PROJECT ON RETAIL

IMPORTING THE NECESSARY DEPENDENCIES

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from datetime import timedelta
from pandas import ExcelWriter
```

Now Lets Import The Data

In [2]:
```
df=pd.read_excel('Online Retail.xlsx')
```

In [3]:
```
df.head()
```

Out[3]:

	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 [4]:
```
# Lets Check The Shape OF The Data----
df.shape
```

Out[4]:
```
(541909, 8)
```

In [5]:
```
# Now Lets Check The Data Info----
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
```

(A) Data Cleaning

Lets Find The Missing Values First-----

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

In [7]:
```
# Calculating The Missing Values Percentage-----
df_null= round((df.isnull().sum()/len(df))*100,2)
df_null
```

Out[7]:
```
InvoiceNo       0.00
StockCode       0.00
Description     0.27
Quantity        0.00
InvoiceDate     0.00
UnitPrice       0.00
CustomerID     24.93
Country         0.00
dtype: float64
```

In [8]:
```
# As we can see two columns in data have missing values.

# Description - 0.27% (1454)
# CustomerID - 24.93% (135080)
```

In [9]:
```
# We can simply drop the Description as the missing values are too small----
# But in the case of CustomerID it is comparatively a large data but as it is a unquie key column we can fill.
```

In [10]:
```
df = df.dropna()
```

In [11]:
```
df.shape
```

Out[11]:
```
(406829, 8)
```

Removing The Duplicate Values

In [12]:
```
df = df.drop_duplicates()
df.shape
```

Out[12]:
```
(401604, 8)
```

Perform descriptive anaylysis on the given data

In [13]:
```
# We can drop Description feature from our data since it is not not going to contribute in our Machine Building
model. df = df.drop('Description', axis=1)
df = df.dropna()
df.shape
```

Out[13]: (401604, 7)

CustomerID is 'float64', changing the datatype of CustomerId to string as Customer ID as numerical data does not make sense

In [14]:
```
df['CustomerID'] = df['CustomerID'].astype(str)
```

In [15]:
```
df.describe(datetime_is_numeric=True)
```

Out[15]:

	Quantity	InvoiceDate	UnitPrice
count	401604.000000	401604	401604.000000
mean	12.183273	2011-07-10 12:08:23.848567552	3.474064
min	-80995.000000	2010-12-01 08:26:00	0.000000
25%	2.000000	2011-04-06 15:02:00	1.250000
50%	5.000000	2011-07-29 15:40:00	1.950000
75%	12.000000	2011-10-20 11:58:30	3.750000
max	80995.000000	2011-12-09 12:50:00	38970.000000
std	250.283037	NaN	69.764035

- Quantity: Average quantity of each product in transaction is 12.18. Also note that minimum value in Quantity column is negative. This implies that some customers had returned the product during our period of analysis.
  InvoiceDate: Our data has transaction between 01-12-2010 to 09-12-2011
- UnitPrice: Average price of each product in transactions is 3.47

In [16]:
```
# For Non-numeric Functions
df.describe(include=['O'])
```

Out[16]:

	InvoiceNo	StockCode	CustomerID	Country
count	401604	401604	401604	401604
unique	22190	3684	4372	37
top	576339	85123A	17841.0	United Kingdom
freq	542	2065	7812	356728

- InvoiceNo: Total entries in preprocessed data are 4,01,602 but transactions are 22,190. Most number of entries are in Invoice No. '576339' that is 542 .
- StockCode: There are total 3684 unique products in our data and product with stock code '85123A' appears most frequently (2065 times) in our data.
- CustomerID: There are 4372 unique customers in our final preprocessed data. Customer with ID '17841' appears most frequently in data (7812 times)
- Country: Company has customers across 37 countries. Most entries are from United Kingdom in our dataset (356726)

(B) Data Transformation

(2) Perform Cohort Analysis

- #### (a) Create month cohort of customers and analyze active customers in each cohort:

In [17]:
```
# Convert to InvoiceDate to Year-Month format
df['month_year'] = df['InvoiceDate'].dt.to_period('M')
df['month_year']
```

Out[17]:
```
0         2010-12
1         2010-12
2         2010-12
3         2010-12
4         2010-12
            ...
541904    2011-12
541905    2011-12
541906    2011-12
541907    2011-12
541908    2011-12
Name: month_year, Length: 401604, dtype: period[M]
```

In [18]:
```
df['month_year'].nunique()
```

Out[18]:
```
13
```

In [19]:
```
month_cohort = df.groupby('month_year')['CustomerID'].nunique()
month_cohort
```

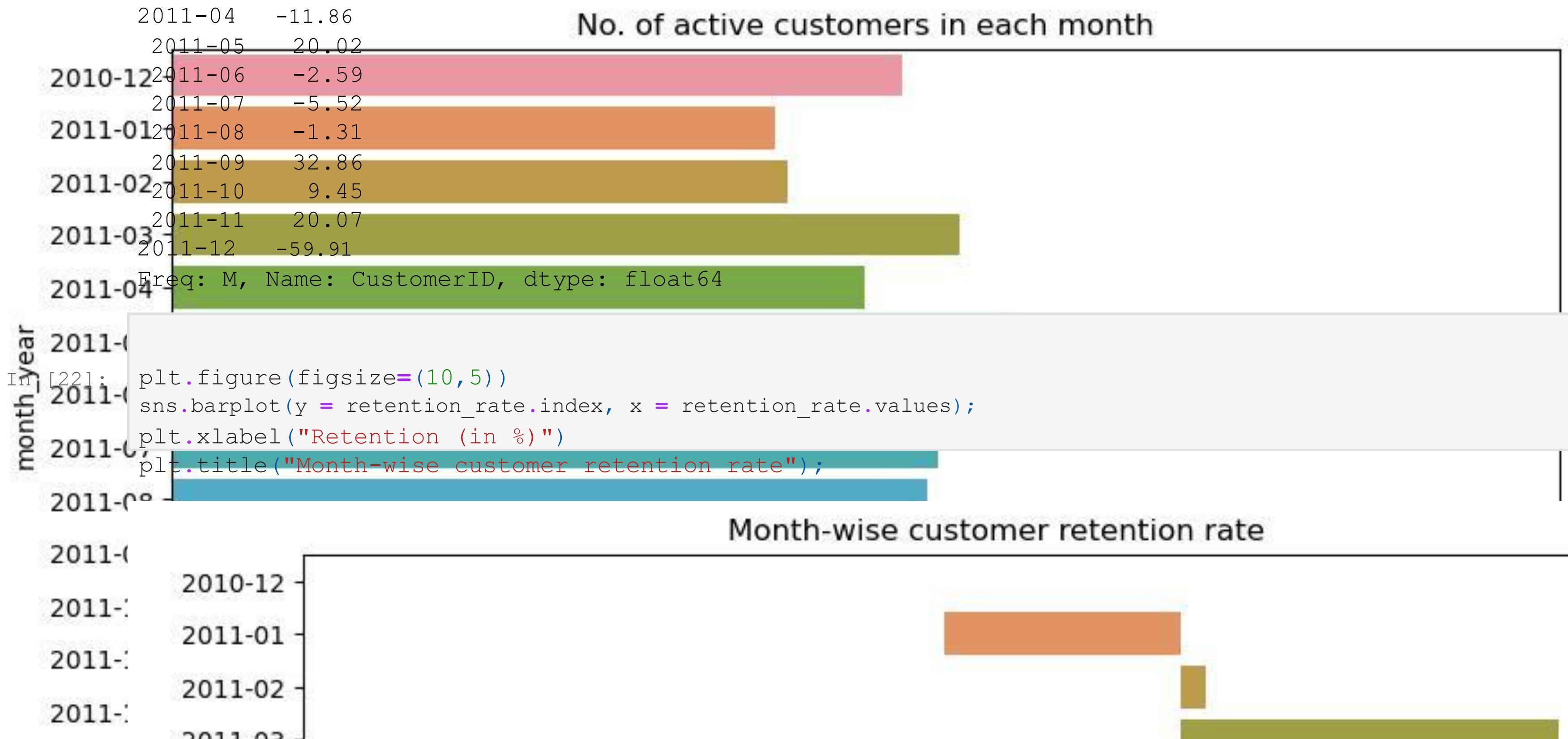
Out[19]:
```
month_year
2010-12     948
2011-01     783
2011-02     798
2011-03    1020
2011-04     899
2011-05    1079
2011-06    1051
2011-07     993
2011-08     980
2011-09    1302
2011-10    1425
2011-11    1711
2011-12     686
Freq: M, Name: CustomerID, dtype: int64
```

In [20]:

In [21]:

Out[21]:

```
plt.figure(figsize=(10,5))
sns.barplot(y = month_cohort.index, x = month_cohort.values);
plt.xlabel("Count of customers")
plt.title("No. of active customers in each month")
plt.show()
```



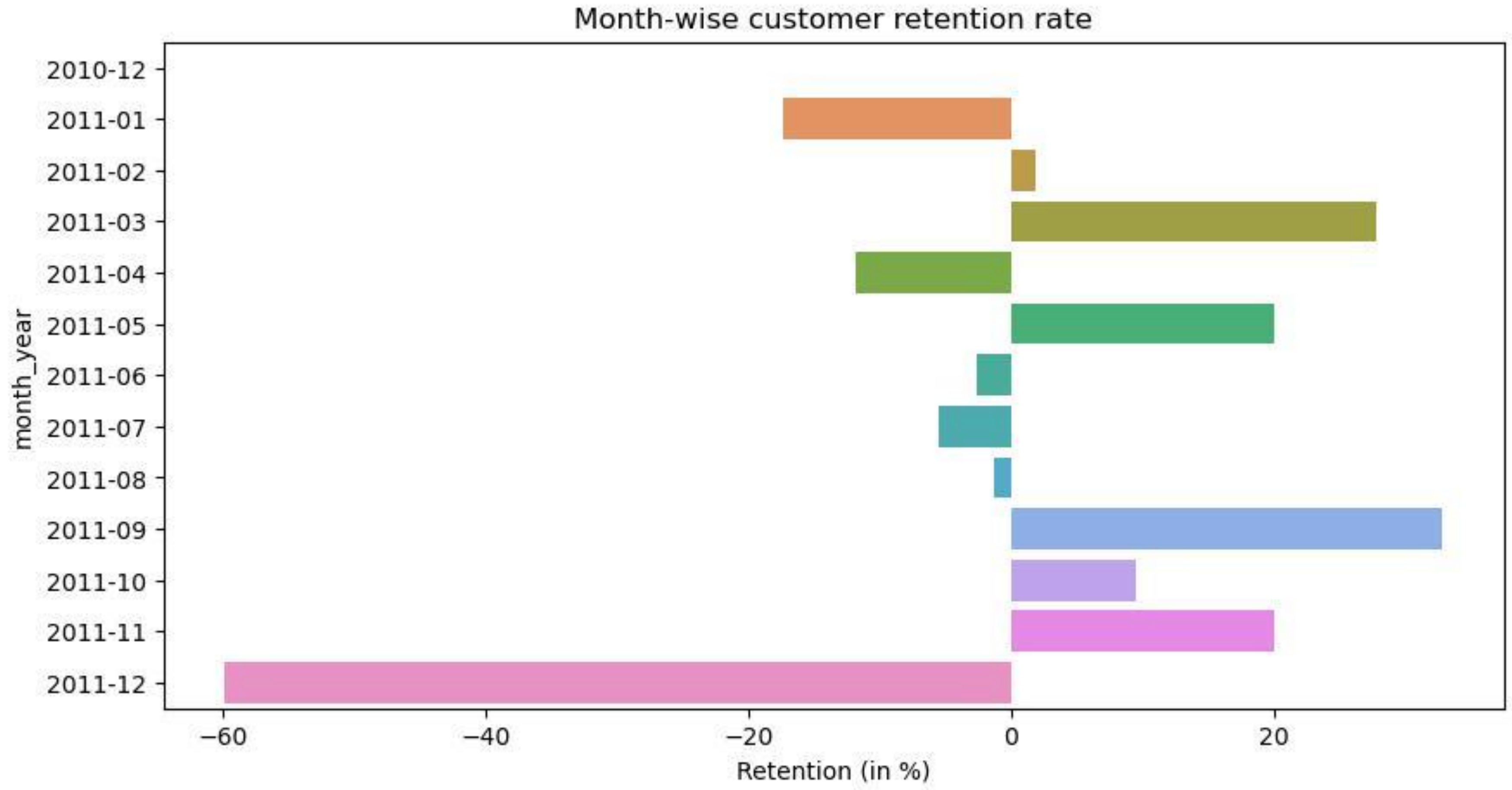
- #### (b) Analyze the retention rate of customers:

```
retention_rate = round(month_cohort.pct_change(periods=1)*100,2)
retention_rate
```

```
month_year
2010-12      NaN
2011-01   -17.41
2011-02     1.92
2011-03    27.82
2011-04   -11.86
2011-05    20.02
2011-06    -2.59
2011-07    -5.52
2011-08    -1.31
2011-09    32.86
2011-10     9.45
2011-11    20.07
2011-12   -59.91
Freq: M, Name: CustomerID, dtype: float64
```

In [22]:

```
plt.figure(figsize=(10,5))
sns.barplot(y = retention_rate.index, x = retention_rate.values);
plt.xlabel("Retention (in %)")
plt.title("Month-wise customer retention rate");
```



RFM Analysis

- ### Recency Analysis

In [23]:

```
# We will fix reference date for calculating recency as last transaction day in data + 1
day ref_day = max(df['InvoiceDate']) + timedelta(days=1)
df['days_to_last_order'] = (ref_day -
df['InvoiceDate']).dt.days df.head()
```

Out[23]:

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	month_year	days_to_last_order
0	536365	85123A	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom	2010-12	374
1	536365	71053	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	2010-12	374
2	536365	84406B	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom	2010-12	374
3	536365	84029G	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	2010-12	374
4	536365	84029E	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	2010-12	374

In [24]:

```
df_recency = df.groupby('CustomerID')['days_to_last_order'].min().reset_index()
df_recency
```

Out[24]:

	CustomerID	days_to_last_order
0	12346.0	326
1	12347.0	2
2	12348.0	75
3	12349.0	19
4	12350.0	310
...	...	...
4367	18280.0	278
4368	18281.0	181
4369	18282.0	8
4370	18283.0	4
4371	18287.0	43

In [25]:

4372 rows × 2 columns

- ### Frequency Analysis:

```
df_frequency = df.groupby('CustomerID').nunique()['InvoiceNo'].reset_index()
df_frequency
```

Out[25]:

	CustomerID	InvoiceNo
0	12346.0	2
1	12347.0	7
2	12348.0	4
3	12349.0	1
4	12350.0	1
...	...	...
4367	18280.0	1
4368	18281.0	1
4369	18282.0	3
4370	18283.0	16
4371	18287.0	3

4372 rows × 2 columns

- ### Monetary analysis:

In [26]:
```
df['amount'] = df['Quantity']*df['UnitPrice']
df.head()
```

Out[26]:

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	month_year	days_to_last_order	amount
0	536365	85123A	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom	2010-12	374	15.30
1	536365	71053	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	2010-12	374	20.34
2	536365	84406B	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom	2010-12	374	22.00
3	536365	84029G	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	2010-12	374	20.34
4	536365	84029E	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	2010-12	374	20.34

In [27]:
```
df_monetary = df.groupby('CustomerID').sum()['amount'].reset_index()
df_monetary
```

Out[27]:

	CustomerID	amount
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
...	...	...
4367	18280.0	180.60
4368	18281.0	80.82
4369	18282.0	176.60
4370	18283.0	2045.53
4371	18287.0	1837.28

4372 rows × 2 columns

Calculate RFM metrics:

In [28]:
```
df_rf = pd.merge(df_recency, df_frequency, on='CustomerID', how='inner')
df_rfm = pd.merge(df_rf, df_monetary, on='CustomerID', how='inner')
df_rfm.columns = ['CustomerID', 'Recency', 'Frequency', 'Monetary']
df_rfm.head()
```

Out[28]:

	CustomerID	Recency	Frequency	Monetary
0	12346.0	326	2	0.00
1	12347.0	2	7	4310.00
2	12348.0	75	4	1797.24
3	12349.0	19	1	1757.55
4	12350.0	310	1	334.40

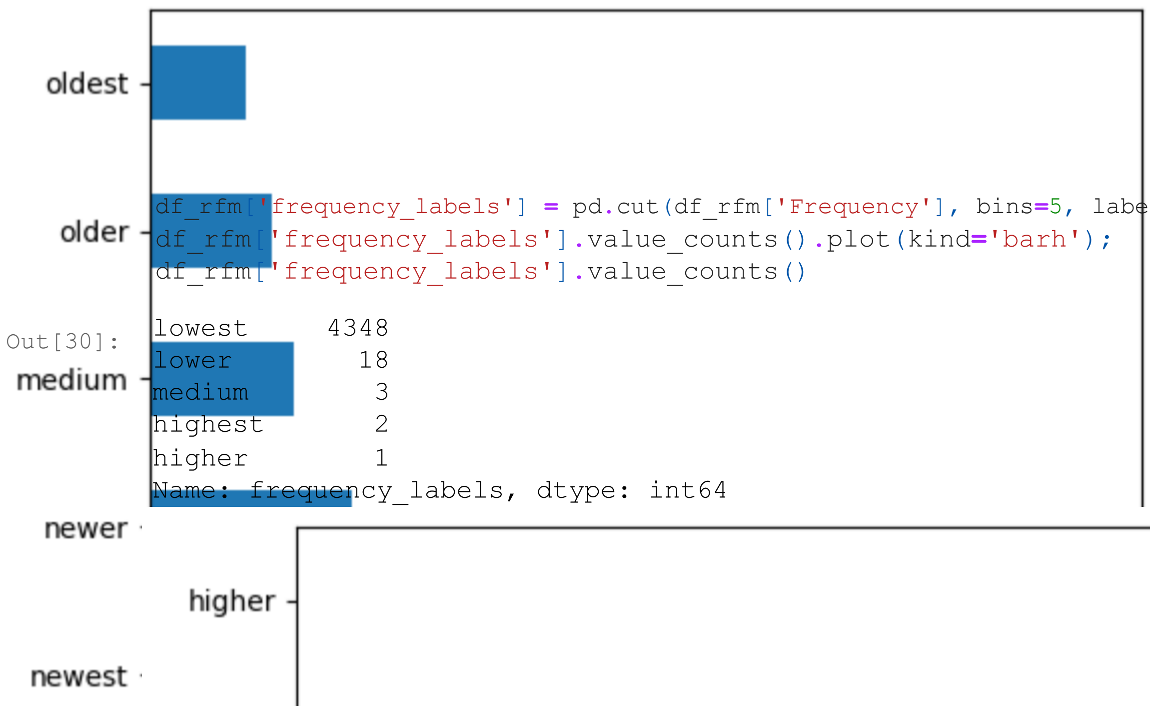
Build RFM Segments:

In [29]:
```
df_rfm['recency_labels'] = pd.cut(df_rfm['Recency'], bins=5,
                                  labels=['newest', 'newer', 'medium', 'older', 'oldest'])
df_rfm['recency_labels'].value_counts().plot(kind='barh');
df_rfm['recency_labels'].value_counts()
```

Out[29]:

In [30]:

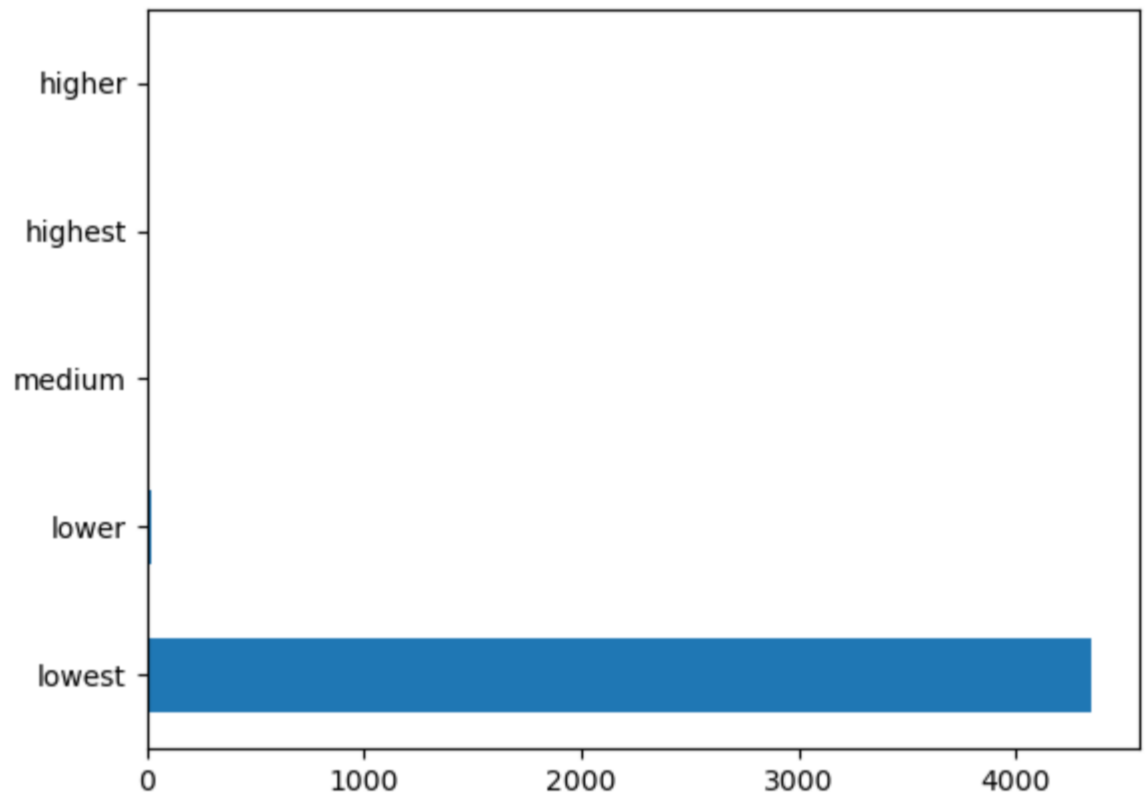
```
newest    2734
newer      588
medium     416
older      353
oldest     281
Name:
recency
_labels
,
dtype:
int64
```




```
df_rfm['frequency_labels'] = pd.cut(df_rfm['Frequency'], bins=5, labels=['lowest', 'lower', 'medium', 'higher', 'highest'])
df_rfm['frequency_labels'].value_counts().plot(kind='barh');
df_rfm['frequency_labels'].value_counts()
```

Out[30]:

```
lowest     4348
lower        18
medium        3
highest       2
higher        1
Name: frequency_labels, dtype: int64
```

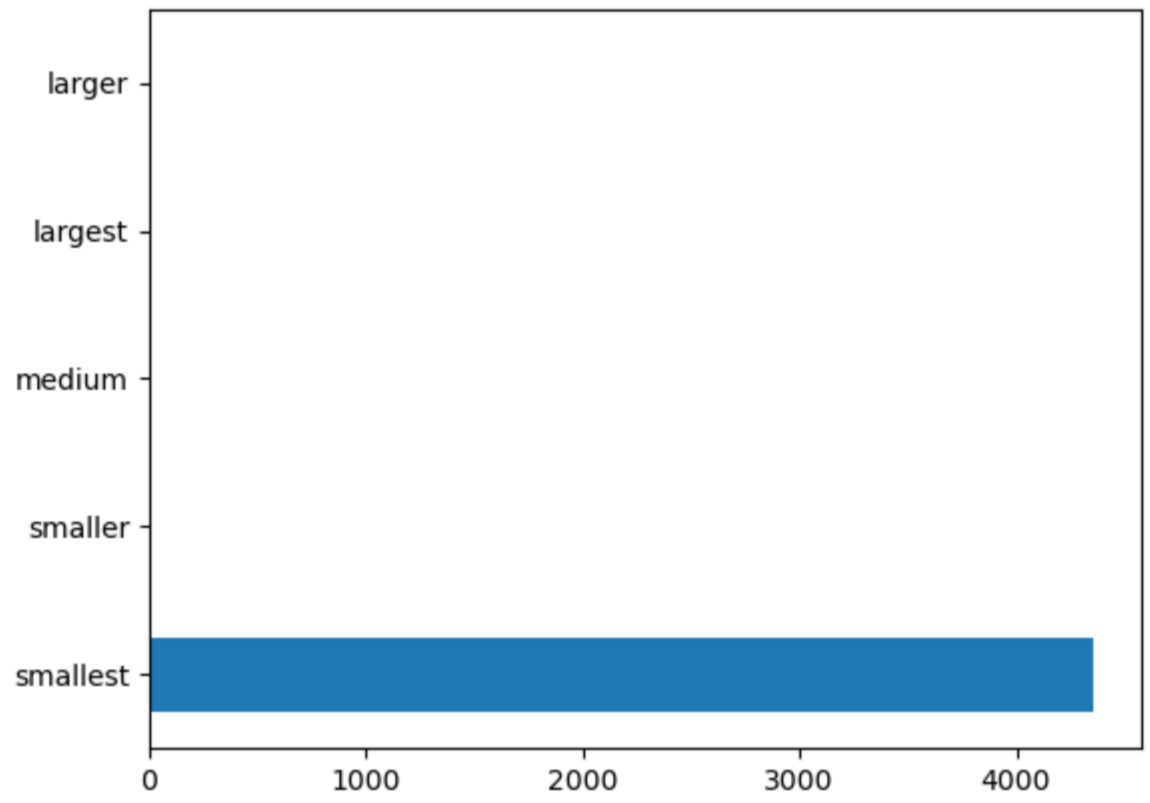


In [31]:

```
df_rfm['monetary_labels'] = pd.cut(df_rfm['Monetary'], bins=5, labels=['smallest', 'smaller', 'medium', 'larger', 'largest'])
df_rfm['monetary_labels'].value_counts().plot(kind='barh');
df_rfm['monetary_labels'].value_counts()
```

Out[31]:

```
smallest    4357
smaller        9
medium         3
largest        2
larger         1
Name: monetary_labels, dtype: int64
```



In [32]:

```
df_rfm['rfm_segment'] = df_rfm[['recency_labels','frequency_labels','monetary_labels']].agg('-'.join, axis=1)
df_rfm.head()
```

Out[32]:

	CustomerID	Recency	Frequency	Monetary	recency_labels	frequency_labels	monetary_labels	rfm_segment
0	12346.0	326	2	0.00	oldest	lowest	smallest	oldest-lowest-smallest
1	12347.0	2	7	4310.00	newest	lowest	smallest	newest-lowest-smallest
2	12348.0	75	4	1797.24	newest	lowest	smallest	newest-lowest-smallest
3	12349.0	19	1	1757.55	newest	lowest	smallest	newest-lowest-smallest
4	12350.0	310	1	334.40	oldest	lowest	smallest	oldest-lowest-smallest

RFM Score:

In [33]:

```
recency_dict = {'newest': 5, 'newer':4, 'medium': 3, 'older':2, 'oldest':1}
frequency_dict = {'lowest':1, 'lower':2, 'medium': 3, 'higher':4, 'highest':5}
monetary_dict = {'smallest':1, 'smaller':2, 'medium': 3, 'larger':4, 'largest':5}

df_rfm['rfm_score'] = df_rfm['recency_labels'].map(recency_dict).astype(int)+ df_rfm['frequency_labels'].map(frequency_dict).astype(int) +
df_rfm['monetary_labels'].map(monetary_dic df_rfm.head(10)
```

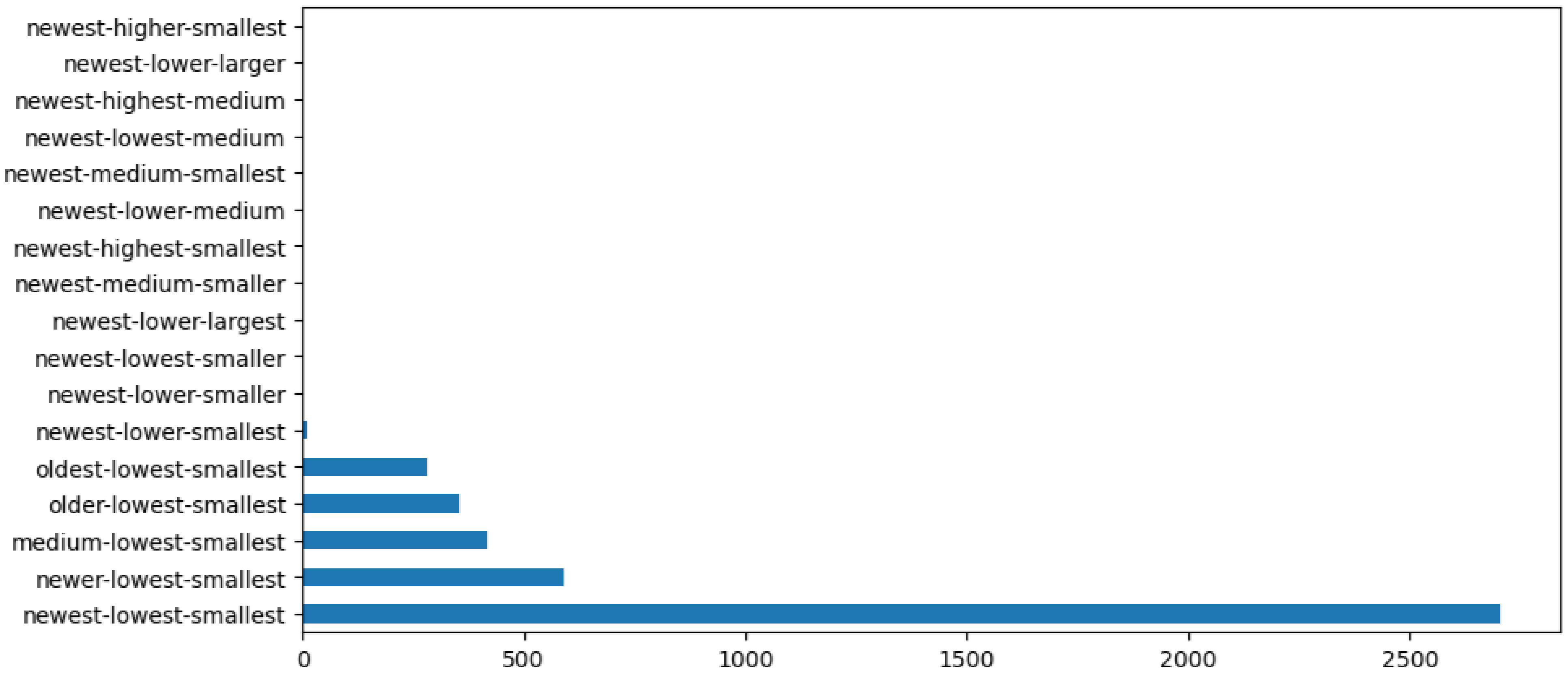
Out[33]:

	CustomerID	Recency	Frequency	Monetary	recency_labels	frequency_labels	monetary_labels	rfm_segment	rfm_score
0	12346.0	326	2	0.00	oldest	lowest	smallest	oldest-lowest-smallest	3
1	12347.0	2	7	4310.00	newest	lowest	smallest	newest-lowest-smallest	7
2	12348.0	75	4	1797.24	newest	lowest	smallest	newest-lowest-smallest	7
3	12349.0	19	1	1757.55	newest	lowest	smallest	newest-lowest-smallest	7
4	12350.0	310	1	334.40	oldest	lowest	smallest	oldest-lowest-smallest	3
5	12352.0	36	11	1545.41	newest	lowest	smallest	newest-lowest-smallest	7
6	12353.0	204	1	89.00	medium	lowest	smallest	medium-lowest-smallest	5

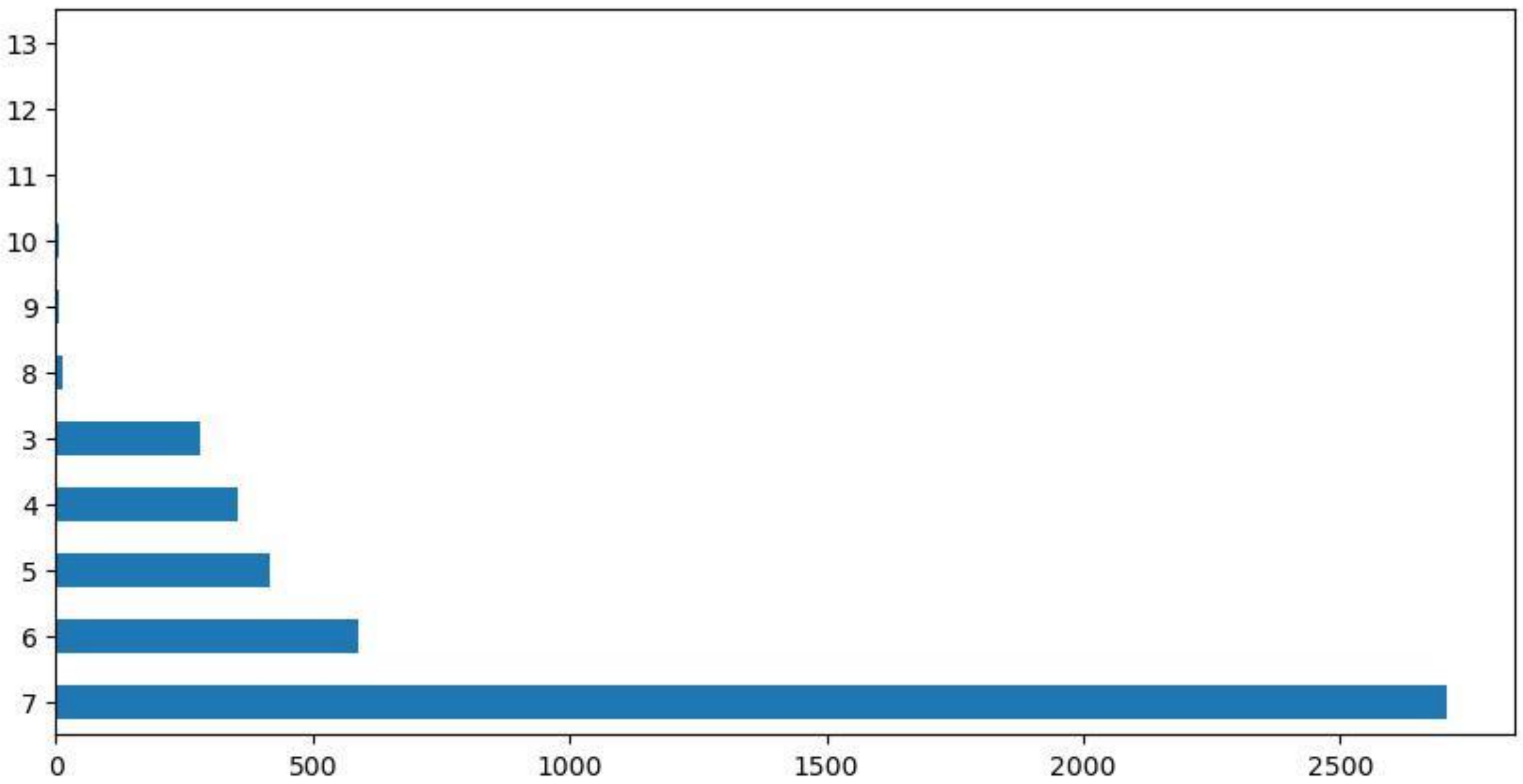
7	12354.0	232	1	1079.40	older	lowest	smallest	older-lowest-smallest	4
8	12355.0	214	1	459.40	medium	lowest	smallest	medium-lowest-smallest	5
9	12356.0	23	3	2811.43	newest	lowest	smallest	newest-lowest-smallest	7

Analyze RFM Segment and Score:

In [34]:
```
df_rfm['rfm_segment'].value_counts().plot(kind='barh', figsize=(10, 5));
```



In [36]:
```
df_rfm['rfm_score'].value_counts().plot(kind='barh', figsize=(10, 5));
```



Data Modeling:

Create clusters using k-means clustering algorithm.

- a. Prepare the data for the algorithm. If the data is asymmetrically distributed, manage the skewness with appropriate transformation. Standardize the data.

In [37]:
```
print(df_rfm.shape)
df_rfm.head()
```

```
(4372, 9)
```

Out[37]:

	CustomerID	Recency	Frequency	Monetary	recency_labels	frequency_labels	monetary_labels	rfm_segment	rfm_score
0	12346.0	326	2	0.00	oldest	lowest	smallest	oldest-lowest-smallest	3
1	12347.0	2	7	4310.00	newest	lowest	smallest	newest-lowest-smallest	7
2	12348.0	75	4	1797.24	newest	lowest	smallest	newest-lowest-smallest	7
3	12349.0	19	1	1757.55	newest	lowest	smallest	newest-lowest-smallest	7
4	12350.0	310	1	334.40	oldest	lowest	smallest	oldest-lowest-smallest	3

Standard Scalar Transformation

In [42]:
```
scaler = StandardScaler()

df_rfm_scaled = scaler.fit_transform(df_rfm[['Recency', 'Frequency', 'Monetary']])
df_rfm_scaled

df_rfm_scaled = pd.DataFrame(df_rfm_scaled)
df_rfm_scaled.columns = ['Recency', 'Frequency', 'Monetary']
df_rfm_scaled.head()
```

Out[42]:

	Recency	Frequency	Monetary
0	2.315110	-0.452915	-0.561869
1	-0.898130	0.412606	1.112411
2	-0.174159	-0.106706	0.136294
3	-0.729534	-0.626019	0.120876
4	2.156431	-0.626019	-0.431966

Build K-Means Clustering Model and Decide the optimum number of clusters to be formed.

In [43]:
```
# k-means with some arbitrary k
kmeans = KMeans(n_clusters=3, max_iter=50)
kmeans.fit(df_rfm_scaled)
```

Out[43]: In [47]:

In [46]:

Out[46]:

```
KMeans(max_iter=50, n_clusters=3)
```

```
kmeans.labels_
```

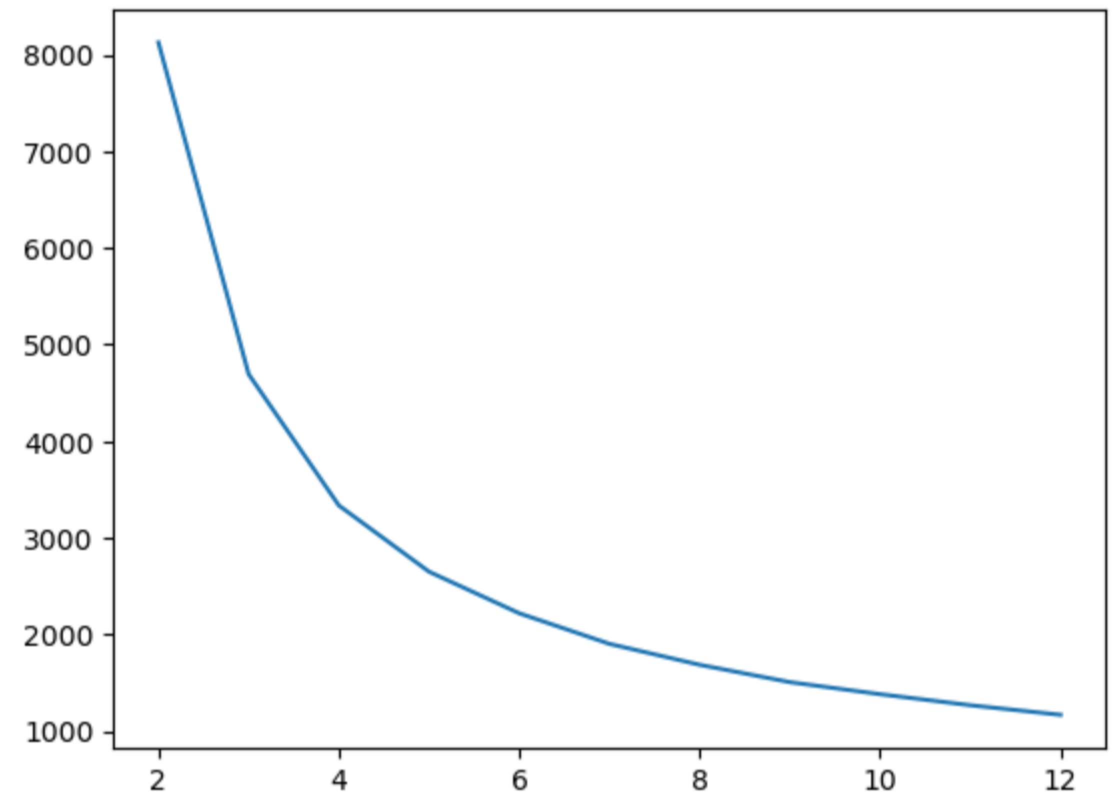
```
array([1, 0, 0, ..., 0, 0, 0])
```

In [48]:

```
# Finding the Optimal Number of Clusters with the help of Elbow Curve/
SSD ssd = []
range_n_clusters = [2, 3, 4, 5, 6, 7, 8, 9, 10, 11,
12] for num_clusters in range_n_clusters:
    kmeans = KMeans(n_clusters=num_clusters,
    max_iter=100) kmeans.fit(df_rfm_scaled)

    ssd.append(kmeans.inertia_)

# plot the SSDs for each n_clusters
plt.plot(range_n_clusters,ssd);
```




```
# Creating dataframe for exporting to create visualization in tableau later
df_inertia = pd.DataFrame(list(zip(range_n_clusters, ssd)), columns=['clusters', 'intertia'])
df_inertia
```

Out[48]:

	clusters	intertia
0	2	8127.082877
1	3	4693.551481
2	4	3334.663585
3	5	2648.613205
4	6	2218.226480
5	7	1901.612620
6	8	1685.108063
7	9	1505.415573
8	10	1380.710050
9	11	1266.564772
10	12	1167.327092

In [49]:

```
# Finding the Optimal Number of Clusters with the help of Silhouette
Analysis range_n_clusters = [2, 3, 4, 5, 6, 7, 8, 9, 10]

for num_clusters in range_n_clusters:
    kmeans = KMeans(n_clusters=num_clusters, max_iter=50)
    kmeans.fit(df_rfm_scaled)

    cluster_labels = kmeans.labels_

    silhouette_avg = silhouette_score(df_rfm_scaled, cluster_labels)
    print("For n_clusters={0}, the silhouette score is {1}".format(num_clusters, silhouette_avg))
```

```
For n_clusters=2, the silhouette score is 0.6307483359906574
For n_clusters=3, the silhouette score is 0.5363959996360127
For n_clusters=4, the silhouette score is 0.5313451516062533
For n_clusters=5, the silhouette score is 0.49103268855197135
For n_clusters=6, the silhouette score is 0.44728831464768926
For n_clusters=7, the silhouette score is 0.42636750442858656
For n_clusters=8, the silhouette score is 0.42490374096739636
For n_clusters=9, the silhouette score is 0.43072614638261847
For n_clusters=10, the silhouette score is 0.36454664654449204
```

In [50]:

```
# Final model with k=3
kmeans = KMeans(n_clusters=3, max_iter=50)
kmeans.fit(df_rfm_scaled)
```

Out[50]:

```
KMeans(max_iter=50, n_clusters=3)
```

Analyze these clusters and comment on the results.

In [51]:

```
# assign the label
df_rfm['Cluster_Id'] = kmeans.labels_
df_rfm.head()
```

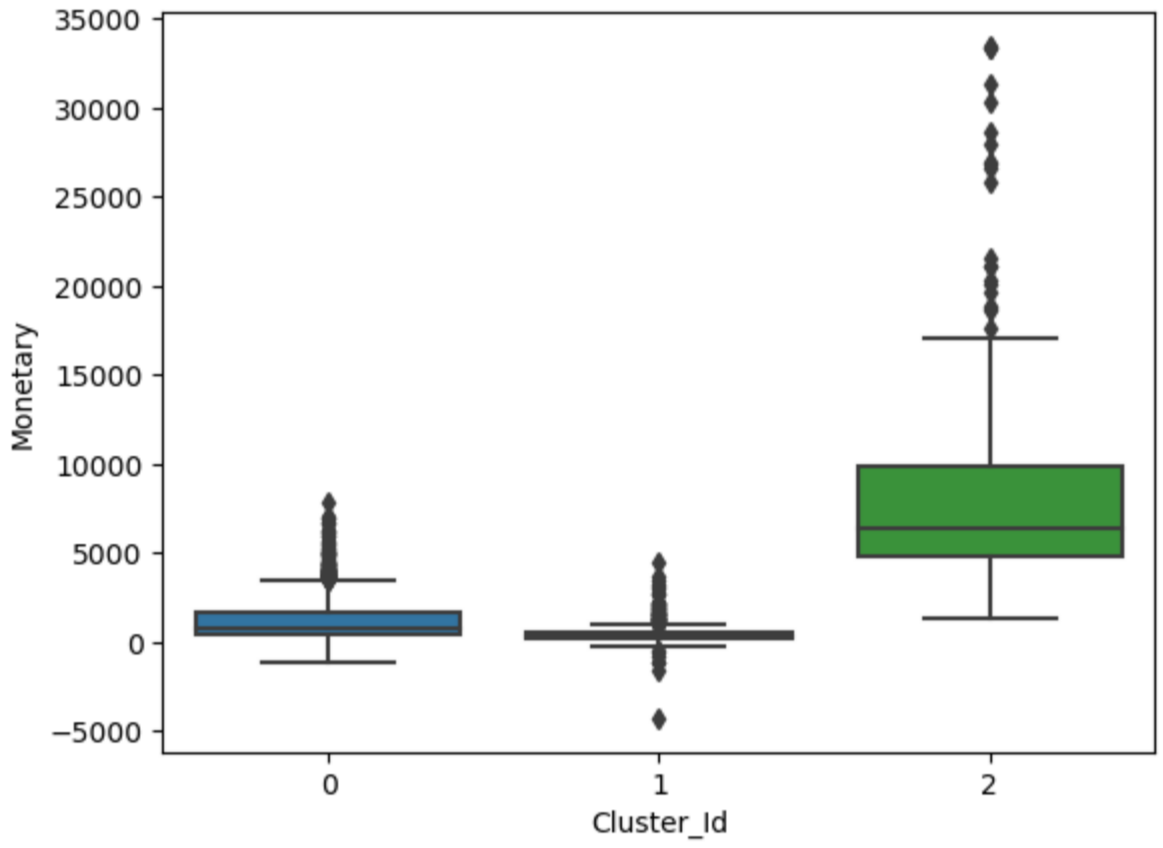
Out[51]:

	CustomerID	Recency	Frequency	Monetary	recency_labels	frequency_labels	monetary_labels	rfm_segment	rfm_score	Cluster_Id
0	12346.0	326	2	0.00	oldest	lowest	smallest	oldest-lowest-smallest	3	1
1	12347.0	2	7	4310.00	newest	lowest	smallest	newest-lowest-smallest	7	0
2	12348.0	75	4	1797.24	newest	lowest	smallest	newest-lowest-smallest	7	0
3	12349.0	19	1	1757.55	newest	lowest	smallest	newest-lowest-smallest	7	0
4	12350.0	310	1	334.40	oldest	lowest	smallest	oldest-lowest-smallest	3	1

In [52]:

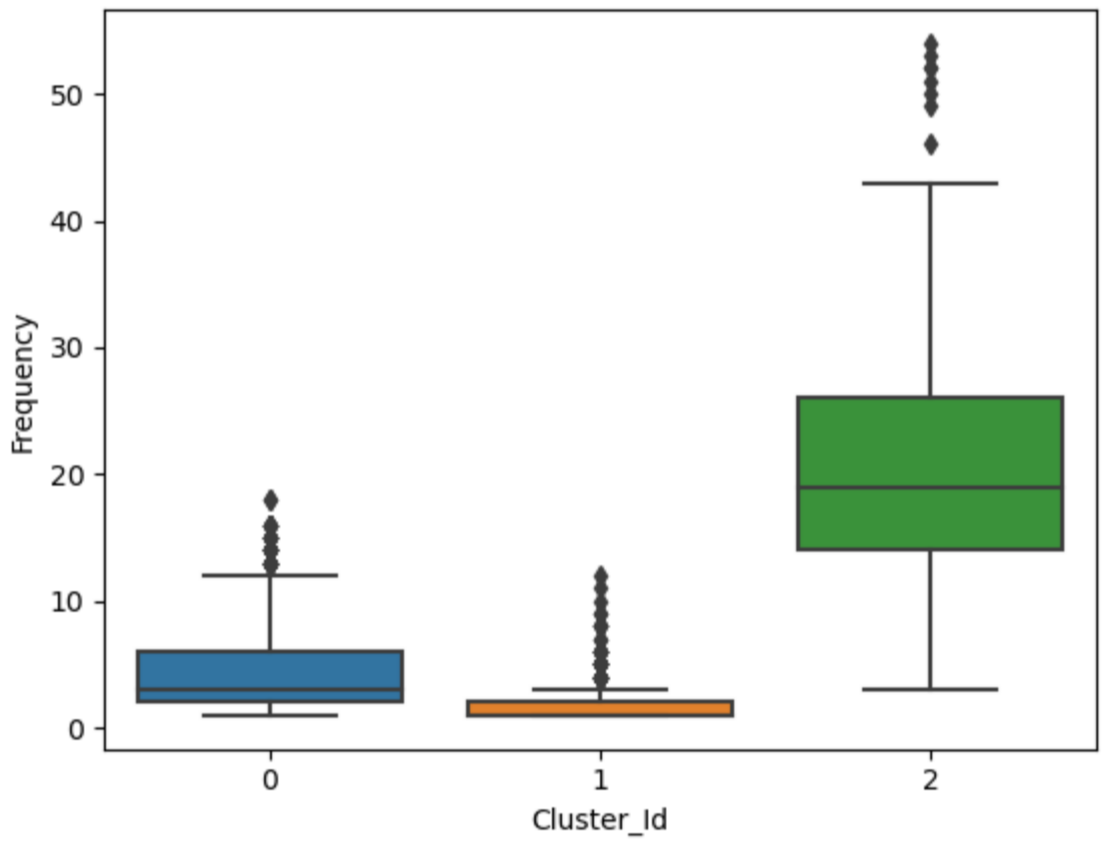
In [53]:

```python
# Box plot to visualize Cluster Id vs Monetary
sns.boxplot(x='Cluster_Id', y='Monetary', data=df_rfm);
```

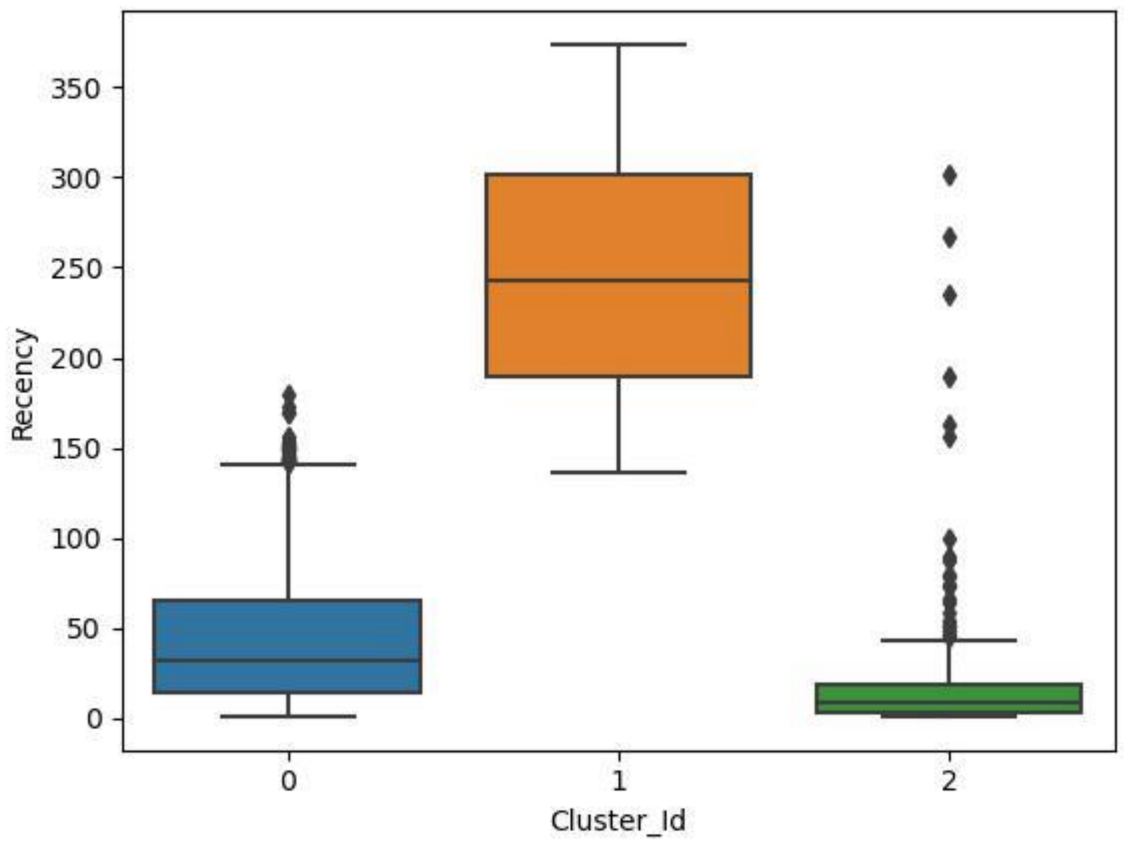


In [54]:

```python
# Box plot to visualize Cluster Id vs Frequency
sns.boxplot(x='Cluster_Id', y='Frequency', data=df_rfm);
```




```python
# Box plot to visualize Cluster Id vs Recency
sns.boxplot(x='Cluster_Id', y='Recency', data=df_rfm);
```



Data Reporting:

Tableau link :-

- https://public.tableau.com/app/profile/srinivas2758/viz/CapstoneProject-RetailPGP_16767371984700/Dashboard?publish=yes

In [ ]: