DATA LOADING

In [165…
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split  # For splitting data into training and testing sets
from sklearn.ensemble import RandomForestRegressor    # For implementing a powerful, flexible tree-based model
from sklearn.metrics import mean_absolute_error       # For evaluating model accuracy
```

In [166…
```python
data=pd.read_csv("/Users/saikiranbarma/Desktop/Walmart DataSet.CSV")
```

In [167…
```python
data.head()
```

Out[167…

	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

In [168…
```python
data.describe()
```

Out[168…

	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 [169…
```python
data .dtypes
```

Out[169…
```
Store             int64
Date             object
Weekly_Sales    float64
Holiday_Flag      int64
Temperature     float64
Fuel_Price      float64
CPI             float64
Unemployment    float64
dtype: object
```

In [170…
```python
#information fo the data
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
```

Data Preprocessing

In [171…
```python
# Date column is in object type so converting 'date' column to a datetime type.
data['Date'] = pd.to_datetime(data['Date'], format='%d-%m-%Y')
```

In [172…
```python
#feature engineering
#We create new columns (Year, Month, day) to capture seasonal patterns in the data
data['Year'] = data['Date'].dt.year
data['Month'] = data['Date'].dt.month
data['Day'] = data['Date'].dt.day
```

In [173…
```python
data.head()
```

Out[173…

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

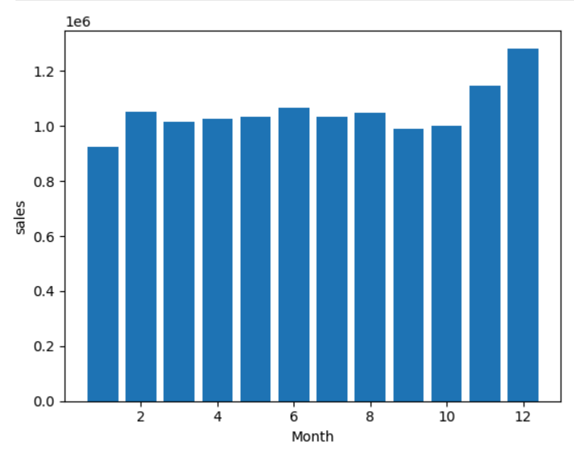
In [174…
```python
#handling missing values
# Count missing values
missing_values = data.isnull().sum()
print("Missing Values Count:")
print(missing_values)
```

```
Missing Values Count:
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
Year            0
Month           0
Day             0
dtype: int64
```

In [175…
```python
# Extract year, month, and day features
daily_sales['Year'] = daily_sales['Date'].dt.year
daily_sales['Month'] = daily_sales['Date'].dt.month
daily_sales['Day'] = daily_sales['Date'].dt.day
```

Explotray Data Anlaysis

In [177…
```python
month_by_sales = data.groupby('Month')['Weekly_Sales'].mean()
plt.bar(month_by_sales.index, month_by_sales.values)
plt.xlabel('Month')
plt.ylabel('sales')
plt.show()
```

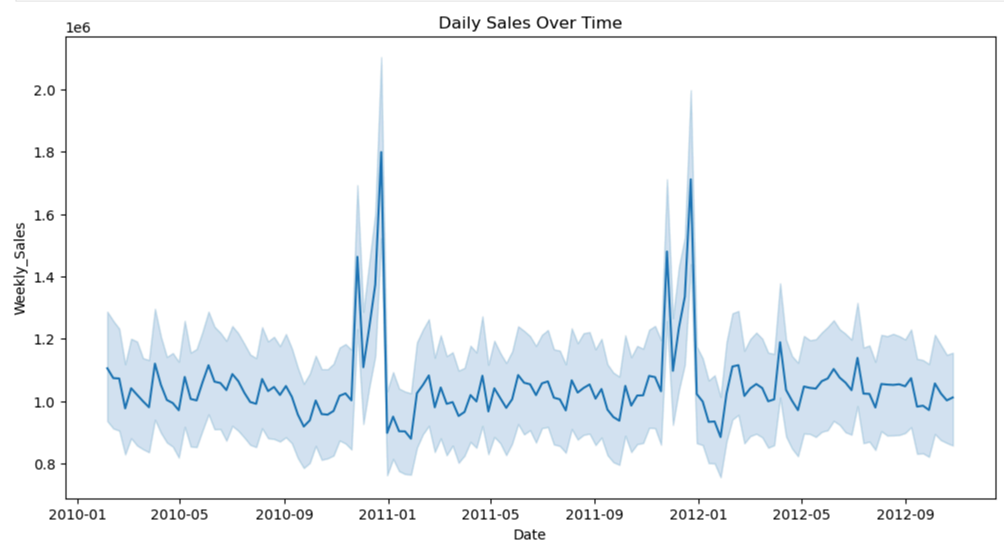


sales were same every month except 11 and 12 th month

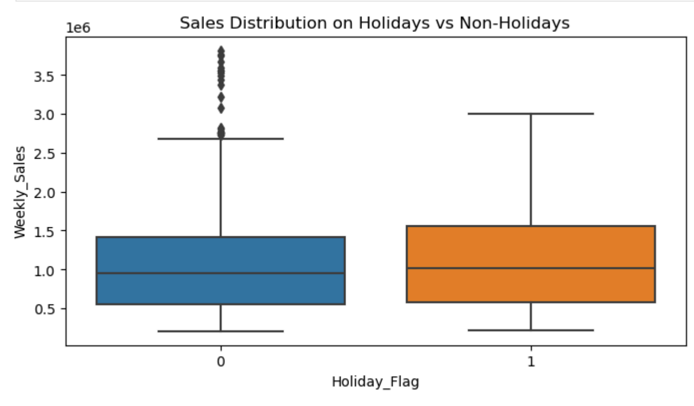
In [178…
```python
# Group by Date and Store to aggregate daily sales
daily_sales = data.groupby(['Date', 'Store']).agg({
    'Weekly_Sales': 'sum',
    'Holiday_Flag': 'max',  # Assuming Holiday_Flag applies to the whole week
    'Temperature': 'mean',
    'Fuel_Price': 'mean',
    'CPI': 'mean',
    'Unemployment': 'mean'
}).reset_index()
```

In [179…
```python
# Replace Inf and -Inf with NaN in the DataFrame
data.replace([np.inf, -np.inf], np.nan, inplace=True)

# Optionally, handle NaN values here, for example, by dropping rows with NaN values:
data.dropna(inplace=True)
```

In [195…
```python
import warnings
warnings.filterwarnings("ignore", category=FutureWarning, message=".*use_inf_as_na*")
plt.figure(figsize=(12, 6))
sns.lineplot(data=daily_sales, x="Date", y="Weekly_Sales")
plt.title("Daily Sales Over Time")
plt.show()
```



In [181…
```python
plt.figure(figsize=(8, 4))
sns.boxplot(data=daily_sales, x="Holiday_Flag", y="Weekly_Sales")
plt.title("Sales Distribution on Holidays vs Non-Holidays")
plt.show()
```



Splitting Data into Train and Test

In [183…
```python
# To prevent data leakage, we split the data chronologically. We train on early data and test on the more recent data.
# Select features and target
features = ['Store', 'Holiday_Flag', 'Temperature', 'Fuel_Price', 'CPI', 'Unemployment', 'Year', 'Month', 'Day']
target = 'Weekly_Sales'

# Split the data by date for train-test
train_data = data[data['Date'] < '2012-01-01']
test_data = data[data['Date'] >= '2012-01-01']

# Extract feature and target variables
X_train = train_data[features]
y_train = train_data[target]
X_test = test_data[features]
y_test = test_data[target]
```

Training a Machine Learning Model

In [185…
```python
# We are using a RandomForestRegressor for its ability to capture non-linear relationships in the data. Fit the model on the training set.
# Initialize and train the model
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

Out[185…
```
▾ RandomForestRegressor
RandomForestRegressor(random_state=42)
```

Evaluating the Model

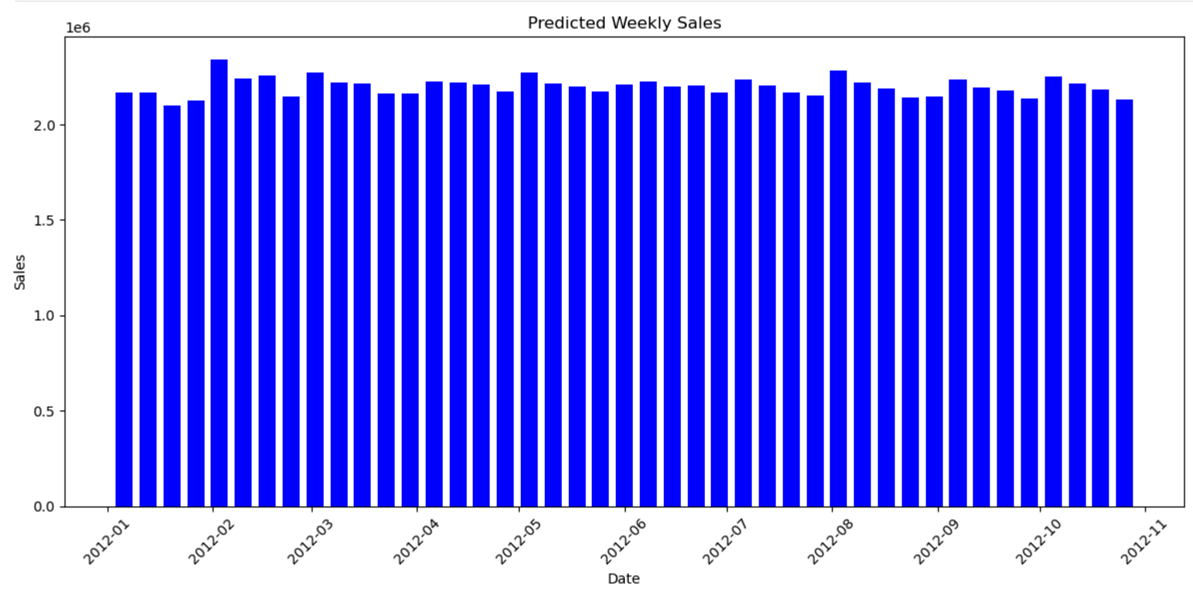
In [187…
```python
#Predicting weekly sales for the test set and evaluate using metrics like Mean Absolute Error (MAE).
# Make predictions
predictions = model.predict(X_test)

# Evaluate the model
mae = mean_absolute_error(y_test, predictions)
print(f"Mean Absolute Error: {mae}")
```

```
Mean Absolute Error: 176392.52793012923
```

our typical sales are around the 75th percentile (1.42 million), then the MAE is roughly 12.4% of this typical value: 176,392/1,420,159≈0.124 or 12.4%

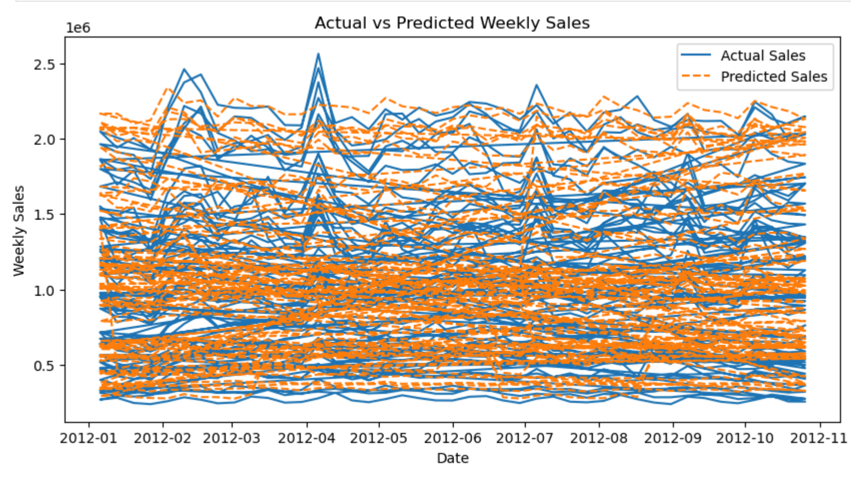
In [196…
```python
# Avoid SettingWithCopyWarning by making a copy and using .loc[]
X_test = X_test.copy()  # Ensures X_test is a separate copy
X_test.loc[:, 'Date'] = data.loc[X_test.index, 'Date']  # Adding 'Date' back for plotting
```

In [197…
```python
X_test['Date'] = data.loc[X_test.index, 'Date']  # Adjust indexing as necessary

# Ensure 'Date' is in datetime format
X_test['Date'] = pd.to_datetime(X_test['Date'])

# Plotting predicted sales using a bar plot
plt.figure(figsize=(12, 6))
plt.bar(X_test['Date'], predictions, color='blue', width=5)  # You can adjust the width as needed
plt.title("Predicted Weekly Sales")
plt.xlabel("Date")
plt.ylabel("Sales")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

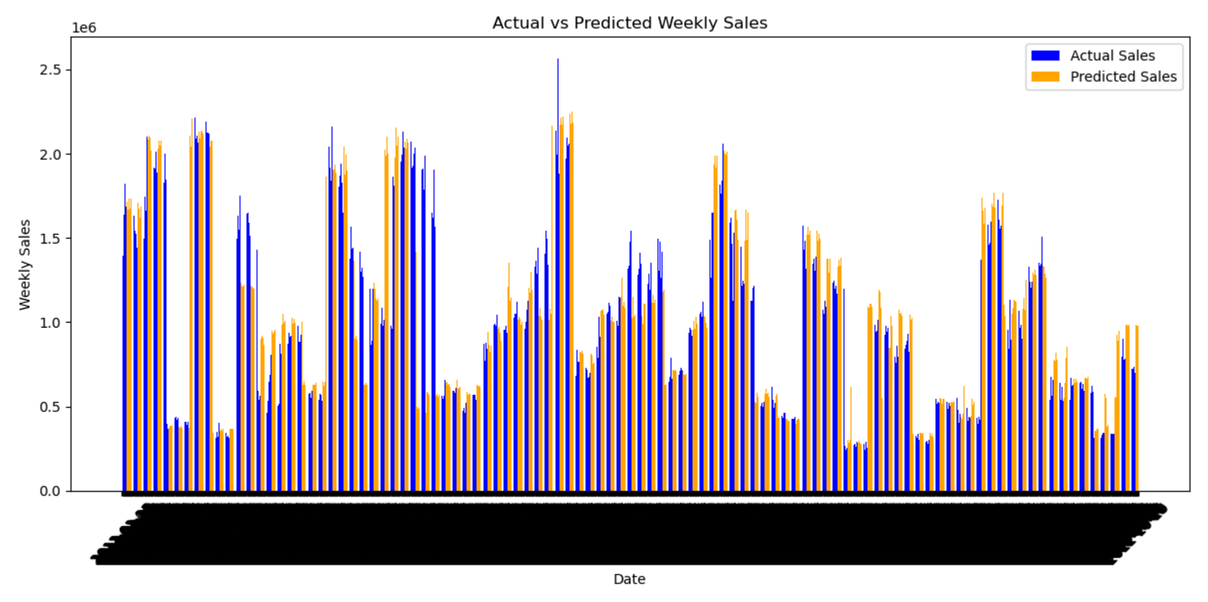


Actual vs Predicted Sales

In [191…
```python
#Plot Actual vs Predicted Sales(line graph)
#Visualizing predictions against actual values helps identify patterns in errors or possible areas for model improvement.
# Plot actual vs predicted sales
plt.figure(figsize=(10, 5))
plt.plot(test_data['Date'], y_test, label="Actual Sales")
plt.plot(test_data['Date'], predictions, label="Predicted Sales", linestyle='--')
plt.xlabel("Date")
plt.ylabel("Weekly Sales")
plt.title("Actual vs Predicted Weekly Sales")
plt.legend()
plt.show()
```



In [192…
```python
#Plot Actual vs Predicted Sales(bar graph)
# Ensure that the 'Date' column is in the correct format using .loc
test_data.loc[:, 'Date'] = pd.to_datetime(test_data['Date'])

# Create a bar plot for actual and predicted sales
plt.figure(figsize=(12, 6))

# Set bar width
bar_width = 0.4

# Create bar positions
x = range(len(test_data))

# Plot actual sales as bars
plt.bar(x, y_test, width=bar_width, label="Actual Sales", color='blue', align='center')

# Plot predicted sales as bars, offset by bar width
plt.bar([i + bar_width for i in x], predictions, width=bar_width, label="Predicted Sales", color='orange', align='edge')

# Adding labels and title
plt.xlabel("Date")
plt.ylabel("Weekly Sales")
plt.title("Actual vs Predicted Weekly Sales")
plt.xticks([i + bar_width / 2 for i in x], test_data['Date'].dt.strftime('%Y-%m-%d'), rotation=45)  # Rotate date labels for clarity
plt.legend()
plt.tight_layout()
plt.show()
```


Actual vs Predicted Weekly Sales
Actual Sales
Predicted Sales
Weekly Sales
Date
1e6
0.0
0.5
1.0
1.5
2.0
2.5