# Ecommerce_Data_Analysis_by_Diptyajit_Das

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# 1 Marketing Insights for E-Commerce Company

## 1.1 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.

## 1.2 Dataset Description

Transaction data has been provided from 1st Jan 2019 to 31st Dec 2019.

### 1.2.1 Datasets:

1. **Online_Sales.csv**
    - **CustomerID**: Customer unique ID
    - **Transaction_ID**: Transaction Unique ID
    - **Transaction_Date**: Date of Transaction
    - **Product_SKU**: SKU ID – Unique Id for product
    - **Product_Description**: Product Description
    - **Product_Category**: Product Category
    - **Quantity**: Number of items ordered
    - **Avg_Price**: Price per one quantity
    - **Delivery_Charges**: Charges for delivery
    - **Coupon_Status**: Any discount coupon applied
2. **Customers_Data.csv**
    - **CustomerID**: Customer Unique ID
    - **Gender**: Gender of customer
    - **Location**: Location of Customer
    - **Tenure_Months**: Tenure in Months
3. **Discount_Coupon.csv**
    - **Month**: Discount coupon applied in that month
    - **Product_Category**: Product category
    - **Coupon_Code**: Coupon Code for given Category and given month
    - **Discount_pct**: Discount Percentage for given coupon
4. **Marketing_Spend.csv**

- **Date**: Date
- **Offline_Spend**: Marketing spend on offline channels like TV, Radio, Newspapers, hoardings etc.
- **Online_Spend**: Marketing spend on online channels like Google keywords, Facebook etc.

5. **Tax_Amount.csv**
   - **Product_Category**: Product Category
   - **GST**: Percentage of GST

[1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind,spearmanr,chi2_contingency,levene,shapiro
#!pip install pingouin
import pingouin as pg

#!pip install mlxtend
from mlxtend.frequent_patterns import apriori, association_rules
from operator import attrgetter

import pickle
from sklearn.cluster import KMeans
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from category_encoders import TargetEncoder
from sklearn.metrics import silhouette_score,mean_squared_error as MSE
from sklearn.linear_model import LinearRegression,Lasso,Ridge
from sklearn.ensemble import StackingRegressor

import warnings
warnings.simplefilter('ignore')
```

[2]:
```python
dfs=pd.read_csv('data/Online_Sales.csv')
dfc=pd.read_csv('data/Customers.csv')
dfd=pd.read_csv('data/Discount_Coupon.csv')
dfm=pd.read_csv('data/Marketing_Spend.csv')
dft=pd.read_csv('data/Tax_amount.csv')
```

[3]:
```python
names=['sales','customers','discounts','marketing','taxes']
df_s=[dfs,dfc,dfd,dfm,dft]
for i in range(5):
    print(f'Shape of {names[i]} dataframe : ')
    print(df_s[i].shape)

    print()
```

```
    print(f'Number of missing values in {names[i]} dataframe : ')
    print(df_s[i].isna().sum().sum())
    print()
```

```
Shape of sales dataframe :
(52924, 10)

Number of missing values in sales dataframe :
0

Shape of customers dataframe :
(1468, 4)

Number of missing values in customers dataframe :
0

Shape of discounts dataframe :
(204, 4)

Number of missing values in discounts dataframe :
0

Shape of marketing dataframe :
(365, 3)

Number of missing values in marketing dataframe :
0

Shape of taxes dataframe :
(20, 2)

Number of missing values in taxes dataframe :
0
```

## 1.3 All datasets have no null values and the following shapes: sales (shape: 52924, 10), customers (shape: 1468, 4), discounts (shape: 204, 4), marketing (shape: 365, 3), and taxes (shape: 20, 2).

## 1.4 Preprocessing and Cleaning

### 1.4.1 Merging with taxes dataframe on `Product_Category`.

[4]:
```
df=dfs.merge(dft,on='Product_Category',how='left')
df.CustomerID=df.CustomerID.astype('object')
df.Transaction_ID=df.Transaction_ID.astype('object')
df.dtypes
```

[4]:
```
CustomerID              object
Transaction_ID          object
Transaction_Date        object
Product_SKU             object
Product_Description     object
Product_Category        object
Quantity                 int64
Avg_Price              float64
Delivery_Charges       float64
Coupon_Status           object
GST                     object
dtype: object
```

### 1.4.2 Converting Transaction_Date to datetime and extracting month.

[5]:
```
df['Transaction_Date'] = pd.to_datetime(df['Transaction_Date'])
df['Month'] = df['Transaction_Date'].dt.strftime('%b')
```

### 1.4.3 Merging with discounts dataframe on Month and Product_Category.

### 1.4.4 Applying coupon if Coupon_Status is 'Used'.

[6]:
```
df=df.merge(dfd,on=['Month','Product_Category'],how='left')
df['Coupon']=df['Coupon_Status'].apply(lambda x:1 if x=='Used' else 0)
df=df.rename(columns={'Coupon_Code_x':'Coupon_Code','Discount_pct_x':
 ↪'Discount_pct'}).drop(columns=['Coupon_Status'])
```

### 1.4.5 Converting GST to integer and calculating total Invoice Value.

[7]:
```
df['GST']=df['GST'].str.replace('%', '').astype(int)
df['Invoice']=(df['Quantity']*df['Avg_Price'])*(df['Coupon']*(1-df['Discount_pct']/
 ↪100))*(1+df['GST']/100)+df['Delivery_Charges']
df.head()
```

[7]:
```
  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  GST Month Coupon_Code  Discount_pct  \
0         1     153.71               6.5   10   Jan      ELEC10          10.0
1         1     153.71               6.5   10   Jan      ELEC10          10.0
2         1       2.05               6.5   10   Jan       OFF10          10.0
3         5      17.53               6.5   18   Jan      SALE10          10.0
4         1      16.50               6.5   18   Jan       AIO10          10.0

   Coupon   Invoice
0       1  158.6729
1       1  158.6729
2       1    8.5295
3       0    6.5000
4       1   24.0230
```

[8]:
```
df=df[['CustomerID','Transaction_ID','Transaction_Date','Product_SKU','Product_Description','I
```

[9]:
```
df.isna().sum()
```

[9]:
```
CustomerID               0
Transaction_ID           0
Transaction_Date         0
Product_SKU              0
Product_Description      0
Invoice                400
Quantity                 0
Product_Category         0
Month                    0
Coupon_Code            400
Coupon                   0
Discount_pct           400
dtype: int64
```

### 1.4.6 Imputing Invoice with the median value for that specific CustomerID.

### 1.4.7 Imputing Coupon_Code with 'No_coupon'

### 1.4.8 Imputing Discount_pct with 0

[10]:
```
df['Invoice'] = df.groupby('CustomerID')['Invoice'].transform(lambda x: x.
  ↪fillna(x.median()))
df['Coupon_Code'] = df.Coupon_Code.fillna('No_coupon')
df['Discount_pct']=df.Discount_pct.fillna(0)
df.isna().sum()
```

[10]:
```
CustomerID             0
Transaction_ID         0
Transaction_Date       0
```

```
Product_SKU             0
Product_Description     0
Invoice                 0
Quantity                0
Product_Category        0
Month                   0
Coupon_Code             0
Coupon                  0
Discount_pct            0
dtype: int64
```

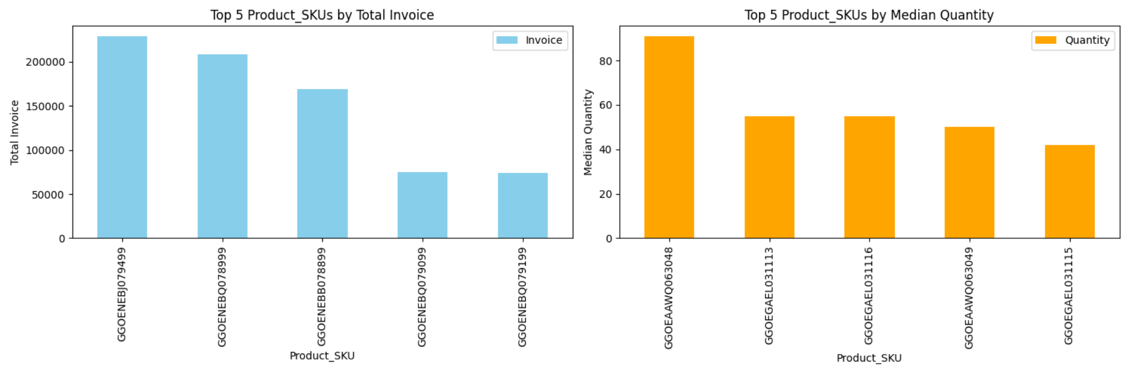
[11]:
```
for col in df.columns:
    print(f'Number of unique values in {col} is : {df[col].nunique()}')
```

```
Number of unique values in CustomerID is : 1468
Number of unique values in Transaction_ID is : 25061
Number of unique values in Transaction_Date is : 365
Number of unique values in Product_SKU is : 1145
Number of unique values in Product_Description is : 404
Number of unique values in Invoice is : 5648
Number of unique values in Quantity is : 151
Number of unique values in Product_Category is : 20
Number of unique values in Month is : 12
Number of unique values in Coupon_Code is : 46
Number of unique values in Coupon is : 2
Number of unique values in Discount_pct is : 4
```

#### 1.4.9 Top 5 Product_SKUs in terms of revenue

[12]:
```
sku_grouped = df.groupby('Product_SKU', as_index=False).agg(Invoice=('Invoice',␣
 ↪'sum'), Quantity=('Quantity', 'median'))

sku_grouped_by_invoice = sku_grouped.sort_values('Invoice', ascending=False).
 ↪head(5)
sku_grouped_by_quantity = sku_grouped.sort_values('Quantity', ascending=False).
 ↪head(5)

fig, axes = plt.subplots(1, 2, figsize=(15, 5))
sku_grouped_by_invoice.plot(kind='bar', x='Product_SKU', y='Invoice',␣
 ↪color='skyblue', ax=axes[0])
axes[0].set_title('Top 5 Product_SKUs by Total Invoice')
axes[0].set_xlabel('Product_SKU')
axes[0].set_ylabel('Total Invoice')

sku_grouped_by_quantity.plot(kind='bar', x='Product_SKU', y='Quantity',␣
 ↪color='orange', ax=axes[1])
axes[1].set_title('Top 5 Product_SKUs by Median Quantity')
```

```
axes[1].set_xlabel('Product_SKU')
axes[1].set_ylabel('Median Quantity')
plt.tight_layout()
plt.show()
```



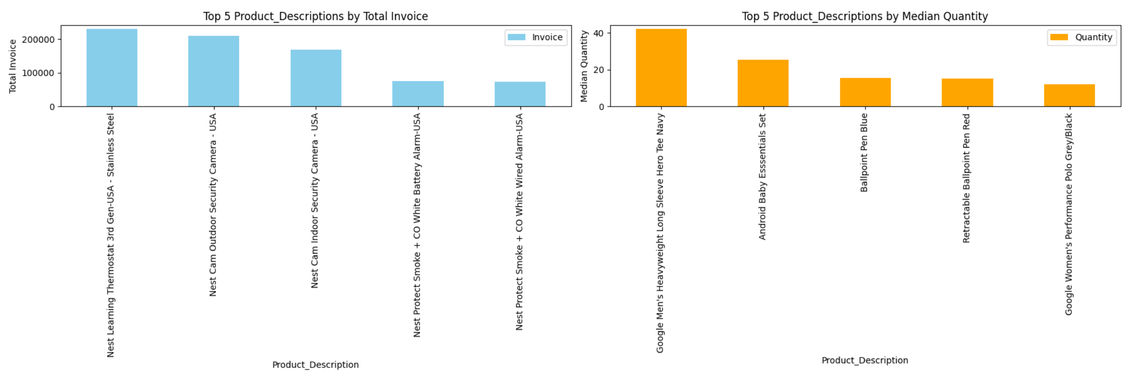

[13]:
```
print("Top 5 Product_SKUs by Total Invoice:")
print(sku_grouped_by_invoice)

print("\nTop 5 Product_SKUs by Median Quantity:")
print(sku_grouped_by_quantity)
```

```
Top 5 Product_SKUs by Total Invoice:
        Product_SKU       Invoice  Quantity
981  GGOENEBJ079499  229191.1732       1.0
983  GGOENEBQ078999  208812.3695       1.0
976  GGOENEBB078899  168999.2536       1.0
984  GGOENEBQ079099   74881.1215       2.0
985  GGOENEBQ079199   74133.9858       2.0

Top 5 Product_SKUs by Median Quantity:
        Product_SKU  Invoice  Quantity
146  GGOEAAWQ063048      6.0      91.0
474  GGOEGAEL031113      6.5      55.0
477  GGOEGAEL031116      6.5      55.0
147  GGOEAAWQ063049      6.0      50.0
476  GGOEGAEL031115      6.5      42.0
```

### 1.4.10 Top 5 Product_Descriptions in terms of revenue

[14]:
```
description_grouped = df.groupby('Product_Description', as_index=False).
 ↪agg(Invoice=('Invoice', 'sum'), Quantity=('Quantity', 'median'))

description_grouped_by_invoice = description_grouped.sort_values('Invoice',␣
 ↪ascending=False)
```

```python
description_grouped_by_quantity = description_grouped.sort_values('Quantity',␣
↪ascending=False)

fig, axes = plt.subplots(1, 2, figsize=(18, 6))
description_grouped_by_invoice.head(5).plot(kind='bar',␣
↪x='Product_Description', y='Invoice', color='skyblue', ax=axes[0])
axes[0].set_title('Top 5 Product_Descriptions by Total Invoice')
axes[0].set_xlabel('Product_Description')
axes[0].set_ylabel('Total Invoice')

description_grouped_by_quantity.head(5).plot(kind='bar',␣
↪x='Product_Description', y='Quantity', color='orange', ax=axes[1])
axes[1].set_title('Top 5 Product_Descriptions by Median Quantity')
axes[1].set_xlabel('Product_Description')
axes[1].set_ylabel('Median Quantity')
plt.tight_layout()
plt.show()
```



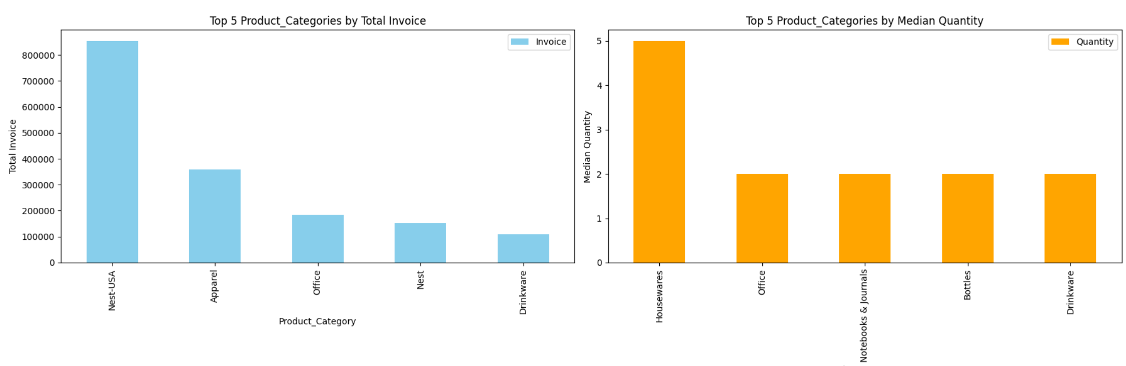

[15]:
```python
print("Top 5 Product_Descriptions by Total Invoice:")
print(description_grouped_by_invoice.head(5))

print("\nTop 5 Product_Descriptions by Median Quantity:")
print(description_grouped_by_quantity.head(5))
```

```
Top 5 Product_Descriptions by Total Invoice:
                                   Product_Description      Invoice  Quantity
316  Nest Learning Thermostat 3rd Gen-USA - Stainle…  229191.1732       1.0
312            Nest Cam Outdoor Security Camera - USA  208812.3695       1.0
310             Nest Cam Indoor Security Camera - USA  168999.2536       1.0
321    Nest Protect Smoke + CO White Battery Alarm-USA   74881.1215       2.0
323      Nest Protect Smoke + CO White Wired Alarm-USA   74133.9858       2.0

Top 5 Product_Descriptions by Median Quantity:
                                   Product_Description     Invoice  Quantity
```

```
162  Google Men's Heavyweight Long Sleeve Hero Tee …   957.38872      42.0
16                        Android Baby Esssentials Set    36.50000      25.5
76                                    Ballpoint Pen Blue  3091.96270      15.5
332                       Retractable Ballpoint Pen Red   670.92760      15.0
251          Google Women's Performance Polo Grey/Black  1644.48912      12.0
```

### 1.4.11 Top 5 Product_Categorys in terms of revenue

[16]:
```python
category_grouped = df.groupby('Product_Category', as_index=False).
 ↪agg(Invoice=('Invoice', 'sum'), Quantity=('Quantity', 'median'))

category_grouped_by_invoice = category_grouped.sort_values('Invoice',␣
 ↪ascending=False)
category_grouped_by_quantity = category_grouped.sort_values('Quantity',␣
 ↪ascending=False)

fig, axes = plt.subplots(1, 2, figsize=(18, 6))
category_grouped_by_invoice.head(5).plot(kind='bar', x='Product_Category',␣
 ↪y='Invoice', color='skyblue', ax=axes[0])
axes[0].set_title('Top 5 Product_Categories by Total Invoice')
axes[0].set_xlabel('Product_Category')
axes[0].set_ylabel('Total Invoice')

category_grouped_by_quantity.head(5).plot(kind='bar', x='Product_Category',␣
 ↪y='Quantity', color='orange', ax=axes[1])
axes[1].set_title('Top 5 Product_Categories by Median Quantity')
axes[1].set_xlabel('Product_Category')
axes[1].set_ylabel('Median Quantity')
plt.tight_layout()
plt.show()
```




[17]:
```python
print("Top 5 Product_Categories by Total Invoice:")
print(category_grouped_by_invoice.head(5))
```

```python
print("\nTop 5 Product_Categories by Median Quantity:")
print(category_grouped_by_quantity.head(5))
```

```
Top 5 Product_Categories by Total Invoice:
   Product_Category        Invoice  Quantity
16         Nest-USA   853645.00510       1.0
2           Apparel   359547.92298       1.0
18           Office   183604.07010       2.0
14             Nest   153509.13940       1.0
6         Drinkware   109896.88510       2.0

Top 5 Product_Categories by Median Quantity:
        Product_Category       Invoice  Quantity
11            Housewares     2934.2164       5.0
18                Office   183604.0701       2.0
17  Notebooks & Journals    43340.5317       2.0
5                Bottles     5893.2286       2.0
6              Drinkware   109896.8851       2.0
```

#### 1.4.12 Top 5 Product SKUs by Total Invoice:

1. **GGOENEBJ079499**: This SKU corresponds to the Nest Learning Thermostat 3rd Gen-USA - Stainless Steel, which aligns with its top position in terms of total invoice amount.
2. **GGOENEBQ078999**: This SKU represents the Nest Cam Outdoor Security Camera - USA, confirming its popularity as the second-highest in total invoice amount.
3. **GGOENEBB078899**: This SKU corresponds to the Nest Cam Indoor Security Camera - USA, reflecting its strong sales performance as the third-highest in total invoice amount.
4. **GGOENEBQ079099**: Despite being ranked fourth, this SKU corresponds to the Nest Protect Smoke + CO White Battery Alarm-USA, indicating significant sales volume for this product variant.
5. **GGOENEBQ079199**: Similar to the previous SKU, this one corresponds to the wired variant of the Nest Protect Smoke + CO White Alarm-USA, indicating consistent demand for both battery and wired options. tegory.

#### 1.4.13 Top 5 Product Descriptions by Total Invoice:

1. **Nest Learning Thermostat 3rd Gen-USA - Stainless Steel**: This product description tops the list in terms of total invoice amount, indicating high demand for this particular Nest product variant.
2. **Nest Cam Outdoor Security Camera - USA**: The outdoor security camera from Nest is the second highest in terms of total invoice amount, suggesting a strong interest in home security products.
3. **Nest Cam Indoor Security Camera - USA**: Following closely behind the outdoor camera, the indoor security camera variant also enjoys significant sales, reflecting a growing concern for home safety.
4. **Nest Protect Smoke + CO White Battery Alarm-USA**: This product description indicates a demand for smoke and CO detectors with battery functionality, as it ranks fourth

in total invoice amount.
5. **Nest Protect Smoke + CO White Wired Alarm-USA**: Similar to the battery-powered variant, the wired smoke and CO detector also sees considerable sales, rounding up the top 5 product d

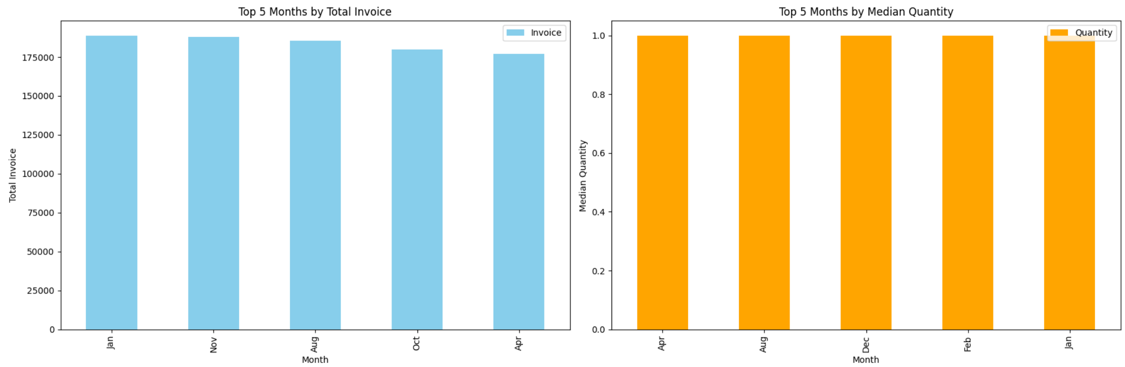
### 1.4.14 Top 5 Product Categories by Total Invoice:

1. **Nest-USA**: Despite having only one item per invoice, Nest-USA has the highest total invoice amount, indicating high-value purchases.
2. **Apparel**: Apparel follows closely behind Nest-USA in terms of total invoice amount, suggesting a strong demand for clothing products.
3. **Office**: Although ranking third, the Office category has a considerable total invoice amount, indicating a significant volume of purchases, likely for office supplies.
4. **Nest**: Similar to Nest-USA, the Nest category also has a high total invoice amount, indicating a strong demand for Nest products overall.
5. **Drinkware**: Despite ranking fifth, Drinkware has a noteworthy total invoice amount, indicating consistent sales in this product category.ry and wired options.

These insights provide a deeper understanding of the top-performing product categories, descriptions, and SKUs based on their total invoice amounts. total invoice amounts.

### 1.4.15 Top 5 Months in terms of revenue

[18]:
```
month_grouped = df.groupby('Month', as_index=False).agg(Invoice=('Invoice',␣
↪'sum'), Quantity=('Quantity', 'median'))

month_grouped_by_invoice = month_grouped.sort_values('Invoice', ascending=False)
month_grouped_by_quantity = month_grouped.sort_values('Quantity',␣
↪ascending=False)

fig, axes = plt.subplots(1, 2, figsize=(18, 6))
month_grouped_by_invoice.head(5).plot(kind='bar', x='Month', y='Invoice',␣
↪color='skyblue', ax=axes[0])
axes[0].set_title('Top 5 Months by Total Invoice')
axes[0].set_xlabel('Month')
axes[0].set_ylabel('Total Invoice')

month_grouped_by_quantity.head(5).plot(kind='bar', x='Month', y='Quantity',␣
↪color='orange', ax=axes[1])
axes[1].set_title('Top 5 Months by Median Quantity')
axes[1].set_xlabel('Month')
axes[1].set_ylabel('Median Quantity')
plt.tight_layout()
plt.show()
```



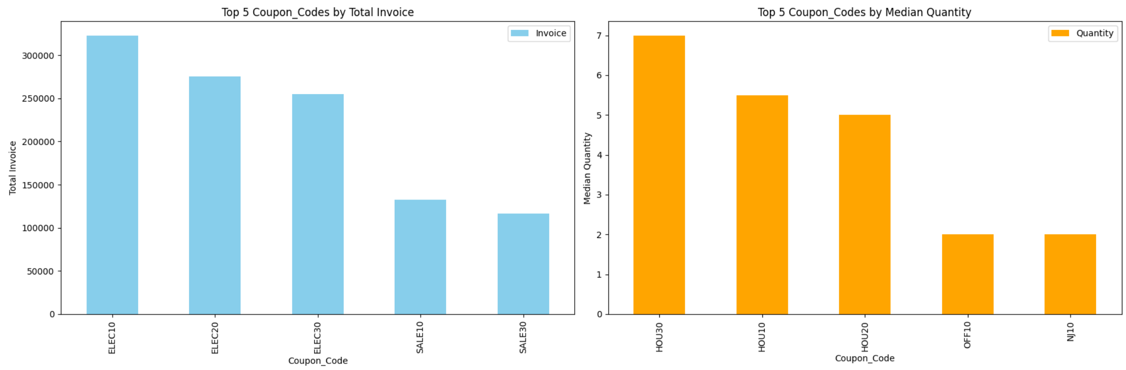

[19]:
```python
print("Top 5 Months by Total Invoice:")
print(month_grouped_by_invoice.head(5))

print("\nTop 5 Months by Median Quantity:")
print(month_grouped_by_quantity.head(5))
```

```
Top 5 Months by Total Invoice:
   Month        Invoice  Quantity
4    Jan   188859.89905       1.0
9    Nov   187969.78576       1.0
1    Aug   185528.76757       1.0
10   Oct   179983.71291       1.0
0    Apr   177094.95322       1.0

Top 5 Months by Median Quantity:
  Month        Invoice  Quantity
0   Apr   177094.95322       1.0
1   Aug   185528.76757       1.0
2   Dec   167504.75299       1.0
3   Feb   135630.25628       1.0
4   Jan   188859.89905       1.0
```

#### 1.4.16 Top 5 Coupon_Codes in terms of revenue

[20]:
```python
coupon_grouped = df.groupby('Coupon_Code', as_index=False).
 ↪agg(Invoice=('Invoice', 'sum'), Quantity=('Quantity', 'median'))

coupon_grouped_by_invoice = coupon_grouped.sort_values('Invoice',␣
 ↪ascending=False)
coupon_grouped_by_quantity = coupon_grouped.sort_values('Quantity',␣
 ↪ascending=False)

fig, axes = plt.subplots(1, 2, figsize=(18, 6))
```

```
coupon_grouped_by_invoice.head(5).plot(kind='bar', x='Coupon_Code',␣
  ↪y='Invoice', color='skyblue', ax=axes[0])
axes[0].set_title('Top 5 Coupon_Codes by Total Invoice')
axes[0].set_xlabel('Coupon_Code')
axes[0].set_ylabel('Total Invoice')

coupon_grouped_by_quantity.head(5).plot(kind='bar', x='Coupon_Code',␣
  ↪y='Quantity', color='orange', ax=axes[1])
axes[1].set_title('Top 5 Coupon_Codes by Median Quantity')
axes[1].set_xlabel('Coupon_Code')
axes[1].set_ylabel('Median Quantity')
plt.tight_layout()
plt.show()
```




[21]:
```
print("Top 5 Coupon_Codes by Total Invoice:")
print(coupon_grouped_by_invoice.head(5))

print("\nTop 5 Coupon_Codes by Median Quantity:")
print(coupon_grouped_by_quantity.head(5))
```

```
Top 5 Coupon_Codes by Total Invoice:
   Coupon_Code        Invoice  Quantity
12      ELEC10   323126.20410       1.0
13      ELEC20   275706.28000       1.0
14      ELEC30   254812.52100       1.0
40      SALE10   132244.53118       1.0
42      SALE30   116555.15028       1.0

Top 5 Coupon_Codes by Median Quantity:
   Coupon_Code       Invoice  Quantity
26       HOU30     833.06800       7.0
24       HOU10    1289.22840       5.5
25       HOU20     811.92000       5.0
37       OFF10   70327.61470       2.0
```

```
33         NJ10  18531.91275        2.0
```

### 1.4.17 Top 5 Months by Total Invoice:

1. **January (Jan)**: January ranks first in terms of total invoice amount, indicating strong sales at the beginning of the year, possibly due to New Year promotions or post-holiday shopping.
2. **November (Nov)**: November closely follows January in total invoice amount, likely boosted by holiday shopping, Black Friday, and Cyber Monday sales.
3. **August (Aug)**: August ranks third in total invoice amount, suggesting strong summer sales, possibly due to back-to-school promotions or end-of-summer clearance events.
4. **October (Oct)**: October comes in fourth place in terms of total invoice amount, possibly benefiting from fall promotions or early holiday shopping.
5. **April (Apr)**: April rounds up the top five months by total invoice amount, indicating solid spring sales, possibly driven by seasonal products or Easter promotions.

### 1.4.18 Top 5 Coupon Codes by Total Invoice:

1. **ELEC10**: This coupon code has the highest total invoice amount, suggesting that customers are taking advantage of a 10% discount on electronic products, driving significant sales volume.
2. **ELEC20**: The ELEC20 coupon code ranks second in terms of total invoice amount, indicating a strong response to a 20% discount on electronic items.
3. **ELEC30**: Despite being lower than ELEC10 and ELEC20, the ELEC30 coupon code still enjoys considerable usage, indicating a demand for products eligible for a 30% discount on electronics.
4. **SALE10**: This coupon code offers a 10% discount and ranks fourth in total invoice amount, indicating moderate usage compared to the electronics-focused codes.
5. **SALE30**: SALE30 ranks fifth in terms of total invoice amount, suggesting that customers are attracted to a 30% discount on a wide range of products, driving notable sales volume.

These insights provide a glimpse into the top-performing months and coupon codes based on their total invoice amounts, indicating peak sales periods and popular discount offerings.

[22]:
```python
print('Range of Dates')
dfm['Date']=pd.to_datetime(dfm['Date'])
print((df['Transaction_Date'].min(), df['Transaction_Date'].max(),␣
↪(df['Transaction_Date'].max() - df['Transaction_Date'].min()).days))
print((dfm['Date'].min(), dfm['Date'].max(), (dfm['Date'].max() - dfm['Date'].
↪min()).days))
```

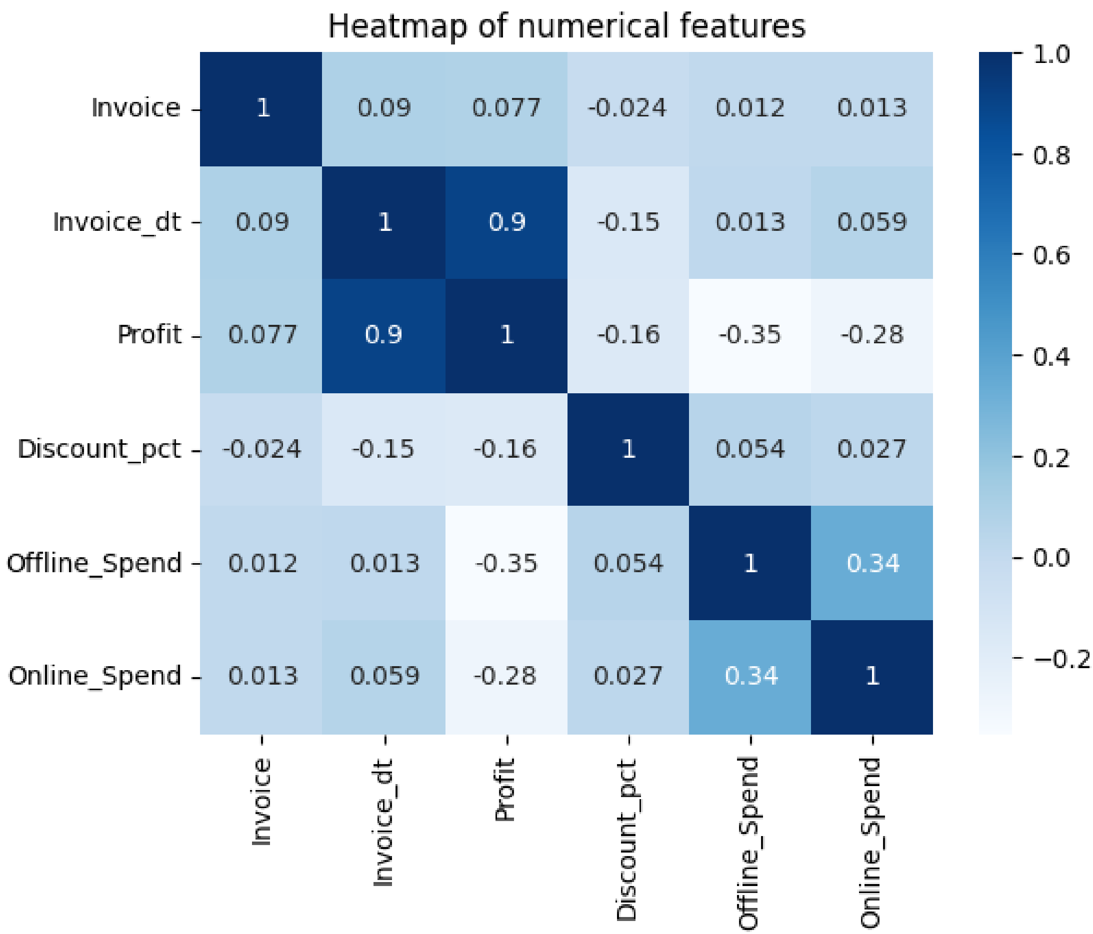
```
Range of Dates
(Timestamp('2019-01-01 00:00:00'), Timestamp('2019-12-31 00:00:00'), 364)
(Timestamp('2019-01-01 00:00:00'), Timestamp('2019-12-31 00:00:00'), 364)
```

### 1.4.19 The data has records from 1st Jan 2019 to 31st December 2019 over a span of 365 days.

### 1.4.20 Merging with marketing dataframe on `Transaction_Date`.

[23]:
```
df=df.merge(dfm,left_on='Transaction_Date',right_on='Date')
df['Invoice_dt']=df.groupby('Date')['Invoice'].transform('sum')
df['Profit']=df['Invoice_dt']-df['Offline_Spend']-df['Online_Spend']
df=df.drop(columns='Date').rename(columns={'Transaction_Date':'Date'})
```

[24]:
```
columns=['Invoice','Invoice_dt','Profit','Discount_pct','Offline_Spend','Online_Spend']
plt.title('Heatmap of numerical features')
sns.heatmap(df[columns].corr(),annot=True,cmap='Blues')
plt.show()
```



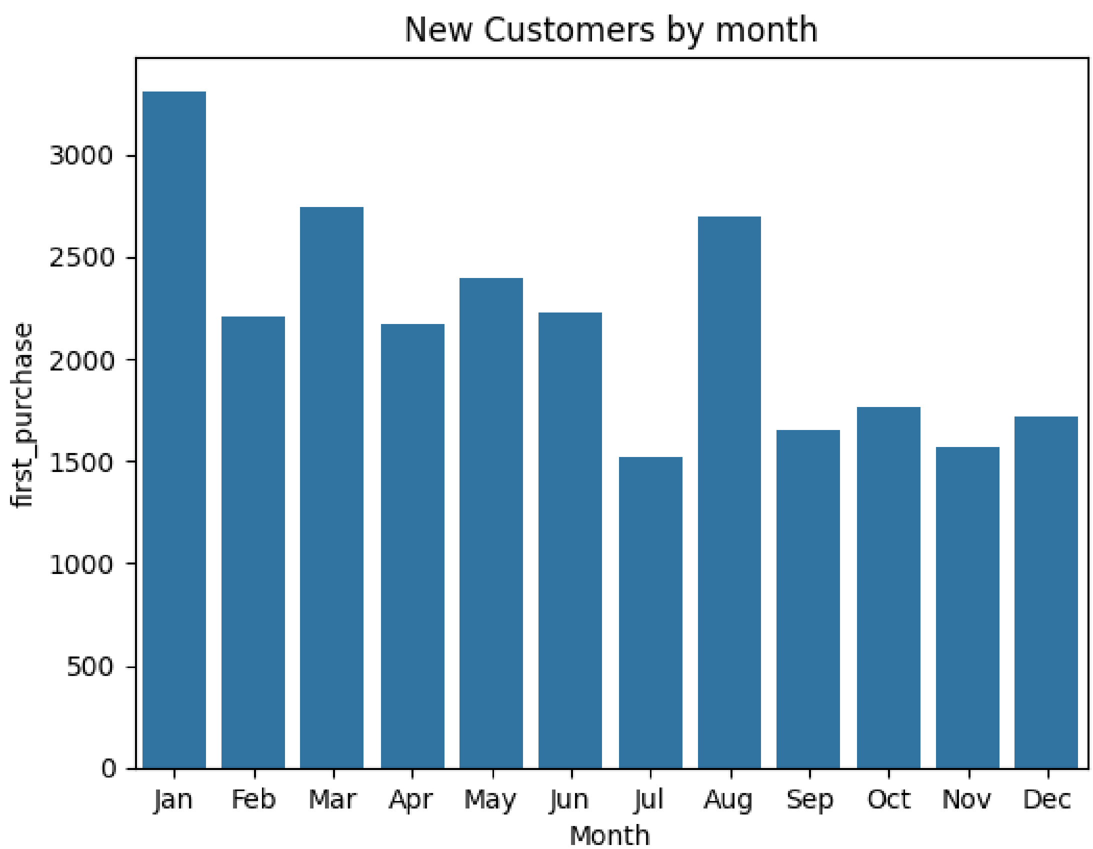
## 1.5 `Profit` and total `Invoice` per date is strongly correlated(.9) which is expected and `Offline_Spend` and `Online_Spend` is mildly correlated(.34).

### 1.5.1 Merging with customers dataframe on `CustomerID`.

[25]:
```
df=df.merge(dfc,on='CustomerID')
```

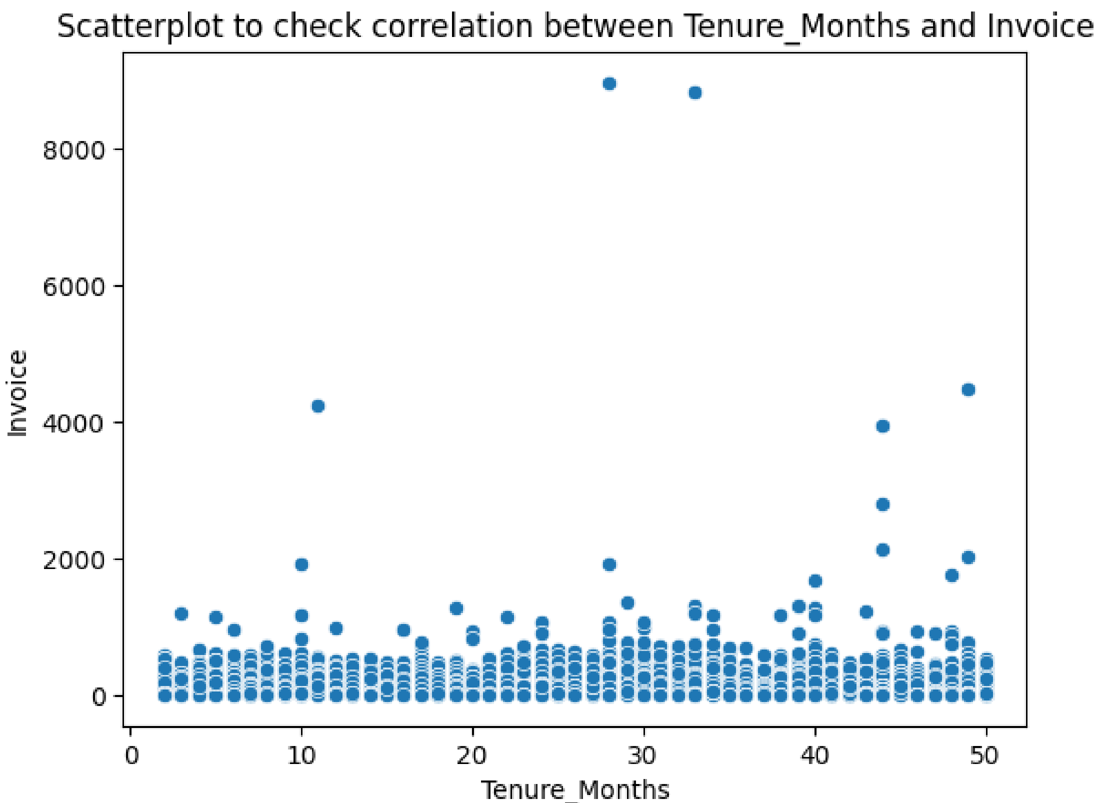
# 2 Customer Acquisition

[26]:
```
df['first_date']=df.groupby(['CustomerID'])['Date'].transform('min')
df['first_purchase']=np.where(df.Date==df.first_date,1,0)
acq_grouped=df.groupby('Month',as_index=False)['first_purchase'].sum()
sns.
 ↪barplot(data=acq_grouped,x='Month',y='first_purchase',order=['Jan','Feb','Mar','Apr','May',
plt.title('New Customers by month')
plt.show()
```



## 2.1 Jan and Mar have the most new users, with time passing lesser new customers are purchasing which calls for better marketing.

[27]:
```
sns.scatterplot(data=df,x='Tenure_Months',y='Invoice')
plt.title('Scatterplot to check correlation between Tenure_Months and Invoice')
plt.show()
print('Spearman rank correlation')
print(spearmanr(df['Tenure_Months'],df['Invoice']))
```




```
Spearman rank correlation
SignificanceResult(statistic=-0.006958459528620117, pvalue=0.10942337964383664)
```

### 2.1.1 Mostly `Invoice` is equally distributed withh respect to different `Tenure_Months` with 2 huge outliers above 8000.

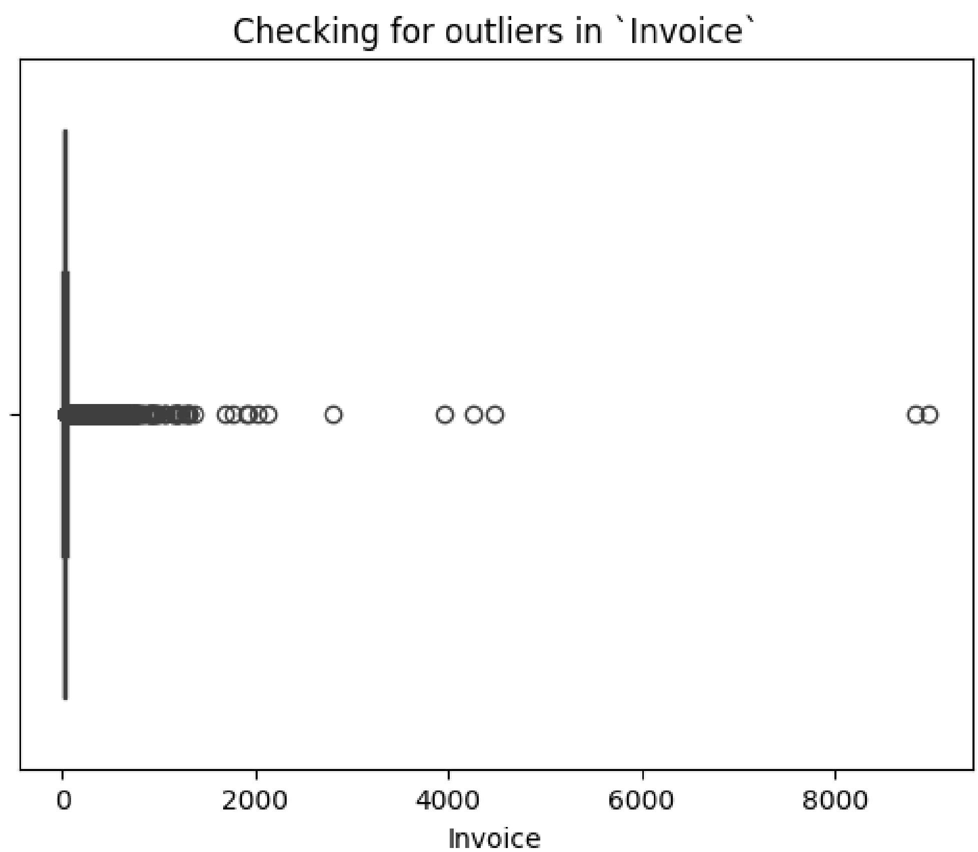
[28]:
```
df[df['Invoice']>8000]
```

[28]:
```
       CustomerID Transaction_ID       Date     Product_SKU  \
3284        12748          24860 2019-04-05  GGOEGHPJ080110
20589       15194          34429 2019-08-02  GGOEGHPJ080310

        Product_Description    Invoice  Quantity Product_Category Month  \
```

```
3284    Google 5-Panel Cap  8979.2750       500          Headgear    Apr
20589  Google Blackout Cap  8836.4076       791          Headgear    Aug

      Coupon_Code  …  Discount_pct  Offline_Spend  Online_Spend  \
3284      HGEAR10  …          10.0           2500       2342.68
20589     HGEAR20  …          20.0           1500       2155.96

        Invoice_dt       Profit  Gender Location Tenure_Months  first_date  \
3284   25367.74380  20525.06380       F  Chicago            28  2019-01-08
20589  23545.09169  19889.13169       M  Chicago            33  2019-03-16

      first_purchase
3284               0
20589              0

[2 rows x 21 columns]
```

### 2.1.2 Outliers in Invoice column

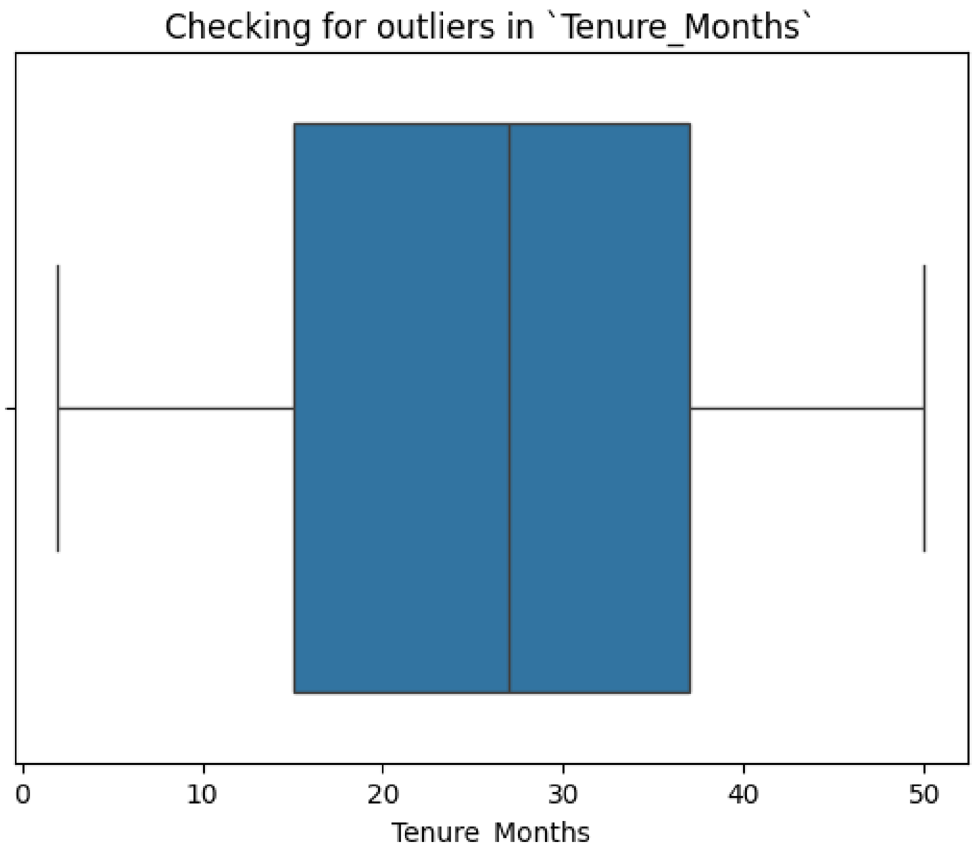
[29]:
```python
sns.boxplot(data=df,x='Invoice')
plt.title('Checking for outliers in `Invoice`')
plt.show()
```



### 2.1.3 No outliers in `Tenure_Months` column

[30]:

```
sns.boxplot(data=df,x='Tenure_Months')
plt.title('Checking for outliers in `Tenure_Months`')
plt.show()
```



## 2.2 Outliers in invoice target column ignored and will use Ttest which is more robust and Linear models for prediction which does not require normality of the target variable and is simple.

## 2.3 Tenure_Months have no outliers with normal distribution with mean around 28 months.

### 2.3.1 Binning Tenure.

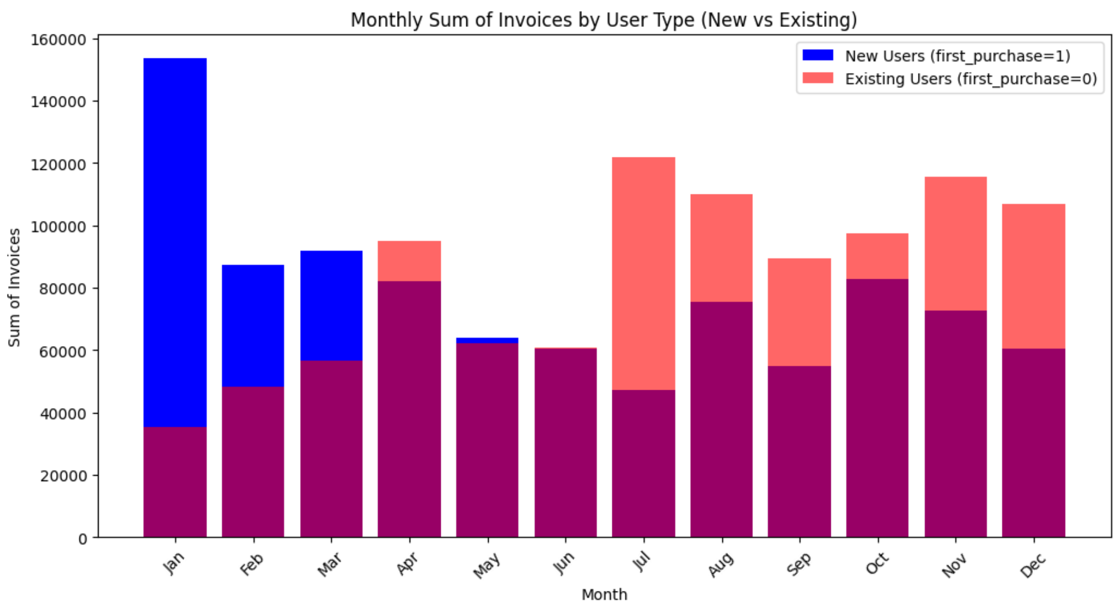
[31]:
```
bin_edges = [0, 10, 20, 30, 40, float('inf')]
bin_labels = ['0-10', '10-20', '20-30', '30-40', '>40']
df['Tenurebin'] = pd.cut(df['Tenure_Months'], bins=bin_edges, labels=bin_labels)
```

[32]:
```
df_profit=df.loc[:
  ↪,['Date','Offline_Spend','Online_Spend','Profit','Invoice_dt']].
  ↪drop_duplicates()
df=df[['CustomerID','Transaction_ID','first_purchase','Date','Product_SKU','Product_Descriptio
  ↪'Coupon_Code']]
df.head()
```

[32]:
```
   CustomerID Transaction_ID  first_purchase        Date     Product_SKU  \
0       17850          16679               1 2019-01-01  GGOENEBJ079499
1       17850          16680               1 2019-01-01  GGOENEBJ079499
2       17850          16681               1 2019-01-01  GGOEGFKQ020399
3       17850          16682               1 2019-01-01  GGOEGAAB010516
4       17850          16682               1 2019-01-01  GGOEGBJL013999

                                 Product_Description   Invoice  Quantity  \
0  Nest Learning Thermostat 3rd Gen-USA - Stainle…  158.6729         1
1  Nest Learning Thermostat 3rd Gen-USA - Stainle…  158.6729         1
2              Google Laptop and Cell Phone Stickers    8.5295         1
3  Google Men's 100% Cotton Short Sleeve Hero Tee…    6.5000         5
4                    Google Canvas Tote Natural/Navy   24.0230         1

  Product_Category  Coupon  Discount_pct Gender Location  Tenure_Months  \
0         Nest-USA       1          10.0      M  Chicago             12
1         Nest-USA       1          10.0      M  Chicago             12
2           Office       1          10.0      M  Chicago             12
3          Apparel       0          10.0      M  Chicago             12
4             Bags       1          10.0      M  Chicago             12

  Tenurebin Month Coupon_Code
0     10-20   Jan      ELEC10
1     10-20   Jan      ELEC10
2     10-20   Jan       OFF10
3     10-20   Jan      SALE10
4     10-20   Jan       AIO10
```

# 3 New vs Existing user sales

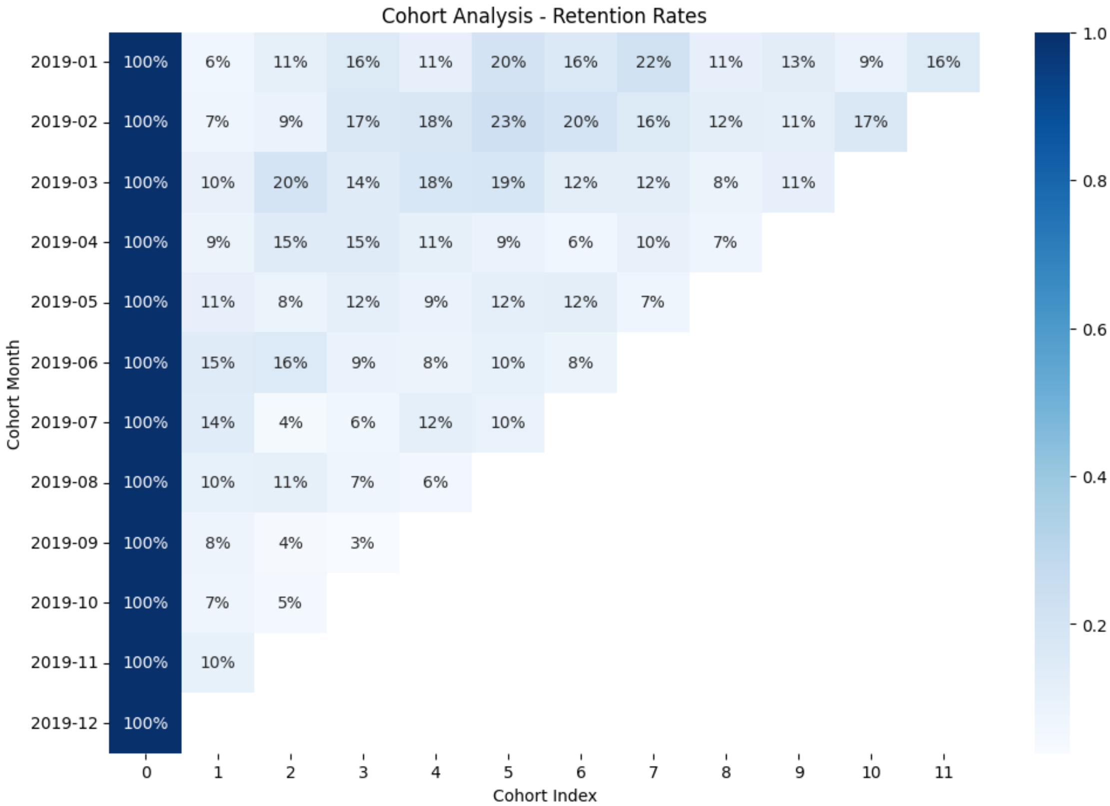
[33]:
```
new_users = df[df['first_purchase'] == 1]
existing_users = df[df['first_purchase'] == 0]

new_users_monthly = new_users.groupby('Month')['Invoice'].sum().reset_index()
existing_users_monthly = existing_users.groupby('Month')['Invoice'].sum().
 ↪reset_index()

month_order = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep',␣
 ↪'Oct', 'Nov', 'Dec']
new_users_monthly['Month'] = pd.Categorical(new_users_monthly['Month'],␣
 ↪categories=month_order, ordered=True)
existing_users_monthly['Month'] = pd.
 ↪Categorical(existing_users_monthly['Month'], categories=month_order,␣
 ↪ordered=True)
new_users_monthly = new_users_monthly.sort_values('Month')
existing_users_monthly = existing_users_monthly.sort_values('Month')

fig, ax = plt.subplots(figsize=(12, 6))
ax.bar(new_users_monthly['Month'], new_users_monthly['Invoice'], color='blue',␣
 ↪label='New Users (first_purchase=1)')
ax.bar(existing_users_monthly['Month'], existing_users_monthly['Invoice'],␣
 ↪color='red', alpha=0.6, label='Existing Users (first_purchase=0)')
plt.xlabel('Month')
plt.ylabel('Sum of Invoices')
plt.title('Monthly Sum of Invoices by User Type (New vs Existing)')
plt.xticks(rotation=45)
plt.legend()
plt.show()
```




### 3.1 From Jan to Jun new users contribute to more sale however from Jun exisiting users contribute to more sales.

## 4 Cohort Analysis

[34]:
```
df['CohortMonth'] = df.groupby('CustomerID')['Date'].transform('min').dt.
  ↪to_period('M')
df['TransactionMonth'] = df['Date'].dt.to_period('M')
df['CohortIndex'] = (df['TransactionMonth'] - df['CohortMonth']).
  ↪apply(attrgetter('n'))
cohort_data = df.groupby(['CohortMonth', 'CohortIndex'])['CustomerID'].
  ↪nunique().reset_index()
cohort_counts = cohort_data.pivot(index='CohortMonth', columns='CohortIndex',␣
  ↪values='CustomerID')
cohort_sizes = cohort_counts.iloc[:,0]
retention = cohort_counts.divide(cohort_sizes, axis=0)

plt.figure(figsize=(12, 8))
sns.heatmap(retention, annot=True, fmt='.0%', cmap='Blues')
plt.title('Cohort Analysis - Retention Rates')
plt.ylabel('Cohort Month')
plt.xlabel('Cohort Index')
plt.show()
```

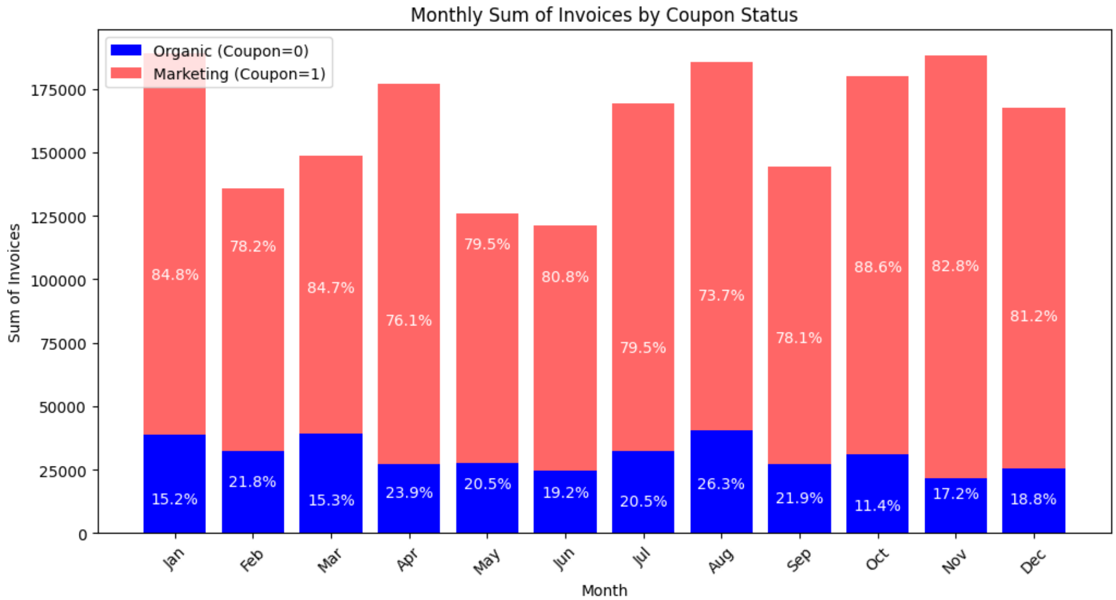



### 4.1 Cohorts '2019-01' and '2019-02' are slightly outperforming in terms of retention with other cohorts.

## 5 Organic vs Marketing Sales

[35]:
```
org = df[df['Coupon'] == 0]
mark = df[df['Coupon'] == 1]

org_monthly = org.groupby('Month')['Invoice'].sum().reset_index()
mark_monthly = mark.groupby('Month')['Invoice'].sum().reset_index()
total_monthly = df.groupby('Month')['Invoice'].sum().reset_index()

org_monthly = pd.merge(org_monthly, total_monthly, on='Month', suffixes=('',
  '_Total'))
mark_monthly = pd.merge(mark_monthly, total_monthly, on='Month', suffixes=('',
  '_Total'))
org_monthly['Percentage'] = (org_monthly['Invoice'] /
  org_monthly['Invoice_Total']) * 100
mark_monthly['Percentage'] = (mark_monthly['Invoice'] /
  mark_monthly['Invoice_Total']) * 100
```

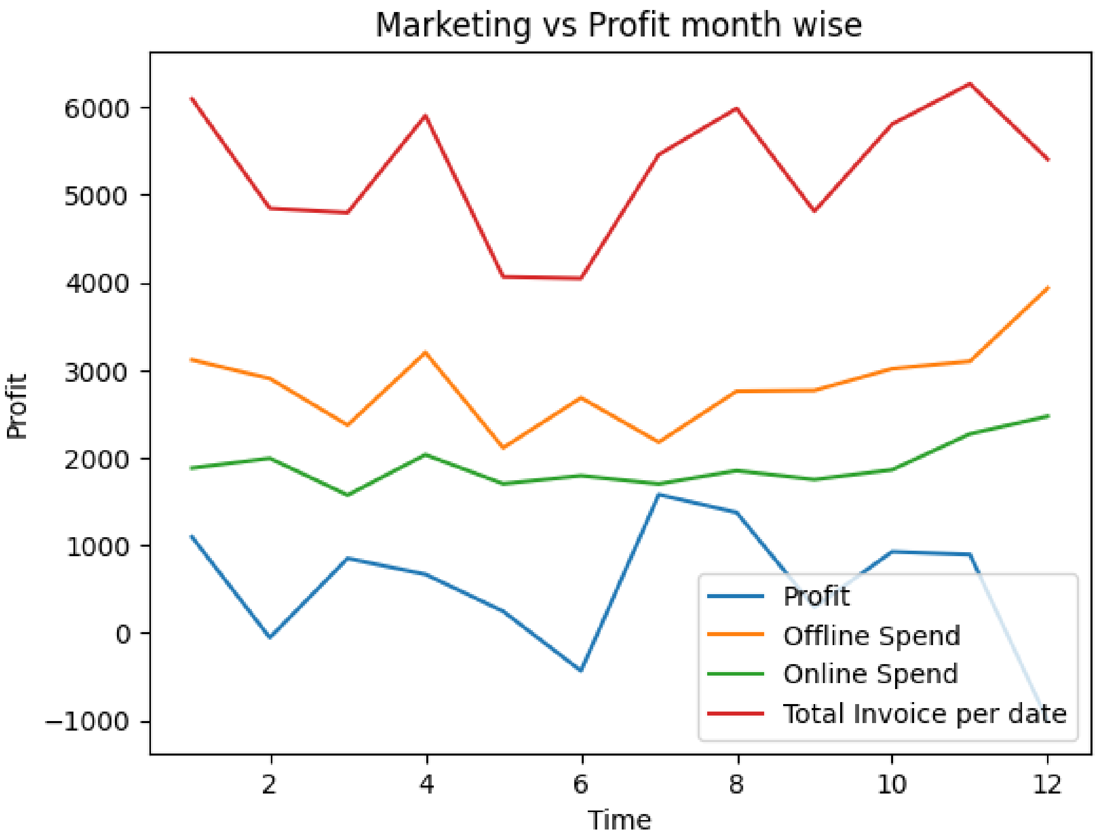
```
month_order = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
org_monthly['Month'] = pd.Categorical(org_monthly['Month'], categories=month_order, ordered=True)
mark_monthly['Month'] = pd.Categorical(mark_monthly['Month'], categories=month_order, ordered=True)
org_monthly = org_monthly.sort_values('Month')
mark_monthly = mark_monthly.sort_values('Month')

fig, ax = plt.subplots(figsize=(12, 6))
ax.bar(org_monthly['Month'], org_monthly['Invoice'], color='blue', label='Organic (Coupon=0)')
ax.bar(mark_monthly['Month'], mark_monthly['Invoice'], bottom=org_monthly['Invoice'], color='red', alpha=0.6, label='Marketing (Coupon=1)')

for i in range(len(org_monthly)):
    ax.text(x=i, y=org_monthly['Invoice'][i] / 2, s=f"{org_monthly['Percentage'][i]:.1f}%",
            color='white', ha='center', va='center', fontsize=10)
    ax.text(x=i, y=org_monthly['Invoice'][i] + mark_monthly['Invoice'][i] / 2, s=f"{mark_monthly['Percentage'][i]:.1f}%",
            color='white', ha='center', va='center', fontsize=10)

plt.xlabel('Month')
plt.ylabel('Sum of Invoices')
plt.title('Monthly Sum of Invoices by Coupon Status')
plt.xticks(rotation=45)
plt.legend()
plt.show()
```



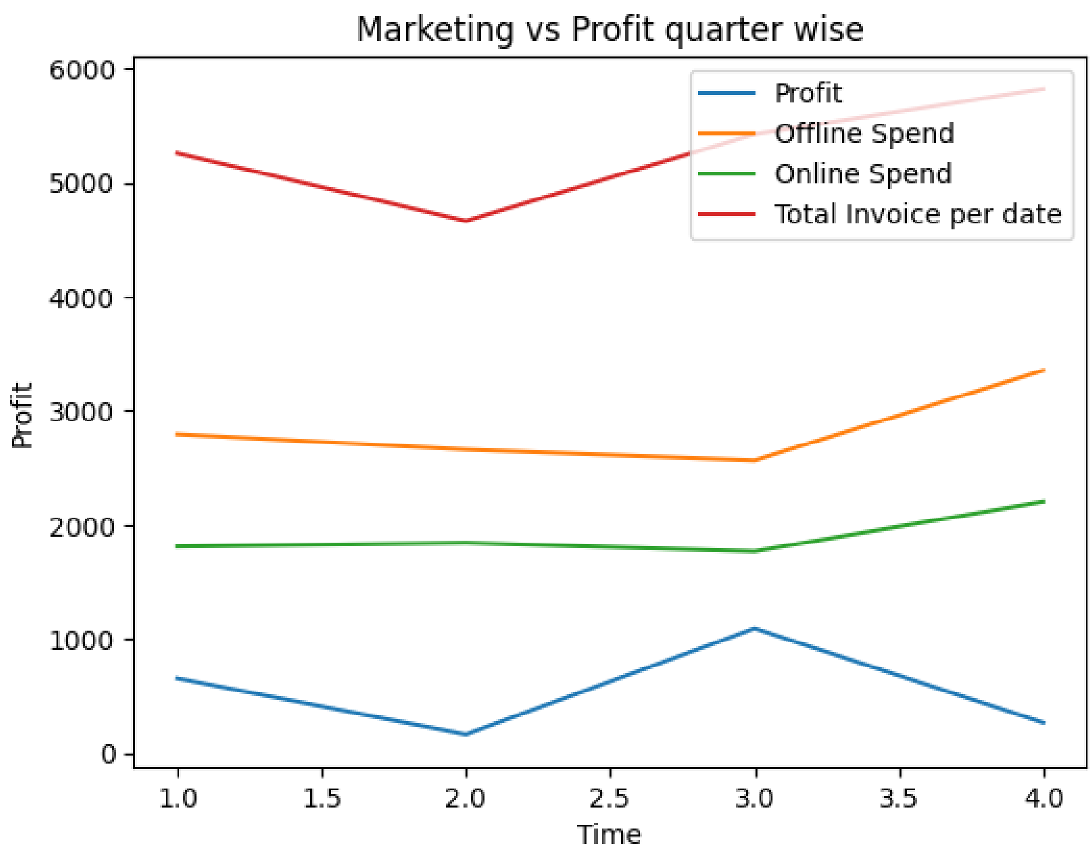

### 5.1 Jan has the highest overall sales, Oct has the highest % marketing sales and August has the highest % organic sales.

## 6 Temporal Trends due to Marketing

[36]:
```
df_profit['Time'] = df_profit.Date.dt.month

sns.lineplot(data=df_profit, x='Time', y='Profit', ci=None, label='Profit')
sns.lineplot(data=df_profit, x='Time', y='Offline_Spend', ci=None,␣
 ↪label='Offline Spend')
sns.lineplot(data=df_profit, x='Time', y='Online_Spend', ci=None, label='Online␣
 ↪Spend')
sns.lineplot(data=df_profit, x='Time', y='Invoice_dt', ci=None, label='Total␣
 ↪Invoice per date')

plt.title('Marketing vs Profit month wise')
plt.legend()

plt.show()
```




[37]:
```
df_profit['Time'] = df_profit.Date.dt.quarter

sns.lineplot(data=df_profit, x='Time', y='Profit', ci=None, label='Profit')
sns.lineplot(data=df_profit, x='Time', y='Offline_Spend', ci=None,␣
↪label='Offline Spend')
sns.lineplot(data=df_profit, x='Time', y='Online_Spend', ci=None, label='Online␣
↪Spend')
sns.lineplot(data=df_profit, x='Time', y='Invoice_dt', ci=None, label='Total␣
↪Invoice per date')

plt.title('Marketing vs Profit quarter wise')
plt.legend()

plt.show()
```




[38]:
```
df_profit['Time'] = df_profit['Date'].dt.isocalendar().week

sns.lineplot(data=df_profit, x='Time', y='Profit', ci=None, label='Profit')
sns.lineplot(data=df_profit, x='Time', y='Offline_Spend', ci=None,␣
↪label='Offline Spend')
sns.lineplot(data=df_profit, x='Time', y='Online_Spend', ci=None, label='Online␣
↪Spend')
sns.lineplot(data=df_profit, x='Time', y='Invoice_dt', ci=None, label='Total␣
↪Invoice per date')

plt.title('Marketing vs Profit week wise')
plt.legend()

plt.show()
```


### 6.1 Middle of the year shows lowest spendings and maximum profit typically in Q02-Q03 and week number 32 in month 7-8.Lowest profit is seen during end of the year when marketing efforts require more spendings and also volume of sales is going down.

## 7 RFM Analysis

[39]:
```
df=df.drop_duplicates(subset=['CustomerID','Transaction_ID','Product_SKU'])
df.shape
```

[39]: (52924, 20)

[40]:
```
df['last']=df.groupby('CustomerID')['Date'].transform('max')
df['days']=(df['last']-df['Date'].min()).dt.days
df['count']=df.groupby('CustomerID')['Transaction_ID'].transform('nunique')
df['frequency_']=df['count']/(1+df['days'])
df['monetary_']=df.groupby('CustomerID')['Invoice'].transform('median') #Taking␣
↪median since heavily skewed
```

```
df['recency_']=-(df['Date'].max()-df['last']).dt.days #Taking minus since␣
↪reverse
```

[41]:
```
df1=df
df=df[['CustomerID','recency_','frequency_','monetary_']].drop_duplicates()
num_quantiles = 5
df['recency'] = pd.qcut(df['recency_'], num_quantiles, labels=False,␣
↪duplicates='drop')
df['frequency'] = pd.qcut(df['frequency_'], num_quantiles, labels=False,␣
↪duplicates='drop')
df['monetary'] = pd.qcut(df['monetary_'], num_quantiles, labels=False,␣
↪duplicates='drop')

# To compensate the dropped ones
df['recency'] += 1
df['frequency'] += 1
df['monetary'] += 1

df['FM'] = np.round((df['frequency'].astype(int) + df['monetary'].astype(int)) /
↪ 2)
```

[42]:
```
df['recency'].value_counts()
```

[42]:
```
recency
3    296
1    294
5    293
2    293
4    292
Name: count, dtype: int64
```

[43]:
```
df['frequency'].value_counts()
```

[43]:
```
frequency
1    296
3    295
5    293
4    293
2    291
Name: count, dtype: int64
```

[44]:
```
df['monetary'].value_counts()
```

[44]:
```
monetary
1    869
3    320
4    267
```

```
2     12
Name: count, dtype: int64
```

[45]:
```
def assign_rfm_segment(row):
    r_score = row['recency']
    fm_score = row['FM']

    if (r_score == 5 and fm_score == 5) or (r_score == 5 and fm_score == 4) or␣
 ↪(r_score == 4 and fm_score == 5):
        return 'Champions'
    elif (r_score == 5 and fm_score == 3) or (r_score == 4 and fm_score == 4)␣
 ↪or (r_score == 3 and fm_score == 5) or (r_score == 3 and fm_score == 4):
        return 'Loyal Customers'
    elif (r_score == 5 and fm_score == 2) or (r_score == 4 and fm_score == 2)␣
 ↪or (r_score == 3 and fm_score == 3) or (r_score == 4 and fm_score == 3):
        return 'Potential Loyalists'
    elif r_score == 5 and fm_score == 1:
        return 'Recent Customers'
    elif (r_score == 4 and fm_score == 1) or (r_score == 3 and fm_score == 1):
        return 'Promising'
    elif (r_score == 3 and fm_score == 2) or (r_score == 2 and fm_score == 3)␣
 ↪or (r_score == 2 and fm_score == 2):
        return 'Customers Needing Attention'
    elif r_score == 2 and fm_score == 1:
        return 'About to Sleep'
    elif (r_score == 2 and fm_score == 5) or (r_score == 2 and fm_score == 4)␣
 ↪or (r_score == 1 and fm_score == 3):
        return 'At Risk'
    elif (r_score == 1 and fm_score == 5) or (r_score == 1 and fm_score == 4):
        return 'Cant Lose Them'
    elif r_score == 1 and fm_score == 2:
        return 'Hibernating'
    elif r_score == 1 and fm_score == 1:
        return 'Lost'

df['rfm_segment'] = df.apply(assign_rfm_segment, axis=1)
df.head()
```

[45]:
```
     CustomerID  recency_  frequency_  monetary_  recency  frequency  monetary  \
0         17850      -339    6.807692    6.50000        1          5         1
297       13047       -13    0.073864    6.50000        5          3         1
341       12583      -151    0.070093    6.50000        3          3         1
383       13748      -364    1.000000    6.50000        1          5         1
384       15100      -123    0.024793   11.16576        3          2         3

      FM                 rfm_segment
0    3.0                     At Risk
```

```
297  2.0          Potential Loyalists
341  2.0   Customers Needing Attention
383  3.0                       At Risk
384  2.0   Customers Needing Attention
```

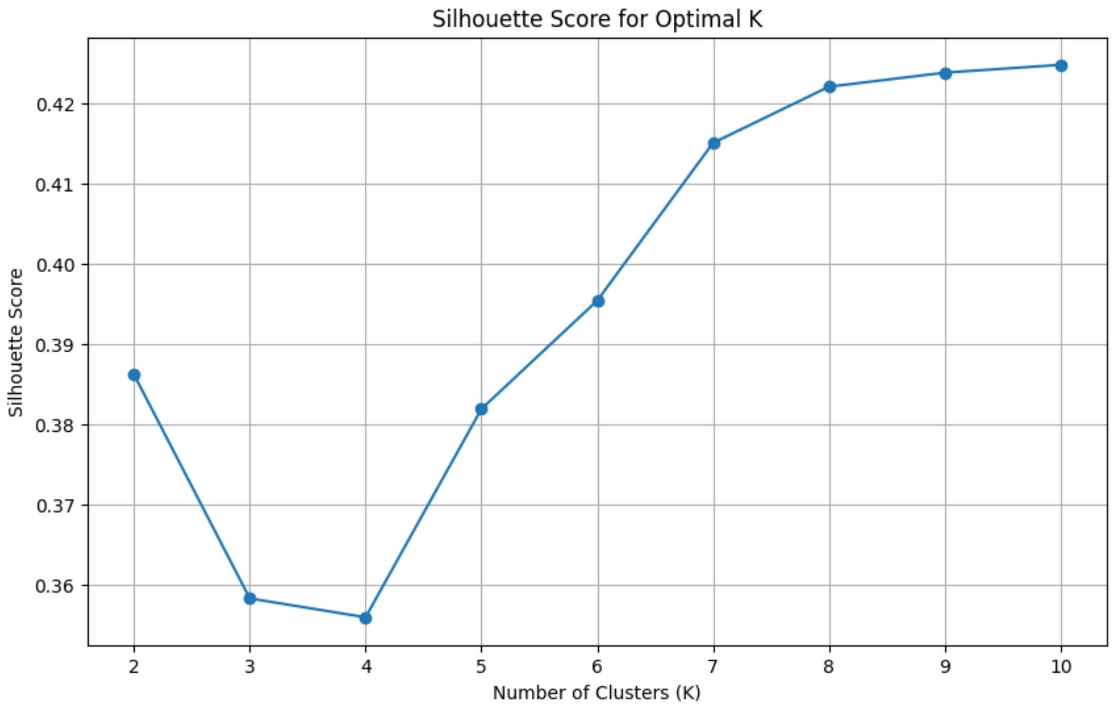
## 7.1 Defining recency score of 1,2 and FM score of 1,2 as churned customer.

### 7.1.1 There is no such fixed rule so I have picked a suitable condition to label churn.

[46]:
```
df['churn']=df.apply(lambda x: 1 if (x['recency']<=2) and (x['FM']<=2) else␣
↪0,axis=1)
```

# 8 KMeans segmentation

[47]:
```
data = df[['recency', 'frequency', 'monetary']]
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(data)

silhouette_scores = []
for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, random_state=95)
    kmeans.fit(scaled_data)
    silhouette_scores.append(silhouette_score(scaled_data, kmeans.labels_))

plt.figure(figsize=(10, 6))
plt.plot(range(2, 11), silhouette_scores, marker='o', linestyle='-')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Score for Optimal K')
plt.xticks(range(2, 11))
plt.grid(True)
plt.show()
```




[48]:
```
optimal_k = 8
kmeans = KMeans(n_clusters=optimal_k, random_state=95)
kmeans.fit(scaled_data)
cluster_labels = kmeans.labels_
df['Cluster'] = cluster_labels
```

[49]:
```
cluster_summary = df.groupby('Cluster')[['recency_', 'frequency_',␣
↪'monetary_']].describe()
cluster_summary.columns = [f"{col[0]}_{col[1]}" for col in cluster_summary.
↪columns]
cluster_summary = cluster_summary.round(2)
cluster_summary = cluster_summary.T
print(cluster_summary)
```

```
Cluster                 0       1       2       3       4       5       6  \
recency__count     273.00  179.00  148.00  197.00  216.00  195.00  124.00
recency__mean      -77.96 -181.90 -252.07  -39.52 -283.15 -185.34  -79.58
recency__std        44.43   61.12   56.71   26.57   59.43   50.85   46.89
recency__min      -161.00 -336.00 -362.00  -98.00 -364.00 -335.00 -161.00
recency__25%      -117.00 -222.00 -288.50  -62.00 -336.00 -221.00 -115.25
recency__50%       -75.00 -166.00 -252.50  -32.00 -292.00 -176.00  -81.50
recency__75%       -40.00 -134.00 -202.75  -18.00 -238.75 -149.50  -39.75
recency__max        -1.00 -100.00 -162.00    0.00 -164.00 -100.00    0.00
frequency__count   273.00  179.00  148.00  197.00  216.00  195.00  124.00
```

```
frequency__mean     0.13    0.02    0.21    0.03    0.61    0.03    0.13
frequency__std      0.12    0.01    0.28    0.02    1.44    0.02    0.10
frequency__min      0.04    0.00    0.04    0.00    0.04    0.00    0.04
frequency__25%      0.07    0.01    0.07    0.02    0.10    0.01    0.08
frequency__50%      0.10    0.02    0.12    0.03    0.18    0.03    0.11
frequency__75%      0.15    0.03    0.21    0.04    0.44    0.04    0.15
frequency__max      1.27    0.07    2.46    0.08   13.33    0.07    0.79
monetary__count   273.00  179.00  148.00  197.00  216.00  195.00  124.00
monetary__mean      6.27   26.88   24.65    6.31    6.39    6.13   12.06
monetary__std       0.25   30.90   48.70    0.25    0.21    0.23    3.40
monetary__min       6.00    7.05    7.13    6.00    6.00    6.00    7.19
monetary__25%       6.00   12.91   10.99    6.00    6.50    6.00   10.23
monetary__50%       6.50   15.42   12.99    6.50    6.50    6.00   12.48
monetary__75%       6.50   24.20   20.05    6.50    6.50    6.38   12.99
monetary__max       6.70  249.53  541.15    6.99    6.79    6.99   35.96

Cluster                7
recency__count    136.00
recency__mean     -42.02
recency__std       30.83
recency__min      -96.00
recency__25%      -74.25
recency__50%      -27.00
recency__75%      -17.00
recency__max        0.00
frequency__count  136.00
frequency__mean     0.03
frequency__std      0.02
frequency__min      0.00
frequency__25%      0.01
frequency__50%      0.03
frequency__75%      0.04
frequency__max      0.07
monetary__count   136.00
monetary__mean     27.20
monetary__std      40.47
monetary__min       7.18
monetary__25%      11.57
monetary__50%      13.12
monetary__75%      20.02
monetary__max     324.00
```

[50]:

```
df_segment=df
df=df1
df=df.merge(df_segment,on='CustomerID')
```

```
[51]: df=df[['CustomerID','Transaction_ID', 'Date', 'Product_SKU',␣
       ↪'Product_Description',
             'Invoice', 'Quantity', 'Product_Category', 'Month', 'Coupon_Code',
             'Coupon', 'Discount_pct', 'Tenurebin', 'Tenure_Months', 'Location',
             'Gender', 'rfm_segment', 'churn']]
```

## 9 Market Basket Analysis

```
[52]: basket = (df
                .groupby(['Transaction_ID', 'Product_Description'])['Quantity']
                .sum().unstack().reset_index().fillna(0)
                .set_index('Transaction_ID'))

      def encode_units(x):
          return 0 if x <= 0 else 1

      basket = basket.applymap(encode_units)
      frequent_itemsets = apriori(basket, min_support=0.01, use_colnames=True)
      rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1)
      rules.sort_values('lift', ascending=False)
```

```
[52]:                                  antecedents  \
      0  (Nest Cam Outdoor Security Camera - USA)
      1   (Nest Cam Indoor Security Camera - USA)

                                       consequents  antecedent support  \
      0   (Nest Cam Indoor Security Camera - USA)            0.132796
      1  (Nest Cam Outdoor Security Camera - USA)            0.128886

         consequent support   support  confidence      lift  leverage  conviction  \
      0            0.128886  0.027653    0.208233  1.615644  0.010537    1.100216
      1            0.132796  0.027653    0.214551  1.615644  0.010537    1.104087

         zhangs_metric
      0       0.439403
      1       0.437430
```

```
[53]: basket = (df
                .groupby(['Transaction_ID', 'Product_SKU'])['Quantity']
                .sum().unstack().reset_index().fillna(0)
                .set_index('Transaction_ID'))

      def encode_units(x):
          return 0 if x <= 0 else 1

      basket = basket.applymap(encode_units)
```

```
frequent_itemsets = apriori(basket, min_support=0.01, use_colnames=True)
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1)
rules.sort_values('lift', ascending=False)
```

[53]:

```
        antecedents       consequents  antecedent support  consequent support  \
0  (GGOEGHGR019499)  (GGOEGHGC019799)            0.014644            0.017677
1  (GGOEGHGC019799)  (GGOEGHGR019499)            0.017677            0.014644
2  (GGOENEBB078899)  (GGOENEBQ078999)            0.128886            0.132796
3  (GGOENEBQ078999)  (GGOENEBB078899)            0.132796            0.128886

    support  confidence       lift  leverage  conviction  zhangs_metric
0  0.010654    0.727520  41.156636  0.010395    3.605126       0.990203
1  0.010654    0.602709  41.156636  0.010395    2.480185       0.993260
2  0.027653    0.214551   1.615644  0.010537    1.104087       0.437430
3  0.027653    0.208233   1.615644  0.010537    1.100216       0.439403
```

[54]:

```
basket = (df
          .groupby(['Transaction_ID', 'Product_Category'])['Quantity']
          .sum().unstack().reset_index().fillna(0)
          .set_index('Transaction_ID'))

def encode_units(x):
    return 0 if x <= 0 else 1

basket = basket.applymap(encode_units)
frequent_itemsets = apriori(basket, min_support=0.01, use_colnames=True)
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1)
rules[rules['zhangs_metric']>=.85].sort_values('lift', ascending=False).
↪reset_index(drop=True)
```

[54]:

```
           antecedents             consequents  antecedent support  \
0          (Lifestyle)          (Bags, Office)            0.068313
1          (Drinkware)          (Bags, Office)            0.100714
2  (Office, Drinkware)             (Lifestyle)            0.046287
3          (Lifestyle)     (Office, Drinkware)            0.068313
4               (Bags)     (Office, Drinkware)            0.061650
5             (Office)       (Lifestyle, Bags)            0.140697
6          (Drinkware)     (Lifestyle, Office)            0.100714
7             (Office)       (Bags, Drinkware)            0.140697
8             (Office)  (Lifestyle, Drinkware)            0.140697
9             (Office)  (Notebooks & Journals)            0.140697

   consequent support   support  confidence      lift  leverage  conviction  \
0            0.026336  0.010175    0.148949  5.655759  0.008376    1.144072
1            0.026336  0.014285    0.141838  5.385774  0.011633    1.134593
2            0.068313  0.016719    0.361207  5.287504  0.013557    1.458511
3            0.046287  0.016719    0.244743  5.287504  0.013557    1.262766
```

```
4             0.046287  0.014285    0.231715  5.006047  0.011432    1.241353
5             0.014963  0.010175    0.072320  4.833091  0.008070    1.061828
6             0.035114  0.016719    0.166006  4.727596  0.013183    1.156946
7             0.021707  0.014285    0.101531  4.677354  0.011231    1.088845
8             0.025857  0.016719    0.118832  4.595736  0.013081    1.105513
9             0.024740  0.013846    0.098412  3.977900  0.010365    1.081714

   zhangs_metric
0       0.883547
1       0.905525
2       0.850229
3       0.870330
4       0.852817
5       0.922949
6       0.876780
7       0.914932
8       0.910513
9       0.871184
```

#### 9.0.1 Single Product Association:

1. **Association between Specific Products:**
   - There is a significant association between the Nest Cam Indoor Security Camera - USA and the Nest Cam Outdoor Security Camera - USA. This association is bidirectional, indicating that customers who purchase one camera are likely to purchase the other as well.
   - Similarly, there is a strong association between product SKUs GGOEGHGC019799 and GGOEGHGR019499, suggesting that customers who buy one SKU are highly likely to purchase the other.

#### 9.0.2 Product Combination and Cross-Category Associations:

2. **Association between Product Combinations and Cross-Category Behavior:**
   - This analysis identifies associations not only between specific product combinations but also across different categories. For instance, it observes a notable association between lifestyle products and the purchase of office and bags items together, indicating that customers interested in lifestyle products tend to also buy office and bags items. Additionally, it uncovers associations between drinkware and office items purchased together, suggesting that customers purchasing drinkware are likely to buy office supplies. Moreover, it recognizes that office items have associations with various other categories such as bags, lifestyle, and drinkware, indicating common purchasing patterns across different product categories. These findings provide insights into customer preferences and behaviors, facilitating opportunities for cross-selling and marketing strategies across a diverse range of product categories.

## 10 Descriptive Statistics

[55]:
```python
df.describe(include='all')
```

[55]:
```
        CustomerID  Transaction_ID                           Date  \
count      52924.0         52924.0                          52924
unique      1468.0         25061.0                            NaN
top        12748.0         32526.0                            NaN
freq         695.0            35.0                            NaN
mean           NaN             NaN  2019-07-05 19:16:09.450532864
min            NaN             NaN            2019-01-01 00:00:00
25%            NaN             NaN            2019-04-12 00:00:00
50%            NaN             NaN            2019-07-13 00:00:00
75%            NaN             NaN            2019-09-27 00:00:00
max            NaN             NaN            2019-12-31 00:00:00
std            NaN             NaN                            NaN

           Product_SKU                                Product_Description  \
count            52924                                              52924
unique            1145                                                404
top     GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
freq              3511                                               3511
mean               NaN                                                NaN
min                NaN                                                NaN
25%                NaN                                                NaN
50%                NaN                                                NaN
75%                NaN                                                NaN
max                NaN                                                NaN
std                NaN                                                NaN

             Invoice      Quantity Product_Category  Month Coupon_Code  \
count   52924.000000  52924.000000            52924  52924       52924
unique           NaN           NaN               20     12          46
top              NaN           NaN          Apparel    Aug      SALE20
freq             NaN           NaN            18126   6150        6373
mean       36.505044      4.497638              NaN    NaN         NaN
min         0.000000      1.000000              NaN    NaN         NaN
25%         6.000000      1.000000              NaN    NaN         NaN
50%         6.500000      1.000000              NaN    NaN         NaN
75%        23.444437      2.000000              NaN    NaN         NaN
max      8979.275000    900.000000              NaN    NaN         NaN
std        99.082101     20.104711              NaN    NaN         NaN

              Coupon  Discount_pct Tenurebin  Tenure_Months Location Gender  \
count   52924.000000  52924.000000     52924   52924.000000    52924  52924
unique           NaN           NaN         5            NaN        5      2
top              NaN           NaN     20-30            NaN  Chicago      F
```

| | | | | | | |
|---|---|---|---|---|---|---|
| freq | NaN | NaN | 12588 | NaN | 18380 | 33007 |
| mean | 0.338296 | 19.802358 | NaN | 26.127995 | NaN | NaN |
| min | 0.000000 | 0.000000 | NaN | 2.000000 | NaN | NaN |
| 25% | 0.000000 | 10.000000 | NaN | 15.000000 | NaN | NaN |
| 50% | 0.000000 | 20.000000 | NaN | 27.000000 | NaN | NaN |
| 75% | 1.000000 | 30.000000 | NaN | 37.000000 | NaN | NaN |
| max | 1.000000 | 30.000000 | NaN | 50.000000 | NaN | NaN |
| std | 0.473134 | 8.278878 | NaN | 13.478285 | NaN | NaN |

| | rfm_segment | churn |
|---|---|---|
| count | 52924 | 52924.000000 |
| unique | 11 | NaN |
| top | Potential Loyalists | NaN |
| freq | 18250 | NaN |
| mean | NaN | 0.068324 |
| min | NaN | 0.000000 |
| 25% | NaN | 0.000000 |
| 50% | NaN | 0.000000 |
| 75% | NaN | 0.000000 |
| max | NaN | 1.000000 |
| std | NaN | 0.252304 |

## 10.1 Descriptive Statistics Insight:

- **Customer Count**: There are 1468 unique customers in the dataset.
- **Transaction Count**: There are 25061 unique transactions in the dataset.
- **Date**: Transactions span from January 1, 2019, to December 31, 2019, with an average transaction date of July 5, 2019.
- **Invoice Amount**: The average invoice amount is $36.51, with a minimum of $0 and a maximum of $8,979.28.
  - Std: $99.08
  - Median: $6.50
- **Quantity**: The average quantity per transaction is 4.50, with a minimum of 1 and a maximum of 900.
  - Std: 20.10
  - Median: 1.00
- **Product Category**: The most frequent product category is Apparel, accounting for 18,126 transactions.
- **Month**: Transactions are spread across 12 months, with August being the most frequent month (6,150 transactions).
- **Coupon Code**: The most frequently used coupon code is SALE20, used in 6,373 transactions.
- **Discount Percentage**: Coupon is applied 33.83% times with mean percentage 19.8% and minimum of 0% and maximum of 30%.
  - Std: 8.29%
  - Median 20%
- **Tenure Months**: The average tenure of customers is approximately 26.13 months, with a range from 2 to 50 months.

    - Std: 13.48 months
    - Median: 27.00 months
- **Location**: The majority of transactions (18380) originate from Chicago.
- **Gender**: Transactions are primarily from female customers, with a frequency of 33,007.
- **RFM Segment**: The most common RFM segment is Potential Loyalists, identified in 18,250 transactions.
- **Churn Rate**: The overall churn rate is approximately 6.83%.

## 11 Multivariate Analysis

#### 11.0.1 Getting the mode Product purchased by each groups.

[56]:
```
df.Product_Description=df.Product_Description.str[:32]
cat_col1 = ['Product_SKU', 'Product_Description']
cat_col2 = ['Gender', 'churn', 'Tenurebin', 'rfm_segment','Location'␣
↪,'Coupon_Code']
```

[57]:
```
print(f'MODE Product_SKU and Product_Description by Month:')
print(df.groupby('Month',as_index=False)[cat_col1].agg(lambda x: pd.Series.
↪mode(x)[0]))
print()
```

```
MODE Product_SKU and Product_Description by Month:
   Month     Product_SKU               Product_Description
0    Apr  GGOENEBB078899  Nest Learning Thermostat 3rd Gen
1    Aug  GGOENEBQ078999  Nest Learning Thermostat 3rd Gen
2    Dec  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
3    Feb  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
4    Jan  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
5    Jul  GGOENEBQ078999  Nest Learning Thermostat 3rd Gen
6    Jun  GGOENEBQ078999  Nest Learning Thermostat 3rd Gen
7    Mar  GGOENEBQ078999  Nest Learning Thermostat 3rd Gen
8    May  GGOENEBB078899  Nest Learning Thermostat 3rd Gen
9    Nov  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
10   Oct  GGOENEBQ078999  Nest Learning Thermostat 3rd Gen
11   Sep  GGOENEBB078899  Nest Learning Thermostat 3rd Gen
```

[58]:
```
print(f'Top 5 Product_SKU by Month and total Invoice:')
print(df.groupby(['Month','Product_SKU'],as_index=False)['Invoice'].sum().
↪sort_values('Invoice',ascending=False).head(5).reset_index(drop=True))
print()
```

```
Top 5 Product_SKU by Month and total Invoice:
  Month     Product_SKU     Invoice
0   Jan  GGOENEBJ079499  40767.5780
1   Jan  GGOENEBQ078999  26076.3675
2   Feb  GGOENEBJ079499  21766.1400
```

```
3   Nov  GGOENEBJ079499  21572.8000
4   Dec  GGOENEBJ079499  20807.1352
```

[59]:
```
print(f'Top 5 Product_Category by Month and total Invoice:')
print(df.groupby(['Month','Product_Category'],as_index=False)['Invoice'].sum().
 ↪sort_values('Invoice',ascending=False).head(5).reset_index(drop=True))
print()
```

```
Top 5 Product_Category by Month and total Invoice:
  Month Product_Category      Invoice
0   Jan         Nest-USA  103309.1541
1   Nov         Nest-USA   91249.8100
2   Dec         Nest-USA   82770.5110
3   Jul         Nest-USA   77164.6700
4   Oct         Nest-USA   76008.7300
```

[60]:
```
for col in cat_col2:
    print(f'MODE Product_SKU and Product_Description by {col} :')
    print(df.groupby(col,as_index=False)[cat_col1].agg(lambda x: pd.Series.
 ↪mode(x)[0]))
    print()
```

```
MODE Product_SKU and Product_Description by Gender :
  Gender     Product_SKU               Product_Description
0      F  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
1      M  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen

MODE Product_SKU and Product_Description by churn :
   churn     Product_SKU               Product_Description
0      0  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
1      1  GGOENEBQ078999  Nest Learning Thermostat 3rd Gen

MODE Product_SKU and Product_Description by Tenurebin :
  Tenurebin     Product_SKU               Product_Description
0      0-10  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
1     10-20  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
2     20-30  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
3     30-40  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
4       >40  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen

MODE Product_SKU and Product_Description by rfm_segment :
                    rfm_segment     Product_SKU  \
0                 About to Sleep  GGOENEBJ079499
1                        At Risk  GGOENEBJ079499
2                 Cant Lose Them  GGOENEBJ079499
3                      Champions  GGOENEBJ079499
```

```
4   Customers Needing Attention  GGOENEBQ078999
5                   Hibernating  GGOENEBB078899
6                          Lost  GGOEGBJC019999
7               Loyal Customers  GGOENEBQ078999
8           Potential Loyalists  GGOENEBJ079499
9                     Promising  GGOENEBJ079499
10             Recent Customers  GGOENEBQ078999

                 Product_Description
0   Android Toddler Short Sleeve T-s
1   Nest Learning Thermostat 3rd Gen
2   Nest Learning Thermostat 3rd Gen
3   Nest Learning Thermostat 3rd Gen
4   Nest Learning Thermostat 3rd Gen
5   Nest Cam Indoor Security Camera
6                  Google Sunglasses
7   Nest Learning Thermostat 3rd Gen
8   Nest Learning Thermostat 3rd Gen
9   Nest Learning Thermostat 3rd Gen
10  Nest Learning Thermostat 3rd Gen

MODE Product_SKU and Product_Description by Location :
        Location     Product_SKU               Product_Description
0     California  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
1        Chicago  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
2     New Jersey  GGOENEBB078899  Nest Learning Thermostat 3rd Gen
3       New York  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
4  Washington DC  GGOENEBQ078999  Nest Learning Thermostat 3rd Gen

MODE Product_SKU and Product_Description by Coupon_Code :
   Coupon_Code     Product_SKU               Product_Description
0        ACC10  GGOEGCKQ084999                Emoji Sticker Sheet
1        ACC20  GGOEAFKA087499  Android Small Removable Sticker
2        ACC30  GGOEGFKA086699          Google Emoji Sticker Pack
3        AIO10  GGOEGBMJ013399                          Sport Bag
4        AIO20  GGOEGBMJ013399                          Sport Bag
5        AIO30  GGOEGBMJ013399                          Sport Bag
6        AND10  GGOEAAAH083314  Android Men's Paradise Short Sle
7        AND20  GGOEAAAH083313  Android Men's Paradise Short Sle
8        AND30  GGOEAAAH083315  Android Men's Paradise Short Sle
9         BT10  GGOEYDHJ056099      22 oz YouTube Bottle Infuser
10        BT20  GGOEADHH055999              22 oz Android Bottle
11        BT30  GGOEADHH055999              22 oz Android Bottle
12      ELEC10  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
13      ELEC20  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
14      ELEC30  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen
15     EXTRA10  GGOEGDHC018299                 Google Sunglasses
16     EXTRA20  GGOEGDHC018299                 Google Sunglasses
```

| | | | |
|---|---|---|---|
| 17 | EXTRA30 | GGOEGDHC018299 | Google Sunglasses |
| 18 | GC10 | GGOEGGCX056399 | Gift Card - $250.00 |
| 19 | GC20 | GGOEGGCX056299 | Gift Card - $25.00 |
| 20 | GC30 | GGOEGGCX056299 | Gift Card - $25.00 |
| 21 | HGEAR10 | GGOEGHPJ080310 | Google Blackout Cap |
| 22 | HGEAR20 | GGOEGHPJ080310 | Google Blackout Cap |
| 23 | HGEAR30 | GGOEGHPJ080310 | Google Blackout Cap |
| 24 | HOU10 | GGOEGCBQ016499 | SPF-15 Slim & Slender Lip Balm |
| 25 | HOU20 | GGOEGCBQ016499 | SPF-15 Slim & Slender Lip Balm |
| 26 | HOU30 | GGOEGCBQ016499 | SPF-15 Slim & Slender Lip Balm |
| 27 | NCA10 | GGOENEBJ081899 | Nest Learning Thermostat 3rd Gen |
| 28 | NCA20 | GGOENEBJ081899 | Nest Learning Thermostat 3rd Gen |
| 29 | NCA30 | GGOENEBJ081899 | Nest Learning Thermostat 3rd Gen |
| 30 | NE10 | GGOENEBQ086799 | Nest Thermostat E - USA |
| 31 | NE20 | GGOENEBQ086799 | Nest Thermostat E - USA |
| 32 | NE30 | GGOENEBQ086799 | Nest Thermostat E - USA |
| 33 | NJ10 | GGOEGOCC077299 | Google RFID Journal |
| 34 | NJ20 | GGOEGOCC077299 | Google RFID Journal |
| 35 | NJ30 | GGOEGOCL077699 | Google Hard Cover Journal |
| 36 | No_coupon | GGOEGOBC078699 | Google Luggage Tag |
| 37 | OFF10 | GGOEGFKQ020399 | Google Laptop and Cell Phone Sti |
| 38 | OFF20 | GGOEGFKQ020399 | Google Laptop and Cell Phone Sti |
| 39 | OFF30 | GGOEGFKQ020399 | Google Laptop and Cell Phone Sti |
| 40 | SALE10 | GGOEGHPB071610 | Google Men's 100% Cotton Short S |
| 41 | SALE20 | GGOEGHPB071610 | Google Men's 100% Cotton Short S |
| 42 | SALE30 | GGOEGHPB071610 | Google Men's 100% Cotton Short S |
| 43 | WEMP10 | GGOEWEBB082699 | Waze Mobile Phone Vent Mount |
| 44 | WEMP20 | GGOEWEBB082699 | Waze Mobile Phone Vent Mount |
| 45 | WEMP30 | GGOEWEBB082699 | Waze Mobile Phone Vent Mount |

### 11.1 GGOENEBJ079499 is the most popular.

### 11.2 For `Coupon_Code` there are variety of most frequent products based on the specific code.

## 12 Hypothesis Testing

#### 12.0.1 Significance level (alpha) is set to .05 if not mentioned otherwise.

#### 12.0.2 Independent ttest to check difference in mean invoice across `Gender` and `churn`

**H0 : The mean Invoice among the 2 subgroups of each category is same.**

**H1 : The mean Invoice among the 2 subgroups of each category is significantly difference.**

**Significance level(alpha) is set to .05 .**

[61]:
```
M,f=df[df['Gender']=='M']['Invoice'],df[df['Gender']=='F']['Invoice']
ttest_gender = ttest_ind(f,M)
if ttest_gender.pvalue <= 0.05:
    print(f"There is a statistically significant difference in mean invoice␣
 ↪between genders. pvalue : {ttest_gender.pvalue}")
else:
    print(f"There is NO statistically significant difference in mean invoice␣
 ↪between genders. pvalue : {ttest_gender.pvalue}")

Nc,c=df[df['churn']==0]['Invoice'],df[df['churn']==1]['Invoice']
ttest_churn = ttest_ind(Nc,c)
if ttest_churn.pvalue <= 0.05:
    print(f"There is a statistically significant difference in mean invoice␣
 ↪between churned and non-churned customers.  pvalue : {ttest_churn.pvalue}")
else:
    print(f"There is NO statistically significant difference in mean invoice␣
 ↪between churned and non-churned customers. pvalue : {ttest_churn.pvalue}")
```

```
There is NO statistically significant difference in mean invoice between
genders. pvalue : 0.2813480064152183
There is a statistically significant difference in mean invoice between churned
and non-churned customers.  pvalue : 4.8909588067553136e-11
```

#### 12.0.3 ANOVA and Kruskal-Walis for Tenurebin and rfm_segment and Location and Coupon_Code.

**H0 : The mean Invoice among the subgroups of each category is same.**

**H1 : The mean Invoice among the subgroups of each category is significantly difference.**

**Significance level(alpha) is set to .05 .**

[62]:
```
pg.normality(df['Invoice'], method='shapiro')
```

[62]:

| | W | pval | normal |
|---|---|---|---|
| Invoice | 0.276398 | 0.0 | False |

**Tenurebin**

[63]:
```
pg.homoscedasticity(df, dv='Invoice', group='Tenurebin')
```

[63]:

| | W | pval | equal_var |
|---|---|---|---|
| levene | 0.60963 | 0.655679 | True |

[64]:
```
pg.anova(data=df, dv='Invoice', between='Tenurebin')
```

[64]:

| | Source | ddof1 | ddof2 | F | p-unc | np2 |
|---|---|---|---|---|---|---|
| 0 | Tenurebin | 4 | 52919 | 0.64025 | 0.63375 | 0.000048 |

[65]:
```
pg.kruskal(data=df, dv='Invoice', between='Tenurebin')
```

[65]:
```
            Source  ddof1          H     p-unc
Kruskal  Tenurebin      4  31.071518  0.000003
```

**rfm_segment**

[66]:
```
pg.homoscedasticity(df, dv='Invoice', group='rfm_segment')
```

[66]:
```
                W          pval  equal_var
levene  14.702842  1.667344e-26      False
```

[67]:
```
pg.anova(data=df, dv='Invoice', between='rfm_segment')
```

[67]:
```
        Source  ddof1  ddof2          F         p-unc       np2
0  rfm_segment     10  52913  15.624663  2.137679e-28  0.002944
```

[68]:
```
pg.kruskal(data=df, dv='Invoice', between='rfm_segment')
```

[68]:
```
              Source  ddof1            H  p-unc
Kruskal  rfm_segment     10  1811.366036    0.0
```

**Location**

[69]:
```
pg.homoscedasticity(df, dv='Invoice', group='Location')
```

[69]:
```
               W      pval  equal_var
levene  0.308458  0.872496       True
```

[70]:
```
pg.anova(data=df, dv='Invoice', between='Location')
```

[70]:
```
     Source  ddof1  ddof2         F     p-unc       np2
0  Location      4  52919  0.294788  0.881518  0.000022
```

[71]:
```
pg.kruskal(data=df, dv='Invoice', between='Location')
```

[71]:
```
           Source  ddof1         H     p-unc
Kruskal  Location      4  7.535014  0.110175
```

**Coupon_Code**

[72]:
```
pg.homoscedasticity(df, dv='Invoice', group='Coupon_Code')
```

[72]:
```
                W  pval  equal_var
levene  46.232491   0.0      False
```

[73]:
```
pg.anova(data=df, dv='Invoice', between='Coupon_Code')
```

[73]:
```
        Source  ddof1  ddof2          F  p-unc       np2
0  Coupon_Code     45  52878  46.106051    0.0  0.037756
```

[74]:
```
pg.kruskal(data=df, dv='Invoice', between='Coupon_Code')
```

[74]:

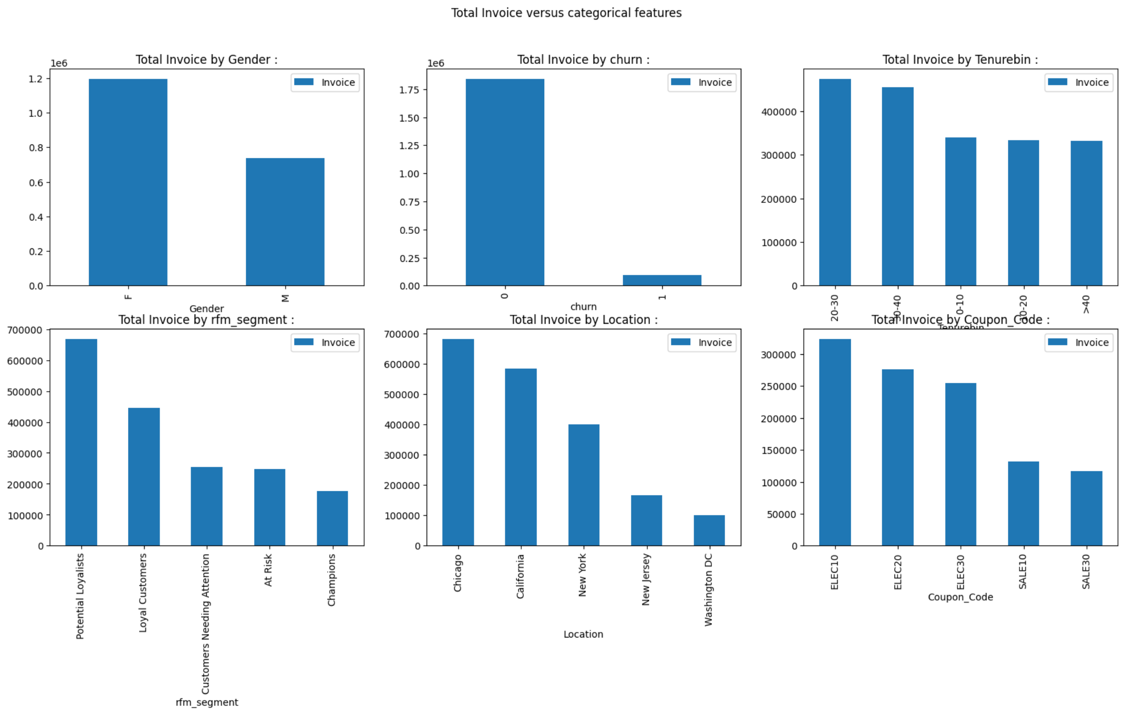
| | Source | ddof1 | H | p-unc |
|---|---|---|---|---|
| Kruskal | Coupon_Code | 45 | 967.448797 | 1.917051e-173 |

### 12.0.4 Statistical Test Results:

1. **Gender Invoice Comparison:**
   - There is NO statistically significant difference in mean invoice between genders (p-value: 0.281).
2. **Churn Invoice Comparison:**
   - There is a statistically significant difference in mean invoice between churned and non-churned customers (p-value: 4.89e-11).
3. **Assessment of Normality:**
   - Invoice data is not normally distributed.
4. **Tenurebin Kruskal-Wallis Test:**
   - Levene's test indicates homogeneity of variance (p-value: 0.61).
   - Kruskal results suggest a statistically significant difference in mean invoice across tenure bins (p-value: 3e-6).
5. **rfm_segment Kruskal-Wallis Test:**
   - Levene's test indicates heterogeneity of variance (p-value: <0.05).
   - Kruskal results suggest a statistically significant difference in mean invoice across RFM segments (p-value: 0.0).
6. **Location Kruskal-Wallis Test:**
   - Levene's test indicates homogeneity of variance (p-value: 0.31).
   - Kruskal-Wallis results suggest no statistically significant difference in mean invoice across locations (p-value: 0.11).
7. **Coupon_Code Kruskal-Wallis Test:**
   - Levene's test indicates heterogeneity of variance (p-value: 0.0).
   - Kruskal-Wallis results suggest statistically significant difference in mean invoice across coupon codes. (p-value: 1.92e-173).

These results provide insights into the differences in mean invoice across different groups, as well as the normality and variance assumptions of the tests performed.

[75]:
```
fig,axes=plt.subplots(2,3,figsize=(20,9))
ax=axes.flatten()
Store=[]
plt.suptitle('Total Invoice versus categorical features')
for i,col in enumerate(cat_col2):
    group=df.groupby(col,as_index=False)['Invoice'].sum().
 ↪sort_values('Invoice',ascending=False).head(5)
    Store.append(group)
    ax[i].set_title(f'Total Invoice by {col} :')
    group.head(5).plot(kind='bar',x=col,y='Invoice',ax=ax[i])
plt.show()
```




[76]:

```python
for i in Store:
    print(i)
    print()
```

```
  Gender       Invoice
0      F  1.193025e+06
1      M  7.389675e+05

   churn       Invoice
0      0  1.837792e+06
1      1  9.420123e+04

  Tenurebin        Invoice
2     20-30   472881.24307
3     30-40   454830.86494
0      0-10   340153.12611
1     10-20   332629.13539
4       >40   331498.55667

                rfm_segment        Invoice
8           Potential Loyalists  666863.19447
7               Loyal Customers  444621.39499
4   Customers Needing Attention  253967.35675
1                       At Risk  246907.04605
3                     Champions  176769.01709
```

```
        Location       Invoice
1        Chicago  679791.55891
0     California  584489.25898
3       New York  400631.41154
2     New Jersey  166720.07400
4  Washington DC  100360.62275

   Coupon_Code       Invoice
12      ELEC10  323126.20410
13      ELEC20  275706.28000
14      ELEC30  254812.52100
40      SALE10  132244.53118
42      SALE30  116555.15028
```

### 12.0.5 Gender Invoice Insights:

- Female customers have a higher total invoice amount ($1,193,025) compared to male customers ($738,967.50).

### 12.0.6 Churn Invoice Insights:

- Customers who did not churn have a significantly higher total invoice amount ($1,837,792) compared to churned customers ($94,201.23).

### 12.0.7 Tenurebin Invoice Insights:

- Customers in the 20-30 tenure months category have the highest total invoice amount ($472,881.24), followed by customers in the 30-40 tenure months category ($454,830.86).

### 12.0.8 RFM Segment Invoice Insights:

- Potential Loyalists, identified as a valuable segment, have the highest total invoice amount ($666,863.19), while the Lost segment has the lowest total invoice amount ($1,905.32).

### 12.0.9 Location Invoice Insights:

- Transactions from Chicago contribute the highest total invoice amount ($679,791.56), followed by California ($584,489.26),and New York ($400,631.41).

### 12.0.10 Coupon_Code Insights:

- ELEC 10,20,30 and SALE 10,20,30 contributes the most to total `Invoice`.

# 13 Churn Analysis

## 13.1 Q. Is there significant relationship between categorical columns and churn?

### 13.1.1 Applying chisquare test of independence with significance value alpha set to .05.

**H0 : The categorical column and churn is not dependent on each other.**

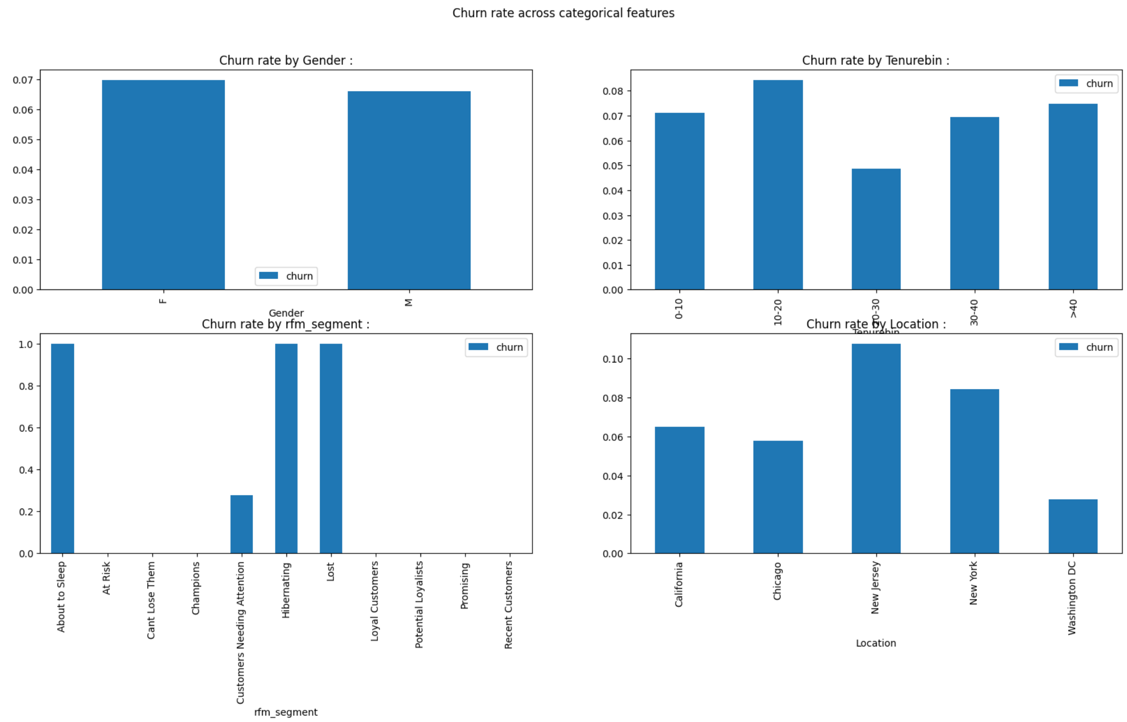
**H1 : There is significant dependence of churn on the categorical column.**

**Significance level(alpha) is set to .05**

[77]:
```
categorical=['Gender', 'Tenurebin', 'rfm_segment','Location' ]
for col in categorical:
    ct=pd.crosstab(df[col],df['churn'])
    pval=chi2_contingency(ct).pvalue
    if pval<=.05:
        print(f'As pvalue({pval})<=alpha(.05) we  reject null hypothesis, churn␣
 ↪is significantly dependent on {col}')
    else:
        print(f'As pvalue({pval})>alpha(.05) we fail to reject null hypothesis,␣
 ↪churn is NOT significantly dependent on {col}')
```

```
As pvalue(0.11502249180753568)>alpha(.05) we fail to reject null hypothesis,
churn is NOT significantly dependent on Gender
As pvalue(4.341700473181041e-25)<=alpha(.05) we  reject null hypothesis, churn
is significantly dependent on Tenurebin
As pvalue(0.0)<=alpha(.05) we  reject null hypothesis, churn is significantly
dependent on rfm_segment
As pvalue(8.669623094961317e-55)<=alpha(.05) we  reject null hypothesis, churn
is significantly dependent on Location
```

[78]:
```
fig,axes=plt.subplots(2,2,figsize=(20,9))
ax=axes.flatten()
Store=[]
plt.suptitle('Churn rate across categorical features')
for i,col in enumerate(categorical):
    group=df.groupby(col,as_index=False)['churn'].mean()
    Store.append(group)
    ax[i].set_title(f'Churn rate by {col} :')
    group.plot(kind='bar',x=col,y='churn',ax=ax[i])
plt.show()
```




[79]:
```
for i in Store:
    print(i)
    print()
```

```
  Gender     churn
0      F  0.069682
1      M  0.066074

  Tenurebin     churn
0      0-10  0.071057
1     10-20  0.084206
2     20-30  0.048697
3     30-40  0.069528
4       >40  0.074701

                   rfm_segment     churn
0               About to Sleep  1.000000
1                      At Risk  0.000000
2               Cant Lose Them  0.000000
3                    Champions  0.000000
4  Customers Needing Attention  0.279327
5                  Hibernating  1.000000
6                         Lost  1.000000
7              Loyal Customers  0.000000
```

```
8           Potential Loyalists  0.000000
9                     Promising  0.000000
10             Recent Customers  0.000000

        Location     churn
0     California  0.065072
1        Chicago  0.057835
2     New Jersey  0.107484
3       New York  0.084400
4  Washington DC  0.027818
```

#### 13.1.2 Churn Dependence Insights:

1. **Gender:**
   - Churn is NOT significantly dependent on gender (p-value: 0.115).
2. **Tenurebin:**
   - Churn is significantly dependent on tenurebin (p-value: 4.34e-25).
   - Customers with tenure between 20-30 months have the lowest churn rate (4.87%), while those with tenure between 10-20 months have the highest churn rate (8.42%).
3. **RFM Segment:**
   - Churn is significantly dependent on RFM segment (p-value: 0.0).
   - Customers categorized as 'At Risk', 'Cant Lose Them', 'Champions', 'Loyal Customers', and 'Potential Loyalists' have the lowest churn rates (0.0%), indicating high loyalty.
4. **Location:**
   - Churn is significantly dependent on location (p-value: 8.67e-55).
   - Customers from Washington DC exhibit the lowest churn rate (2.78%), while those from New Jersey have the highest churn rate (10.75%).

These insights highlight the factors influencing churn rates, including tenure, RFM segment, and location. Understanding these dependencies can help in devising targeted retention strategies and improving customer loyalty.

#### 13.1.3 Crosschecking by checking if mean `Invoice` and mean `Tenure` is signficantly different for churn and not churn.

**H0 : Not churned customers have mean invoice less than or equal to that of churned customer.**

**H1 : Not churned customers have mean invoice greater than that of churned customer.**

**Significance level(alpha)=.05**

[80]:
```python
C,Nc=df[df['churn']==1]['Invoice'],df[df['churn']==0]['Invoice']
levene(Nc,C)
```

[80]:
```
LeveneResult(statistic=42.93837475167171, pvalue=5.70083792022353e-11)
```

**As Levene test pvalue<.05 equal_var is set to False**

[81]:
```
ttest_ind(Nc,C,alternative='greater',equal_var=False)
```

[81]:
```
TtestResult(statistic=10.502516703639804, pvalue=7.411181740803589e-26,
df=5391.8653543032015)
```

#### 13.1.4 As pvalue< .05 we reject null hypothesis and can conclude that not churned customers have higher mean `Invoice` value which is expected by definition.

**H0 : Not churned customers have mean tenure greater than or equal to that of churned customer.**

**H1 : Not churned customers have mean tenure less than that of churned customer.**

**Significance level(alpha) is set to .05.**

[82]:
```
C,Nc=df[df['churn']==1]['Tenure_Months'],df[df['churn']==0]['Tenure_Months']
levene(Nc,C)
```

[82]:
```
LeveneResult(statistic=58.40757862523135, pvalue=2.166461537104734e-14)
```

**As Levene test pvalue<.05 equal_var is set to False**

[83]:
```
ttest_ind(Nc,C,alternative='less',equal_var=False)
```

[83]:
```
TtestResult(statistic=0.2037658181614431, pvalue=0.580726699025027,
df=4106.604928531195)
```

#### 13.1.5 As pvalue> .05 we fail to reject null hypothesis and cannot conclude that not churned customers have lower mean `Tenure_Months` value.

- **`Invoice` Value Analysis:**
  - The statistical test indicates that non-churned customers have a significantly higher mean invoice value compared to churned customers ($p < 0.05$). This aligns with expectations, as loyal customers tend to make more larger purchases over time.
- **`Tenure_Months` Analysis:**
  - The analysis reveals that non-churned customers do not have lower mean tenure value.

# 14 Customer Lifetime Value (CLTV)

#### 14.0.1 Feature Engineering

[84]:
```
df.Coupon=df.Discount_pct*df.Coupon

#Encoding
encoder = TargetEncoder()
df['Location_enc'] = encoder.fit_transform(df['Location'], df['Invoice'])

#Grouping
```

```
customer_df = df.groupby('CustomerID').agg({'Invoice': 'sum','Transaction_ID':
↪'nunique','Location_enc':'mean',
    'Quantity':'median','Tenure_Months': 'median','Coupon': 'mean','churn':
↪'mean',
}).reset_index().rename(columns={'Transaction_ID':'Total_Transactions'})

#Scaling
columns_to_normalize = ['Total_Transactions', 'Quantity', 'Tenure_Months',
↪'Coupon', 'churn', 'Location_enc']
scaler = MinMaxScaler()
customer_df[columns_to_normalize] = scaler.
↪fit_transform(customer_df[columns_to_normalize])
```

### 14.0.2 Splitting and Tuning and Stacking

[85]:
```
# Data preparation
X = customer_df[['Total_Transactions', 'Quantity', 'Tenure_Months', 'Coupon',
↪'churn', 'Location_enc']]
y = customer_df['Invoice']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↪random_state=95)

# Linear Regression
param_grid_lr = {'fit_intercept': [True, False]}
model_lr = LinearRegression()
grid_search_lr = GridSearchCV(estimator=model_lr, param_grid=param_grid_lr,
↪cv=3, scoring='r2', n_jobs=-1)
grid_search_lr.fit(X_train, y_train)
best_model_lr = grid_search_lr.best_estimator_

# Lasso
param_grid_lasso = {'alpha': [0.001, 0.01, 0.1, 1, 10, 100]}
model_lasso = Lasso(random_state=95)
grid_search_lasso = GridSearchCV(estimator=model_lasso,
↪param_grid=param_grid_lasso, cv=3, scoring='r2', n_jobs=-1)
grid_search_lasso.fit(X_train, y_train)
best_model_lasso = grid_search_lasso.best_estimator_

# Ridge
param_grid_ridge = {'alpha': [0.001, 0.01, 0.1, 1, 10, 100]}
model_ridge = Ridge(random_state=95)
grid_search_ridge = GridSearchCV(estimator=model_ridge,
↪param_grid=param_grid_ridge, cv=3, scoring='r2', n_jobs=-1)
grid_search_ridge.fit(X_train, y_train)
best_model_ridge = grid_search_ridge.best_estimator_
```

```
# Stacking
stacked_estimators = [
    ('linear', best_model_lr),
    ('lasso', best_model_lasso),
    ('ridge', best_model_ridge)]
stacked_model =␣
 ↪StackingRegressor(estimators=stacked_estimators,final_estimator=LinearRegression())
stacked_model.fit(X_train, y_train)
```

[85]:
```
StackingRegressor(estimators=[('linear', LinearRegression(fit_intercept=False)),
                              ('lasso', Lasso(alpha=1, random_state=95)),
                              ('ridge', Ridge(alpha=0.1, random_state=95))],
                  final_estimator=LinearRegression())
```

#### 14.0.3 Evaluation

[86]:
```
# Evaluating the stacked model
y_pred_stacked = stacked_model.predict(X_test)

rmse_stacked = np.sqrt(MSE(y_test, y_pred_stacked))
r2_stacked = stacked_model.score(X_test, y_test)

print(f"Stacked Model RMSE: {rmse_stacked}")
print(f"Stacked Model R² score: {r2_stacked}")
```

```
Stacked Model RMSE: 744.0948124033317
Stacked Model R² score: 0.8469546623725761
```

### 14.1 Through stacking and hyperparameter tuning a regression model is built with decent .85 r^2 value and 744 RMSE which predicts total revenue that a customer generates based on the features Location, count of transactions, median Quantity bought, Tenure, median Coupon discount availed and churn.

## 15 Recommendations Based on Insights

1. **Targeted Marketing for Top Products:** Focus marketing campaigns on top-performing products such as the Nest Learning Thermostat 3rd Gen-USA and Nest Cam Outdoor Security Camera. Highlight their features and benefits to capitalize on their high demand.
2. **Leverage Peak Sales Months:** Increase promotional activities and special offers during January, November, and August, as these months show the highest total invoice amounts. Utilize events like New Year sales, Black Friday, and back-to-school promotions to maximize revenue.
3. **Optimize Coupon Strategies:** Promote and potentially expand successful coupon codes like ELEC10, ELEC20, and ELEC30. These codes drive significant sales volume and should be a focal point in discount strategies.

4. **Enhance Customer Retention Programs:** Develop loyalty programs targeting customers with tenure between 20-30 months, who exhibit the lowest churn rates and maximum revenue. Personalized offers and engagement strategies can help maintain their loyalty and reduce churn.
5. **Address High Churn Regions:** Implement targeted retention strategies for regions with high churn rates, particularly New Jersey. Tailor marketing efforts and customer service improvements to address specific needs and reduce churn in these areas.
6. **Promote Product Bundles:** Highlight product combinations that show significant associations, such as the Nest Cam Indoor and Outdoor Security Cameras. Cross-sell these products to customers to increase average transaction values.
7. **Improve Customer Experience for High-Value Segments:** Focus on enhancing the customer experience for high-value RFM segments like Loyal Customers and Potential Loyalists. Provide exclusive benefits and personalized services to keep them engaged and loyal.
8. **Expand Successful Product Categories:** Increase the variety and visibility of high-demand categories such as Nest-USA, Apparel and Office supplies. Tailor marketing campaigns to showcase the range and quality of products in these categories.
9. **Monitor Seasonal Spending Patterns:** Develop strategies and discounts to boost sales during typically lower profit periods such as from Q1-Q2 and Q3-Q4. Also utilize high profit during Q2-Q3 by further increasing sales volume through discounts and other strategies.
10. **Leverage High-Retention Cohorts:** Focus retention efforts on high-performing cohorts like ‘2019-01’ and ‘2019-02’. Analyze what contributed to their higher retention rates and replicate successful strategies across other cohorts.
11. **Utilize CLTV predictions:** Use the predictive model’s CLTV estimates to prioritize retention efforts, personalize marketing strategies, and optimize resource allocation for maximum long-term profitability.
12. **Target High Revenue Segments for Enhanced Profitability:** Focus retention efforts on female customers and those in the Potential Loyalists segment. Prioritize high-invoice regions like Chicago, California, and New York.

[ ]:
```

```