ScalerMart Sales Decline: A Data-Driven Approach to Customer Insights and Sales Improvement

Problem Statement:

ScalerMart, a leading global electronics retailer, has faced a concerning decline in sales, experiencing a nearly 50% revenue drop in 2020 compared to 2019. This report aims to leverage customer-level transactional data to identify the root causes behind this substantial sales decrease.

Objective:

Through in-depth analysis, this study will uncover customer buying patterns, product trends, and potential market shifts that might be contributing to the decline. By gaining these insights, the report will recommend data-driven strategies for ScalerMart to improve sales performance and regain its market position.

Importing required Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Loading Customer, Product and Sales Data Sets

```
cust = pd.read_csv('Customers.csv', encoding='unicode_escape')
prod = pd.read_csv('Products.csv')
sales = pd.read_csv('Sales.csv')
```

1. EDA of Customer Data

```
cust.shape
```

```
(15266, 11)
```

Customer data has 15266 rows and 11 columns.

```
cust.head()
```

```
   CustomerKey  Gender                Name           City State
Code  \
0          301  Female       Lilly Harding  WANDEARAH EAST          SA

1          325  Female        Madison Hull      MOUNT BUDD          WA

2          554  Female       Claire Ferres       WINJALLOK         VIC

3          786    Male  Jai Poltpalingada    MIDDLE RIVER          SA

4         1042    Male     Aidan Pankhurst   TAWONGA SOUTH         VIC


               State Zip Code    Country  Continent    Birthday  year

0    South Australia     5523  Australia  Australia    7/3/1939  1939

1  Western Australia     6522  Australia  Australia   9/27/1979  1979

2           Victoria     3380  Australia  Australia   5/26/1947  1947

3    South Australia     5223  Australia  Australia   9/17/1957  1957

4           Victoria     3698  Australia  Australia  11/19/1965  1965
```

```
cust.dtypes
```

```
CustomerKey     int64
Gender         object
Name           object
City           object
State Code     object
State          object
Zip Code       object
Country        object
Continent      object
Birthday       object
dtype: object
```

```
cust.isnull().sum()
```

```
CustomerKey     0
Gender          0
Name            0
City            0
State Code     10
State           0
Zip Code        0
Country         0
Continent       0
```

```
Birthday        0
dtype: int64
```

Filling null values with 'NA' as they are state codes.

```
cust.fillna('NA',inplace=True)

cust.isnull().sum()

CustomerKey    0
Gender         0
Name           0
City           0
State Code     0
State          0
Zip Code       0
Country        0
Continent      0
Birthday       0
year           0
dtype: int64
```

Customer data is now free of null values and is ready for analysis.

```
print("Following is the UniqueCount of columns in customer data")
for i in list(cust.columns):
              print(i, ' : ',cust[i].nunique())

Following is the UniqueCount of columns in customer data
CustomerKey  :  15266
Gender  :  2
Name  :  15118
City  :  8258
State Code  :  468
State  :  512
Zip Code  :  9505
Country  :  8
Continent  :  3
Birthday  :  11270
year  :  68
```

Slicing year from customer date of birth to analyze the which customer group demograpics.

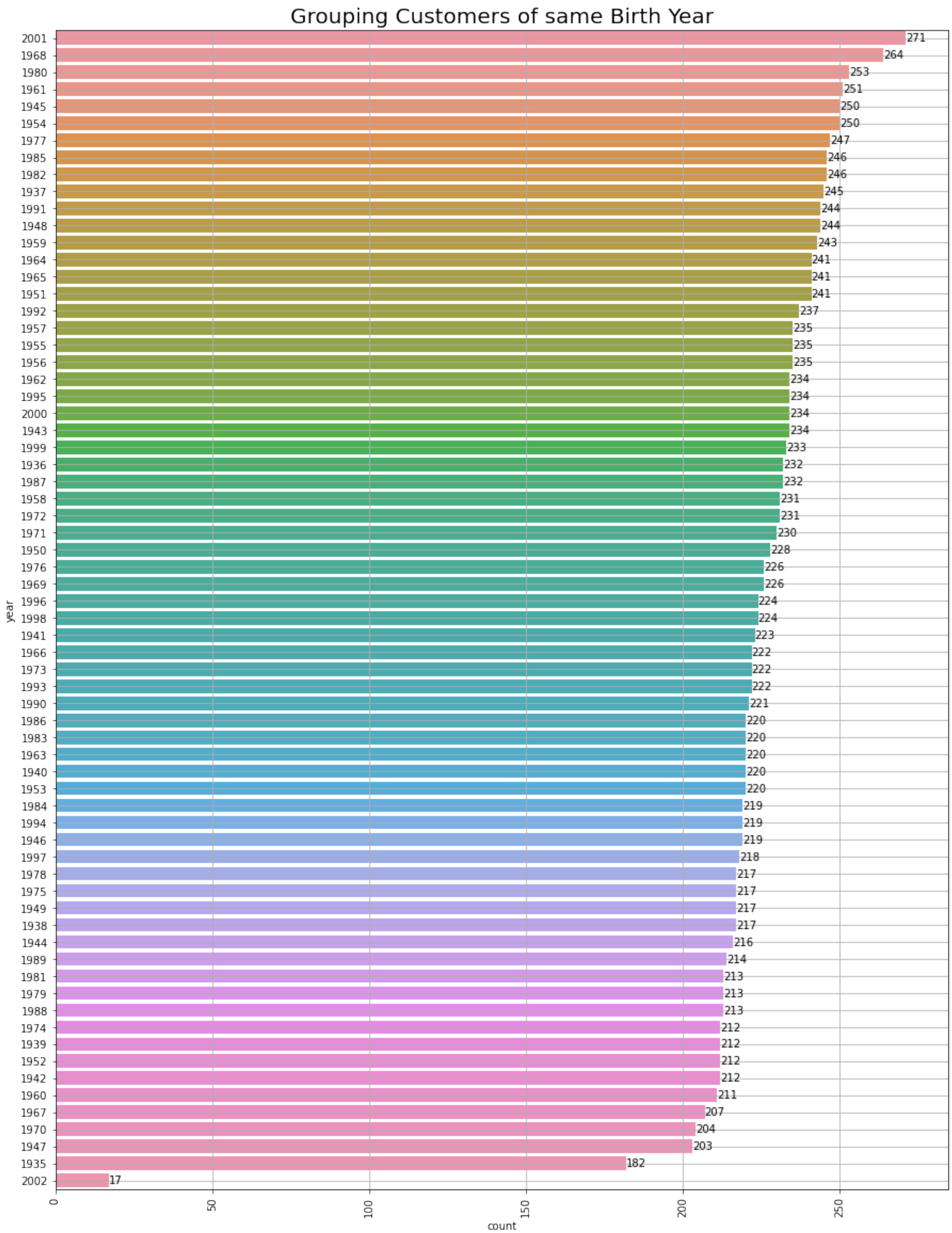
```
cust['Birthday']= cust['Birthday'].astype(str)

cust['Birthday'].values

array(['7/3/1939', '9/27/1979', '5/26/1947', ..., '11/9/1937',
       '10/12/1937', '8/18/1965'], dtype=object)
```

```
cust['year'] = cust['Birthday'].str.slice(-1, -5,-1).str[::-1]
```

Univariate Analysis of Customer Data

```
#Grouping Customers of same Birth Year
plt.figure(figsize=(15,20))
ax=sns.countplot(y=cust['year'],order =
cust['year'].value_counts().index)
plt.grid(True)
for container in ax.containers:
    ax.bar_label(container)
plt.xticks(rotation=90)
plt.title("Grouping Customers of same Birth Year", fontsize=20)
plt.show
```

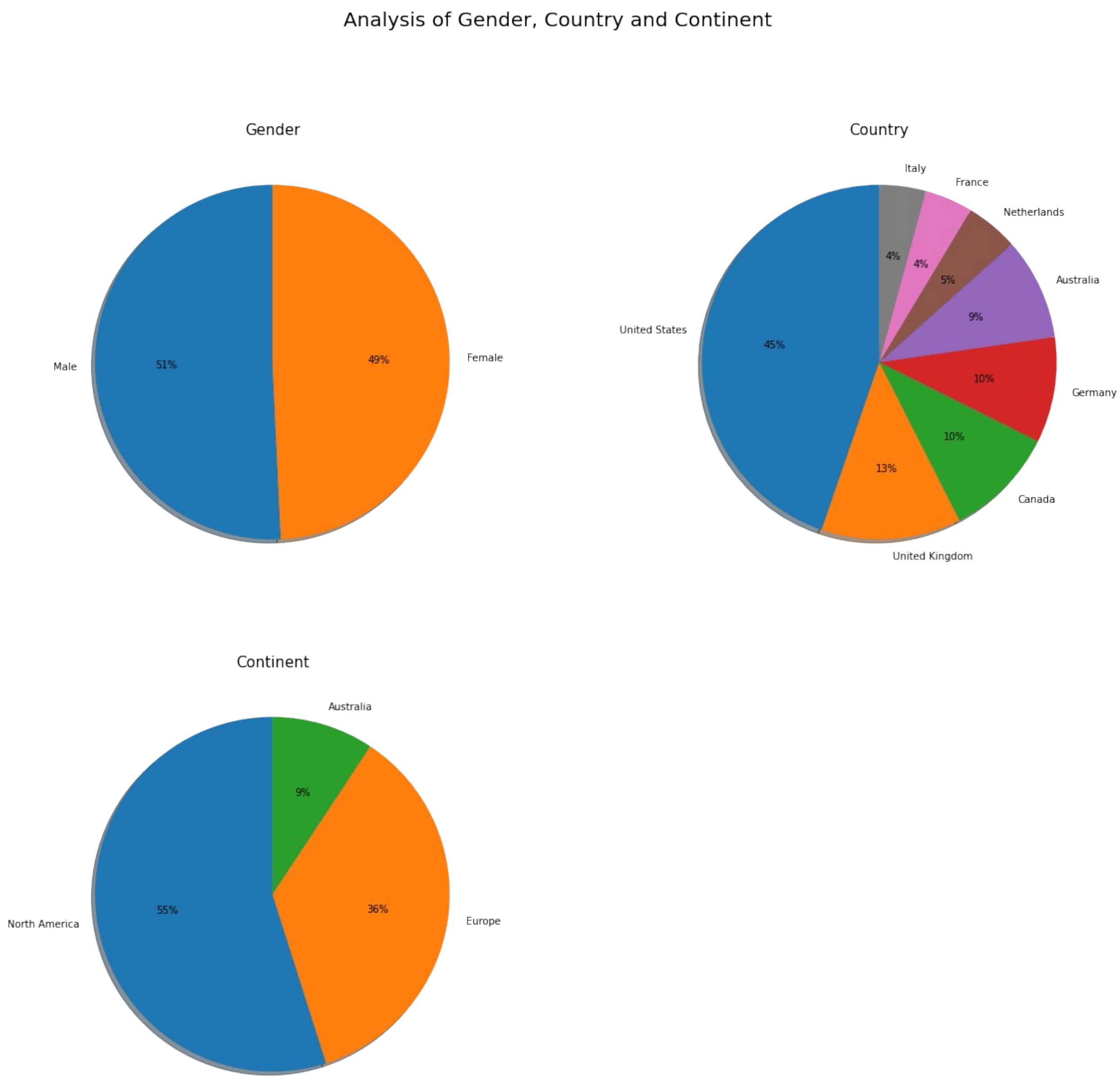
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



Insights:

Maximum customer base were born in the year 2001 and next to it comes 1968,1980,1961. where there is no much trend observed w.r.t to birth year.

```
#analysing some categorical columns
cust_cat_cols=['Gender','Country','Continent']

fig = plt.figure(figsize=(20,18))
for n,col in enumerate(cust_cat_cols):
    plt.subplot(int(len(cust_cat_cols)/2 +1), 2, n+1)
    plt.pie(list(cust[col].value_counts().values),
            labels = list(cust[col].value_counts().index),
autopct='%.0f%%', shadow= True,
            startangle = 90,  radius= 1)
    plt.title(col, fontsize = 15)
    plt.xticks(rotation = 45)
fig.suptitle("Analysis of Gender, Country and Continent", fontsize=
20, color = 'black')
plt.show()
```



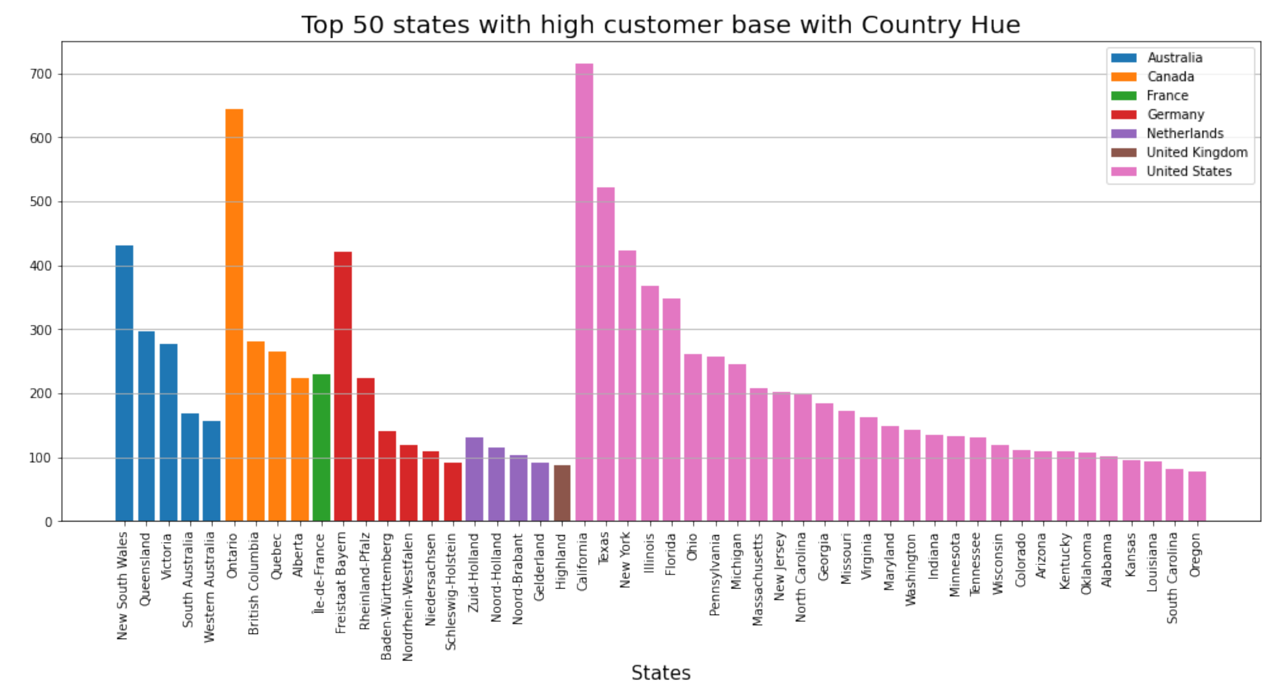
Insights:

```
51% of the customers are Male and 49% are Female.
45% of the customers are from United states, 13% from UK, 10% Canada
and 10% Germany.
55% of customrs are from NorthAmerica, 36% from Europe and 9% from
Australia
```

Bivariate Analysis Of Customer Data

```
#top 50 states with highest number of customers from each country
## grouping data by country and state , counting each type in each
```

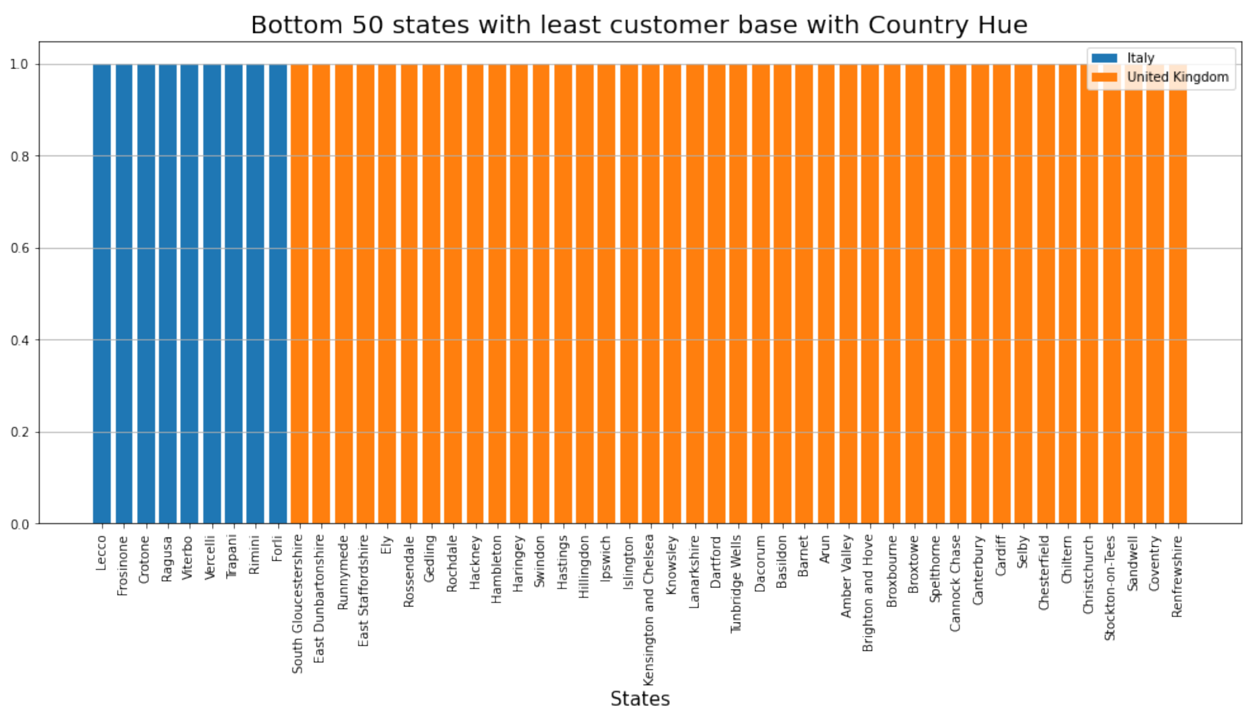
```
group
group_data =
cust.groupby(['Country','State']).size().sort_values(ascending=False)
[0:50].reset_index(name='count')

plt.figure(figsize=(17,7))

for country,group in group_data.groupby('Country'):
    plt.bar(group['State'],group['count'],label=country)
plt.grid(True, axis='y')
plt.xlabel('States', fontsize=15)
plt.title('Top 50 states with high customer base with Country Hue',
fontsize='20')
plt.xticks(rotation=90)
plt.legend()
plt.show()
```



Insight:

```
US,Canada,Germany and Australia are the countryies having states with
highest coustomer base.
California is the top state with more than 700 customers, next comes
Ontario with 650 customers and next comes texas with more than 500
customers.
Follows other states Newyork,Frelsaat Bayern,New South Wales,Illions,
Florida,Qeensland, British Columbia.

#Bottom 50 states with highest number of customers from each country
## grouping data by country and state , counting each type in each
```

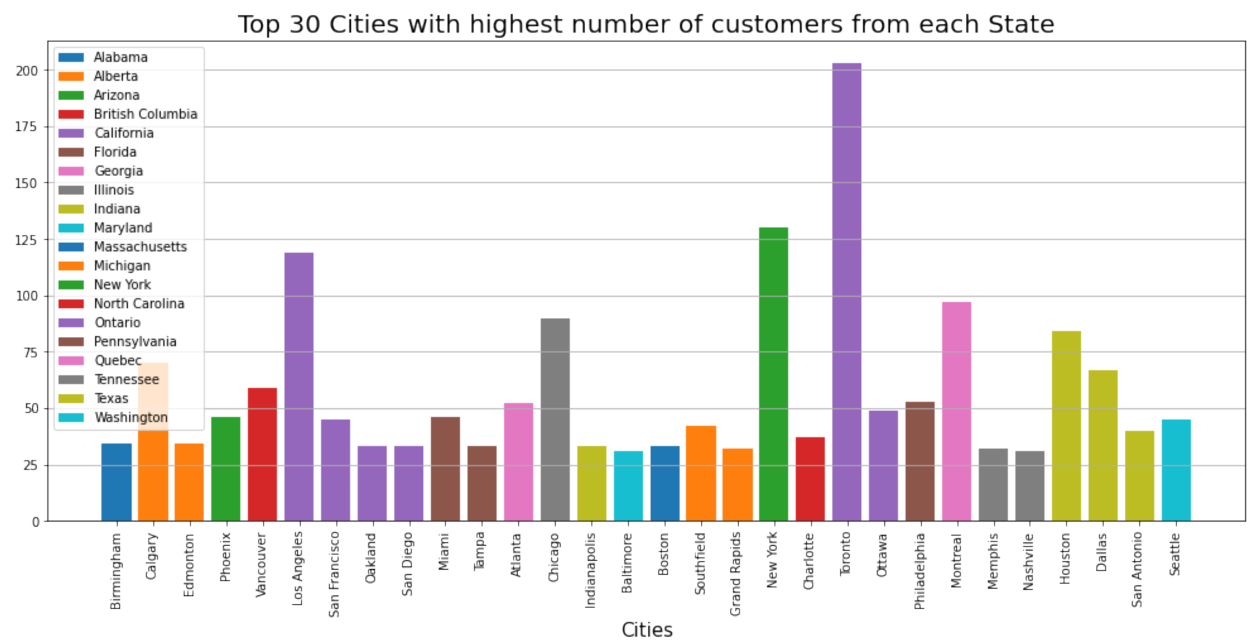
```python
group
group_data =
cust.groupby(['Country','State']).size().sort_values(ascending=True)
[0:50].reset_index(name='count')

plt.figure(figsize=(17,7))

for country,group in group_data.groupby('Country'):
    plt.bar(group['State'],group['count'],label=country)
plt.grid(True, axis='y')
plt.xlabel('States', fontsize=15)
plt.title('Bottom 50 states with least customer base with Country
Hue', fontsize='20')
plt.xticks(rotation=90)
plt.legend()
plt.show()
```



Insights:

```
Italy and Uk are having most of the least customer states where the
organization can concentrate to increase their sales.

#Top 50 Cities with highest number of customers from each State
## grouping data by state and city , counting each type in each group
group_city_data =
cust.groupby(['State','City']).size().sort_values(ascending=False)
[0:30].reset_index(name='count')
```

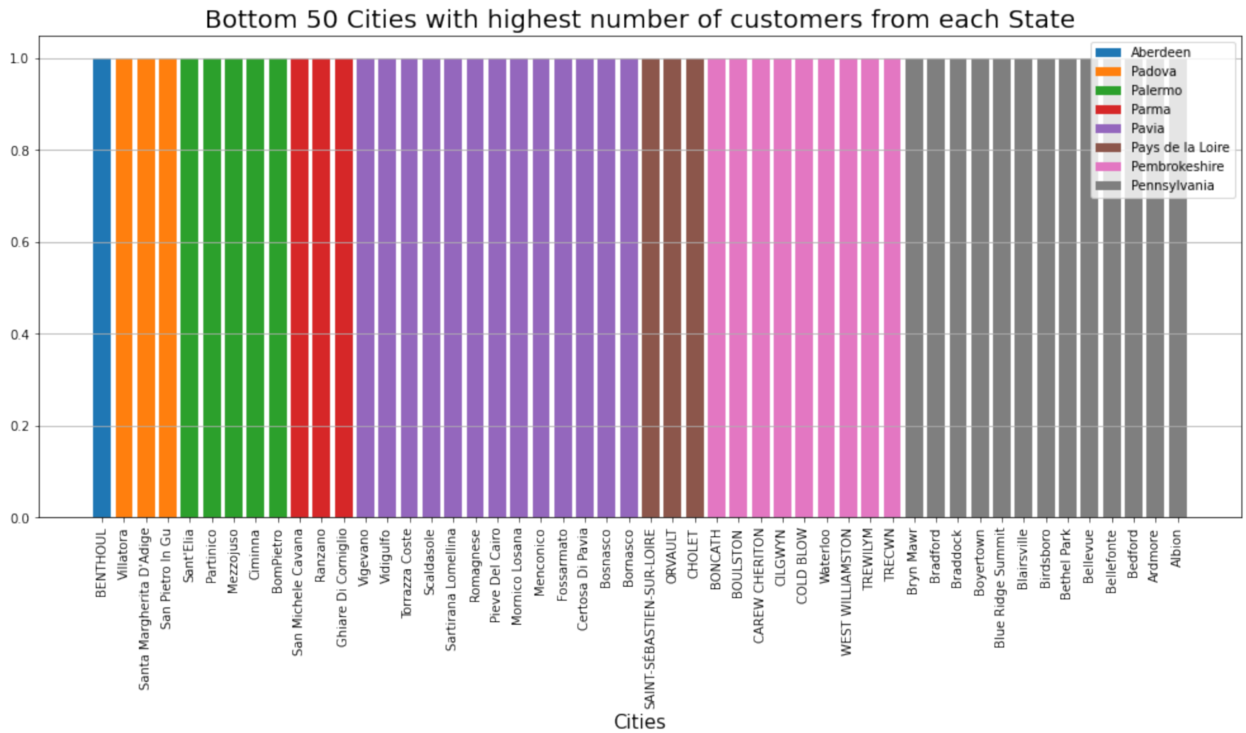
```
plt.figure(figsize=(17,7))

for state,group in group_city_data.groupby('State'):
    plt.bar(group['City'],group['count'],label=state)
plt.grid(True, axis='y')
plt.xlabel('Cities', fontsize=15)
plt.title('Top 30 Cities with highest number of customers from each 
State', fontsize='20')
plt.xticks(rotation=90)
plt.legend()
plt.show()
```



Insights:

```
Toranto From Ontrio and Losangeles from California are the cities with 
highest customer base.

#Botton 50 Cities with highest number of customers from each State
## grouping data by state and city , counting each type in each group
group_city_data = 
cust.groupby(['State','City']).size().sort_values(ascending=True)
[0:50].reset_index(name='count')

plt.figure(figsize=(17,7))

for state,group in group_city_data.groupby('State'):
    plt.bar(group['City'],group['count'],label=state)
plt.grid(True, axis='y')
plt.xlabel('Cities', fontsize=15)
plt.title('Bottom 50 Cities with highest number of customers from each 
```

```
State', fontsize='20')
plt.xticks(rotation=90)
plt.legend()
plt.show()
```



Insights:

```
Pavia and Pensnsylvania are the states that can be concentrated for
improving sales.

## grouping data by state and type , counting each type in each group
group_data =
df.groupby(['state','type']).size().reset_index(name='count')

plt.figure(figsize=(10,10))

for state,group in group_data.groupby('state'):
    plt.bar(group['type'],group['count'],label=state)

plt.xlabel('type')
plt.ylabel('count')
plt.title('count of EV types by state')
plt.xticks(rotation=90)
plt.legend()
plt.show()
```

2. EDA of Product Data

```
prod.head()
```

```
   ProductKey                          Product Name    Brand   Color  \
0           1  Contoso 512MB MP3 Player E51 Silver  Contoso  Silver
1           2    Contoso 512MB MP3 Player E51 Blue  Contoso    Blue
2           3     Contoso 1G MP3 Player E100 White  Contoso   White
3           4    Contoso 2G MP3 Player E200 Silver  Contoso  Silver
4           5       Contoso 2G MP3 Player E200 Red  Contoso     Red

   Unit Cost USD  Unit Price USD  SubcategoryKey Subcategory
CategoryKey  \
0           0.62            2.99             101     MP4&MP3
1
1           0.62            2.99             101     MP4&MP3
1
2           0.40            4.52             101     MP4&MP3
1
3           1.00            1.57             101     MP4&MP3
1
4           1.00            1.57             101     MP4&MP3
1

  Category  profit
0    Audio    2.37
1    Audio    2.37
2    Audio    4.12
3    Audio    0.57
4    Audio    0.57
```

```
prod.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2517 entries, 0 to 2516
Data columns (total 10 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   ProductKey      2517 non-null   int64
 1   Product Name    2517 non-null   object
 2   Brand           2517 non-null   object
 3   Color           2517 non-null   object
 4   Unit Cost USD   2517 non-null   object
 5   Unit Price USD  2517 non-null   object
 6   SubcategoryKey  2517 non-null   int64
 7   Subcategory     2517 non-null   object
 8   CategoryKey     2517 non-null   int64
 9   Category        2517 non-null   object
dtypes: int64(3), object(7)
memory usage: 196.8+ KB
```

Insights:

```
No null values found
```

```
prod.shape
```

```
(2517, 10)
```

There are 2517 rows and 10 columns in Product data

```
print(list(prod.columns))
```

```
['ProductKey', 'Product Name', 'Brand', 'Color', 'Unit Cost USD',
'Unit Price USD', 'SubcategoryKey', 'Subcategory', 'CategoryKey',
'Category']
```

```
print('Number of unique items for each column in product data')
for col in list(prod.columns):
    print(col," : ",prod[col].nunique())
```

```
Number of unique items for each column in product data
ProductKey  :  2517
Product Name  :  2517
Brand  :  11
Color  :  16
Unit Cost USD  :  480
Unit Price USD  :  426
SubcategoryKey  :  32
Subcategory  :  32
CategoryKey  :  8
Category  :  8
```

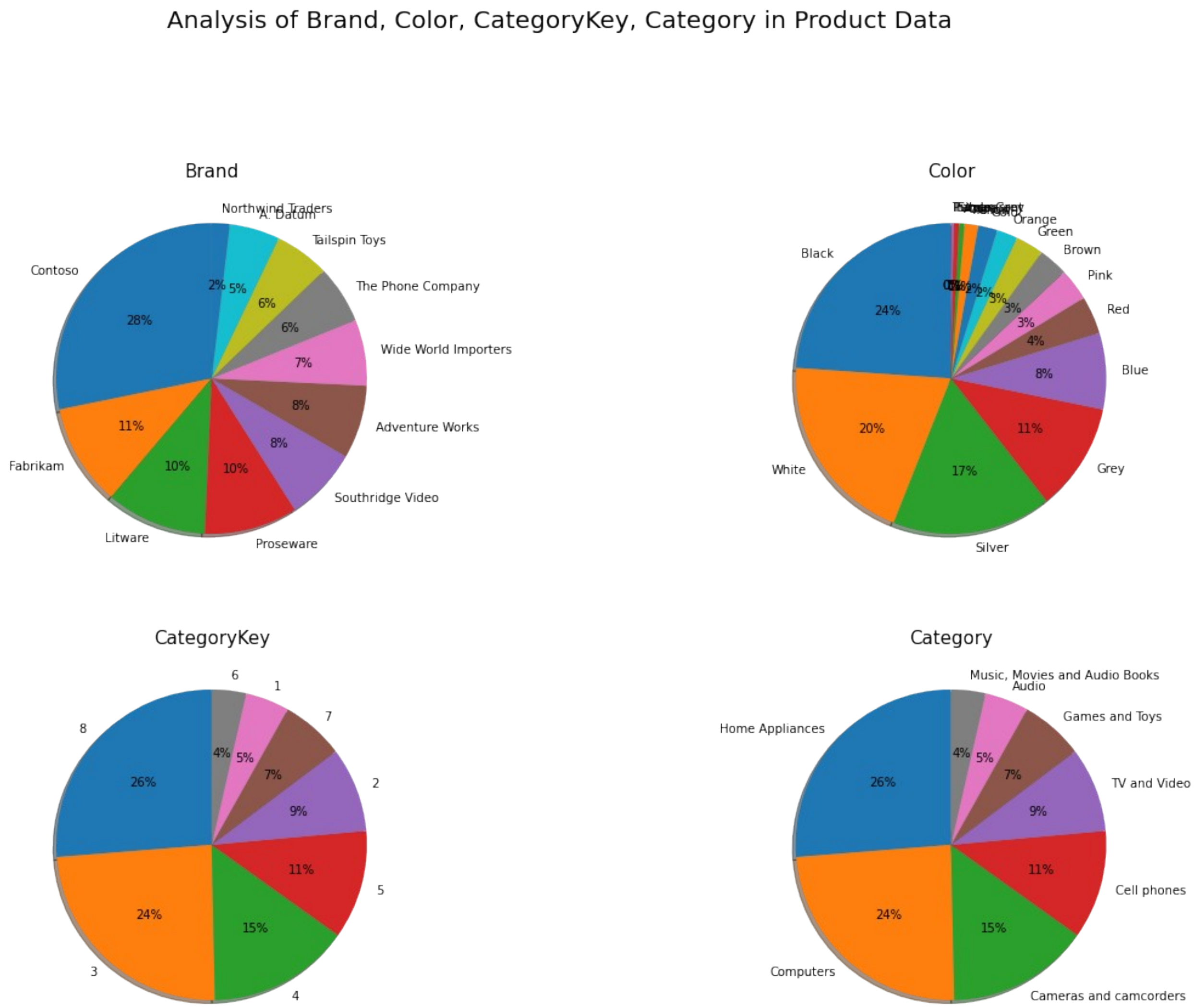
Insights:

```
Product Name and Product Key are unique. Analysis can be made on other
columns.
```

Univariate Analysis of Product Data

```
prod_cols=['Brand', 'Color', 'CategoryKey', 'Category']

fig = plt.figure(figsize=(20,20))
for n,col in enumerate(prod_cols):
    plt.subplot(int(len(prod_cols)/2 +1), 2, n+1)
    plt.pie(list(prod[col].value_counts().values),
            labels = list(prod[col].value_counts().index),
autopct='%.0f%%', shadow= True,
            startangle = 90,  radius= 1)
    plt.title(col, fontsize = 15)
    plt.yticks(rotation = 90)
```

```
fig.suptitle("Analysis of Brand, Color, CategoryKey, Category in
Product Data", fontsize= 20, color = 'black')
plt.show()
```

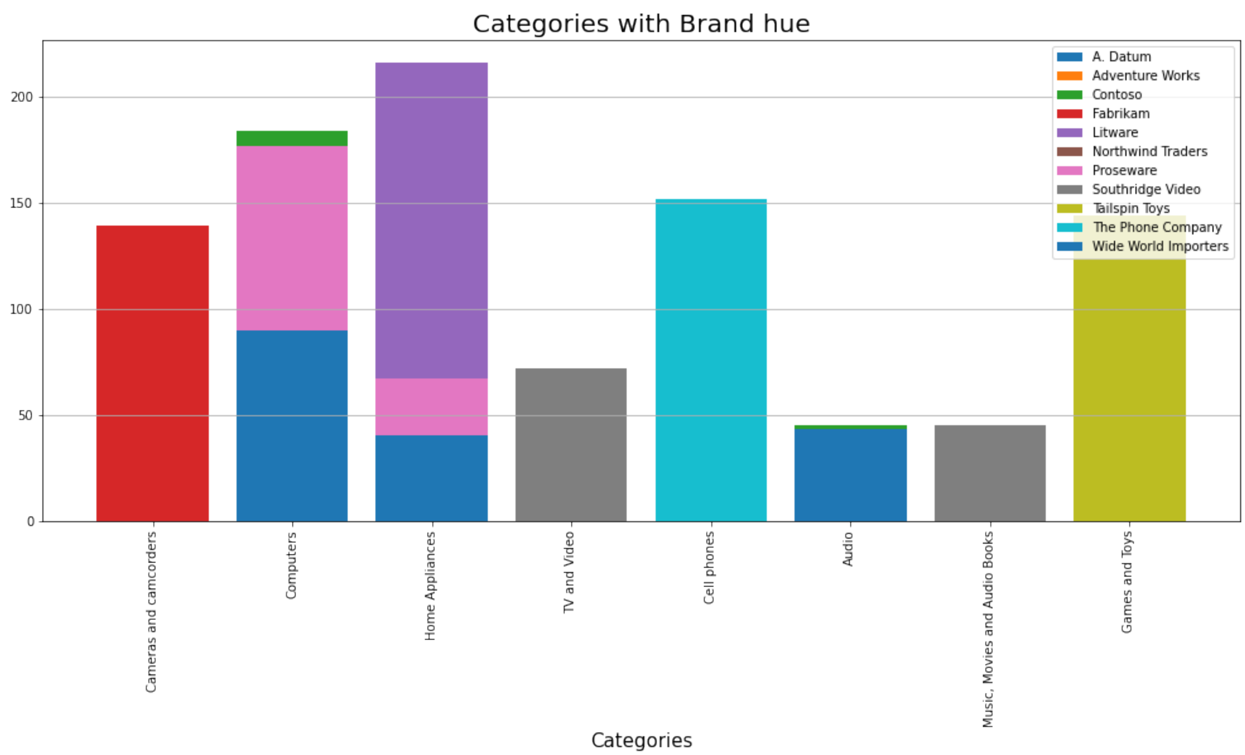


Insights:

```
Contoso, Fabrikam, Litware and Poseware are the leading product brands
in the product data with 28, 11 10 and 10 Percent of overall products
respectively.
Black, White,Silver, Grey are the more produced colors.
Home Appliances, Computers, Cameras & Camcorders and Cell phones are
the highest percent occupiers with 26, 24, 15, 11 percent of overall
product Category respectively.
```

Bivariate Analysis of Product Data

```
## grouping data by Brand and Category
group_subcat_data =
prod.groupby(['Brand','Category']).size().sort_values(ascending=False)
.reset_index(name='count')

plt.figure(figsize=(17,7))

for brand,group in group_subcat_data.groupby('Brand'):
    plt.bar(group['Category'],group['count'],label=brand)
plt.grid(True, axis='y')
plt.xlabel('Categories', fontsize=15)
plt.title('Categories with Brand hue', fontsize='20')
plt.xticks(rotation=90)
plt.legend()
plt.show()
```

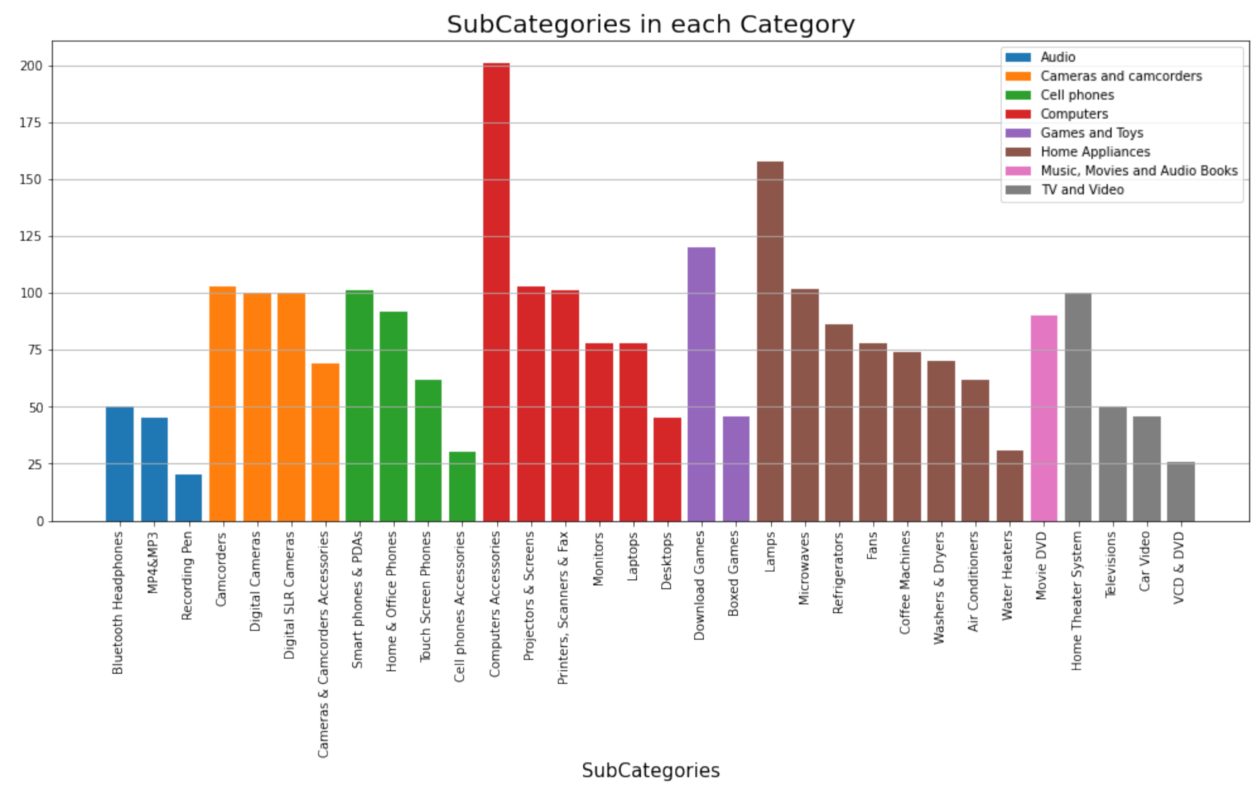


Insights:

```
Even if Contoso is the brand selling highest number of products it has
limited categories like computers and audio.
Litware is the brand exclusive for Home Appliances.
The Phone Company is exclusive Cellphone brand.
Fabricam is the brand selling Cameras and camcorders.
WorldWideImporters ia the brand with categories like Computers, Audio
and HomeAppliances.
```

```
Tailspin Toys is an exclusive Games and Toy brand.
Porsware is a brand selling Computers and HomeAppliances.
NorthWindTraders is an exclusive HomAppliances seller.
```

```python
## grouping data by Category and subcategory , counting each type in each group
group_subcat_data = prod.groupby(['Category','Subcategory']).size().sort_values(ascending=False).reset_index(name='count')

plt.figure(figsize=(17,7))

for cat,group in group_subcat_data.groupby('Category'):
    plt.bar(group['Subcategory'],group['count'],label=cat)
plt.grid(True, axis='y')
plt.xlabel('SubCategories', fontsize=15)
plt.title('SubCategories in each Category', fontsize='20')
plt.xticks(rotation=90)
plt.legend()
plt.show()
```



Insights:

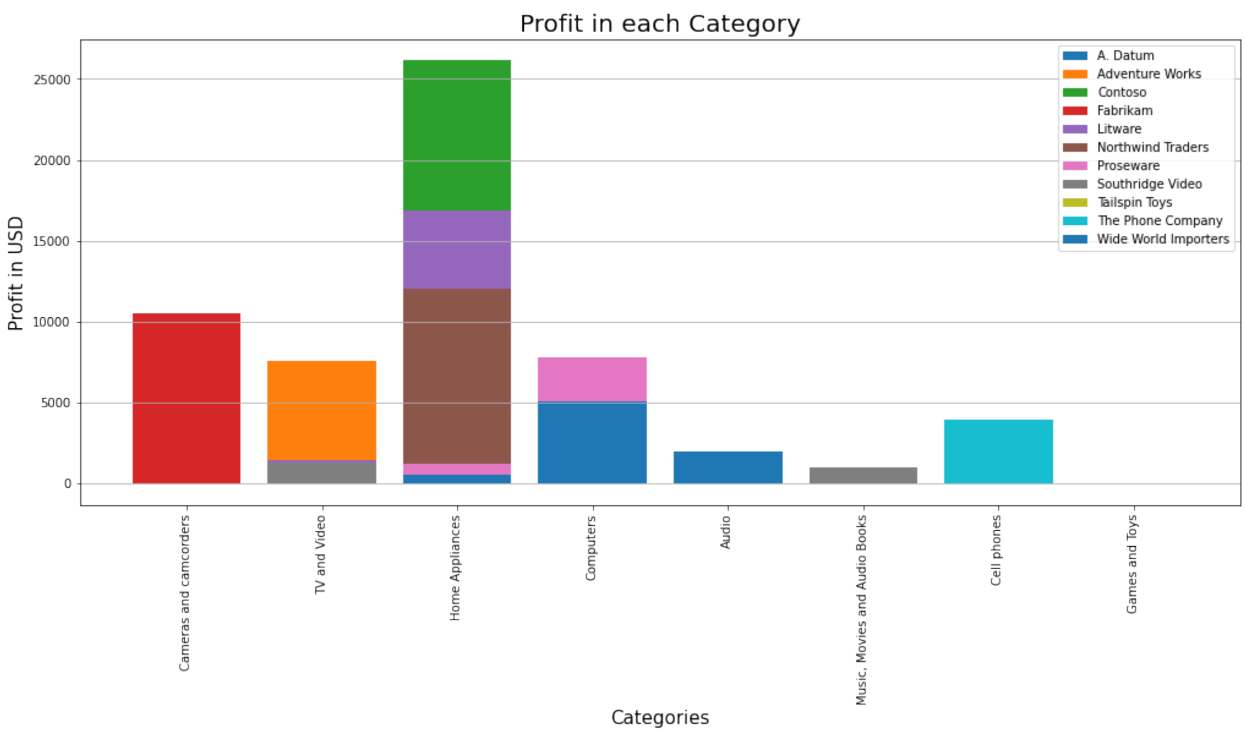
```
HomeAppliances  and computers are the highest sold categories with
includes brands like WorldWideImporters, Contoso and Litware.
Computers&Accessories, Lamps and DownloadedGames are the subcategories
```

sold more from the categories Computers, HomeAppliances and Games & Toys respectively.

```
prod.dtypes
```

```
ProductKey          int64
Product Name       object
Brand              object
Color              object
Unit Cost USD      object
Unit Price USD     object
SubcategoryKey      int64
Subcategory        object
CategoryKey         int64
Category           object
dtype: object
```

```
#Removing $ from values and converting into float type
prod['Unit Cost USD']=prod['Unit Cost USD'].str[1:]
prod['Unit Cost USD'] = prod['Unit Cost USD'].str.replace(',', '')

prod['Unit Price USD']=prod['Unit Price USD'].str[1:]
prod['Unit Price USD'] = prod['Unit Price USD'].str.replace(',', '')

prod['Unit Cost USD']=prod['Unit Cost USD'].astype(float)
prod['Unit Price USD']=prod['Unit Price USD'].astype(float)

#Calculating profit and adding profit column
prod['profit']=prod['Unit Price USD']-prod['Unit Cost USD']

## grouping data by Category and subcategory , counting each type in each group
group_profit_data = prod.groupby(['Brand','Category'])
['profit'].sum().sort_values(ascending=False).reset_index(name='count'
)

plt.figure(figsize=(17,7))

for brand,group in group_profit_data.groupby('Brand'):
    plt.bar(group['Category'],group['count'],label=brand)
plt.grid(True, axis='y')
plt.xlabel('Categories', fontsize=15)
plt.ylabel('Profit in USD', fontsize=15)
plt.title('Profit in each Category', fontsize='20')
plt.xticks(rotation=90)
plt.legend()
plt.show()
```



Insights:

```
Home Appliances is the category with highest profits with 2.5k USD.
Next to it is Camreras and Camrecorders fom the brand Fabrikam.
Least profit category is Muisc,movies and Audiobooks from SouthRidge
Video which inturn is the least profit brand.
```

3. EDA for Sales Data

```
sales.head()

   Order Number  Line Item Order Date Delivery Date  CustomerKey
StoreKey  \
0        366000          1   1/1/2016           NaN       265598
10
1        366001          1   1/1/2016     1/13/2016      1269051
0
2        366001          2   1/1/2016     1/13/2016      1269051
0
3        366002          1   1/1/2016     1/12/2016       266019
0
4        366002          2   1/1/2016     1/12/2016       266019
0

   ProductKey  Quantity Currency Code
0        1304         1           CAD
```

```
1        1048         2           USD
2        2007         1           USD
3        1106         7           CAD
4         373         1           CAD
```

```python
sales.dtypes
```

```
Order Number                int64
Line Item                   int64
Order Date         datetime64[ns]
Delivery Date      datetime64[ns]
CustomerKey                 int64
StoreKey                    int64
ProductKey                  int64
Quantity                    int64
Currency Code              object
dtype: object
```

```python
sales.shape
```

```
(62884, 9)
```

```python
sales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 62884 entries, 0 to 62883
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Order Number   62884 non-null  int64 
 1   Line Item      62884 non-null  int64 
 2   Order Date     62884 non-null  object
 3   Delivery Date  13165 non-null  object
 4   CustomerKey    62884 non-null  int64 
 5   StoreKey       62884 non-null  int64 
 6   ProductKey     62884 non-null  int64 
 7   Quantity       62884 non-null  int64 
 8   Currency Code  62884 non-null  object
dtypes: int64(6), object(3)
memory usage: 4.3+ MB
```

```python
sales.isnull().sum()
```

```
Order Number         0
Line Item            0
Order Date           0
Delivery Date    49719
CustomerKey          0
StoreKey             0
ProductKey           0
Quantity             0
```

```
Currency Code         0
dtype: int64
```

```python
sales[sales.isnull().any(axis=1)]
```

```
       Order Number  Line Item Order Date Delivery Date
CustomerKey  \
97           368000          1 2016-01-03           NaT        892838

98           368001          1 2016-01-03           NaT       1670789

116          370000          1 2016-01-05           NaT       2032025

117          370000          2 2016-01-05           NaT       2032025

118          370000          3 2016-01-05           NaT       2032025

...             ...        ...        ...           ...           ...

62292       2224002          2 2021-02-01           NaT        239066

62293       2224003          1 2021-02-01           NaT       1098687

62294       2224003          2 2021-02-01           NaT       1098687

62295       2224005          1 2021-02-01           NaT       2063886

62296       2224005          2 2021-02-01           NaT       2063886


       StoreKey  ProductKey  Quantity Currency Code
97           32        1440         1           EUR
98           64        1598         3           USD
116          51        1360         4           USD
117          51        1158         4           USD
118          51         457         2           USD
...         ...         ...       ...           ...
62292         9        1612         3           CAD
62293        36        1794         4           GBP
62294        36        1625         4           GBP
62295        49        1375         7           USD
62296        49        1633         1           USD

[3043 rows x 9 columns]
```

```python
#converting Order Date and Delivery Date type to date
sales['Order Date']=pd.to_datetime(sales['Order Date'])

sales['Delivery Date'] = pd.to_datetime(sales['Delivery Date'])

sales['Delivery Date'].dt.year.unique()
```

```
array([  nan, 2016., 2017., 2018., 2019., 2020., 2021.])
```

Handling Missing Values in DeliveryDate

```python
# Filling missing values grouping by Order date and forward fill
sales['Delivery Date'] = sales.groupby('Order Date')['Delivery
Date'].fillna(method='ffill')

sales.isnull().sum()
```

```
Order Number         0
Line Item            0
Order Date           0
Delivery Date    12453
CustomerKey          0
StoreKey             0
ProductKey           0
Quantity             0
Currency Code        0
dtype: int64
```

```python
# Filling remaining missing values grouping by Order date and backward
fill
sales['Delivery Date'] = sales.groupby('Order Date')['Delivery
Date'].fillna(method='bfill')

sales.isnull().sum()
```

```
Order Number        0
Line Item           0
Order Date          0
Delivery Date    3043
CustomerKey         0
StoreKey            0
ProductKey          0
Quantity            0
Currency Code       0
dtype: int64
```

```python
# Filling remaining missing values which doesnt have any delivery date
in grouped data with normal backward fill
sales['Delivery Date'] = sales['Delivery Date'].fillna(method='bfill')

sales.isnull().sum()
```

```
Order Number     0
Line Item        0
Order Date       0
Delivery Date    0
CustomerKey      0
StoreKey         0
```

```
ProductKey        0
Quantity          0
Currency Code     0
dtype: int64
```

Insight:

```
Now the data is free of missing values.
Data is ready for analysis
```

Extracting Features like OrderYear, OrderMonth , TotalItems, DaysForDelivery

```
sales['OrderYear']= sales['Order Date'].dt.year

sales['OrderMonth']= sales['Order Date'].dt.month

sales['Total Items']= sales['Line Item']* sales['Quantity']

sales['DaysForDelivery']= (sales['Delivery Date']- sales['Order
Date']).dt.days

sales['DaysForDelivery']

0        12
1        12
2        12
3        11
4        11
         ..
62879     7
62880     4
62881     3
62882     3
62883     3
Name: DaysForDelivery, Length: 62884, dtype: int64
```

Merging data sets Sales and Customer

```
merged_data = pd.merge(sales, cust, on='CustomerKey')

merged_data.columns

Index(['Order Number', 'Line Item', 'Order Date', 'Delivery Date',
       'CustomerKey', 'StoreKey', 'ProductKey', 'Quantity', 'Currency
Code',
       'OrderYear', 'OrderMonth', 'Total Items', 'DaysForDelivery',
'Gender',
       'Name', 'City', 'State Code', 'State', 'Zip Code', 'Country',
```

```
       'Continent', 'Birthday', 'year'],
      dtype='object')
```

merged_data

```
       Order Number  Line Item Order Date Delivery Date
CustomerKey  \
0            366000          1 2016-01-01    2016-01-13       265598

1            891000          1 2017-06-09    2017-06-13       265598

2            891000          2 2017-06-09    2017-06-13       265598

3            891000          3 2017-06-09    2017-06-13       265598

4            891000          4 2017-06-09    2017-06-13       265598

...             ...        ...        ...           ...          ...

62879       2242018          1 2021-02-19    2021-02-22        13365

62880       2243005          1 2021-02-20    2021-02-21       151326

62881       2243005          2 2021-02-20    2021-02-21       151326

62882       2243005          3 2021-02-20    2021-02-21       151326

62883       2243017          1 2021-02-20    2021-02-26      1237927


       StoreKey  ProductKey  Quantity Currency Code  OrderYear  ...
Gender  \
0            10        1304         1           CAD       2016  ...
Male
1             9         385         2           CAD       2017  ...
Male
2             9         174         1           CAD       2017  ...
Male
3             9         685         1           CAD       2017  ...
Male
4             9          87         1           CAD       2017  ...
Male
...         ...         ...       ...           ...        ...  ...
...
62879         6         598         1           AUD       2021  ...
Male
62880         1        1648         3           AUD       2021  ...
Female
62881         1         132         8           AUD       2021  ...
Female
62882         1        1702         1           AUD       2021  ...
```

```
Female
62883       43      2496       3         USD      2021  ...
Female

                   Name     City State Code           State Zip Code
\
0          Tyler Vaught   London         ON         Ontario  N5W 5K6

1          Tyler Vaught   London         ON         Ontario  N5W 5K6

2          Tyler Vaught   London         ON         Ontario  N5W 5K6

3          Tyler Vaught   London         ON         Ontario  N5W 5K6

4          Tyler Vaught   London         ON         Ontario  N5W 5K6

...                 ...      ...        ...             ...      ...

62879  Mitchell Cutlack   MOONEM        NSW  New South Wales     2471

62880       Kate Salmon  IREDALE        QLD       Queensland     4352

62881       Kate Salmon  IREDALE        QLD       Queensland     4352

62882       Kate Salmon  IREDALE        QLD       Queensland     4352

62883   Stephanie Green  Jackson         MS      Mississippi    39211


             Country      Continent   Birthday  year
0             Canada  North America  3/23/1971  1971
1             Canada  North America  3/23/1971  1971
2             Canada  North America  3/23/1971  1971
3             Canada  North America  3/23/1971  1971
4             Canada  North America  3/23/1971  1971
...              ...            ...        ...   ...
62879      Australia      Australia   1/2/1961  1961
62880      Australia      Australia   1/2/1980  1980
62881      Australia      Australia   1/2/1980  1980
62882      Australia      Australia   1/2/1980  1980
62883  United States  North America  5/19/1961  1961

[62884 rows x 23 columns]
```

```
merged_data.shape
```

```
(62884, 23)
```

```
sales.shape
```

```
(62884, 13)
```

```
merged_data.CustomerKey.nunique()
```

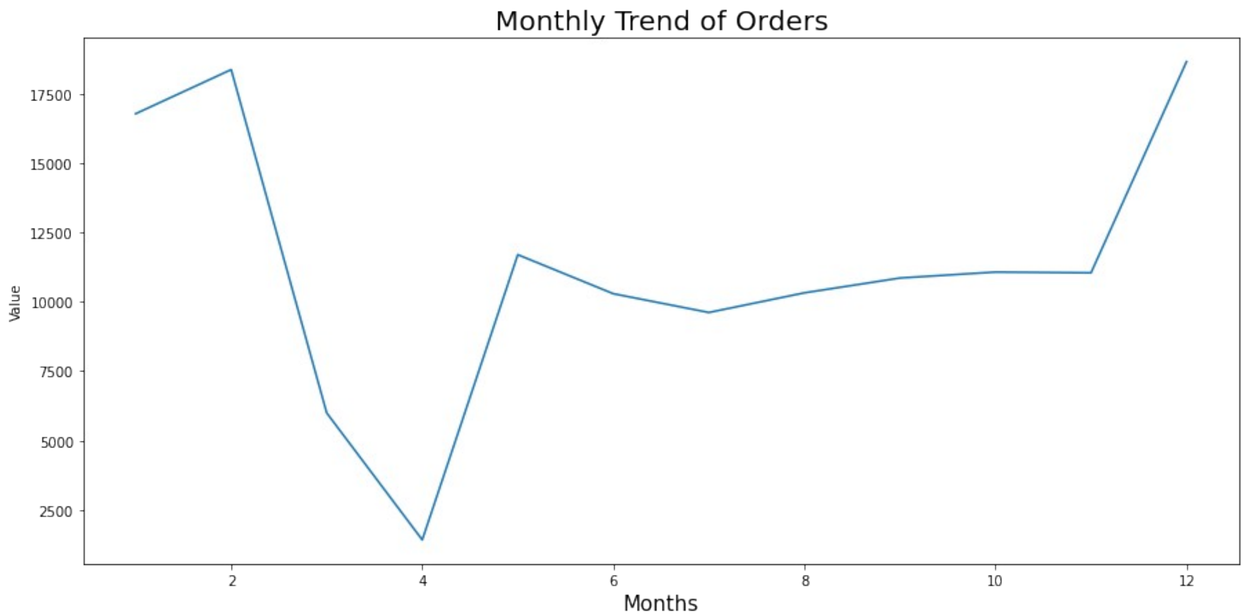
```
11887
```

```
#Yearly Trend of Orders
grp_data_yr= merged_data.groupby('OrderYear')['Line
Item'].sum().reset_index(name='count')
plt.figure(figsize=(15,7))
sns.lineplot(x=grp_data_yr['OrderYear'], y=grp_data_yr['count'])
plt.xlabel("Years", fontsize=15)
plt.ylabel("Value")
plt.title("Yearly Trend of Orders", fontsize='20')
plt.show()
```

Inisghts:

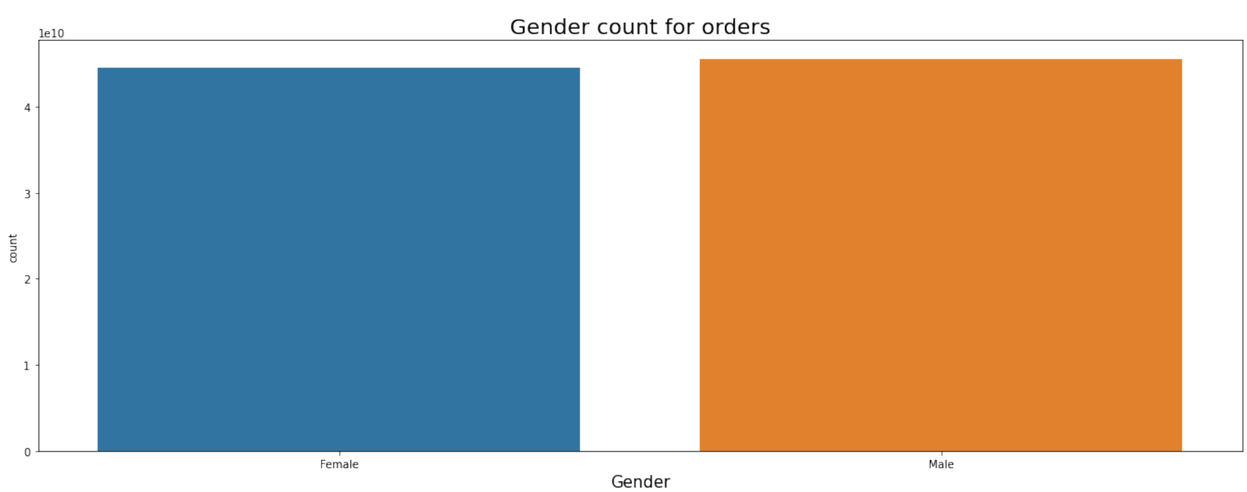
```
Highest sales happend in the year 2019 and 2020, there is a drastic
decrease after 2020.
```

```
#Monthly Trend of Orders
grp_data_mnth= merged_data.groupby('OrderMonth')['Line
Item'].sum().reset_index(name='count')
plt.figure(figsize=(15,7))
sns.lineplot(x=grp_data_mnth['OrderMonth'], y=grp_data_mnth['count'])
plt.xlabel("Months", fontsize=15)
plt.ylabel("Value")
plt.title("Monthly Trend of Orders", fontsize='20')
plt.show()
```



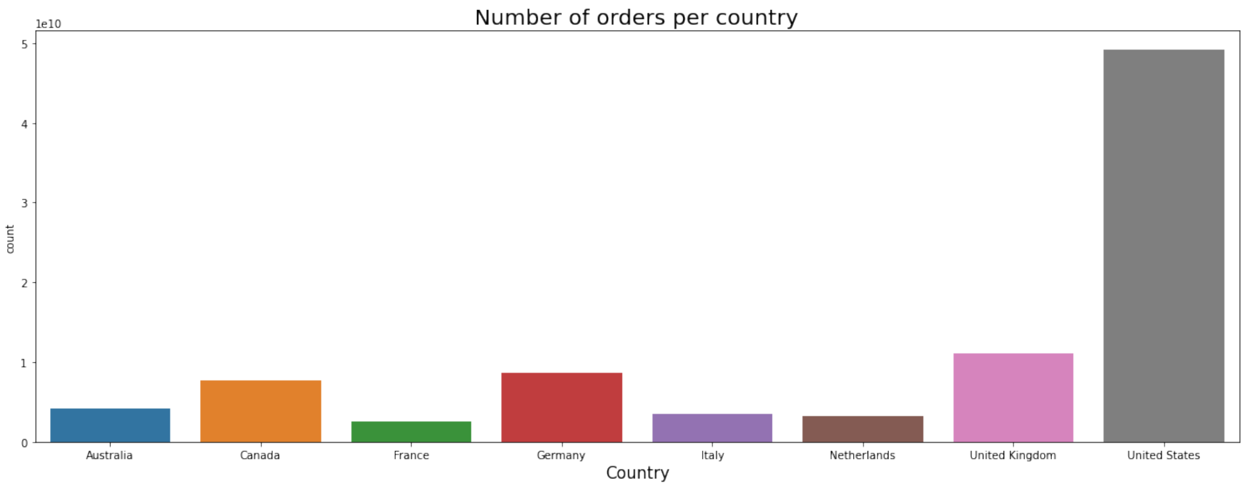
Inisghts:

```
There is trend of decrease in orders in the 4th month(April) hike in
2nd and 12th months(Feb and Dec).

#Gender count for orders
plt.figure(figsize=(20,7))
sns.barplot(x=merged_data.groupby('Gender')['Order
Number'].sum().index,y = merged_data.groupby('Gender')['Order
Number'].sum().values)
plt.xlabel("Gender", fontsize=15)
plt.ylabel("count")
plt.title("Gender count for orders", fontsize=20)
plt.show()
```



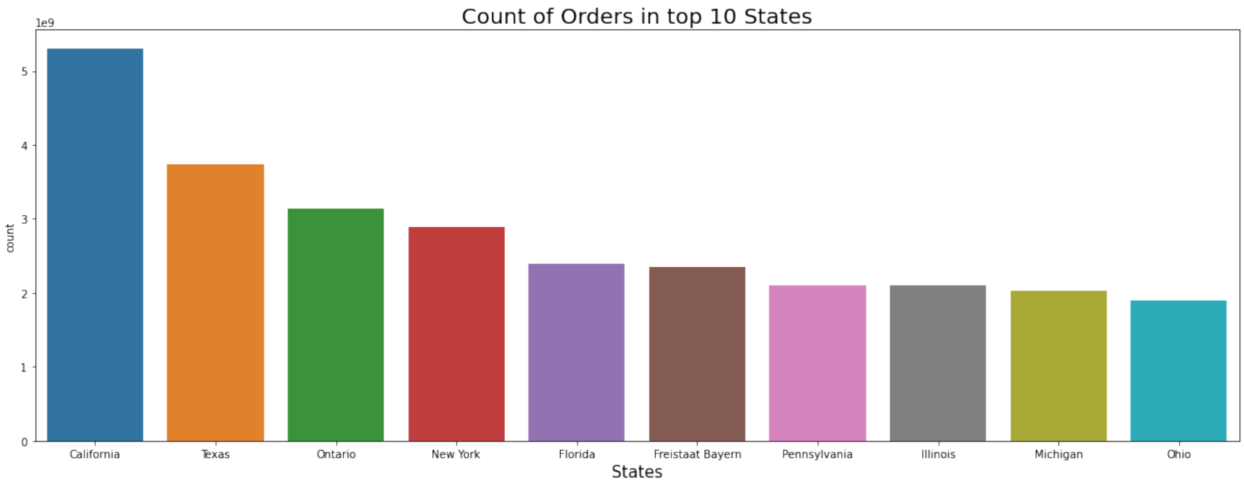
Insights:

```
Male orders are slightly more than female orders.

#Country count for orders
plt.figure(figsize=(20,7))
sns.barplot(x=merged_data.groupby('Country')['Order
Number'].sum().index, y = merged_data.groupby('Country')['Order
Number'].sum().values)
plt.xlabel("Country", fontsize=15)
plt.ylabel("count")
plt.title("Number of orders per country", fontsize=20)
plt.show()
```



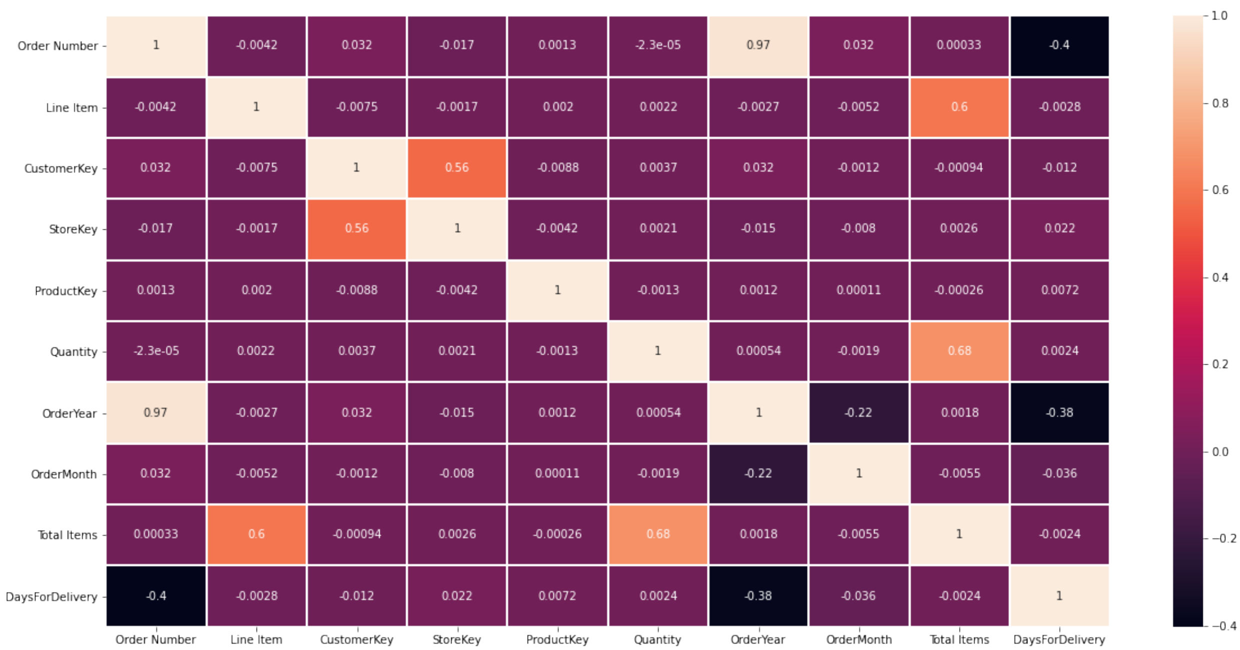
Insights:

```
UnitedStates is in the top of list of total order per country.. Next
is UK, Germany and Canada.

#top 10 State count for orders
plt.figure(figsize=(20,7))
sns.barplot(x=merged_data.groupby('State')['Order
Number'].sum().sort_values(ascending=False)
[0:10].index,y=merged_data.groupby('State')['Order
Number'].sum().sort_values(ascending=False)[0:10].values )
plt.xlabel("States", fontsize=15)
plt.ylabel("count")
plt.title("Count of Orders in top 10 States", fontsize=20)
plt.show()
```



Insights:

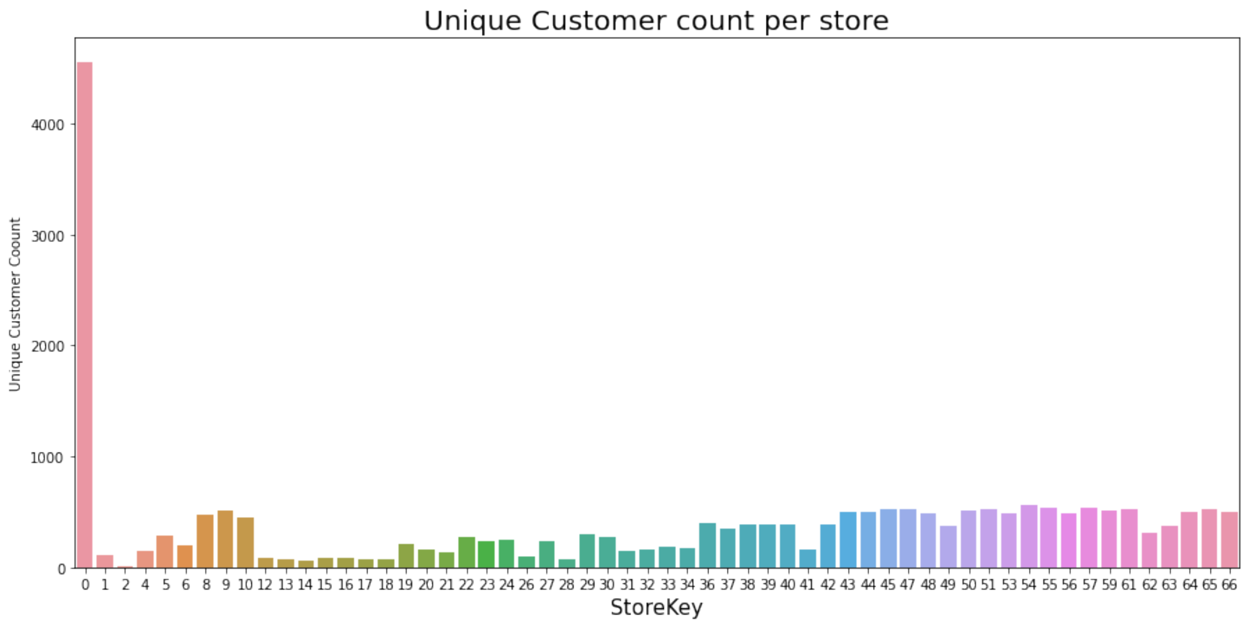
```
California is the state with highest number of orders and next to it
is Texas and Ontario.

#Correlation matrix for merged data of sales and customers
plt.figure(figsize=(20,10))
sns.heatmap(merged_data.corr(),annot=True,linewidths=0.2,
linecolor='white')
plt.show()
```



Insights:

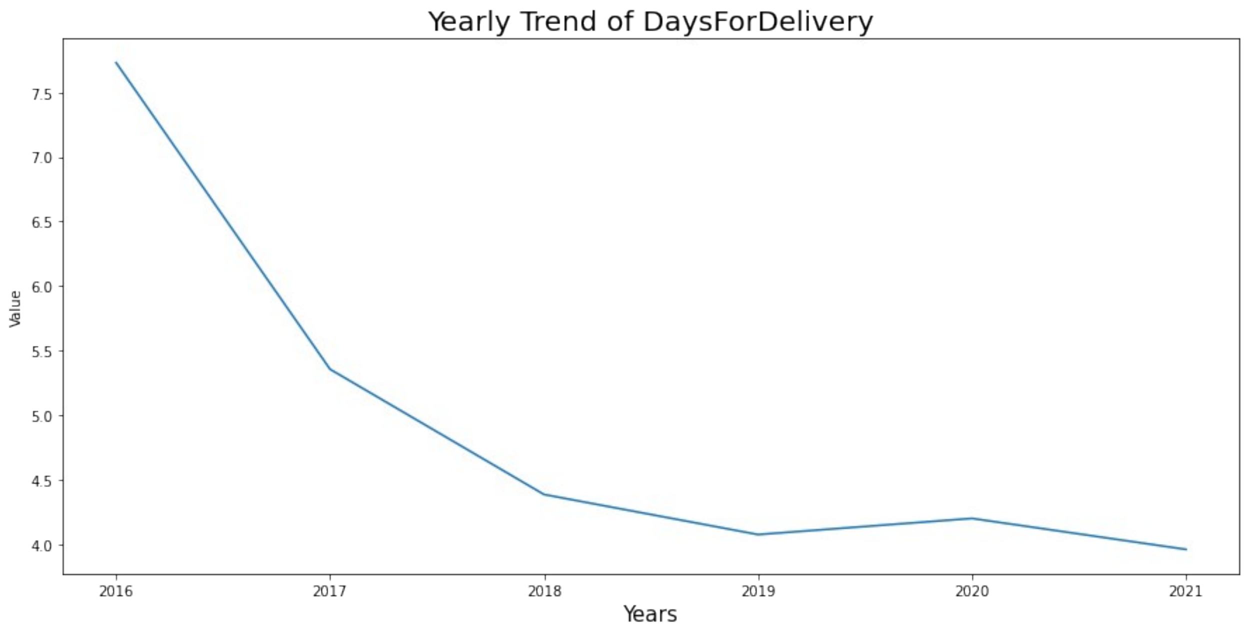
```
Correlation matrix of sales and customer data gives strong relation
for customerkey and storekey, saying Customers are store centric.
```

```
#Store vs customers
grp_store_cust= merged_data.groupby('StoreKey')
['CustomerKey'].nunique().reset_index(name='count')
plt.figure(figsize=(15,7))
sns.barplot(x=grp_store_cust['StoreKey'], y=grp_store_cust['count'])
plt.xlabel("StoreKey", fontsize=15)
plt.ylabel("Unique Customer Coount")
plt.title("Unique Customer count per store", fontsize='20')
plt.show()
```



Insights:

```
Store 0 is having highest number of customers.

#Yearly Trend of DaysForDelivery
grp_data_Dd= merged_data.groupby('OrderYear')
['DaysForDelivery'].mean().reset_index(name='count')
plt.figure(figsize=(15,7))
sns.lineplot(x=grp_data_Dd['OrderYear'], y=grp_data_Dd['count'])
plt.xlabel("Years", fontsize=15)
plt.ylabel("Value")
plt.title("Yearly Trend of DaysForDelivery", fontsize='20')
plt.show()
```



Insights:

```
The number of days reuired for delivery from 2016 gradually decreased
saying that the access for delivery became easy.
Till 2019 the average days of delivery per year decreased but
increased in the year 2020 due to the pandemic stituations which are
againn set back in the year 2021.
```

Merging Product with Sales and Customer

```
#merging sales and product datasets
sale_prod_data =  pd.merge(merged_data, prod, on='ProductKey')

sale_prod_data.shape

(62884, 33)
```

The total rows after merging are 62884 and 33 columns

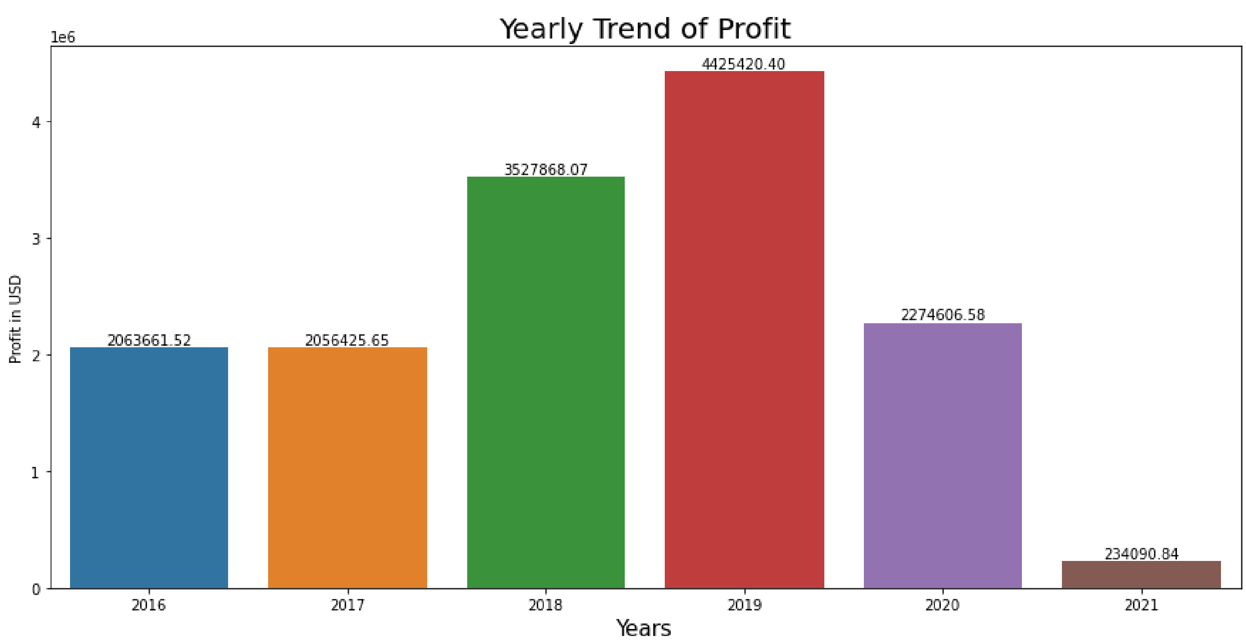
```
sale_prod_data.columns

Index(['Order Number', 'Line Item', 'Order Date', 'Delivery Date',
       'CustomerKey', 'StoreKey', 'ProductKey', 'Quantity', 'Currency
Code',
       'OrderYear', 'OrderMonth', 'Total Items', 'DaysForDelivery',
'Gender',
       'Name', 'City', 'State Code', 'State', 'Zip Code', 'Country',
       'Continent', 'Birthday', 'year', 'Product Name', 'Brand',
'Color',
       'Unit Cost USD', 'Unit Price USD', 'SubcategoryKey',
'Subcategory',
```

```
       'CategoryKey', 'Category', 'profit'],
      dtype='object')

sale_prod_data.head()

   Order Number  Line Item Order Date Delivery Date  CustomerKey
StoreKey  \
0        366000          1 2016-01-01    2016-01-13       265598
10
1        378002          2 2016-01-13    2016-01-24      1599716
45
2       1673007          2 2019-07-31    2019-08-03      1617106
61
3       1816030          1 2019-12-21    2019-12-24       946719
0
4        868008          2 2017-05-17    2017-05-21      1540067
51

   ProductKey  Quantity Currency Code  OrderYear  ...  \
0        1304         1           CAD       2016  ...
1        1304         1           USD       2016  ...
2        1304         9           USD       2019  ...
3        1304         1           GBP       2019  ...
4        1304         1           USD       2017  ...

                      Product Name    Brand  Color Unit Cost USD  \
0  Contoso Lens Adapter M450 White  Contoso  White          1.27
1  Contoso Lens Adapter M450 White  Contoso  White          1.27
2  Contoso Lens Adapter M450 White  Contoso  White          1.27
3  Contoso Lens Adapter M450 White  Contoso  White          1.27
4  Contoso Lens Adapter M450 White  Contoso  White          1.27

  Unit Price USD SubcategoryKey                       Subcategory
CategoryKey  \
0            8.0            406  Cameras & Camcorders Accessories
4
1            8.0            406  Cameras & Camcorders Accessories
4
2            8.0            406  Cameras & Camcorders Accessories
4
3            8.0            406  Cameras & Camcorders Accessories
4
4            8.0            406  Cameras & Camcorders Accessories
4

                 Category profit
0  Cameras and camcorders   6.73
1  Cameras and camcorders   6.73
2  Cameras and camcorders   6.73
3  Cameras and camcorders   6.73
```

```
4   Cameras and camcorders    6.73

[5 rows x 33 columns]
```

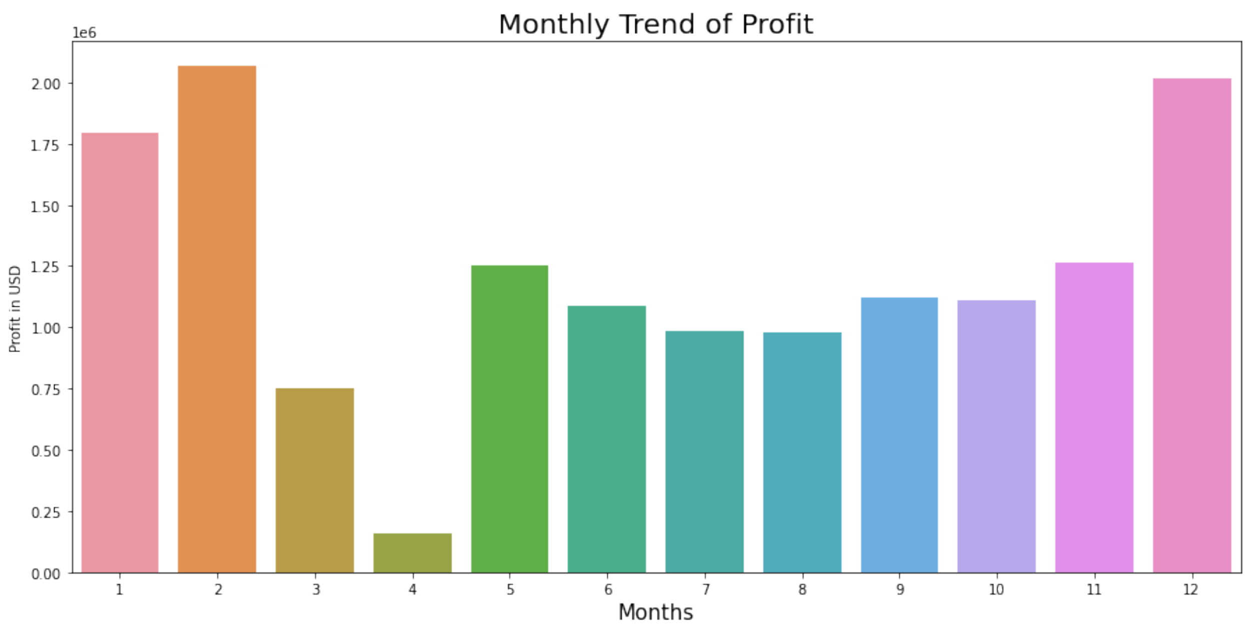
Calculating totalPurchase column from TotalItems and UnitPriceUSD . TotalProfit from profit and TotalItems columns.

```
sale_prod_data['TotalPurchase']=sale_prod_data['Total
Items']*sale_prod_data['Unit Price USD']

sale_prod_data['TotalProfit']=
sale_prod_data['profit']*sale_prod_data['Total Items']

#Yearly Trend of Profit
plt.figure(figsize=(15,7))
ax = sns.barplot(x=sale_prod_data.groupby('OrderYear')
['TotalProfit'].sum().index, y=sale_prod_data.groupby('OrderYear')
['TotalProfit'].sum().values)
# Get container object (assuming single container plot)
container = ax.containers[0]

# Add values as labels on bars
ax.bar_label(container, fmt='{:.2f}')  # Format to display two decimal
places

plt.xlabel("Years", fontsize=15)
plt.ylabel("Profit in USD")
plt.title("Yearly Trend of Profit", fontsize='20')
plt.show()
```



Insights:

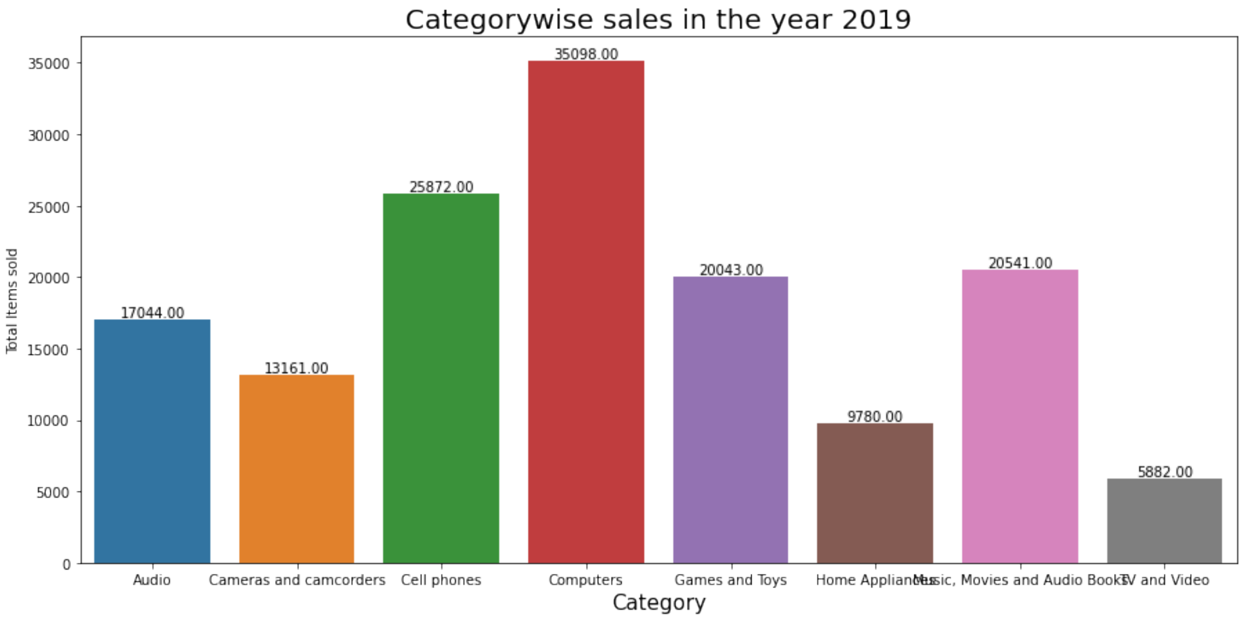
```
Like the sales the trend of profits is also high in the year 2019 and almost halved in 2020 and nearly 5% of the profit of 2019.

#Monthly Trend of Profit
plt.figure(figsize=(15,7))
sns.barplot(x=sale_prod_data.groupby('OrderMonth')
['TotalProfit'].sum().index, y=sale_prod_data.groupby('OrderMonth')
['TotalProfit'].sum().values)
plt.xlabel("Months", fontsize=15)
plt.ylabel("Profit in USD")
plt.title("Monthly Trend of Profit", fontsize='20')
plt.show()
```

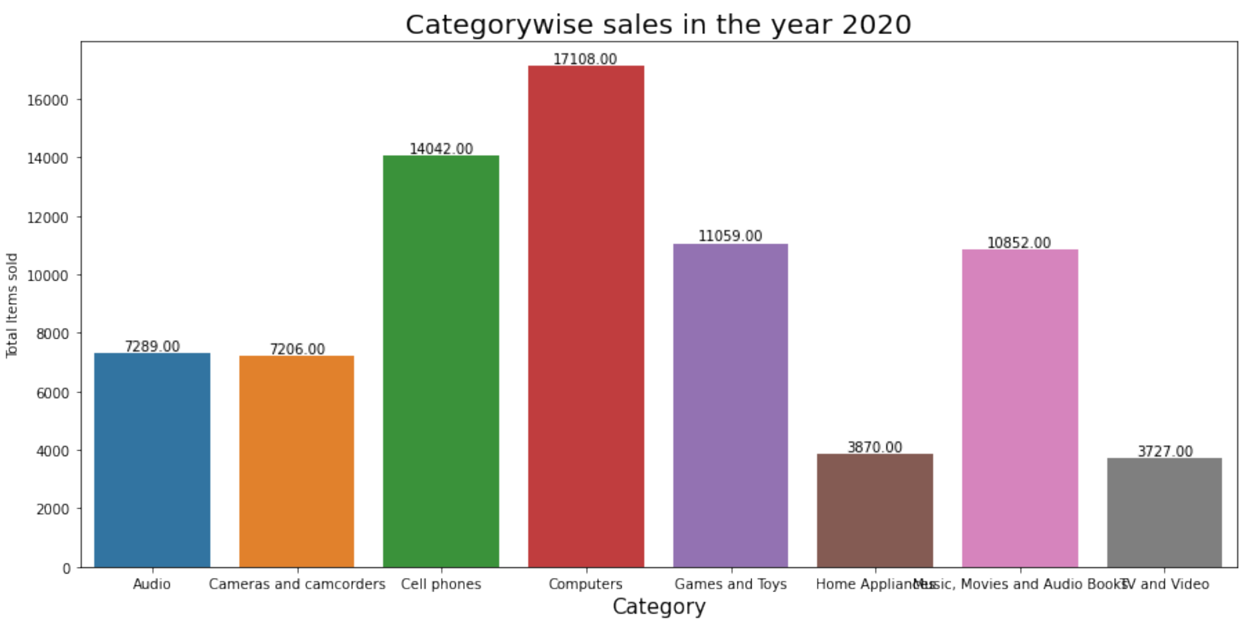


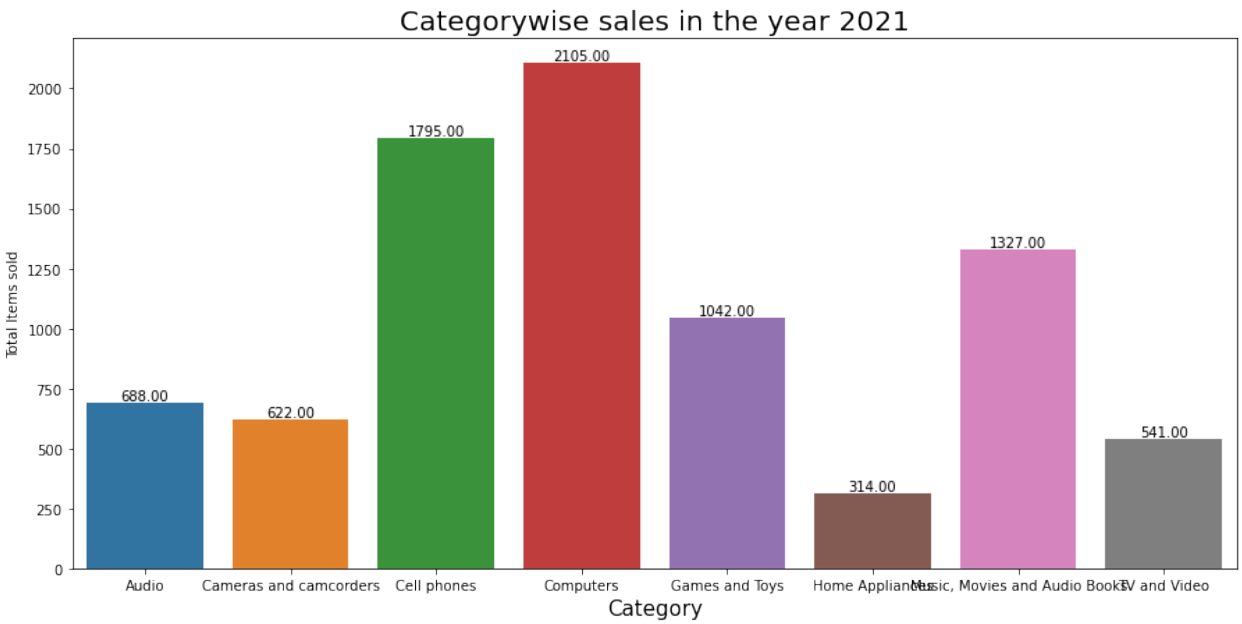
Insights:

```
The trend of profits follows the orders. The Profits are least in the month of April and highest in the month of Dec and Feb.

#Categorywise sales for years 2019, 2020, 2021
for i in [2019,2020,2021]:
    data = sale_prod_data[sale_prod_data['OrderYear']==i]
    plt.figure(figsize=(15,7))
    ax=sns.barplot(x=data.groupby('Category')['Total
Items'].sum().index, y=data.groupby('Category')['Total
Items'].sum().values)
    container = ax.containers[0]
    ax.bar_label(container, fmt='{:.2f}')
    plt.xlabel("Category", fontsize=15)
    plt.ylabel("Total Items sold")
```

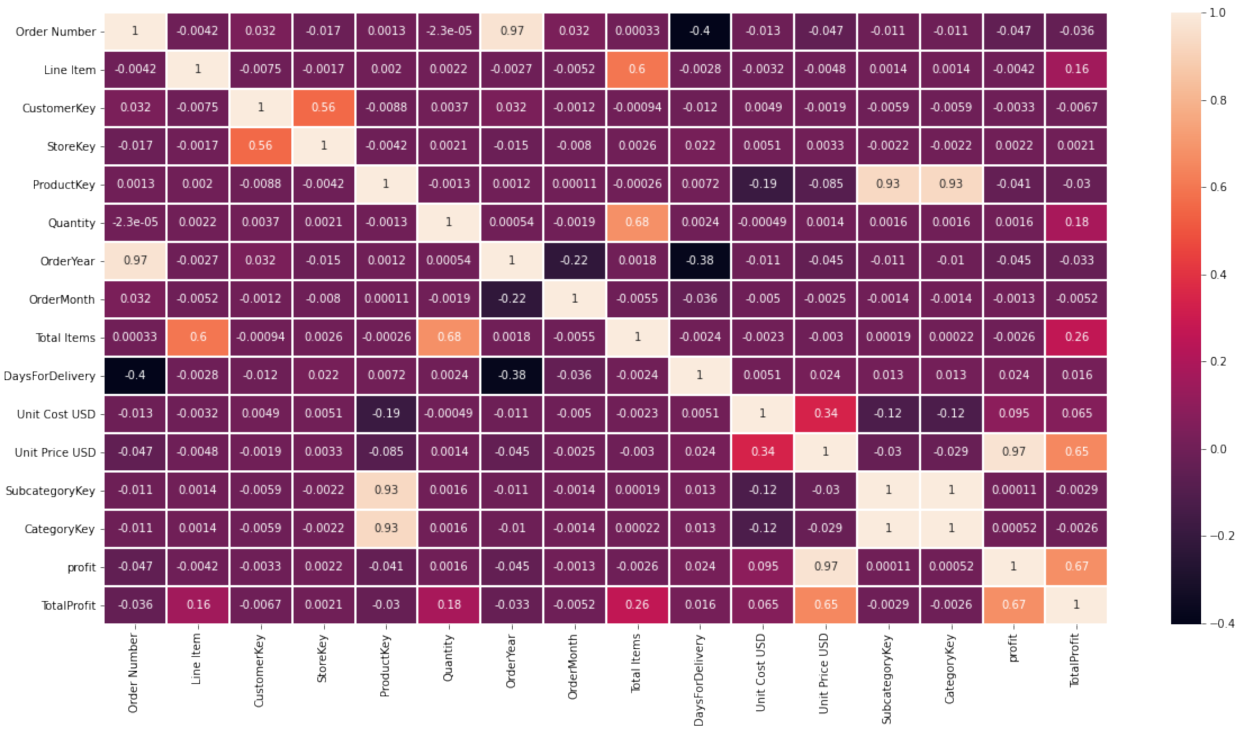
```
    plt.title(f"Categorywise sales in the year {i}", fontsize='20')
    plt.show()
```







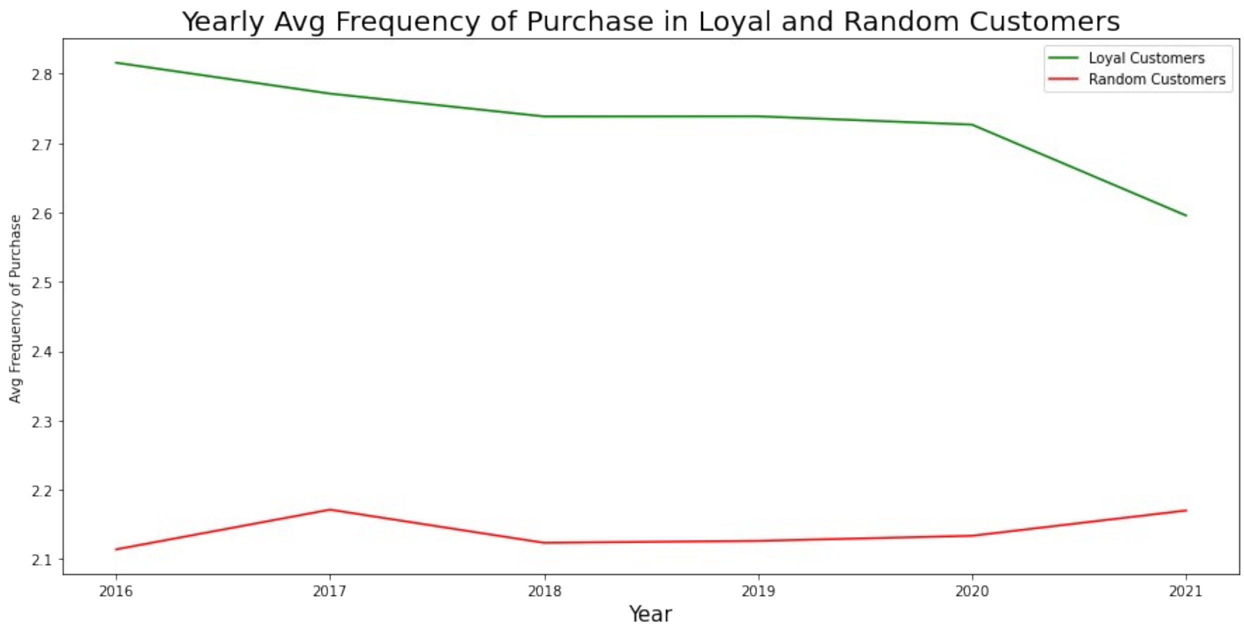

```
Insights:

    The category wise sales for the Category 'Computers' decreased
from 35000 items to 2100 from year 2019 to 2021. The sales almost
decreases by 16 times.

plt.figure(figsize=(20,10))
sns.heatmap(sale_prod_data.corr(),annot=True,linewidths=0.2,
linecolor='white')
plt.show()
```




```
grp_data_cust= sale_prod_data.groupby('CustomerKey')
['TotalPurchase'].sum().reset_index(name='count')
plt.figure(figsize=(15,7))
sns.lineplot(x=grp_data_cust['CustomerKey'], y=grp_data_cust['count'])
plt.xlabel("CustomerKey", fontsize=15)
plt.ylabel("Purchase amount in USD")
plt.title("Customer Lifetime Purchases", fontsize='20')
plt.show()
```

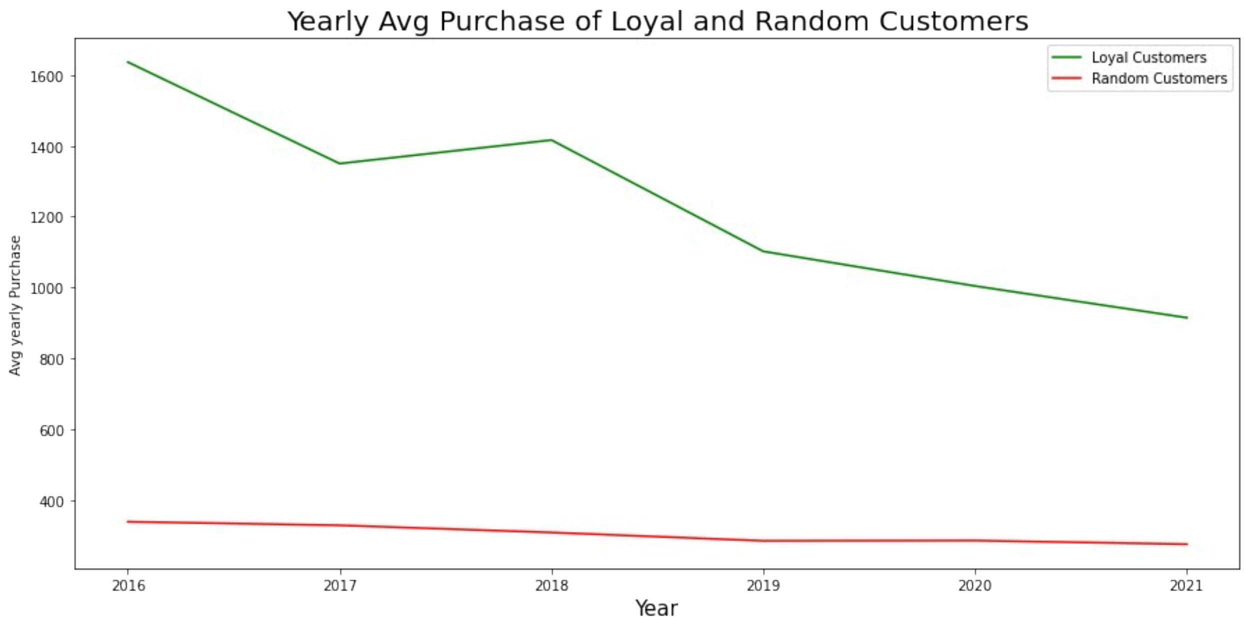
Insights:

```
This is the graph for Customer life time purchases based on which we
can segment the customers into loyal and random customers.

#let us take customers whose life time purchase is >10000 USD
cust_lf_pur = sale_prod_data.groupby('CustomerKey')
['TotalPurchase'].sum().sort_values(ascending=False).reset_index(name=
'amount')

#loyal or high valued customers whose lifetimepurchase>10000 USD
loyal_customers=cust_lf_pur[cust_lf_pur.amount>10000].CustomerKey
len(loyal_customers)

263

#loyal customers whose lifetimepurchase>10000 USD
random_customers=cust_lf_pur[cust_lf_pur.amount<10000].CustomerKey
len(random_customers)

11624

#Extracting Loyal customer data bbased on customer keys from loyal
customers
loyal_customer_data =
sale_prod_data[sale_prod_data['CustomerKey'].isin(loyal_customers)]

#Extracting Random customer data bbased on customer keys from random
customers
random_customer_data =
sale_prod_data[sale_prod_data['CustomerKey'].isin(random_customers)]

#Yearly Avg Frequency of Purchase in Loyal and Random Customers
lyl_data_yr= loyal_customer_data.groupby('OrderYear')['Line
Item'].mean().reset_index(name='count')

randm_data_yr= random_customer_data.groupby('OrderYear')['Line
Item'].mean().reset_index(name='count')

plt.figure(figsize=(15,7))
sns.lineplot(x=lyl_data_yr['OrderYear'], y=lyl_data_yr['count'],
color='g',label='Loyal Customers')
sns.lineplot(x=randm_data_yr['OrderYear'], y=randm_data_yr['count'],
color='r',label='Random Customers')
plt.xlabel("Year", fontsize=15)
plt.ylabel("Avg Frequency of Purchase")
plt.title("Yearly Avg Frequency of Purchase in Loyal and Random
Customers", fontsize='20')
plt.show()
```



Insights:

```
The yearly average purchases in loyal customers decrease from yaer
2020 saying that it will be the reason for decline in the revenue
genereation after 2020.

#Yearly Avg Purchase of Loyal and Random Customers
lyl_data_yr= loyal_customer_data.groupby('OrderYear')
['TotalPurchase'].mean().reset_index(name='count')

randm_data_yr= random_customer_data.groupby('OrderYear')
['TotalPurchase'].mean().reset_index(name='count')

plt.figure(figsize=(15,7))
sns.lineplot(x=lyl_data_yr['OrderYear'], y=lyl_data_yr['count'],
color='g',label='Loyal Customers')
sns.lineplot(x=randm_data_yr['OrderYear'], y=randm_data_yr['count'],
color='r',label='Random Customers')
plt.xlabel("Year", fontsize=15)
plt.ylabel("Avg yearly Purchase")
plt.title("Yearly Avg Purchase of Loyal and Random Customers",
fontsize='20')
plt.show()
```



Insights:

```
From the above plot of customer loyality defined in the terms of
amount of purchase over the year, it is observed that the trend of
purchases got declined after 2020 from 1600 to 1000 which will be an
amount of $600*263(loyalcustomers)= $157800 decrease in the revenue.
```

```
#taking highest avg for loyal customers
high_avg = loyal_customer_data.groupby('OrderYear')
['TotalPurchase'].mean().sort_values(ascending=False).reset_index(name
='count')['count'][0]
high_avg
```

```
1636.748404494382
```

```
#taking lowest avg for loyal customers
low_avg = loyal_customer_data.groupby('OrderYear')
['TotalPurchase'].mean().sort_values(ascending=True).reset_index(name=
'count')['count'][0]
low_avg
```

```
914.5095505617978
```

```
#Contribution of loyal cutomers for purchases per year
loyal_pur_contrbution = (high_avg-low_avg)*len(loyal_customers)
loyal_pur_contrbution
```

```
189948.8185842696
```

```
#Percentage of loyal cutomers for purchases per year
prcnt_role_loyl_cust = (loyal_pur_contrbution/profit_decline_2020)*100
prcnt_role_loyl_cust
```

```
9.308862002761538
```

Insights:

```
There is approximately 9.3% decrease in profits due to loyal
customers. That means there should be some measures taken for loyal
customer engagement so that the number of avg purchases increases,
increasing the revenue from the loyal customer end.
```

```
#taking highest avg for random customers
high_avg_ran = random_customer_data.groupby('OrderYear')
['TotalPurchase'].mean().sort_values(ascending=False).reset_index(name
='count')['count'][0]
high_avg_ran
```

```
338.1163405572714
```

```
#taking lowest avg for random customers
low_avg_ran = random_customer_data.groupby('OrderYear')
['TotalPurchase'].mean().sort_values(ascending=True).reset_index(name=
'count')['count'][0]
low_avg_ran
```

```
274.6891718610862
```

```
#Contribution of random cutsomers for purchases per year
ran_pur_contrbution = (high_avg_ran-low_avg_ran)*len(random_customers)
ran_pur_contrbution
```

```
737277.408924457
```

```
#Percentage of random cutsomers for purchases per year
prcnt_role_ran_cust = (ran_pur_contrbution/profit_decline_2020)*100
prcnt_role_ran_cust
```

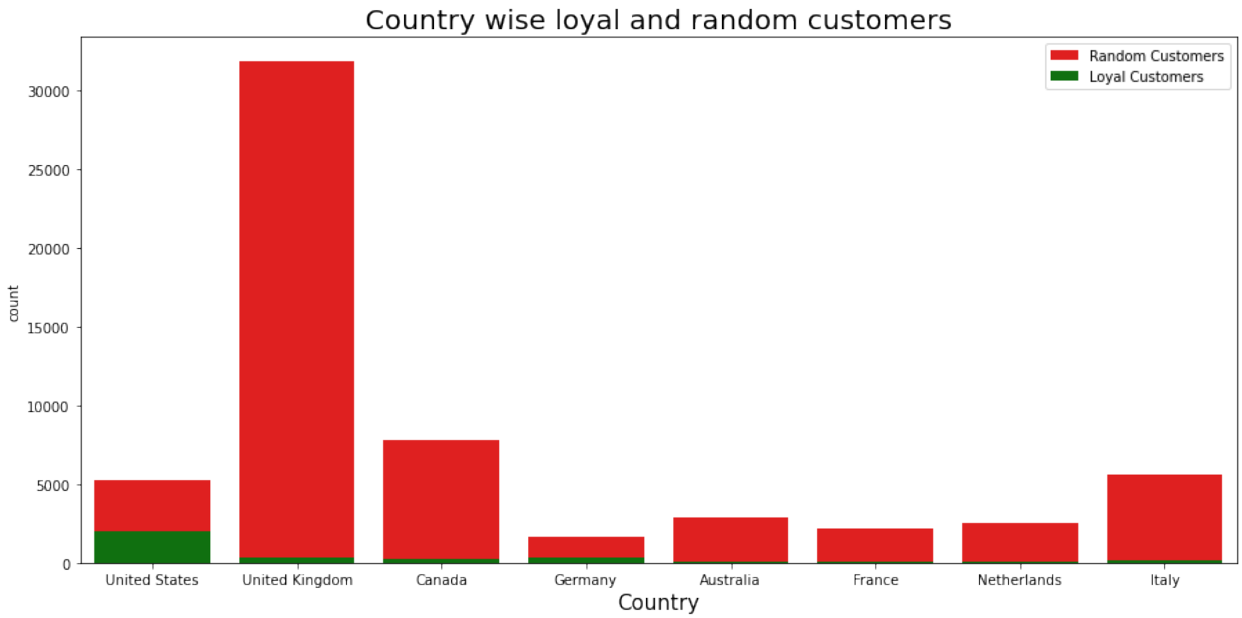
```
36.13191020920478
```

Insights:

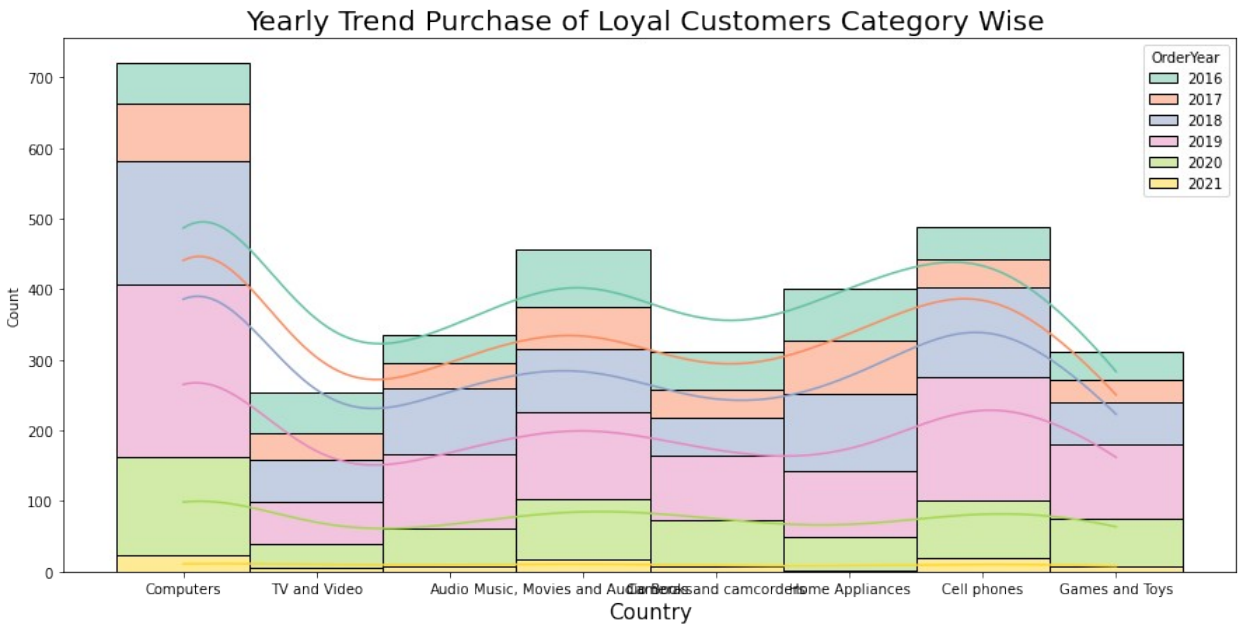
```
There is approximately 36% decrease in profits due to random
customers. That means there should be some measures taken for random
customer retention so that the number of avg purchases increases,
increasing the revenue from the random customer end.
```

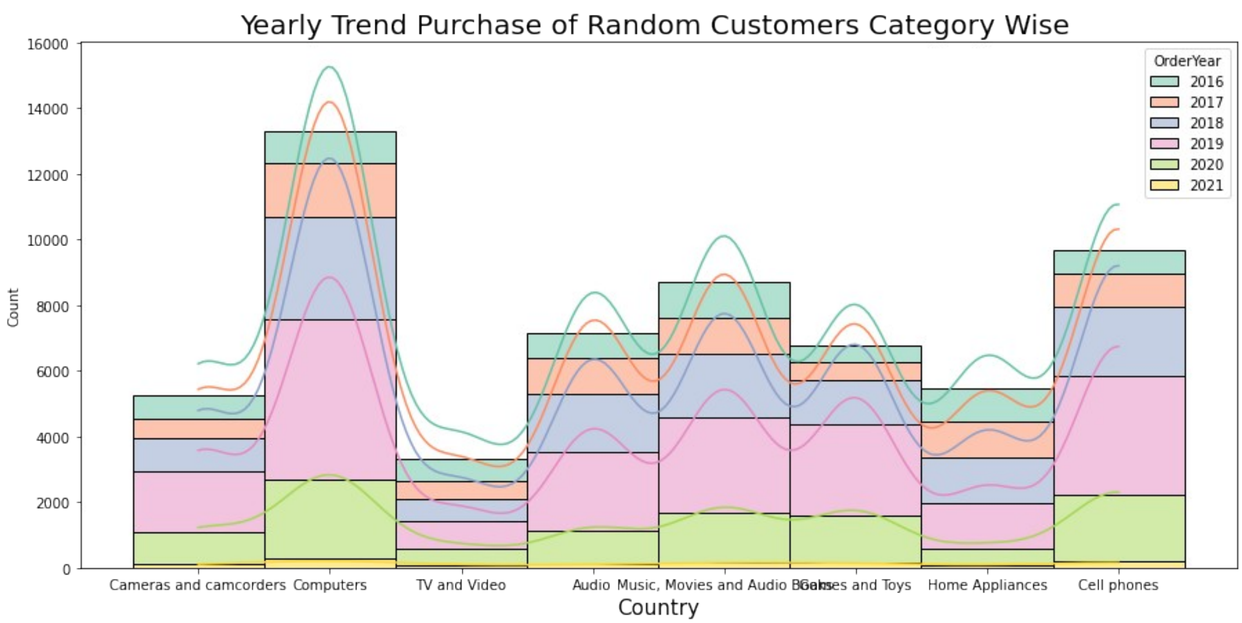
```
#loyal customers from which country
plt.figure(figsize=(15,7))
sns.countplot(x=random_customer_data.Country,color='r',label='Random
Customers')
sns.countplot(x=loyal_customer_data.Country,color='g', label='Loyal
Customers')
plt.legend()
```

```
plt.xlabel("Country", fontsize=15)
plt.title("Country wise loyal and random customers", fontsize=20)
plt.show()
```




```
#loyal customers purchase in each category for all years
plt.figure(figsize=(15,7))
sns.histplot(x=loyal_customer_data.Category, hue=
loyal_customer_data['OrderYear'],
kde=True ,palette='Set2',multiple="stack")
plt.xlabel("Country", fontsize=15)
plt.title("Yearly Trend Purchase of Loyal Customers Category Wise ",
fontsize=20)
plt.show()

#Random customers purchase in each category for all years
plt.figure(figsize=(15,7))
sns.histplot(x=random_customer_data.Category, hue=
random_customer_data['OrderYear'],
kde=True ,palette='Set2',multiple="stack"  )
plt.xlabel("Country", fontsize=15)
plt.title("Yearly Trend Purchase of Random Customers Category Wise ",
fontsize=20)
plt.show()
```






```
Insights:

    The yearly trend of loyal and random customers based on category
is shown in the above plots.
    Fromt above plots it is observed that the purchases in all the
categories decreased in case of both loyal and random customers.
```