())
#plotting the graph for top performing stores
fig = px.bar(
    best_store,
    x='Year',
    y='Yearly_Sales',
    color='Store',
    color_discrete_sequence=px.colors.qualitative.Set1,
    category_orders={"Year": sorted(best_store['Year'].unique())},  # Enforce order with

)
fig.update_layout(
        xaxis=dict(
        tickmode='array',
        tickvals=unique_years,
        dtick=1,  # Set the tick interval to 1 to display only integer values
),
    title='<b>Yearly Sales Trends: Top Performing Stores (2010-2012)</b>',
    xaxis_title='<b>Year</b>',
    yaxis_title='<b>Yearly  Sales</b>',
    showlegend=True,
    font=dict(
        family="Arial,  sans-serif",
        size=14,
        color="black"
    ),
    title_font=dict(
        family="Arial,  sans-serif",
        size=22,
        color="green",
        )
)
fig.show()
```

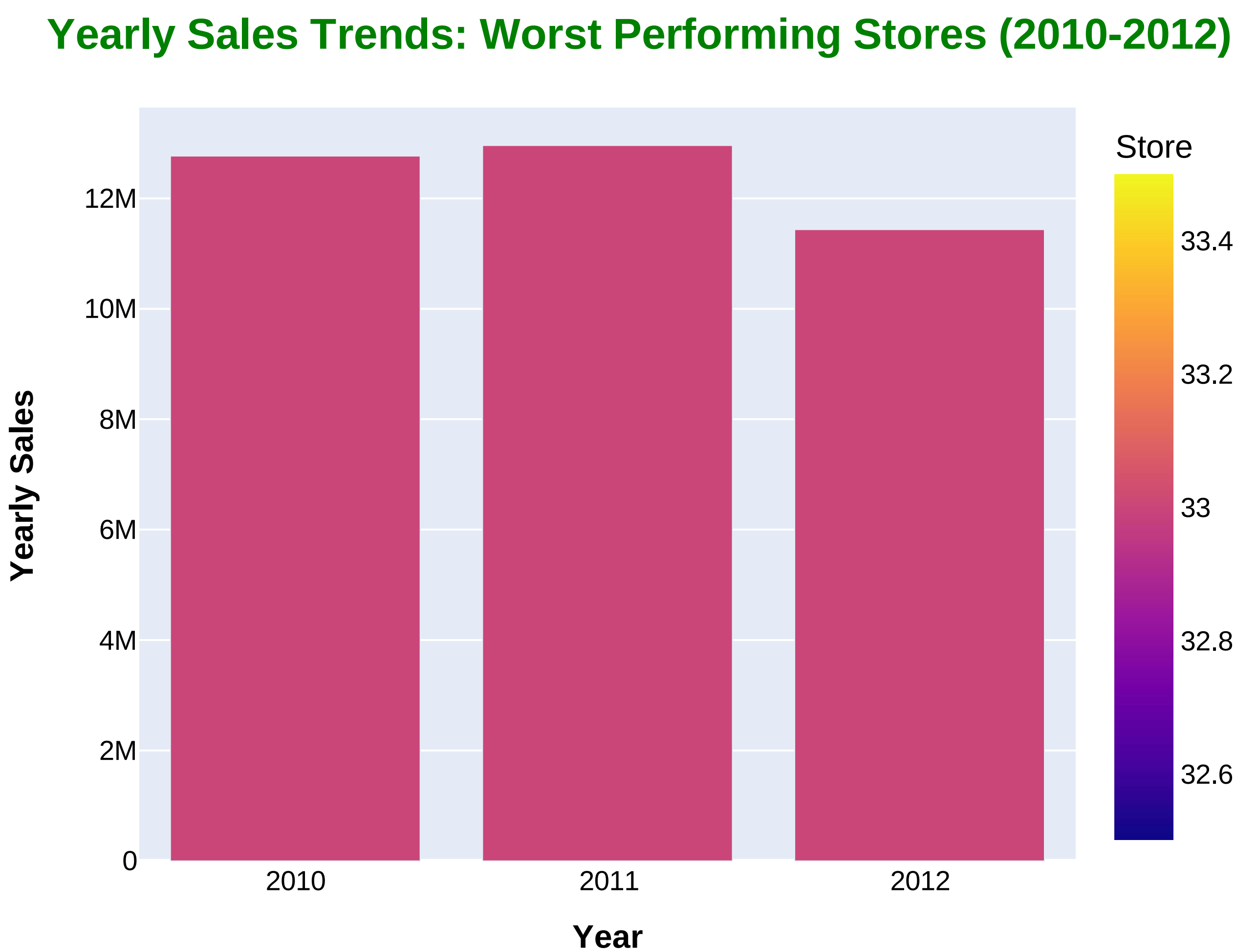




WORST Performing Stores according to the historical data

In [38]:
```
worst_store = pd.DataFrame()
# getting unique values in Year column
year = df_Walmart.Year.unique()
for i in year:
    # Filter the top performers for the current year
    filt = (performers['Year']==i)
    min_sale = performers[filt]['Yearly_Sales'].min()
    mask  =  (performers[filt]['Yearly_Sales']==min_sale)
    worst_store  =  pd.concat([worst_store,performers[filt][mask]])

worst_store.reset_index(drop = True,inplace=True)

#Changing the datatype to int for Store column
worst_store['Store']  =  worst_store['Store'].astype('int')
unique_years = sorted(worst_store['Year'].unique())
#plotting the graph for top performing stores
fig = px.bar(
    worst_store,
    x='Year',
    y='Yearly_Sales',
    color='Store',
    color_discrete_sequence=px.colors.qualitative.Set1,
    category_orders={"Year": sorted(worst_store['Year'].unique())},   # Enforce order wit

)
fig.update_layout(
        xaxis=dict(
        tickmode='array',
        tickvals=unique_years,
        dtick=1,  # Set the tick interval to 1 to display only integer values
),
    title='<b>Yearly Sales Trends: Worst Performing Stores (2010-2012)</b>',
    xaxis_title='<b>Year</b>',
    yaxis_title='<b>Yearly Sales</b>',
    showlegend=True,
    font=dict(
        family="Arial, sans-serif",
        size=14,
        color="black"
    ),
    title_font=dict(
        family="Arial, sans-serif",
```

```
            size=22,
            color="green",
            )
)
fig.show()
```



How significant is the difference between the HIGHEST and LOWEST Performing Stores

In [39]:

```
# To assess the significance of the difference between the highest and lowest performing
# we will calculate various statistical measures.

for i in year:
    filt = (performers['Year']==i)
    sales_range  =  performers[filt]['Yearly_Sales'].max()  -  performers[filt]['Yearly_Sale
    print('Stats for Yearly Sales in the year ',i)
    print('Range : ',sales_range)

    sales_mean = performers[filt]['Yearly_Sales'].mean() # Avg sales
    print('Average Sales : ',sales_mean)

    sales_std  =  performers[filt]['Yearly_Sales'].std()#std  deviation
    print('Standtard Deviation : ',sales_std)

    cv = (sales_std / sales_mean) * 100#coefficient of Variance
    print('Relative Variance : ',cv)

    #percentile  analysis
    sales_25th_percentile  =  performers[filt]['Yearly_Sales'].quantile(0.25)
    sales_75th_percentile  =  performers[filt]['Yearly_Sales'].quantile(0.75)
    print('25th_percentile : ',sales_25th_percentile)
```

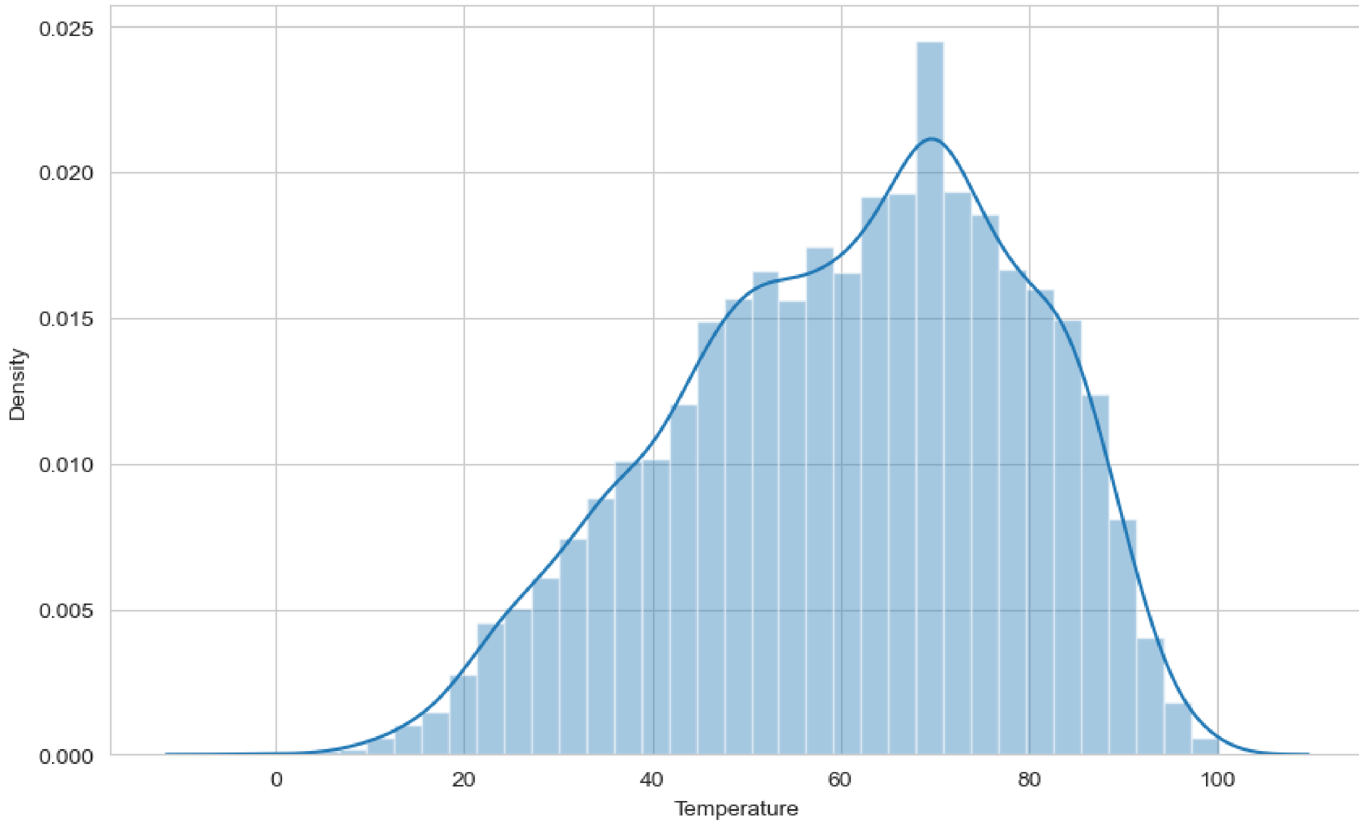
```
    print('75th_percentile  :  ',sales_75th_percentile)
    print(' ')
```

```
Stats for Yearly Sales in the year 2010
Range :  83192150.55
Average Sales : 49501474.735999994
Standtard Deviation :  24543508.62317917
Relative Variance : 49.58136854320803
25th_percentile :  25568078.15
75th_percentile :  65782276.32

Stats for Yearly Sales in the year 2011
Range :  89769365.03999999
Average Sales : 53434914.90044444
Standtard Deviation :  26897017.527062986
Relative Variance : 50.33603511332488
25th_percentile :  29117302.669999998
75th_percentile :  74169225.52

Stats for Yearly Sales in the year 2012
Range :  81335638.21
Average Sales : 44447396.87444445
Standtard Deviation :  23019092.759410933
Relative Variance : 51.78951834780234
25th_percentile :  24827530.71
75th_percentile :  59212433.28
```

Distribution graph of columns

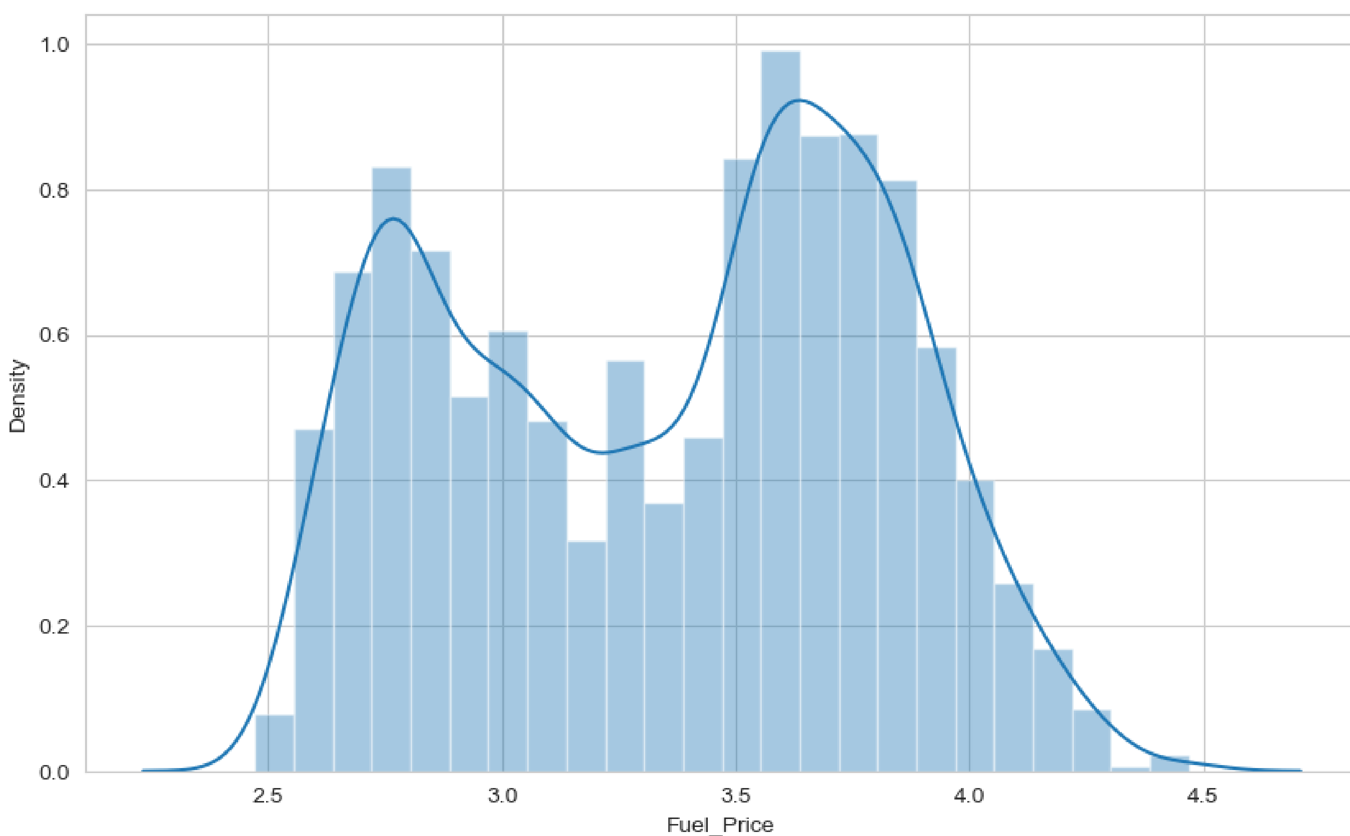
Temperature

In [40]:
```
plt.figure(figsize=(10,6))
sns.distplot(df_Walmart['Temperature'])
plt.show()
```



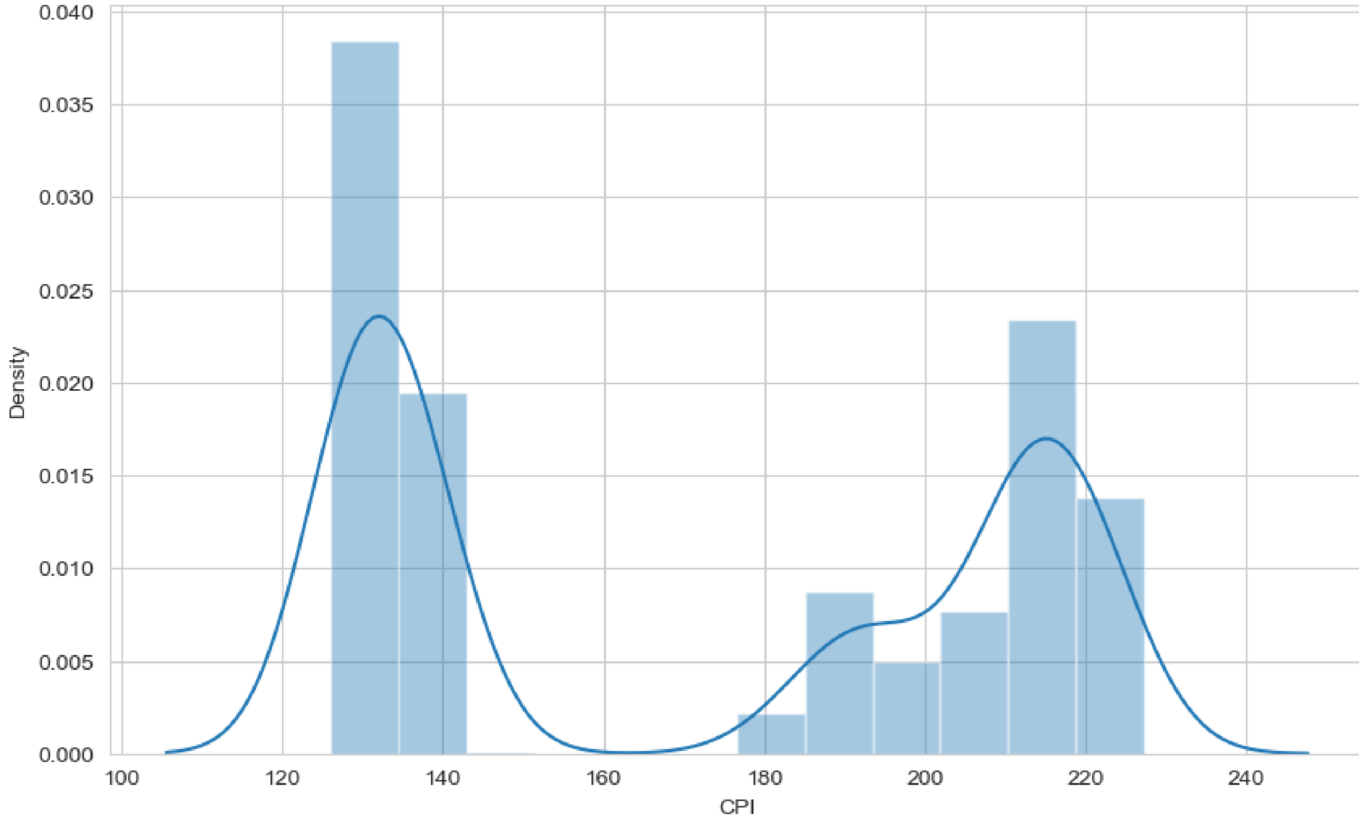
Fuel Price

In [41]:
```
plt.figure(figsize=(10,6))
sns.distplot(df_Walmart['Fuel_Price'])
plt.show()
```



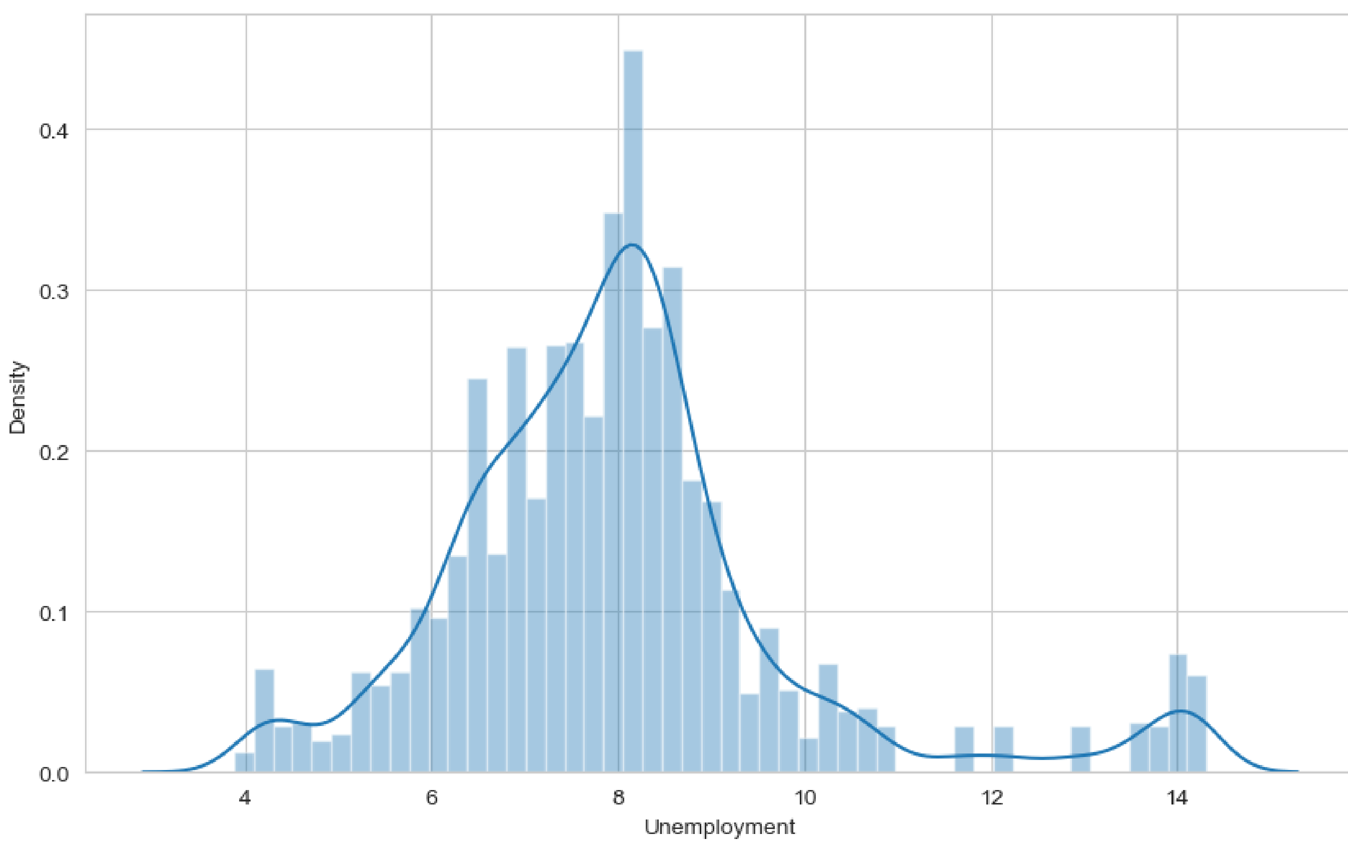
CPI

In [42]:
```
plt.figure(figsize=(10,6))
sns.distplot(df_Walmart['CPI'])
plt.show()
```



Unemployment

In [43]:
```
plt.figure(figsize=(10,6))
sns.distplot(df_Walmart['Unemployment'])
plt.show()
```



In [44]:
```
df_Walmart.skew()
```

Out[44]:
```
Weekly_Sales    0.497428
Temperature    -0.344571
Fuel_Price     -0.101046
CPI             0.061319
Unemployment    1.186512
Year            0.057389
Week            0.021496
Month           0.027883
dtype: float64
```

VIF check for multicollinearity

In [45]:
```
lst = list(df_Walmart.columns)
lst.remove('Weekly_Sales')
lst.remove('Store')
lst.remove('Holiday_Flag')
lst.remove('Date')
X = df_Walmart[lst]
y = df_Walmart['Weekly_Sales']
```

In [46]:
```
# VIF dataframe
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns

# calculating VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
print(vif_data)
```

```
        feature         VIF
0   Temperature   13.291808
1    Fuel_Price   60.255810
2           CPI   24.527554
3  Unemployment   22.061234
4          Year  145.332635
5          Week  606.455295
6         Month  691.535853
```

In [47]:
```
#we can drop year,month,week columns as those columns were not there in the original dat
df_Walmart.drop(columns=['Year','Week','Month'],inplace = True)
```

Insights from distribution and skewness for selection of transformers

Temperature & Fuel need Power

Transformer Unemployment needs

Function Transformer

To select features we need to do a statistical assessment to remove multicollinear columns

In [48]:
```
X = df_Walmart[['Temperature', 'Fuel_Price', 'CPI', 'Unemployment']]
y = df_Walmart['Weekly_Sales']

model = sm.OLS(y, sm.add_constant(X)).fit()
```

In [49]:
```
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
```

Dep. Variable: Weekly_Sales R-squared: 0.022

```
Model:                            OLS   Adj. R-squared:                  0.022
Method:                 Least Squares   F-statistic:                     36.53
Date:                Sun, 26 Nov 2023   Prob (F-statistic):           3.06e-30
Time:                        22:17:14   Log-Likelihood:                -93560.
No. Observations:                6401   AIC:                         1.871e+05
Df Residuals:                    6396   BIC:                         1.872e+05
Df Model:                           4
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const         1.651e+06   7.72e+04     21.378      0.000     1.5e+06     1.8e+06
Temperature   -318.2821    384.464     -0.828      0.408   -1071.960     435.396
Fuel_Price   -4817.1235   1.53e+04     -0.316      0.752   -3.47e+04    2.51e+04
CPI          -1524.2365    189.384     -8.048      0.000   -1895.493   -1152.980
Unemployment -3.971e+04   3848.319    -10.319      0.000   -4.73e+04   -3.22e+04
==============================================================================
Omnibus:                      555.168   Durbin-Watson:                   0.090
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              370.723
Skew:                           0.474   Prob(JB):                     3.15e-81
Kurtosis:                       2.299   Cond. No.                     2.16e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 2.16e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

We will select models which are robust to multicollinearity or handle it gracefully

Decision Tree

Random Forest

XGBoost

Predictive Models:

FEATURE TRANSFORMATION AND SELECTION:

Feature Transformation and Predicting

In [50]:
```python
#setting Date column to index
df_Walmart.set_index('Date',inplace = True)
```

In [51]:
```python
df_Walmart.head()
```

Out[51]:

Date	Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
2010-05-02	1	1643690.90	0	42.31	2.572	211.096358	8.106
2010-12-02	1	1641957.44	1	38.51	2.548	211.242170	8.106

2010-02-19	1	1611968.17	0	39.93	2.514	211.289143	8.106
2010-02-26	1	1409727.59	0	46.63	2.561	211.319643	8.106
2010-05-03	1	1554806.68	0	46.50	2.625	211.350143	8.106

In [52]:
```
lst  =  list(df_Walmart.columns)
lst.remove('Weekly_Sales')
X = df_Walmart[lst]
y = df_Walmart['Weekly_Sales']
```

In [53]:
```
function_list  =  ['Unemployment']
power_list =  ['Temperature','Fuel_Price']
skip_list  =  ['Store','Holiday_Flag','CPI']
```

In [54]:
```
transformers  =   [('function',FunctionTransformer(np.log1p),function_list),
                ('power',PowerTransformer(),power_list),
                ('skip','passthrough',skip_list)]
```

In [55]:
```
column_Transformer  =  ColumnTransformer(transformers=transformers,remainder  =  'passthroug
```

In [56]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)

results_df = pd.DataFrame(columns=['Model', 'y_test', 'y_pred', 'R2 Score'])
# Define models and their respective hyperparameter grids
models = {
    'Decision  Tree':  (DecisionTreeRegressor(),  {'model__max_depth': [None, 5, 10, 15]}),
    'Random  Forest':  (RandomForestRegressor(),  {'model__n_estimators': [10, 50, 100], 'm
    'XGBoost':  (XGBRegressor(),  {'model__n_estimators': [50, 100, 200], 'model__max_dept
}

# Perform hyperparameter tuning and evaluation for each model
for model_name, (model, param_grid) in models.items():
    pipeline = Pipeline([
        ('preprocessing', column_Transformer),  # Include any necessary preprocessing st
        ('model', model),
    ])

    # Create a GridSearchCV object
    grid_search = GridSearchCV(
        pipeline,
        param_grid,
        scoring='r2',  # Use mean squared error as the scoring metric
        cv=5,  # 5-fold cross-validation
        n_jobs=-1   # Use all available CPU cores
    )

    # Fit the GridSearchCV object on the training data
    grid_search.fit(X_train,  y_train)

    # Print the best hyperparameters and corresponding mean squared error
    best_params  =  grid_search.best_params_
    best_mse = -grid_search.best_score_
    print(f"{model_name} - Best Hyperparameters: {best_params}, Best Mean Squared Error:

    # Make predictions on the test set using the best model
    y_pred  =  grid_search.predict(X_test)

    # Evaluate the model on the test set
    r2 = r2_score(y_test, y_pred)

    # Append results to the DataFrame
```

```
    results_df = results_df.append({
        'Model': model_name,
        'y_test': y_test.values,
        'y_pred': y_pred,
        'R2 Score': r2
    }, ignore_index=True)
```

```
Decision Tree - Best Hyperparameters: {'model__max_depth': 10}, Best Mean Squared Error:
-0.9206793331169172
Random Forest - Best Hyperparameters: {'model__max_depth': None, 'model__n_estimators':
100}, Best Mean Squared Error: -0.9461783055997636
XGBoost - Best Hyperparameters: {'model__max_depth': 5, 'model__n_estimators': 200}, Bes
t Mean Squared Error: -0.95688975410082
```

In [57]:

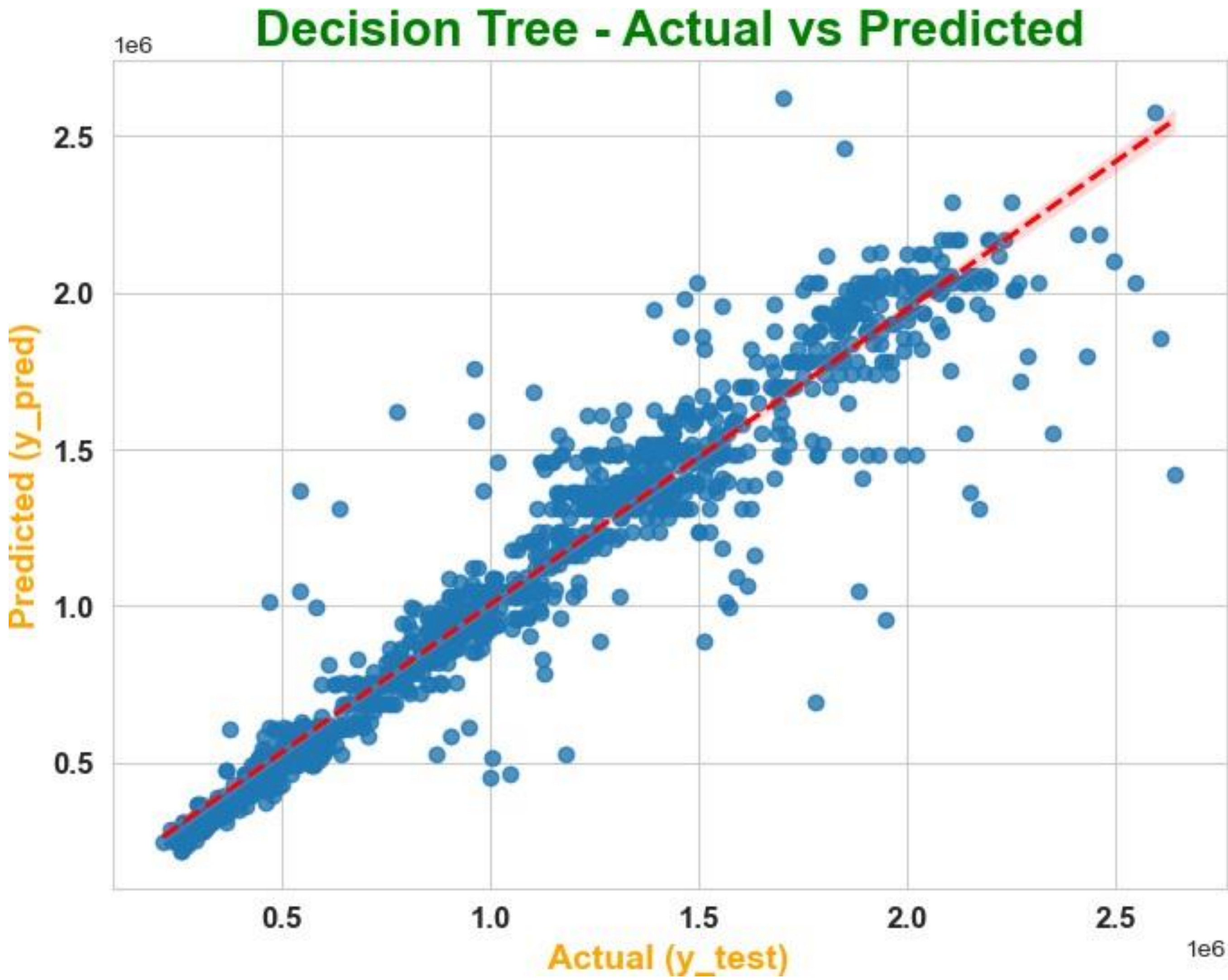
```
# Display the results DataFrame
results_df
```

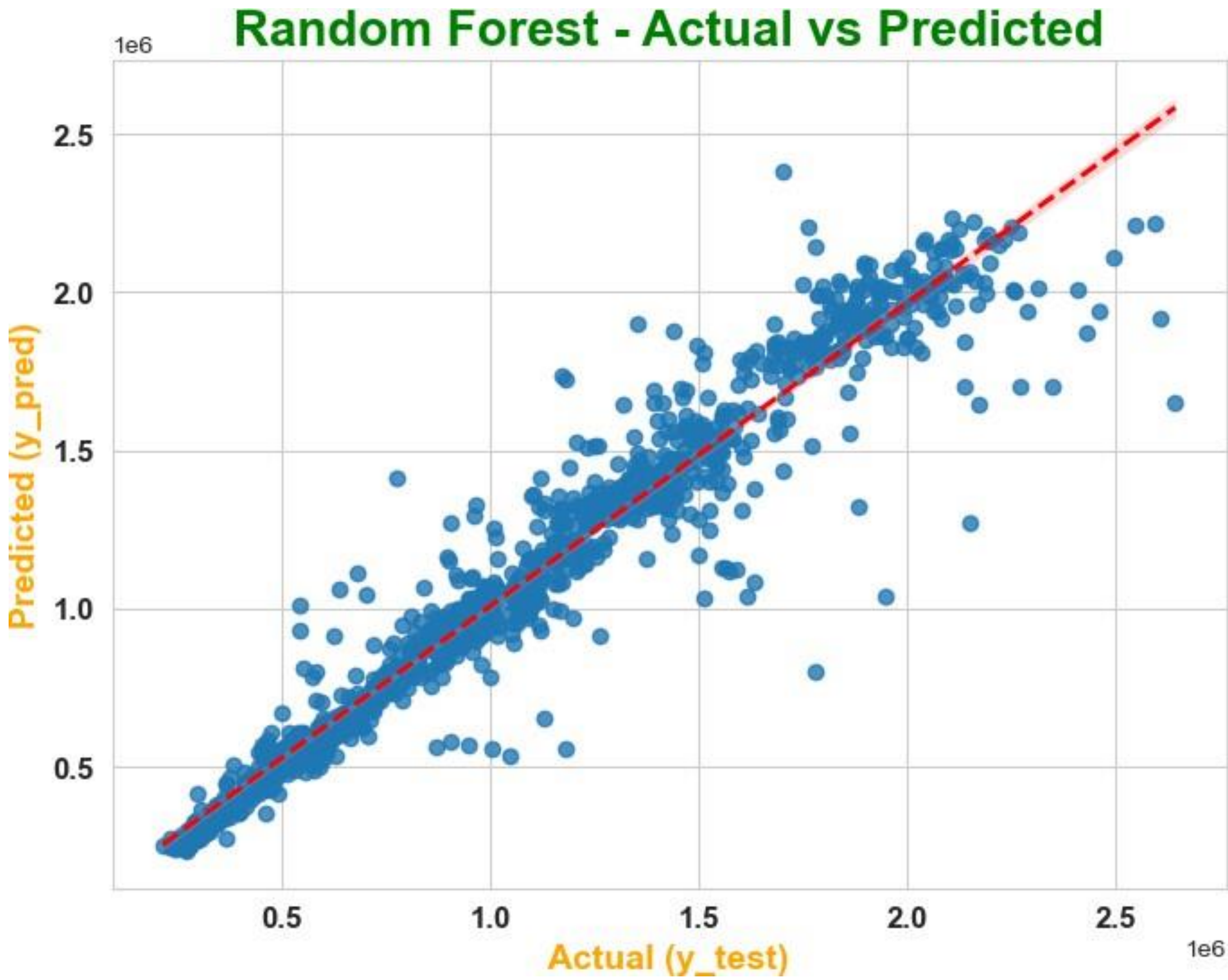
Out[57]:

	Model	y_test	y_pred	R2 Score
0	Decision Tree	[1054454.4, 1591920.42, 1415473.91, 498580.87,...	[1085797.6744444445, 1095429.9233333333, 14192...	0.919111
1	Random Forest	[1054454.4, 1591920.42, 1415473.91, 498580.87,...	[1070848.9127000018, 1124118.5976999989, 13974...	0.942977
2	XGBoost	[1054454.4, 1591920.42, 1415473.91, 498580.87,...	[1053759.5, 1379877.9, 1402597.4, 820874.1, 17...	0.964359

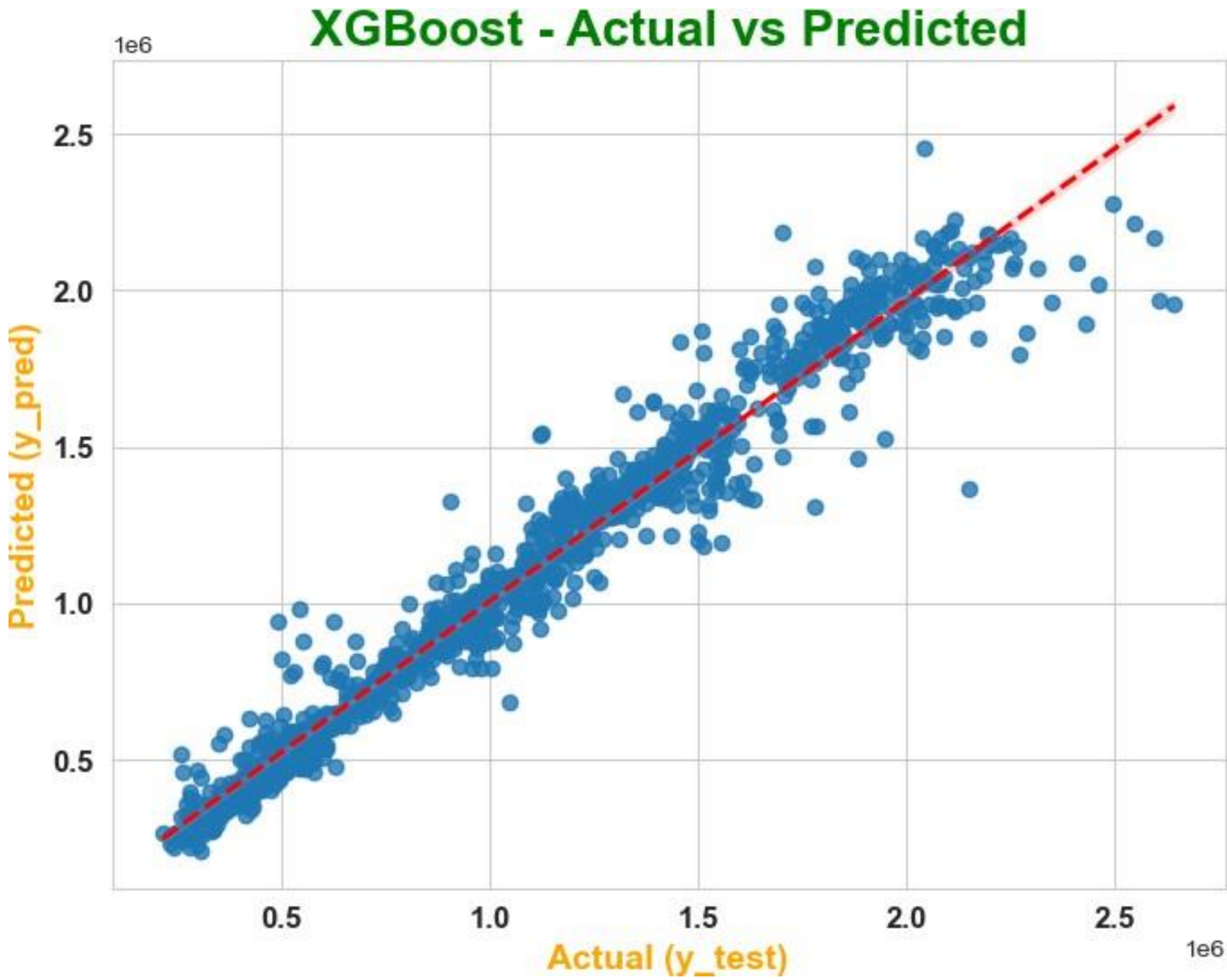
In [58]:

```
for i, row in results_df.iterrows():
    plt.figure(figsize=(8, 6))
    sns.regplot(x=row['y_test'],  y=row['y_pred'],  line_kws={'color':  'red',  'linestyle':
    plt.title(f"{row['Model']}  -  Actual  vs  Predicted",fontdict={'fontsize':20,'color':'G
    plt.xlabel('Actual   (y_test)',fontdict={'fontsize':14,'color':'orange','fontweight':'
    plt.ylabel('Predicted   (y_pred)',fontdict={'fontsize':14,'color':'orange','fontweight
    plt.xticks(fontweight='bold', fontsize=12)
    plt.yticks(fontweight='bold',  fontsize=12)
    plt.show()
```


Decision Tree - Actual vs Predicted
1e6
2.5
2.0
1.5
1.0
0.5
Predicted (y_pred)
0.5
1.0
1.5
2.0
2.5
1e6
Actual (y_test)



Random Forest - Actual vs Predicted
1e6
2.5
2.0
1.5
1.0
0.5
Predicted (y_pred)
0.5
1.0
1.5
2.0
2.5
1e6
Actual (y_test)



Insights:

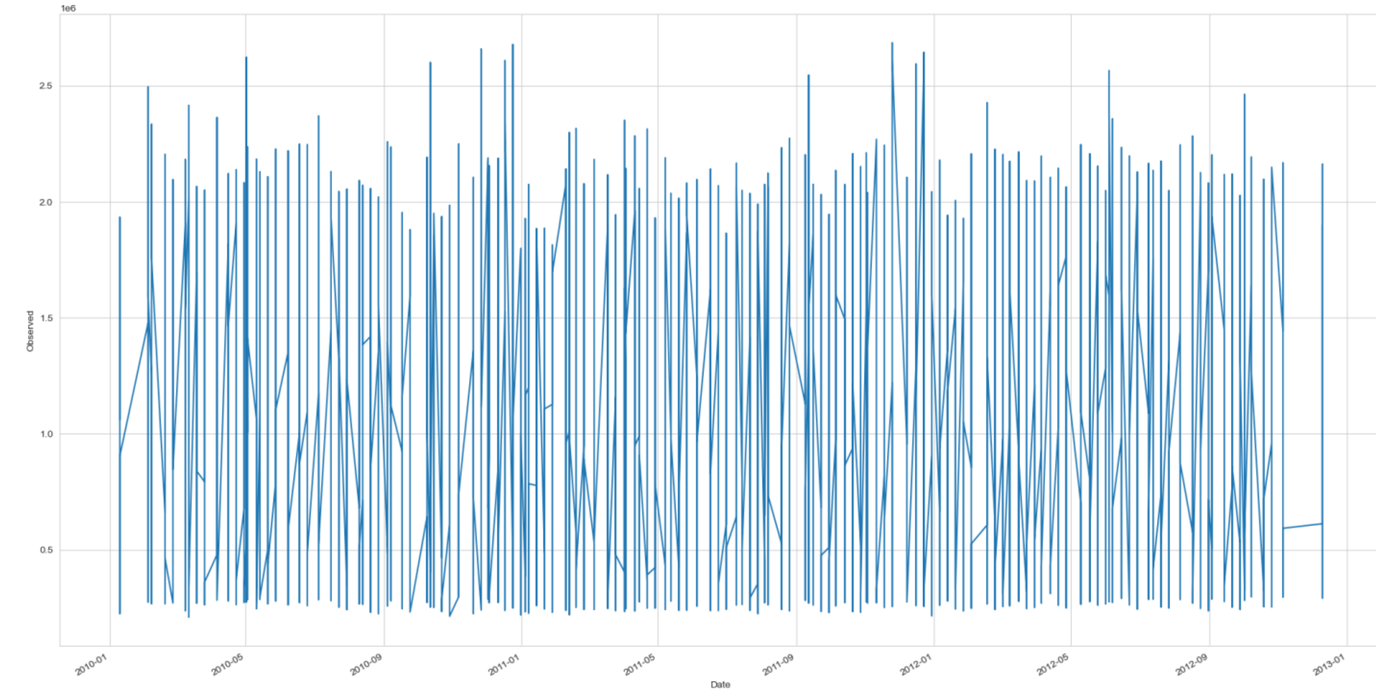
XGBOOST performs the best

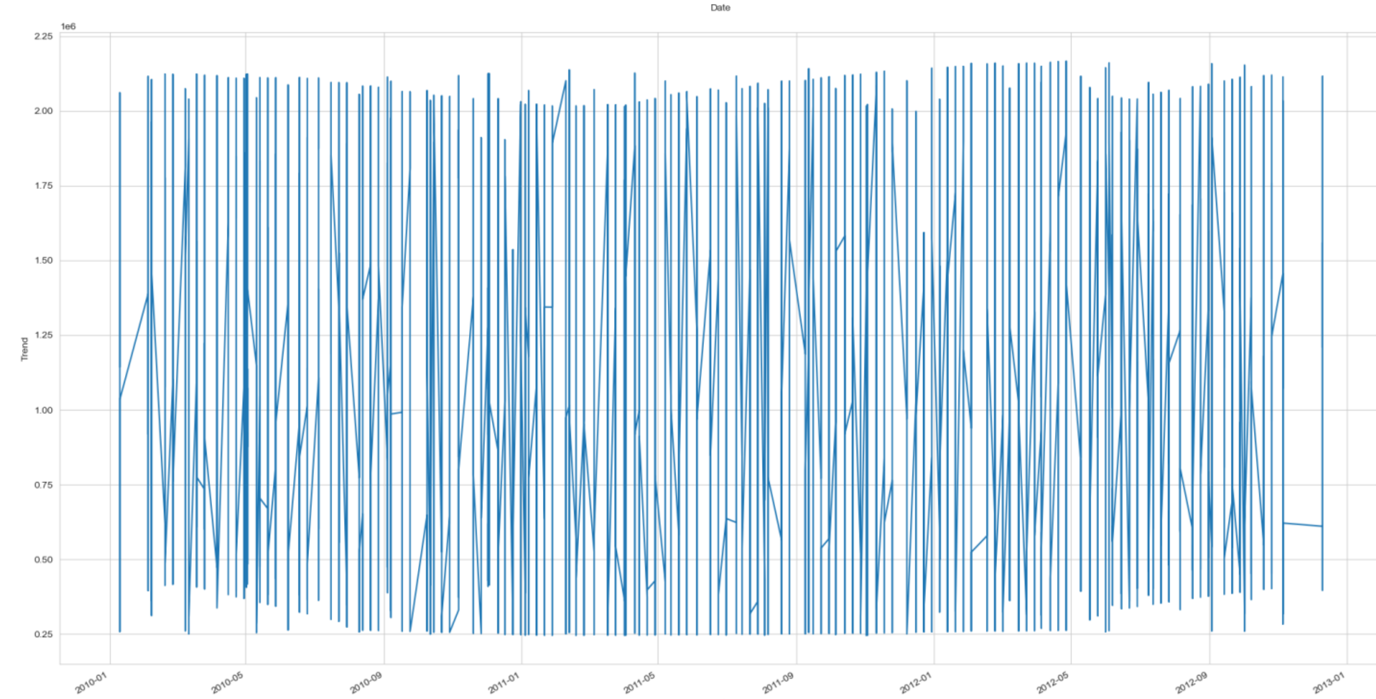
FORECAST the Weekly_Sales for each Stores for the NEXT 12 WEEKS.

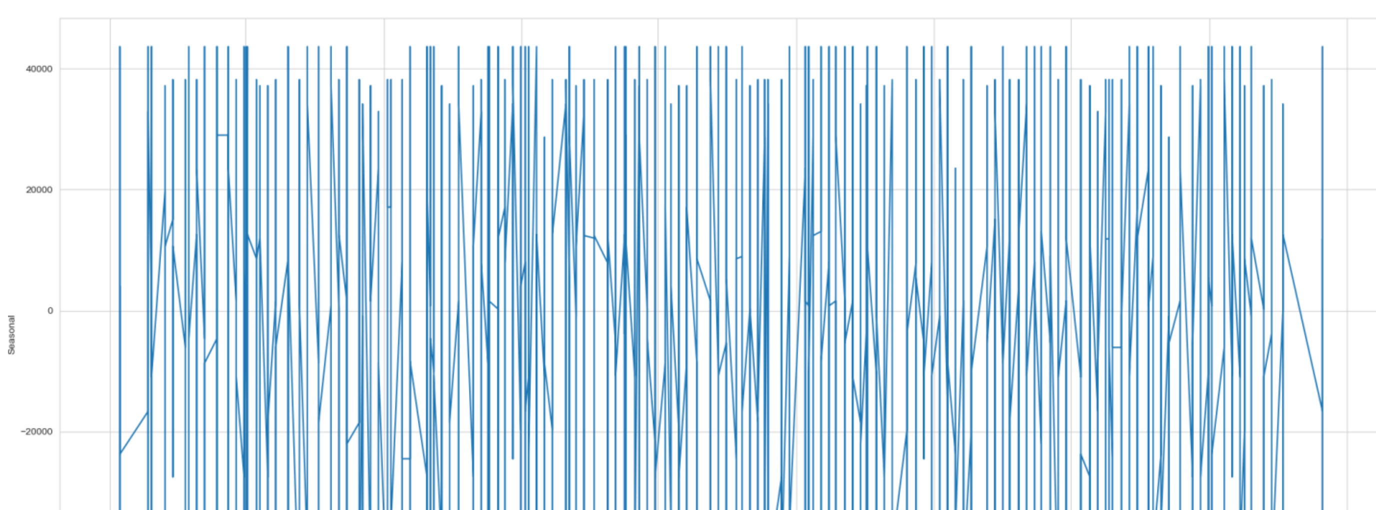
Time Series for forecasting:

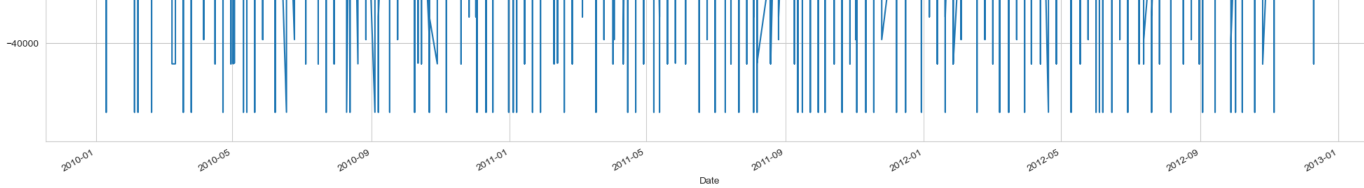
In [59]:
```
#Apply time series analysis to identify seasonal trends:

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

# 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])
```

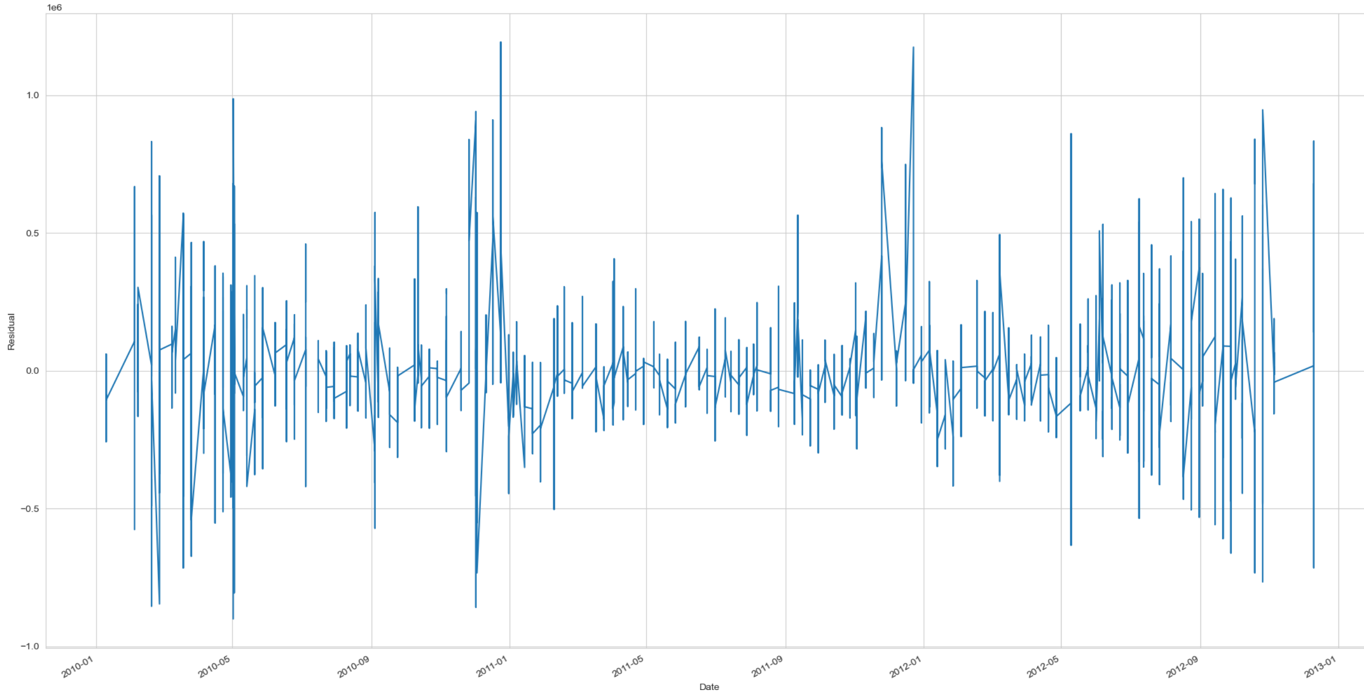
```
ax[2].set_ylabel('Seasonal')
result.resid.plot(ax=ax[3])
ax[3].set_ylabel('Residual')

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











In [ ]:

```

```

Future Possibilities:

1. **Advanced Predictive Modeling**: While the current models (Decision Tree, Random Forest, XGBoost) provided satisfactory results, future work could explore more advanced forecasting models, including neural networks and time series models like ARIMA or SARIMA.

2. **Dynamic Feature Engineering**: Incorporate additional features or engineered features to enhance model accuracy. For example, adding promotional events, economic indicators, or regional data could provide a more comprehensive understanding of sales dynamics.

3. **Fine-Tuning Models**: Further hyperparameter tuning and optimization of the selected models could improve their predictive performance. Grid search techniques and Bayesian optimization can be explored for this purpose.

4. **Dynamic Inventory Management**: Utilize insights gained to optimize inventory management strategies.

Understanding the impact of external factors can help Walmart plan for demand fluctuations and reduce stockouts or overstock situations.

5. **Real-Time Data Integration**: Implement real-time data integration to capture the most recent information. This would enable Walmart to adapt its strategies promptly based on changing economic conditions, consumer behavior, or external events.

6. **Geospatial Analysis**: Incorporate geospatial analysis to understand the impact of location on sales. Factors such as population density, competition, and local events can play a crucial role in store performance.

7. **Customer Segmentation**: Analyze customer segmentation to tailor marketing and sales strategies for different consumer groups. This can be achieved by leveraging data on purchasing behavior, demographics, and preferences.

8. **Collaborative Filtering**: Implement collaborative filtering techniques to provide personalized recommendations to customers. This can enhance the customer shopping experience and potentially boost sales.

9. **Real-time Dashboard**: Developing a real-time dashboard to visualize the predicted versus actual sales, key performance indicators, and relevant metrics could assist stakeholders in making informed decisions promptly. This would enable quick reactions to emerging trends or anomalies.

By continuously refining models, incorporating new data sources, and adopting advanced analytics techniques, Walmart can stay ahead in the highly competitive retail landscape and make informed, data-driven decisions.

This concludes the analysis and provides a roadmap for future enhancements and strategic planning for Walmart's sales forecasting.

Conclusion:

In conclusion, the analysis of Walmart's sales data has provided valuable insights into various factors affecting weekly sales across its multiple stores. The key findings are:

1. **Unemployment Impact**: There is a negative correlation between Weekly Sales and Unemployment Rate. Some stores show a stronger negative correlation, indicating that economic conditions may influence sales.

2. **Seasonal Trends**: The analysis suggests the presence of seasonal trends, especially during holiday weeks, which significantly impact Weekly Sales. This insight can help Walmart better prepare for peak sales periods.

3. **Temperature Influence**: Temperature appears to have an impact on Weekly Sales, with a slight positive correlation. Further analysis indicates that during colder months, sales tend to increase.

4. **CPI and Fuel Prices**: The Consumer Price Index (CPI) shows varying impacts on Weekly Sales across different stores. Fuel prices also exhibit an influence on sales, but the relationship is not as straightforward.

5. **Store Performance**: The analysis identifies top-performing and worst-performing stores based on yearly sales trends. Understanding the performance of individual stores can guide strategic decision-making.

6. **Statistical Analysis**: Detailed statistical measures, including range, average sales, standard deviation, and coefficient of variance, were computed to assess the significance of the difference between the highest and lowest performing stores.

7. **The predictive modeling**: The predictive models, particularly XGBoost, demonstrated strong performance in forecasting weekly sales. However, the future possibilities outlined suggest avenues for further refinement and enhancement of the forecasting process.

References:

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). Time Series Analysis: Forecasting and Control. Wiley. Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '16). Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: Principles and Practice. OTexts. Pedregosa, F., et al. (2011). Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research, 12, 2825–2830. Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing, 50, 159-175.