Project - 3

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

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.

    b. Remove duplicate data records.

    c. Perform descriptive analytics on the given data.
```

Data Transformation:

```
2. Perform cohort analysis (a cohort is a group of subjects that share a defining characteristic). Observe ho
w a cohort behaves across time and compare it to other cohorts.

    a. Create month cohorts and analyze active customers for each cohort.

    b. Analyze the retention rate of customers.
```

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

Out[2]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

In [3]:
```
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
```

In [4]:
```
df.shape
```

Out[4]: (541909, 8)

In [5]:
```
df.isnull().sum()
```

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

In [6]:
```
df = df.drop('Description', axis=1)
df = df.dropna()
df.shape
```

Out[6]:
```
(406829, 7)
```

In [7]:
```
df = df.drop_duplicates()
df.shape
```

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

In [8]:
```
df['CustomerID'] = df['CustomerID'].astype(str)
```

In [9]:
```
df.describe()
```

Out[9]:

	Quantity	UnitPrice
count	401602.000000	401602.000000
mean	12.182579	3.474064
std	250.283248	69.764209
min	-80995.000000	0.000000
25%	2.000000	1.250000
50%	5.000000	1.950000
75%	12.000000	3.750000
max	80995.000000	38970.000000

In [10]:
```
df['month_year'] = df['InvoiceDate'].dt.to_period('M')
df['month_year'].nunique()
```

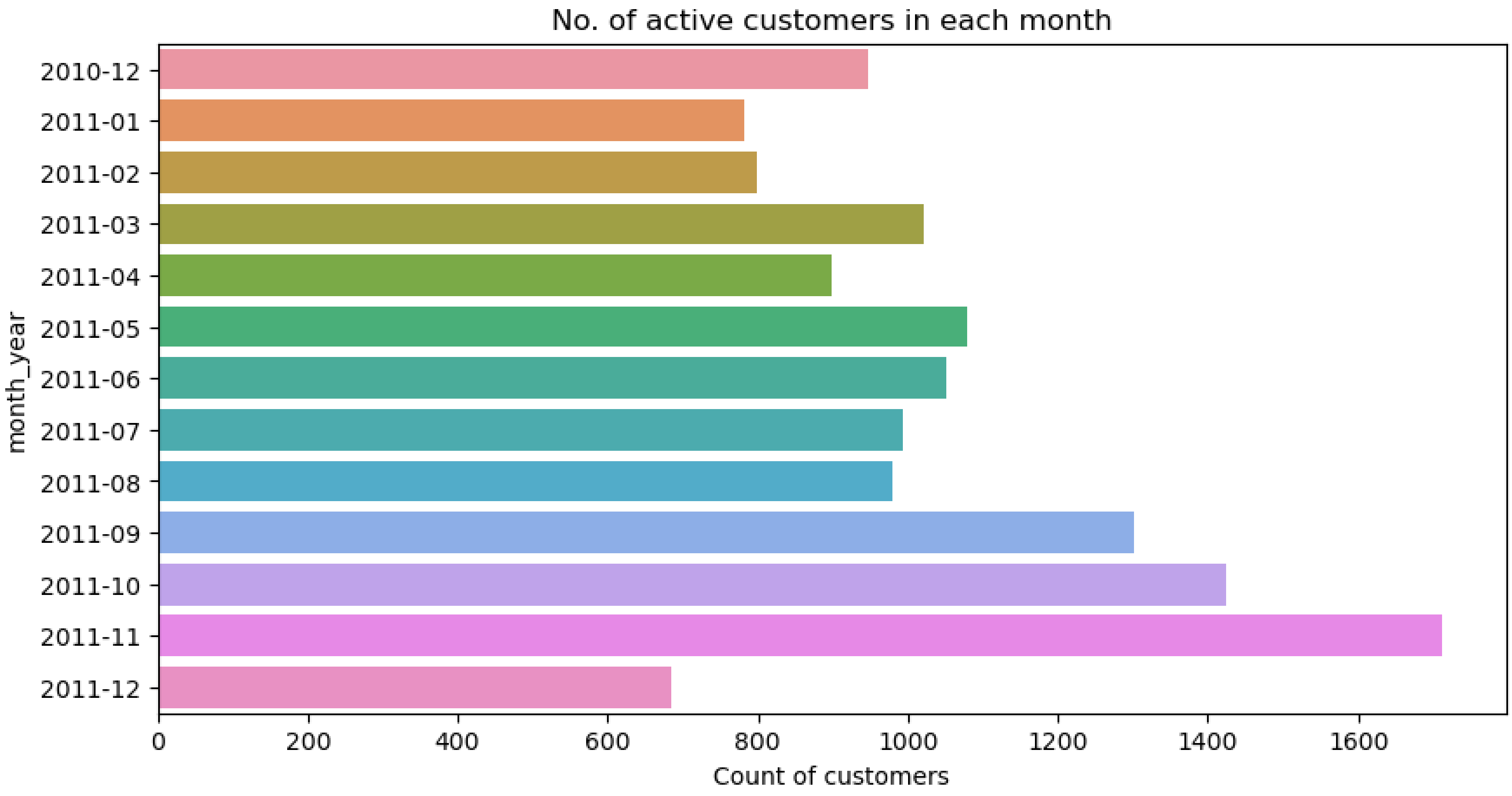
Out[10]:
```
13
```

In [11]:
```
month_cohort = df.groupby('month_year')['CustomerID'].nunique()
month_cohort
```

Out[11]:
```
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 [12]:
```
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[12]:
```
Text(0.5, 1.0, 'No. of active customers in each month')
```



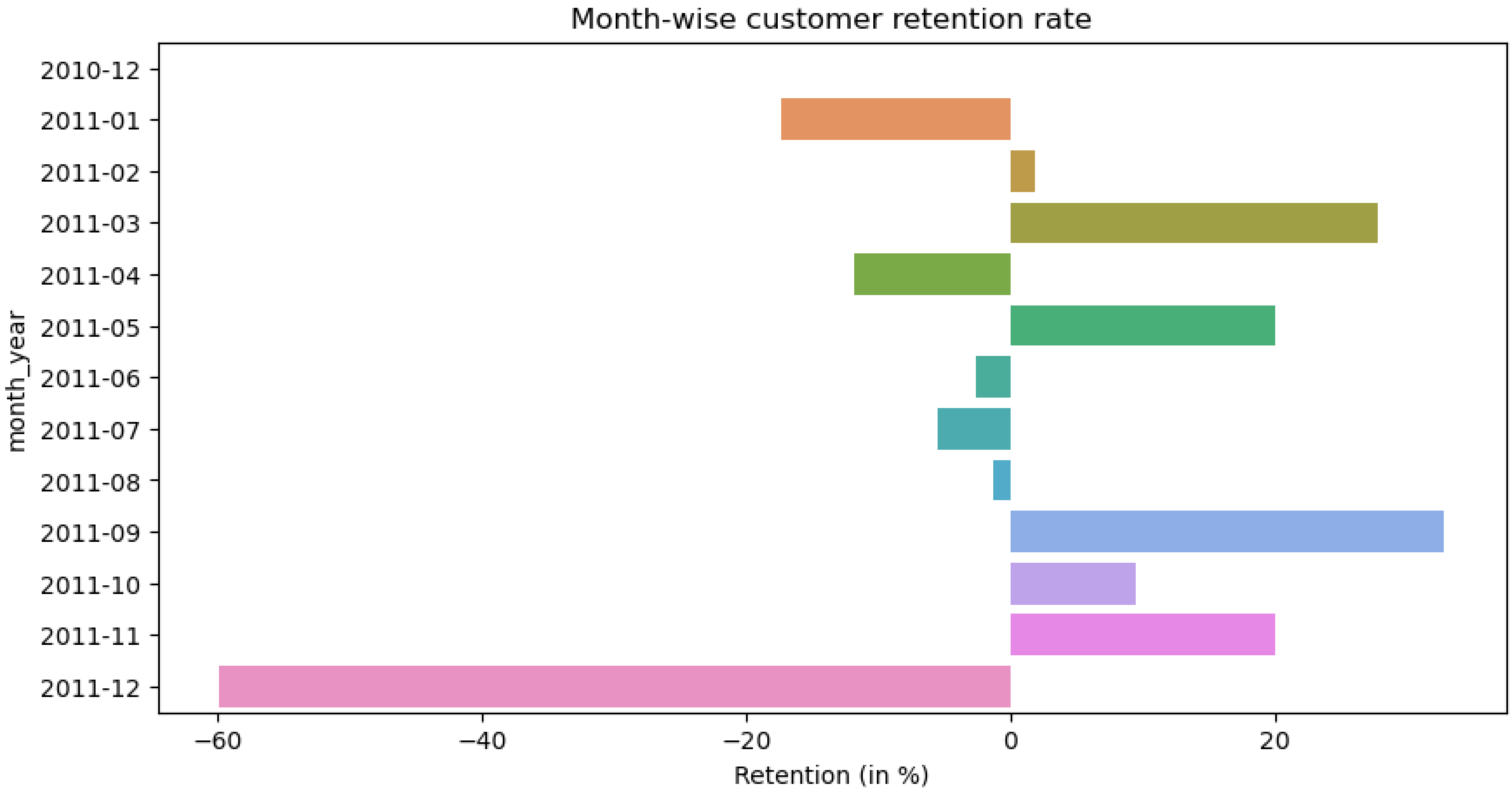
In [13]:
```
month_cohort - month_cohort.shift(1)
```

Out[13]:
```
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 [14]:
```
retention_rate = round(month_cohort.pct_change(periods=1)*100,2)
retention_rate
```

Out[14]:
```
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 [15]:
```
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");
```



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 yea
r. Monetary is the total amount of money a customer spent in that given period. Therefore, big spenders will
be differentiated among other customers such as MVP (Minimum Viable Product) or VIP.

2. Calculate RFM metrics.

3. Build RFM Segments. Give recency, frequency, and monetary scores individually by dividing them into quarti
les.

    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.

    Note: Rate "recency" for customer who has been active more recently higher than the less recent customer,
because each company wants its customers to be recent.

    Note: Rate "frequency" and "monetary" higher, because the company wants the customer to visit more often
```

In [16]:
```
df['Sales'] = df['Quantity']*df['UnitPrice']
df.head()
```

Out[16]:

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	month_year	Sales
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 [17]:
```
df_monetary = df.groupby('CustomerID').sum()['Sales'].reset_index()
df_monetary
```

Out[17]:

	CustomerID	Sales
0	12346.0	0.00
1	12347.0	4310.00
2	12348.0	1797.24
3	12349.0	1757.55
4	12350.0	334.40
...	...	...
4367	18280.0	180.60
4368	18281.0	80.82
4369	18282.0	176.60
4370	18283.0	2045.53
4371	18287.0	1837.28

4372 rows × 2 columns

In [18]:
```
df_frequency = df.groupby('CustomerID').nunique()['InvoiceNo'].reset_index()
df_frequency
```

Out[18]:

	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

In [19]:
```
from datetime import timedelta
```

In [20]:
```
ref_day = max(df['InvoiceDate']) + timedelta(days=1)
df['days_to_last_order'] = (ref_day - df['InvoiceDate']).dt.days
df.head()
```

Out[20]:

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	month_year	Sales	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 [21]:
```
df_recency = df.groupby('CustomerID')['days_to_last_order'].min().reset_index()
df_recency
```

Out[21]:

	CustomerID	days_to_last_order
0	12346.0	326
1	12347.0	2
2	12348.0	75
3	12349.0	19
4	12350.0	310
...	...	...
4367	18280.0	278
4368	18281.0	181
4369	18282.0	8
4370	18283.0	4
4371	18287.0	43

4372 rows × 2 columns

In [22]:
```
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
```

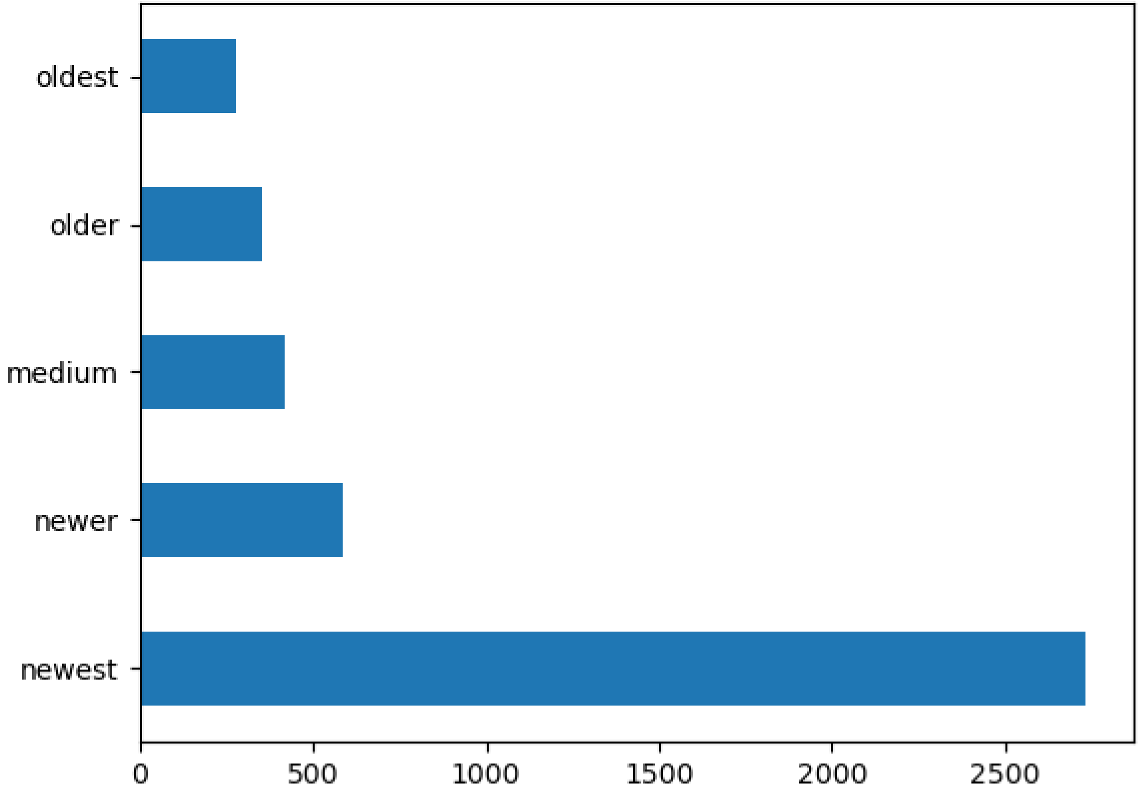
Out[22]:

	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
...	...	...	...	...
4367	18280.0	278	1	180.60
4368	18281.0	181	1	80.82
4369	18282.0	8	3	176.60
4370	18283.0	4	16	2045.53
4371	18287.0	43	3	1837.28

4372 rows × 4 columns

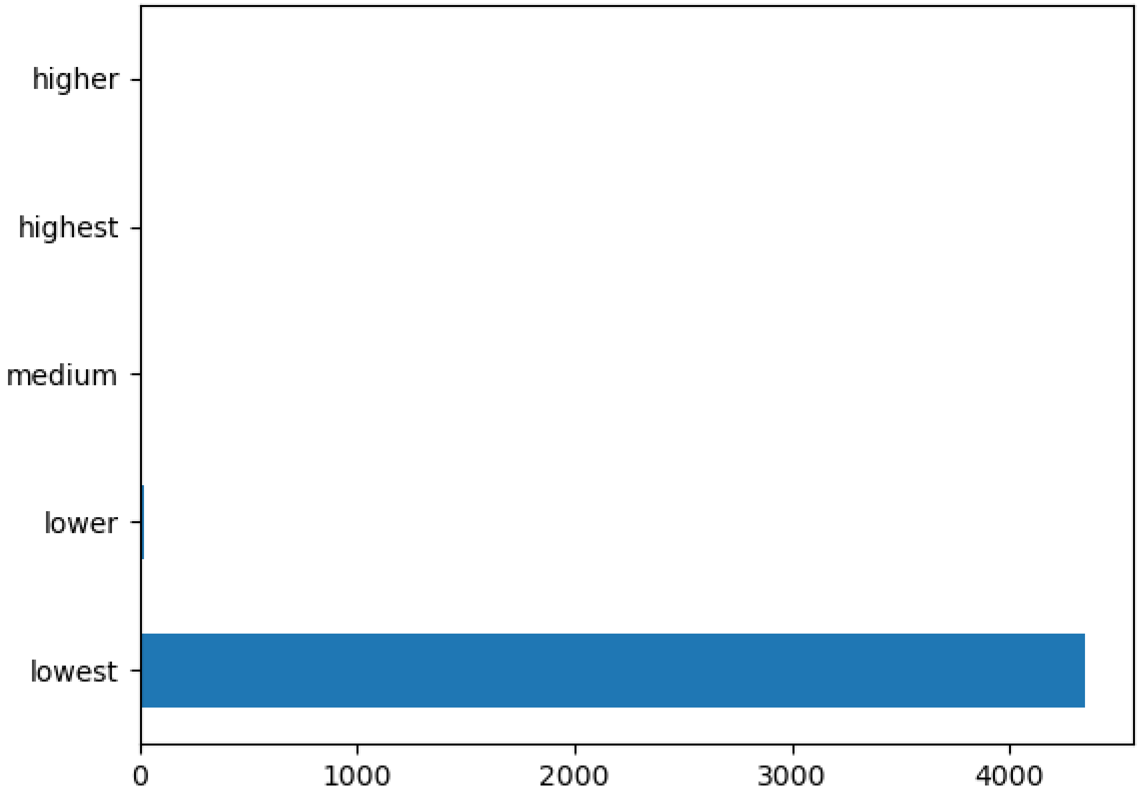
In [23]:
```
df_rfm['recency_labels'] = pd.cut(df_rfm['Recency'], bins=5,
                                   labels=['newest', 'newer', 'medium', 'older', 'oldest'])
df_rfm['recency_labels'].value_counts().plot(kind='barh');
df_rfm['recency_labels'].value_counts()
```

Out[23]:
```
newest    2734
newer      588
medium     416
older      353
oldest     281
Name: recency_labels, dtype: int64
```



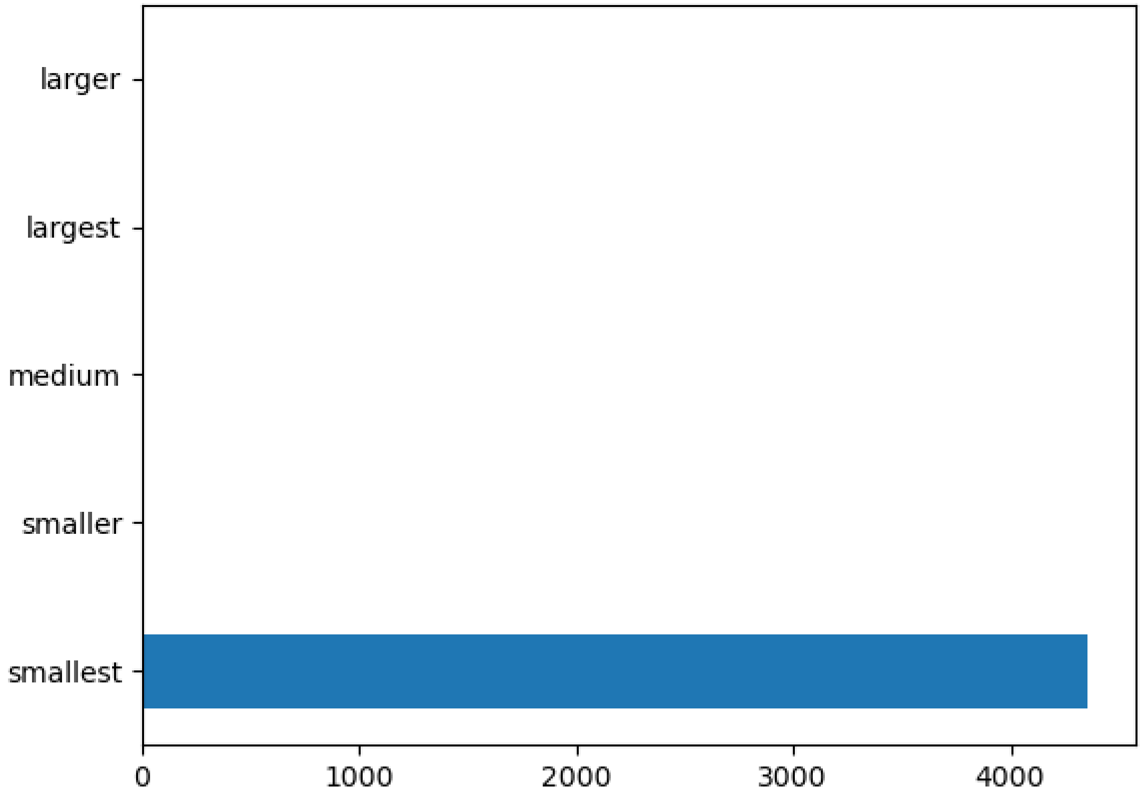
In [24]:
```
df_rfm['frequency_labels'] = pd.cut(df_rfm['Frequency'], bins=5, labels=['lowest', 'lower', 'medium', 'higher', 'highe
df_rfm['frequency_labels'].value_counts().plot(kind='barh');
df_rfm['frequency_labels'].value_counts()
```

Out[24]:
```
lowest     4348
lower        18
medium        3
highest       2
higher        1
Name: frequency_labels, dtype: int64
```



In [25]:
```
df_rfm['monetary_labels'] = pd.cut(df_rfm['Monetary'], bins=5, labels=['smallest', 'smaller', 'medium', 'larger', 'lar
df_rfm['monetary_labels'].value_counts().plot(kind='barh');
df_rfm['monetary_labels'].value_counts()
```

Out[25]:
```
smallest    4357
smaller        9
medium         3
largest        2
larger         1
Name: monetary_labels, dtype: int64
```



In [26]:
```
df_rfm['rfm_segment'] = df_rfm[['recency_labels','frequency_labels','monetary_labels']].agg('-'.join, axis=1)
df_rfm.head()
```

Out[26]:

	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

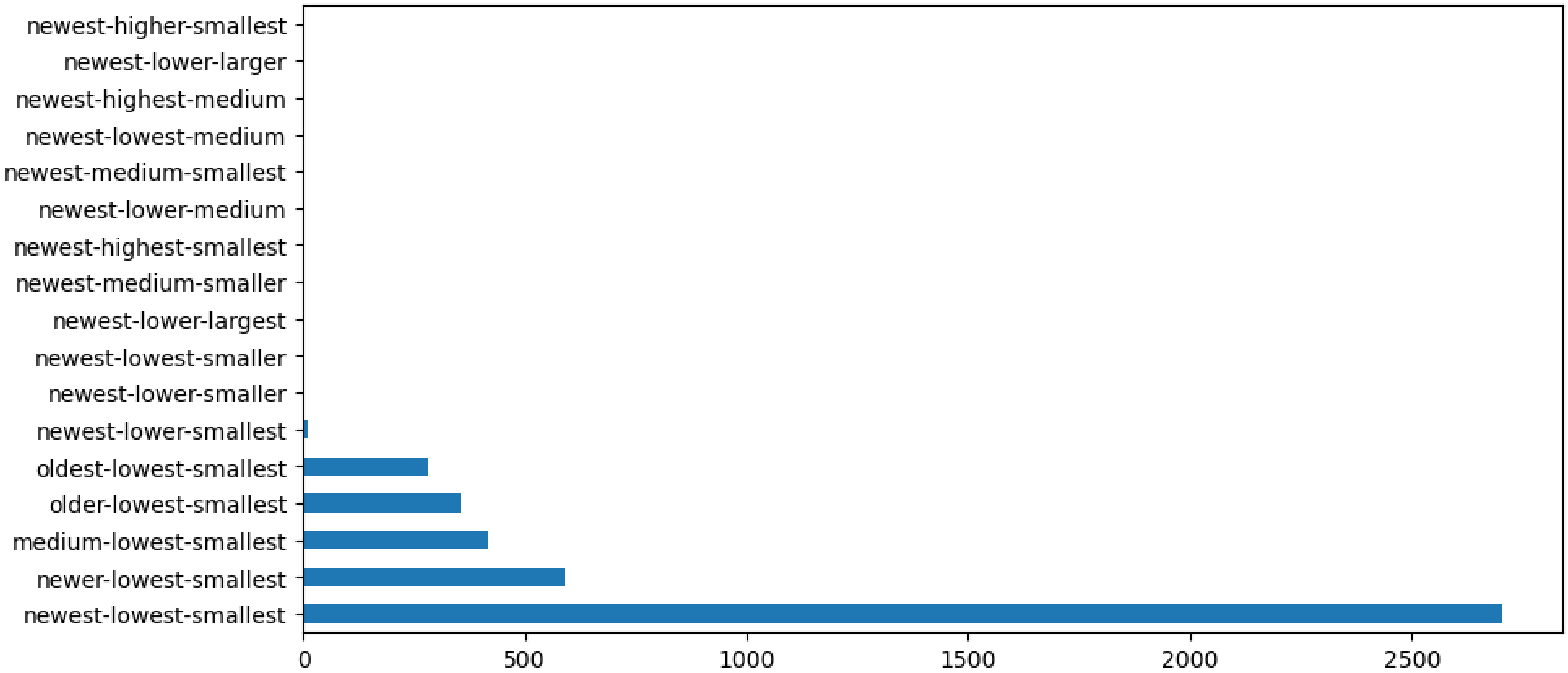
In [27]:
```
recency_dict = {'newest': 5, 'newer':4, 'medium': 3, 'older':2, 'oldest':1}
frequency_dict = {'lowest':1, 'lower':2, 'medium': 3, 'higher':4, 'highest':5}
monetary_dict = {'smallest':1, 'smaller':2, 'medium': 3, 'larger':4, 'largest':5}

df_rfm['rfm_score'] = df_rfm['recency_labels'].map(recency_dict).astype(int)+ df_rfm['frequency_labels'].map(frequency
df_rfm.head(5)
```

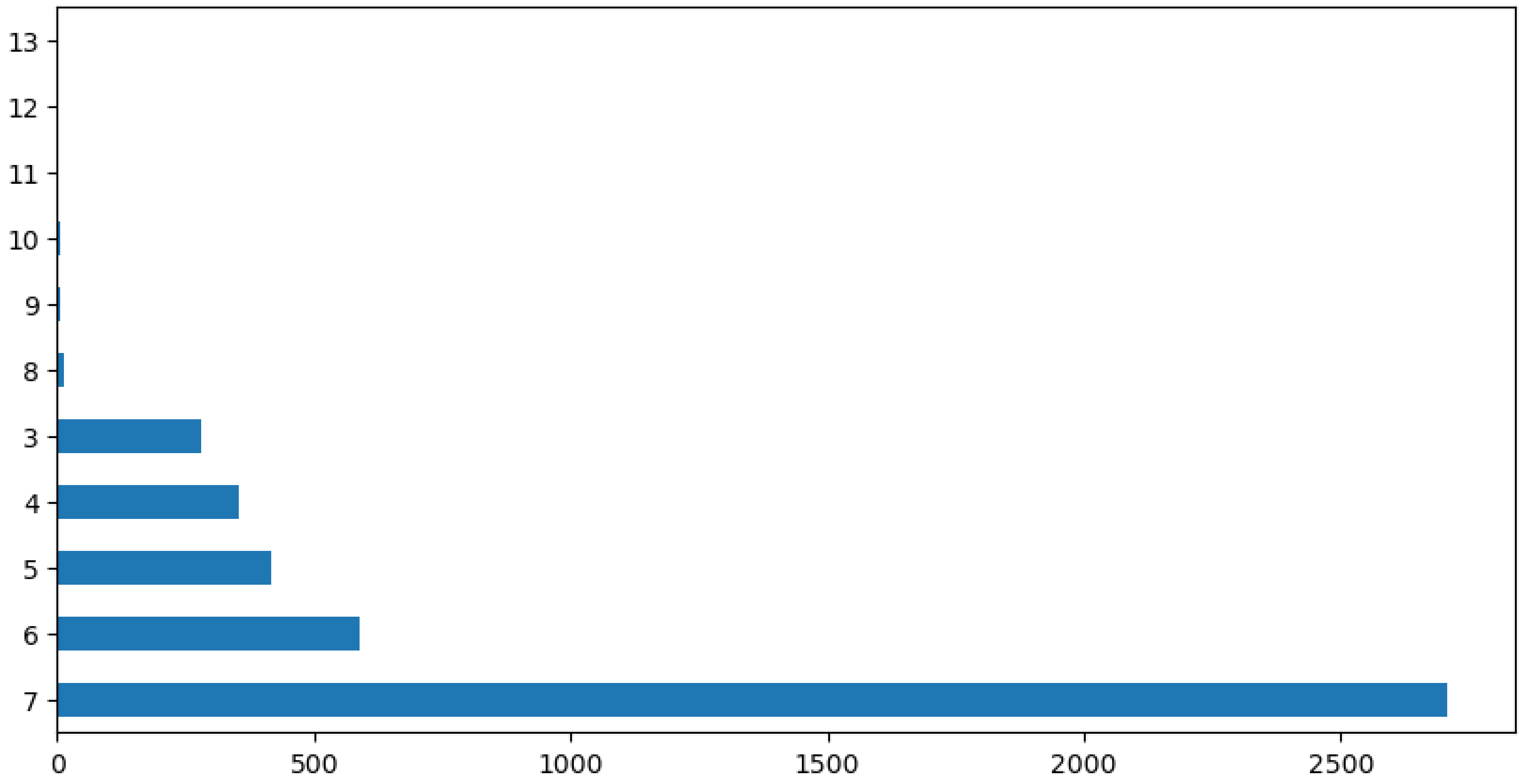
Out[27]:

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

In [28]:
```
df_rfm['rfm_segment'].value_counts().plot(kind='barh', figsize=(10, 5));
```



In [29]:
```
df_rfm['rfm_score'].value_counts().plot(kind='barh', figsize=(10, 5));
```



Project Task: 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 wit

In [30]:
```
print(df_rfm.shape)
df_rfm.head()
```

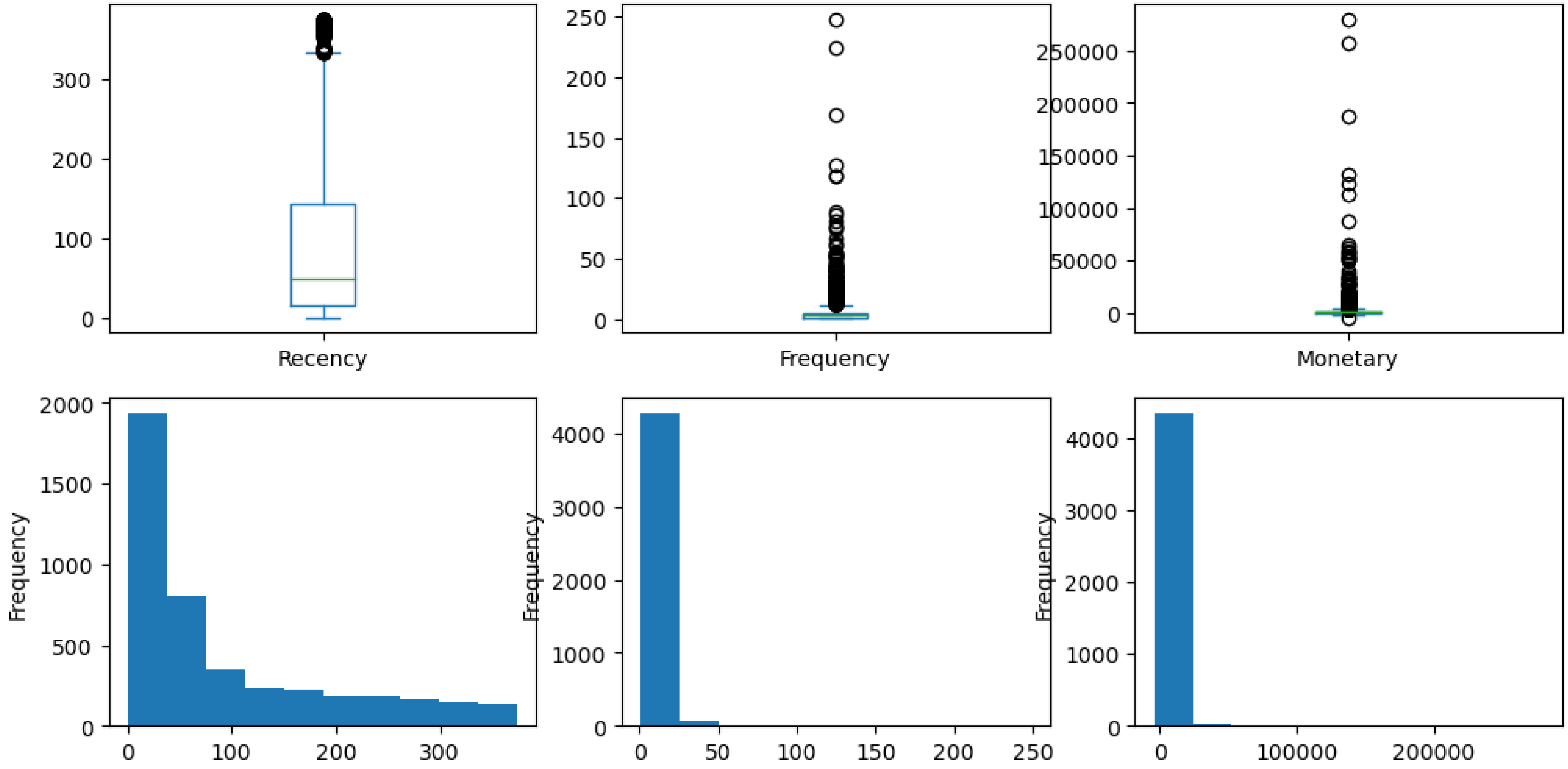
```
(4372, 9)
```

Out[30]:

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

In [31]:
```
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')
```

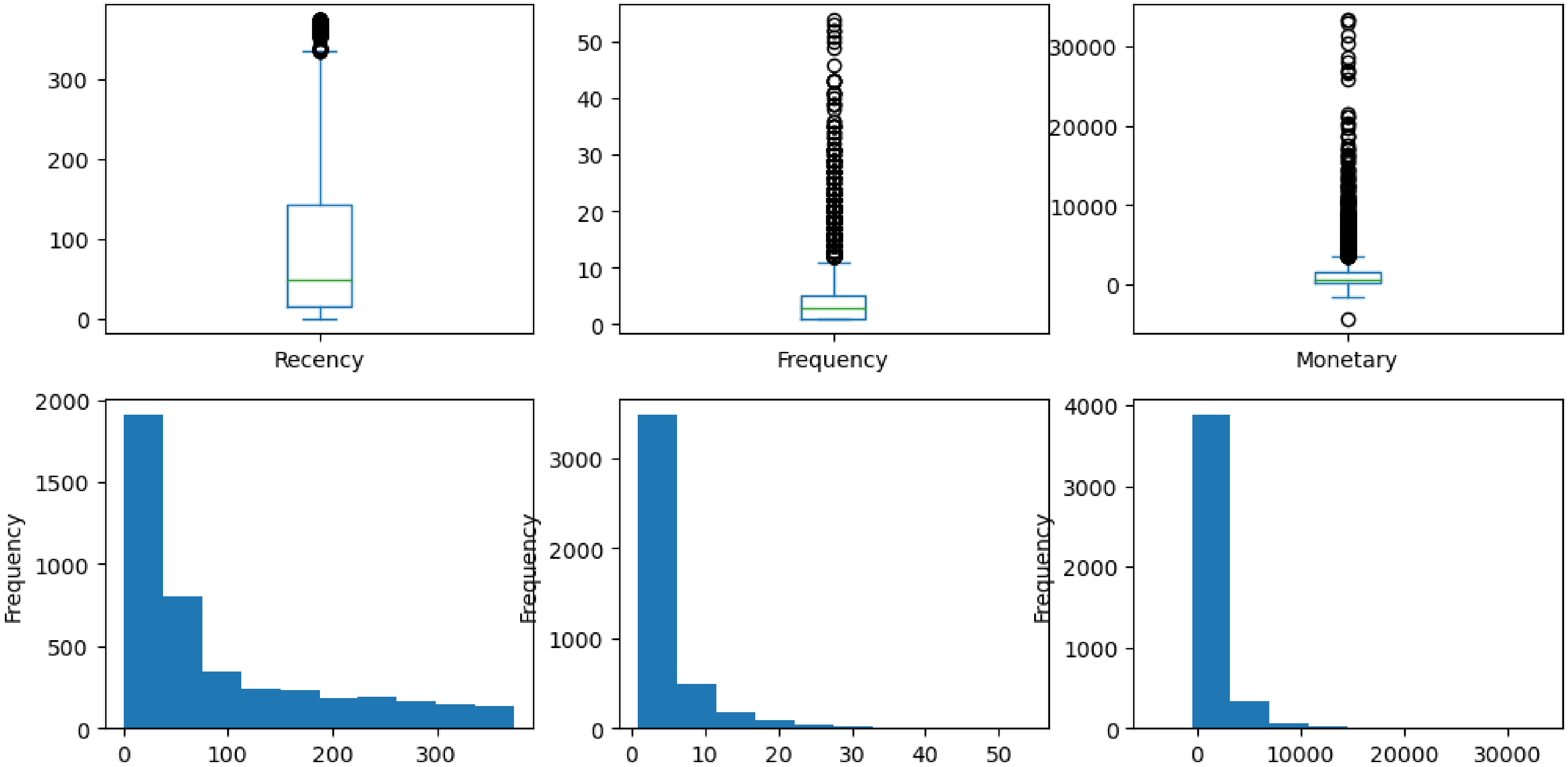


In [32]:
```
df_rfm = df_rfm[(df_rfm['Frequency']<60) & (df_rfm['Monetary']<40000)]
df_rfm.shape
```

Out[32]: (4346, 9)

In [33]:
```
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')
```



In [34]:
```
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)
```

In [35]:
```
from sklearn.preprocessing import StandardScaler
```

In [36]:
```
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[36]:

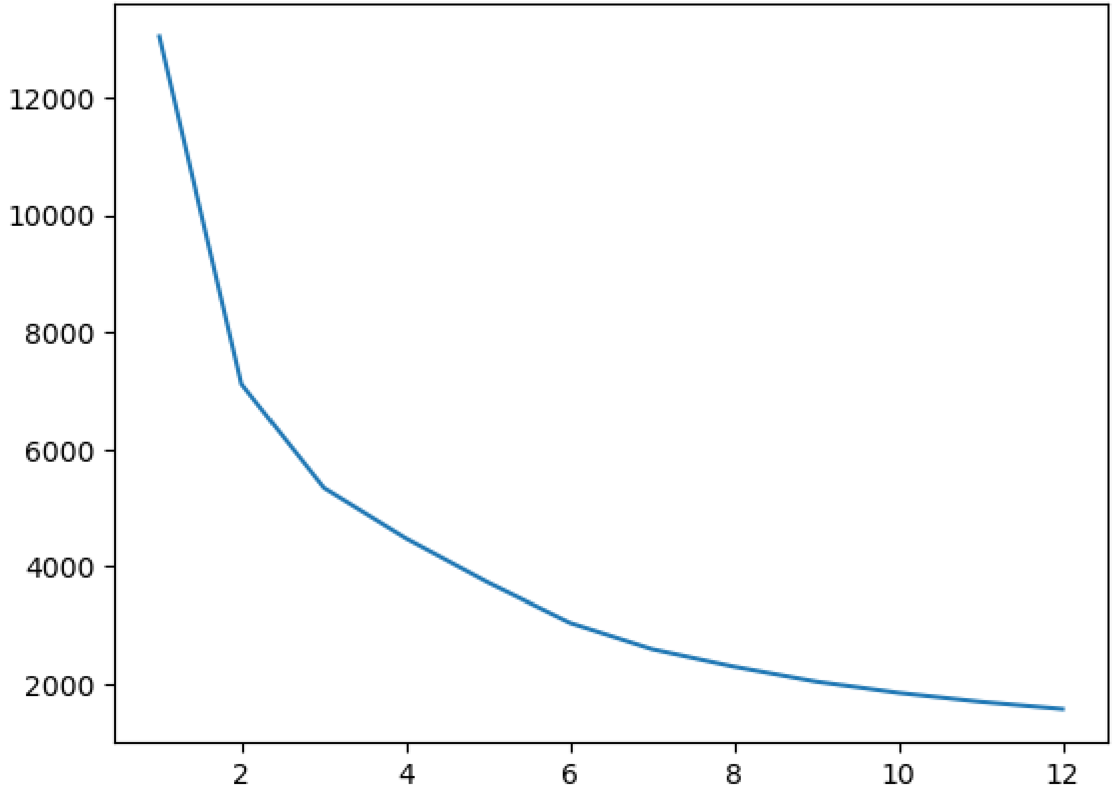
	Recency	Frequency	Monetary
0	1.402988	-0.388507	-0.770922
1	-2.100874	0.967301	1.485132
2	0.392218	0.361655	0.364190
3	-0.552268	-1.138669	0.342970
4	1.368370	-1.138669	-0.527416

In [37]:
```
from sklearn.cluster import KMeans
```

In [38]:
```
css = []
range_n_clusters = [1, 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)

    css.append(kmeans.inertia_)

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



From Elbow Method, we can take the number of clusters : 3 i.e., K=3

In [39]:
```
kmeans = KMeans(n_clusters=3, max_iter=50)
kmeans.fit(df_rfm_scaled)
```

Out[39]:
```
KMeans(max_iter=50, n_clusters=3)
```

In [40]:
```
kmeans.labels_
```

Out[40]:
```
array([1, 0, 2, ..., 2, 0, 2])
```

In [41]:
```
df_inertia = pd.DataFrame(list(zip(range_n_clusters, css)), columns=['clusters', 'intertia'])
df_inertia
```

Out[41]:

	clusters	intertia
0	1	13038.000000
1	2	7113.097396
2	3	5343.136928
3	4	4481.004515
4	5	3730.922591
5	6	3044.898802
6	7	2598.303803
7	8	2299.162353
8	9	2044.740060
9	10	1852.943294
10	11	1700.386975
11	12	1576.815706

In [42]:
```
df_rfm['Cluster_Id'] = kmeans.labels_
df_rfm.head()
```

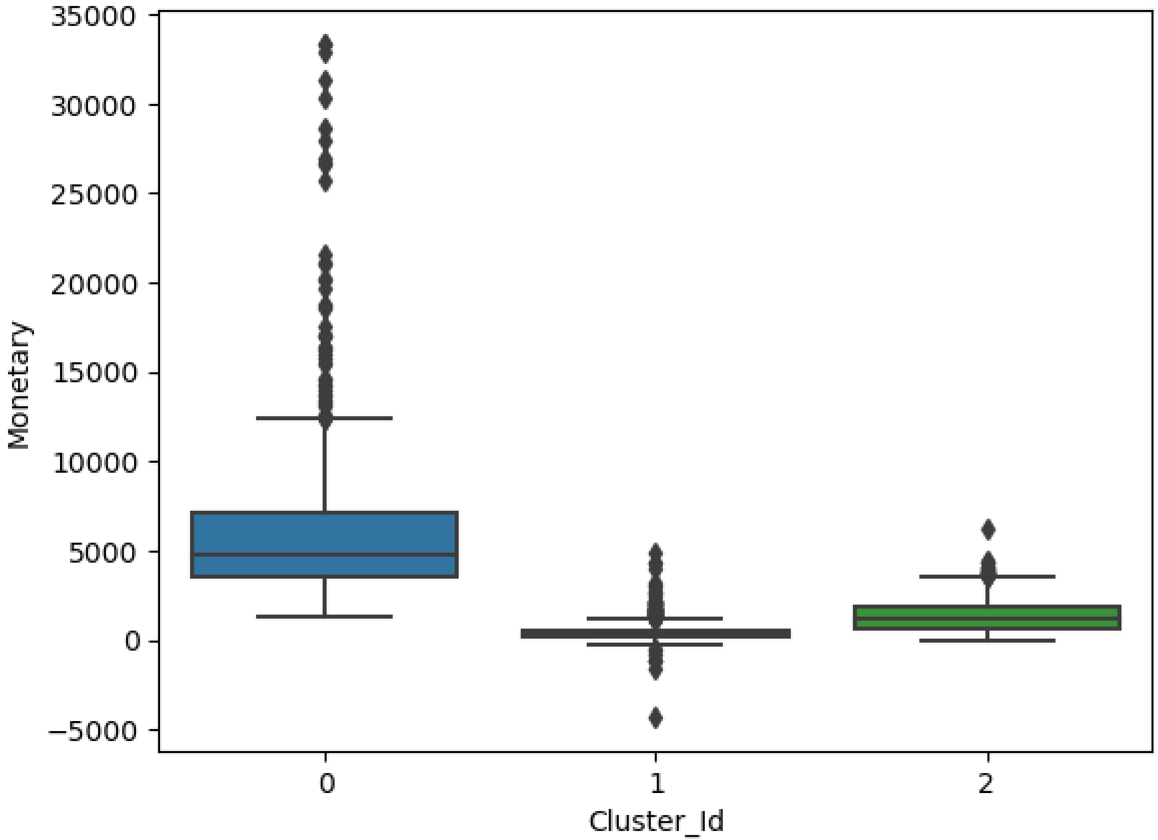
```
C:\Users\Vinosh\AppData\Local\Temp\ipykernel_11852\497853074.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returnin
g-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versu
s-a-copy)
  df_rfm['Cluster_Id'] = kmeans.labels_
```

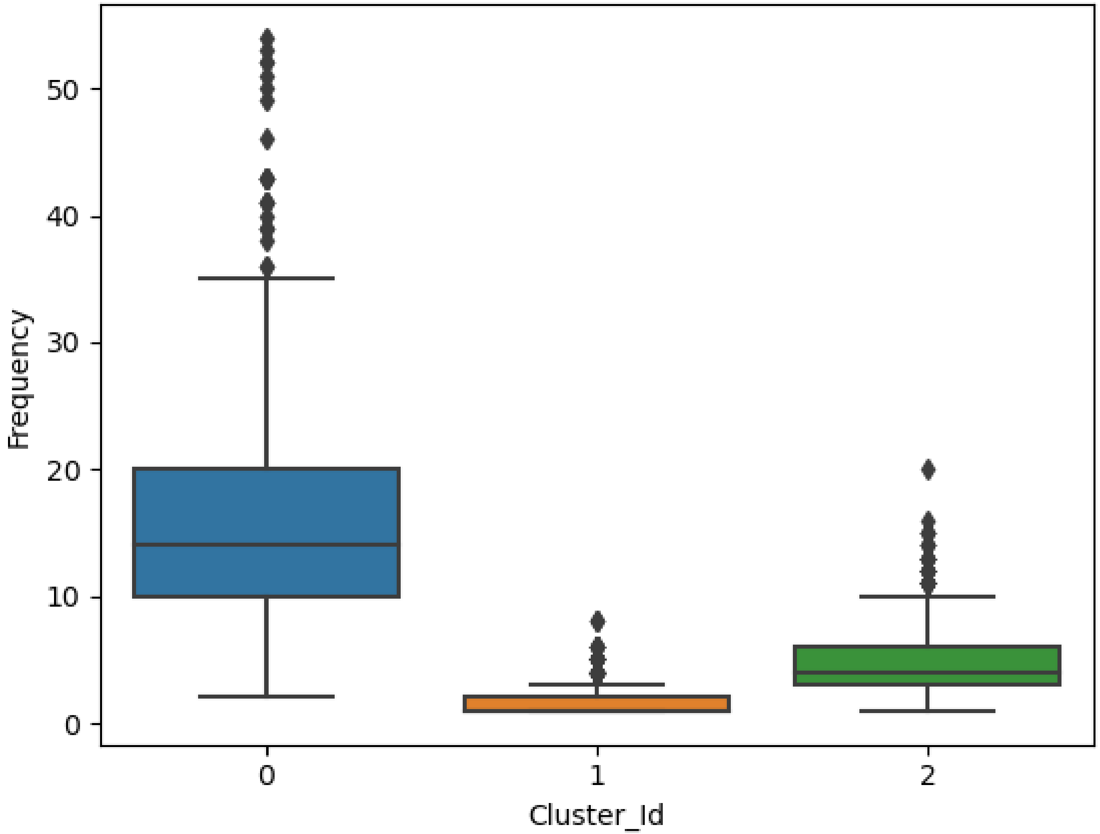
Out[42]:

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

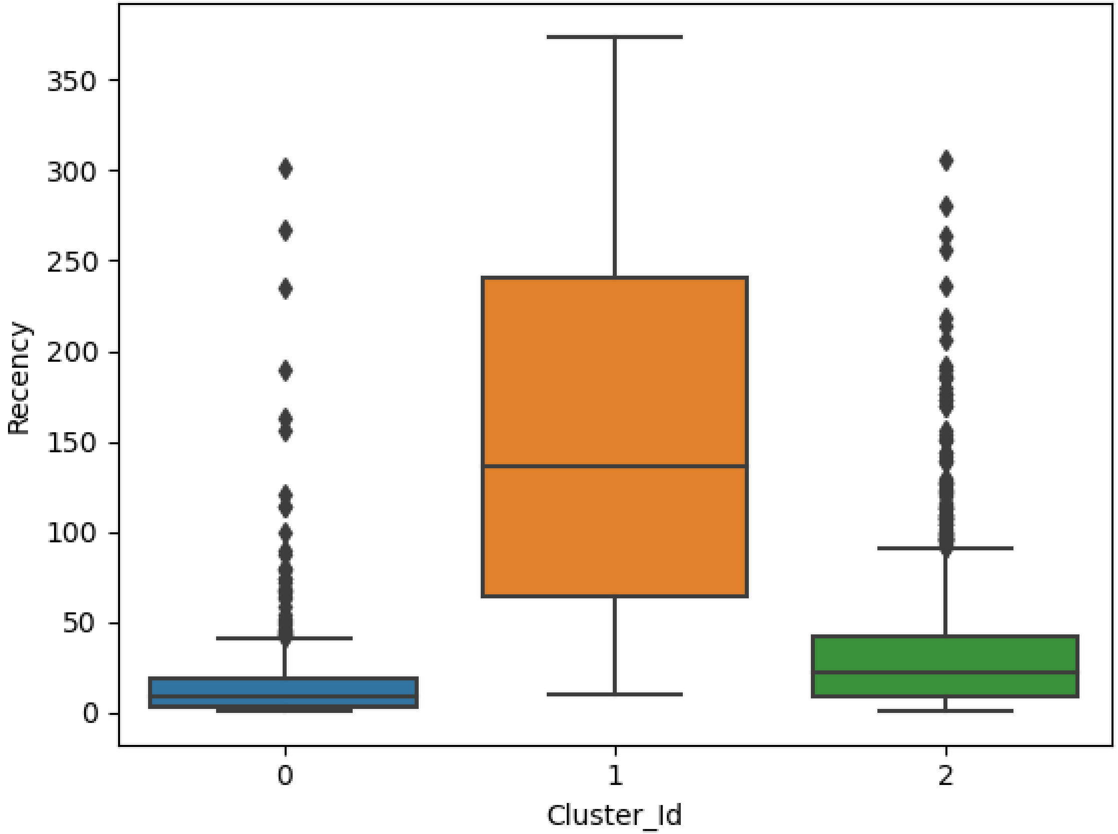
In [43]:
```
sns.boxplot(x='Cluster_Id', y='Monetary', data=df_rfm)
plt.show()
```



In [44]:
```
sns.boxplot(x='Cluster_Id', y='Frequency', data=df_rfm)
plt.show()
```



In [45]:
```
sns.boxplot(x='Cluster_Id', y='Recency', data=df_rfm)
plt.show()
```



Refrence from the Plots

```
1. 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.

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

3. 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.
```

Project Task: 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 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 [46]:
```
df.to_excel('master_data.xlsx', index=False)
```

In [47]:
```
df_rfm.to_excel('rfm_data.xlsx', index=False)
```

In [48]:
```
df_inertia.to_excel('inertia.xlsx', index=False)
```

In [49]:
```
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)
```

Check the tableau link for the Dashboard

In [ ]:

```

```