RETAIL_PROJECT

February 17, 2023

(A) DATA CLEANING

(1) Reading Data and Preliminary Data Inspection

[34]:
```
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
```

[4]:
```
df=pd.read_excel("Online Retail.xlsx")
df.head()
```

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

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

[5]:
```
df.shape                       #shaepe of data
```

[5]:
```
(541909, 8)
```

[6]:
```
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
```

Missing value Treatment

[8]:
```
df.isna().sum()
```

[8]:
```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

[9]:
```
# Calculating the Missing Values % contribution in DF
df_null = round(df.isnull().sum()/len(df)*100,2)
df_null
```

[9]:
```
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
```

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.

[12]:
```
invoice_null_custid = set(df[df['CustomerID'].isnull()]['InvoiceNo'])
df[df['InvoiceNo'].isin(invoice_null_custid) & (~df['CustomerID'].isnull())]
```

[12]:
```
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.

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

[13]:
```
df = df.drop('Description', axis=1)
df = df.dropna()
df.shape
```

[13]:
```
(406829, 7)
```

(b) Removing duplicate records

[14]:
```
df.drop_duplicates(inplace=True)
df.shape
```

[14]:
```
(401602, 7)
```

(c) Perform descriptive anaylysis:

[15]:
```
df['CustomerID']
```

[15]:
```
0         17850.0
1         17850.0
2         17850.0
3         17850.0
4         17850.0
           …
541904    12680.0
541905    12680.0
541906    12680.0
541907    12680.0
541908    12680.0
Name: CustomerID, Length: 401602, dtype: float64
```

[16]:
```
# CustomerID is 'float64', changing the datatype of CustomerId to string
df['CustomerID'] = df['CustomerID'].astype(str)
```

[17]:
```
df.describe(datetime_is_numeric=True)
```

[17]:

	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

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*

[18]:
```
df.describe(include=['O'])
```

[18]:

	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)

(B) Data Transformation

(2) Performing Cohort Analysis

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

[19]:
```
# Convert to InvoiceDate to Year-Month format
df['month_year'] = df['InvoiceDate'].dt.to_period('M')
df['month_year'].nunique()
```

[19]: 13

[20]:
```
df['month_year']
```

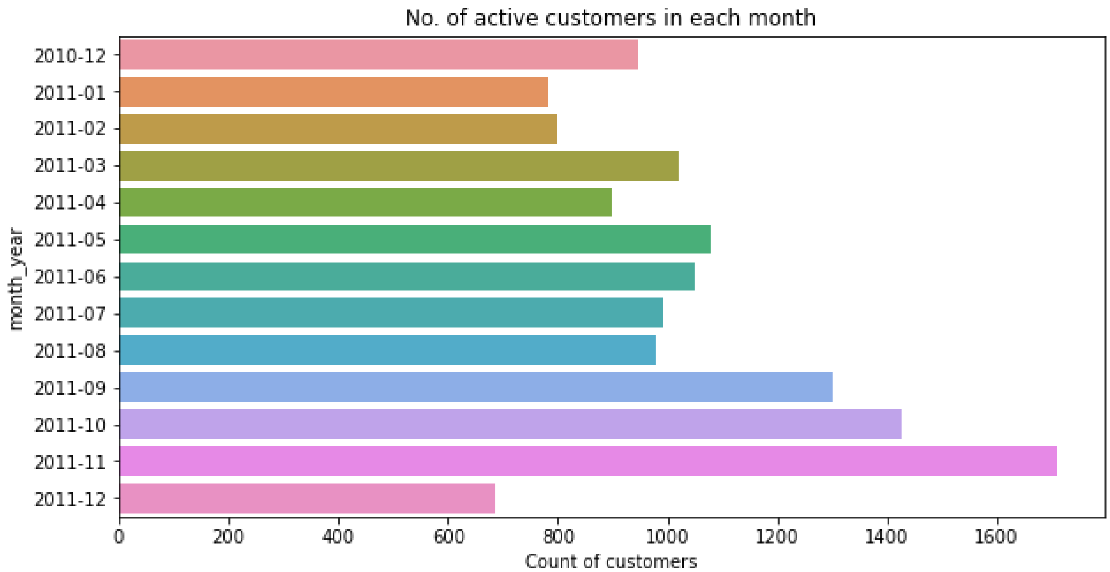
[20]:
```
0         2010-12
1         2010-12
2         2010-12
3         2010-12
4         2010-12
            …
541904    2011-12
541905    2011-12
541906    2011-12
541907    2011-12
541908    2011-12
Name: month_year, Length: 401602, dtype: period[M]
```

[21]:
```
month_cohort = df.groupby('month_year')['CustomerID'].nunique()
month_cohort
```

[21]:
```
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
```

[22]:
```
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")
```

[22]:
```
Text(0.5, 1.0, 'No. of active customers in each month')
```



(b) Analyzing the retention rate of customers:

[23]:
```
month_cohort - month_cohort.shift(1)
```

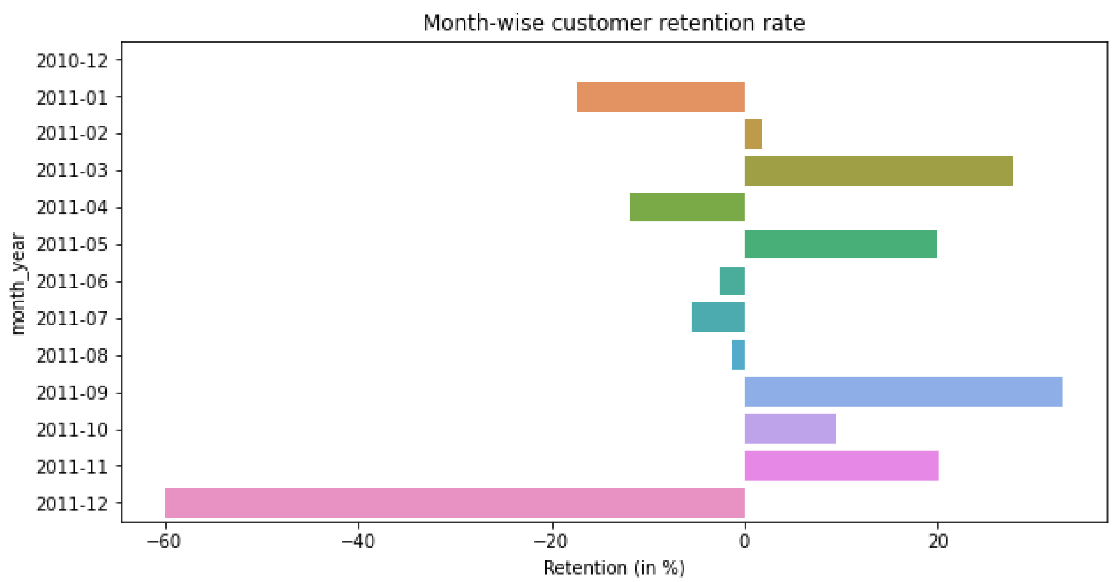
[23]:
```
month_year
2010-12       NaN
2011-01    -165.0
2011-02      15.0
2011-03     222.0
2011-04    -121.0
2011-05     180.0
2011-06     -28.0
2011-07     -58.0
2011-08     -13.0
2011-09     322.0
2011-10     123.0
2011-11     286.0
2011-12   -1025.0
Freq: M, Name: CustomerID, dtype: float64
```

[26]:
```
retention_rate = round(month_cohort.pct_change(periods=1)*100,2)
retention_rate
```

[26]:
```
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
```

[27]:
```
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");
```



Monetary analysis:

[28]:
```
df['amount'] = df['Quantity']*df['UnitPrice']
df.head()
```

[28]:

	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
```

[29]:
```python
df_monetary = df.groupby('CustomerID').sum()['amount'].reset_index()
df_monetary
```

[29]:

	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:

[32]:
```python
df_frequency = df.groupby('CustomerID').nunique()['InvoiceNo'].reset_index()
df_frequency
```

[32]:

	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:

[35]:
```
# 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()
```

[35]:
```
  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
```

[36]:
```
df_recency = df.groupby('CustomerID')['days_to_last_order'].min().reset_index()
df_recency
```

[36]:
```
      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]
```

Calculating RFM metrics:

[37]:
```
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()
```

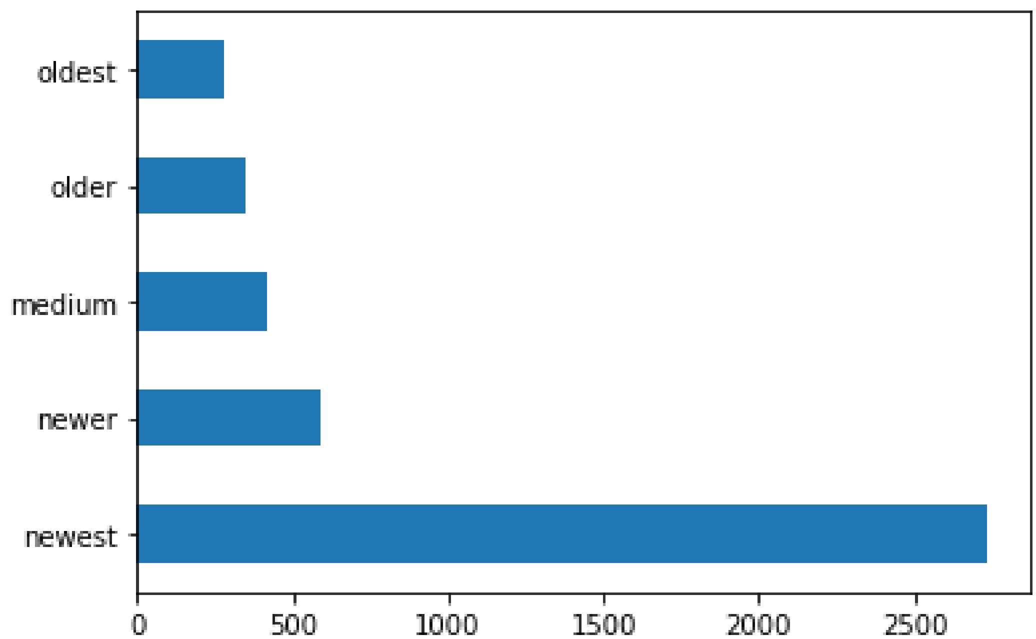
[37]:
```
  CustomerID  Recency  Frequency  Monetary
0    12346.0      326          2      0.00
```

```
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
```

Building RFM Segments:

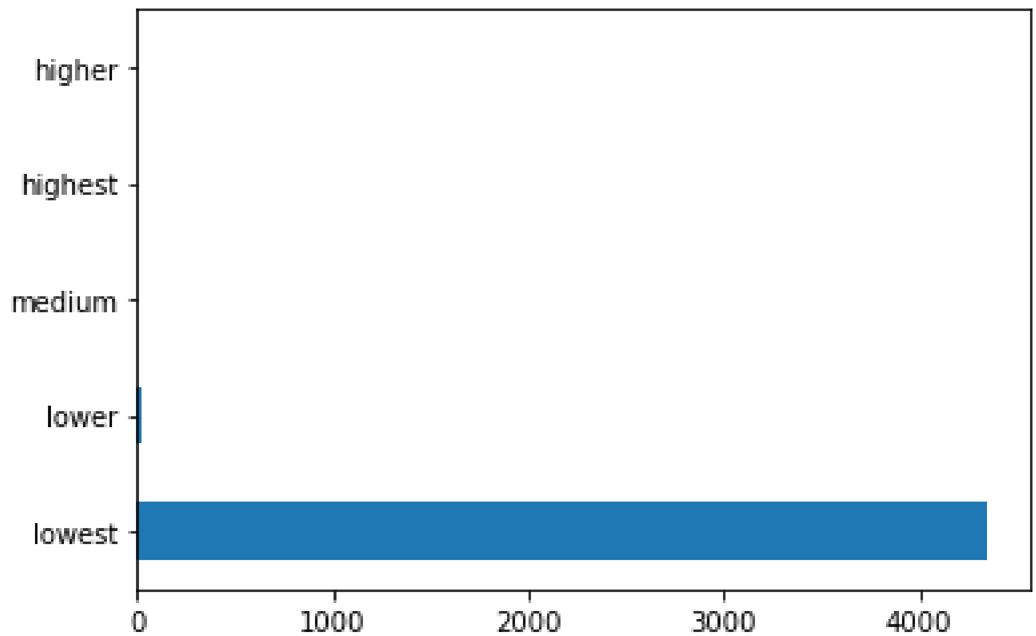
[39]:
```
df_rfm['recency_labels'] = pd.cut(df_rfm['Recency'], bins=5,
                                    labels=['newest', 'newer', 'medium',␣
 ↪'older', 'oldest'])
df_rfm['recency_labels'].value_counts().plot(kind='barh');
df_rfm['recency_labels'].value_counts()
```

[39]:
```
newest    2734
newer      588
medium     416
older      353
oldest     281
Name: recency_labels, dtype: int64
```



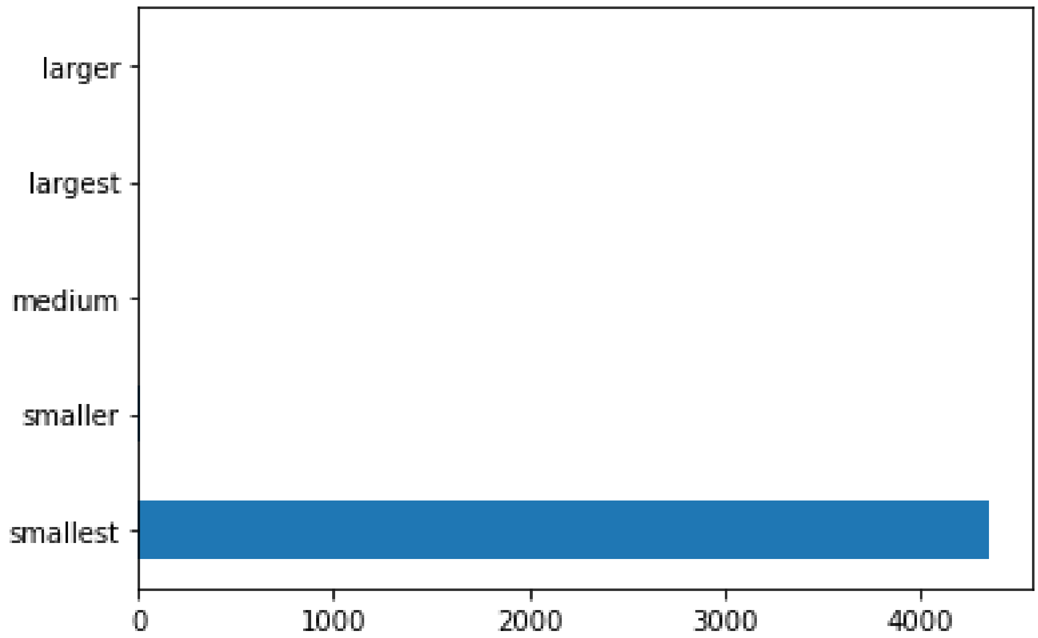
[40]:
```
df_rfm['frequency_labels'] = pd.cut(df_rfm['Frequency'], bins=5,␣
 ↪labels=['lowest', 'lower', 'medium', 'higher', 'highest'])
df_rfm['frequency_labels'].value_counts().plot(kind='barh');
df_rfm['frequency_labels'].value_counts()
```

[40]:
```
lowest     4348
lower        18
medium        3
highest       2
higher        1
Name: frequency_labels, dtype: int64
```



[41]:
```
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()
```

[41]:
```
smallest    4357
smaller        9
medium         3
largest        2
larger         1
Name: monetary_labels, dtype: int64
```



[42]:
```
df_rfm['rfm_segment'] =␣
↪df_rfm[['recency_labels','frequency_labels','monetary_labels']].agg('-'.
↪join, axis=1)
df_rfm.head()
```

[42]:
```
   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:

[43]:
```
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)
```

[43]:

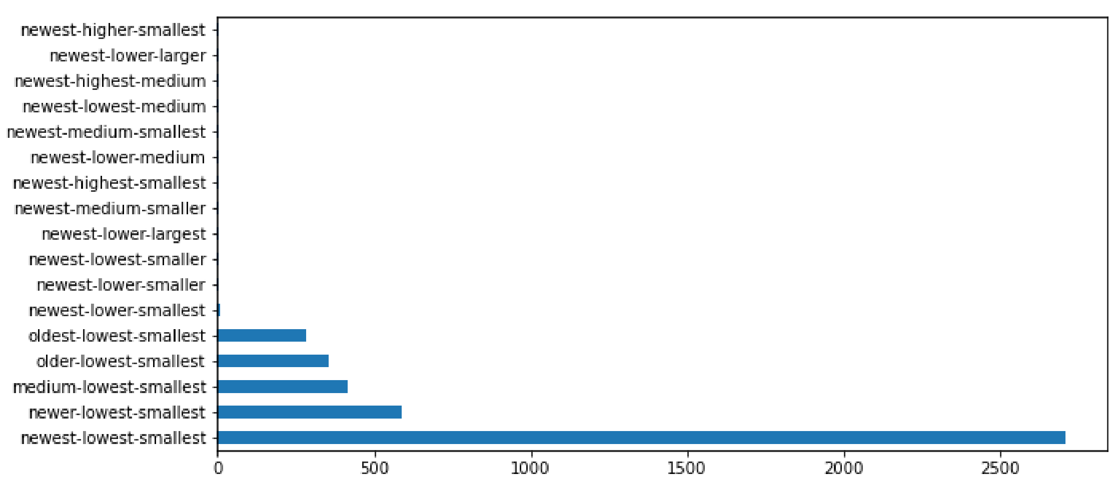
```
   CustomerID  Recency  Frequency  Monetary recency_labels frequency_labels  \
0     12346.0      326          2      0.00         oldest           lowest
1     12347.0        2          7   4310.00         newest           lowest
2     12348.0       75          4   1797.24         newest           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
```

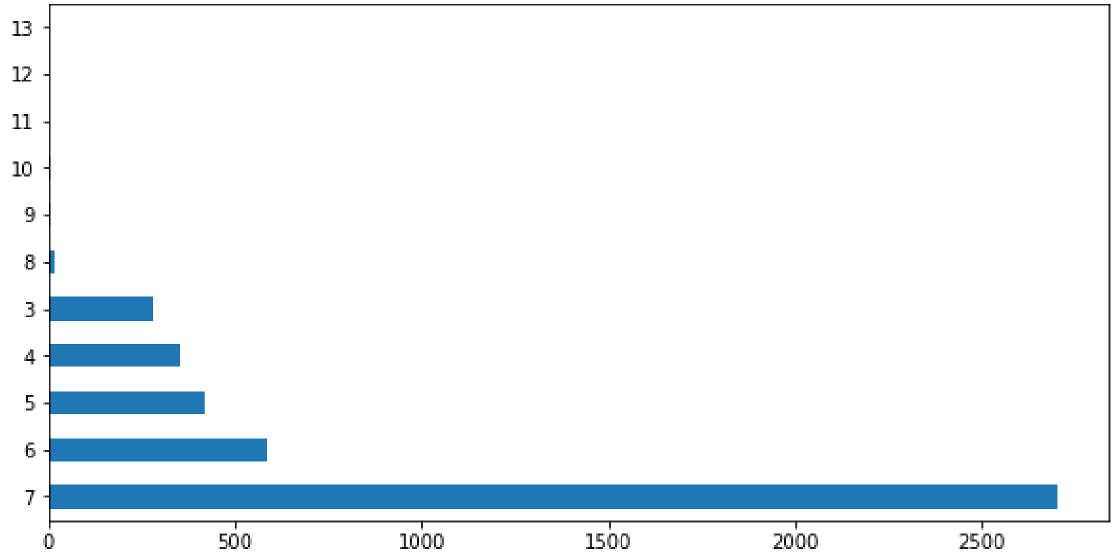
Analyze RFM Segment and Score:

[44]:

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



[45]:
```
df_rfm['rfm_score'].value_counts().plot(kind='barh', figsize=(10, 5));
```



Data Modeling:

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

Standardize the data.

[46]:
```
print(df_rfm.shape)
df_rfm.head()
```

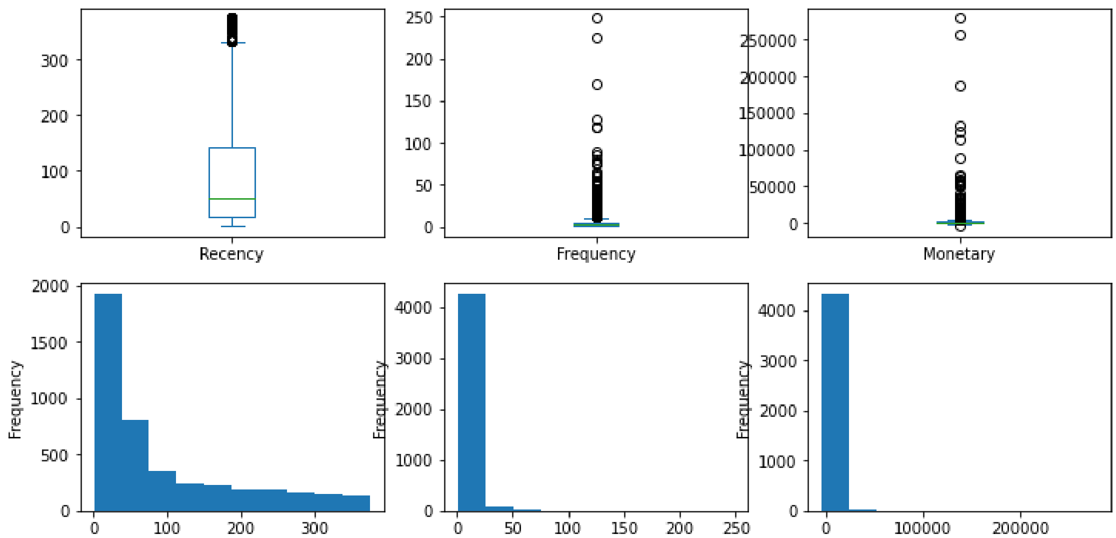
```
(4372, 9)
```

[46]:
```
   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
```

[47]:
```
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')
```



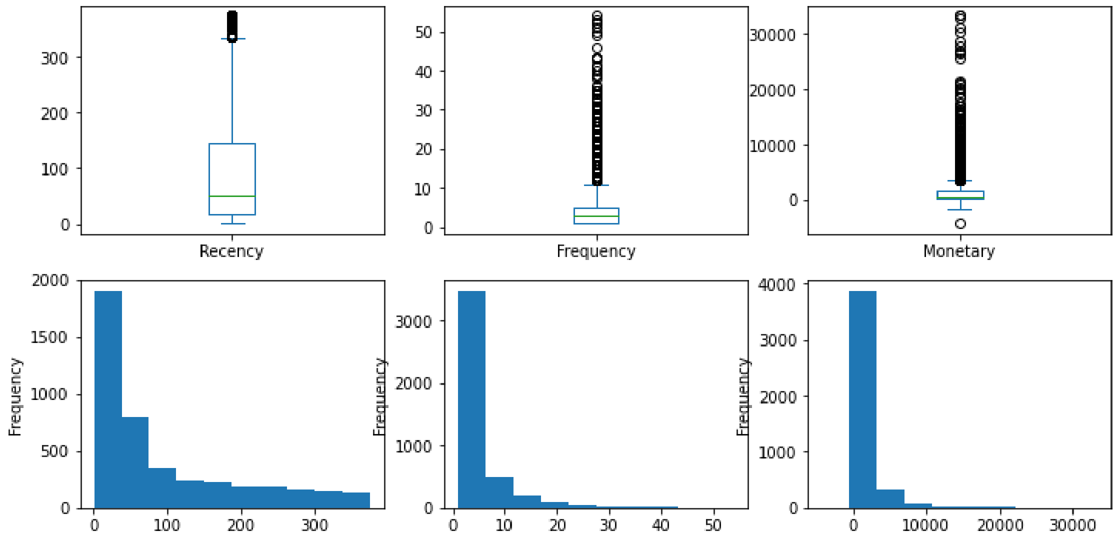
Outliers: Frequency and Monetary features in above data seem to have lot of outliers. Lets drop them.

[48]:
```
df_rfm = df_rfm[(df_rfm['Frequency']<60) & (df_rfm['Monetary']<40000)]
df_rfm.shape
```

[48]: (4346, 9)

[49]:
```
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.

[50]:
```
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.

[51]:
```
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()
```

[51]:

	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.

[53]:
```
# k-means with some arbitrary k
kmeans = KMeans(n_clusters=3, max_iter=50)
kmeans.fit(df_rfm_scaled)
```

[53]:
```
KMeans(max_iter=50, n_clusters=3)
```

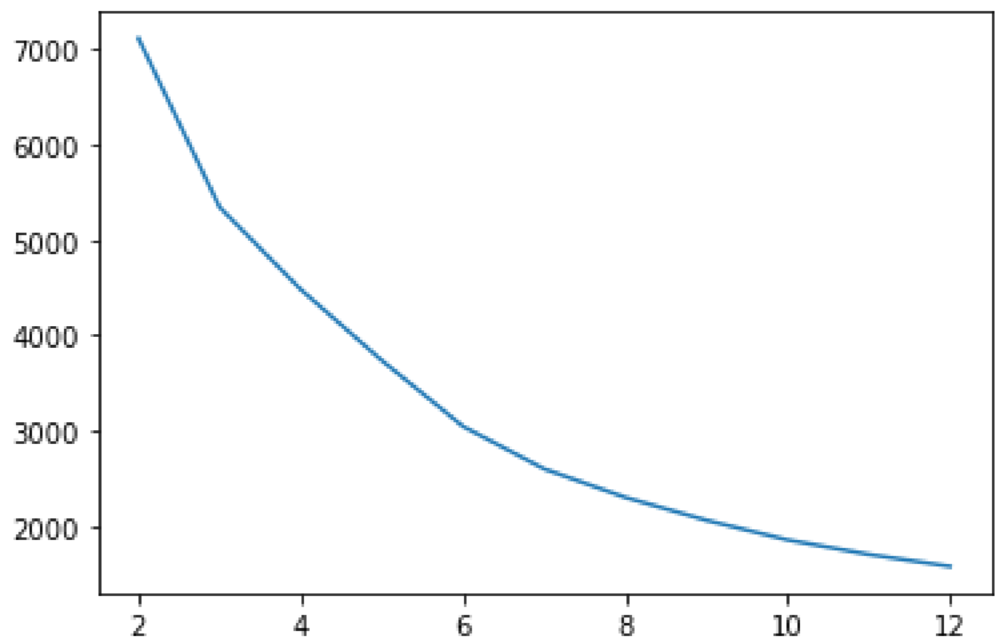
[54]:
```
kmeans.labels_
```

[54]:
```
array([0, 2, 1, …, 1, 2, 1])
```

[55]:
```
# 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);
```



[56]:
```
# 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
```

[56]:

	clusters	intertia
0	2	7113.097396
1	3	5343.174616
2	4	4481.024256
3	5	3734.426149
4	6	3044.587885
5	7	2598.370571
6	8	2299.200834
7	9	2059.009775
8	10	1852.937433
9	11	1700.650181
10	12	1575.548988

[57]:

```
# 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 0.3623384810124692
For n_clusters=5, the silhouette score is 0.3647805446931691
For n_clusters=6, the silhouette score is 0.3441911617174347
For n_clusters=7, the silhouette score is 0.34298427395677433
For n_clusters=8, the silhouette score is 0.3354342829039683
For n_clusters=9, the silhouette score is 0.34646043171996077
For n_clusters=10, the silhouette score is 0.3560807144631476
```

We can select optimum number of clusters as 3 in our final model

[58]:

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

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

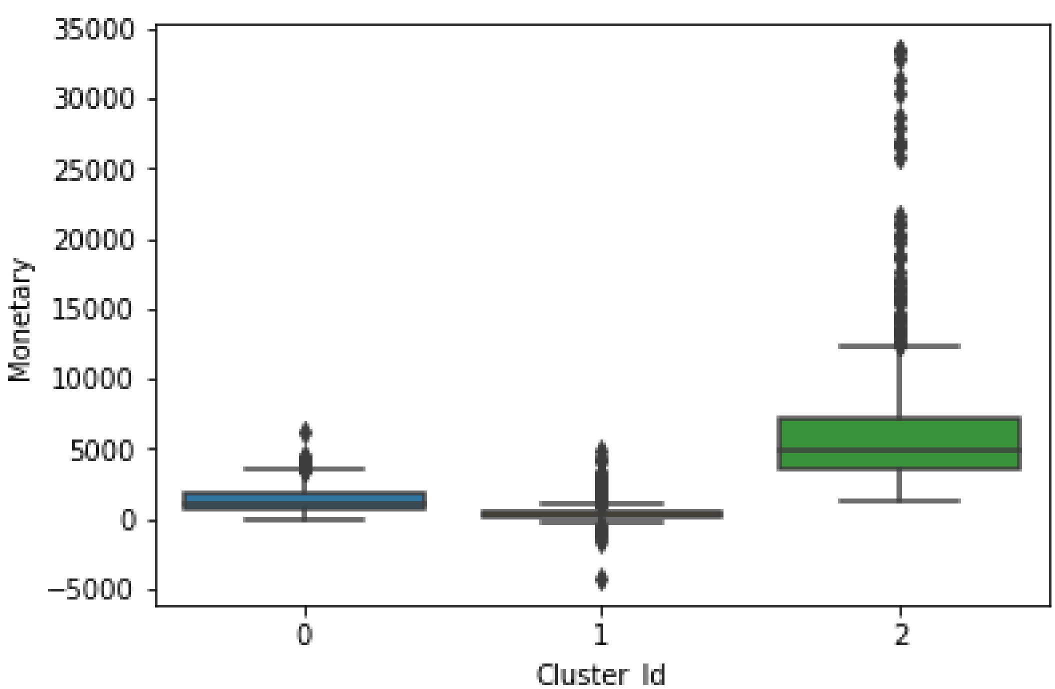
c. Analyze these clusters and comment on the results.

[60]:
```
# assign the label
df_rfm['Cluster_Id'] = kmeans.labels_
df_rfm.head()
```

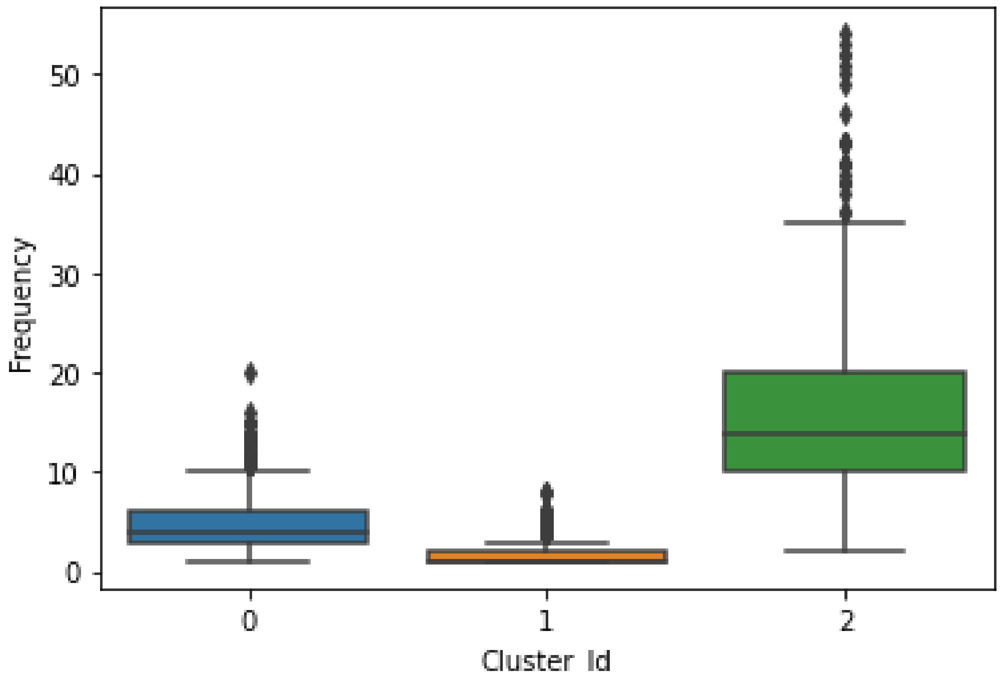
[60]:
```
   CustomerID  Recency  Frequency  Monetary recency_labels frequency_labels  \
0     12346.0      326          2      0.00         oldest           lowest
1     12347.0        2          7   4310.00         newest           lowest
2     12348.0       75          4   1797.24         newest           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
```

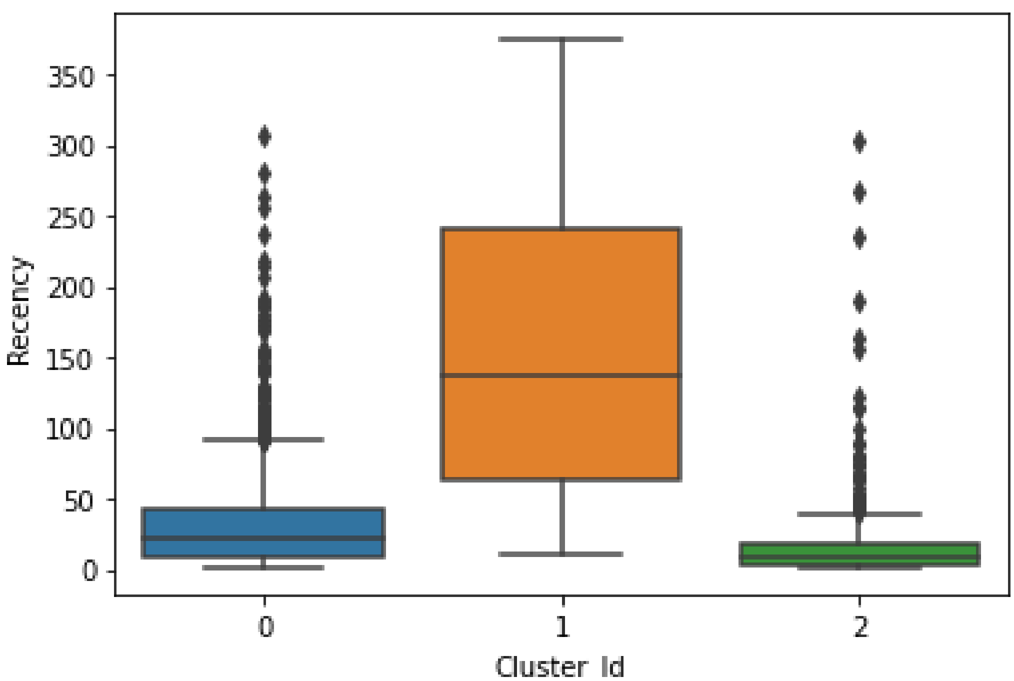
[61]:
```
# Box plot to visualize Cluster Id vs Monetary
sns.boxplot(x='Cluster_Id', y='Monetary', data=df_rfm);
```



[62]:
```
# Box plot to visualize Cluster Id vs Frequency
sns.boxplot(x='Cluster_Id', y='Frequency', data=df_rfm);
```



[63]:
```
# Box plot to visualize Cluster Id vs Recency
sns.boxplot(x='Cluster_Id', y='Recency', data=df_rfm);
```



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.

Data Reporting:

[65]:
```
# Writing dataframe to excel file for creating visualization in tableau
writer = pd.ExcelWriter('C:\\Users\\91940\\Documents\\Retail Capstone␣
↪Project\\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()
```

[ ]:
```
```