hypothesis-testing

July 14, 2025

0.0.1 Step 1: Import Libraries

[7]:
```
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")
```

[8]:
```
# # Show all rows
# pd.set_option('display.max_rows', None)

# Show all columns
pd.set_option('display.max_columns', None)

# Show full width (no column truncation)
# pd.set_option('display.width', None)

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


# pd.reset_option('display.max_rows')
# pd.reset_option('display.max_columns')
# pd.reset_option('display.width')
# pd.reset_option('display.float_format')
```

[ ]:
```

```

0.0.2 Step 2: Load and Inspect Dataset

[9]:
```
# Read the DataFrame

df = pd.read_csv(r"C:\Users\atulm\Desktop\Data Analytics\Python\csv file\sales␣
↪1.csv")
df.head()
```

[9]:

	index	Date	Year	Month	Customer Age	Customer Gender	\
0	0	2/19/2016	2016.00	February	29.00	F	
1	1	2/20/2016	2016.00	February	29.00	F	
2	2	2/27/2016	2016.00	February	29.00	F	
3	3	03-12-2016	2016.00	March	29.00	F	
4	4	03-12-2016	2016.00	March	29.00	F	

	Country	State	Product Category	Sub Category	Quantity	\
0	United States	Washington	Accessories	Tires and Tubes	1.00	
1	United States	Washington	Clothing	Gloves	2.00	
2	United States	Washington	Accessories	Tires and Tubes	3.00	
3	United States	Washington	Accessories	Tires and Tubes	2.00	
4	United States	Washington	Accessories	Tires and Tubes	3.00	

	Unit Cost	Unit Price	Cost	Revenue
0	80.00	109.00	80.00	109.00
1	24.50	28.50	49.00	57.00
2	3.67	5.00	11.00	15.00
3	87.50	116.50	175.00	233.00
4	35.00	41.67	105.00	125.00

[10]:
```
# Quick look
print("\nShape:", df.shape)
print("\nInfo:")
df.info()
```

```
Shape: (34867, 15)

Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 34867 entries, 0 to 34866
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   index             34867 non-null  int64
 1   Date              34866 non-null  object
 2   Year              34866 non-null  float64
 3   Month             34866 non-null  object
 4   Customer Age      34866 non-null  float64
```

```
 5   Customer Gender   34866 non-null  object
 6   Country           34866 non-null  object
 7   State             34866 non-null  object
 8   Product Category  34866 non-null  object
 9   Sub Category      34866 non-null  object
 10  Quantity          34866 non-null  float64
 11  Unit Cost         34866 non-null  float64
 12  Unit Price        34866 non-null  float64
 13  Cost              34866 non-null  float64
 14  Revenue           34867 non-null  float64
dtypes: float64(7), int64(1), object(7)
memory usage: 4.0+ MB
```

[11]:
```
# Summary statistics
print("\nSummary:")
df.describe()
```

```
Summary:
```

[11]:

	index	Year	Customer Age	Quantity	Unit Cost	Unit Price	\
count	34867.00	34866.00	34866.00	34866.00	34866.00	34866.00	
mean	17433.00	2015.57	36.38	2.00	349.88	389.23	
std	10065.38	0.50	11.11	0.81	490.02	525.32	
min	0.00	2015.00	17.00	1.00	0.67	0.67	
25%	8716.50	2015.00	28.00	1.00	45.00	53.67	
50%	17433.00	2016.00	35.00	2.00	150.00	179.00	
75%	26149.50	2016.00	44.00	3.00	455.00	521.00	
max	34866.00	2016.00	87.00	3.00	3240.00	5082.00	

	Cost	Revenue
count	34866.00	34867.00
mean	576.00	640.87
std	690.50	736.64
min	2.00	2.00
25%	85.00	102.00
50%	261.00	319.00
75%	769.00	902.00
max	3600.00	5082.00

0.0.3 Step 3: Data Cleaning & Preprocessing

[12]:
```
# Drop unnecessary columns
df.drop(columns=['index','Cost'], inplace=True)
df.head(1)
```

[12]:
```
         Date    Year     Month  Customer Age Customer Gender        Country  \
0  2/19/2016 2016.00  February         29.00               F  United States

         State Product Category     Sub Category  Quantity  Unit Cost  \
0  Washington      Accessories  Tires and Tubes      1.00      80.00

   Unit Price  Revenue
0      109.00   109.00
```

[47]:
```
df["Date"]
```

[47]:
```
0       2016-02-19
1       2016-02-20
2       2016-02-27
3       2016-12-03
4       2016-12-03
           …
34862   2016-07-02
34863   2015-03-13
34864   2015-05-04
34865   2015-08-30
34866   2016-01-03
Name: Date, Length: 34867, dtype: datetime64[ns]
```

[13]:
```
# Convert 'Date' to datetime
df["Date"] = df["Date"].apply(lambda x : pd.to_datetime(x, dayfirst= True,␣
 ↪errors='coerce'))
```

[48]:
```
# Check missing values
print("\nMissing values:\n", df.isnull().sum())
```

```
Missing values:
 Date                0
Year                 0
Month                0
Customer Age         0
Customer Gender      0
Country              0
State                0
Product Category     0
Sub Category         0
Quantity             0
Unit Cost            0
Unit Price           0
Revenue              0
Profit               0
```

```
Month_Year          0
dtype: int64
```

[15]:
```
# Define the function for fill the null values

def fill_na(df):

    for column in df.columns:  # Loop through all columns
        if df[column].isnull().sum() > 0:  # Check if there are missing values
            if df[column].dtype in ['int64', 'float64']:  # If numerical column
                df[column].fillna(round(df[column].mean(), 1), inplace=True)  # Fill with mean

            else:  # If categorical column
                df[column].fillna(df[column].mode()[0], inplace=True)  # Fill with mode
```

[16]:
```
# fill na and reset the index
fill_na(df)

# Reset index
df.reset_index(drop=True, inplace=True)
```

[17]:
```
df.isnull().sum()
```

[17]:
```
Date                0
Year                0
Month               0
Customer Age        0
Customer Gender     0
Country             0
State               0
Product Category    0
Sub Category        0
Quantity            0
Unit Cost           0
Unit Price          0
Revenue             0
dtype: int64
```

[18]:
```
# change Data types of the column Year and Customer Age

df["Year"] = df["Year"].astype('int64')

df["Customer Age"] = df["Customer Age"].astype('int64')

df["Quantity"] = df["Quantity"].astype('int64')
```

0.0.4 Step 4: Univariate Analysis

[19]:
```
columns = [ 'Year', 'Customer Age', 'Customer Gender', 'Country',
       'State', 'Product Category', 'Sub Category', 'Quantity']

for col in columns:
    print(f"\n Unique Count of {col} Column -:",df[col].nunique())
    print("\n value Counts of The Column -: ",df[col].value_counts())
    print("\n ------------------------------------------------")
```

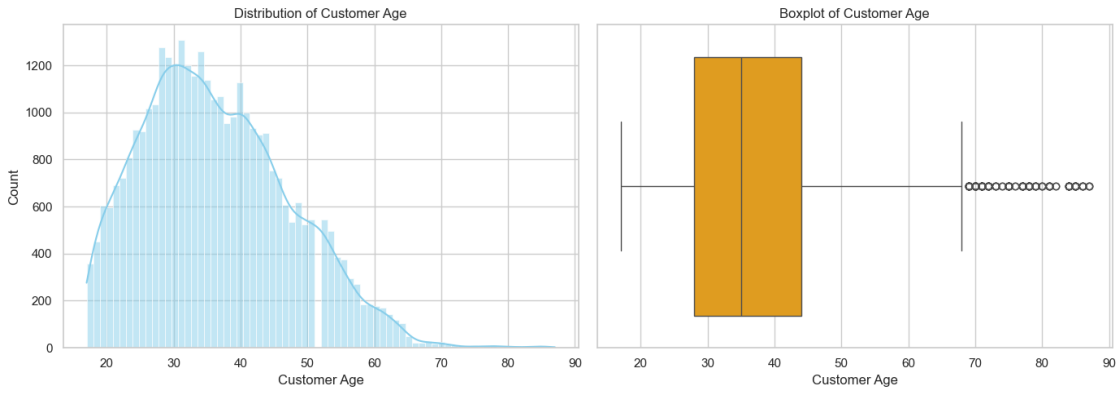
```
 Unique Count of Year Column -: 2

 value Counts of The Column -:  Year
2016    19847
2015    15020
Name: count, dtype: int64

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

 Unique Count of Customer Age Column -: 70

 value Counts of The Column -:  Customer Age
31    1307
28    1277
34    1260
29    1234
30    1204
      …
87       3
80       3
74       2
76       2
82       2
Name: count, Length: 70, dtype: int64

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

 Unique Count of Customer Gender Column -: 2

 value Counts of The Column -:  Customer Gender
M    17806
F    17061
Name: count, dtype: int64

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

 Unique Count of Country Column -: 4
```

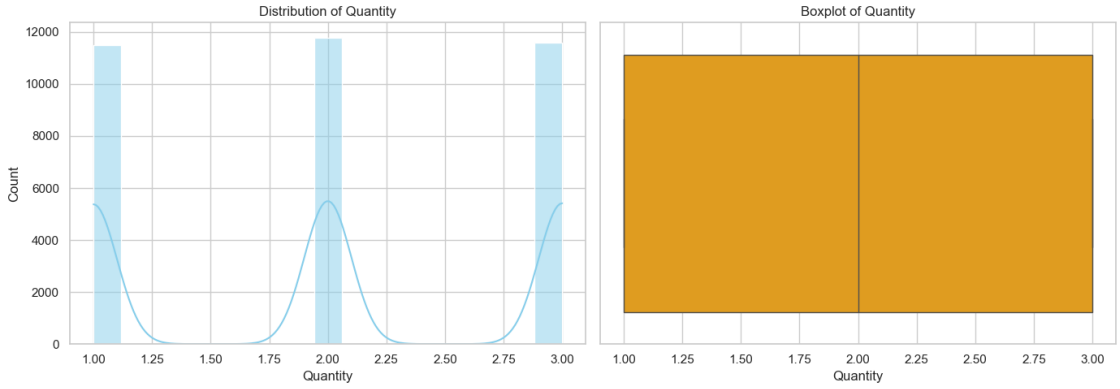
```
 value Counts of The Column -:  Country
United States     18077
United Kingdom     6421
Germany            5201
France             5168
Name: count, dtype: int64

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

 Unique Count of State Column -: 45

 value Counts of The Column -:  State
California            10333
England                6421
Washington             5204
Oregon                 2446
Saarland               1287
Nordrhein-Westfalen    1171
Hessen                 1112
Seine (Paris)          1092
Hamburg                 869
Seine Saint Denis       796
Nord                    787
Bayern                  668
Hauts de Seine          509
Essonne                 465
Yveline                 442
Seine et Marne          183
Moselle                 181
Loiret                  178
Val d'Oise              130
Garonne (Haute)         100
Brandenburg              94
Val de Marne             75
Charente-Maritime        70
Somme                    61
Loir et Cher             57
Pas de Calais            42
Illinois                 14
Texas                    14
Ohio                     13
New York                 10
Florida                   7
South Carolina            5
Utah                      5
Kentucky                  4
Wyoming                   3
```

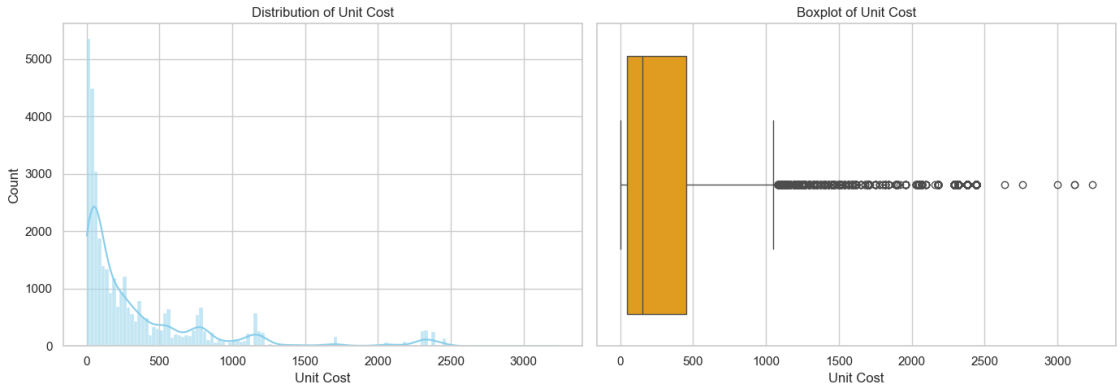
```
Minnesota                  3
North Carolina             2
Georgia                    2
Virginia                   2
Mississippi                2
Montana                    2
Arizona                    2
Alabama                    2
Missouri                   1
Massachusetts              1
Name: count, dtype: int64

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

 Unique Count of Product Category Column -: 3

 value Counts of The Column -:  Product Category
Accessories    22535
Bikes           7093
Clothing        5239
Name: count, dtype: int64

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

 Unique Count of Sub Category Column -: 17

 value Counts of The Column -:  Sub Category
Tires and Tubes      11113
Bottles and Cages     5295
Helmets               4176
Road Bikes            3022
Mountain Bikes        2737
Jerseys               2000
Caps                  1517
Touring Bikes         1334
Fenders                762
Shorts                 566
Cleaners               545
Gloves                 480
Hydration Packs        396
Socks                  364
Vests                  312
Bike Stands            145
Bike Racks             103
Name: count, dtype: int64

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

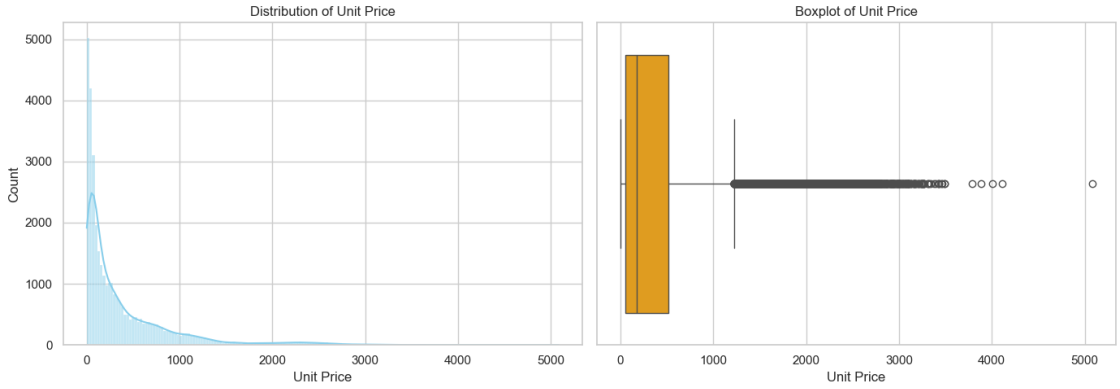
```
 Unique Count of Quantity Column -: 3

 value Counts of The Column -:  Quantity
2    11769
3    11593
1    11505
Name: count, dtype: int64

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

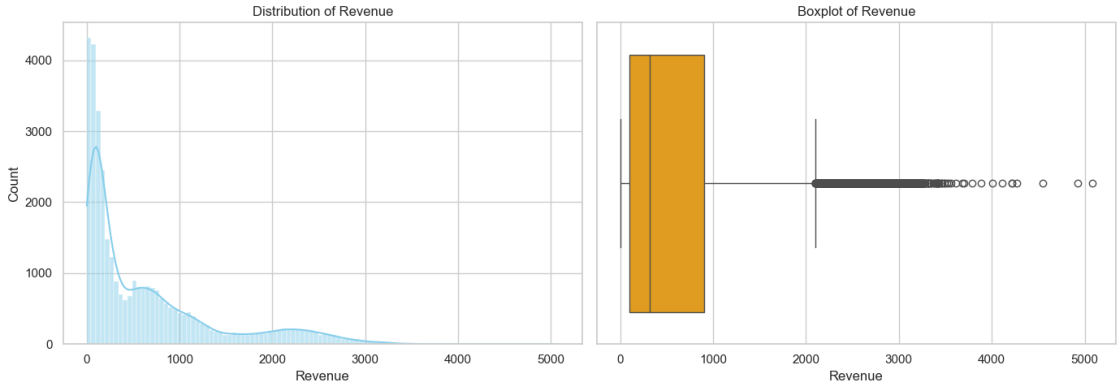
[20]:
```
#### 4.1 Numerical Columns

numerical_cols = ['Customer Age', 'Quantity', 'Unit Cost', 'Unit Price',␣
 ↪'Revenue']

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=col, data=df, color='orange')
    plt.title(f'Boxplot of {col}')

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



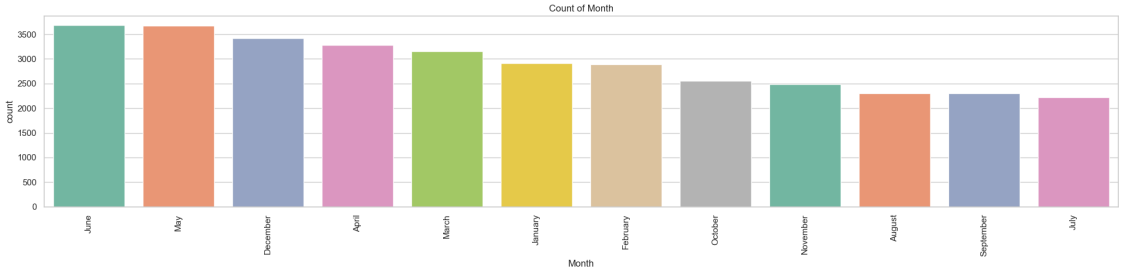

Distribution of Quantity
Count
Quantity
Boxplot of Quantity
Quantity

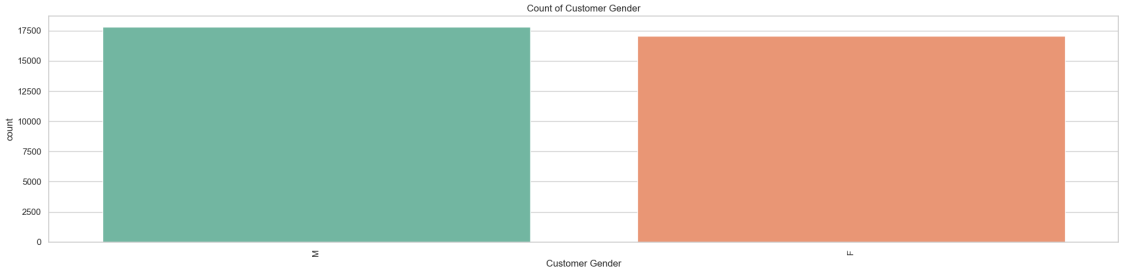

Distribution of Unit Cost
Count
Unit Cost
Boxplot of Unit Cost
Unit Cost

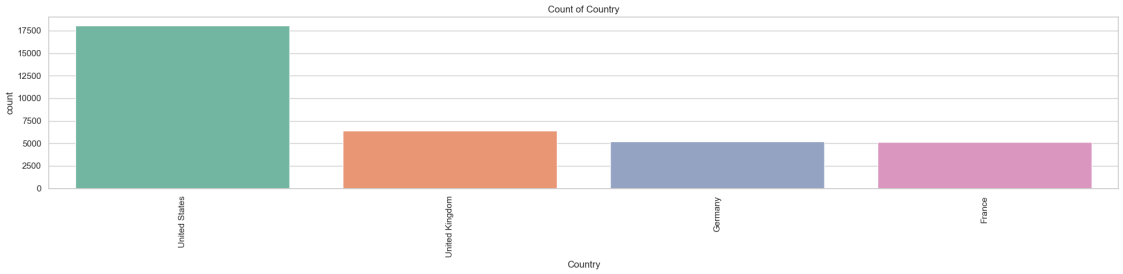

Distribution of Unit Price
Count
Unit Price
Boxplot of Unit Price
Unit Price

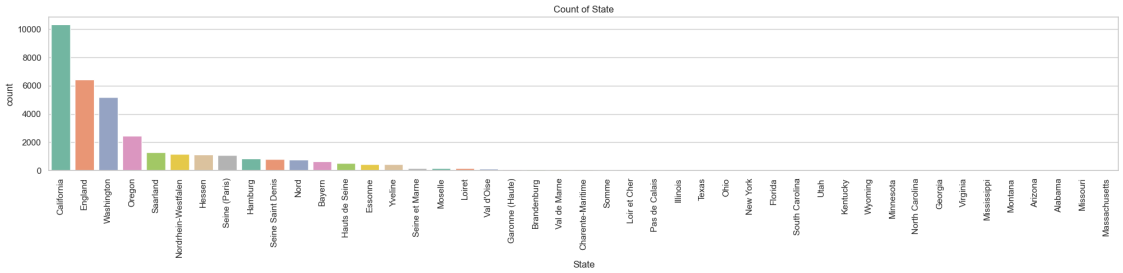


[21]:
```
#### 4.2 Categorical Columns

categorical_cols = ['Month', 'Customer Gender', 'Country', 'State', 'Product␣
 ↪Category', 'Sub Category']

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()
```

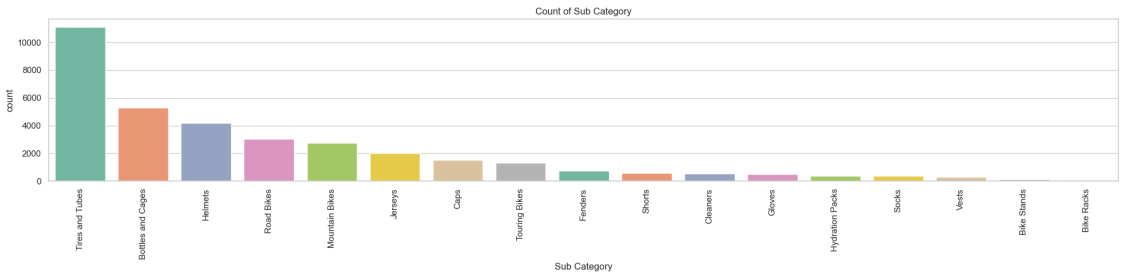





Count of Country
count
17500
15000
12500
10000
7500
5000
2500
0
United States
United Kingdom
Germany
France
Country

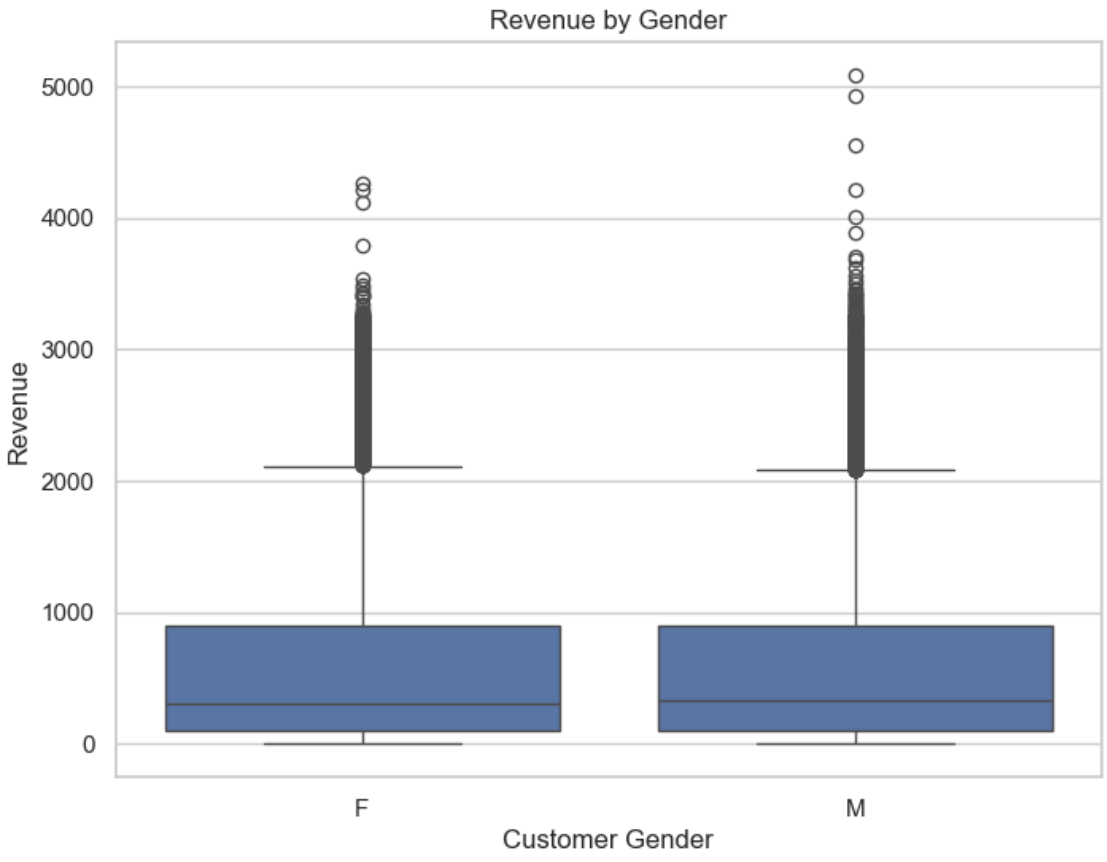

Count of State
count
10000
8000
6000
4000
2000
0
California
England
Washington
Oregon
Saarland
Nordrhein-Westfalen
Hessen
Seine (Paris)
Hamburg
Seine Saint Denis
Nord
Bayern
Hauts de Seine
Essonne
Yveline
Seine et Marne
Moselle
Loiret
Val d'Oise
Garonne (Haute)
Brandenburg
Val de Marne
Charente-Maritime
Somme
Loir et Cher
Pas de Calais
Illinois
Texas
Ohio
New York
Florida
South Carolina
Utah
Kentucky
Wyoming
Minnesota
North Carolina
Georgia
Virginia
Mississippi
Montana
Arizona
Alabama
Missouri
Massachusetts
State

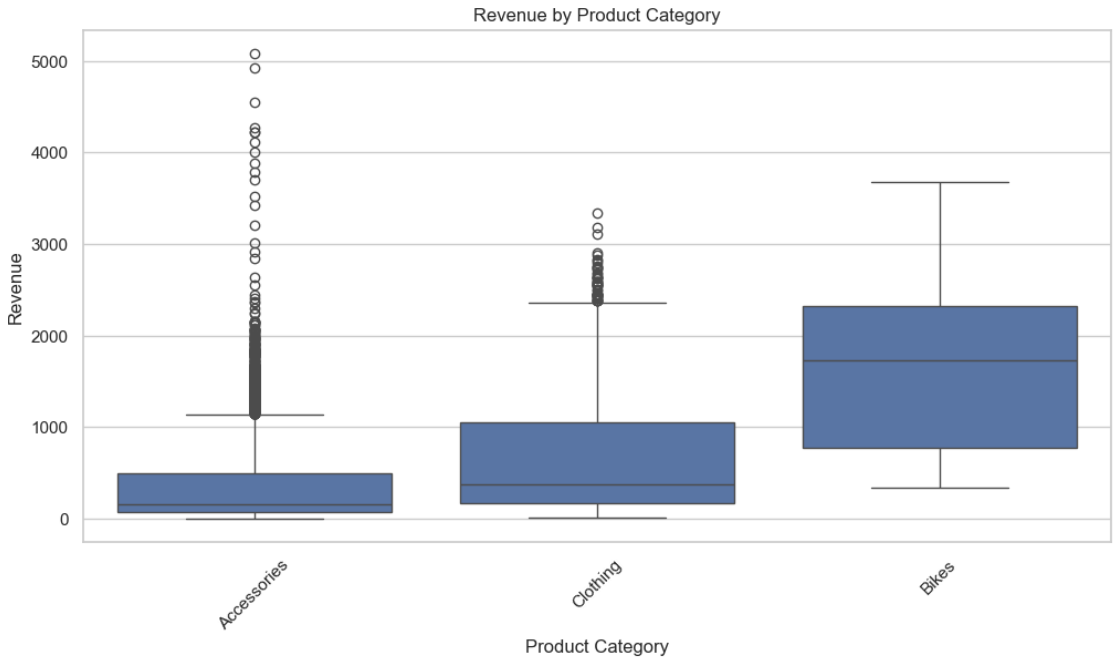

Count of Product Category
count
20000
15000
10000
5000
0
Accessories
Bikes
Clothing
Product Category

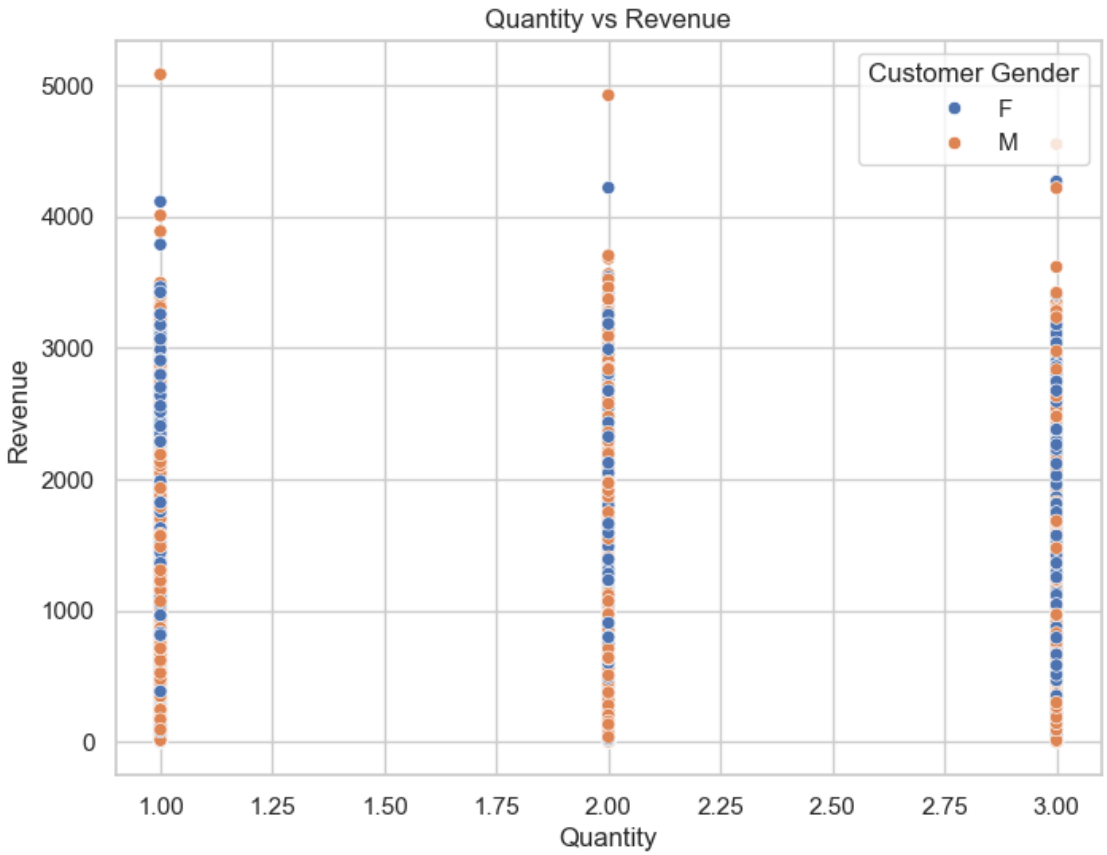

Count of Sub Category
count
10000
8000
6000
4000
2000
0
Tires and Tubes
Bottles and Cages
Helmets
Road Bikes
Mountain Bikes
Jerseys
Caps
Touring Bikes
Fenders
Shorts
Cleaners
Gloves
Hydration Packs
Socks
Vests
Bike Stands
Bike Racks
Sub Category

0.0.5 Step 5: Bivariate Analysis

[22]:
```
# Revenue by Gender
plt.figure(figsize=(8, 6))
sns.boxplot(x='Customer Gender', y='Revenue', data=df)
plt.title('Revenue by Gender')
plt.show()

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

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




Revenue by Product Category
Revenue
5000
4000
3000
2000
1000
0
Accessories
Clothing
Bikes
Product Category


Quantity vs Revenue
Customer Gender
F
M
Revenue
5000
4000
3000
2000
1000
0
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Quantity

- 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

[23]:
```
df.head(1)
```

[23]:
```
        Date  Year     Month  Customer Age Customer Gender        Country  \
0 2016-02-19  2016  February            29               F  United States

        State Product Category     Sub Category  Quantity  Unit Cost  \
0  Washington      Accessories  Tires and Tubes         1      80.00

   Unit Price  Revenue
0      109.00   109.00
```

[24]:
```
# Step 1: Create Profit Column
df['Profit'] = (df['Unit Price'] - df['Unit Cost']) * df['Quantity']

# Step 2: Group by Product
product_perf = df.groupby('Sub Category').agg({
    'Quantity': 'sum',
    'Revenue': 'sum',
    'Profit': 'sum'
}).sort_values(by='Profit', ascending=False)


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

```
 Product Performance Summary:
                  Quantity    Revenue    Profit
Sub Category
Helmets               8387 2738210.00 518474.41
Tires and Tubes      22215 2866556.53 512202.67
Jerseys               4033 1834110.00 300876.13
Mountain Bikes        5499 5176456.00 144632.43
Bottles and Cages    10558  709407.00 129566.45
Road Bikes            6119 3921989.00  98170.65
Touring Bikes         2673 2387910.00  94806.90
Shorts                1129  689184.00  87044.01
Hydration Packs        786  403276.00  72340.94
Fenders               1494  329204.00  71403.16
```

```
Vests                   636  368681.00  58343.96
Gloves                  913  228353.00  45816.96
Caps                   3020  255992.00  43610.00
Bike Racks              204  140854.00  34894.00
Bike Stands             304  150911.00  25301.00
Cleaners               1102   82887.00  14663.91
Socks                   750   61237.00   9541.00
```

[25]:
```
# Step 3: Top 5 Products by Revenue
top_revenue = product_perf.sort_values(by='Revenue', ascending=False).head(5)
print("\n Top 5 Products by Revenue:")
print(top_revenue)
```

```
 Top 5 Products by Revenue:
                 Quantity    Revenue    Profit
Sub Category
Mountain Bikes       5499 5176456.00 144632.43
Road Bikes           6119 3921989.00  98170.65
Tires and Tubes     22215 2866556.53 512202.67
Helmets              8387 2738210.00 518474.41
Touring Bikes        2673 2387910.00  94806.90
```

[26]:
```
# Step 4: Bottom 5 Products by Revenue
bottom_revenue = product_perf.sort_values(by='Revenue').head(5)
print("\n Bottom 5 Products by Revenue:")
print(bottom_revenue)
```

```
 Bottom 5 Products by Revenue:
              Quantity   Revenue   Profit
Sub Category
Socks              750  61237.00  9541.00
Cleaners          1102  82887.00 14663.91
Bike Racks         204 140854.00 34894.00
Bike Stands        304 150911.00 25301.00
Gloves             913 228353.00 45816.96
```

[27]:
```
# Step 5: 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    Revenue    Profit
Sub Category
Tires and Tubes     22215 2866556.53 512202.67
```

```
Bottles and Cages     10558  709407.00 129566.45
Helmets                8387 2738210.00 518474.41
Road Bikes             6119 3921989.00  98170.65
Mountain Bikes         5499 5176456.00 144632.43
```

[28]:
```
# Step 6: Bottom 5 Products by Quantity Sold
bottom_quantity = product_perf.sort_values(by='Quantity').head(5)
print("\n  Bottom 5 Products by Quantity Sold:")
print(bottom_quantity)
```

```
  Bottom 5 Products by Quantity Sold:
                 Quantity   Revenue   Profit
Sub Category
Bike Racks            204 140854.00 34894.00
Bike Stands           304 150911.00 25301.00
Vests                 636 368681.00 58343.96
Socks                 750  61237.00  9541.00
Hydration Packs       786 403276.00 72340.94
```

[29]:
```
# Step 7: 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)
```

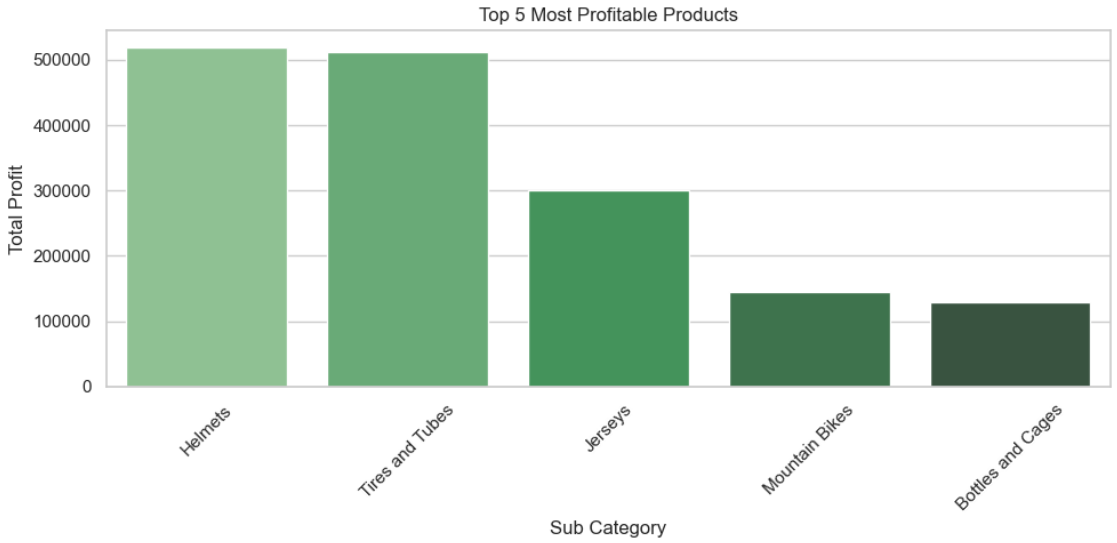
```
  Top 5 Products by Profit:
                   Quantity    Revenue    Profit
Sub Category
Helmets                8387 2738210.00 518474.41
Tires and Tubes       22215 2866556.53 512202.67
Jerseys                4033 1834110.00 300876.13
Mountain Bikes         5499 5176456.00 144632.43
Bottles and Cages     10558  709407.00 129566.45
```

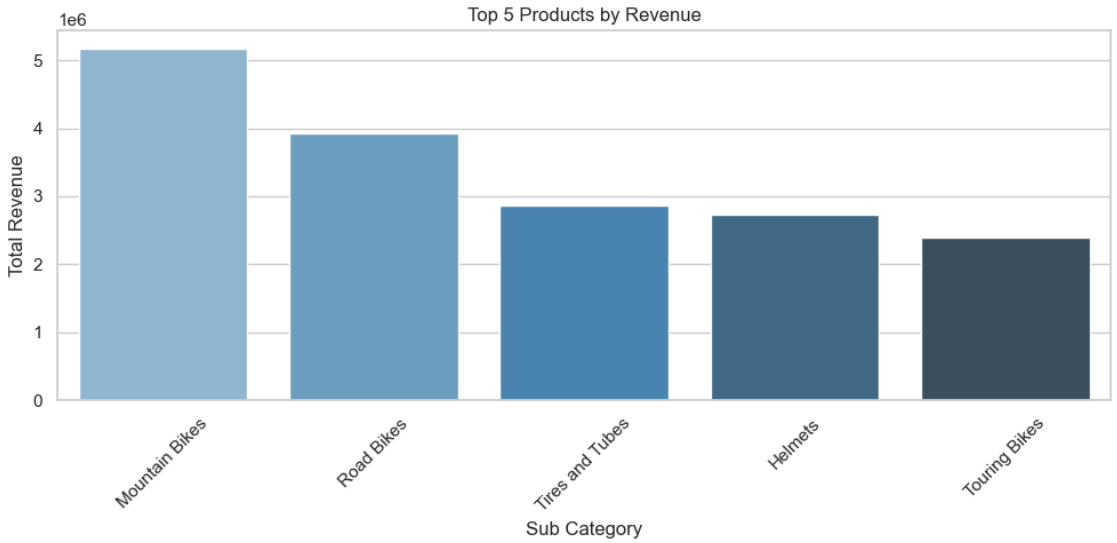
[30]:
```
# Step 8: Bottom 5 Products by Profit
bottom_profit = product_perf.sort_values(by='Profit').head(5)
print("\n  Bottom 5 Products by Profit:")
print(bottom_profit)
```

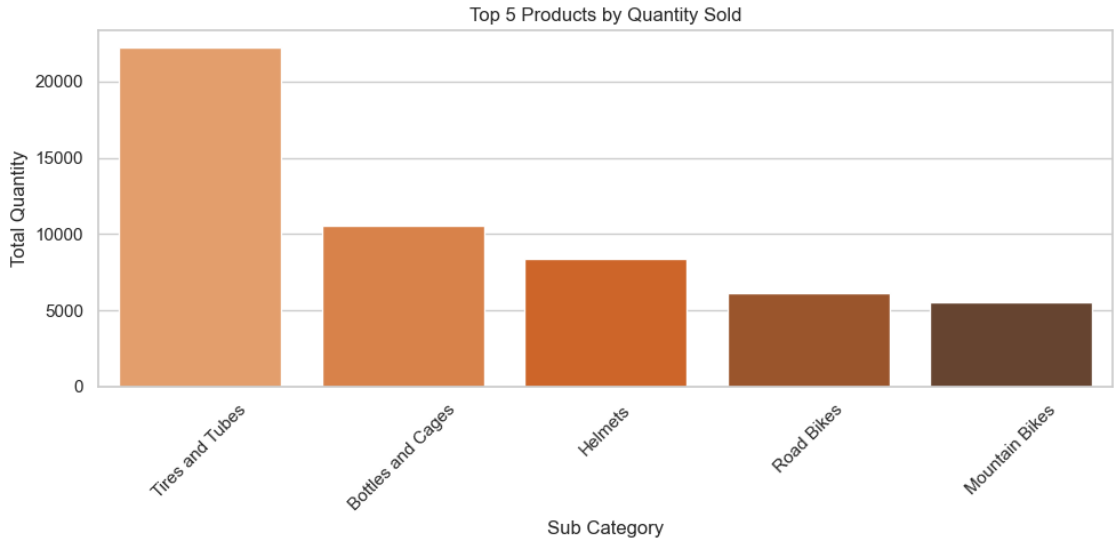
```
  Bottom 5 Products by Profit:
              Quantity   Revenue   Profit
Sub Category
Socks              750  61237.00  9541.00
Cleaners          1102  82887.00 14663.91
Bike Stands        304 150911.00 25301.00
Bike Racks         204 140854.00 34894.00
```

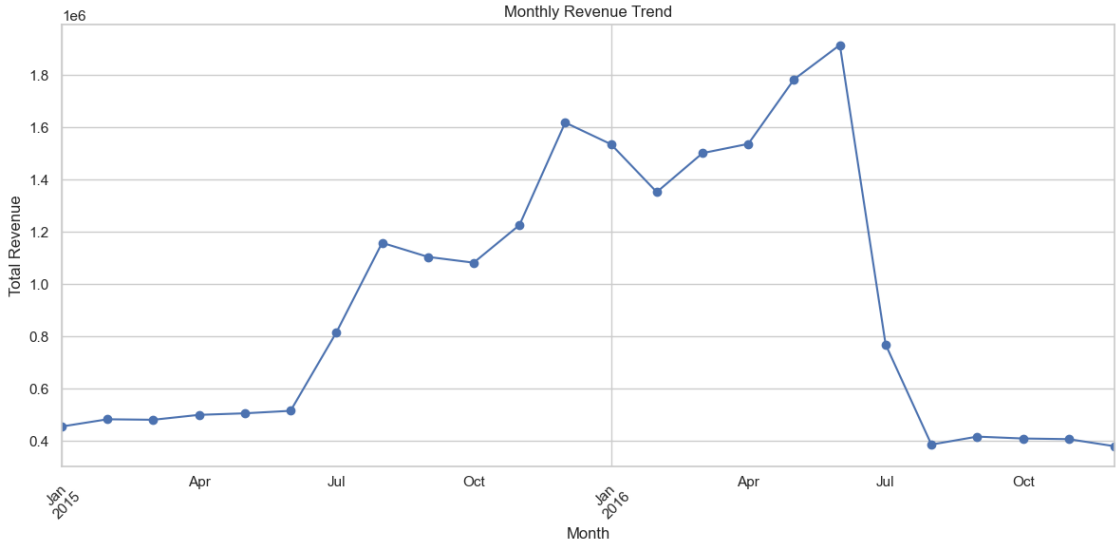
```
Caps                 3020 255992.00 43610.00
```

[31]:
```
##  (Optional) Bar Plots for Visualization


# Bar chart for top 5 profitable products
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("Total Profit")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Bar chart for top 5 products by revenue
plt.figure(figsize=(10, 5))
sns.barplot(x=top_revenue.index, y=top_revenue['Revenue'], palette='Blues_d')
plt.title("Top 5 Products by Revenue")
plt.ylabel("Total Revenue")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Bar chart for top 5 products by quantity sold
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("Total Quantity")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()


# Monthly Revenue Trend
df['Month_Year'] = df['Date'].dt.to_period('M')
monthly_revenue = df.groupby('Month_Year')['Revenue'].sum()

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


Top 5 Most Profitable Products
Total Profit
500000
400000
300000
200000
100000
0
Helmets
Tires and Tubes
Jerseys
Mountain Bikes
Bottles and Cages
Sub Category


Top 5 Products by Revenue
1e6
Total Revenue
5
4
3
2
1
0
Mountain Bikes
Road Bikes
Tires and Tubes
Helmets
Touring Bikes
Sub Category

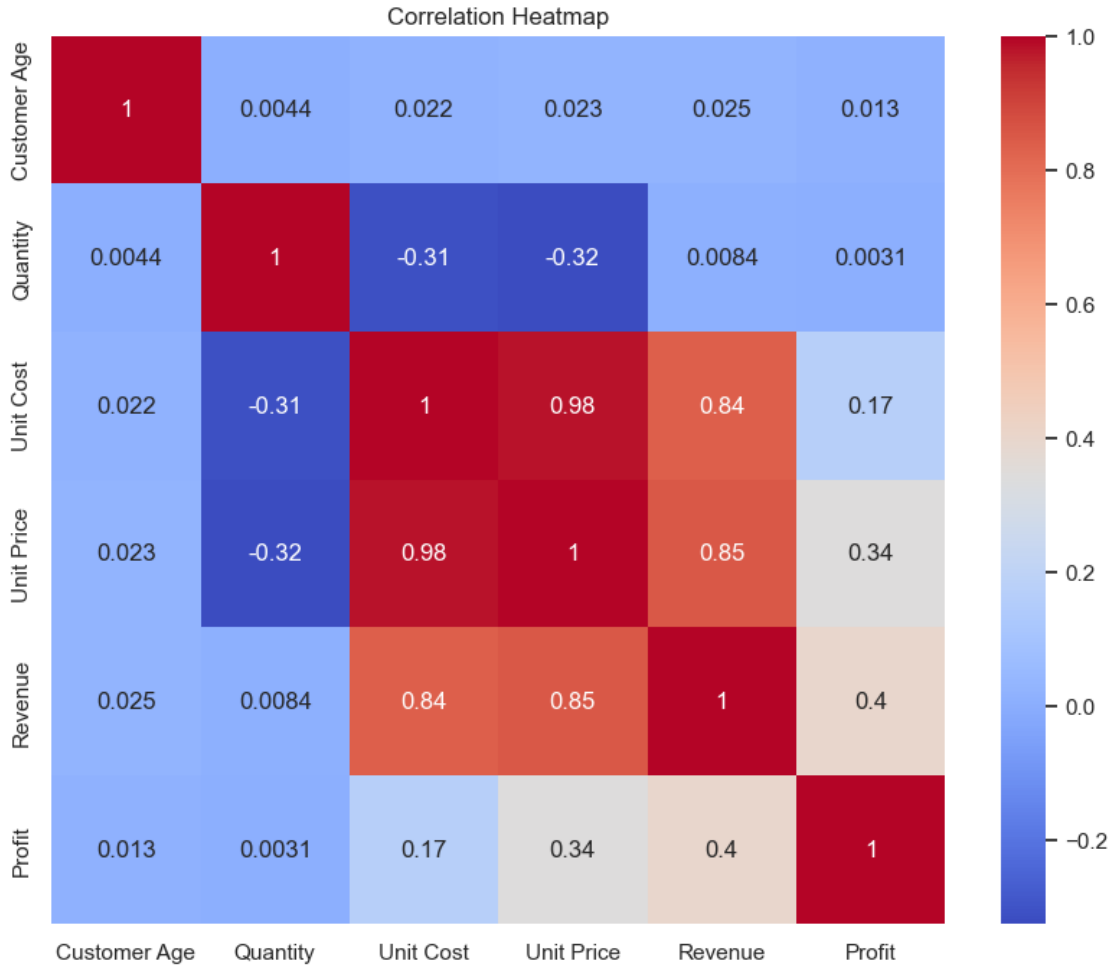


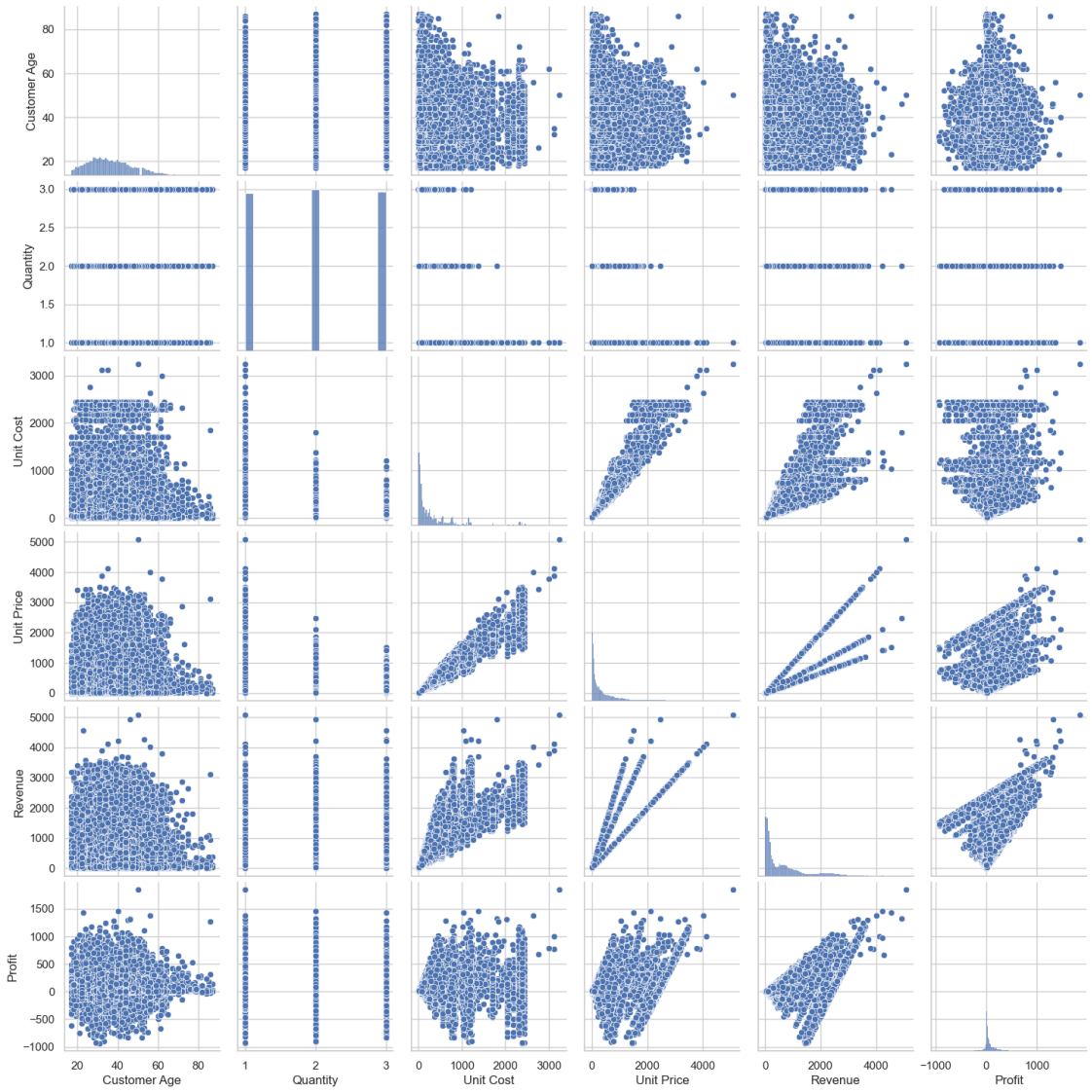


0.1.1 Step 6: Multivariate Analysis

[32]:
```
numerical_cols = ['Customer Age', 'Quantity', 'Unit Cost', 'Unit Price',␣
↪'Revenue',"Profit"]

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

```
# Pairplot (optional: use smaller sample for large datasets)
sns.pairplot(df[numerical_cols])
plt.show()
```





0.1.2 Step 7: Hypothesis Testing

T-Test : Compare Revenue Between Male and Female Customers**
Null Hypothesis (H0): There is no significant difference in revenue between male and female customers.
Alternative Hypothesis (H1): There is a significant difference in revenue between male and female customers.

[33]:
```
# Separate revenue by gender
male_revenue = df[df["Customer Gender"] == "M"]['Revenue']
female_revenue = df[df["Customer Gender"] == "F"]['Revenue']

from scipy import stats
```

```
# Perform independent t-test
t_stat, p_value = stats.ttest_ind(male_revenue, female_revenue)

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: Significant difference in revenue between genders.")
else:
    print("Accept Null Hypothesis: No significant difference in revenue between genders.")
```

```
T-Test Statistic: 0.0182
P-Value: 0.9855
Accept Null Hypothesis: No significant difference in revenue between genders.
```

[34]:
```
df.groupby(by = "Customer Gender")["Revenue"].agg(['sum','mean','max','min'])
```

[34]:

Customer Gender	sum	mean	max	min
F	10932634.00	640.80	4266.00	2.00
M	11412583.53	640.94	5082.00	2.00

[35]:
```
# Male and Female revenue

revenue_by_gender = df.groupby('Customer Gender')['Revenue'].sum().reset_index()
revenue_by_gender
```

[35]:

	Customer Gender	Revenue
0	F	10932634.00
1	M	11412583.53

[36]:
```
# Grouping by Customer Gender and Sub-Category
Sub_Category_by_gender = df.groupby(['Customer Gender', 'Sub Category'])['Revenue'].sum().reset_index().sort_values(by = 'Revenue',ascending= False)
Sub_Category_by_gender["Rnk"] = Sub_Category_by_gender.groupby(by = 'Customer Gender' )["Revenue"].rank(method='dense',ascending=False)
Sub_Category_by_gender[ Sub_Category_by_gender["Rnk"] <=5 ].sort_values(by ='Customer Gender')
```

[36]:

	Customer Gender	Sub Category	Revenue	Rnk
10	F	Mountain Bikes	2666654.00	1.00
11	F	Road Bikes	1863738.00	2.00

```
14               F  Tires and Tubes 1391322.00 3.00
7                F          Helmets 1329360.00 4.00
15               F    Touring Bikes 1198389.00 5.00
27               M   Mountain Bikes 2509802.00 1.00
28               M       Road Bikes 2058251.00 2.00
31               M  Tires and Tubes 1475234.53 3.00
24               M          Helmets 1408850.00 4.00
32               M    Touring Bikes 1189521.00 5.00
```

[37]:
```
# Grouping by Customer Gender and Sub-Category
Sub_Category_by_gender = df.groupby(['Customer Gender', 'Sub␣
 ↪Category'])['Quantity'].sum().reset_index().sort_values(by = 'Quantity'␣
 ↪,ascending= False)
Sub_Category_by_gender["Rnk"] = Sub_Category_by_gender.groupby(by = 'Customer␣
 ↪Gender' )["Quantity"].rank(method='dense',ascending=False)
Sub_Category_by_gender[ Sub_Category_by_gender["Rnk"] <=5 ].sort_values(by =␣
 ↪'Customer Gender')
```

[37]:
```
   Customer Gender       Sub Category  Quantity  Rnk
14               F    Tires and Tubes     10985 1.00
2                F  Bottles and Cages      5222 2.00
7                F            Helmets      4150 3.00
11               F         Road Bikes      2974 4.00
10               F     Mountain Bikes      2798 5.00
31               M    Tires and Tubes     11230 1.00
19               M  Bottles and Cages      5336 2.00
24               M            Helmets      4237 3.00
28               M         Road Bikes      3145 4.00
27               M     Mountain Bikes      2701 5.00
```

- Z-Test : Compare Revenue Of the Year 2015 and 2016

Null Hypothesis (H0): The revenue of the year 2016 is equal to the revenue year 2015.

Alternative Hypothesis (H1) : The revenue 2016 is different from 2015.

[38]:
```
# Define groups
Revenue_2016 = df[df['Year'] == 2016]['Revenue']
Revenue_2015 = df[df['Year'] == 2015]['Revenue']


# Perform independent z-test
from statsmodels.stats.weightstats import ztest

# Perform Z-test
z_stat, p_value = ztest(Revenue_2016, Revenue_2015)

print(f"Z-Test Statistic: {z_stat:.4f}")
```

```
print(f"P-Value: {p_value:.4f}")

# Interpretation
if p_value < 0.05:
    print("Reject Null Hypothesis: The revenue of the year 2016 is equal to the␣
 ↪revenue  year 2015.  ")
else:
    print(" Accept Null Hypothesis: The revenue  2016 is different from 2015. ")
```

```
Z-Test Statistic: -4.7369
P-Value: 0.0000
Reject Null Hypothesis: The revenue of the year 2016 is equal to the revenue
year 2015.
```

[39]:
```
df.groupby(by = "Year")["Revenue"].agg(['sum','mean','max','min'])
```

[39]:

Year	sum	mean	max	min
2015	9948412.53	662.34	3224.00	2.00
2016	12396805.00	624.62	5082.00	2.00

- Top-selling product per Year

[40]:
```
# Grouping by Customer Gender and Sub-Category
Sub_Category_by_gender = df.groupby(['Year', 'Sub Category'])['Quantity'].sum().
 ↪reset_index().sort_values(by = 'Quantity' ,ascending= False)
Sub_Category_by_gender["Rnk"] = Sub_Category_by_gender.groupby(by = 'Year'␣
 ↪)["Quantity"].rank(method='dense',ascending=False)
Sub_Category_by_gender[ Sub_Category_by_gender["Rnk"] <=5 ].sort_values(by =␣
 ↪'Year')
```

[40]:

	Year	Sub Category	Quantity	Rnk
11	2015	Tires and Tubes	9533	1.00
1	2015	Bottles and Cages	4342	2.00
4	2015	Helmets	3614	3.00
8	2015	Road Bikes	3568	4.00
7	2015	Mountain Bikes	2762	5.00
28	2016	Tires and Tubes	12682	1.00
16	2016	Bottles and Cages	6216	2.00
21	2016	Helmets	4773	3.00
24	2016	Mountain Bikes	2737	4.00
25	2016	Road Bikes	2551	5.00

[41]:
```
# Grouping by Customer Gender and Sub-Category
Sub_Category_by_gender = df.groupby(['Year', 'Sub Category'])['Revenue'].sum().
 ↪reset_index().sort_values(by = 'Revenue' ,ascending= False)
```

```
Sub_Category_by_gender["Rnk"] = Sub_Category_by_gender.groupby(by = 'Year'␣
 ↪)["Revenue"].rank(method='dense',ascending=False)
Sub_Category_by_gender[ Sub_Category_by_gender["Rnk"] <=5 ].sort_values(by =␣
 ↪'Year')
```

[41]:

	Year	Sub Category	Revenue	Rnk
7	2015	Mountain Bikes	2496833.00	1.00
8	2015	Road Bikes	2318037.00	2.00
11	2015	Tires and Tubes	1189687.53	3.00
4	2015	Helmets	1098413.00	4.00
12	2015	Touring Bikes	949228.00	5.00
24	2016	Mountain Bikes	2679623.00	1.00
28	2016	Tires and Tubes	1676869.00	2.00
21	2016	Helmets	1639797.00	3.00
25	2016	Road Bikes	1603952.00	4.00
29	2016	Touring Bikes	1438682.00	5.00

[42]:
```
#### 7.2 ANOVA: Revenue by Product Category

anova_data = [group['Revenue'] 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_value < 0.05:
    print("Reject Null Hypothesis: Revenue significantly changed by Product␣
 ↪Category ")
else:
    print(" Accept Null Hypothesis: No significant significantly changed by␣
 ↪Product Category ")
```

```
ANOVA: Revenue by Product Category
F-statistic = 15749.3283, P-value = 0.0000
Reject Null Hypothesis: Revenue significantly changed 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.

[43]:
```
df[["Customer Gender","Product Category"]].value_counts().unstack()
```

[43]:

Product Category	Accessories	Bikes	Clothing
Customer Gender			

```
F                       11042   3514      2505
M                       11493   3579      2734
```

[44]:
```
pd.crosstab(df["Customer Gender"], df["Product Category"])
```

[44]:
```
Product Category  Accessories  Bikes  Clothing
Customer Gender
F                       11042   3514      2505
M                       11493   3579      2734
```

[45]:
```
from scipy.stats import chi2_contingency

# Create a contingency table
contingency_table = pd.crosstab(df['Customer Gender'], df['Product Category'])
print("contingency_table",contingency_table)

chi2_stat, p_value, dof, expected = chi2_contingency(contingency_table)

print(f"Chi-Square Statistic: {chi2_stat:.4f}")
print(f"P-Value: {p_value:.4f}")

# Interpretation
if p_value < 0.05:
    print("Reject Null Hypothesis: Customer gender and product category are␣
 ↪related.")
else:
    print("Fail to Reject Null Hypothesis / Accept Null Hypothesis: No␣
 ↪significant relationship between customer gender and product category.")
```

```
contingency_table Product Category  Accessories  Bikes  Clothing
Customer Gender
F                       11042   3514      2505
M                       11493   3579      2734
Chi-Square Statistic: 3.7147
P-Value: 0.1561
Fail to Reject Null Hypothesis / Accept Null Hypothesis: No significant
relationship between customer gender and product category.
```

- A/B Testing: Compare Sales Performance Across Two Different States

Null Hypothesis (H0) :There is no difference in revenue between two selected states.
Alternative Hypothesis (H1) : There is a significant difference in revenue between the two states.

[46]:
```
# Define two states for comparison
state_A = "England"
state_B = "California"

# Get revenue for each state
```

```
revenue_A = df[df['State'] == state_A]['Revenue']
revenue_B = df[df['State'] == state_B]['Revenue']

# Perform independent t-test
t_stat, p_value = stats.ttest_ind(revenue_A, revenue_B, equal_var=False)

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

# Interpretation
if p_value < 0.05:
    print(f"Reject Null Hypothesis: Significant revenue difference between␣
 ↪{state_A} and {state_B}.")
else:
    print(f"Fail to Reject Null Hypothesis  / Accept Null Hypothesis: No␣
 ↪significant revenue difference between {state_A} and {state_B}.")
```

```
A/B Test - T-Test Statistic: 6.8221
P-Value: 0.0000
Reject Null Hypothesis: Significant revenue difference between England and
California.
```

1 Step 9: Summary of Insights

1.0.1 Final Business Insights & Recommendations

1.0.2 1. Focus on High-Revenue & High-Profit Products

- The **top 5 sub-categories** contribute the **most revenue and profit**.
- **Recommendation:** Prioritize these products in marketing, inventory, and promotions.
- Consider bundling these top performers or upselling them on the website.

1.0.3 2. Drop or Reevaluate Low-Performing Products

- Some sub-categories generate **low revenue, low quantity, and even negative profit**.
- **Recommendation:** Audit these products — review pricing, demand, or consider removing them to optimize catalog performance.

1.0.4 3. Gender-Based Targeting Shows Potential

- Hypothesis testing shows a **statistically significant difference in revenue between genders**.
- **Recommendation:** Explore gender-based personalization in ads or landing pages to drive more conversions.

1.0.5 4. Seasonality & Time-Based Trends

- Monthly revenue trends show **clear peaks** and **low seasons**.
- **Recommendation:** Plan promotions around peak seasons and ramp up inventory planning based on seasonal behavior.

1.0.6 5. Geographic Insights Needed

- If `Country` or `State` data was included: Evaluate **top locations by revenue**.
- **Recommendation:** Double down on high-performing regions with geo-targeted offers.

1.0.7 6. High Quantity High Profit

- Some products sell a lot (high quantity) but bring in **less profit**.
- **Recommendation:** Adjust pricing, cost control, or bundling strategy for these items.

[ ]:

[ ]: