```
In [1]:
           1 import pandas as pd
           2 import numpy as np
           3 #viz Libraries
           4
              import matplotlib.pyplot as plt
              plt.style.use('ggplot')
           6
              import seaborn as sns
           7
              #datetime
           8 import datetime as dt
           9 #StandardSccaler
          10 from sklearn.preprocessing import StandardScaler
          11 #KMeans
          12 from sklearn.cluster import KMeans
In [11]:
              df = pd.read_csv(r"C:\Users\kavet\Desktop\BE_Sem_7_Assignments-main\BE_Ser
           1
           2
              df.shape #Dimensions of the data
           3
           4
In [12]:
           1 df.head() #Glimpse of the data
           2
           3
Out[12]:
             ORDERNUMBER QUANTITYORDERED PRICEEACH ORDERLINENUMBER SALES ORDERDA
                                                                                      2/24/20
          0
                     10107
                                                                         2 2871.00
                                          30
                                                   95.70
          1
                     10121
                                          34
                                                   81.35
                                                                         5 2765.90 5/7/2003 0
                     10134
                                                   94.74
                                                                         2 3884.34 7/1/2003 0
                                                                                      8/25/20
                     10145
                                                   83.26
                                                                         6 3746.70
          3
                                          45
                                                                                     10/10/20
                     10159
                                          49
                                                  100.00
                                                                        14 5205.27
                                                                                          0
         5 rows × 25 columns
```

QUANTITYORDERED 0
PRICEEACH 0
ORDERLINENUMBER 0
SALES 0

```
In [13]:
           1 #Removing the variables which dont add significant value fot the analysis
              to_drop = ['PHONE','ADDRESSLINE1','ADDRESSLINE2','STATE','POSTALCODE']
           2
           3
              df = df.drop(to_drop, axis=1)
           4
              df.isnull().sum()
           5
           6
           7
Out[13]: ORDERNUMBER
                                  0
                                  0
         QUANTITYORDERED
         PRICEEACH
                                  0
         ORDERLINENUMBER
                                  0
         SALES
                                  0
         ORDERDATE
         STATUS
                                  0
         QTR_ID
         MONTH ID
         YEAR ID
                                  0
         PRODUCTLINE
                                  0
         MSRP
         PRODUCTCODE
         CUSTOMERNAME
                                  0
                                  0
         CITY
         COUNTRY
                                  0
         TERRITORY
                               1074
         CONTACTLASTNAME
                                  0
         CONTACTFIRSTNAME
                                  0
         DEALSIZE
                                  0
         dtype: int64
In [14]:
           1 df.dtypes
           3
             df['ORDERDATE'] = pd.to_datetime(df['ORDERDATE'])
           5 df['ORDERDATE'] = [d.date() for d in df['ORDERDATE']]
           6 df.head()
Out[14]:
             ORDERNUMBER QUANTITYORDERED PRICEEACH ORDERLINENUMBER SALES ORDERDA
                     10107
                                                                          2 2871.00
                                                                                      2003-02-
          0
                                                    95.70
          1
                     10121
                                           34
                                                    81.35
                                                                          5 2765.90
                                                                                      2003-05
                     10134
          2
                                           41
                                                    94.74
                                                                          2 3884.34
                                                                                      2003-07-
          3
                     10145
                                           45
                                                    83.26
                                                                            3746.70
                                                                                      2003-08
                     10159
                                           49
                                                   100.00
                                                                         14 5205.27
                                                                                      2003-10-
              # Calculate Recency, Frequency and Monetary value for each customer
In [15]:
              latest_date = df['ORDERDATE'].max() + dt.timedelta(days=1) #latest date if
           3
              df_RFM = df.groupby(['CUSTOMERNAME'])
           4
              df_RFM = df_RFM.agg({
           5
           6
                   'ORDERDATE': lambda x: (latest_date - x.max()).days,
           7
                   'ORDERNUMBER': 'count',
                   'SALES': 'sum'})
           8
In [16]:
           1 #Renaming the columns
           2 dấtBFM.d€nAAM(ţokumeseý'ORPFBQAēāċġ', RMosetwryValue']]
In [17]:
                                  'ORDERNUMBER': 'Frequency',
           3
              data.head()
                                  'SALES': 'MonetaryValue'}, inplace=True)
Out[17]:
                               Recency Frequency MonetaryValue
               CUSTOMERNAME
                  AV Stores, Co.
                                              51
                                                     157807.81
                                   196
                  Alpha Cognac
                                    65
                                              20
                                                      70488.44
             Amica Models & Co.
                                   265
                                              26
                                                      94117.26
```

153996.13

46

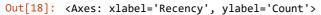
84

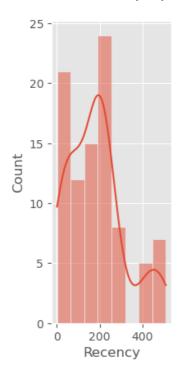
Anna's Decorations, Ltd

## Recency Frequency MonetaryValue

## CUSTOMERNAME

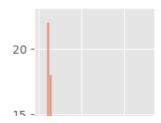
AV Stores, Co.	196	51	157807.81
Alpha Cognac	65	20	70488.44
Amica Models & Co.	265	26	94117.26
Anna's Decorations, Ltd	84	46	153996.13
Atelier graphique	188	7	24179.96



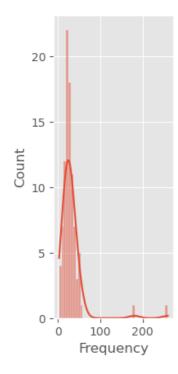


```
In [19]: 1 plt.subplot(1,3,2)
2 sns.histplot(data['Frequency'], kde=True)
```

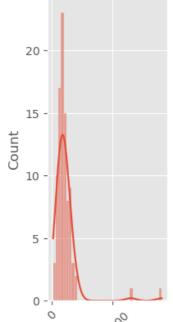
Out[19]: <Axes: xlabel='Frequency', ylabel='Count'>



Out[19]: <Axes: xlabel='Frequency', ylabel='Count'>



Out[20]: <Axes: xlabel='MonetaryValue', ylabel='Count'>



```
In [21]: 1 plt.title('Distribution of Recency, Frequency and MonetaryValue')
2 plt.legend()
3 plt.show()
```

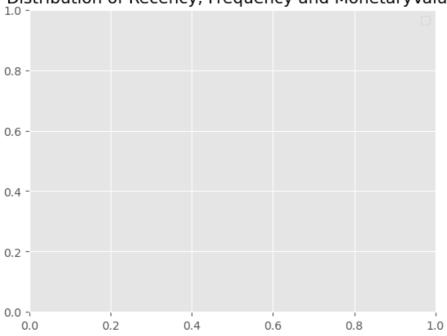
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argumen t.

Distribution of Recency, Frequency and Monetary Value  $^{\rm 1.0}$  -

```
In [21]: 1 plt.title('Distribution of Recency, Frequency and MonetaryValue')
2 plt.legend()
3 plt.show(elaryValue
```

No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argumen t.

Distribution of Recency, Frequency and Monetary Value



```
In [22]: 1 data_log = np.log(data)
```

In [23]: 1 data\_log.head()

Out[23]:

## Recency Frequency MonetaryValue

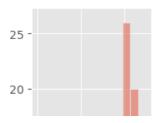
## CUSTOMERNAME

AV Stores, Co.	5.278115	3.931826	11.969133
Alpha Cognac	4.174387	2.995732	11.163204
Amica Models & Co.	5.579730	3.258097	11.452297
Anna's Decorations, Ltd	4.430817	3.828641	11.944683
Atelier graphique	5.236442	1.945910	10.093279

```
In [24]: 1 plt.figure(figsize=(10,6))
```

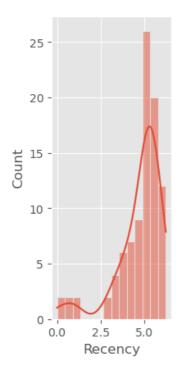
```
In [25]: 1 plt.subplot(1,3,1)
2 sns.histplot(data_log['Recency'], kde=True)
```

```
Out[25]: <Axes: xlabel='Recency', ylabel='Count'>
```



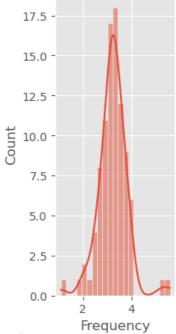
```
In [25]: 1 plt.subplot(1,3,1)
2 sns.histplot(data_log['Recency'], kde=True)
```

Out[25]: <Axes: xlabel='Recency', ylabel='Count'>



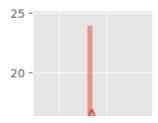
```
In [26]: 1 plt.subplot(1,3,2)
2 sns.histplot(data_log['Frequency'], kde=True)
```

Out[26]: <Axes: xlabel='Frequency', ylabel='Count'>



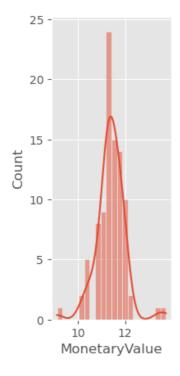
```
In [27]: 1 plt.subplot(1,3,3)
2 sns.histplot(data_log['MonetaryValue'], kde=True)
```

Out[27]: <Axes: xlabel='MonetaryValue', ylabel='Count'>



```
In [27]: 1 plt.subplot(1,3,3)
2 sns.histplot(data_log['MonetaryValue'], kde=True)
```

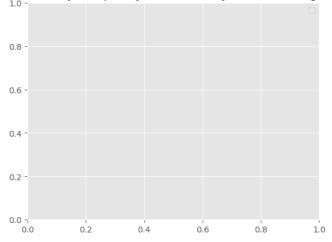
Out[27]: <Axes: xlabel='MonetaryValue', ylabel='Count'>



No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argumen  $\mathsf{t}.$ 

Out[29]: <matplotlib.legend.Legend at 0x1e3e66fce90>

Distribution of Recency, Frequency and MonetaryValue after Log Transformation



```
In [32]: 1 #Iritialize a scaler

Out[32]: 1 # Initialize a scaler

*StandardScaler()

StandardScaler()
```

```
In [33]: 1 # Scale and center the data
2 data_normalized = scaler.transform(data_log)
```

```
In [34]: 1 # Create a pandas DataFrame
```

```
1 plt show() scaler
In [39]:
           2 scaler.fit(data_log)
           1 # Initialize a scaler

√25tandaledS∈aStandardScaler()

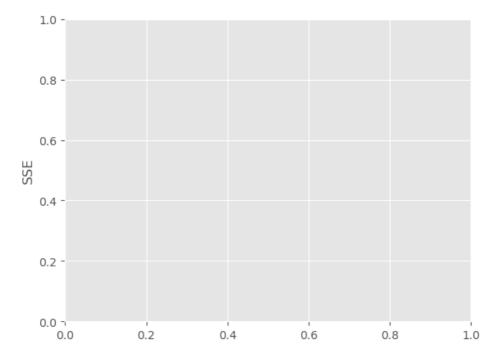
          StandardScaler()
In [33]:
           1 # Scale and center the data
           2 | data_normalized = scaler.transform(data_log)
In [34]:
           1 # Create a pandas DataFrame
            data normalized = pd.DataFrame(data normalized, index=data log.index, colu
In [35]:
           1 # Print summary statistics
           2 data_normalized.describe().round(2)
Out[35]:
                Recency Frequency MonetaryValue
          count
                   92.00
                            92.00
                                         92.00
          mean
                   0.00
                             -0.00
                                          0.00
            std
                   1.01
                             1.01
                                          1.01
           min
                   -3.51
                             -3.67
                                          -3.82
           25%
                   -0.24
                             -0.41
                                          -0.39
           50%
                   0.37
                             0.06
                                          -0.04
           75%
                   0.53
                             0.45
                                          0.52
                             4 03
                                          3 92
                   1 12
           max
In [36]:
           1 # Fit KMeans and calculate SSE for each k
             sse={}
           2
           3
             for k in range(1, 21):
                  kmeans = KMeans(n_clusters=k, random_state=1)
           4
                  kmeans.fit(data_normalized)
                  sse[k] = kmeans.inertia_
         ans.py:1412: FutureWarning: The detault value of n_init will change from
         10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the
           super()._check_params_vs_input(X, default_n_init=10)
         C:\Users\kavet\anaconda3\New folder\Lib\site-packages\sklearn\cluster\_kme
         ans.py:1436: UserWarning: KMeans is known to have a memory leak on Windows
         with MKL, when there are less chunks than available threads. You can avoid
         it by setting the environment variable OMP_NUM_THREADS=1.
           warnings.warn(
         C:\Users\kavet\anaconda3\New folder\Lib\site-packages\sklearn\cluster\_kme
         ans.py:1412: FutureWarning: The default value of `n_init` will change from
         10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the
         warning
           super()._check_params_vs_input(X, default_n_init=10)
         C:\Users\kavet\anaconda3\New folder\Lib\site-packages\sklearn\cluster\_kme
         ans.py:1436: UserWarning: KMeans is known to have a memory leak on Windows
         with MKL, when there are less chunks than available threads. You can avoid
         it by setting the environment variable OMP_NUM_THREADS=1.
           warnings.warn(
         C:\Users\kavet\anaconda3\New folder\Lib\site-packages\sklearn\cluster\ kme
In [37]:
           1 plt.figure(figsize=(10,6))
           plt.title('The Elbow Method')
Out[37]: Text(0.5, 1.0, 'The Elbow Method')
                                         The Elbow Method
          1.0
```

0.8

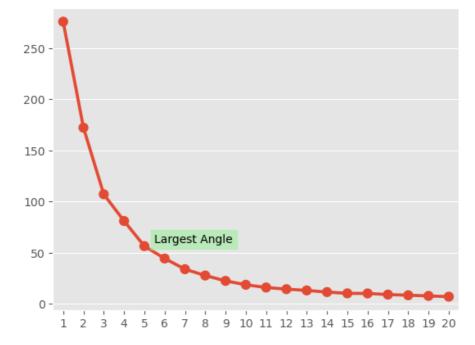
```
plt.figure(figsize=(10,6))
plt.title('The Elbow Method')
In [37]:
Out[37]: Text(0.5, 1.0, 'The Elbow Method')
                                             The Elbow Method
           1.0 -
           0.8 -
           0.6
           0.4 -
           0.2 -
           0.0
                             0.2
                                             0.4
                                                              0.6
                                                                              0.8
                                                                                             1.0
In [38]:
            1 # Add X-axis label "k"
            plt.xlabel('k')
            3
Out[38]: Text(0.5, 0, 'k')
            1.0 -
            0.8 -
            0.6 -
            0.4 -
            0.2 -
            0.0 ¬
                             0.2
                                            0.4
                                                          0.6
                                                                         0.8
               0.0
                                                                                       1.0
                                                    k
In [39]:
            1 # Add Y-axis label "SSE"
            plt.ylabel('SSE')
Out[39]: Text(0, 0.5, 'SSE')
               1.0 -
               0.8 -
```

```
In [39]: 1 # Add Y-axis Label "SSE"
2 plt.ylabel('SSE')
```

Out[39]: Text(0, 0.5, 'SSE')



In [40]: 1 # Plot SSE values for each key in the dictionary
2 sns.pointplot(x=list(sse.keys()), y=list(sse.values()))
3 plt.text(4.5,60,"Largest Angle",bbox=dict(facecolor='lightgreen', alpha=0
4 plt.show()



```
##iRunningankMennstwithg5onluntenormalized data set

| ##iRunningankMennstwithg5onluntenormalized data set
| ##iRunningankMennstwithg5onluntenormalized data set
| ##iRunningankMennstwithg5onluntenormalized data set
| ##iRunningankMennstwithg5onluntenormalized data set
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| ##iRunningankMennstwithg5onluntenormalized data set
| ##iRunningankMennstwithg5onluntenormalized data
```

super().\_check\_params\_vs\_input(X, default\_n\_init=10)
C:\Users\kavet\anaconda3\New folder\Lib\site-packages\sklearn\cluster\\_kmean
s.py:1436: UserWarning: KMeans is known to have a memory leak on Windows with
MKL, when there are less chunks than available threads. You can avoid it by s
etting the environment variable OMP\_NUM\_THREADS=1.
 warnings.warn(

warnings.warn

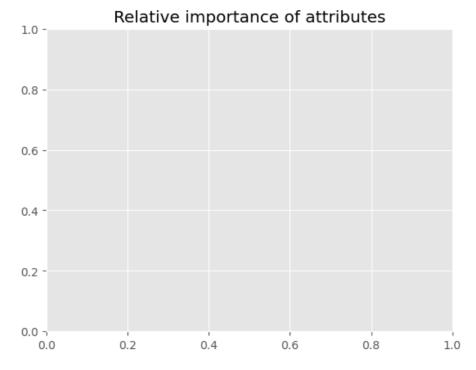
```
# #iRuRnmeansMeanstwithg5onl#กระกอrmalized data set
In [41]:
              #meansifit(datMenormalized)
              kmeans = KMeans(n_clusters=5, random_state=1)
           3
         C:\Users\kavet\anaconda3\New folder\Lib\site-packages\sklearn\cluster\ kmean
         s.py:1412: FutureWarning: The default value of `n_init` will change from 10 t
         o 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
           super()._check_params_vs_input(X, default_n_init=10)
         C:\Users\kavet\anaconda3\New folder\Lib\site-packages\sklearn\cluster\_kmean
         s.py:1436: UserWarning: KMeans is known to have a memory leak on Windows with
         MKL, when there are less chunks than available threads. You can avoid it by s
         etting the environment variable OMP_NUM_THREADS=1.
           warnings.warn(
Out[42]:
                          KMeans
          KMeans(n_clusters=5, random_state=1)
In [43]:
           1 # Extract cluster labels
           2 cluster_labels = kmeans.labels_
In [44]:
           1 | # Assigning Cluster Labels to Raw Data
             # Create a DataFrame by adding a new cluster label column
             data_rfm = data.assign(Cluster=cluster_labels)
           4 data_rfm.head()
Out[44]:
                              Recency Frequency MonetaryValue Cluster
               CUSTOMERNAME
                  AV Stores, Co.
                                  196
                                             51
                                                    157807.81
                                                                  1
                  Alpha Cognac
                                   65
                                             20
                                                     70488.44
                                                                  2
                                                                  2
             Amica Models & Co.
                                  265
                                             26
                                                     94117.26
          Anna's Decorations, Ltd
                                   84
                                             46
                                                    153996.13
                                                                  1
                                  188
                                              7
                                                     24179.96
                                                                  0
               Atelier graphique
In [45]:
           1 # Group the data by cluster
              grouped = data_rfm.groupby(['Cluster'])
In [46]:
           1
              # Calculate average RFM values and segment sizes per cluster value
           2
              grouped.agg({
           3
                  'Recency': 'mean',
                  'Frequency': 'mean',
           4
           5
                  'MonetaryValue': ['mean', 'count']
                }).round(1)
Out[46]:
                 Recency Frequency MonetaryValue
                 mean
                          mean
                                   mean
                                            count
          Cluster
                    324.2
                               10.7
                                    35628.7
                                              12
                    126.5
                               37.1 133158.0
               1
                                              31
               2
                    209 2
                               22 1
                                    78633.2
                                              43
                              219.5 783576.1
                     2.0
In [47]:
           1 #4-----4---#
           2 # # Calculating relative importance of each attribute
           3 # Calculate average RFM values for each cluster
           4 | cluster_avg = data_rfm.groupby(['Cluster']).mean()
           5 print(cluster_avg)
                                Frequency MonetaryValue
                      Recency
         Cluster
                   324.250000
                                10.666667
                                            35628.653333
         1
                   126.548387
                                37.129032
                                           133158.014516
                                            78633.205814
                   209.162791
                                22.093023
         2
         3
                    2.000000
                               219.500000
                                           783576.085000
         4
                     2.000000
                                38.750000 132201.635000
```

```
210.0 100010.1
In [47]:
         1 #4----4--#
          2 | # # Calculating relative importance of each attribute
          3 # Calculate average RFM values for each cluster
          4 cluster avg = data rfm.groupby(['Cluster']).mean()
          5 print(cluster_avg)
                    Recency
                             Frequency MonetaryValue
        Cluster
                 324.250000
                            10.666667
                                         35628.653333
         0
                              37.129032
                                        133158.014516
         1
                 126.548387
         2
                 209.162791
                              22.093023
                                         78633.205814
         3
                   2.000000
                             219.500000
                                        783576.085000
         4
                   2.000000
                              38.750000 132201.635000
In [48]:
         1 # Calculate average RFM values for the total customer population
          population_avg = data.mean()
          3 print(population_avg)
                            182.826087
         Recency
         Frequency
                             30.684783
                         109050.313587
         MonetaryValue
         dtype: float64
In [49]:
          1 # Calculate relative importance of cluster's attribute value compared to
          2 relative_imp = cluster_avg / population_avg - 1
In [50]:
          1 # Print relative importance score rounded to 2 decimals
          2 print(relative_imp.round(2))
                 Recency Frequency MonetaryValue
         Cluster
                    0.77
                              -0.65
                                            -0.67
         1
                    -0.31
                               0.21
                                             0.22
                                            -0.28
                    0.14
                              -0.28
         2
                   -0.99
         3
                               6.15
                                             6.19
                   -0.99
                               0.26
                                             0.21
In [51]:
          1 #Plot Relative Importance
          2 # Initialize a plot with a figure size of 8 by 2 inches
          3 plt.figure(figsize=(8, 2))
Out[51]: <Figure size 800x200 with 0 Axes>
         <Figure size 800x200 with 0 Axes>
In [52]:
          1 # Add the plot title
          2 plt.title('Relative importance of attributes')
Out[52]: Text(0.5, 1.0, 'Relative importance of attributes')
                        Relative importance of attributes
          1.0 -
```

0.8 -

```
In [52]: 1 # Add the plot title
2 plt.title('Relative importance of attributes')
```

Out[52]: Text(0.5, 1.0, 'Relative importance of attributes')



In [53]: 1 # Plot the heatmap
2 sns.heatmap(data=relative\_imp, annot=True, fmt='.2f', cmap='RdYlGn')
3 plt.show()

