EXPLORATORY DATA ANALYSIS ON RETAIL DATASET

Applying EDA on the sales data of a fictitious company to discover the transactional patterns and gain insights which can help the sales and marketing teams in business decision making.

Import the necessary libraries

In [1]:
```
# import the needed libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import plotly.express as px
from plotly.subplots import make_subplots
from datetime import datetime
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# Import wordcloud
### Word Cloud
from PIL import Image
!pip install wordcloud
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
```

```
Requirement already satisfied: wordcloud in c:\users\jeremy\anaconda3\lib\site-packages (1.8.2.2)
Requirement already satisfied: pillow in c:\users\jeremy\anaconda3\lib\site-packages (from wordcloud) (9.0.1)
Requirement already satisfied: numpy>=1.6.1 in c:\users\jeremy\anaconda3\lib\site-packages (from wordcloud) (1.21.5)
Requirement already satisfied: matplotlib in c:\users\jeremy\anaconda3\lib\site-packages (from wordcloud) (3.5.1)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\jeremy\anaconda3\lib\site-packages (from matplotlib->wordcloud) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\jeremy\anaconda3\lib\site-packages (from matplotlib->wordcloud) (1.3.2)
Requirement already satisfied: cycler>=0.10 in c:\users\jeremy\anaconda3\lib\site-packages (from matplotlib->wordcloud) (0.11.0)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\jeremy\anaconda3\lib\site-packages (from matplotlib->wordcloud) (2.8.2)
Requirement already satisfied: pyparsing>=2.2.1 in c:\users\jeremy\anaconda3\lib\site-packages (from matplotlib->wordcloud) (3.0.4)
Requirement already satisfied: packaging>=20.0 in c:\users\jeremy\anaconda3\lib\site-packages (from matplotlib->wordcloud) (21.3)
Requirement already satisfied: six>=1.5 in c:\users\jeremy\anaconda3\lib\site-packages (from python-dateutil>=2.7->matplotlib->wordcloud) (1.16.0)
```

In [3]:
```
# this is used to show the current working directory
import os
```

In [4]:
```
# show the current working directory
os.getcwd()
```

Out[4]:
```
'C:\\Users\\Jeremy\\Documents\\My portfolio projects\\Python Project\\Sales'
```

In [5]:
```
#read the data
sales_df = pd.read_csv("C:\\Users\\Jeremy\\Documents\\My portfolio projects\\Python Project\\Sales\\sales_data.csv")
```

Overview the Data: A sneak peak into the data

View the 1st 5 rows and the last 5 rows of the data using the .head() and .tail() methods

In [6]:
```
#.head() returns only the 1st 5 rows of the dataframe
sales_df.head()
```

Out[6]:

	Date	Customer_Age	Age_Group	Customer_Gender	Country	State	Product_Category	Sub_Category	Product	Order_Quantity	Unit_Cost	Unit_Price	Cost
0	26/11/2013	19	Youth (<25)	M	Canada	British Columbia	Accessories	Bike Racks	Hitch Rack - 4-Bike	8	45	120	360
1	26/11/2015	19	Youth (<25)	M	Canada	British Columbia	Accessories	Bike Racks	Hitch Rack - 4-Bike	8	45	120	360
2	23/03/2014	49	Adults (35-64)	M	Australia	New South Wales	Accessories	Bike Racks	Hitch Rack - 4-Bike	23	45	120	1035
3	23/03/2016	49	Adults (35-64)	M	Australia	New South Wales	Accessories	Bike Racks	Hitch Rack - 4-Bike	20	45	120	900
4	15/05/2014	47	Adults (35-64)	F	Australia	New South Wales	Accessories	Bike Racks	Hitch Rack - 4-Bike	4	45	120	180

In [7]:

```
#.tail returns the last 5 of the dataframe
sales_df.tail()
```

Out[7]:

	Date	Customer_Age	Age_Group	Customer_Gender	Country	State	Product_Category	Sub_Category	Product	Order_Quantity	Unit_Cost	Unit_Price	Cost
113031	12/04/2016	41	Adults (35-64)	M	United Kingdom	England	Clothing	Vests	Classic Vest, S	3	24	64	72
113032	02/04/2014	18	Youth (<25)	M	Australia	Queensland	Clothing	Vests	Classic Vest, M	22	24	64	528
113033	02/04/2016	18	Youth (<25)	M	Australia	Queensland	Clothing	Vests	Classic Vest, M	22	24	64	528
113034	04/03/2014	37	Adults (35-64)	F	France	Seine (Paris)	Clothing	Vests	Classic Vest, L	24	24	64	576
113035	04/03/2016	37	Adults (35-64)	F	France	Seine (Paris)	Clothing	Vests	Classic Vest, L	23	24	64	552

Get the summary of the data using the .info() method. The following information are returned:

- index
- column names
- data types
- non-non values
- memory usage

In [8]:

```
# look closer at the dataset
sales_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113036 entries, 0 to 113035
Data columns (total 13 columns):
 #   Column            Non-Null Count   Dtype 
---  ------            --------------   ----- 
 0   Date              113036 non-null  object
 1   Customer_Age      113036 non-null  int64 
 2   Age_Group         113036 non-null  object
 3   Customer_Gender   113036 non-null  object
 4   Country           113036 non-null  object
 5   State             113036 non-null  object
 6   Product_Category  113036 non-null  object
 7   Sub_Category      113036 non-null  object
 8   Product           113036 non-null  object
 9   Order_Quantity    113036 non-null  int64 
 10  Unit_Cost         113036 non-null  int64 
 11  Unit_Price        113036 non-null  int64 
 12  Cost              113036 non-null  int64 
dtypes: int64(5), object(8)
memory usage: 11.2+ MB
```

View Summary Statistics with the .describe() method

In [9]:
```
# check the statistical analysis of the data
sales_df.describe()
```

Out[9]:

	Customer_Age	Order_Quantity	Unit_Cost	Unit_Price	Cost
count	113036.000000	113036.000000	113036.000000	113036.000000	113036.000000
mean	35.919212	11.901660	267.296366	452.938427	469.318695
std	11.021936	9.561857	549.835483	922.071219	884.866118
min	17.000000	1.000000	1.000000	2.000000	1.000000
25%	28.000000	2.000000	2.000000	5.000000	28.000000
50%	35.000000	10.000000	9.000000	24.000000	108.000000
75%	43.000000	20.000000	42.000000	70.000000	432.000000
max	87.000000	32.000000	2171.000000	3578.000000	42978.000000

In [10]:
```
#How many elements/ data points are there?
sales_df.size
```

Out[10]:
```
1469468
```

View all column names in the data set using .columns

In [11]:
```
#What are the column names in the data set?
sales_df.columns
```

Out[11]:
```
Index(['Date', 'Customer_Age', 'Age_Group', 'Customer_Gender', 'Country',
       'State', 'Product_Category', 'Sub_Category', 'Product',
       'Order_Quantity', 'Unit_Cost', 'Unit_Price', 'Cost'],
      dtype='object')
```

Check the dimensions of the data

In [12]:
```
# Check the shape (dimension) of the data
sales_df.shape
```

Out[12]:
```
(113036, 13)
```

- The data has 113036 rows and 13 columns

Data Cleaning and Preparation

Checking for anomalies and discrepancies in the dataset.

Check for missing values

In [13]:
```
#Check for null values for each column
sales_df.isnull().sum()
```

Out[13]:
```
Date                0
Customer_Age        0
Age_Group           0
Customer_Gender     0
Country             0
State               0
Product_Category    0
Sub_Category        0
Product             0
Order_Quantity      0
Unit_Cost           0
Unit_Price          0
Cost                0
dtype: int64
```

> - There's no null value / missing value in the dataset

In [14]:
```
#What types of columns we have in this data frame?
sales_df.dtypes
```

Out[14]:
```
Date                object
Customer_Age         int64
Age_Group           object
Customer_Gender     object
Country             object
State               object
Product_Category    object
Sub_Category        object
Product             object
Order_Quantity       int64
Unit_Cost            int64
Unit_Price           int64
Cost                 int64
dtype: object
```

> - Date is not in the right data type.
> - All other columns are in the right data type
> - The date data type needs to be converted from object to date time

Converting the date from object to datetime

In [15]:
```
# Changing the date from object to datetime
sales_df['Date']= pd.to_datetime(sales_df['Date'])
```

In [16]:
```
#checking to see what the new date type is
sales_df.dtypes
```

Out[16]:
```
Date                datetime64[ns]
Customer_Age                 int64
Age_Group                   object
Customer_Gender             object
Country                     object
State                       object
Product_Category            object
Sub_Category                object
Product                     object
Order_Quantity               int64
Unit_Cost                    int64
Unit_Price                   int64
Cost                         int64
dtype: object
```

In [17]:
```
#confirmatory check
sales_df.head()
```

Out[17]:

	Date	Customer_Age	Age_Group	Customer_Gender	Country	State	Product_Category	Sub_Category	Product	Order_Quantity	Unit_Cost	Unit_Price	Cost
0	2013-11-26	19	Youth (<25)	M	Canada	British Columbia	Accessories	Bike Racks	Hitch Rack - 4-Bike	8	45	120	360
1	2015-11-26	19	Youth (<25)	M	Canada	British Columbia	Accessories	Bike Racks	Hitch Rack - 4-Bike	8	45	120	360
2	2014-03-23	49	Adults (35-64)	M	Australia	New South Wales	Accessories	Bike Racks	Hitch Rack - 4-Bike	23	45	120	1035
3	2016-03-23	49	Adults (35-64)	M	Australia	New South Wales	Accessories	Bike Racks	Hitch Rack - 4-Bike	20	45	120	900
4	2014-05-15	47	Adults (35-64)	F	Australia	New South Wales	Accessories	Bike Racks	Hitch Rack - 4-Bike	4	45	120	180

Extract the year, month and day and put them into separate columns in the same dateframe under the following names: Year, Month, Day

In [18]:
```
# Extracting the Year, Month and Day from the Date Column
sales_df['Year']=sales_df['Date'].dt.year
sales_df['Month']=sales_df['Date'].dt.month
sales_df['Day']=sales_df['Date'].dt.day

#check the new columns created
sales_df.head()
```

Out[18]:

	Date	Customer_Age	Age_Group	Customer_Gender	Country	State	Product_Category	Sub_Category	Product	Order_Quantity	Unit_Cost	Unit_Price	Cost	Year	Month	Day
0	2013-11-26	19	Youth (<25)	M	Canada	British Columbia	Accessories	Bike Racks	Hitch Rack - 4-Bike	8	45	120	360	2013	11	26
1	2015-11-26	19	Youth (<25)	M	Canada	British Columbia	Accessories	Bike Racks	Hitch Rack - 4-Bike	8	45	120	360	2015	11	26
2	2014-03-23	49	Adults (35-64)	M	Australia	New South Wales	Accessories	Bike Racks	Hitch Rack - 4-Bike	23	45	120	1035	2014	3	23
3	2016-03-23	49	Adults (35-64)	M	Australia	New South Wales	Accessories	Bike Racks	Hitch Rack - 4-Bike	20	45	120	900	2016	3	23
4	2014-05-15	47	Adults (35-64)	F	Australia	New South Wales	Accessories	Bike Racks	Hitch Rack - 4-Bike	4	45	120	180	2014	5	15

Create 2 new columns for sales and profit: Calculate the Total sales and Profit per order

In [19]:
```
# Calculate the Total sales and Profit per order
# Total sales = Quantity ordered * price each
sales_df['Sales'] = sales_df["Order_Quantity"] * sales_df["Unit_Price"]
sales_df['Profit'] = sales_df["Sales"] - sales_df["Cost"]
sales_df.head()
```

Out[19]:

	Date	Customer_Age	Age_Group	Customer_Gender	Country	State	Product_Category	Sub_Category	Product	Order_Quantity	Unit_Cost	Unit_Price	Cost	Year	Month	Day	Sales	Profit
0	2013-11-26	19	Youth (<25)	M	Canada	British Columbia	Accessories	Bike Racks	Hitch Rack - 4-Bike	8	45	120	360	2013	11	26	960	600
1	2015-11-26	19	Youth (<25)	M	Canada	British Columbia	Accessories	Bike Racks	Hitch Rack - 4-Bike	8	45	120	360	2015	11	26	960	600
2	2014-03-23	49	Adults (35-64)	M	Australia	New South Wales	Accessories	Bike Racks	Hitch Rack - 4-Bike	23	45	120	1035	2014	3	23	2760	1725
3	2016-03-23	49	Adults (35-64)	M	Australia	New South Wales	Accessories	Bike Racks	Hitch Rack - 4-Bike	20	45	120	900	2016	3	23	2400	1500
4	2014-05-15	47	Adults (35-64)	F	Australia	New South Wales	Accessories	Bike Racks	Hitch Rack - 4-Bike	4	45	120	180	2014	5	15	480	300

- Profit and Sales have been calculated

Check the unique values for all the categorical columns to answer the following:

- What is the customer demographic, in terms of age?
- What countries and states does the company serve?
- What products does the company sells?
- How are the products categorized?

In [20]:

```
# Check the unique values for all the categorical columns
object_columns = sales_df.select_dtypes(include = 'object').columns.tolist()
for i in object_columns:
    print(f'column_name-> {i}')
    print(sales_df[i].unique())
    print('*'*100)
```

```
column_name-> Age_Group
['Youth (<25)' 'Adults (35-64)' 'Young Adults (25-34)' 'Seniors (64+)']
****************************************************************************************************
column_name-> Customer_Gender
['M' 'F']
****************************************************************************************************
column_name-> Country
['Canada' 'Australia' 'United States' 'Germany' 'France' 'United Kingdom']
****************************************************************************************************
column_name-> State
['British Columbia' 'New South Wales' 'Victoria' 'Oregon' 'California'
 'Saarland' 'Seine Saint Denis' 'Moselle' 'Queensland' 'England' 'Nord'
 'Washington' 'Hessen' 'Nordrhein-Westfalen' 'Hamburg' 'Loir et Cher'
 'Kentucky' 'Seine (Paris)' 'South Australia' 'Loiret' 'Alberta' 'Bayern'
 'Hauts de Seine' 'Yveline' 'Essonne' "Val d'Oise" 'Tasmania'
 'Seine et Marne' 'Val de Marne' 'Pas de Calais' 'Charente-Maritime'
 'Garonne (Haute)' 'Brandenburg' 'Texas' 'New York' 'Florida' 'Somme'
 'Illinois' 'South Carolina' 'North Carolina' 'Georgia' 'Virginia' 'Ohio'
 'Ontario' 'Wyoming' 'Missouri' 'Montana' 'Utah' 'Minnesota' 'Mississippi'
 'Massachusetts' 'Arizona' 'Alabama']
****************************************************************************************************
column_name-> Product_Category
['Accessories' 'Clothing' 'Bikes']
****************************************************************************************************
column_name-> Sub_Category
['Bike Racks' 'Bike Stands' 'Bottles and Cages' 'Caps' 'Cleaners'
 'Fenders' 'Gloves' 'Helmets' 'Hydration Packs' 'Jerseys' 'Mountain Bikes'
 'Road Bikes' 'Shorts' 'Socks' 'Tires and Tubes' 'Touring Bikes' 'Vests']
****************************************************************************************************
column_name-> Product
['Hitch Rack - 4-Bike' 'All-Purpose Bike Stand' 'Mountain Bottle Cage'
 'Water Bottle - 30 oz.' 'Road Bottle Cage' 'AWC Logo Cap'
 'Bike Wash - Dissolver' 'Fender Set - Mountain' 'Half-Finger Gloves, L'
 'Half-Finger Gloves, M' 'Half-Finger Gloves, S' 'Sport-100 Helmet, Black'
 'Sport-100 Helmet, Red' 'Sport-100 Helmet, Blue'
 'Hydration Pack - 70 oz.' 'Short-Sleeve Classic Jersey, XL'
 'Short-Sleeve Classic Jersey, L' 'Short-Sleeve Classic Jersey, M'
 'Short-Sleeve Classic Jersey, S' 'Long-Sleeve Logo Jersey, M'
 'Long-Sleeve Logo Jersey, XL' 'Long-Sleeve Logo Jersey, L'
 'Long-Sleeve Logo Jersey, S' 'Mountain-100 Silver, 38'
 'Mountain-100 Silver, 44' 'Mountain-100 Black, 48'
 'Mountain-100 Silver, 48' 'Mountain-100 Black, 38'
 'Mountain-200 Silver, 38' 'Mountain-100 Black, 44'
 'Mountain-100 Silver, 42' 'Mountain-200 Black, 46'
 'Mountain-200 Silver, 42' 'Mountain-200 Silver, 46'
 'Mountain-200 Black, 38' 'Mountain-100 Black, 42'
 'Mountain-200 Black, 42' 'Mountain-400-W Silver, 46'
 'Mountain-500 Silver, 40' 'Mountain-500 Silver, 44'
 'Mountain-500 Black, 48' 'Mountain-500 Black, 40'
 'Mountain-400-W Silver, 42' 'Mountain-500 Silver, 52'
 'Mountain-500 Black, 52' 'Mountain-500 Silver, 42'
 'Mountain-500 Black, 44' 'Mountain-500 Silver, 48'
 'Mountain-400-W Silver, 38' 'Mountain-400-W Silver, 40'
 'Mountain-500 Black, 42' 'Road-150 Red, 48' 'Road-150 Red, 62'
 'Road-750 Black, 48' 'Road-750 Black, 58' 'Road-750 Black, 52'
 'Road-150 Red, 52' 'Road-150 Red, 44' 'Road-150 Red, 56'
 'Road-750 Black, 44' 'Road-350-W Yellow, 40' 'Road-350-W Yellow, 42'
 'Road-250 Black, 44' 'Road-250 Black, 48' 'Road-350-W Yellow, 48'
 'Road-550-W Yellow, 44' 'Road-550-W Yellow, 38' 'Road-250 Black, 52'
 'Road-550-W Yellow, 48' 'Road-250 Red, 58' 'Road-250 Black, 58'
 'Road-250 Red, 52' 'Road-250 Red, 48' 'Road-250 Red, 44'
 'Road-550-W Yellow, 42' 'Road-550-W Yellow, 40' 'Road-650 Red, 48'
 'Road-650 Red, 60' 'Road-650 Black, 48' 'Road-350-W Yellow, 44'
 'Road-650 Red, 52' 'Road-650 Black, 44' 'Road-650 Red, 62'
```

```
 'Road-650 Red, 58' 'Road-650 Black, 60' 'Road-650 Black, 58'
 'Road-650 Black, 52' 'Road-650 Black, 62' 'Road-650 Red, 44'
 "Women's Mountain Shorts, M" "Women's Mountain Shorts, S"
 "Women's Mountain Shorts, L" 'Racing Socks, L' 'Racing Socks, M'
 'Mountain Tire Tube' 'Touring Tire Tube' 'Patch Kit/8 Patches'
 'HL Mountain Tire' 'LL Mountain Tire' 'Road Tire Tube' 'LL Road Tire'
 'Touring Tire' 'ML Mountain Tire' 'HL Road Tire' 'ML Road Tire'
 'Touring-1000 Yellow, 50' 'Touring-1000 Blue, 46'
 'Touring-1000 Yellow, 60' 'Touring-1000 Blue, 50'
 'Touring-3000 Yellow, 50' 'Touring-3000 Blue, 54' 'Touring-3000 Blue, 58'
 'Touring-3000 Yellow, 44' 'Touring-3000 Yellow, 54'
 'Touring-3000 Blue, 62' 'Touring-3000 Blue, 44' 'Touring-1000 Blue, 54'
 'Touring-1000 Yellow, 46' 'Touring-1000 Blue, 60'
 'Touring-3000 Yellow, 62' 'Touring-1000 Yellow, 54'
 'Touring-2000 Blue, 54' 'Touring-3000 Blue, 50' 'Touring-3000 Yellow, 58'
 'Touring-2000 Blue, 46' 'Touring-2000 Blue, 50' 'Touring-2000 Blue, 60'
 'Classic Vest, L' 'Classic Vest, M' 'Classic Vest, S']
****************************************************************************************************
```

Univariate Analysis

Measure of the central tendency and dispersion

The target variable in this analysis is 'Sales' variable. The central tendency and the dispersion of the 'Sales' variable shall be checked.

The 'Central Tendency' is a statistical measure which identifies a single value as representative of an entire distribution. The mean is the most common central tendency. For a skewed distribution, the median is used as the central tendency.

Dispersion shows the distribution or spread of the data. The most common measures of dispersion are standard deviation, variansxe and interquartile range.

The describe() method gives a summary of the data which includes the central tendency and the dispersion.

In [21]:
```
print(sales_df['Sales'].describe())
```

```
count    113036.000000
mean        842.000053
std        1466.202934
min           2.000000
25%          70.000000
50%         245.000000
75%         880.000000
max       69136.000000
Name: Sales, dtype: float64
```

The above result show the following about the 'Sales' variable:

- The minimun sales value is 2, the maximum sales value is 69136 and the count is 113036.
- The measure of dispersion (standard deviation) is 1466.202934.
- The central tendency given by the mean is 842.000053, and given by the median is 245.000000.
- The 25%, 50% and 75% values represent the corresponding percentiles (the 50% percentile is the median of the distribution)
- IQR is the difference between the 75th and 25th percentile: that is, IQR = 880 - 70 = 810

Checking the skewness of the Sales Variable

In [22]:
```
sales_df['Sales'].skew()
```

Out[22]:
```
4.891490417507355
```

The skewness of the 'Sales' variable is greater than +1, therefore the sales variable is highly positively skewed.

Frequency Distribution of Categorical Variables

In [23]:
```
#checking the names of only the categorical columns
object_columns
```

Out[23]:
```
['Age_Group',
 'Customer_Gender',
 'Country',
 'State',
 'Product_Category',
 'Sub_Category',
 'Product']
```

In [24]:
```
object_columns = sales_df.select_dtypes(include = 'object').columns.tolist()
for i in object_columns:
    #print(f'column_name-> {i}')
    print(f'======== {i}========\n')
    print(sales_df.groupby([i]).size().sort_values(ascending=False).reset_index(name='Count'))
    print('*'*100)
    print('\n')
```

```
======== Age_Group========

             Age_Group  Count
0       Adults (35-64)  55824
1  Young Adults (25-34)  38654
2          Youth (<25)  17828
3        Seniors (64+)    730
****************************************************************************************************


======== Customer_Gender========

  Customer_Gender  Count
0               M  58312
1               F  54724
****************************************************************************************************


======== Country========

          Country  Count
0   United States  39206
1       Australia  23936
2          Canada  14178
3  United Kingdom  13620
4         Germany  11098
5          France  10998
****************************************************************************************************


======== State========

                  State  Count
0            California  22450
1      British Columbia  14116
2               England  13620
3            Washington  11264
4       New South Wales  10412
5              Victoria   6016
6                Oregon   5286
7            Queensland   5220
8              Saarland   2770
9   Nordrhein-Westfalen   2484
10               Hessen   2384
11        Seine (Paris)   2328
12              Hamburg   1836
13    Seine Saint Denis   1684
14                 Nord   1670
15      South Australia   1564
16               Bayern   1426
17       Hauts de Seine   1084
18              Essonne    994
19              Yveline    954
20             Tasmania    724
21       Seine et Marne    394
22              Moselle    386
23               Loiret    382
24           Val d'Oise    264
25      Garonne (Haute)    208
26          Brandenburg    198
27         Val de Marne    158
28    Charente-Maritime    148
29                Somme    134
30         Loir et Cher    120
```

```
31        Pas de Calais     90
32              Alberta     56
33                Texas     30
34             Illinois     28
35                 Ohio     28
36             New York     20
37              Florida     14
38       South Carolina     10
39                 Utah     10
40             Kentucky     10
41              Wyoming      8
42              Georgia      8
43              Montana      6
44            Minnesota      6
45             Missouri      6
46              Ontario      6
47              Arizona      4
48             Virginia      4
49              Alabama      4
50       North Carolina      4
51          Mississippi      4
52        Massachusetts      2
****************************************************************************************************


======== Product_Category========

  Product_Category  Count
0      Accessories  70120
1            Bikes  25982
2         Clothing  16934
****************************************************************************************************


======== Sub_Category========

         Sub_Category  Count
0     Tires and Tubes  33870
1   Bottles and Cages  15876
2          Road Bikes  13430
3             Helmets  12158
4      Mountain Bikes   8854
5             Jerseys   6010
6                Caps   4358
7             Fenders   4032
8       Touring Bikes   3698
9              Gloves   2686
10           Cleaners   1802
11             Shorts   1794
12    Hydration Packs   1334
13              Socks   1122
14              Vests    964
15         Bike Racks    592
16        Bike Stands    456
****************************************************************************************************


======== Product========

                    Product  Count
0      Water Bottle - 30 oz.  10794
1        Patch Kit/8 Patches  10416
2         Mountain Tire Tube   6816
3               AWC Logo Cap   4358
```

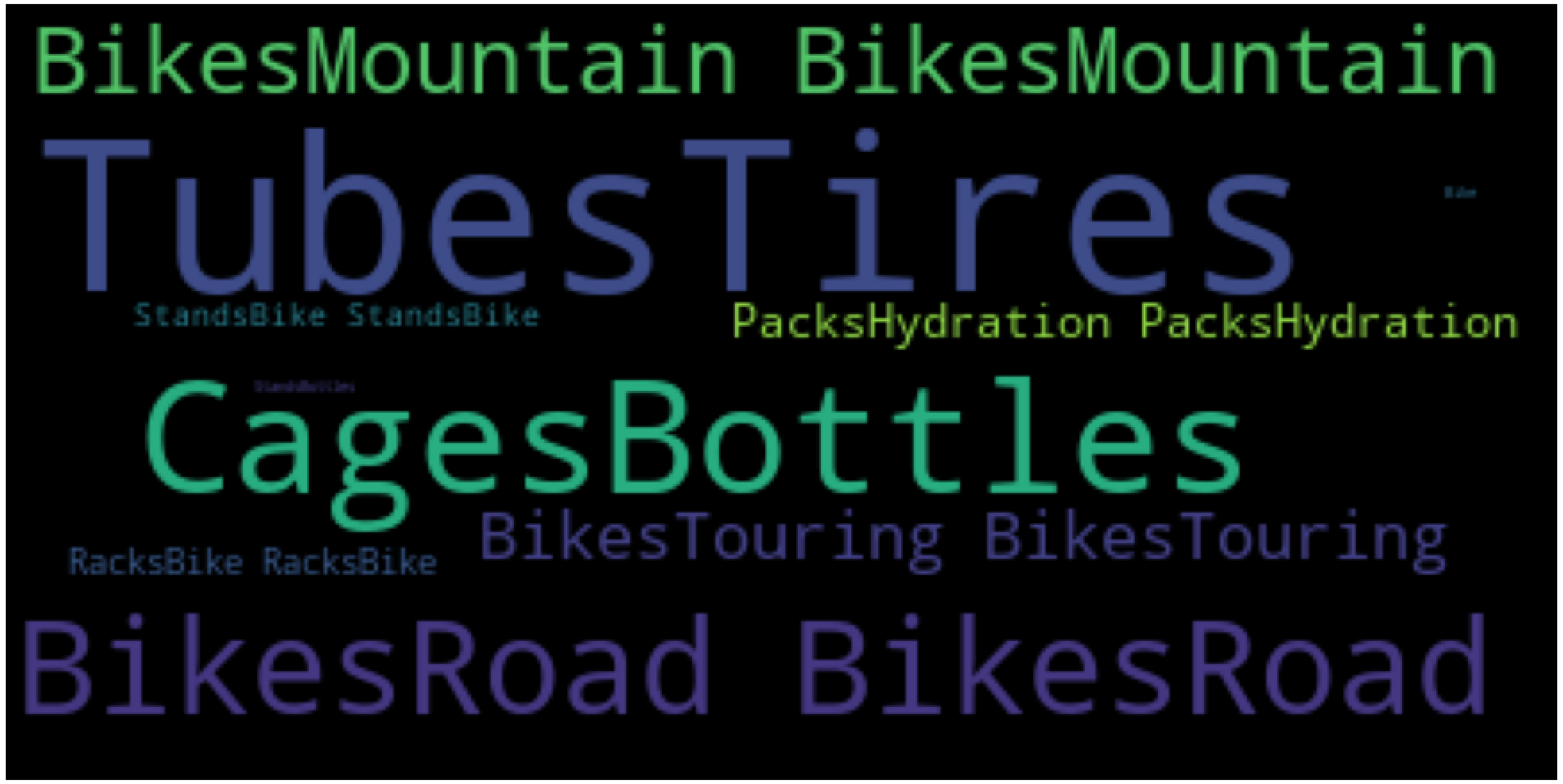
```
4       Sport-100 Helmet, Red   4220
..                       ...     ...
125  Mountain-100 Silver, 48      58
126  Mountain-100 Silver, 42      54
127  Mountain-500 Silver, 48      40
128         Road-650 Red, 52      32
129   Mountain-500 Black, 52      22

[130 rows x 2 columns]
****************************************************************************************************
```

Data Visualization

Creating a Word Cloud of the Sub_Product Category

In [25]:
```
fields = ['Sub_Category']
text = pd.read_csv("C:\\Users\\Jeremy\\Documents\\My portfolio projects\\Python Project\\Sales\\sales_data.csv", usecols=fields)
```

In [26]:
```
text1= ''.join(text['Sub_Category'])
wordcloud2 = WordCloud().generate(text1)
# Generate the plot
plt.figure(figsize=(20,8))
plt.imshow(wordcloud2)
plt.axis('off')
plt.show()
```



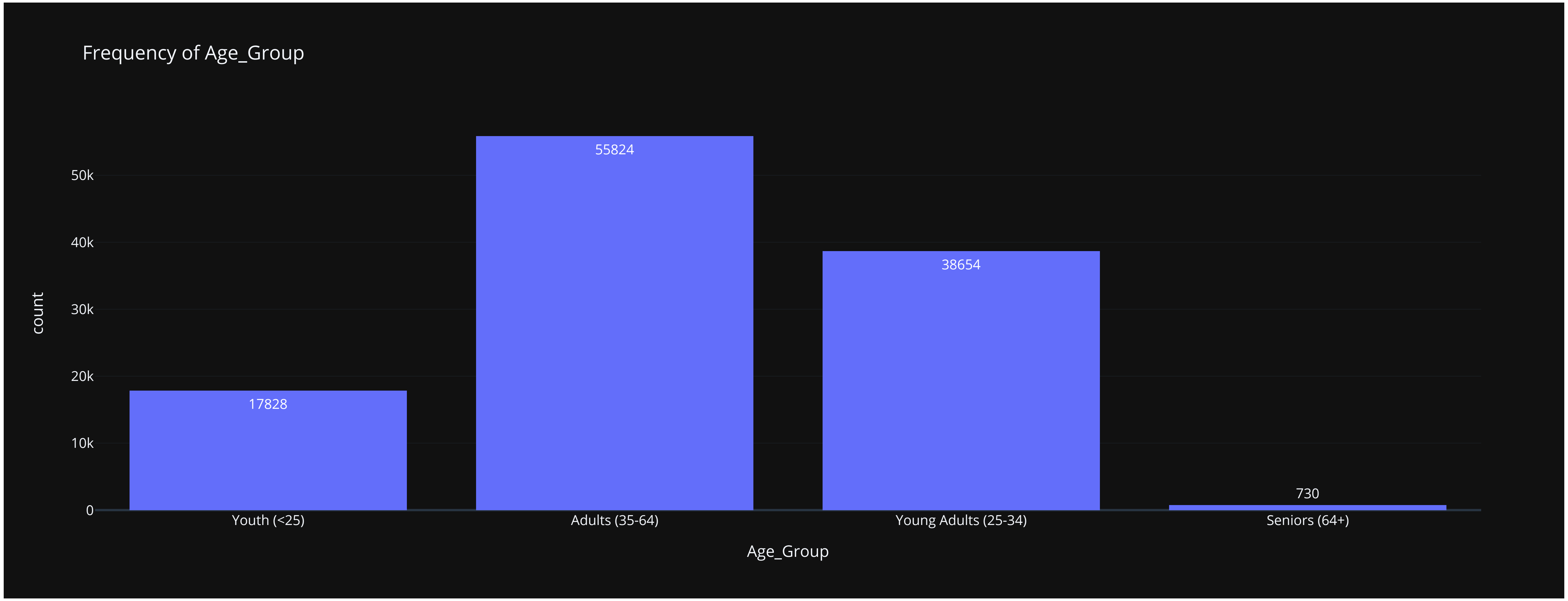
Visualization of Frequency Distribution

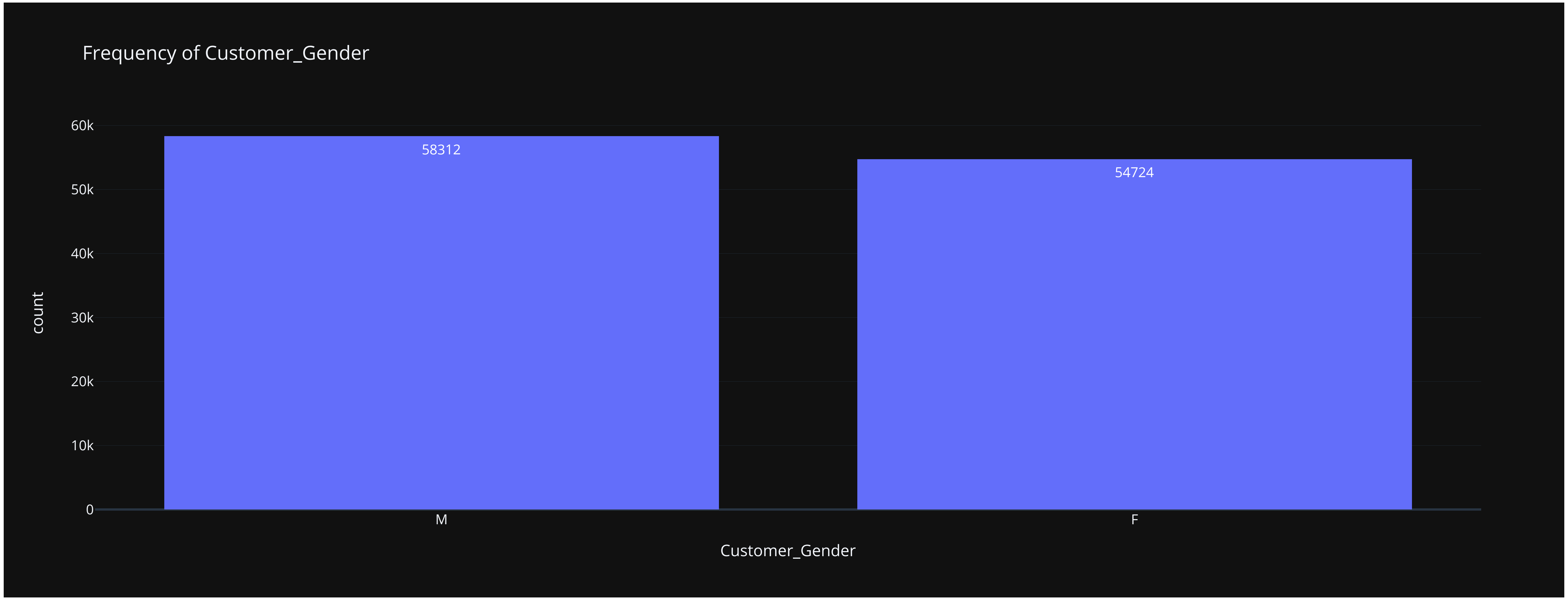
In [27]:
```
def barplot(i):
```

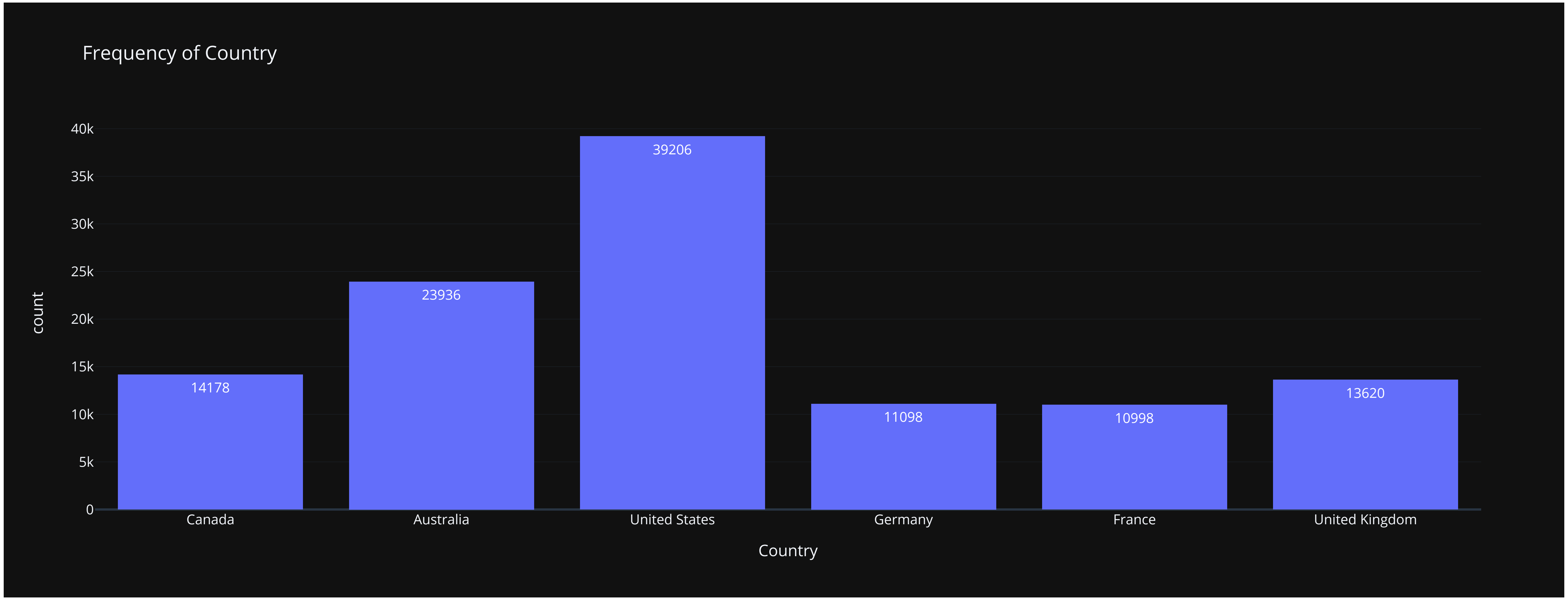
```
    df=sales_df.groupby([i]).size().sort_values(ascending=False)
    fig=px.histogram(sales_df, x= sales_df[i],  template = 'plotly_dark',
                     title = f' Frequency of {i}', text_auto  = 'd3-format')
    fig.show()
```

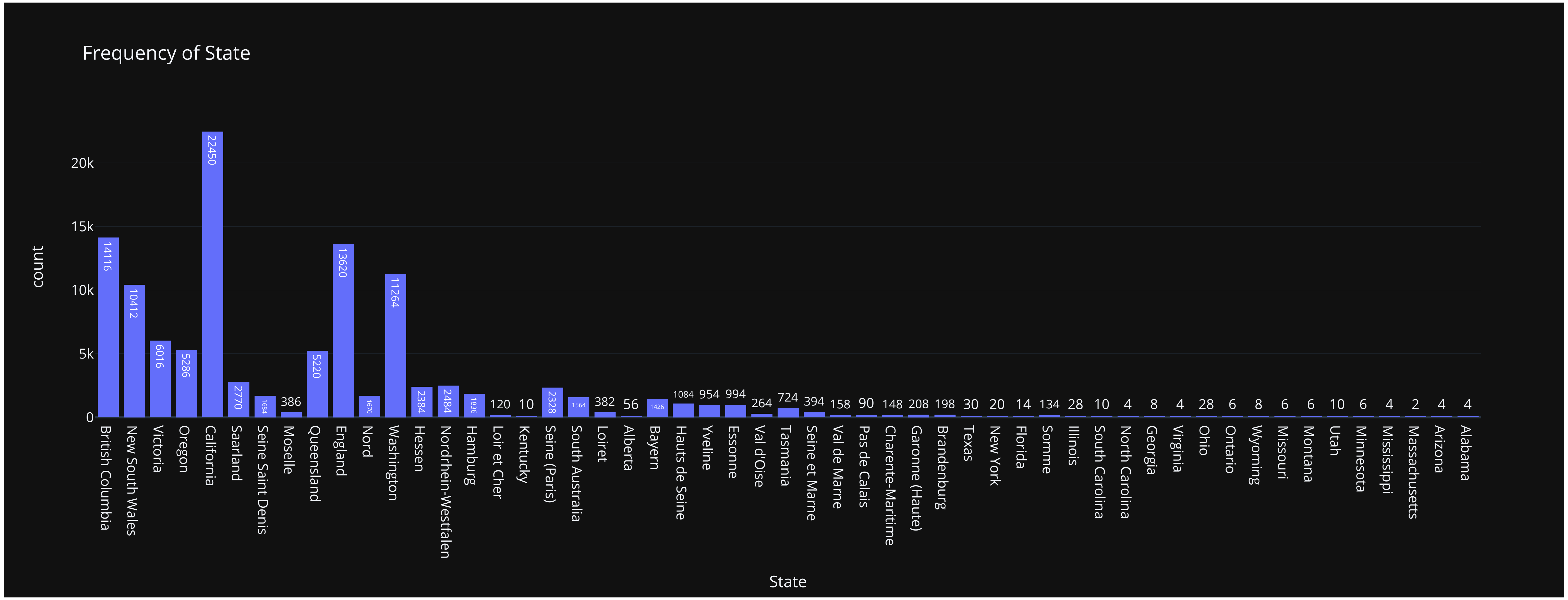
In [28]:

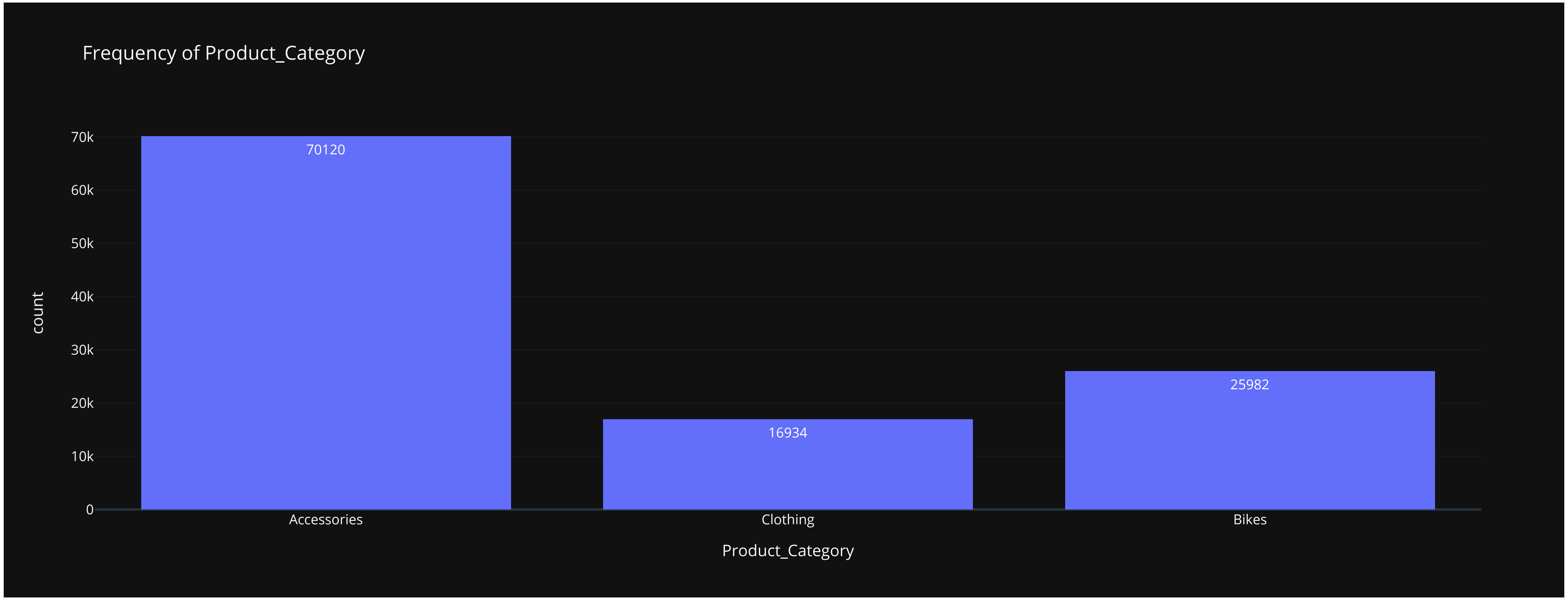
```
barplot('Age_Group')
barplot('Customer_Gender')
barplot('Country')
barplot('State')
barplot('Product_Category')
barplot('Sub_Category')
barplot('Product')
```

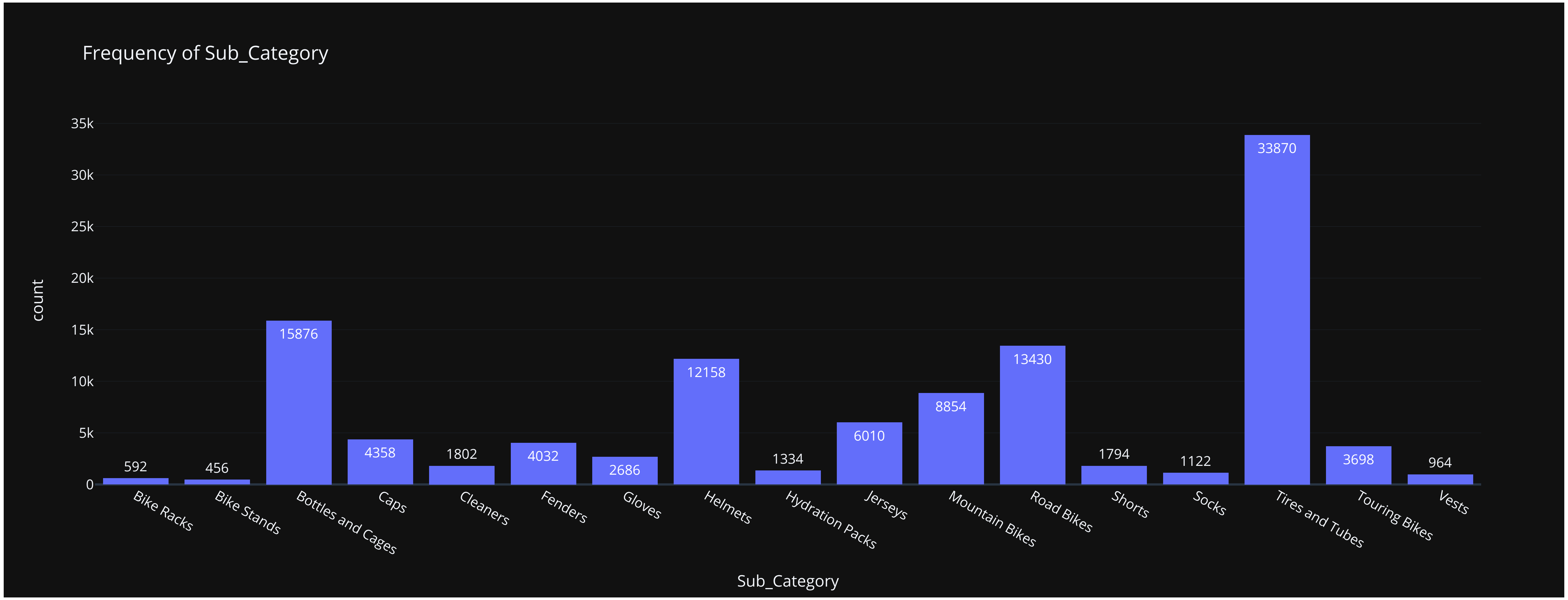


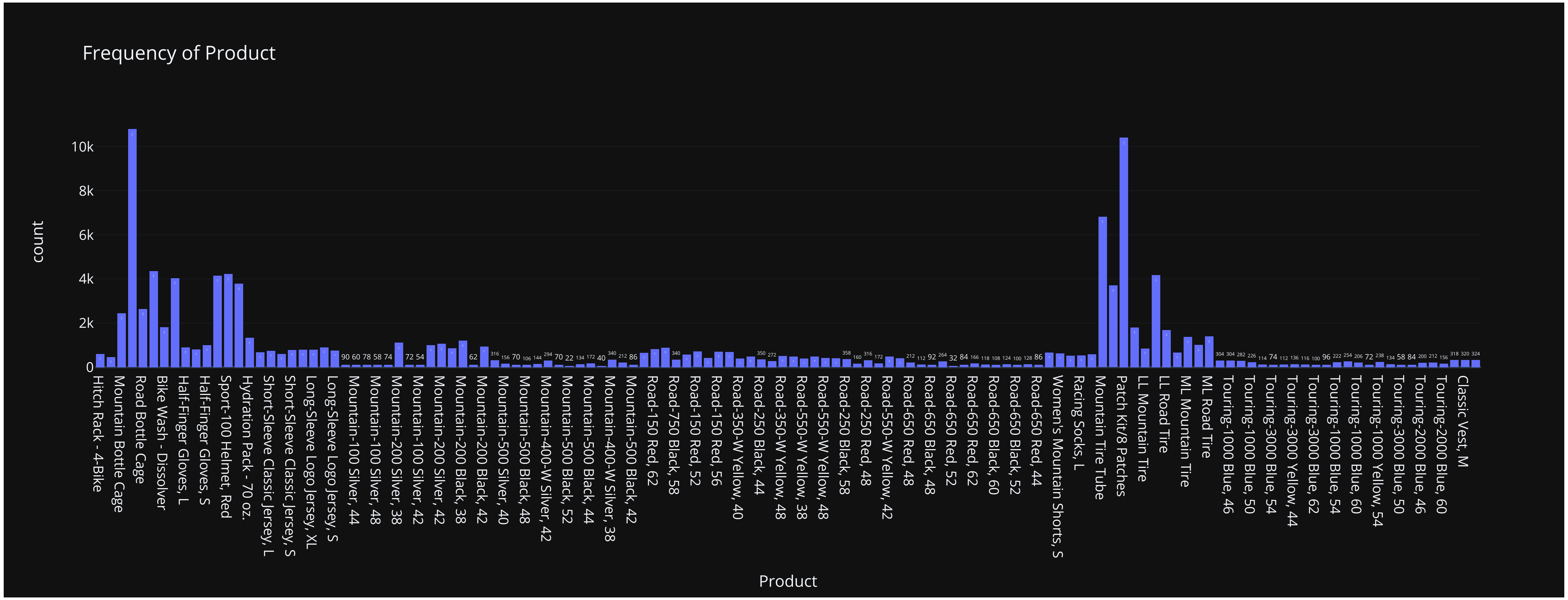

Frequency of Customer_Gender
60k
50k
40k
30k
20k
10k
0
count
58312
54724
M
F
Customer_Gender


Frequency of Country
count
40k
35k
30k
25k
20k
15k
10k
5k
0
14178
23936
39206
11098
10998
13620
Canada
Australia
United States
Germany
France
United Kingdom
Country


Frequency of State
count
State
0
5k
10k
15k
20k
British Columbia 14116
New South Wales 10412
Victoria 6016
Oregon 5286
California 22450
Saarland 2770
Seine Saint Denis 1684
Moselle 386
Queensland 5220
England 13620
Nord 1670
Washington 11264
Hessen 2384
Nordrhein-Westfalen 2484
Hamburg 1836
Loir et Cher 120
Kentucky 10
Seine (Paris) 2328
South Australia 1564
Loiret 382
Alberta 56
Bayern 1426
Hauts de Seine 1084
Yveline 954
Essonne 994
Val d'Oise 264
Tasmania 724
Seine et Marne 394
Val de Marne 158
Pas de Calais 90
Charente-Maritime 148
Garonne (Haute) 208
Brandenburg 198
Texas 30
New York 20
Florida 14
Somme 134
Illinois 28
South Carolina 10
North Carolina 4
Georgia 8
Virginia 4
Ohio 28
Ontario 6
Wyoming 8
Missouri 6
Montana 6
Utah 10
Minnesota 6
Mississippi 4
Massachusetts 2
Arizona 4
Alabama 4


Frequency of Product_Category
70k
60k
50k
40k
30k
20k
10k
0
count
70120
16934
25982
Accessories
Clothing
Bikes
Product_Category


Frequency of Sub_Category
count
35k
30k
25k
20k
15k
10k
5k
0
592
456
15876
4358
1802
4032
2686
12158
1334
6010
8854
13430
1794
1122
33870
3698
964
Bike Racks
Bike Stands
Bottles and Cages
Caps
Cleaners
Fenders
Gloves
Helmets
Hydration Packs
Jerseys
Mountain Bikes
Road Bikes
Shorts
Socks
Tires and Tubes
Touring Bikes
Vests
Sub_Category

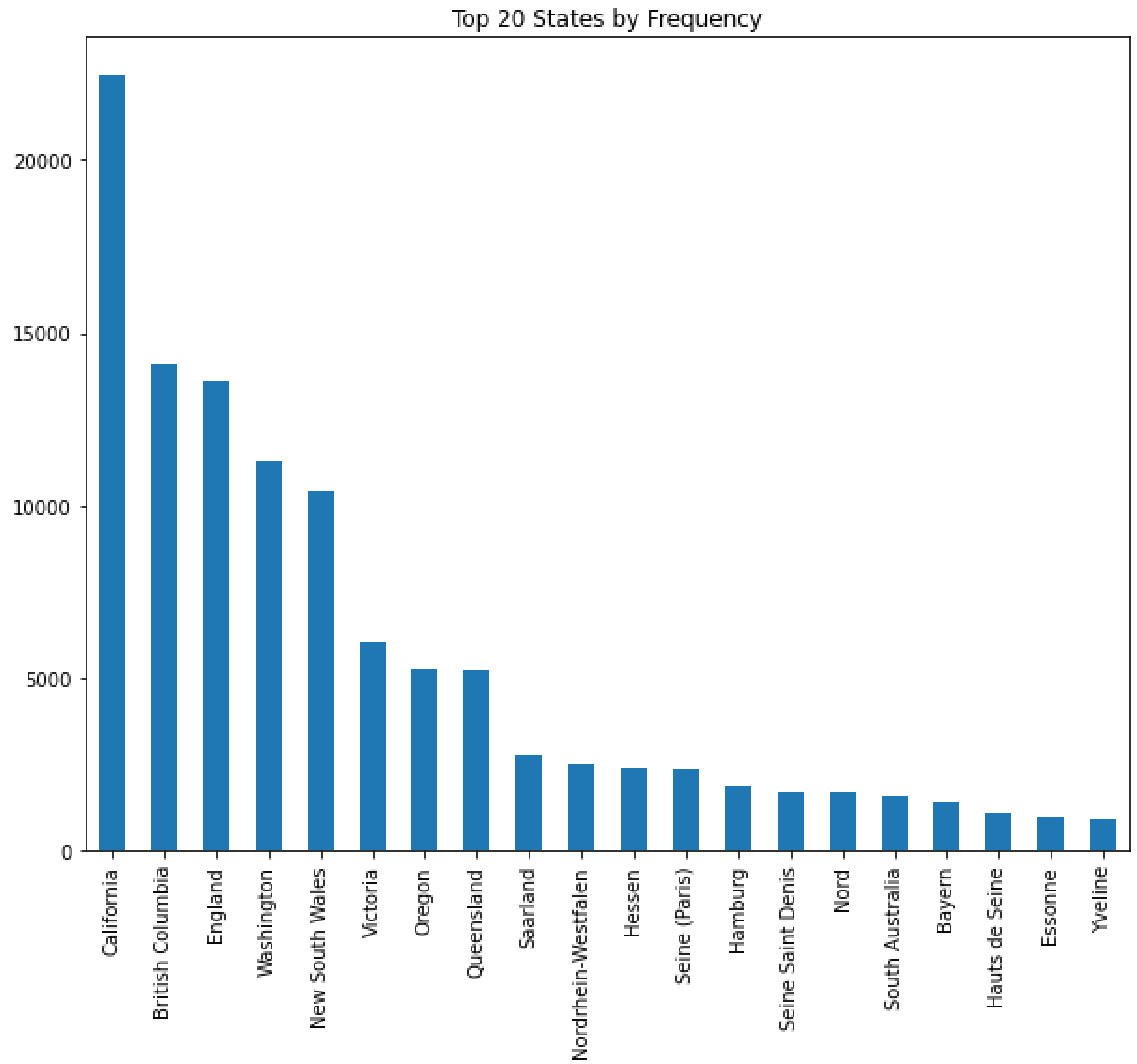


In [29]:

```
# check the top 20 states by Frequency
top_state =sales_df['State'].value_counts()[:20]
top_state.plot(kind='bar', figsize=(10,8))
plt.title('Top 20 States by Frequency')
```

Out[29]:

```
Text(0.5, 1.0, 'Top 20 States by Frequency')
```

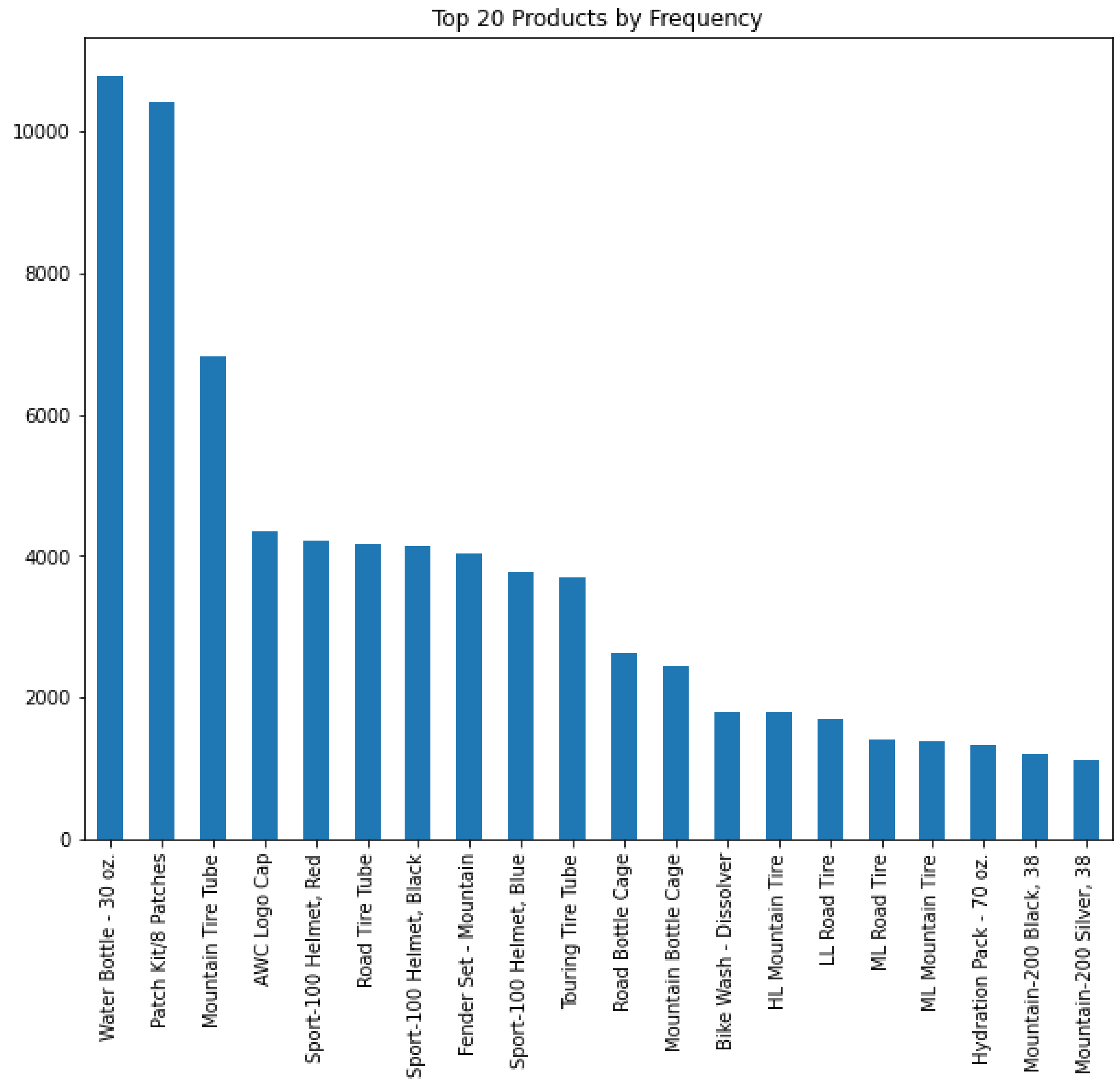


In [30]:

```
# check the top 20 Products
top_products =sales_df['Product'].value_counts()[:20]
top_products.plot(kind='bar', figsize=(10,8))
plt.title('Top 20 Products by Frequency')
```

Out[30]:

```
Text(0.5, 1.0, 'Top 20 Products by Frequency')
```



Conclusions

Since the data does not have the order_id and customer_id, it is impossible to ascertain if some of the orders are by the same customers or if they are all from unique customers.

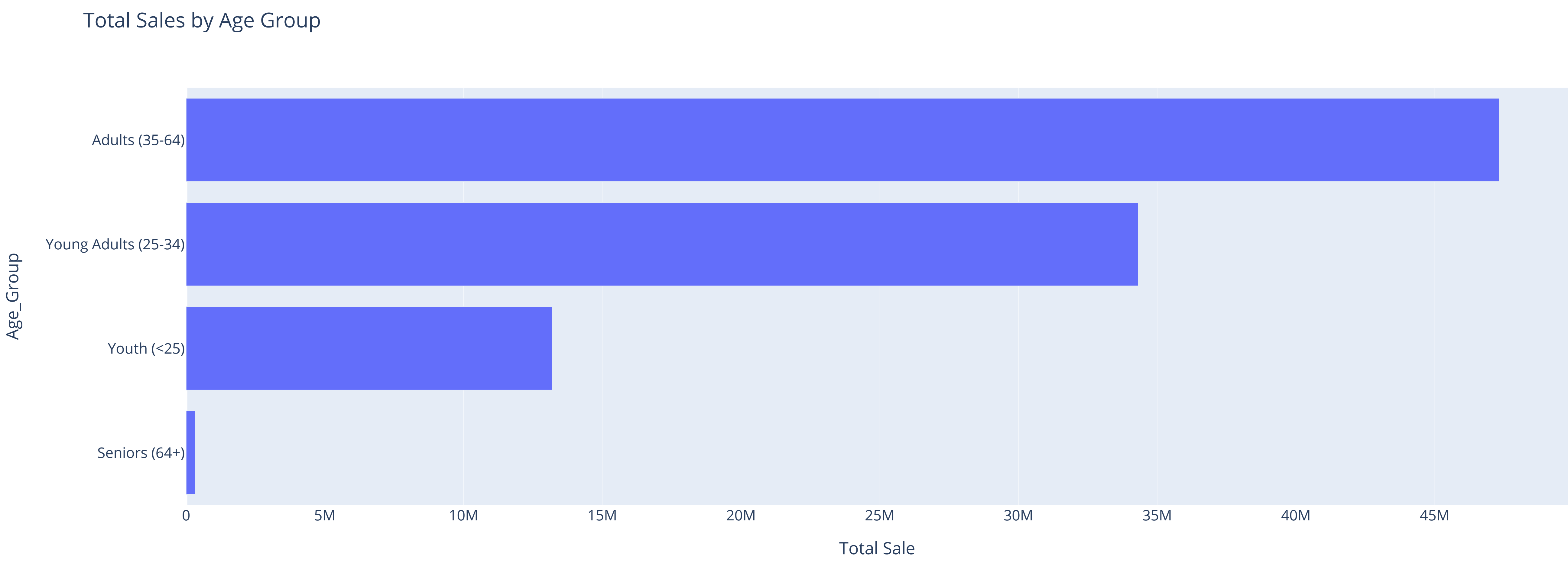
The conclusion below is based on the assumption that all orders are from unique customers.

- Most of the company's customers are adults, between the ages of 35 and 64. This is followed by the adults group (between the ages of 25 and 34. It means the sales and marketing team should focus most of their marketing efforts at this groups since thats where majority of their customers are. Another way to look at it is that, the company needs to come up with a marketing strategy to attract the older population 64 and above (if they want to get more of this age demographic).
- Most of the company's customers are male. But then the number of female customers are not so far behind.
- United states has the highest frequency of sale and Germany has the lowest. The reasons for this can then be further analyzed using more data from the company.
- California stands out as the state with the highest frequency, followed by British Columbia.
- Accessories are the most in demand product category
- Tires and tubes are the most in demand sub category
- Water Bottle 30 is the most in demand product.

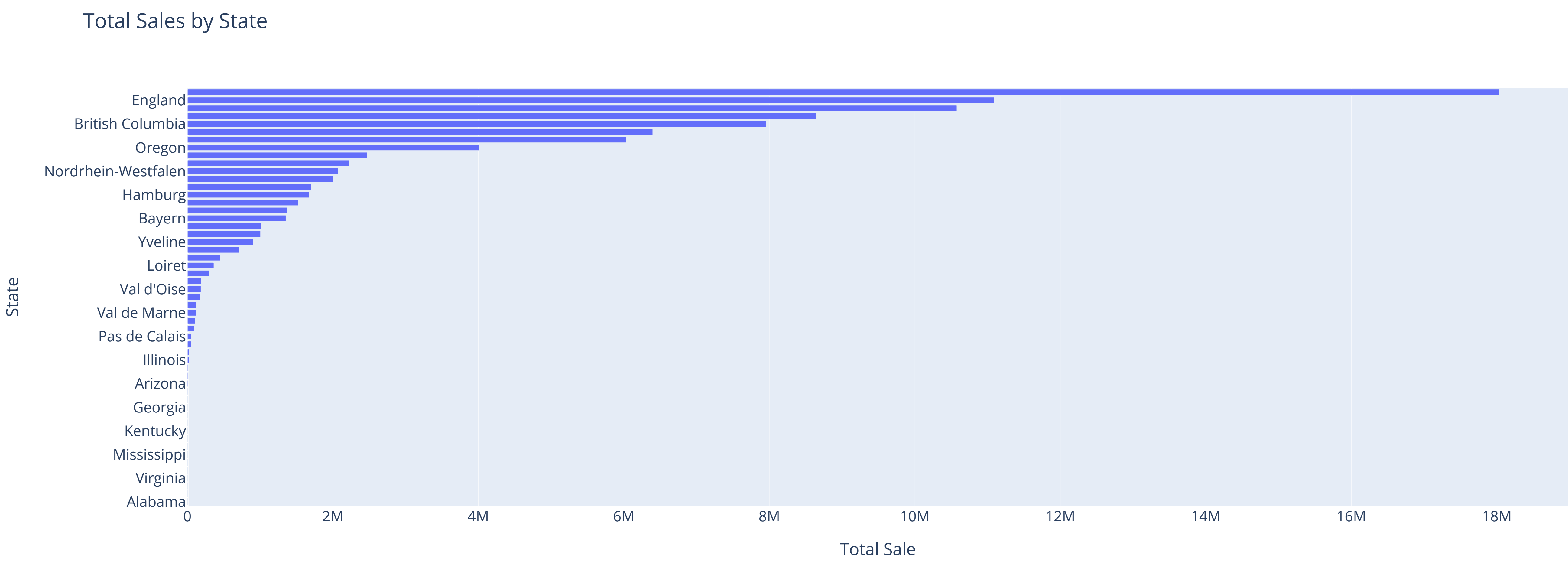
Bivariate Analysis

Checking Total sales by the different categorical variables

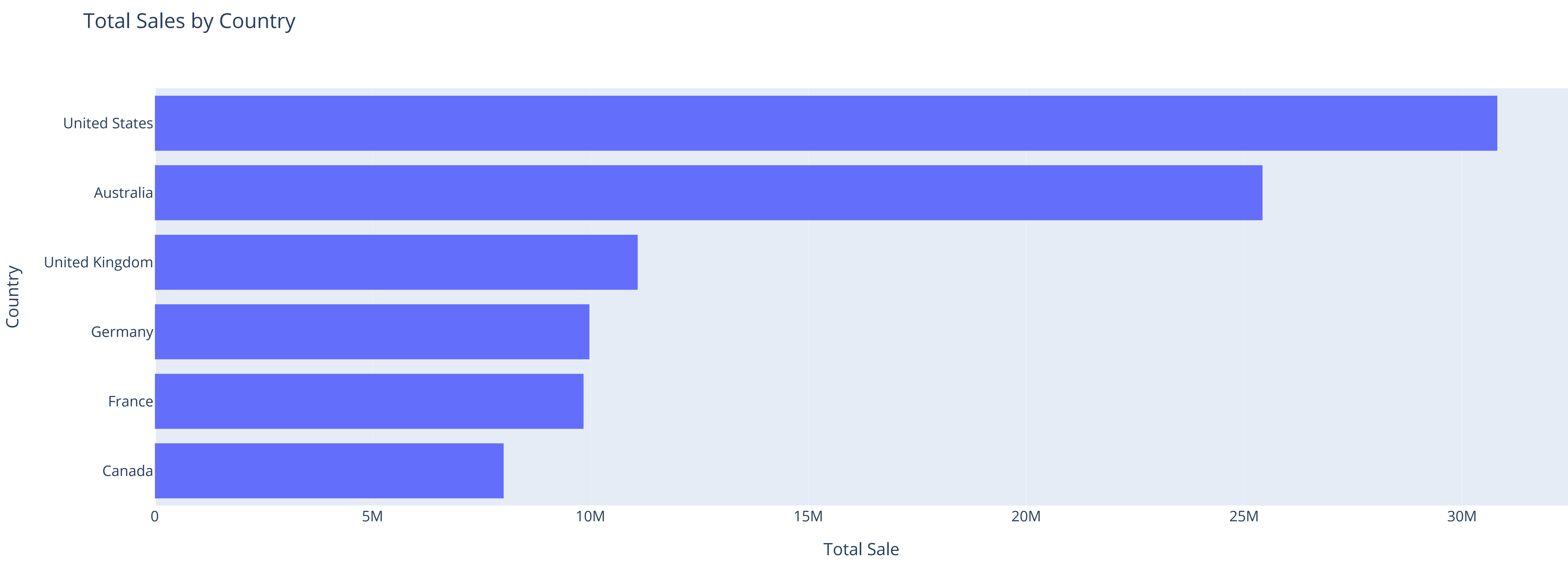
In [31]:
```
total_sale = pd.DataFrame(sales_df.groupby('Age_Group')['Sales'].sum().sort_values(ascending=True))
total_sale = total_sale.reset_index()
total_sale.columns = ['Age_Group', 'Total Sale']

fig=px.bar(total_sale, x='Total Sale', y = 'Age_Group', title='Total Sales by Age Group')
fig.show()
```



In [32]:
```
# Total Sales by State
total_sale = pd.DataFrame(sales_df.groupby('State')['Sales'].sum().sort_values(ascending=True))
total_sale = total_sale.reset_index()
total_sale.columns = ['State', 'Total Sale']

fig=px.bar(total_sale, x='Total Sale', y = 'State', title='Total Sales by State')
fig.show()
```

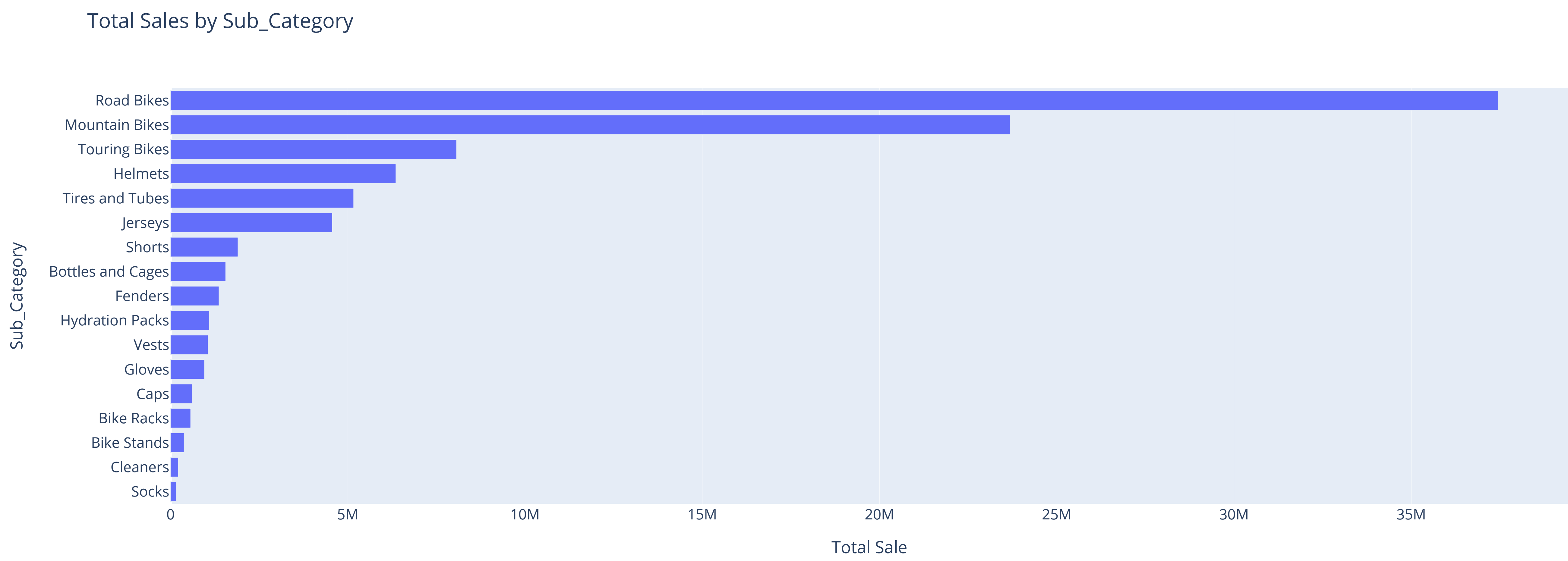


In [33]:
```
#Total Sales by Country
total_sale = pd.DataFrame(sales_df.groupby('Country')['Sales'].sum().sort_values(ascending=True))
total_sale = total_sale.reset_index()
total_sale.columns = ['Country', 'Total Sale']

fig=px.bar(total_sale, x='Total Sale', y = 'Country', title='Total Sales by Country')
fig.show()
```



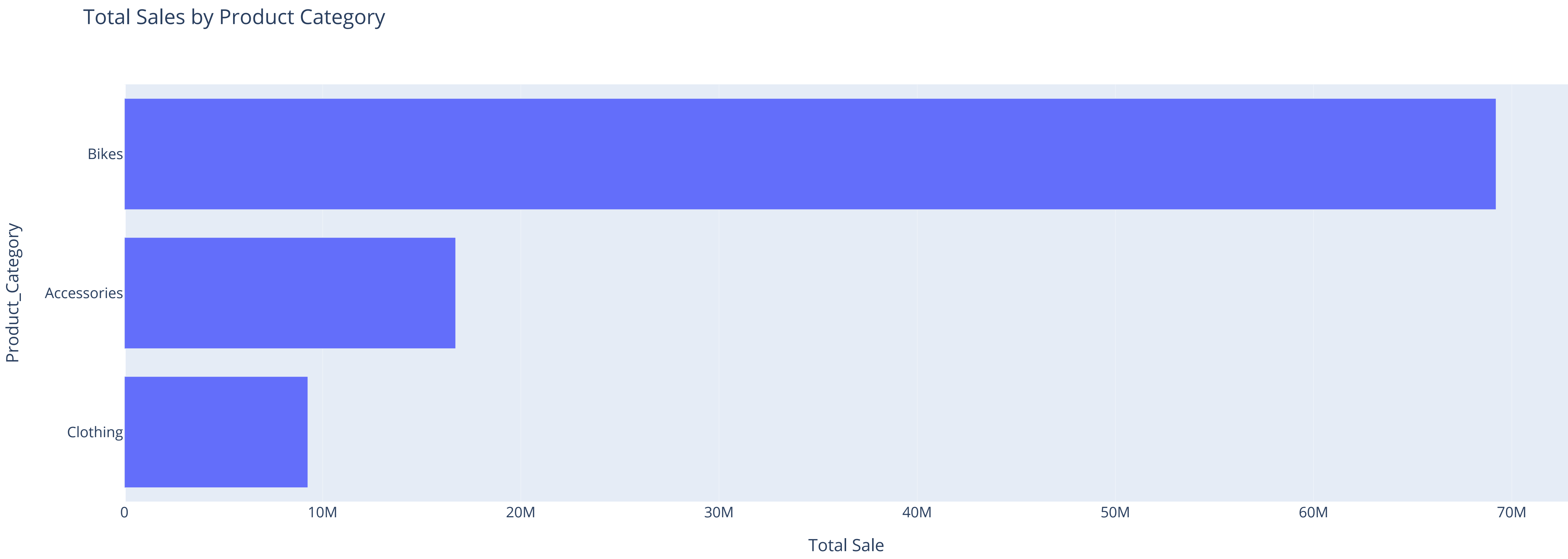
In [34]:

```
# Total Sales by Sub_Category
total_sale = pd.DataFrame(sales_df.groupby('Sub_Category')['Sales'].sum().sort_values(ascending=True))
total_sale = total_sale.reset_index()
total_sale.columns = ['Sub_Category', 'Total Sale']

fig=px.bar(total_sale, x='Total Sale', y = 'Sub_Category', title='Total Sales by Sub_Category')
fig.show()
```

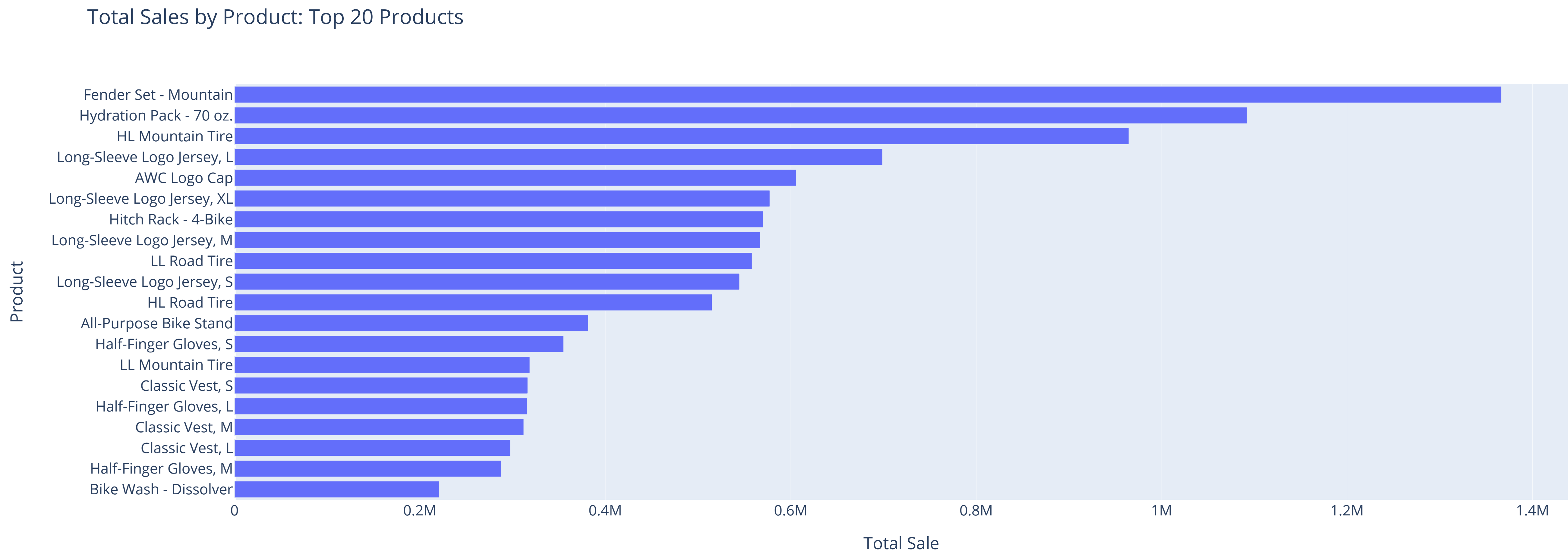


In [35]:

```
# Total Sales by Product Category
total_sale = pd.DataFrame(sales_df.groupby('Product_Category')['Sales'].sum().sort_values(ascending=True))
total_sale = total_sale.reset_index()
total_sale.columns = ['Product_Category', 'Total Sale']

fig=px.bar(total_sale, x='Total Sale', y = 'Product_Category', title='Total Sales by Product Category')
fig.show()
```



In [36]:
```
# Total Sales by Product (Top 20 Products)
total_sale = pd.DataFrame(sales_df.groupby('Product')['Sales'].sum()[:20].sort_values(ascending=True))

total_sale = total_sale.reset_index()
total_sale.columns = ['Product', 'Total Sale']

fig=px.bar(total_sale, x='Total Sale', y = 'Product', title='Total Sales by Product: Top 20 Products')
fig.show()
```



Conclusions

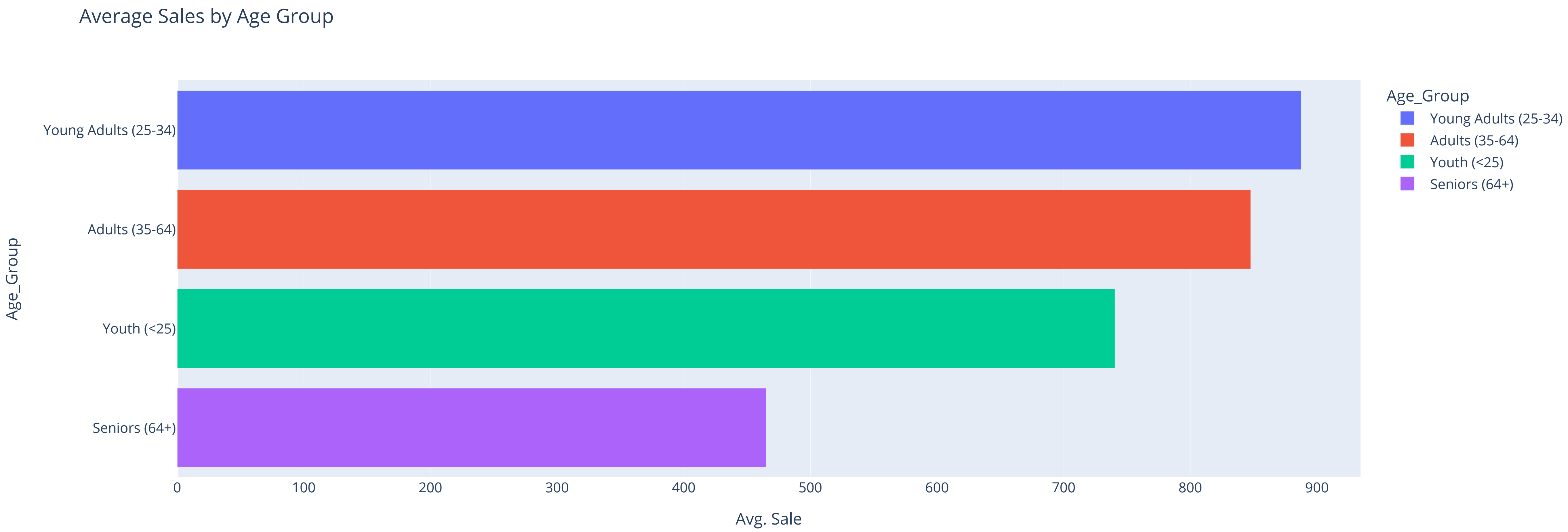
Using the total sales as the KPI, the follwowing observations were made:

- Adults (35 - 64) are the highest customer demographic in terms of age, followed by Young Adults (25 - 34). Seniors make the lowest customer demographic.
- England and British Columbia have the highest sales. Alabama has the lowest sales.
- The United States of America, followed by Australia have the highest sale.
- Road Bikes and Mountain Bikes sub-category brought in the highest sales.
- The highest selling product is the Fender set mountain bike.

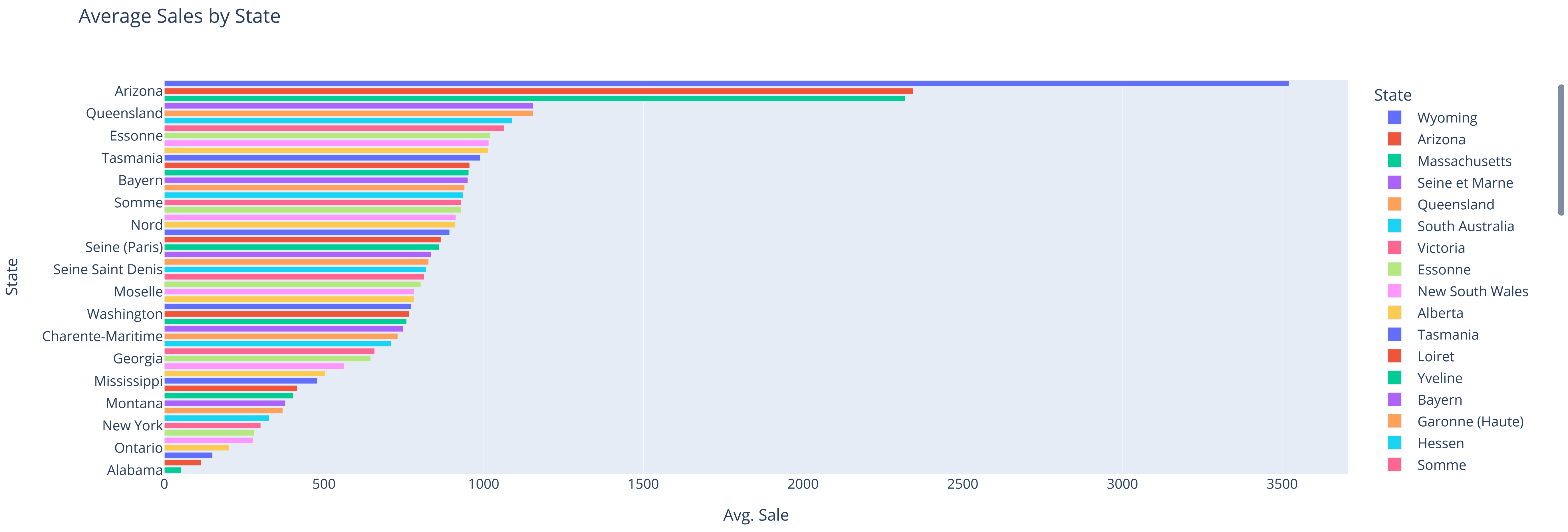
The sales and marketing team can use this information to improve their marketing strategies.

Checking the Average Sales by different categorical attributes

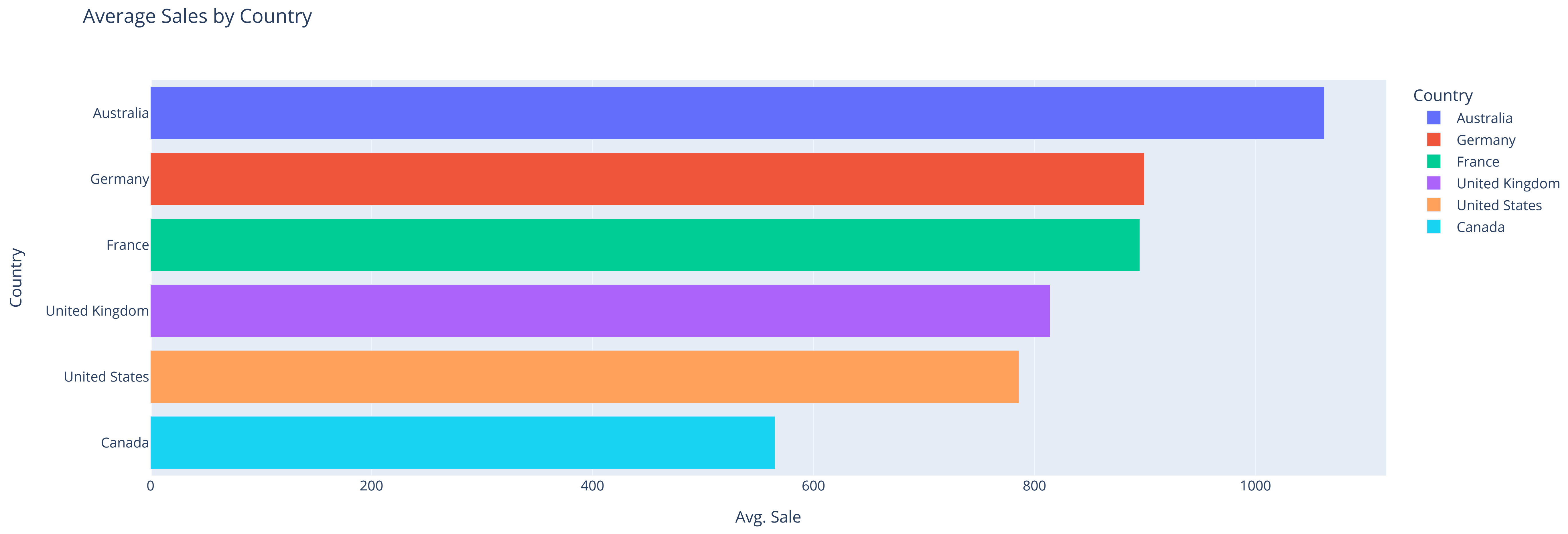
In [37]:
```
avg_sale = pd.DataFrame(sales_df.groupby('Age_Group')['Sales'].mean().sort_values(ascending=False))
avg_sale = avg_sale.reset_index()
avg_sale.columns = ['Age_Group', 'Avg. Sale']

fig=px.bar(avg_sale, x='Avg. Sale', y = 'Age_Group', color='Age_Group', title='Average Sales by Age Group')
fig.show()
```



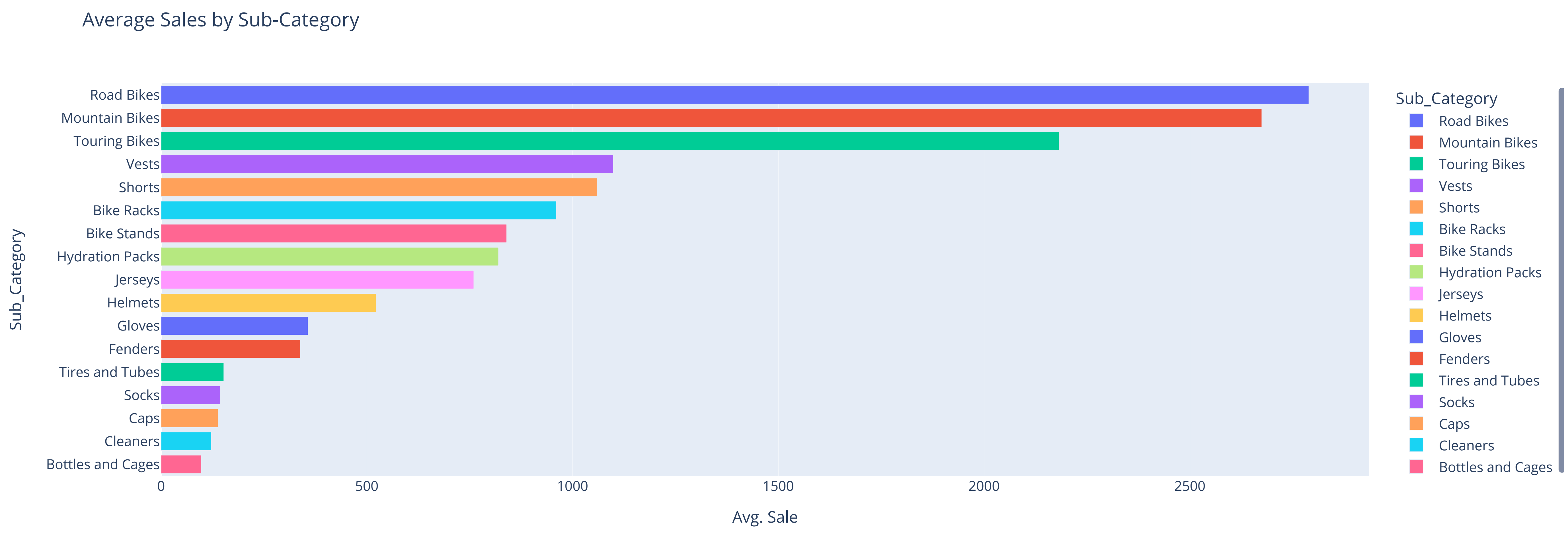
In [38]:
```
avg_sale = pd.DataFrame(sales_df.groupby('State')['Sales'].mean().sort_values(ascending=False))
avg_sale = avg_sale.reset_index()
avg_sale.columns = ['State', 'Avg. Sale']

fig=px.bar(avg_sale, x='Avg. Sale', y = 'State', color='State', title ='Average Sales by State')
fig.show()
```



In [39]:
```
avg_sale = pd.DataFrame(sales_df.groupby('Country')['Sales'].mean().sort_values(ascending=False))
avg_sale = avg_sale.reset_index()
avg_sale.columns = ['Country', 'Avg. Sale']

fig=px.bar(avg_sale, x='Avg. Sale', y = 'Country', color='Country', title ='Average Sales by Country')
fig.show()
```

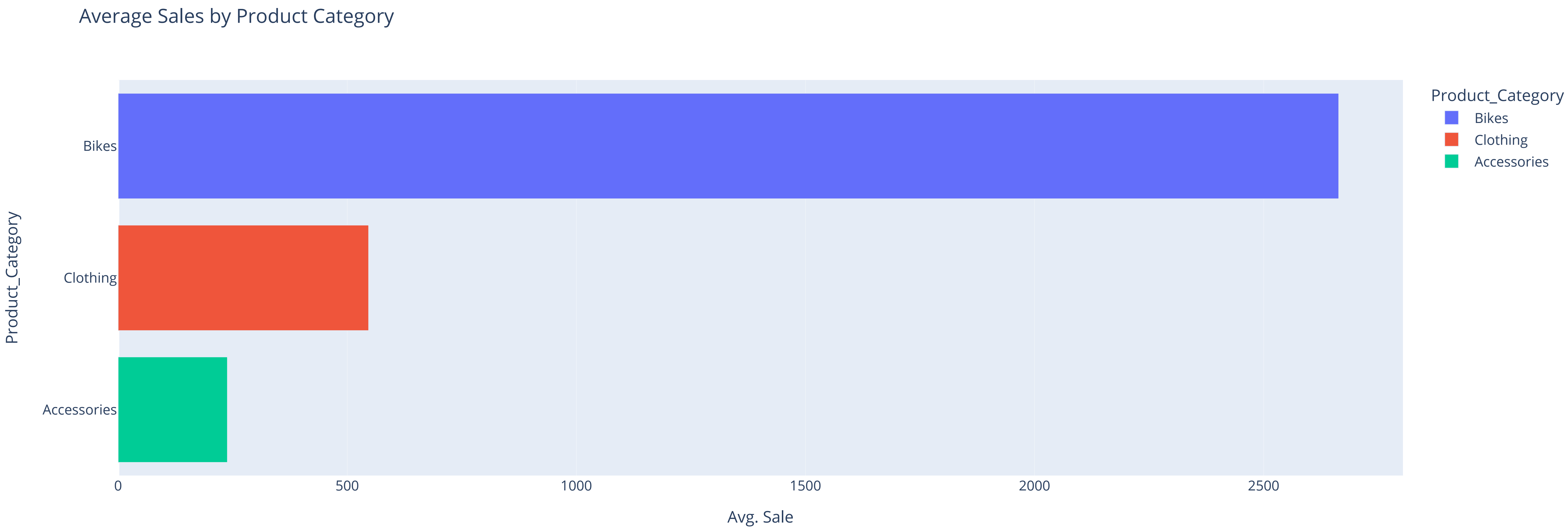


In [40]:
```
avg_sale = pd.DataFrame(sales_df.groupby('Sub_Category')['Sales'].mean().sort_values(ascending=False))
avg_sale = avg_sale.reset_index()
avg_sale.columns = ['Sub_Category', 'Avg. Sale']

fig=px.bar(avg_sale, x='Avg. Sale', y = 'Sub_Category', color='Sub_Category', title= 'Average Sales by Sub-Category')
fig.show()
```



In [41]:

```
avg_sale = pd.DataFrame(sales_df.groupby('Product_Category')['Sales'].mean().sort_values(ascending=False))
avg_sale = avg_sale.reset_index()
avg_sale.columns = ['Product_Category', 'Avg. Sale']

fig=px.bar(avg_sale, x='Avg. Sale', y = 'Product_Category', color='Product_Category', title='Average Sales by Product Category')
fig.show()
```



Conclusion

The following conclusions were observed when analyzing the different categorical variables by the average sales:

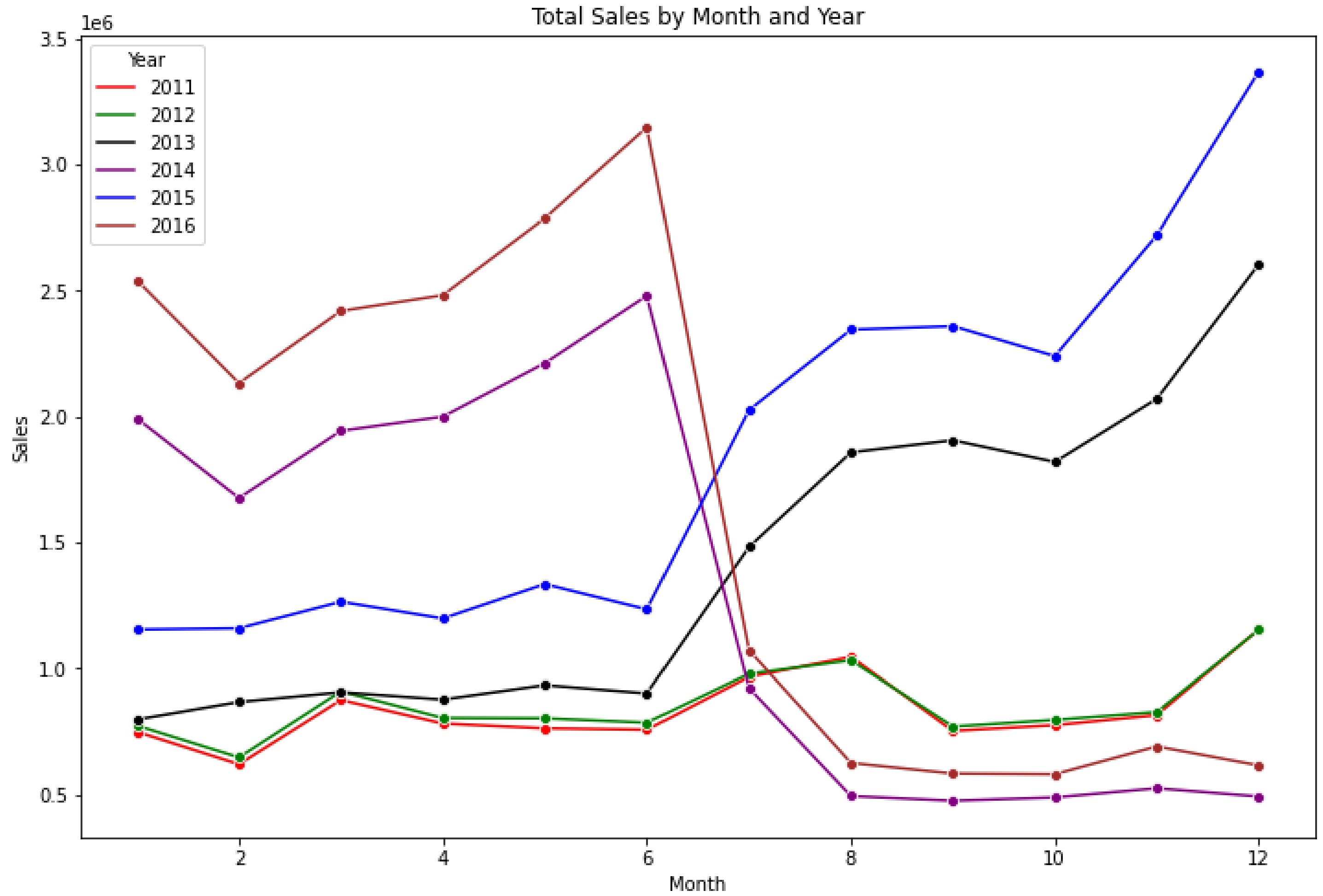
- The young adult age group bring in the most sales had a higher sales average than the Adults. Seniors are still the lowest. The company might then want to look into ways to continue attracting the young adult age group and then come up with more strategies to grow the seniors age group. They might also want to further look into why the senior demographics are so low.
- Arizona state has the highest sales average. The company might want to look into what factors are contributing to Alabama's high sales average and then seeing if they can replicate some of these in the lower performing states like Alabama and Ontario.
- Australia has the higest performance, while Canada is performing the lowest.
- Road bikes (products) and Bikes (sub category) has the highest sales average. Using this data, the company can decide on ways to continue maintaining sales of their bike product, while devising strategies to improve the low performing products like the cleaners, and Bottles and Cages. They could also decide if they want to focus on only the higher performing products and reduce the quantity of lower performing products they offer in their stores.

In all, knowing how their various products, countries and customer demographic are performing using the metric 'Average sales' would help the business tailor their sales and marketing strategy, and make data driven decisions.

Checking the Total Sales by Month and Year

In [42]:
```
# Total Sales by Month and Year
plt.figure(figsize=(12,8))

monthly_sales = sales_df.groupby(['Year','Month'])['Sales'].sum().reset_index()
monthly_sales
sns.lineplot(x="Month", y="Sales",hue="Year", data=monthly_sales, marker='o',
```

```
             palette=['red', 'green', 'black', 'purple', 'blue', 'brown'])
plt.xlabel('Month')
plt.ylabel('Sales')
plt.title('Total Sales by Month and Year')
plt.show()
```



Conclusion

Comparing the total sales across the 6 years of data analysied, the following conclusions were drawn:

- 2014 and 2016 have a similar sales trend. Sales are higher in January and then it dips by Febraury. Then it starts to grow in March. By July, sales reach a peak and then has a downward trend all the way to December. This trend raises a lot of questions which would lead to further data gathering and analysis.

  > - Knowing that the company's highest sales come from bikes, could this upward trend from March and peak in July be because of Summer? Do more people buy bikes in summer?
  > - Could the lower trend in August to December be because of the approaching winter months?
  > - What can the company then do to ensure they are still making sales between August and December?
  > - Would they want to focus on stronger marketing for their other product catergories during the colder months when less people purchase bikes?

- 2015 and 2013 have similiar sales trend, which are the opposite of what was observed in 2014 and 2016. Sales are lower in the 1st half of the year and higher in the 2nd half. This is quite interesting and it leads to more questions.

  > - What changed? Are there seasonal factors?
  > - Why is 2015 so different from 2016?
  > - What did the company do or not do in 2016 and 2014 that weren't done or were done in 2013 and 2015?
  > - Why is the trend in 2013 and 2015 the opposite of the trend in 2014 and 2016?

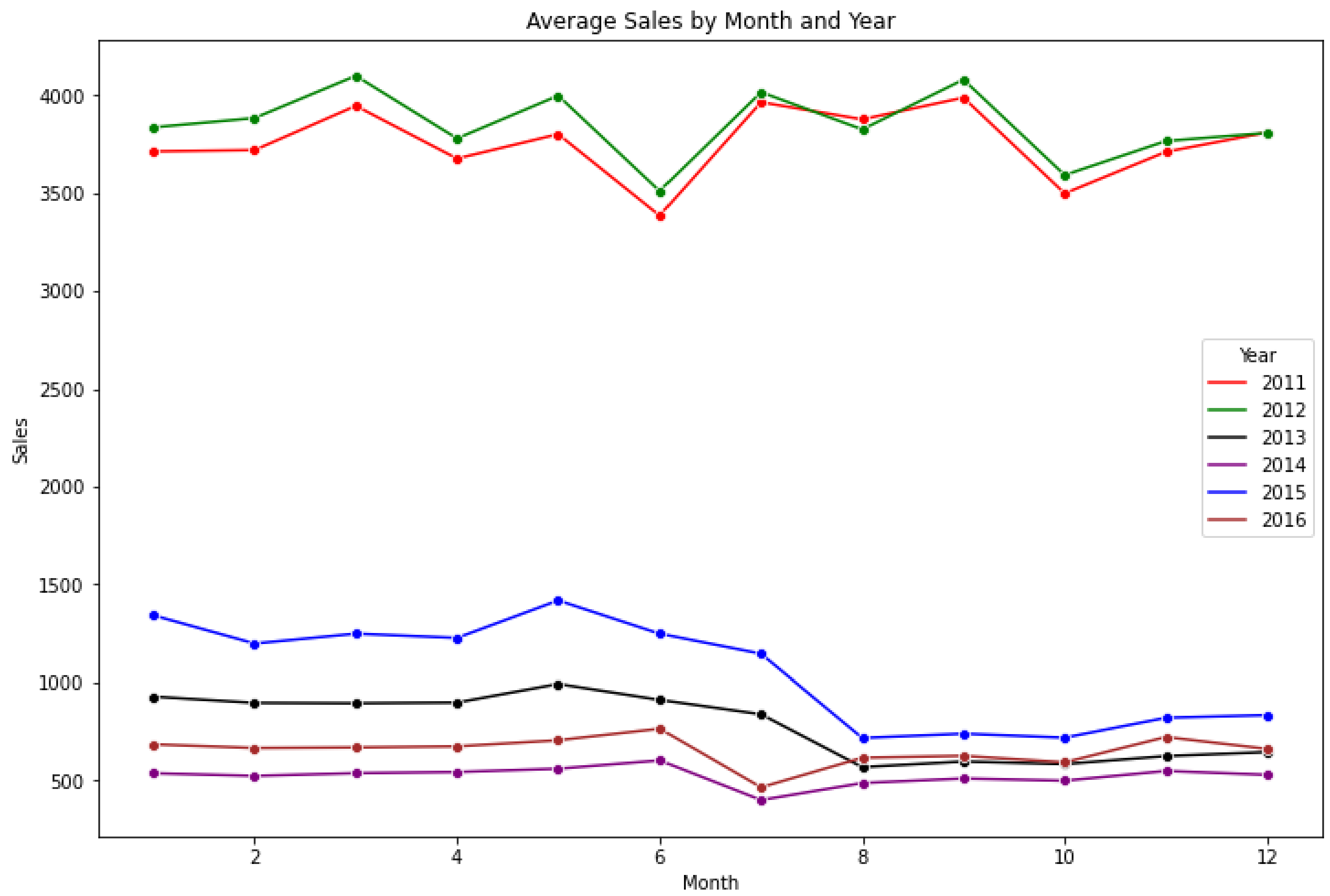
- 2011 and 2012 have a similar trend as well.

> - Is there something in the company that gets done or not done every 2 years?
> - Is there a review of processes?
> - Why are there similar trends occuring?

Observing the monthly and yearly trends opens the door for further investigation and analysis.

Checking the Average Sales by Month and Year.

In [43]:
```
#Monthly Revenue
plt.figure(figsize=(12,8))

monthly_sales = sales_df.groupby(['Year','Month'])['Sales'].mean().reset_index()
monthly_sales
sns.lineplot(x="Month", y="Sales",hue="Year", data=monthly_sales, marker='o',
             palette=['red', 'green', 'black', 'purple', 'blue', 'brown'])
plt.xlabel('Month')
plt.ylabel('Sales')
plt.title('Average Sales by Month and Year')
plt.show()
```



Conclusion

- There is a similar trend observed in 2013, 2014, 2015 and 2016.
- The average sales are Start at high point in January and then dips in February, but starts to grow in April.
- Between May and June, the average sales reach a peak which plummets by August.

This leads to more questions, for further investigation.

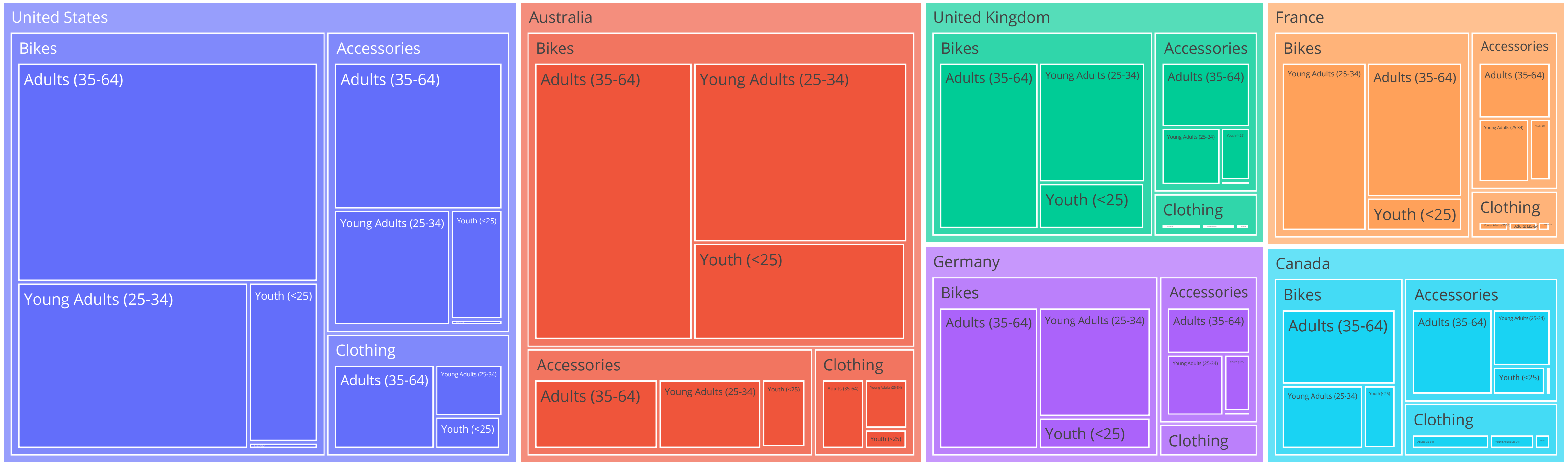
- 2011 and 2012 have a similar trend.

Multivariate Analysis

Tree Maps

What was our profit in the different countries, and in what product categories?

In [44]:
```
px.treemap(sales_df, path = ['Country', 'Product_Category', 'Age_Group'], values='Profit')
```

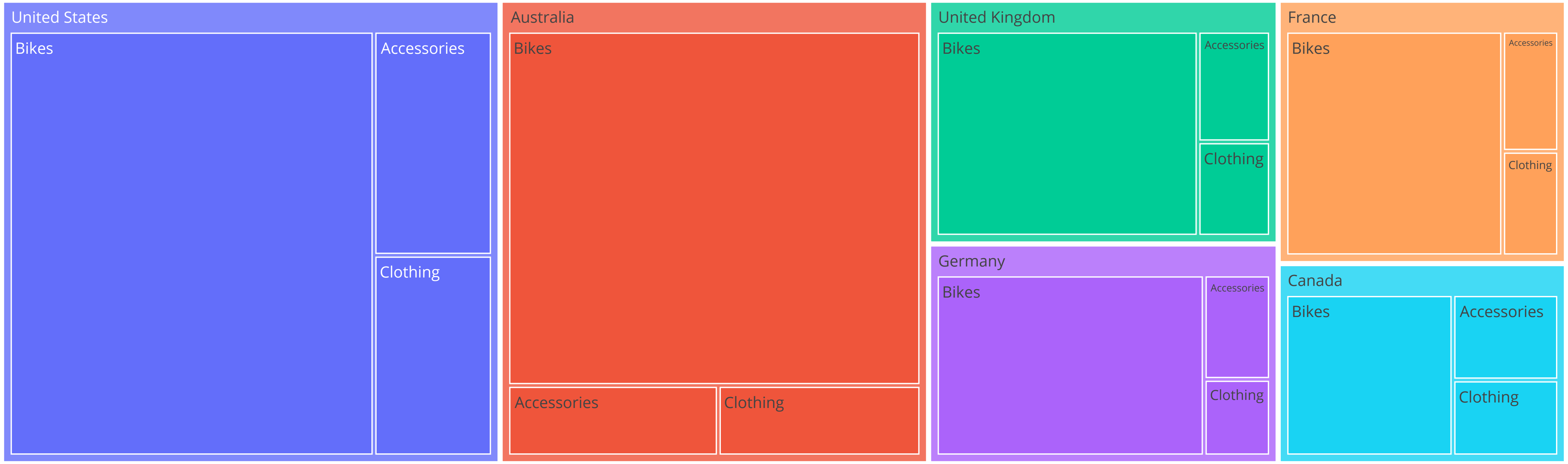


What was our cost in different countries and in the different categories?

Insights

- The United States is the most profitable of all the countries the company operates, followed by Autrialia. Canada is the least profitable country.
- The product category with the highest profit in the United states and across all the other countries is Bikes, followed by accessories and lastly clothing
- In all countries, Adults age group formed the most profitable demographic, except for France where the Young Adult age group led the Adults age group by almost $200,000

In [45]:
```
px.treemap(sales_df, path = ['Country', 'Product_Category'], values='Cost')
```



Insights

- The United States had the highest cost, followed by Australia and Canada had the lowest.
- Bikes also has the highest cost, followed by accessories and clothing last in all countries the company operates.

Estimating Correlation coefficients

In [46]:
```
correlation_df =sales_df.corr()
```

In [47]:
```
correlation_df['Sales'].sort_values(ascending=False)
```

Out[47]:
```
Sales             1.000000
Cost              0.993769
Profit            0.986170
Unit_Price        0.821468
Unit_Cost         0.820789
Day               0.002043
Month            -0.000075
Customer_Age     -0.012505
Year             -0.209921
Order_Quantity   -0.314561
Name: Sales, dtype: float64
```

In [48]:
```
#create correlation matrix
sales_df[['Sales', 'Cost', 'Profit', 'Unit_Price', 'Unit_Cost', 'Customer_Age', 'Month', 'Order_Quantity']].corr()
```

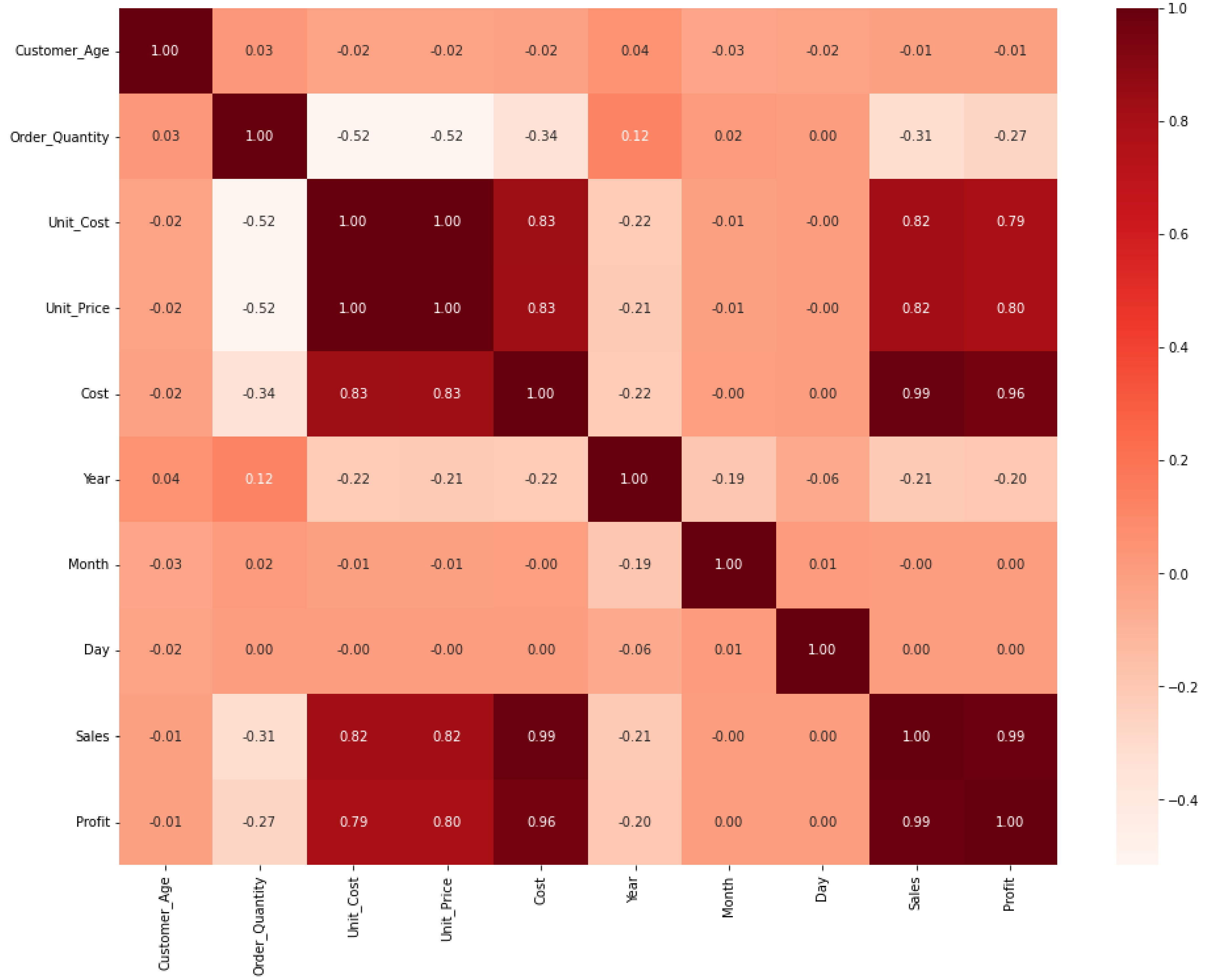
Out[48]:

	Sales	Cost	Profit	Unit_Price	Unit_Cost	Customer_Age	Month	Order_Quantity
Sales	1.000000	0.993769	0.986170	0.821468	0.820789	-0.012505	-0.000075	-0.314561
Cost	0.993769	1.000000	0.961552	0.826301	0.829869	-0.016013	-0.001361	-0.340382
Profit	0.986170	0.961552	1.000000	0.795308	0.788331	-0.006998	0.001839	-0.268903
Unit_Price	0.821468	0.826301	0.795308	1.000000	0.997894	-0.020262	-0.011404	-0.515925
Unit_Cost	0.820789	0.829869	0.788331	0.997894	1.000000	-0.021374	-0.012056	-0.515835
Customer_Age	-0.012505	-0.016013	-0.006998	-0.020262	-0.021374	1.000000	-0.032373	0.026887
Month	-0.000075	-0.001361	0.001839	-0.011404	-0.012056	-0.032373	1.000000	0.016241
Order_Quantity	-0.314561	-0.340382	-0.268903	-0.515925	-0.515835	0.026887	0.016241	1.000000

Heat Maps

In [92]:

```
# Creating a heatmap
plt.figure(figsize=(16, 12))
sns.heatmap(sales_df.corr(), cmap='Reds', annot=True, fmt='.2f');
```



Interpretation

There is a positive correlation between sales and cost

A high correlation shows a strong relationship between 2 variables and a low correlation means a weak relation.

Correlation coefficient ranges between -1 and +1. A positive correlation between 2 variables means that both variables move in the same direction, that is, an increase in one variable leads to an increase in another.

```
In [ ]:
```