Marketing Insights for E-Commerce Company

July 9, 2024

1 Marketing Analysis for E-Commerce Company

Problem statement:

A rapidly growing e-commerce company aims to transition from intuition-based marketing to a data-driven approach. By analyzing customer demographics, transaction data, marketing spend, and discount details from 2019, the company seeks to gain a comprehensive understanding of customer behavior. The objectives are to optimize marketing campaigns across various channels, leverage data insights to enhance customer retention, predict customer lifetime value, and ultimately drive sustainable revenue growth.

1.1 Importing libraries and downloading dataset

[7]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import warnings
warnings.filterwarnings('ignore')
from itertools import combinations

# downloading datasets
!gdown --folder 1VXaZSDFqN_Zi3FxucRlthz97Etl1CYfJ

# e-commerce datasets
cust_df = pd.read_csv('/content/Block 2 project/Customers.csv')
disc_coupon_df = pd.read_csv('/content/Block 2 project/Discount_Coupon.csv')
mrkt_spend_df = pd.read_csv('/content/Block 2 project/Marketing_Spend.csv')
online_sales_df = pd.read_csv('/content/Block 2 project/Online_Sales.csv')
tax_amt_df = pd.read_csv('/content/Block 2 project/Tax_amount.csv')
```

```
Retrieving folder contents
Processing file 1nKb67meAvoFNRG_VueNXh_-k_2F9Oisc Customers.csv
Processing file 1fI7Kg4iXh3GTxFlto4n0UQ-5nOzAM78- Dataset Description.docx
Processing file 144wrGLTgzCm8FZdl0rasbjsm6dKG_yvB Discount_Coupon.csv
Processing file 1xgzPmbSCU8KM6Lt1rJXLFADHxgsy9u4t Marketing_Spend.csv
Processing file 1F8EPu3t_GbXX3BQ3OQSXsoieeSsCR5ly Online_Sales.csv
```

```
Processing file 1CmZ0j83nKoNeOqbGgZHSa92-kdXHkXIP Tax_amount.csv
Retrieving folder contents completed
Building directory structure
Building directory structure completed
Downloading…
From: https://drive.google.com/uc?id=1nKb67meAvoFNRG_VueNXh_-k_2F9Oisc
To: /content/Block 2 project/Customers.csv
100% 31.8k/31.8k [00:00<00:00, 66.4MB/s]
Downloading…
From: https://drive.google.com/uc?id=1fI7Kg4iXh3GTxFlto4n0UQ-5n0zAM78-
To: /content/Block 2 project/Dataset Description.docx
100% 7.52k/7.52k [00:00<00:00, 24.1MB/s]
Downloading…
From: https://drive.google.com/uc?id=144wrGLTgzCm8FZdl0rasbjsm6dKG_yvB
To: /content/Block 2 project/Discount_Coupon.csv
100% 4.92k/4.92k [00:00<00:00, 18.4MB/s]
Downloading…
From: https://drive.google.com/uc?id=1xgzPmbSCU8KM6Lt1rJXLFADHxgsy9u4t
To: /content/Block 2 project/Marketing_Spend.csv
100% 8.67k/8.67k [00:00<00:00, 30.5MB/s]
Downloading…
From: https://drive.google.com/uc?id=1F8EPu3t_GbXX3BQ3OQSXsoieeSsCR5ly
To: /content/Block 2 project/Online_Sales.csv
100% 5.24M/5.24M [00:00<00:00, 128MB/s]
Downloading…
From: https://drive.google.com/uc?id=1CmZ0j83nKoNeOqbGgZHSa92-kdXHkXIP
To: /content/Block 2 project/Tax_amount.csv
100% 297/297 [00:00<00:00, 635kB/s]
Download completed
```

1.2 Basic Metrics

[ ]:
```
online_sales_df.head()
```

[ ]:
```
   CustomerID  Transaction_ID Transaction_Date     Product_SKU  \
0       17850           16679         1/1/2019  GGOENEBJ079499
1       17850           16680         1/1/2019  GGOENEBJ079499
2       17850           16681         1/1/2019  GGOEGFKQ020399
3       17850           16682         1/1/2019  GGOEGAAB010516
4       17850           16682         1/1/2019  GGOEGBJL013999

                               Product_Description Product_Category  \
0  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
1  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
2              Google Laptop and Cell Phone Stickers           Office
3  Google Men's 100% Cotton Short Sleeve Hero Tee…          Apparel
4                    Google Canvas Tote Natural/Navy             Bags
```

```
   Quantity  Avg_Price  Delivery_Charges Coupon_Status
0         1     153.71               6.5          Used
1         1     153.71               6.5          Used
2         1       2.05               6.5          Used
3         5      17.53               6.5      Not Used
4         1      16.50               6.5          Used
```

[ ]:
```python
online_sales_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 52924 entries, 0 to 52923
Data columns (total 10 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   CustomerID           52924 non-null  int64
 1   Transaction_ID       52924 non-null  int64
 2   Transaction_Date     52924 non-null  object
 3   Product_SKU          52924 non-null  object
 4   Product_Description  52924 non-null  object
 5   Product_Category     52924 non-null  object
 6   Quantity             52924 non-null  int64
 7   Avg_Price            52924 non-null  float64
 8   Delivery_Charges     52924 non-null  float64
 9   Coupon_Status        52924 non-null  object
dtypes: float64(2), int64(3), object(5)
memory usage: 4.0+ MB
```

[ ]:
```python
online_sales_df.duplicated().sum()
```

[ ]: 0

[ ]:
```python
online_sales_df['Product_Category'].nunique()
```

[ ]: 20

- 52934 Transactions happened in the year 2019.
- There are 20 unique Product categories.
- No null values or duplicates found in online sales data.

[ ]:
```python
cust_df.head()
```

[ ]:
```
   CustomerID Gender    Location  Tenure_Months
0       17850      M     Chicago             12
1       13047      M  California             43
2       12583      M     Chicago             33
3       13748      F  California             30
4       15100      M  California             49
```

[ ]:
```
cust_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1468 entries, 0 to 1467
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   CustomerID     1468 non-null   int64 
 1   Gender         1468 non-null   object
 2   Location       1468 non-null   object
 3   Tenure_Months  1468 non-null   int64 
dtypes: int64(2), object(2)
memory usage: 46.0+ KB
```

[ ]:
```
cust_df.duplicated().sum()
```

[ ]: 0

- 1468 Customers made purchase in this e-commerce company.
- No null values or duplicates found in the customers data.

[ ]:
```
disc_coupon_df.head()
```

[ ]:

	Month	Product_Category	Coupon_Code	Discount_pct
0	Jan	Apparel	SALE10	10
1	Feb	Apparel	SALE20	20
2	Mar	Apparel	SALE30	30
3	Jan	Nest-USA	ELEC10	10
4	Feb	Nest-USA	ELEC20	20

[ ]:
```
disc_coupon_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 204 entries, 0 to 203
Data columns (total 4 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   Month             204 non-null    object
 1   Product_Category  204 non-null    object
 2   Coupon_Code       204 non-null    object
 3   Discount_pct      204 non-null    int64 
dtypes: int64(1), object(3)
memory usage: 6.5+ KB
```

[ ]:
```
disc_coupon_df.duplicated().sum()
```

[ ]: 0

[ ]:
```
disc_coupon_df['Coupon_Code'].nunique()
```

[ ]: 48

[ ]:
```
disc_coupon_df['Product_Category'].nunique()
```

[ ]: 17

- 48 copon codes were offered for 17 Product categories.
- No null values or duplicates found in the discount coupon data.

[ ]:
```
mrkt_spend_df.head()
```

[ ]:

	Date	Offline_Spend	Online_Spend
0	1/1/2019	4500	2424.50
1	1/2/2019	4500	3480.36
2	1/3/2019	4500	1576.38
3	1/4/2019	4500	2928.55
4	1/5/2019	4500	4055.30

[ ]:
```
mrkt_spend_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 365 entries, 0 to 364
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Date           365 non-null    object
 1   Offline_Spend  365 non-null    int64
 2   Online_Spend   365 non-null    float64
dtypes: float64(1), int64(1), object(1)
memory usage: 8.7+ KB
```

- No null values or duplicates found in marketing spend data

[ ]:
```
mrkt_spend_df.duplicated().sum()
```

[ ]: 0

[ ]:
```
tax_amt_df.head()
```

[ ]:

	Product_Category	GST
0	Nest-USA	10%
1	Office	10%
2	Apparel	18%
3	Bags	18%
4	Drinkware	18%

[ ]:
```
tax_amt_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20 entries, 0 to 19
Data columns (total 2 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Product_Category  20 non-null     object
 1   GST               20 non-null     object
dtypes: object(2)
memory usage: 448.0+ bytes
```

[ ]:
```
tax_amt_df.duplicated().sum()
```

[ ]: 0

- No null values or dupicates found in the tax amount data.

1.3 Descriptive Statistics

[2]:
```
sales_df = online_sales_df.copy()

sales_df['CustomerID'] = sales_df['CustomerID'].astype(str)
sales_df['Transaction_Date'] = pd.to_datetime(sales_df['Transaction_Date'])
sales_df['Transaction_Day'] = sales_df['Transaction_Date'].dt.day_name()
sales_df['Transaction_Month'] = sales_df['Transaction_Date'].dt.month_name()

cust_df['CustomerID'] = cust_df['CustomerID'].astype(str)
cust_df['Gender'] = cust_df['Gender'].replace({'F': 'Female', 'M': 'Male'})
sales_df = pd.merge(sales_df, cust_df, how='left', on='CustomerID')

month_mapping = { 'Jan': 'January', 'Feb': 'February', 'Mar': 'March', 'Apr':␣
 ↪'April', 'May': 'May', 'Jun': 'June', 'Jul': 'July', 'Aug': 'August', 'Sep':␣
 ↪'September', 'Oct': 'October', 'Nov': 'November', 'Dec': 'December' }
disc_coupon_df['Month'] = disc_coupon_df['Month'].replace(month_mapping)

sales_df = pd.merge(sales_df, disc_coupon_df, how='left',␣
 ↪left_on=['Product_Category', 'Transaction_Month'],␣
 ↪right_on=['Product_Category', 'Month'])
sales_df.drop(columns=['Month'], inplace=True)
sales_df['Coupon_Code'] = sales_df['Coupon_Code'].fillna('No Coupon')
sales_df['Discount_pct'] = sales_df['Discount_pct'].fillna(0)

sales_df = pd.merge(sales_df, tax_amt_df, how='left', on='Product_Category')
sales_df['GST_pct'] = sales_df['GST'].str.rstrip('%').astype(float)

sales_df['Price'] = sales_df['Quantity'] * sales_df['Avg_Price']
```

```
sales_df['Discounted_price'] = sales_df['Price'] * (1-sales_df['Discount_pct']/
 ↪100)
sales_df['Invoice_Value'] = (sales_df['Discounted_price'] * (1+␣
 ↪sales_df['GST_pct']/100)) + sales_df['Delivery_Charges']
sales_df.drop(columns=['Price', 'Discounted_price', 'GST'], inplace=True)

sales_df.head()
```

[2]:

```
   CustomerID  Transaction_ID Transaction_Date     Product_SKU  \
0       17850           16679       2019-01-01  GGOENEBJ079499
1       17850           16680       2019-01-01  GGOENEBJ079499
2       17850           16681       2019-01-01  GGOEGFKQ020399
3       17850           16682       2019-01-01  GGOEGAAB010516
4       17850           16682       2019-01-01  GGOEGBJL013999

                               Product_Description Product_Category  \
0  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
1  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
2              Google Laptop and Cell Phone Stickers           Office
3  Google Men's 100% Cotton Short Sleeve Hero Tee…          Apparel
4                    Google Canvas Tote Natural/Navy             Bags

   Quantity  Avg_Price  Delivery_Charges Coupon_Status Transaction_Day  \
0         1     153.71               6.5          Used         Tuesday
1         1     153.71               6.5          Used         Tuesday
2         1       2.05               6.5          Used         Tuesday
3         5      17.53               6.5      Not Used         Tuesday
4         1      16.50               6.5          Used         Tuesday

  Transaction_Month Gender Location  Tenure_Months Coupon_Code  Discount_pct  \
0           January   Male  Chicago             12      ELEC10          10.0
1           January   Male  Chicago             12      ELEC10          10.0
2           January   Male  Chicago             12       OFF10          10.0
3           January   Male  Chicago             12      SALE10          10.0
4           January   Male  Chicago             12       AIO10          10.0

   GST_pct  Invoice_Value
0     10.0       158.6729
1     10.0       158.6729
2     10.0         8.5295
3     18.0        99.5843
4     18.0        24.0230
```

[ ]:

```
sales_df.describe(include='object')
```

[ ]:

```
       CustomerID     Product_SKU  \
count       52924           52924
```

```
unique       1468            1145
top         12748   GGOENEBJ079499
freq          695            3511

                                      Product_Description Product_Category  \
count                                               52924            52924
unique                                                404               20
top     Nest Learning Thermostat 3rd Gen-USA - Stainle…          Apparel
freq                                                 3511            18126

       Coupon_Status Transaction_Day Transaction_Month  Gender Location  \
count          52924           52924             52924   52924    52924
unique             3               7                12       2        5
top          Clicked          Friday            August  Female  Chicago
freq           26926            9266              6150   33007    18380

       Coupon_Code
count        52924
unique          46
top         SALE20
freq          6373
```

[ ]:
```
sales_df[['Quantity','Discount_pct','Delivery_Charges','Invoice_Value']].
↪describe()
```

[ ]:

	Quantity	Discount_pct	Delivery_Charges	Invoice_Value
count	52924.000000	52924.000000	52924.000000	52924.000000
mean	4.497638	19.802358	10.517630	89.080787
std	20.104711	8.278878	19.475613	152.506512
min	1.000000	0.000000	0.000000	4.375440
25%	1.000000	10.000000	6.000000	18.545760
50%	1.000000	20.000000	6.000000	40.683740
75%	2.000000	30.000000	6.500000	123.447600
max	900.000000	30.000000	521.360000	8979.275000

- Customer having CustomerID 12748 made more transactions.
- Product having SKU GGOENEBJ079499 were sold most.
- Products from category Apparel were sold most.
- Most of the customers clicked the coupon.
- Majority of the sales were done in August month and on Fridays.
- Coupon Code SALE20 is used by most of the customers.
- On an average, a customer purchases 4 products.
- Average delivery chares is USD 10.
- Average discount rate is 20%.
- Invoice value ranges from USD 4 to USD 8980 with average being USD 90.

[ ]:
```
cust_df.describe(include='object')
```

```
[ ]:        CustomerID  Gender    Location
     count        1468    1468        1468
     unique       1468       2           5
     top         17850  Female  California
     freq            1     934         464
```

```
[ ]: cust_df['Tenure_Months'].describe()
```

```
[ ]: count    1468.000000
     mean       25.912125
     std        13.959667
     min         2.000000
     25%        14.000000
     50%        26.000000
     75%        38.000000
     max        50.000000
     Name: Tenure_Months, dtype: float64
```

- Most of the Customers are Females i.e., 934 out of 1468.
- Most of the Customers are from California.
- Average Tenure of the Customers is 25 months.

```
[ ]: mrkt_spend_df.describe()
```

```
[ ]:        Offline_Spend  Online_Spend
     count     365.000000    365.000000
     mean     2843.561644   1905.880740
     std       952.292448    808.856853
     min       500.000000    320.250000
     25%      2500.000000   1258.600000
     50%      3000.000000   1881.940000
     75%      3500.000000   2435.120000
     max      5000.000000   4556.930000
```

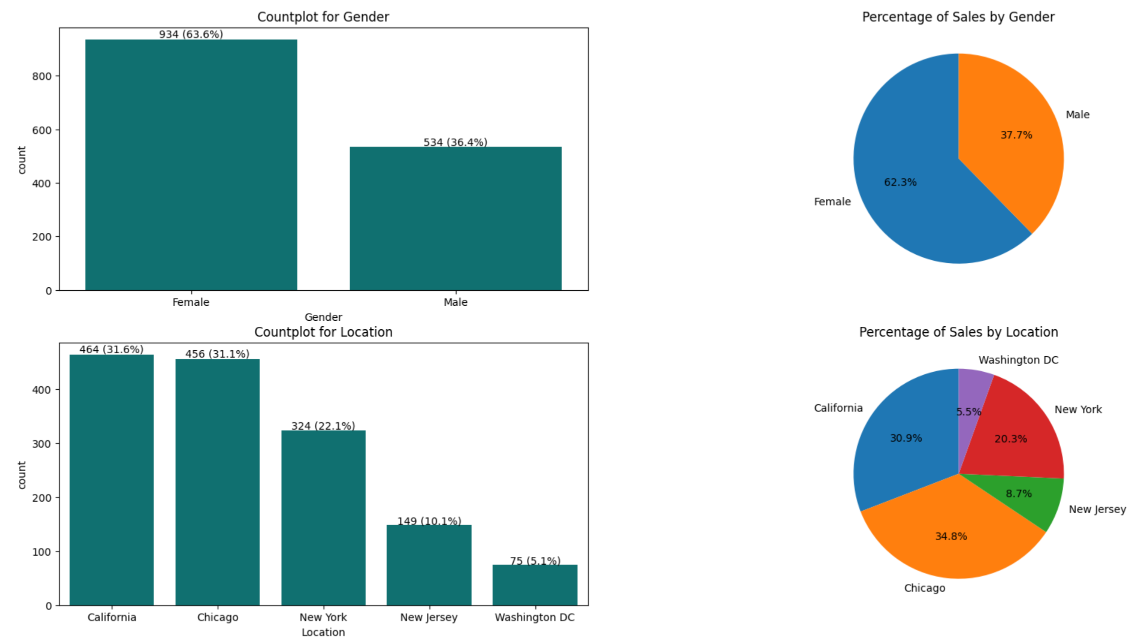
- Average Offline marketing spend is USD 2850.
- Average Online marketing spend is USD 1905.

1.4 Univarient Analysis

1.4.1 Gender and Location

```
[ ]: plt.figure(figsize=(20, 10))
     cols = ['Gender', 'Location']
     for i in cols:
       plt.subplot(2, 2, cols.index(i)*2+1)
       plt.title('Countplot for '+i)
       g = sns.countplot(x=i, data=cust_df, order=cust_df[i].value_counts().index,␣
      ↪color = 'teal')
```

```
    for p in g.patches:
        g.annotate('{0:.0f} ({1:.1f}%)'.format(p.get_height(), (p.get_height()/
↪1468)*100), (p.get_x() + p.get_width() / 2, p.get_height()*1.01), ha =␣
↪'center')

    plt.subplot(2, 2, cols.index(i)*2+2)
    plt.title('Percentage of Sales by '+i)
    bill = sales_df.groupby(i)['Invoice_Value'].sum()
    plt.pie(bill, labels=bill.index, autopct='%1.1f%%', startangle=90)

plt.show()
```



[ ]:
```
sales_df.groupby('Gender')['Invoice_Value'].sum().reset_index()
```

[ ]:
```
   Gender  Invoice_Value
0  Female   2.937366e+06
1    Male   1.777146e+06
```

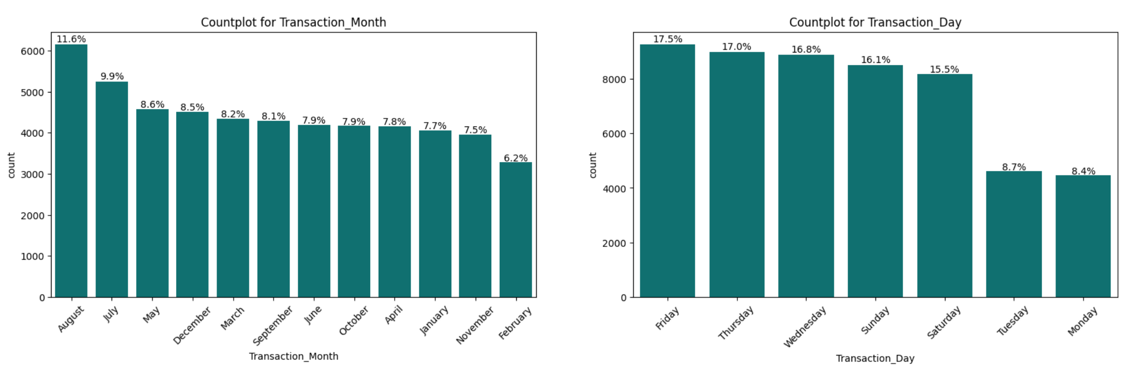
[ ]:
```
sales_df.groupby('Location')['Invoice_Value'].sum().reset_index()
```

[ ]:
```
        Location  Invoice_Value
0     California   1.455051e+06
1        Chicago   1.638484e+06
2     New Jersey   4.079342e+05
3       New York   9.551380e+05
4  Washington DC   2.579037e+05
```

- Around 64% of the Customers are females and rest 36% are males i.e., 934 are females and 534 are males.
- Females contibutes 62% of the total sales i.e., around 3 Million USD whereas Males contributes only 38% i.e., around 1.8 Million USD.
- Around 63% of the customers are from California and Chicago, 22% of the customers are from New York and rest 15% are from New Jercy and Washington DC.
- Chicago contributes around 35% of the total sales which stands at top i.e., around 1.6 Million USD followed by California which contributes 31% i.e., around 1.4 Million USD.
- New York contributes 20% of sales i.e, around 955K USD.
- Washington DC contributes around 9% i.e., 258K USD.
- New Jersey contributes only 5.5% of sales which stands at the last i.e., around 400K USD.

1.4.2 Transaction Month and Day

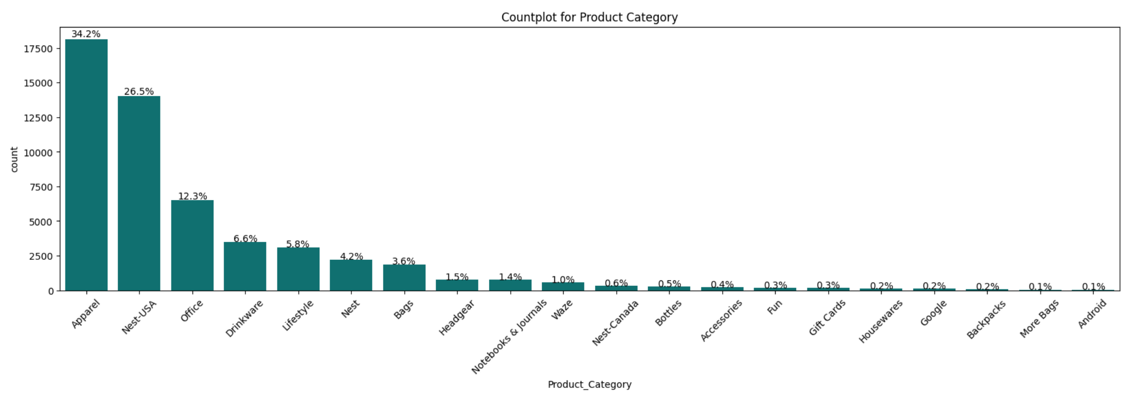
[ ]:
```
plt.figure(figsize=(20, 5))
cols = ['Transaction_Month', 'Transaction_Day']
for i in cols:
  plt.subplot(1, 2, cols.index(i)+1)
  plt.title('Countplot for '+i)
  plt.xticks(rotation=45)
  g = sns.countplot(x=i, data=sales_df, order=sales_df[i].value_counts().index, color = 'teal')
  for p in g.patches:
    g.annotate(format((p.get_height()/len(sales_df))*100, '.1f')+'%', (p.get_x() + p.get_width() / 2, p.get_height()*1.01), ha = 'center')
plt.show()
```



- August month stands top on number of purchases i.e., 11% followed by July with 10% and rest of the months got average purchases of 7.5% - 8.5% except frebruary which got less number of purchases i.e., 6%.
- Most of the purchases happened on Fridays and Thursdays.
- Wednesday, Saturday and Sundays got above average sales whereas Tuesdays and Mondays got below average sales

1.4.3 Product Category

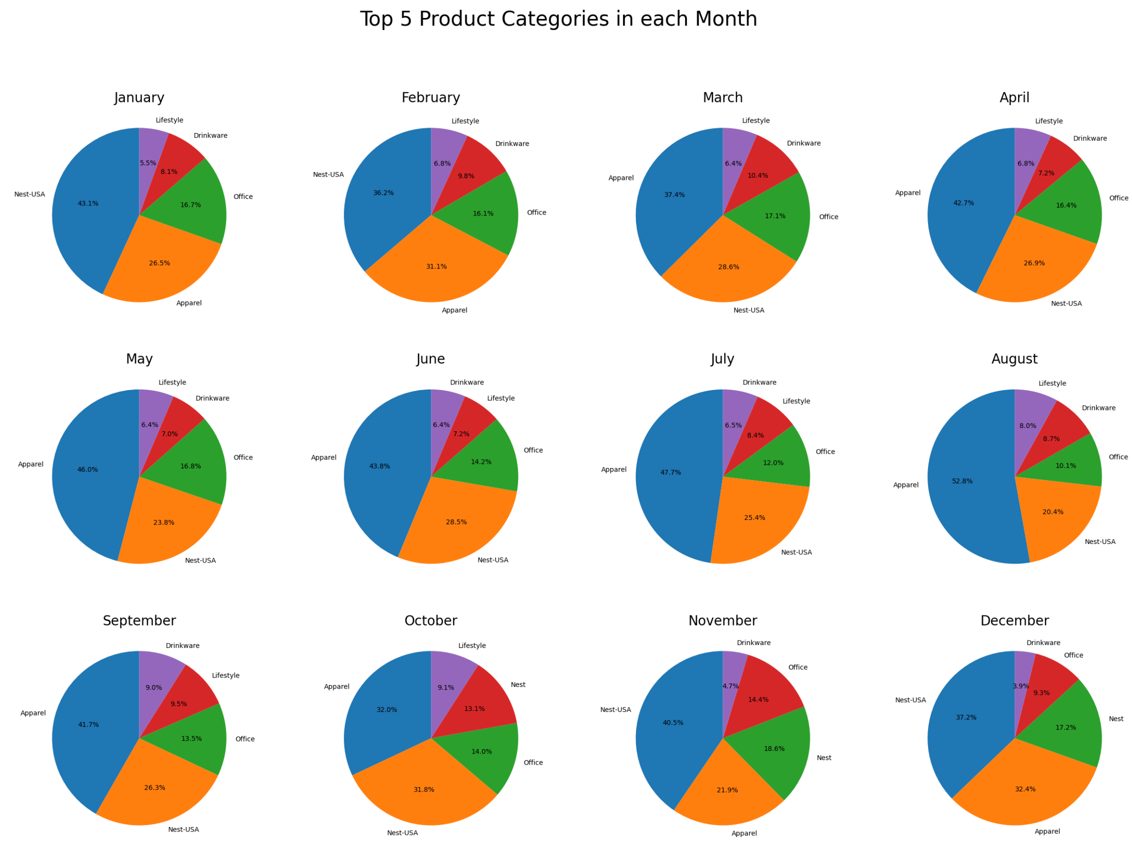
[ ]:
```python
plt.figure(figsize=(20, 5))
plt.title('Countplot for Product Category')
plt.xticks(rotation=45)
g = sns.countplot(x='Product_Category', data=sales_df, order=sales_df['Product_Category'].value_counts().index, color = 'teal')
for p in g.patches:
  g.annotate(format((p.get_height()/len(sales_df))*100, '.1f')+'%', (p.get_x() + p.get_width() / 2, p.get_height()*1.01), ha = 'center')
plt.show()
```



- Apparel Product Category stand top on most number of sales i.e., around 34.2% followed by Nest-USA with 26.5% of sales and Office with 12.3% of sales.
- Drinkware, Lifestyle, Nest and Bags all together contributes to 20% of sales whereas rest of the Categories contributes 7%.

Top 5 Product Categories in each Month

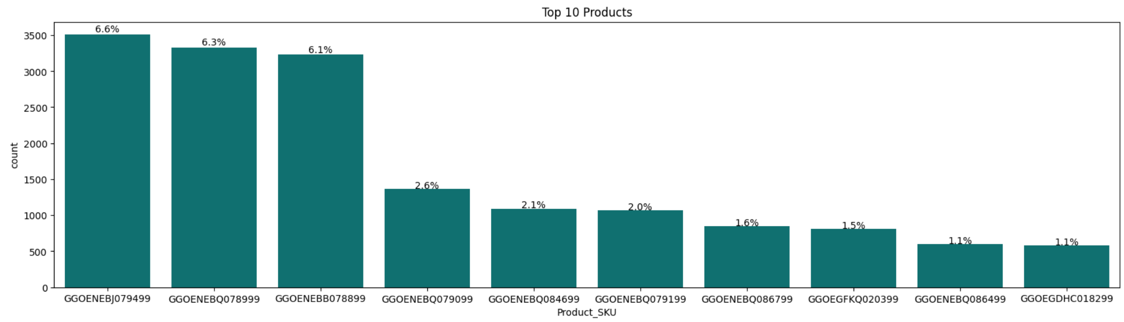
[ ]:
```python
plt.figure(figsize=(30,20)).suptitle('Top 5 Product Categories in each Month', fontsize=30)
months = ['January', 'February', 'March', 'April', 'May', 'June', 'July', 'August', 'September', 'October', 'November', 'December']
for i in months:
  plt.subplot(3, 4, months.index(i)+1)
  plt.title(i, fontsize=20)
  data = sales_df[sales_df['Transaction_Month']==i]['Product_Category'].value_counts().head(5)
  plt.pie(data, labels=data.index, autopct='%1.1f%%', startangle=90)
plt.show()
```



- Apparel product category is the highest sold in Spring Months whereas Nest-USA is the highest sold in winter months.
- Nest product category has greater sales in October, November and December.
- Office, Drinkware and Lifestyle has consistent sales each month.
- Drinkware came in top 5 sales during fall months.

1.4.4 Products

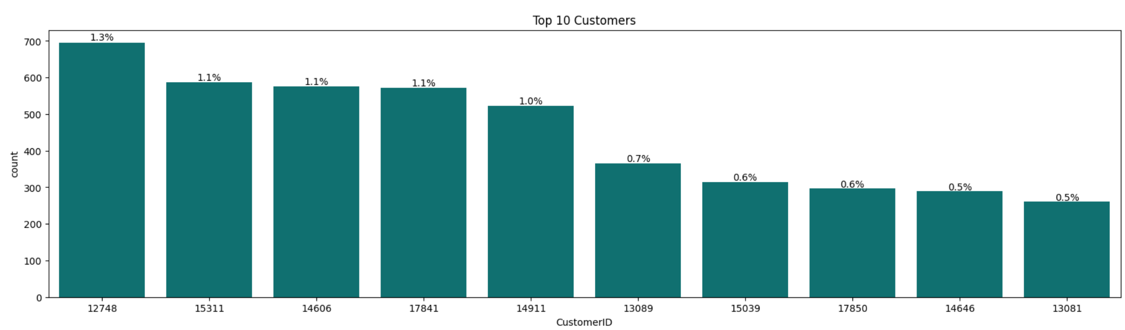
[ ]:
```
plt.figure(figsize=(20, 5))
plt.title('Top 10 Products')
data = sales_df[sales_df['Product_SKU'].isin(sales_df['Product_SKU'].
 ↪value_counts().head(10).index)]
g = sns.countplot(data, x='Product_SKU', order=data['Product_SKU'].
 ↪value_counts().index, color = 'teal')
for p in g.patches:
  g.annotate(format((p.get_height()/len(sales_df))*100, '.1f')+'%', (p.get_x()␣
 ↪+ p.get_width() / 2, p.get_height()*1.01), ha = 'center')
plt.show()
```



- GGOENEBJ079499, GGOENEBQ078999, GGOENEBB078899 are the top 3 products respectively contributes to 19% of the sales altogether.
- GGOENEBQ079099, GGOENEBQ084699, GGOENEBQ079199, GGOENEBQ086799, GGOEGFKQ020399, GGOENEBQ086499, GGOEGDHC018299 are the top 4 to 10 products respectively which contributes to 12% of sales.

1.4.5 Customers

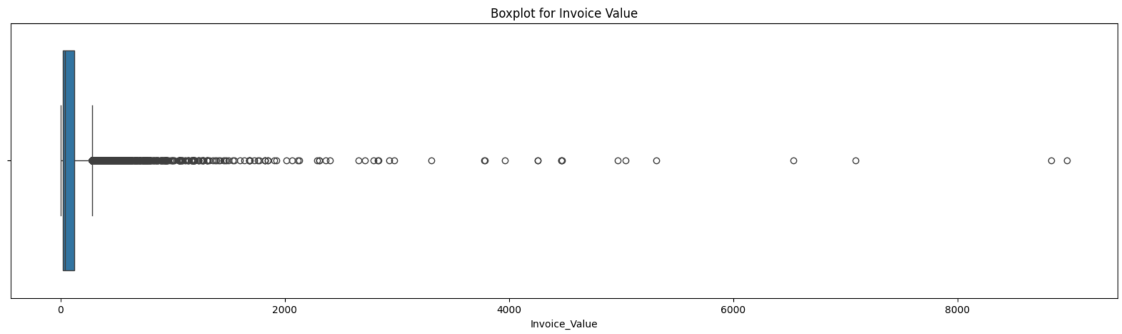
[ ]:
```
plt.figure(figsize=(20, 5))
plt.title('Top 10 Customers')
data = sales_df[sales_df['CustomerID'].isin(sales_df['CustomerID'].
 ↪value_counts().head(10).index)]
g = sns.countplot(data, x='CustomerID', order=data['CustomerID'].value_counts().
 ↪index, color = 'teal')
for p in g.patches:
  g.annotate(format((p.get_height()/len(sales_df))*100, '.1f')+'%', (p.get_x()␣
 ↪+ p.get_width() / 2, p.get_height()*1.01), ha = 'center')
plt.show()
```



- Customer with CustomerID 12748 stands top in number of purchases contributing 1.3% of purchases followed by 15311, 14606, 17841.

1.4.6 Invoice Value

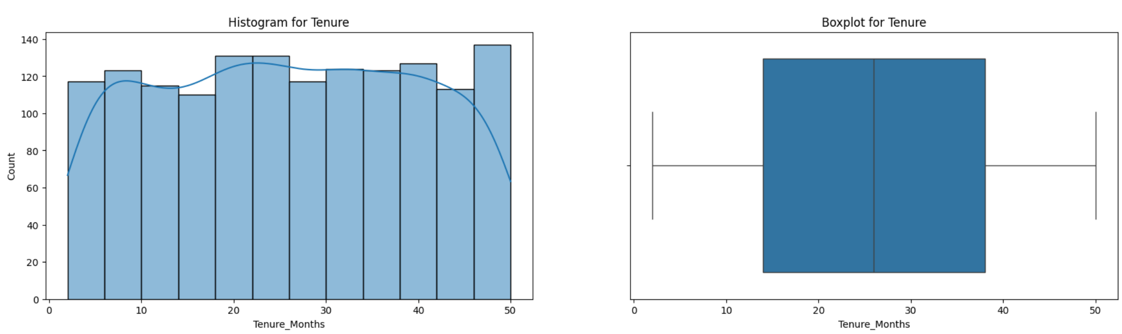
[ ]:
```
plt.figure(figsize=(20, 5))
plt.title('Boxplot for Invoice Value')
sns.boxplot(data=sales_df, x='Invoice_Value')
plt.show()
```



- Invoice value contains so many outliers
- It is clearly not a normal distribution

1.4.7 Tenure

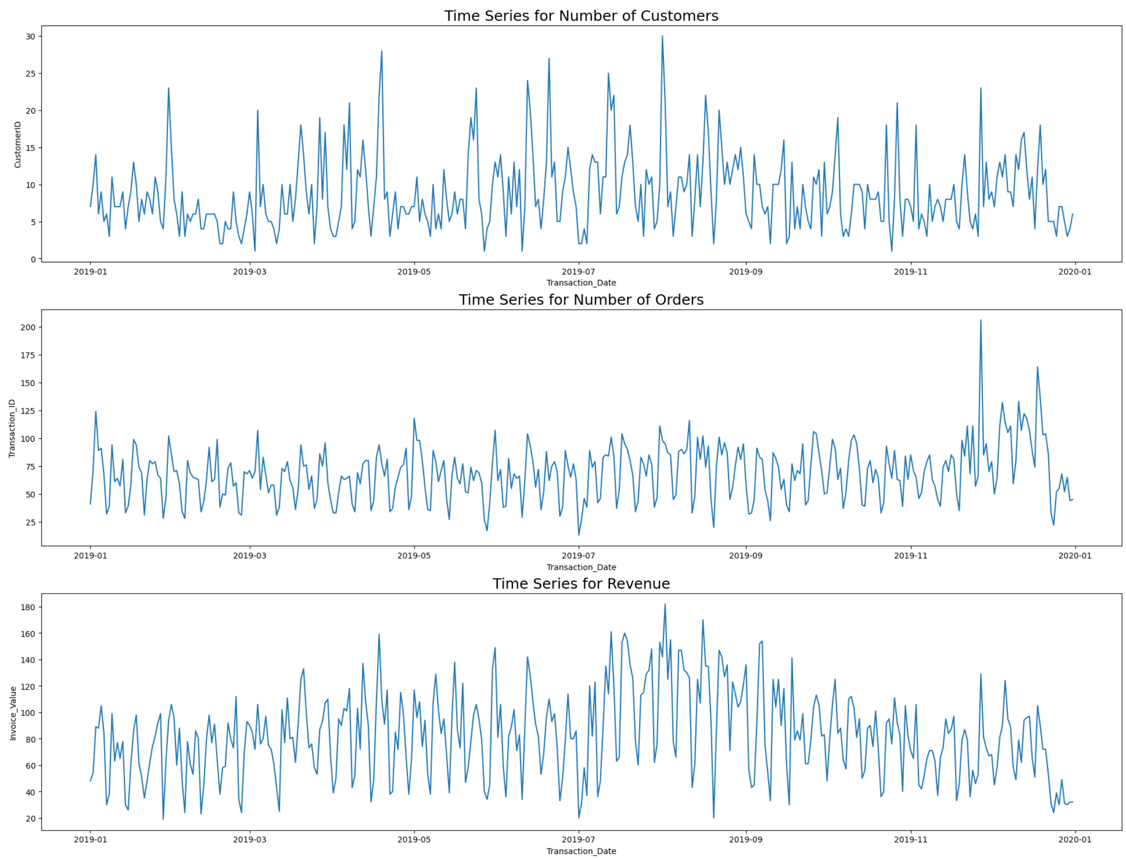
[ ]:
```
plt.figure(figsize=(20, 5))

plt.subplot(1, 2, 1)
plt.title('Histogram for Tenure')
sns.histplot(cust_df['Tenure_Months'],kde=True)

plt.subplot(1, 2, 2)
plt.title('Boxplot for Tenure')
sns.boxplot(data=cust_df, x='Tenure_Months')

plt.show()
```



- Tenure follows normal distribution.
- Tenure ranges from 2 to 50 months with an average being 26 months.

1.4.8 Time Series Analysis

[ ]:
```
plt.figure(figsize=(24, 18))

cols = ['CustomerID', 'Transaction_ID', 'Invoice_Value']
for i in cols:
  if cols.index(i) == 0:
    title = 'Number of Customers'
  elif cols.index(i) == 1:
    title = 'Number of Orders'
  else:
    title = 'Revenue'

  plt.subplot(3, 1, cols.index(i)+1)
  plt.title('Time Series for '+ title, fontsize=18)
  data = sales_df.groupby('Transaction_Date')[i].nunique().reset_index()
  sns.lineplot(x='Transaction_Date', y=i, data=data)

plt.show()
```



- Time series for all three (Number of Customers, Number of Orders and Revenue) appears to fluctuate throughout the year without a clear upward or downward trend.
- There are noticeable spikes in customer numbers around late January, late April, and late July.
- There is a significant spike in the number of orders in early November, which is much higher than other days.
- There is a noticeable upward trend in revenue from the beginning of the year until mid-2019, after which the revenue appears to fluctuate more without a clear trend.

1.5 Exploratory Data Analysis (EDA)

1.5.1 Cross selling products

[25]:
```
transactions = sales_df.groupby(['CustomerID',␣
↪'Transaction_Date'])['Product_SKU'].apply(set).reset_index()
transactions['Product_Pairs'] = transactions['Product_SKU'].apply(lambda x :␣
↪list(combinations(x,2)))
transactions.head()
```

[25]:
```
   CustomerID Transaction_Date  \
0       12346       2019-09-15
1       12347       2019-03-24
2       12347       2019-11-01
3       12347       2019-11-02
4       12348       2019-06-22

                                         Product_SKU  \
0                   {GGOEAAAJ080816, GGOEGOAR013099}
1  {GGOEGAEL031116, GGOENEBB078899, GGOEGAEL03111…
2   {GGOEAKDH019899, GGOEGHPB071610, GGOEGFKQ020799}
3  {GGOEYAEJ029516, GGOENEBQ092299, GGOENEBJ07949…
4  {GGOEGFSR022099, GGOEGDHQ015399, GGOEGBMJ01339…

                                       Product_Pairs
0                 [(GGOEAAAJ080816, GGOEGOAR013099)]
1  [(GGOEGAEL031116, GGOENEBB078899), (GGOEGAEL03…
2  [(GGOEAKDH019899, GGOEGHPB071610), (GGOEAKDH01…
3  [(GGOEYAEJ029516, GGOENEBQ092299), (GGOEYAEJ02…
4  [(GGOEGFSR022099, GGOEGDHQ015399), (GGOEGFSR02…
```

[26]:
```
cross_selling_products = transactions['Product_Pairs'].explode().value_counts().
↪reset_index()
# Top 10 cross selling products
cross_selling_products.head(10)
```

[26]:

```
                         Product_Pairs  count
0  (GGOENEBB078899, GGOENEBQ078999)   1088
1  (GGOENEBJ079499, GGOENEBQ078999)   1001
2  (GGOENEBJ079499, GGOENEBQ079099)    680
3  (GGOENEBB078899, GGOENEBQ079099)    645
4  (GGOENEBQ079099, GGOENEBQ078999)    626
5  (GGOENEBB078899, GGOENEBJ079499)    571
6  (GGOENEBQ079199, GGOENEBQ078999)    553
7  (GGOENEBB078899, GGOENEBQ084699)    500
8  (GGOENEBQ084699, GGOENEBQ078999)    487
9  (GGOENEBJ079499, GGOENEBQ084699)    486
```

- The product pair (GGOENEBB078899, GGOENEBQ078999) has the highest cross-selling count of 1088.
- GGOENEBJ079499 and GGOENEBQ078999 frequently appear in top pairs, indicating their popularity.

1.5.2 Are sales related with Discount rate ?

[ ]:

```
(sales_df['Discount_pct'].value_counts(normalize=True)*100).round(1)
```

[ ]:

```
Discount_pct
20.0    33.7
10.0    33.0
30.0    32.5
0.0      0.8
Name: proportion, dtype: float64
```

- 99.2% of the products were purchased on discounts which shows that people are willing to buy products only on discounts.

[ ]:

```
sales_df.groupby('Discount_pct')['Invoice_Value'].mean().reset_index()
```

[ ]:

```
   Discount_pct  Invoice_Value
0           0.0      92.373352
1          10.0     101.361462
2          20.0      85.762760
3          30.0      79.983016
```

- From this data we can see that there is no much difference in the mean sales.
- Let's test this with hypothesis testing by using kruskal wallis as there are multiple categorical columns and invoice_value does not satisfies assumptions of Anova

[ ]:

```
# Kruskal Wallis test
H0 = 'Discount rate and Invoice value are dependent'
Ha = 'Discount rate and Invoice value are independent'
print('\033[1m'+'Null Hypothesis: '+'\033[0m'+H0)
print('\033[1m'+'Alternative Hypothesis: '+'\033[0m'+Ha+'\n')
```

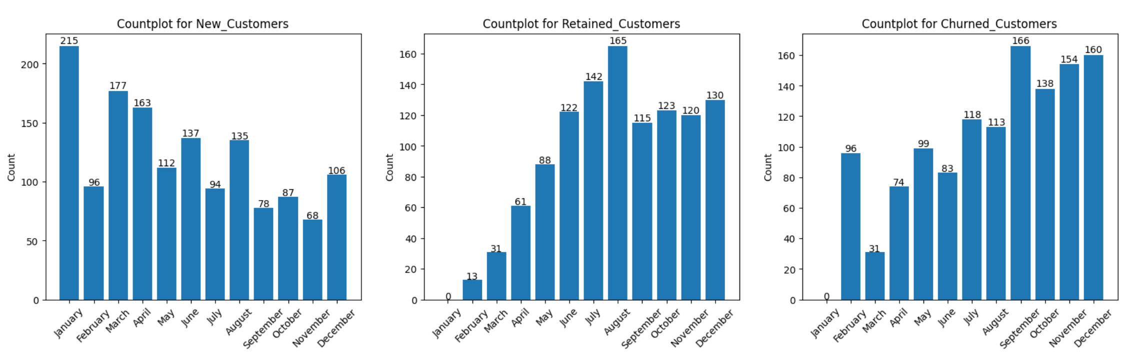
```
alpha = 0.05
k,p = stats.kruskal(sales_df[sales_df['Discount_pct'] == 0]['Invoice_Value'],␣
↪sales_df[sales_df['Discount_pct'] == 10]['Invoice_Value'],␣
↪sales_df[sales_df['Discount_pct'] == 20]['Invoice_Value'],␣
↪sales_df[sales_df['Discount_pct'] == 30]['Invoice_Value'])

print('\033[1m'+'Significance Level: '+'\033[0m',alpha)
print('\033[1m'+'P-Value: '+'\033[0m',p)
print('\033[1m'+'K-Statistic: '+'\033[0m',k,'\n')

if p < alpha:
  print('\033[1m'+'Result: '+'\033[0m'+ 'Reject Null Hypothesis')
  print('\033[1m'+'Conclusion: '+'\033[0m'+Ha)
else:
  print('\033[1m'+'Result: '+'\033[0m'+ 'Fail to Reject Null Hypothesis')
  print('\033[1m'+'Conclusion: '+'\033[0m'+H0)
```

```
Null Hypothesis: Discount rate and Invoice value are dependent
Alternative Hypothesis: Discount rate and Invoice value are independent

Significance Level:  0.05
P-Value:  2.5752890202495375e-39
K-Statistic:  182.47561924484012

Result: Reject Null Hypothesis
Conclusion: Discount rate and Invoice value are independent
```

1.5.3 Count of New, Retained and Churned Customers per month

[ ]:
```
month_dict = {}
months = ['January', 'February', 'March', 'April', 'May', 'June', 'July',␣
↪'August', 'September', 'October', 'November', 'December']

for i in months:
   month_dict[i] = sales_df[sales_df['Transaction_Month']==i]['CustomerID'].
↪unique().tolist()

Retained_Customers= []
New_Customers = []
Churned_Customers = []

prev = set()
churned = set()

for i in range(12):
  curr = set(month_dict[months[i]])
```

```
  New_Customers.append(len(curr - prev))
  Retained_Customers.append(len(curr & prev))

  future_customers = set()
  for j in range(i + 1, 12):
    future_customers.update(month_dict[months[j]])

  Churned_Customers.append(len(prev - curr - future_customers - churned))

  churned.update(prev - curr - future_customers)

  prev = prev | curr

cust_stats_df = pd.DataFrame({'Month': months, 'New_Customers': New_Customers,␣
 ↪'Retained_Customers': Retained_Customers, 'Churned_Customers':␣
 ↪Churned_Customers})

plt.figure(figsize=(20, 5))
cols = ['New_Customers', 'Retained_Customers', 'Churned_Customers']

for i in cols:
  plt.subplot(1, 3, cols.index(i)+1)
  plt.title('Countplot for '+i)
  plt.bar(cust_stats_df['Month'], cust_stats_df[i])
  for j in range(12):
    plt.text(x=j, y = cust_stats_df[i][j]*1.01, s=cust_stats_df[i][j],␣
 ↪ha='center')
  plt.xlabel('Months')
  plt.ylabel('Count')
  plt.xticks(rotation=45)

plt.show()
```



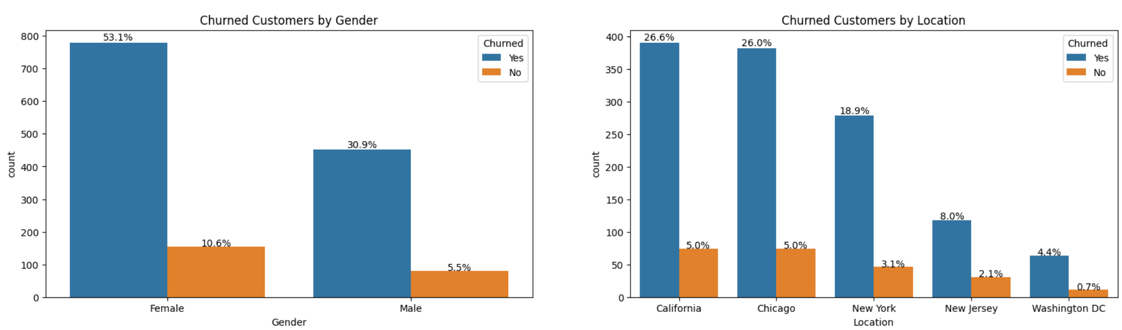
1.5.4 Churned Customers

[ ]:
```python
cust_df['Churned'] = np.where(cust_df['CustomerID'].isin(churned), 'Yes', 'No')
cust_df.head()
```

[ ]:

	CustomerID	Gender	Location	Tenure_Months	Churned
0	17850	Male	Chicago	12	Yes
1	13047	Male	California	43	No
2	12583	Male	Chicago	33	Yes
3	13748	Female	California	30	Yes
4	15100	Male	California	49	Yes

[ ]:
```python
plt.figure(figsize=(20, 5))
cols = ['Gender', 'Location']

for i in cols:
  plt.subplot(1, 2, cols.index(i)+1)
  plt.title('Churned Customers by '+i)
  g = sns.countplot(data=cust_df, x=i, hue='Churned', order=cust_df[i].
↪value_counts().index)
  for p in g.patches:
    if p.get_height():
      g.annotate(format((p.get_height()/len(cust_df))*100, '.1f')+'%', (p.
↪get_x() + p.get_width() / 2, p.get_height()*1.01), ha = 'center')

plt.show()
```



- 84% of the customers got churned out of which 53% are females and rest 31% are males.
- California and Chicago have almost same percentage of churned customers i.e., 26%, New York has 19%, New gercy has 8% and Washington DC has 4.5%

1.5.5 Retention Rate and Churn Rate

[ ]:
```
cust_stats_df['Total_Customers'] = cust_stats_df['New_Customers'] +␣
↪cust_stats_df['Retained_Customers'] + cust_stats_df['Churned_Customers']
# Shift total customers by 1 to get previous month total customers
cust_stats_df['Prev_Month_Customers'] = cust_stats_df['Total_Customers'].
↪shift(1)
cust_stats_df['Retention_Rate'] = (cust_stats_df['Retained_Customers'] /␣
↪cust_stats_df['Prev_Month_Customers']).round(2)
cust_stats_df['Churn_Rate'] = (cust_stats_df['Churned_Customers'] /␣
↪cust_stats_df['Prev_Month_Customers']).round(2)
cust_stats_df
```

[ ]:
```
        Month  New_Customers  Retained_Customers  Churned_Customers  \
0     January            215                   0                  0
1    February             96                  13                 96
2       March            177                  31                 31
3       April            163                  61                 74
4         May            112                  88                 99
5        June            137                 122                 83
6        July             94                 142                118
7      August            135                 165                113
8   September             78                 115                166
9     October             87                 123                138
10   November             68                 120                154
11   December            106                 130                160

    Total_Customers  Prev_Month_Customers  Retention_Rate  Churn_Rate
0               215                   NaN             NaN         NaN
1               205                 215.0            0.06        0.45
2               239                 205.0            0.15        0.15
3               298                 239.0            0.26        0.31
4               299                 298.0            0.30        0.33
5               342                 299.0            0.41        0.28
6               354                 342.0            0.42        0.35
7               413                 354.0            0.47        0.32
8               359                 413.0            0.28        0.40
9               348                 359.0            0.34        0.38
10              342                 348.0            0.34        0.44
11              396                 342.0            0.38        0.47
```

- August month has highest rention rate.
- December month has highest churn rate.

[ ]:
```
cust_stats_df[['Retention_Rate', 'Churn_Rate']].mean().round(2)
```

```
[ ]: Retention_Rate    0.31
     Churn_Rate        0.35
     dtype: float64
```

- Average monthly retention rate is 31% whereas average monthly churn rate is 35%

1.5.6 Marketing Spend vs Revenue and Orders

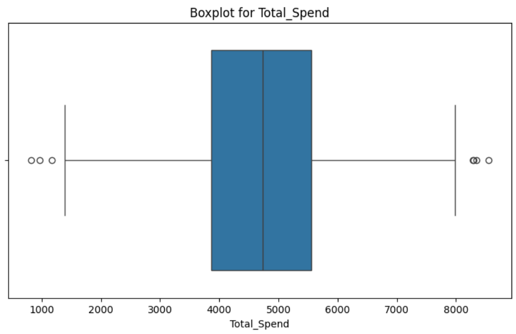
```
[ ]: mrkt_spend_df['Date'] = pd.to_datetime(mrkt_spend_df['Date'])
     mrkt_spend_df['Month'] = pd.Categorical(mrkt_spend_df['Date'].dt.month_name(),␣
      ↪categories=months, ordered=True)
     mrkt_spend_df['Total_Spend'] = mrkt_spend_df['Online_Spend'] +␣
      ↪mrkt_spend_df['Offline_Spend']
     mrkt_spend_df['Total_Revenue'] = sales_df.
      ↪groupby('Transaction_Date')['Invoice_Value'].sum().values.round(2)
     mrkt_spend_df['Total_Orders'] = sales_df.
      ↪groupby('Transaction_Date')['Transaction_ID'].nunique().values
     mrkt_spend_df.head()
```

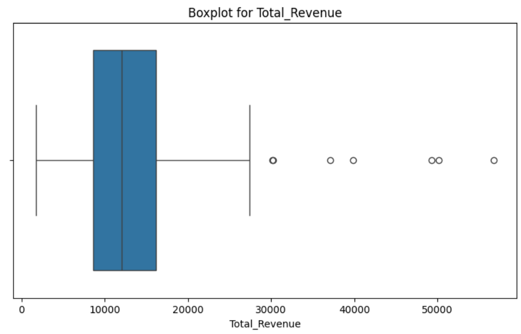
```
[ ]:         Date  Offline_Spend  Online_Spend    Month  Total_Spend  \
     0 2019-01-01           4500       2424.50  January      6924.50
     1 2019-01-02           4500       3480.36  January      7980.36
     2 2019-01-03           4500       1576.38  January      6076.38
     3 2019-01-04           4500       2928.55  January      7428.55
     4 2019-01-05           4500       4055.30  January      8555.30

        Total_Revenue  Total_Orders
     0        8489.73            41
     1       14244.70            71
     2       27379.80           124
     3       18185.88            89
     4       19884.09            91
```

Marketing Spend vs Total Revenue

- Lets find the relation between Total Marketing Spend and Total Revenue.
- Since both are numerical categories, we have to choose pearson or spearman correlation test.
- Lets check the distribution and decide what test to be used.

```
[ ]: plt.figure(figsize=(20, 5))
     cols = ['Total_Spend', 'Total_Revenue']

     for i in cols:
       plt.subplot(1, 2, cols.index(i)+1)
       plt.title('Boxplot for '+i)
       sns.boxplot(data=mrkt_spend_df, x=i)
     plt.show()
```





- Since both the data contains outliers and also Total Revenue seems to be right skewed data, let's use spearman correlation.

[ ]:
```
# Spearman Correlation test
H0 = 'There is no Correlation between Marketing Spend and Revenue generated'
Ha = 'There is a Correlation between Marketing Spend and Revenue generated'
print('\033[1m'+'Null Hypothesis: '+'\033[0m'+H0)
print('\033[1m'+'Alternative Hypothesis: '+'\033[0m'+Ha+'\n')

alpha = 0.05
s,p = stats.spearmanr(mrkt_spend_df['Total_Spend'],
 ↪mrkt_spend_df['Total_Revenue'])

print('\033[1m'+'Significance Level: '+'\033[0m',alpha)
print('\033[1m'+'P-Value: '+'\033[0m',p)
print('\033[1m'+'Spearman-Coefficient: '+'\033[0m',s,'\n')

if p < alpha:
  print('\033[1m'+'Result: '+'\033[0m'+ 'Reject Null Hypothesis')
  print('\033[1m'+'Conclusion: '+'\033[0m'+Ha)
else:
  print('\033[1m'+'Result: '+'\033[0m'+ 'Fail to Reject Null Hypothesis')
  print('\033[1m'+'Conclusion: '+'\033[0m'+H0)
```

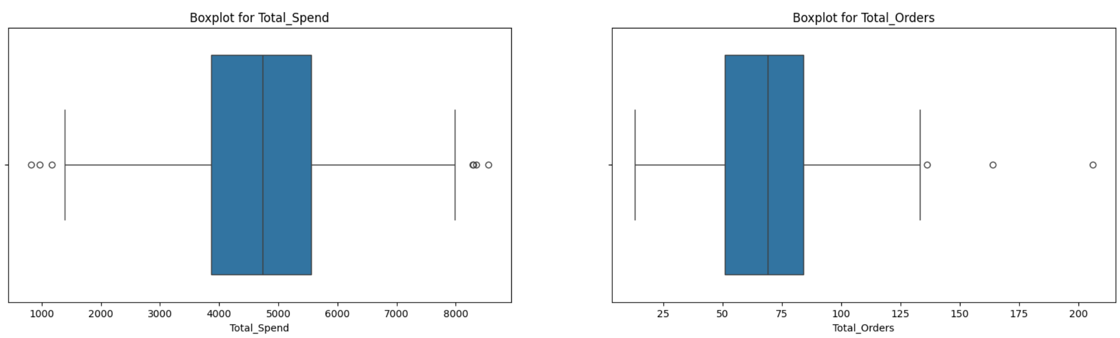
```
Null Hypothesis: There is no Correlation between Marketing Spend and
Revenue generated
Alternative Hypothesis: There is a Correlation between Marketing Spend
and Revenue generated

Significance Level:  0.05
P-Value:  0.12839228661900493
Spearman-Coefficient:  0.07973190070652457

Result: Fail to Reject Null Hypothesis
Conclusion: There is no Correlation between Marketing Spend and Revenue
```

generated

Marketing Spend vs Total no.of Orders

- Lets find the relation between Total Marketing Spend and Total number of Orders.
- Since both are numerical categories, we have to choose pearson or spearman correlation test.
- Lets check the distribution and decide what test to be used.

[ ]:
```
plt.figure(figsize=(20, 5))
cols = ['Total_Spend', 'Total_Orders']

for i in cols:
  plt.subplot(1, 2, cols.index(i)+1)
  plt.title('Boxplot for '+i)
  sns.boxplot(data=mrkt_spend_df, x=i)
plt.show()
```



- Since both the data contains very less number of outliers and also data seems to be normal without those outliers, let's use pearson correlation.

[ ]:
```
# Pearson Correlation test
H0 = 'There is no Correlation between Marketing Spend and Number of Orders'
Ha = 'There is a Correlation between Marketing Spend and Number of Orders'
print('\033[1m'+'Null Hypothesis: '+'\033[0m'+H0)
print('\033[1m'+'Alternative Hypothesis: '+'\033[0m'+Ha+'\n')

alpha = 0.05
s,p = stats.pearsonr(mrkt_spend_df['Total_Spend'],␣
↪mrkt_spend_df['Total_Orders'])

print('\033[1m'+'Significance Level: '+'\033[0m',alpha)
print('\033[1m'+'P-Value: '+'\033[0m',p)
print('\033[1m'+'Pearson-Coefficient: '+'\033[0m',s,'\n')

if p < alpha:
  print('\033[1m'+'Result: '+'\033[0m'+ 'Reject Null Hypothesis')
```

```
  print('\033[1m'+'Conclusion: '+'\033[0m'+Ha)
else:
  print('\033[1m'+'Result: '+'\033[0m'+ 'Fail to Reject Null Hypothesis')
  print('\033[1m'+'Conclusion: '+'\033[0m'+H0)
```

Null Hypothesis: There is no Correlation between Marketing Spend and Number of Orders
Alternative Hypothesis: There is a Correlation between Marketing Spend and Number of Orders

Significance Level: 0.05
P-Value: 0.041749318074568297
Pearson-Coefficient: 0.10663139258532109

Result: Reject Null Hypothesis
Conclusion: There is a Correlation between Marketing Spend and Number of Orders

1.5.7 Monthly Cohort Analysis

[ ]:
```
monthly_df = pd.DataFrame({'Month': months})
monthly_df['Total_Customers'] = cust_stats_df['Total_Customers']
monthly_df['Market_Spend'] = mrkt_spend_df.groupby('Month')['Total_Spend'].
  ↪sum().values
monthly_df['Orders'] = mrkt_spend_df.groupby('Month')['Total_Orders'].sum().
  ↪values
monthly_df['Revenue'] = mrkt_spend_df.groupby('Month')['Total_Revenue'].sum().
  ↪values
monthly_df['Retention_Rate'] = cust_stats_df['Retention_Rate']
monthly_df['Churn_Rate'] = cust_stats_df['Churn_Rate']
monthly_df
```

[ ]:

	Month	Total_Customers	Market_Spend	Orders	Revenue	\
0	January	215	154928.95	2102	463883.04	
1	February	205	137107.92	1664	327896.55	
2	March	239	122250.09	1991	336805.20	
3	April	298	157026.83	1813	447999.17	
4	May	299	118259.64	2034	318556.30	
5	June	342	134318.14	1940	289830.33	
6	July	354	120217.85	2080	423982.35	
7	August	413	142904.15	2414	418160.58	
8	September	359	135514.54	1932	321128.37	
9	October	348	151224.65	2125	450837.45	
10	November	342	161144.96	2282	475902.16	
11	December	396	198648.75	2684	439530.01	

Retention_Rate Churn_Rate

```
0               NaN          NaN
1              0.06         0.45
2              0.15         0.15
3              0.26         0.31
4              0.30         0.33
5              0.41         0.28
6              0.42         0.35
7              0.47         0.32
8              0.28         0.40
9              0.34         0.38
10             0.34         0.44
11             0.38         0.47
```

1.5.8 Customer Lifetime Value (CLV) vs Customer Aquisation Cost (CAC)

[ ]:
```
total_revenue = sales_df['Invoice_Value'].sum()
num_orders = sales_df['Transaction_ID'].nunique()
num_purchases = len(sales_df)
num_cust = sales_df['CustomerID'].nunique()

# Average Purchase Value
apv = total_revenue / num_orders
# Average Purchase Frequency Rate
apfr = num_purchases / num_cust

# Customer Value
cv = apv * apfr

#  Average Customer Lifespan
acl = sales_df.groupby('CustomerID')['Transaction_Month'].nunique().mean()

# Customer Lifetime Value (CLV)
clv = cv * acl

print('Customer Lifetime Value (CLV): ', clv.round(2))
```

```
Customer Lifetime Value (CLV):  11910.27
```

[ ]:
```
mrkt_online_spend = mrkt_spend_df.groupby('Month')['Online_Spend'].sum().
  ↪reset_index()
mrkt_offline_spend = mrkt_spend_df.groupby('Month')['Offline_Spend'].sum().
  ↪reset_index()
marketing_spends = pd.merge(mrkt_online_spend, mrkt_offline_spend, how='inner',␣
  ↪on='Month')

marketing_spends['New_Customers'] = cust_stats_df['New_Customers']
```

```
marketing_spends['CAC'] = ((marketing_spends['Online_Spend'] +␣
↪marketing_spends['Offline_Spend'])/marketing_spends['New_Customers']).
↪round(2)
marketing_spends['CLV:CAV'] = (clv/marketing_spends['CAC']).round(2)

marketing_spends
```

[ ]:

	Month	Online_Spend	Offline_Spend	New_Customers	CAC	CLV:CAV
0	January	58328.95	96600	215	720.60	16.53
1	February	55807.92	81300	96	1428.21	8.34
2	March	48750.09	73500	177	690.68	17.24
3	April	61026.83	96000	163	963.35	12.36
4	May	52759.64	65500	112	1055.89	11.28
5	June	53818.14	80500	137	980.42	12.15
6	July	52717.85	67500	94	1278.91	9.31
7	August	57404.15	85500	135	1058.55	11.25
8	September	52514.54	83000	78	1737.37	6.86
9	October	57724.65	93500	87	1738.21	6.85
10	November	68144.96	93000	68	2369.78	5.03
11	December	76648.75	122000	106	1874.04	6.36

[ ]:
```
marketing_spends[['CAC', 'CLV:CAV']].mean().round(2)
```

[ ]:
```
CAC        1324.67
CLV:CAV      10.30
dtype: float64
```

- Customer Lifetime Value (CLV) of this E-commerce company is 11910 USD.
- Average Customer Acquisition Cost (CAC) per month is 1325 USD.
- Average ratio of CLV to CAV is 10 which means this E-commerce company is earning 10 times more than how much they spend to get a new customer.

2 Insights

Customer Demographics

- In 2019, the company had **1468 customers**, with **females making up two-thirds (64%)** of the customer base.
- Females contributed a **greater share of sales (62%)** compared to males (38%).

Customer Location

- **California and Chicago** were the dominant customer locations, accounting for **around 63%** of the customer base.
- New York followed with **22%**, while New Jersey and Washington D.C. combined for the remaining **15%**.
- **Chicago led in sales (35%)**, followed by California (31%), New York (20%), Washington D.C. (9%), and New Jersey (5.5%).

Purchase Patterns

- **August** saw the **highest number of purchases (11%)**, followed by July (10%). February had the fewest purchases (6%).
- **Fridays and Thursdays** were the **strongest sales days**. Wednesdays, Saturdays, and Sundays also saw **above-average sales**, while Tuesdays and Mondays lagged behind.
- **Apparel** was the **top-selling category in spring**, while **Nest products** dominated **winter sales (October-December)**. Office, Drinkware, and Lifestyle categories had **consistent sales throughout the year**, with Drinkware performing well in fall.

Top Products and Customers

- **Three products (GGOENEBJ079499, GGOENEBQ078999, GGOENEBB078899)** were the **top sellers**, contributing **19% of total sales** combined.
- A customer with **CustomerID 12748** made the **most purchases (1.3%)**, followed by customers 15311, 14606, and 17841.
- The product pair **(GGOENEBB078899, GGOENEBQ078999)** has the highest cross-selling count of **1088**.
- **GGOENEBJ079499 and GGOENEBQ078999 frequently appear in top pairs**, indicating their popularity.

Order Value and Discounts

- Invoice value ranged from **USD 4 to USD 8980**, with an average of **USD 90**.
- **Nearly all products (99.2%) were bought on discount**, suggesting a discount-driven customer base.

Customer Retention

- **Customer churn rate was high (84%)**, with **females (53%) slightly more likely to churn than males (31%)**.
- **California and Chicago** had the **highest churn rates (26%)**, followed by New York (19%), New Jersey (8%), and Washington D.C. (4.5%).
- **August had the highest retention rate**, while December had the highest churn rate.
- The average monthly **retention rate was 31%**, compared to a **35% churn rate**.

Marketing and Customer Lifetime Value

- There was **no correlation between marketing spend and revenue generated**, but there was a **correlation between marketing spend and the number of orders**.
- The average **Customer Lifetime Value (CLV)** was **USD 11,910**, while the average monthly **Customer Acquisition Cost (CAC)** was **USD 1,325**. This translates to a **10:1 CLV to CAC ratio**, indicating a profitable customer acquisition strategy.

3 Recommendations

Focus on Female Customers - Tailor marketing and products to attract and retain female customers, who form 64% of your base and 62% of sales.

Key Locations - Prioritize California and Chicago in marketing and logistics since they account for 63% of your customer base and the majority of sales. - **Expand efforts in New York** and other areas to grow these markets.

Seasonal and Daily Trends - **Promote apparel in spring** and **Nest products in winter**. Consistently market Office, Drinkware, and Lifestyle items. - **Boost promotions on Fridays and Thursdays**, the highest sales days.

Best Sellers and Top Customers - **Highlight top-selling products** and offer special deals to encourage more purchases. - **Reward top customers** with loyalty programs and personalized offers. - **Marketing and inventory on popular pairs**, especially those involving GGOENEBJ079499 and GGOENEBQ078999. - **Bundle high-demand product pairs** to boost sales.

Discounts and Order Value - **Evaluate discount strategy** to ensure profitability. Consider alternatives like bundle deals. - **Encourage higher spending** with free shipping thresholds and upselling.

Retention Strategies - **Address high churn rates** with personalized follow-ups and special offers, focusing on females and key regions like California and Chicago. - **Boost retention in December** with holiday-specific campaigns and incentives.

Marketing Efficiency - **Optimize marketing spend** to focus on strategies that drive orders rather than just increasing spend. - **Leverage data** to refine customer acquisition and retention strategies.

Customer Experience - **Enhance customer service** and offer easy returns to improve overall satisfaction. - **Collect and act on feedback** to continually improve the shopping experience.