Week 1

(A) Data Cleaning

(1) Reading Data and Preliminary Data Inspection

In [1]:

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

In [5]:

```
df = pd.read_excel("Online Retail.xlsx")
df.head()
```

Out[5]:

	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 [6]:

```
# Check shape of data
df.shape
```

Out[6]:

```
(541909, 8)
```

In [7]:

```
# 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
```

```
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 33.1+ MB
```

(a) Missing values treatment:

In [8]:

```
# Check missing values in data
df.isnull().sum()
```

Out[8]:

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

In [9]:

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

Out[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
```

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.

In [10]:

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

Out[10]:

InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country

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.

will drop all rows having null values in **CustomerID**.

In [11]:

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

Out[11]:

```
(406829, 7)
```

- **Remove Duplicate Data Records**

In [12]:

```
df = df.drop_duplicates()
df.shape
```

Out[12]:

```
(401602, 7)
```

- **Perform descriptive anaylysis on the given data:**

In [13]:

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

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

In [14]:

```
df.describe(datetime_is_numeric=True)
```

Out[14]:

	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

In [15]:

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

Out[15]:

	InvoiceNo	StockCode	CustomerID	Country
count	401602	401602	401602	401602

	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) Perform Cohort Analysis

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

In [16]:

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

Out[16]:

```
13
```

In [17]:

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

Out[17]:

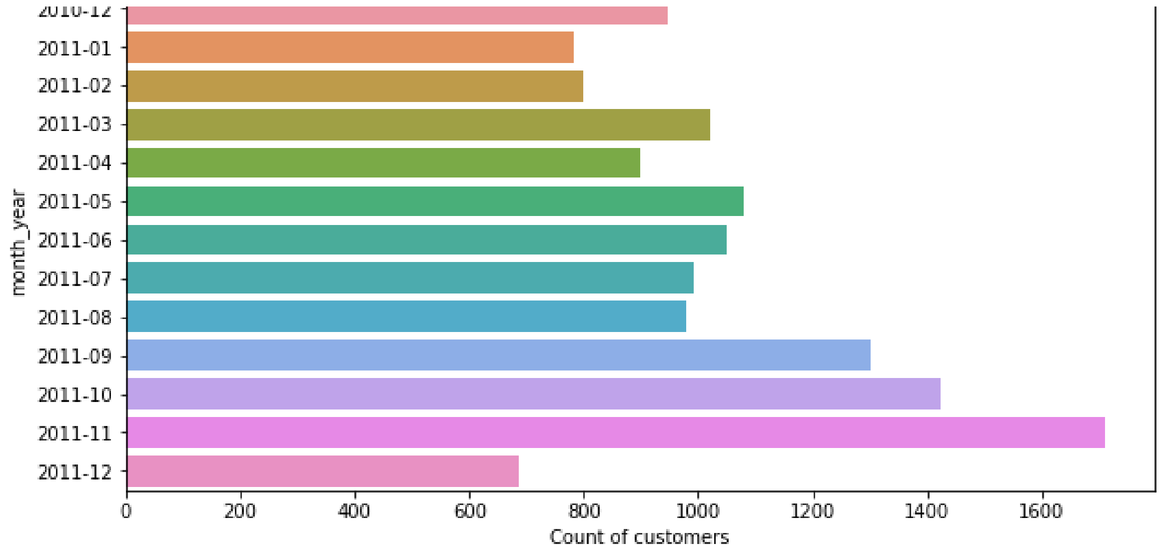
```
month_year
2010-12     948
2011-01     783
2011-02     798
2011-03    1020
2011-04     899
2011-05    1079
2011-06    1051
2011-07     993
2011-08     980
2011-09    1302
2011-10    1425
2011-11    1711
2011-12     686
Freq: M, Name: CustomerID, dtype: int64
```

In [18]:

```
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[18]:

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



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

In [19]:

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

Out[19]:

```
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 [20]:

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

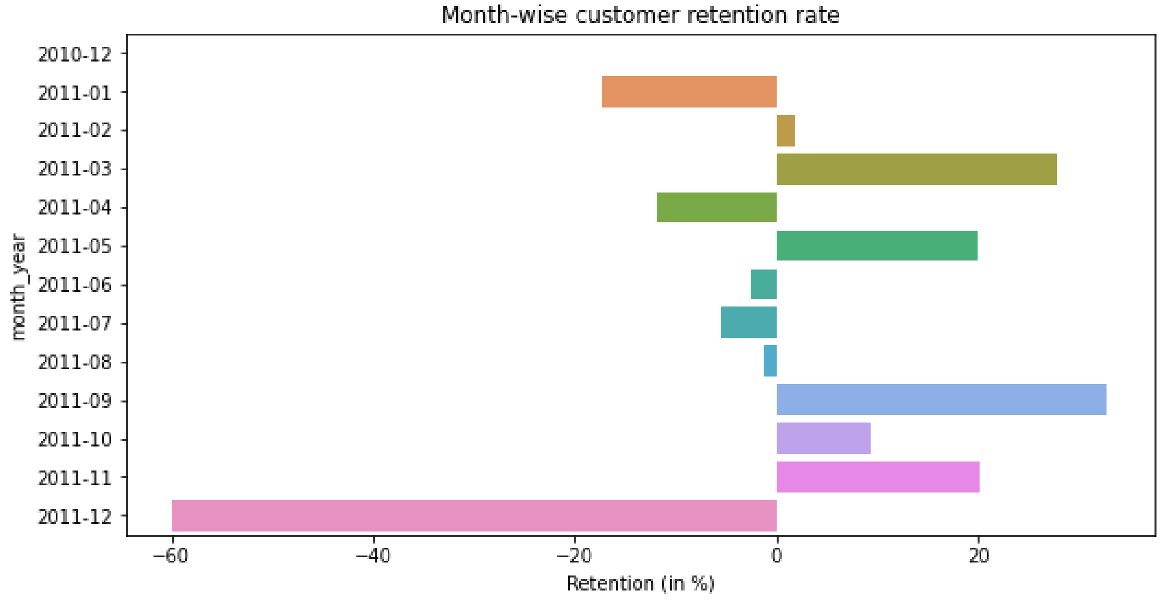
Out[20]:

```
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 [21]:

```
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");
```



Week 2

Monetary analysis:

In [22]:

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

Out[22]:

	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 [23]:

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

Out[23]:

	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

	CustomerID	amount
4371	18287.0	1837.28

4372 rows × 2 columns

Frequency Analysis:

In [24]:

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

Out[24]:

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

4372 rows × 2 columns

Recency Analysis:

In [25]:

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

Out[25]:

	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 [26]:

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

Out[26]:

	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

Calculate RFM metrics:

In [27]:

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

Out[27]:

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

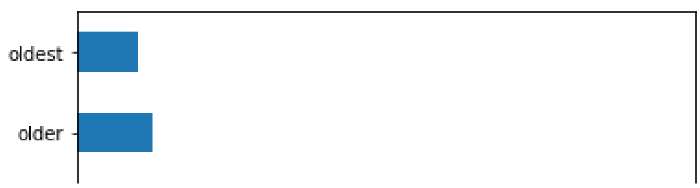
Build RFM Segments:

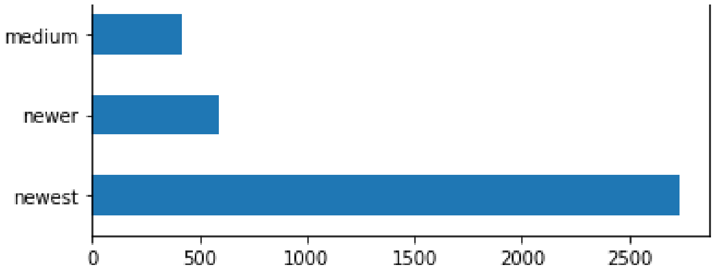
In [28]:

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

Out[28]:

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



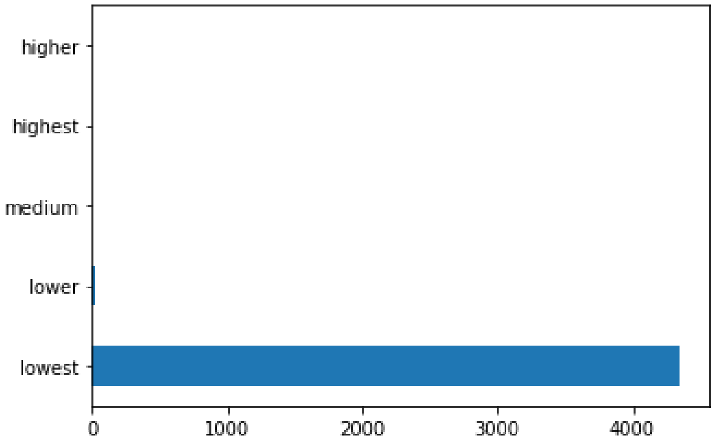


In [29]:

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

Out[29]:

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

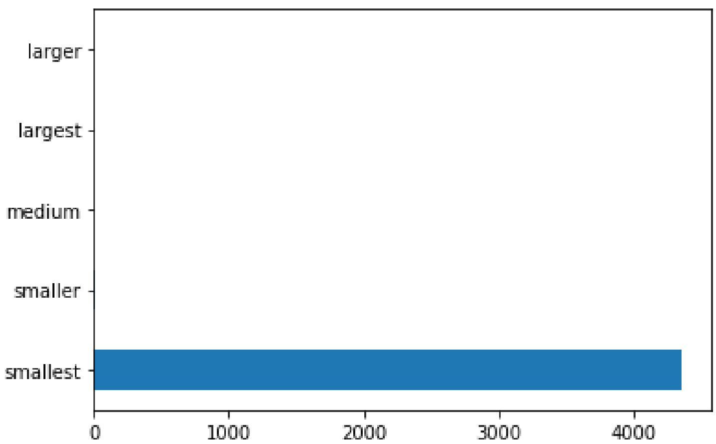


In [30]:

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

Out[30]:

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



In [31]:

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

Out[31]:

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

RFM Score:

In [32]:

```
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['fr
equency_labels'].map(frequency_dict).astype(int) + df_rfm['monetary_labels'].map(monetary
_dict).astype(int)
df_rfm.head(10)
```

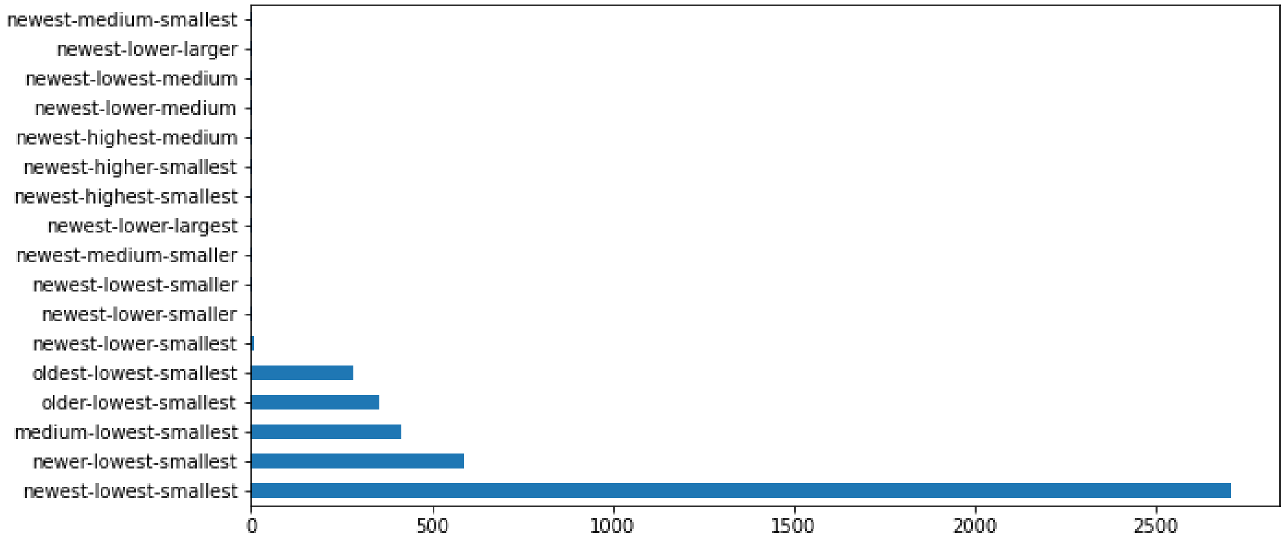
Out[32]:

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

Analyze RFM Segment and Score:

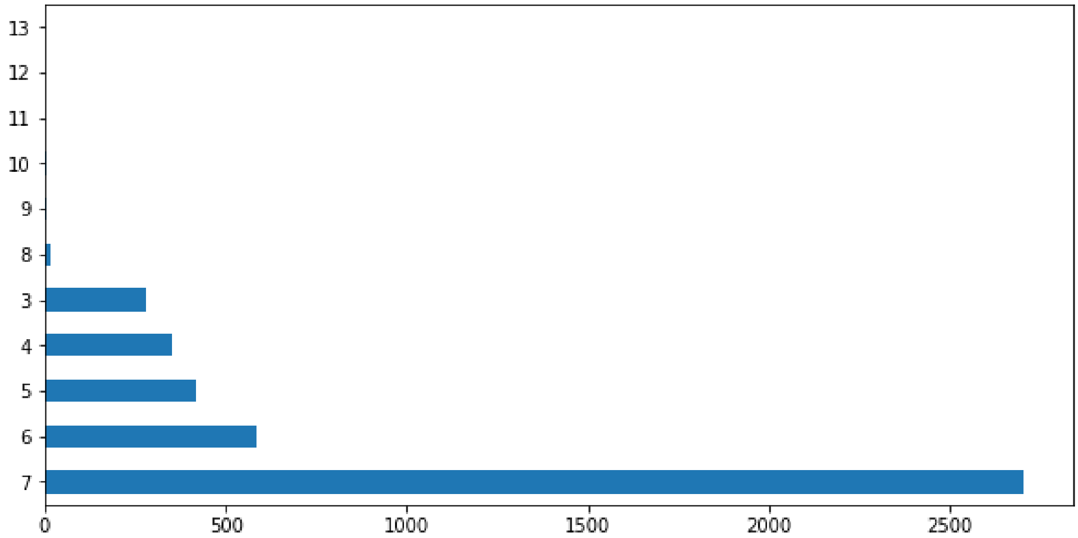
In [33]:

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



In [34]:

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



Week 3

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.

In [35]:

```
print(df_rfm.shape)
df_rfm.head()
```

```
(4372, 9)
```

Out[35]:

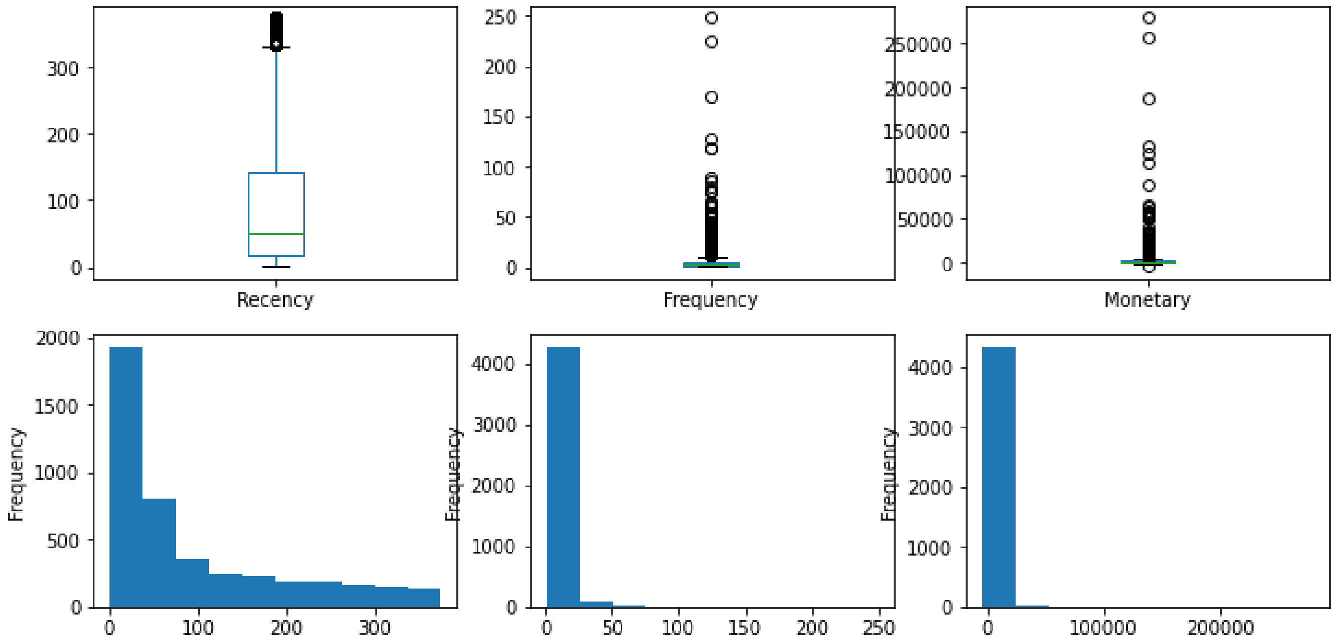
	CustomerID	Recency	Frequency	Monetary	recency_labels	frequency_labels	monetary_labels	rfm_segment	rfm_score
0	12346.0	326	2	0.00	oldest	lowest	smallest	oldest-lowest-smallest	3

	CustomerID	Recency	Frequency	Monetary	recency_labels	frequency_labels	monetary_labels	rfm_segment	rfm_score
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 [36]:

```
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.

In [37]:

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

Out[37]:

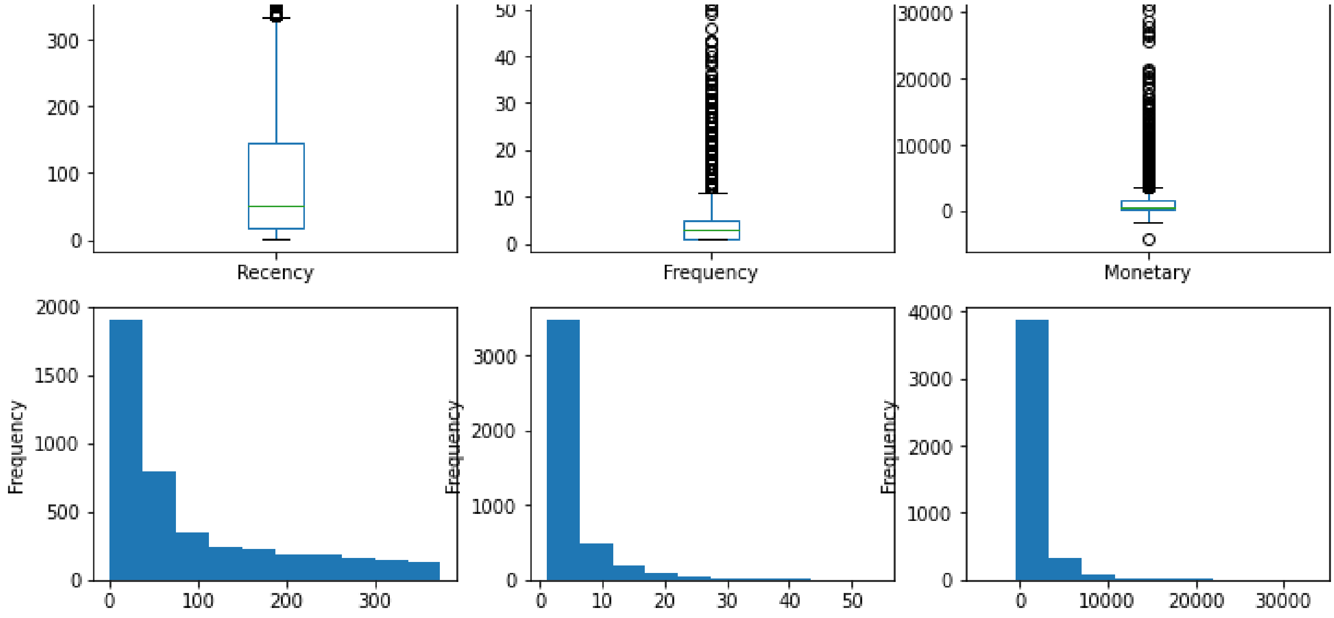
```
(4346, 9)
```

26 Customers removed as outlier from out data.

In [38]:

```
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.

In [39]:

```
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.

In [40]:

```
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()
```

Out[40]:

	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

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

In [41]:

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

Out[41]:

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

In [42]:

```
kmeans.labels_
```

Out[42]:

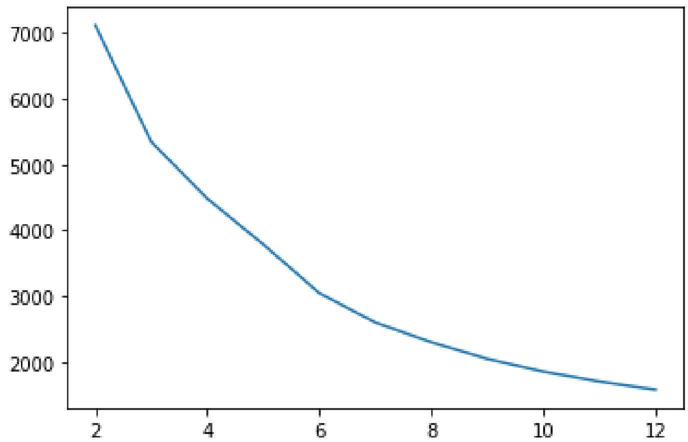
```
array([1, 2, 0, ..., 0, 2, 0], dtype=int32)
```

In [44]:

```
# 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);
```



In [45]:

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

Out[45]:

	clusters	intertia
0	2	7113.109513
1	3	5342.971796
2	4	4481.048697
3	5	3785.373165
4	6	3044.762404
5	7	2598.356762
6	8	2299.190463
7	9	2046.139776
8	10	1852.942921
9	11	1701.037621
10	12	1577.637020

In [46]:

```
# 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, silhouet
te_avg))
```

```
For n_clusters=2, the silhouette score is 0.44128763222934275
For n_clusters=3, the silhouette score is 0.378607043168158
For n_clusters=4, the silhouette score is 0.3624403057293662
For n_clusters=5, the silhouette score is 0.36658309957878316
For n_clusters=6, the silhouette score is 0.34567607415791557
For n_clusters=7, the silhouette score is 0.34283740266136054
For n_clusters=8, the silhouette score is 0.33527304671436015
For n_clusters=9, the silhouette score is 0.34655190413990344
For n_clusters=10, the silhouette score is 0.3559680772943256
```

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

In [47]:

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

Out[47]:

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

Analyze these clusters and comment on the results.

In [48]:

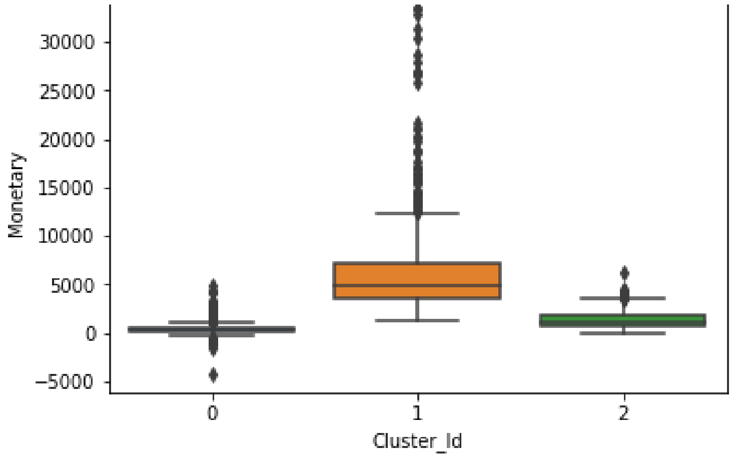
```
# assign the label
df_rfm['Cluster_Id'] = kmeans.labels_
df_rfm.head()
```

Out[48]:

	CustomerID	Recency	Frequency	Monetary	recency_labels	frequency_labels	monetary_labels	rfm_segment	rfm_score	C
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	

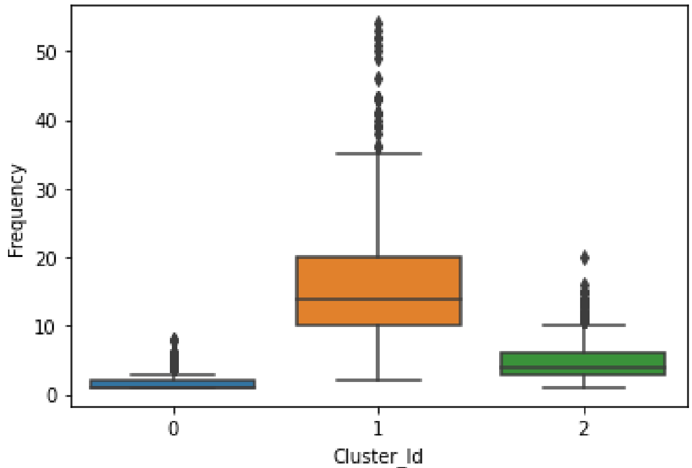
In [49]:

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



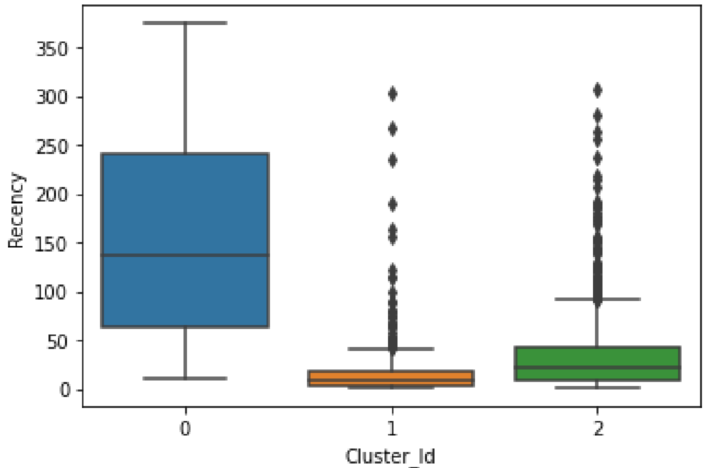
In [50]:

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



In [51]:

```
# 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.**

Week 4

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 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

In [ ]:

```
# Writing dataframe to excel file for creating visualization in tableau
writer = pd.ExcelWriter('C:\\Users\\mgupt\\mgpython\\Capstone Project\\Retail - PGP\\out
put_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()
```

In [ ]:

```
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)
```

Please refer Dashboard created in Tableau for visualization and graphs