Superstore Sales Analysis

This project analyzes sales data from a global superstore to uncover trends, profitability drivers, and actionable insights for business optimization.

Objective

- Analyze sales performance by region, category, and customer segment
- Identify high-profit and loss-making products
- Discover trends over time to assist in forecasting
- Provide data-driven business recommendations

Tools & Libraries

- Python, Pandas, Numpy
- Matplotlib, Seaborn, Plotly
- Jupyter Notebook

Project Workflow

1. **Import Libraries & Load Data**
2. **Data Overview & Cleaning**
3. **Exploratory Data Analysis (EDA)**
4. **Feature Engineering**
5. **Data Visualization**
6. **Insights & Recommendations**
7. **Conclusion**

1. Import Libraries & Load Data

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

In [2]:
```
df = pd.read_csv("C:/Users/Admin/Desktop/Superstore.csv", encoding='ISO-8859-1')
```

In [18]:
```python
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 23 columns):
 #   Column         Non-Null Count  Dtype         
---  ------         --------------  -----         
 0   Row ID         9994 non-null   int64         
 1   Order ID       9994 non-null   object        
 2   Order Date     9994 non-null   datetime64[ns]
 3   Ship Date      9994 non-null   datetime64[ns]
 4   Ship Mode      9994 non-null   object        
 5   Customer ID    9994 non-null   object        
 6   Customer Name  9994 non-null   object        
 7   Segment        9994 non-null   object        
 8   Country        9994 non-null   object        
 9   City           9994 non-null   object        
 10  State          9994 non-null   object        
 11  Postal Code    9994 non-null   int64         
 12  Region         9994 non-null   object        
 13  Product ID     9994 non-null   object        
 14  Category       9994 non-null   object        
 15  Sub-Category   9994 non-null   object        
 16  Product Name   9994 non-null   object        
 17  Sales          9994 non-null   float64       
 18  Quantity       9994 non-null   int64         
 19  Discount       9994 non-null   float64       
 20  Profit         9994 non-null   float64       
 21  Month-Year     9994 non-null   object        
 22  Delivery Time  9994 non-null   int64         
dtypes: datetime64[ns](2), float64(3), int64(4), object(14)
memory usage: 1.8+ MB
None
```

In [4]:
```python
# Check the shape of the dataset (rows, columns)
print(df.shape)

# View basic statistics for numerical columns
print(df.describe())
```

```
(9994, 21)
            Row ID   Postal Code         Sales     Quantity     Discount  \
count  9994.000000   9994.000000   9994.000000  9994.000000  9994.000000
mean   4997.500000  55190.379428    229.858001     3.789574     0.156203
std    2885.163629  32063.693350    623.245101     2.225110     0.206452
min       1.000000   1040.000000      0.444000     1.000000     0.000000
25%    2499.250000  23223.000000     17.280000     2.000000     0.000000
50%    4997.500000  56430.500000     54.490000     3.000000     0.200000
75%    7495.750000  90008.000000    209.940000     5.000000     0.200000
max    9994.000000  99301.000000  22638.480000    14.000000     0.800000

            Profit
count  9994.000000
mean     28.656896
std     234.260108
min   -6599.978000
25%       1.728750
50%       8.666500
75%      29.364000
max    8399.976000
```

CHECKING FOR NULL VALUES

In [5]:
```
# Check for missing values in each column
print(df.isnull().sum())
```

```
Row ID           0
Order ID         0
Order Date       0
Ship Date        0
Ship Mode        0
Customer ID      0
Customer Name    0
Segment          0
Country          0
City             0
State            0
Postal Code      0
Region           0
Product ID       0
Category         0
Sub-Category     0
Product Name     0
Sales            0
Quantity         0
Discount         0
Profit           0
dtype: int64
```

CHECKING FOR DUPLICATE VALUES

In [6]:
```
# Check for duplicate rows
duplicate_rows = df[df.duplicated()]

# Optionally, view the duplicates
print(duplicate_rows)
```

```
Empty DataFrame
Columns: [Row ID, Order ID, Order Date, Ship Date, Ship Mode, Customer ID, Customer Name, Segment, Country,
City, State, Postal Code, Region, Product ID, Category, Sub-Category, Product Name, Sales, Quantity, Discoun
t, Profit]
Index: []

[0 rows x 21 columns]
```

MONTHLY TOTAL SALES OVER TIME (LINE CHART)

In [8]:
```
df['Order Date'] = pd.to_datetime(df['Order Date'])
df['Ship Date'] = pd.to_datetime(df['Ship Date'])
```

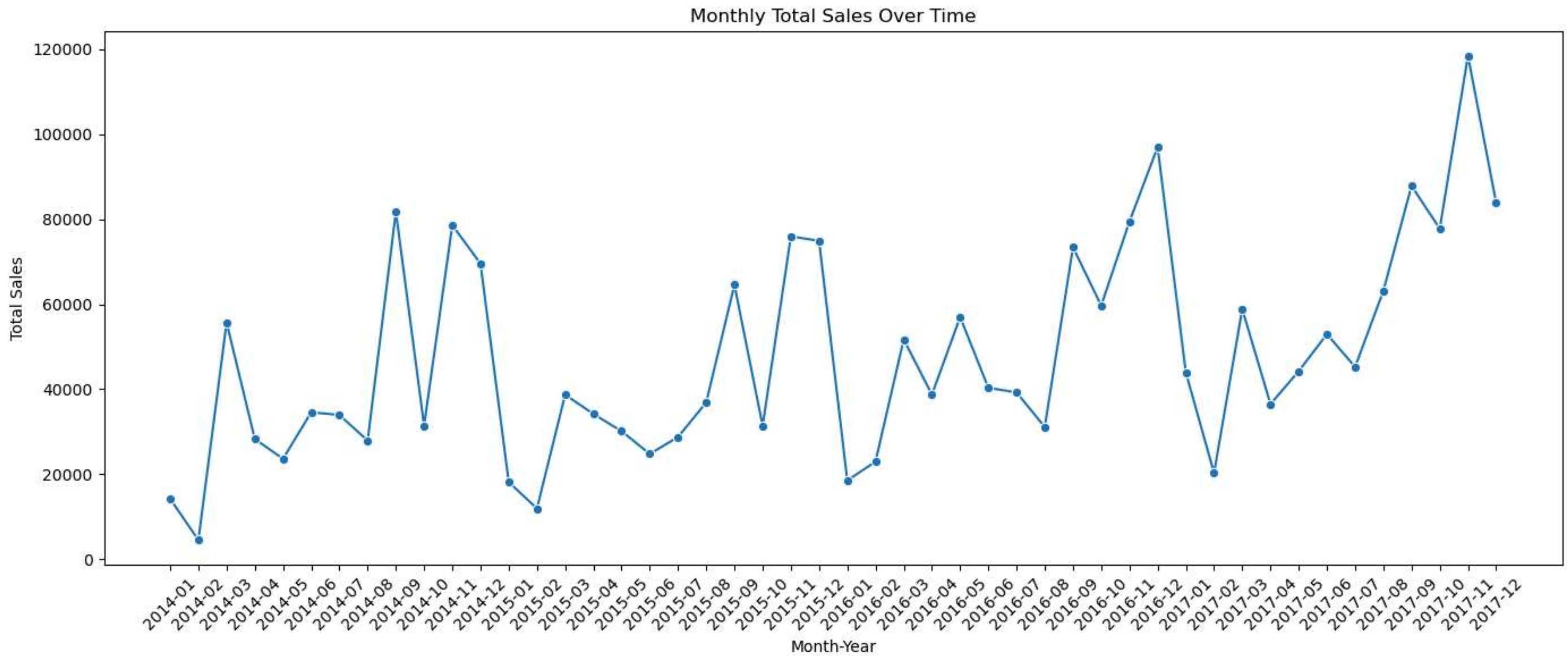
In [10]:

```python
# Create 'Month-Year' column
df['Month-Year'] = df['Order Date'].dt.to_period('M').astype(str)

# Aggregate sales
monthly_sales = df.groupby('Month-Year')['Sales'].sum().reset_index()

# Plot
plt.figure(figsize=(14,6))
sns.lineplot(data=monthly_sales, x='Month-Year', y='Sales', marker='o')
plt.xticks(rotation=45)
plt.title('Monthly Total Sales Over Time')
plt.xlabel('Month-Year')
plt.ylabel('Total Sales')
plt.tight_layout()
plt.show()
```

```
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is
deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Admin\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is
deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



Monthly Total Sales Over Time
Total Sales
Month-Year
0
20000
40000
60000
80000
100000
120000
2014-01
2014-02
2014-03
2014-04
2014-05
2014-06
2014-07
2014-08
2014-09
2014-10
2014-11
2014-12
2015-01
2015-02
2015-03
2015-04
2015-05
2015-06
2015-07
2015-08
2015-09
2015-10
2015-11
2015-12
2016-01
2016-02
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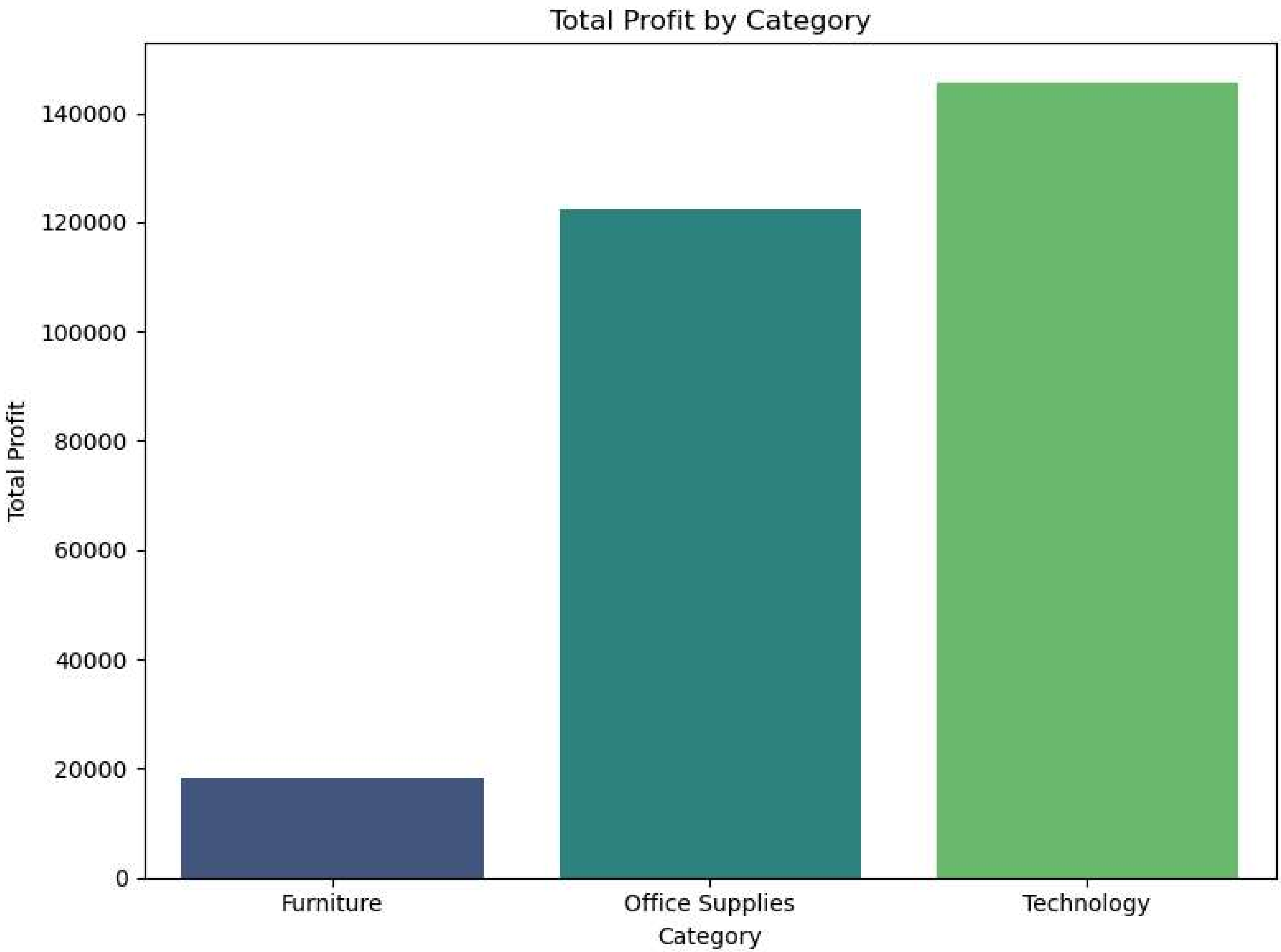
2016-04
2016-05
2016-06
2016-07
2016-08
2016-09
2016-10
2016-11
2016-12
2017-01
2017-02
2017-03
2017-04
2017-05
2017-06
2017-07
2017-08
2017-09
2017-10
2017-11
2017-12

TOTAL PROFIT BY CATEGORY (BAR CHART)

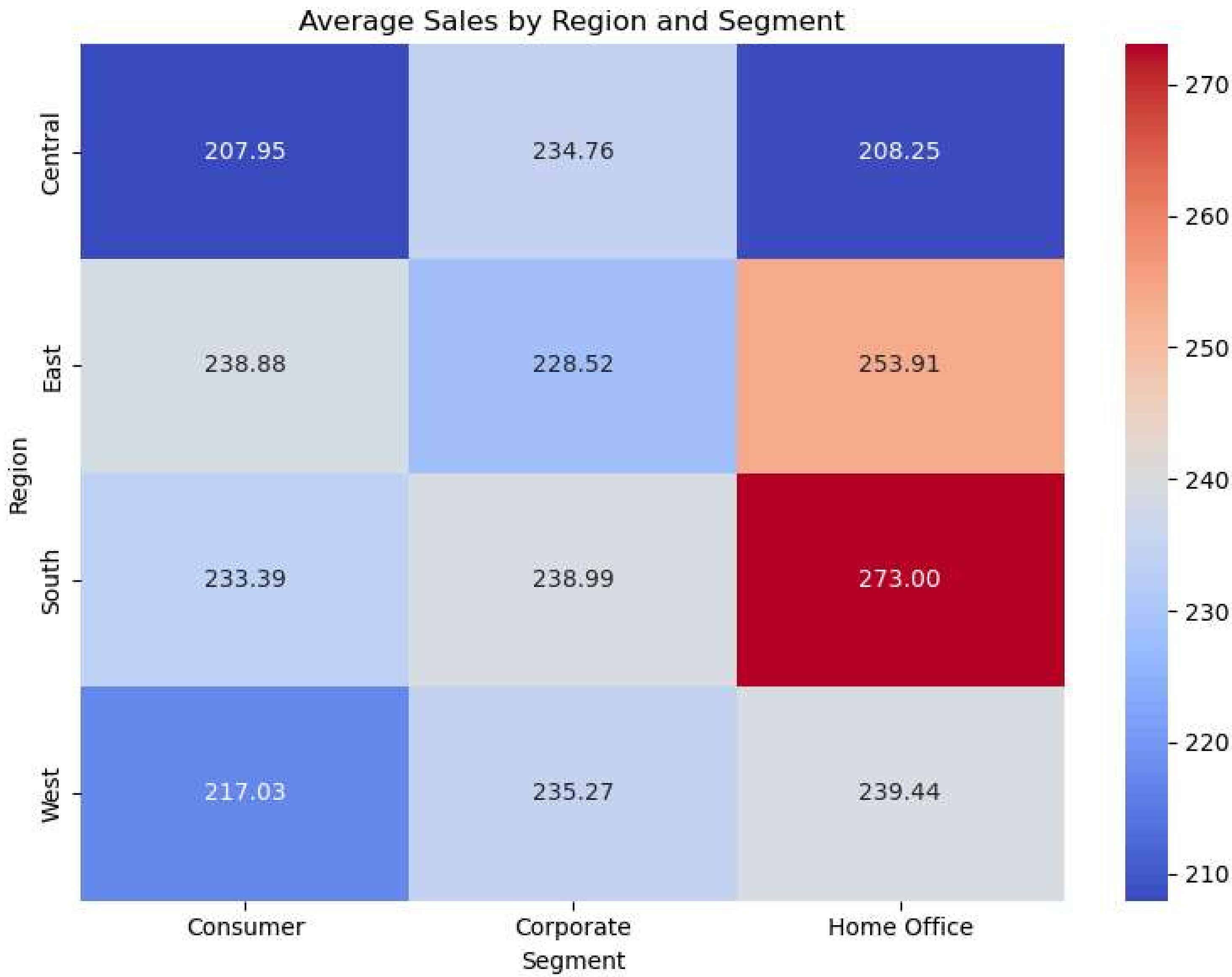
In [11]:
```
category_profit = df.groupby('Category')['Profit'].sum().reset_index()

plt.figure(figsize=(8,6))
sns.barplot(data=category_profit, x='Category', y='Profit', palette='viridis')
plt.title('Total Profit by Category')
plt.xlabel('Category')
plt.ylabel('Total Profit')
plt.tight_layout()
plt.show()
```


Total Profit by Category
140000
120000
100000
80000
60000
40000
20000
0
Total Profit
Furniture
Office Supplies
Technology
Category

AVERAGE SALES BY REGION AND SEGMENT (HEAT MAP)

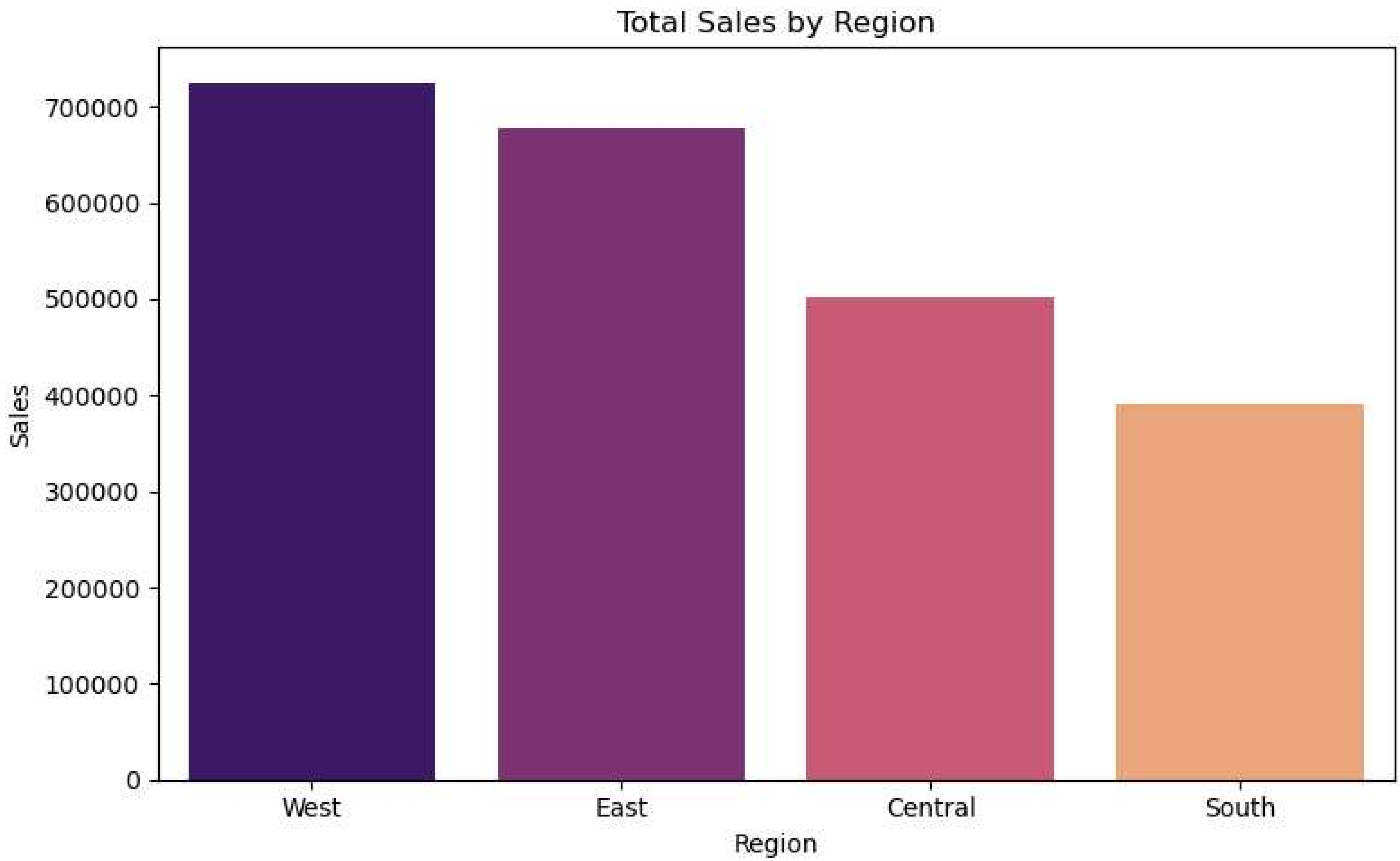
In [12]:

```
region_segment_sales = df.groupby(['Region', 'Segment'])['Sales'].mean().unstack()

plt.figure(figsize=(8,6))
sns.heatmap(region_segment_sales, annot=True, fmt=".2f", cmap='coolwarm')
plt.title('Average Sales by Region and Segment')
plt.xlabel('Segment')
plt.ylabel('Region')
plt.tight_layout()
plt.show()
```


Average Sales by Region and Segment
Central
East
South
West
Region
Consumer
Corporate
Home Office
Segment
207.95
234.76
208.25
238.88
228.52
253.91
233.39
238.99
273.00
217.03
235.27
239.44
270
260
250
240
230
220
210

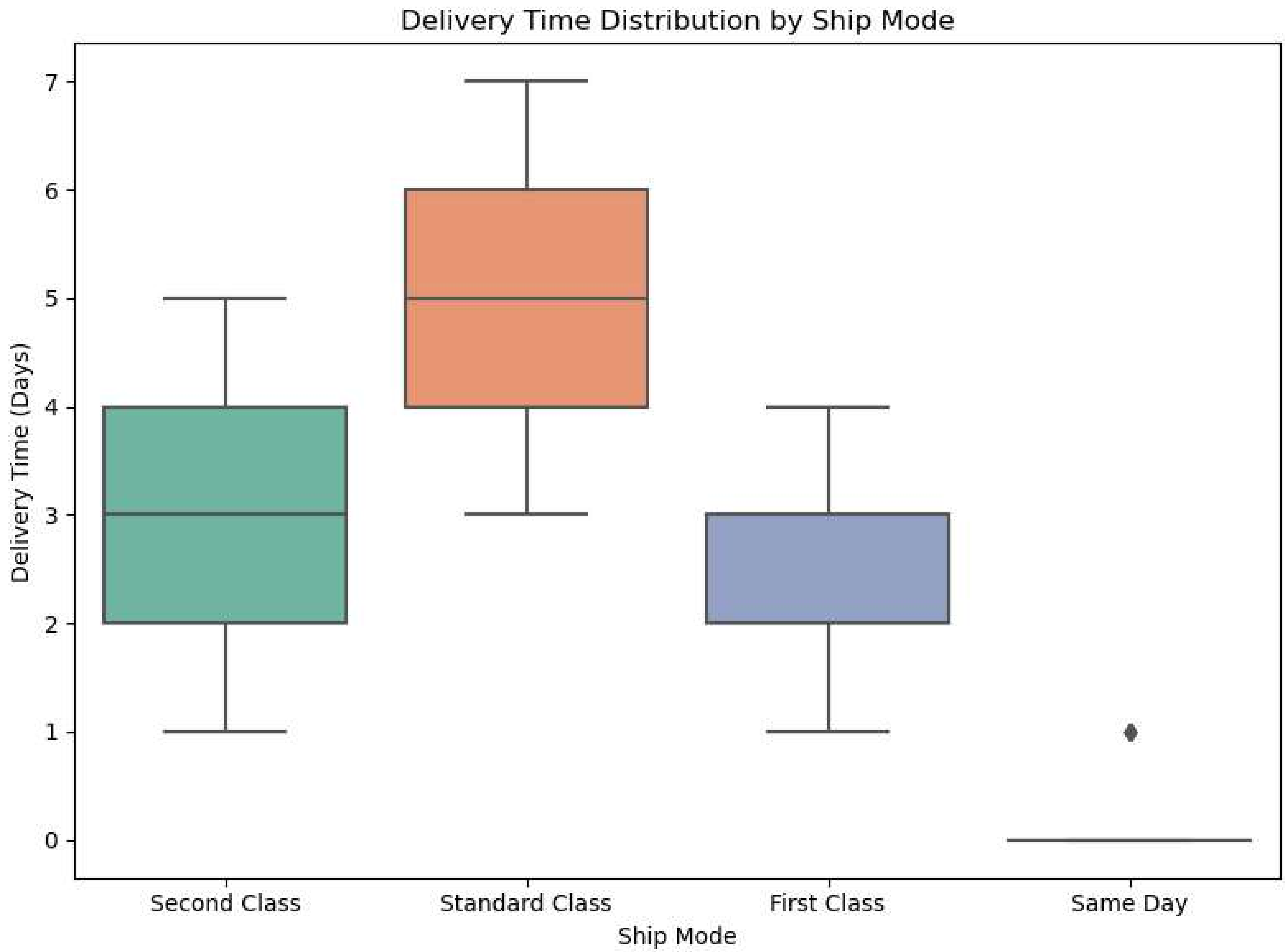
TOTAL SALES BY REGION

In [13]:
```
# Sales by Region
region_sales = df.groupby('Region')['Sales'].sum().sort_values(ascending=False)

plt.figure(figsize=(8, 5))
sns.barplot(x=region_sales.index, y=region_sales.values, palette='magma')
plt.title("Total Sales by Region")
plt.ylabel("Sales")
plt.xlabel("Region")
plt.tight_layout()
plt.show()
```


Total Sales by Region
700000
600000
500000
400000
300000
200000
100000
0
Sales
West
East
Central
South
Region

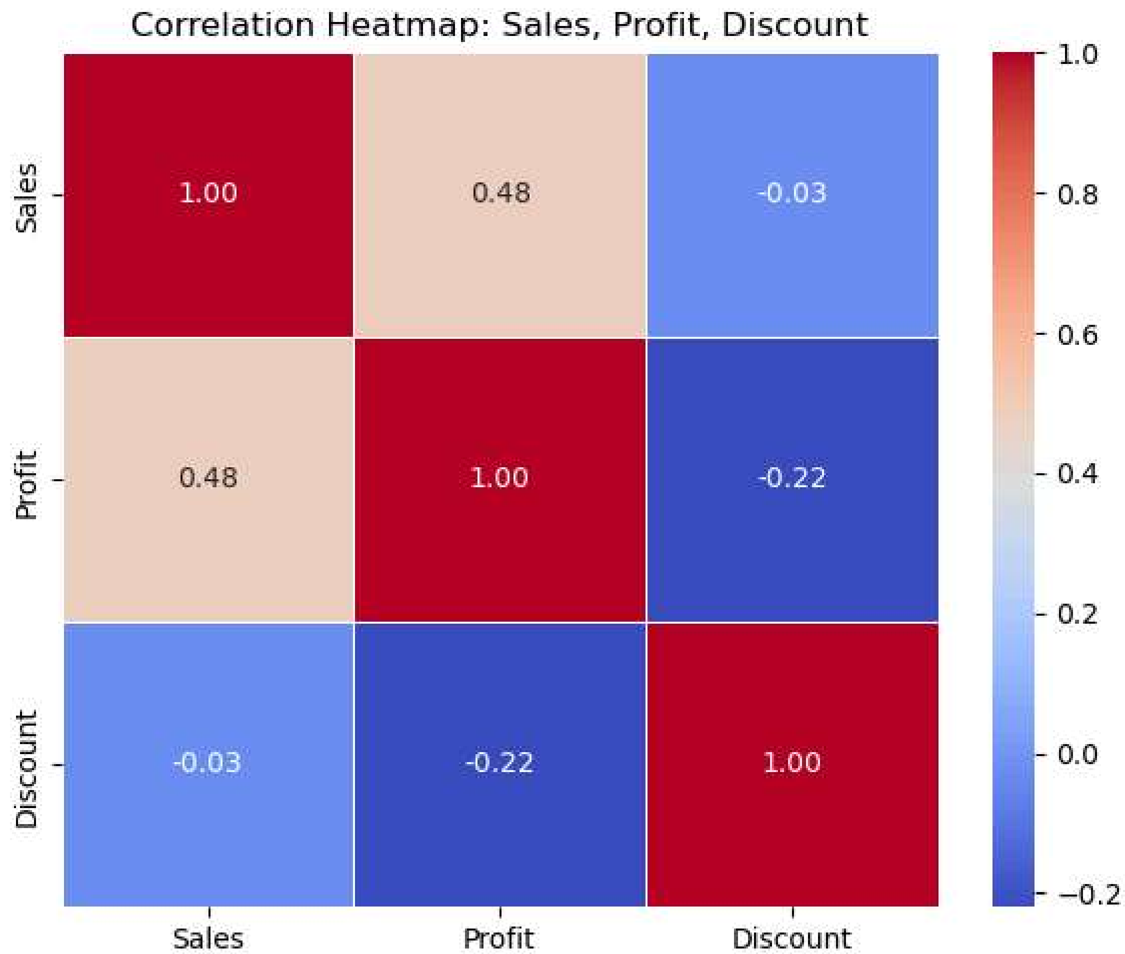
DELIVERY TIME DISTRIBUTION BY SHIP MODE

In [14]:
```
# datetime conversion
df['Order Date'] = pd.to_datetime(df['Order Date'])
df['Ship Date'] = pd.to_datetime(df['Ship Date'])

# Calculate delivery time
df['Delivery Time'] = (df['Ship Date'] - df['Order Date']).dt.days

# Plot boxplot
plt.figure(figsize=(8,6))
sns.boxplot(data=df, x='Ship Mode', y='Delivery Time', palette='Set2')
plt.title('Delivery Time Distribution by Ship Mode')
plt.xlabel('Ship Mode')
plt.ylabel('Delivery Time (Days)')
plt.tight_layout()
plt.show()
```


Delivery Time Distribution by Ship Mode
Delivery Time (Days)
0
1
2
3
4
5
6
7
Second Class
Standard Class
First Class
Same Day
Ship Mode

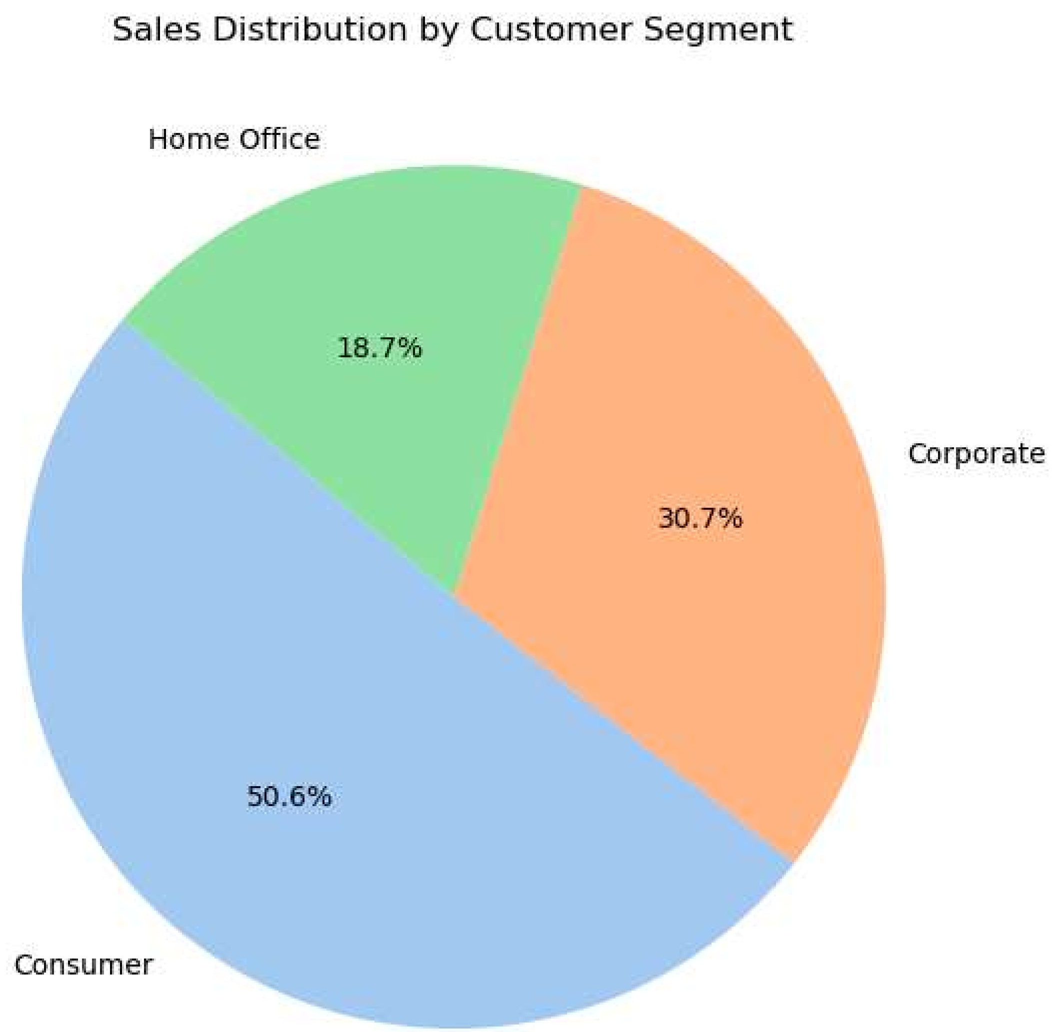
CORRELATION BETWEEN: SALES, PROFIT AND DISCOUNT

In [15]:
```
# Select relevant columns
corr_data = df[['Sales', 'Profit', 'Discount']]

# Compute correlation matrix
corr_matrix = corr_data.corr()

plt.figure(figsize=(6, 5))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title("Correlation Heatmap: Sales, Profit, Discount")
plt.tight_layout()
plt.show()
```


Correlation Heatmap: Sales, Profit, Discount
Sales
Profit
Discount
1.00
0.48
-0.03
0.48
1.00
-0.22
-0.03
-0.22
1.00
Sales
Profit
Discount
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

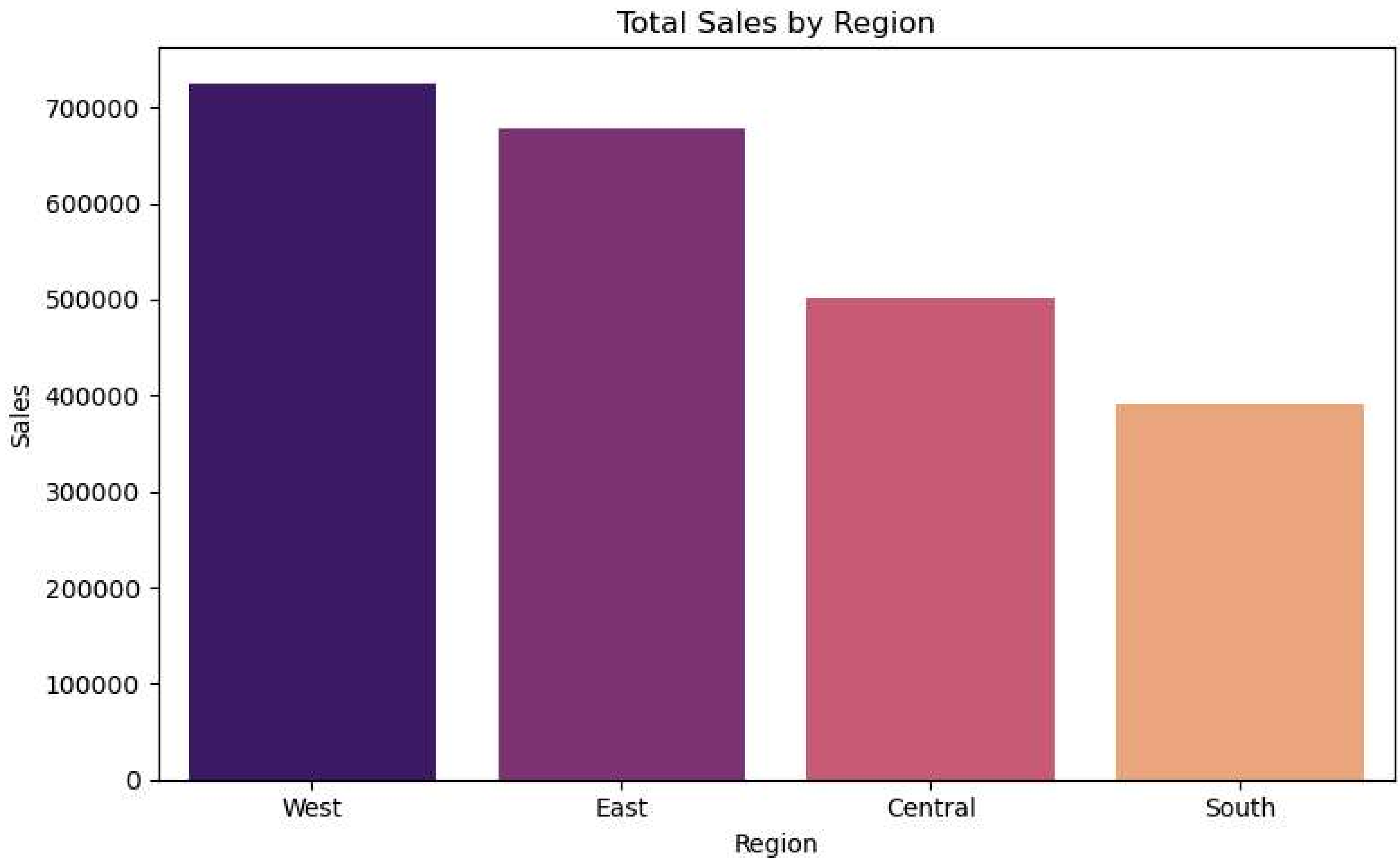
SALES BY SEGMENT

In [16]:
```
# Sales by Segment
segment_sales = df.groupby('Segment')['Sales'].sum()

plt.figure(figsize=(6, 6))
plt.pie(segment_sales, labels=segment_sales.index, autopct='%1.1f%%', startangle=140, colors=sns.color_palette
plt.title("Sales Distribution by Customer Segment")
plt.tight_layout()
plt.show()
```


Sales Distribution by Customer Segment
Home Office
18.7%
Corporate
30.7%
50.6%
Consumer

In [17]:

```
# Sales by Region
region_sales = df.groupby('Region')['Sales'].sum().sort_values(ascending=False)

plt.figure(figsize=(8, 5))
sns.barplot(x=region_sales.index, y=region_sales.values, palette='magma')
plt.title("Total Sales by Region")
plt.ylabel("Sales")
plt.xlabel("Region")
plt.tight_layout()
plt.show()
```



Conclusion & Key Insights

- The **West region** showed the highest profit margins, while **Central** had higher losses.
- **Technology** and **Office Supplies** categories were the most profitable overall.
- Discounts beyond 30% significantly reduced profitability.
- Customer Segment **Corporate** yielded the highest profit-to-sales ratio.
- Recommendation: Optimize discounts and focus marketing on high-margin categories.

```
In [ ]:
```