In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from mlxtend.frequent_patterns import apriori, association_rules
from scipy.stats import ttest_ind
```

In [ ]:
```
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning, module="ipykernel.ip
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarn
ing: `should_run_async` will not call `transform_cell` automatically in the futur
e. Please pass the result to `transformed_cell` argument and any exception that ha
ppen during thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

In [ ]:
```
d4 = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Business Case Study_Scaler
d2 = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Business Case Study_Scaler
marketing = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Business Case Study
sales = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Business Case Study_Sca
d5 = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Business Case Study_Scaler
```

Problem Statement

A fast-expanding e-commerce company is shifting from intuition-based marketing to a data-driven strategy. By analyzing customer demographics, transaction data, marketing spend, and discount details from 2019, the company aims to understand customer behavior. the company intends to refine its marketing tactics, better understand its customers, and foster long-term financial growth.

Data Pre-processing

In [ ]:
```
sales.shape
```

Out[ ]:
```
(52924, 10)
```

In [ ]:
```
# Creating 'Month' column in Online_Sales data to merge with Discount_Coupon data
sales['Month'] = pd.to_datetime(sales['Transaction_Date']).dt.strftime('%b')
```

In [ ]:
```
# Merging Customers table, Discount_Coupon table and Tax_amount table with "Online_
sales = sales.merge(d4, on='CustomerID', how='left').merge(d2, on=['Product_Categor
sales = sales.merge(d5, on='Product_Category', how='left')
```

In [ ]:
```
# Calculating total marketing spend and merging with 'Sales' data

marketing['marketing_spend'] = marketing['Offline_Spend']+marketing['Online_Spend']
marketing['Month'] = pd.to_datetime(marketing['Date']).dt.strftime('%b')
marketing_spend1 = marketing.groupby('Month')['marketing_spend'].sum().reset_index(
sales = sales.merge(marketing_spend1, on='Month', how='left')
```

In [ ]:
```
sales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 52924 entries, 0 to 52923
Data columns (total 18 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 
 10  Month                52924 non-null  object 
 11  Gender               52924 non-null  object 
 12  Location             52924 non-null  object 
 13  Tenure_Months        52924 non-null  int64  
 14  Coupon_Code          52524 non-null  object 
 15  Discount_pct         52524 non-null  float64
 16  GST                  52924 non-null  object 
 17  marketing_spend      52924 non-null  float64
dtypes: float64(4), int64(4), object(10)
memory usage: 7.3+ MB
```

In [ ]:
```
# Converting Datatypes as required

# Transaction_Date --> object to datetime
# CustomerID --> int64 to object
# Transaction_ID --> int64 to object
# GST --> object to float

sales['Transaction_Date'] = pd.to_datetime(sales['Transaction_Date'])
sales['CustomerID'] = sales['CustomerID'].astype('object')
sales['Transaction_ID'] = sales['Transaction_ID'].astype('object')
sales['GST']= sales['GST'].str.rstrip('%').astype('float')
```

In [ ]:
```
sales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 52924 entries, 0 to 52923
Data columns (total 18 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   CustomerID           52924 non-null  object
 1   Transaction_ID       52924 non-null  object
 2   Transaction_Date     52924 non-null  datetime64[ns]
 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
 10  Month                52924 non-null  object
 11  Gender               52924 non-null  object
 12  Location             52924 non-null  object
 13  Tenure_Months        52924 non-null  int64
 14  Coupon_Code          52524 non-null  object
 15  Discount_pct         52524 non-null  float64
 16  GST                  52924 non-null  float64
 17  marketing_spend      52924 non-null  float64
dtypes: datetime64[ns](1), float64(5), int64(2), object(10)
memory usage: 7.3+ MB
```

In [ ]:
```
sales.isna().sum()
```

Out[ ]:
```
CustomerID               0
Transaction_ID           0
Transaction_Date         0
Product_SKU              0
Product_Description      0
Product_Category         0
Quantity                 0
Avg_Price                0
Delivery_Charges         0
Coupon_Status            0
Month                    0
Gender                   0
Location                 0
Tenure_Months            0
Coupon_Code            400
Discount_pct           400
GST                      0
marketing_spend          0
dtype: int64
```

In [ ]:
```
# Handling Null values

sales['Discount_pct'].fillna(0, inplace=True)
sales['Coupon_Code'].fillna('No Code', inplace=True)
```

In [ ]:
```
sales.isna().sum()
```

Out[ ]:
```
CustomerID             0
Transaction_ID         0
Transaction_Date       0
Product_SKU            0
Product_Description    0
Product_Category       0
Quantity               0
Avg_Price              0
Delivery_Charges       0
Coupon_Status          0
Month                  0
Gender                 0
Location               0
Tenure_Months          0
Coupon_Code            0
Discount_pct           0
GST                    0
marketing_spend        0
dtype: int64
```

In [ ]:
```
# Creating 'Invoice amount' using below formula which is the total amount a custome
sales['Invoice_value'] = ((sales['Quantity'] * sales['Avg_Price']) * (1 - (sales['D
```

In [ ]:
```
sales.tail()
```

Out[ ]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Description	Proc
52919	14410	48493	2019-12-31	GGOENEBB078899	Nest Cam Indoor Security Camera - USA	
52920	14410	48494	2019-12-31	GGOEGAEB091117	Google Zip Hoodie Black	
52921	14410	48495	2019-12-31	GGOENEBQ084699	Nest Learning Thermostat 3rd Gen-USA - White	
52922	14600	48496	2019-12-31	GGOENEBQ079199	Nest Protect Smoke + CO White Wired Alarm-USA	
52923	14600	48497	2019-12-31	GGOENEBQ079099	Nest Protect Smoke + CO White Battery Alarm-USA	

In [ ]:
```
sales.describe(include='all')
```

Out[ ]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_Description	Pr
count	52924.0	52924.0	52924	52924	52924	
unique	1468.0	25061.0	NaN	1145	404	
top	12748.0	32526.0	NaN	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	
freq	695.0	35.0	NaN	3511	3511	
mean	NaN	NaN	2019-07-05 19:16:09.450532864	NaN	NaN	
min	NaN	NaN	2019-01-01 00:00:00	NaN	NaN	
25%	NaN	NaN	2019-04-12 00:00:00	NaN	NaN	
50%	NaN	NaN	2019-07-13 00:00:00	NaN	NaN	
75%	NaN	NaN	2019-09-27 00:00:00	NaN	NaN	
max	NaN	NaN	2019-12-31 00:00:00	NaN	NaN	
std	NaN	NaN	NaN	NaN	NaN	

Observations

1. The online sales data provided is from January to December 2019
2. Total customers are 1468
3. There are 20 product categories with total SKU's of 1145
4. Most number of purchases are done by Female customers

Graphical Analysis

In [ ]:

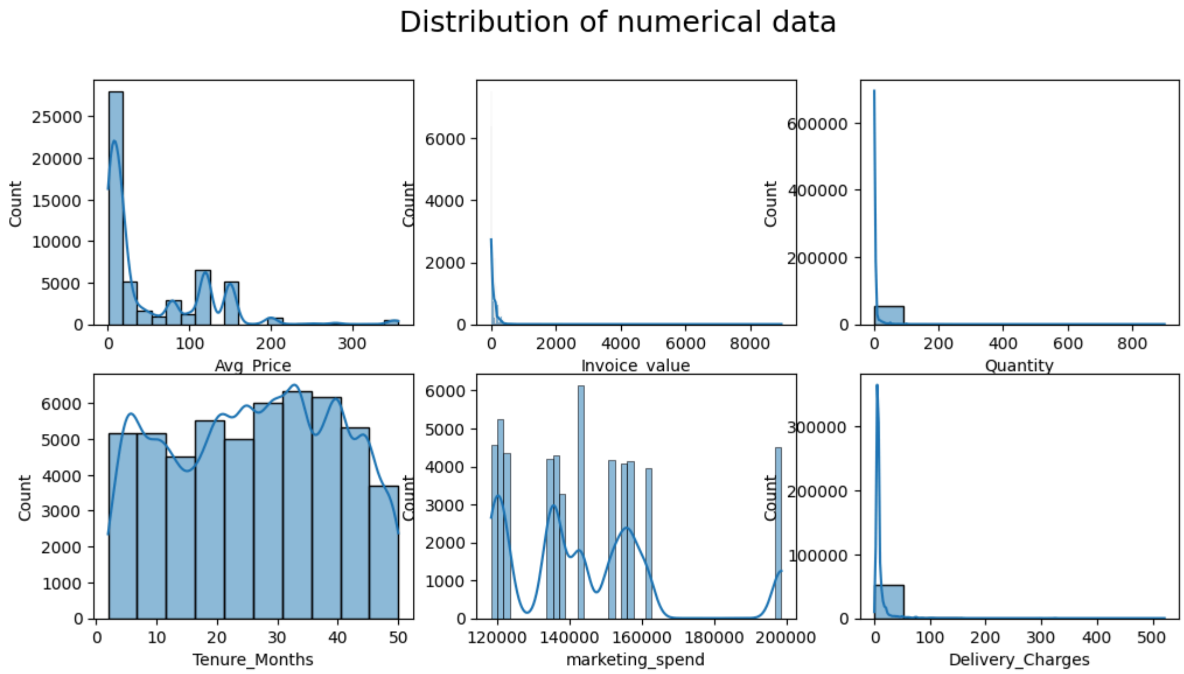
```
sales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 52924 entries, 0 to 52923
Data columns (total 19 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   CustomerID           52924 non-null  object
 1   Transaction_ID       52924 non-null  object
 2   Transaction_Date     52924 non-null  datetime64[ns]
 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
 10  Month                52924 non-null  object
 11  Gender               52924 non-null  object
 12  Location             52924 non-null  object
 13  Tenure_Months        52924 non-null  int64
 14  Coupon_Code          52924 non-null  object
 15  Discount_pct         52924 non-null  float64
 16  GST                  52924 non-null  float64
 17  marketing_spend      52924 non-null  float64
 18  Invoice_value        52924 non-null  float64
dtypes: datetime64[ns](1), float64(6), int64(2), object(10)
memory usage: 7.7+ MB
```

In [ ]:
```
sales['Discount_pct'].value_counts()
```

Out[ ]:
```
Discount_pct
20.0    17830
10.0    17470
30.0    17224
0.0       400
Name: count, dtype: int64
```

In [ ]:
```
plt.figure(figsize = (12,6))

plt.subplot(2,3,1)
sns.histplot(data=sales, x='Avg_Price', bins=20,kde=True)

plt.subplot(2,3,2)
sns.histplot(data=sales, x='Invoice_value',kde=True)

plt.subplot(2,3,3)
sns.histplot(data=sales, x='Quantity',bins=10, kde=True)

plt.subplot(2,3,4)
sns.histplot(data=sales, x='Tenure_Months',bins=10, kde=True)

plt.subplot(2,3,5)
sns.histplot(data=sales, x='marketing_spend', kde=True)

plt.subplot(2,3,6)
sns.histplot(data=sales, x='Delivery_Charges', bins=10, kde=True)

plt.suptitle("Distribution of numerical data", size = 18, fontweight = "medium")
plt.show()
```

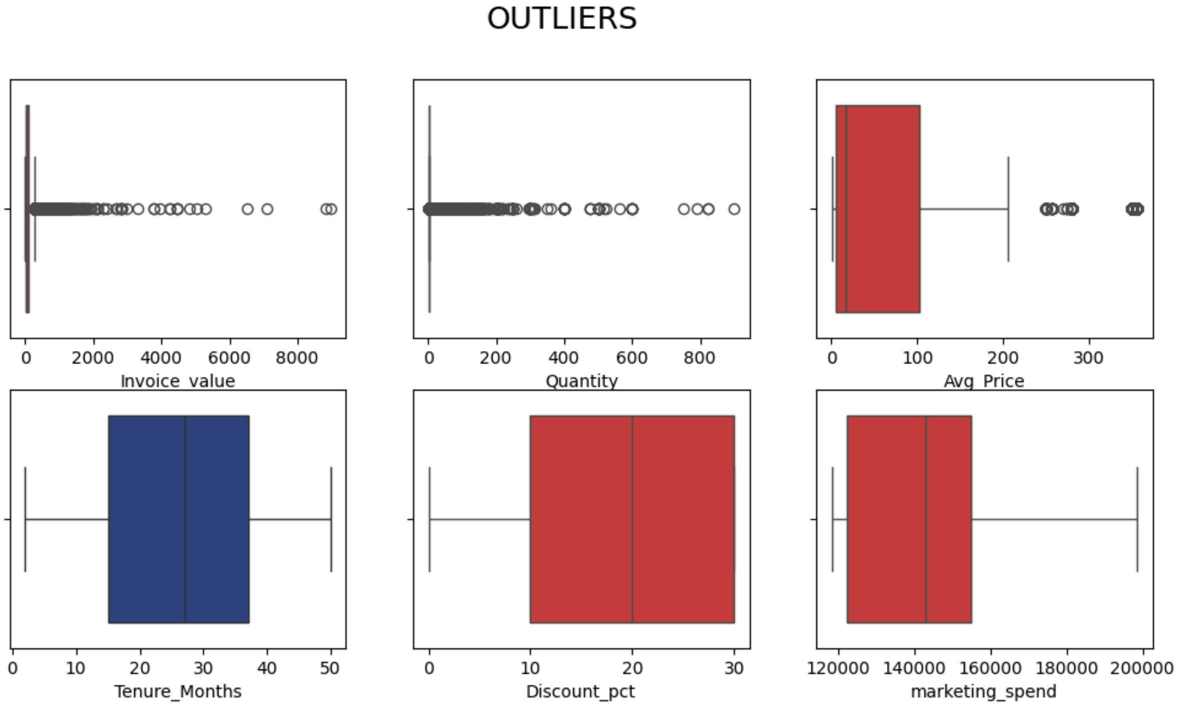


Observations

1. Avg_Price, Invoice_value, Quantity and Delivery_Charges follows Log-Normal distribution.
2. Tenure_months observed to follow a uniform distribution
3. marketing_spend data shows a multi-modal distribution

In [ ]:
```
# Checking outliers using boxplot

aero_blue = "#243e8d"
aero_grey = "#808080"
aero_red = "#db2926"

plt.figure(figsize = (12,6))

plt.subplot(2,3,1)
sns.boxplot(data = sales, x = "Invoice_value", orient = "v",color = aero_red)

plt.subplot(2,3,3)
sns.boxplot(data = sales, x = "Avg_Price", orient = "v",color = aero_red)

plt.subplot(2,3,2)
sns.boxplot(data = sales, x = "Quantity", orient = "v", color = aero_grey)

plt.subplot(2,3,4)
sns.boxplot(data = sales, x = "Tenure_Months", orient = "h", color = aero_blue)

plt.subplot(2,3,5)
sns.boxplot(data = sales, x = "Discount_pct", orient = "h", color = aero_red)

plt.subplot(2,3,6)
sns.boxplot(data = sales, x = "marketing_spend", orient = "h", color = aero_red)

plt.suptitle("OUTLIERS", size = 18, fontweight = "medium")
plt.show()
```

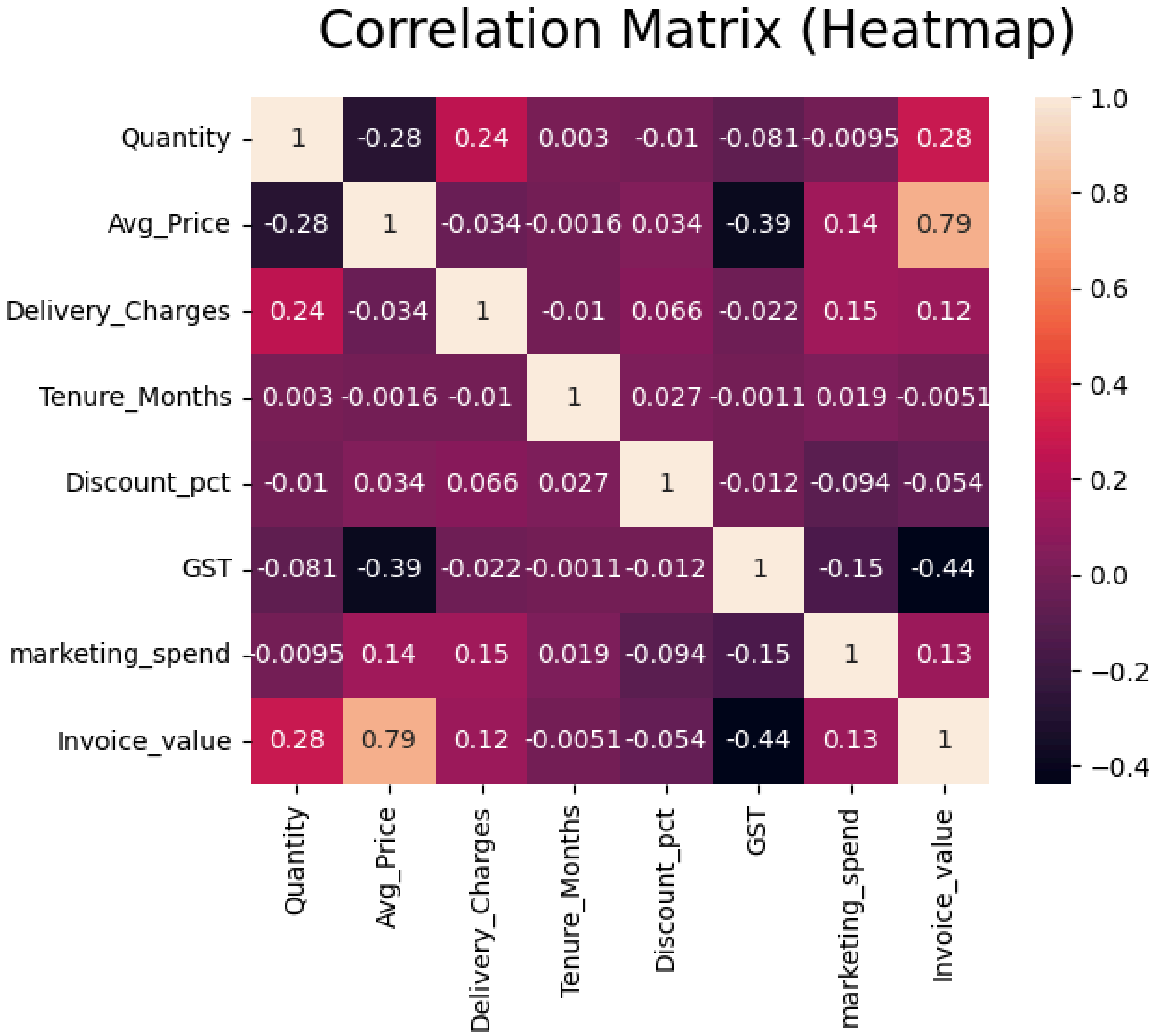
```
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:1608: UserWarning: Vertic
al orientation ignored with only `x` specified.
  warnings.warn(single_var_warning.format("Vertical", "x"))
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:1608: UserWarning: Vertic
al orientation ignored with only `x` specified.
  warnings.warn(single_var_warning.format("Vertical", "x"))
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:1608: UserWarning: Vertic
al orientation ignored with only `x` specified.
  warnings.warn(single_var_warning.format("Vertical", "x"))
```



Observations

1. avg_price, Invoice_value and Quantity observed to have large number of outliers on the right side. Which explains there are less frequent purchases with large quantity and higher invoice_values
2. The average tenure of customers engaging with the purchasing observed to be between 15 to 38 months
3. Most of the marketing revenue spent was observed to be between USD 120000 and USD 160000

In [ ]:
```
sns.heatmap(sales.corr(numeric_only=True, method='spearman'), annot = True)

plt.suptitle("Correlation Matrix (Heatmap)", size = 20, fontweight = "medium")
plt.show()
```



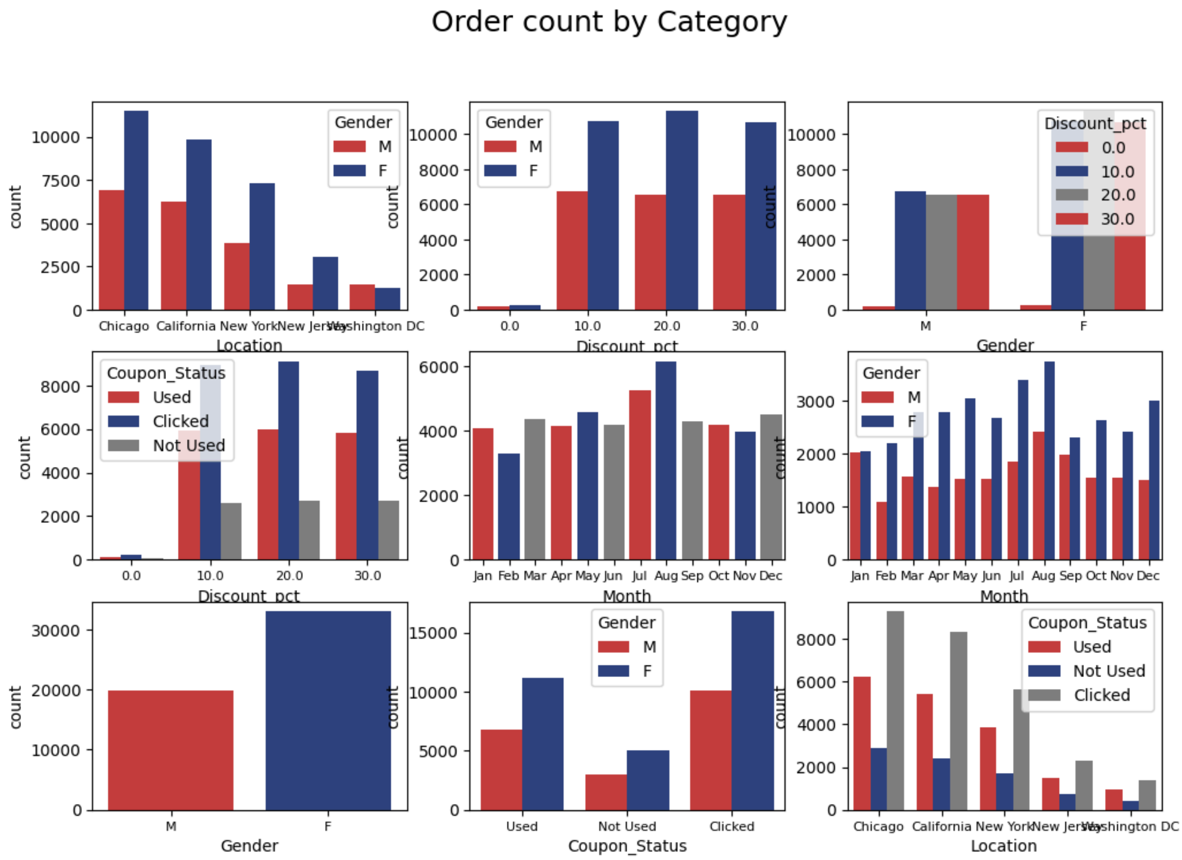
Observations

1. No significant positive correlations observed between marketing spend, Quantity, Discount percentages and price/Invoice values

In [ ]:
```
plt.figure(figsize = (12,8))

aero_blue = "#243e8d"
aero_grey = "#808080"
aero_red = "#db2926"
colors = [aero_red, aero_blue, aero_grey]

plt.subplot(3,3,1)
sns.countplot(data=sales, x='Location', hue='Gender', palette=colors)
plt.xticks(fontsize=8)

plt.subplot(3,3,2)
sns.countplot(data=sales, x='Discount_pct', hue='Gender', palette=colors)
plt.xticks(fontsize=8)

plt.subplot(3,3,3)
sns.countplot(data=sales, x='Gender', hue='Discount_pct', palette=colors)
plt.xticks(fontsize=8)

plt.subplot(3,3,4)
sns.countplot(data=sales, x='Discount_pct', hue='Coupon_Status', palette=colors)
plt.xticks(fontsize=8)

plt.subplot(3,3,5)
```

```
sns.countplot(data=sales, x='Month', palette=colors)
plt.xticks(fontsize=8)

plt.subplot(3,3,6)
sns.countplot(data=sales, x='Month', hue='Gender', palette=colors)
plt.xticks(fontsize=8)

plt.subplot(3,3,7)
sns.countplot(data=sales, x='Gender', palette=colors)
plt.xticks(fontsize=8)

plt.subplot(3,3,8)
sns.countplot(data=sales, x='Coupon_Status', hue='Gender', palette=colors)
plt.xticks(fontsize=8)

plt.subplot(3,3,9)
sns.countplot(data=sales, x='Location', hue='Coupon_Status', palette=colors)
plt.xticks(fontsize=8)

plt.suptitle("Order count by Category", size = 18, fontweight = "medium")
plt.show()
```

```
<ipython-input-195-f69cf9eca18d>:9: UserWarning: The palette list has more values
(3) than needed (2), which may not be intended.
  sns.countplot(data=sales, x='Location', hue='Gender', palette=colors)
<ipython-input-195-f69cf9eca18d>:13: UserWarning: The palette list has more values
(3) than needed (2), which may not be intended.
  sns.countplot(data=sales, x='Discount_pct', hue='Gender', palette=colors)
<ipython-input-195-f69cf9eca18d>:17: UserWarning:
The palette list has fewer values (3) than needed (4) and will cycle, which may pr
oduce an uninterpretable plot.
  sns.countplot(data=sales, x='Gender', hue='Discount_pct', palette=colors)
<ipython-input-195-f69cf9eca18d>:25: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.
14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=sales, x='Month', palette=colors)
<ipython-input-195-f69cf9eca18d>:25: UserWarning:
The palette list has fewer values (3) than needed (12) and will cycle, which may p
roduce an uninterpretable plot.
  sns.countplot(data=sales, x='Month', palette=colors)
<ipython-input-195-f69cf9eca18d>:29: UserWarning: The palette list has more values
(3) than needed (2), which may not be intended.
  sns.countplot(data=sales, x='Month', hue='Gender', palette=colors)
<ipython-input-195-f69cf9eca18d>:33: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.
14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=sales, x='Gender', palette=colors)
<ipython-input-195-f69cf9eca18d>:33: UserWarning: The palette list has more values
(3) than needed (2), which may not be intended.
  sns.countplot(data=sales, x='Gender', palette=colors)
<ipython-input-195-f69cf9eca18d>:37: UserWarning: The palette list has more values
(3) than needed (2), which may not be intended.
  sns.countplot(data=sales, x='Coupon_Status', hue='Gender', palette=colors)
```

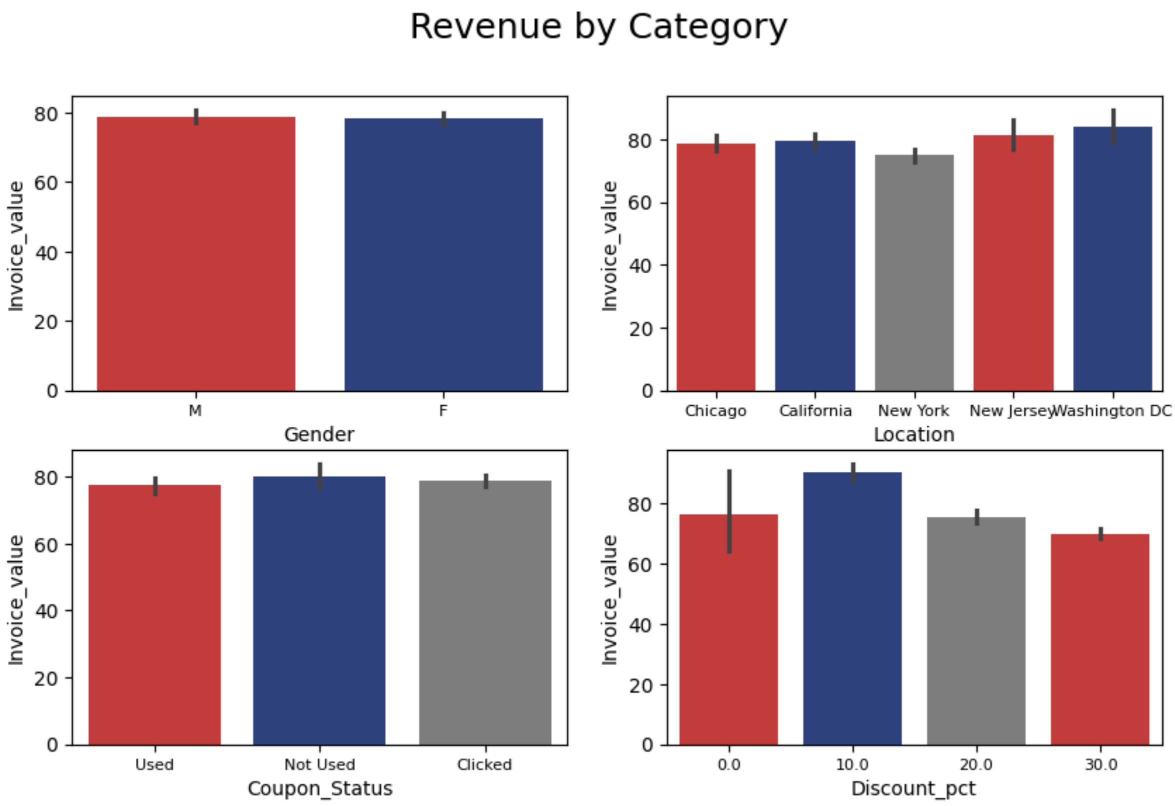


Observations

1. Most number of orders are placed from Chicago, California and New York regions having most number of customers who engaged with coupons
2. Female customers tend to purchase more across Chicago, California and New York with most purchase done between the month of March and August

In [ ]:
```
plt.figure(figsize = (10,6))

aero_blue = "#243e8d"
aero_grey = "#808080"
aero_red = "#db2926"
colors = [aero_red, aero_blue, aero_grey]

plt.subplot(2,2,1)
sns.barplot(data=sales, x='Gender', y='Invoice_value', palette=colors)
plt.xticks(fontsize=8)

plt.subplot(2,2,2)
sns.barplot(data=sales, x='Location', y='Invoice_value', palette=colors)
plt.xticks(fontsize=8)

plt.subplot(2,2,3)
sns.barplot(data=sales, x='Coupon_Status', y='Invoice_value', palette=colors)
plt.xticks(fontsize=8)

plt.subplot(2,2,4)
sns.barplot(data=sales, x='Discount_pct', y='Invoice_value', palette=colors)
plt.xticks(fontsize=8)

plt.suptitle("Revenue by Category", size = 18, fontweight = "medium")
plt.show()
```

```
<ipython-input-196-43c874c95f2b>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.
14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(data=sales, x='Gender', y='Invoice_value', palette=colors)
<ipython-input-196-43c874c95f2b>:9: UserWarning: The palette list has more values
(3) than needed (2), which may not be intended.
  sns.barplot(data=sales, x='Gender', y='Invoice_value', palette=colors)
<ipython-input-196-43c874c95f2b>:13: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.
14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(data=sales, x='Location', y='Invoice_value', palette=colors)
<ipython-input-196-43c874c95f2b>:13: UserWarning:
The palette list has fewer values (3) than needed (5) and will cycle, which may pr
oduce an uninterpretable plot.
  sns.barplot(data=sales, x='Location', y='Invoice_value', palette=colors)
<ipython-input-196-43c874c95f2b>:17: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.
14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(data=sales, x='Coupon_Status', y='Invoice_value', palette=colors)
<ipython-input-196-43c874c95f2b>:21: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.
14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(data=sales, x='Discount_pct', y='Invoice_value', palette=colors)
<ipython-input-196-43c874c95f2b>:21: UserWarning:
The palette list has fewer values (3) than needed (4) and will cycle, which may pr
oduce an uninterpretable plot.
  sns.barplot(data=sales, x='Discount_pct', y='Invoice_value', palette=colors)
```

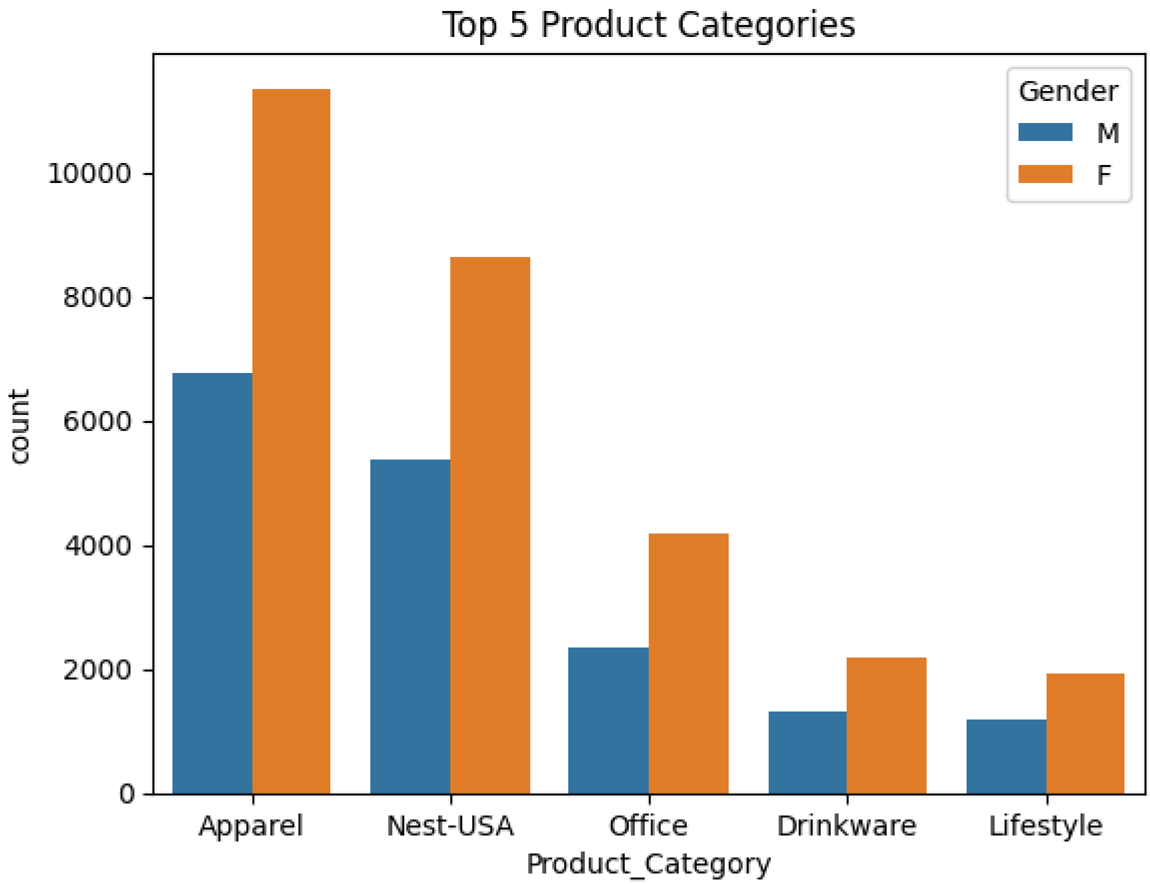


Observations

1. There is no difference in the overall purchase value between male and female customers, Locations, and Coupon_status
2. Discount of 10% is observed to contribute more revenue compared to 20% and 30% discount percentages

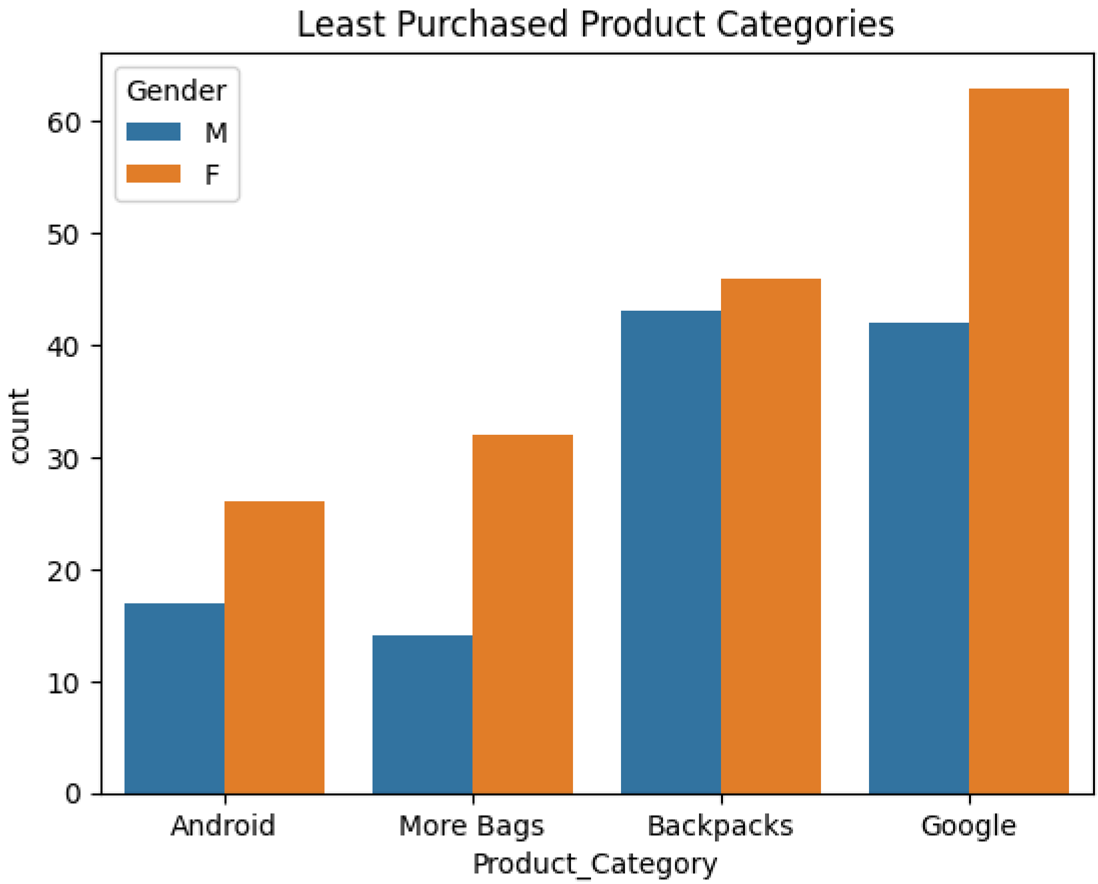
In [ ]:
```
top_category = sales['Product_Category'].value_counts(ascending=False)
plt.title('Top 5 Product Categories')
sns.countplot(data=sales, x='Product_Category', order = top_category.index[:5], hue
```

Out[ ]:
```
<Axes: title={'center': 'Top 5 Product Categories'}, xlabel='Product_Category', yl
abel='count'>
```



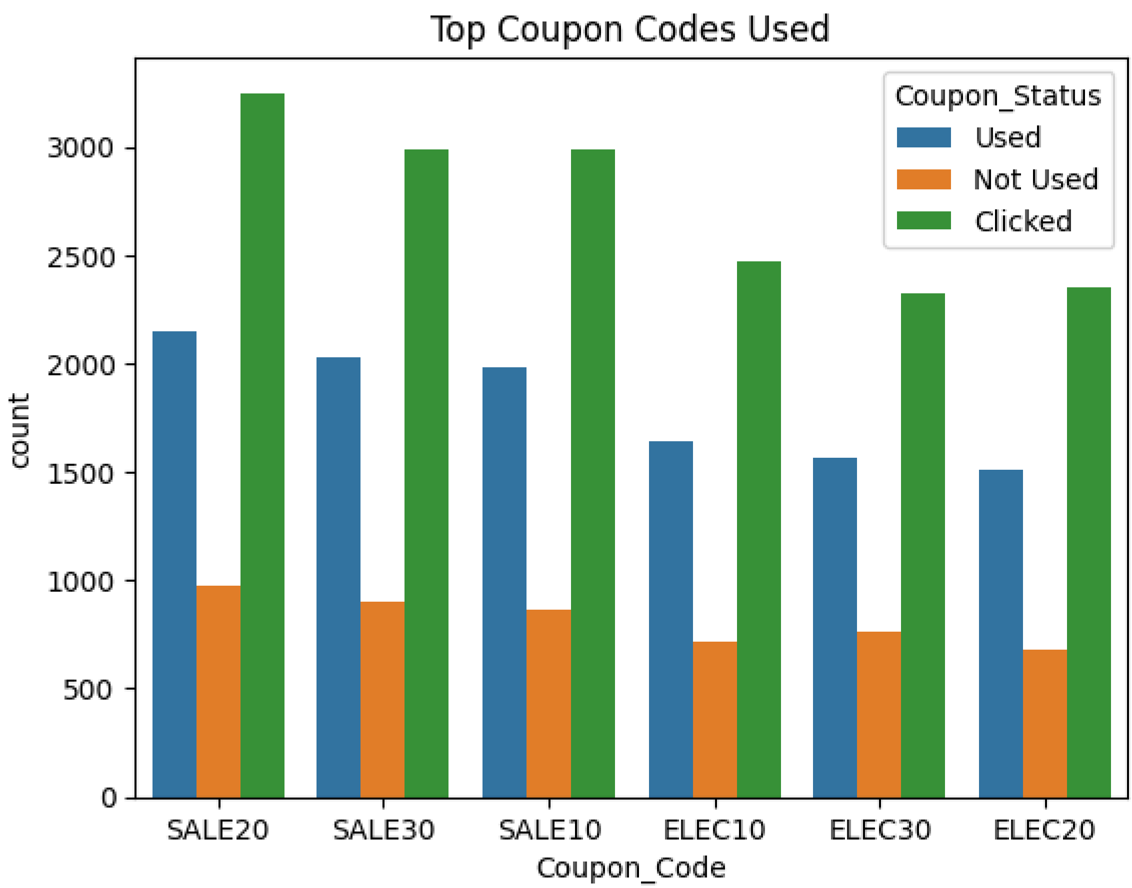
In [ ]:
```
plt.title('Least Purchased Product Categories')
sns.countplot(data=sales, x='Product_Category', order = top_category.index[-1:-5:-1
```

Out[ ]:
```
<Axes: title={'center': 'Least Purchased Product Categories'}, xlabel='Product_Cat
egory', ylabel='count'>
```



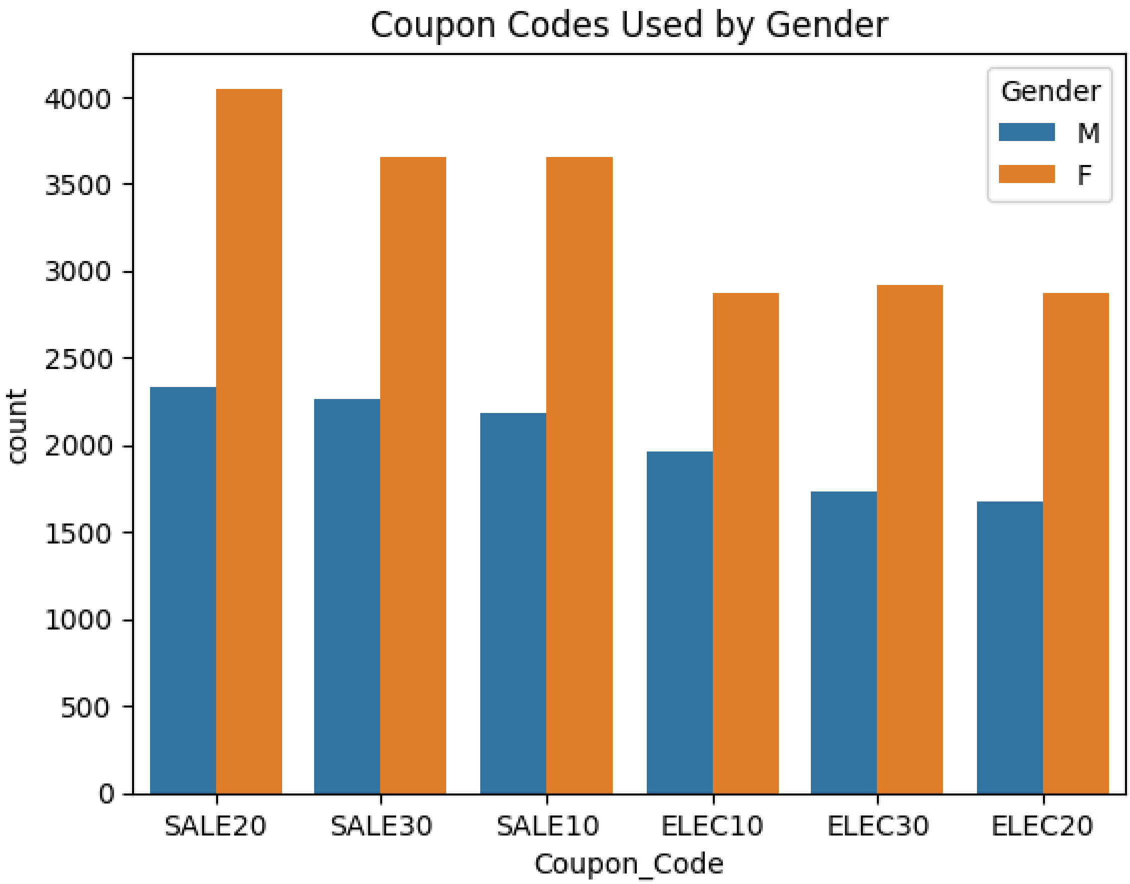
In [ ]:
```
top_coupons = sales['Coupon_Code'].value_counts(ascending=False)
plt.title('Top Coupon Codes Used')
sns.countplot(data=sales, x='Coupon_Code', order = top_coupons.index[:6], hue='Coup
```

Out[ ]:
```
<Axes: title={'center': 'Top Coupon Codes Used'}, xlabel='Coupon_Code', ylabel='co
unt'>
```



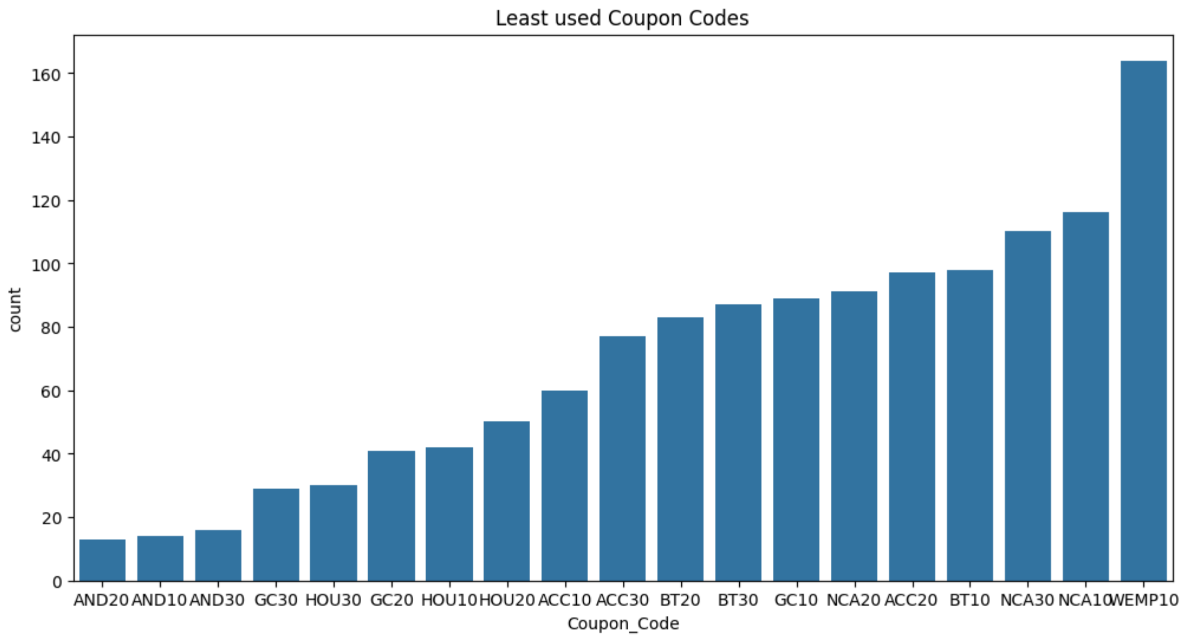
In [ ]:
```
plt.title('Coupon Codes Used by Gender')
sns.countplot(data=sales, x='Coupon_Code', order = top_coupons.index[:6], hue='Genc
```

Out[ ]:
```
<Axes: title={'center': 'Coupon Codes Used by Gender'}, xlabel='Coupon_Code', ylab
el='count'>
```



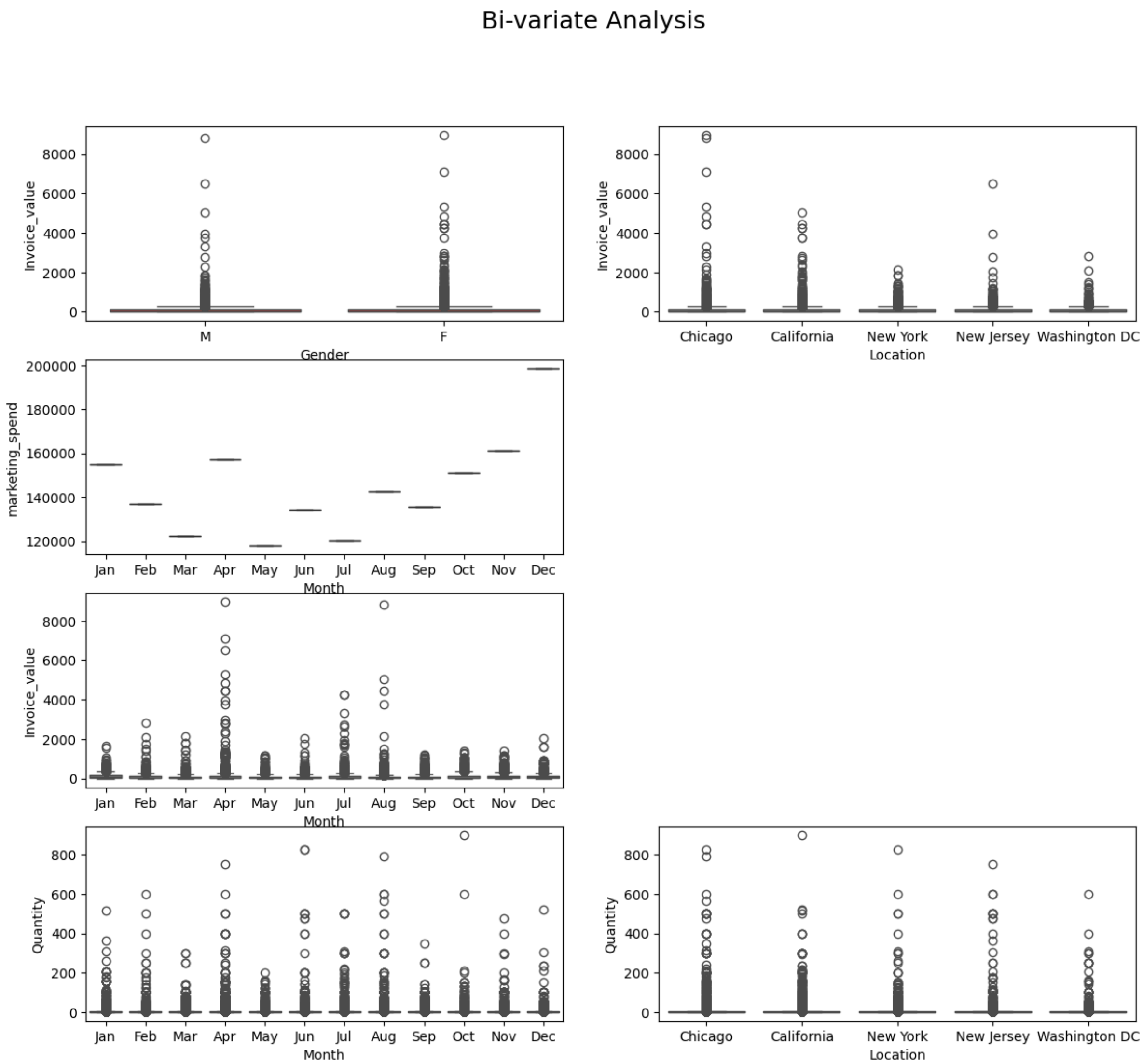
In [ ]:
```
plt.figure(figsize=(12,6))
plt.title('Least used Coupon Codes')
sns.countplot(data=sales, x='Coupon_Code', order = top_coupons.index[-1:-20:-1])
```

Out[ ]:
```
<Axes: title={'center': 'Least used Coupon Codes'}, xlabel='Coupon_Code', ylabel
='count'>
```



In [ ]:
```
aero_blue = "#243e8d"
aero_grey = "#808080"
aero_red = "#db2926"
```

```
plt.figure(figsize = (14,12))

plt.subplot(4,2,1)
sns.boxplot(data=sales, x='Gender', y='Invoice_value', color = aero_red)

plt.subplot(4,2,2)
sns.boxplot(data=sales, x='Location', y='Invoice_value', color = aero_grey)

plt.subplot(4,2,3)
sns.boxplot(data=sales, x='Month', y='marketing_spend', color = aero_blue)

plt.subplot(4,2,5)
sns.boxplot(data=sales, x='Month', y='Invoice_value', color = aero_grey)

plt.subplot(4,2,7)
sns.boxplot(data=sales, x='Month', y='Quantity', color = aero_red)

plt.subplot(4,2,8)
sns.boxplot(data=sales, x='Location', y='Quantity', color = aero_red)


plt.suptitle("Bi-variate Analysis", size = 18, fontweight = "medium")
plt.show()
```



Observations

1. Invoive values, marketing spend and Quantity observed to show significant outliers across Month, Gender and Locations

Basic Metrics Analysis (KPIs)

In [ ]:
```
# Average Order Value
aov = sales['Invoice_value'].sum() / sales['Transaction_ID'].nunique()
print(f'Average Order Value : ${round(aov,2)}')
```

```
Average Order Value : $165.91
```

In [ ]:
```
# Average order value across different Discount percentages

aov_0 = sales[sales['Discount_pct']==0.0]['Invoice_value'].sum() / sales[sales['Dis
aov_10 = sales[sales['Discount_pct']==10.0]['Invoice_value'].sum() / sales[sales['D
aov_20 = sales[sales['Discount_pct']==20.0]['Invoice_value'].sum() / sales[sales['D
aov_30 = sales[sales['Discount_pct']==30.0]['Invoice_value'].sum() / sales[sales['D

print(f'Average Order Value at 0% discount  : ${round(aov_0,2)}')
print(f'Average Order Value at 10% discount : ${round(aov_10,2)}')
print(f'Average Order Value at 20% discount : ${round(aov_20,2)}')
print(f'Average Order Value at 30% discount : ${round(aov_30,2)}')
```

```
Average Order Value at 0% discount  : $119.08
Average Order Value at 10% discount : $2176.0
Average Order Value at 20% discount : $2066.05
Average Order Value at 30% discount : $1642.9
```

In [ ]:
```
# Customer Value = AOV * AOFR
customer_value = aov * aofr
print(f'Customer Value : ${round(customer_value,2)}')
```

```
Customer Value : $2832.34
```

In [ ]:
```
# Average Customer Lifespan

customer_lifespan = sales.groupby('CustomerID')['Transaction_Date'].agg(['min', 'ma
customer_lifespan.columns = ['CustomerID', 'first_purchase_date', 'last_purchase_da

customer_lifespan['lifespan'] = (customer_lifespan['last_purchase_date'] - customer
acl = customer_lifespan['lifespan'].mean() / 365
print(f'Average Customer Lifespan : {round(acl,2)}')
```

```
Average Customer Lifespan : 0.18
```

In [ ]:
```
# Customer Life Time Value (LTV) = Customer Value * Avg. Customer Lifespan

ltv = customer_value * acl
print(f'Customer Life Time Value : ${round(ltv,2)}')
```

```
Customer Life Time Value : $499.42
```

In [ ]:
```
# Customer Acquisition cost --> Total marketing spend / Total number of new custome
# Calculating the count of New customers per month from first purchase date

first_purchase = sales.groupby('CustomerID')['Transaction_Date'].min().reset_index(
first_purchase.rename(columns={'Transaction_Date': 'First_Purchase_Date'}, inplace=
first_purchase.head()
```

Out[ ]:

	CustomerID	First_Purchase_Date
0	12346	2019-09-15
1	12347	2019-03-24
2	12348	2019-06-22
3	12350	2019-12-14
4	12356	2019-09-15

In [ ]:

```
first_purchase['month'] = first_purchase['First_Purchase_Date'].dt.to_period('M')
new_customers_per_month = first_purchase.groupby('month')['CustomerID'].nunique().r
new_customers_per_month.head()
```

Out[ ]:

	month	CustomerID
0	2019-01	215
1	2019-02	96
2	2019-03	177
3	2019-04	163
4	2019-05	112

In [ ]:

```
# Customer Acquisition Cost

cac = marketing_spend['marketing_spend'].sum() / new_customers_per_month['CustomerI
print(f'Customer Acquisition Cost : ${round(cac,2)}')
```

```
Customer Acquisition Cost : $1180.89
```

In [ ]:

```
# CAC to LTV Ratio --> Ideally, your CAC should be about one-third or less of your
# Common Benchmark --> LTV / CAC >= 3

cac_ltv_ratio = ltv / cac
print(f'CAC to LTV Ratio : {round(cac_ltv_ratio,2)}')
```

```
CAC to LTV Ratio : 0.42
```

Cohort Analysis

In [ ]:

```
first_purchase['cohort'] = first_purchase['First_Purchase_Date'].dt.to_period('M')
sales['purchase_month'] = sales['Transaction_Date'].dt.to_period('M')

sales = pd.merge(sales, first_purchase[['CustomerID','cohort']], on='CustomerID')
```

In [ ]:

```
cohort_data = sales.groupby(['cohort', 'purchase_month']).agg(
    Customers = ('CustomerID', 'nunique'),
    Orders = ('Transaction_ID', 'count'),
    Revenue = ('Invoice_value', 'sum')
).reset_index()
cohort_data
```

Out[ ]:

	cohort	purchase_month	Customers	Orders	Revenue
0	2019-01	2019-01	215	4063	404640.73705
1	2019-01	2019-02	13	437	35012.22768
2	2019-01	2019-03	24	620	37201.79533
3	2019-01	2019-04	34	768	116014.30099
4	2019-01	2019-05	23	450	26115.65248
...	...	...	...	...	...
73	2019-10	2019-11	6	56	8416.28840
74	2019-10	2019-12	4	27	2105.46455
75	2019-11	2019-11	68	1787	189722.84568
76	2019-11	2019-12	7	33	3404.58111
77	2019-12	2019-12	106	2181	189754.48961

78 rows × 5 columns

In [ ]:

```
cohort_data['cohort_month'] = (cohort_data['purchase_month'] - cohort_data['cohort'
cohort_data
```

Out[ ]:

	cohort	purchase_month	Customers	Orders	Revenue	cohort_month
0	2019-01	2019-01	215	4063	404640.73705	0
1	2019-01	2019-02	13	437	35012.22768	1
2	2019-01	2019-03	24	620	37201.79533	2
3	2019-01	2019-04	34	768	116014.30099	3
4	2019-01	2019-05	23	450	26115.65248	4
...	...	...	...	...	...	...
73	2019-10	2019-11	6	56	8416.28840	1
74	2019-10	2019-12	4	27	2105.46455	2
75	2019-11	2019-11	68	1787	189722.84568	0
76	2019-11	2019-12	7	33	3404.58111	1
77	2019-12	2019-12	106	2181	189754.48961	0

78 rows × 6 columns

In [ ]:

```
cohort_pivot1 = cohort_data.pivot_table(
    index='cohort', columns='cohort_month', values=['Customers']
)
cohort_pivot1
```

Out[ ]:

cohort_month	Customers 0	1	2	3	4	5	6	7	8	9	10	11
cohort												
2019-01	215.0	13.0	24.0	34.0	23.0	44.0	35.0	47.0	23.0	28.0	20.0	34.0
2019-02	96.0	7.0	9.0	16.0	17.0	22.0	19.0	15.0	12.0	11.0	16.0	NaN
2019-03	177.0	18.0	35.0	25.0	32.0	33.0	22.0	22.0	15.0	19.0	NaN	NaN
2019-04	163.0	14.0	24.0	24.0	18.0	15.0	10.0	16.0	12.0	NaN	NaN	NaN
2019-05	112.0	12.0	9.0	13.0	10.0	13.0	14.0	8.0	NaN	NaN	NaN	NaN
2019-06	137.0	20.0	22.0	12.0	11.0	14.0	11.0	NaN	NaN	NaN	NaN	NaN
2019-07	94.0	13.0	4.0	6.0	11.0	9.0	NaN	NaN	NaN	NaN	NaN	NaN
2019-08	135.0	14.0	15.0	10.0	8.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-09	78.0	6.0	3.0	2.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-10	87.0	6.0	4.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-11	68.0	7.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-12	106.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [ ]:

```
cohort_pivot2 = cohort_data.pivot_table(
    index='cohort', columns='cohort_month', values=['Orders']
)
cohort_pivot2
```

Out[ ]:

cohort_month	Orders 0	1	2	3	4	5	6	7	8	9	10	11
cohort												
2019-01	4063.0	437.0	620.0	768.0	450.0	767.0	1021.0	749.0	525.0	472.0	317.0	749.0
2019-02	2847.0	143.0	160.0	360.0	319.0	691.0	387.0	523.0	175.0	216.0	393.0	NaN
2019-03	3583.0	372.0	509.0	334.0	594.0	806.0	555.0	342.0	241.0	333.0	NaN	NaN
2019-04	2850.0	233.0	222.0	431.0	316.0	285.0	142.0	370.0	166.0	NaN	NaN	NaN
2019-05	3020.0	90.0	187.0	280.0	164.0	428.0	257.0	113.0	NaN	NaN	NaN	NaN
2019-06	2461.0	226.0	215.0	214.0	148.0	332.0	158.0	NaN	NaN	NaN	NaN	NaN
2019-07	2101.0	242.0	90.0	176.0	146.0	229.0	NaN	NaN	NaN	NaN	NaN	NaN
2019-08	3155.0	90.0	119.0	213.0	114.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-09	1842.0	19.0	26.0	6.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-10	2143.0	56.0	27.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-11	1787.0	33.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-12	2181.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [ ]:

```
cohort_pivot3 = cohort_data.pivot_table(
    index='cohort', columns='cohort_month', values=['Revenue']
```

```
)
cohort_pivot3
```

Out[ ]:

cohort_month	0	1	2	3	4	5	
cohort							
2019-01	404640.73705	35012.22768	37201.79533	116014.30099	26115.65248	40370.77256	83
2019-02	243667.73252	6427.06319	12789.26894	19901.90572	18366.86237	41616.49010	19
2019-03	232376.40531	41329.21303	32685.00656	24074.97013	46342.70803	62012.19732	37
2019-04	236384.67227	20937.78912	13053.19791	29799.81371	22193.86344	23352.12824	15
2019-05	177519.77668	5360.82274	11958.23849	12591.94768	13247.86624	35561.06964	33
2019-06	151090.12360	10565.30240	11361.89248	11923.97735	9973.52640	32161.82928	11
2019-07	151017.18783	13176.14284	5596.66539	14477.13351	21141.90628	22235.61249	
2019-08	171218.55900	8170.34778	10977.43536	25138.79760	12752.55058	NaN	
2019-09	114115.61815	1916.60076	2218.10240	497.01589	NaN	NaN	
2019-10	214982.89234	8416.28840	2105.46455	NaN	NaN	NaN	
2019-11	189722.84568	3404.58111	NaN	NaN	NaN	NaN	
2019-12	189754.48961	NaN	NaN	NaN	NaN	NaN	

In [ ]:

```
# Customer Cohort Retention Rate

Customer_cohort_sizes = cohort_pivot1.iloc[:, 0]
Customer_retention_rate = cohort_pivot1.divide(Customer_cohort_sizes, axis=0)*100
Customer_retention_rate
```

Out[ ]:

cohort_month cohort	0	1	2	3	4	5	6	7
2019-01	100.0	6.046512	11.162791	15.813953	10.697674	20.465116	16.279070	21.860465
2019-02	100.0	7.291667	9.375000	16.666667	17.708333	22.916667	19.791667	15.625000
2019-03	100.0	10.169492	19.774011	14.124294	18.079096	18.644068	12.429379	12.429379
2019-04	100.0	8.588957	14.723926	14.723926	11.042945	9.202454	6.134969	9.815951
2019-05	100.0	10.714286	8.035714	11.607143	8.928571	11.607143	12.500000	7.142857
2019-06	100.0	14.598540	16.058394	8.759124	8.029197	10.218978	8.029197	NaN
2019-07	100.0	13.829787	4.255319	6.382979	11.702128	9.574468	NaN	NaN
2019-08	100.0	10.370370	11.111111	7.407407	5.925926	NaN	NaN	NaN
2019-09	100.0	7.692308	3.846154	2.564103	NaN	NaN	NaN	NaN
2019-10	100.0	6.896552	4.597701	NaN	NaN	NaN	NaN	NaN
2019-11	100.0	10.294118	NaN	NaN	NaN	NaN	NaN	NaN
2019-12	100.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [ ]:

```
# Orders Cohort Retention Rate

Orders_cohort_sizes = cohort_pivot2.iloc[:, 0]
Orders_retention_rate = cohort_pivot2.divide(Orders_cohort_sizes, axis=0)*100
Orders_retention_rate
```

Out[ ]:

cohort_month cohort	0	1	2	3	4	5	6	7
2019-01	100.0	10.755599	15.259660	18.902289	11.075560	18.877677	25.129215	18.434654
2019-02	100.0	5.022831	5.619951	12.644889	11.204777	24.271163	13.593256	18.370214
2019-03	100.0	10.382361	14.205973	9.321797	16.578286	22.495116	15.489813	9.545074
2019-04	100.0	8.175439	7.789474	15.122807	11.087719	10.000000	4.982456	12.982456
2019-05	100.0	2.980132	6.192053	9.271523	5.430464	14.172185	8.509934	3.741722
2019-06	100.0	9.183259	8.736286	8.695652	6.013816	13.490451	6.420154	NaN
2019-07	100.0	11.518325	4.283674	8.376963	6.949072	10.899572	NaN	NaN
2019-08	100.0	2.852615	3.771791	6.751189	3.613312	NaN	NaN	NaN
2019-09	100.0	1.031488	1.411509	0.325733	NaN	NaN	NaN	NaN
2019-10	100.0	2.613159	1.259916	NaN	NaN	NaN	NaN	NaN
2019-11	100.0	1.846670	NaN	NaN	NaN	NaN	NaN	NaN
2019-12	100.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [ ]:
```
# Revenue Cohort Retention Rate

Revenue_cohort_sizes = cohort_pivot3.iloc[:, 0]
Revenue_retention_rate = cohort_pivot3.divide(Revenue_cohort_sizes, axis=0)*100
Revenue_retention_rate
```

Out[ ]:

cohort_month cohort	0	1	2	3	4	5	6	7
2019-01	100.0	8.652670	9.193784	28.670940	6.454034	9.976942	20.748942	11.001688
2019-02	100.0	2.637634	5.248651	8.167641	7.537667	17.079196	8.203418	14.328957
2019-03	100.0	17.785460	14.065544	10.360333	19.942949	26.686099	16.152215	16.890115
2019-04	100.0	8.857507	5.522015	12.606492	9.388876	9.878867	6.543023	20.904539
2019-05	100.0	3.019845	6.736285	7.093265	7.462755	20.032173	18.686312	4.937824
2019-06	100.0	6.992715	7.519944	7.891963	6.601045	21.286520	7.834814	NaN
2019-07	100.0	8.724929	3.705979	9.586414	13.999669	14.723895	NaN	NaN
2019-08	100.0	4.771882	6.411358	14.682285	7.448112	NaN	NaN	NaN
2019-09	100.0	1.679525	1.943733	0.435537	NaN	NaN	NaN	NaN
2019-10	100.0	3.914864	0.979364	NaN	NaN	NaN	NaN	NaN
2019-11	100.0	1.794502	NaN	NaN	NaN	NaN	NaN	NaN
2019-12	100.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Observations

1. As we observe the cohort sizes, we see there is inconsistancy in the acquisition of new customers / new orders / increase in revenue each month
2. The Customer retention rates for all the cohorts majorly lie between 9% and 20%. January, Febuary and March Cohorts observed to have better retention rates compared to other months
3. The order retention rates for January and March months were better compared to other months which are between 10% and 20% on an average
4. The revenue retention rates for January and March months were better compared to other months which are between 10% and 20% on an average
5. Overall, January and March month Cohorts have better retention rate (however less than the ideal requirement)

RFM Analysis

In [ ]:
```
# Calculate frequency (number of transactions) for each customer
frequency = sales.groupby('CustomerID')['Transaction_ID'].nunique().reset_index()
frequency.rename(columns={'Transaction_ID': 'Frequency'}, inplace=True)
frequency.head()
```

Out[ ]:

	CustomerID	Frequency
0	12346	1
1	12347	31
2	12348	8
3	12350	11
4	12356	13

In [ ]:

```
monetary = sales.groupby('CustomerID')['Invoice_value'].sum().reset_index()
monetary.rename(columns={'Invoice_value': 'Monetary'}, inplace=True)
monetary.head()
```

Out[ ]:

	CustomerID	Monetary
0	12346	24.98174
1	12347	11425.15580
2	12348	1304.77620
3	12350	1055.83394
4	12356	1115.96086

In [ ]:

```
recency = sales.groupby('CustomerID')['Transaction_Date'].max().reset_index()
recency.rename(columns={'Transaction_Date': 'Last_Purchase_Date'}, inplace=True)
recency['Recency'] = (recency['Last_Purchase_Date'].max() - recency['Last_Purchase_
recency.head()
```

Out[ ]:

	CustomerID	Last_Purchase_Date	Recency
0	12346	2019-09-15	107
1	12347	2019-11-02	59
2	12348	2019-10-19	73
3	12350	2019-12-14	17
4	12356	2019-09-15	107

In [ ]:

```
rfm = pd.merge(frequency, monetary, on='CustomerID')
rfm = pd.merge(rfm, recency.drop_duplicates(), on='CustomerID')
rfm.drop('Last_Purchase_Date', axis=1, inplace=True)
rfm.head()
```

Out[ ]:

	CustomerID	Frequency	Monetary	Recency
0	12346	1	24.98174	107
1	12347	31	11425.15580	59
2	12348	8	1304.77620	73
3	12350	11	1055.83394	17
4	12356	13	1115.96086	107

In [ ]:
```
quantiles = rfm.quantile(q=[0.25, 0.5, 0.75])
quantiles
```

Out[ ]:

	CustomerID	Frequency	Monetary	Recency
0.25	13830.50	5.0	568.407542	55.0
0.50	15300.00	11.0	1567.683615	131.0
0.75	16882.25	23.0	3506.883418	220.0

In [ ]:
```
def r_score(x):
    if x <= quantiles['Recency'][0.25]:
        return 4
    elif x <= quantiles['Recency'][0.5]:
        return 3
    elif x <= quantiles['Recency'][0.75]:
        return 2
    else:
        return 1
def f_score(x):
    if x <= quantiles['Frequency'][0.25]:
        return 4
    elif x <= quantiles['Frequency'][0.5]:
        return 3
    elif x <= quantiles['Frequency'][0.75]:
        return 2
    else:
        return 1
def m_score(x):
    if x <= quantiles['Monetary'][0.25]:
        return 4
    elif x <= quantiles['Monetary'][0.5]:
        return 3
    elif x <= quantiles['Monetary'][0.75]:
        return 2
    else:
        return 1

rfm['R'] = rfm['Recency'].apply(r_score)
rfm['F'] = rfm['Frequency'].apply(f_score)
rfm['M'] = rfm['Monetary'].apply(m_score)
```

In [ ]:
```
rfm['RFM_Score'] = rfm['R'].map(str) + rfm['F'].map(str) + rfm['M'].map(str)
rfm
```

Out[ ]:

	CustomerID	Frequency	Monetary	Recency	R	F	M	RFM_Score
0	12346	1	24.98174	107	3	4	4	344
1	12347	31	11425.15580	59	3	1	1	311
2	12348	8	1304.77620	73	3	3	3	333
3	12350	11	1055.83394	17	4	3	3	433
4	12356	13	1115.96086	107	3	2	3	323
...	...	...	...	...	...	...	...	...
1463	18259	3	538.07980	270	1	4	4	144
1464	18260	19	2014.82033	87	3	2	2	322
1465	18269	2	104.16092	194	2	4	4	244
1466	18277	1	295.02000	69	3	4	4	344
1467	18283	53	6253.06527	82	3	1	1	311

1468 rows × 8 columns

In [ ]:

```
seg_map = {
    r'[1-2][1-2][1-5]': 'lost',
    r'[1-2][3-4][3-4]': 'at_Risk',
    r'[1-2][4-5][3-5]': 'cant_loose',
    r'[1-3][1-3][2-5]': 'need_attention',
    r'[3-4][4-5][1-5]': 'loyal_customers',
    r'5[4-5][4-5]': 'champions',
    r'4[2-5][2-5]': 'promising',
    r'[3-5][1-2][1-2]': 'new_customers',
    r'[1-2][3-4][1-5]': 'hibernating'
}
rfm['RFM_Segment'] = rfm['RFM_Score'].replace(seg_map, regex=True)
rfm.head()
```

Out[ ]:

	CustomerID	Frequency	Monetary	Recency	R	F	M	RFM_Score	RFM_Segment
0	12346	1	24.98174	107	3	4	4	344	loyal_customers
1	12347	31	11425.15580	59	3	1	1	311	new_customers
2	12348	8	1304.77620	73	3	3	3	333	need_attention
3	12350	11	1055.83394	17	4	3	3	433	promising
4	12356	13	1115.96086	107	3	2	3	323	need_attention

In [ ]:

```
rfm[["RFM_Segment", "Recency", "Frequency", "Monetary"]].groupby("RFM_Segment").agg
```

Out[ ]:

	Recency			Frequency			Monetary		
	mean	count	max	mean	count	max	mean	count	max
RFM_Segment									
at_Risk	232.158654	416	364	4.579327	416	11	542.565426	416	1561.34384
hibernating	267.166667	6	360	4.166667	6	5	3287.941275	6	6819.53292
lost	226.111940	268	363	25.861940	268	177	3904.771090	268	34684.67341
loyal_customers	68.875862	145	131	2.875862	145	5	424.919352	145	2195.19354
need_attention	120.943396	212	363	12.735849	212	33	1773.419617	212	3479.13864
new_customers	51.156489	262	130	48.240458	262	328	8167.342636	262	71702.7843C
promising	25.232704	159	54	12.666667	159	23	1814.722874	159	3444.33167

Observations

1. Considering loyal_customers and promising as active customers, ~300 customers are actively purchasing by placing ~2200 orders in a span of every ~50 days inducing an average revenue of USD 330000
2. More than ~720 customers are under need_attention, at_Risk and hibernate segments who are not engaged enough to continue to purchase
3. There are ~262 new customers added between January and December months

Churn Analysis

In [ ]:

```
# Churn Rate --> Considering 'lost' & 'at_Risk' segments as churned customers
churn_rate = round(((rfm[rfm['RFM_Segment']=='lost'].shape[0]) / rfm.shape[0])* 10(
print("Total customers churned :",rfm[rfm['RFM_Segment']=='lost'].shape[0])
print(f'Total customers : {rfm.shape[0]}')
print(f'Customer Churn Rate = {churn_rate}%')
```

```
Total customers churned : 268
Total customers : 1468
Customer Churn Rate = 18.26%
```

In [ ]:

```
sales = sales.merge(rfm[['CustomerID','RFM_Segment']], on='CustomerID', how='left')
```

In [ ]:

```
# Number of churned customers by month
sales[sales['RFM_Segment']=='lost'].groupby('Month')['CustomerID'].nunique()
```

Out[ ]:

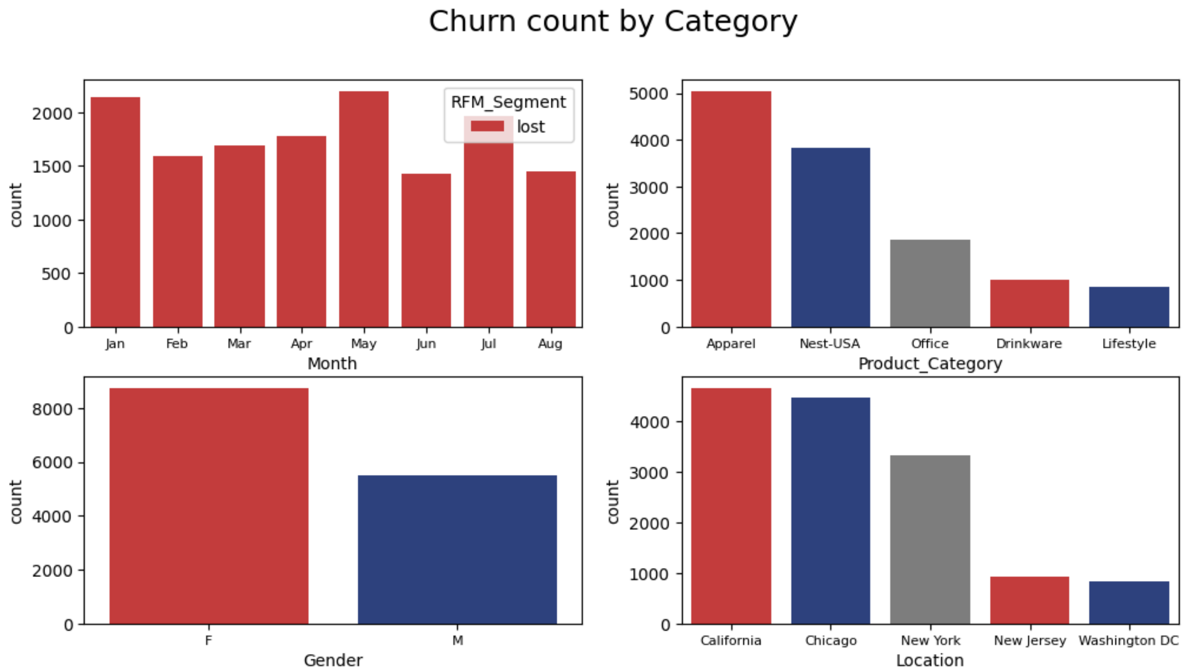
```
Month
Apr    57
Aug    47
Feb    37
Jan    57
Jul    54
Jun    59
Mar    52
May    59
Name: CustomerID, dtype: int64
```

In [ ]:

```
# Churn analysis by Month, Product Categoty, Gender & Location

churned_customers = sales[sales['RFM_Segment']=='lost']
```

```
churn_by_product_category = churned_customers['Product_Category'].value_counts(asce
churn_by_gender = churned_customers['Gender'].value_counts(ascending=False)
churn_by_location = churned_customers['Location'].value_counts(ascending=False)

colors = [aero_red, aero_blue, aero_grey]
plt.figure(figsize=(12,6))

plt.subplot(2,2,1)
sns.countplot(data=churned_customers, x='Month', hue='RFM_Segment', palette=colors)
plt.xticks(fontsize=8)

plt.subplot(2,2,2)
sns.countplot(data=churned_customers, x='Product_Category', order=churn_by_product_
plt.xticks(fontsize=8)

plt.subplot(2,2,3)
sns.countplot(data=churned_customers, x='Gender', order=churn_by_gender.index, pale
plt.xticks(fontsize=8)

plt.subplot(2,2,4)
sns.countplot(data=churned_customers, x='Location', order=churn_by_location.index,
plt.xticks(fontsize=8)

plt.suptitle("Churn count by Category", size = 18, fontweight = "medium")
plt.show()
```

```
<ipython-input-210-5c8722dca68f>:13: UserWarning: The palette list has more values
(3) than needed (1), which may not be intended.
  sns.countplot(data=churned_customers, x='Month', hue='RFM_Segment', palette=colo
rs)
<ipython-input-210-5c8722dca68f>:17: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.
14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=churned_customers, x='Product_Category', order=churn_by_produ
ct_category.index[:5], palette=colors)
<ipython-input-210-5c8722dca68f>:17: UserWarning:
The palette list has fewer values (3) than needed (5) and will cycle, which may pr
oduce an uninterpretable plot.
  sns.countplot(data=churned_customers, x='Product_Category', order=churn_by_produ
ct_category.index[:5], palette=colors)
<ipython-input-210-5c8722dca68f>:21: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.
14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=churned_customers, x='Gender', order=churn_by_gender.index, p
alette=colors)
<ipython-input-210-5c8722dca68f>:21: UserWarning: The palette list has more values
(3) than needed (2), which may not be intended.
  sns.countplot(data=churned_customers, x='Gender', order=churn_by_gender.index, p
alette=colors)
<ipython-input-210-5c8722dca68f>:25: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.
14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=churned_customers, x='Location', order=churn_by_location.inde
x, palette=colors)
<ipython-input-210-5c8722dca68f>:25: UserWarning:
The palette list has fewer values (3) than needed (5) and will cycle, which may pr
oduce an uninterpretable plot.
  sns.countplot(data=churned_customers, x='Location', order=churn_by_location.inde
x, palette=colors)
```



Observations

1. The Customer Churn rate is at 18.26%
2. Female customers tend to churn more than male customers
3. California, Chicago and New York regions observed to have more churn rates
4. As observed, customers purchasing product categories - Apparel and Nest-USA have churned more with no further purchases

Market Basket Analysis (Using One-hot Encoding)

In [ ]:
```
basket = sales.groupby(['Transaction_ID', 'Product_Description'])['Product_Descript
basket = basket.applymap(lambda x: 1 if x > 0 else 0)
```

In [ ]:
```
frequent_itemsets = apriori(basket, min_support=1.0, use_colnames=True)
frequent_itemsets
```

```
/usr/local/lib/python3.10/dist-packages/mlxtend/frequent_patterns/fpcommon.py:110:
DeprecationWarning: DataFrames with non-bool types result in worse computationalpe
rformance and their support might be discontinued in the future.Please use a DataF
rame with bool type
  warnings.warn(
```

Out[ ]:

support	itemsets

Observations

1. As observed, there are no products found to have a co-purchase trend

Hypothesis Testing

`Coupon Status & Gender/Location/Discount percentage`

In [ ]:
```
from scipy.stats import chi2_contingency
from scipy.stats import kruskal
```

In [ ]:
```
# Null Hypothesis (Ho)      : Coupon usage is independent on Gender
# Alternate Hypothesis (Ha) : Coupon usage is dependent on Gender

alpha = 0.05

test_statistic, p_value, dof, expected_values = chi2_contingency(pd.crosstab(sales[

print(f'test statistic : {test_statistic}')
print(f'p value : {p_value}')
print(f'degrees of freedom : {dof}')
print(f'expected values : {expected_values}')
print('\n')
if p_value < alpha:
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
test statistic : 0.24208876086611553
p value : 0.8859946378946084
degrees of freedom : 2
expected values : [[16792.88190613  5047.96799184 11166.15010203]
 [10133.11809387  3046.03200816  6737.84989797]]


Fail to Reject Null Hypothesis
```

In [ ]:

```python
# Null Hypothesis (Ho)      : Coupon usage is independent on Gender
# Alternate Hypothesis (Ha) : Coupon usage is dependent on Gender

alpha = 0.05

test_statistic, p_value, dof, expected_values = chi2_contingency(pd.crosstab(sales[

print(f'test statistic : {test_statistic}')
print(f'p value : {p_value}')
print(f'degrees of freedom : {dof}')
print(f'expected values : {expected_values}')
print('\n')
if p_value < alpha:
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
test statistic : 11.141965729311998
p value : 0.1937842584963792
degrees of freedom : 8
expected values : [[8209.46897438 2467.77991082 5458.75111481]
 [9351.14277077 2810.96893659 6217.88829265]
 [2290.97910211  688.67209584 1523.34880206]
 [5684.45691936 1708.75712342 3779.78595722]
 [1389.95223339  417.82193334  924.22583327]]


Fail to Reject Null Hypothesis
```

In [ ]:

```python
# Null Hypothesis (Ho)      : Coupon usage is independent on Gender
# Alternate Hypothesis (Ha) : Coupon usage is dependent on Gender

alpha = 0.05

test_statistic, p_value, dof, expected_values = chi2_contingency(pd.crosstab(sales[

print(f'test statistic : {test_statistic}')
print(f'p value : {p_value}')
print(f'degrees of freedom : {dof}')
print(f'expected values : {expected_values}')
print('\n')
if p_value < alpha:
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
test statistic : 5.920250728873888
p value : 0.4321827661635701
degrees of freedom : 6
expected values : [[ 203.50691558   61.1745144   135.31857002]
 [8888.16453783 2671.79691633 5910.03854584]
 [9071.32076185 2726.85397929 6031.82525886]
 [8763.00778475 2634.17458998 5826.81762527]]


Fail to Reject Null Hypothesis
```

Marketing Spend Vs Orders / Revenue

In [ ]:

```python
# Check Marketing impact on number of Order & Revenue

orders = sales.groupby('Month')['Transaction_ID'].nunique().reset_index()
orders.rename(columns={'Transaction_ID': 'orders'}, inplace=True)

revenue = sales.groupby('Month')['Invoice_value'].sum().reset_index()
revenue.rename(columns={'Invoice_value': 'revenue'}, inplace=True)

marketing_spend = marketing.groupby('Month')['marketing_spend'].sum().reset_index(
```

In [ ]:

```python
# Checking the correlation between Marketing spend with Orders and Revenue over the
from scipy.stats import spearmanr

# Marketing Spend Vs Orders --> By month

# A correlation coefficient closer to 1 indicates a strong positive correlation (vo
# A correlation coefficient closer to -1 indicates a strong negative correlation (v
# A correlation coefficient closer to 0 indicates no correlation

# Ho : There is a relation between Marketing spend and number of orders
# Ha : There is no relation between Marketing spend and number of orders

rho, pval = spearmanr(marketing_spend['marketing_spend'],orders['orders'])
print(f'rho = {rho}, pval = {pval}')
```

```
rho = 0.41958041958041964, pval = 0.1745190081300594
```

There is no correlation between Marketing spend and number of orders

In [ ]:

```python
# Marketing Spend Vs Revenue --> By month

# Ho : There is a relation between Marketing spend and revenue
# Ha : There is no relation between Marketing spend and revenue

rho, pval = spearmanr(marketing_spend['marketing_spend'], revenue['revenue'])
print(f'rho = {rho}, pval = {pval}')
```

```
rho = 0.7692307692307694, pval = 0.0034464502618274493
```

There is a significant positive correlation between marketing spend and revenue which indicates that the increase in orders is associated with increasing expenditure in marketing acitvities

Gender/Location/Product Category Vs Churn

In [ ]:

```python
# Null Hypothesis (Ho)      : Churn rate is independent on Gender
# Alternate Hypothesis (Ha) : Churn rate is dependent on Gender
```

```
alpha = 0.05

test_statistic, p_value, dof, expected_values = chi2_contingency(pd.crosstab(sales[

print(f'test statistic : {test_statistic}')
print(f'p value : {p_value}')
print(f'degrees of freedom : {dof}')
print(f'expected values : {expected_values}')
print('\n')
if p_value < alpha:
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
test statistic : 6.686342376277394
p value : 0.009715433545310835
degrees of freedom : 1
expected values : [[24129.71109516  8877.28890484]
 [14560.28890484  5356.71109516]]


Reject Null Hypothesis
```

We can conclude that Churn rate is dependent on Gender and the churn rate is high for Female customers

In [ ]:
```
# Null Hypothesis (Ho)      : Churn rate is independent on Location
# Alternate Hypothesis (Ha) : Churn rate is dependent on Location

alpha = 0.05

test_statistic, p_value, dof, expected_values = chi2_contingency(pd.crosstab(sales[

print(f'test statistic : {test_statistic}')
print(f'p value : {p_value}')
print(f'degrees of freedom : {dof}')
print(f'expected values : {expected_values}')
print('\n')
if p_value < alpha:
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
test statistic : 256.46995760252264
p value : 2.628066773748 76e-54
degrees of freedom : 4
expected values : [[11796.19529892  4339.80470108]
 [13436.6676744   4943.3323256 ]
 [ 3291.9104754   1211.0895246 ]
 [ 8168.00260751  3004.99739249]
 [ 1997.22394377   734.77605623]]


Reject Null Hypothesis
```

We can conclude that Churn rate is dependent on Location and the churn rate is high in California, Chicago and New York regions

In [ ]:
```
# Null Hypothesis (Ho)      : Churn rate is independent on Product Category
# Alternate Hypothesis (Ha) : Churn rate is dependent on Product Category

alpha = 0.05
```

```
test_statistic, p_value, dof, expected_values = chi2_contingency(pd.crosstab(sales[

print(f'test statistic : {test_statistic}')
print(f'p value : {p_value}')
print(f'degrees of freedom : {dof}')
print(f'expected values : {expected_values}')
print('\n')
if p_value < alpha:
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
test statistic : 964.8260616523212
p value : 1.701513833386582e-192
degrees of freedom : 19
expected values : [[1.71065301e+02 6.29346988e+01]
 [3.14350767e+01 1.15649233e+01]
 [1.32509814e+04 4.87501859e+03]
 [6.50632983e+01 2.39367017e+01]
 [1.37583289e+03 5.06167108e+02]
 [1.95920943e+02 7.20790568e+01]
 [2.54624121e+03 9.36758786e+02]
 [1.16967727e+02 4.30322727e+01]
 [1.16236679e+02 4.27633210e+01]
 [7.67600710e+01 2.82399290e+01]
 [5.63638236e+02 2.07361764e+02]
 [8.91878921e+01 3.28121079e+01]
 [2.26040133e+03 8.31598670e+02]
 [3.36282216e+01 1.23717784e+01]
 [1.60684415e+03 5.91155846e+02]
 [2.31742310e+02 8.52576903e+01]
 [1.02441798e+04 3.76882023e+03]
 [5.47555173e+02 2.01444827e+02]
 [4.76131755e+03 1.75168245e+03]
 [4.05000756e+02 1.48999244e+02]]


Reject Null Hypothesis
```

We can conclude that Churn rate is dependent on Product categories and the churn rate is high for Apparel and Nest-USA product categories

Invoice amount Vs Discount percentage

In [ ]:

```
# Ho : Average invoice value for 10% Discount coupon is same as 20% Discount coupor
# Ha : Average invoice value for 10% Discount coupon is different from 20% Discount

# Considering the confidence level as 95%
alpha = 0.05

test_stat, p_value = ttest_ind(sales[sales['Discount_pct'] == 10.0]['Invoice_value'
print('test statistic :',test_stat, 'p value :',p_value)

if p_value < alpha:
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
test statistic : 8.229192274614231 p value : 9.743988417884067e-17
Reject Null Hypothesis
```

In [ ]:
```
# Ho : Average invoice value for 10% Discount coupon is same as 20% Discount coupor
# Ha : Average invoice value for 10% Discount coupon is different from 20% Discount

# Considering the confidence level as 95%
alpha = 0.05

test_stat, p_value = ttest_ind(sales[sales['Discount_pct'] == 20.0]['Invoice_value'
print('test statistic :',test_stat, 'p value :',p_value)

if p_value < alpha:
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
test statistic : 4.376581960441401 p value : 6.045152666518693e-06
Reject Null Hypothesis
```

In [ ]:
```
# Ho : Average invoice value for 10% Discount coupon is same as 20% Discount coupor
# Ha : Average invoice value for 10% Discount coupon is different from 20% Discount

# Considering the confidence level as 95%
alpha = 0.05

test_stat, p_value = ttest_ind(sales[sales['Discount_pct'] == 10.0]['Invoice_value'
print('test statistic :',test_stat, 'p value :',p_value)

if p_value < alpha:
  print("Reject Null Hypothesis")
else:
  print("Fail to Reject Null Hypothesis")
```

```
test statistic : 12.36441559601003 p value : 2.413350501492791e-35
Reject Null Hypothesis
```

We can conclude that the average revenue is high from the purchases made using 10% discount coupon followed by 20% and then 30%. Which may indicate that customers tend to purchase products having lesser avg_price which predominently accompains with 10% discount coupons

Recommendations

1. High number of purchases are made by female customers and also the churn rate is high in female customers. It is recommended to strategize product catalogue which appeal more to female customers and also male customers to increase their purchase rate
2. Continue to focus marketing in the top locations - Chicago, California and New York as there is a high churn rate and customers about to be inactive.
3. It is recommended to work on pricing strategies and product portfolio as we see no repeat purchases for high priced products
4. As the CAC (USD 1180.89) is very high compared to Customer lifetime Value (USD 499.42), it is highly recommended to rework on the marketing strategies to be more efficient and continue to accuire customers.
5. The retention rates on an averge are ~10% which needs to be addressed by devising an effective customer retention strategies like repeat purchase offers, special days

discounts and added right product portfolios which are more relavent

6. The marketing expenditure is observed to be high w.r.t CAC and retention rates. There is need to rework on marketing campaign strategies like focussing primarily on existing customers who are under the segment of 'Can't loos', 'at_Risk' and 'need_attention' along with new customer acquisitions
7. SALE(10/20/30) and ELEC(10/20/30) are the most used coupons compared to other coupon codes. As most most purchases are done using 10% discount coupons, it is recommended to devise an effective discount mechanisms where 20% and 30% coupons are more effectively used which may help in customer retention
8. It is recommended add products which have high probability to co-purchase with other products to maximize the purchase order values