In [1]:

```
#Importimg the libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

import sklearn
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

from scipy.cluster.hierarchy import linkage
from scipy.cluster.hierarchy import dendrogram
from scipy.cluster.hierarchy import cut_tree
```

In [2]:

```
#Loading the data into sales as pandas dataframe
sales = pd.read_excel("sales_data.xlsx")
sales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 40 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   CustomerID                  5000 non-null   int64
 1   TOTAL_ORDERS                5000 non-null   int64
 2   REVENUE                     5000 non-null   float64
 3   AVERAGE_ORDER_VALUE         5000 non-null   float64
 4   CARRIAGE_REVENUE            5000 non-null   float64
 5   AVERAGESHIPPING             5000 non-null   float64
 6   FIRST_ORDER_DATE            5000 non-null   datetime64[ns]
 7   LATEST_ORDER_DATE           5000 non-null   datetime64[ns]
 8   AVGDAYSBETWEENORDERS        5000 non-null   float64
 9   DAYSSINCELASTORDER          5000 non-null   int64
 10  MONDAY_ORDERS               5000 non-null   int64
 11  TUESDAY_ORDERS              5000 non-null   int64
 12  WEDNESDAY_ORDERS            5000 non-null   int64
 13  THURSDAY_ORDERS             5000 non-null   int64
 14  FRIDAY_ORDERS               5000 non-null   int64
 15  SATURDAY_ORDERS             5000 non-null   int64
 16  SUNDAY_ORDERS               5000 non-null   int64
 17  MONDAY_REVENUE              5000 non-null   float64
 18  TUESDAY_REVENUE             5000 non-null   float64
 19  WEDNESDAY_REVENUE           5000 non-null   float64
 20  THURSDAY_REVENUE            5000 non-null   float64
 21  FRIDAY_REVENUE              5000 non-null   float64
 22  SATURDAY_REVENUE            5000 non-null   float64
 23  SUNDAY_REVENUE              5000 non-null   float64
 24  WEEK1_DAY01_DAY07_ORDERS    5000 non-null   int64
 25  WEEK2_DAY08_DAY15_ORDERS    5000 non-null   int64
 26  WEEK3_DAY16_DAY23_ORDERS    5000 non-null   int64
 27  WEEK4_DAY24_DAY31_ORDERS    5000 non-null   int64
 28  WEEK1_DAY01_DAY07_REVENUE   5000 non-null   float64
 29  WEEK2_DAY08_DAY15_REVENUE   5000 non-null   float64
 30  WEEK3_DAY16_DAY23_REVENUE   5000 non-null   float64
 31  WEEK4_DAY24_DAY31_REVENUE   5000 non-null   float64
 32  TIME_0000_0600_ORDERS       5000 non-null   int64
 33  TIME_0601_1200_ORDERS       5000 non-null   int64
 34  TIME_1200_1800_ORDERS       5000 non-null   int64
 35  TIME_1801_2359_ORDERS       5000 non-null   int64
 36  TIME_0000_0600_REVENUE      5000 non-null   float64
```

```
 37  TIME_0601_1200_REVENUE     5000 non-null   float64
 38  TIME_1200_1800_REVENUE     5000 non-null   float64
 39  TIME_1801_2359_REVENUE     5000 non-null   float64
dtypes: datetime64[ns](2), float64(20), int64(18)
memory usage: 1.5 MB
```

In [3]:

```
#sorting the data according to 'CustomerID'
sales = sales.sort_values(by=['CustomerID'])
sales.head()
```

Out[3]:

	CustomerID	TOTAL_ORDERS	REVENUE	AVERAGE_ORDER_VALUE	CARRIAGE_REVENUE	AVERAGESHIPPING
2266	1	61	34847.40	571.27	297.50	4.88
2876	2	59	32486.98	550.63	218.68	3.71
2267	3	53	24178.97	456.21	43.97	0.83
1153	4	84	18554.49	220.89	421.29	5.02
3377	5	26	16884.99	649.42	54.89	2.11

5 rows × 40 columns

RFM ANALYSIS Since we're performing an RFM analysis thus we need to consider only the Recency (How recently the orders were made), Frequency(How frequently a particular customer made the order or the total number of orders made by the customer in the given time period) and Monetary value (What was the avg amount of order made by customer).

In [4]:

```
#FREQUENCY
frequency = sales[['CustomerID','TOTAL_ORDERS']]
frequency.head()
```

Out[4]:

	CustomerID	TOTAL_ORDERS
2266	1	61
2876	2	59
2267	3	53
1153	4	84
3377	5	26

In [5]:

```
frequency = frequency.reset_index()
frequency.drop(['index'], axis=1,inplace=True)
frequency.head()
```

Out[5]:

	CustomerID	TOTAL_ORDERS
0	1	61
1	2	59
2	3	53
3	4	84
4	5	26

In [6]:

```
#MONETARY
groupDf = sales[['CustomerID','AVERAGE_ORDER_VALUE']]
```

```
groupDf = groupDf.reset_index()
groupDf.drop(['index'],axis=1,inplace=True)
groupDf.head()
```

Out[6]:

	CustomerID	AVERAGE_ORDER_VALUE
0	1	571.27
1	2	550.63
2	3	456.21
3	4	220.89
4	5	649.42

In [7]:

```
#Merging Frequency and Monetary DFs(groupDf)
groupDf = pd.merge(groupDf,frequency, on='CustomerID', how='inner')
groupDf.head()
```

Out[7]:

	CustomerID	AVERAGE_ORDER_VALUE	TOTAL_ORDERS
0	1	571.27	61
1	2	550.63	59
2	3	456.21	53
3	4	220.89	84
4	5	649.42	26

In [8]:

```
groupDf.columns = ['CustomerID','amount','frequency']
groupDf.head()
```

Out[8]:

	CustomerID	amount	frequency
0	1	571.27	61
1	2	550.63	59
2	3	456.21	53
3	4	220.89	84
4	5	649.42	26

In [9]:

```
#RECENCY
recency = sales[['CustomerID','DAYSSINCELASTORDER']]
recency = recency.reset_index()
recency.drop(['index'],axis=1,inplace=True)
recency.head()
```

Out[9]:

	CustomerID	DAYSSINCELASTORDER
0	1	53
1	2	94
2	3	53
3	4	5
4	5	130

In [10]:
```
#Merging groupDf and RECENCY dfs to get a consolidated one
groupDf = pd.merge(groupDf, recency, on='CustomerID', how='inner')
groupDf.head()
```

Out[10]:

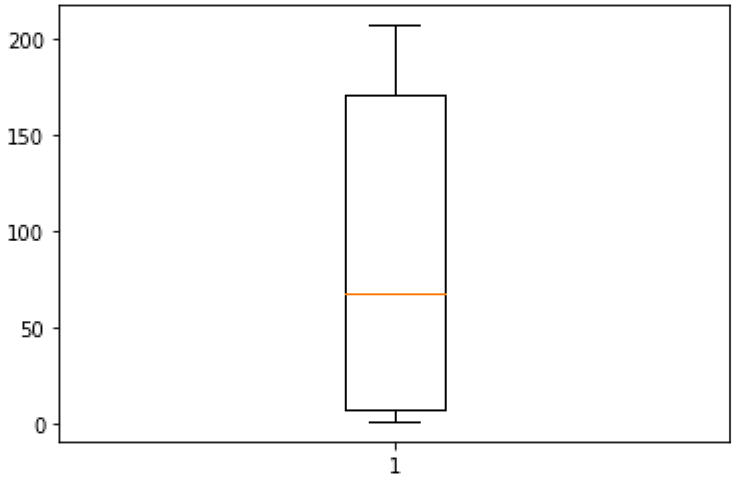
	CustomerID	amount	frequency	DAYSSINCELASTORDER
0	1	571.27	61	53
1	2	550.63	59	94
2	3	456.21	53	53
3	4	220.89	84	5
4	5	649.42	26	130

In [11]:
```
groupDf.columns = ['CustomerID','amount','frequency','recency']
groupDf.head()
```

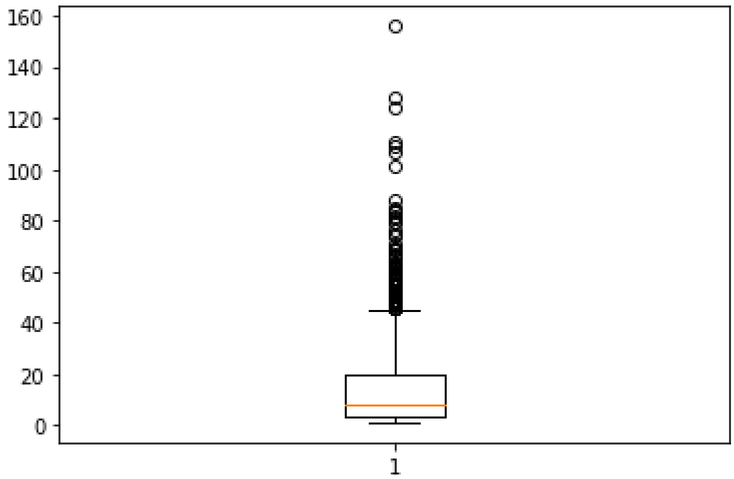
Out[11]:

	CustomerID	amount	frequency	recency
0	1	571.27	61	53
1	2	550.63	59	94
2	3	456.21	53	53
3	4	220.89	84	5
4	5	649.42	26	130

In [12]:
```
#checking the data for further clustering prcessing and analysis
plt.boxplot(groupDf['recency'])
plt.show()
```

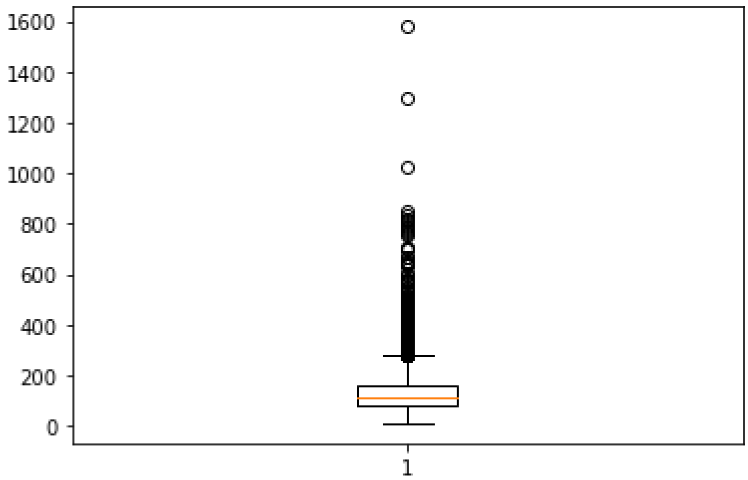


In [13]:
```
plt.boxplot(groupDf['frequency'])
plt.show()
```



In [14]:

```
plt.boxplot(groupDf['amount'])
plt.show()
```



Since there are a lot of outliers in the data, in frequency and amount. Thus proceeding with outlier's treatment.

Outlier's Treatment

In [15]:

```
# for amount
q1 = groupDf.amount.quantile(0.05)
q3 = groupDf.amount.quantile(0.95)
iqr = q3-q1
groupDf = groupDf[(groupDf.amount >= q1 - 1.5*iqr)&(groupDf.amount <= q3+1.5*iqr)]

# for frequency
q1 = groupDf.frequency.quantile(0.05)
q3 = groupDf.frequency.quantile(0.95)
iqr = q3-q1
groupDf = groupDf[(groupDf.frequency >= q1 - 1.5*iqr)&(groupDf.frequency <= q3+1.5*iqr)]

# for recency
q1 = groupDf.recency.quantile(0.05)
q3 = groupDf.recency.quantile(0.95)
iqr = q3-q1
groupDf = groupDf[(groupDf.recency >= q1 - 1.5*iqr)&(groupDf.recency <= q3+1.5*iqr)]
groupDf.head()
```

Out[15]:

	CustomerID	amount	frequency	recency
0	1	571.27	61	53

	CustomerID	amount	frequency	recency
1	2	550.63	59	94
2	3	456.21	53	53
3	4	220.89	84	5
4	5	649.42	26	130

In [16]:

```
# Rescaling the data
rfmDf = groupDf[['amount','frequency','recency']]

# instantiating
scaler = StandardScaler()

# Using Fit-Transform

rfmDfScaled = scaler.fit_transform(rfmDf)
rfmDfScaled.shape
```

Out[16]:

```
(4973, 3)
```

In [17]:

```
rfmDfScaled = pd.DataFrame(rfmDfScaled)
rfmDfScaled.columns = ['amount','frequency','recency']
rfmDfScaled.head()
```

Out[17]:

	amount	frequency	recency
0	5.507327	4.025029	-0.430091
1	5.247431	3.858249	0.080965
2	4.058503	3.357910	-0.430091
3	1.095377	5.942994	-1.028399
4	6.491385	1.106386	0.529696

Modelling

Using K-Means Algorithm

In [18]:

```
# Using an arbitrary number (n_cluster = 4)
kmeans = KMeans(n_clusters=4, max_iter=50)
kmeans.fit(rfmDfScaled)
```

Out[18]:

```
KMeans(max_iter=50, n_clusters=4)
```

In [19]:

```
kmeans.labels_
```

Out[19]:

```
array([3, 3, 3, ..., 1, 1, 0])
```

In [20]:

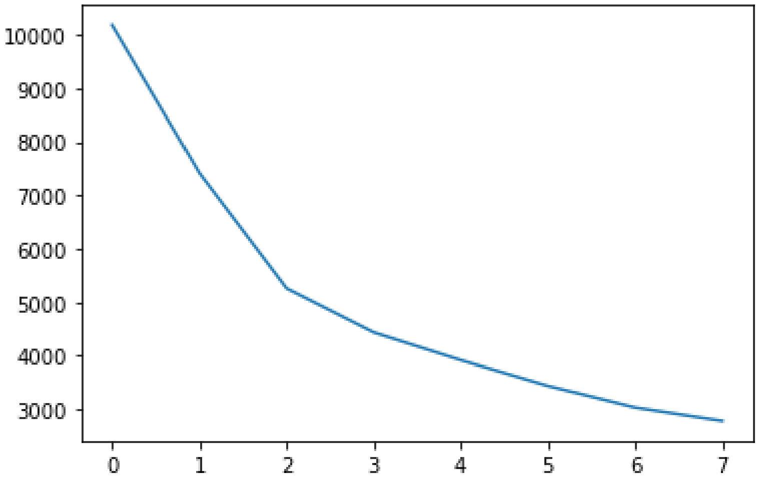
```
# sum of squared distance (ssd)
ssd=[]
range_n_clusters= [2,3,4,5,6,7,8,9]
for num_clusters in range_n_clusters:
    kmeans = KMeans(n_clusters = num_clusters, max_iter=50)
    kmeans.fit(rfmDfScaled)
```

```
    ssd.append(kmeans.inertia_)

plt.plot(ssd)
```

Out[20]:

```
[<matplotlib.lines.Line2D at 0x255bc4223a0>]
```



Hopkins Test

Going for Hopkins Test to chack if the data is clusterable

In [21]:

```
from sklearn.neighbors import NearestNeighbors
from random import sample
from numpy.random import uniform
import numpy as np
from math import isnan

def hopkins(X):
    d = X.shape[1]
    #d = len(vars) # columns
    n = len(X) # rows
    m = int(0.1 * n)
    nbrs = NearestNeighbors(n_neighbors=1).fit(X.values)

    rand_X = sample(range(0, n, 1), m)

    ujd = []
    wjd = []
    for j in range(0, m):
        u_dist, _ = nbrs.kneighbors(uniform(np.amin(X,axis=0),np.amax(X,axis=0),d).reshape(1, -
        ujd.append(u_dist[0][1])
        w_dist, _ = nbrs.kneighbors(X.iloc[rand_X[j]].values.reshape(1, -1), 2, return_distance
        wjd.append(w_dist[0][1])

    H = sum(ujd) / (sum(ujd) + sum(wjd))
    if isnan(H):
        print(ujd, wjd)
        H = 0

    return H
```

In [22]:

```
hopkins(rfmDfScaled)
```

Out[22]:

```
0.9209553084102718
```

Since the number is close to one thus the data is clusterable. Now proceeding with Silhouette's Analysis.

Silhouette's Analysis

From th elbow curve we found that the X-point (2) ,i.e, 4 clusters are optimal for the data. Thus using 4 as the optimal number.

In [23]:
```
kmeans = KMeans(n_clusters = 4,max_iter=50)
kmeans.fit(rfmDfScaled)
```

Out[23]:
```
KMeans(max_iter=50, n_clusters=4)
```

In [24]:
```
kmeans.labels_
```

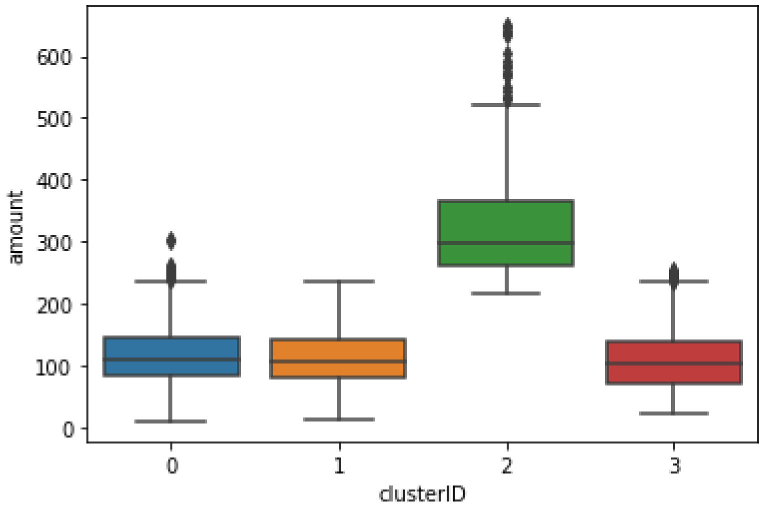
Out[24]:
```
array([2, 2, 2, ..., 3, 3, 1])
```

In [25]:
```
# Assigning the cluster label to the groupDf
groupDf['clusterID'] = kmeans.labels_
groupDf.head()
```

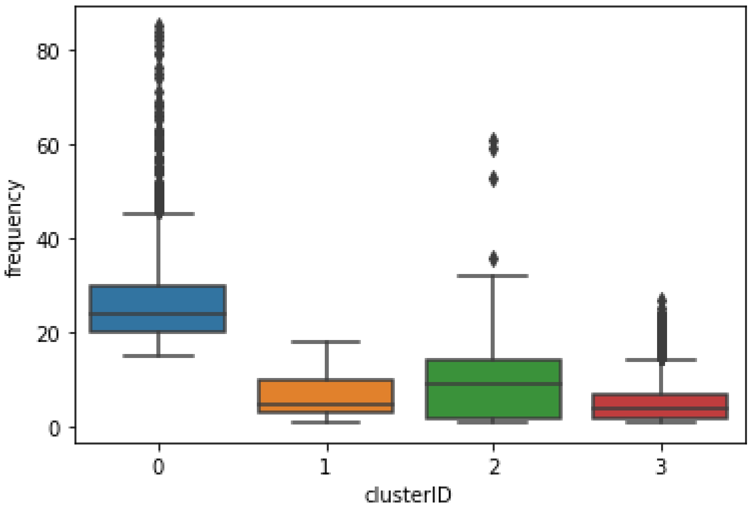
Out[25]:

	CustomerID	amount	frequency	recency	clusterID
0	1	571.27	61	53	2
1	2	550.63	59	94	2
2	3	456.21	53	53	2
3	4	220.89	84	5	0
4	5	649.42	26	130	2

In [26]:
```
#plotting
sns.boxplot(x='clusterID',y='amount',data=groupDf)
plt.show()
```

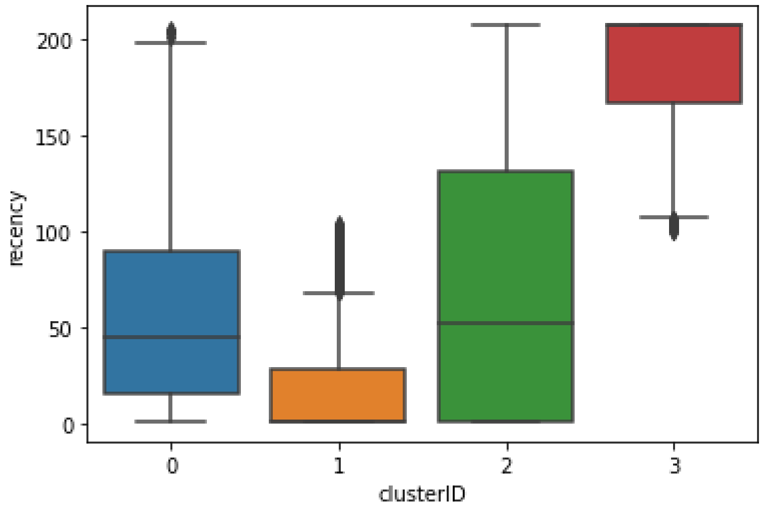


In [27]:
```
sns.boxplot(x='clusterID',y='frequency',data=groupDf)
plt.show()
```



In [28]:

```
sns.boxplot(x='clusterID',y='recency',data=groupDf)
plt.show()
```



In [29]:

```
rfmDfScaled.head()
```

Out[29]:

	amount	frequency	recency
0	5.507327	4.025029	-0.430091
1	5.247431	3.858249	0.080965
2	4.058503	3.357910	-0.430091
3	1.095377	5.942994	-1.028399
4	6.491385	1.106386	0.529696

Hierarchical Clustering

In [30]:

```
# viewing the data
rfmDfScaled.head()
```

Out[30]:

	amount	frequency	recency
0	5.507327	4.025029	-0.430091
1	5.247431	3.858249	0.080965
2	4.058503	3.357910	-0.430091

	amount	frequency	recency
3	1.095377	5.942994	-1.028399
4	6.491385	1.106386	0.529696

In [31]:

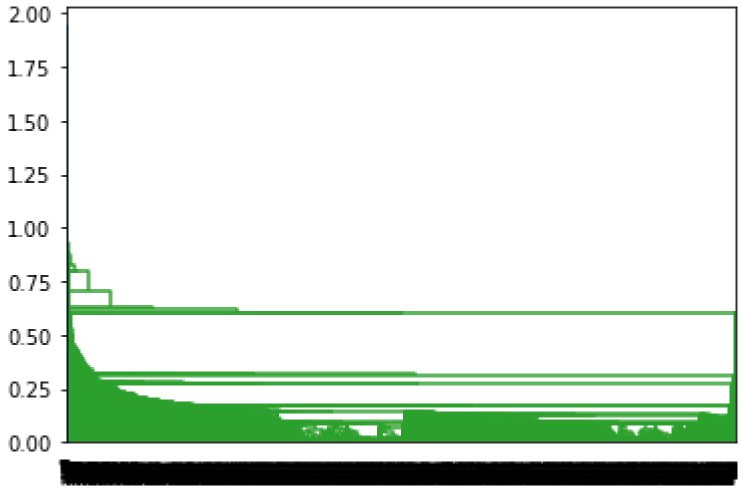
```
groupDf.head()
```

Out[31]:

	CustomerID	amount	frequency	recency	clusterID
0	1	571.27	61	53	2
1	2	550.63	59	94	2
2	3	456.21	53	53	2
3	4	220.89	84	5	0
4	5	649.42	26	130	2

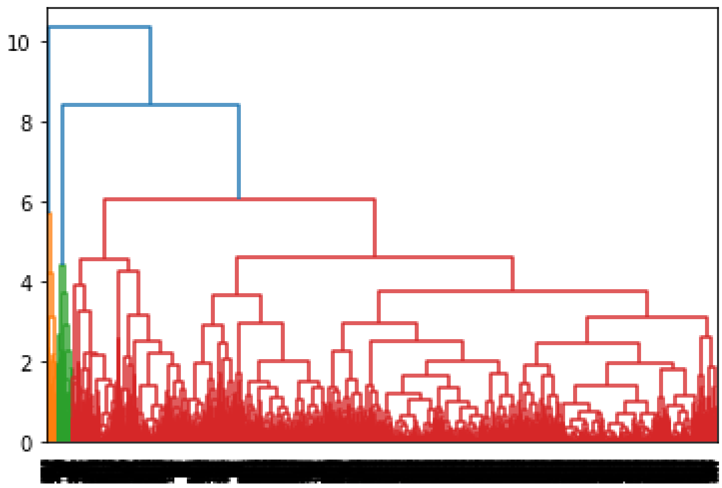
In [32]:

```
# performing the Single Linkage
mergings = linkage(rfmDfScaled , method = 'single' , metric = 'euclidean')
dendrogram(mergings)
plt.show()
```



In [33]:

```
# Complete Linkage
mergings = linkage(rfmDfScaled, method = 'complete', metric = 'euclidean')
dendrogram(mergings)
plt.show()
```



In [34]:

```
# 4 clusters
cluster_labels = cut_tree(mergings,n_clusters = 4).reshape(-1,)
cluster_labels
```

Out[34]:

```
array([0, 0, 0, ..., 3, 3, 3])
```

In [35]:

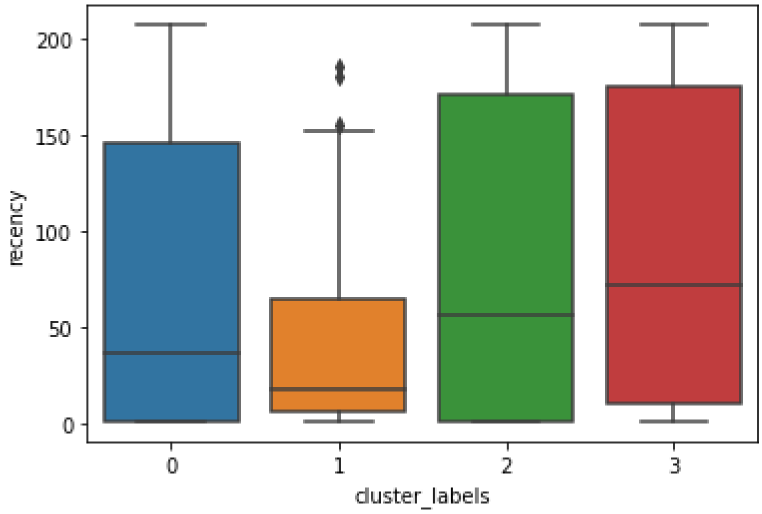
```
groupDf['cluster_labels'] = cluster_labels
groupDf.head()
```

Out[35]:

	CustomerID	amount	frequency	recency	clusterID	cluster_labels
0	1	571.27	61	53	2	0
1	2	550.63	59	94	2	0
2	3	456.21	53	53	2	0
3	4	220.89	84	5	0	1
4	5	649.42	26	130	2	0

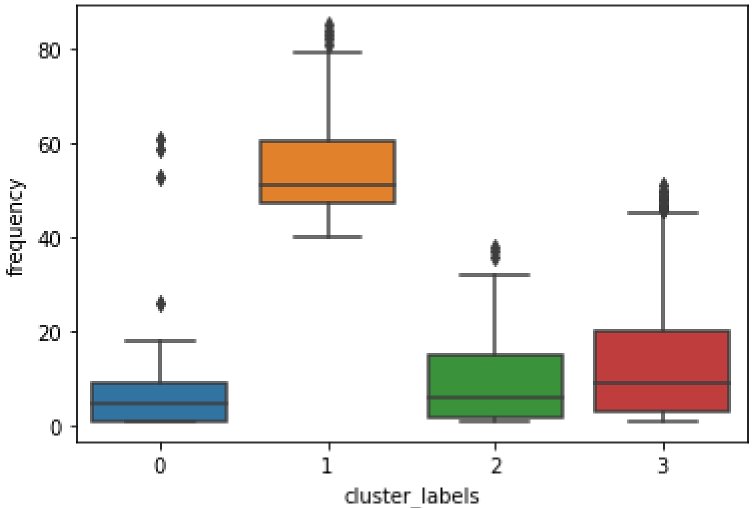
In [36]:

```
sns.boxplot(x = 'cluster_labels', y = 'recency', data = groupDf)
plt.show()
```



In [37]:

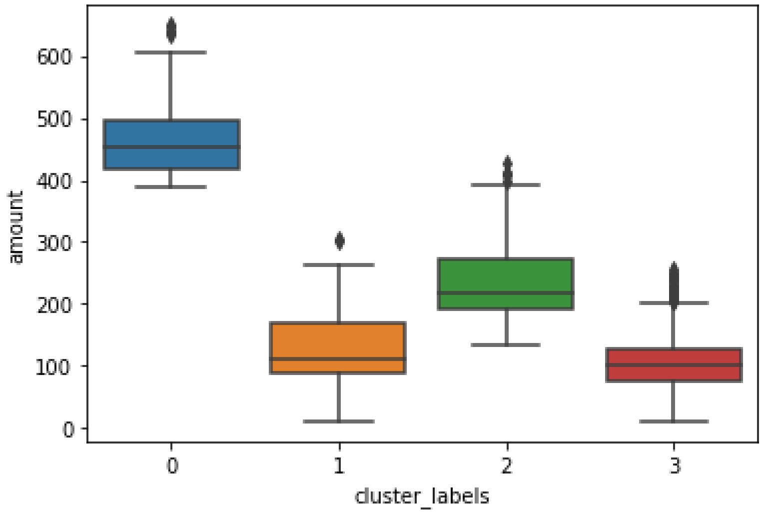
```
sns.boxplot(x = 'cluster_labels', y = 'frequency', data = groupDf)
plt.show()
```



In [38]:

```
sns.boxplot(x = 'cluster_labels', y = 'amount', data = groupDf)
```

```
plt.show()
```



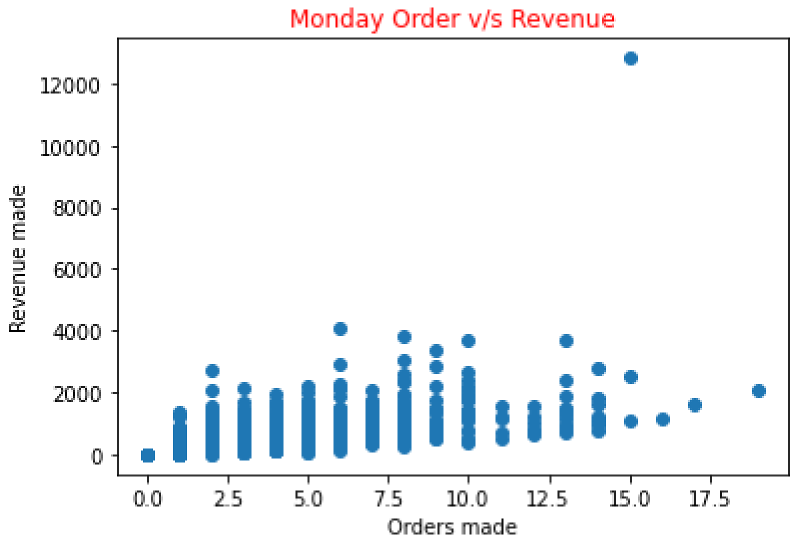
As we can see from the above three boxplots, the Cluster 4 (cluster_label = 3) has made the most recent order and it also makes the orders more frequently as compared to others. However when we compare the average amount per order it turns out to be the least for the customers in the cluster 4. We can also consider cluster 3 (cluster_label = 2) for the most recent order after cluster 4 and cluster 3 has made the most frequent orders after cluster 4 however when we compare the average amount per order cluster 3 (cluster_labels = 2) scores a second position again. So we should be focusing on Cluster 3 (cluster_labels = 2) if we want to have a good amount of sales and profits.

We could also see that cluster 1 (cluster_labels = 0) has made the purchase for highest amounts but have made the order less frequently. We could ask our marketing team to roll out more attention grabbing advertisements for those particular set of customers in order to have more revenue as they have also made orders recently which means Cluster 1 customers are loyal too.

We could also proceed with the scatter plot and see which users have made the highest number of orders on each day of the week with the highest revenue. Similarly we could go with the weekwise data and a particular day's time wise data so that we could target the potential customers when there's a high likelihood for them to buy.

For example: For checking customerwise report of orders and revenue on monday we could use a scatter plot.

In [46]:
```
plt.scatter(x=sales['MONDAY_ORDERS'],y=sales['MONDAY_REVENUE'])
plt.title('Monday Order v/s Revenue', color= 'Red')
plt.xlabel('Orders made')
plt.ylabel('Revenue made')
plt.show()
```


Monday Order v/s Revenue
Revenue made
Orders made
0
2000
4000
6000
8000
10000
12000
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

```
In [ ]:
```