```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import datetime as dt
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans

# Load dataset
df = pd.read_csv('sales_data_sample.csv', encoding='unicode_escape')

df.head()
```

```
   ORDERNUMBER  QUANTITYORDERED  PRICEEACH  ORDERLINENUMBER
SALES  \
0        10107               30      95.70                2  2871.00

1        10121               34      81.35                5  2765.90

2        10134               41      94.74                2  3884.34

3        10145               45      83.26                6  3746.70

4        10159               49     100.00               14  5205.27


         ORDERDATE   STATUS  QTR_ID  MONTH_ID  YEAR_ID  ...  \
0   2/24/2003 0:00  Shipped       1         2     2003  ...
1    5/7/2003 0:00  Shipped       2         5     2003  ...
2    7/1/2003 0:00  Shipped       3         7     2003  ...
3   8/25/2003 0:00  Shipped       3         8     2003  ...
4  10/10/2003 0:00  Shipped       4        10     2003  ...

                    ADDRESSLINE1  ADDRESSLINE2           CITY STATE  \
0        897 Long Airport Avenue           NaN            NYC    NY
1             59 rue de l'Abbaye           NaN          Reims   NaN
2  27 rue du Colonel Pierre Avia           NaN          Paris   NaN
3             78934 Hillside Dr.           NaN       Pasadena    CA
4                7734 Strong St.           NaN  San Francisco    CA

  POSTALCODE COUNTRY TERRITORY CONTACTLASTNAME CONTACTFIRSTNAME
DEALSIZE
0      10022     USA       NaN              Yu             Kwai
Small
1      51100  France      EMEA        Henriot             Paul
Small
2      75508  France      EMEA       Da Cunha           Daniel
Medium
3      90003     USA       NaN           Young            Julie
Medium
4        NaN     USA       NaN           Brown            Julie
Medium
```

```
[5 rows x 25 columns]

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2823 entries, 0 to 2822
Data columns (total 25 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   ORDERNUMBER       2823 non-null   int64
 1   QUANTITYORDERED   2823 non-null   int64
 2   PRICEEACH         2823 non-null   float64
 3   ORDERLINENUMBER   2823 non-null   int64
 4   SALES             2823 non-null   float64
 5   ORDERDATE         2823 non-null   object
 6   STATUS            2823 non-null   object
 7   QTR_ID            2823 non-null   int64
 8   MONTH_ID          2823 non-null   int64
 9   YEAR_ID           2823 non-null   int64
 10  PRODUCTLINE       2823 non-null   object
 11  MSRP              2823 non-null   int64
 12  PRODUCTCODE       2823 non-null   object
 13  CUSTOMERNAME      2823 non-null   object
 14  PHONE             2823 non-null   object
 15  ADDRESSLINE1      2823 non-null   object
 16  ADDRESSLINE2      302 non-null    object
 17  CITY              2823 non-null   object
 18  STATE             1337 non-null   object
 19  POSTALCODE        2747 non-null   object
 20  COUNTRY           2823 non-null   object
 21  TERRITORY         1749 non-null   object
 22  CONTACTLASTNAME   2823 non-null   object
 23  CONTACTFIRSTNAME  2823 non-null   object
 24  DEALSIZE          2823 non-null   object
dtypes: float64(2), int64(7), object(16)
memory usage: 551.5+ KB

# Drop unnecessary columns
to_drop = ['ADDRESSLINE1', 'ADDRESSLINE2', 'STATE', 'POSTALCODE',
'PHONE']
df = df.drop(to_drop, axis=1)

#Check for null values
df.isnull().sum()

ORDERNUMBER         0
QUANTITYORDERED     0
PRICEEACH           0
ORDERLINENUMBER     0
```

```
SALES                    0
ORDERDATE                0
STATUS                   0
QTR_ID                   0
MONTH_ID                 0
YEAR_ID                  0
PRODUCTLINE              0
MSRP                     0
PRODUCTCODE              0
CUSTOMERNAME             0
CITY                     0
COUNTRY                  0
TERRITORY             1074
CONTACTLASTNAME          0
CONTACTFIRSTNAME         0
DEALSIZE                 0
dtype: int64
```

```
#Bhai bhai look at territory, Vishwajeet shocked other admin rocked
#But territory does not have significant impact on analysis like RFM
segmentation or clustering so ignore it

df.dtypes
```

```
ORDERNUMBER            int64
QUANTITYORDERED        int64
PRICEEACH            float64
ORDERLINENUMBER        int64
SALES                float64
ORDERDATE             object
STATUS                object
QTR_ID                 int64
MONTH_ID               int64
YEAR_ID                int64
PRODUCTLINE           object
MSRP                   int64
PRODUCTCODE           object
CUSTOMERNAME          object
CITY                  object
COUNTRY               object
TERRITORY             object
CONTACTLASTNAME       object
CONTACTFIRSTNAME      object
DEALSIZE              object
dtype: object
```

```
#ORDERDATE Should be in date time
df['ORDERDATE'] = pd.to_datetime(df['ORDERDATE'])
```

```python
# RFM Feature Calculation
snapshot_date = df['ORDERDATE'].max() + dt.timedelta(days=1)
df_RFM = df.groupby('CUSTOMERNAME').agg({
    'ORDERDATE': lambda x: (snapshot_date - x.max()).days,
    'ORDERNUMBER': 'count',
    'SALES': 'sum'
})

# Rename columns
df_RFM.rename(columns={
    'ORDERDATE': 'Recency',
    'ORDERNUMBER': 'Frequency',
    'SALES': 'MonetaryValue'
}, inplace=True)

# Quartile segmentation
df_RFM['M'] = pd.qcut(df_RFM['MonetaryValue'], q=4, labels=range(1,5))
df_RFM['R'] = pd.qcut(df_RFM['Recency'], q=4, labels=list(range(4,0,-
1)))
df_RFM['F'] = pd.qcut(df_RFM['Frequency'], q=4, labels=range(1,5))

df_RFM.head()
```

```
                        Recency  Frequency  MonetaryValue  M  R  F
CUSTOMERNAME
AV Stores, Co.              196         51      157807.81  4  2  4
Alpha Cognac                 65         20       70488.44  2  4  2
Amica Models & Co.          265         26       94117.26  3  1  2
Anna's Decorations, Ltd      84         46      153996.13  4  3  4
Atelier graphique           188          7       24179.96  1  2  1
```

```python
# RFM Score
df_RFM['RFM_Score'] = df_RFM[['R','F','M']].sum(axis=1)

# RFM Level
def rfm_level(df):
    if df['RFM_Score'] >= 10:
        return 'High Value Customer'
    elif 6 <= df['RFM_Score'] < 10:
        return 'Mid Value Customer'
    else:
        return 'Low Value Customer'

df_RFM['RFM_Level'] = df_RFM.apply(rfm_level, axis=1)
print(df_RFM.head())
```

```
                        Recency  Frequency  MonetaryValue  M  R  F  \
CUSTOMERNAME
AV Stores, Co.              196         51      157807.81  4  2  4
Alpha Cognac                 65         20       70488.44  2  4  2
Amica Models & Co.          265         26       94117.26  3  1  2
```

```
Anna's Decorations, Ltd       84          46       153996.13  4  3  4
Atelier graphique            188           7        24179.96  1  2  1

                          RFM_Score            RFM_Level
CUSTOMERNAME
AV Stores, Co.                   10  High Value Customer
Alpha Cognac                      8   Mid Value Customer
Amica Models & Co.                6   Mid Value Customer
Anna's Decorations, Ltd          11  High Value Customer
Atelier graphique                 4   Low Value Customer

# Data Preparation for Clustering
data = df_RFM[['Recency', 'Frequency', 'MonetaryValue']]
```

We create levels for our Customers

RFM Score > 10 : High Value Customers

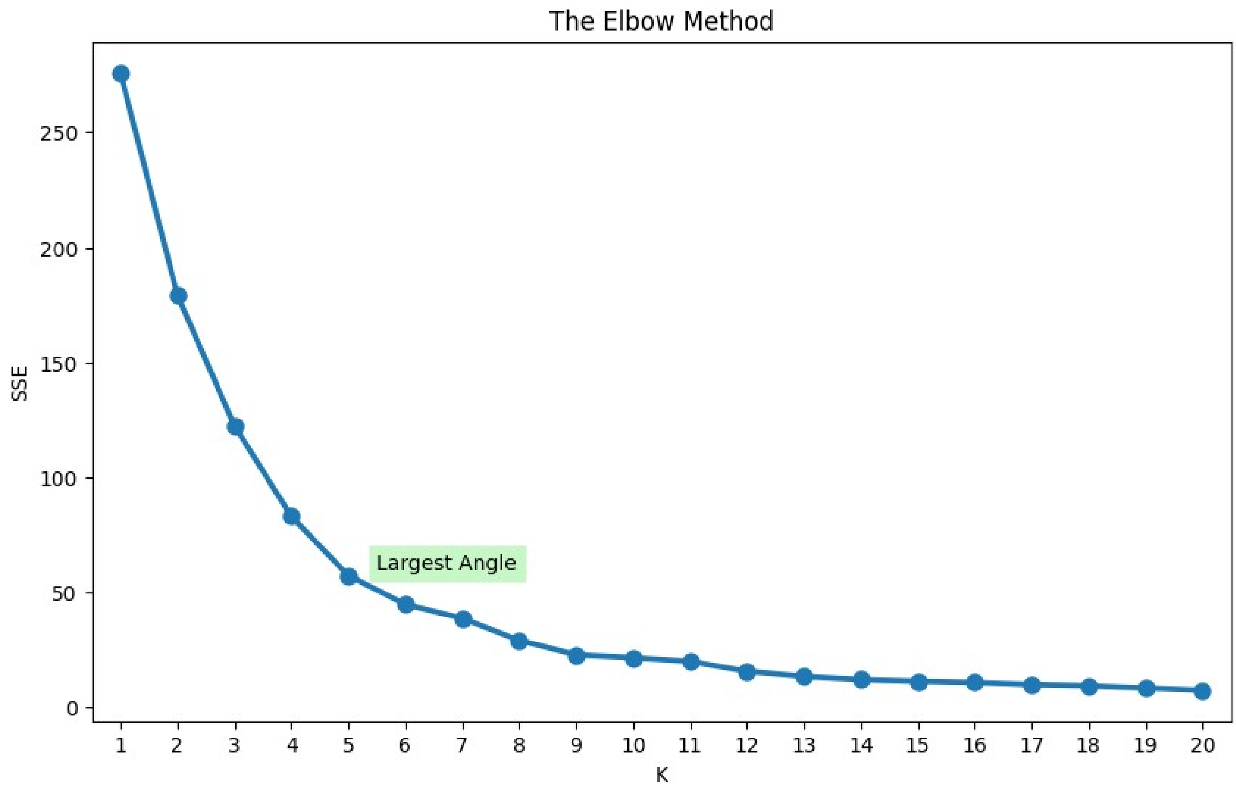
RFM Score < 10 and RFM Score >= 6 : Mid Value Customers

RFM Score < 6 : Low Value Customers

```
# Log transformation to reduce skew
data_log = np.log1p(data)  # log(1 + x)

# Standardization
scaler = StandardScaler()
data_normalized = pd.DataFrame(scaler.fit_transform(data_log),
                               index=data_log.index,
                               columns=data_log.columns)
print(data_normalized.describe().round(2))

       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      -3.26      -3.41          -3.82
25%      -0.29      -0.43          -0.39
50%       0.37       0.05          -0.04
75%       0.54       0.44           0.52
max       1.18       4.16           3.92

# Our data is skewed we must remove it by performing log
transformation
data_log = np.log(data)
data_log.head()
```

```
                              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
```

```
#Fit KMeans and use elbow method to choose the number of clusters
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans

sse = {}

for k in range(1, 21):
    kmeans = KMeans(n_clusters = k, random_state = 1)
    kmeans.fit(data_normalized)
    sse[k] = kmeans.inertia_

plt.figure(figsize=(10,6))
plt.title('The Elbow Method')

plt.xlabel('K')
plt.ylabel('SSE')
plt.style.use('ggplot')

sns.pointplot(x=list(sse.keys()), y = list(sse.values()))
plt.text(4.5, 60, "Largest Angle", bbox = dict(facecolor =
'lightgreen', alpha = 0.5))
plt.show()
```




```
kmeans = KMeans(n_clusters=5, random_state=1)
kmeans.fit(data_normalized)
cluster_labels = kmeans.labels_

data_rfm = data.assign(Cluster = cluster_labels)
data_rfm.head()
```

	Recency	Frequency	MonetaryValue	Cluster
CUSTOMERNAME				
AV Stores, Co.	196	51	157807.81	4
Alpha Cognac	65	20	70488.44	2
Amica Models & Co.	265	26	94117.26	2
Anna's Decorations, Ltd	84	46	153996.13	4
Atelier graphique	188	7	24179.96	1