In [1]:
```
# Importing all the required libraries and packages:

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
```

In [2]:
```
Data = pd.read_excel(r'C:\Users\gkoppadx\OneDrive - Intel Corporation\Desktop\simple\A CAPSTONE PROJECT\Project 3/Online Retail.xl
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]:
```
# Checking shape of data

Data.shape
```

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

In [4]:
```
# Check feature details of data

Data.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
```

In [5]:

```
# Checking the missing values in data

Data.isnull().sum()
```

Out[5]:

```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

In [6]:

```
# Calculating the Missing Values % contribution in DF

Data_null = round(Data.isnull().sum()/len(Data)*100,2)
Data_null
```

Out[6]:

```
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 [7]:

```
# CustomerID is important feature of our analysis since our analysis is centered around Customers only,
# so we can not impute null values CustomerID with mean/ median/ mode in this case.

# We will check possibility to fill null values in CustomerID column,
# By looking up for InvoiceNo of row having null CustomerID in other rows where CustomerID is present.

# If there are still any null values in CustomerID after this process then we will drop complete row having missing CustomerID.
# So we will drop all rows having null values in CustomerID.

invoice_null_custid = set(Data[Data['CustomerID'].isnull()]['InvoiceNo'])
Data[Data['InvoiceNo'].isin(invoice_null_custid) & (Data['CustomerID'].isnull())]
```

Out[7]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
622	536414	22139	NaN	56	2010-12-01 11:52:00	0.00	NaN	United Kingdom
1443	536544	21773	DECORATIVE ROSE BATHROOM BOTTLE	1	2010-12-01 14:32:00	2.51	NaN	United Kingdom
1444	536544	21774	DECORATIVE CATS BATHROOM BOTTLE	2	2010-12-01 14:32:00	2.51	NaN	United Kingdom
1445	536544	21786	POLKADOT RAIN HAT	4	2010-12-01 14:32:00	0.85	NaN	United Kingdom
1446	536544	21787	RAIN PONCHO RETROSPOT	2	2010-12-01 14:32:00	1.66	NaN	United Kingdom
...	...	...	...	...	...	...	...	...
541536	581498	85099B	JUMBO BAG RED RETROSPOT	5	2011-12-09 10:26:00	4.13	NaN	United Kingdom
541537	581498	85099C	JUMBO BAG BAROQUE BLACK WHITE	4	2011-12-09 10:26:00	4.13	NaN	United Kingdom
541538	581498	85150	LADIES & GENTLEMEN METAL SIGN	1	2011-12-09 10:26:00	4.96	NaN	United Kingdom
541539	581498	85174	S/4 CACTI CANDLES	1	2011-12-09 10:26:00	10.79	NaN	United Kingdom
541540	581498	DOT	DOTCOM POSTAGE	1	2011-12-09 10:26:00	1714.17	NaN	United Kingdom

135080 rows × 8 columns

In [8]:

```
Data[Data['InvoiceNo'].isin(invoice_null_custid) & (~Data['CustomerID'].isnull())]
```

Out[8]:

InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country

In [9]:

```
# We can drop Description feature from our data since it is not not going to contribute in our model.

Data = Data.drop('Description', axis=1)
Data = Data.dropna()
Data.shape
```

Out[9]:

```
(406829, 7)
```

In [10]:

```
Data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 406829 entries, 0 to 541908
Data columns (total 7 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    406829 non-null  object
 1   StockCode    406829 non-null  object
 2   Quantity     406829 non-null  int64
 3   InvoiceDate  406829 non-null  datetime64[ns]
 4   UnitPrice    406829 non-null  float64
 5   CustomerID   406829 non-null  float64
 6   Country      406829 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(3)
memory usage: 24.8+ MB
```

In [11]:

```
# Remove duplicate data records

Data = Data.drop_duplicates()
Data.shape
```

Out[11]:

```
(401602, 7)
```

In [12]:

```
# Perform descriptive anaylysis on the given data

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

```
Data['CustomerID'] = Data['CustomerID'].astype(str)
```

In [13]:
```
Data.describe(datetime_is_numeric=True)
```

Out[13]:

	Quantity	InvoiceDate	UnitPrice
count	401602.000000	401602	401602.000000
mean	12.182579	2011-07-10 12:08:08.129839872	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 11:58:00	3.750000
max	80995.000000	2011-12-09 12:50:00	38970.000000
std	250.283248	NaN	69.764209

In [14]:
```
# From above data:
# 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 [15]:
```
Data.describe(include=['O'])
# include=['O'], it pulls out the objects dtypes attributes and shows their count/frequency/max/quartiles.
```

Out[15]:

	InvoiceNo	StockCode	CustomerID	Country
count	401602	401602	401602	401602
unique	22190	3684	4372	37
top	576339	85123A	17841.0	United Kingdom

	InvoiceNo	StockCode	CustomerID	Country
freq	542	2065	7812	356726

In [16]:

```
# From above data:
# InvoiceNo: Total entries in preprocessed data are 4,01,602 but transactions are 22,190.
# Most number of entries (count of unique products) are in Invoice No. '576339' and is 542 nos.

# 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)
```

In [17]:

```
# Data Transformation:Perform Cohort Analysis
# Cohort analysis is a tool to measure user engagement over time.
# It helps to know whether user engagement is actually getting better over time or is only appearing to improve because of growth.

# Create month cohort of customers and analyze active customers in each cohort
```

In [18]:

```
# Convert InvoiceDate to Year-Month format

Data['month_year'] = Data['InvoiceDate'].dt.to_period('M')
Data['month_year'].nunique()
```

Out[18]:

```
13
```

In [19]:

```
month_cohort = Data.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
```

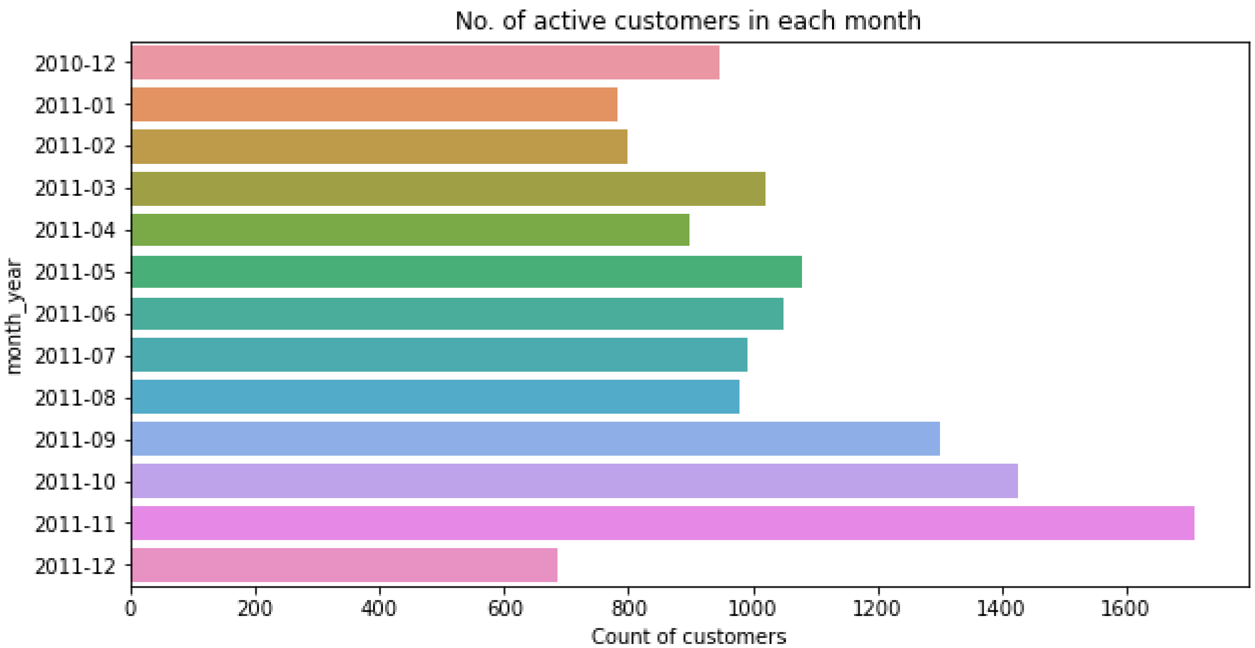
```
2011-05    1079
2011-06    1051
2011-07     993
2011-08     980
2011-09    1302
2011-10    1425
2011-11    1711
2011-12     686
Freq: M, Name: CustomerID, dtype: int64
```

In [20]:

```
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")
```

Out[20]:

```
Text(0.5, 1.0, 'No. of active customers in each month')
```



In [21]:

```
#  Analyze the retention rate of customers:
```

In [22]:

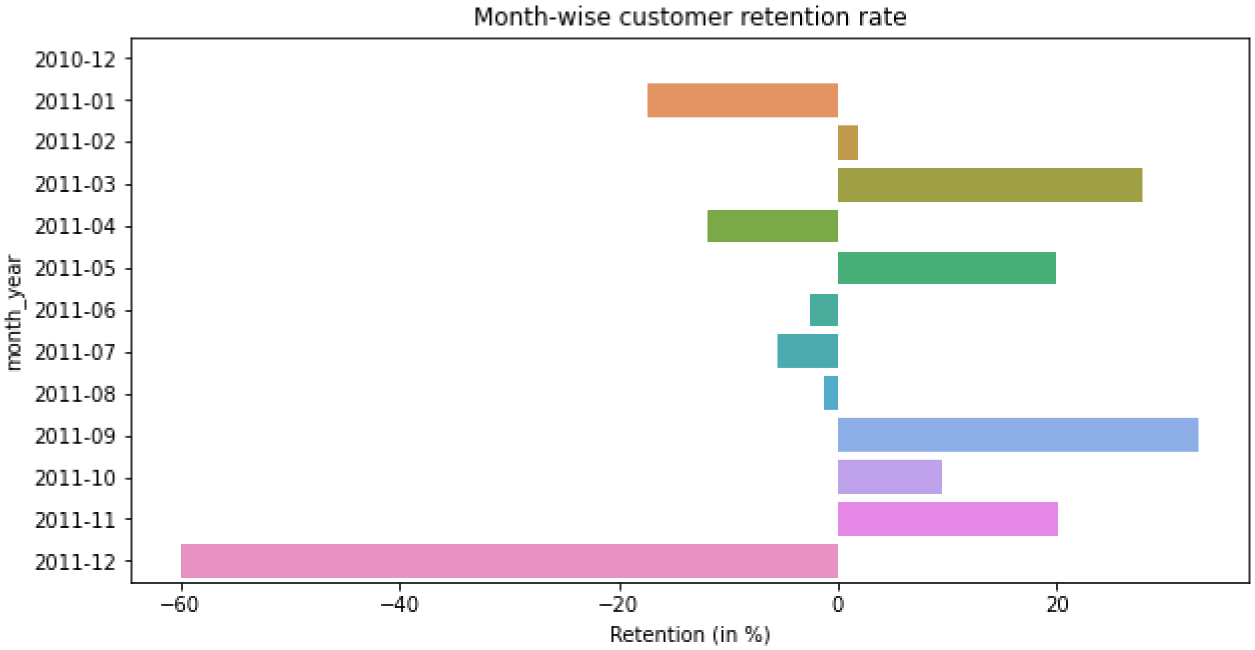
```
month_cohort - month_cohort.shift(1)
```

Out[22]:
```
month_year
2010-12        NaN
2011-01     -165.0
2011-02       15.0
2011-03      222.0
2011-04     -121.0
2011-05      180.0
2011-06      -28.0
2011-07      -58.0
2011-08      -13.0
2011-09      322.0
2011-10      123.0
2011-11      286.0
2011-12    -1025.0
Freq: M, Name: CustomerID, dtype: float64
```

In [23]:
```
retention_rate = round(month_cohort.pct_change(periods=1)*100,2)
retention_rate
```

Out[23]:
```
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 [24]:
```
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");
```



In [25]:

```
# Monetary analysis:
```

In [26]:

```
Data['amount'] = Data['Quantity']*Data['UnitPrice']
Data.head()
```

Out[26]:

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

In [27]:

```
Data_monetary = Data.groupby('CustomerID').sum()['amount'].reset_index()
Data_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

In [28]:
```
# Frequency Analysis:
```

In [29]:
```
Data_frequency = Data.groupby('CustomerID').nunique()['InvoiceNo'].reset_index()
Data_frequency
```

Out[29]:

	CustomerID	InvoiceNo
0	12346.0	2
1	12347.0	7
2	12348.0	4
3	12349.0	1
4	12350.0	1

	CustomerID	InvoiceNo
...	...	...
4367	18280.0	1
4368	18281.0	1
4369	18282.0	3
4370	18283.0	16
4371	18287.0	3

4372 rows × 2 columns

In [30]:

```
# Recency Analysis:
```

In [31]:

```
# We will fix reference date for calculating recency as last transaction day in data + 1 day

ref_day = max(Data['InvoiceDate']) + timedelta(days=1)
ref_day
```

Out[31]:

```
Timestamp('2011-12-10 12:50:00')
```

In [32]:

```
Data['days_to_last_order'] = (ref_day - Data['InvoiceDate']).dt.days
Data.head()
```

Out[32]:

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

In [33]:
```
Data_recency = Data.groupby('CustomerID')['days_to_last_order'].min().reset_index()
Data_recency
```

Out[33]:

	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

4372 rows × 2 columns

In [34]:
```
# Calculate RFM metrics:
```

In [35]:
```
Data_rf = pd.merge(Data_recency, Data_frequency,  on='CustomerID', how='inner')
Data_rfm = pd.merge(Data_rf, Data_monetary, on='CustomerID', how='inner')
Data_rfm.columns = ['CustomerID', 'Recency', 'Frequency', 'Monetary']
Data_rfm.head()
```

Out[35]:

	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

	CustomerID	Recency	Frequency	Monetary
3	12349.0	19	1	1757.55
4	12350.0	310	1	334.40

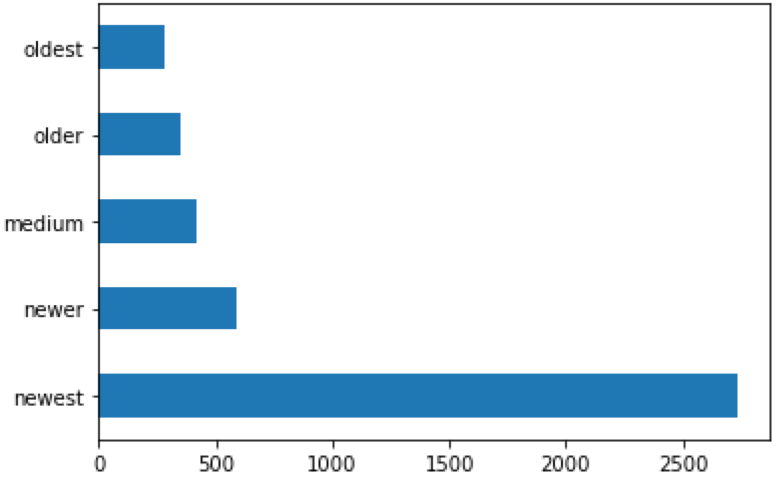
In [36]:

```
# Build RFM Segments:

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

Out[36]:

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

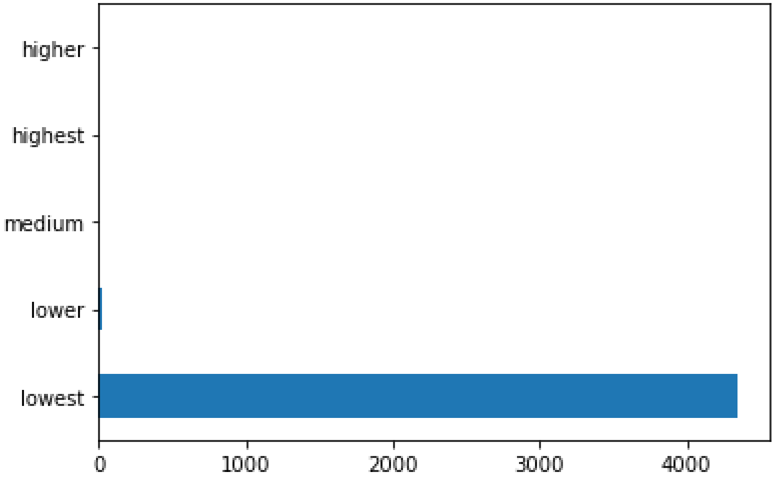


In [37]:

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

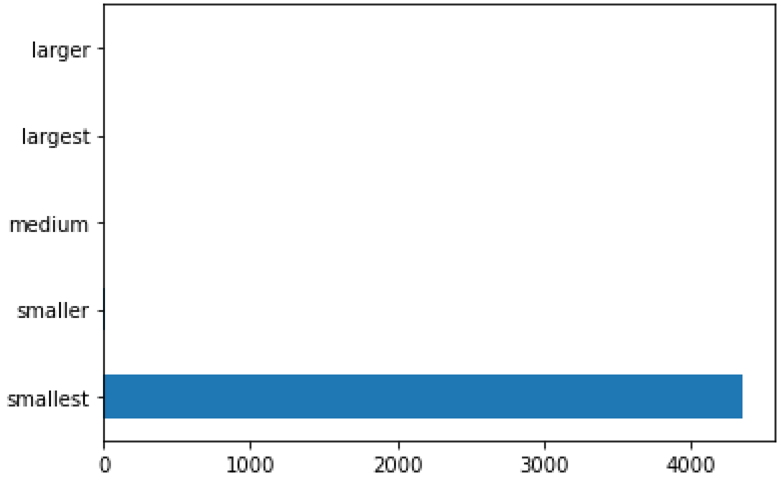
```
lowest     4348
```

Out[37]:
```
lower        18
medium        3
highest       2
higher        1
Name: frequency_labels, dtype: int64
```



In [38]:
```
Data_rfm['monetary_labels'] = pd.cut(Data_rfm['Monetary'], bins=5,
                                     labels=['smallest', 'smaller', 'medium', 'larger', 'largest'])
Data_rfm['monetary_labels'].value_counts().plot(kind='barh');
Data_rfm['monetary_labels'].value_counts()
```

Out[38]:
```
smallest    4357
smaller        9
medium         3
largest        2
larger         1
Name: monetary_labels, dtype: int64
```



In [39]:

```
Data_rfm.head()
```

Out[39]:

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

In [40]:

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

Out[40]:

	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

	CustomerID	Recency	Frequency	Monetary	recency_labels	frequency_labels	monetary_labels	rfm_segment
4	12350.0	310	1	334.40	oldest	lowest	smallest	oldest_lowest_smallest

In [41]:

```
# RFM Score:

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}

Data_rfm['rfm_score'] = (Data_rfm['recency_labels'].map(recency_dict).astype(int)+ Data_rfm['frequency_labels']
                         .map(frequency_dict).astype(int) + Data_rfm['monetary_labels'].map(monetary_dict).astype(int))

Data_rfm.head(10)
```

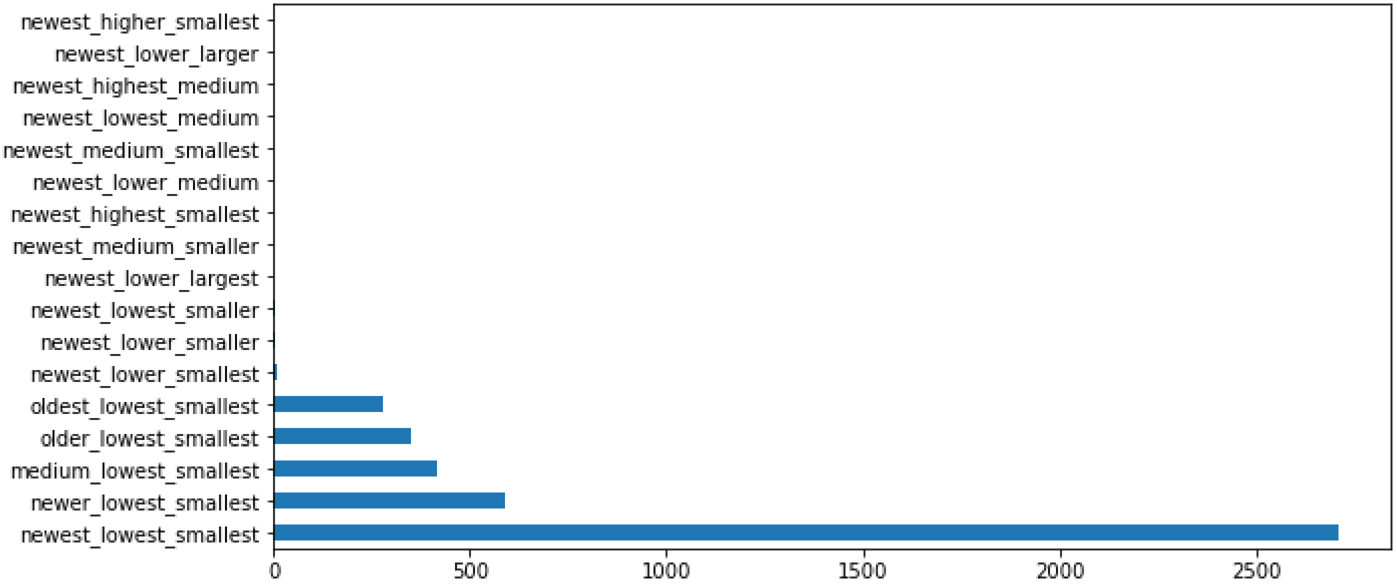
Out[41]:

	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

In [42]:

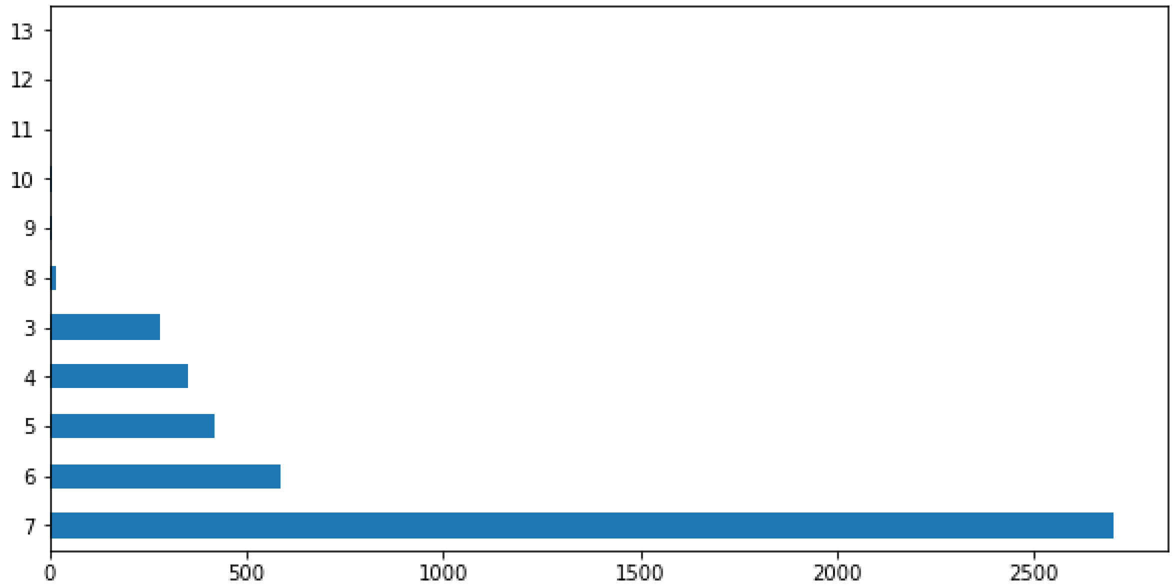
```
# Analyze RFM Segment and Score:

Data_rfm['rfm_segment'].value_counts().plot(kind='barh', figsize=(10, 5));
```



In [43]:

```
Data_rfm['rfm_score'].value_counts().plot(kind='barh', figsize=(10, 5));
```



Data Modeling:

In [44]:
```
# Create clusters using k-means clustering algorithm.

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

In [45]:
```
print(Data_rfm.shape)
Data_rfm.head()
```

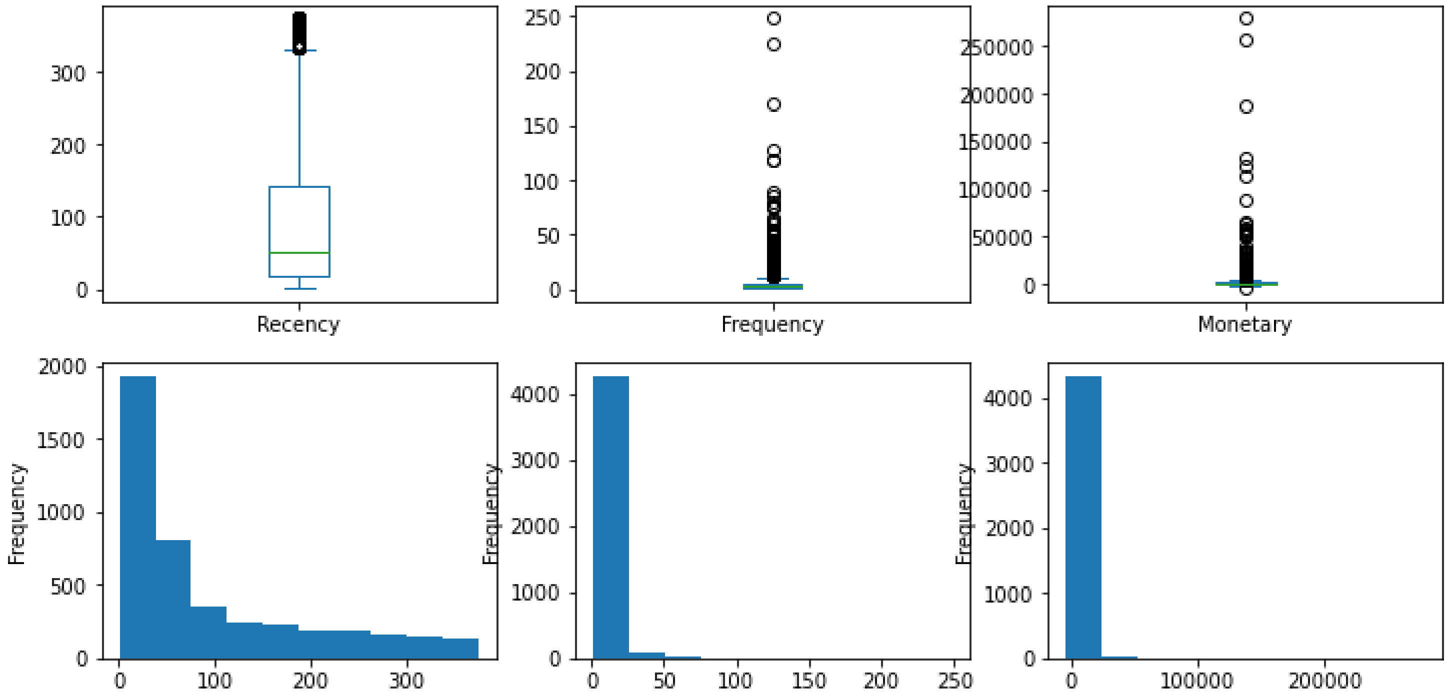
(4372, 9)

Out[45]:

	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

In [46]:
```
plt.figure(figsize=(12,6))

for i, feature in enumerate(['Recency', 'Frequency', 'Monetary']):
    plt.subplot(2,3,i+1)
    Data_rfm[feature].plot(kind='box')
    plt.subplot(2,3,i+1+3)
    Data_rfm[feature].plot(kind='hist')
```



In [47]:

```
# From above data:
# Frequency and Monetary features in above data seem to have lot of outliers. Lets drop them.
```

In [48]:

```
Data_rfm = Data_rfm[(Data_rfm['Frequency']<60) & (Data_rfm['Monetary']<40000)]
Data_rfm.shape
```

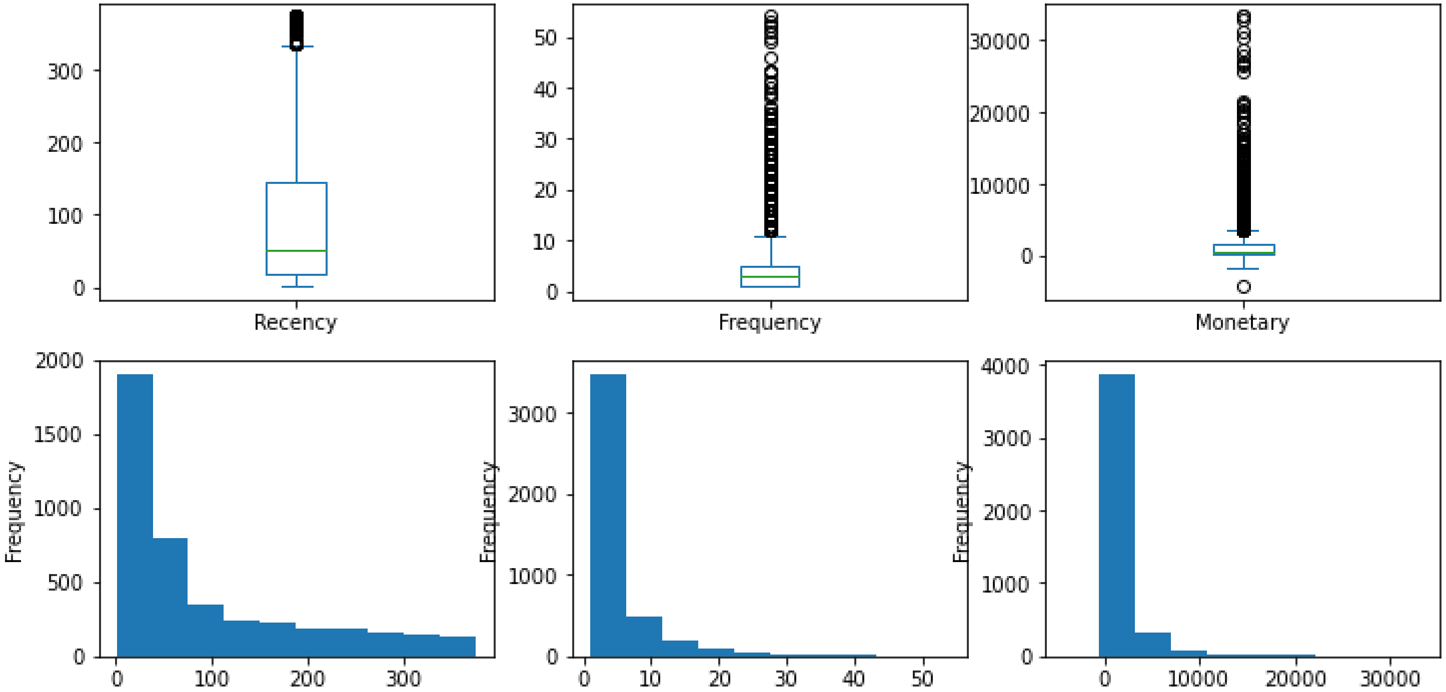
Out[48]:

```
(4346, 9)
```

In [49]:

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

for i, feature in enumerate(['Recency', 'Frequency', 'Monetary']):
    plt.subplot(2,3,i+1)
    Data_rfm[feature].plot(kind='box')
    plt.subplot(2,3,i+1+3)
    Data_rfm[feature].plot(kind='hist')
```



In [50]:

```
# Now since all three features have right skewed data, we will use log transformation of these features in our model.
```

In [51]:

```
Data_rfm_log_trans = pd.DataFrame()
Data_rfm_log_trans['Recency'] = np.log(Data_rfm['Recency'])
Data_rfm_log_trans['Frequency'] = np.log(Data_rfm['Frequency'])
Data_rfm_log_trans['Monetary'] = np.log(Data_rfm['Monetary']-Data_rfm['Monetary'].min()+1)
```

In [52]:

```
Data_rfm_log_trans.head()
```

Out[52]:

	Recency	Frequency	Monetary
0	5.786897	0.693147	8.363723
1	0.693147	1.945910	9.059358
2	4.317488	1.386294	8.713725

	Recency	Frequency	Monetary
3	2.944439	0.000000	8.707182
4	5.736572	0.000000	8.438806

In [53]:

```
# Standard Scalar Transformation: It is extremely important to rescale the features so that they have a comparable scale.
```

In [54]:

```
scaler = StandardScaler()

Data_rfm_scaled = scaler.fit_transform(Data_rfm_log_trans[['Recency', 'Frequency', 'Monetary']])
Data_rfm_scaled

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

Out[54]:

	Recency	Frequency	Monetary
0	1.402988	-0.388507	-0.770922
1	-2.100874	0.967301	1.485132
2	0.392218	0.361655	0.364190
3	-0.552268	-1.138669	0.342970
4	1.368370	-1.138669	-0.527416

In [55]:

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

In [56]:

```
# k-means with some arbitrary k
kmeans = KMeans(n_clusters=3, max_iter=50)
kmeans.fit(Data_rfm_scaled)
```

Out[56]:

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

In [57]:

```
kmeans.labels_
```

Out[57]:
```
array([1, 0, 2, ..., 2, 0, 2])
```

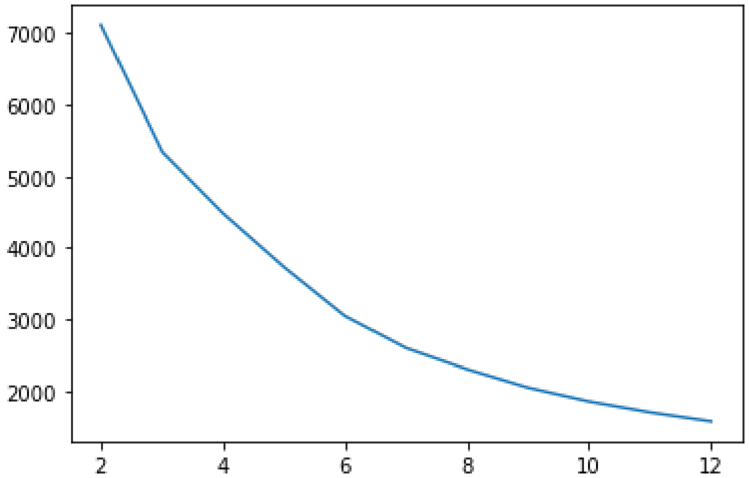
In [58]:
```
# Finding the Optimal Number of Clusters with the help of Elbow Curve/ SSD

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(Data_rfm_scaled)

    ssd.append(kmeans.inertia_)


# plot the SSDs for each n_clusters

plt.plot(range_n_clusters,ssd);
```



In [59]:
```
# Creating dataframe for exporting to create visualization in tableau later
Data_inertia = pd.DataFrame(list(zip(range_n_clusters, ssd)), columns=['clusters', 'intertia'])
Data_inertia
```

Out[59]:

clusters	intertia

	clusters	intertia
0	2	7113.097396
1	3	5343.136928
2	4	4481.022293
3	5	3730.805717
4	6	3045.029702
5	7	2598.464837
6	8	2301.370633
7	9	2044.740060
8	10	1852.941597
9	11	1700.376798
10	12	1575.512062

In [60]:

```
# 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(Data_rfm_scaled)

    cluster_labels = kmeans.labels_

    silhouette_avg = silhouette_score(Data_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 0.44132753537785846
For n_clusters=3, the silhouette score is 0.37962225322302756
For n_clusters=4, the silhouette score is 0.3623606426972478
For n_clusters=5, the silhouette score is 0.36686786887528716
For n_clusters=6, the silhouette score is 0.3441911617174347
For n_clusters=7, the silhouette score is 0.3428617732216645
For n_clusters=8, the silhouette score is 0.3352730467143602
```

```
For n_clusters=9, the silhouette score is 0.346301798458803
For n_clusters=10, the silhouette score is 0.3560807144631476
```

In [61]:

```python
# From above data
# We can select optimum number of clusters as 3 in our final model
```

In [62]:

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

Out[62]:

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

In [63]:

```python
 # Analyze these clusters and comment on the results.
```

In [64]:

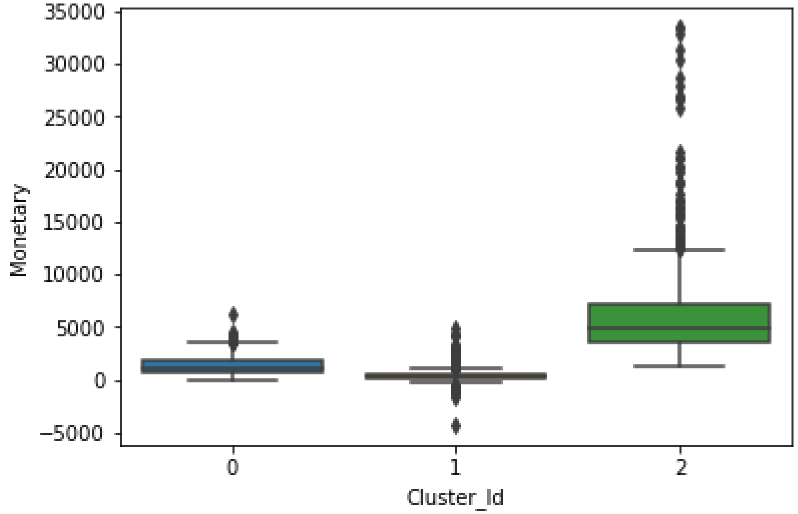
```python
# assign the label
Data_rfm['Cluster_Id'] = kmeans.labels_
Data_rfm.head()
```

Out[64]:

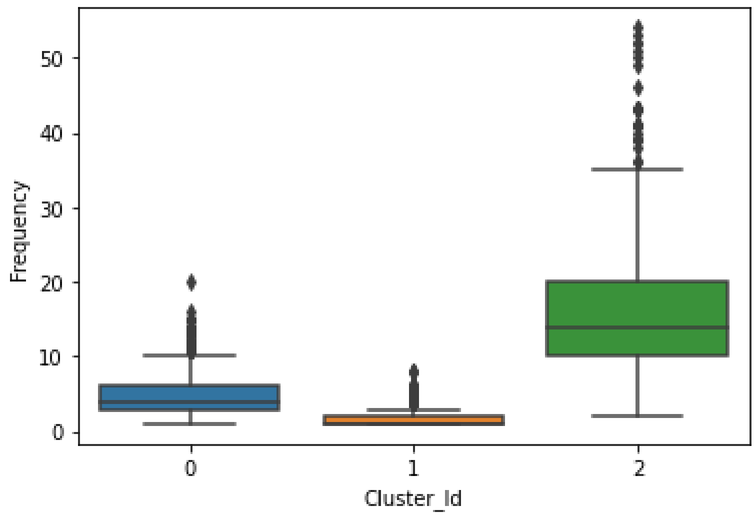
	CustomerID	Recency	Frequency	Monetary	recency_labels	frequency_labels	monetary_labels	rfm_segment	rfm_score	Cluster_Id
0	12346.0	326	2	0.00	oldest	lowest	smallest	oldest_lowest_smallest	3	1
1	12347.0	2	7	4310.00	newest	lowest	smallest	newest_lowest_smallest	7	2
2	12348.0	75	4	1797.24	newest	lowest	smallest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

In [65]:

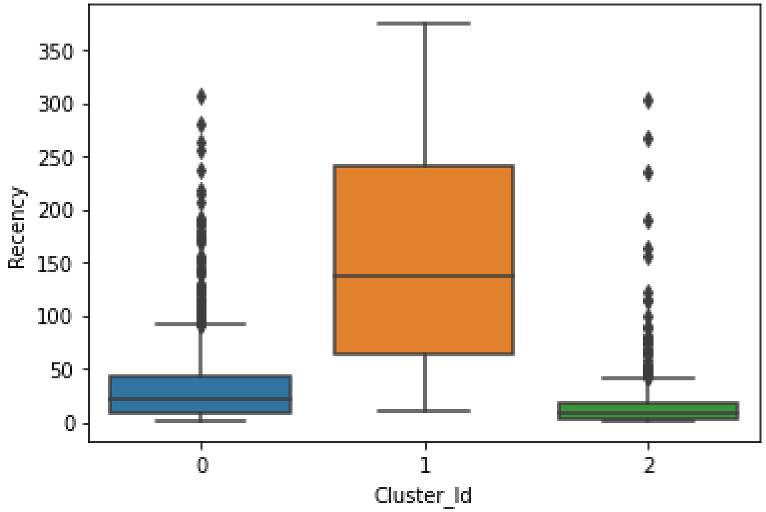
```python
# Box plot to visualize Cluster Id vs Monetary
sns.boxplot(x='Cluster_Id', y='Monetary', data=Data_rfm);
```



In [66]:
```
# Box plot to visualize Cluster Id vs Frequency
sns.boxplot(x='Cluster_Id', y='Frequency', data=Data_rfm);
```



In [67]:
```
# Box plot to visualize Cluster Id vs Recency
sns.boxplot(x='Cluster_Id', y='Recency', data=Data_rfm);
```



Final Inference from the Analysis:

As we can observe from above boxplots that our model has nicely created 3 segements of customer with the interpretation as below:

Customers with Cluster Id 0 are less frequent buyers with low monetary expenditure and also they have not purchased anything in recent time and hence least important for business.

Customers with Cluster Id 1 are the customers having Recency, Frequency and Monetary score in the medium range.

Customers with Cluster Id 2 are the most frequent buyers, spending high amount and recently placing orders so they are the most important customers from business point of view.

In [72]:
```
# Writing dataframe to excel file for creating visualization in tableau

writer = pd.ExcelWriter('C:\\Users\\gkoppadx\\OneDrive - Intel Corporation\\Desktop\\simple\\A CAPSTONE PROJECT\\output_data.xlsx'

Data.to_excel(writer, sheet_name='master_data', index=False)
Data_rfm.to_excel(writer, sheet_name='rfm_data', index=False)
Data_inertia.to_excel(writer, sheet_name='inertia', index=False)
writer.save()
```

In [74]:
```
product_desc = pd.read_excel(r'C:\Users\gkoppadx\OneDrive - Intel Corporation\Desktop\simple\A CAPSTONE PROJECT\Project 3/Online R
product_desc = product_desc[['StockCode', 'Description']]
product_desc = product_desc.drop_duplicates()
product_desc.to_csv('product_desc.csv', index=False)
```

In [76]:
```
product_desc.head()
```

Out[76]:

	StockCode	Description
0	85123A	WHITE HANGING HEART T-LIGHT HOLDER
1	71053	WHITE METAL LANTERN
2	84406B	CREAM CUPID HEARTS COAT HANGER
3	84029G	KNITTED UNION FLAG HOT WATER BOTTLE
4	84029E	RED WOOLLY HOTTIE WHITE HEART.

In [ ]: