Retail CapstoneCP

June 17, 2023

[1]:
```python
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
```

[2]:
```python
df = pd.read_excel("Online Retail.xlsx")
df.head()
```

[2]:
```
  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
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
```

[3]:
```python
# Check shape of data
df.shape
```

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

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

[5]:
```
# Check missing values in data
df.isnull().sum()
```

[5]:
```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

[6]:
```
# Calculating the Missing Values % contribution in DF
df_null = round(df.isnull().sum()/len(df)*100,2)
df_null
```

[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
```

As we can see two columns in data have missing values. * Description - 0.27% (1454 nos.) * CustomerID - 24.93% (135080)

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 the 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.

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

[7]:
```python
invoice_null_custid = set(df[df['CustomerID'].isnull()]['InvoiceNo'])
df[df['InvoiceNo'].isin(invoice_null_custid) & (~df['CustomerID'].isnull())]
```

[7]:
```
Empty DataFrame
Columns: [InvoiceNo, StockCode, Description, Quantity, InvoiceDate, UnitPrice,
CustomerID, Country]
Index: []
```

We could not find any value to impute null values in **CustomerID** column since all entries for a particular **InvoiceNo** have missing **CustomerID** if that particular **InvoiceNo** has null **CustomerID** in even one entry. So we will drop all rows having null values in **CustomerID**.

[8]:
```python
df = df.drop('Description', axis=1)
df = df.dropna()
df.shape
```

[8]:
```
(406829, 7)
```

- **(b) Remove duplicate data records:** Since our data is transactional data and it has duplicate entries for InvoiceNo and CustomerID, we will drop only those rows which are completely duplicated, not on the basis of any one particular column such as InvoiceNo or CustomerID etc.

[9]:
```python
df = df.drop_duplicates()
df.shape
```

[9]:
```
(401602, 7)
```

- **(c) Perform descriptive anaylysis on the given data:**

[10]:
```python
# CustomerID is 'float64', changing the datatype of CustomerId to string as␣
↪Customer ID as numerical data does not make sense

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

[11]:
```python
df.describe(datetime_is_numeric=True)
```

[11]:

	Quantity	InvoiceDate	UnitPrice
count	401602.000000	401602	401602.000000
mean	12.182579	2011-07-10 12:08:08.129743104	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
```

- **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

[12]:
```
df.describe(include=['O'])
```

[12]:
```
       InvoiceNo StockCode CustomerID         Country
count     401602    401602     401602          401602
unique     22190      3684       4372              37
top       576339    85123A    17841.0  United Kingdom
freq         542      2065       7812          356726
```

- **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)

0.0.1 (B) Data Transformation

(2) Perform Cohort Analysis * (a) Create month cohort of customers and analyze active customers in each cohort:

[13]:
```
# Convert to InvoiceDate to Year-Month format
df['month_year'] = df['InvoiceDate'].dt.to_period('M')
df['month_year'].nunique()
```

[13]:
```
13
```

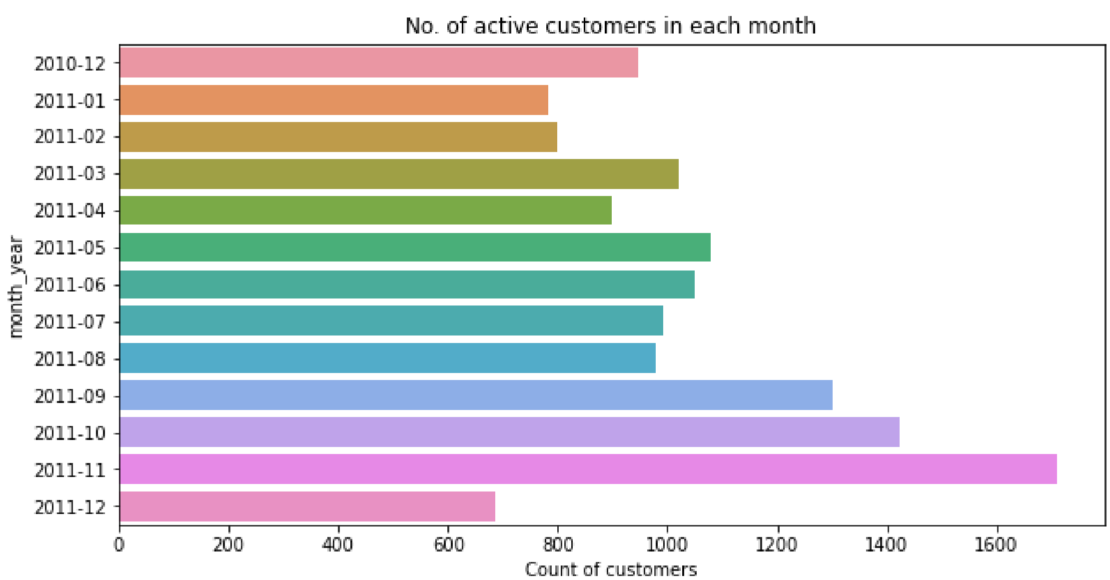
[14]:
```
month_cohort = df.groupby('month_year')['CustomerID'].nunique()
month_cohort
```

[14]:
```
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
```

[15]:
```python
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")
```

[15]:
```
Text(0.5, 1.0, 'No. of active customers in each month')
```



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

[16]:
```python
month_cohort - month_cohort.shift(1)
```

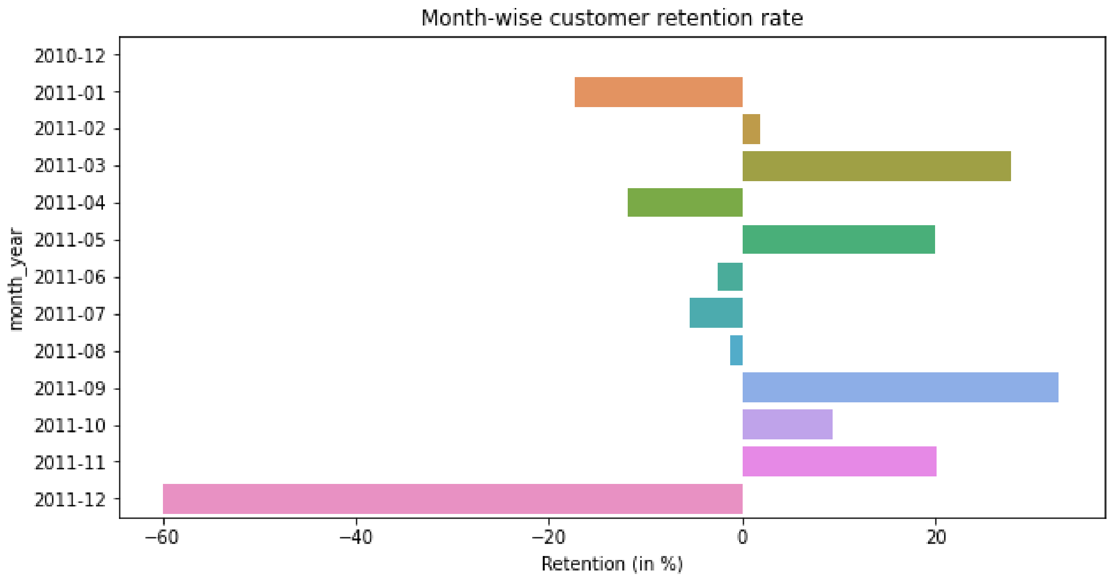
[16]:
```
month_year
2010-12        NaN
2011-01     -165.0
2011-02       15.0
2011-03      222.0
2011-04     -121.0
2011-05      180.0
2011-06      -28.0
```

```
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
```

[17]:
```python
retention_rate = round(month_cohort.pct_change(periods=1)*100,2)
retention_rate
```

[17]:
```
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
```

[18]:
```python
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");
```



0.1 Week 2:

Monetary analysis:

[20]:
```
df['amount'] = df['Quantity']*df['UnitPrice']
df.head()
```

[20]:
```
  InvoiceNo StockCode  Quantity         InvoiceDate  UnitPrice CustomerID  \
0    536365    85123A         6 2010-12-01 08:26:00       2.55    17850.0
1    536365     71053         6 2010-12-01 08:26:00       3.39    17850.0
2    536365    84406B         8 2010-12-01 08:26:00       2.75    17850.0
3    536365    84029G         6 2010-12-01 08:26:00       3.39    17850.0
4    536365    84029E         6 2010-12-01 08:26:00       3.39    17850.0

          Country month_year  amount
0  United Kingdom    2010-12   15.30
1  United Kingdom    2010-12   20.34
2  United Kingdom    2010-12   22.00
3  United Kingdom    2010-12   20.34
4  United Kingdom    2010-12   20.34
```

[21]:
```
df_monetary = df.groupby('CustomerID').sum()['amount'].reset_index()
df_monetary
```

[21]:
```
     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 x 2 columns]
```

Frequency Analysis:

[22]:
```
df_frequency = df.groupby('CustomerID').nunique()['InvoiceNo'].reset_index()
# df_freqency = df.drop_duplicates('InvoiceNo').groupby('CustomerID').
 ↪count()['InvoiceNo'].reset_index()
df_frequency
```

[22]:
```
      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 x 2 columns]
```

Recency Analysis:

[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()
```

[23]:
```
  InvoiceNo StockCode  Quantity         InvoiceDate  UnitPrice  CustomerID  \
0    536365    85123A         6 2010-12-01 08:26:00       2.55     17850.0
1    536365     71053         6 2010-12-01 08:26:00       3.39     17850.0
2    536365    84406B         8 2010-12-01 08:26:00       2.75     17850.0
3    536365    84029G         6 2010-12-01 08:26:00       3.39     17850.0
4    536365    84029E         6 2010-12-01 08:26:00       3.39     17850.0
```

```
          Country month_year  amount  days_to_last_order
0  United Kingdom    2010-12   15.30                 374
1  United Kingdom    2010-12   20.34                 374
2  United Kingdom    2010-12   22.00                 374
3  United Kingdom    2010-12   20.34                 374
4  United Kingdom    2010-12   20.34                 374
```

[24]:
```python
df_recency = df.groupby('CustomerID')['days_to_last_order'].min().reset_index()
df_recency
```

[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

[4372 rows x 2 columns]
```

Calculate RFM metrics:

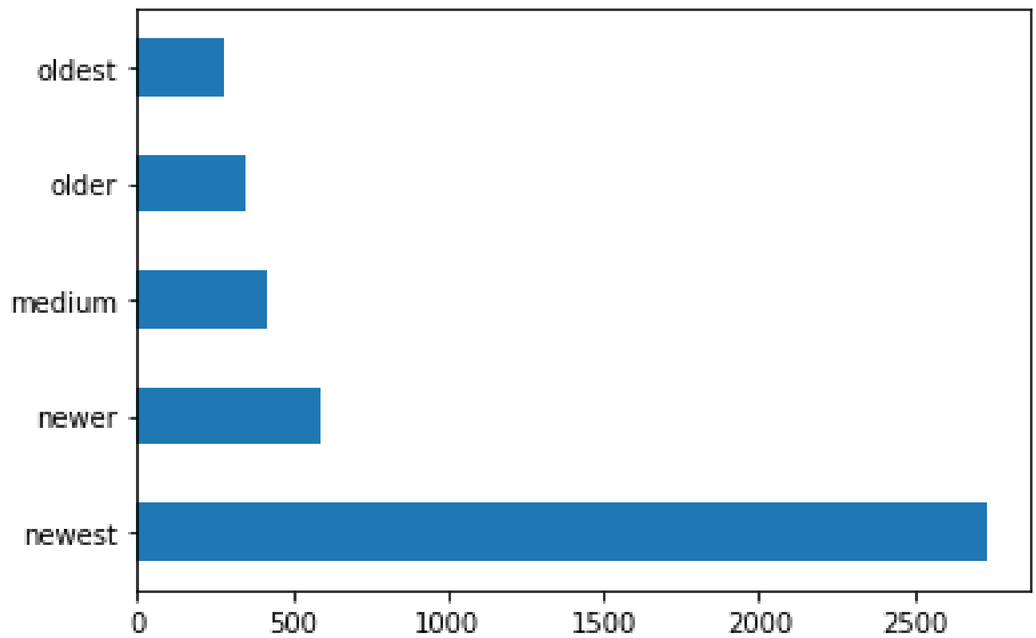
[25]:
```python
df_rf = pd.merge(df_recency, df_frequency,  on='CustomerID', how='inner')
df_rfm = pd.merge(df_rf, df_monetary, on='CustomerID', how='inner')
df_rfm.columns = ['CustomerID', 'Recency', 'Frequency', 'Monetary']
df_rfm.head()
```

[25]:
```
   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:

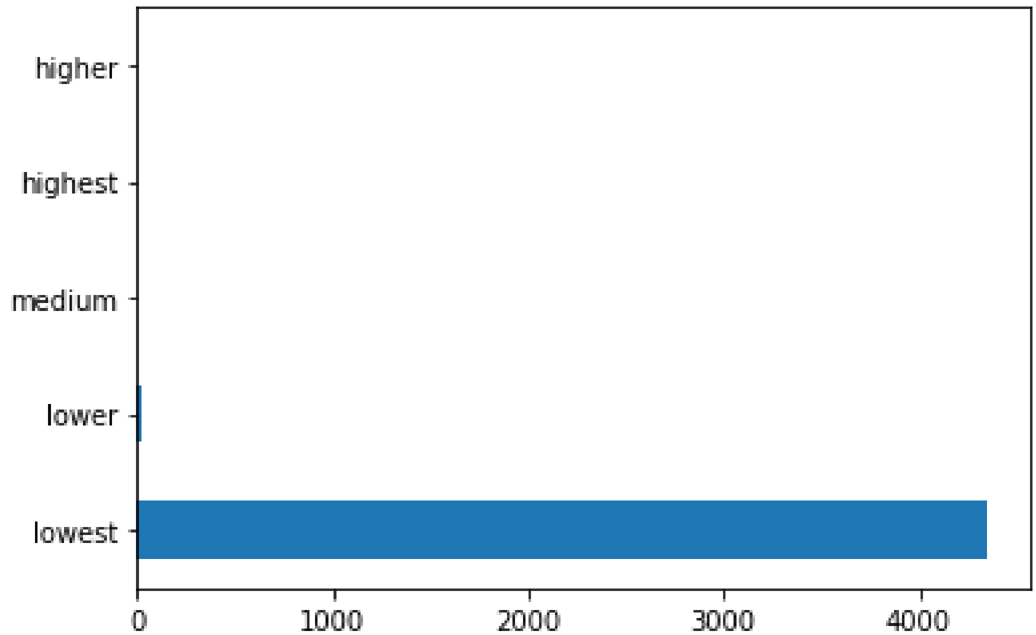
[26]:
```python
df_rfm['recency_labels'] = pd.cut(df_rfm['Recency'], bins=5,
                                     labels=['newest', 'newer', 'medium',␣
 ↪'older', 'oldest'])
df_rfm['recency_labels'].value_counts().plot(kind='barh');
df_rfm['recency_labels'].value_counts()
```

[26]:
```
newest     2734
newer       588
medium      416
older       353
oldest      281
Name: recency_labels, dtype: int64
```



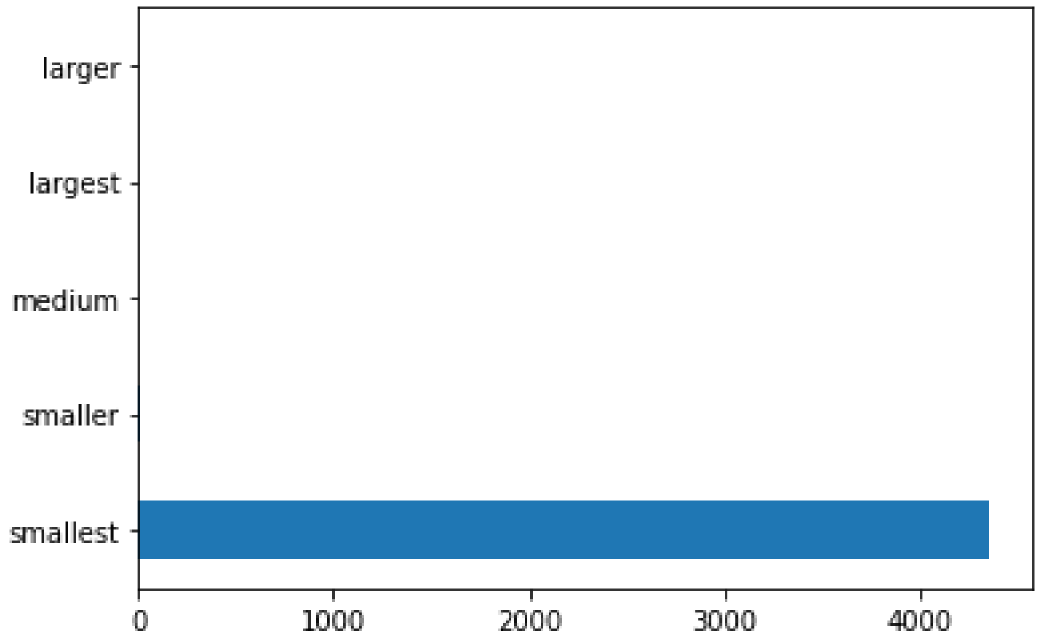
[27]:
```python
df_rfm['frequency_labels'] = pd.cut(df_rfm['Frequency'], bins=5,␣
 ↪labels=['lowest', 'lower', 'medium', 'higher', 'highest'])
df_rfm['frequency_labels'].value_counts().plot(kind='barh');
df_rfm['frequency_labels'].value_counts()
```

[27]:
```
lowest      4348
lower         18
medium         3
highest        2
higher         1
Name: frequency_labels, dtype: int64
```



[28]:
```
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()
```

[28]:
```
smallest    4357
smaller        9
medium         3
largest        2
larger         1
Name: monetary_labels, dtype: int64
```



[29]:
```
df_rfm['rfm_segment'] =␣
↪df_rfm[['recency_labels','frequency_labels','monetary_labels']].agg('-'.
↪join, axis=1)
df_rfm.head()
```

[29]:
```
   CustomerID  Recency  Frequency  Monetary recency_labels frequency_labels  \
0     12346.0      326          2      0.00         oldest           lowest
1     12347.0        2          7   4310.00         newest           lowest
2     12348.0       75          4   1797.24         newest           lowest
3     12349.0       19          1   1757.55         newest           lowest
4     12350.0      310          1    334.40         oldest           lowest

  monetary_labels             rfm_segment
0        smallest  oldest-lowest-smallest
1        smallest  newest-lowest-smallest
2        smallest  newest-lowest-smallest
3        smallest  newest-lowest-smallest
4        smallest  oldest-lowest-smallest
```

RFM Score:

[30]:
```
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_dict).astype(int)
df_rfm.head(10)
```

[30]:

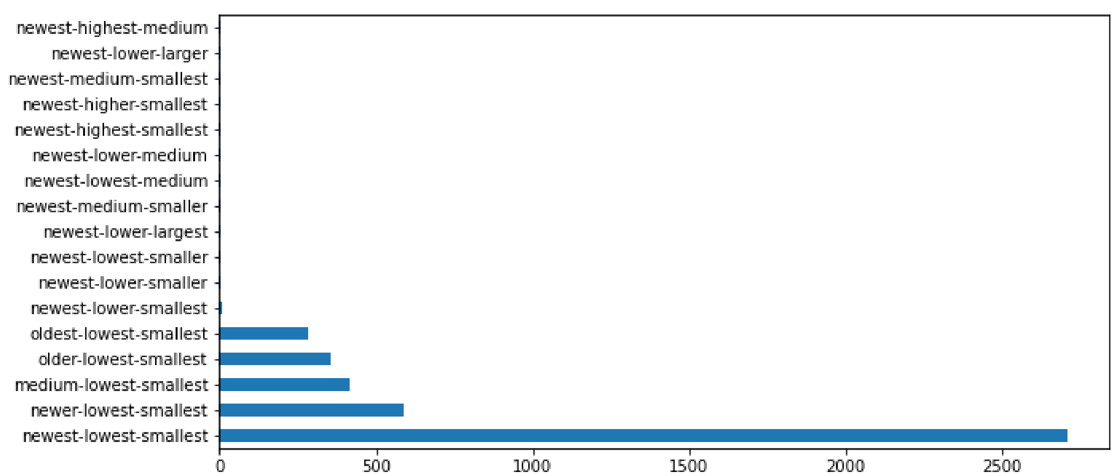
```
   CustomerID  Recency  Frequency  Monetary recency_labels frequency_labels  \
0     12346.0      326          2      0.00         oldest           lowest
1     12347.0        2          7   4310.00         newest           lowest
2     12348.0       75          4   1797.24         newest           lowest
3     12349.0       19          1   1757.55         newest           lowest
4     12350.0      310          1    334.40         oldest           lowest
5     12352.0       36         11   1545.41         newest           lowest
6     12353.0      204          1     89.00         medium           lowest
7     12354.0      232          1   1079.40          older           lowest
8     12355.0      214          1    459.40         medium           lowest
9     12356.0       23          3   2811.43         newest           lowest

  monetary_labels              rfm_segment  rfm_score
0        smallest  oldest-lowest-smallest          3
1        smallest  newest-lowest-smallest          7
2        smallest  newest-lowest-smallest          7
3        smallest  newest-lowest-smallest          7
4        smallest  oldest-lowest-smallest          3
5        smallest  newest-lowest-smallest          7
6        smallest  medium-lowest-smallest          5
7        smallest   older-lowest-smallest          4
8        smallest  medium-lowest-smallest          5
9        smallest  newest-lowest-smallest          7
```

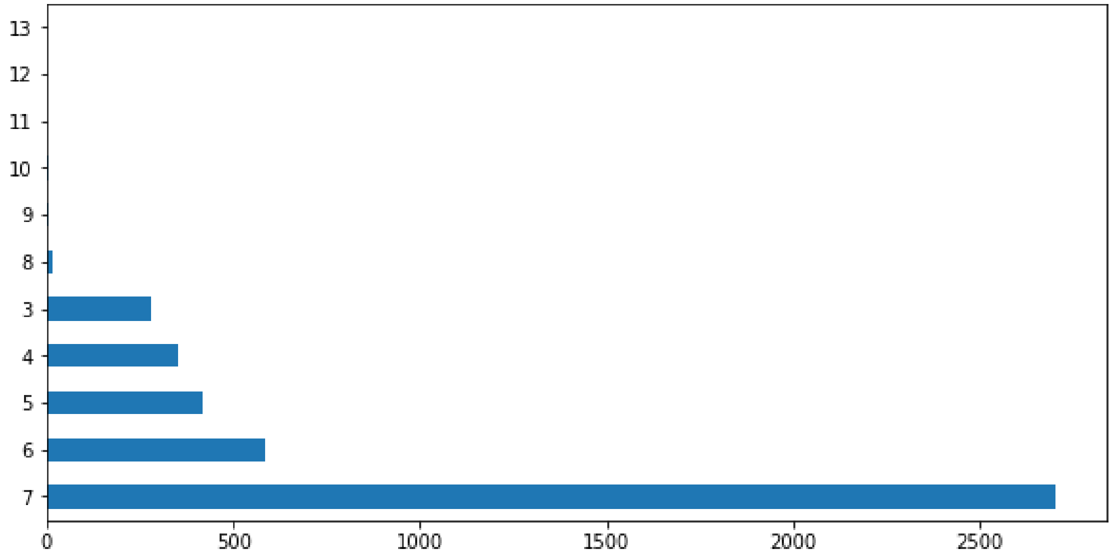
Analyze RFM Segment and Score:

[32]:

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



[33]:
```
df_rfm['rfm_score'].value_counts().plot(kind='barh', figsize=(10, 5));
```



0.2 Week 3

0.2.1 Data Modeling:

1. 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.

[34]:
```
print(df_rfm.shape)
df_rfm.head()
```

```
(4372, 9)
```

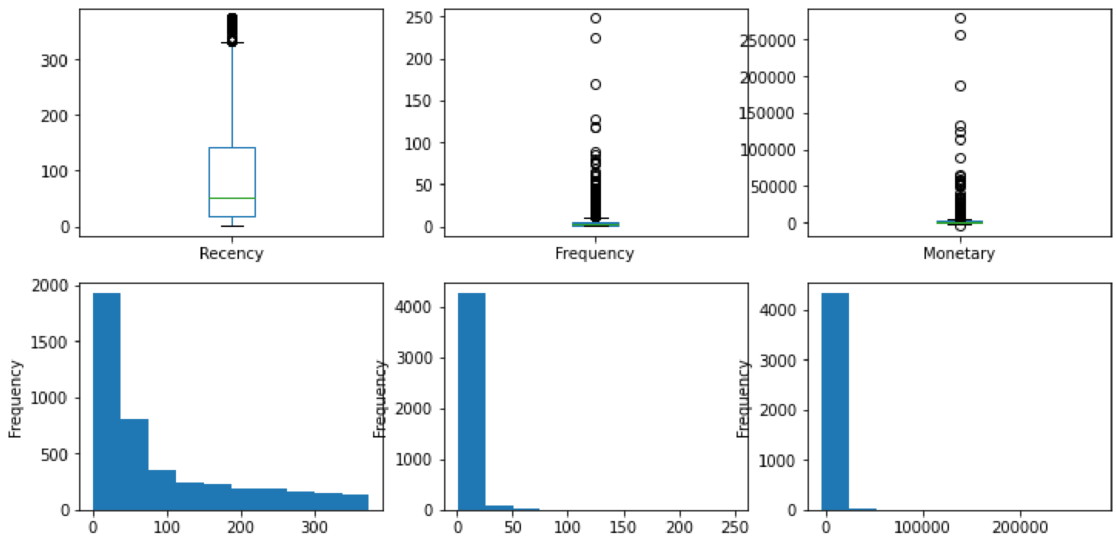
[34]:
```
   CustomerID  Recency  Frequency  Monetary recency_labels frequency_labels  \
0     12346.0      326          2      0.00         oldest           lowest
1     12347.0        2          7   4310.00         newest           lowest
2     12348.0       75          4   1797.24         newest           lowest
3     12349.0       19          1   1757.55         newest           lowest
4     12350.0      310          1    334.40         oldest           lowest

  monetary_labels             rfm_segment  rfm_score
0        smallest  oldest-lowest-smallest          3
1        smallest  newest-lowest-smallest          7
2        smallest  newest-lowest-smallest          7
```

```
3        smallest  newest-lowest-smallest        7
4        smallest  oldest-lowest-smallest        3
```

[36]:
```python
plt.figure(figsize=(12,6))

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



0.3 Week 3

0.3.1 Data Modeling:

1. 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.

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

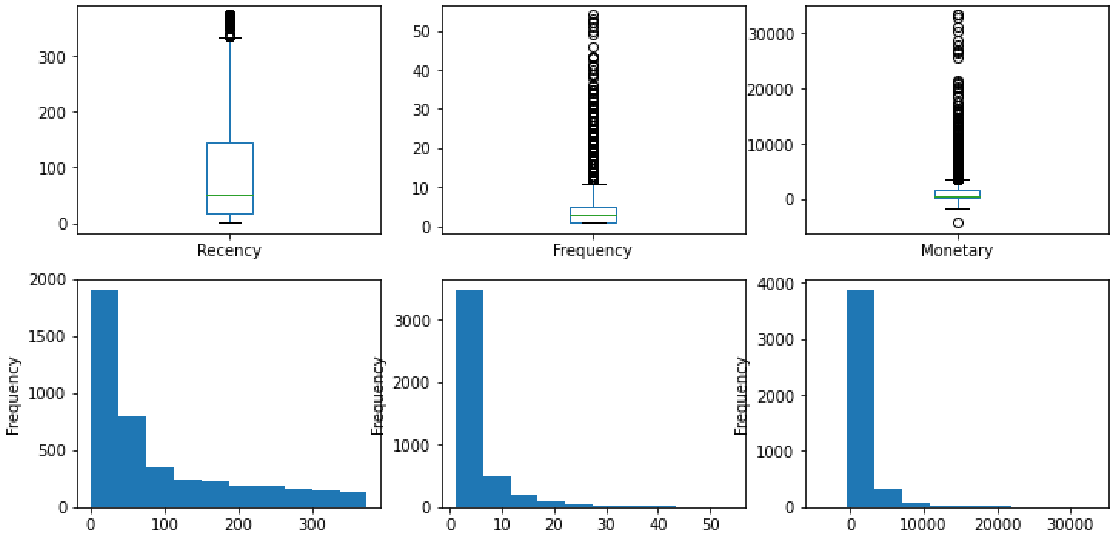
[37]:
```python
df_rfm = df_rfm[(df_rfm['Frequency']<60) & (df_rfm['Monetary']<40000)]
df_rfm.shape
```

[37]: (4346, 9)

26 Customers removed as outlier from out data.

[39]:
```python
plt.figure(figsize=(12,6))

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



Log Transformation: Now since all three features have right skewed data therefore we will use log transformation of these features in our model.

[40]:
```python
df_rfm_log_trans = pd.DataFrame()
df_rfm_log_trans['Recency'] = np.log(df_rfm['Recency'])
df_rfm_log_trans['Frequency'] = np.log(df_rfm['Frequency'])
df_rfm_log_trans['Monetary'] = np.log(df_rfm['Monetary']-df_rfm['Monetary'].
 ↪min()+1)
```

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

[41]:
```python
scaler = StandardScaler()

df_rfm_scaled = scaler.fit_transform(df_rfm_log_trans[['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()
```

[41]:
```
    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
```

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

[42]:
```python
# k-means with some arbitrary k
kmeans = KMeans(n_clusters=3, max_iter=50)
kmeans.fit(df_rfm_scaled)
```

[42]:
```
KMeans(max_iter=50, n_clusters=3)
```

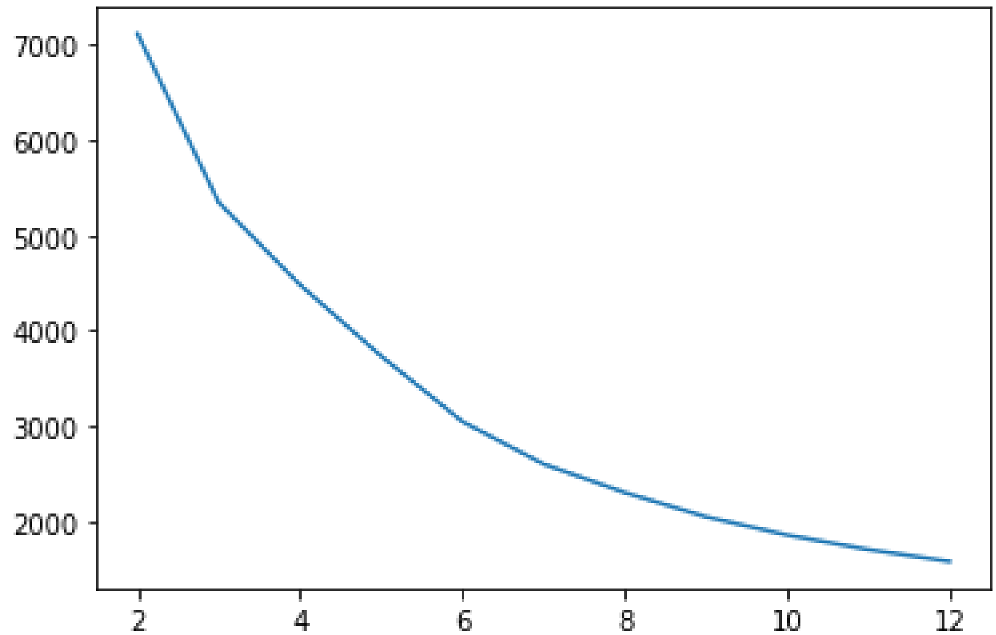
[43]:
```python
kmeans.labels_
```

[43]:
```
array([2, 1, 0, …, 0, 1, 0], dtype=int32)
```

[45]:
```python
# 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);
```



[46]:
```
# 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
```

[46]:

	clusters	intertia
0	2	7113.079519
1	3	5343.136928
2	4	4480.972122
3	5	3730.838474
4	6	3044.921651
5	7	2598.297835
6	8	2299.191284
7	9	2044.597189
8	10	1852.964018
9	11	1700.376798
10	12	1575.623062

[47]:
```
# 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 0.44132753537785846
For n_clusters=3, the silhouette score is 0.38135409490825667
For n_clusters=4, the silhouette score is 0.3623606426972478
For n_clusters=5, the silhouette score is 0.36479947836332627
For n_clusters=6, the silhouette score is 0.34419116171743463
For n_clusters=7, the silhouette score is 0.34288879825359414
For n_clusters=8, the silhouette score is 0.3354507509941627
For n_clusters=9, the silhouette score is 0.3463017984588029
For n_clusters=10, the silhouette score is 0.3560796733393901
```

[48]:
```
# Final model with k=3
kmeans = KMeans(n_clusters=3, max_iter=50)
kmeans.fit(df_rfm_scaled)
```

[48]:
```
KMeans(max_iter=50, n_clusters=3)
```

c. Analyze these clusters and comment on the results.

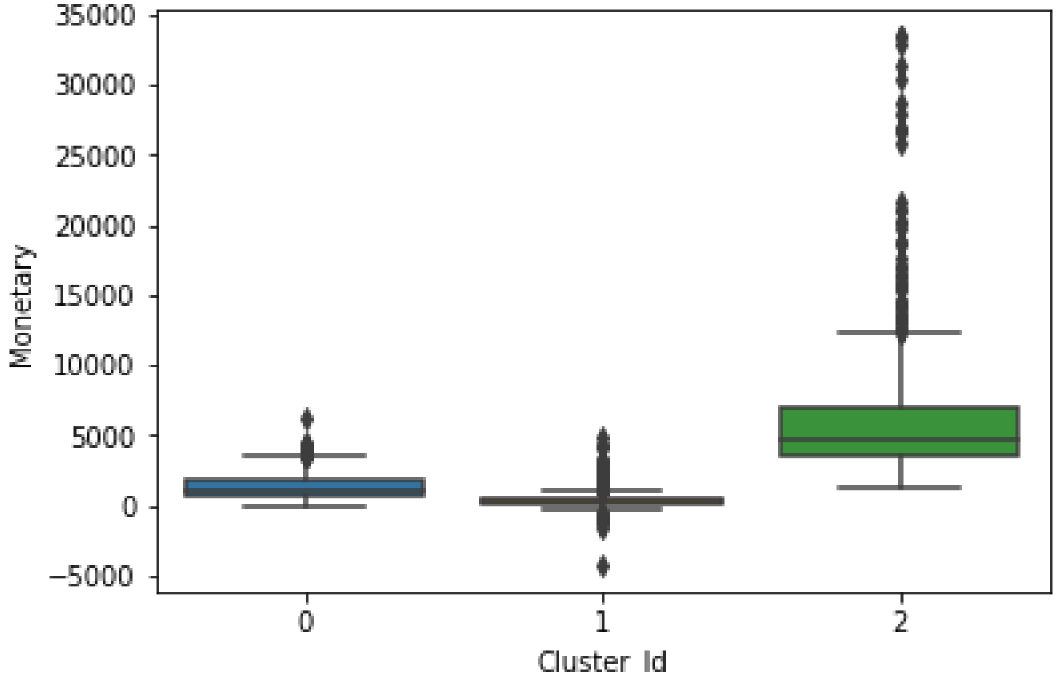
[49]:
```
# assign the label
df_rfm['Cluster_Id'] = kmeans.labels_
df_rfm.head()
```

[49]:

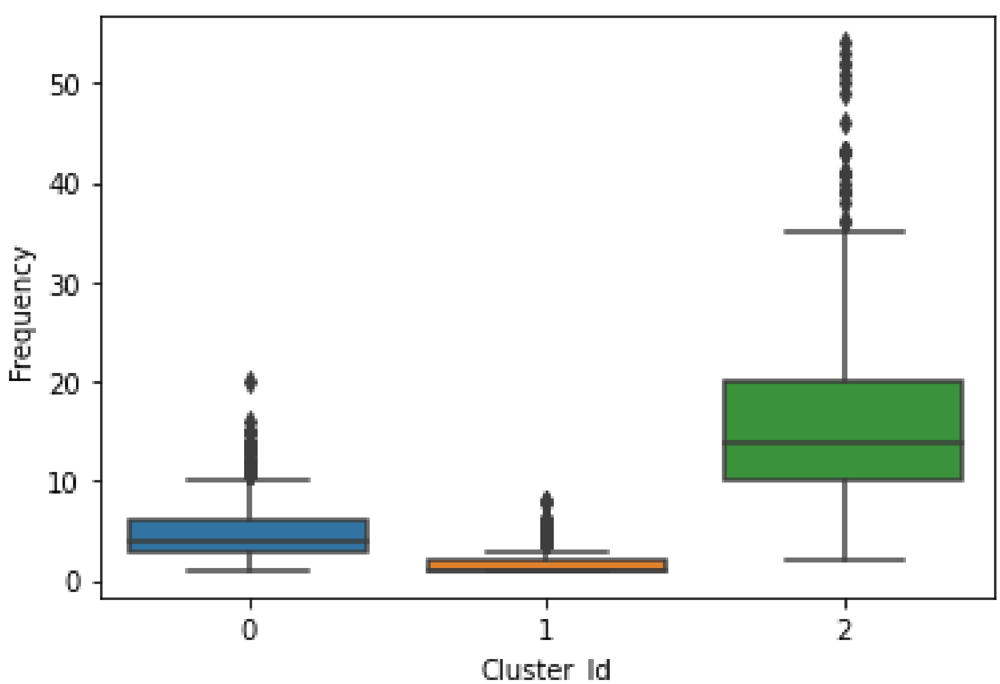
	CustomerID	Recency	Frequency	Monetary	recency_labels	frequency_labels	\
0	12346.0	326	2	0.00	oldest	lowest	
1	12347.0	2	7	4310.00	newest	lowest	
2	12348.0	75	4	1797.24	newest	lowest	
3	12349.0	19	1	1757.55	newest	lowest	
4	12350.0	310	1	334.40	oldest	lowest	

	monetary_labels	rfm_segment	rfm_score	Cluster_Id
0	smallest	oldest-lowest-smallest	3	1
1	smallest	newest-lowest-smallest	7	2
2	smallest	newest-lowest-smallest	7	0
3	smallest	newest-lowest-smallest	7	1
4	smallest	oldest-lowest-smallest	3	1

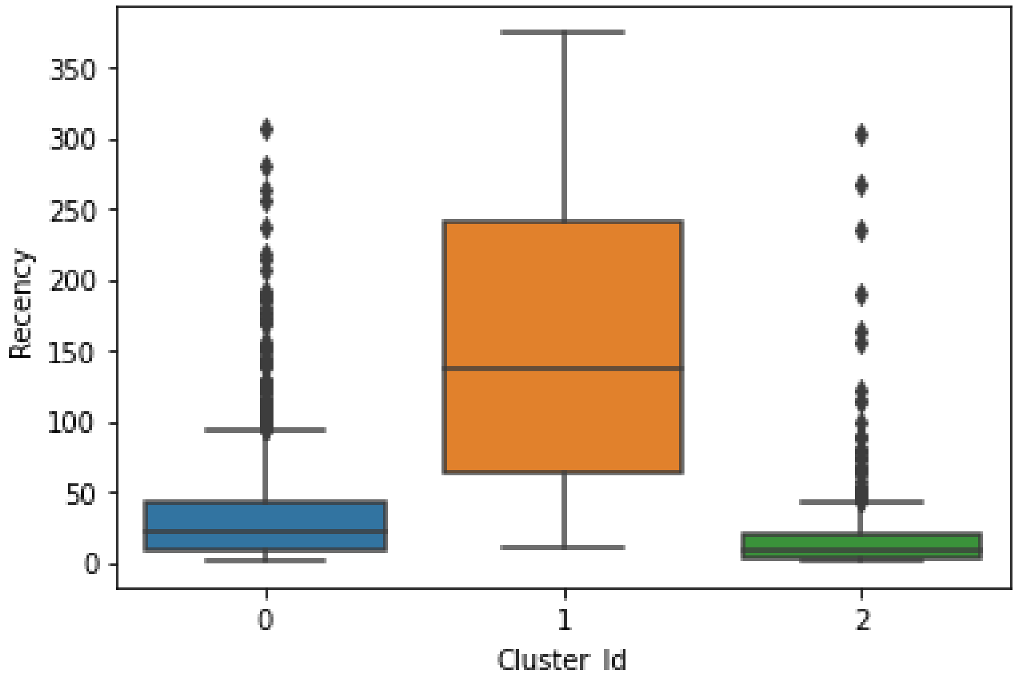
[50]:
```
# Box plot to visualize Cluster Id vs Monetary
sns.boxplot(x='Cluster_Id', y='Monetary', data=df_rfm);
```



[51]:
```
# Box plot to visualize Cluster Id vs Frequency
sns.boxplot(x='Cluster_Id', y='Frequency', data=df_rfm);
```



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



0.3.2 Inference:

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.

0.4 Week 4:

Data Reporting: 1. Create a dashboard in tableau by choosing appropriate chart types and metrics useful for the business. The dashboard must entail the following:

```
a. Country-wise analysis to demonstrate average spend. Use a bar chart to show the monthly
b. Bar graph of top 15 products which are mostly ordered by the users to show the number o
c. Bar graph to show the count of orders vs. hours throughout the day
d. Plot the distribution of RFM values using histogram and frequency charts
e. Plot error (cost) vs. number of clusters selected
f. Visualize to compare the RFM values of the clusters using heatmap
```

[ ]:
```
# Writing dataframe to excel file for creating visualization in tableau
writer = pd.ExcelWriter('C:\\Users\\mgupt\\mgpython\\Capstone Project\\Retail -␣
↪PGP\\output_data.xlsx', engine='xlsxwriter')

df.to_excel(writer, sheet_name='master_data', index=False)
df_rfm.to_excel(writer, sheet_name='rfm_data', index=False)
df_inertia.to_excel(writer, sheet_name='inertia', index=False)
writer.save()
```

[ ]:
```
product_desc = pd.read_excel("Online Retail.xlsx")
product_desc = product_desc[['StockCode', 'Description']]
product_desc = product_desc.drop_duplicates()
product_desc.to_csv('product_desc.csv', index=False)
```

[ ]:
```

```