Customer Segmentation by Sena Kaya

September 3, 2023

1 RFM Customer Segmentation

DBDA.X408.(34) Introduction to Machine Learning by Sena Kaya

This is a transnational data set which contains all the transactions occurring between 01/12/2010 and 09/12/2011 for a UK-based and registered non-store online retail. The company mainly sells unique all-occasion gifts. Many customers of the company are wholesalers. Dataset source: http://archive.ics.uci.edu/dataset/352/online+retail

Feature Information:

InvoiceNo: Invoice number. *Nominal*, a 6-digit integral number uniquely assigned to each transaction. If this code starts with letter 'c', it indicates a cancellation. **StockCode**: Product (item) code. *Nominal*, a 5-digit integral number uniquely assigned to each distinct product. **Description**: Product (item) name. *Nominal*. **Quantity**: The quantities of each product (item) per transaction. *Numeric*. **InvoiceDate**: Invoice Date and time. *Numeric*, the day and time when each transaction was generated. **UnitPrice**: Unit price. *Numeric*, Product price per unit in sterling. **CustomerID**: Customer number. *Nominal*, a 5-digit integral number uniquely assigned to each customer. **Country**: Country name. *Nominal*, the name of the country where each customer resides.

RFM: Recency, Frequency and Monetary

To prepare the data for RFM analysis, conduct exploratory data analysis (EDA) and data visualization to observe data structure and missing values. Perform descriptive analysis to understand feature relationships, clear noise, and address missing values in the dataset, making it ready for RFM analysis. Analyze distribution of Orders, Customers, and Countries before RFM analysis to inform sales policies and resource utilization.

Focus on UK transactions for RFM Analysis, Customer Segmentation, and K-Means Clustering due to its highest sales revenue and customer count. Use RFM Analysis, a customer segmentation technique based on past purchasing behavior, to develop targeted approaches for better customer understanding, trend observation, and increased retention and sales. Calculate Recency, Frequency, and Monetary values for UK transactions to create an RFM table.

In the Customer Segmentation section, create an RFM Segmentation Table to categorize customers based on their RFM values (e.g., "Big Spenders," "Lost Customer").

Compare manual customer segmentation with K-Means, DBSCAN, and Gaussian Mixture Clustering algorithm results to evaluate its effectiveness in customer clustering. Preprocess data for K-Means Clustering, including examining feature correlations, distributions, and normalizing the data. Determine the optimal number of clusters using the Elbow method and Silhouette Analysis. Visualize cluster distribution using a scatter plot and interpret results using boxplots.

2 Project Structures

-Data Cleaning & Feature Engineering -Exploratory Data Analysis -RFM Analysis -Customer Segmentation -Applying K-Means Clustering -Applying DBSCAN Clustering -Applying Gaussian Mixture Clustering

Data Cleaning & Feature Engineering

[1]:
```
#!conda install -c conda-forge ydata-profiling
```

[2]:
```
import pandas as pd
# from pandas_profiling import ProfileReport
from ydata_profiling import ProfileReport
```

[3]:
```
#importing libraries
import re
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.cm as cm
import sklearn.cluster as cluster
import sklearn.cluster as KMeans
import sklearn.preprocessing as StandardScaler
from sklearn.metrics import silhouette_samples, silhouette_score
from sklearn.datasets import make_blobs
%matplotlib inline
#from pandas_profiling import ProfileReport
```

[4]:
```
#importing dataset
df=pd.read_excel ("/Users/senakaya/Desktop/UCSC/Machine Learning/retail project/
↪Online Retail 2.xlsx")
df.head(10)
```

[4]:
```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6
5    536365     22752         SET 7 BABUSHKA NESTING BOXES         2
6    536365     21730    GLASS STAR FROSTED T-LIGHT HOLDER         6
7    536366     22633               HAND WARMER UNION JACK         6
8    536366     22632            HAND WARMER RED POLKA DOT         6
```

```
9     536367      84879         ASSORTED COLOUR BIRD ORNAMENT        32

          InvoiceDate  UnitPrice  CustomerID         Country
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
5 2010-12-01 08:26:00       7.65     17850.0  United Kingdom
6 2010-12-01 08:26:00       4.25     17850.0  United Kingdom
7 2010-12-01 08:28:00       1.85     17850.0  United Kingdom
8 2010-12-01 08:28:00       1.85     17850.0  United Kingdom
9 2010-12-01 08:34:00       1.69     13047.0  United Kingdom
```

[5]:
```
#dimensions of dataset
df.shape
```

[5]: (541909, 8)

[6]:
```
#summary of the dataframe's structure
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    541909 non-null  object
 1   StockCode    541909 non-null  object
 2   Description  540455 non-null  object
 3   Quantity     541909 non-null  int64
 4   InvoiceDate  541909 non-null  datetime64[ns]
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 33.1+ MB
```

[7]:
```
#descriptive statistics of quantitative variables
df.describe()
```

[7]:

	Quantity	UnitPrice	CustomerID
count	541909.000000	541909.000000	406829.000000
mean	9.552250	4.611114	15287.690570
std	218.081158	96.759853	1713.600303
min	-80995.000000	-11062.060000	12346.000000
25%	1.000000	1.250000	13953.000000
50%	3.000000	2.080000	15152.000000

```
75%        10.000000      4.130000   16791.000000
max     80995.000000  38970.000000   18287.000000
```

[8]:
```python
#descriptive statistics of object variables
df.describe(include='object')
```

[8]:
```
       InvoiceNo StockCode                         Description  \
count     541909    541909                              540455
unique     25900      4070                                4223
top       573585    85123A  WHITE HANGING HEART T-LIGHT HOLDER
freq        1114      2313                                2369

               Country
count           541909
unique              38
top     United Kingdom
freq            495478
```

[9]:
```python
#descriptive statistics of all variables
df.describe(include='all')
```

```
/var/folders/6z/wvkv_pyn7p15h1q5x5g4_qb00000gn/T/ipykernel_88713/3933383000.py:2
: FutureWarning: Treating datetime data as categorical rather than numeric in
`.describe` is deprecated and will be removed in a future version of pandas.
Specify `datetime_is_numeric=True` to silence this warning and adopt the future
behavior now.
  df.describe(include='all')
```

[9]:
```
       InvoiceNo StockCode                         Description  \
count   541909.0    541909                              540455
unique   25900.0      4070                                4223
top     573585.0    85123A  WHITE HANGING HEART T-LIGHT HOLDER
freq      1114.0      2313                                2369
first        NaN       NaN                                 NaN
last         NaN       NaN                                 NaN
mean         NaN       NaN                                 NaN
std          NaN       NaN                                 NaN
min          NaN       NaN                                 NaN
25%          NaN       NaN                                 NaN
50%          NaN       NaN                                 NaN
75%          NaN       NaN                                 NaN
max          NaN       NaN                                 NaN

             Quantity          InvoiceDate      UnitPrice     CustomerID  \
count   541909.000000               541909  541909.000000  406829.000000
unique            NaN                23260            NaN            NaN
top               NaN  2011-10-31 14:41:00            NaN            NaN
freq              NaN                 1114            NaN            NaN
```

```
first              NaN  2010-12-01 08:26:00            NaN            NaN
last               NaN  2011-12-09 12:50:00            NaN            NaN
mean          9.552250                  NaN       4.611114   15287.690570
std         218.081158                  NaN      96.759853    1713.600303
min      -80995.000000                  NaN  -11062.060000   12346.000000
25%           1.000000                  NaN       1.250000   13953.000000
50%           3.000000                  NaN       2.080000   15152.000000
75%          10.000000                  NaN       4.130000   16791.000000
max       80995.000000                  NaN   38970.000000   18287.000000

               Country
count           541909
unique              38
top     United Kingdom
freq            495478
first              NaN
last               NaN
mean               NaN
std                NaN
min                NaN
25%                NaN
50%                NaN
75%                NaN
max                NaN
```

[10]:

```python
# Generate the Pandas Profiling report

profile = ProfileReport(df, title='Pandas Profiling Report', explorative=True)
profile
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

[10]:

[11]:

```python
# Count columns with name "InvoiceNo" starting with letter "c"

df['InvoiceNo'] = df['InvoiceNo'].astype('str')
df_invoiceCancel = df[df['InvoiceNo'].str.contains('C')]
df_invoiceCancel.head()

print("Number of columns with name 'InvoiceNo' starting with 'C':",
 ↪df_invoiceCancel.shape[0])
```

```
Number of columns with name 'InvoiceNo' starting with 'C': 9288
```

[12]:
```python
# the number of transaction with negative quantity
df_negativeTransaction=df['Quantity'] <= 0
count_negativeT_no = sum(df_negativeTransaction)

print("Number of transaction with negative quantity: ", count_negativeT_no)
```

```
Number of transaction with negative quantity:  10624
```

Some transactions with negative amount do not belong to canceled ones.

[13]:
```python
#the number of missing customer Id
sum(pd.isnull(df['CustomerID']))
```

[13]:
```
135080
```

[14]:
```python
#Rows with missing customer ID need to be deleted
df.dropna(subset=['CustomerID'],inplace=True)
print(sum(df['CustomerID'].isnull()))
#check the new dataset
df.shape
```

```
0
```

[14]:
```
(406829, 8)
```

[15]:
```python
#duplicate entries need to be deleted to avoid any bias
num_duplicates = df.duplicated().sum()
print(num_duplicates)
df.drop_duplicates(inplace=True)
#check the new dataset
df.shape
```

```
5225
```

[15]:
```
(401604, 8)
```

[16]:
```python
# The number of cancellations by each customer.
CancelbyCustomer = df_invoiceCancel.groupby('CustomerID').count()['InvoiceNo'].
↪reset_index().sort_values("InvoiceNo",ascending=False)
CancelbyCustomer.rename(columns={'InvoiceNo': 'Cancellations'}, inplace=True)
CancelbyCustomer.head(10)
```

[16]:

	CustomerID	Cancellations
736	14911.0	226
1485	17841.0	136
1397	17511.0	113
848	15311.0	112
89	12607.0	101
605	14410.0	93
417	13798.0	90

```
652       14606.0              82
246       13113.0              79
36        12471.0              71
```

[17]:
```
df['year']=df['InvoiceDate'].apply(lambda x : x.year)
df['month']=df['InvoiceDate'].apply(lambda x : x.month_name())
df['day']=df['InvoiceDate'].apply(lambda x : x.day_name())
df['hour']=df['InvoiceDate'].apply(lambda x : x.hour)
```

[18]:
```
df['TimeSegment'] = np.where((df["hour"]>5)&(df["hour"]<18), np.where(
                           df["hour"]<12, 'Morning','Afternoon'),'Evening')
df.head(5)
```

[18]:
```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6

          InvoiceDate  UnitPrice  CustomerID         Country  year     month  \
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom  2010  December
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom  2010  December
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom  2010  December
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom  2010  December
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom  2010  December

         day  hour TimeSegment
0  Wednesday     8     Morning
1  Wednesday     8     Morning
2  Wednesday     8     Morning
3  Wednesday     8     Morning
4  Wednesday     8     Morning
```

[19]:
```
df['Revenue']=df['UnitPrice']*df['Quantity']
df.head()
```

[19]:
```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6

          InvoiceDate  UnitPrice  CustomerID         Country  year     month  \
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom  2010  December
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom  2010  December
```

```
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom  2010   December
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom  2010   December
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom  2010   December

         day  hour TimeSegment  Revenue
0  Wednesday     8     Morning    15.30
1  Wednesday     8     Morning    20.34
2  Wednesday     8     Morning    22.00
3  Wednesday     8     Morning    20.34
4  Wednesday     8     Morning    20.34
```

[20]:
```
dfCancelOrders=df[df['InvoiceNo'].str.contains('C')]
dfCancelOrders.head()
```

[20]:
```
    InvoiceNo StockCode                       Description  Quantity  \
141   C536379         D                          Discount        -1
154   C536383    35004C   SET OF 3 COLOURED  FLYING DUCKS        -1
235   C536391     22556    PLASTERS IN TIN CIRCUS PARADE        -12
236   C536391     21984  PACK OF 12 PINK PAISLEY TISSUES        -24
237   C536391     21983  PACK OF 12 BLUE PAISLEY TISSUES        -24

            InvoiceDate  UnitPrice  CustomerID         Country  year  \
141 2010-12-01 09:41:00      27.50     14527.0  United Kingdom  2010
154 2010-12-01 09:49:00       4.65     15311.0  United Kingdom  2010
235 2010-12-01 10:24:00       1.65     17548.0  United Kingdom  2010
236 2010-12-01 10:24:00       0.29     17548.0  United Kingdom  2010
237 2010-12-01 10:24:00       0.29     17548.0  United Kingdom  2010

        month        day  hour TimeSegment  Revenue
141  December  Wednesday     9     Morning   -27.50
154  December  Wednesday     9     Morning    -4.65
235  December  Wednesday    10     Morning   -19.80
236  December  Wednesday    10     Morning    -6.96
237  December  Wednesday    10     Morning    -6.96
```

[21]:
```
#Rows containing order cancellations need to be deleted so as not to adversely␣
 ↪affect our results
df=df[~df['InvoiceNo'].str.contains('C')]
print(f'Dimensions of cleaned data to get results {df.shape}')
```

```
Dimensions of cleaned data to get results (392732, 14)
```

[22]:
```
# Generate the Pandas Profiling report after feature engineering

profile = ProfileReport(df, title='Pandas Profiling Report', explorative=True)
profile
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]
```

```
Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

[22]:

Outcomes according to the ProfileReport -There is no missing data. -Number of observations is 392732 and number of variables is 14. -There are 37 different countries in the dataset and 88.9% of them are United Kingdom. -According to the month column, the most preferred months for shopping were November (16.1%), followed by October (12.4%) and December (10.9%). -According to the day column, the most preferred days for shopping were Thursday (20.2%), followed by Wednesday (17.3%) and Tuesday (16.7%). -According to the TimeSegment column; customers tend to shop in the afternoon (68%), then in the morning (30%). -When we dive into data for quantity: - median is 6 - 95-th percentile is 36 - maximum quantity is 80995 for an order, 2nd max is 74215, 3rd max is 12540 and 4th max is 4800. Therefore, the row has quantity more than 5000 can be deleted to avoid bias.

[23]:
```
# Generate the Pandas Profiling report for cancellation orders

profileCancelOrders = ProfileReport(dfCancelOrders, title='Pandas Profiling␣
↪Report', explorative=True)
profileCancelOrders
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

[23]:

[24]:
```
df[df['Quantity'] > 5000]
```

[24]:
```
       InvoiceNo StockCode                      Description  Quantity  \
61619     541431     23166  MEDIUM CERAMIC TOP STORAGE JAR     74215
502122    578841     84826  ASSTD DESIGN 3D PAPER STICKERS     12540
540421    581483     23843     PAPER CRAFT , LITTLE BIRDIE     80995

               InvoiceDate  UnitPrice  CustomerID         Country  year  \
61619  2011-01-18 10:01:00       1.04     12346.0  United Kingdom  2011
502122 2011-11-25 15:57:00       0.00     13256.0  United Kingdom  2011
540421 2011-12-09 09:15:00       2.08     16446.0  United Kingdom  2011

           month      day  hour TimeSegment   Revenue
61619    January  Tuesday    10     Morning   77183.6
502122  November   Friday    15   Afternoon       0.0
540421  December   Friday     9     Morning  168469.6
```

[25]:
```python
#quantity > 500 need to be deleted
df=df[df['Quantity'] <= 5000]
print(f'Dimensions of cleaned data to get results {df.shape}')
```

```
Dimensions of cleaned data to get results (392729, 14)
```

Exploratory Data Analysis

****Explore the Customers****

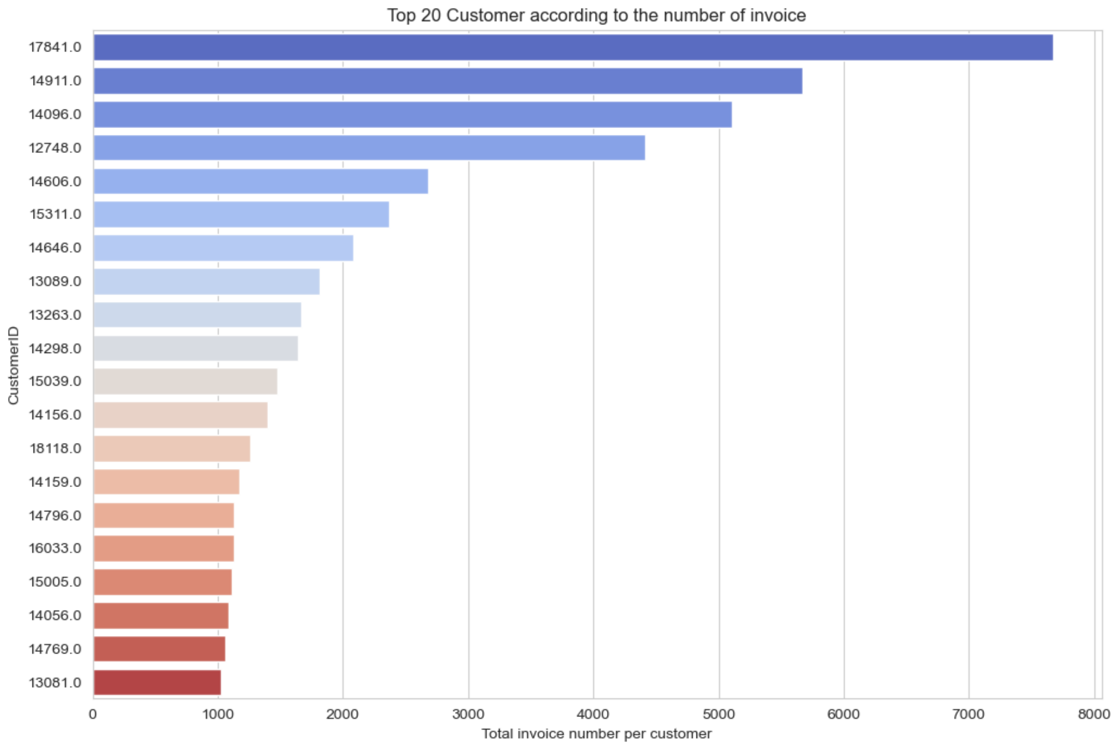
[26]:
```python
#the unique number of InvoiceNo per customer to calculate the number of␣
↪purchases per customer
InvoiceNobyCustomer = pd.DataFrame(df.groupby(['CustomerID'])['InvoiceNo'].
↪count()).reset_index().sort_values('InvoiceNo',ascending=False)[0:20]
InvoiceNobyCustomer.head(10)
```

[26]:

	CustomerID	InvoiceNo
4009	17841.0	7676
1878	14911.0	5672
1288	14096.0	5111
325	12748.0	4413
1660	14606.0	2677
2175	15311.0	2366
1688	14646.0	2080
561	13089.0	1814
689	13263.0	1667
1433	14298.0	1637

[27]:
```python
#plot top 20 Customer according to the number of invoice
sns.set_style('whitegrid')
plt.figure(figsize=(12,8))
plt.title('Top 20 Customer according to the number of invoice')
sns.barplot(y='CustomerID',x='InvoiceNo',
            data=InvoiceNobyCustomer, palette='coolwarm', orient='h',␣
↪order=InvoiceNobyCustomer['CustomerID']).set(xlabel='Total invoice number␣
↪per customer')
```

[27]:
```
[Text(0.5, 0, 'Total invoice number per customer')]
```



Explore the Transactions

[28]:
```python
#number of quantities per transaction
QuantitiesperOrder = pd.DataFrame(df.groupby(['InvoiceNo'])['Quantity'].sum()).
↪reset_index().sort_values('Quantity',ascending=False)[0:20]
QuantitiesperOrder.head(10)
```

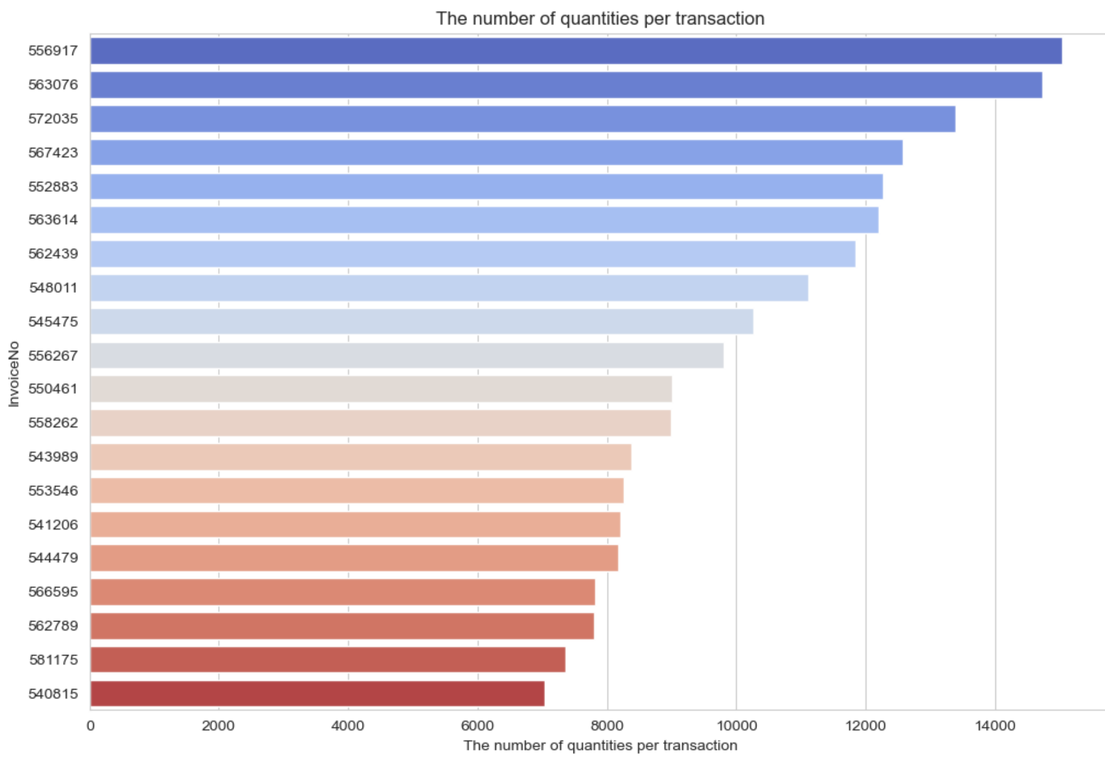
[28]:

	InvoiceNo	Quantity
8111	556917	15049
10611	563076	14730
14370	572035	13392
12418	567423	12572
6436	552883	12266
10842	563614	12196
10343	562439	11848
4540	548011	11116
3493	545475	10272
7883	556267	9811

[29]:
```python
#plot the number of quantities per transaction
sns.set_style('whitegrid')
plt.figure(figsize=(12,8))
plt.title('The number of quantities per transaction')
```

```
sns.barplot(y='InvoiceNo',x='Quantity',
            data=QuantitiesperOrder, palette='coolwarm', orient='h',␣
 ↪order=QuantitiesperOrder['InvoiceNo']).set(xlabel='The number of quantities␣
 ↪per transaction')
```

[29]: [Text(0.5, 0, 'The number of quantities per transaction')]



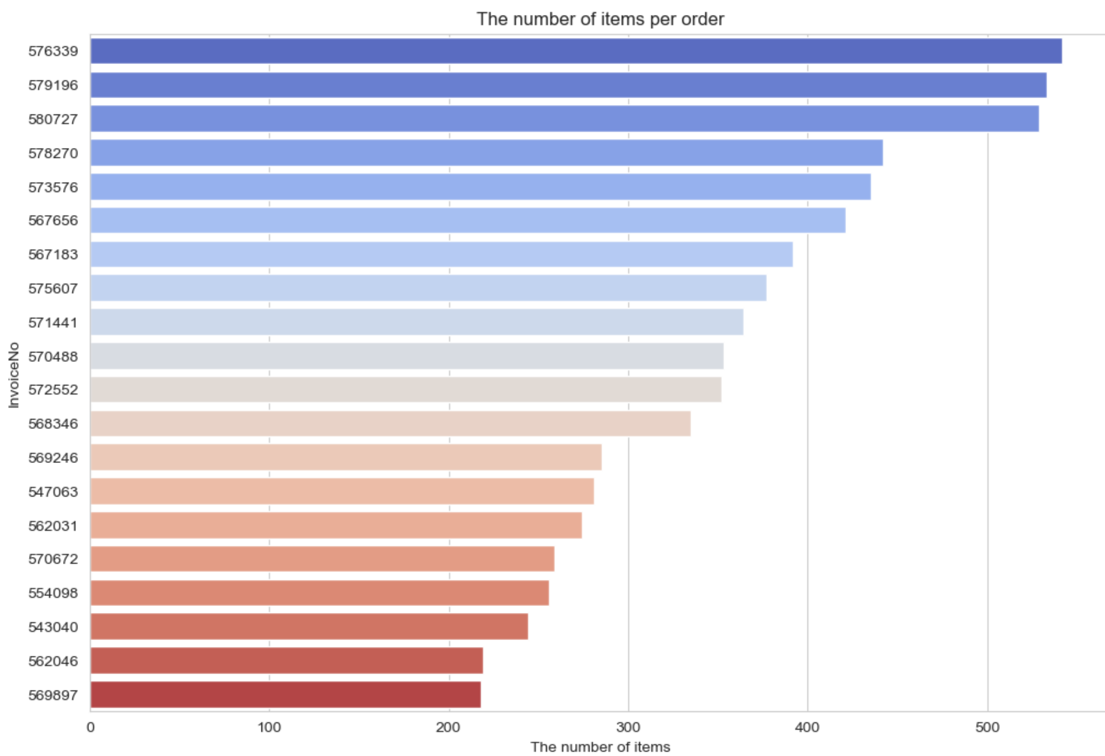
[30]:
```
#the number of items per purchase (InvoiceNo)
kindofitemsforOrder = pd.DataFrame(df.groupby(['InvoiceNo'])['StockCode'].
 ↪count()).reset_index().sort_values('StockCode',ascending=False)[0:20]
kindofitemsforOrder.head(10)
```

[30]:

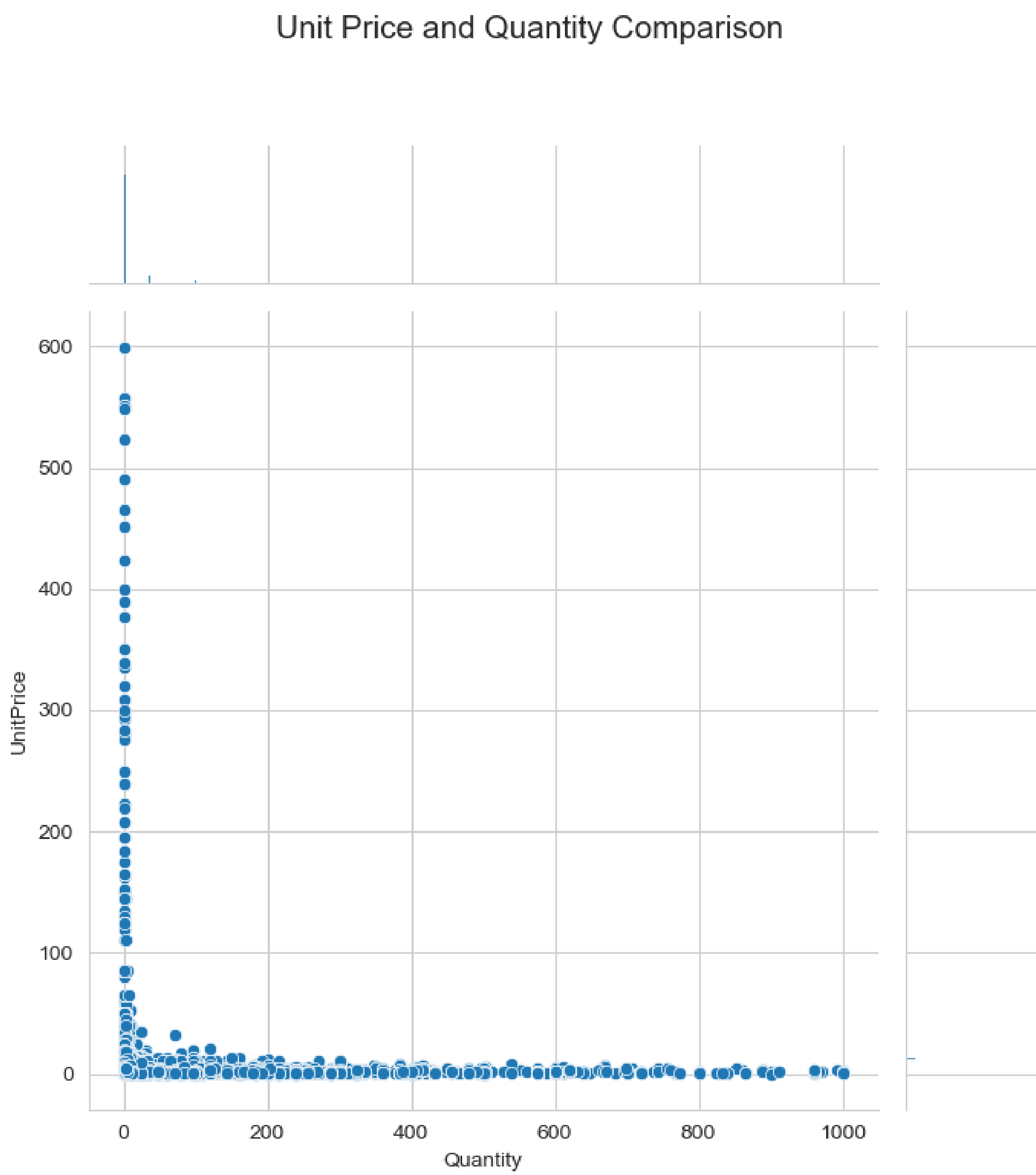
	InvoiceNo	StockCode
16241	576339	542
17522	579196	533
18163	580727	529
17127	578270	442
15080	573576	435
12513	567656	421
12325	567183	392
15895	575607	377
14159	571441	364
13763	570488	353

[31]:
```
#the number of items per purchase
sns.set_style('whitegrid')
plt.figure(figsize=(12,8))
plt.title('The number of items per order')
sns.barplot(y='InvoiceNo',x='StockCode',
            data=kindofitemsforOrder, palette='coolwarm', orient='h',␣
 ↪order=kindofitemsforOrder['InvoiceNo']).set(xlabel='The number of items')
```

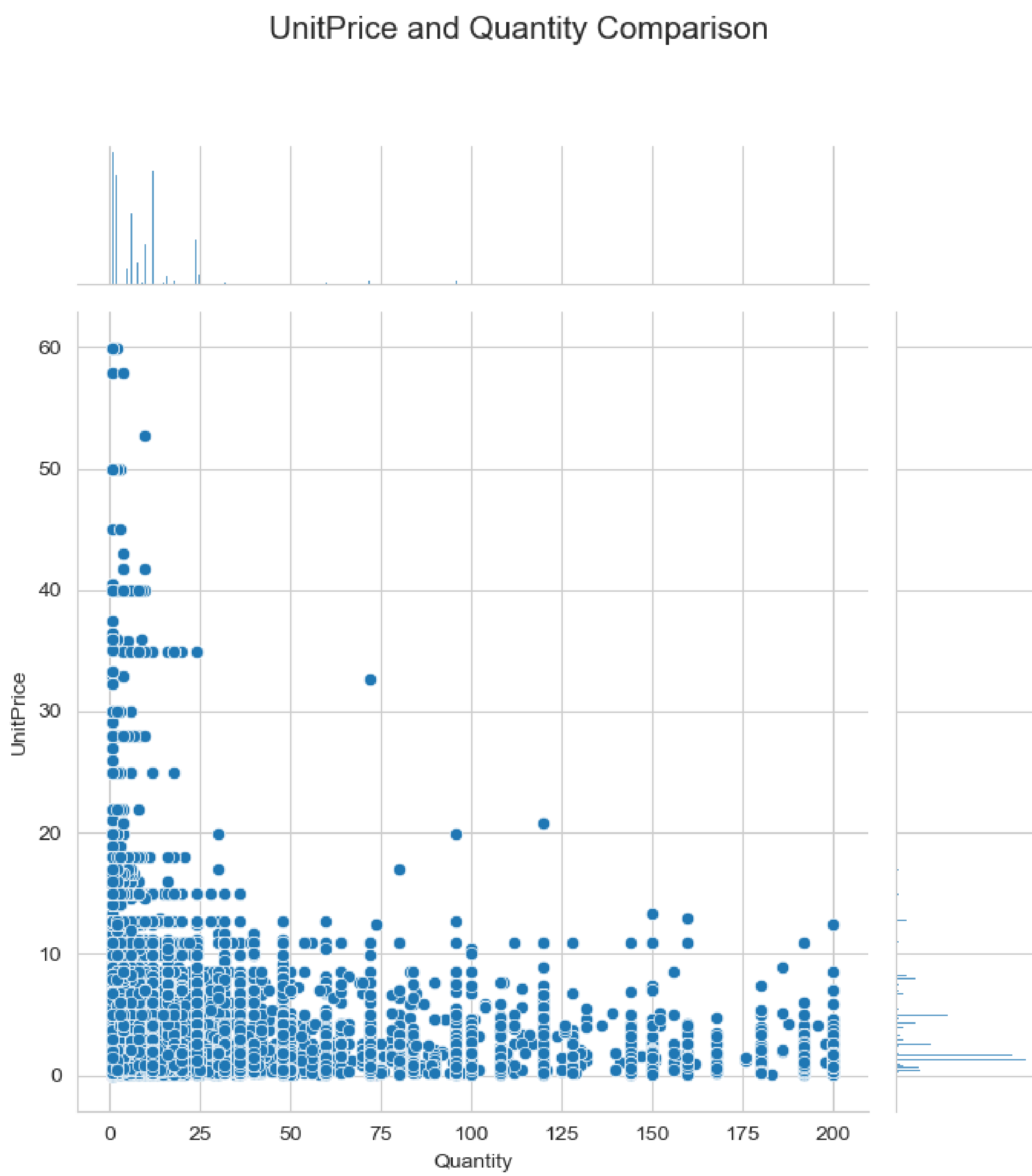
[31]:
```
[Text(0.5, 0, 'The number of items')]
```



[32]:
```
#plotting the quantity vs unitprice
Corr = sns.jointplot(x="Quantity", y="UnitPrice", data = df[(df['UnitPrice'] ␣
 ↪>0) & (df['Quantity']<= 1000) & (df['UnitPrice'] < 600 )], height = 7)
Corr.fig.suptitle("Unit Price and Quantity Comparison", fontsize = 15, y = 1.1)
plt.show()
```



[33]:
```
#plotting the quantity vs unit price to look closer
Corr = sns.jointplot(x="Quantity", y="UnitPrice", data = df[(df['UnitPrice'] ␣
↪>0) & (df['Quantity']<= 200) & (df['UnitPrice'] < 60 )], height = 7)
Corr.fig.suptitle("UnitPrice and Quantity Comparison", fontsize = 15, y = 1.1)
plt.show()
```



Explore the Descriptions

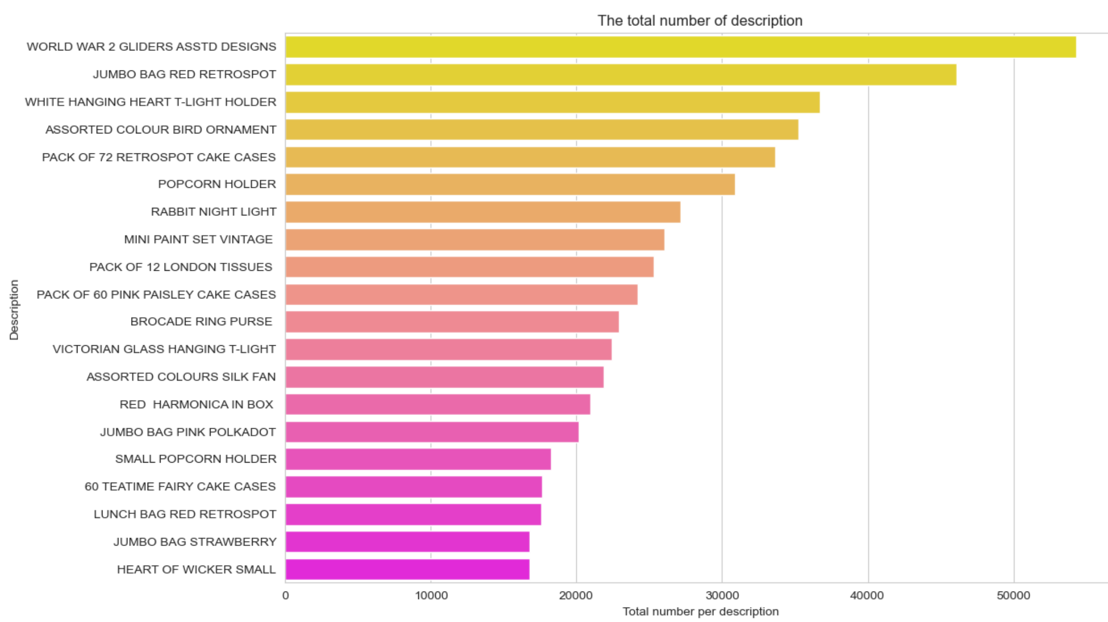
[34]:
```
#total number per description
totalnumberofDescription = pd.DataFrame(df.groupby(['Description'])['Quantity'].
  ↪sum()).reset_index().sort_values('Quantity',ascending=False)[0:20]
totalnumberofDescription.head(10)
```

[34]:
```
                              Description  Quantity
3785    WORLD WAR 2 GLIDERS ASSTD DESIGNS     54319
```

```
1762                JUMBO BAG RED RETROSPOT     46078
3697   WHITE HANGING HEART T-LIGHT HOLDER     36706
216          ASSORTED COLOUR BIRD ORNAMENT     35263
2269      PACK OF 72 RETROSPOT CAKE CASES     33670
2599                       POPCORN HOLDER     30919
2655                   RABBIT NIGHT LIGHT     27153
2047               MINI PAINT SET VINTAGE     26076
2235            PACK OF 12 LONDON TISSUES     25329
2267   PACK OF 60 PINK PAISLEY CAKE CASES     24230
```

[35]:
```
#plot total number per description
sns.set_style('whitegrid')
plt.figure(figsize=(12,8))
plt.title('The total number of description')
sns.barplot(y='Description',x='Quantity',
           data=totalnumberofDescription, palette='spring_r', orient='h',␣
 ↪order=totalnumberofDescription['Description']).set(xlabel='Total number per␣
 ↪description')
```

[35]: [Text(0.5, 0, 'Total number per description')]



[36]:
```
#total amount of revenue per description
totalamountperDescription = pd.DataFrame(df.groupby(['Description'])['Revenue'].
 ↪sum()).reset_index().sort_values('Revenue',ascending=False)[0:20]
totalamountperDescription.head(10)
```

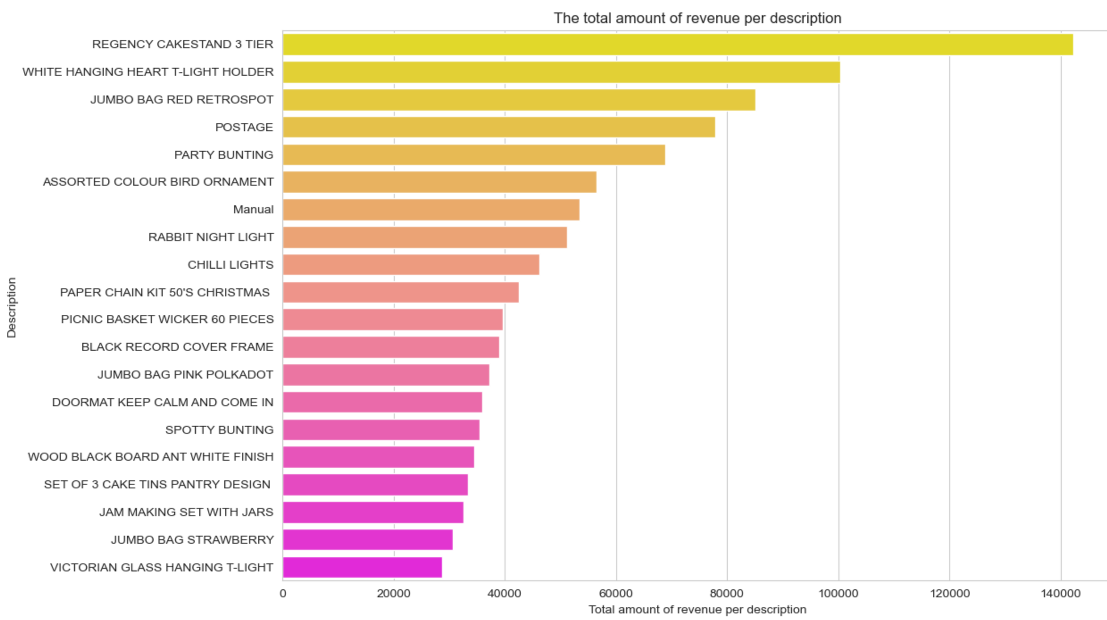
[36]:

```
                          Description    Revenue
2766           REGENCY CAKESTAND 3 TIER  142264.75
3697  WHITE HANGING HEART T-LIGHT HOLDER  100392.10
1762            JUMBO BAG RED RETROSPOT   85040.54
2610                            POSTAGE   77803.96
2344                      PARTY BUNTING   68785.23
216       ASSORTED COLOUR BIRD ORNAMENT   56413.03
2130                             Manual   53419.93
2655                 RABBIT NIGHT LIGHT   51251.24
722                       CHILLI LIGHTS   46265.11
2313    PAPER CHAIN KIT 50'S CHRISTMAS    42584.13
```

[37]:

```python
#plot total amount of revenue per description
sns.set_style('whitegrid')
plt.figure(figsize=(12,8))
plt.title('The total amount of revenue per description')
sns.barplot(y='Description',x='Revenue',
           data=totalamountperDescription, palette='spring_r', orient='h',␣
 ↪order=totalamountperDescription['Description']).set(xlabel='Total amount of␣
 ↪revenue per description')
```

[37]: [Text(0.5, 0, 'Total amount of revenue per description')]



Explore by Time

[38]:

```python
#total amount of revenue per month
```

```
totalamountperMonth = pd.DataFrame(df.groupby(['month'])['Revenue'].sum()).
 ↪reset_index().sort_values('Revenue',ascending=False)[0:20]
totalamountperMonth.head(10)
```

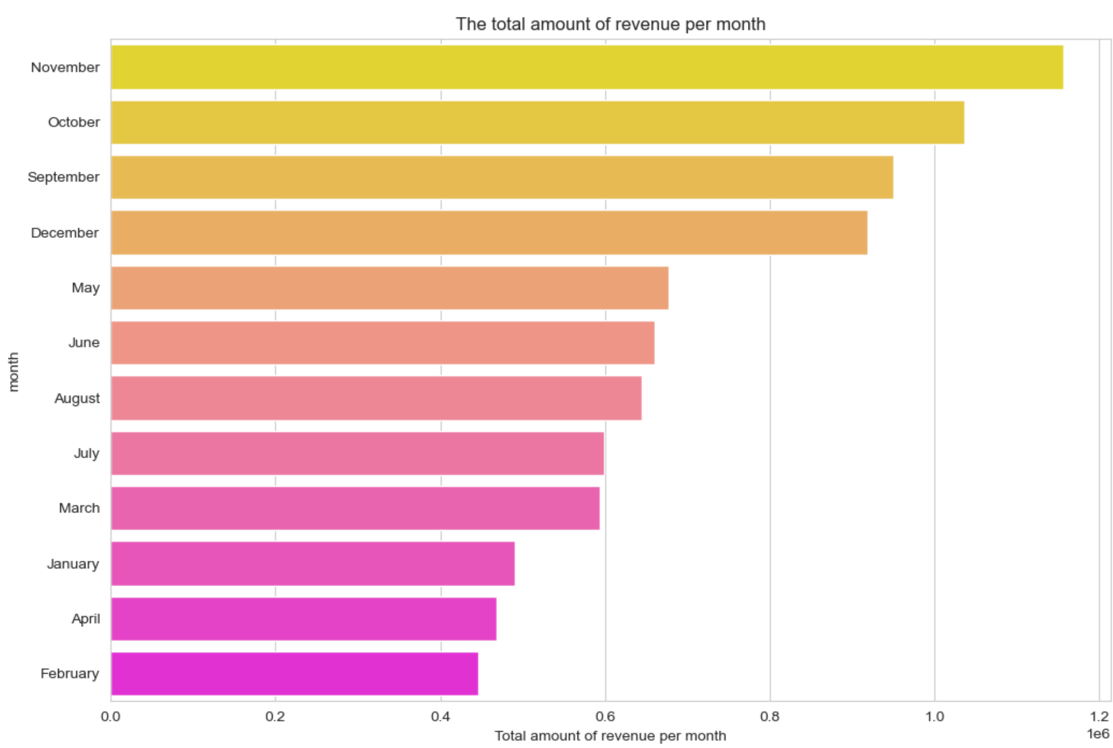
[38]:

	month	Revenue
9	November	1156205.610
10	October	1035642.450
11	September	950690.202
2	December	919143.570
8	May	677355.150
6	June	660046.050
1	August	644051.040
5	July	598962.901
7	March	594081.760
4	January	490917.710

[39]:

```
#plot total amount of revenue per month
sns.set_style('whitegrid')
plt.figure(figsize=(12,8))
plt.title('The total amount of revenue per month')
sns.barplot(y='month',x='Revenue',
            data=totalamountperMonth, palette='spring_r', orient='h',␣
 ↪order=totalamountperMonth['month']).set(xlabel='Total amount of revenue per␣
 ↪month')
```

[39]: [Text(0.5, 0, 'Total amount of revenue per month')]



The important point is that all transactions that took place between 01/12/2010 (dd/mm/yy) and 09/12/2011. November is in the top rank in terms of total revenue, followed by October.

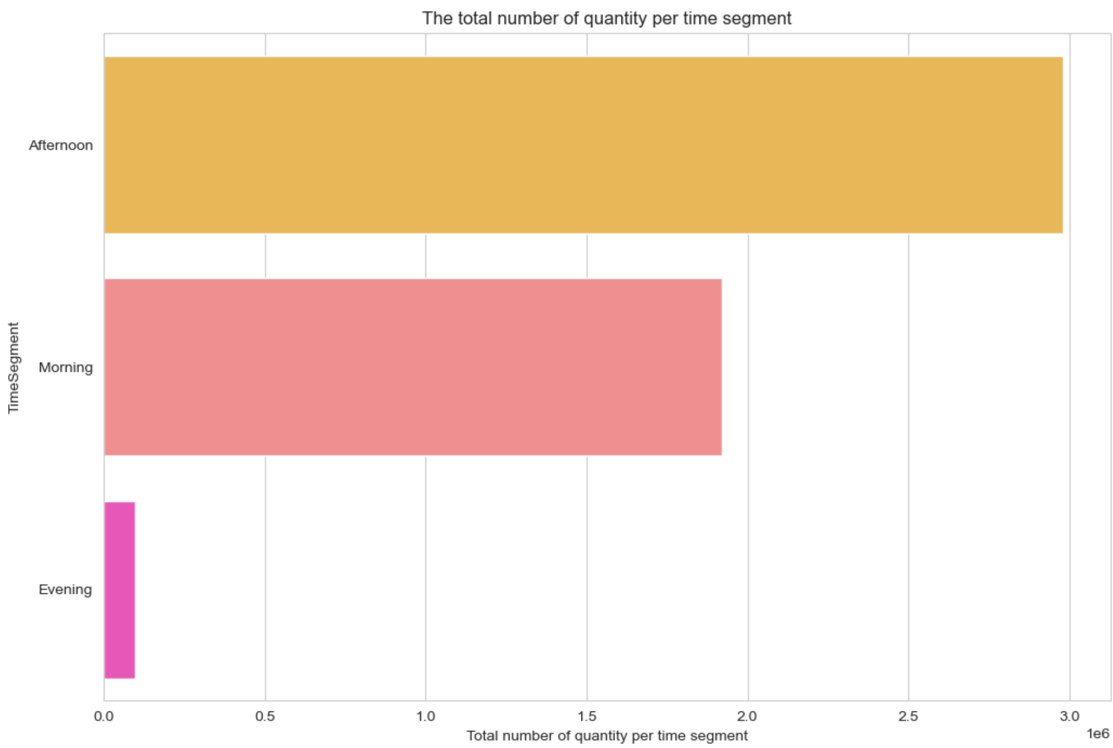
[40]:
```python
#total number of quantity per time segment
totalQuantityperTimeSegment = pd.DataFrame(df.
 ↪groupby(['TimeSegment'])['Quantity'].sum()).reset_index().
 ↪sort_values('Quantity',ascending=False)[0:20]
totalQuantityperTimeSegment.head(10)
```

[40]:

	TimeSegment	Quantity
0	Afternoon	2980610
2	Morning	1920613
1	Evening	96913

[41]:
```python
#plot total number of quantity per time segment
sns.set_style('whitegrid')
plt.figure(figsize=(12,8))
plt.title('The total number of quantity per time segment')
sns.barplot(y='TimeSegment',x='Quantity',
            data=totalQuantityperTimeSegment, palette='spring_r', orient='h',␣
 ↪order=totalQuantityperTimeSegment['TimeSegment']).set(xlabel='Total number␣
 ↪of quantity per time segment')
```

[41]: [Text(0.5, 0, 'Total number of quantity per time segment')]



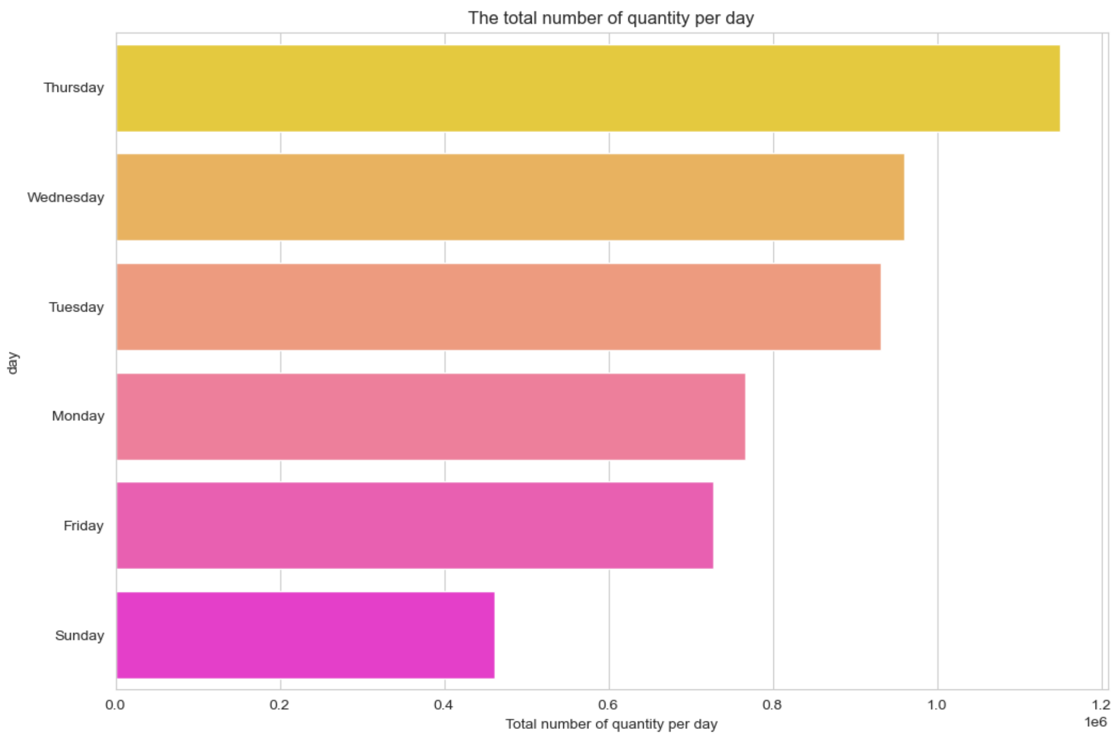
[42]:
```
#total number of quantity per day
totalQuantityperDay = pd.DataFrame(df.groupby(['day'])['Quantity'].sum()).
 ↪reset_index().sort_values('Quantity',ascending=False)[0:20]
totalQuantityperDay.head(10)
```

[42]:

	day	Quantity
3	Thursday	1150224
5	Wednesday	960128
4	Tuesday	931557
1	Monday	766919
0	Friday	728324
2	Sunday	460984

[43]:
```
#plot total number of quantity per day
sns.set_style('whitegrid')
plt.figure(figsize=(12,8))
plt.title('The total number of quantity per day')
sns.barplot(y='day',x='Quantity',
           data=totalQuantityperDay, palette='spring_r', orient='h',␣
 ↪order=totalQuantityperDay['day']).set(xlabel='Total number of quantity per␣
 ↪day')
```

[43]: [Text(0.5, 0, 'Total number of quantity per day')]



Explore by Country

[44]:
```python
#total number of quantity per country
totalQuantityperCountry = pd.DataFrame(df.groupby(['Country'])['Quantity'].
    ↪sum()).reset_index().sort_values('Quantity',ascending=False)[0:20]
totalQuantityperCountry.head(10)
```

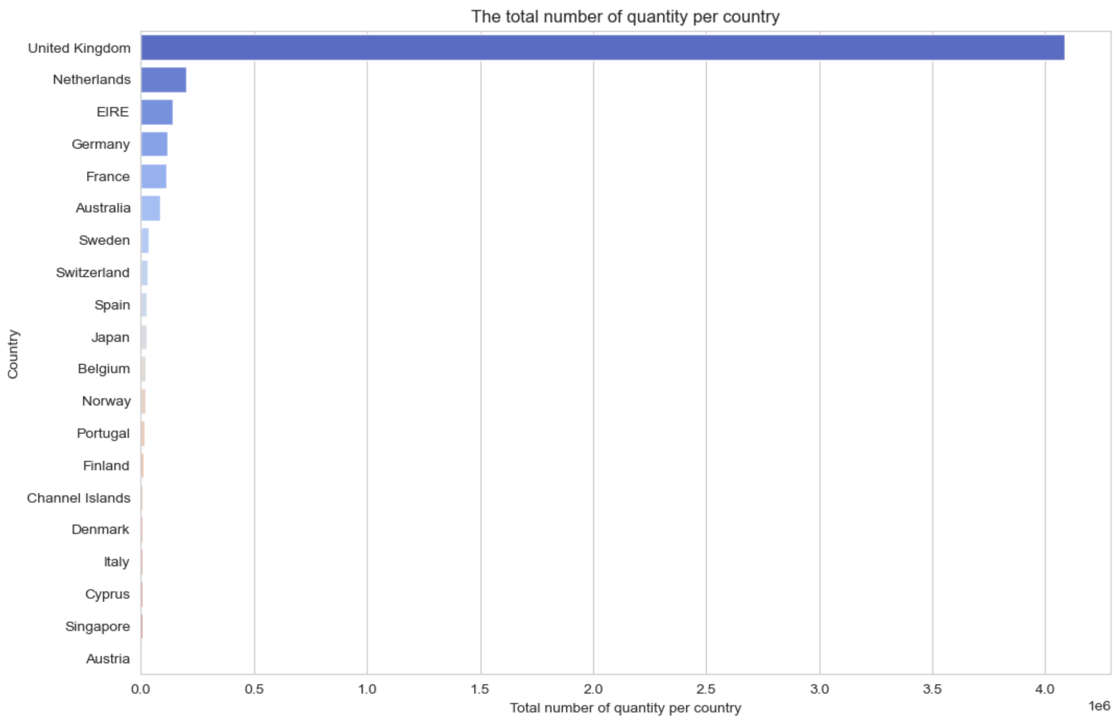
[44]:

	Country	Quantity
35	United Kingdom	4086287
23	Netherlands	200937
10	EIRE	140383
14	Germany	119156
13	France	111429
0	Australia	84199
31	Sweden	36078
32	Switzerland	30083
30	Spain	27944
19	Japan	26016

[45]:
```python
#plot total number of quantity per country
sns.set_style('whitegrid')
plt.figure(figsize=(12,8))
plt.title('The total number of quantity per country')
sns.barplot(y='Country',x='Quantity',
```

```
            data=totalQuantityperCountry, palette='coolwarm', orient='h',␣
↪order=totalQuantityperCountry['Country']).set(xlabel='Total number of␣
↪quantity per country')
```

[45]: [Text(0.5, 0, 'Total number of quantity per country')]



Explore Cancel Orders

[46]:
```
#the unique number of InvoiceNo per customer
CancelInvoiceNobyCustomer = pd.DataFrame(dfCancelOrders.
 ↪groupby(['CustomerID','Country'])['InvoiceNo'].count()).reset_index().
 ↪sort_values('InvoiceNo',ascending=False)[0:20]
CancelInvoiceNobyCustomer.head(10)
```

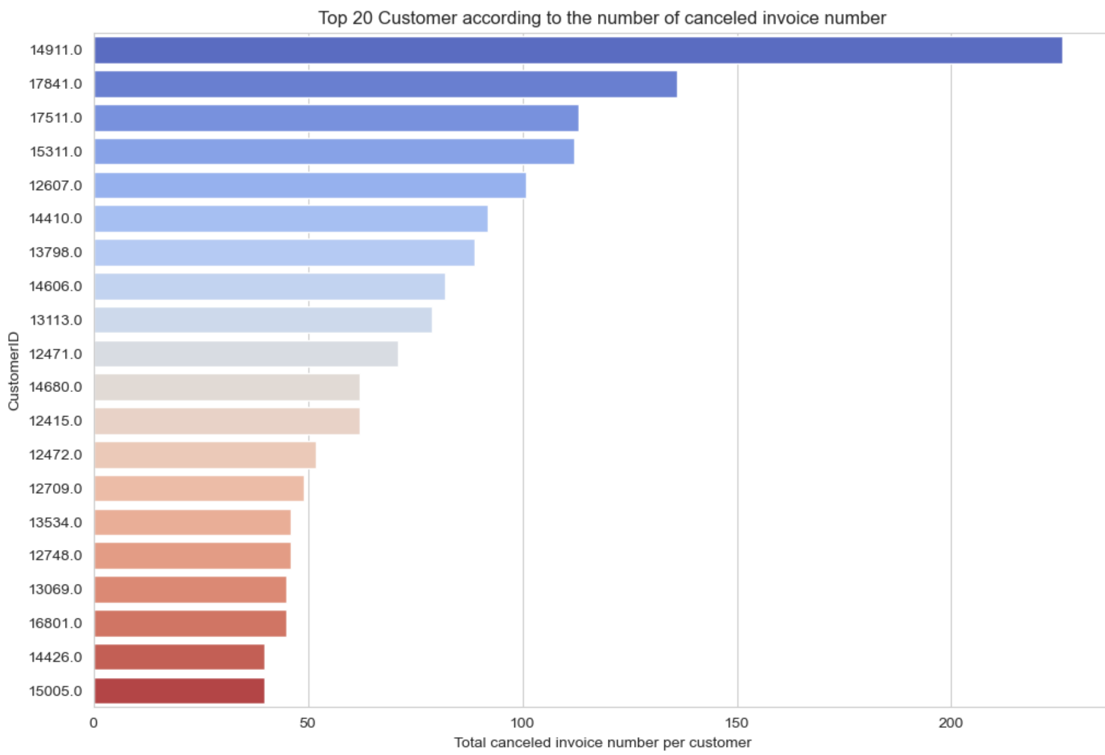
[46]:

	CustomerID	Country	InvoiceNo
737	14911.0	EIRE	226
1486	17841.0	United Kingdom	136
1398	17511.0	United Kingdom	113
849	15311.0	United Kingdom	112
90	12607.0	USA	101
606	14410.0	United Kingdom	92
418	13798.0	United Kingdom	89
653	14606.0	United Kingdom	82
247	13113.0	United Kingdom	79

```
37        12471.0         Germany         71
```

[47]:
```
#plot top 20 Customer according to the number of canceled invoice number
sns.set_style('whitegrid')
plt.figure(figsize=(12,8))
plt.title('Top 20 Customer according to the number of canceled invoice number')
sns.barplot(y='CustomerID',x='InvoiceNo',
            data=CancelInvoiceNobyCustomer, palette='coolwarm', orient='h',␣
 ↪order=CancelInvoiceNobyCustomer['CustomerID']).set(xlabel='Total canceled␣
 ↪invoice number per customer')
```

[47]:
```
[Text(0.5, 0, 'Total canceled invoice number per customer')]
```



[48]:
```
#the total amount of revenue per customer
CancelRevenuebyCustomer = pd.DataFrame(dfCancelOrders.
 ↪groupby(['CustomerID','Country'])['Revenue'].sum()).reset_index().
 ↪sort_values('Revenue',ascending=True)[0:20]
CancelRevenuebyCustomer.head(10)
```

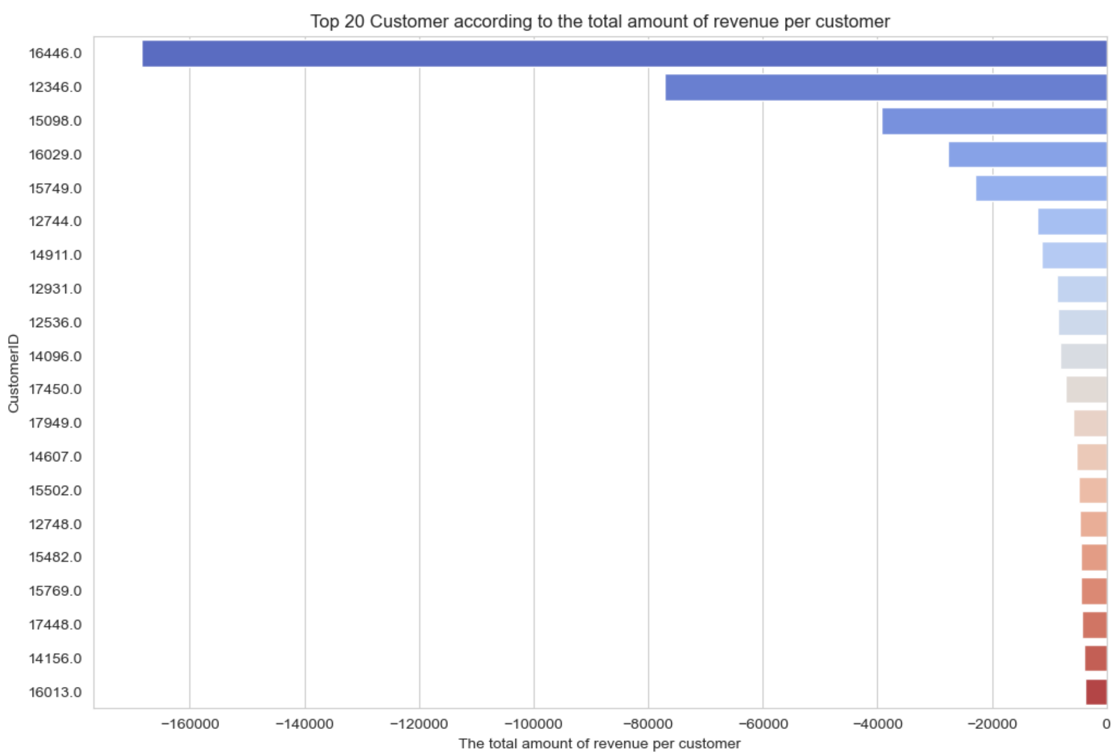
[48]:

	CustomerID	Country	Revenue
1137	16446.0	United Kingdom	-168469.60
0	12346.0	United Kingdom	-77183.60
780	15098.0	United Kingdom	-39267.00

```
1040    16029.0  United Kingdom  -27682.15
966     15749.0  United Kingdom  -22998.40
137     12744.0       Singapore  -12158.90
737     14911.0            EIRE  -11252.44
186     12931.0  United Kingdom   -8593.15
61      12536.0          France   -8495.01
498     14096.0  United Kingdom   -8043.88
```

[49]:
```
#plot top 20 Customer according to the total amount of revenue per customer
sns.set_style('whitegrid')
plt.figure(figsize=(12,8))
plt.title('Top 20 Customer according to the total amount of revenue per␣
↪customer')
sns.barplot(y='CustomerID',x='Revenue',
            data=CancelRevenuebyCustomer, palette='coolwarm', orient='h',␣
↪order=CancelRevenuebyCustomer['CustomerID']).set(xlabel='The total amount of␣
↪revenue per customer')
```

[49]:
```
[Text(0.5, 0, 'The total amount of revenue per customer')]
```



2.1 RFM Analysis

The RFM model is a marketing analysis framework used to segment and understand customer behavior based on three key factors: Recency, Frequency, and Monetary Value. It is commonly employed by businesses to categorize their customer base into distinct groups, which can then be used for targeted marketing strategies and personalized communication. **Recency** – ***How recently did the customer purchase?*** **Frequency** – ***How often do they purchase?*** **Monetary** – ***How much do they spend?*** ***Recency*** - In order to find the recency value of each customer, we need to determine the last invoice date as the current date and subtract the last purchasing date of each customer from this date.

Frequency - In order to find the frequency value of each customer, we need to determine how many times the customers make purchases.

Monetary - In order to find the monetary value of each customer, we need to determine how much do the customers spend on purchases. By analyzing these three dimensions, businesses can segment their customer base into various groups. Here's a general breakdown of how this segmentation might occur:

High-Value Customers: These are customers who have recently made frequent purchases of high monetary value. They are often the most valuable segment as they contribute significantly to the business's revenue.

Recent Customers: These are customers who have made purchases or engaged with the business recently. While they might not have a long history with the brand, their recent activity suggests potential interest.

Loyal Customers: This group comprises customers who make frequent purchases, regardless of the monetary value. They may not spend as much as high-value customers individually, but their consistent engagement is valuable.

Churned Customers: These are customers who were active in the past but haven't interacted with the business recently. Identifying and re-engaging with these customers can help reduce churn.

Low-Value Customers: These customers might have made a few low-value purchases, but their overall impact on the business's revenue is relatively small.

Inactive Customers: This group includes customers who haven't engaged with the business for a significant period. These customers might require special re-engagement efforts to bring them back.

Benefits of RFM Analysis

- Increased customer retention/ decrease churn
- Increased response rate
- Increased conversion rate
- Increased revenue

The RFM model can provide businesses with insights into customer behavior, allowing them to tailor marketing campaigns, offers, and communication strategies to each segment's unique characteristics. It's important to note that while the RFM model is a useful tool, its effectiveness can be enhanced when combined with additional data and more advanced analytics techniques

[50]:
```python
import datetime as dt
print(df['InvoiceDate'].min())
print(df['InvoiceDate'].max())
```

```
2010-12-01 08:26:00
2011-12-09 12:50:00
```

[51]:
```python
presence=dt.datetime(2011,12,10)

#Create RFM scores for each customer
#Recency = Presence - Last Invoice Data
#Frequency = Total Number of Transactions
#Monetary = Total money spent
df_rfm=df.groupby('CustomerID').agg({'InvoiceDate': lambda x: (presence-x.
 ↪max()).days,
                                    'InvoiceNo': lambda x: len(x),
                                    'Revenue': lambda x: x.sum()})

#Convert Invoice Date into type int
df_rfm['InvoiceDate']= df_rfm['InvoiceDate'].astype(int)

#Rename column names to Recency, Frequency and Monetary
df_rfm.rename(columns={'InvoiceDate': 'Recency',
                      'InvoiceNo':'Frequency',
                      'Revenue': 'Monetary'}, inplace=True)

df_rfm.head(10)
```

[51]:

CustomerID	Recency	Frequency	Monetary
12347.0	2	182	4310.00
12348.0	75	31	1797.24
12349.0	18	73	1757.55
12350.0	310	17	334.40
12352.0	36	85	2506.04
12353.0	204	4	89.00
12354.0	232	58	1079.40
12355.0	214	13	459.40
12356.0	22	59	2811.43
12357.0	33	131	6207.67

[52]:
```python
#descriptive statistics of all variables
df_rfm.describe(include='all')
```

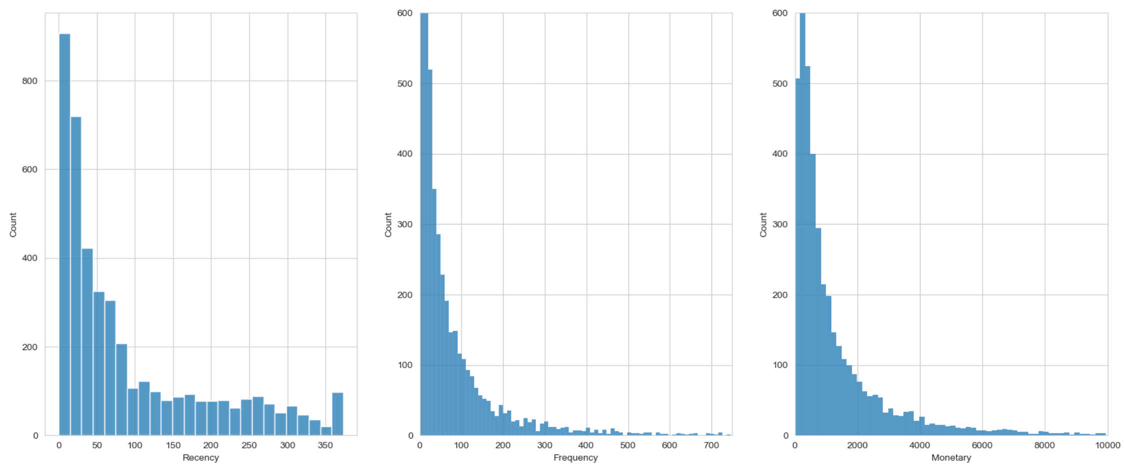
[52]:

	Recency	Frequency	Monetary
count	4337.000000	4337.000000	4337.000000
mean	92.053032	90.553147	1992.519182
std	99.966159	225.559226	8547.583474

```
min        0.000000     1.000000       2.900000
25%       17.000000    17.000000     306.450000
50%       50.000000    41.000000     668.430000
75%      142.000000    98.000000    1657.280000
max      373.000000  7676.000000  280206.020000
```

[53]:
```
#plot the data distribution
fig, axis = plt.subplots(nrows=1, ncols=3, figsize=(20,8))
sns.histplot(df_rfm['Recency'], ax=axis[0])
sns.histplot(df_rfm['Frequency'], ax=axis[1])
axis[1].set_xlim(0, 750)
axis[1].set_ylim(0,600)
sns.histplot(df_rfm['Monetary'], ax=axis[2])
axis[2].set_xlim(0, 10000)
axis[2].set_ylim(0,600)
```

[53]: (0.0, 600.0)



2.2 Customer Segmentation with RFM Scores

Businesses have an enduring desire to comprehend their customers deeply. Enhanced customer understanding leads to improved service delivery, subsequently resulting in heightened financial returns from each customer. This strategic pursuit of comprehending customers, termed as Customer Segmentation, has been a practice since the inception of trade. Customer Segmentation involves categorizing customers based on their specific requirements. Common techniques for such categorization include evaluating their Recency-Frequency-Monetary (RFM) values, analyzing demographic factors like gender, geographic location, and employing business-derived scoring systems. For the current case, we will utilize the RFM values.

In the subsequent section, an RFM Segmentation Table will be constructed to categorize customers according to the RFM table. For instance, designations like “Big Spenders” will be assigned to the highest value customers, while those who have disengaged might be labeled as “Lost Customers”.

2.3 Calculate RFM Scoring

The simplest way to create customer segments from an RFM model is by using **Quartiles**. We will assign a score from 1 to 4 to each category (Recency, Frequency, and Monetary) with 4 being the highest/best value. The final RFM score is calculated by combining all RFM values. For Customer Segmentation, you will use the df_rfm data set resulting from the RFM analysis.

Segment	RFM	Description	Marketing
Best Customers	444	Bought most recently and most often, and spend the most	No price incentives, new products, and loyalty programs
Loyal Customers	X4X	Buy most frequently	Use R and M to further segment
Big Spenders	XX4	Spend the most	Market your most expensive products
Almost Lost	244	Haven't purchased for some time, but purchased frequently and spend the most	Aggressive price incentives
Lost Customers	144	Haven't purchased for some time, but purchased frequently and spend the most	Aggressive price incentives
Lost Cheap Customers	111	Last purchased long ago, purchased few, and spent little	Don't spend too much trying to re-acquire

Source Note: The author in the article scores 1 as the highest and 4 as the lowest.

[54]:
```
#Calculating R_score, F_score and M_score by splitting them by quantiles
df_rfm['R_score']=pd.qcut(df_rfm['Recency'], q=4, labels=[4,3,2,1]).astype(int)
df_rfm['F_score']=pd.qcut(df_rfm['Frequency'], q=4, labels=[1,2,3,4]).
    ↪astype(int)
df_rfm['M_score']=pd.qcut(df_rfm['Monetary'], q=4, labels=[1,2,3,4]).astype(int)

#Calculating RFM score for each customer
df_rfm['RFM_Score']=df_rfm['R_score']+df_rfm['F_score']+df_rfm['M_score']

# Finding the rfm group for each customer
df_rfm['RFM'] = 100*df_rfm['R_score'] + 10*df_rfm['F_score'] + df_rfm['M_score']

df_rfm.head()
```

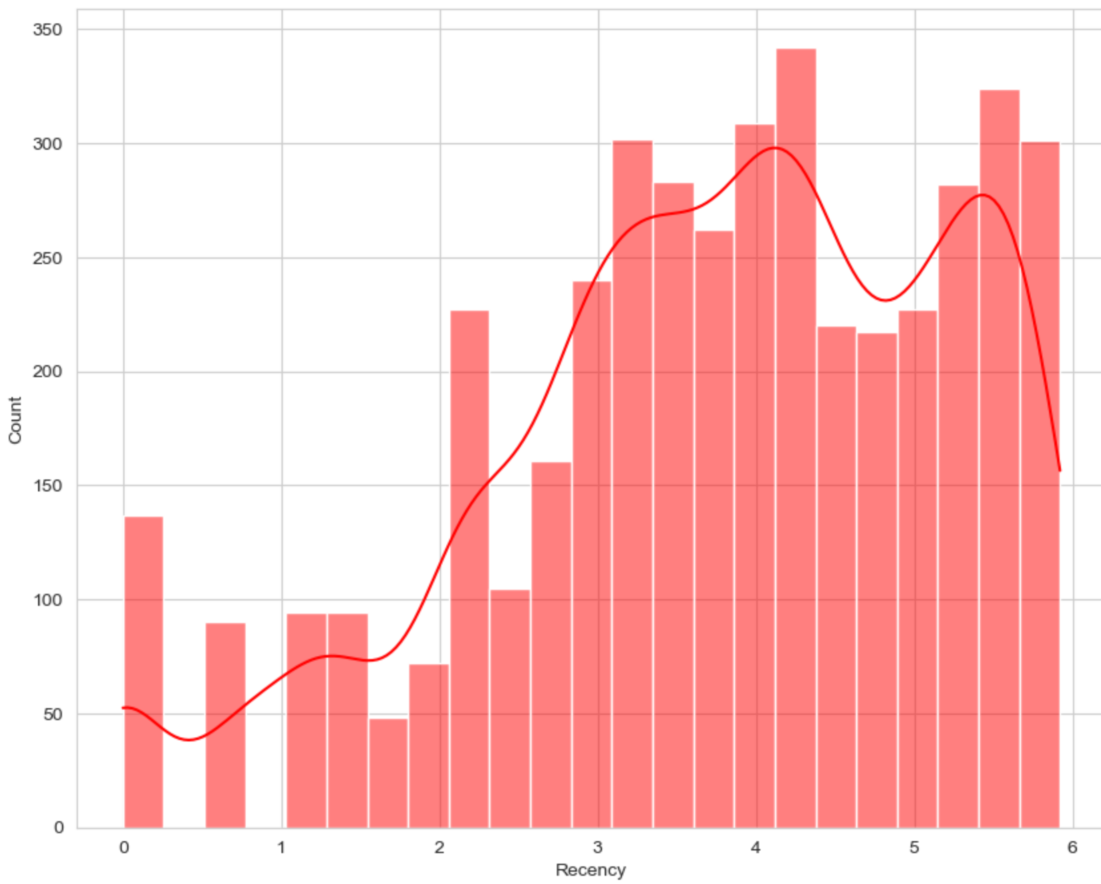
[54]:
```
            Recency  Frequency  Monetary  R_score  F_score  M_score  \
CustomerID
12347.0           2        182   4310.00        4        4        4
12348.0          75         31   1797.24        2        2        4
```

```
12349.0          18          73   1757.55        3         3         4
12350.0         310          17    334.40        1         1         2
12352.0          36          85   2506.04        3         3         4

            RFM_Score  RFM
CustomerID
12347.0            12  444
12348.0             8  224
12349.0            10  334
12350.0             4  112
12352.0            10  334
```

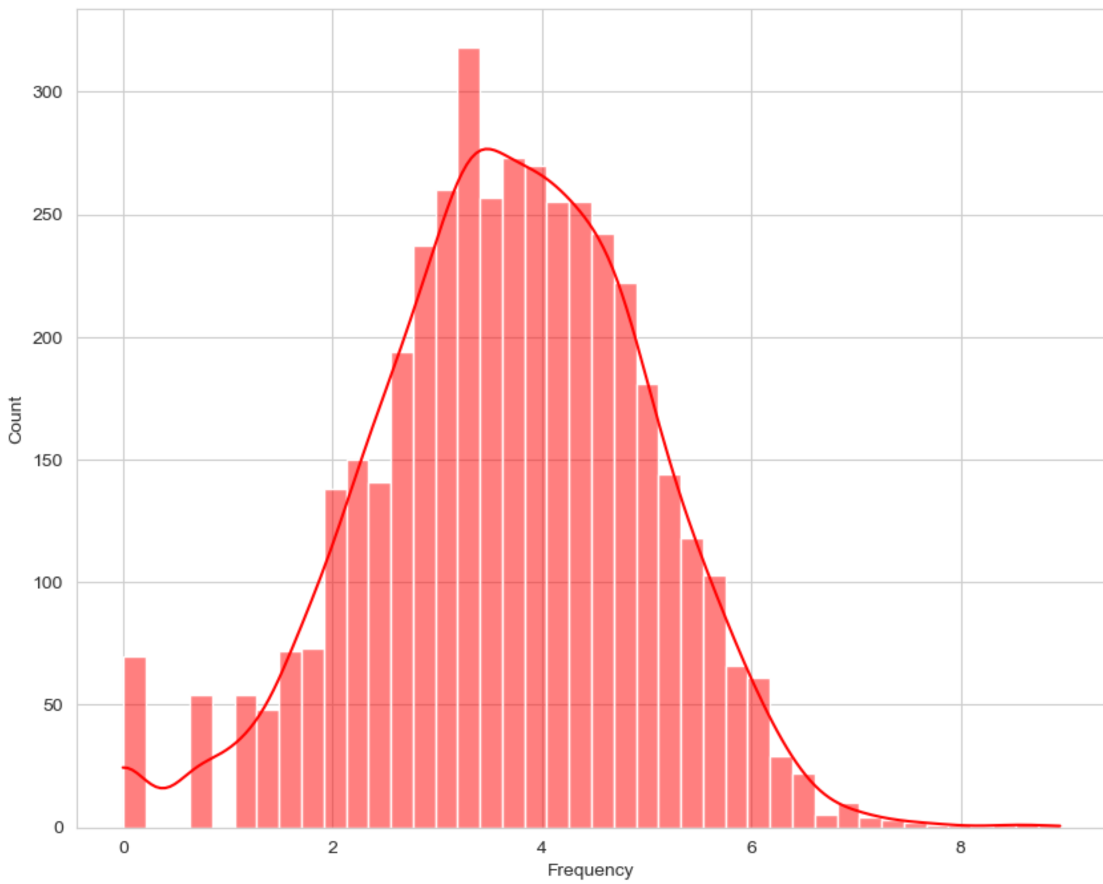
[55]:
```python
#Handling negative and zero values
def handle_neg_n_zero(num):
    if num <= 0:
        return 1
    else:
        return num

#Applying handle_neg_n_zero function to Recency and Monetary columns
df_rfm['Recency'] = [handle_neg_n_zero(x) for x in df_rfm.Recency]
df_rfm['Monetary'] = [handle_neg_n_zero(x) for x in df_rfm.Monetary]

#Performing Log transformation on columns for smoothening the distribution to␣
↪handle big differences between values
Log_Tfd_Data = df_rfm[['Recency', 'Frequency', 'Monetary']].apply(np.log, axis␣
↪= 1).round(3)
Log_Tfd_Data.head()
```

[55]:
```
            Recency  Frequency  Monetary
CustomerID
12347.0       0.693      5.204     8.369
12348.0       4.317      3.434     7.494
12349.0       2.890      4.290     7.472
12350.0       5.737      2.833     5.812
12352.0       3.584      4.443     7.826
```

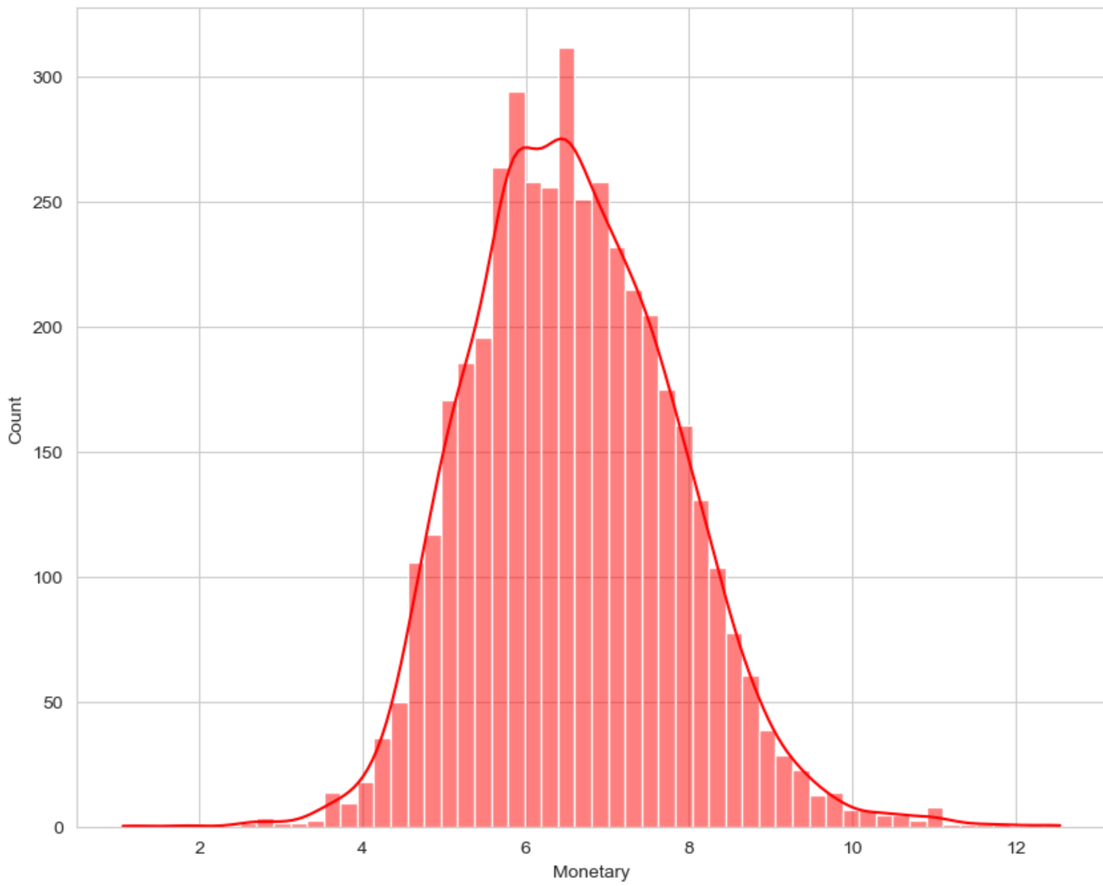
[56]:
```python
# Data distribution after data normalization for Recency
Plot_R = Log_Tfd_Data['Recency']
plt.figure(figsize=(10, 8))
sns.histplot(data=Plot_R, color='r', kde=True)
plt.show()
```



[57]:
```
# Data distribution after data normalization for Frequency
Plot_F = Log_Tfd_Data['Frequency']
plt.figure(figsize=(10, 8))
sns.histplot(data=Plot_F, color='r', kde=True)
plt.show()
```



[58]:
```
# Data distribution after data normalization for Monetary
Plot_M = Log_Tfd_Data['Monetary']
plt.figure(figsize=(10, 8))
sns.histplot(data=Plot_M, color='r', kde=True)
plt.show()
```

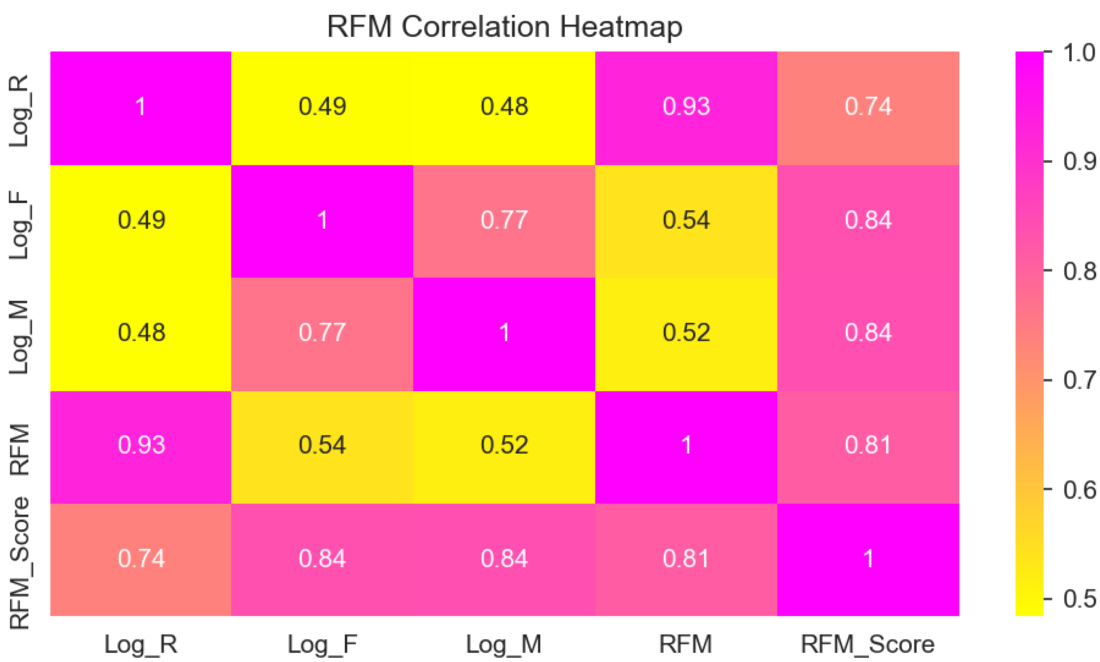


[59]:
```
df_rfm['Log_R']=Log_Tfd_Data['Recency']
df_rfm['Log_F']=Log_Tfd_Data['Frequency']
df_rfm['Log_M']=Log_Tfd_Data['Monetary']
df_rfm.head()
```

[59]:
```
            Recency  Frequency  Monetary  R_score  F_score  M_score  \
CustomerID
12347.0           2        182   4310.00        4        4        4
12348.0          75         31   1797.24        2        2        4
12349.0          18         73   1757.55        3        3        4
12350.0         310         17    334.40        1        1        2
12352.0          36         85   2506.04        3        3        4

            RFM_Score  RFM  Log_R  Log_F  Log_M
CustomerID
12347.0            12  444  0.693  5.204  8.369
12348.0             8  224  4.317  3.434  7.494
12349.0            10  334  2.890  4.290  7.472
12350.0             4  112  5.737  2.833  5.812
```

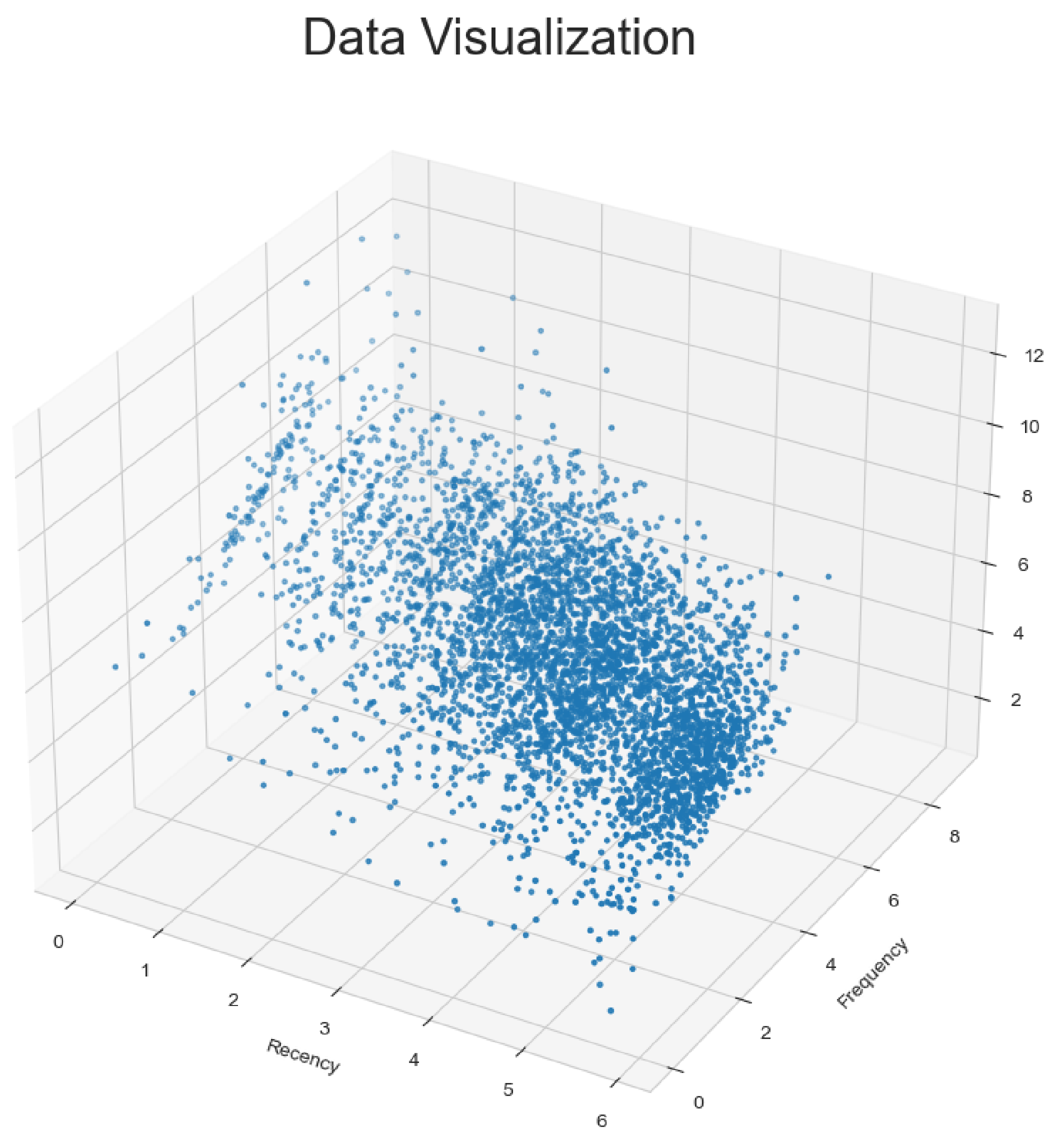
```
12352.0            10  334  3.584  4.443  7.826
```

[60]:
```python
# Visualizing the correlations among features
column = ['Log_R','Log_F','Log_M','RFM','RFM_Score']

plt.figure(figsize=(8,4), dpi=150)
sns.heatmap(abs(df_rfm[column].corr()), annot=True, cmap='spring_r')
plt.title('RFM Correlation Heatmap')
plt.show()
```



[61]:
```python
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

# plot data points in 3D space
fig = plt.figure(figsize=(10,10))
ax = fig.add_subplot(111, projection='3d')
x = df_rfm['Log_R']
y = df_rfm['Log_F']
z = df_rfm['Log_M']
ax.scatter(x, y, z, marker='.')
ax.set_xlabel('Recency')
ax.set_ylabel('Frequency')
ax.set_zlabel('Monetary')
plt.title("Data Visualization", size=25)
```

[61]: Text(0.5, 0.92, 'Data Visualization')



2.4 K-Means Clustering

Clustering is an unsupervised machine learning technique used to uncover underlying groups within data. One common approach for this is the K-means clustering algorithm, which is frequently employed to identify distinct segments within a customer dataset.

Our dataset is large so Hierarchical clustering is not well suited for analysis.

During the process of building a KMeans model, it's essential to specify the number of clusters beforehand. To determine the most appropriate number of clusters, various methods like silhouette analysis and the elbow method can be utilized. These techniques aid in selecting the optimal number of clusters that best represents the inherent structure of the data.

Elbow Method One of the most common ways to choose a value for K is known as the elbow method, which involves creating a plot with the number of clusters on the x-axis and the total within sum of squares on the y-axis and then identifying where an "elbow" or bend appears in the plot.

The point on the x-axis where the "elbow" occurs tells us the optimal number of clusters to use in the k-means clustering algorithm.

[62]:
```python
#create a new dataset to cluster customers by recency, frequency and monetary
df_cluster=df_rfm[['Log_R','Log_F','Log_M']]
df_cluster = df_cluster.reset_index(drop=True)
df_cluster.head()
```

[62]:

	Log_R	Log_F	Log_M
0	0.693	5.204	8.369
1	4.317	3.434	7.494
2	2.890	4.290	7.472
3	5.737	2.833	5.812
4	3.584	4.443	7.826

[63]:
```python
#df_clusterScaled=df_cluster
```

[64]:
```python
from sklearn.preprocessing import StandardScaler
import pandas as pd

#Scaled df_cluster where each variable has mean of 0 and standard dev of 1
df_cluster = pd.DataFrame(df_cluster)
scaler = StandardScaler()
df_clusterScaled = scaler.fit_transform(df_cluster)

print(df_clusterScaled)
```

```
[[-2.06658152e+00  1.16054770e+00  1.41835454e+00]
 [ 3.93073233e-01 -1.80688607e-01  7.23820703e-01]
 [-5.75449762e-01  4.67954489e-01  7.06358138e-01]
 …
 [-1.21615453e+00 -8.99803441e-01 -1.11133613e+00]
 [-1.79102417e+00  2.20398408e+00  8.26214834e-01]
 [ 9.85909588e-05  4.36128543e-01  7.41283268e-01]]
```

[65]:
```python
import pandas as pd
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# calculate Elbow method scores
# sum of squared errors
sse = {}
```

```python
# use cluster from range 1 to 20
for k in range(1, 21):
    # Initialize KMeans with k clusters
    kmeans = KMeans(n_clusters=k, random_state=1)
    # Fit KMeans on the dataset
    kmeans.fit(df_clusterScaled)
    # Assign sum of squared distances to k element of dictionary
    sse[k] = kmeans.inertia_ # Used for Plotting the elbow plot
```

```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
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```

```
explicitly to suppress the warning
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/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
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/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
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/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
```

```
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/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
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`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```
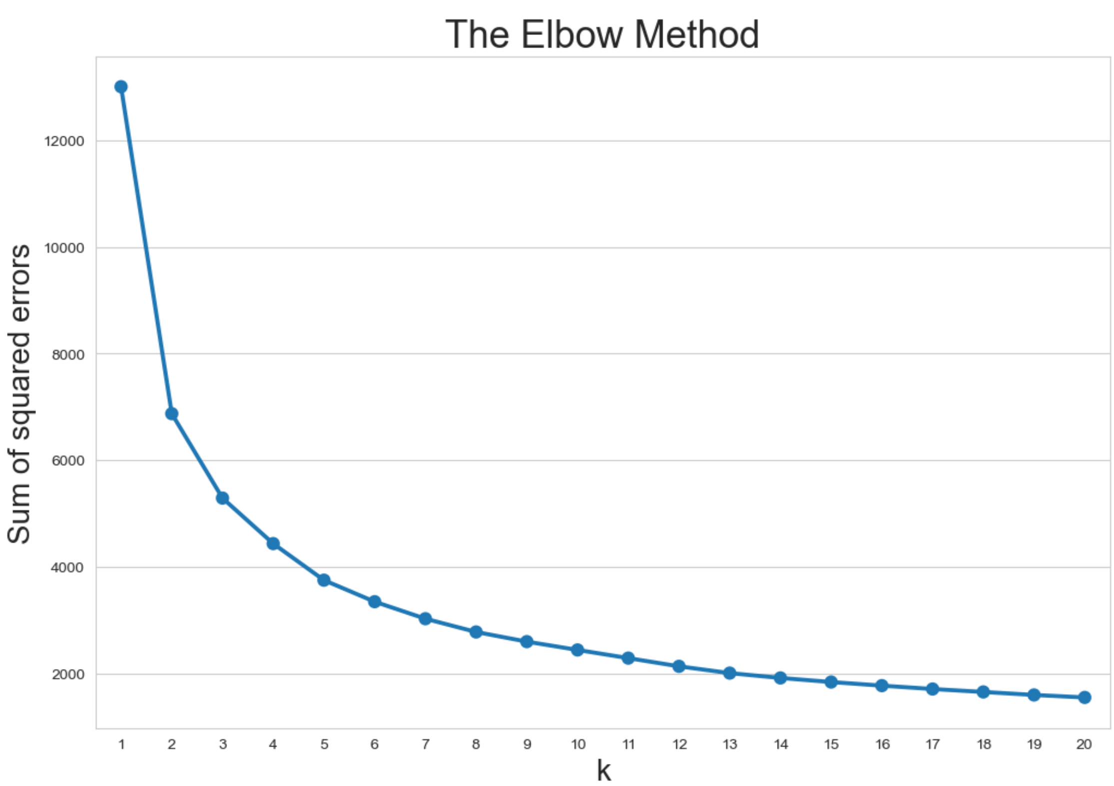

[66]:

```
# the elbow plot
plt.figure(figsize=(12,8))
plt.title('The Elbow Method', size=25)
plt.xlabel('k', size=20);
plt.ylabel('Sum of squared errors', size=20)
sns.pointplot(x=list(sse.keys()), y=list(sse.values()))
```

[66]:

```
<AxesSubplot: title={'center': 'The Elbow Method'}, xlabel='k', ylabel='Sum of
squared errors'>
```



As we analyze the graph depicting the sum of squared errors for various values of K, it's evident that the error tends to decrease with the increasing number of clusters. However, upon closer examination, when K reaches around 4 or 5, the rate of error reduction becomes notably steeper. This implies that by adding more clusters, the reduction in error becomes marginal compared to the increment in cluster count.

Each cluster in this context corresponds to a distinct customer segment. Implementing tailored policies for each of these segments requires additional resources and planning. As the number of clusters rises, the organization incurs extra costs to devise and execute individualized strategies for each segment.

Hence, while it's tempting to consider a higher number of clusters to capture finer details in customer behavior, this can lead to diminishing returns in terms of error reduction and increased operational complexity. Striking a balance is crucial, and in this case, opting for K=4 appears reasonable. This choice offers a good compromise between reducing errors through segmentation and managing the practicality of implementing policies for the distinct customer groups.

Silhouette Coefficient The overall silhouette score for a clustering can be computed by taking the average silhouette coefficient across all data points. This score provides insight into how well the data is clustered and whether the chosen number of clusters is appropriate. Higher silhouette scores indicate better-defined clusters.

[67]:
```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

# Calculate Silhouette score
# Initialize the list to store silhouette scores
score = []

# Initializing the list of clusters for tuning the best clusters
n_clusters = list(range(2, 20))

# Load your data or create your data frame df_clusterScaled

for k in n_clusters:
    kmeans = KMeans(n_clusters=k, random_state=0)  # Initialize KMeans model
    y_preds = kmeans.fit_predict(df_clusterScaled)  # Fit the model and get␣
 ↪cluster assignments
    score.append(silhouette_score(df_clusterScaled, y_preds))  # Append the␣
 ↪silhouette score to the list

# Now you have a list 'score' containing silhouette scores for different␣
 ↪numbers of clusters
```

```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
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```

```
  super()._check_params_vs_input(X, default_n_init=10)
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```

```
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explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```
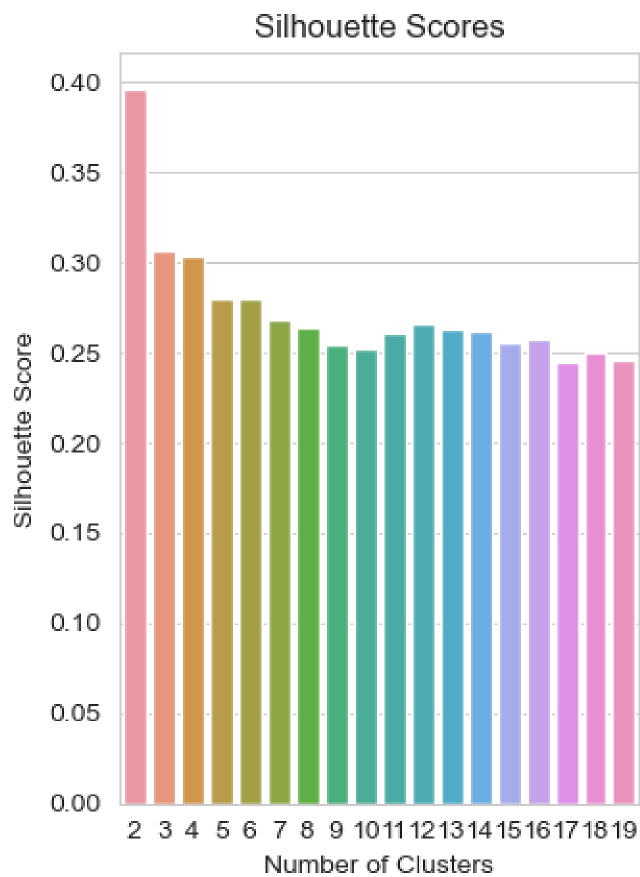

[68]:
```
# Silhouette Score v/s Number of Clusters
plt.subplot(1, 2, 2)
sns.barplot(x=n_clusters, y=score)
plt.xlabel('Number of Clusters')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Scores')
plt.tight_layout()
```



Outcomes by Elbow method and Silhoutte score

Based on the results obtained, selecting the ***highest silhouette score*** suggests that there could be ***two*** distinct clusters. On the other hand, choosing the ***lowest elbow squared error*** indicates that there might be around ***ten*** clusters.

As a result, in order to determine the most suitable number of clusters based on graphics, it is necessary to carefully consider the outcomes, and it appears that opting for a solution with ***four different cluster groups*** could be a ***balanced approach***.

K=4 have optimal score. Let's visualize these clusters.

[69]:
```
clusterer = KMeans(n_clusters=4, random_state=1)
cluster_label = clusterer.fit_predict(df_clusterScaled)
```

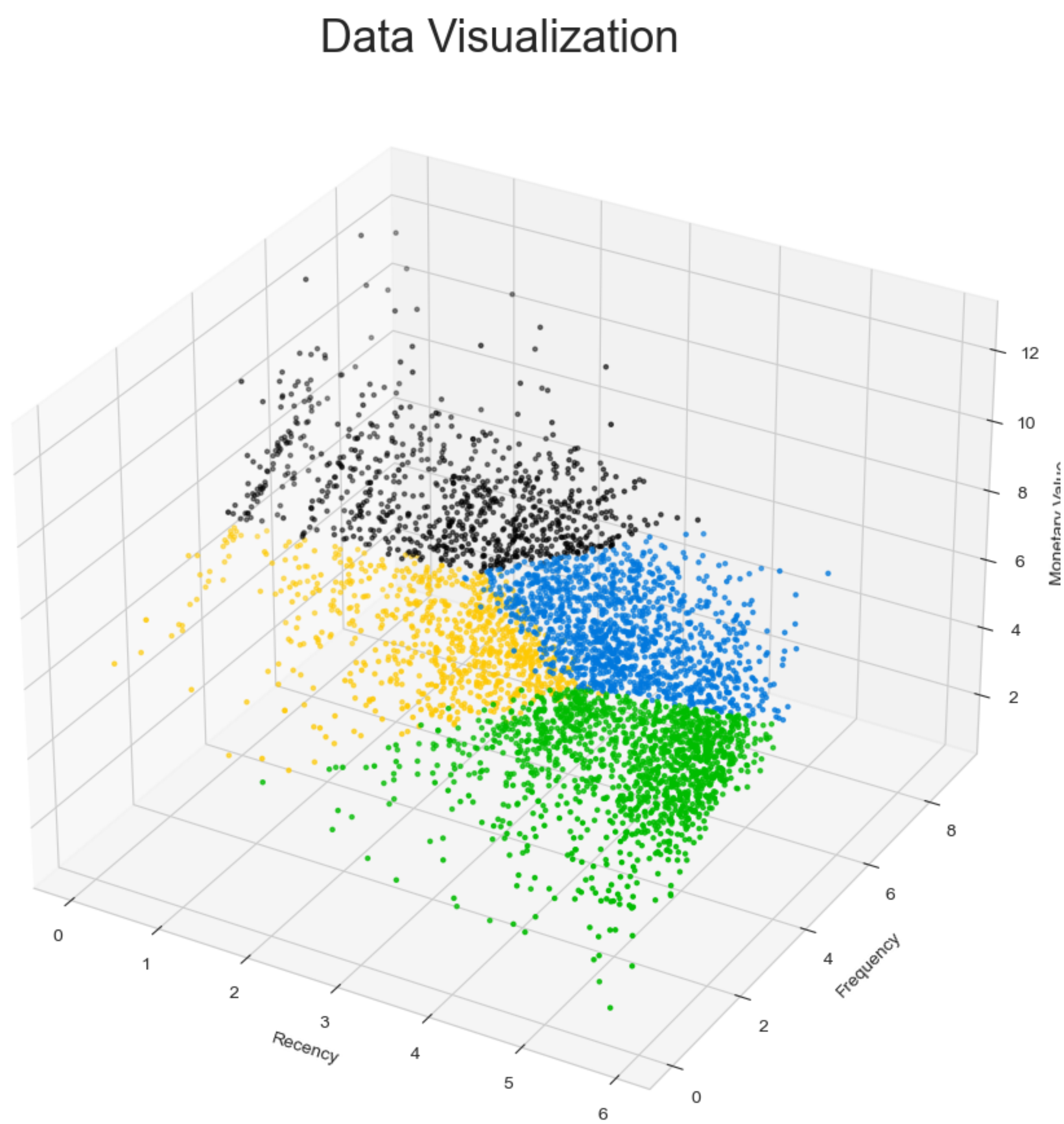
```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

[70]:
```
cluster_label
```

[70]:
```
array([0, 1, 1, …, 3, 0, 1], dtype=int32)
```

[71]:
```
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
# plot data points in 3D space
fig = plt.figure(figsize=(11,11))
ax = fig.add_subplot(111, projection='3d')
x = df_cluster['Log_R']
y = df_cluster['Log_F']
z = df_cluster['Log_M']
colors = cm.nipy_spectral(cluster_label.astype(float) / 4)
ax.scatter(x, y, z, c=colors, marker='.')
ax.set_xlabel('Recency')
ax.set_ylabel('Frequency')
ax.set_zlabel('Monetary Value')
plt.title("Data Visualization", size=25)
```

[71]:
```
Text(0.5, 0.92, 'Data Visualization')
```



[72]:
```
from sklearn.cluster import KMeans
from sklearn.datasets import make_blobs
from sklearn.metrics import silhouette_samples, silhouette_score

#applying silhouette method on RFM
range_n_clusters = [2,3,4,5,6,7,8,9,10]

for n_clusters in range_n_clusters:
    # Create a subplot with 1 row and 2 columns
    fig, (ax1, ax2) = plt.subplots(1, 2)
    fig.set_size_inches(18, 7)
```

```python
    # The 1st subplot is the silhouette plot
    # The silhouette coefficient can range from -1, 1 but in this all lie␣
↪within [-0.1, 1]
    ax1.set_xlim([-0.1, 1])
    # The (n_clusters+1)*10 is for inserting blank space between silhouette
    # plots of individual clusters, to demarcate them clearly.
    ax1.set_ylim([0, len(df_clusterScaled) + (n_clusters + 1) * 10])

    # Initialize the clusterer with n_clusters value and a random generator
    # seed of 10 for reproducibility.
    clusterer = KMeans(n_clusters=n_clusters, random_state=10)
    cluster_labels = clusterer.fit_predict(df_clusterScaled)

    # The silhouette_score gives the average value for all the samples.
    # This gives a perspective into the density and separation of the formed␣
↪clusters
    silhouette_avg = silhouette_score(df_clusterScaled, cluster_labels)
    print("For n_clusters =", n_clusters,
          "The average silhouette_score is :", silhouette_avg)

    # Compute the silhouette scores for each sample
    sample_silhouette_values = silhouette_samples(df_clusterScaled,␣
↪cluster_labels)

    y_lower = 10
    for i in range(n_clusters):
        # Aggregate the silhouette scores for samples belonging to
        # cluster i, and sort them
        ith_cluster_silhouette_values = \
            sample_silhouette_values[cluster_labels == i]

        ith_cluster_silhouette_values.sort()

        size_cluster_i = ith_cluster_silhouette_values.shape[0]
        y_upper = y_lower + size_cluster_i

        color = cm.nipy_spectral(float(i) / n_clusters)
        ax1.fill_betweenx(np.arange(y_lower, y_upper),
                          0, ith_cluster_silhouette_values,
                          facecolor=color, edgecolor=color, alpha=0.7)

        # Label the silhouette plots with their cluster numbers at the middle
        ax1.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))

        # Compute the new y_lower for next plot
        y_lower = y_upper + 10  # 10 for the 0 samples
```

```
    ax1.set_title("The silhouette plot for the various clusters.")
    ax1.set_xlabel("The silhouette coefficient values")
    ax1.set_ylabel("Cluster label")

    # The vertical line for average silhouette score of all the values
    ax1.axvline(x=silhouette_avg, color="red", linestyle="--")

    ax1.set_yticks([])  # Clear the yaxis labels / ticks
    ax1.set_xticks([-0.1, 0, 0.2, 0.4, 0.6, 0.8, 1])

    # 2nd Plot showing the actual clusters formed
    colors = cm.nipy_spectral(cluster_labels.astype(float) /n_clusters)
    ax2.scatter(df_clusterScaled[:, 0], df_clusterScaled[:, 1], marker='.',␣
↪s=30, lw=0, alpha=0.7,
                c=colors, edgecolor='k')

    # Labeling the clusters
    centers = clusterer.cluster_centers_
    # Draw white circles at cluster centers
    ax2.scatter(centers[:, 0], centers[:, 1], marker='o',
                c="white", alpha=1, s=200, edgecolor='k')

    for i, c in enumerate(centers):
        ax2.scatter(c[0], c[1], marker='$%d$' % i, alpha=1,
                    s=50, edgecolor='k')

    ax2.set_title("The visualization of the clustered data.")
    ax2.set_xlabel("Feature space for the 1st feature")
    ax2.set_ylabel("Feature space for the 2nd feature")
    plt.suptitle(("Silhouette analysis for KMeans clustering on sample data "
                  "with n_clusters = %d" % n_clusters),
                 fontsize=14, fontweight='bold')

plt.show()



# Source: https://scikit-learn.org/stable/auto_examples/cluster/
↪plot_kmeans_silhouette_analysis.html
```

```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

```
For n_clusters = 2 The average silhouette_score is : 0.3961133647496796
```

```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

```
For n_clusters = 3 The average silhouette_score is : 0.30400676642553737
```

```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

```
For n_clusters = 4 The average silhouette_score is : 0.30316289190060947
```

```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

```
For n_clusters = 5 The average silhouette_score is : 0.2797007629285468
```

```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

```
For n_clusters = 6 The average silhouette_score is : 0.27956889687891856
```

```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

```
For n_clusters = 7 The average silhouette_score is : 0.2633029005431065
```

```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

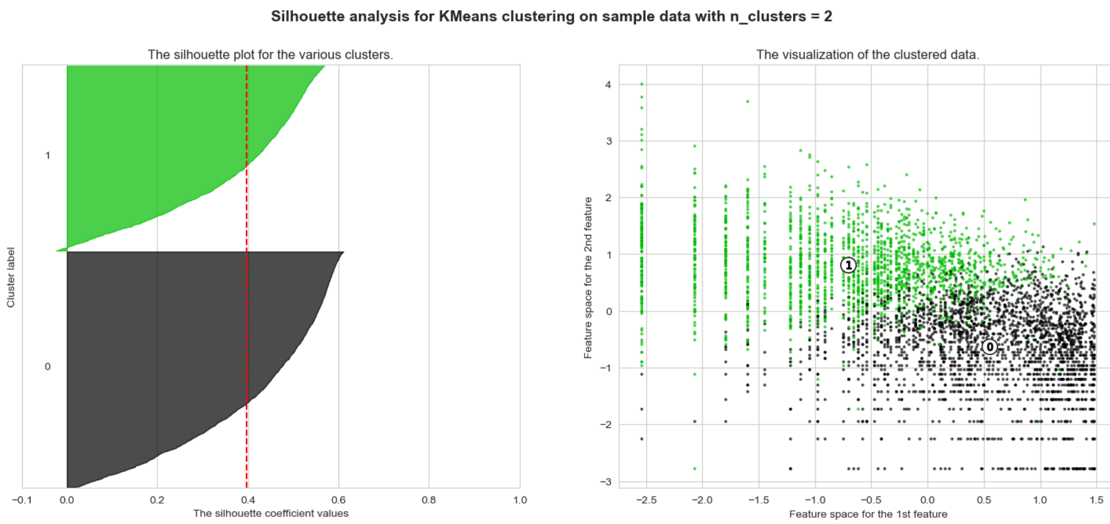
```
For n_clusters = 8 The average silhouette_score is : 0.2665353161429569
```

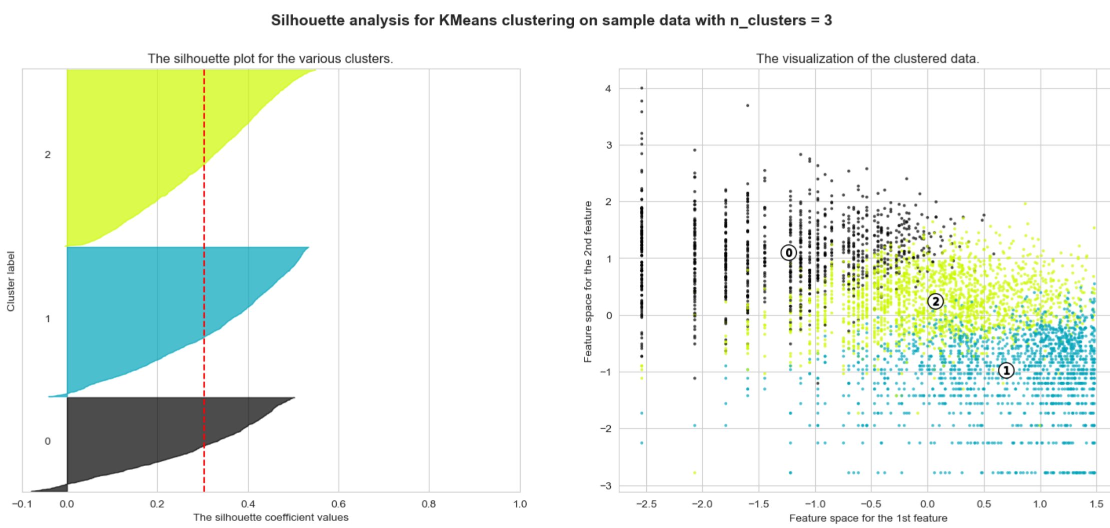
```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

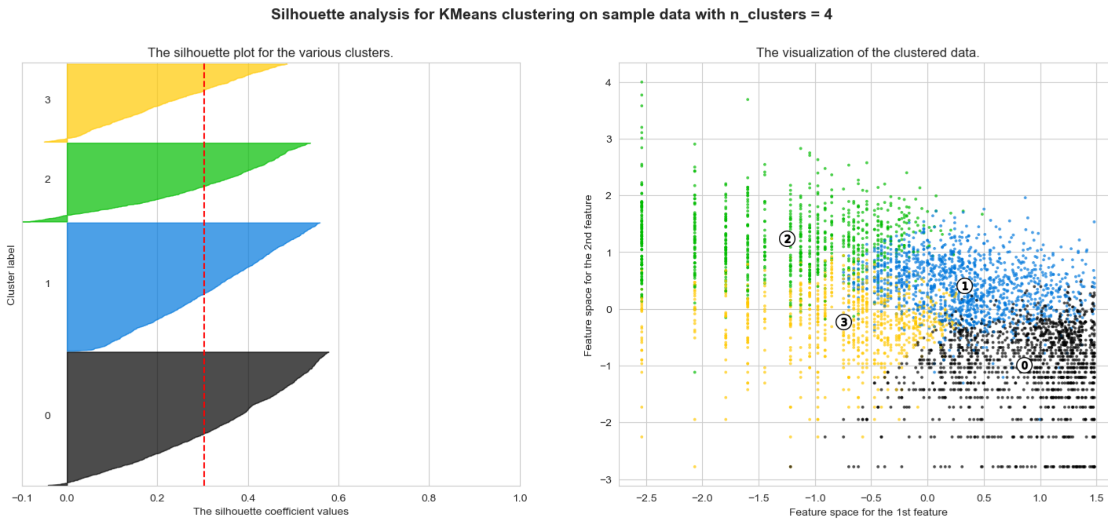
```
For n_clusters = 9 The average silhouette_score is : 0.25827775253105306
```

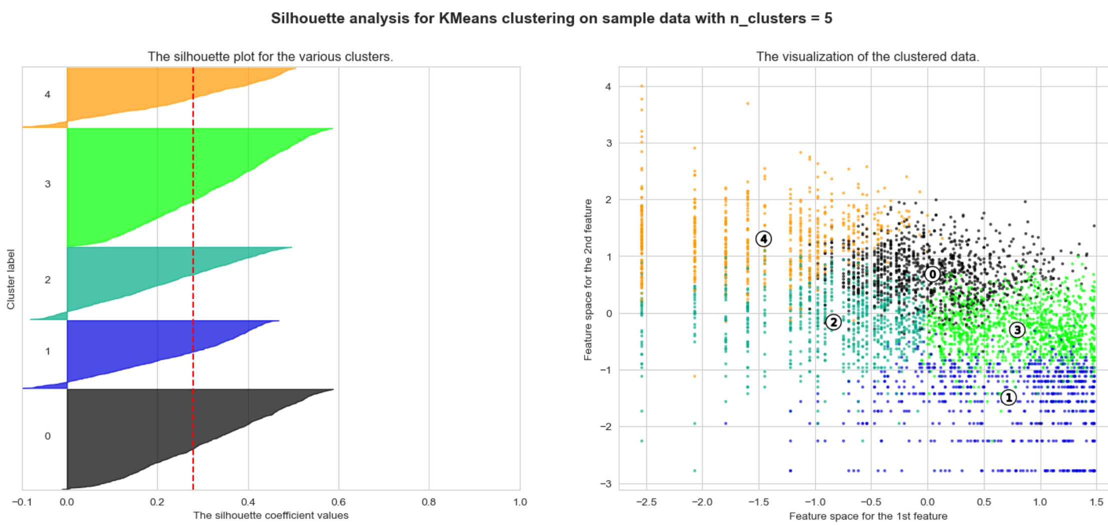
```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/sklearn/cluster/_kmeans.py:1412: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

```
For n_clusters = 10 The average silhouette_score is : 0.26038301809249415
```

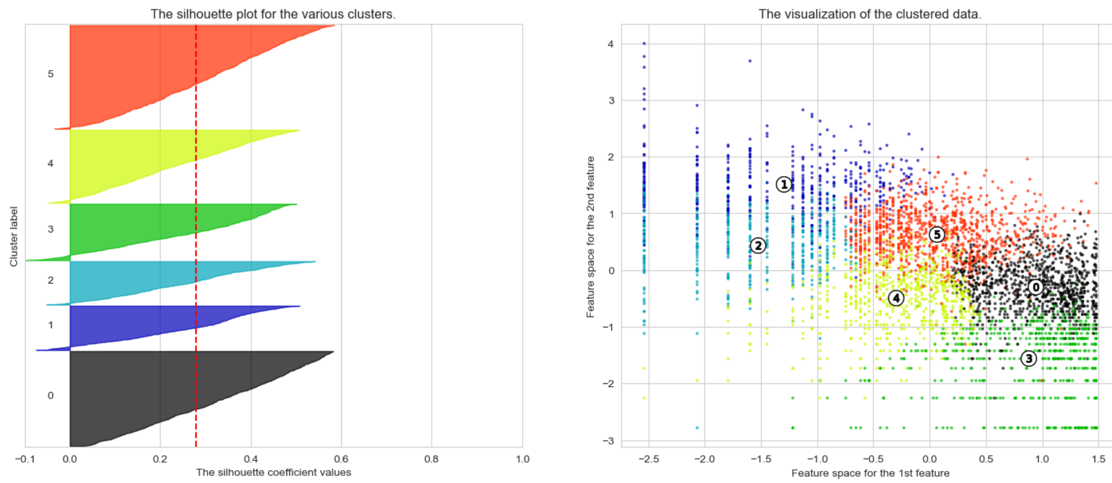




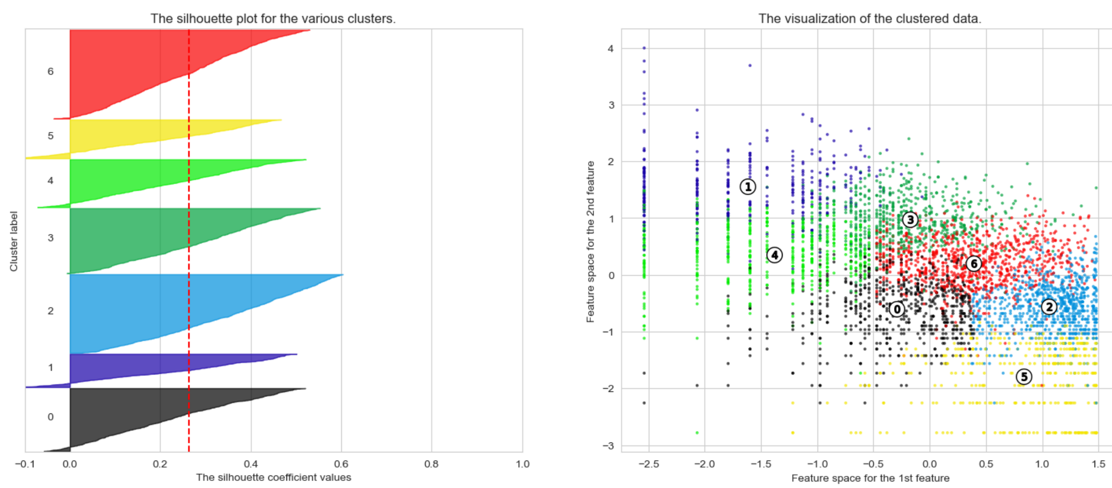

Silhouette analysis for KMeans clustering on sample data with n_clusters = 4
The silhouette plot for the various clusters.
Cluster label
The silhouette coefficient values
The visualization of the clustered data.
Feature space for the 2nd feature
Feature space for the 1st feature

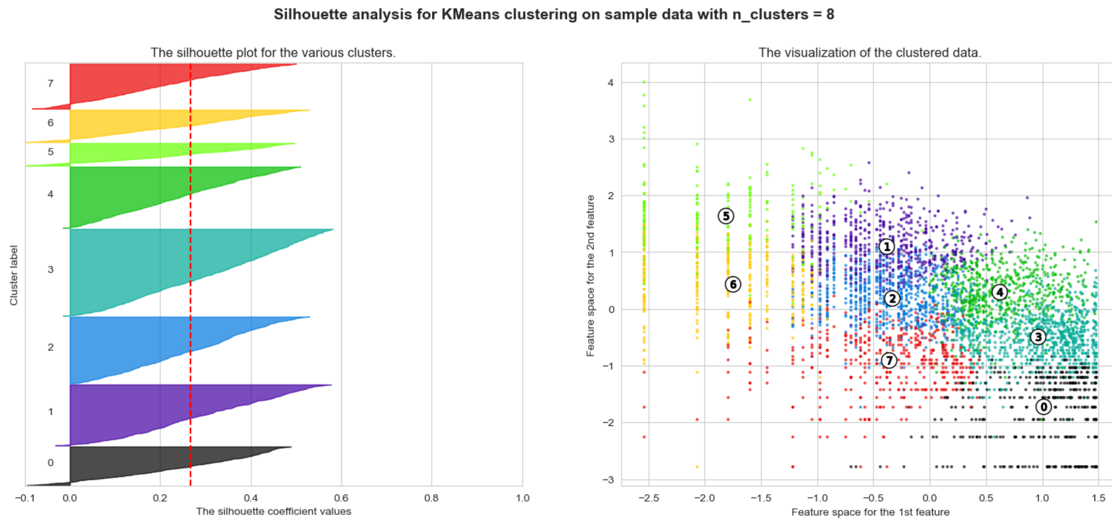

Silhouette analysis for KMeans clustering on sample data with n_clusters = 5
The silhouette plot for the various clusters.
Cluster label
The silhouette coefficient values
The visualization of the clustered data.
Feature space for the 2nd feature
Feature space for the 1st feature

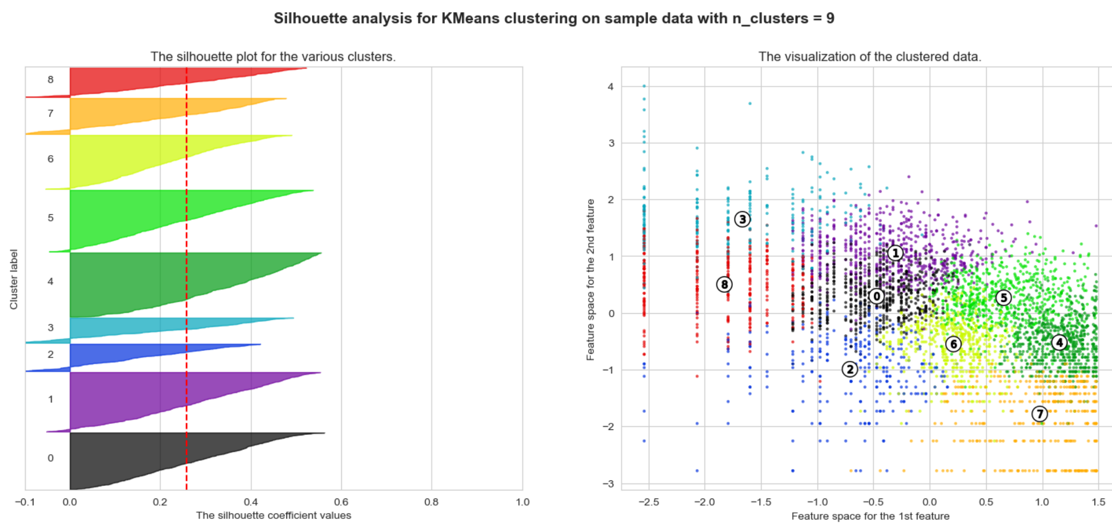
Silhouette analysis for KMeans clustering on sample data with n_clusters = 6

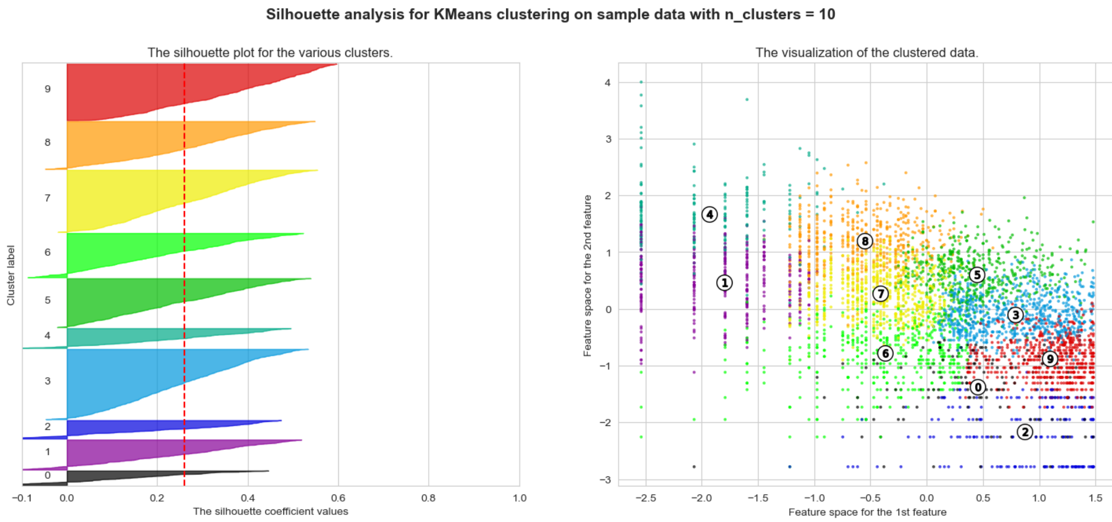


Silhouette analysis for KMeans clustering on sample data with n_clusters = 7




Silhouette analysis for KMeans clustering on sample data with n_clusters = 8
The silhouette plot for the various clusters.
Cluster label
The silhouette coefficient values
The visualization of the clustered data.
Feature space for the 2nd feature
Feature space for the 1st feature


Silhouette analysis for KMeans clustering on sample data with n_clusters = 9
The silhouette plot for the various clusters.
Cluster label
The silhouette coefficient values
The visualization of the clustered data.
Feature space for the 2nd feature
Feature space for the 1st feature



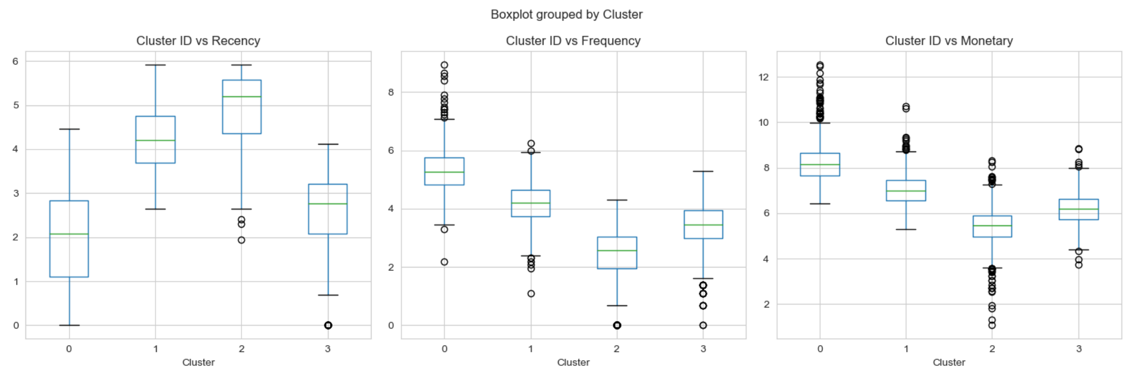
[73]:
```python
#add cluster label as a new column
df_cluster['Cluster']=cluster_label
df_cluster.head(10)
```

[73]:

	Log_R	Log_F	Log_M	Cluster
0	0.693	5.204	8.369	0
1	4.317	3.434	7.494	1
2	2.890	4.290	7.472	1
3	5.737	2.833	5.812	2
4	3.584	4.443	7.826	1
5	5.318	1.386	4.489	2
6	5.447	4.060	6.984	1
7	5.366	2.565	6.130	2
8	3.091	4.078	7.941	1
9	3.497	4.875	8.734	0

[74]:
```python
import matplotlib.pyplot as plt
import pandas as pd


# Create subplots
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(15, 5))

# Box plot for Cluster ID vs Recency
df_cluster.boxplot(column='Log_R', by='Cluster', ax=axes[0])
axes[0].set_title('Cluster ID vs Recency')

# Box plot for Cluster ID vs Frequency
df_cluster.boxplot(column='Log_F', by='Cluster', ax=axes[1])
```

```
axes[1].set_title('Cluster ID vs Frequency')

# Box plot for Cluster ID vs Monetary
df_cluster.boxplot(column='Log_M', by='Cluster', ax=axes[2])
axes[2].set_title('Cluster ID vs Monetary')

# Adjust layout
plt.tight_layout()
plt.show()
```



[75]:
```
# calculate mean of each feature for clusters
df_cluster = df_cluster.groupby('Cluster').mean()
df_cluster
```

[75]:

Cluster	Log_R	Log_F	Log_M
0	1.935237	5.316998	8.248923
1	4.250298	4.196378	7.036944
2	4.973349	2.377658	5.423984
3	2.576578	3.413324	6.175867

[76]:
```
# We have log-transformed the features now to get more intuition take␣
↪exponential of each feature
df_cluster = df_cluster.applymap(np.exp)
df_cluster = df_cluster.applymap(int)
df_cluster
```

[76]:

Cluster	Log_R	Log_F	Log_M
0	6	203	3823
1	70	66	1137
2	144	10	226
3	13	30	480

Cluster Number	RFM Decoding Customer Value	Type of Customer
0	Bought most recently and most often, and spend the most	Best Customers
1	Last bought while ago and less frequent and spend the most	Risky Customers
2	Bought long time ago and least frequency and monetary	Churned Customer
3	Bought most recently but low frequency and monetary	New Customers

2.5 DBSCAN (Density-Based Spatial Clustering of Applications with Noise) Clustering

DBSCAN Clustering Algorithm K-Means and Hierarchical Clustering struggle with creating clusters of complex shapes and adapting to varying densities. In contrast, DBSCAN excels by grouping densely packed data points into clusters and effectively identifying clusters in large spatial datasets based on local density. The most exciting feature of DBSCAN clustering is that it is robust to outliers.

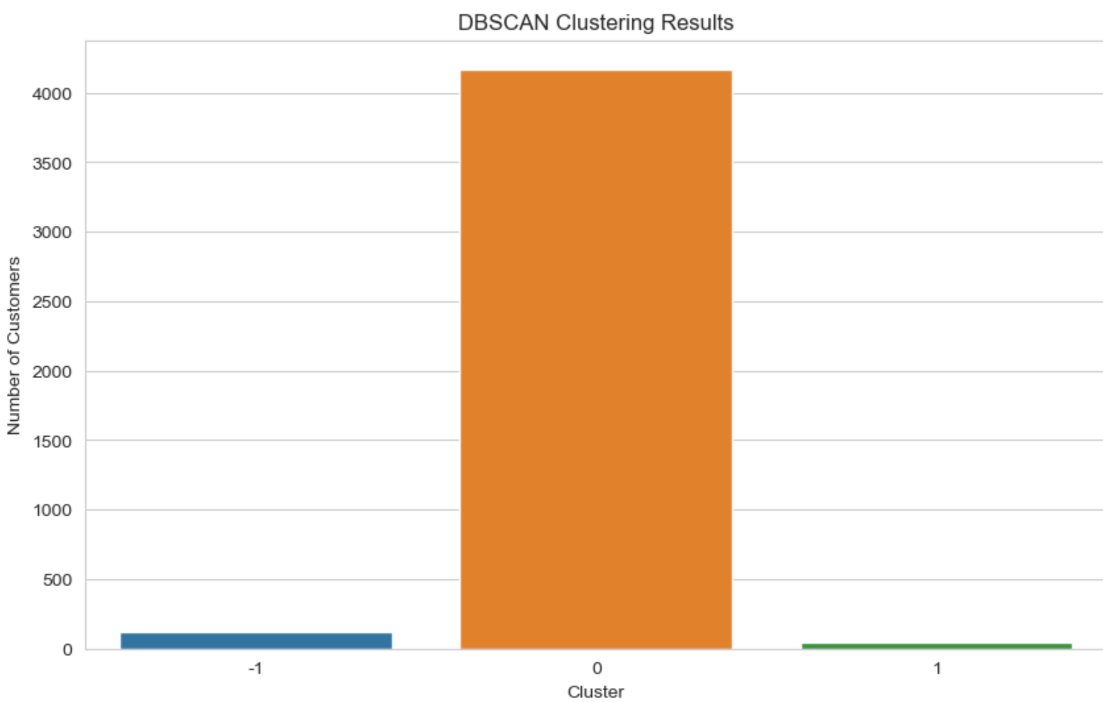
[77]:
```
df_clusterScaled
```

[77]:
```
array([[-2.06658152e+00,  1.16054770e+00,  1.41835454e+00],
       [ 3.93073233e-01, -1.80688607e-01,  7.23820703e-01],
       [-5.75449762e-01,  4.67954489e-01,  7.06358138e-01],
       …,
       [-1.21615453e+00, -8.99803441e-01, -1.11133613e+00],
       [-1.79102417e+00,  2.20398408e+00,  8.26214834e-01],
       [ 9.85909588e-05,  4.36128543e-01,  7.41283268e-01]])
```

[78]:
```
from sklearn.cluster import DBSCAN
from sklearn.preprocessing import StandardScaler

# Select features for DBSCAN
#df_dbscan = df_rfm[['Log_R', 'Log_F', 'Log_M']]

# Standardize the features
#scaler = StandardScaler()
#df_dbscan_scaled = scaler.fit_transform(df_dbscan)

# Initialize DBSCAN
dbscan = DBSCAN(eps=0.5, min_samples=9)  # Adjust eps and min_samples based on␣
 ↪your data

# Fit and predict clusters
cluster_labels = dbscan.fit_predict(df_clusterScaled)
```

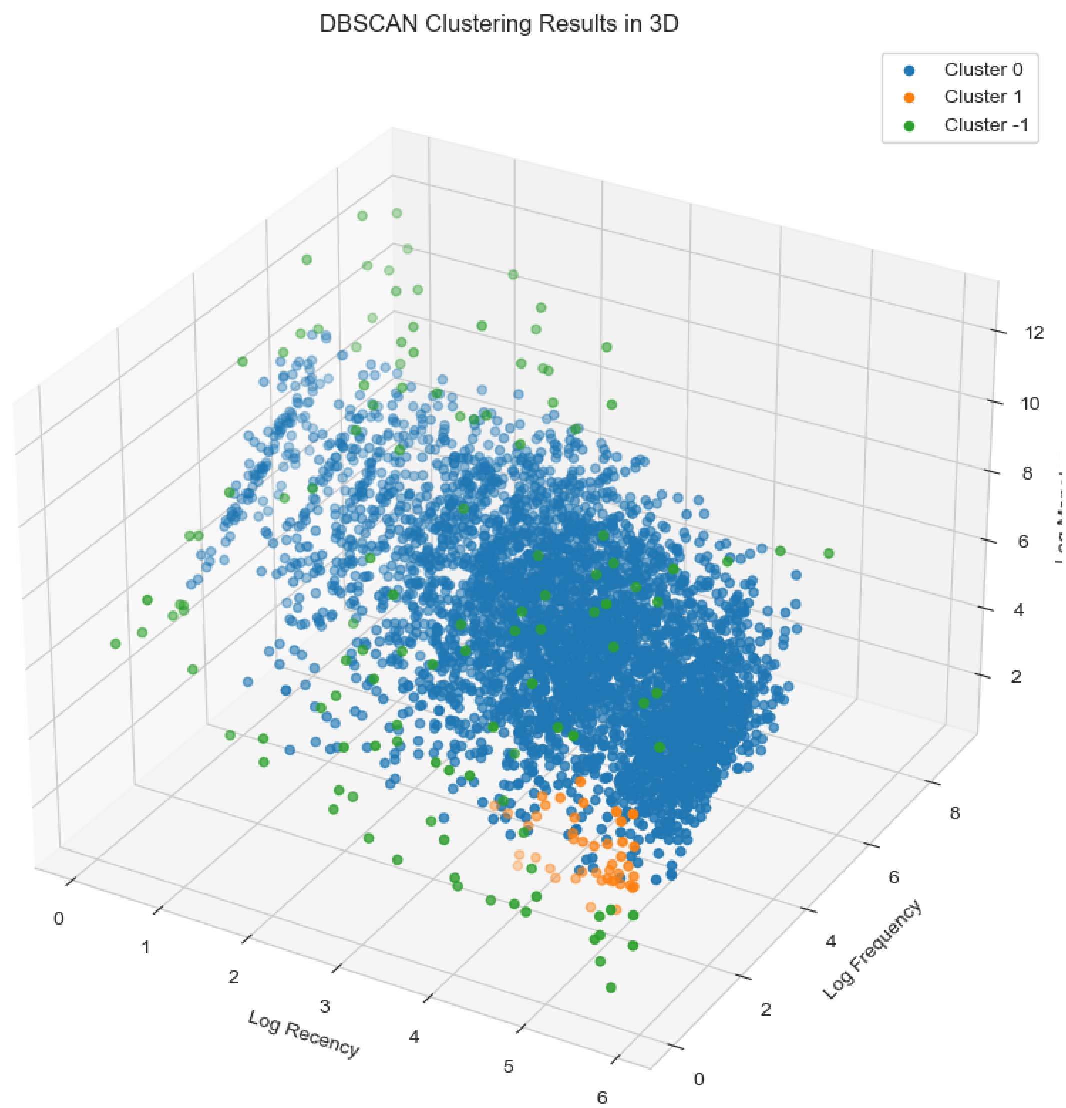
```python
# Add cluster labels to the original dataset
df_rfm['DBSCAN_Cluster'] = cluster_labels

# Count the number of customers in each cluster
cluster_counts = df_rfm['DBSCAN_Cluster'].value_counts().sort_index()

# Display cluster counts
print(cluster_counts)

# Plot the distribution of clusters
plt.figure(figsize=(10, 6))
sns.barplot(x=cluster_counts.index, y=cluster_counts.values)
plt.xlabel('Cluster')
plt.ylabel('Number of Customers')
plt.title('DBSCAN Clustering Results')
plt.show()
```

```
-1      124
 0     4169
 1       44
Name: DBSCAN_Cluster, dtype: int64
```



[79]:

```python
from mpl_toolkits.mplot3d import Axes3D

# Create a 3D scatter plot of the clusters
fig = plt.figure(figsize=(10, 10))
ax = fig.add_subplot(111, projection='3d')

# Extract cluster labels and corresponding data
cluster_labels = df_rfm['DBSCAN_Cluster']
x = df_rfm['Log_R']
y = df_rfm['Log_F']
z = df_rfm['Log_M']

# Create a scatter plot for each cluster
for cluster_id in set(cluster_labels):
    cluster_mask = (cluster_labels == cluster_id)
    ax.scatter(x[cluster_mask], y[cluster_mask], z[cluster_mask],␣
 ↪label=f'Cluster {cluster_id}')

# Set labels and title
ax.set_xlabel('Log Recency')
ax.set_ylabel('Log Frequency')
ax.set_zlabel('Log Monetary')
ax.set_title('DBSCAN Clustering Results in 3D')
ax.legend()

plt.show()
```



[80]:
```
df_rfm.head()
```

[80]:
```
            Recency  Frequency  Monetary  R_score  F_score  M_score  \
CustomerID
12347.0           2        182   4310.00        4        4        4
12348.0          75         31   1797.24        2        2        4
12349.0          18         73   1757.55        3        3        4
12350.0         310         17    334.40        1        1        2
12352.0          36         85   2506.04        3        3        4

            RFM_Score  RFM  Log_R  Log_F  Log_M  DBSCAN_Cluster
CustomerID
```

```
12347.0           12  444  0.693  5.204  8.369              0
12348.0            8  224  4.317  3.434  7.494              0
12349.0           10  334  2.890  4.290  7.472              0
12350.0            4  112  5.737  2.833  5.812              0
12352.0           10  334  3.584  4.443  7.826              0
```

[81]:
```python
# Calculate the mean of each feature for clusters
cluster_means = df_rfm.groupby('DBSCAN_Cluster')[['Recency', 'Frequency',␣
 ↪'Monetary']].mean()

# Print the cluster means
print(cluster_means)
```

```
                  Recency   Frequency      Monetary
DBSCAN_Cluster
-1              61.645161  396.040323  21853.746774
 0              91.347325   82.412089   1420.666600
 1             245.386364    1.000000    203.000909
```

[82]:
```python
# Take exponential of log-transformed features
cluster_means_original_scale = cluster_means.applymap(np.exp)
cluster_means_original_scale=cluster_means.applymap(int)


# Print the cluster means in the original scale
print(cluster_means_original_scale)
print('cluster_counts')
print(cluster_counts)
```

```
                Recency  Frequency  Monetary
DBSCAN_Cluster
-1                   61        396     21853
 0                   91         82      1420
 1                  245          1       203
cluster_counts
-1     124
 0    4169
 1      44
Name: DBSCAN_Cluster, dtype: int64
```

```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/pandas/core/frame.py:9651: RuntimeWarning: overflow encountered in exp
  return lib.map_infer(x.astype(object)._values, func, ignore_na=ignore_na)
```

Cluster Number	RFM Decoding Customer Value	Type of Customer
-1	Bought most recently and most often, and spend the most	Best Customers
0	Last bought while ago and less frequent and spend the most	Risky Customers
1	Bought long time ago and least frequency and monetary	Churned Customer

2.6 Gaussian Mixture Models (GMM)

Gaussian Mixture Models is a statistical model that represents data as a combination of multiple Gaussian distributions. It assumes that the data is generated from a mix of these distributions, each characterized by its own average, spread, and weight. GMMs are used for tasks like clustering and data modeling. They assign probabilities to data points belonging to each Gaussian component and find the best parameters through the Expectation-Maximization (EM) algorithm. This makes GMMs valuable for understanding complex datasets with hidden patterns or clusters.

[83]:
```
df_rfm.shape
```

[83]:
```
(4337, 12)
```

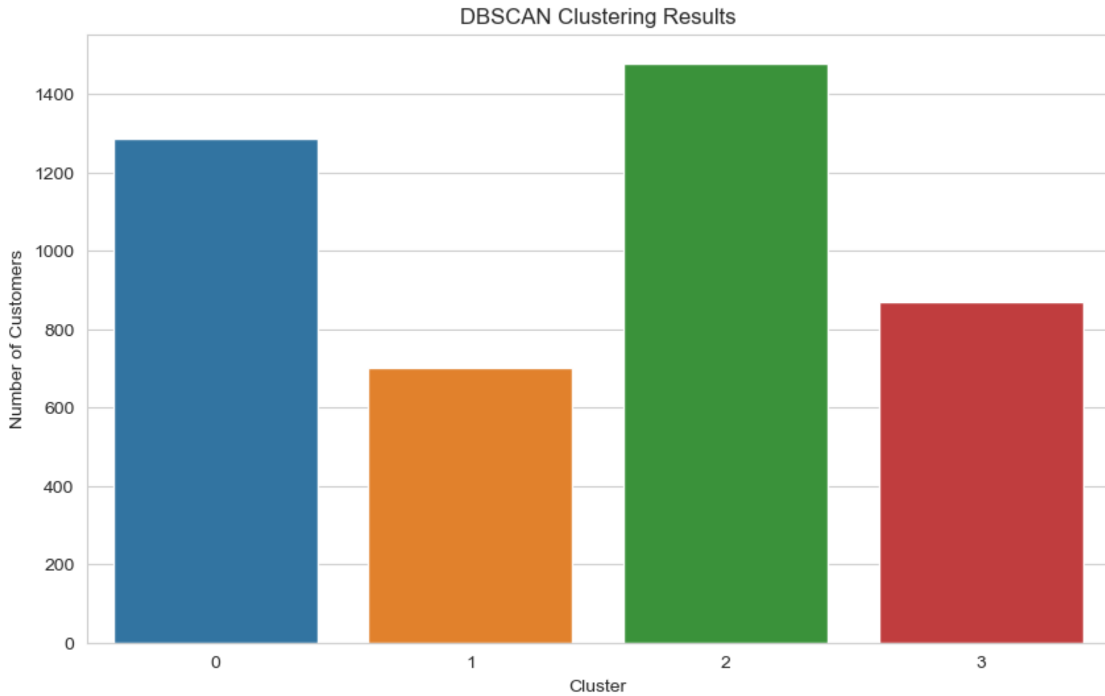
[84]:
```
df_clusterScaled
```

[84]:
```
array([[-2.06658152e+00,  1.16054770e+00,  1.41835454e+00],
       [ 3.93073233e-01, -1.80688607e-01,  7.23820703e-01],
       [-5.75449762e-01,  4.67954489e-01,  7.06358138e-01],
       …,
       [-1.21615453e+00, -8.99803441e-01, -1.11133613e+00],
       [-1.79102417e+00,  2.20398408e+00,  8.26214834e-01],
       [ 9.85909588e-05,  4.36128543e-01,  7.41283268e-01]])
```

[85]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.mixture import GaussianMixture


# Initialize Gaussian Mixture Model
#n_components = 4  # Number of clusters you want to identify
gmm = GaussianMixture(n_components=4)

# Fit the GMM model
gmm.fit(df_clusterScaled)

# Predict cluster labels for each data point
```

```python
cluster_label_GMM = gmm.predict(df_clusterScaled)
print(cluster_label_GMM)


# Add cluster labels to the original dataset
df_rfm['GMM_Cluster'] = cluster_label_GMM

# Count the number of customers in each cluster
cluster_countGMM = df_rfm['GMM_Cluster'].value_counts().sort_index()

# Display cluster counts
print(cluster_countGMM)


# Plot the distribution of clusters
plt.figure(figsize=(10, 6))
sns.barplot(x=cluster_countGMM.index, y=cluster_countGMM.values)
plt.xlabel('Cluster')
plt.ylabel('Number of Customers')
plt.title('DBSCAN Clustering Results')
plt.show()
```

```
[2 0 2 … 2 1 0]
0    1286
1     702
2    1479
3     870
Name: GMM_Cluster, dtype: int64
```



[86]:
```python
df_rfm.head()
```

[86]:
```
            Recency  Frequency  Monetary  R_score  F_score  M_score  \
CustomerID
12347.0           2        182   4310.00        4        4        4
12348.0          75         31   1797.24        2        2        4
12349.0          18         73   1757.55        3        3        4
12350.0         310         17    334.40        1        1        2
12352.0          36         85   2506.04        3        3        4

            RFM_Score  RFM  Log_R  Log_F  Log_M  DBSCAN_Cluster  GMM_Cluster
CustomerID
12347.0            12  444  0.693  5.204  8.369               0            2
12348.0             8  224  4.317  3.434  7.494               0            0
12349.0            10  334  2.890  4.290  7.472               0            2
12350.0             4  112  5.737  2.833  5.812               0            3
12352.0            10  334  3.584  4.443  7.826               0            0
```

[87]:
```python
# Calculate the mean of each feature for clusters
cluster_meansGMM = df_rfm.groupby('GMM_Cluster')[['Recency', 'Frequency',␣
 ↪'Monetary']].mean()

# Print the cluster means
print(cluster_meansGMM)
```

```
                Recency   Frequency     Monetary
GMM_Cluster
0             52.348367  111.142302  1428.713049
1             41.427350  154.772080  6083.724217
2             54.503719   79.734956  1512.054181
3            255.465517   26.691954   341.526644
```

[88]:

```
# Calculate the mean of each feature for clusters
cluster_means_GMM = df_rfm.groupby('GMM_Cluster')[['Recency', 'Frequency',␣
 ↪'Monetary']].mean()

# Print the cluster means
print(cluster_means_GMM)
```

```
                Recency   Frequency     Monetary
GMM_Cluster
0             52.348367  111.142302  1428.713049
1             41.427350  154.772080  6083.724217
2             54.503719   79.734956  1512.054181
3            255.465517   26.691954   341.526644
```

[89]:

```
# Take exponential of log-transformed features
cluster_means_scale_GMM = cluster_means_GMM.applymap(np.exp)
cluster_means_scale_GMM=cluster_means_GMM.applymap(int)


# Print the cluster means in the original scale
print(cluster_means_scale_GMM)
print('cluster_counts of GMM')
print(cluster_countGMM)
```

```
             Recency  Frequency  Monetary
GMM_Cluster
0                 52        111      1428
1                 41        154      6083
2                 54         79      1512
3                255         26       341
cluster_counts of GMM
0    1286
1     702
2    1479
3     870
Name: GMM_Cluster, dtype: int64
```

```
/Users/senakaya/anaconda3/envs/customer_segment/lib/python3.8/site-
packages/pandas/core/frame.py:9651: RuntimeWarning: overflow encountered in exp
  return lib.map_infer(x.astype(object)._values, func, ignore_na=ignore_na)
```

Cluster Number	RFM Decoding Customer Value	Type of Customer
0	Bought most recently and most often, and spend the most	Best Customers
1	Bought long time ago and least frequency and monetary	Churned Customer
2	Bought most recently but low frequency and monetary	New Customers
3	Last bought while ago and less frequent and spend the most	Risky Customers

[ ]:

```

```