Task 3: Data-driven Insights and Reporting

Instructions:

1. Receive a dataset related to a business problem or research question.
2. Perform in-depth data analysis using advanced statistical techniques.
3. Identify relevant variables and relationships within the dataset.
4. Develop predictive models, forecasting techniques, or segmentation methods.
5. Interpret and validate the results, providing clear explanations and actionable insights.
6. Prepare a concise report summarizing the analysis approach, key findings, and recommendations.
7. Present findings using data visualizations and accessible language.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
data = pd.read_csv("Datasets/walmart_sales/Walmart_Store_sales.csv")
data.head()
```

Out[2]:

	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

1. Dataset acquired

Dataset details

- Walmart stores historical sales data
- Source: https://www.kaggle.com/datasets/rutuspatel/walmart-dataset-retail
- Column details:

  Store - the store number

  Date - the week of sales

  Weekly_Sales - sales for the given store

  Holiday_Flag - whether the week is a special holiday week 1 – Holiday week 0 – Non-holiday week

  Temperature - Temperature on the day of sale

  Fuel_Price - Cost of fuel in the region

  CPI – Prevailing consumer price index

  Unemployment - Prevailing unemployment rate
- Holidays events: Super Bowl: 12-Feb-10, 11-Feb-11, 10-Feb-12, 8-Feb-13

  Labour Day: 10-Sep-10, 9-Sep-11, 7-Sep-12, 6-Sep-13

  Thanksgiving: 26-Nov-10, 25-Nov-11, 23-Nov-12, 29-Nov-13

  Christmas: 31-Dec-10, 30-Dec-11, 28-Dec-12, 27-Dec-13

  2. EDA

In [3]:
```
data.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
```

In [26]:
```
# Changing datatime format.
data['Date'] = data['Date'].astype('datetime64[ns]')
# data.head()
```

Out[26]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Day	Month	Year
0	1	2010-05-02	1643690.90	0	42.31	2.572	211.096358	8.106	2	5	2010
1	1	2010-12-02	1641957.44	1	38.51	2.548	211.242170	8.106	2	12	2010
2	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106	19	2	2010
3	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	8.106	26	2	2010
4	1	2010-05-03	1554806.68	0	46.50	2.625	211.350143	8.106	3	5	2010

In [5]:
```
data.describe()
```

Out[5]:

	Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
count	6435.000000	6.435000e+03	6435.000000	6435.000000	6435.000000	6435.000000	6435.000000
mean	23.000000	1.046965e+06	0.069930	60.663782	3.358607	171.578394	7.999151
std	12.988182	5.643666e+05	0.255049	18.444933	0.459020	39.356712	1.875885
min	1.000000	2.099862e+05	0.000000	-2.060000	2.472000	126.064000	3.879000
25%	12.000000	5.533501e+05	0.000000	47.460000	2.933000	131.735000	6.891000
50%	23.000000	9.607460e+05	0.000000	62.670000	3.445000	182.616521	7.874000
75%	34.000000	1.420159e+06	0.000000	74.940000	3.735000	212.743293	8.622000
max	45.000000	3.818686e+06	1.000000	100.140000	4.468000	227.232807	14.313000

In [6]:
```
# Check any null in the entire dataframe.
data.isnull().values.any()
```

Out[6]:
```
False
```

In [7]:
```
# Check if any column contains a null value.
data.isnull().sum()
```

Out[7]:
```
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
dtype: int64
```

In [8]:
```
# Getting top 10 stores with high sales
total_sales = data.groupby('Store')['Weekly_Sales'].sum().round().sort_values(ascending=False)
total_sales.head(10)
```

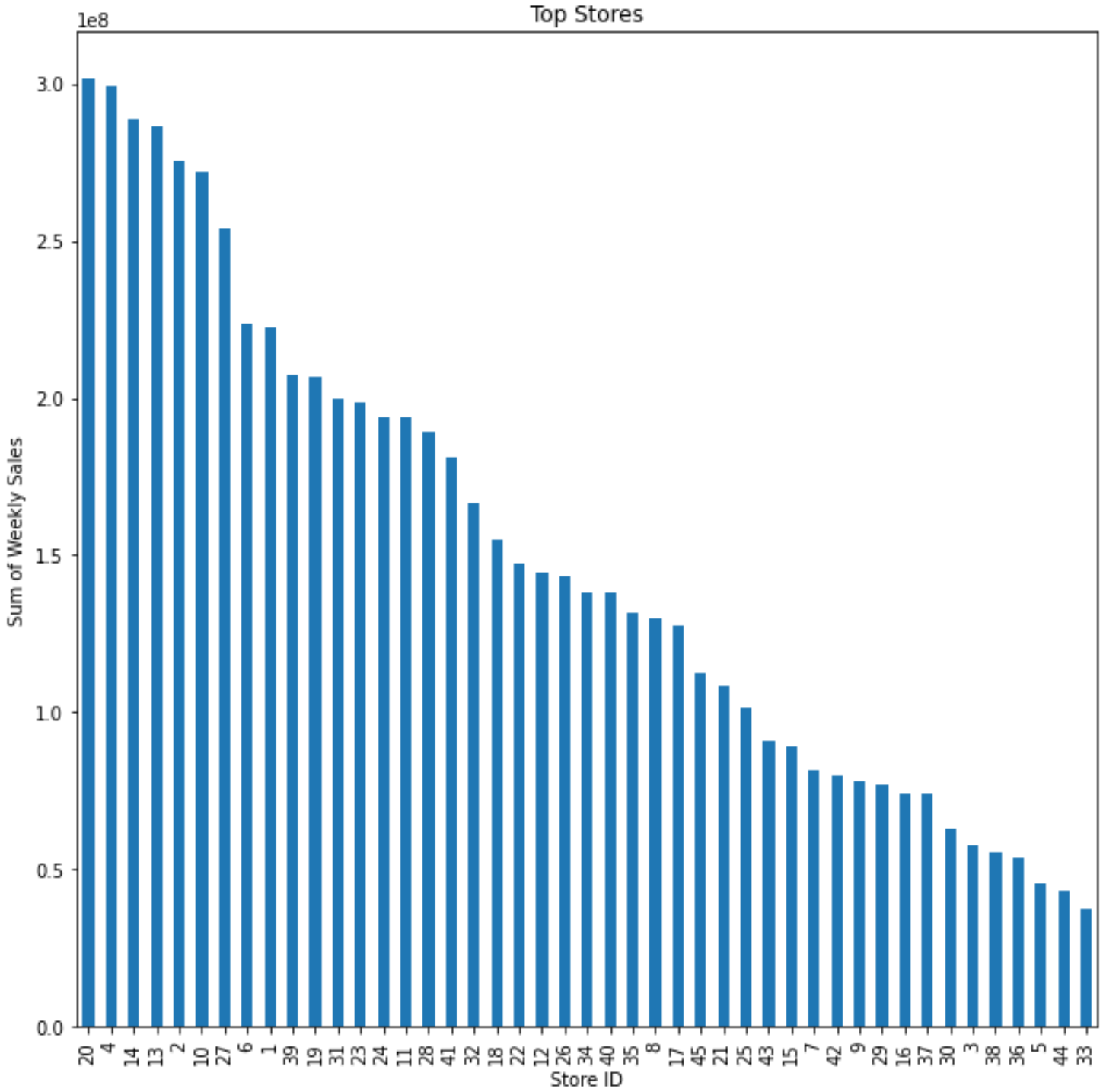
Out[8]:
```
Store
20    301397792.0
4     299543953.0
14    288999911.0
13    286517704.0
2     275382441.0
10    271617714.0
27    253855917.0
6     223756131.0
1     222402809.0
39    207445542.0
Name: Weekly_Sales, dtype: float64
```

In [9]:
```
# Display top 10 Stores of Weekly Sales performance deviation.
data_std = data.groupby('Store')['Weekly_Sales'].std().round(2).sort_values(ascending=False)
data_std.head(10)
```

Out[9]:
```
Store
14    317569.95
10    302262.06
20    275900.56
4     266201.44
13    265507.00
23    249788.04
27    239930.14
2     237683.69
39    217466.45
6     212525.86
Name: Weekly_Sales, dtype: float64
```

In [10]:
```
# Plotting the top stores with high sales
pandaplot = total_sales.plot.bar(figsize=(10,10))
pandaplot.set_title('Top Stores')
pandaplot.set_xlabel('Store ID')
pandaplot.set_ylabel('Sum of Weekly Sales')
```

Out[10]:
```
Text(0, 0.5, 'Sum of Weekly Sales')
```



In [11]:
```
# Define the dates of the Public Holiday.
Super_Bowl = ['12-2-2010', '11-2-2011', '10-2-2012']
```

```
Labour_Day =  ['10-9-2010', '9-9-2011', '7-9-2012']
Thanksgiving =  ['26-11-2010', '25-11-2011', '23-11-2012']
Christmas = ['31-12-2010', '30-12-2011', '28-12-2012']
```

In [28]:
```
# Filter dataframe to calculate the average Sales in Public Holiday.
Super_Bowl_sales = round(data.loc[data.Date.isin(Super_Bowl)]['Weekly_Sales'].mean(),2)
Labour_Day_sales = round(data.loc[data.Date.isin(Labour_Day)]['Weekly_Sales'].mean(),2)
Thanksgiving_sales = round(data.loc[data.Date.isin(Thanksgiving)]['Weekly_Sales'].mean(),2)
Christmas_sales = round(data.loc[data.Date.isin(Christmas)]['Weekly_Sales'].mean(),2)
print(Super_Bowl_sales, Labour_Day_sales, Thanksgiving_sales, Christmas_sales)
```

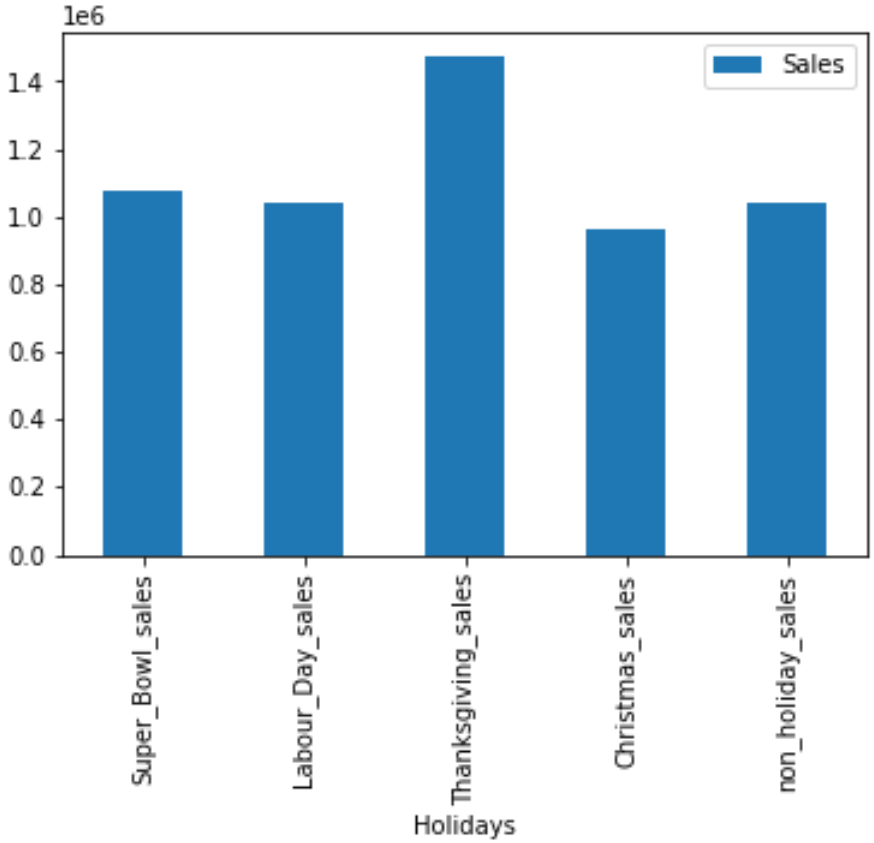
```
1079127.99 1042427.29 1471273.43 960833.11
```

In [13]:
```
# Filter dataframe to calculate the average Sales in Non-Holiday.
non_holiday_sales = round(data[(data['Holiday_Flag'] == 0)]['Weekly_Sales'].mean(),2)
print(non_holiday_sales)
```

```
1041256.38
```

In [34]:
```
 # creating dataframe
df = pd.DataFrame({
    'Holidays': ['Super_Bowl_sales', 'Labour_Day_sales', 'Thanksgiving_sales', 'Christmas_sales', 'non_holiday_sa
    'Sales': [1079127.99, 1042427.29, 1471273.43, 960833.11, 1041256.38]
})

# plotting graph
df.plot(x="Holidays", y=["Sales"], kind="bar")
```

Out[34]:
```
<AxesSubplot:xlabel='Holidays'>
```



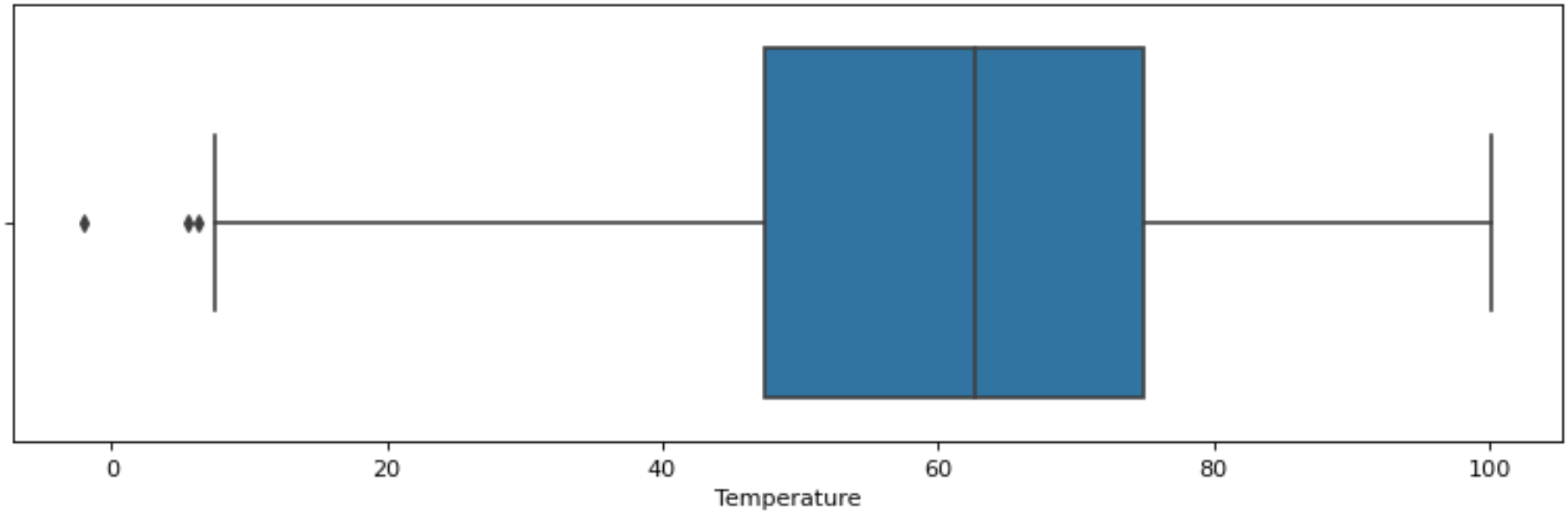
In [14]:
```
# Create Day, Month, and Year columns in the dataframe based on the Date column.
data['Day'] = pd.DatetimeIndex(data['Date']).day
data['Month'] = pd.DatetimeIndex(data['Date']).month
data['Year'] = pd.DatetimeIndex(data['Date']).year
data.head()
```

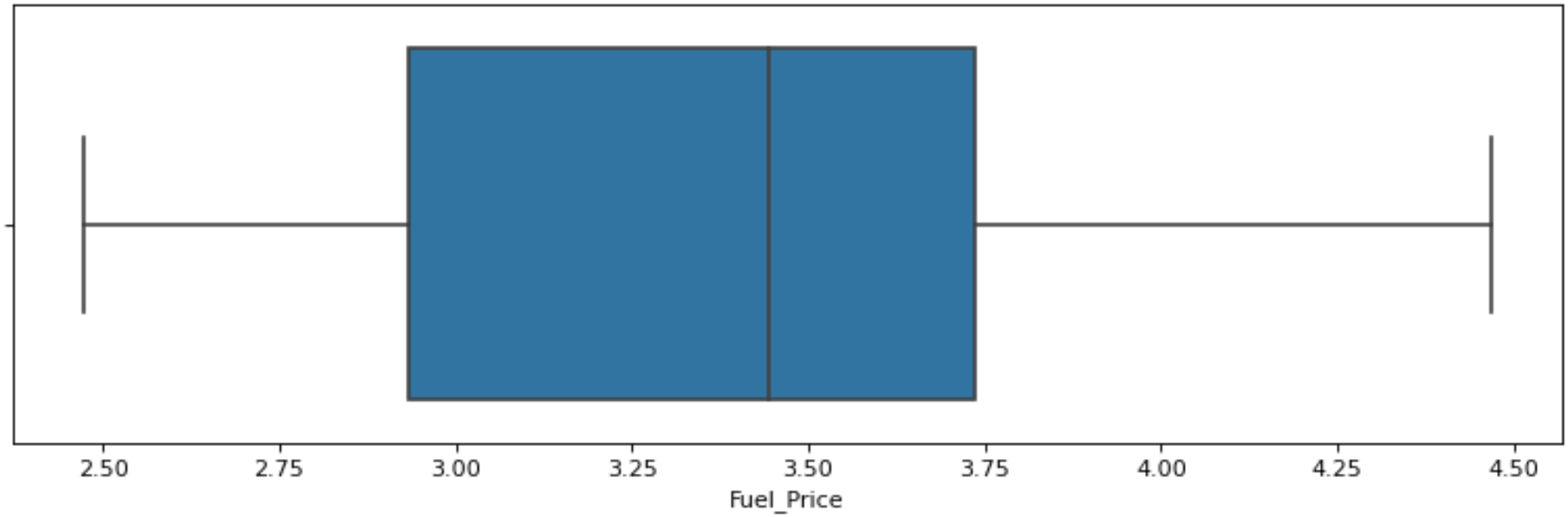
Out[14]:

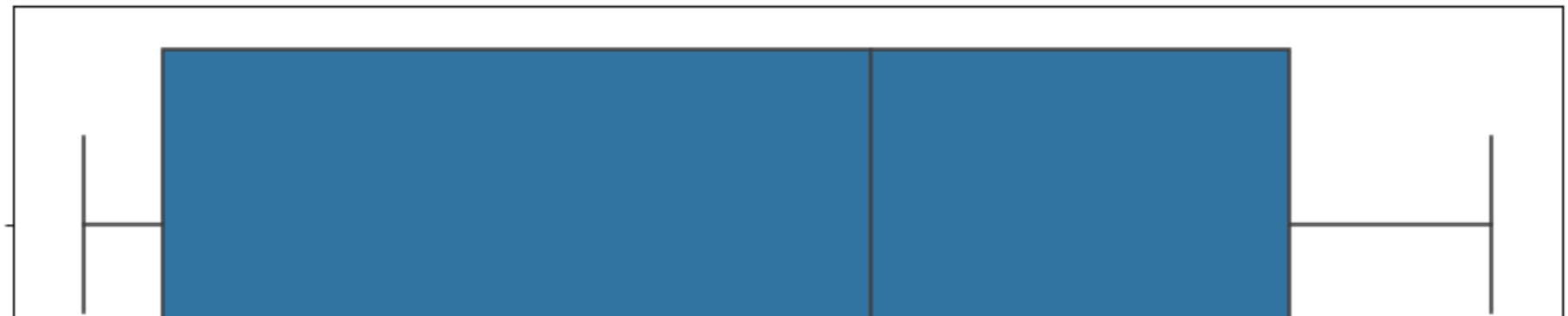
	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Day	Month	Year
0	1	2010-05-02	1643690.90	0	42.31	2.572	211.096358	8.106	2	5	2010
1	1	2010-12-02	1641957.44	1	38.51	2.548	211.242170	8.106	2	12	2010
2	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106	19	2	2010
3	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	8.106	26	2	2010
4	1	2010-05-03	1554806.68	0	46.50	2.625	211.350143	8.106	3	5	2010

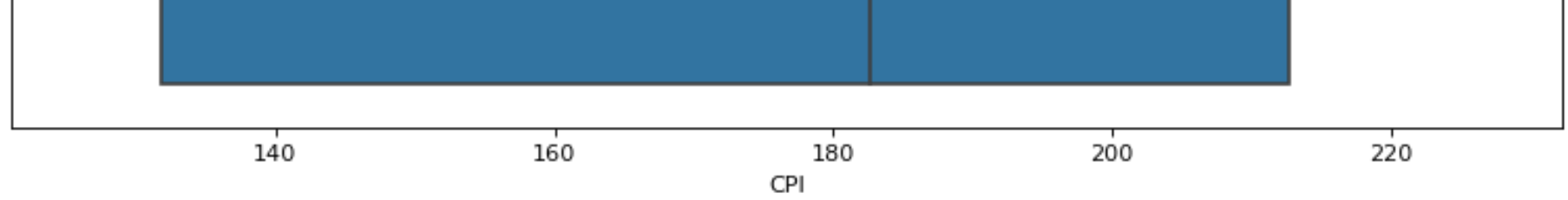
In [15]:
```python
# Display data distribution of Temperature, Fuel Price, CPI, and Unemployment columns.
fig, axis = plt.subplots(4, figsize=(12,16), dpi=80)
x = data[['Temperature','Fuel_Price','CPI','Unemployment']]

for i, column in enumerate(x):
    sns.boxplot(data[column], ax=axis[i])

import warnings
warnings.filterwarnings('ignore')
```

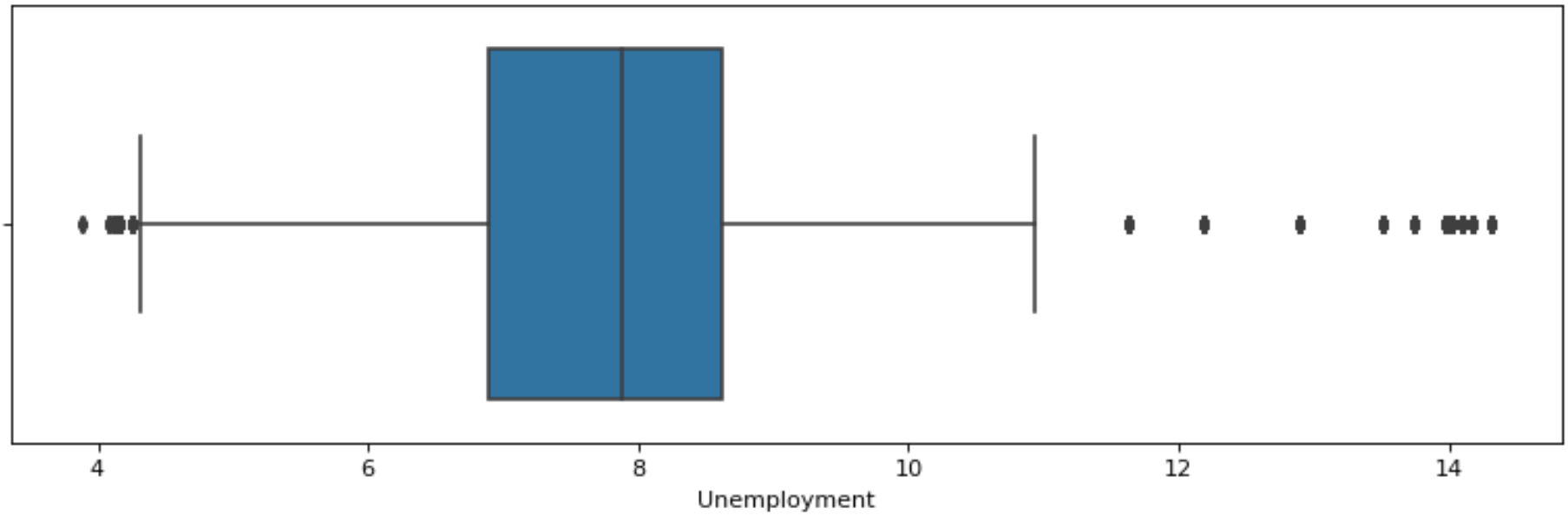
```
C:\Users\MAHAVIR\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variabl
e as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other ar
guments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\MAHAVIR\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variabl
e as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other ar
guments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\MAHAVIR\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variabl
e as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other ar
guments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\MAHAVIR\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variabl
e as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other ar
guments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```


0
20
40
60
80
100
Temperature


2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25
4.50
Fuel_Price

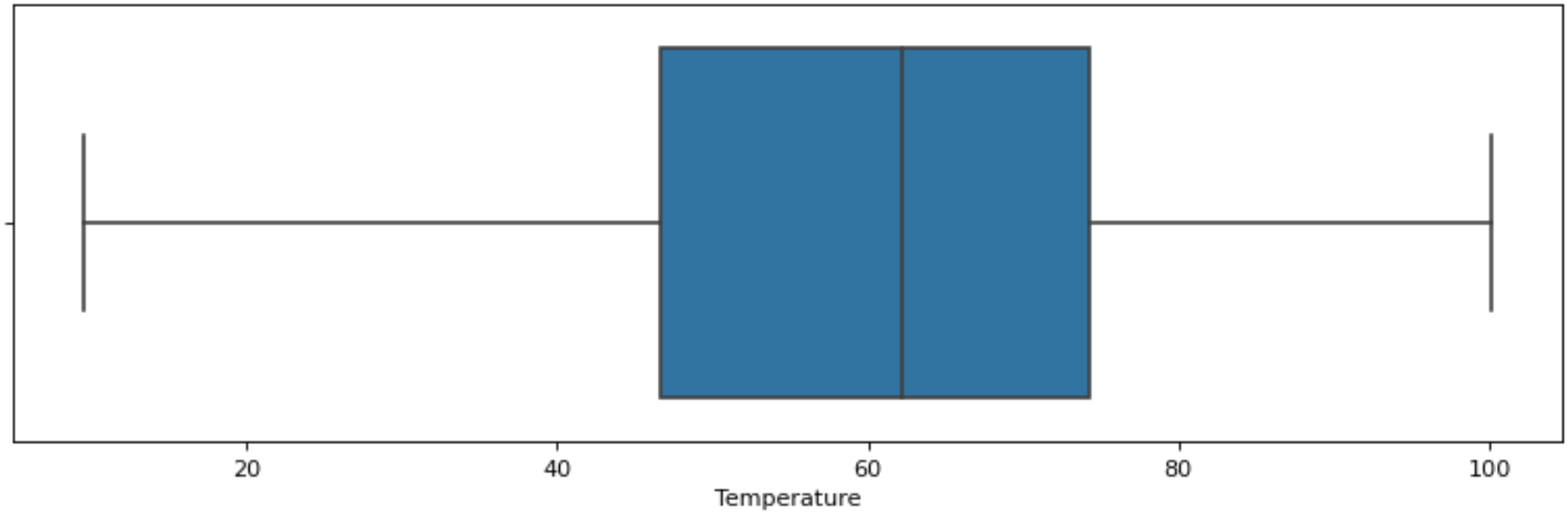


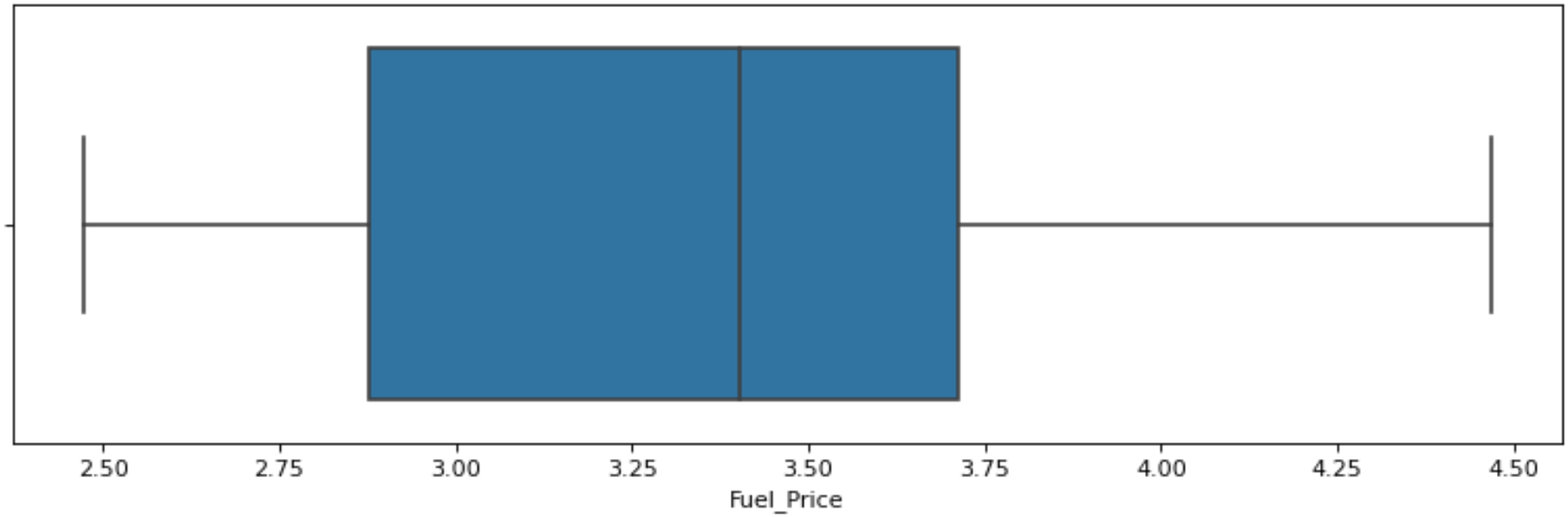


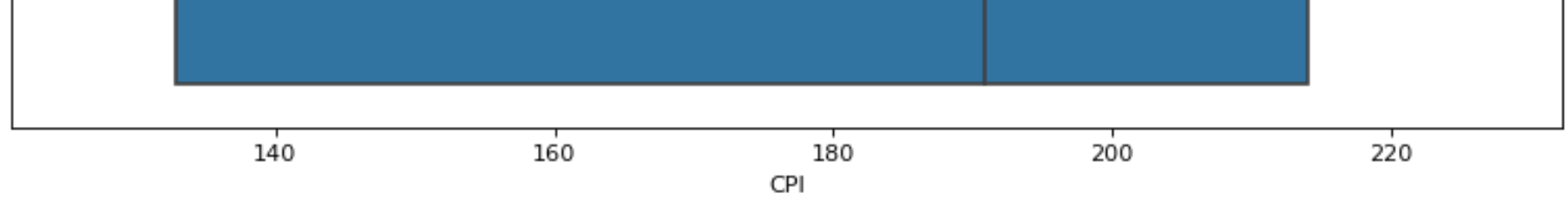


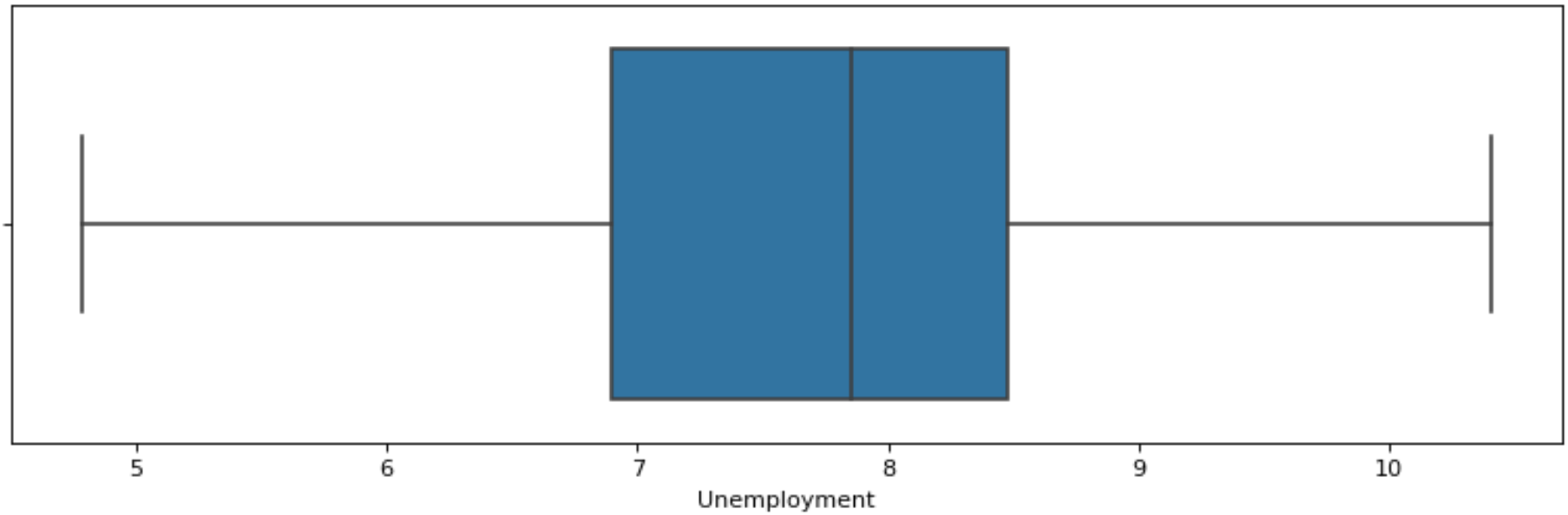
In [16]:
```
# Filter dataframe in Temperature and Unemployment.
data = data[data['Temperature'] >= 8]
data = data[data['Unemployment'] <= 10.5]
data = data[data['Unemployment'] >= 4.7]
```

In [17]:
```
# Display data distribution of Temperature, Fuel Price, CPI, and Unemployment columns.
fig, axis = plt.subplots(4, figsize=(12,16), dpi=80)
x = data[['Temperature','Fuel_Price','CPI','Unemployment']]

for i, column in enumerate(x):
    sns.boxplot(data[column], ax=axis[i])

import warnings
warnings.filterwarnings('ignore')
```


20
40
60
80
100
Temperature

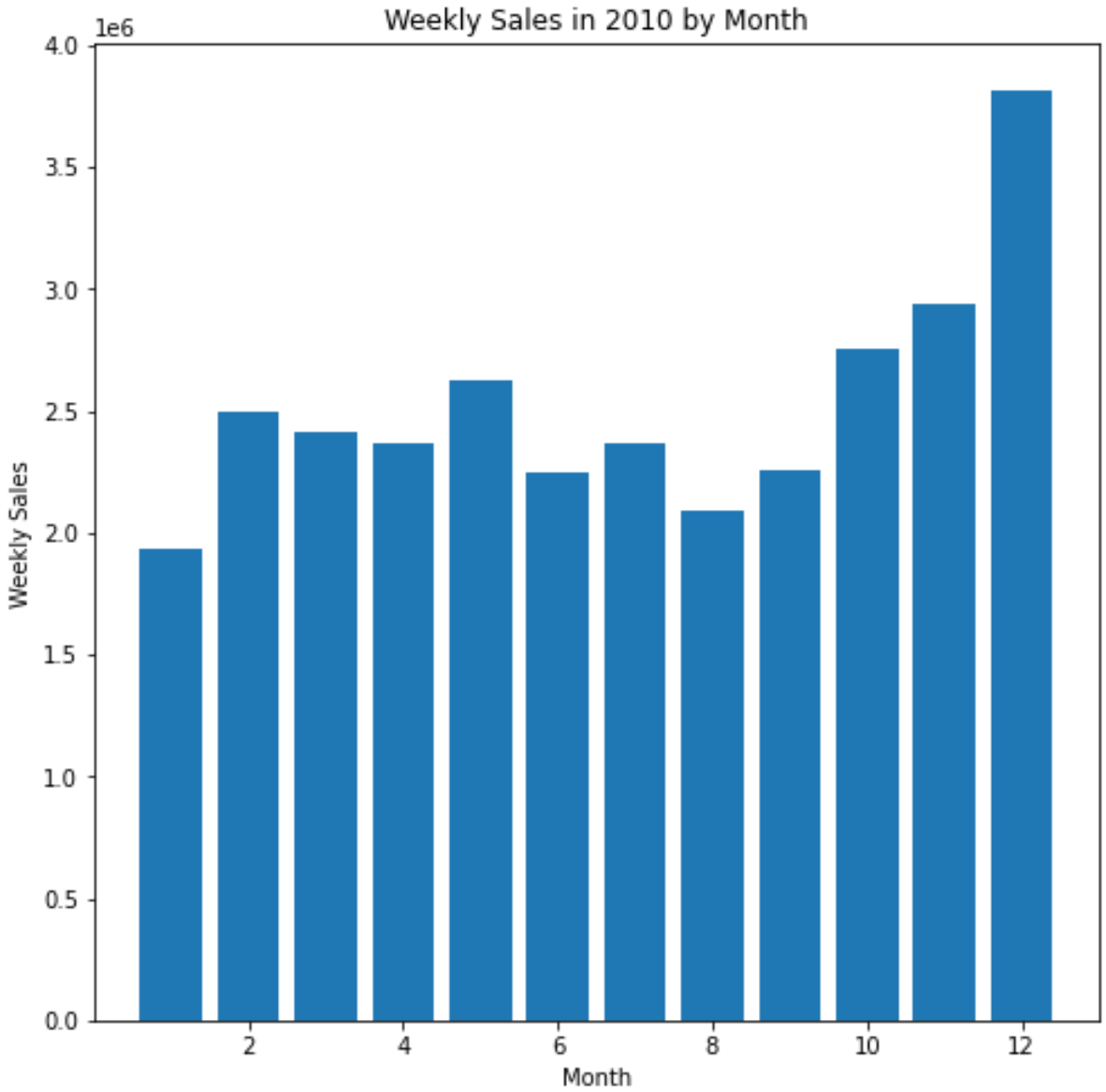

2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25
4.50
Fuel_Price





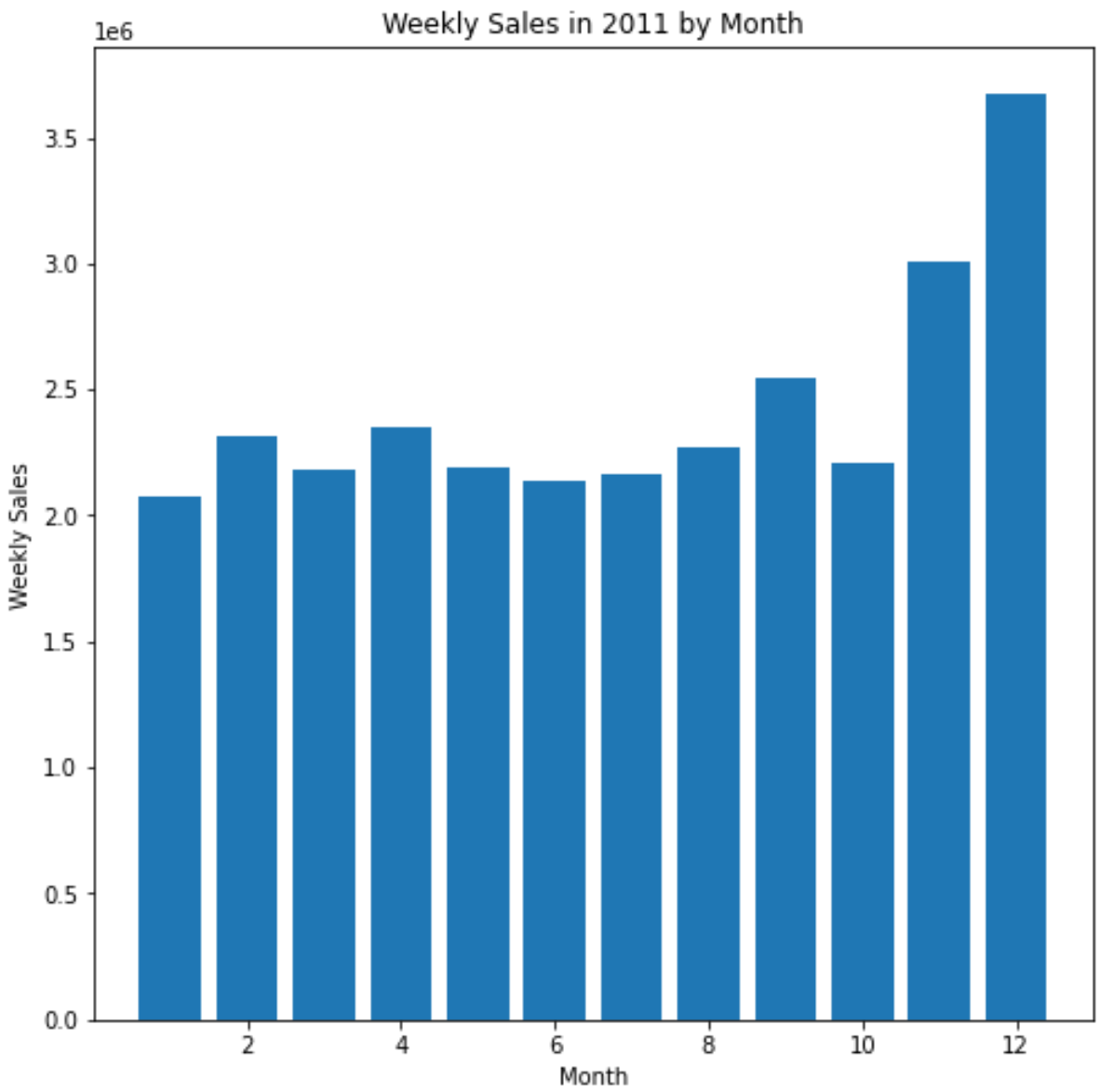
In [18]:
```
# Display Sales in 2010 by Month.
data_2010 = data[data.Year==2010]
plt.figure(figsize = (8, 8))
plt.xlabel('Month')
plt.ylabel('Weekly Sales')
plt.title('Weekly Sales in 2010 by Month')
plt.bar(data_2010['Month'],data_2010['Weekly_Sales'])
plt.show
```

Out[18]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [19]:
```
# Display Sales in 2011 by Month.
data_2011 = data[data.Year==2011]
plt.figure(figsize = (8, 8))
plt.xlabel('Month')
plt.ylabel('Weekly Sales')
plt.title('Weekly Sales in 2011 by Month')
plt.bar(data_2011['Month'],data_2011['Weekly_Sales'])
plt.show
```

Out[19]: <function matplotlib.pyplot.show(close=None, block=None)>

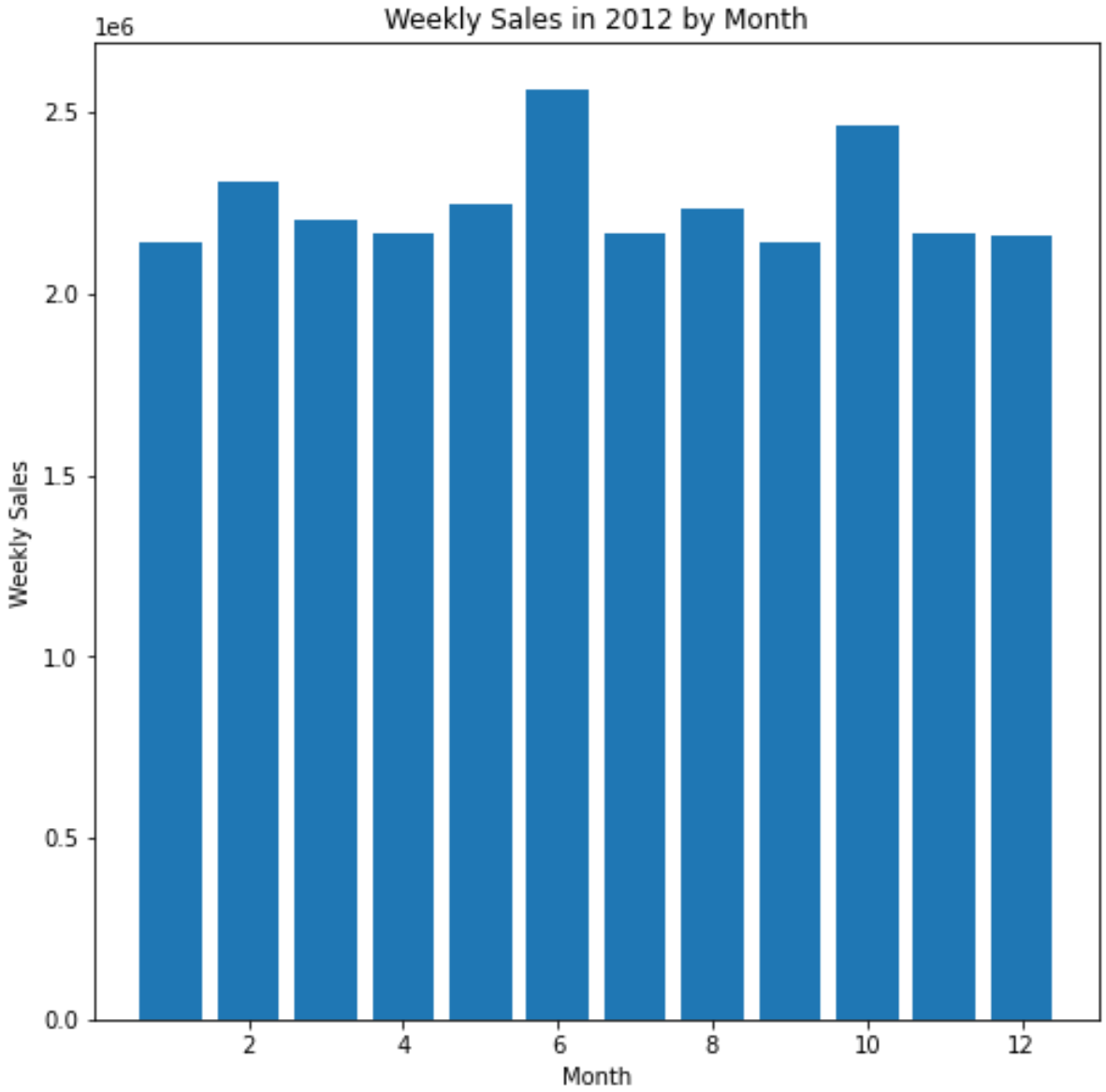


In [20]:
```
# Display Sales in 2012 by Month.
data_2012 = data[data.Year==2012]
plt.figure(figsize = (8, 8))
plt.xlabel('Month')
plt.ylabel('Weekly Sales')
plt.title('Weekly Sales in 2012 by Month')
```

```
plt.bar(data_2012['Month'],data_2012['Weekly_Sales'])
plt.show
```

Out[20]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```

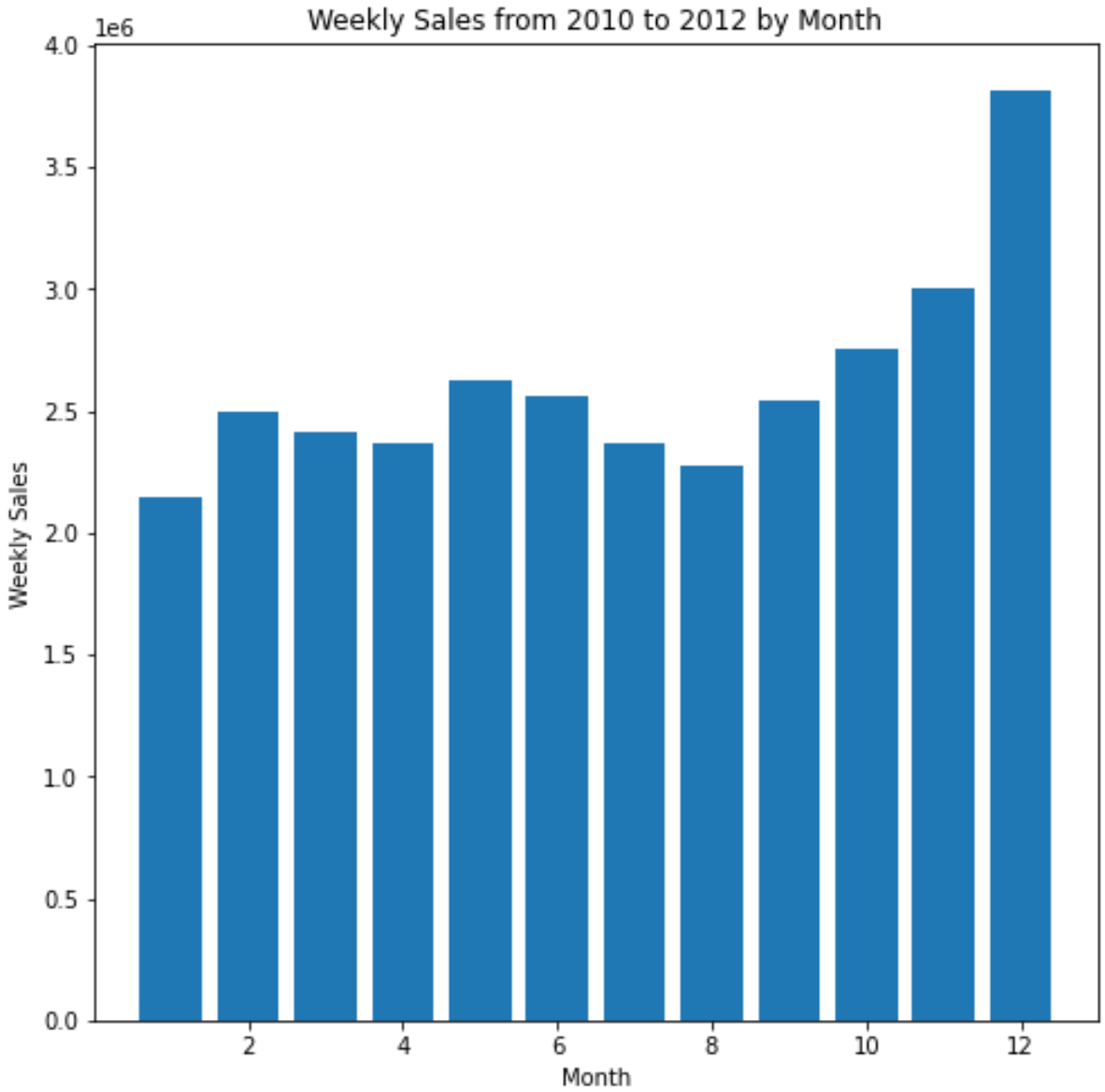


In [21]:

```
# Display Sales from 2010 to 2012 by Month.
plt.figure(figsize = (8, 8))
plt.xlabel('Month')
plt.ylabel('Weekly Sales')
```

```
plt.title('Weekly Sales from 2010 to 2012 by Month')
plt.bar(data['Month'],data['Weekly_Sales'])
plt.show
```

Out[21]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```

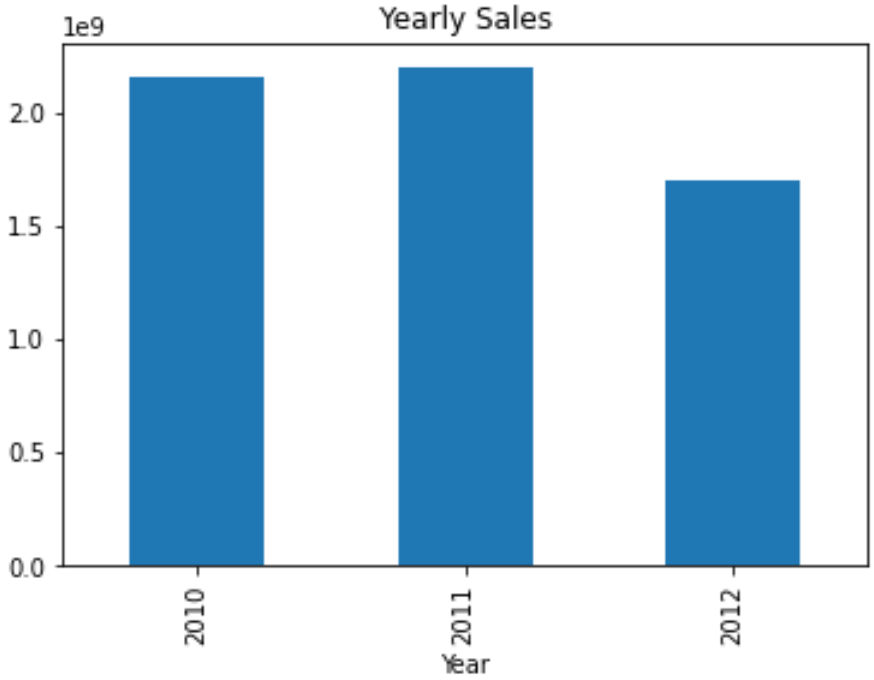


In [22]:
```
# Display Sales from 2010 to 2012 by Year.
plt.figure(figsize=(10,7), dpi=80)
```

```
data.groupby('Year')[['Weekly_Sales']].sum().plot(kind='bar', legend=False)
plt.title('Yearly Sales')
```

Out[22]:

```
Text(0.5, 1.0, 'Yearly Sales')

<Figure size 800x560 with 0 Axes>
```



5. Actionalble insights from data visulization

Insights from charts and Holiday sales

- Sales are highest during Holidays and maximum sales are achieved every year during the month of December
- Sales go lowest during January after the peak December season and also after every major holiday sales consecutive month sales are quite lower
- These insights help the business to make proper decisions and planning (such as more manpower and goods needed in December every year)

4. Predictive models (RFClassifier)

First we prepare the data for the model:

1.Training data and corresponding label.

2.Train & Test data split.

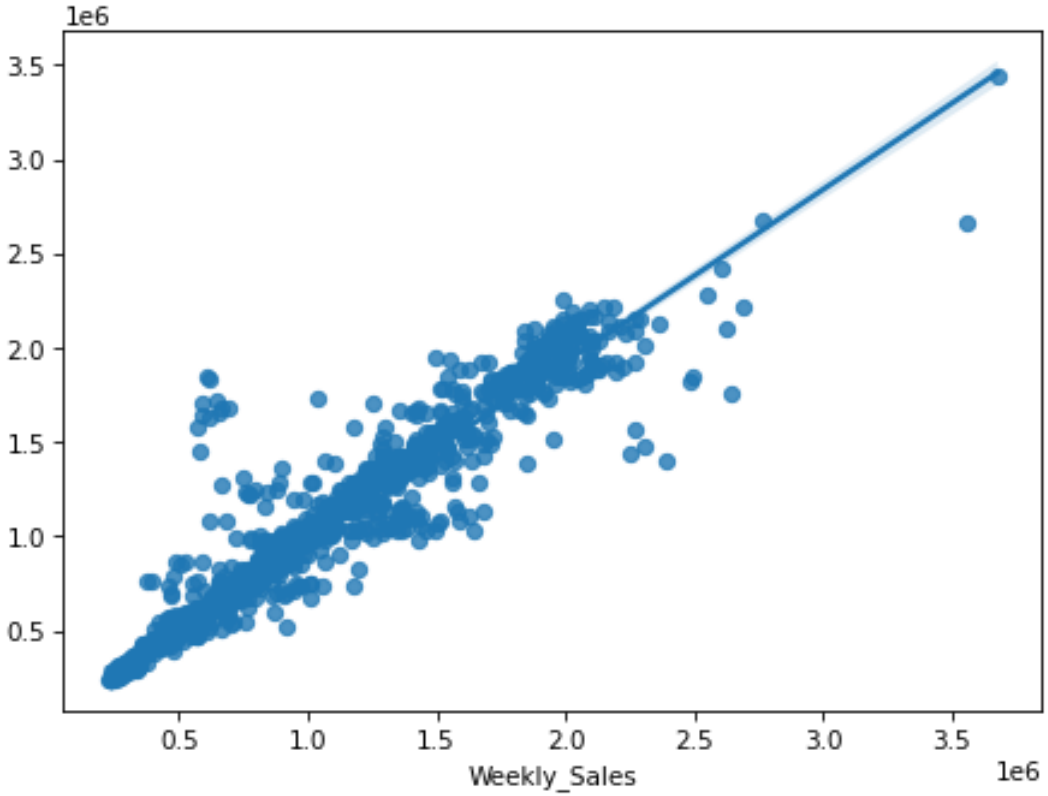
3.standardize features by removing the mean and scaling to unit variance.

In [23]:
```
# Prepare the training data and labels.
x = data[['Store', 'Fuel_Price', 'CPI', 'Unemployment', 'Day', 'Month', 'Year']]
y = data['Weekly_Sales']

# Perform Train & Test split.
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)

# Feature Scaling using StandardScaler
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.fit_transform(x_test)
```

Analysis using Random forest Classifier:

In [24]:
```
# Import Scikit-Learn and related libraries for Random Forest modeling.
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score

# Perform Random Forest model training and print out Train & Test Accuracy.
rfr = RandomForestRegressor()
rfr.fit(x_train,y_train)
rfr_y_pred = rfr.predict(x_test)

print('* Random Forest Regressor *\n')
print('Train Accuracy Score: {0:.2f} %'.format(rfr.score(x_train, y_train)*100))
print('Test Accuracy Score: {0:.2f} %'.format(r2_score(y_test, rfr_y_pred)*100))

plt.figure(figsize=(7,5), dpi=75)
sns.regplot(y_test, rfr_y_pred)
```

```
* Random Forest Regressor *

Train Accuracy Score: 99.28 %
Test Accuracy Score: 89.86 %
```
Out[24]:
```
<AxesSubplot:xlabel='Weekly_Sales'>
```



Output Analysis:

- Test accuracy of 93.5% using Randome forest.
- Precitive model(Random Forest) helps in predicting future sales and thus providing actionable information for the business
- We can also see that

6. Summary of steps taken and Recommendation

Steps taken in analysis:

- Loading data and performing EDA

- Checking nulls and Outlier removal
- Correcting datetime format and adding new labels for analysis (date, month and year)
- Visulization and getting useful patterns and trends (Visulising sales based on year, month, Holiday events)
- Preparing data for predictive models and implementing RFClassifier.

Further improvements to business may include

- Implementing more models to predict sales by adding various new features
- Adding data related to various other public events and other conditions affecting sales such as weather, transportation, etc.
- Getting customer feedback to improve sales and analysing customer sentiments for better delivery