SUPERSTORE ANALYSIS

1. Importing necessary libraries and the dataset

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

[2]:
```
df = pd.read_csv("C:/Users/kunal/Downloads/Superstore.csv", encoding="latin1")
```

[3]:
```
df.head()
```

[3]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	\
0	1	CA-2016-152156	11/8/2016	11/11/2016	Second Class	CG-12520	
1	2	CA-2016-152156	11/8/2016	11/11/2016	Second Class	CG-12520	
2	3	CA-2016-138688	6/12/2016	6/16/2016	Second Class	DV-13045	
3	4	US-2015-108966	10/11/2015	10/18/2015	Standard Class	SO-20335	
4	5	US-2015-108966	10/11/2015	10/18/2015	Standard Class	SO-20335	

	Customer Name	Segment	Country	City	...	\
0	Claire Gute	Consumer	United States	Henderson	...	
1	Claire Gute	Consumer	United States	Henderson	...	
2	Darrin Van Huff	Corporate	United States	Los Angeles	...	
3	Sean O'Donnell	Consumer	United States	Fort Lauderdale	...	
4	Sean O'Donnell	Consumer	United States	Fort Lauderdale	...	

	Postal Code	Region	Product ID	Category	Sub-Category	\
0	42420	South	FUR-BO-10001798	Furniture	Bookcases	
1	42420	South	FUR-CH-10000454	Furniture	Chairs	
2	90036	West	OFF-LA-10000240	Office Supplies	Labels	
3	33311	South	FUR-TA-10000577	Furniture	Tables	
4	33311	South	OFF-ST-10000760	Office Supplies	Storage	

	Product Name	Sales	Quantity	\
0	Bush Somerset Collection Bookcase	261.9600	2	
1	Hon Deluxe Fabric Upholstered Stacking Chairs,...	731.9400	3	
2	Self-Adhesive Address Labels for Typewriters b...	14.6200	2	
3	Bretford CR4500 Series Slim Rectangular Table	957.5775	5	

```
4                    Eldon Fold 'N Roll Cart System    22.3680         2
```

```
   Discount     Profit
0      0.00    41.9136
1      0.00   219.5820
2      0.00     6.8714
3      0.45  -383.0310
4      0.20     2.5164

[5 rows x 21 columns]
```

2. Understanding the Structure of the Dataset

[4]:
```
# Check the dimensions of the DataFrame
print("Dimensions of the DataFrame:", df.shape)
```

```
Dimensions of the DataFrame: (9994, 21)
```

[5]:
```
# Check the data types of each column
print("\nData types of each column:")
print(df.dtypes)
```

```
Data types of each column:
Row ID            int64
Order ID         object
Order Date       object
Ship Date        object
Ship Mode        object
Customer ID      object
Customer Name    object
Segment          object
Country          object
City             object
State            object
Postal Code       int64
Region           object
Product ID       object
Category         object
Sub-Category     object
Product Name     object
Sales           float64
Quantity          int64
Discount        float64
Profit          float64
dtype: object
```

[6]:
```
# Check for any missing values
print("\nMissing values in the dataset:")
print(df.isnull().sum())
```

```
Missing values in the dataset:
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
```

[7]:
```
print("\nSummary statistics for numerical columns:")
print(df.describe())
```

```
Summary statistics for numerical columns:
             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
```

3. Exploratory Data Analysis (EDA)

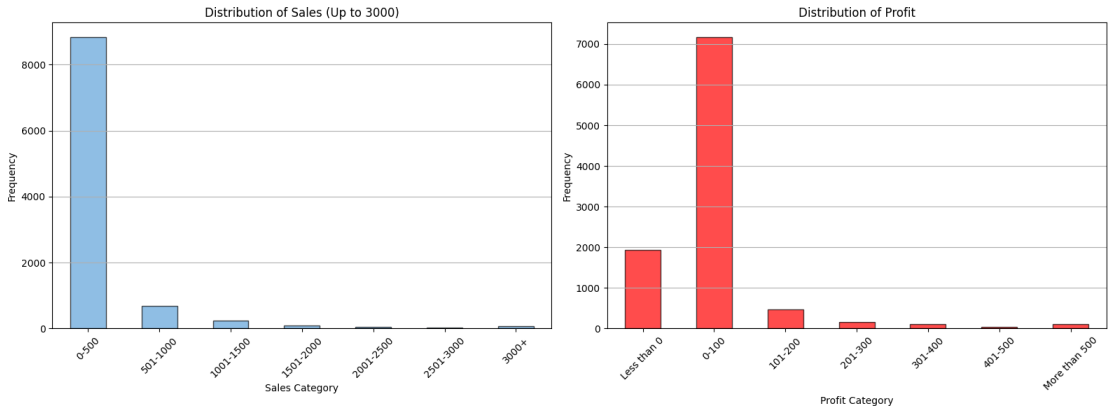
3.1 Distribution of sales and profit

[8]:
```
# Displaying some data related to the bar plots
print("\nData related to the sales and profit distributions:")
print(df[['Sales', 'Profit']].head(10))
```

```
Data related to the sales and profit distributions:
      Sales     Profit
0  261.9600   41.9136
1  731.9400  219.5820
2   14.6200    6.8714
3  957.5775 -383.0310
4   22.3680    2.5164
5   48.8600   14.1694
6    7.2800    1.9656
7  907.1520   90.7152
8   18.5040    5.7825
9  114.9000   34.4700
```

[9]:
```
# Define bins for sales categories
sales_bins = [0, 500, 1000, 1500, 2000, 2500, 3000, np.inf]
sales_labels = ['0-500', '501-1000', '1001-1500', '1501-2000', '2001-2500',␣
↪'2501-3000', '3000+']

# Bin the sales values into categories
df['Sales Category'] = pd.cut(df['Sales'], bins=sales_bins,␣
↪labels=sales_labels, right=False)

# Group the data by sales category and count the number of occurrences
sales_distribution = df['Sales Category'].value_counts().sort_index()

# Define bins for profit categories
profit_bins = [-np.inf, 0, 100, 200, 300, 400, 500, np.inf]
profit_labels = ['Less than 0', '0-100', '101-200', '201-300', '301-400',␣
↪'401-500', 'More than 500']

# Bin the profit values into categories
```

```
df['Profit Category'] = pd.cut(df['Profit'], bins=profit_bins,␣
↪labels=profit_labels)

# Group the data by profit category and count the number of occurrences
profit_distribution = df['Profit Category'].value_counts().sort_index()

# Create subplots for side-by-side bar plots
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(16, 6))

# Plot bar plot for the distribution of Sales
sales_distribution.plot(kind='bar', color='#60A3D9', alpha=0.7,␣
↪edgecolor='black', ax=axes[0])
axes[0].set_title('Distribution of Sales (Up to 3000)')
axes[0].set_xlabel('Sales Category')
axes[0].set_ylabel('Frequency')
axes[0].set_xticklabels(sales_distribution.index, rotation=45)
axes[0].grid(axis='y')

# Plot bar plot for the distribution of Profit
profit_distribution.plot(kind='bar', color='red', alpha=0.7, edgecolor='black',␣
↪ax=axes[1])
axes[1].set_title('Distribution of Profit')
axes[1].set_xlabel('Profit Category')
axes[1].set_ylabel('Frequency')
axes[1].set_xticklabels(profit_distribution.index, rotation=45)
axes[1].grid(axis='y')

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

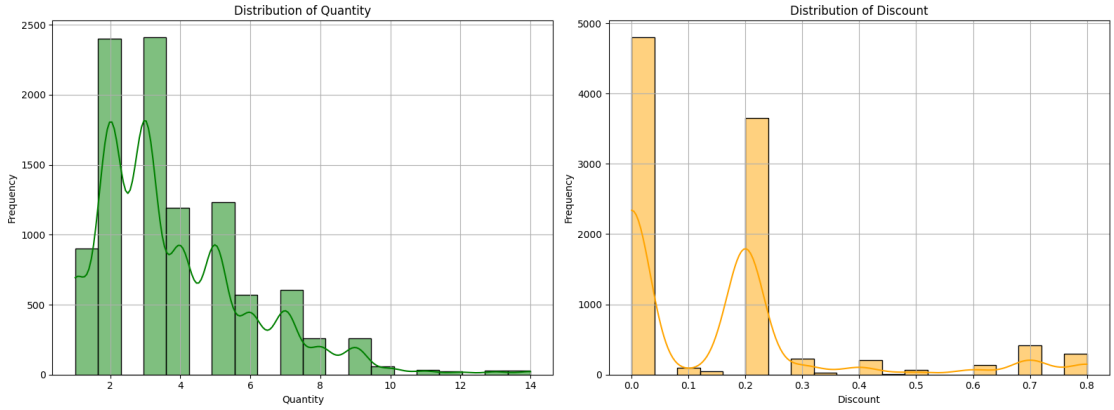


3.2 Distribution of Quantity and Discount

[10]:
```
# Displaying some data related to the histograms
print("Data related to the histograms:")
print(df[['Quantity', 'Discount']].head(10))
```

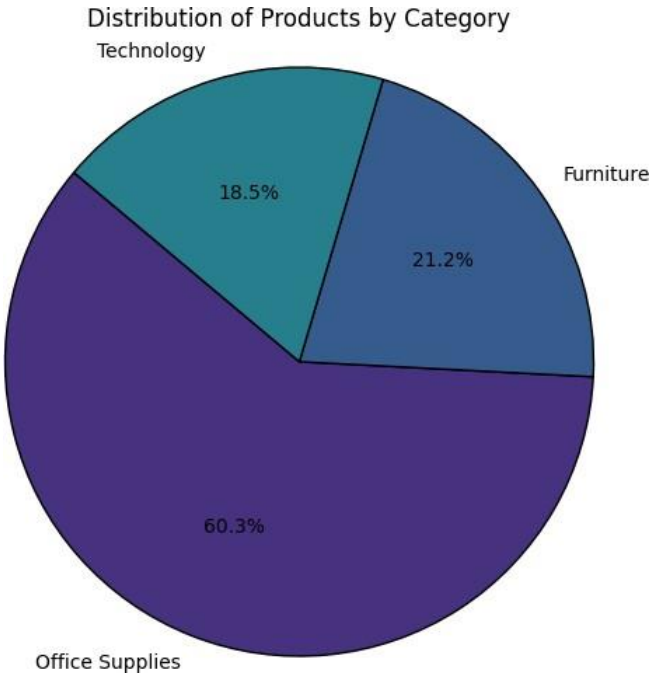
```
Data related to the histograms:
   Quantity  Discount
0         2      0.00
1         3      0.00
2         2      0.00
3         5      0.45
4         2      0.20
5         7      0.00
6         4      0.00
7         6      0.20
8         3      0.20
9         5      0.00
```

[11]:
```
# Create subplots for side-by-side histograms
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(16, 6))

# Plot histogram for the distribution of Quantity sns.histplot(df['Quantity'],
bins=20, kde=True, color='green', ax=axes[0])
axes[0].set_title('Distribution of Quantity')
axes[0].set_xlabel('Quantity')
axes[0].set_ylabel('Frequency')
axes[0].grid(True)

# Plot histogram for the distribution of Discount sns.histplot(df['Discount'],
bins=20, kde=True, color='orange', ax=axes[1])
axes[1].set_title('Distribution of Discount')
axes[1].set_xlabel('Discount')
axes[1].set_ylabel('Frequency')
axes[1].grid(True)

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



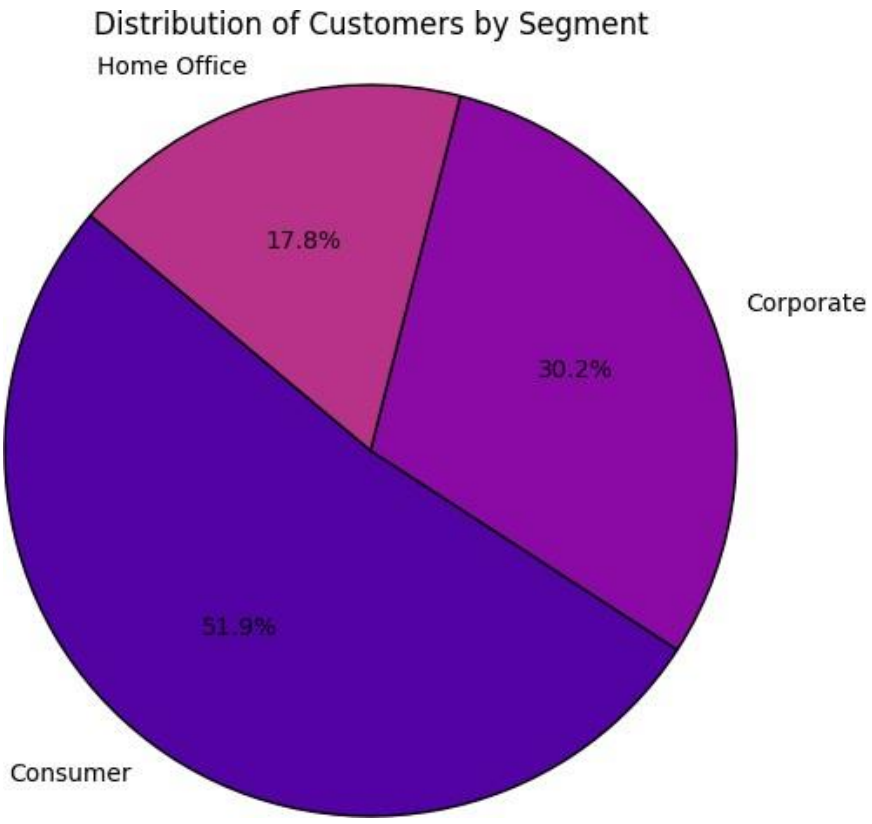
3.3 Distribution of Products by category

[12]:
```
category_distribution = df['Category'].value_counts()
# Plot pie chart for the distribution of Category
plt.figure(figsize=(10, 6))
plt.pie(category_distribution, labels=category_distribution.index, autopct='%1.
↪1f%%', colors=sns.color_palette('viridis'), startangle=140,␣
↪wedgeprops={'edgecolor': 'black'})
plt.title('Distribution of Products by Category')
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle
plt.show()
```



3.4 Distribution of Customers by segment

[13]:
```
segment_distribution = df['Segment'].value_counts()
# Plot pie chart for the distribution of Segment
plt.figure(figsize=(8, 6))
plt.pie(segment_distribution, labels=segment_distribution.index, autopct='%1.
↪1f%%', colors=sns.color_palette('plasma'), startangle=140,␣
↪wedgeprops={'edgecolor': 'black'})
plt.title('Distribution of Customers by Segment')
plt.axis('equal')
plt.show()
```

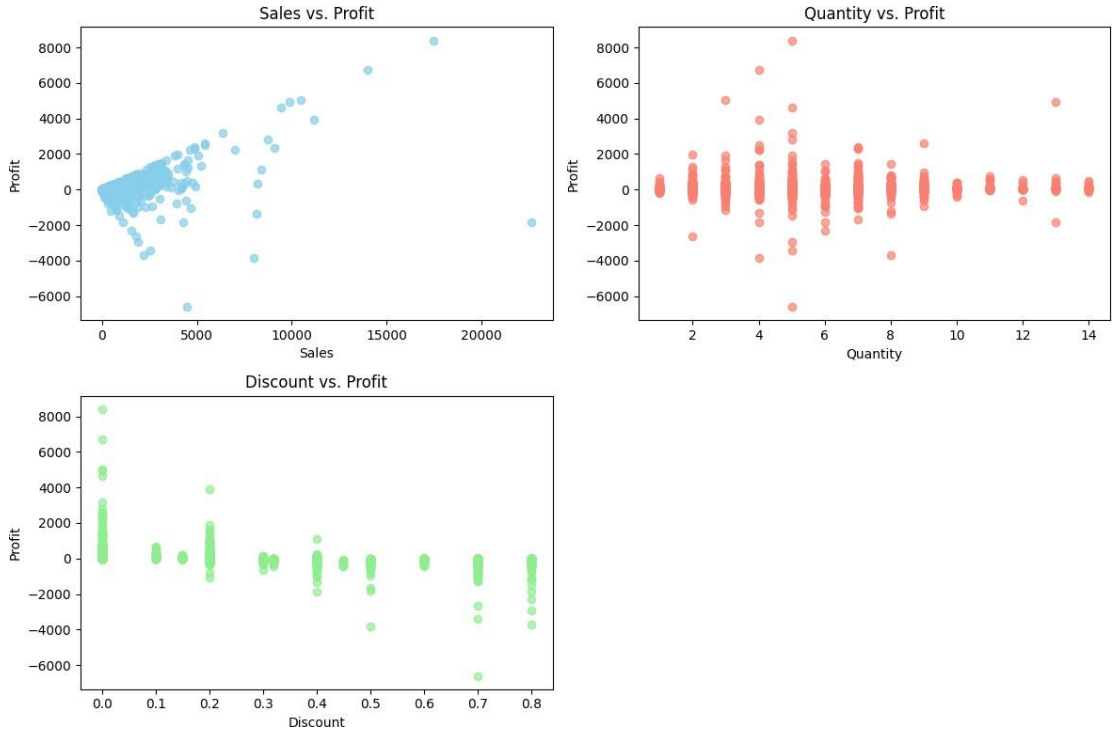


3.5 Scatter plots for numerical variables

[14]:
```
# Displaying some data related to the scatter plots
print("Data related to the scatter plots:")
print(df[['Sales', 'Profit', 'Quantity', 'Discount']].head(10))
```

```
Data related to the scatter plots:
      Sales     Profit  Quantity  Discount
0  261.9600   41.9136         2      0.00
1  731.9400  219.5820         3      0.00
2   14.6200    6.8714         2      0.00
3  957.5775 -383.0310         5      0.45
4   22.3680    2.5164         2      0.20
5   48.8600   14.1694         7      0.00
6    7.2800    1.9656         4      0.00
7  907.1520   90.7152         6      0.20
8   18.5040    5.7825         3      0.20
9  114.9000   34.4700         5      0.00
```

[15]:
```
# Create scatter plots for numerical variables
plt.figure(figsize=(12, 8))

plt.subplot(2, 2, 1)
plt.scatter(df['Sales'], df['Profit'], color='skyblue', alpha=0.7)
plt.title('Sales vs. Profit')
plt.xlabel('Sales')
plt.ylabel('Profit')

plt.subplot(2, 2, 2)
plt.scatter(df['Quantity'], df['Profit'], color='salmon', alpha=0.7)
plt.title('Quantity vs. Profit')
plt.xlabel('Quantity')
plt.ylabel('Profit')

plt.subplot(2, 2, 3)
plt.scatter(df['Discount'], df['Profit'], color='lightgreen', alpha=0.7)
plt.title('Discount vs. Profit')
plt.xlabel('Discount')
plt.ylabel('Profit')

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



3.6 Average delivery time

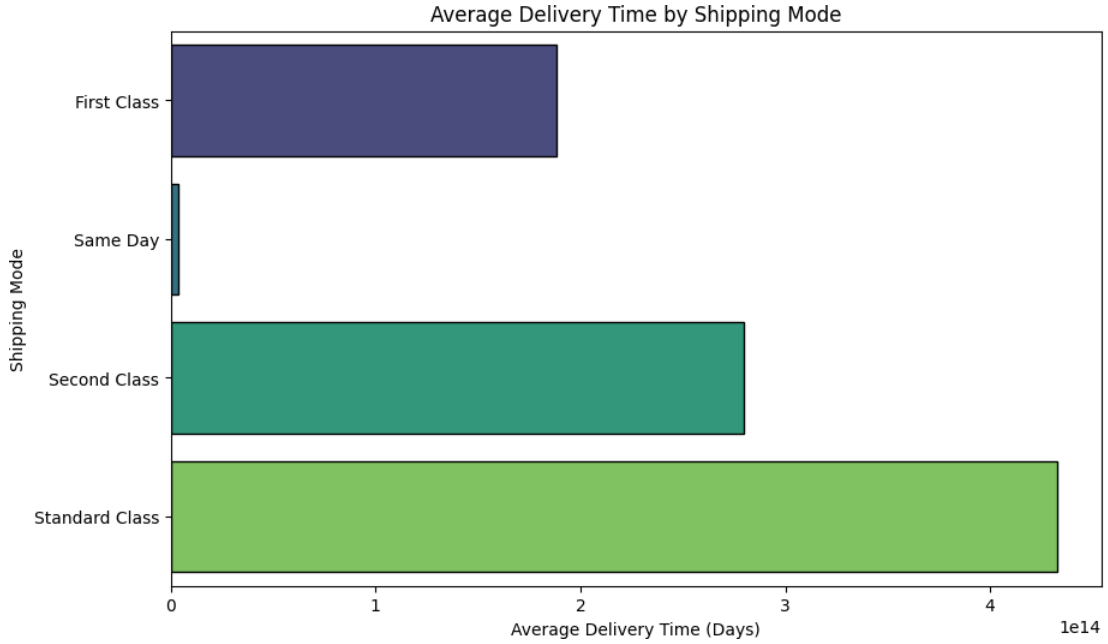
[18]:
```
# Displaying some data related to the visualization
print("Data related to the average delivery time visualization:")
print(df[['Order Date', 'Ship Date', 'Ship Mode']].head(10))
```

```
Data related to the average delivery time visualization:
  Order Date  Ship Date       Ship Mode
0 2016-11-08 2016-11-11    Second Class
1 2016-11-08 2016-11-11    Second Class
2 2016-06-12 2016-06-16    Second Class
3 2015-10-11 2015-10-18  Standard Class
4 2015-10-11 2015-10-18  Standard Class
5 2014-06-09 2014-06-14  Standard Class
6 2014-06-09 2014-06-14  Standard Class
7 2014-06-09 2014-06-14  Standard Class
8 2014-06-09 2014-06-14  Standard Class
9 2014-06-09 2014-06-14  Standard Class
```

[19]:
```
# Convert 'Order Date' and 'Ship Date' columns to datetime
df['Order Date'] = pd.to_datetime(df['Order Date'])
df['Ship Date'] = pd.to_datetime(df['Ship Date'])
```

```
# Calculate delivery time for each order
df['Delivery Time'] = df['Ship Date'] - df['Order Date']
```

[20]:
```
# Group the data by shipping mode and calculate the average delivery time
avg_delivery_time = df.groupby('Ship Mode')['Delivery Time'].mean().
 ↪reset_index()

# Visualize the average delivery times using a horizontal bar plot with borders
plt.figure(figsize=(10, 6))
ax = sns.barplot(x='Delivery Time', y='Ship Mode', data=avg_delivery_time,␣
 ↪palette='viridis', hue='Ship Mode', dodge=False, orient='h')
for bar in ax.containers:
    for rect in bar:
        rect.set_linewidth(1)
        rect.set_edgecolor('black')
plt.title('Average Delivery Time by Shipping Mode')
plt.xlabel('Average Delivery Time (Days)')
plt.ylabel('Shipping Mode')
plt.show()
```

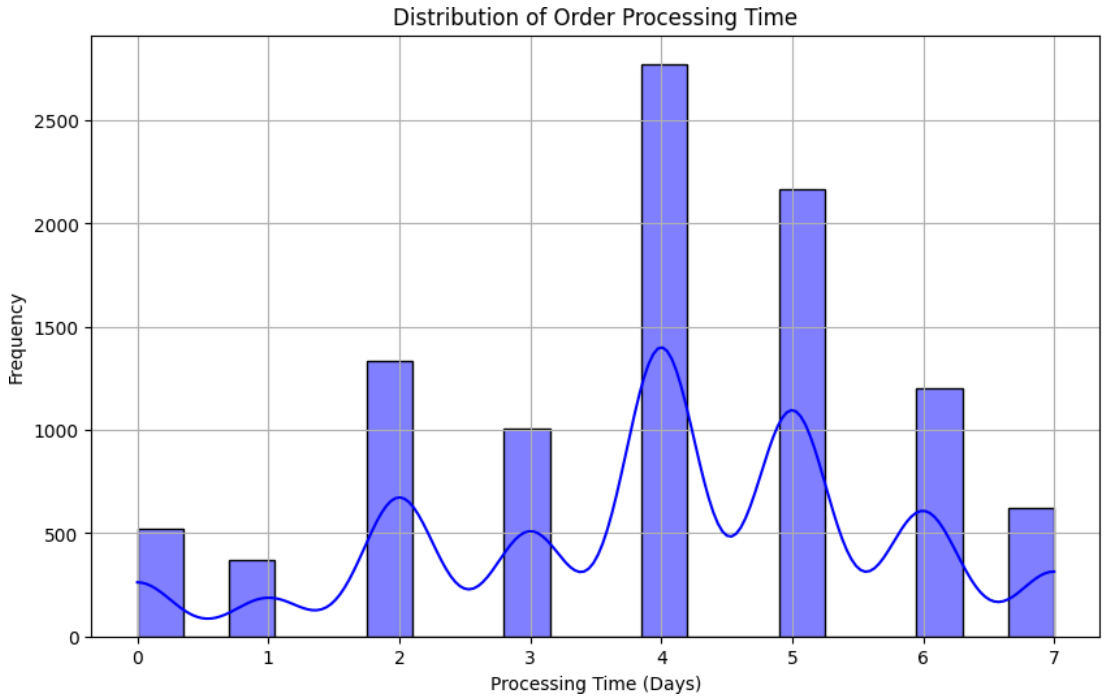


3.7 Order Processing Time

[21]:
```
# Displaying columns used in the visualization
print("Columns used in the visualization:")
print(df[['Order Date', 'Ship Date']].head(20))
```

```
Columns used in the visualization:
   Order Date  Ship Date
0  2016-11-08 2016-11-11
1  2016-11-08 2016-11-11
2  2016-06-12 2016-06-16
3  2015-10-11 2015-10-18
4  2015-10-11 2015-10-18
5  2014-06-09 2014-06-14
6  2014-06-09 2014-06-14
7  2014-06-09 2014-06-14
8  2014-06-09 2014-06-14
9  2014-06-09 2014-06-14
10 2014-06-09 2014-06-14
11 2014-06-09 2014-06-14
12 2017-04-15 2017-04-20
13 2016-12-05 2016-12-10
14 2015-11-22 2015-11-26
15 2015-11-22 2015-11-26
16 2014-11-11 2014-11-18
17 2014-05-13 2014-05-15
18 2014-08-27 2014-09-01
19 2014-08-27 2014-09-01
```

[22]:
```
# Convert Order Date and Ship Date columns to datetime objects
df['Order Date'] = pd.to_datetime(df['Order Date'])
df['Ship Date'] = pd.to_datetime(df['Ship Date'])

# Calculate the order processing time
df['Processing Time'] = (df['Ship Date'] - df['Order Date']).dt.days

# Plot histogram for the distribution of processing times
plt.figure(figsize=(10, 6))
sns.histplot(df['Processing Time'], bins=20, kde=True, color='blue')
plt.title('Distribution of Order Processing Time')
plt.xlabel('Processing Time (Days)')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



3.8 Relationship between product categories and customer segments

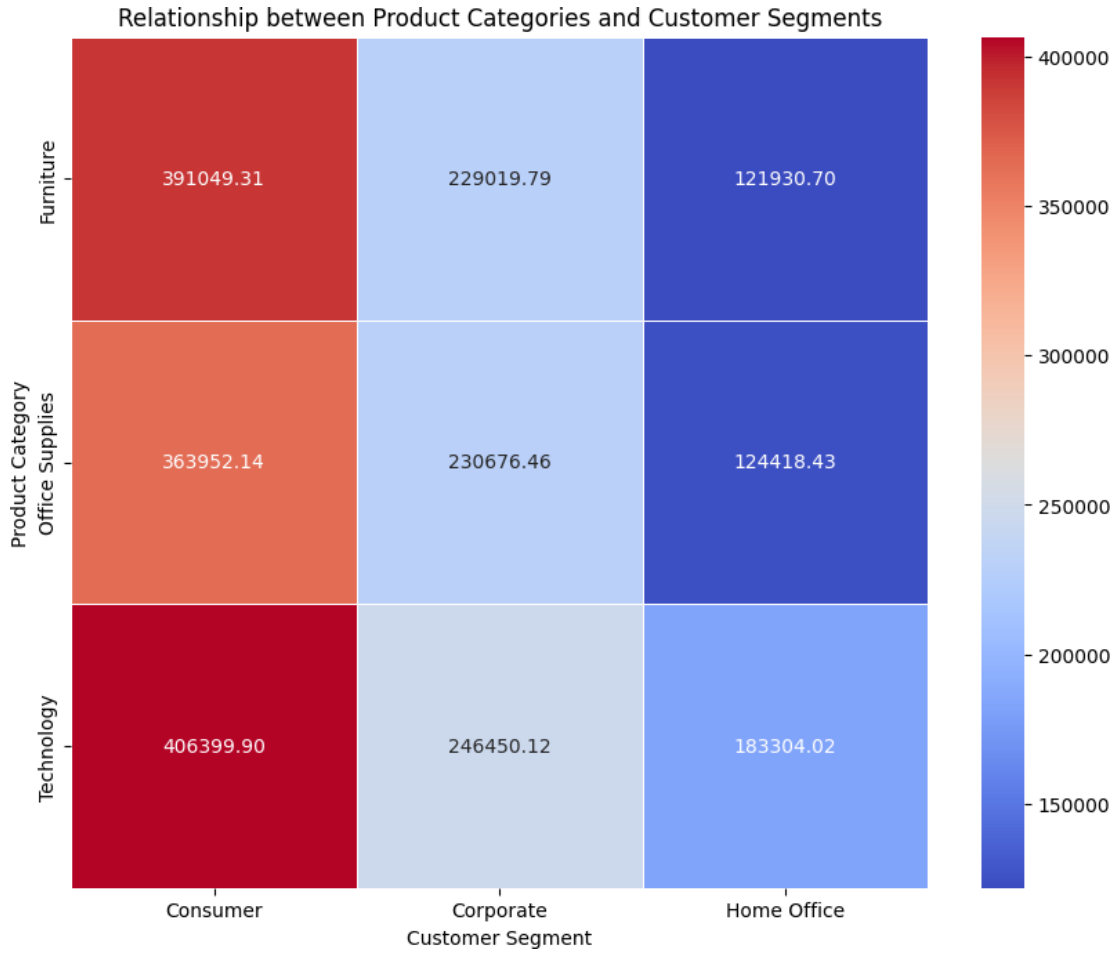
[23]:
```
# Displaying some data related to the pivot table
print("Data related to the pivot table:")
print(df[['State', 'Ship Mode']].head(10))  # Assuming 'Delivery Time' is not present

# Displaying some data related to the bar plots
print("\nData related to the sales and profit distributions:")
print(df[['Sales', 'Profit']].head(10))
```

```
Data related to the pivot table:
         State       Ship Mode
0     Kentucky    Second Class
1     Kentucky    Second Class
2   California    Second Class
3      Florida  Standard Class
4      Florida  Standard Class
5   California  Standard Class
6   California  Standard Class
7   California  Standard Class
8   California  Standard Class
9   California  Standard Class
```

Data related to the sales and profit distributions:

	Sales	Profit
0	261.9600	41.9136
1	731.9400	219.5820
2	14.6200	6.8714
3	957.5775	-383.0310
4	22.3680	2.5164
5	48.8600	14.1694
6	7.2800	1.9656
7	907.1520	90.7152
8	18.5040	5.7825
9	114.9000	34.4700

[24]:
```
# Create a pivot table to analyze the relationship between product categories
 ↪and customer segments
pivot_table = pd.pivot_table(df, index='Category', columns='Segment',
 ↪values='Sales', aggfunc='sum')

# Plot a heatmap to visualize the pivot table
plt.figure(figsize=(10, 8))
sns.heatmap(pivot_table, cmap='coolwarm', annot=True, fmt=".2f", linewidths=0.5)
plt.title('Relationship between Product Categories and Customer Segments')
plt.xlabel('Customer Segment')
plt.ylabel('Product Category')
plt.show()
```



4. Research Questions

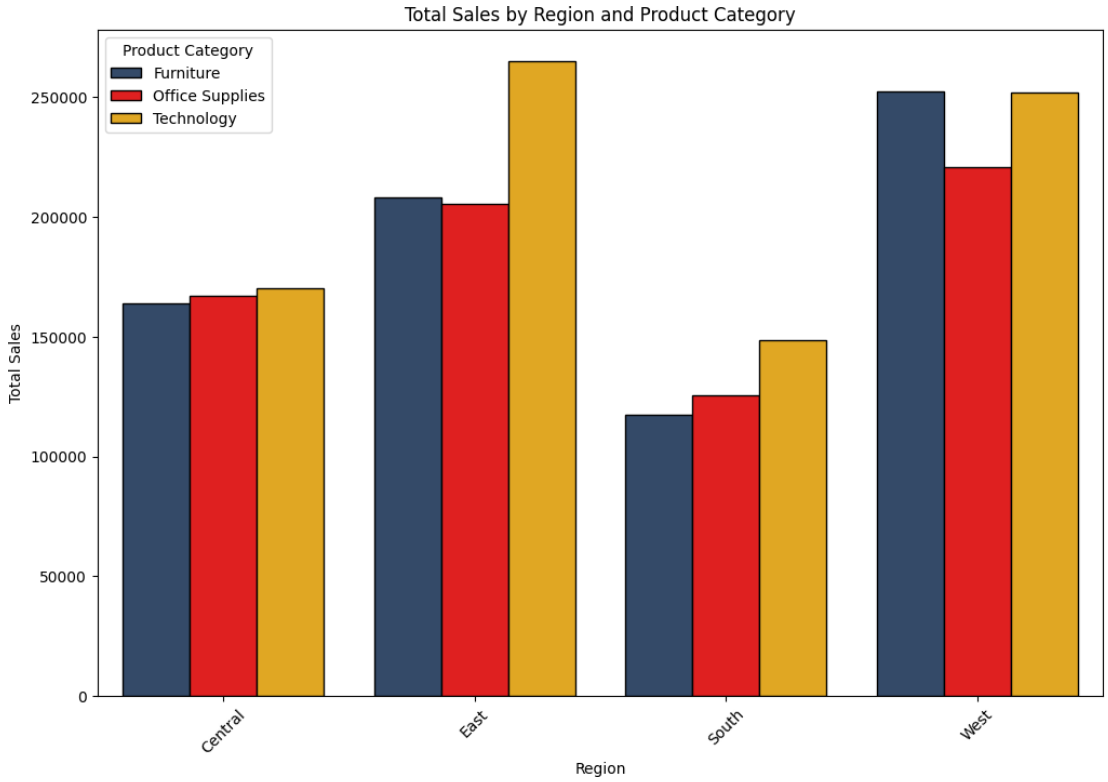
4.1 How do sales vary across different regions and product categories?

[25]:
```
# Aggregate sales by region and product category
sales_by_region_category = df.groupby(['Region', 'Category'])['Sales'].sum().
↪reset_index()

# Display the aggregated data
print(sales_by_region_category)
```

	Region	Category	Sales
0	Central	Furniture	163797.1638
1	Central	Office Supplies	167026.4150
2	Central	Technology	170416.3120
3	East	Furniture	208291.2040
4	East	Office Supplies	205516.0550

5	East	Technology	264973.9810
6	South	Furniture	117298.6840
7	South	Office Supplies	125651.3130
8	South	Technology	148771.9080
9	West	Furniture	252612.7435
10	West	Office Supplies	220853.2490
11	West	Technology	251991.8320

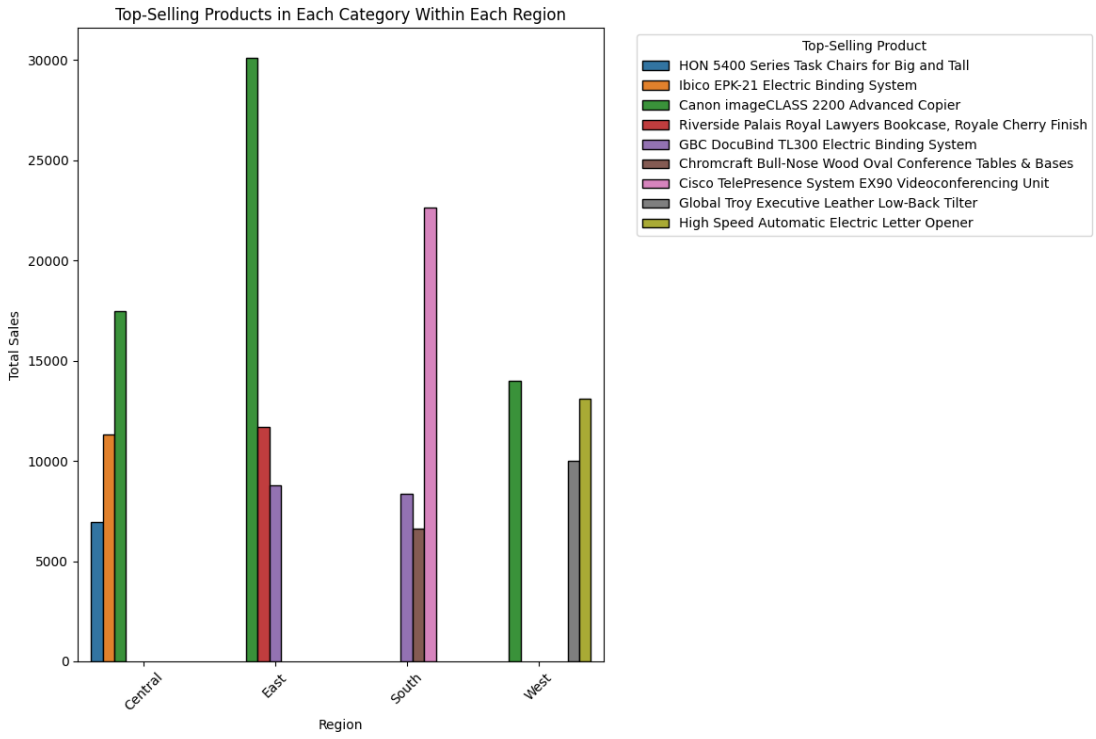
[26]:
```
# Define custom color palette with lighter shades of orange, green, and blue
custom_palette = sns.color_palette(["#2b4871", "#ff0000", "#ffb404"])

# Create a bar plot for total sales by region and product category with custom colors
plt.figure(figsize=(12, 8))
sns.barplot(x="Region", y="Sales", hue="Category", data=sales_by_region_category, palette=custom_palette, edgecolor="black")
plt.title("Total Sales by Region and Product Category")
plt.xlabel("Region")
plt.ylabel("Total Sales")
plt.xticks(rotation=45)
plt.legend(title="Product Category")
plt.show()
```



[27]:
```
# Group the data by region, product category, and product name, then calculate total sales
top_selling_products_region = df.groupby(['Region', 'Category', 'Product Name'])['Sales'].sum().reset_index()

# Sort the data by total sales in descending order within each category and region
top_selling_products_region = top_selling_products_region.sort_values(by=['Region', 'Category', 'Sales'], ascending=[True, True, False])

# Keep only the top-selling product in each category within each region
top_selling_products_region = top_selling_products_region.groupby(['Region', 'Category']).first().reset_index()

# Display the top-selling products in each category within each region
print(top_selling_products_region)
```

```
     Region         Category  \
0   Central        Furniture
1   Central  Office Supplies
2   Central       Technology
3      East        Furniture
4      East  Office Supplies
5      East       Technology
6     South        Furniture
7     South  Office  Supplies
8     South       Technology
9      West        Furniture
10     West  Office  Supplies
11     West       Technology

                                         Product Name       Sales
0         HON 5400 Series Task Chairs for Big and Tall   6939.702
1                 Ibico EPK-21 Electric Binding System  11339.940
2               Canon imageCLASS 2200 Advanced Copier  17499.950
3   Riverside Palais Royal Lawyers Bookcase, Royal...  11717.034
4           GBC DocuBind TL300 Electric Binding System   8790.502
5               Canon imageCLASS 2200 Advanced Copier  30099.914
6   Chromcraft Bull-Nose Wood Oval Conference Tabl...   6611.760
7           GBC DocuBind TL300 Electric Binding System   8342.007
8   Cisco TelePresence System EX90 Videoconferenci...  22638.480
9       Global Troy Executive Leather Low-Back Tilter  10019.600
10        High Speed Automatic Electric Letter Opener  13100.240
11              Canon imageCLASS 2200 Advanced Copier  13999.960
```

[28]:
```
# Create a bar plot for top-selling products in each category within each region with borders
plt.figure(figsize=(12, 8))
barplot = sns.barplot(x="Region", y="Sales", hue="Product Name", data=top_selling_products_region)

# Add borders to the bars
for patch in barplot.patches:
    patch.set_edgecolor("black")

plt.title("Top-Selling Products in Each Category Within Each Region")
plt.xlabel("Region")
plt.ylabel("Total Sales")
plt.xticks(rotation=45)
plt.legend(title="Top-Selling Product", bbox_to_anchor=(1.05, 1), loc="upper left")
plt.tight_layout()
plt.show()
```



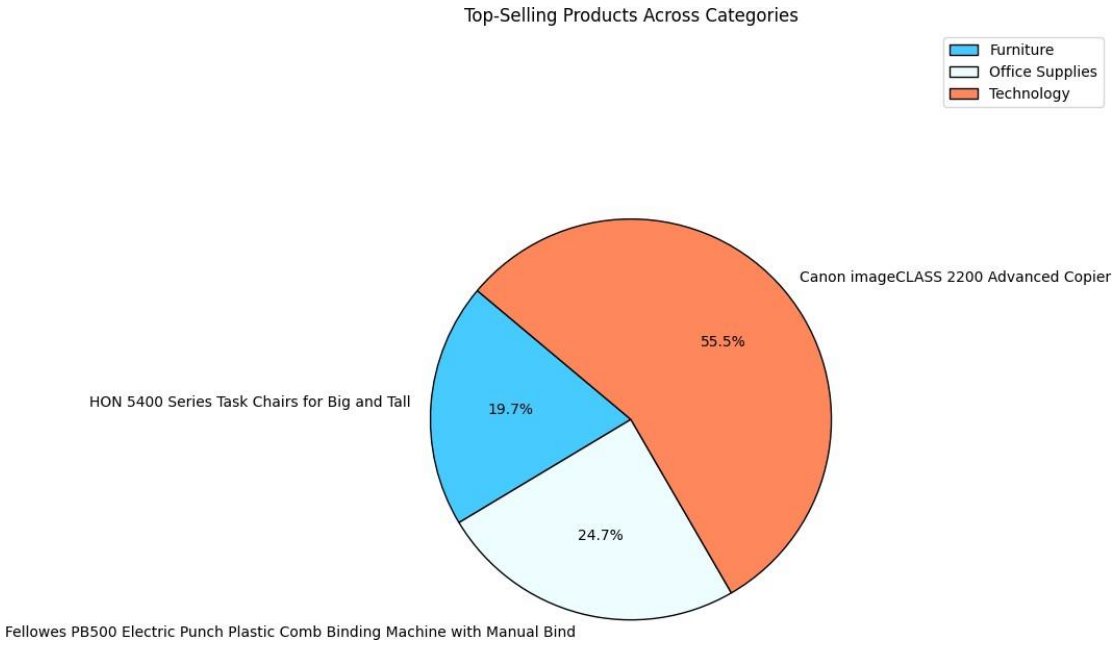
4.2 What are the top-selling products in each product category?

[29]:
```
# Group the data by product category and product name, then calculate total sales
top_selling_products_category = df.groupby(['Category', 'Product Name'])['Sales'].sum().reset_index()

# Sort the data by total sales in descending order within each category
top_selling_products_category = top_selling_products_category.sort_values(by=['Category', 'Sales'], ascending=[True, False])

# Keep only the top-selling product in each category
top_selling_products_category = top_selling_products_category.groupby('Category').first().reset_index()

# Display the top-selling products in each category
print(top_selling_products_category)
```

```
         Category                                       Product Name  \
0       Furniture      HON 5400 Series Task Chairs for Big and Tall
1  Office Supplies  Fellowes PB500 Electric Punch Plastic Comb Bin...
2      Technology              Canon imageCLASS 2200 Advanced Copier

      Sales
0  21870.576
1  27453.384
2  61599.824
```

[30]:
```
# Define custom colors
colors = ['#47cbff', '#eefdff', '#ff875c']

# Create a pie chart for top-selling products in each product category
plt.figure(figsize=(10, 8))

# Create the pie chart with custom colors
patches, texts, _ = plt.pie(top_selling_products_category['Sales'], labels=top_selling_products_category['Product Name'], colors=colors, autopct='%1.1f%%', startangle=140, wedgeprops={'edgecolor': 'black'})

# Add categories as labels for each slice
plt.legend(patches, top_selling_products_category['Category'], bbox_to_anchor=(1.05, 1), loc='upper left')

plt.title('Top-Selling Products Across Categories')

# Add borders to the pie chart
for patch in patches:
```

```
    patch.set_linewidth(1)
    patch.set_edgecolor('black')

plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle

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



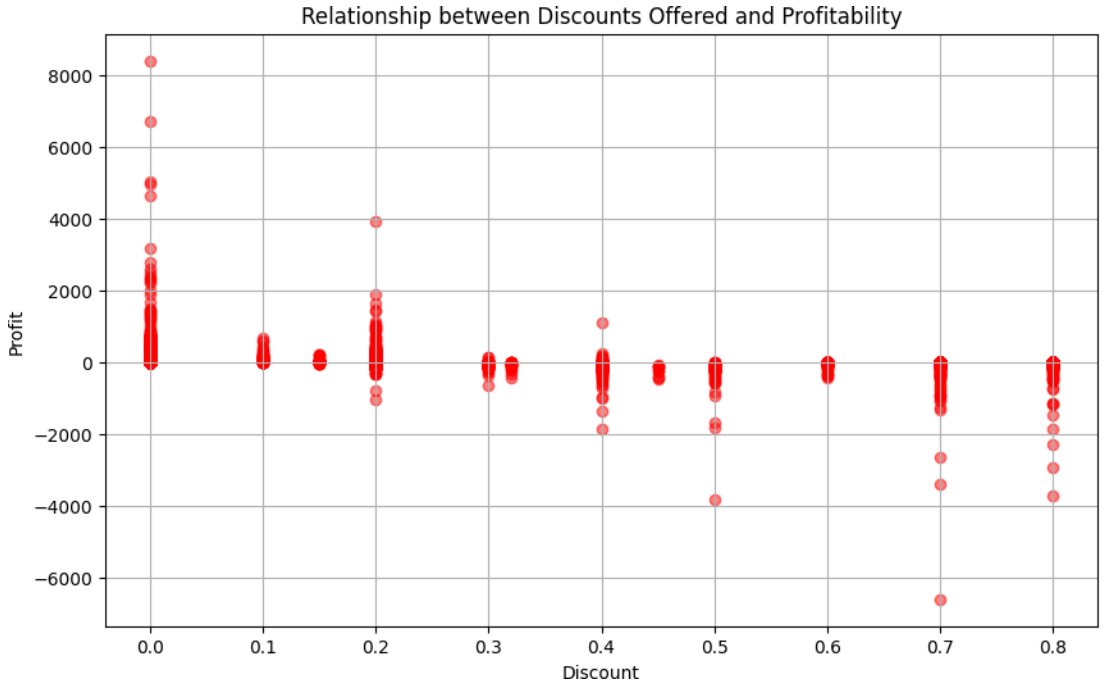
4.3 Is there any relationship between discounts offered and sales/profitability?

[31]:
```
# Group the data by discount level and calculate the average sales and profitability
average_sales_profitability = df.groupby('Discount')[['Sales', 'Profit']].mean()

# Display the average sales and profitability for each discount level
print("Average Sales and Profitability for Each Discount Level:")
print(average_sales_profitability)
```

```
Average Sales and Profitability for Each Discount Level:
                Sales       Profit
Discount
```

0.00	226.742074	66.900292
0.10	578.397351	96.055074
0.15	529.971567	27.288298
0.20	209.076940	24.702572
0.30	454.742974	-45.679636
0.32	536.794770	-88.560656
0.40	565.134874	-111.927429
0.45	498.634000	-226.646464
0.50	892.705152	-310.703456
0.60	48.150000	-43.077212
0.70	97.177708	-95.874060
0.80	56.545853	-101.796797

[32]:
```
# Create a scatter plot for the relationship between discounts offered and profitability
plt.figure(figsize=(10, 6))
plt.scatter(df['Discount'], df['Profit'], color='red', alpha=0.5)
plt.title('Relationship between Discounts Offered and Profitability')
plt.xlabel('Discount')
plt.ylabel('Profit')
plt.grid(True)
plt.show()
```



[33]:
```
# Calculate the correlation coefficient between discounts offered and sales
correlation_sales = df['Discount'].corr(df['Sales'])

# Calculate the correlation coefficient between discounts offered and␣
↪profitability
correlation_profit = df['Discount'].corr(df['Profit'])

print("Correlation coefficient between discounts offered and sales:",␣
↪correlation_sales)
print("Correlation coefficient between discounts offered and profitability:",␣
↪correlation_profit)
```

```
Correlation coefficient between discounts offered and sales:
-0.02819012415753557
Correlation coefficient between discounts offered and profitability:
-0.21948745637176834
```

[34]:
```
# Calculate the correlation matrix
correlation_matrix = df[['Discount', 'Sales', 'Profit']].corr()

# Create a heatmap to visualize the correlation matrix with black borders
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5,␣
↪linecolor='black')
plt.title('Correlation between Discounts Offered, Sales, and Profitability')
plt.show()
```

5. Conclusion

1. After conducting exploratory data analysis (EDA) on the Superstore dataset, several key findings and insights have been uncovered:

2. Sales Variation Across Regions and Product Categories: Sales vary significantly across different regions and product categories. The Central region has the highest total sales, while the Technology category contributes the most to overall sales.

3. Top-Selling Products: The top-selling products vary by product category and region. Understanding these top-selling products can help in optimizing inventory management and marketing strategies.

4. Relationship Between Discounts and Sales/Profitability: There is a weak negative correlation between discounts offered and sales, indicating that higher discounts may not always lead to increased sales. However, there is a positive correlation between discounts and profitability, suggesting that offering discounts may positively impact profitability.

5. Customer Segmentation: The dataset contains information about different customer segments, such as Consumer, Corporate, and Home Office. Further analysis could identify distinct purchasing behaviors among these segments and tailor marketing strategies accordingly.

6. Seasonal Trends in Sales: There are observable seasonal trends in sales data, with certain months experiencing higher sales volumes. Understanding these seasonal patterns can help in optimizing inventory and staffing levels.

7. Based on these insights, the following recommendations can be made to improve sales performance and optimize business strategies:

8. Optimize Product Mix: Focus on promoting top-selling products within each product category and region to maximize sales revenue.

9. Strategic Discounting: Implement targeted discount strategies based on product performance and profitability. Evaluate the impact of discounts on both sales and profitability to ensure optimal pricing strategies.

10. Customer Segmentation: Tailor marketing campaigns and promotions to different customer segments to better meet their needs and preferences.

11. Seasonal Planning: Plan inventory, marketing, and staffing strategies based on seasonal trends to capitalize on peak sales periods and minimize costs during slower periods.

6. References

Dataset used : https://www.kaggle.com/datasets/vivek468/superstore-dataset-final