code

January 28, 2025

[103]:
```
import pandas as pd
import numpy as np
from docx import Document
import io
import matplotlib.pyplot as plt
import missingno as msno
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
import shap
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, roc_auc_score, confusion_matrix
from sklearn.metrics import RocCurveDisplay
from sklearn.metrics import mean_absolute_error
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.seasonal import STL
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.seasonal import seasonal_decompose
from scipy.fft import fft
from sklearn.inspection import PartialDependenceDisplay
```

[38]:
```
#read the data as a ready
train_df = pd.read_csv('train.csv')
test_df = pd.read_csv('test.csv')
store_data = pd.read_csv('store.csv')
```

```
C:\Users\murui\AppData\Local\Temp\ipykernel_27272\2998720372.py:2: DtypeWarning:
Columns (7) have mixed types. Specify dtype option on import or set
low_memory=False.
  train_df = pd.read_csv('train.csv')
```

[39]:
```
doc = Document()
# add title
doc.add_heading('Store Data Summary', level=1)
def output_table(doc, data, head):
```

```
    # Add the first few rows of the data
    doc.add_heading(head, level=2)
    table = doc.add_table(rows=1, cols=len(data.columns))
    hdr_cells = table.rows[0].cells
    for i, column in enumerate(data.columns):
        hdr_cells[i].text = column
    for index, row in data.iterrows():
        row_cells = table.add_row().cells
        for i, cell in enumerate(row):
            row_cells[i].text = str(cell)
```

0.1 Data Description

[40]:
```
# check the data
print(store_data.head())
#print to doc
output_table(doc, store_data.head(), "Head of Store Data")
```

```
   Store StoreType Assortment  CompetitionDistance  CompetitionOpenSinceMonth
0      1         c          a               1270.0                        9.0  \
1      2         a          a                570.0                       11.0
2      3         a          a              14130.0                       12.0
3      4         c          c                620.0                        9.0
4      5         a          a              29910.0                        4.0

   CompetitionOpenSinceYear  Promo2  Promo2SinceWeek  Promo2SinceYear
0                    2008.0       0              NaN              NaN  \
1                    2007.0       1             13.0           2010.0
2                    2006.0       1             14.0           2011.0
3                    2009.0       0              NaN              NaN
4                    2015.0       0              NaN              NaN

     PromoInterval
0              NaN
1  Jan,Apr,Jul,Oct
2  Jan,Apr,Jul,Oct
3              NaN
4              NaN
```

[41]:
```
# check infor
print(store_data.info())
# output store_data to Microsoft Word
buffer = io.StringIO()
store_data.info(buf=buffer)
info_str = buffer.getvalue()
info_lines = info_str.split('\n')[5:-3]
```

```
# Convert information to table format
info_table = pd.DataFrame([line.split() for line in info_lines[1:]],␣
 ↪columns=info_lines[0].split())

output_table(doc,info_table, "Info of Store Data")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1115 entries, 0 to 1114
Data columns (total 10 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Store                      1115 non-null   int64
 1   StoreType                  1115 non-null   object
 2   Assortment                 1115 non-null   object
 3   CompetitionDistance        1112 non-null   float64
 4   CompetitionOpenSinceMonth  761 non-null    float64
 5   CompetitionOpenSinceYear   761 non-null    float64
 6   Promo2                     1115 non-null   int64
 7   Promo2SinceWeek            571 non-null    float64
 8   Promo2SinceYear            571 non-null    float64
 9   PromoInterval              571 non-null    object
dtypes: float64(5), int64(2), object(3)
memory usage: 87.2+ KB
None
```

[42]:
```
# View Statistical Summary of Data
print(store_data.describe())

output_table(doc, store_data.describe(), "Describe of Store Data")
```

```
            Store  CompetitionDistance  CompetitionOpenSinceMonth  \
count  1115.00000          1112.000000                 761.000000
mean    558.00000          5404.901079                   7.224704
std     322.01708          7663.174720                   3.212348
min       1.00000            20.000000                   1.000000
25%     279.50000           717.500000                   4.000000
50%     558.00000          2325.000000                   8.000000
75%     836.50000          6882.500000                  10.000000
max    1115.00000         75860.000000                  12.000000

       CompetitionOpenSinceYear       Promo2  Promo2SinceWeek  Promo2SinceYear
count                761.000000  1115.000000       571.000000       571.000000
mean                2008.668857     0.512108        23.595447      2011.763573
std                    6.195983     0.500078        14.141984         1.674935
min                 1900.000000     0.000000         1.000000      2009.000000
25%                 2006.000000     0.000000        13.000000      2011.000000
50%                 2010.000000     1.000000        22.000000      2012.000000
75%                 2013.000000     1.000000        37.000000      2013.000000
```

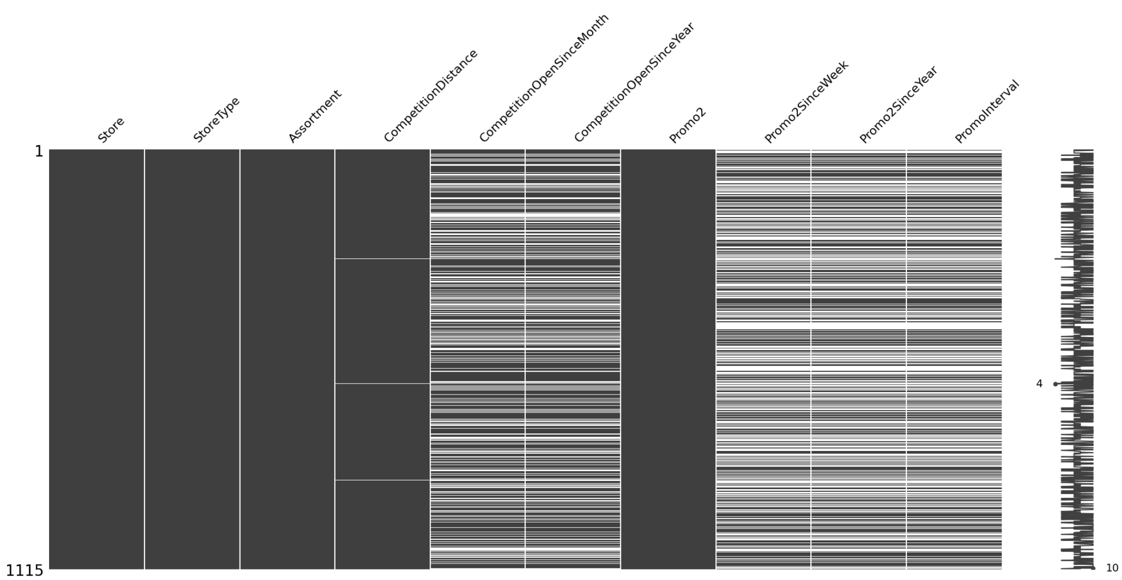
```
max                    2015.000000      1.000000        50.000000       2015.000000
```

0.2 Feature engineering

0.2.1 missing value

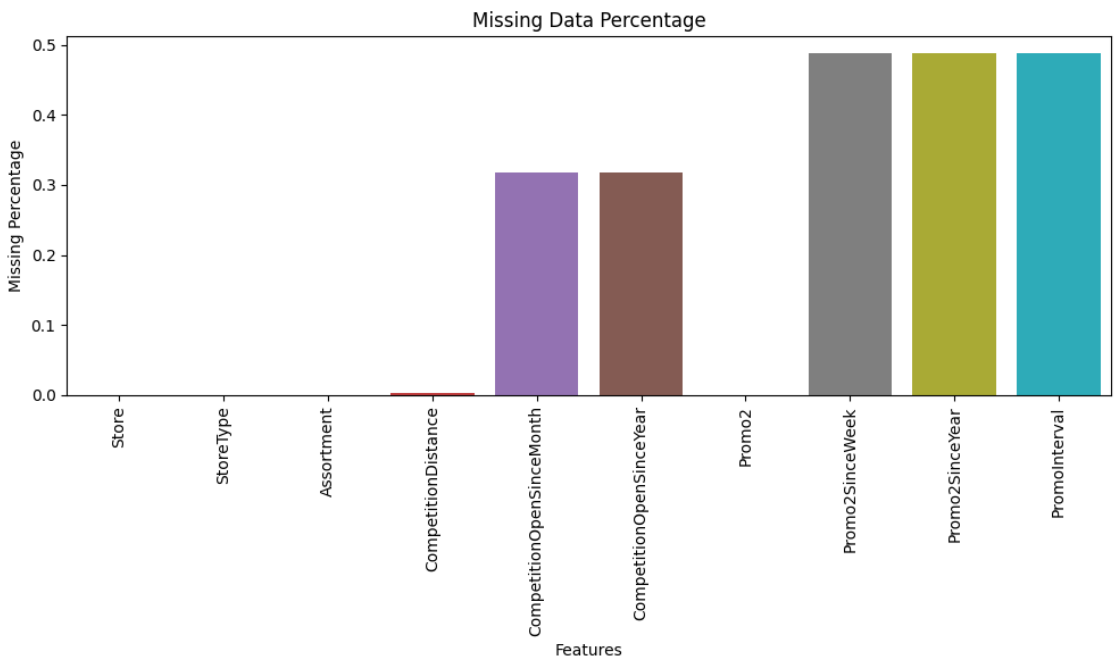
[43]:
```
# check missing values
missing_values = store_data.isnull().sum()
print(missing_values)
msno.matrix(store_data)
plt.show()
```

```
Store                          0
StoreType                      0
Assortment                     0
CompetitionDistance            3
CompetitionOpenSinceMonth    354
CompetitionOpenSinceYear     354
Promo2                         0
Promo2SinceWeek              544
Promo2SinceYear              544
PromoInterval                544
dtype: int64
```



[44]:
```
# Calculate the proportion of missing values
missing_percentage = store_data.isnull().sum() / len(store_data)

# Plot the proportion of missing values
plt.figure(figsize=(10, 6))
```

```
sns.barplot(x=missing_percentage.index, y=missing_percentage.values)
plt.xticks(rotation=90)
plt.xlabel("Features")
plt.ylabel("Missing Percentage")
plt.title("Missing Data Percentage")
plt.tight_layout()
plt.show()
```



[45]:
```
# Output the missing value table
missing_table = pd.DataFrame({'Feature': missing_percentage.index, 'Missing␣
↪Values(%)': missing_percentage.values})
output_table(doc, missing_table, "Missing Values Table")
```

[46]:
```
# Create new variable: Is there a competitor nearby
store_data['HasCompetition'] = store_data['CompetitionDistance'].apply(lambda x:
↪ 0 if pd.isna(x) else 1)

# check new variable
print(store_data[['Store', 'CompetitionDistance', 'HasCompetition']].head())
```

```
   Store  CompetitionDistance  HasCompetition
0      1               1270.0               1
1      2                570.0               1
2      3              14130.0               1
3      4                620.0               1
4      5              29910.0               1
```

[47]:
```
handel1=store_data[store_data['CompetitionDistance'].isnull()]
```

[48]:
```
output_table(doc, handel1, "handle for competition distance missing value")
```

[49]:
```
train_df = train_df[train_df['Open']!=0]
```

[50]:
```
test_df = test_df[test_df['Open'].notnull()]
test_df.loc[test_df['Open'] == 0, ['Customers', 'Sales']] = 0
```

[51]:
```
filtered_data = train_df[(train_df['Sales'] == 0) & (train_df['Customers'] !=␣
↪0)]

print(filtered_data)
output_table(doc, filtered_data, "Filtered Data with Sales=0 but other columns␣
↪not equal to 0")
```

```
        Store  DayOfWeek        Date  Sales  Customers  Open  Promo  \
478649   1100          2  29/04/2014      0          3     1      1
889932    948          4  25/04/2013      0          5     1      1

       StateHoliday  SchoolHoliday
478649            0              0
889932            0              0
```

[52]:
```
store_data['PromoInterval'].fillna('None', inplace=True)
store_data['Promo2SinceWeek'] = store_data['Promo2SinceWeek'].fillna(0)
store_data['Promo2SinceYear'] = store_data['Promo2SinceYear'].fillna(0)
```

[53]:
```
# Ensure that the date is in datetime format.
train_df['Date'] = pd.to_datetime(train_df['Date'])
test_df['Date'] = pd.to_datetime(test_df['Date'])
```

```
C:\Users\murui\AppData\Local\Temp\ipykernel_27272\1678962669.py:2: UserWarning:
Parsing dates in %d/%m/%Y format when dayfirst=False (the default) was
specified. Pass `dayfirst=True` or specify a format to silence this warning.
  train_df['Date'] = pd.to_datetime(train_df['Date'])
C:\Users\murui\AppData\Local\Temp\ipykernel_27272\1678962669.py:3: UserWarning:
Parsing dates in %d/%m/%Y format when dayfirst=False (the default) was
specified. Pass `dayfirst=True` or specify a format to silence this warning.
  test_df['Date'] = pd.to_datetime(test_df['Date'])
```

[54]:
```
store_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1115 entries, 0 to 1114
Data columns (total 11 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Store                      1115 non-null   int64
```

```
 1   StoreType                   1115 non-null   object
 2   Assortment                  1115 non-null   object
 3   CompetitionDistance         1112 non-null   float64
 4   CompetitionOpenSinceMonth  761 non-null    float64
 5   CompetitionOpenSinceYear   761 non-null    float64
 6   Promo2                      1115 non-null   int64
 7   Promo2SinceWeek             1115 non-null   float64
 8   Promo2SinceYear             1115 non-null   float64
 9   PromoInterval               1115 non-null   object
 10  HasCompetition              1115 non-null   int64
dtypes: float64(5), int64(3), object(3)
memory usage: 95.9+ KB
```

[55]:

```
# let StoreType and Assortment to Label Encoding
label_encoder = LabelEncoder()
store_data['StoreType'] = label_encoder.fit_transform(store_data['StoreType'])
store_data['Assortment'] = label_encoder.fit_transform(store_data['Assortment'])
store_data['PromoInterval'] = store_data['PromoInterval'].astype(str)
store_data['PromoInterval'] = label_encoder.
 ↪fit_transform(store_data['PromoInterval'])

# check
print(store_data['StoreType'].value_counts())
print(store_data['Assortment'].value_counts())
print(store_data['PromoInterval'].value_counts())
```

```
StoreType
0    602
3    348
2    148
1     17
Name: count, dtype: int64
Assortment
0    593
2    513
1      9
Name: count, dtype: int64
PromoInterval
3    544
1    335
0    130
2    106
Name: count, dtype: int64
```

[56]:

```
# Convert all values in 'StateHoliday' column to strings
train_df['StateHoliday'] = train_df['StateHoliday'].astype(str)

# Encode the 'StateHoliday' column
```

```
train_df['StateHoliday'] = label_encoder.fit_transform(train_df['StateHoliday'])
```

[57]:
```
# Convert all values in 'StateHoliday' column to strings
test_df['StateHoliday'] = test_df['StateHoliday'].astype(str)

# Encode the 'StateHoliday' column
test_df['StateHoliday'] = label_encoder.fit_transform(test_df['StateHoliday'])
```

0.2.2 Data consolidation

[58]:
```
# merge data sets
train_df = train_df.merge(store_data, on='Store', how='left')
test_df = test_df.merge(store_data, on='Store', how='left')
```

[59]:
```
# create new features
train_df['Year'] = pd.DatetimeIndex(train_df['Date']).year
train_df['Month'] = pd.DatetimeIndex(train_df['Date']).month
train_df['Day'] = pd.DatetimeIndex(train_df['Date']).day
test_df['Year'] = pd.DatetimeIndex(test_df['Date']).year
test_df['Month'] = pd.DatetimeIndex(test_df['Date']).month
test_df['Day'] = pd.DatetimeIndex(test_df['Date']).day
```

[60]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 844392 entries, 0 to 844391
Data columns (total 22 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   Store                      844392 non-null  int64
 1   DayOfWeek                  844392 non-null  int64
 2   Date                       844392 non-null  datetime64[ns]
 3   Sales                      844392 non-null  int64
 4   Customers                  844392 non-null  int64
 5   Open                       844392 non-null  int64
 6   Promo                      844392 non-null  int64
 7   StateHoliday               844392 non-null  int32
 8   SchoolHoliday              844392 non-null  int64
 9   StoreType                  844392 non-null  int32
 10  Assortment                 844392 non-null  int32
 11  CompetitionDistance        842206 non-null  float64
 12  CompetitionOpenSinceMonth  575773 non-null  float64
 13  CompetitionOpenSinceYear   575773 non-null  float64
 14  Promo2                     844392 non-null  int64
 15  Promo2SinceWeek            844392 non-null  float64
 16  Promo2SinceYear            844392 non-null  float64
 17  PromoInterval              844392 non-null  int32
 18  HasCompetition             844392 non-null  int64
```

```
 19   Year                          844392 non-null  int32
 20   Month                         844392 non-null  int32
 21   Day                           844392 non-null  int32
dtypes: datetime64[ns](1), float64(5), int32(7), int64(9)
memory usage: 119.2 MB
```

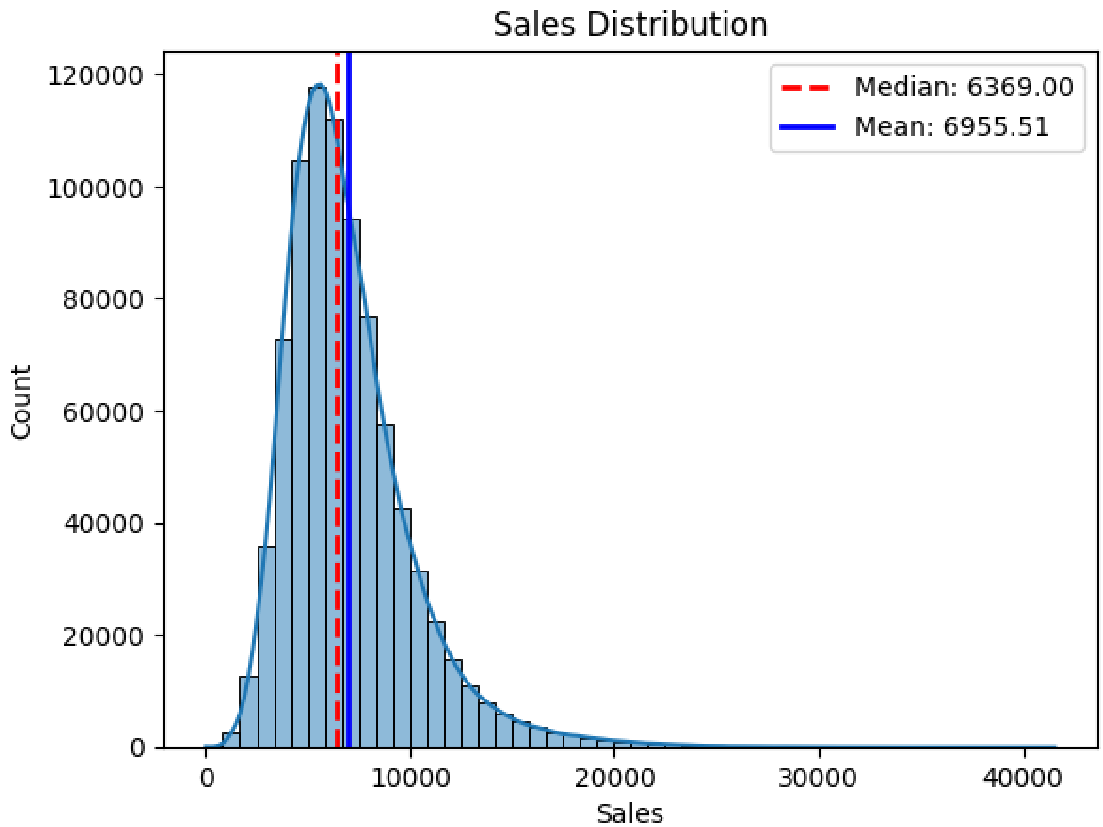
[61]:
```
test_df.info()
```

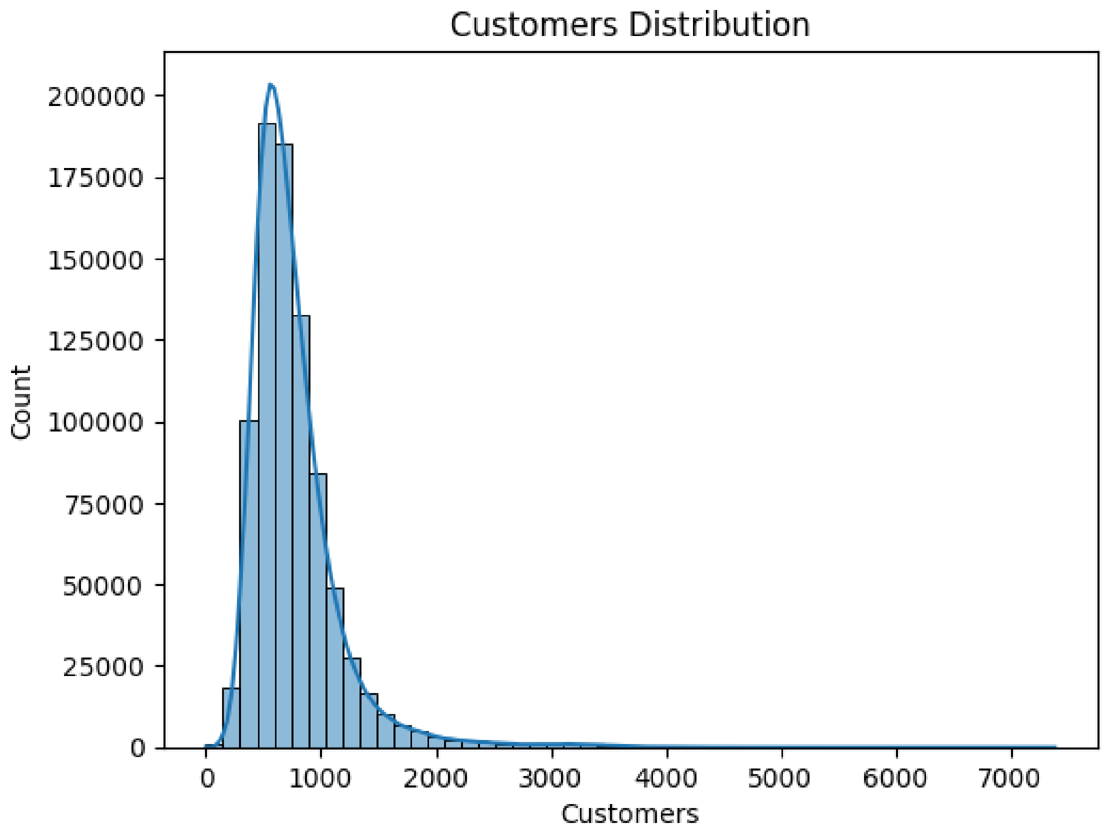
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41077 entries, 0 to 41076
Data columns (total 22 columns):
 #    Column                       Non-Null Count  Dtype
---   ------                       --------------  -----
 0    Store                        41077 non-null  int64
 1    DayOfWeek                    41077 non-null  int64
 2    Date                         41077 non-null  datetime64[ns]
 3    Sales                        5984 non-null   float64
 4    Customers                    5984 non-null   float64
 5    Open                         41077 non-null  float64
 6    Promo                        41077 non-null  int64
 7    StateHoliday                 41077 non-null  int32
 8    SchoolHoliday                41077 non-null  int64
 9    StoreType                    41077 non-null  int32
 10   Assortment                   41077 non-null  int32
 11   CompetitionDistance          40992 non-null  float64
 12   CompetitionOpenSinceMonth    25872 non-null  float64
 13   CompetitionOpenSinceYear     25872 non-null  float64
 14   Promo2                       41077 non-null  int64
 15   Promo2SinceWeek              41077 non-null  float64
 16   Promo2SinceYear              41077 non-null  float64
 17   PromoInterval                41077 non-null  int32
 18   HasCompetition               41077 non-null  int64
 19   Year                         41077 non-null  int32
 20   Month                        41077 non-null  int32
 21   Day                          41077 non-null  int32
dtypes: datetime64[ns](1), float64(8), int32(7), int64(6)
memory usage: 5.8 MB
```

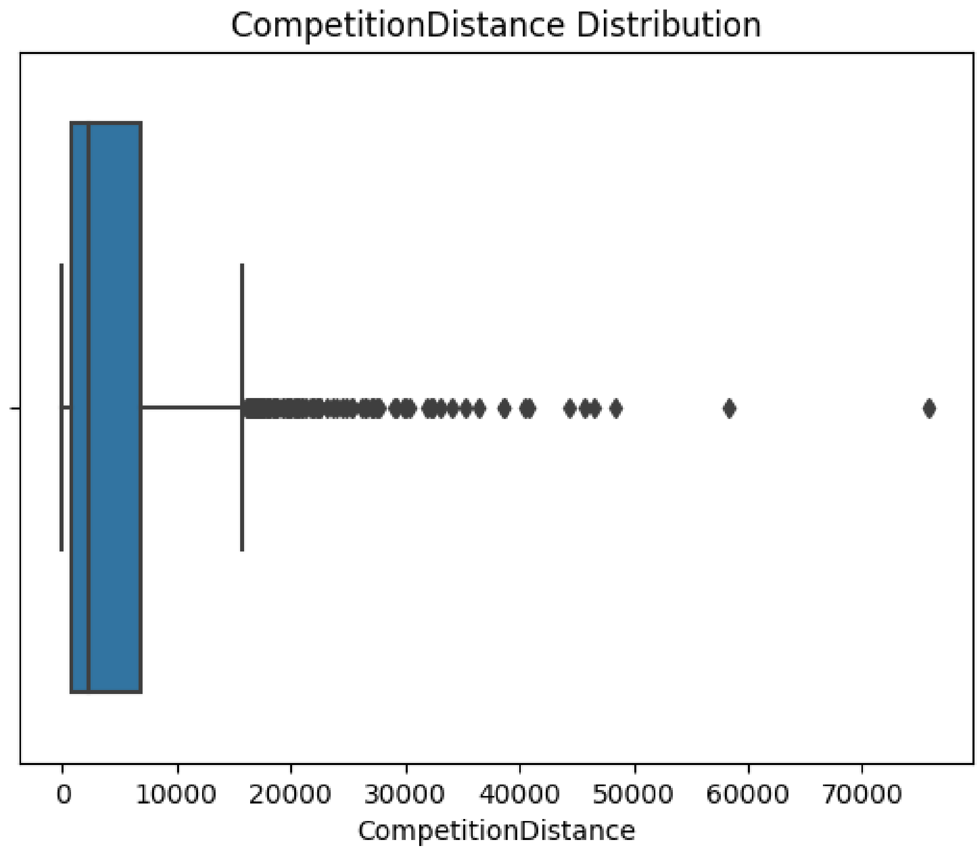
0.3 Data visualisation

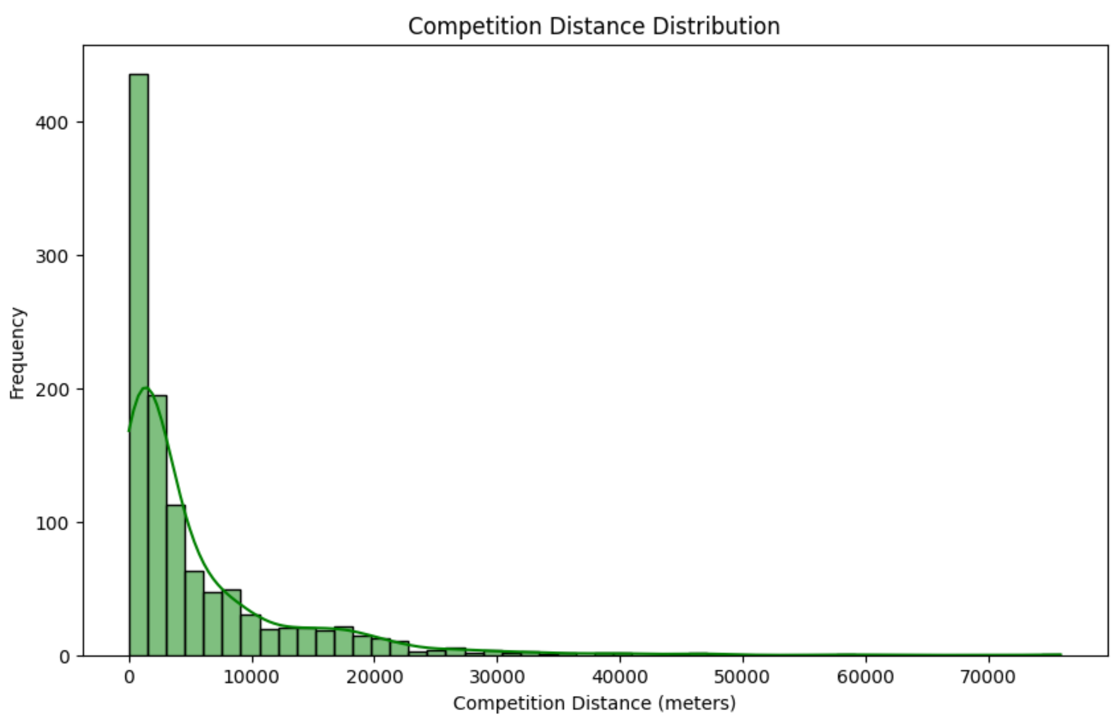
[62]:
```
sns.histplot(train_df['Sales'], bins=50, kde=True)
plt.title("Sales Distribution")

# Calculate median and mean
median_sales = train_df['Sales'].median()
mean_sales = train_df['Sales'].mean()

# Add vertical lines for median and mean
```

```
plt.axvline(median_sales, color='red', linestyle='--', linewidth=2,␣
↪label=f'Median: {median_sales:.2f}')
plt.axvline(mean_sales, color='blue', linestyle='-', linewidth=2, label=f'Mean:␣
↪{mean_sales:.2f}')

# Show legend
plt.legend()

plt.show()

sns.histplot(train_df['Customers'], bins=50, kde=True)
plt.title("Customers Distribution")
plt.show()

# competitive distance distribution
sns.boxplot(x=store_data['CompetitionDistance'])
plt.title("CompetitionDistance Distribution")
plt.show()


plt.figure(figsize=(10, 6))
sns.histplot(store_data['CompetitionDistance'].dropna(), bins=50, kde=True,␣
↪color='green')
plt.title('Competition Distance Distribution')
plt.xlabel('Competition Distance (meters)')
plt.ylabel('Frequency')
plt.show()
```

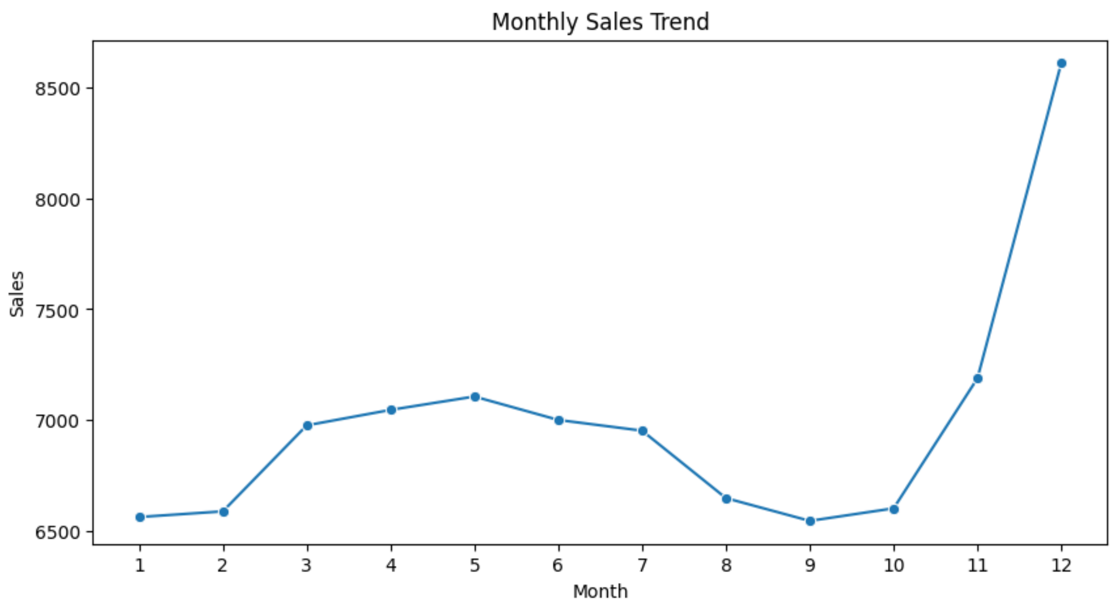

Sales Distribution
Median: 6369.00
Mean: 6955.51
Count
Sales
0
20000
40000
60000
80000
100000
120000
0
10000
20000
30000
40000

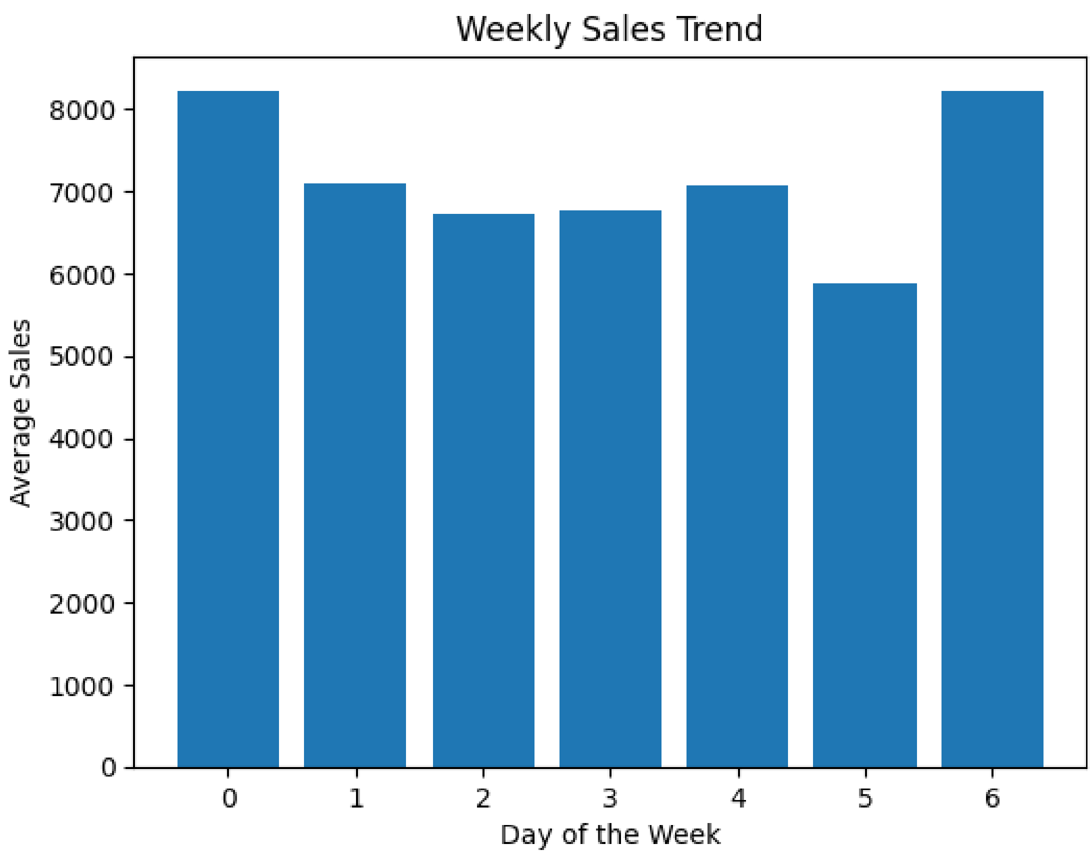

Customers Distribution
Count
200000
175000
150000
125000
100000
75000
50000
25000
0
0
1000
2000
3000
4000
5000
6000
7000
Customers


CompetitionDistance Distribution
0
10000
20000
30000
40000
50000
60000
70000
CompetitionDistance

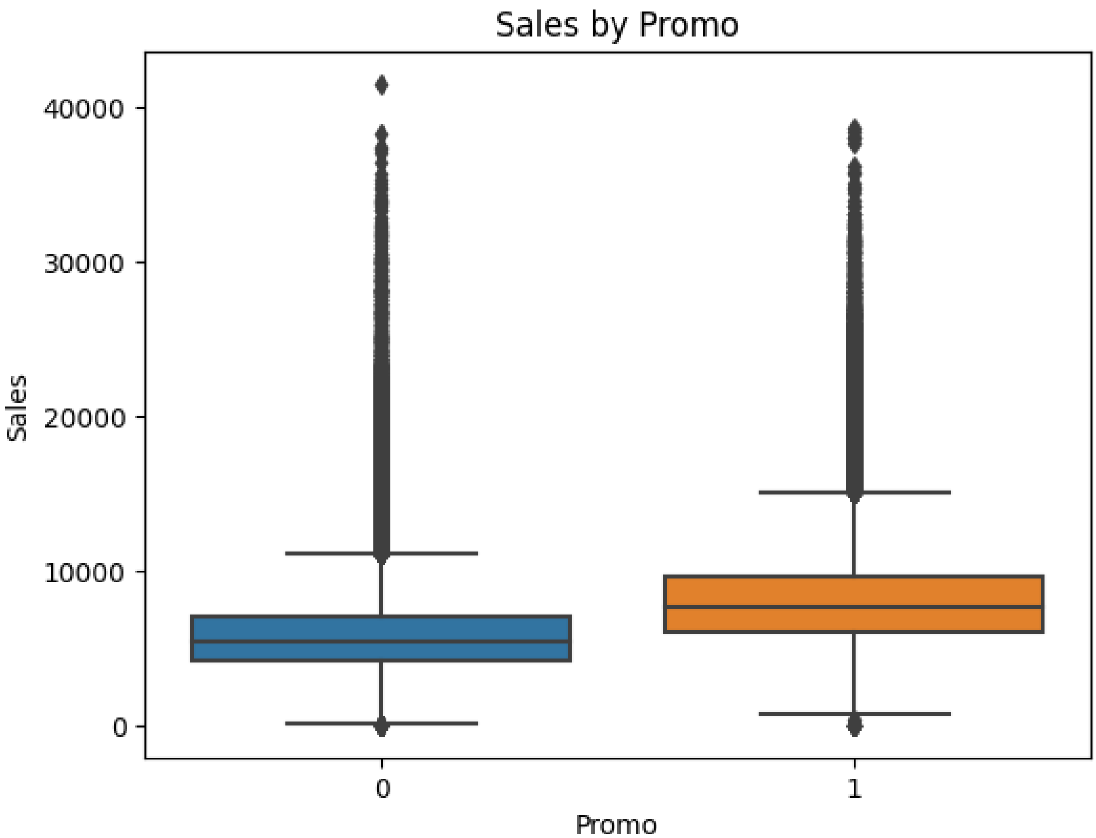

Competition Distance Distribution
400
300
200
100
0
Frequency
0
10000
20000
30000
40000
50000
60000
70000
Competition Distance (meters)

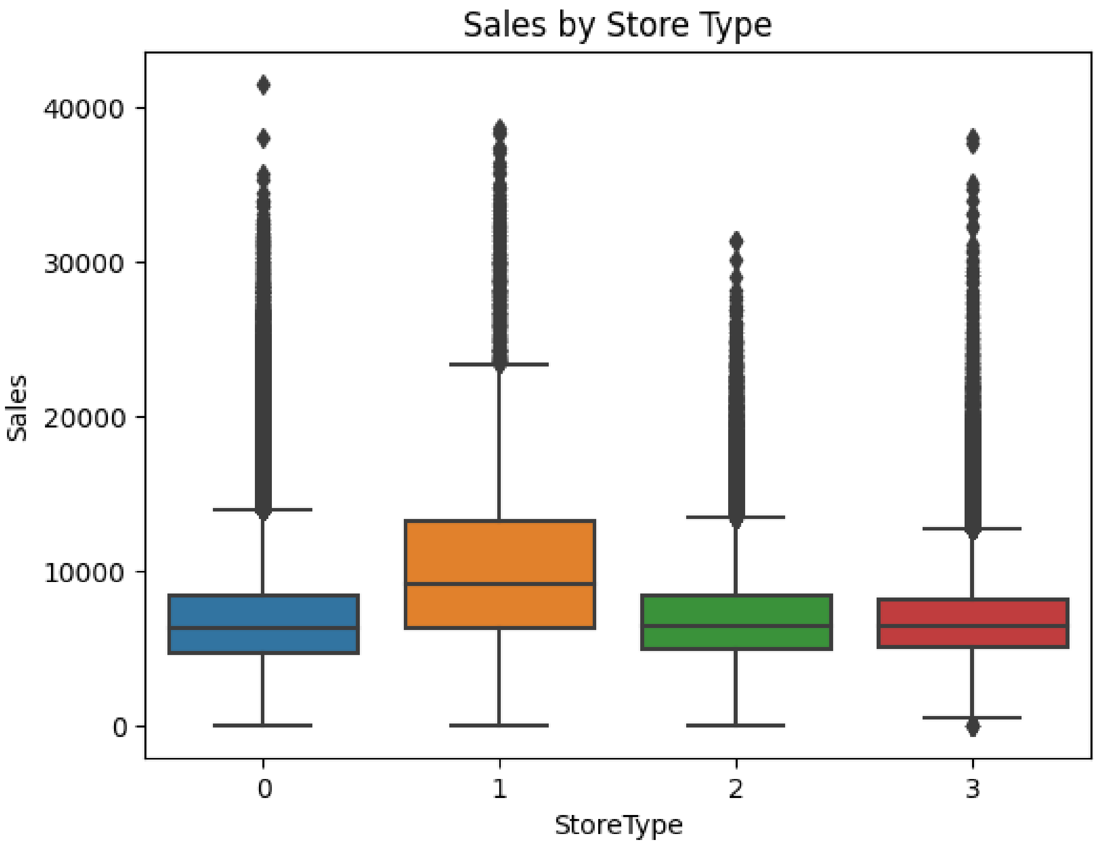
[63]:
```
# Sales are aggregated on a monthly basis
train_df['Month'] = train_df['Date'].dt.month
monthly_sales = train_df.groupby('Month')['Sales'].mean()

plt.figure(figsize=(10,5))
sns.lineplot(data=train_df.groupby('Month')['Sales'].mean().reset_index(),␣
↪x='Month', y='Sales', marker='o')
plt.title("Monthly Sales Trend")
plt.xticks(range(1,13))
plt.show()

# Sales are aggregated on a weekly basis
train_df['DayOfWeek'] = train_df['Date'].dt.dayofweek
weekly_sales = train_df.groupby('DayOfWeek')['Sales'].mean()

plt.bar(weekly_sales.index, weekly_sales.values)
plt.title("Weekly Sales Trend")
plt.xlabel("Day of the Week")
plt.ylabel("Average Sales")
plt.show()
```

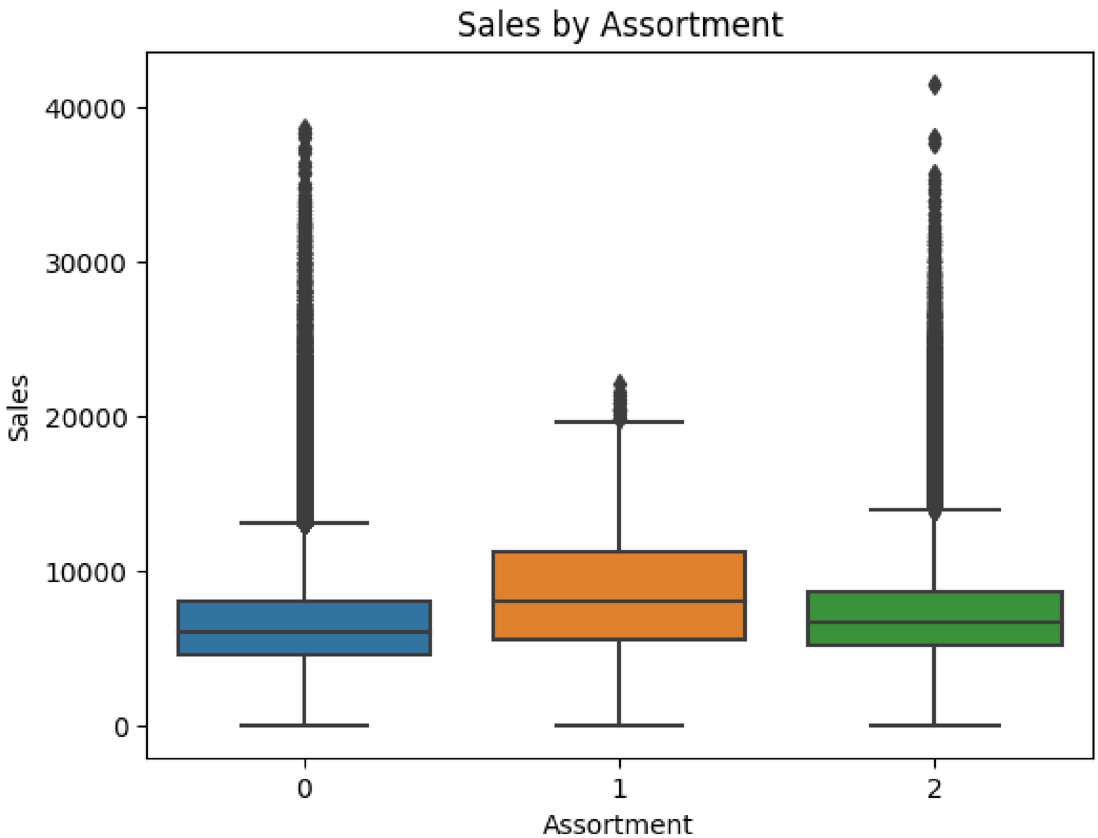




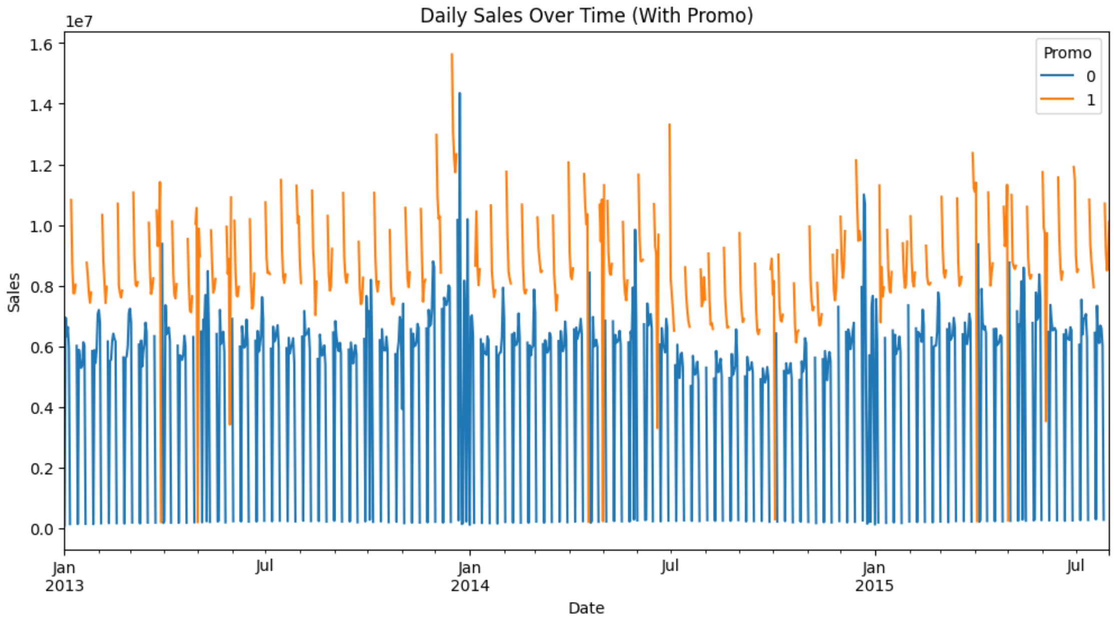
[64]:
```
# The relationship between sales and promotional activities
sns.boxplot(data=train_df, x='Promo', y='Sales')
plt.title("Sales by Promo")
plt.show()

# Sales in relation to store type
sns.boxplot(data=train_df, x='StoreType', y='Sales')
plt.title("Sales by Store Type")
plt.show()

# The relationship between sales and product categories
sns.boxplot(data=train_df, x='Assortment', y='Sales')
plt.title("Sales by Assortment")
plt.show()
```


Sales by Promo
40000
30000
20000
10000
0
Sales
0
1
Promo

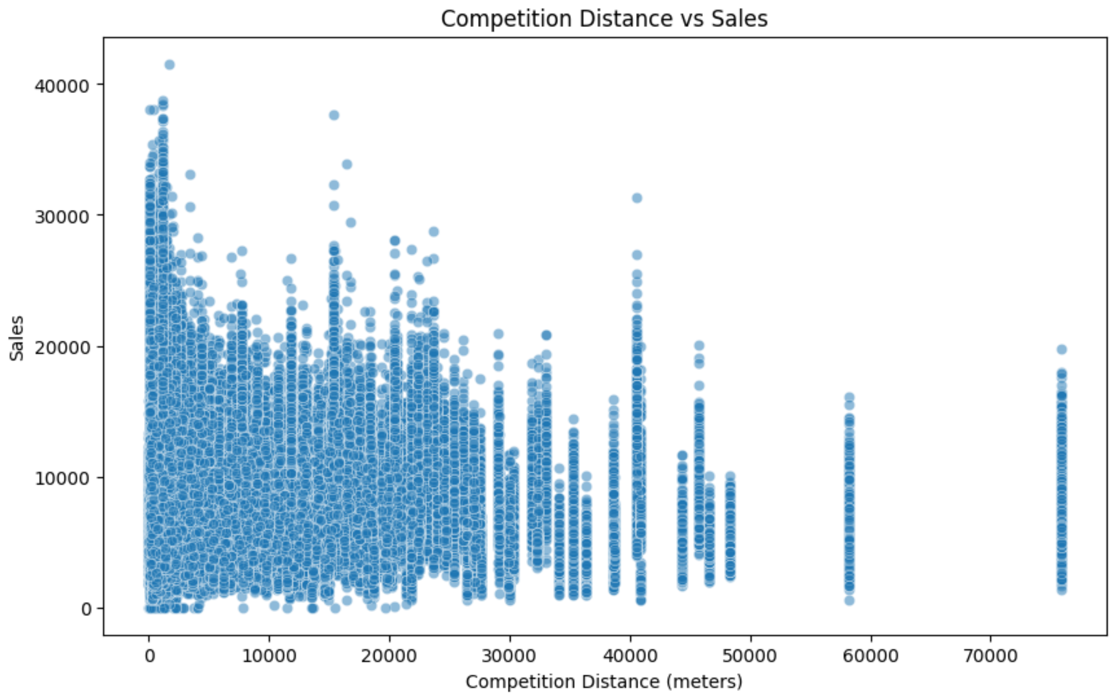

Sales by Store Type
40000
30000
20000
10000
0
Sales
0
1
2
3
StoreType



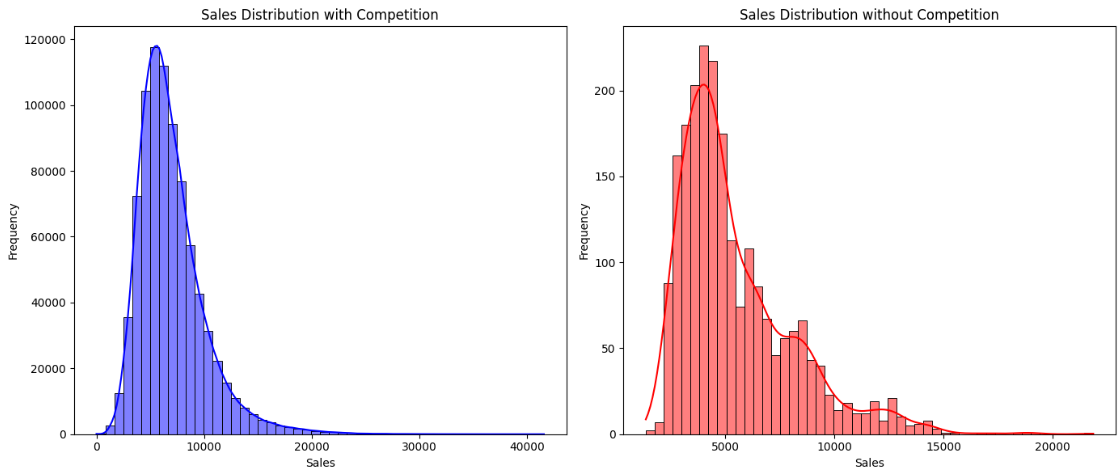
[65]:
```
# Aggregate sales by date and whether discounted or not
daily_sales_promo = train_df.groupby(['Date', 'Promo'])['Sales'].sum().unstack()

# Plotting sales trends over time
plt.figure(figsize=(12, 6))
daily_sales_promo.plot(ax=plt.gca())
plt.title('Daily Sales Over Time (With Promo)')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.legend(title='Promo')
plt.show()
```



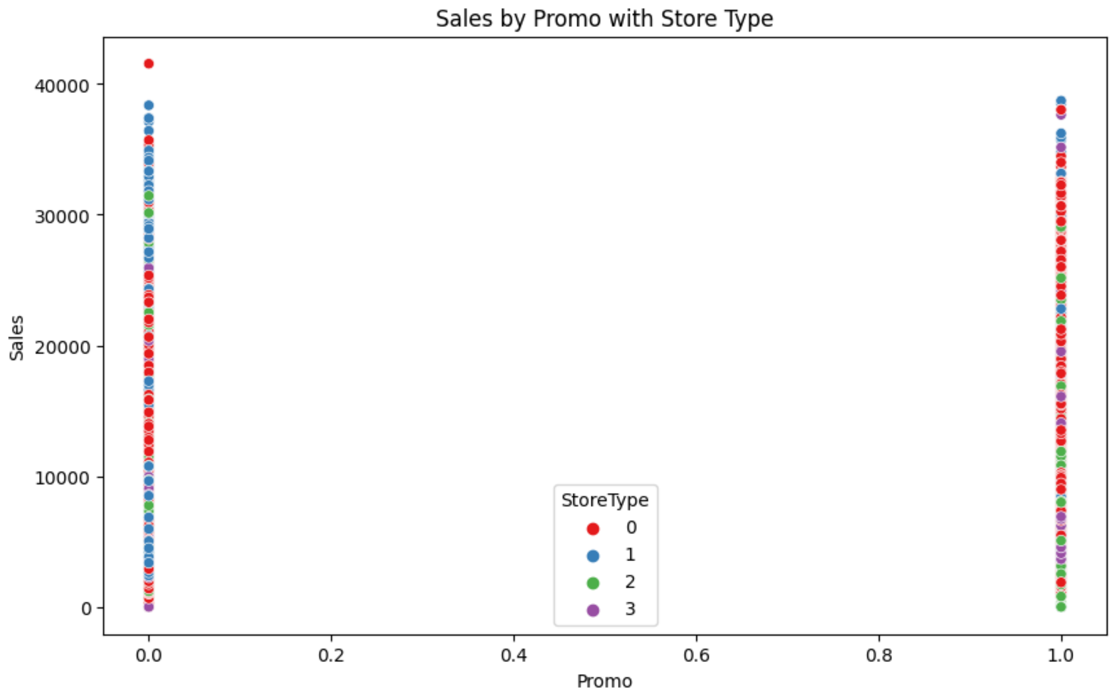
[66]:
```python
# Plot the relationship between CompetitionDistance and Sales.
plt.figure(figsize=(10, 6))
sns.scatterplot(x='CompetitionDistance', y='Sales', data=train_df, alpha=0.5)
plt.title('Competition Distance vs Sales')
plt.xlabel('Competition Distance (meters)')
plt.ylabel('Sales')
plt.show()
```

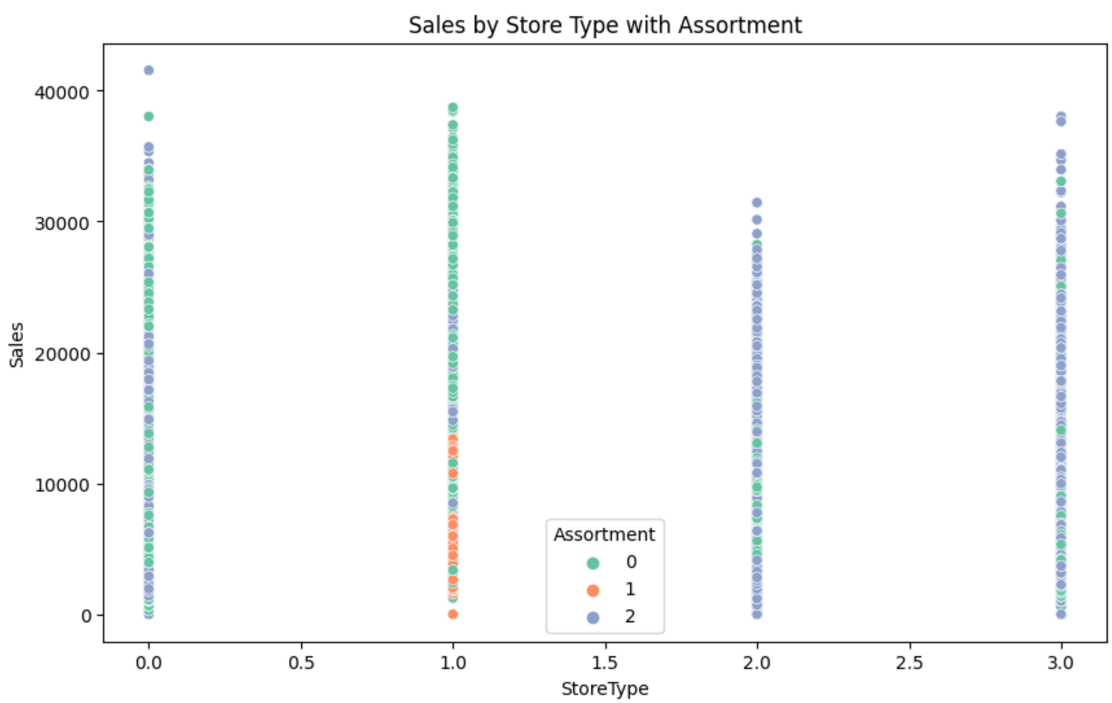


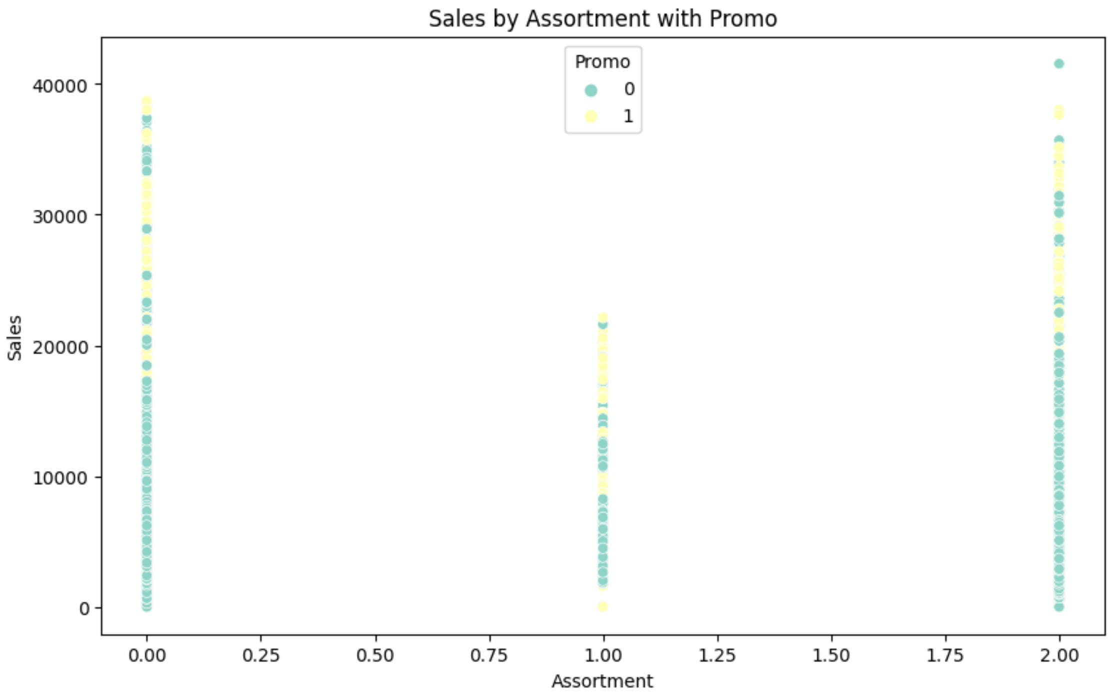
[67]:
```
plt.figure(figsize=(14, 6))

# Sales distribution by competitor
plt.subplot(1, 2, 1)
sns.histplot(train_df[train_df['HasCompetition'] == 1]['Sales'], bins=50,␣
↪kde=True, color='blue')
plt.title('Sales Distribution with Competition')
plt.xlabel('Sales')
plt.ylabel('Frequency')

# Sales distribution by no competitor
plt.subplot(1, 2, 2)
sns.histplot(train_df[train_df['HasCompetition'] == 0]['Sales'], bins=50,␣
↪kde=True, color='red')
plt.title('Sales Distribution without Competition')
plt.xlabel('Sales')
plt.ylabel('Frequency')

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



[ ]:
```
# Relationship between sales and promotional activities (scatter plot)
plt.figure(figsize=(10, 6))
sns.scatterplot(data=train_df, x='Promo', y='Sales', hue='StoreType',␣
 ↪palette='Set1')
plt.title("Sales by Promo with Store Type")
plt.show()

# Relationship between sales and store type (scatter plot)
plt.figure(figsize=(10, 6))
sns.scatterplot(data=train_df, x='StoreType', y='Sales', hue='Assortment',␣
 ↪palette='Set2')
plt.title("Sales by Store Type with Assortment")
plt.show()

#Relationship between sales and product category (scatter plot)
plt.figure(figsize=(10, 6))
sns.scatterplot(data=train_df, x='Assortment', y='Sales', hue='Promo',␣
 ↪palette='Set3')
plt.title("Sales by Assortment with Promo")
plt.show()
```

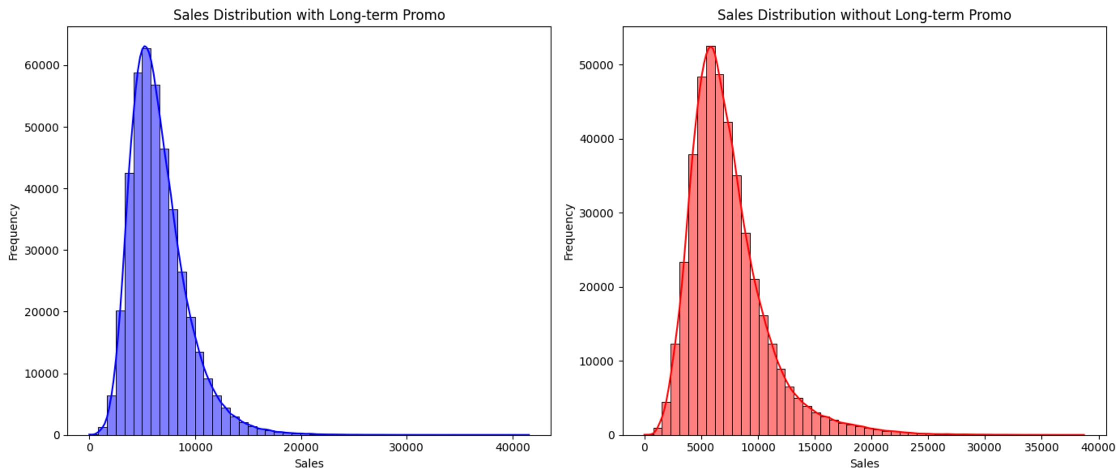

Sales by Promo with Store Type
Sales
Promo
StoreType
0
1
2
3
0
10000
20000
30000
40000
0.0
0.2
0.4
0.6
0.8
1.0


Sales by Store Type with Assortment
Sales
StoreType
Assortment
0
1
2
0
10000
20000
30000
40000
0.0
0.5
1.0
1.5
2.0
2.5
3.0

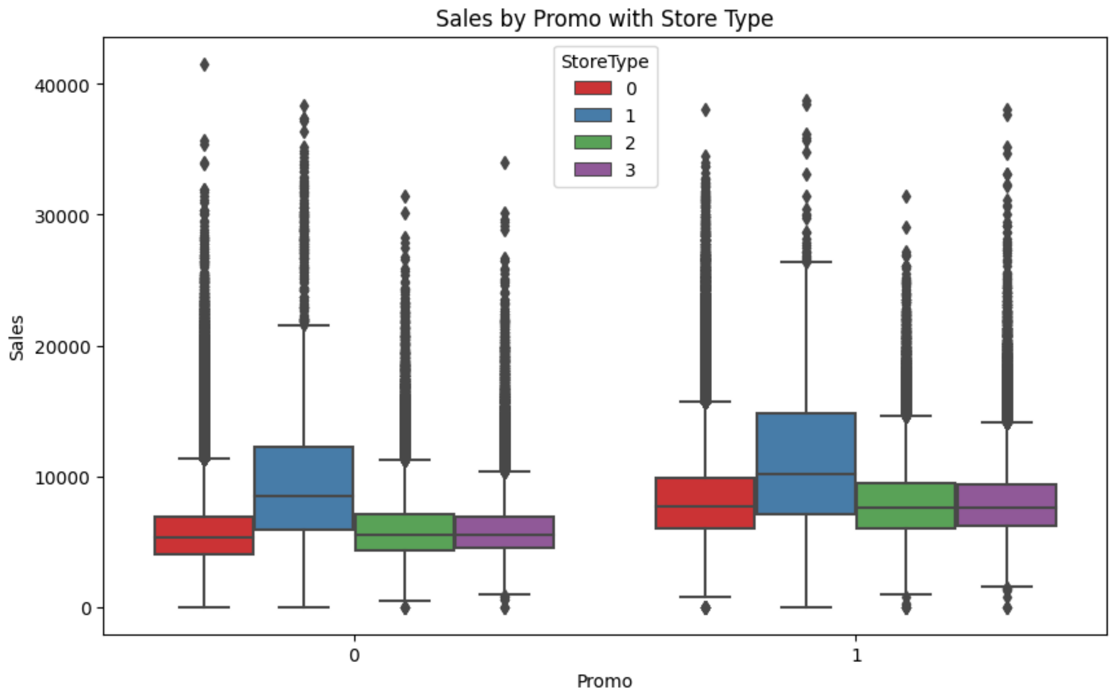


[ ]:

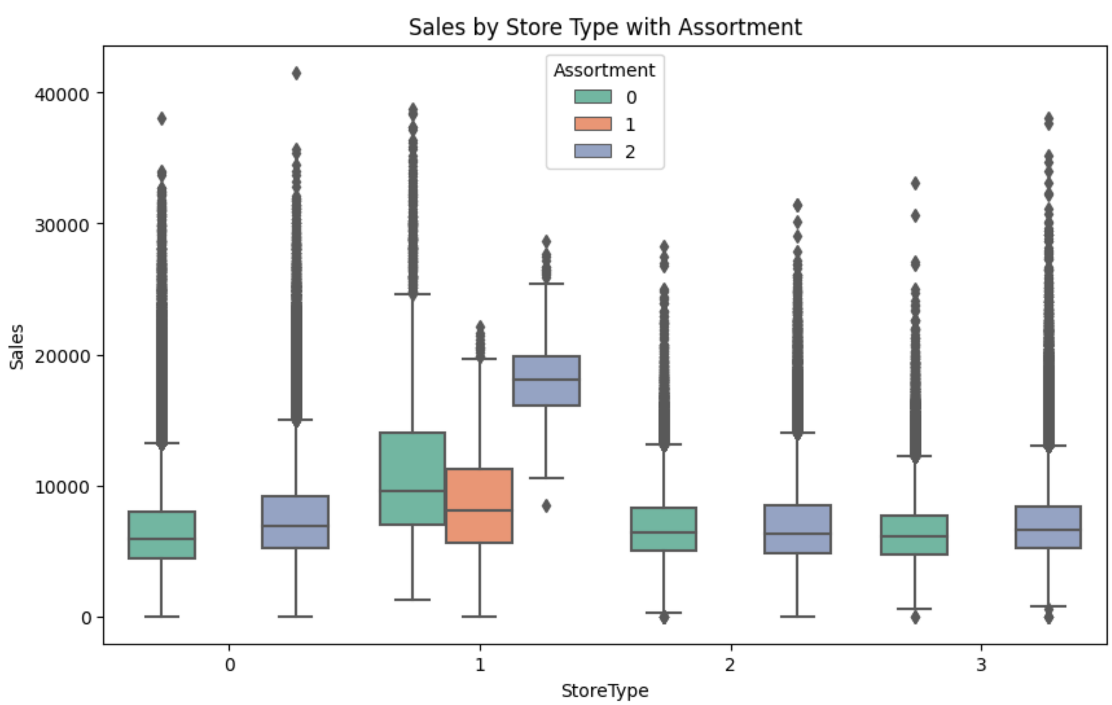
```
plt.figure(figsize=(14, 6))

# Sales breakdown by long-term promotion
plt.subplot(1, 2, 1)
sns.histplot(train_df[train_df['Promo2'] == 1]['Sales'], bins=50, kde=True,␣
↪color='blue')
plt.title('Sales Distribution with Long-term Promo')
plt.xlabel('Sales')
plt.ylabel('Frequency')

#Sales breakdown without participation in long-term promotions
plt.subplot(1, 2, 2)
sns.histplot(train_df[train_df['Promo2'] == 0]['Sales'], bins=50, kde=True,␣
↪color='red')
plt.title('Sales Distribution without Long-term Promo')
plt.xlabel('Sales')
plt.ylabel('Frequency')

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



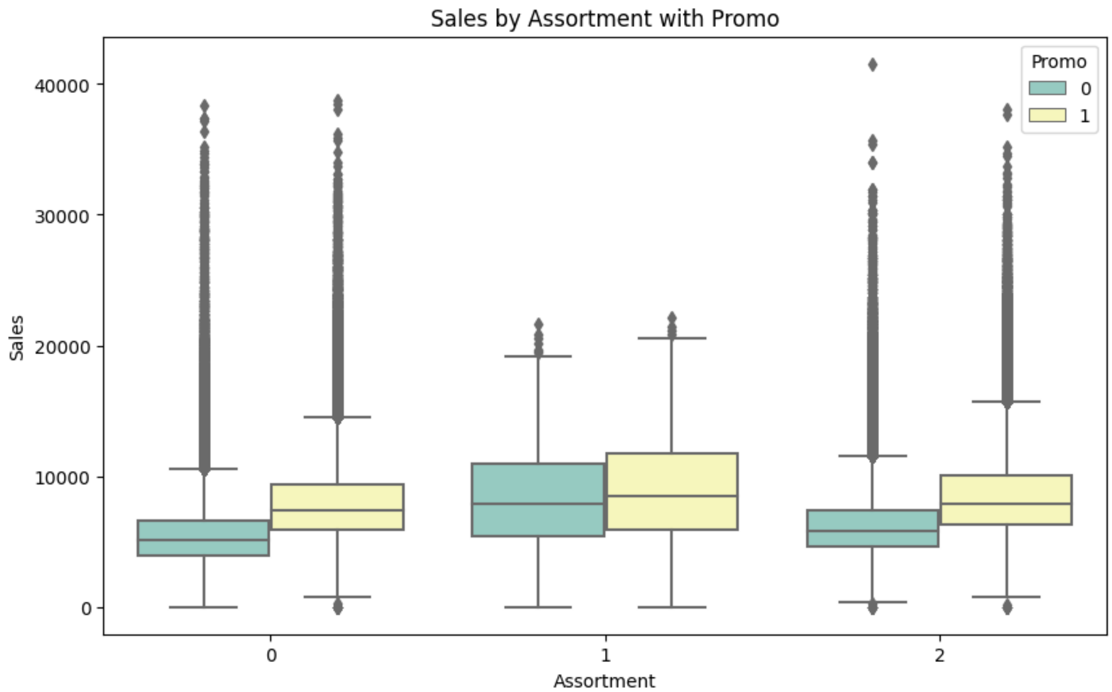

```
[ ]: # Relationship between sales and promotional activities (box plot)
plt.figure(figsize=(10, 6))
sns.boxplot(data=train_df, x='Promo', y='Sales', hue='StoreType',␣
 ↪palette='Set1')
plt.title("Sales by Promo with Store Type")
plt.show()

# Sales in relation to store type (box plot)
plt.figure(figsize=(10, 6))
sns.boxplot(data=train_df, x='StoreType', y='Sales', hue='Assortment',␣
 ↪palette='Set2')
plt.title("Sales by Store Type with Assortment")
plt.show()

# Relationship between sales and product categories (box plot)
plt.figure(figsize=(10, 6))
sns.boxplot(data=train_df, x='Assortment', y='Sales', hue='Promo',␣
 ↪palette='Set3')
plt.title("Sales by Assortment with Promo")
plt.show()
```



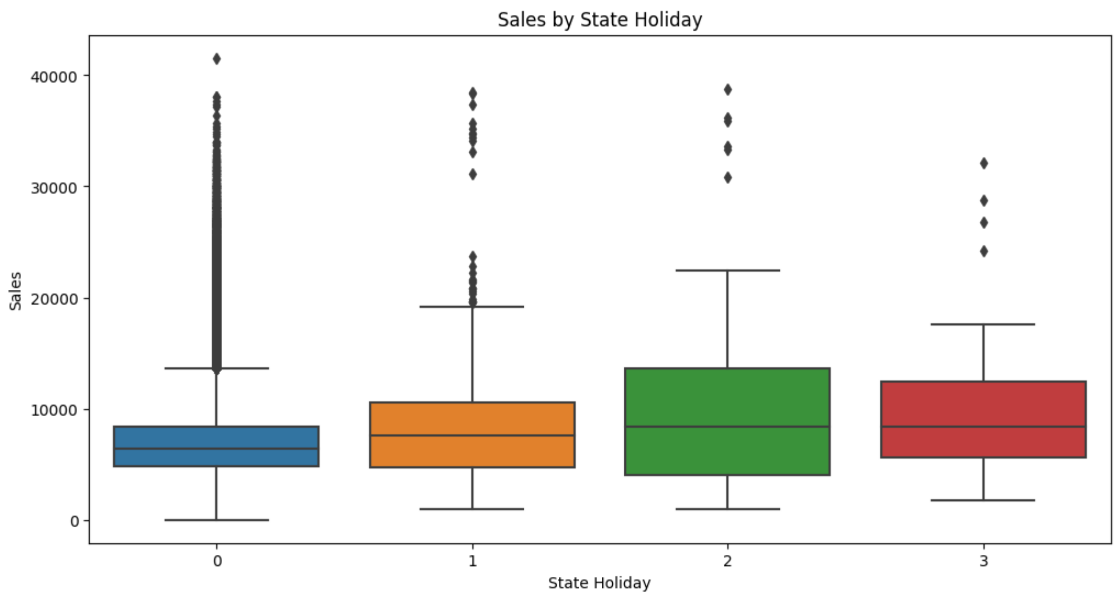
Sales by Promo with Store Type
StoreType
0
1
2
3
Sales
40000
30000
20000
10000
0
Promo
0
1

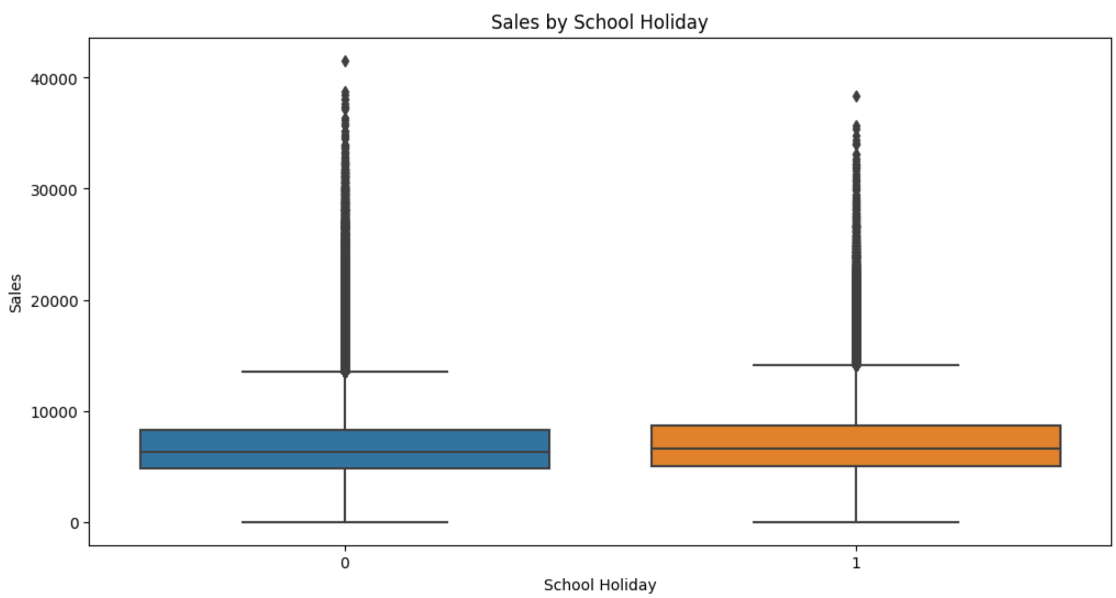


Sales by Store Type with Assortment
Assortment
0
1
2
Sales
40000
30000
20000
10000
0
StoreType
0
1
2
3



[ ]:
```
# Visualising the impact of public holidays on sales
plt.figure(figsize=(12, 6))
sns.boxplot(data=train_df, x='StateHoliday', y='Sales')
plt.title("Sales by State Holiday")
plt.xlabel("State Holiday")
plt.ylabel("Sales")
plt.show()

#  Visualising the impact of school holidays on sales
plt.figure(figsize=(12, 6))
sns.boxplot(data=train_df, x='SchoolHoliday', y='Sales')
plt.title("Sales by School Holiday")
plt.xlabel("School Holiday")
plt.ylabel("Sales")
plt.show()
```

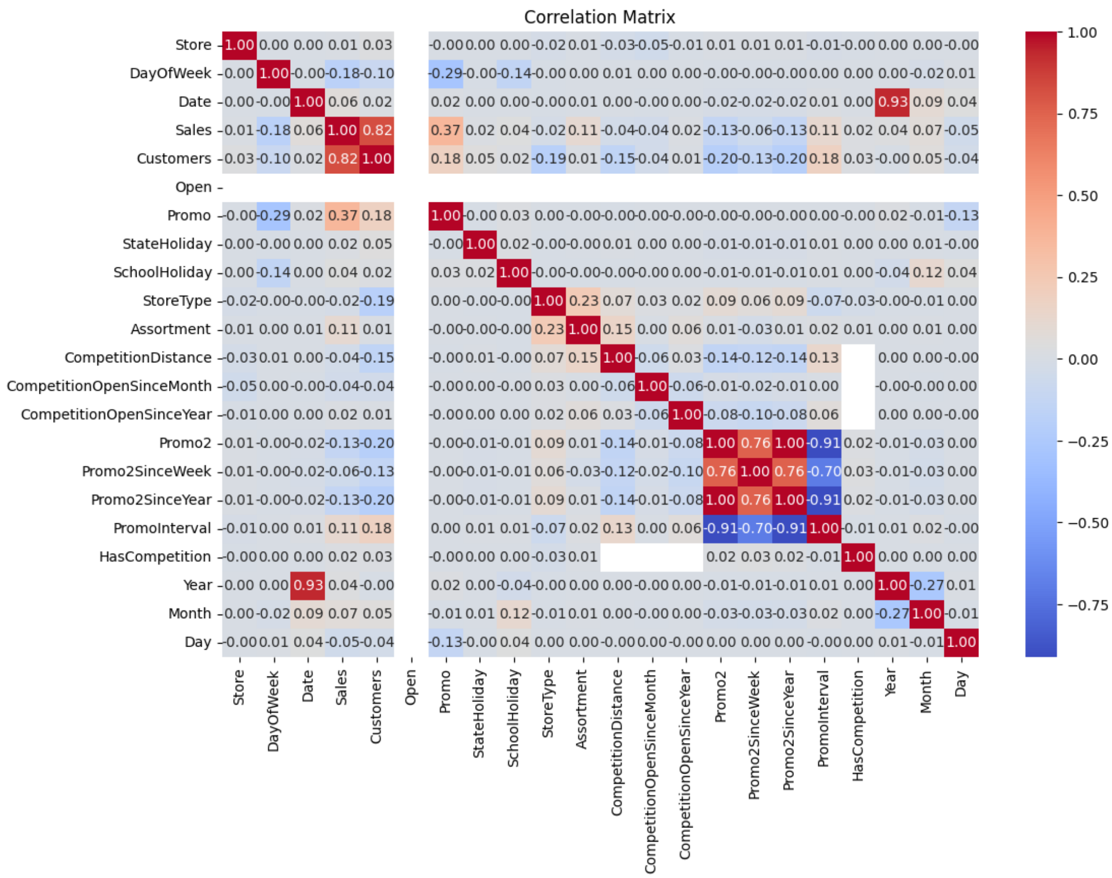




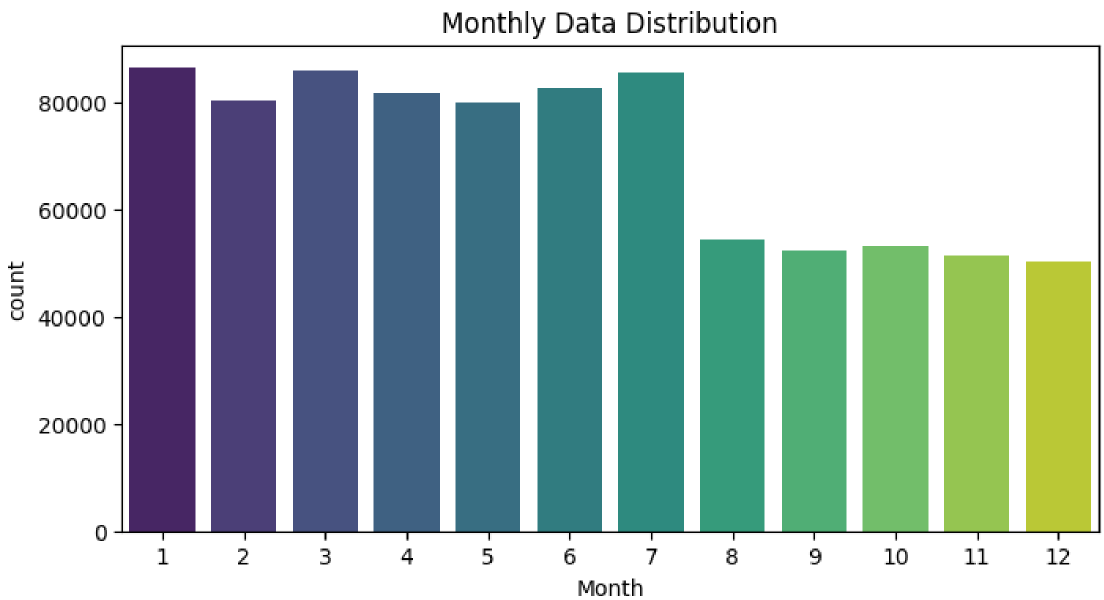
[ ]:

```
#Calculate the correlation matrix
correlation_matrix = train_df.corr()

# Visualising correlation matrices
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
```

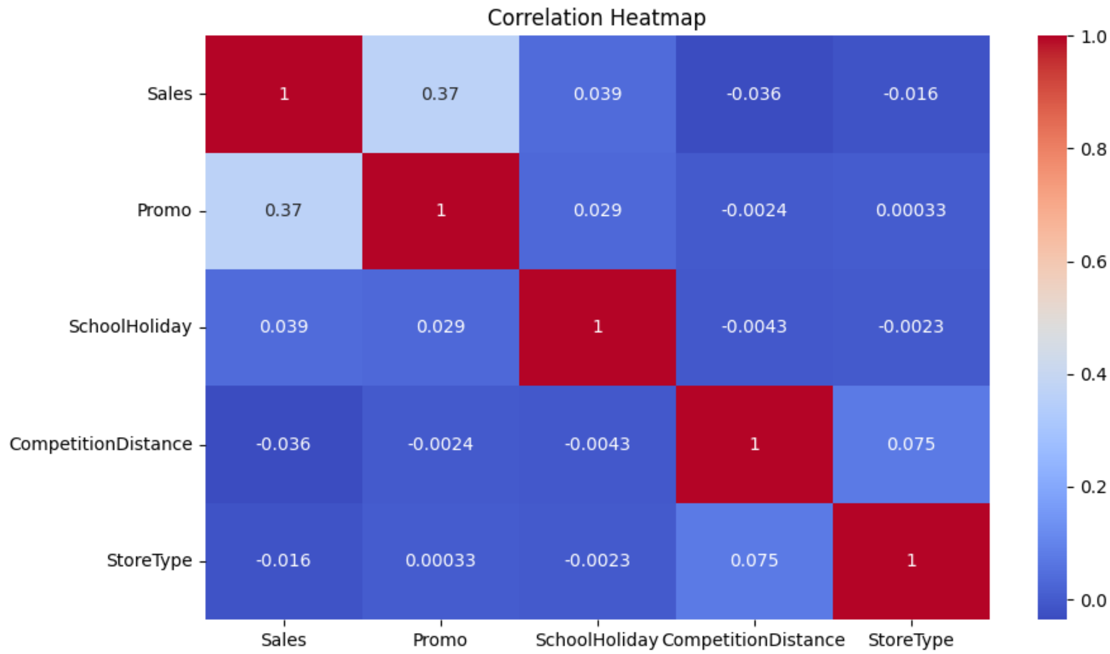
```
plt.show()
```

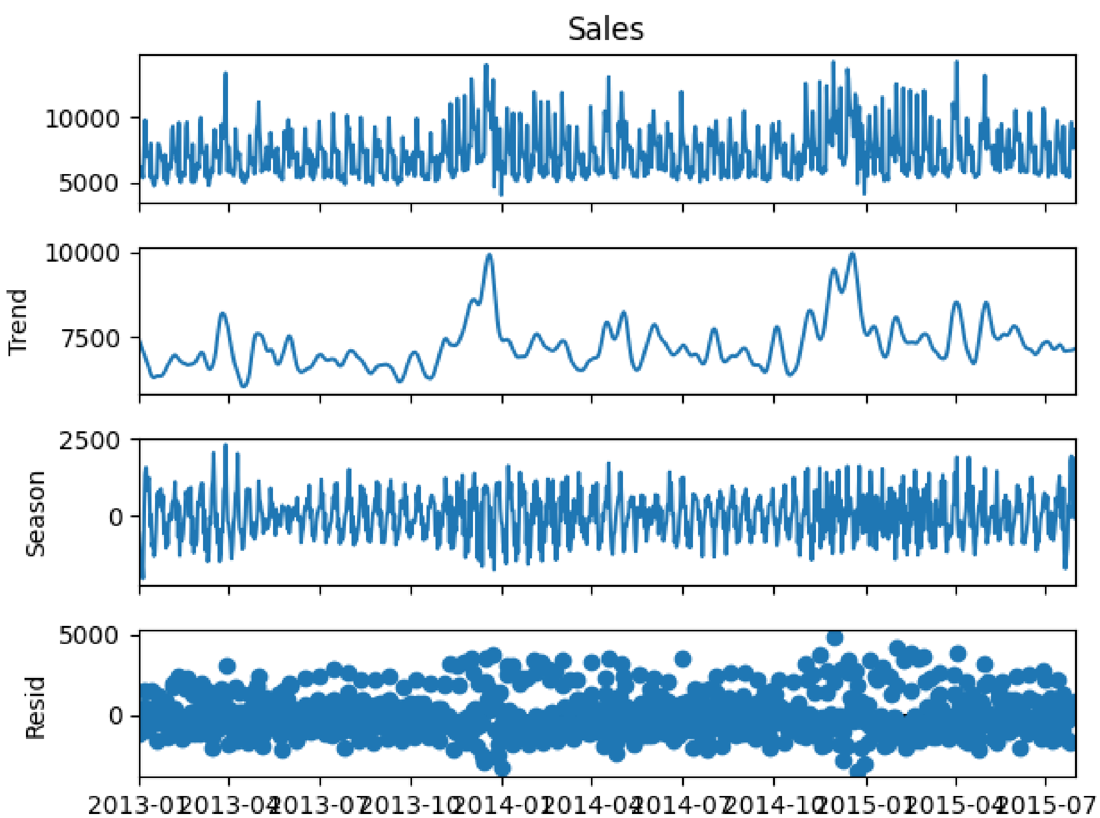


```
[ ]: # Univariate: distribution by month
plt.figure(figsize=(8,4))
sns.countplot(data=train_df, x='Month', palette='viridis')
plt.title("Monthly Data Distribution")
plt.show()
```



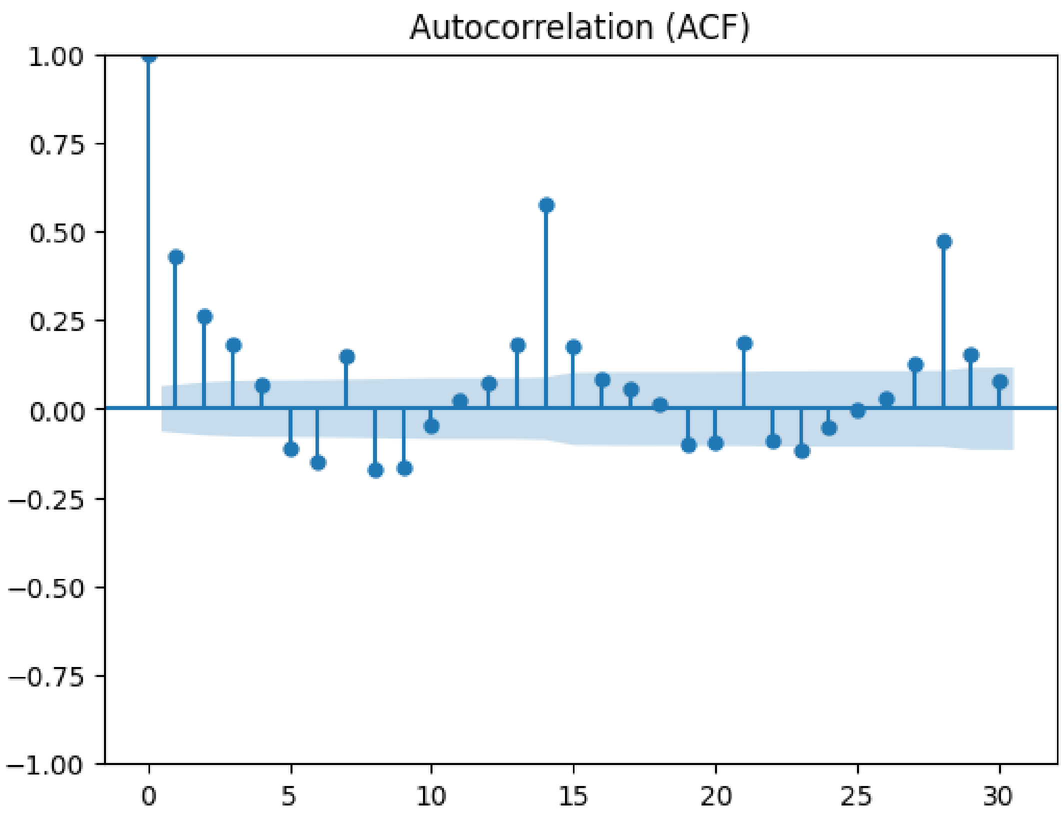
[ ]:
```
# Heat map: multi-factor correlation
plt.figure(figsize=(10,6))
corr_matrix = train_df[['Sales', 'Promo', 'SchoolHoliday',␣
↪'CompetitionDistance', 'StoreType']].corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()

ts = train_df.groupby('Date')['Sales'].mean()
result = STL(ts, period=12).fit()
result.plot()
plt.show()
```


Correlation Heatmap
Sales
Promo
SchoolHoliday
CompetitionDistance
StoreType
1
0.37
0.039
-0.036
-0.016
0.029
-0.0024
0.00033
-0.0043
-0.0023
0.075
1.0
0.8
0.6
0.4
0.2
0.0

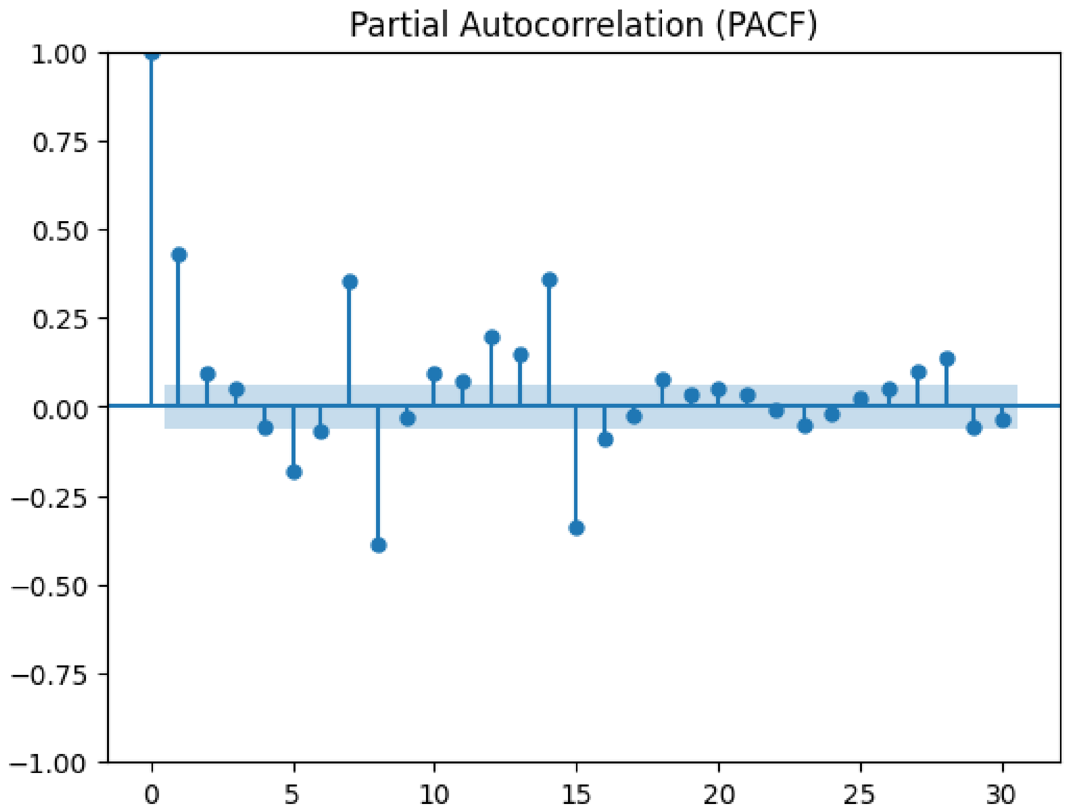

Sales
Trend
Season
Resid
10000
5000
7500
2500
0
2013-01
2013-04
2013-07
2013-10
2014-01
2014-04
2014-07
2014-10
2015-01
2015-04
2015-07

```
[ ]: # Aggregate by date to daily sales (assuming that missing values have been␣
     ↪processed)
     ts_daily = train_df.groupby('Date')['Sales'].mean()

     # Plot ACF and PACF (set maximum lag to seasonal period, e.g. monthly period =␣
     ↪30 days)
     plt.figure(figsize=(12, 6))
     plot_acf(ts_daily, lags=30, alpha=0.05, title='Autocorrelation (ACF)')
     plt.show()

     plt.figure(figsize=(12, 6))
     plot_pacf(ts_daily, lags=30, alpha=0.05, title='Partial Autocorrelation (PACF)')
     plt.show()
```

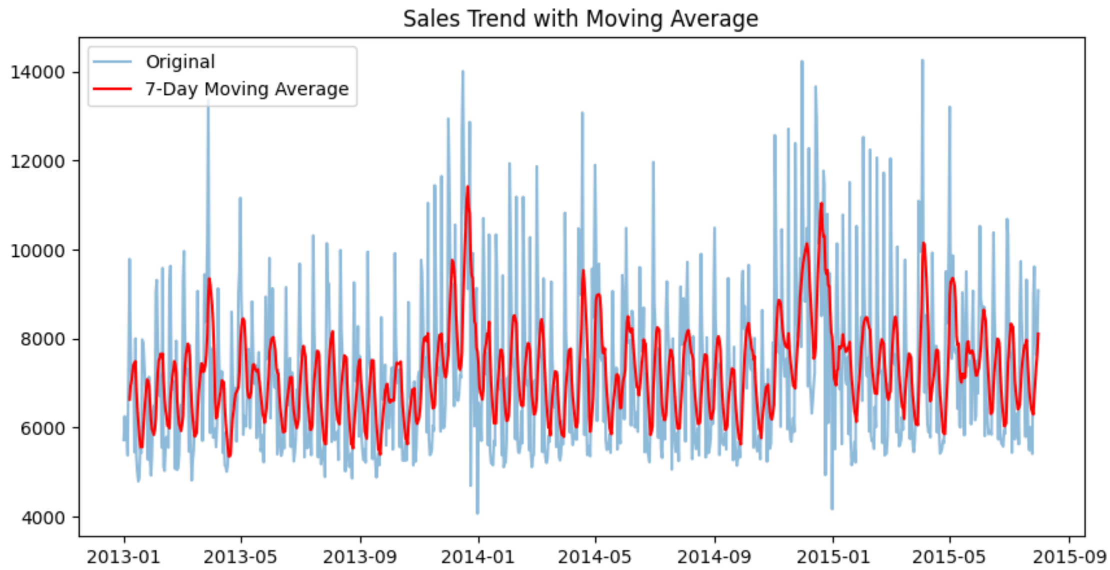
```
<Figure size 1200x600 with 0 Axes>
```



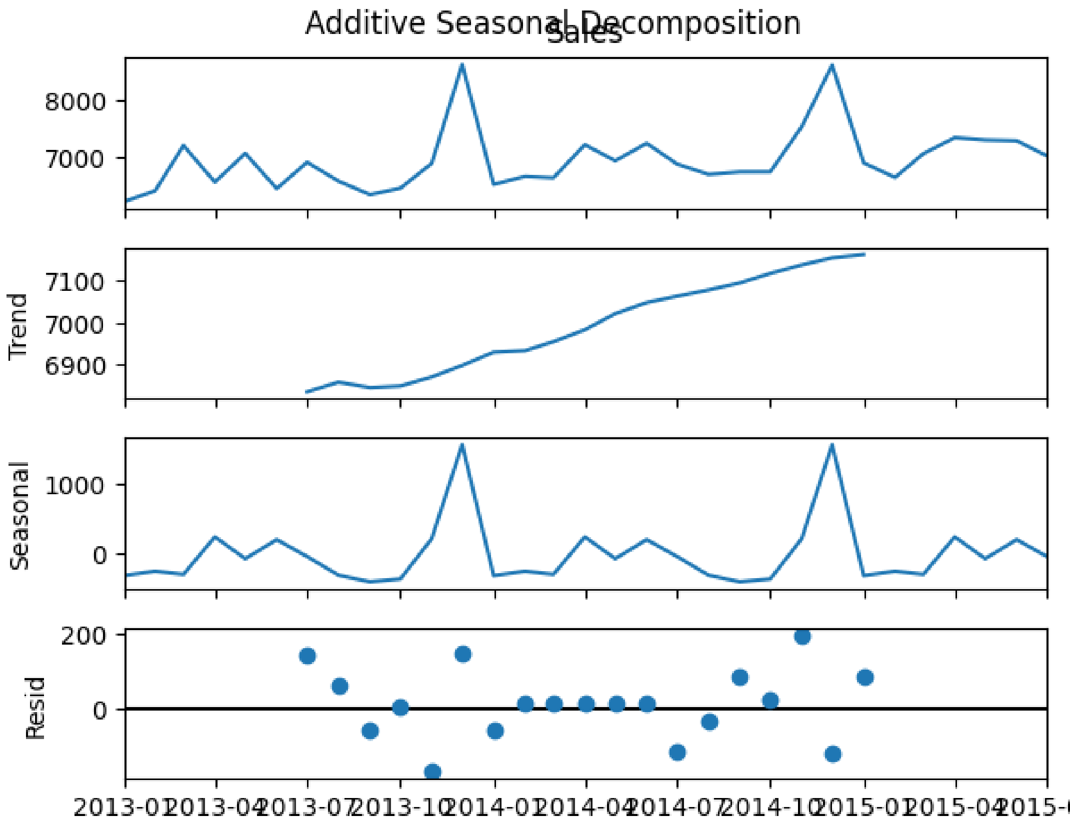

```
<Figure size 1200x600 with 0 Axes>
```

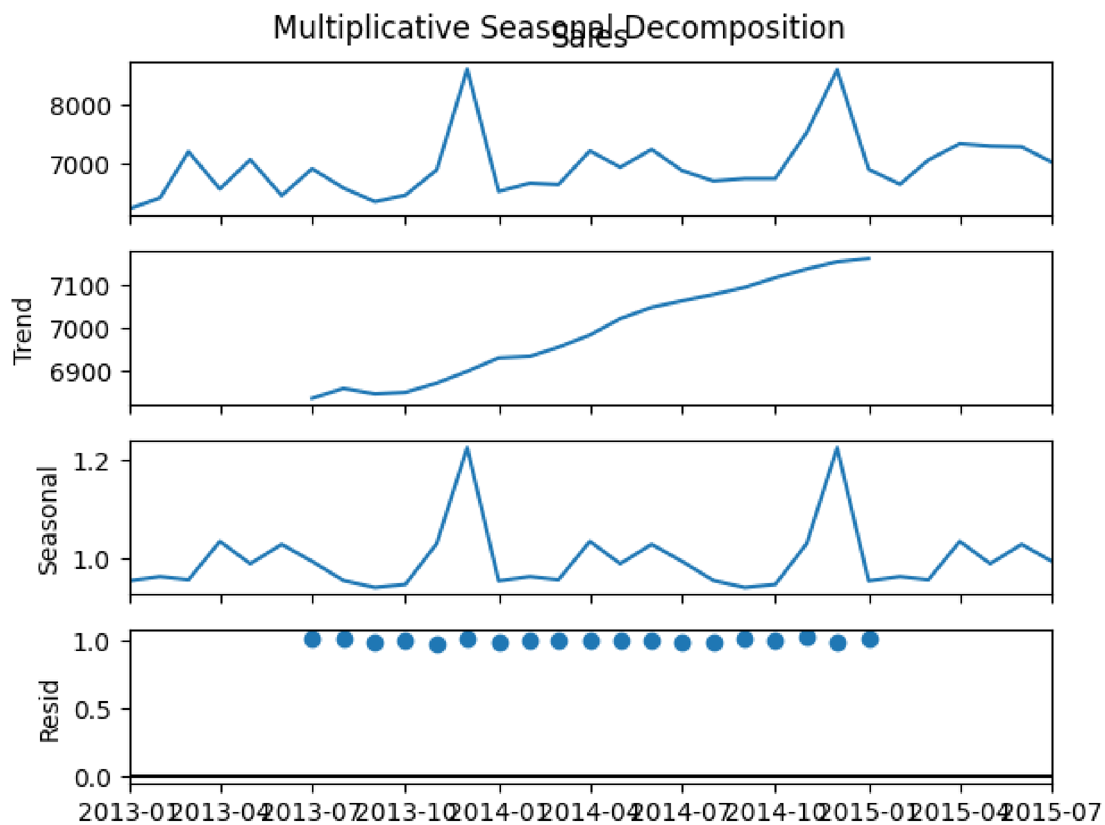


[ ]:
```
# Calculation of 7-day moving average (weekly trend)
ts_ma = ts_daily.rolling(window=7).mean()

plt.figure(figsize=(10,5))
plt.plot(ts_daily, label='Original', alpha=0.5)
plt.plot(ts_ma, label='7-Day Moving Average', color='red')
plt.title("Sales Trend with Moving Average")
plt.legend()
plt.show()
```



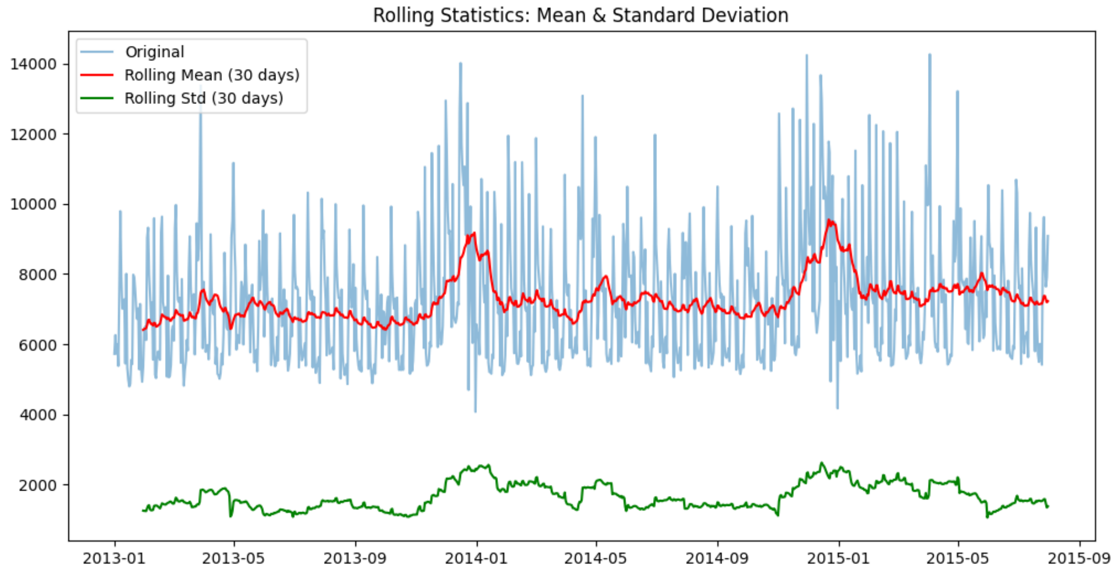
[ ]:
```python
# Aggregation by month (assuming monthly data)
ts_monthly = train_df.groupby(['Year', 'Month'])['Sales'].mean().reset_index()
ts_monthly['Date'] = pd.to_datetime(ts_monthly[['Year', 'Month']].assign(day=1))
ts_monthly = ts_monthly.set_index('Date')['Sales']

# Additive model decomposition
result_add = seasonal_decompose(ts_monthly, model='additive', period=12)
result_add.plot()
plt.suptitle("Additive Seasonal Decomposition")
plt.show()

# Decomposition of the multiplicative model (applicable when seasonal␣
↪fluctuations increase with the trend)
result_mul = seasonal_decompose(ts_monthly, model='multiplicative', period=12)
result_mul.plot()
plt.suptitle("Multiplicative Seasonal Decomposition")
plt.show()
```


Additive Seasonal Decomposition
Sales
8000
7000
Trend
7100
7000
6900
Seasonal
1000
0
Resid
200
0
2013-01
2013-04
2013-07
2013-10
2014-01
2014-04
2014-07
2014-10
2015-01
2015-04
2015-07

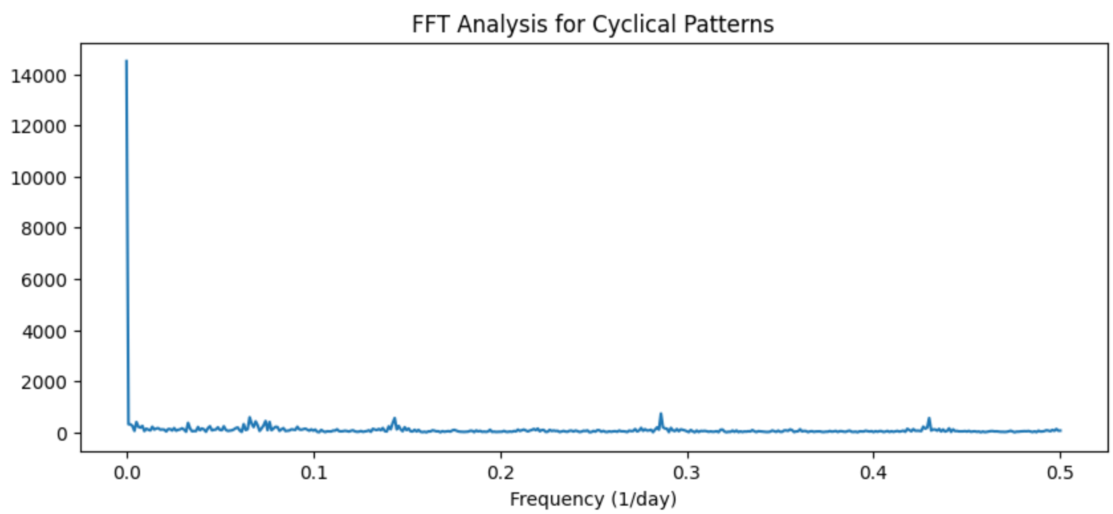


[ ]:

```
# Rolling average and standard deviation (window = 30 days)
rolling_mean = ts_daily.rolling(window=30).mean()
rolling_std = ts_daily.rolling(window=30).std()

plt.figure(figsize=(12,6))
plt.plot(ts_daily, label='Original', alpha=0.5)
plt.plot(rolling_mean, label='Rolling Mean (30 days)', color='red')
plt.plot(rolling_std, label='Rolling Std (30 days)', color='green')
plt.title("Rolling Statistics: Mean & Standard Deviation")
plt.legend()
plt.show()
```




```
[ ]: # Fourier transform analysis (requires continuous data without missing values)
ts_clean = ts_daily.dropna()
yf = fft(ts_clean.values)
N = len(ts_clean)
xf = np.linspace(0, 1/(2*1), N//2)

plt.figure(figsize=(10,4))
plt.plot(xf, 2.0/N * np.abs(yf[:N//2]))
plt.xlabel('Frequency (1/day)')
plt.title("FFT Analysis for Cyclical Patterns")
plt.show()
```



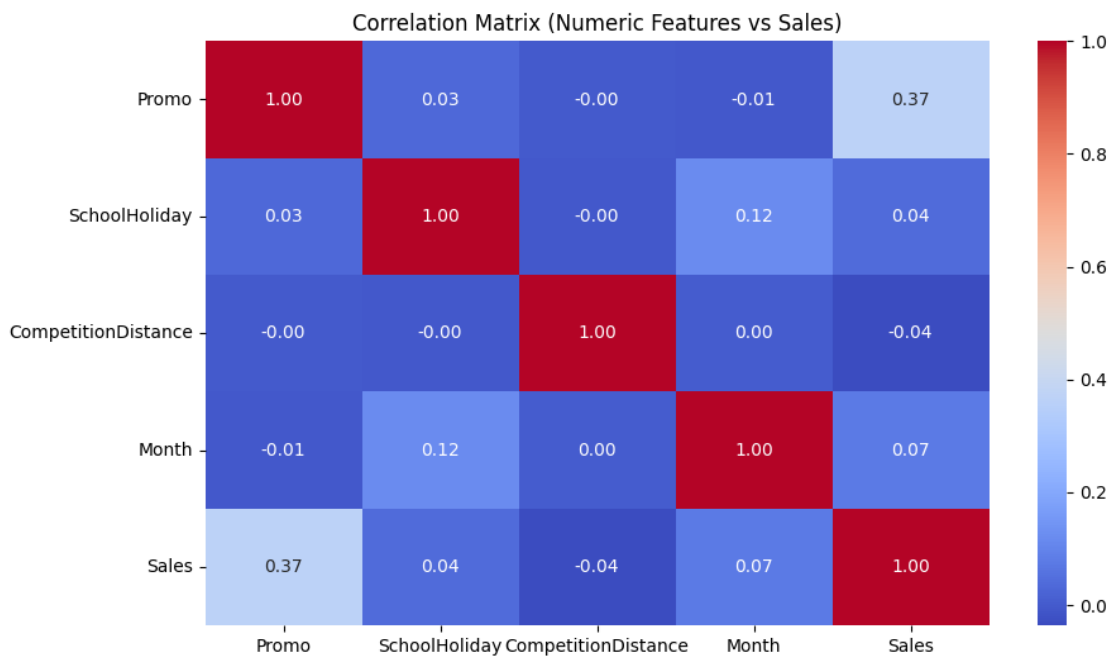
0.4 Model

[80]:
```
df = train_df.copy()

features = df.drop(['Sales','Customers'], axis=1).select_dtypes(include=np.
 ↪number).columns
target = ['Sales','Customers']

median_distance = df['CompetitionDistance'].median()
df['CompetitionDistance'] = df['CompetitionDistance'].fillna(median_distance)
df['CompetitionOpenSinceMonth'] = df['CompetitionOpenSinceMonth'].fillna(0)
df['CompetitionOpenSinceYear'] = df['CompetitionOpenSinceYear'].fillna(0)
```

[81]:
```
df2 = test_df[test_df['Open']==1].copy()

median_distance = df2['CompetitionDistance'].median()
df2['CompetitionDistance'] = df2['CompetitionDistance'].fillna(median_distance)
df2['CompetitionOpenSinceMonth'] = df2['CompetitionOpenSinceMonth'].fillna(0)
df2['CompetitionOpenSinceYear'] = df2['CompetitionOpenSinceYear'].fillna(0)
```

[82]:
```
# Divide the training set and the test set
X_train, X_test, y_train, y_test = train_test_split(
    df[features], df[target], test_size=0.2, random_state=42
)
```

[ ]:
```
numeric_features = ['Promo', 'SchoolHoliday', 'CompetitionDistance', 'Month']
corr_matrix = train_df[numeric_features + ['Sales']].corr()

plt.figure(figsize=(10,6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Matrix (Numeric Features vs Sales)")
plt.show()
```



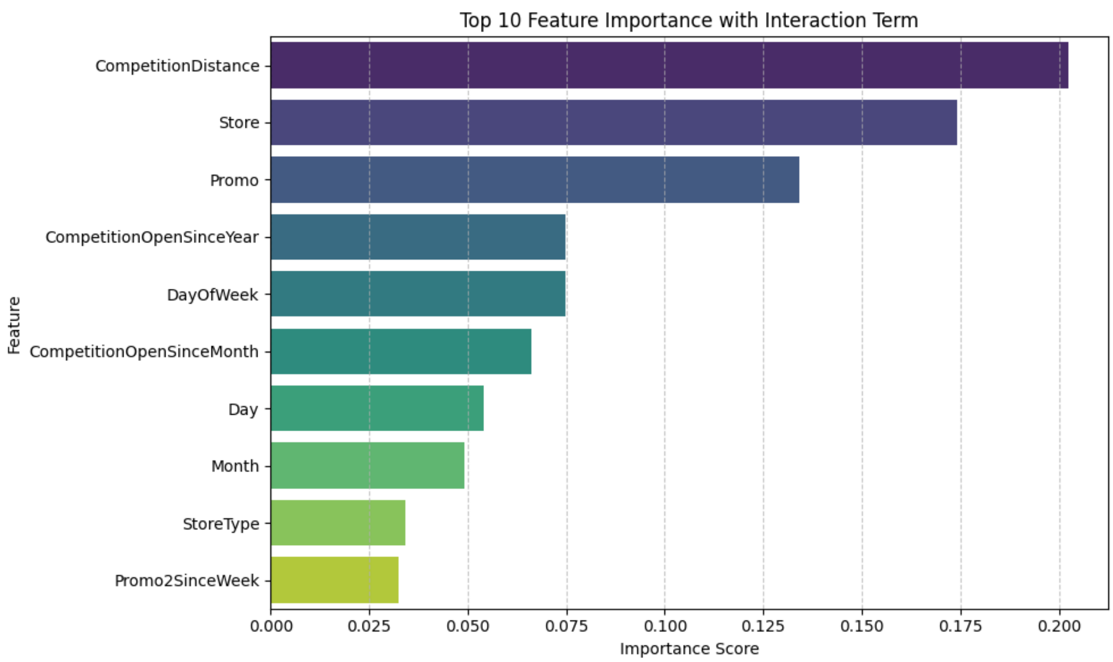
[84]:
```python
def calculate_rmspe(y_true, y_pred):
    y_true = np.array(y_true)
    y_pred = np.array(y_pred)

    # avoid division by zero
    non_zero_indices = y_true != 0
    y_true = y_true[non_zero_indices]
    y_pred = y_pred[non_zero_indices]

    # Calculate percentage error
    percentage_error = (y_true - y_pred) / y_true

    # Calculate the root mean square percentage error
    rmspe = np.sqrt(np.mean(percentage_error ** 2)) * 100

    return rmspe
```

[ ]:
```python
# train model
rf = RandomForestRegressor(n_estimators=10,random_state=42)
rf.fit(X_train, y_train)

# access the model
y_pred = rf.predict(X_test)
print(f"R² Score: {r2_score(y_test, y_pred):.3f}")
```

```python
# calculate RMSPE
rmspe = calculate_rmspe(y_test, y_pred)
print(f"RMSPE: {rmspe:.2f}%")


# feature importance
importance = pd.Series(rf.feature_importances_, index=features).
 ↪sort_values(ascending=False)
print("\nFeature Importance:")
print(importance)

# Visualize feature importance
importance = rf.feature_importances_
feature_importance = pd.DataFrame({
    'Feature': features,
    'Importance': importance
}).sort_values(by='Importance', ascending=False)



plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importance.head(10),␣
 ↪palette='viridis')
plt.title('Top 10 Feature Importance with Interaction Term')
plt.xlabel('Importance Score')
plt.ylabel('Feature')
plt.grid(axis='x', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

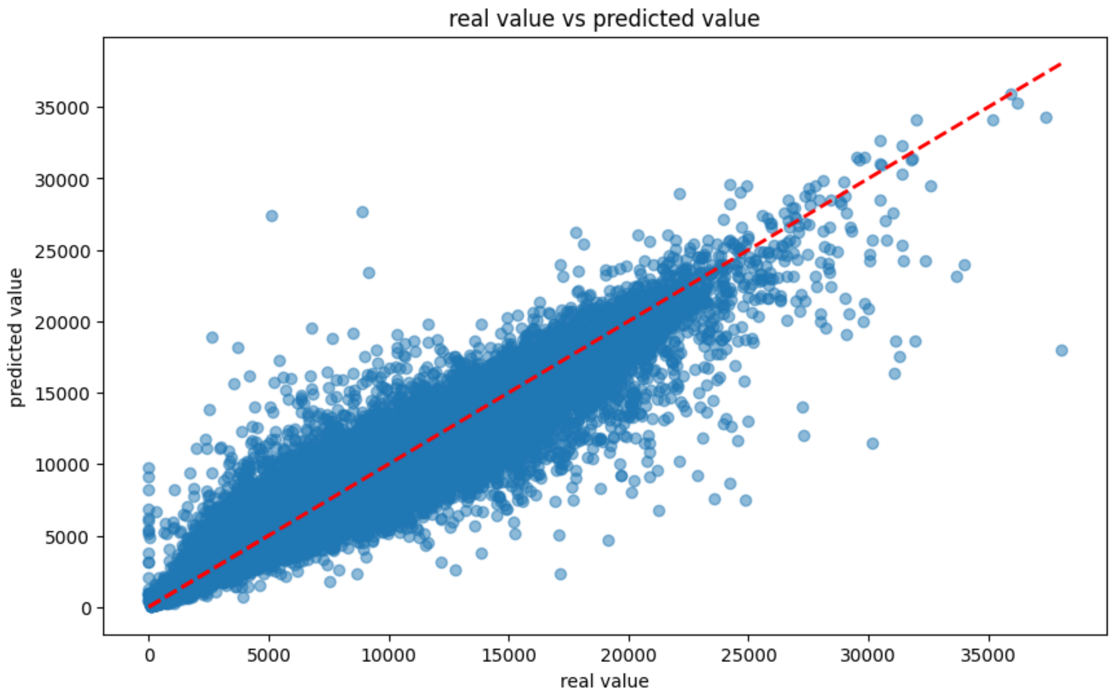
```
R² Score: 0.924
RMSPE: 25.92%

Feature Importance:
CompetitionDistance          0.202386
Store                        0.174246
Promo                        0.134207
CompetitionOpenSinceYear     0.074910
DayOfWeek                    0.074669
CompetitionOpenSinceMonth    0.066193
Day                          0.053915
Month                        0.049088
StoreType                    0.034265
Promo2SinceWeek              0.032457
Assortment                   0.030943
Promo2SinceYear              0.030317
Year                         0.017172
```

```
PromoInterval              0.013962
SchoolHoliday              0.006495
Promo2                     0.002620
StateHoliday               0.001777
HasCompetition             0.000377
Open                       0.000000
dtype: float64
```

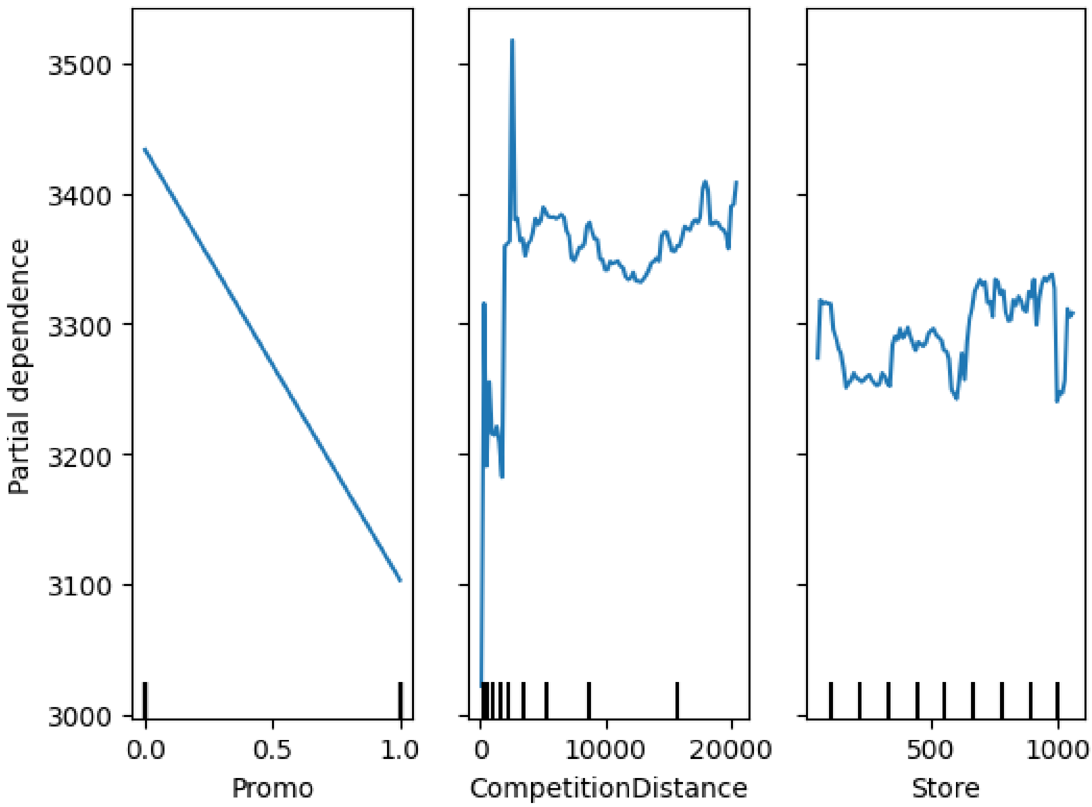


[86]:

```
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)


# Visualise the scatterplot of predicted and true values.
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--',␣
 ↪lw=2)
plt.xlabel('real value')
plt.ylabel('predicted value')
plt.title('real value vs predicted value')
plt.show()
```



[ ]:
```
# Partial dependency mapping
features2 = ['Promo', 'CompetitionDistance','Store']  # choose features to plot
PartialDependenceDisplay.from_estimator(rf, X_train, features2,
    feature_names=X_train.columns)
plt.show()
```

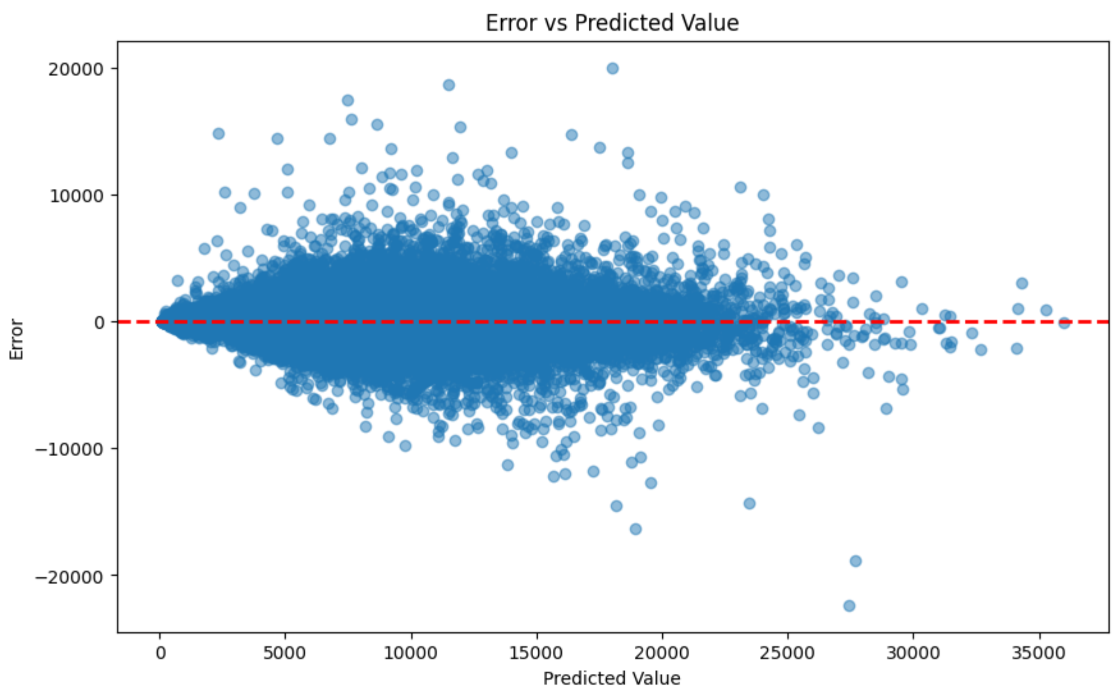



```
[ ]: def rmse_scorer(model, X, y):
         y_pred = model.predict(X)
         return np.sqrt(mean_squared_error(y, y_pred))

     #  cross validation
     cv_scores = cross_val_score(rf, X_train, y_train, cv=5, scoring=rmse_scorer)


     print(f"Std RMSE: {np.std(cv_scores):.2f}")


     # Prediction on the training set
     y_train_pred = rf.predict(X_train)
     rmspe_train = calculate_rmspe(y_train, y_train_pred)
     r2 = r2_score(y_train, y_train_pred)
     print(f"R² Score: {r2:.4f}")
     print(f"RMSPE: {rmspe_train:.2f}%")


     feature_importances = pd.Series(rf.feature_importances_,
```

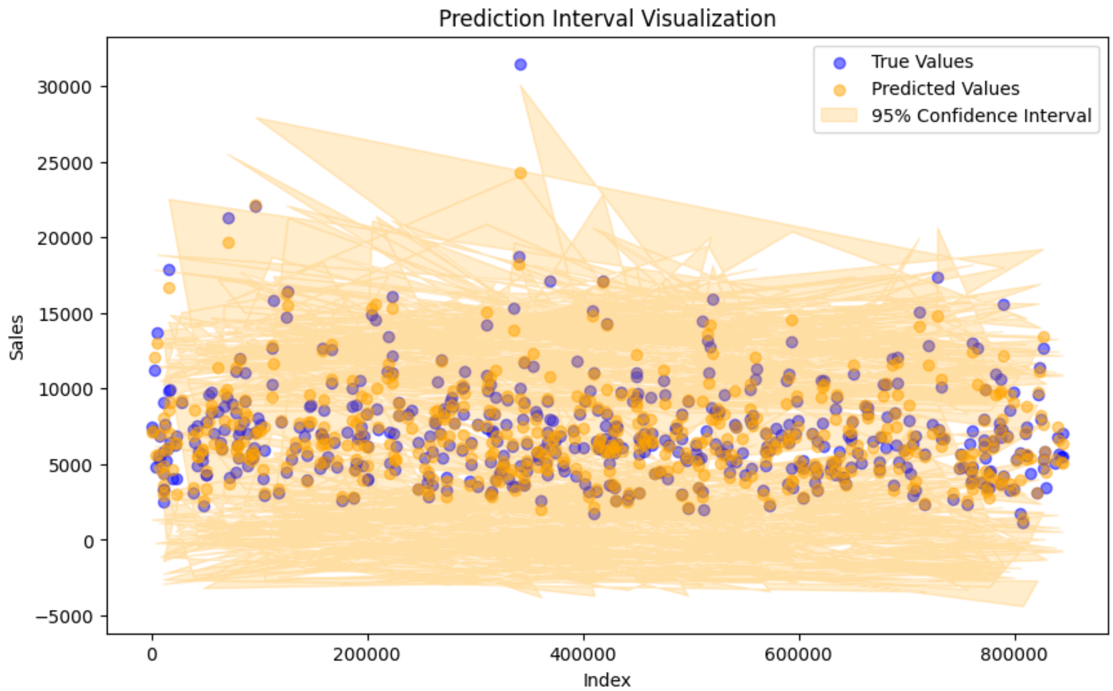
```
                              index=X_train.columns).
↪sort_values(ascending=False)


print("\nFeature Importances:")
for feature, importance in feature_importances.items():
    print(f"{feature:<25} {importance:.6f}")

print("\ndtype:", feature_importances.dtype)
```

```
Std RMSE: 2.92
R² Score: 0.9860
RMSPE: 20.66%

Feature Importances:
CompetitionDistance       0.202386
Store                     0.174246
Promo                     0.134207
CompetitionOpenSinceYear  0.074910
DayOfWeek                 0.074669
CompetitionOpenSinceMonth 0.066193
Day                       0.053915
Month                     0.049088
StoreType                 0.034265
Promo2SinceWeek           0.032457
Assortment                0.030943
Promo2SinceYear           0.030317
Year                      0.017172
PromoInterval             0.013962
SchoolHoliday             0.006495
Promo2                    0.002620
StateHoliday              0.001777
HasCompetition            0.000377
Open                      0.000000

dtype: float64
```

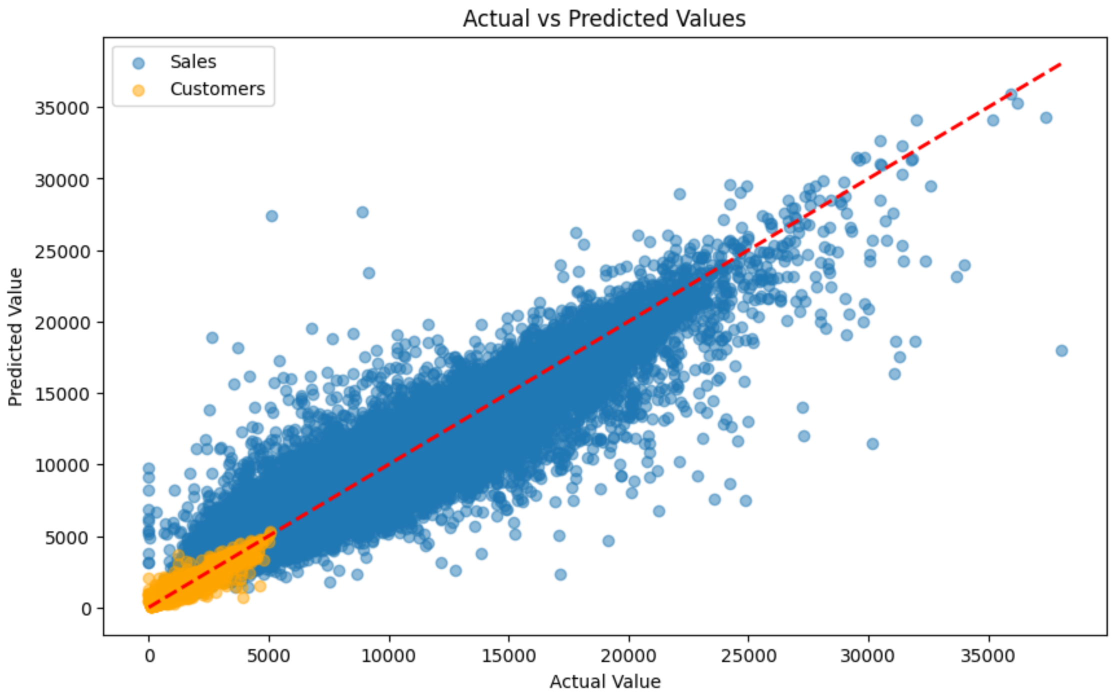
[ ]:
```
errors = y_test - y_pred

# Visualise the relationship between the forecast error and the forecast value.
plt.figure(figsize=(10, 6))
plt.scatter(y_pred, errors, alpha=0.5)
plt.axhline(y=0, color='r', linestyle='--', linewidth=2)
plt.xlabel('Predicted Value')
plt.ylabel('Error')
plt.title('Error vs Predicted Value')
plt.show()
```



[91]:
```
# Calculate the prediction intervals for 'Sales'
sales_pred = y_pred[:, 0]  # Select the 'Sales' predictions
predictions_mean = np.mean(sales_pred)
predictions_std = np.std(sales_pred)
confidence_interval = 1.96 * predictions_std  # 95% confidence interval

# Sample the data to reduce the number of markers
sampled_indices = np.linspace(0, len(y_test) - 1, 500, dtype=int)  # Sample 500␣
↪points

# Plot the prediction intervals
plt.figure(figsize=(10, 6))
plt.scatter(y_test.index[sampled_indices], y_test['Sales'].
↪iloc[sampled_indices], label='True Values', color='blue', alpha=0.5)
plt.scatter(y_test.index[sampled_indices], sales_pred[sampled_indices],␣
↪label='Predicted Values', color='orange', alpha=0.5)
plt.fill_between(y_test.index[sampled_indices], sales_pred[sampled_indices] -␣
↪confidence_interval, sales_pred[sampled_indices] + confidence_interval,␣
↪color='orange', alpha=0.2, label='95% Confidence Interval')
plt.xlabel('Index')
plt.ylabel('Sales')
plt.title('Prediction Interval Visualization')
plt.legend()
plt.show()
```




```
[ ]: # Visualisation of the relationship between actual and forecast values
plt.figure(figsize=(10, 6))
plt.scatter(y_test['Sales'], y_pred[:, 0], alpha=0.5, label='Sales')
plt.scatter(y_test['Customers'], y_pred[:, 1], alpha=0.5, label='Customers',␣
 ↪color='orange')
plt.plot([y_test['Sales'].min(), y_test['Sales'].max()], [y_test['Sales'].
 ↪min(), y_test['Sales'].max()], 'r--', lw=2)
plt.xlabel('Actual Value')
plt.ylabel('Predicted Value')
plt.title('Actual vs Predicted Values')
plt.legend()
plt.show()
```

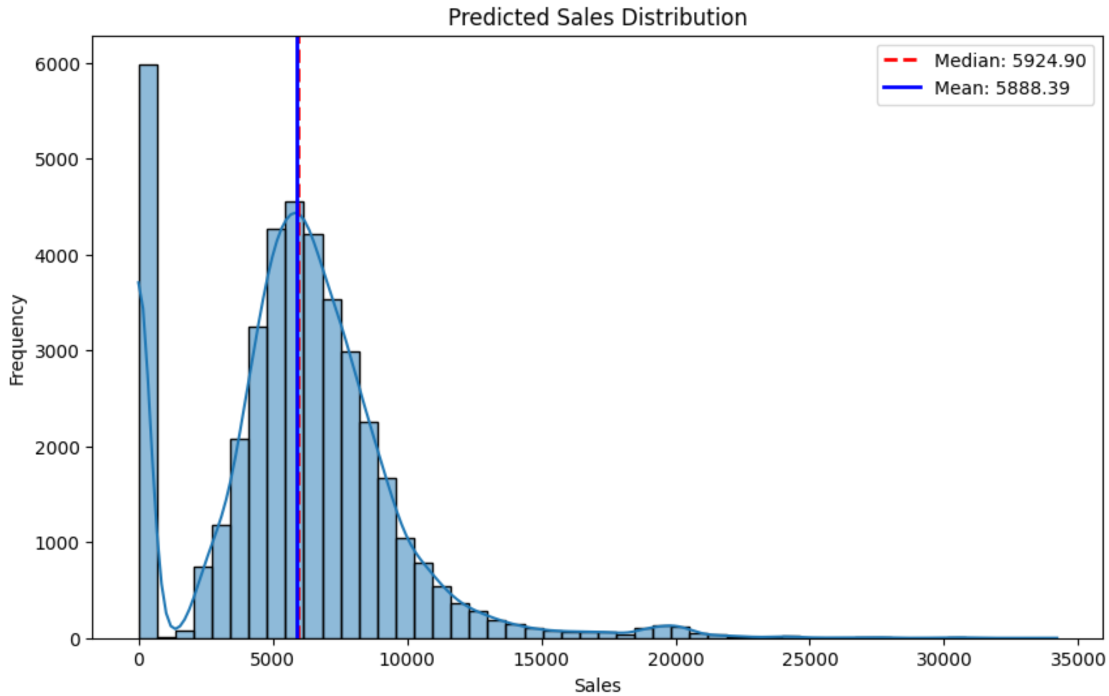


[93]:
```
test_or = pd.read_csv('test.csv')
```

[94]:
```
test_predictions = rf.predict(df2[features])

test_or.loc[test_or['Open'] == 0, ['Sales', 'Customers']] = 0

test_or.loc[test_or['Open'] == 1, ['Sales', 'Customers']] = test_predictions

test_or.to_csv('test_predictions.csv', index=False)
```

[ ]:
```
plt.figure(figsize=(10, 6))
sns.histplot(test_or['Sales'], bins=50, kde=True)
plt.title("Predicted Sales Distribution")
plt.xlabel("Sales")
plt.ylabel("Frequency")

median_sales = test_or['Sales'].median()
mean_sales = test_or['Sales'].mean()

plt.axvline(median_sales, color='red', linestyle='--', linewidth=2,␣
↪label=f'Median: {median_sales:.2f}')
plt.axvline(mean_sales, color='blue', linestyle='-', linewidth=2, label=f'Mean:␣
↪{mean_sales:.2f}')
```

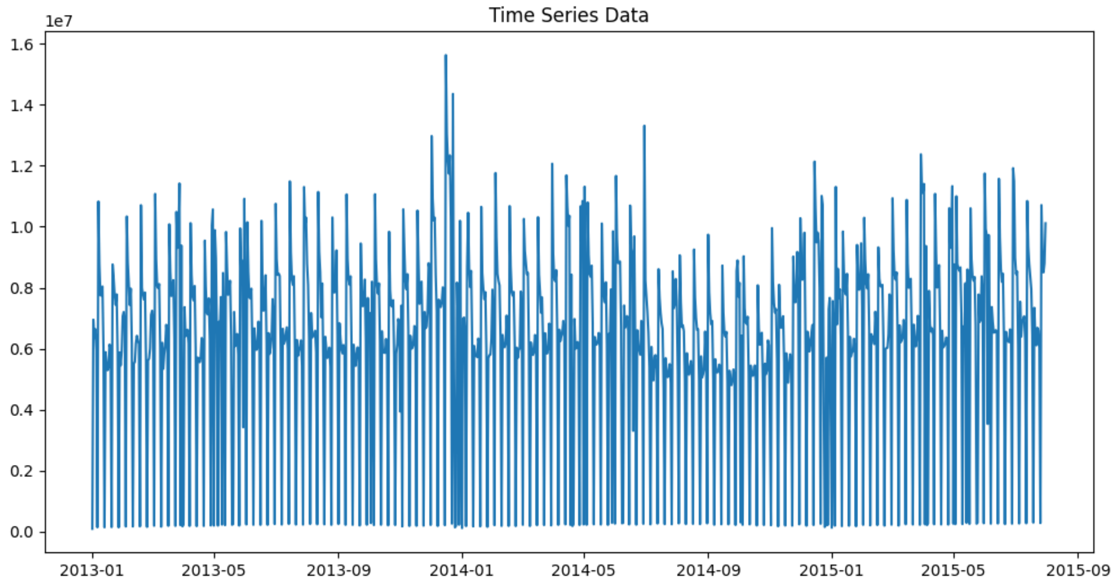
```python
plt.legend()

plt.show()
```



[105]:

```python
sales_data = train_df.groupby('Date')['Sales'].sum()

plt.figure(figsize=(12, 6))
plt.plot(sales_data)
plt.title('Time Series Data')
plt.show()

train_data = sales_data[:-12]
test_data = sales_data[-12:]


model = ARIMA(train_data, order=(5, 1, 0))
model_fit = model.fit()


predictions = model_fit.forecast(steps=len(test_data))


rmse = np.sqrt(mean_squared_error(test_data, predictions))
print(f'RMSE: {rmse}')
```

```python
plt.figure(figsize=(12, 6))
plt.plot(test_data, label='Actual')
plt.plot(predictions, label='Predicted')
plt.title('ARIMA predicted result')
plt.legend()
plt.show()
```




```
C:\Users\murui\AppData\Roaming\Python\Python311\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
C:\Users\murui\AppData\Roaming\Python\Python311\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
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C:\Users\murui\AppData\Roaming\Python\Python311\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
```
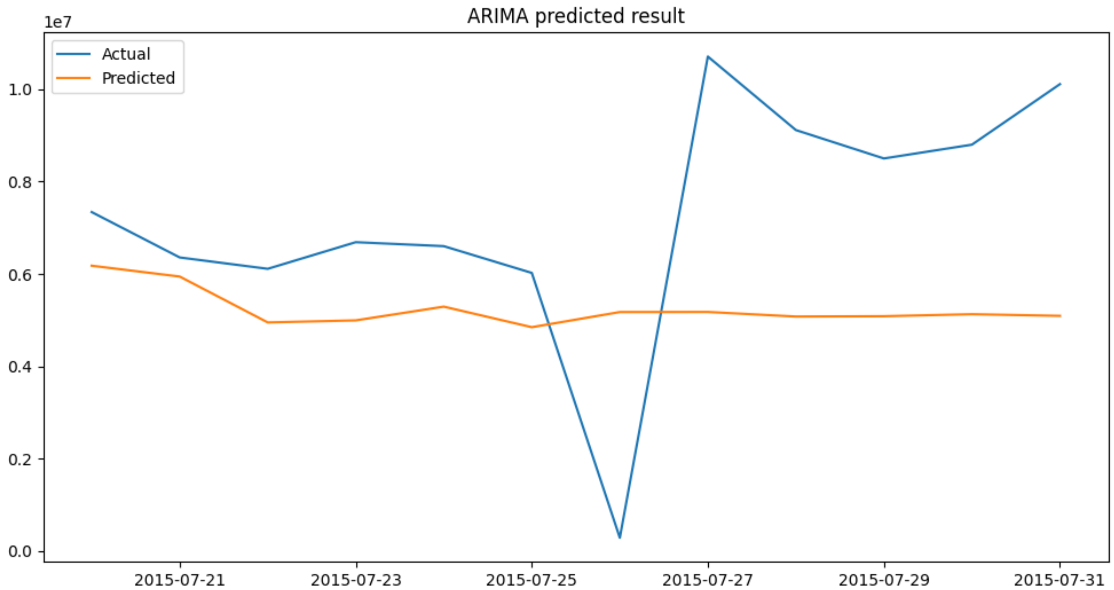

RMSE: 3290805.8900924935



[97]:
```
rmspe_train = calculate_rmspe(y_train, y_train_pred)
r2 = r2_score(y_train, y_train_pred)
print(f"R² Score: {r2:.4f}")
print(f"RMSPE: {rmspe_train:.2f}%")
```

```
R² Score: 0.9860
RMSPE: 20.66%
```

[98]:
```
# save document
doc.save('store_data_summary.docx')
```