jlzcq1na6

September 6, 2025

0.0.1 Step 1: Import Libraries

[11]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from scipy import stats

import warnings
warnings.filterwarnings("ignore")

sns.set(style="whitegrid")
```

[12]:
```
# show all columns
pd.set_option('display.max_column',None)

# present scientific notation (optional)
pd.set_option('display.float_format','{:.2f}'.format)
```

0.0.2 Step 2: Load and Inspect Dataset

[13]:
```
df = pd.read_csv(r"C:\Users\atulm\Desktop\Data Analytics\Python\Project\New␣
↪folder\retail_sales_50k.csv")
df.head()
```

[13]:
```
   Order_ID Customer_ID  Gender  Age  Country Product_Category  Quantity  \
0     10001      C00861    Male   40  Germany          Fashion         7
1     10002      C03773  Female   32    India             Home         7
2     10003      C03093    Male   28    India             Home         4
3     10004      C00467  Female   38      UAE             Home         4
4     10005      C04427    Male   56       UK        Groceries         7

   Unit_Price  Discount                     Order_Date Payment_Method  \
0        5232      0.00  2023-01-01 00:00:00.000000000    Credit Card
1        8563      0.00  2023-01-01 00:21:01.465229304     Debit Card
2        3369      0.10  2023-01-01 00:42:02.930458609     Debit Card
```

```
3        6796      0.10  2023-01-01 01:03:04.395687913     Debit Card
4        2949      0.15  2023-01-01 01:24:05.860917218            COD

  Ad_Campaign Returned  Total_Sales
0           B       No     36624.00
1           A       No     59941.00
2           A       No     12128.40
3           A       No     24465.60
4           A       No     17546.55
```

[14]:

```python
# Quick look
print("\nshape:",df.shape)
print("\ninfo:")
df.info()
```

```
shape: (50000, 14)

info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 14 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Order_ID          50000 non-null  int64
 1   Customer_ID       50000 non-null  object
 2   Gender            50000 non-null  object
 3   Age               50000 non-null  int64
 4   Country           50000 non-null  object
 5   Product_Category  50000 non-null  object
 6   Quantity          50000 non-null  int64
 7   Unit_Price        50000 non-null  int64
 8   Discount          50000 non-null  float64
 9   Order_Date        50000 non-null  object
 10  Payment_Method    50000 non-null  object
 11  Ad_Campaign       50000 non-null  object
 12  Returned          50000 non-null  object
 13  Total_Sales       50000 non-null  float64
dtypes: float64(2), int64(4), object(8)
memory usage: 5.3+ MB
```

[15]:

```python
# Summary Statistics
print('summary:')
df.describe()
```

```
summary:
```

[15]:
```
         Order_ID      Age  Quantity  Unit_Price  Discount  Total_Sales
count  50000.00 50000.00  50000.00    50000.00  50000.00     50000.00
mean   35000.50    38.50      5.00     5058.98      0.06     23590.88
std    14433.90    12.12      2.59     2857.42      0.07     19358.09
min    10001.00    18.00      1.00      100.00      0.00        89.60
25%    22500.75    28.00      3.00     2580.00      0.00      7671.90
50%    35000.50    39.00      5.00     5068.00      0.05     18160.10
75%    47500.25    49.00      7.00     7549.00      0.10     35309.10
max    60000.00    59.00      9.00     9999.00      0.20     89991.00
```

0.0.3 Step 3: Data Cleaning & Preprocessing

[16]:
```
df["Order_Date"]
```

[16]:
```
0        2023-01-01 00:00:00.000000000
1        2023-01-01 00:21:01.465229304
2        2023-01-01 00:42:02.930458609
3        2023-01-01 01:03:04.395687913
4        2023-01-01 01:24:05.860917218
                     …
49995    2024-12-30 22:35:54.139082784
49996    2024-12-30 22:56:55.604312088
49997    2024-12-30 23:17:57.069541392
49998    2024-12-30 23:38:58.534770696
49999    2024-12-31 00:00:00.000000000
Name: Order_Date, Length: 50000, dtype: object
```

[17]:
```
# Change Format remove text unes..
df["Order_Date"] = pd.to_datetime(df["Order_Date"])
df["Order_Date"] = df["Order_Date"].dt.strftime("%Y-%m-%d")
df["Order_Date"]
```

[17]:
```
0        2023-01-01
1        2023-01-01
2        2023-01-01
3        2023-01-01
4        2023-01-01
            …
49995    2024-12-30
49996    2024-12-30
49997    2024-12-30
49998    2024-12-30
49999    2024-12-31
Name: Order_Date, Length: 50000, dtype: object
```

[18]:
```
# Check Missing Values
print("\nMissing Values :\n")
```

```
df.isnull().sum()
```

```
Missing Values :
```

[18]:
```
Order_ID            0
Customer_ID         0
Gender              0
Age                 0
Country             0
Product_Category    0
Quantity            0
Unit_Price          0
Discount            0
Order_Date          0
Payment_Method      0
Ad_Campaign         0
Returned            0
Total_Sales         0
dtype: int64
```

[19]:
```
df.head()
```

[19]:
```
   Order_ID Customer_ID  Gender  Age  Country Product_Category  Quantity  \
0     10001      C00861    Male   40  Germany          Fashion         7
1     10002      C03773  Female   32    India             Home         7
2     10003      C03093    Male   28    India             Home         4
3     10004      C00467  Female   38      UAE             Home         4
4     10005      C04427    Male   56       UK        Groceries         7

   Unit_Price  Discount  Order_Date Payment_Method Ad_Campaign Returned  \
0        5232      0.00  2023-01-01    Credit Card           B       No
1        8563      0.00  2023-01-01     Debit Card           A       No
2        3369      0.10  2023-01-01     Debit Card           A       No
3        6796      0.10  2023-01-01     Debit Card           A       No
4        2949      0.15  2023-01-01            COD           A       No

   Total_Sales
0     36624.00
1     59941.00
2     12128.40
3     24465.60
4     17546.55
```

0.0.4 Step 4: Univariate Analysis

[21]:
```
columns = ['Year', 'Age', 'Gender', 'Country',
           'Product_Category', 'Quantity', 'Payment_Method', 'Ad_Campaign']

for col in columns:
    if col in df.columns:
        print(f"\nUnique Count of {col} Column -: {df[col].nunique()}")
        print("\nValue Counts of the Column -:\n", df[col].value_counts())
        print("\n---------------------------------------------------")
    else:
        print(f"\nColumn '{col}' not found in the DataFrame!")
        print("\n---------------------------------------------------")
```

```
Column 'Year' not found in the DataFrame!

---------------------------------------------------

Unique Count of Age Column -: 42

Value Counts of the Column -:
 Age
40    1284
18    1247
50    1241
28    1239
44    1236
54    1232
37    1219
32    1219
48    1217
56    1215
58    1214
29    1213
31    1211
33    1210
19    1207
39    1202
30    1201
55    1198
43    1189
47    1187
25    1185
34    1184
22    1180
57    1179
24    1173
```

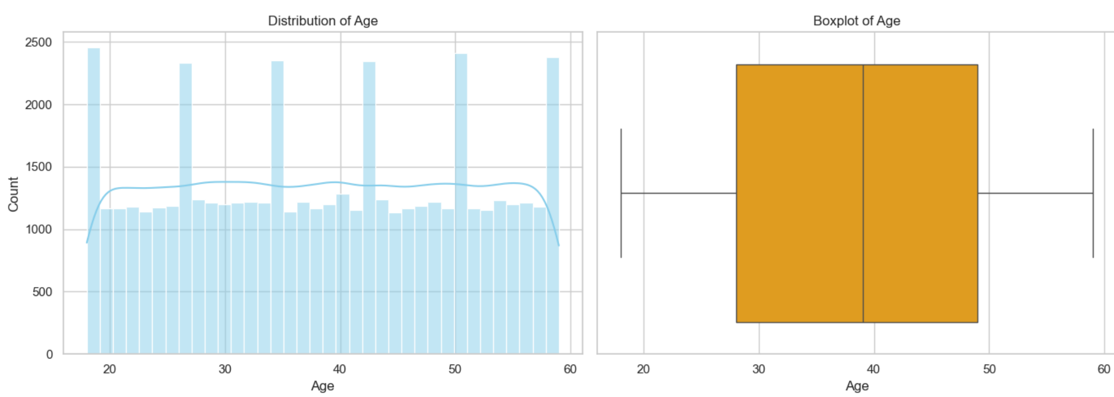
```
51    1171
49    1170
26    1169
38    1168
46    1168
21    1167
20    1166
52    1166
35    1165
59    1163
27    1161
42    1157
53    1155
41    1152
23    1144
36    1143
45    1133
Name: count, dtype: int64

--------------------------------------------------

Unique Count of Gender Column -: 2

Value Counts of the Column -:
 Gender
Female    25114
Male      24886
Name: count, dtype: int64

--------------------------------------------------

Unique Count of Country Column -: 5

Value Counts of the Column -:
 Country
India      19877
UAE        10053
USA         9933
UK          5119
Germany     5018
Name: count, dtype: int64

--------------------------------------------------

Unique Count of Product_Category Column -: 5

Value Counts of the Column -:
 Product_Category
```

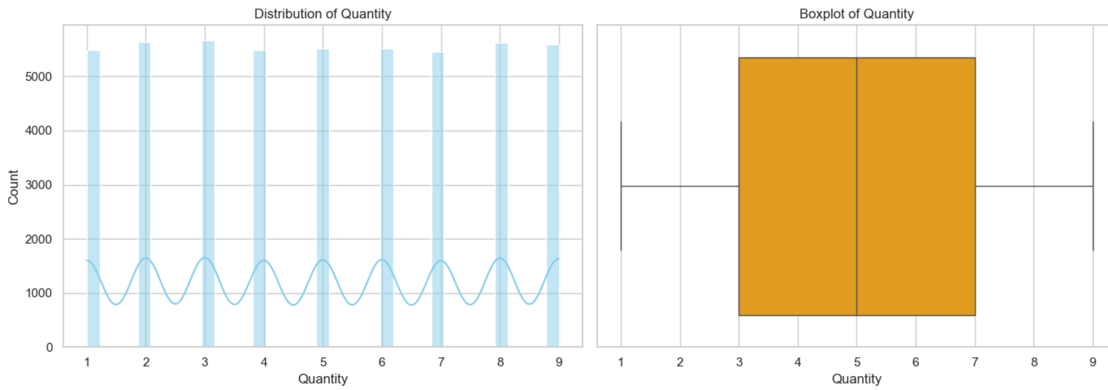
```
Sports         10111
Home           10000
Electronics     9973
Fashion         9969
Groceries       9947
Name: count, dtype: int64

--------------------------------------------------

Unique Count of Quantity Column -: 9

Value Counts of the Column -:
 Quantity
3    5664
2    5635
8    5628
9    5598
6    5525
5    5513
1    5491
4    5483
7    5463
Name: count, dtype: int64

--------------------------------------------------

Unique Count of Payment_Method Column -: 4

Value Counts of the Column -:
 Payment_Method
UPI            12629
Debit Card     12469
COD            12469
Credit Card    12433
Name: count, dtype: int64

--------------------------------------------------

Unique Count of Ad_Campaign Column -: 2

Value Counts of the Column -:
 Ad_Campaign
A    25093
B    24907
Name: count, dtype: int64

--------------------------------------------------
```

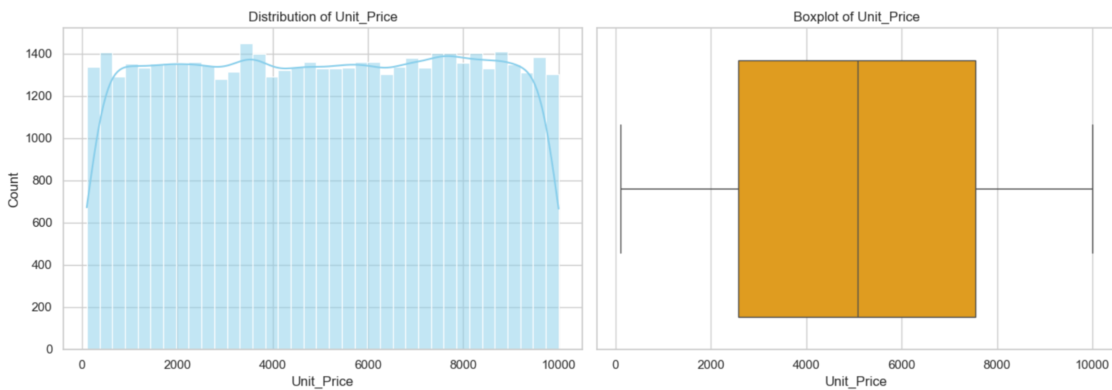
[22]:
```
df.head(1)
```

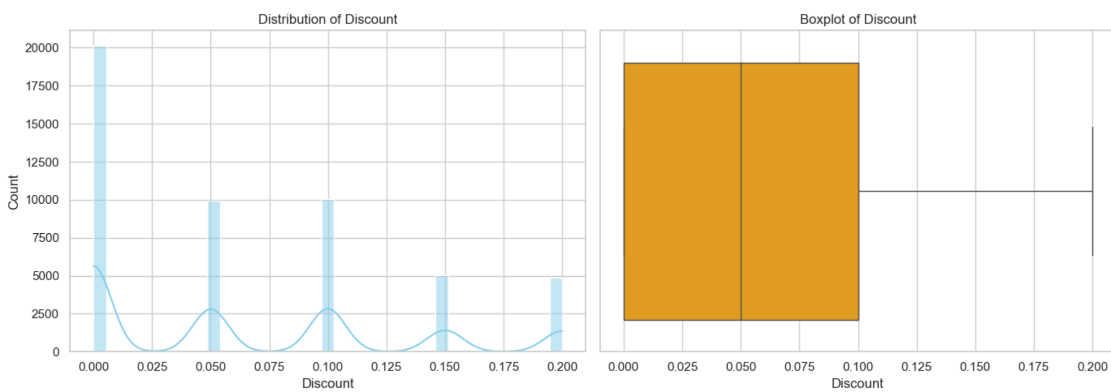
[22]:
```
   Order_ID Customer_ID Gender  Age  Country Product_Category  Quantity  \
0     10001      C00861   Male   40  Germany          Fashion         7

   Unit_Price  Discount  Order_Date Payment_Method Ad_Campaign Returned  \
0        5232      0.00  2023-01-01    Credit Card           B       No

   Total_Sales
0     36624.00
```

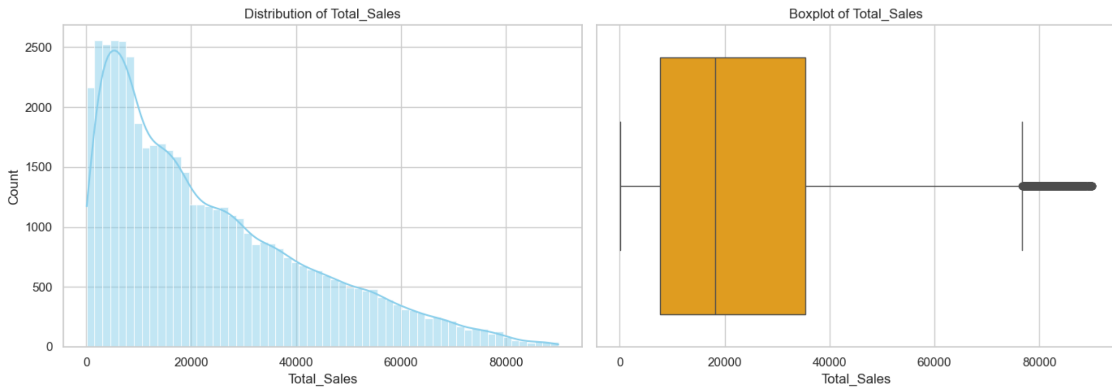
[23]:
```
numerical_cols = ['Age', 'Quantity', 'Unit_Price', 'Discount', 'Total_Sales']

for col in numerical_cols:
    plt.figure(figsize=(14, 5))

    # Histogram
    plt.subplot(1, 2, 1)
    sns.histplot(df[col], kde=True, color='skyblue')
    plt.title(f'Distribution of {col}')

    # Boxplot
    plt.subplot(1, 2, 2)
    sns.boxplot(x=df[col], color='orange')
    plt.title(f'Boxplot of {col}')

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



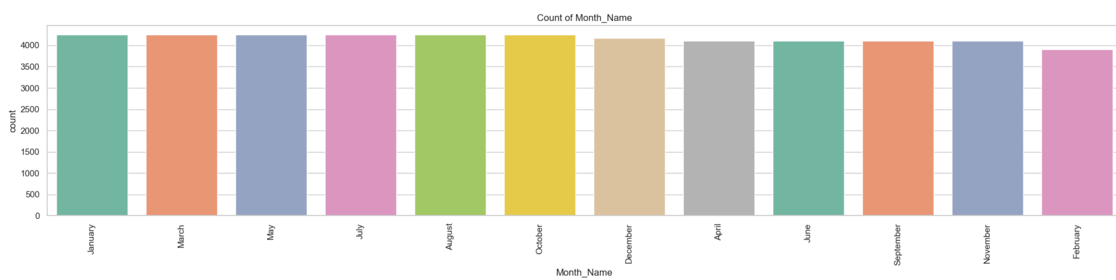

Distribution of Quantity
Count
Quantity
Boxplot of Quantity
Quantity

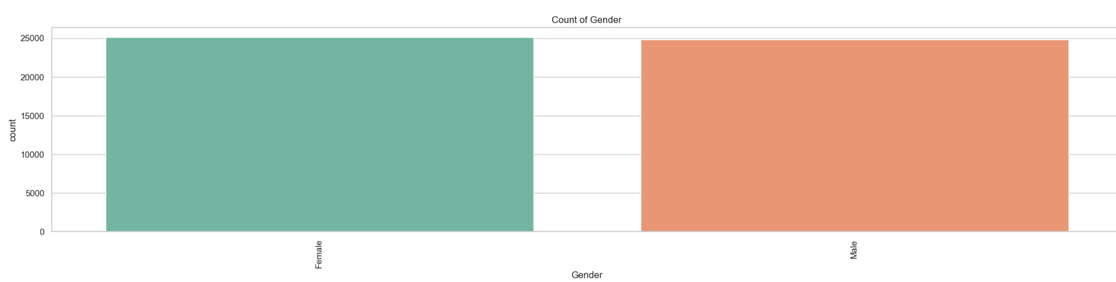

Distribution of Unit_Price
Count
Unit_Price
Boxplot of Unit_Price
Unit_Price

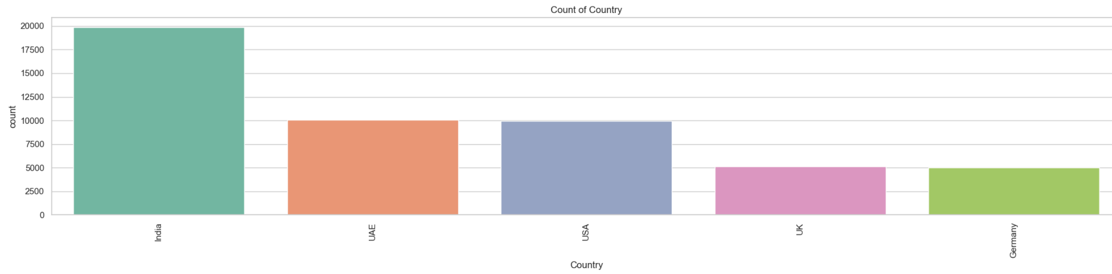

Distribution of Discount
Count
Discount
Boxplot of Discount
Discount



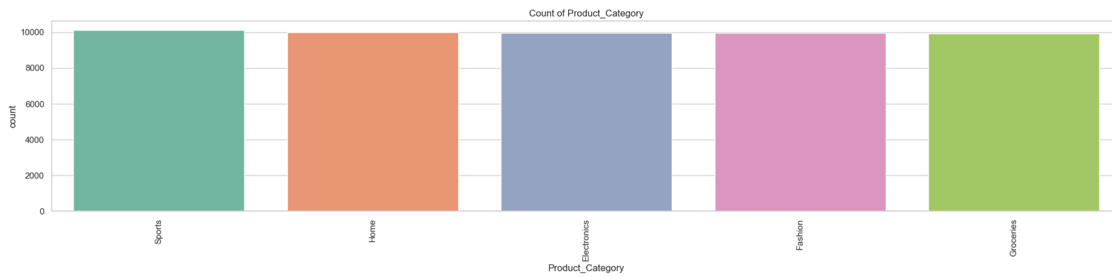

```
[ ]: categorical_cols = ['Month_Name', 'Gender', 'Country',
                         'Product_Category', 'Payment_Method',
                         'Ad_Campaign', 'Returned']

     for col in categorical_cols:
         plt.figure(figsize=(20, 5))
         sns.countplot(x=col, data=df, order=df[col].value_counts().index,␣
      ↪palette='Set2')
         plt.xticks(rotation=90)
         plt.title(f'Count of {col}')
         plt.tight_layout()
         plt.show()
```



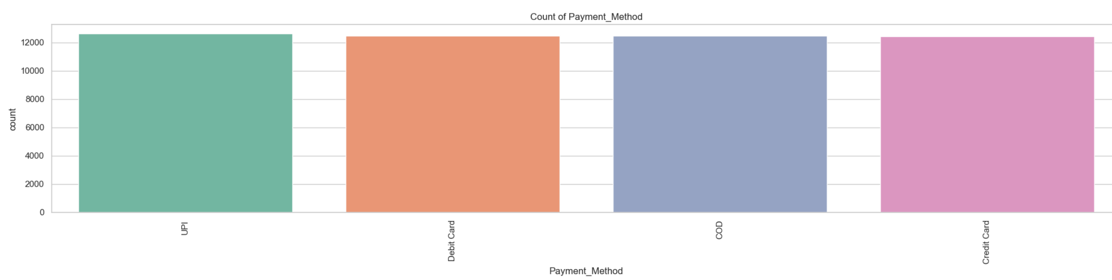




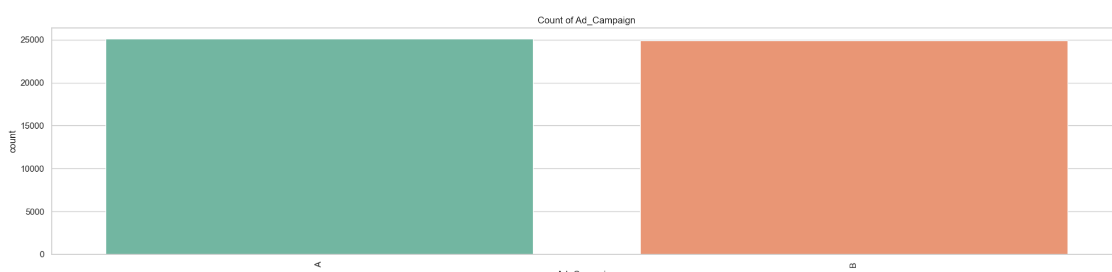
Count of Country
count
20000
17500
15000
12500
10000
7500
5000
2500
0
India
UAE
USA
UK
Germany
Country



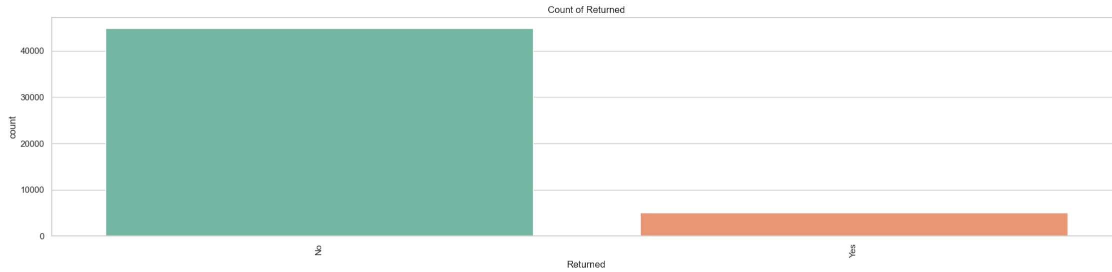
Count of Product_Category
count
10000
8000
6000
4000
2000
0
Sports
Home
Electronics
Fashion
Groceries
Product_Category



Count of Payment_Method
count
12000
10000
8000
6000
4000
2000
0
UPI
Debit Card
COD
Credit Card
Payment_Method



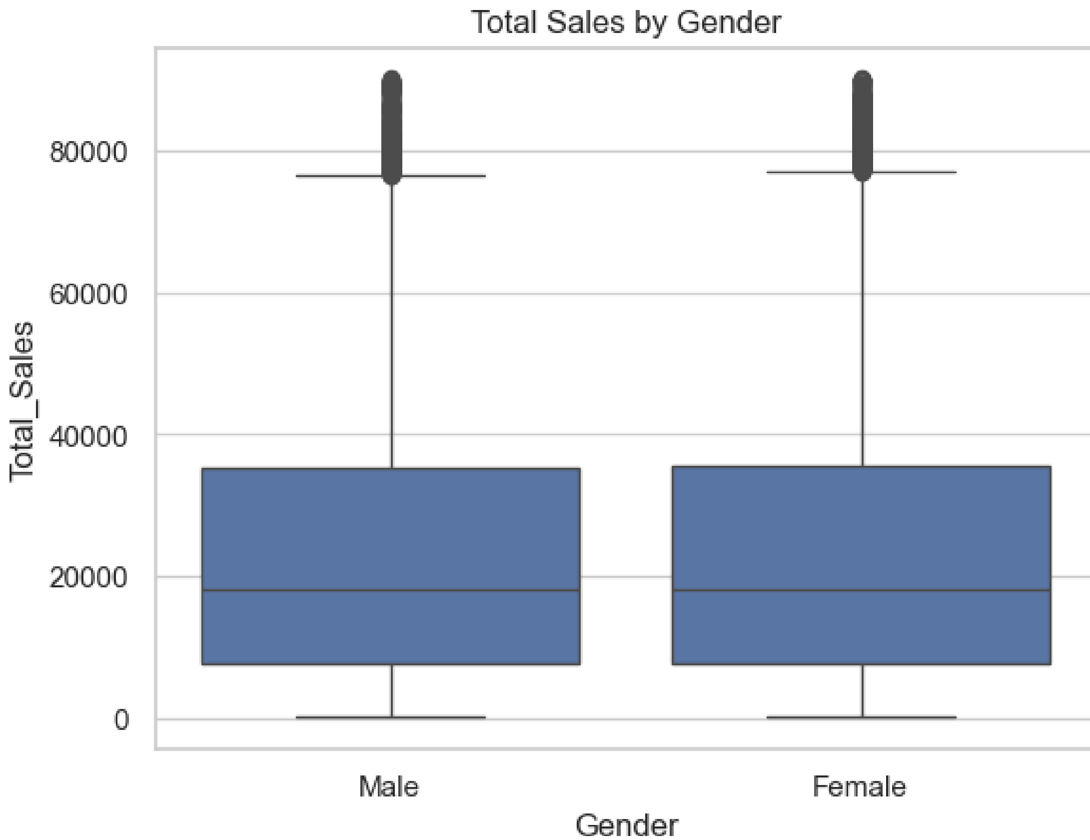
Count of Ad_Campaign
count
25000
20000
15000
10000
5000
0
A
B
Ad_Campaign

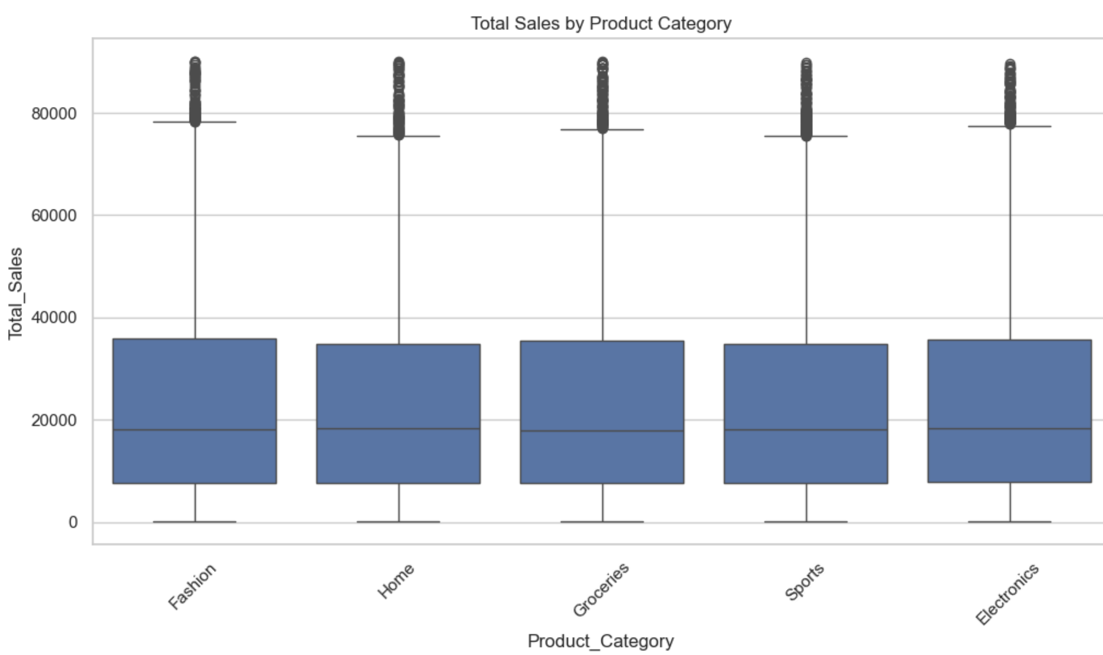


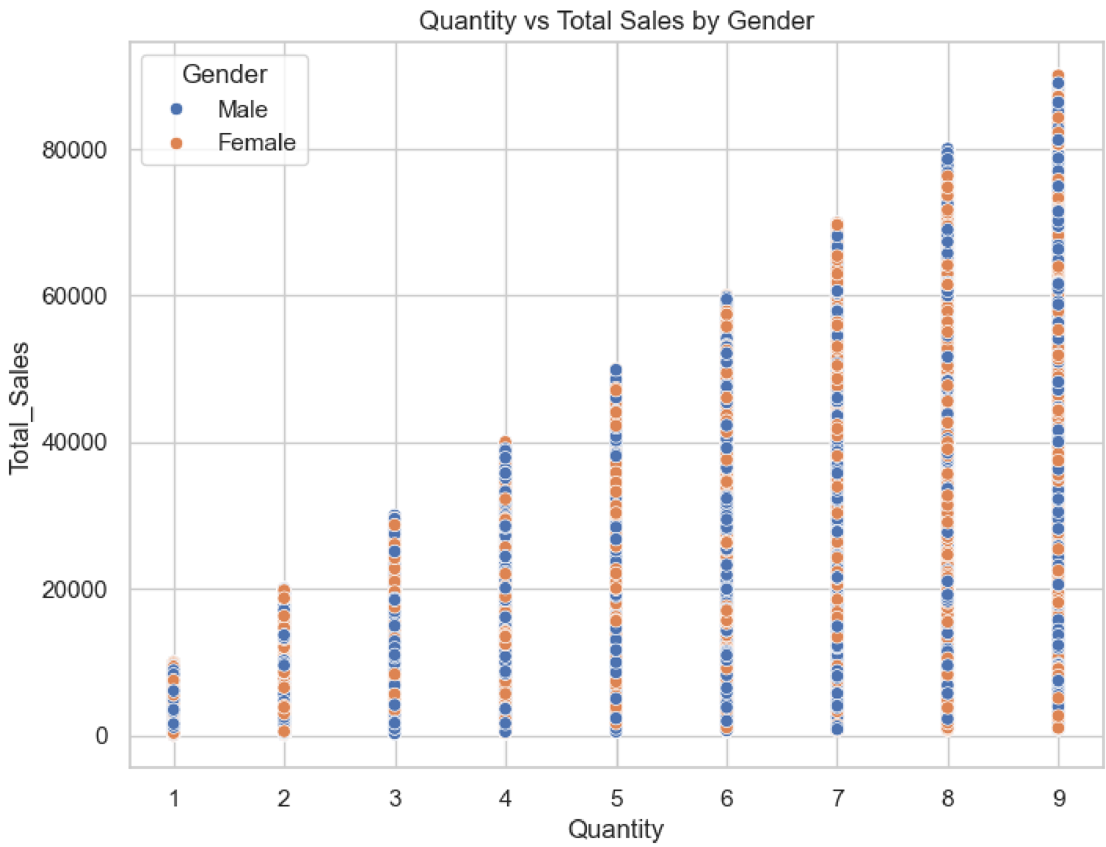
0.0.5 Step 5: Bivariate Analysis

Definition: Bivariate Analysis ka matlab hai do variables ke beech relationship ko samajhna.

[ ]:
```
# Revenue by Gender
sns.boxplot(x='Gender', y='Total_Sales', data=df)
plt.title('Total Sales by Gender')
plt.show()

# Revenue by Product Category
plt.figure(figsize=(12,6))
sns.boxplot(x='Product_Category', y='Total_Sales', data=df)
plt.xticks(rotation=45)
plt.title('Total Sales by Product Category')
plt.show()

# Quantity vs Revenue (Scatter)
plt.figure(figsize=(8,6))
sns.scatterplot(x='Quantity', y='Total_Sales', data=df, hue='Gender')
plt.title("Quantity vs Total Sales by Gender")
plt.show()
```


Total Sales by Gender
80000
60000
40000
20000
0
Total_Sales
Male
Female
Gender


Total Sales by Product Category
80000
60000
40000
20000
0
Total_Sales
Fashion
Home
Groceries
Sports
Electronics
Product_Category



- Top & bottom **products by total revenue**
- Top & bottom **products by total quantity sold**
- Top & bottom **products by total profit** (assuming `Profit = Revenue - Cost`)

0.1 Top & Bottom Products Analysis – Full Code

[ ]:
```
df.head(1)
```

[ ]:
```
   Order_ID Customer_ID Gender  Age  Country Product_Category  Quantity  \
0     10001      C00861   Male   40  Germany          Fashion         7

   Unit_Price  Discount  Order_Date Payment_Method Ad_Campaign Returned  \
0        5232      0.00  2023-01-01    Credit Card           B       No

   Total_Sales  Year Month_Name
0     36624.00  2023    January
```

[ ]:
```
# Step 1: Create Unit_Cost and Profit
df['Unit_Cost'] = df['Unit_Price'] * 0.7       # assume 70% cost
df['Profit'] = (df['Unit_Price'] - df['Unit_Cost']) * df['Quantity']
```

```
# Step 2: Group by Product_Category
product_perf = df.groupby('Product_Category').agg({
    'Quantity': 'sum',
    'Total_Sales': 'sum',
    'Profit': 'sum'
}).sort_values(by='Profit', ascending=False)

# Step 3: Show the full performance table
print("\n  Product Performance Summary:")
print(product_perf)
```

```
 Product Performance Summary:
                  Quantity  Total_Sales      Profit
Product_Category
Electronics          50168 238001936.80 76289367.30
Sports               50242 237584019.20 76223923.20
Fashion              49945 235476486.00 75491202.90
Home                 49915 234025872.70 75115932.30
Groceries            49777 234455479.45 75091210.80
```

[ ]:
```
# Top 5 Products by Total Sales
top5_sales = product_perf.sort_values(by='Total_Sales', ascending=False).head(5)

print("  Top 5 Products by Total Sales:")
print(top5_sales)
```

```
 Top 5 Products by Total Sales:
                  Quantity  Total_Sales      Profit
Product_Category
Electronics          50168 238001936.80 76289367.30
Sports               50242 237584019.20 76223923.20
Fashion              49945 235476486.00 75491202.90
Groceries            49777 234455479.45 75091210.80
Home                 49915 234025872.70 75115932.30
```

[ ]:
```
# Bottom 5 Products by Total Sales (Revenue)
bottom_sales = product_perf.sort_values(by='Total_Sales', ascending=True).
 ↪head(5)

print("\n  Bottom 5 Products by Total Sales:")
print(bottom_sales)
```

```
 Bottom 5 Products by Total Sales:
                  Quantity  Total_Sales      Profit
Product_Category
```

```
Home                   49915 234025872.70 75115932.30
Groceries              49777 234455479.45 75091210.80
Fashion                49945 235476486.00 75491202.90
Sports                 50242 237584019.20 76223923.20
Electronics            50168 238001936.80 76289367.30
```

[ ]:
```
# Top 5 Products by Quantity Sold
top_quantity = product_perf.sort_values(by='Quantity', ascending=False).head(5)
print("\n  Top 5 Products by Quantity Sold:")
print(top_quantity)
```

```
 Top 5 Products by Quantity Sold:
                  Quantity  Total_Sales      Profit
Product_Category
Sports                 50242 237584019.20 76223923.20
Electronics            50168 238001936.80 76289367.30
Fashion                49945 235476486.00 75491202.90
Home                   49915 234025872.70 75115932.30
Groceries              49777 234455479.45 75091210.80
```

[ ]:
```
# Bottom 5 Products by Quantity Sold
bottom_quantity = product_perf.sort_values(by='Quantity', ascending=True).
 ↪head(5)
print("\n  Bottom 5 Products by Quantity Sold:")
print(bottom_quantity)
```

```
 Bottom 5 Products by Quantity Sold:
                  Quantity  Total_Sales      Profit
Product_Category
Groceries              49777 234455479.45 75091210.80
Home                   49915 234025872.70 75115932.30
Fashion                49945 235476486.00 75491202.90
Electronics            50168 238001936.80 76289367.30
Sports                 50242 237584019.20 76223923.20
```

[ ]:
```
# Top 5 Products by Profit
top_profit = product_perf.sort_values(by='Profit', ascending=False).head(5)
print("\n  Top 5 Products by Profit:")
print(top_profit)
```

```
 Top 5 Products by Profit:
                  Quantity  Total_Sales      Profit
Product_Category
Electronics            50168 238001936.80 76289367.30
Sports                 50242 237584019.20 76223923.20
```

```
Fashion              49945 235476486.00 75491202.90
Home                 49915 234025872.70 75115932.30
Groceries            49777 234455479.45 75091210.80
```

[ ]:
```
# Bottom 5 Products by Profit
bottom_profit = product_perf.sort_values(by='Profit', ascending=True).head(5)
print("\n  Bottom 5 Products by Profit:")
print(bottom_profit)
```

```
 Bottom 5 Products by Profit:
                  Quantity  Total_Sales      Profit
Product_Category
Groceries            49777 234455479.45 75091210.80
Home                 49915 234025872.70 75115932.30
Fashion              49945 235476486.00 75491202.90
Sports               50242 237584019.20 76223923.20
Electronics          50168 238001936.80 76289367.30
```

[ ]:
```
# Category-wise Revenue/Profit Share
category_share = product_perf[['Total_Sales', 'Profit']].apply(lambda x: x/x.
 ↪sum() * 100)
print(category_share)
```

```
                  Total_Sales  Profit
Product_Category
Electronics             20.18   20.17
Sports                  20.14   20.15
Fashion                 19.96   19.96
Home                    19.84   19.86
Groceries               19.88   19.85
```

[ ]:
```
# Revenue vs Quantity Correlation
product_perf[['Quantity','Total_Sales','Profit']].corr()
```

[ ]:

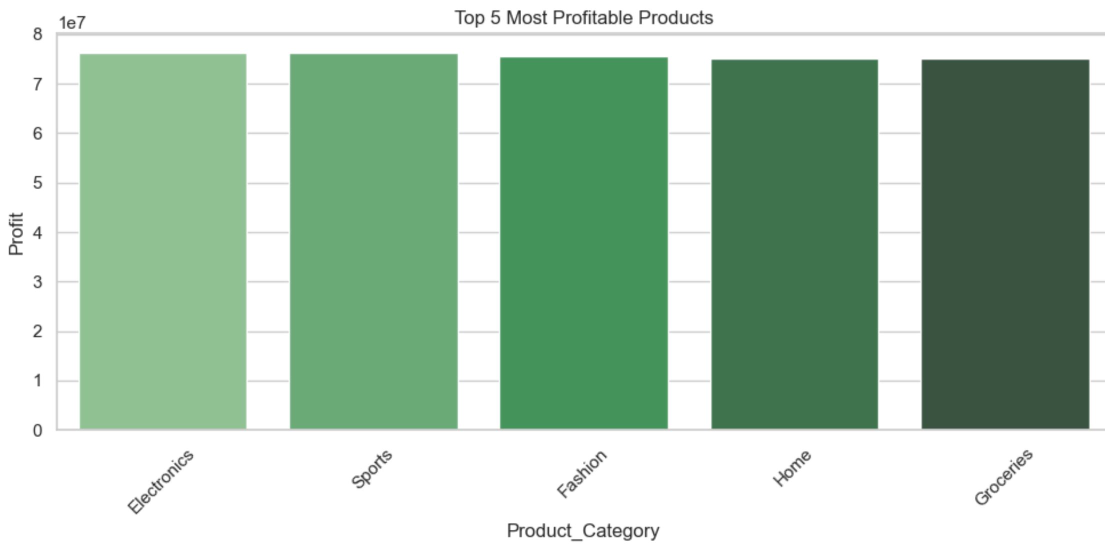
	Quantity	Total_Sales	Profit
Quantity	1.00	0.92	0.95
Total_Sales	0.92	1.00	0.99
Profit	0.95	0.99	1.00

[ ]:
```
gender_perf = df.groupby('Gender').agg({
    'Total_Sales':'sum',
    'Profit':'sum'
})
print(gender_perf)
```

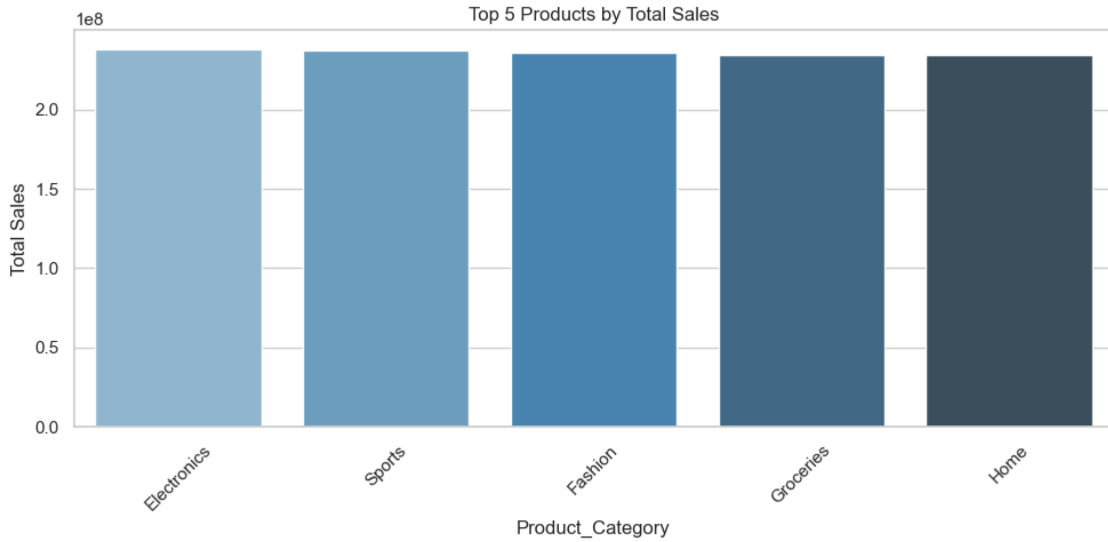
```
        Total_Sales       Profit
Gender
```

```
Female 594913301.40 190727994.90
Male   584630492.75 187483641.60
```

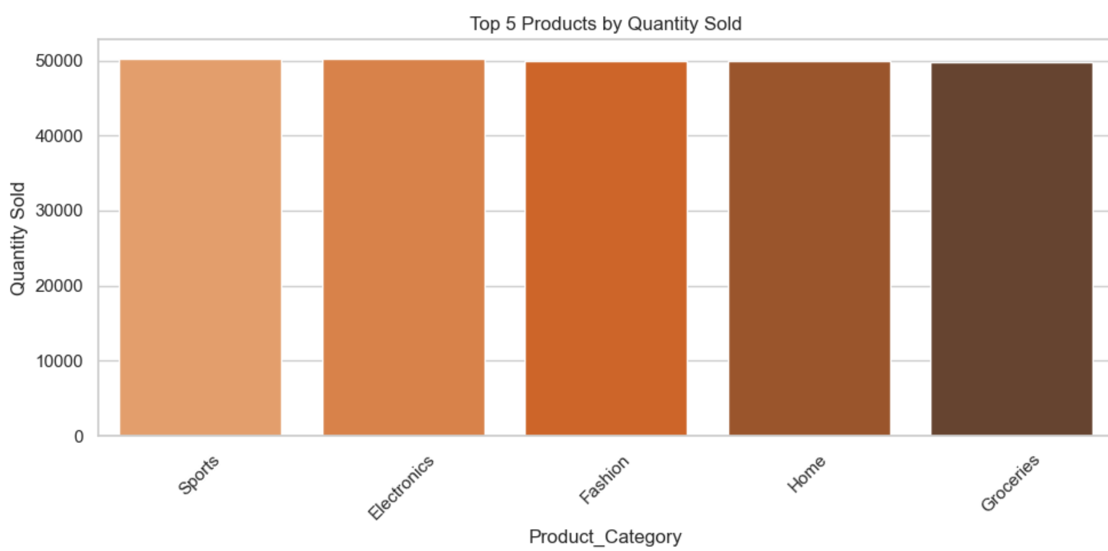
[ ]:
```python
#  Top 5 Profitable Products
top_profit = product_perf.sort_values(by='Profit', ascending=False).head(5)
plt.figure(figsize=(10,5))
sns.barplot(x=top_profit.index, y=top_profit['Profit'], palette='Greens_d')
plt.title("Top 5 Most Profitable Products")
plt.ylabel("Profit")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



[ ]:
```python
#  Top 5 Products by Total Sales
top_sales = product_perf.sort_values(by='Total_Sales', ascending=False).head(5)
plt.figure(figsize=(10,5))
sns.barplot(x=top_sales.index, y=top_sales['Total_Sales'], palette='Blues_d')
plt.title("Top 5 Products by Total Sales")
plt.ylabel("Total Sales")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

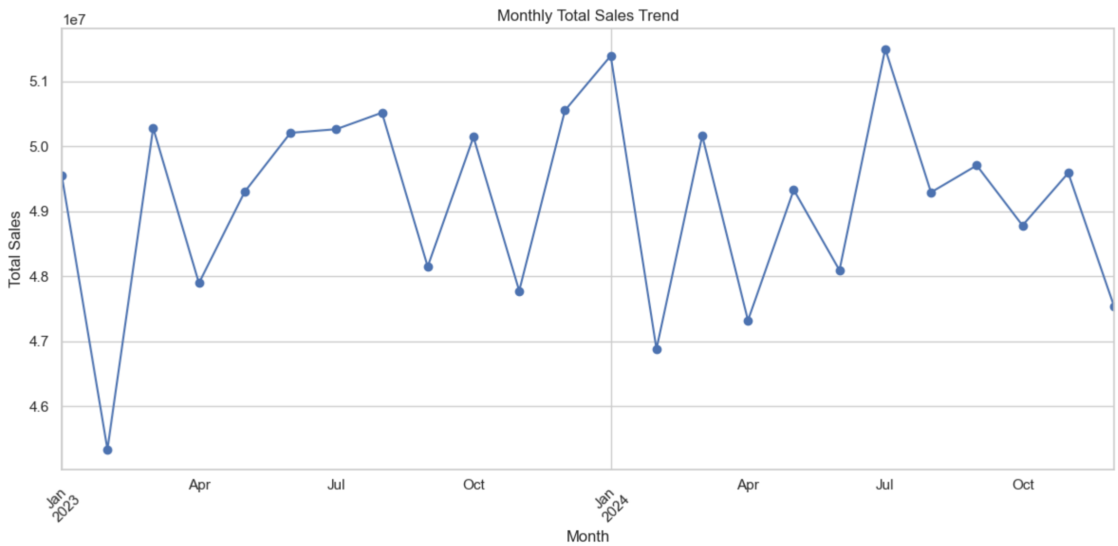


[ ]:
```
#   Top 5 Products by Quantity Sold
top_quantity = product_perf.sort_values(by='Quantity', ascending=False).head(5)
plt.figure(figsize=(10,5))
sns.barplot(x=top_quantity.index, y=top_quantity['Quantity'],␣
  ↪palette='Oranges_d')
plt.title("Top 5 Products by Quantity Sold")
plt.ylabel("Quantity Sold")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



[ ]:
```
df['Order_Date'] = pd.to_datetime(df['Order_Date'], errors='coerce')
```

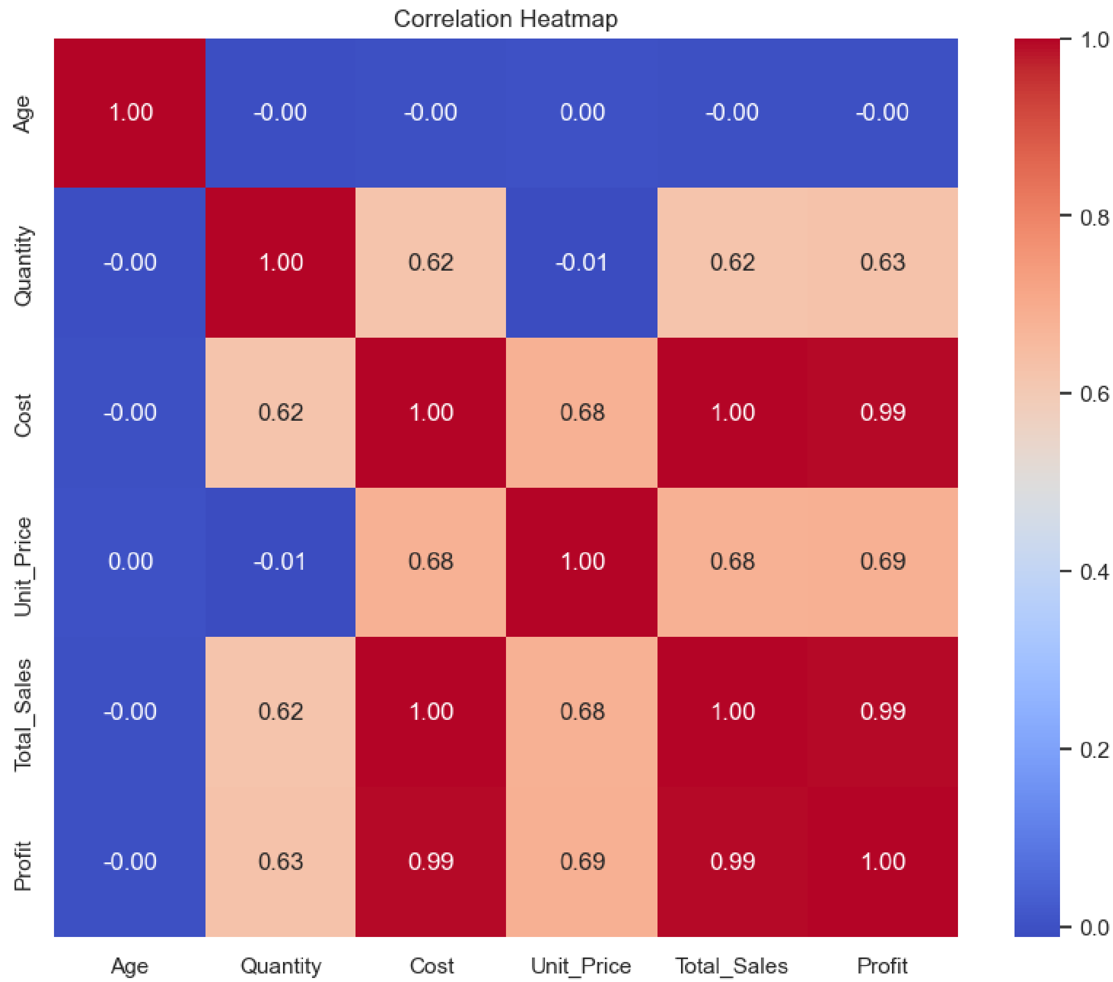
[ ]:
```
#  Monthly Total Sales Trend
df['Month_Year'] = df['Order_Date'].dt.to_period('M')
monthly_sales = df.groupby('Month_Year')['Total_Sales'].sum()

plt.figure(figsize=(12,6))
monthly_sales.plot(marker='o')
plt.title("Monthly Total Sales Trend")
plt.ylabel("Total Sales")
plt.xlabel("Month")
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



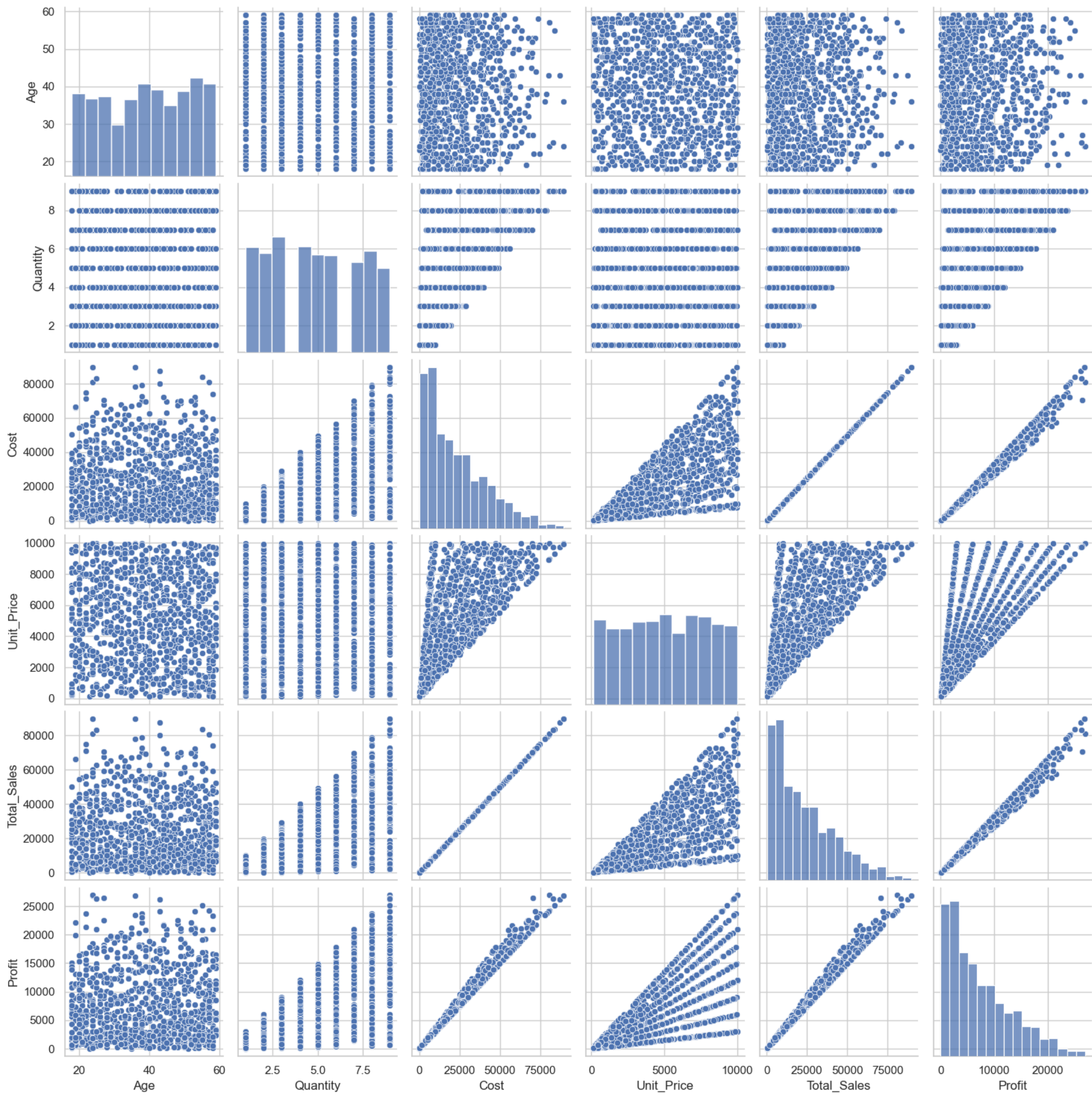
[ ]:
```
gender_perf[['Total_Sales','Profit']].plot(kind='bar', figsize=(8,5))
plt.title("Revenue & Profit by Gender")
plt.ylabel("Amount")
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```

0.1.1 Step 6: Multivariate Analysis

```
[ ]: # Numerical columns
numerical_cols = ['Age', 'Quantity', 'Cost', 'Unit_Price', 'Total_Sales',␣
 ↪'Profit']

# 1  Correlation Heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(df[numerical_cols].corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()

# 2  Pairplot (sample for large dataset)
sample_df = df[numerical_cols].sample(1000, random_state=1)  # 1000 random rows
sns.pairplot(sample_df)
plt.show()
```



Correlation Heatmap
Age
Quantity
Cost
Unit_Price
Total_Sales
Profit
1.00
-0.00
-0.00
0.00
-0.00
-0.00
-0.00
1.00
0.62
-0.01
0.62
0.63
-0.00
0.62
1.00
0.68
1.00
0.99
0.00
-0.01
0.68
1.00
0.68
0.69
-0.00
0.62
1.00
0.68
1.00
0.99
-0.00
0.63
0.99
0.69
0.99
1.00
1.0
0.8
0.6
0.4
0.2
0.0



0.1.2 Step 7: Hypothesis Testing

[ ]:
```
df.groupby('Gender')['Total_Sales'].agg(['sum','mean','max','min'])
```

[ ]:
```
                 sum      mean       max    min
Gender
Female  594913301.40  23688.51  89991.00  97.85
Male    584630492.75  23492.34  89991.00  89.60
```

[ ]:
```
# Male and Female Total_Sales
revenue_by_gender = df.groupby('Gender')['Total_Sales'].sum().reset_index()
revenue_by_gender
```

[ ]:
```
   Gender   Total_Sales
0  Female 594913301.40
1    Male 584630492.75
```

[ ]:
```
# Grouping by Gender and Product_Category
subcat_by_gender = df.groupby(['Gender', 'Product_Category'])['Total_Sales'].
↪sum().reset_index()
subcat_by_gender = subcat_by_gender.sort_values(by='Total_Sales',␣
↪ascending=False)

# Ranking per Gender
subcat_by_gender["Rnk"] = subcat_by_gender.groupby('Gender')["Total_Sales"].
↪rank(method='dense', ascending=False)

# Top 5 per Gender
top5_subcat_by_gender = subcat_by_gender[subcat_by_gender["Rnk"] <= 5].
↪sort_values(by='Gender')
top5_subcat_by_gender
```

[ ]:
```
   Gender Product_Category  Total_Sales  Rnk
0  Female      Electronics 120577510.10 1.00
4  Female           Sports 120082832.05 2.00
2  Female        Groceries 118984478.40 3.00
1  Female          Fashion 117639557.85 4.00
3  Female             Home 117628923.00 5.00
6    Male          Fashion 117836928.15 1.00
9    Male           Sports 117501187.15 2.00
5    Male      Electronics 117424426.70 3.00
8    Male             Home 116396949.70 4.00
7    Male        Groceries 115471001.05 5.00
```

[ ]:
```
# Grouping by Gender and Product_Category
subcat_by_gender_qty = df.groupby(['Gender', 'Product_Category'])['Quantity'].
↪sum().reset_index()
subcat_by_gender_qty = subcat_by_gender_qty.sort_values(by='Quantity',␣
↪ascending=False)

# Ranking per Gender
subcat_by_gender_qty["Rnk"] = subcat_by_gender_qty.
↪groupby('Gender')["Quantity"].rank(method='dense', ascending=False)

# Top 5 per Gender
top5_subcat_by_gender_qty = subcat_by_gender_qty[subcat_by_gender_qty["Rnk"] <=␣
↪5].sort_values(by='Gender')
top5_subcat_by_gender_qty
```

[ ]:
```
   Gender Product_Category  Quantity  Rnk
0  Female      Electronics     25297 1.00
4  Female           Sports     25279 2.00
2  Female        Groceries     25141 3.00
1  Female          Fashion     24899 4.00
3  Female             Home     24854 5.00
8    Male             Home     25061 1.00
6    Male          Fashion     25046 2.00
9    Male           Sports     24963 3.00
5    Male      Electronics     24871 4.00
7    Male        Groceries     24636 5.00
```

[ ]:
```
df['Year'].unique()
```

[ ]:
```
array([2023, 2024])
```

Z-Test : Compare Revenue Of the Year 2023 and 2024

Null Hypothesis (H0): The revenue of the year 2023 is equal to the revenue year 2024.

Alternative Hypothesis (H1) : The revenue 2023 is different from 2024.

[ ]:
```
from scipy import stats

# Select revenue for each year
revenue_2023 = df[df['Year'] == 2023]['Total_Sales']
revenue_2024 = df[df['Year'] == 2024]['Total_Sales']

# Perform independent two-sample t-test
t_stat, p_value = stats.ttest_ind(revenue_2023, revenue_2024, equal_var=False) ␣
 ↪# Welch's t-test

print(f"T-Test Statistic: {t_stat:.4f}")
print(f"P-Value: {p_value:.4f}")

# Interpretation
if p_value < 0.05:
    print("Reject Null Hypothesis: Revenue in 2023 and 2024 is significantly␣
 ↪different.")
else:
    print("Accept Null Hypothesis: No significant difference in revenue between␣
 ↪2023 and 2024.")
```

```
T-Test Statistic: 0.0904
P-Value: 0.9280
Accept Null Hypothesis: No significant difference in revenue between 2023 and
2024.
```

[ ]:
```python
df.groupby(by = "Year")["Total_Sales"].agg(['sum','mean','max','min'])
```

[ ]:
```
                sum      mean      max    min
Year
2023 589967593.95 23598.70 89991.00 96.30
2024 589576200.20 23583.05 89991.00 89.60
```

- Top-selling product per Year

[ ]:
```python
# Grouping by Year and Product_Category
Category_by_year = df.groupby(['Year', 'Product_Category'])['Quantity'].sum().
↪reset_index()

# Rank categories per year
Category_by_year["Rnk"] = Category_by_year.groupby('Year')["Quantity"].
↪rank(method='dense', ascending=False)

# Filter top 5 per year
top5_categories_per_year = Category_by_year[Category_by_year["Rnk"] <= 5].
↪sort_values(by='Year')

# Show final table
top5_categories_per_year
```

[ ]:
```
   Year Product_Category  Quantity  Rnk
0  2023      Electronics     24851 4.00
1  2023          Fashion     25150 2.00
2  2023        Groceries     25186 1.00
3  2023             Home     24885 3.00
4  2023           Sports     24839 5.00
5  2024      Electronics     25317 2.00
6  2024          Fashion     24795 4.00
7  2024        Groceries     24591 5.00
8  2024             Home     25030 3.00
9  2024           Sports     25403 1.00
```

[ ]:
```python
from scipy import stats

# ANOVA: Revenue by Product Category
anova_data = [group['Total_Sales'] for name, group in df.
↪groupby('Product_Category')]
f_stat, p_val = stats.f_oneway(*anova_data)

print("ANOVA: Revenue by Product Category")
print(f"F-statistic = {f_stat:.4f}, P-value = {p_val:.4f}")

# Interpretation
```

```
if p_val < 0.05:
    print("Reject Null Hypothesis: Revenue significantly changed by Product␣
↪Category")
else:
    print("Accept Null Hypothesis: Revenue did not significantly change by␣
↪Product Category")
```

```
ANOVA: Revenue by Product Category
F-statistic = 0.8026, P-value = 0.5233
Accept Null Hypothesis: Revenue did not significantly change by Product Category
```

- Chi-Square Test: Relationship Between Customer Gender and Product Category

Null Hypothesis (H0) : There is no relationship between customer gender and product category. Alternative Hypothesis (H1) : There is a significant relationship between customer gender and product category.

[ ]:
```
# Contingency table
contingency = pd.crosstab(df['Gender'], df['Product_Category'])
print("Contingency Table:\n", contingency)

# Chi-square test
chi2, p, dof, expected = chi2_contingency(contingency)

print(f"\nChi-Square Statistic: {chi2:.4f}")
print(f"Degrees of Freedom: {dof}")
print(f"P-Value: {p:.4f}")

# Interpretation
if p < 0.05:
    print("  Reject Null Hypothesis: Gender and Product Category are dependent.
↪")
else:
    print("  Accept Null Hypothesis: No significant relationship between Gender␣
↪and Product Category.")
```

```
Contingency Table:
 Product_Category  Electronics  Fashion  Groceries  Home  Sports
Gender
Female                   4994     5015       4984  5017    5104
Male                     4979     4954       4963  4983    5007

Chi-Square Statistic: 0.4467
Degrees of Freedom: 4
P-Value: 0.9785
  Accept Null Hypothesis: No significant relationship between Gender and Product
Category.
```

[ ]:
```
df.columns
```

[ ]:
```
Index(['Order_ID', 'Customer_ID', 'Gender', 'Age', 'Country',
       'Product_Category', 'Quantity', 'Unit_Price', 'Discount', 'Order_Date',
       'Payment_Method', 'Ad_Campaign', 'Returned', 'Total_Sales', 'Year',
       'Month_Name', 'Cost', 'Profit', 'Unit_Cost', 'Month_Year'],
      dtype='object')
```

[ ]:
```
df[["Gender", "Product_Category"]].value_counts().unstack()
```

[ ]:
```
Product_Category  Electronics  Fashion  Groceries  Home  Sports
Gender
Female                   4994     5015       4984  5017    5104
Male                     4979     4954       4963  4983    5007
```

0.1.3 Business Insights & Recommendations

Top Products (Revenue & Profit)
- Electronics (20.2%), Sports (20.1%), and Fashion (20.0%) together drive ~60% of total revenue.
- **Recommendation:** Prioritize inventory allocation, promotional spend, and marketing focus on these categories.

Underperforming Categories
- Home (19.8%) and Groceries (19.9%) contribute the least to overall revenue and profit.
- **Recommendation:** Run targeted pricing/discount campaigns; if performance doesn't improve, consider rationalizing SKUs.

Customer Gender Insights
- Female customers generated **$594.9M**, slightly higher than males at **$584.6M**.
- **Recommendation:** Develop gender-specific campaigns — loyalty programs for females, product bundling for males.

Seasonality Trends
- Sales peak during **Nov–Dec** (festive season) and dip in **Mar–Apr**.
- **Recommendation:** Increase stock levels and intensify promotions in festive months; optimize costs in low-demand periods.

High Volume High Profitability
- Example: Groceries record high sales volume but deliver the lowest margin (~19.8% of profit).
- **Recommendation:** Improve margins through pricing adjustments, product bundling, or promoting premium/high-value alternatives.