Problem statement

It is a business critical requirement to understand the value derived from a customer. RFM is a method used for analyzing customer value. Perform customer segmentation using RFM analysis. The resulting segments can be ordered from most valuable (highest recency, frequency, and value) to least valuable (lowest recency, frequency, and value). Identifying the most valuable RFM segments can capitalize on chance relationships in the data used for this analysis.

Data Description:

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.

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.

More about RFM analysis:

RFM stands for Recency, Frequency, Monetary value. This concept is basically used to divide the customers into different segmenets, like high-value customer, medium value custoemr or low-value customers and similarly others.

Steps to follow:

1. Data collection and importation
2. Data cleaning and pre-processing
3. Cohort analysis
4. Model development- RFM Model

1. Data collection and importation

In [1]:
```
# import necessary libaries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# load the dataset
data=pd.read_excel("Online Retail.xlsx")
data.head()
```

Out[2]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

In [3]:
```
data.shape
```

Out[3]:
```
(541909, 8)
```

There are 8 features and 5,41,909 data.

2. Data Cleaning and Pre-processing

In [4]:
```
# checking for the null and duplicate values
data.isna().sum()
```

Out[4]:
```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

For the description feature and customer ID there are only few missing values so deleting the null values in description feature and since customerID are the unique id given to each customer so there is no way we can impute the customer ID manually so dropping the null values in both features.

In [5]:
```
data=data.dropna()
data.isna().sum()
```

Out[5]:
```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
CustomerID     0
Country        0
dtype: int64
```

In [6]:
```
data.shape
```

Out[6]:
```
(406829, 8)
```

In [7]:
```
# data.to_csv('Retail_data.csv')
```

In [8]:
```
# descriptive analysis
data.describe()
```

Out[8]:

	Quantity	UnitPrice	CustomerID
count	406829.000000	406829.000000	406829.000000
mean	12.061303	3.460471	15287.690570
std	248.693370	69.315162	1713.600303
min	-80995.000000	0.000000	12346.000000
25%	2.000000	1.250000	13953.000000
50%	5.000000	1.950000	15152.000000
75%	12.000000	3.750000	16791.000000
max	80995.000000	38970.000000	18287.000000

3. Cohort analysis

In [9]:
```
data.columns
```
Out[9]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country'],
      dtype='object')
```

In [10]:
```
data.info()
```
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 406829 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    406829 non-null  object
 1   StockCode    406829 non-null  object
 2   Description  406829 non-null  object
 3   Quantity     406829 non-null  int64
 4   InvoiceDate  406829 non-null  datetime64[ns]
 5   UnitPrice    406829 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      406829 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 27.9+ MB
```

In [11]:
```
# creating a cohort of months
# extracting months from the Invoice date and assigning new feature called month
data['Month']=data['InvoiceDate'].dt.month
```

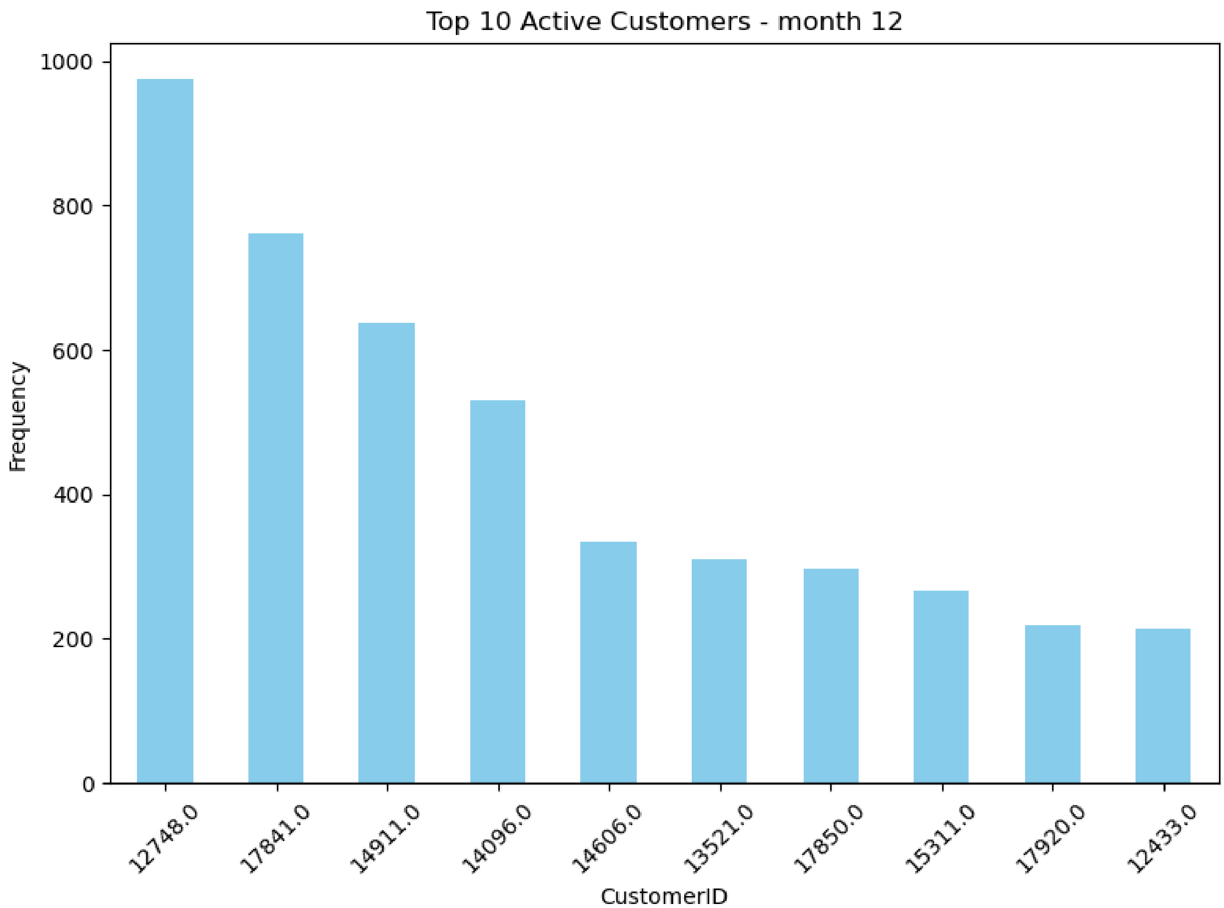
In [12]:
```
data.head()
```
Out[12]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Month
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom	12
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	12
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom	12
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	12
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	12

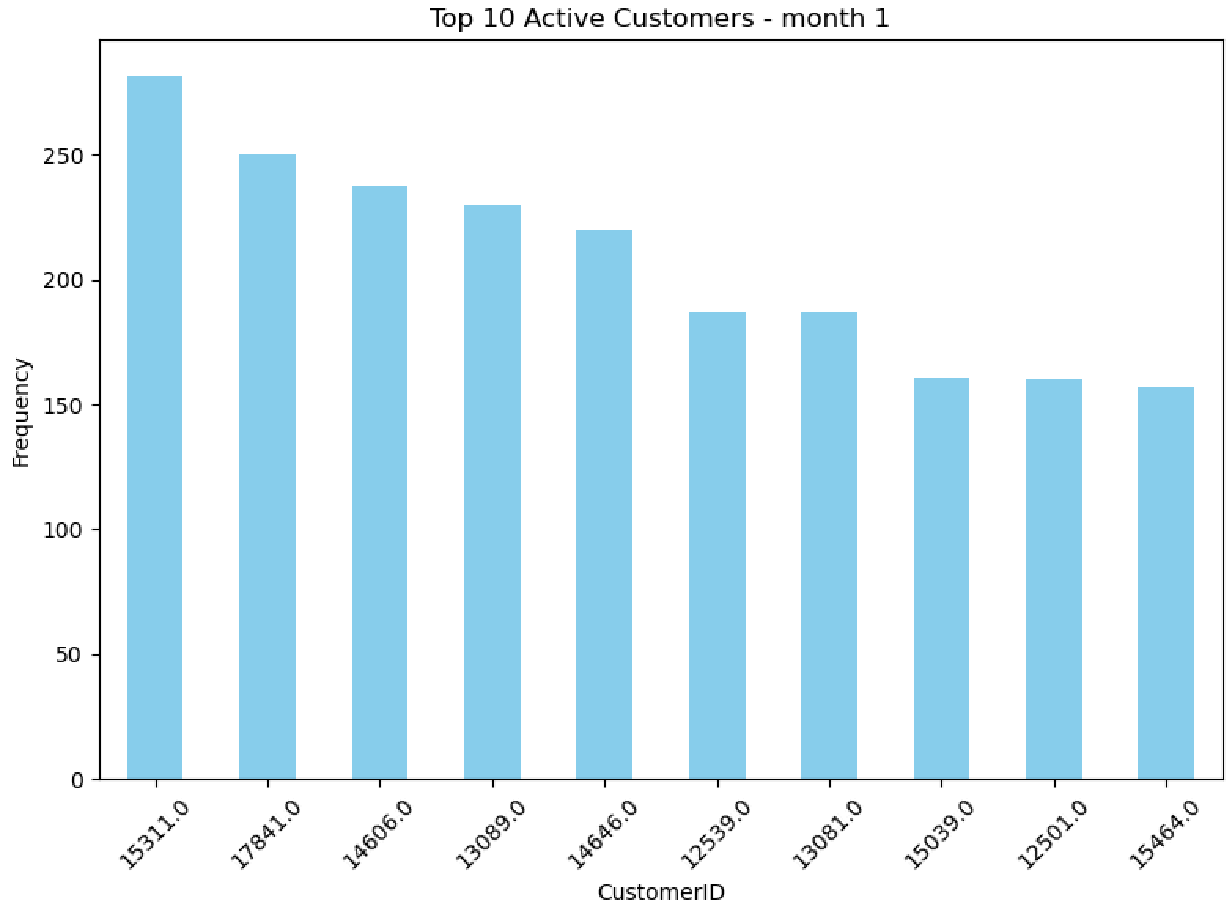
In [13]:
```
month_groupby=data.groupby('Month')
```

In [14]:
```
for month in data['Month'].unique():
    print(f"Month: {month}")
    get_data = month_groupby.get_group(month)
    print(f"Total customers for month {month} are: {len(get_data['CustomerID'].value_cou

    # Plotting for each month
    plt.figure(figsize=(8, 6))  # Adjust the figure size as needed
    get_data['CustomerID'].value_counts().head(10).plot(kind='bar', color='skyblue')
    plt.title(f"Top 10 Active Customers - month {month}")
    plt.xlabel('CustomerID')
    plt.ylabel('Frequency')
    plt.xticks(rotation=45)  # Rotating x-axis labels for better readability
    plt.tight_layout()  # Adjust layout to prevent overlapping labels
    plt.show()
```

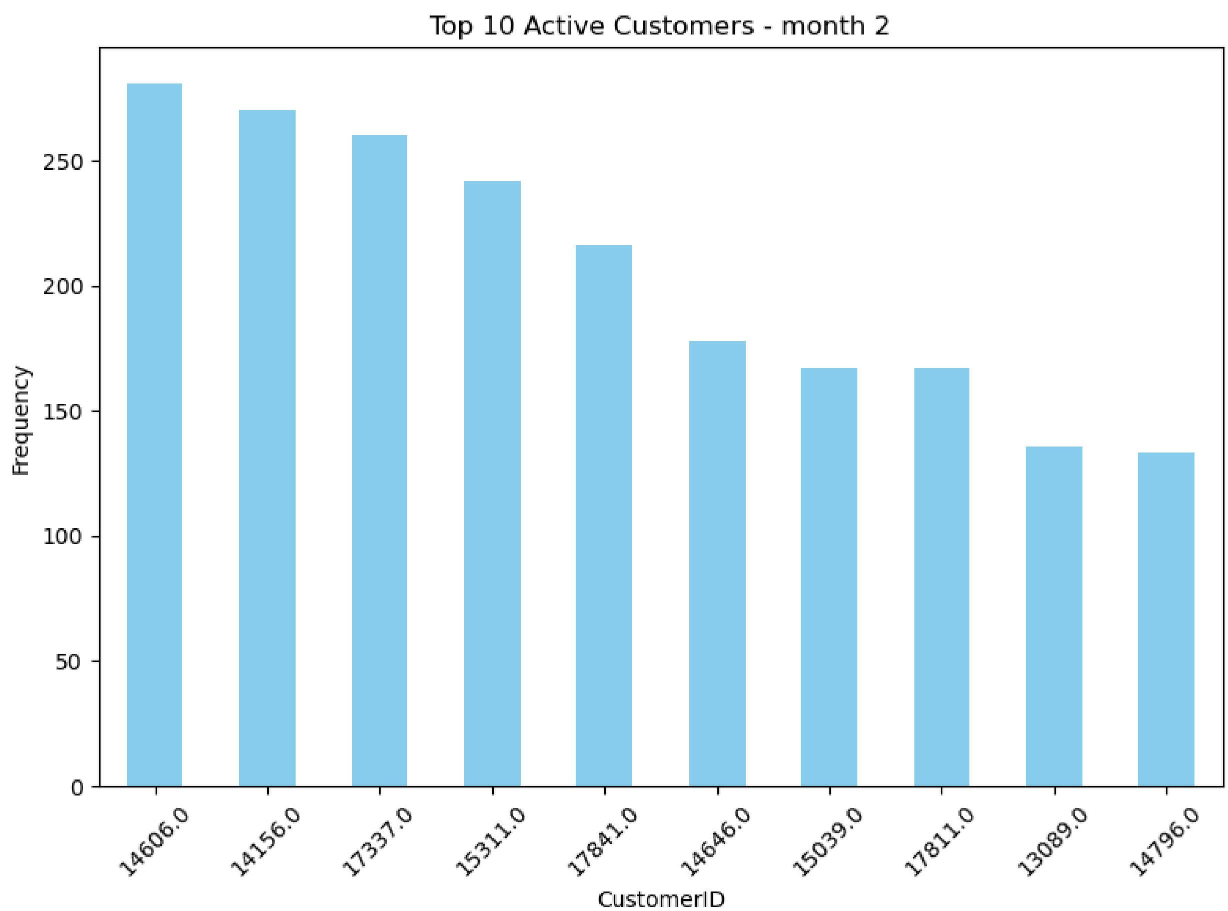
```
Month: 12
Total customers for month 12 are: 1374
```



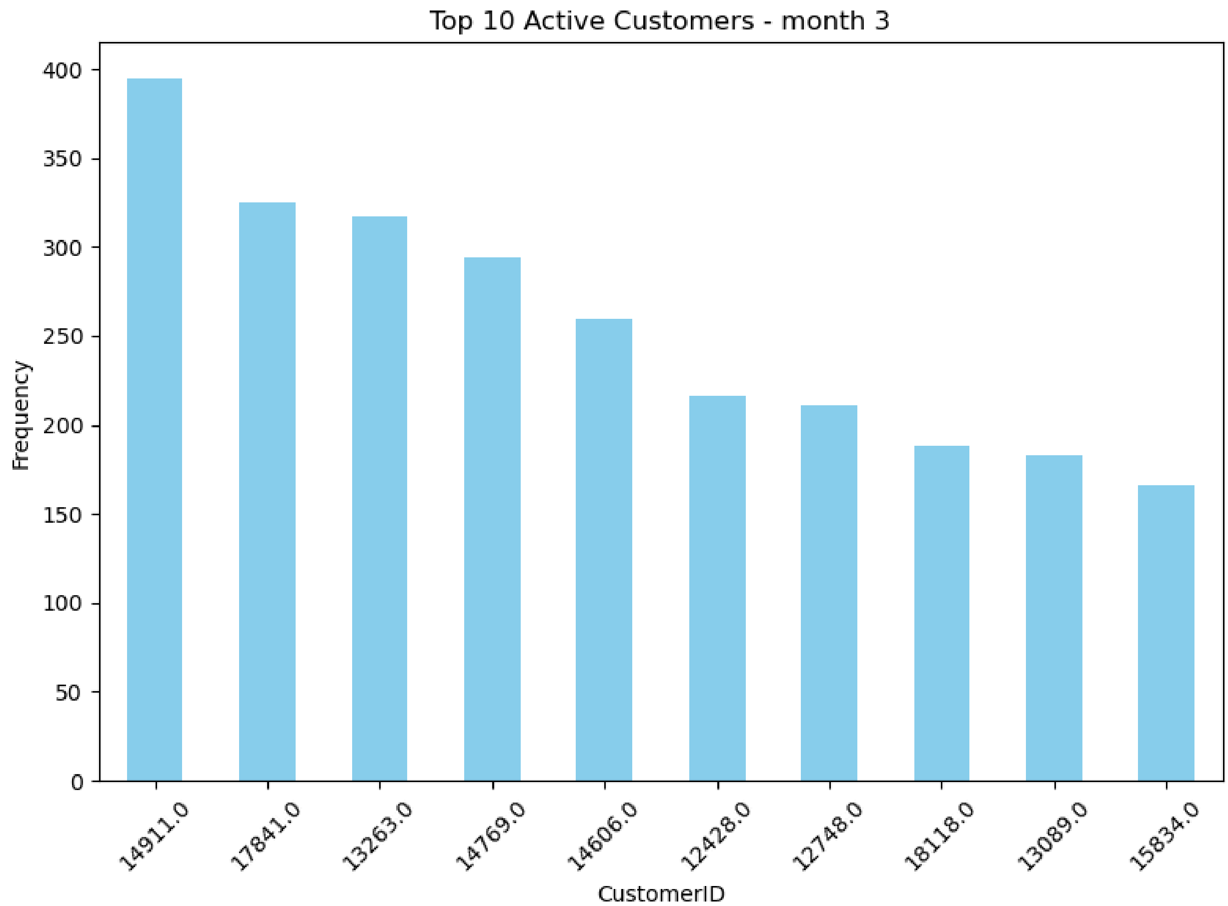

```
Month: 1
Total customers for month 1 are: 783
```



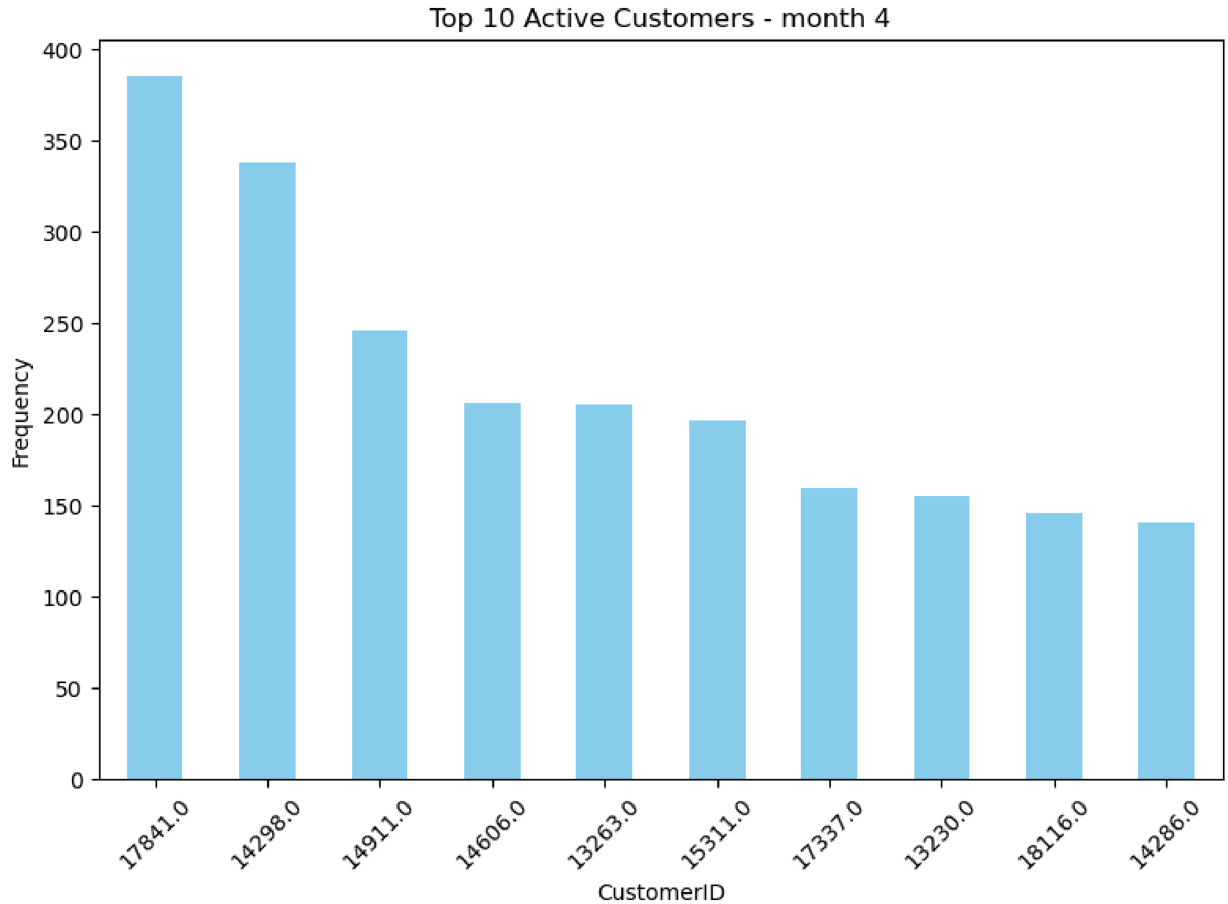

```
Month: 2
Total customers for month 2 are: 798
```



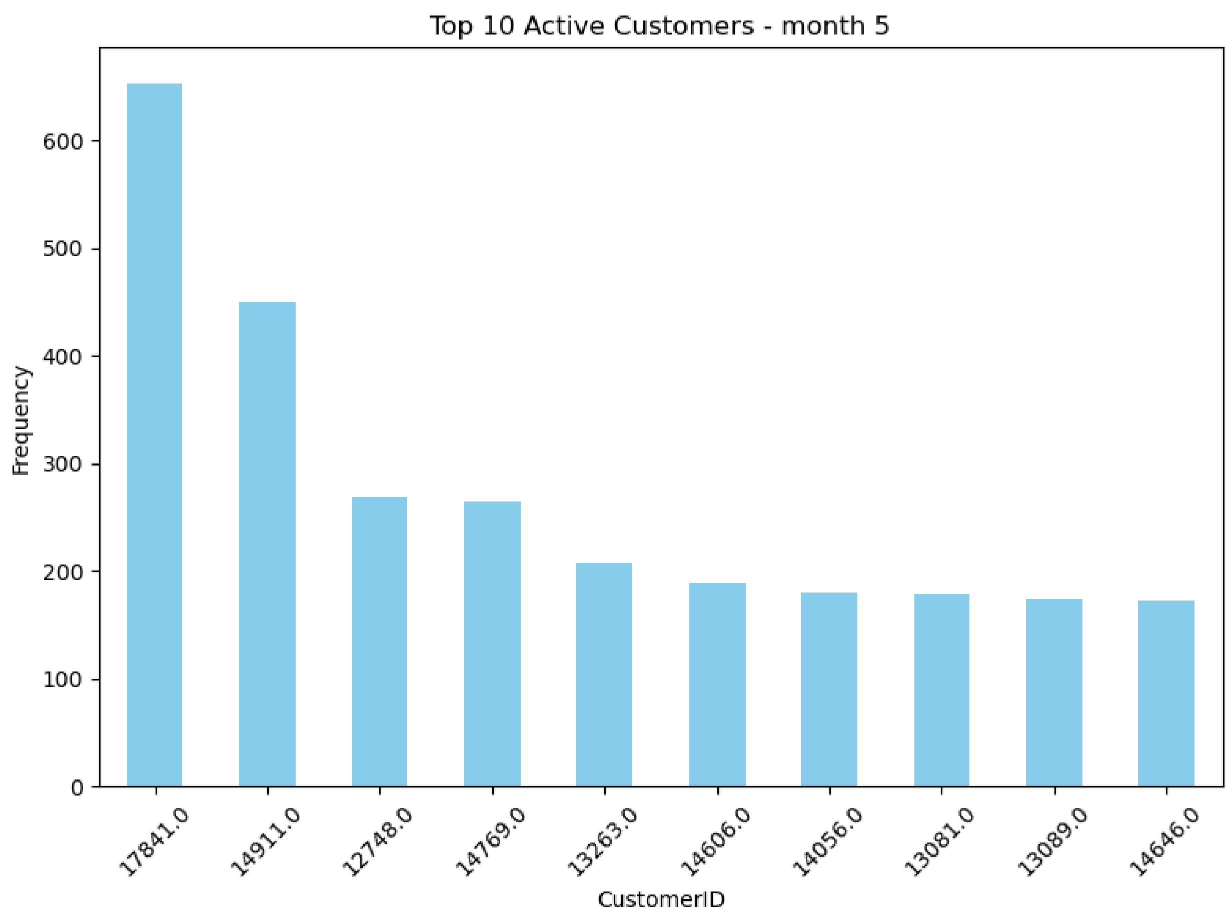
```
Month: 3
Total customers for month 3 are: 1020
```



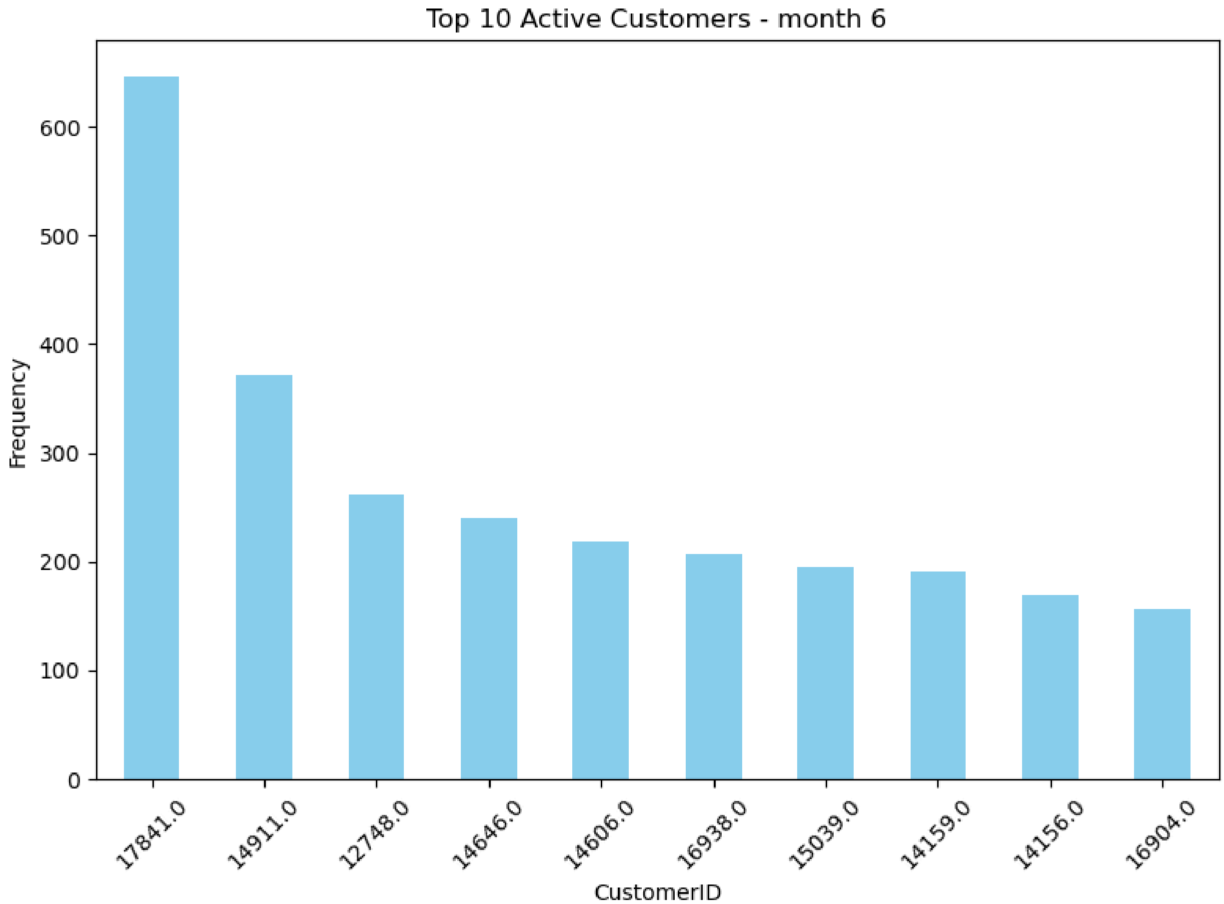

```
Month: 4
Total customers for month 4 are: 899
```



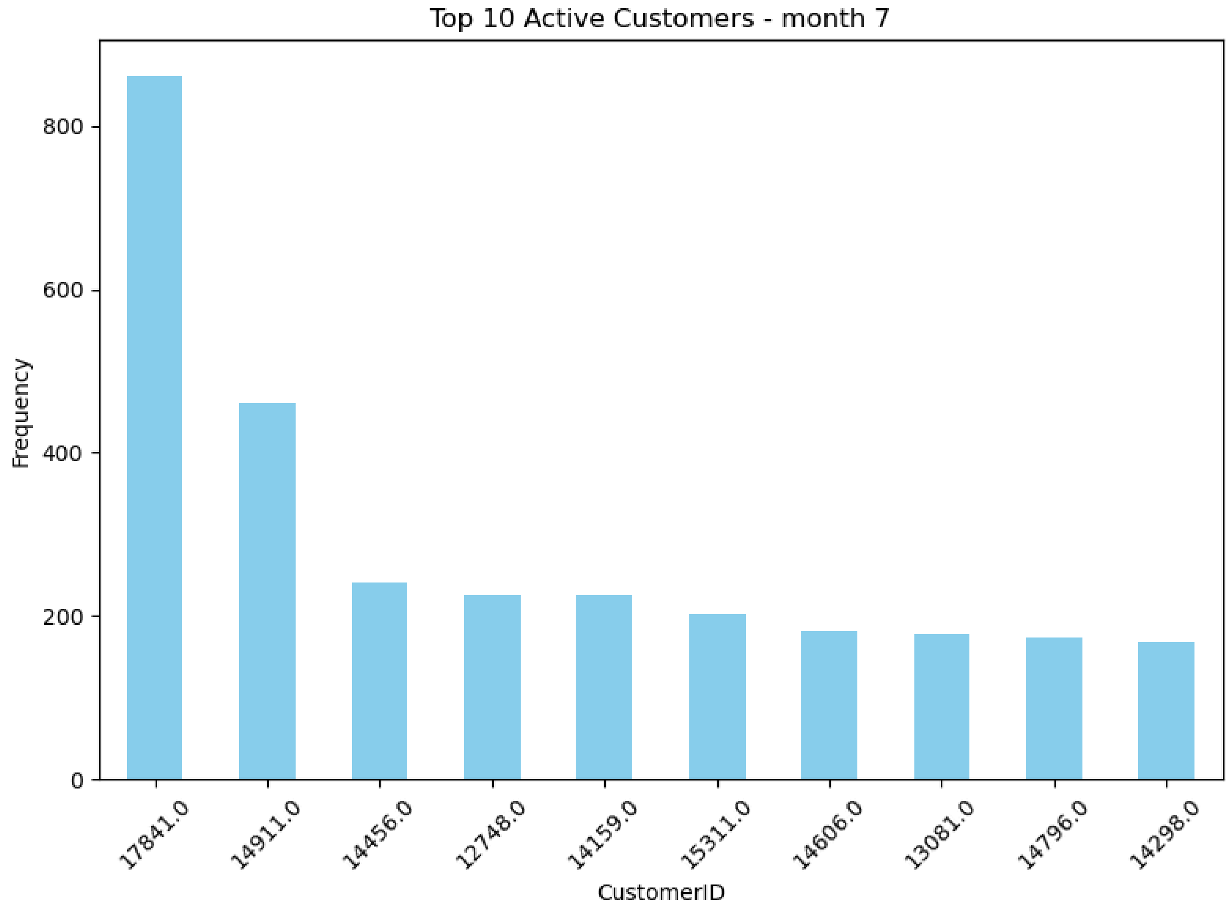

```
Month: 5
Total customers for month 5 are: 1079
```



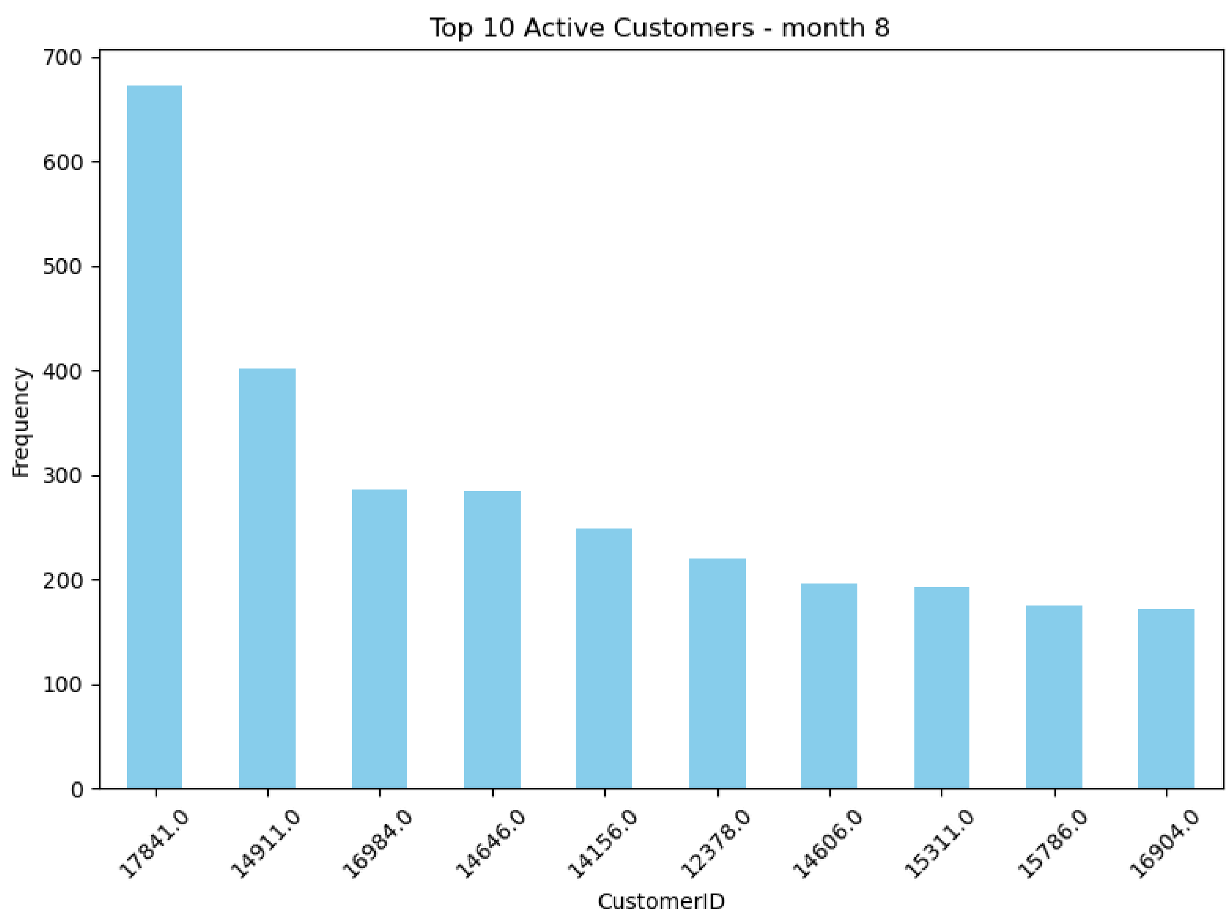
```
Month: 6
Total customers for month 6 are: 1051
```



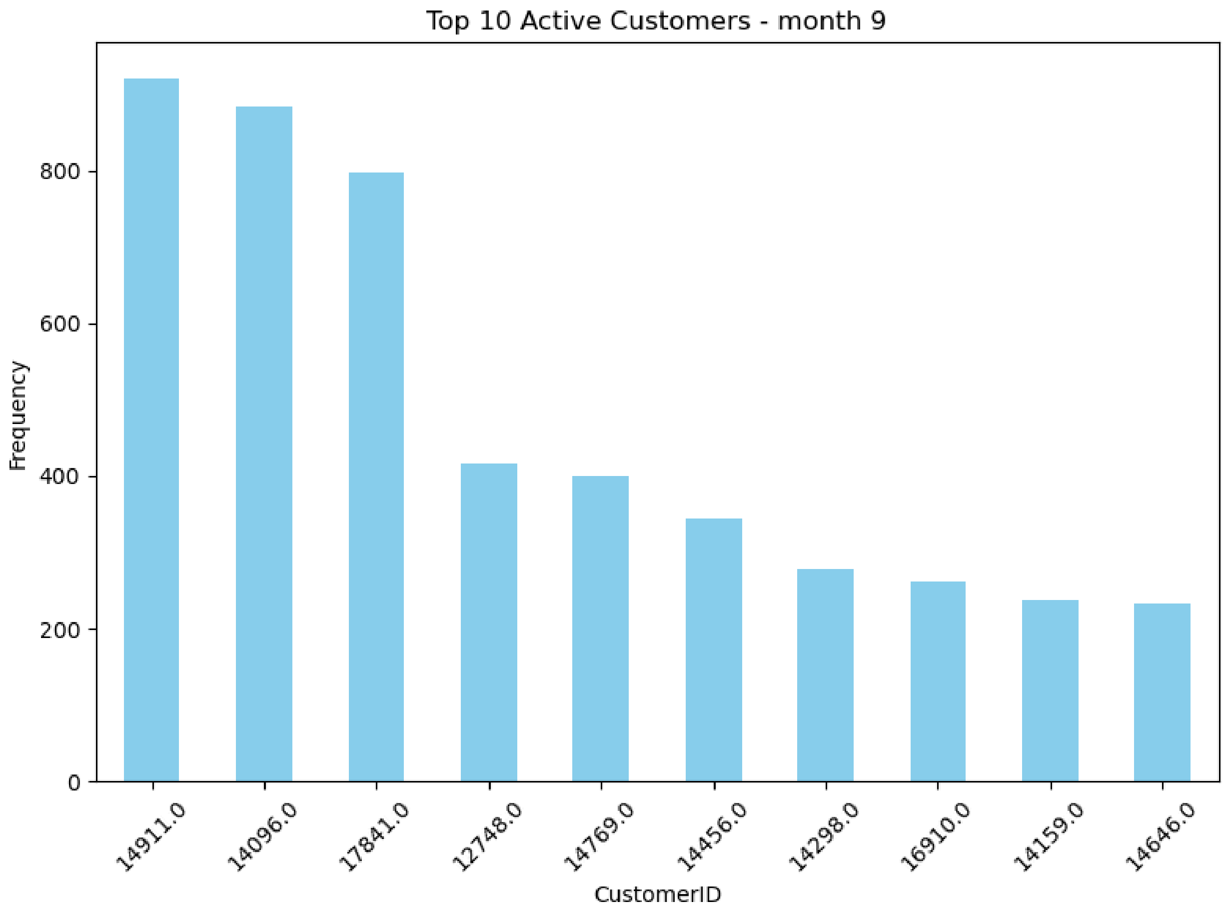

```
Month: 7
Total customers for month 7 are: 993
```



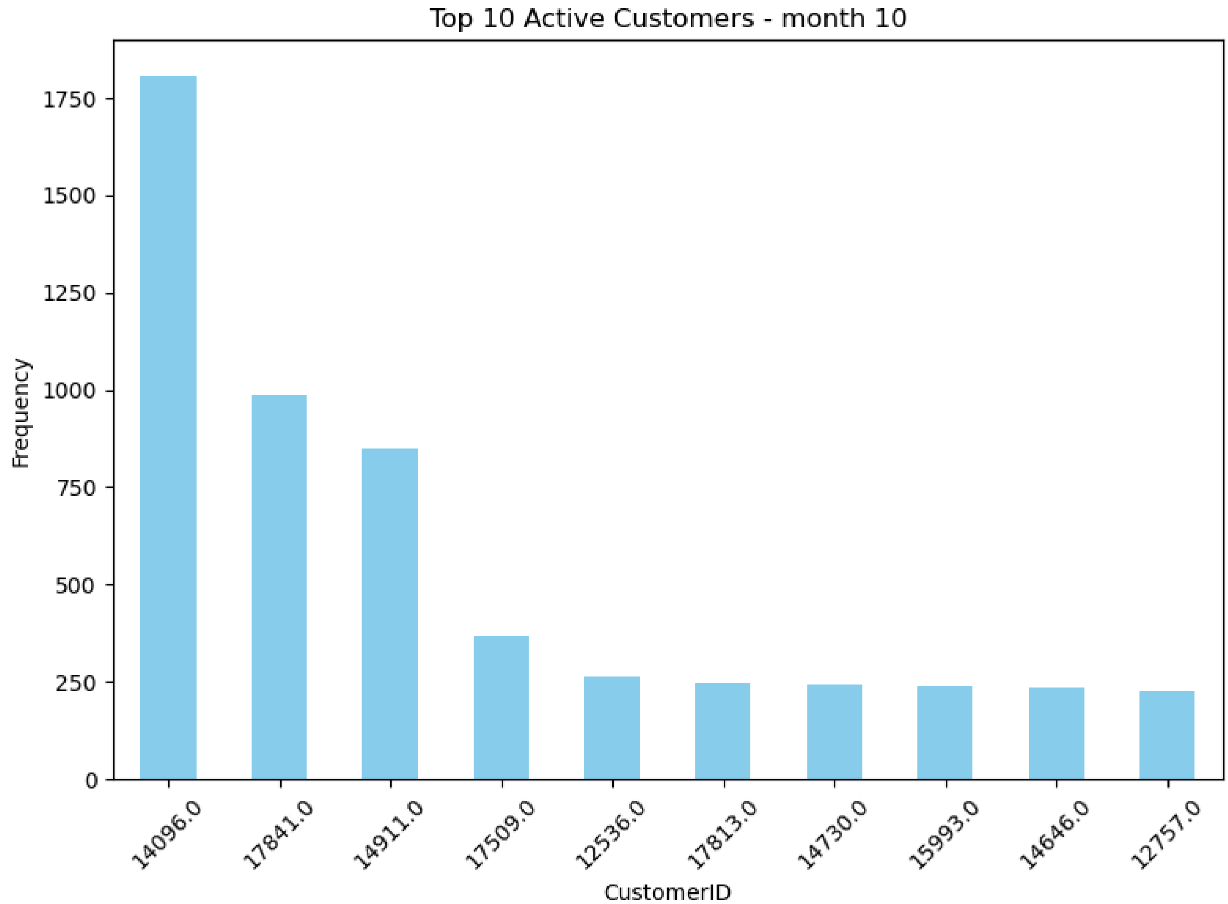

```
Month: 8
Total customers for month 8 are: 980
```



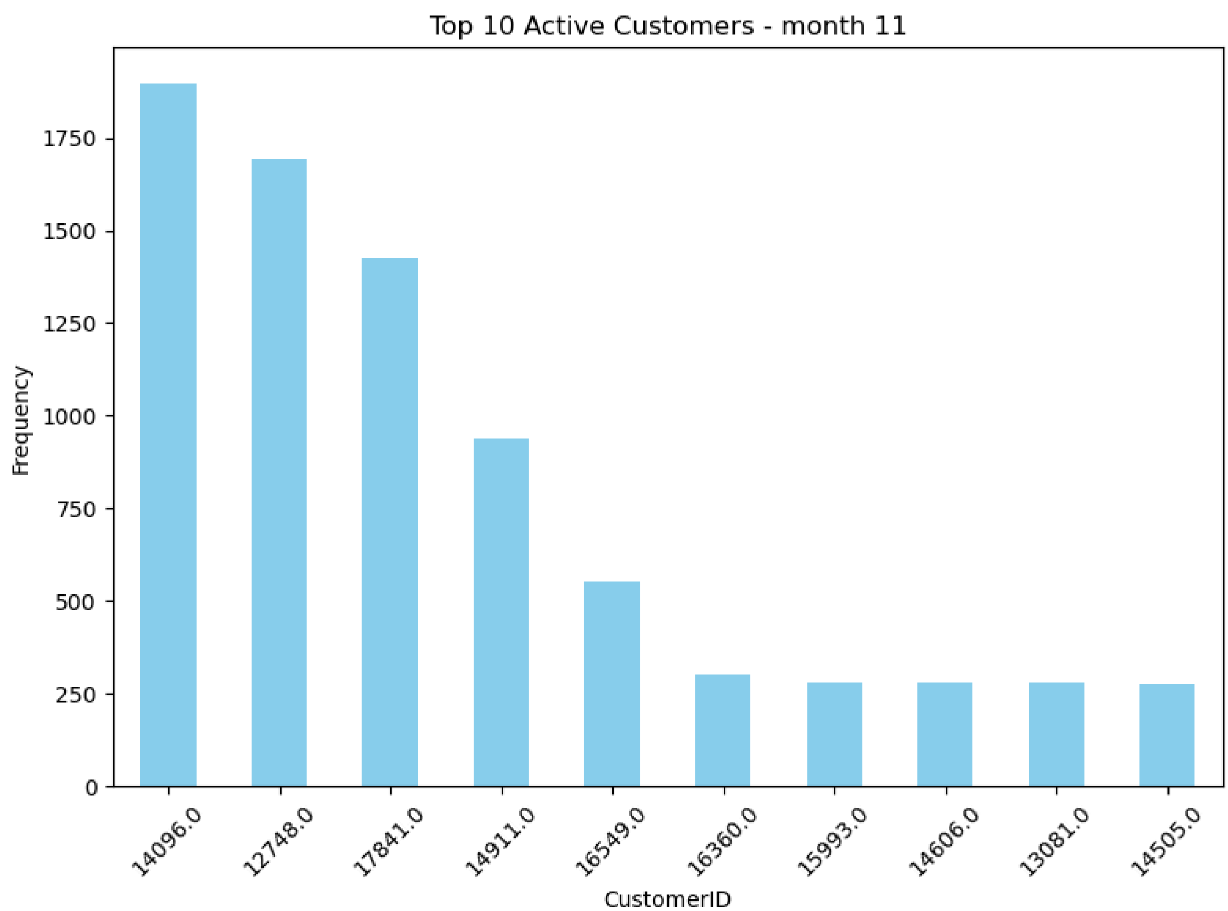
```
Month: 9
Total customers for month 9 are: 1302
```




```
Month: 10
Total customers for month 10 are: 1425
```




```
Month: 11
Total customers for month 11 are: 1711
```



Retention rate calculation by month

Since the data is from 01/12/2010 - 09/12/2011 Retention Rate will be calculated based on the number of active customer which were present in the month of 01/12/2010 and how many were there are in 01/11/2011.

In [15]:
```
# making a copy of the original dataset for experimentation
data_copy=data.copy()
```

In [16]:
```
data_copy['Date']=data_copy['InvoiceDate'].dt.date
```

In [17]:
```
data_copy.head()
```

Out[17]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Month
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom	12
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	12
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom	12
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	12
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	12

In [18]:
```
data_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 406829 entries, 0 to 541908
Data columns (total 10 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    406829 non-null  object
 1   StockCode    406829 non-null  object
 2   Description  406829 non-null  object
 3   Quantity     406829 non-null  int64
 4   InvoiceDate  406829 non-null  datetime64[ns]
 5   UnitPrice    406829 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      406829 non-null  object
 8   Month        406829 non-null  int64
 9   Date         406829 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(2), object(5)
memory usage: 34.1+ MB
```

In [19]:
```
# convert date into datetime format
data_copy['Date']=pd.to_datetime(data_copy['Date'])
```

In [20]:
```
# Counting the total customers who were present at the beginning of the sales month in t
customer_at_start = data_copy.loc[(data_copy['Date'] >= '2010-12-01') & (data_copy['Date
# for the customer count for the end I am going to count the customer who are active in
customer_at_end=data_copy.loc[(data_copy['Date'] >= '2011-11-01') & (data_copy['Date'] <
```

In [21]:
```
customer_at_start, customer_at_end
```

Out[21]:
```
(948, 1954)
```

In [22]:
```
# calculating the retention rate
new_customer_acquired=customer_at_end-customer_at_start
retention_rate=((customer_at_end - new_customer_acquired)/customer_at_start)*100
# print the retention rate
print(f"The retention rate for the whole period is:{retention_rate:.2f}%")
```

```
The retention rate for the whole period is:100.00%
```

It was impressive that the retention rate was 100% which means that there is 0% churn rate.

4. Model development

For RFM analysis first step is to calculate the Recency, then Frequency and Monetary.

Recency: How recently has the customer made a transaction

Frequency: How frequent is the customer in ordering/buying some product

Monetary: How much does the customer spend on purchasing products.

In [23]:
```
data_copy.head()
```

Out[23]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Month
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom	12
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	12
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom	12
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	12
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	12

In [ ]:

In [ ]:

calculating the recency

In [24]:

```
df_recency=data_copy.groupby(by='CustomerID', as_index=False)['Date'].max()

df_recency.columns=['CustomerID','LastPurchaseDate']
recent_date=df_recency['LastPurchaseDate'].max()
df_recency['Recency']=df_recency['LastPurchaseDate'].apply(lambda x:(recent_date - x).da
df_recency.head()
```

Out[24]:

	CustomerID	LastPurchaseDate	Recency
0	12346.0	2011-01-18	325
1	12347.0	2011-12-07	2
2	12348.0	2011-09-25	75
3	12349.0	2011-11-21	18
4	12350.0	2011-02-02	310

calculating Frequency

In [25]:
```
frequency_df = data_copy.drop_duplicates().groupby(
    by=['CustomerID'], as_index=False)['Date'].count()
frequency_df.columns = ['CustomerID', 'Frequency']
frequency_df.head()
```

Out[25]:

	CustomerID	Frequency
0	12346.0	2
1	12347.0	182
2	12348.0	31
3	12349.0	73
4	12350.0	17

In [26]:
```
data_copy.head()
```

Out[26]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Month
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom	12
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	12
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom	12
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	12
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	12

calculating the Monetary value

In [27]:
```
data_copy['Total'] = data_copy['UnitPrice']*data_copy['Quantity']
monetary_df = data_copy.groupby(by='CustomerID', as_index=False)['Total'].sum()
monetary_df.columns = ['CustomerID', 'Monetary']
monetary_df.head()
```

Out[27]:

	CustomerID	Monetary
0	12346.0	0.00
1	12347.0	4310.00
2	12348.0	1797.24
3	12349.0	1757.55
4	12350.0	334.40

Merging all three columns in one Data frame

In [28]:

```
rf_df=df_recency.merge(frequency_df, on='CustomerID')
rfm_df=rf_df.merge(monetary_df, on='CustomerID').drop(columns='LastPurchaseDate')
rfm_df.head()
```

Out[28]:

	CustomerID	Recency	Frequency	Monetary
0	12346.0	325	2	0.00
1	12347.0	2	182	4310.00
2	12348.0	75	31	1797.24
3	12349.0	18	73	1757.55
4	12350.0	310	17	334.40

Now we have all three values in one dataframe

To rank the customer based on the RFM values here I am going to divide the dataset into 5 quartiles to do that I have here used pandas qcut function which will automatically divide the data into 5 quartile and assign the given labels based on their recency, frequency and Monetary values.

In [29]:

```
r=pd.qcut(rfm_df['Recency'], q=5, labels=range(5,0,-1))
f=pd.qcut(rfm_df['Frequency'], q=5, labels=range(1,6))
m=pd.qcut(rfm_df['Monetary'], q=5, labels=range(1,6))

rfm=rfm_df.assign(R=r.values, F=f.values, M=m.values)
print(rfm)
```

```
      CustomerID  Recency  Frequency  Monetary  R  F  M
0        12346.0      325          2      0.00  1  1  1
1        12347.0        2        182   4310.00  5  5  5
2        12348.0       75         31   1797.24  2  3  4
3        12349.0       18         73   1757.55  4  4  4
4        12350.0      310         17    334.40  1  2  2
...          ...      ...        ...       ... .. .. ..
4367     18280.0      277         10    180.60  1  1  1
4368     18281.0      180          7     80.82  1  1  1
4369     18282.0        7         13    176.60  5  1  1
4370     18283.0        3        721   2094.88  5  5  5
4371     18287.0       42         70   1837.28  3  4  4

[4372 rows x 7 columns]
```

Here we have got RFM values:

Note:

```
* For R value higher value means most recent customer lower means
customer who bought something after long time or they didn't but it

* For F and M higher score means more recent and more spending
```

In [30]:
```
# Now here we will calculate the RFM score at first segmenting the RFM quartile values t
rfm['RFM_segment']= rfm.R.astype(str)+rfm.F.astype(str)+rfm.M.astype(str)
rfm.head()
```

Out[30]:

	CustomerID	Recency	Frequency	Monetary	R	F	M	RFM_segment
0	12346.0	325	2	0.00	1	1	1	111
1	12347.0	2	182	4310.00	5	5	5	555
2	12348.0	75	31	1797.24	2	3	4	234
3	12349.0	18	73	1757.55	4	4	4	444
4	12350.0	310	17	334.40	1	2	2	122

We have our RFM segments to calculate the RFM score here we will count the unique segments.

In [31]:
```
rfm_quique_count=rfm.groupby('RFM_segment')['RFM_segment'].nunique()
print(rfm_quique_count.sum())
```

```
119
```

There are 119 unique RFM segments

In [32]:
```
# calculate the RFM score
rfm['RFM_score']=rfm[['R','F','M']].sum(axis=1)
rfm
```

Out[32]:

	CustomerID	Recency	Frequency	Monetary	R	F	M	RFM_segment	RFM_score
0	12346.0	325	2	0.00	1	1	1	111	3
1	12347.0	2	182	4310.00	5	5	5	555	15
2	12348.0	75	31	1797.24	2	3	4	234	9
3	12349.0	18	73	1757.55	4	4	4	444	12
4	12350.0	310	17	334.40	1	2	2	122	5
...	...	...	...	...	...	...	...	...	...
4367	18280.0	277	10	180.60	1	1	1	111	3
4368	18281.0	180	7	80.82	1	1	1	111	3
4369	18282.0	7	13	176.60	5	1	1	511	7
4370	18283.0	3	721	2094.88	5	5	5	555	15
4371	18287.0	42	70	1837.28	3	4	4	344	11

4372 rows × 9 columns

let's analyse the segments

since the range of value of R, F and M are in the 1 to 5 which means the most valueable customer will be the customer whose RFM score is either 555 or RFM score of 15

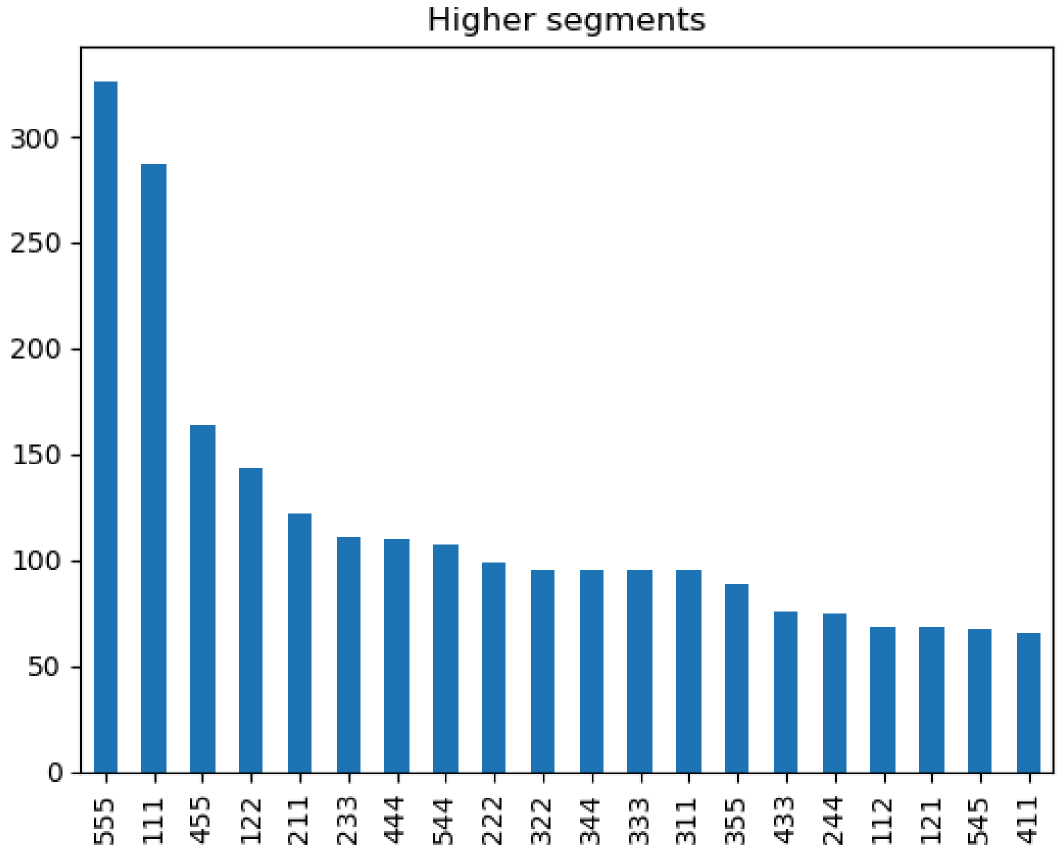
In [33]:
```
rfm.describe()
```

Out[33]:

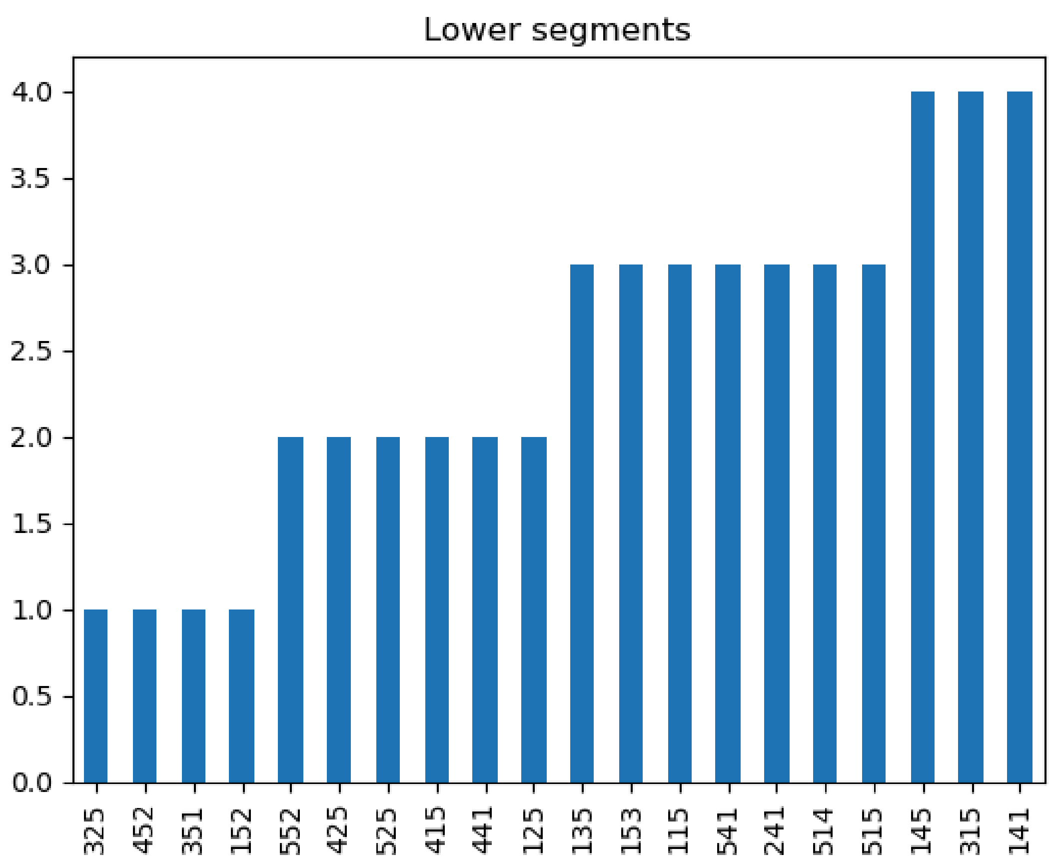
	CustomerID	Recency	Frequency	Monetary	RFM_score
count	4372.000000	4372.000000	4372.000000	4372.000000	4372.000000
mean	15299.677722	91.581199	91.858188	1898.459701	8.997941
std	1722.390705	100.772139	229.223566	8219.345141	3.605804
min	12346.000000	0.000000	1.000000	-4287.630000	3.000000
25%	13812.750000	16.000000	17.000000	293.362500	6.000000
50%	15300.500000	50.000000	41.000000	648.075000	9.000000
75%	16778.250000	143.000000	99.250000	1611.725000	12.000000
max	18287.000000	373.000000	7812.000000	279489.020000	15.000000

Let's find out the different segments of customer

In [34]:
```
rfm['RFM_segment'].value_counts(ascending=False).head(20).plot(kind='bar')
plt.title('Higher segments')
plt.show()
```



In [35]:
```
rfm['RFM_segment'].value_counts(ascending=True).head(20).plot(kind='bar')
plt.title('Lower segments')
plt.show()
```



using clustering techniques to group the cluster based on the features

steps:

- Data preparation
- Finding the optimum clusters
- Analysing the clusters

Data preparation

In this step since the data range of variables shows large variation it is necessary to normalize the data. Since we are using K-means it is distance based so it is necessary to adjust the common range to avoid building biased model.

In [36]:
```
# import required libaries from scikit learn
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
```

In order to perform clustering here I have taken only few features R,F and M

In [37]:
```
filterd_data=rfm[['R','F','M']]
filterd_data
```

Out[37]:

	R	F	M
0	1	1	1
1	5	5	5
2	2	3	4
3	4	4	4
4	1	2	2
...	...	...	...
4367	1	1	1
4368	1	1	1
4369	5	1	1
4370	5	5	5
4371	3	4	4

4372 rows × 3 columns

In [38]:
```
# initializing the standardScaler
scaler=StandardScaler()
rfm_normalizedDf=pd.DataFrame(scaler.fit_transform(filterd_data))
```

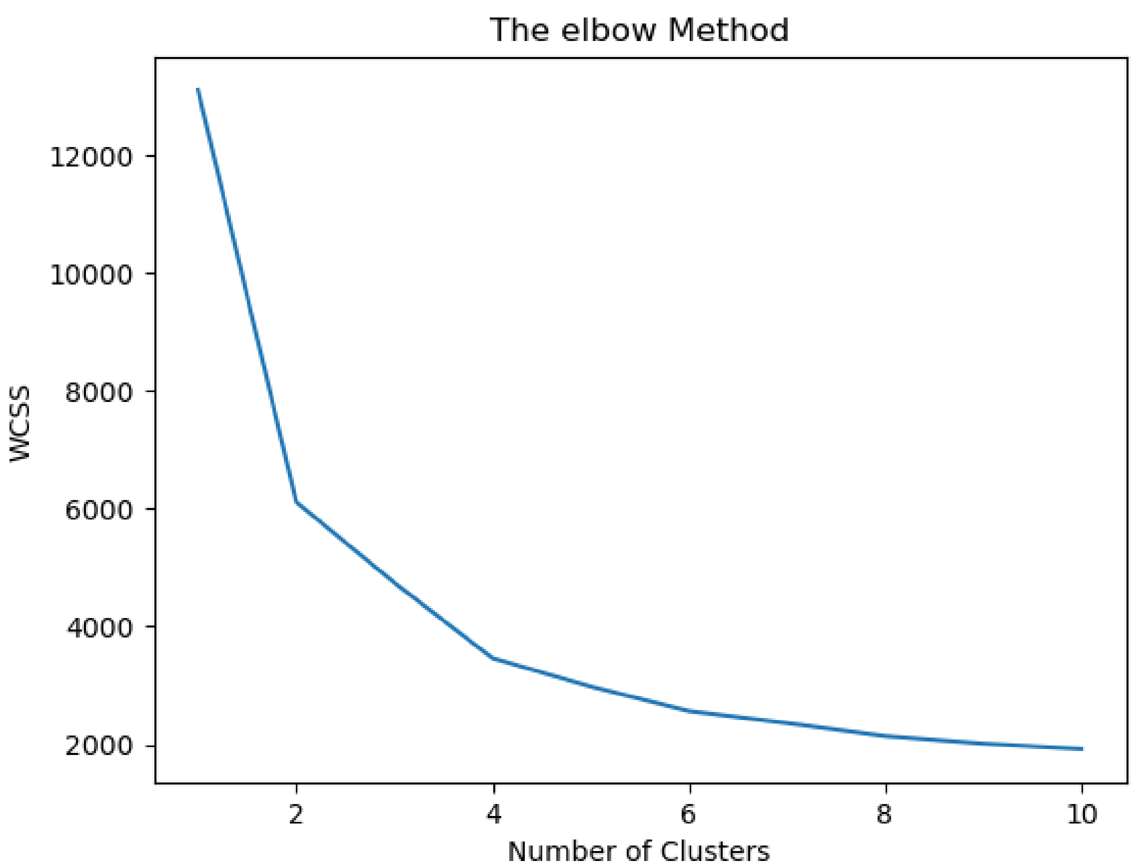
```
rfm_normalizedDf.columns=['n_Recency','n_Frequency','n_Monetary']
rfm_normalizedDf.describe()
```

Out[38]:

	n_Recency	n_Frequency	n_Monetary
count	4.372000e+03	4.372000e+03	4372.000000
mean	2.794167e-17	2.849200e-17	0.000000
std	1.000114e+00	1.000114e+00	1.000114
min	-1.419309e+00	-1.390071e+00	-1.413890
25%	-7.152906e-01	-6.886987e-01	-0.706945
50%	-1.127203e-02	1.267347e-02	0.000000
75%	6.927466e-01	7.140456e-01	0.706945
max	1.396765e+00	1.415418e+00	1.413890

In [39]:

```
# for finding the optimum number of cluster here I am using elbow method
wcss=[]
for i in range(1,11):
    kmeans=KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(rfm_normalizedDf)
    wcss.append(kmeans.inertia_)

plt.plot(range(1,11),wcss)
plt.title('The elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
```



As shown in the above chart the elbow was formed at cluster 4

In [40]:
```
# using the cluster 4 to create cluster in the data
kmeans=KMeans(n_clusters=4)
kmeans.fit(rfm_normalizedDf)
```

Out[40]:
```
KMeans(n_clusters=4)
```

In [41]:
```
cluster=kmeans.labels_
```

print(cluster)

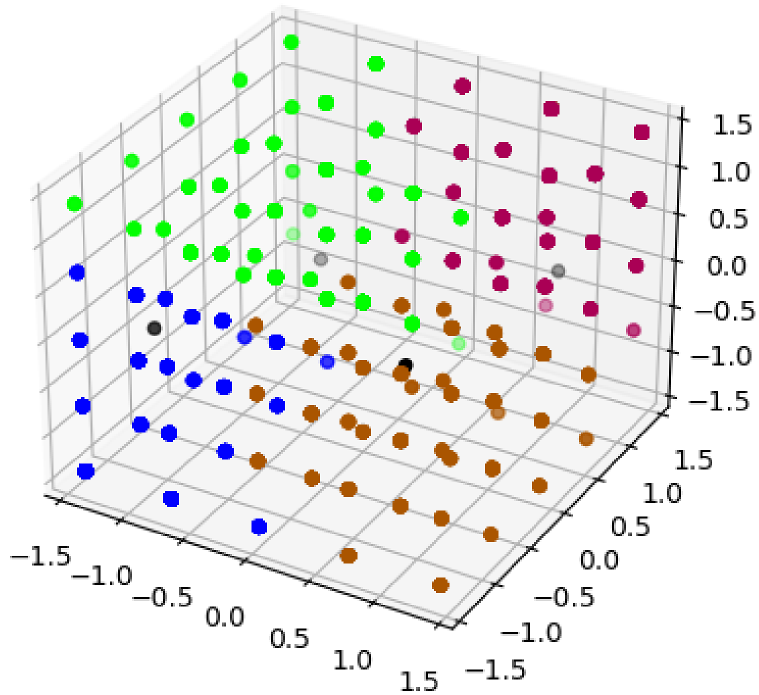
In [42]:
```
# creating and assigning the cluster number to their correspondin values
rfm['Cluster']=cluster
rfm
```

Out[42]:

	CustomerID	Recency	Frequency	Monetary	R	F	M	RFM_segment	RFM_score	Cluster
0	12346.0	325	2	0.00	1	1	1	111	3	0
1	12347.0	2	182	4310.00	5	5	5	555	15	1
2	12348.0	75	31	1797.24	2	3	4	234	9	3
3	12349.0	18	73	1757.55	4	4	4	444	12	1
4	12350.0	310	17	334.40	1	2	2	122	5	0
...	...	...	...	...	...	...	...	...	...	...
4367	18280.0	277	10	180.60	1	1	1	111	3	0
4368	18281.0	180	7	80.82	1	1	1	111	3	0
4369	18282.0	7	13	176.60	5	1	1	511	7	2
4370	18283.0	3	721	2094.88	5	5	5	555	15	1
4371	18287.0	42	70	1837.28	3	4	4	344	11	3

4372 rows × 10 columns

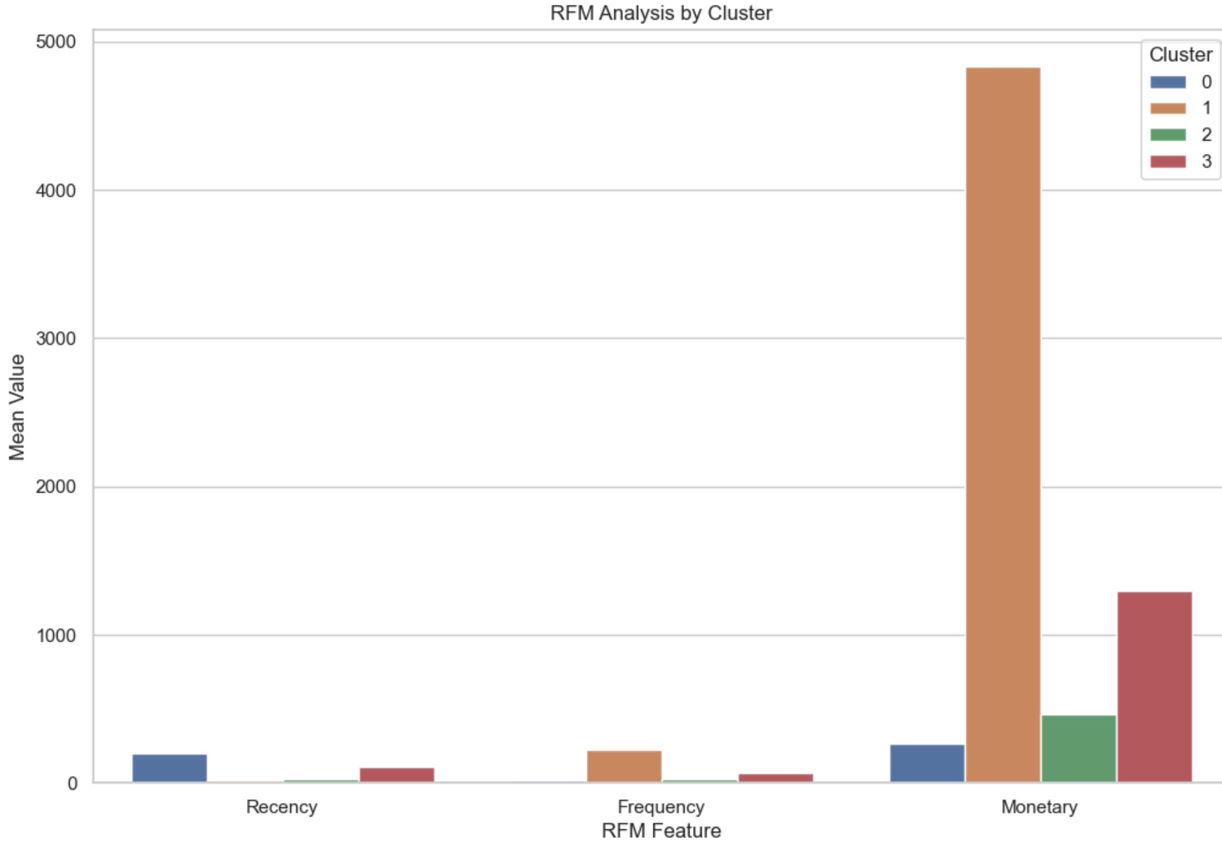
In [43]:
```
centers=kmeans.cluster_centers_
fig=plt.figure()
ax=fig.add_subplot(111, projection='3d')
ax.scatter(rfm_normalizedDf['n_Recency'],rfm_normalizedDf['n_Frequency'],rfm_normalizedD
ax.scatter(centers[:,0], centers[:,1], c='black')
plt.show()
```



In [44]:
```python
# now we have got the cluster let's analyse the clusters
# grouping the data based on the clusters
grouped_cluster=rfm.groupby('Cluster').agg({'Recency':'mean','Frequency':'mean','Monetar

print(grouped_cluster)
```

```
            Recency   Frequency     Monetary
Cluster
0        202.896552   15.669607   266.207957
1         16.227790  221.646925  4835.016105
2         26.832207   27.484234   459.558423
3        111.067391   71.466304  1295.978698
```

In [45]:
```python
# Plot histograms for each RFM feature within each cluster
rfm_melted = rfm.melt(id_vars=['Cluster'], value_vars=['Recency', 'Frequency', 'Monetary

plt.figure(figsize=(12, 8))
sns.set(style="whitegrid")
sns.barplot(x='variable', y='value', hue='Cluster', data=rfm_melted, ci=None)
plt.title('RFM Analysis by Cluster')
plt.xlabel('RFM Feature')
plt.ylabel('Mean Value')
plt.legend(title='Cluster')
plt.show()

# Compare the size of each cluster
cluster_sizes = rfm['Cluster'].value_counts().sort_index()
print(cluster_sizes)
```




```
0    1247
1    1317
2     888
3     920
Name: Cluster, dtype: int64
```

As shown in the above chart and stats we can say that:

- cluster 0:
  - Recency: The average time since the last purchase in this cluster is approximately 29 days.
  - Frequency: The average frequency of purchases is around 26 times
  - Monetary: The average monetary value of purchase is approximately £428.37
- cluster 1:
  - Recency: The average time since the last purchase in this cluster is approximately 16 days which indicates that the customer in this cluster tends to make more frequenct purcases.
  - Frequency: The average frequency of purchases is around 222 times which indicates that this cluster customer makes large number of purchases.
  - Monetary: The average monetary value of purchase is approximately £ 4835.02 which means that the customer in this cluster are high spender and contribute significantly to revenue.
- cluster 2:
  - Recency: The average time since the last purchase in this cluster is approximately 111 days which means that there is a longer gap in between purchases.
  - Frequency: The average frequency of purchases is around 71 times which means the customer in this cluster makes moderate number of purchases.

  - Monetary: The average monetary value of purchase is approximately £1296 which suggest that customer in this cluster spends a moderate amount on purchases.

- cluster 3:
  - Recency: The average time since the last purchase in this cluster is approximately 215 days which means that there is a longer gap between the customer purchases.
  - Frequency: The average frequency of purchases is around 16 times which is relatively low as compare to other clusters.
  - Monetary: The average monetary value of purchase is approximately £277 which indicates that customer in this cluster spend less on purchases.

In [ ]:

As shown in the above chart cluster 1 hass more number of customers as compare to other

Giving labels to each customer based on the behaviour

For cluster 0 → New customer

Cluster 1 → High-value customer

Cluster 2 → Churned Customer

cluster 3 → Low-value Customer

In [46]:

```
# create function to categorize customer based on the clusters
def categorized_customer(clusters):
    if clusters==0:
        return 'New customer'
    elif clusters==1:
        return 'High-Value Customer'
    elif clusters==2:
        return 'Churned Customer'
    else:
        return 'Low-value Customer'

rfm['CustomerCategory']=rfm['Cluster'].apply(categorized_customer)
```

In [47]:

```
rfm
```

Out[47]:

	CustomerID	Recency	Frequency	Monetary	R	F	M	RFM_segment	RFM_score	Cluster	Custor
0	12346.0	325	2	0.00	1	1	1	111	3	0	N
1	12347.0	2	182	4310.00	5	5	5	555	15	1	
2	12348.0	75	31	1797.24	2	3	4	234	9	3	
3	12349.0	18	73	1757.55	4	4	4	444	12	1	
4	12350.0	310	17	334.40	1	2	2	122	5	0	N
...	...	...	...	...	...	...	...	...	...	...	
4367	18280.0	277	10	180.60	1	1	1	111	3	0	N
4368	18281.0	180	7	80.82	1	1	1	111	3	0	N
4369	18282.0	7	13	176.60	5	1	1	511	7	2	Churn
4370	18283.0	3	721	2094.88	5	5	5	555	15	1	
4371	18287.0	42	70	1837.28	3	4	4	344	11	3	

4372 rows × 11 columns

In [48]:

```python
# Plot the distribution of customers in each cluster
plt.figure(figsize=(10, 6))
sns.countplot(x='CustomerCategory', data=rfm, palette='viridis')
plt.title('Customer Distribution by Cluster')
plt.xlabel('Customer Type')
plt.ylabel('Number of Customers')
plt.show()
```

In [49]:
```
cluster_3=rfm[rfm['Cluster']==3]
```

In [ ]:

In [50]:
```
rfm.columns
```

Out[50]:
```
Index(['CustomerID', 'Recency', 'Frequency', 'Monetary', 'R', 'F', 'M',
       'RFM_segment', 'RFM_score', 'Cluster', 'CustomerCategory'],
      dtype='object')
```

In [51]:
```
data_copy.columns
```

Out[51]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country', 'Month', 'Date', 'Total'],
      dtype='object')
```

In [52]:
```
final_sales_data=pd.merge(data_copy, rfm, on ='CustomerID', suffixes=('_data_copy','_rfm
final_sales_data
```

Out[52]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Mo
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom	
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom	
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	
...	...	...	...	...	...	...	...	...	
406824	581578	22993	SET OF 4 PANTRY JELLY MOULDS	12	2011-12-09 12:16:00	1.25	12713.0	Germany	
406825	581578	22907	PACK OF 20 NAPKINS PANTRY DESIGN	12	2011-12-09 12:16:00	0.85	12713.0	Germany	
406826	581578	22908	PACK OF 20 NAPKINS RED APPLES	12	2011-12-09 12:16:00	0.85	12713.0	Germany	
406827	581578	23215	JINGLE BELL HEART ANTIQUE SILVER	12	2011-12-09 12:16:00	2.08	12713.0	Germany	
406828	581578	22736	RIBBON REEL MAKING SNOWMEN	10	2011-12-09 12:16:00	1.65	12713.0	Germany	

406829 rows × 21 columns

In [53]:

```
final_sales_data.columns
```

Out[53]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country', 'Month', 'Date', 'Total',
       'Recency', 'Frequency', 'Monetary', 'R', 'F', 'M', 'RFM_segment',
       'RFM_score', 'Cluster', 'CustomerCategory'],
      dtype='object')
```

In [54]:
```
final_sales_data.shape
```

Out[54]:
```
(406829, 21)
```

In [55]:
```
final_sales_data.isna().sum()
```

Out[55]:
```
InvoiceNo           0
StockCode           0
Description         0
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID          0
Country             0
Month               0
Date                0
Total               0
Recency             0
Frequency           0
Monetary            0
R                   0
F                   0
M                   0
RFM_segment         0
RFM_score           0
Cluster             0
CustomerCategory    0
dtype: int64
```

In [56]:
```
final_sales_data.to_excel('Final Retail sales data.xlsx')
```

In [ ]:
```
jupyter nbconvert --execute --to pdf notebook.ipynb
```