Untitled

July 12, 2023

0.1 Importing some of the required libraries

[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
import warnings
warnings.filterwarnings('ignore')
```

1 loading datasets

[2]:
```
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]:
```
# Check shape of data
df.shape
```

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

[4]:
```
# 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
```

1.1 Project Task: Week 1 Data Cleaning: 1. Perform a preliminary data inspection and data cleaning. ### a. Check for missing data and formulate an apt strategy to treat them

[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.
```

[17]:
```
#We can drop Description feature from our data since it is not not going to␣
↪contribute in our mode
```

[18]:
```
invoice_null_custid = set(df[df['CustomerID'].isnull()]['InvoiceNo'])
df[df['InvoiceNo'].isin(invoice_null_custid) & (~df['CustomerID'].isnull())]
```

[18]:
```
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.
```

[21]:
```
df = df.drop('Description', axis=1)
df = df.dropna()
df.shape
```

[21]:
```
(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.
```

[23]:
```
 df = df.drop_duplicates()
df.shape
```

[23]: (401602, 7)

[25]:
```
#(c) Perform descriptive anaylysis on the given data:
```

[26]:
```
# CustomerID is 'float64', changing the datatype of CustomerId to string as␣
  ↪Customer I
df['CustomerID'] = df['CustomerID'].astype(str)
```

[27]:
```
df.describe(datetime_is_numeric=True)
```

[27]:

	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
```

[28]:
```
df.describe(include=['O'])
```

[28]:

	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)

1.2 (B) Data Transformation (2) Perform Cohort Analysis (a) Create month cohort of customers and analyze active customers in each cohort:

[29]:
```
# Convert to InvoiceDate to Year-Month format
df['month_year'] = df['InvoiceDate'].dt.to_period('M')
df['month_year'].nunique()
```

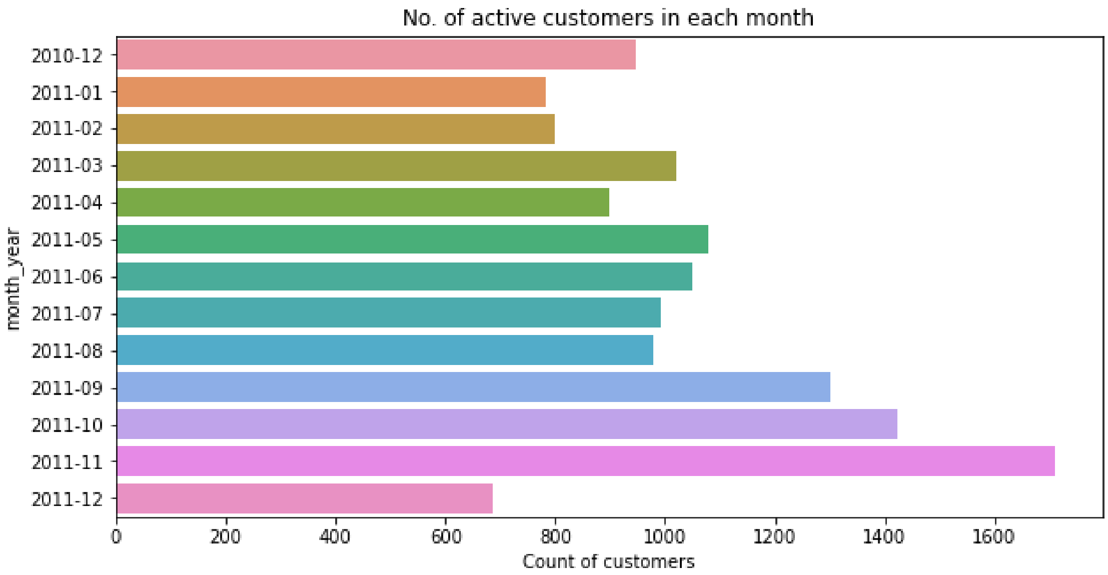
[29]:
```
13
```

[30]:
```
month_cohort = df.groupby('month_year')['CustomerID'].nunique()
month_cohort
```

[30]:
```
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
```

[32]:
```
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")
```

[32]:
```
Text(0.5, 1.0, 'No. of active customers in each month')
```



2 (b) Analyze the retention rate of customers:

[33]:
```
month_cohort - month_cohort.shift(1)
```

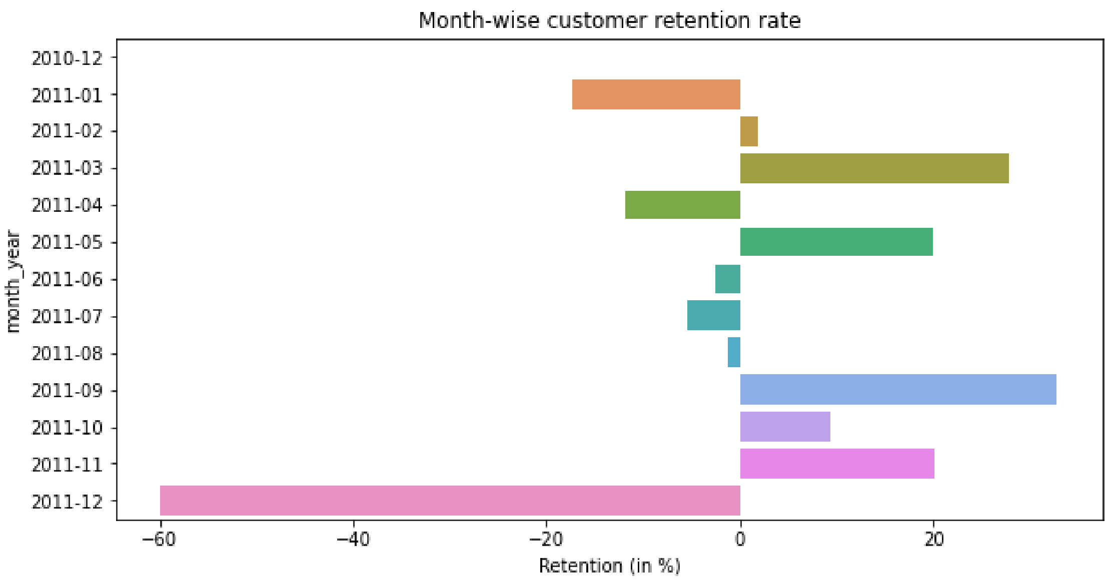
[33]:
```
month_year
2010-12       NaN
2011-01    -165.0
2011-02      15.0
2011-03     222.0
2011-04    -121.0
2011-05     180.0
2011-06     -28.0
2011-07     -58.0
2011-08     -13.0
2011-09     322.0
2011-10     123.0
2011-11     286.0
2011-12   -1025.0
Freq: M, Name: CustomerID, dtype: float64
```

[34]:
```
retention_rate = round(month_cohort.pct_change(periods=1)*100,2)
retention_rate
```

[34]:
```
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
```

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



2.1 Project Task: Week 2 Data Modeling :

1.Build a RFM (Recency Frequency Monetary) model. Recency means the number of days since a customer made the last purchase. Frequency is the number of purchase in a given period. It could be 3 months, 6 months or 1 year. Monetary is the total amount of money a customer spent in that given period.Therefore, big spenders will be differentiated among othercustomers such as MVP (Minimum Viable Product) or VIP.

[36]:
```
df['amount'] = df['Quantity']*df['UnitPrice']
df.head()
```

[36]:
```
  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
```

[51]:
```
df_monetary = df.groupby('CustomerID').sum()['amount'].reset_index()
df_monetary
```

[51]:
```
      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]
```

2.1.1 Frequency Analysis:

[50]:
```
df_frequency = df.groupby('CustomerID').nunique()['InvoiceNo'].reset_index()
# df_freqency = df.drop_duplicates('InvoiceNo').groupby('CustomerID').
 ↪count()['Invoice
df_frequency
```

[50]:
```
      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]
```

3 Recency analysis

[38]:
```python
# We will fix reference date for calculating recency as last transaction day␣
↪in data +
ref_day = max(df['InvoiceDate']) + timedelta(days=1)
df['days_to_last_order'] = (ref_day - df['InvoiceDate']).dt.days
df.head()
```

[38]:
```
  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
```

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

[ ]:
```
      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]
```

3.0.1 2.Calculate RFM metrics:

[52]:
```
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()
```

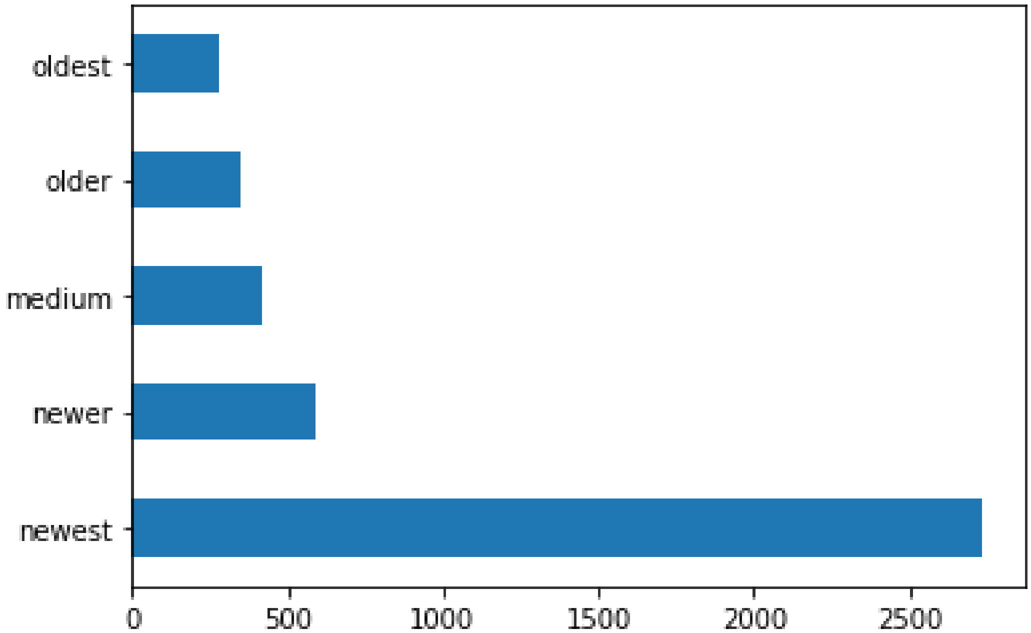
[52]:

	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

3. Build RFM Segments. Give recency, frequency, and monetary scores individually by dividing them into quartiles. b1. Combine three ratings to get a RFM segment (as strings).b2. Get the RFM score by adding up the three ratings.b3. Analyze the RFM segments by summarizing them and comment on the findings

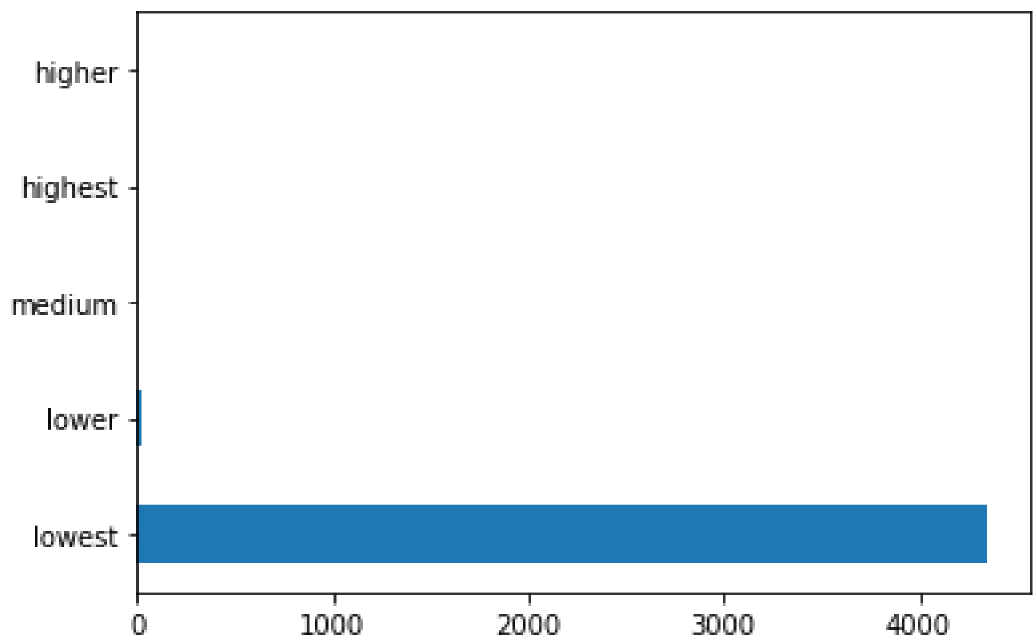
[58]:
```
df_rfm['recency_labels'] = pd.cut(df_rfm['Recency'], bins=5,
                                     labels=['newest', 'newer', 'medium',␣
 ↪'older', 'oldest'])
df_rfm['recency_labels'].value_counts().plot(kind='barh');
df_rfm['recency_labels'].value_counts()
```

[58]:
```
newest    2734
newer      588
medium     416
older      353
oldest     281
Name: recency_labels, dtype: int64
```



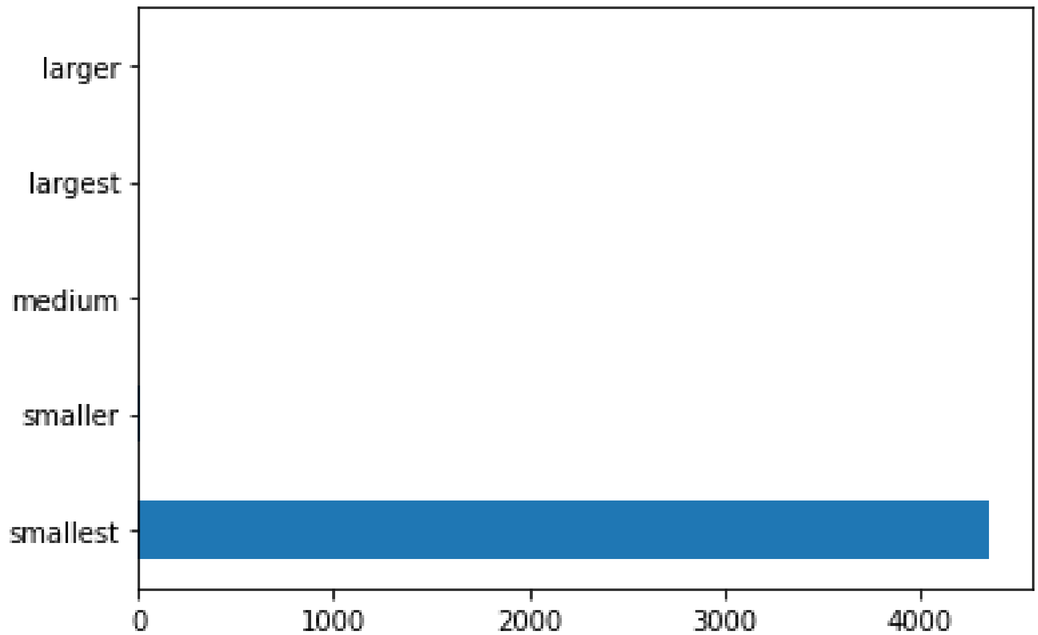
[59]:
```
df_rfm['frequency_labels'] = pd.cut(df_rfm['Frequency'], bins=5,␣
 ↪labels=['lowest', 'lower', 'medium', 'higher', 'highest'])
df_rfm['frequency_labels'].value_counts().plot(kind='barh');
df_rfm['frequency_labels'].value_counts()
```

[59]:
```
lowest     4348
lower        18
medium        3
highest       2
higher        1
Name: frequency_labels, dtype: int64
```



[60]:
```
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()
```

[60]:
```
smallest    4357
smaller        9
medium         3
largest        2
larger         1
Name: monetary_labels, dtype: int64
```



[61]:
```
df_rfm['rfm_segment] =␣
↪df_rfm[['recency_labels','frequency_labels','monetary_labels']].agg('-'.
↪join, axis=1)
df_rfm.head()
```

[61]:
```
   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
```

3.0.2 RFM Score:

[62]:
```
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)
```

[62]:

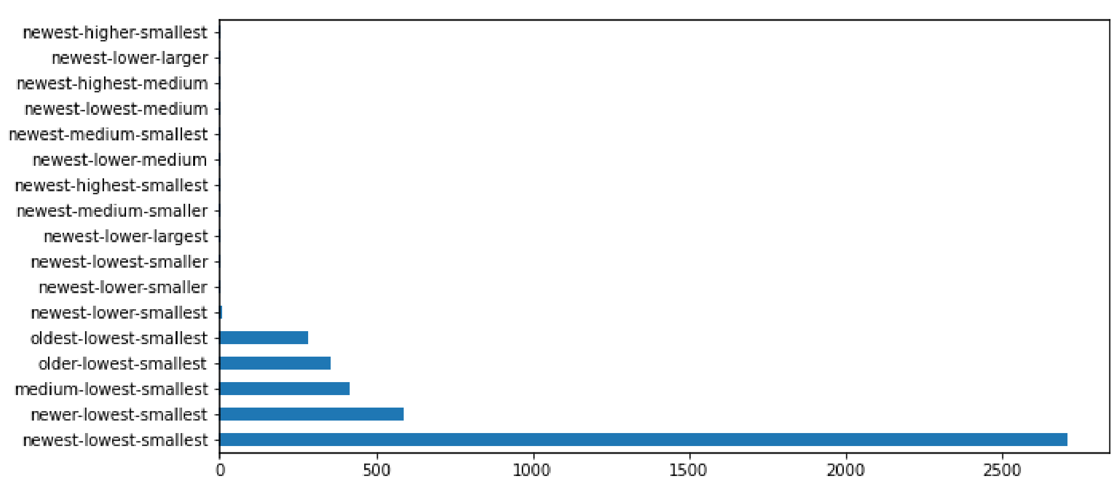
```
   CustomerID  Recency  Frequency  Monetary recency_labels frequency_labels  \
0     12346.0      326          2      0.00         oldest           lowest
1     12347.0        2          7   4310.00         newest           lowest
2     12348.0       75          4   1797.24         newest       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

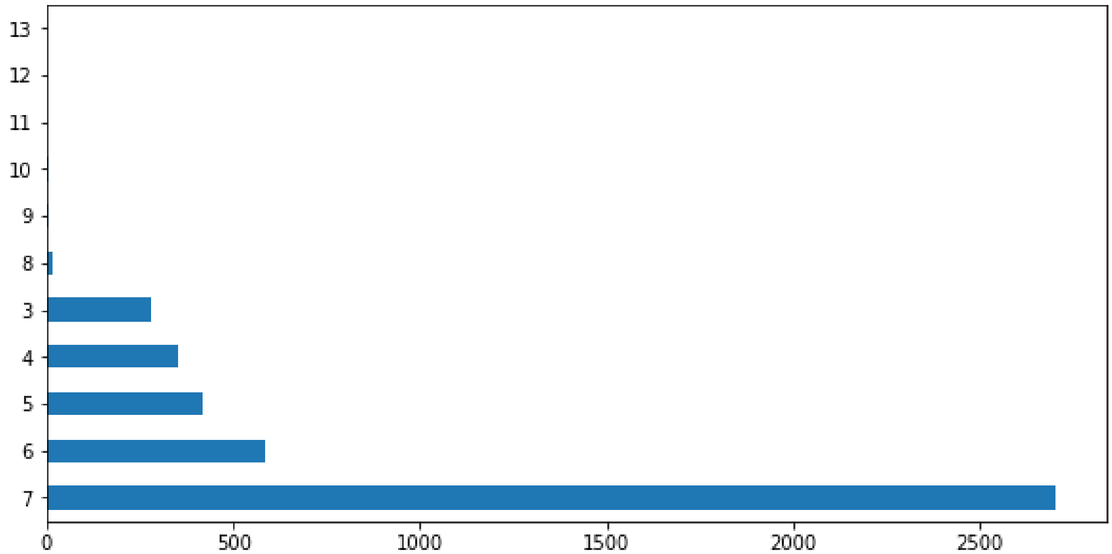
Analyze RFM Segment and Score:

[63]:

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



[65]:
```
df_rfm['rfm_score'].value_counts().plot(kind='barh', figsize=(10, 5));
```



3.0.3 Week 3 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.

[66]:
```
print(df_rfm.shape)
df_rfm.head()
```

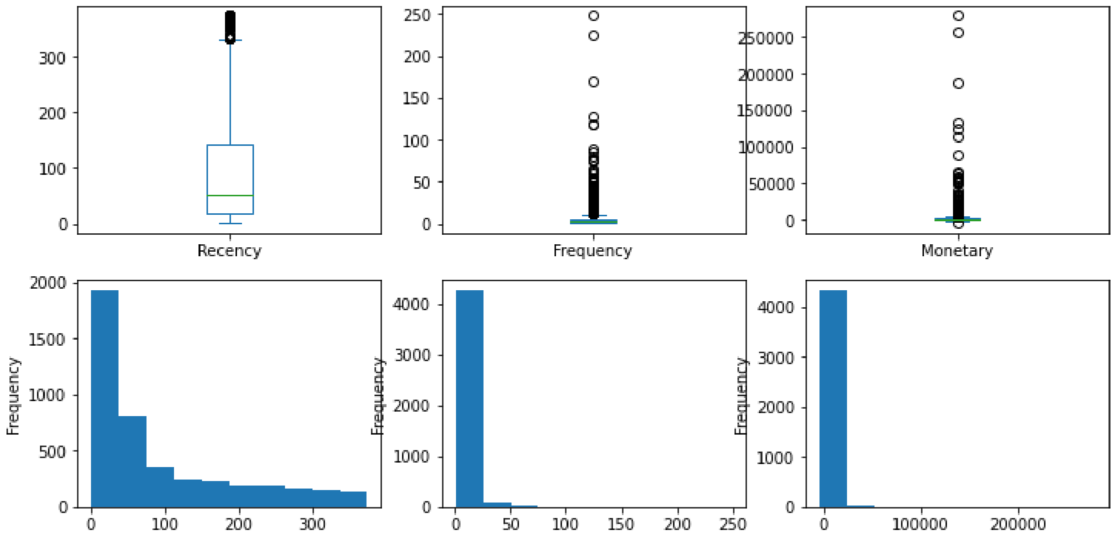
(4372, 9)

[66]:

	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

[67]:
```
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')
```



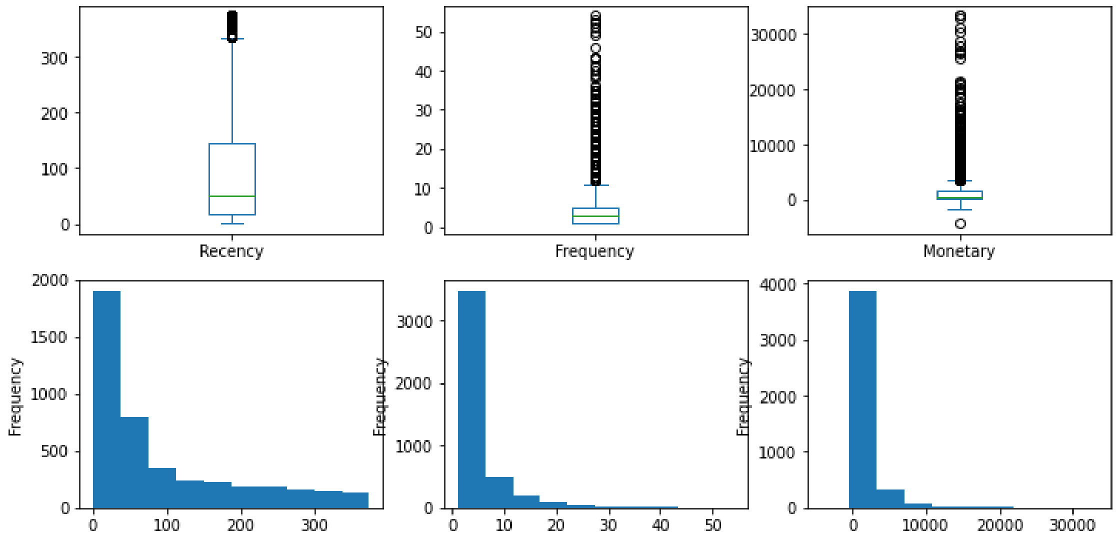
[68]:
```
df_rfm = df_rfm[(df_rfm['Frequency']<60) & (df_rfm['Monetary']<40000)]
df_rfm.shape
```

[68]: (4346, 9)

[69]:
```
#26 Customers removed as outlier from out data
```

[ ]:
```
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.

[75]:
```
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.

[79]:
```
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()
```

[79]:

	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

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

[80]:
```
# k-means with some arbitrary k
kmeans = KMeans(n_clusters=3, max_iter=50)
kmeans.fit(df_rfm_scaled)
```

[80]:
```
KMeans(max_iter=50, n_clusters=3)
```

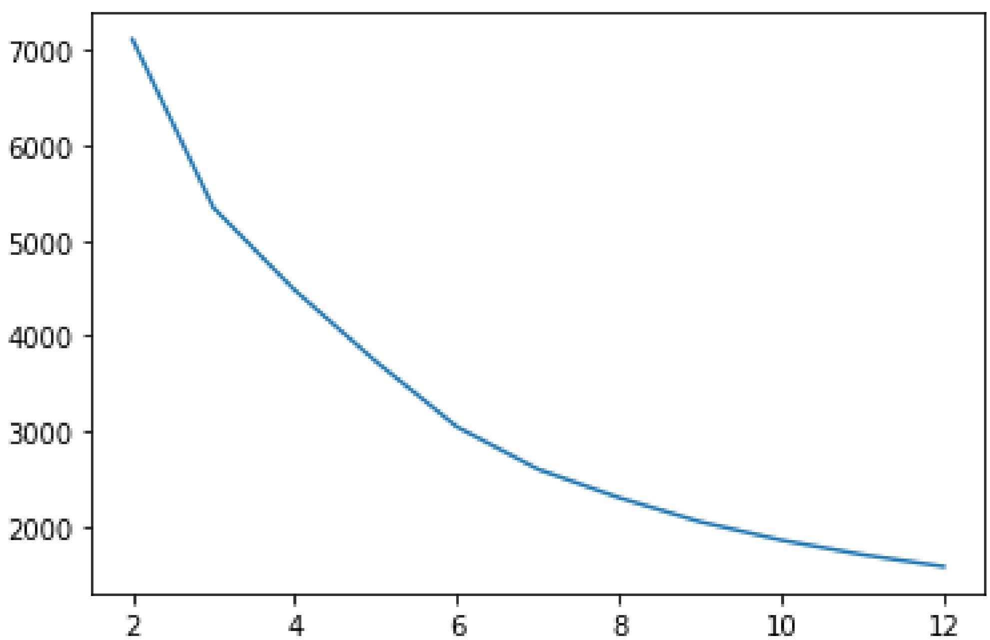
[81]:
```
kmeans.labels_
```

[81]:
```
array([0, 2, 1, …, 1, 2, 1], dtype=int32)
```

[82]:
```
# 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);
```



[83]:
```
# 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
```

[83]:

	clusters	intertia
0	2	7113.097396
1	3	5343.182393
2	4	4480.985776
3	5	3730.676741
4	6	3044.917979
5	7	2598.356279
6	8	2299.142287
7	9	2046.008391
8	10	1852.939782
9	11	1700.381102
10	12	1575.800345

[84]:
```
# 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 0.3811235033662067
For n_clusters=4, the silhouette score is 0.3625766786588676
For n_clusters=5, the silhouette score is 0.3648264755963477
For n_clusters=6, the silhouette score is 0.3439832765349906
For n_clusters=7, the silhouette score is 0.34286177322166456
For n_clusters=8, the silhouette score is 0.33661053193907375
For n_clusters=9, the silhouette score is 0.3471980079870914
For n_clusters=10, the silhouette score is 0.35525328655734983
```

[85]:
```
# Final model with k=3
kmeans = KMeans(n_clusters=3, max_iter=50)
kmeans.fit(df_rfm_scaled)
```

[85]:
```
KMeans(max_iter=50, n_clusters=3)
```

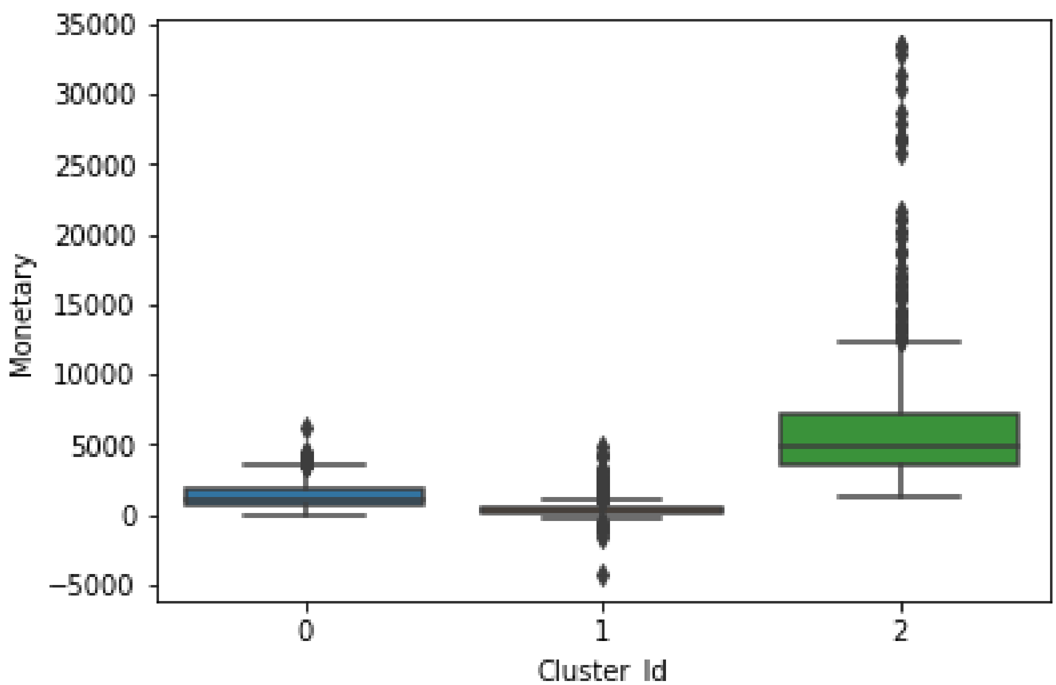
3.0.5 c. Analyze these clusters and comment on the results.

[86]:
```
# assign the label
df_rfm['Cluster_Id'] = kmeans.labels_
df_rfm.head()
```

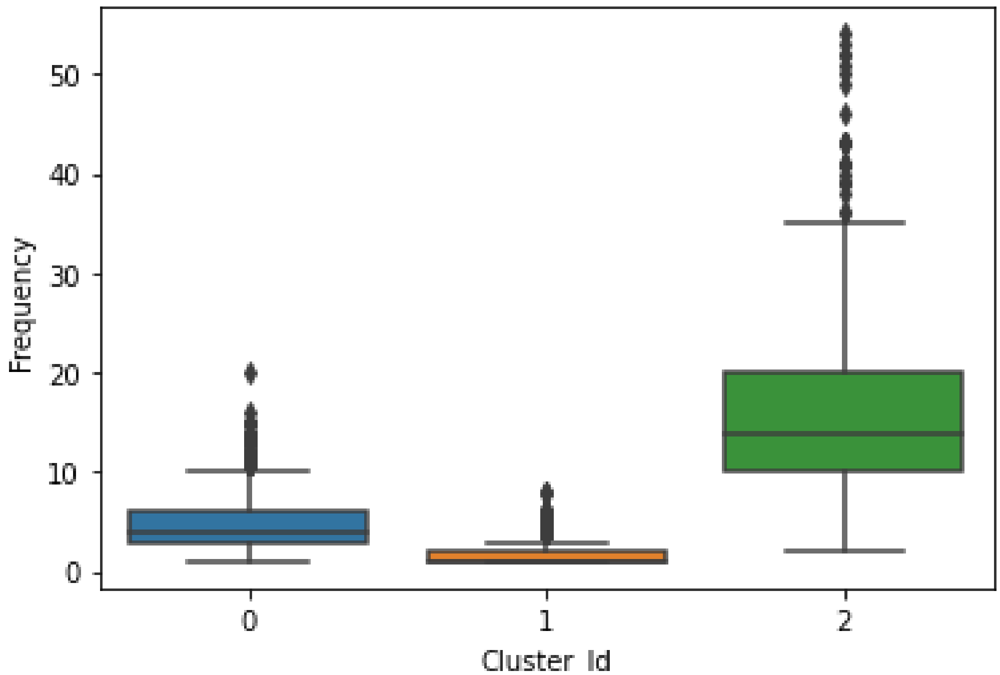
[86]:
```
   CustomerID  Recency  Frequency  Monetary recency_labels frequency_labels  \
0     12346.0      326          2      0.00         oldest           lowest
1     12347.0        2          7   4310.00         newest           lowest
2     12348.0       75          4   1797.24         newest           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
```

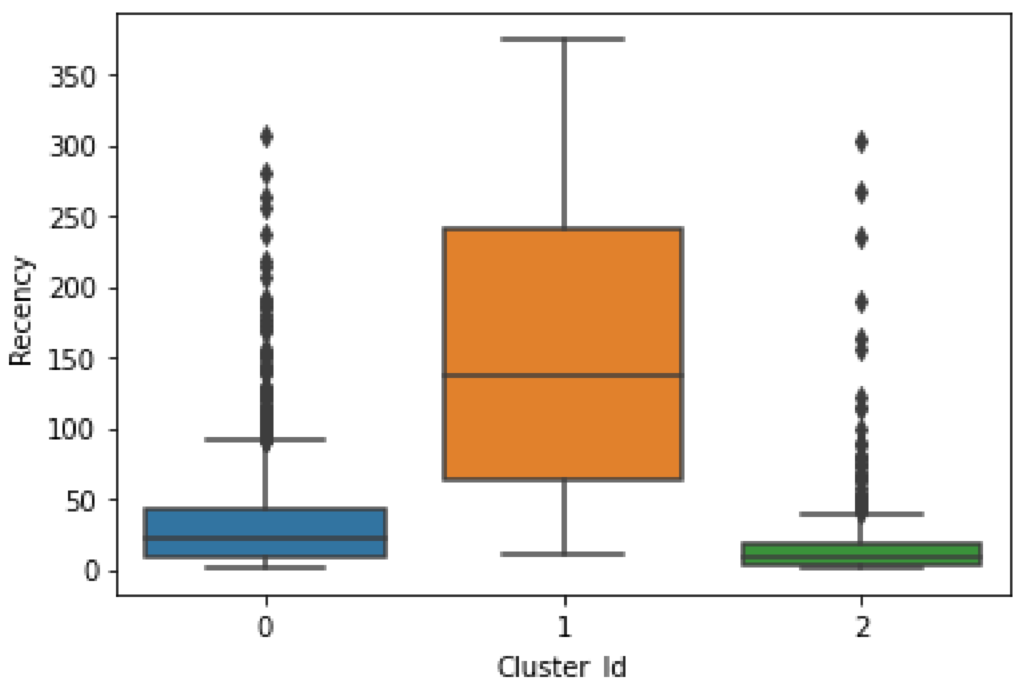
[87]:
```
# Box plot to visualize Cluster Id vs Monetary
sns.boxplot(x='Cluster_Id', y='Monetary', data=df_rfm);
```



[88]:
```
# Box plot to visualize Cluster Id vs Frequency
sns.boxplot(x='Cluster_Id', y='Frequency', data=df_rfm);
```



[89]:
```
# Box plot to visualize Cluster Id vs Recency
sns.boxplot(x='Cluster_Id', y='Recency', data=df_rfm);
```



3.1 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.

3.2 Week 4:

Data Reporting:

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 figures
b. Bar graph of top 15 products which are mostly ordered by the users to show the number of products sold
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\\mgpython\\Capstone Project\\Retail -␣
↪retail\\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()
```

[93]:
```
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)
```

[ ]:
```

```