Implement K-Means clustering/ hierarchical clustering on sales_data_sample.csv dataset. Determine the number of clusters using the elbow method.

Dataset link : https://www.kaggle.com/datasets/kyanyoga/sample-sales-data (https://www.kaggle.com/datasets/kyanyoga/sample-sales-data)

In [1]:
```
import pandas as pd
import numpy as np
```

In [20]:
```
df = pd.read_csv('sales_data_sample.csv', encoding='unicode_escape')
```

In [22]:
```
df.head()
```

Out[22]:

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	STATUS
0	10107	30	95.70	2	2871.00	2/24/2003 0:00	Shipped
1	10121	34	81.35	5	2765.90	5/7/2003 0:00	Shipped
2	10134	41	94.74	2	3884.34	7/1/2003 0:00	Shipped
3	10145	45	83.26	6	3746.70	8/25/2003 0:00	Shipped
4	10159	49	100.00	14	5205.27	10/10/2003 0:00	Shipped

5 rows × 25 columns

In [23]:
```
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
```

In [5]:
```
#Columns to Remove
to_drop = ['ADDRESSLINE1', 'ADDRESSLINE2', 'STATE', 'POSTALCODE', 'PHONE']
df = df.drop(to_drop, axis=1)
```

In [6]:
```python
#Check for null values
df.isnull().sum()
```

Out[6]:
```
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
```

In [25]:
```python
df.dtypes
```

Out[25]:
```
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
PHONE                object
ADDRESSLINE1         object
ADDRESSLINE2         object
CITY                 object
STATE                object
POSTALCODE           object
COUNTRY              object
TERRITORY            object
CONTACTLASTNAME      object
CONTACTFIRSTNAME     object
DEALSIZE             object
dtype: object
```

In [26]:
```
#ORDERDATE Should be in date time
df['ORDERDATE'] = pd.to_datetime(df['ORDERDATE'])
```

In [27]:
```
#We need to create some features in order to create cluseters
#Recency: Number of days between customer's latest order and today's date
#Frequency : Number of purchases by the customers
#MonetaryValue : Revenue generated by the customers
import datetime as dt
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 the columns
df_RFM.rename(columns = {
    'ORDERDATE' : 'Recency',
    'ORDERNUMBER' : 'Frequency',
    'SALES' : 'MonetaryValue'
}, inplace=True)
```

In [28]:
```

df_RFM.head()
```

Out[28]:

	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 [29]:
```python
# Divide into segments
# We create 4 quartile ranges
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()
```

Out[29]:

	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

In [30]:
```python
#Create another column for RFM score
df_RFM['RFM_Score'] = df_RFM[['R', 'M', 'F']].sum(axis=1)
df_RFM.head()
```

Out[30]:

	Recency	Frequency	MonetaryValue	M	R	F	RFM_Score
CUSTOMERNAME							
AV Stores, Co.	196	51	157807.81	4	2	4	10
Alpha Cognac	65	20	70488.44	2	4	2	8
Amica Models & Co.	265	26	94117.26	3	1	2	6
Anna's Decorations, Ltd	84	46	153996.13	4	3	4	11
Atelier graphique	188	7	24179.96	1	2	1	4

In [31]:
```
def rfm_level(df):
    if bool(df['RFM_Score'] >= 10):
        return 'High Value Customer'

    elif bool(df['RFM_Score'] < 10) and bool(df['RFM_Score'] >= 6):
        return 'Mid Value Customer'
    else:
        return 'Low Value Customer'
df_RFM['RFM_Level'] = df_RFM.apply(rfm_level, axis = 1)
df_RFM.head()
```

Out[31]:

CUSTOMERNAME	Recency	Frequency	MonetaryValue	M	R	F	RFM_Score	RFM_Level
AV Stores, Co.	196	51	157807.81	4	2	4	10	High Value Customer
Alpha Cognac	65	20	70488.44	2	4	2	8	Mid Value Customer
Amica Models & Co.	265	26	94117.26	3	1	2	6	Mid Value Customer
Anna's Decorations, Ltd	84	46	153996.13	4	3	4	11	High Value Customer
Atelier graphique	188	7	24179.96	1	2	1	4	Low Value Customer

In [32]:
```
# Time to perform KMeans
data = df_RFM[['Recency', 'Frequency', 'MonetaryValue']]
data.head()
```

Out[32]:

CUSTOMERNAME	Recency	Frequency	MonetaryValue
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 [33]:
```
# Our data is skewed we must remove it by performing log transformation
data_log = np.log(data)
data_log.head()
```

Out[33]:

CUSTOMERNAME	Recency	Frequency	MonetaryValue
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 [34]:
```
#Standardization
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(data_log)
data_normalized = scaler.transform(data_log)
data_normalized = pd.DataFrame(data_normalized, index = data_log.index, columns=data_log
data_normalized.describe().round(2)
```

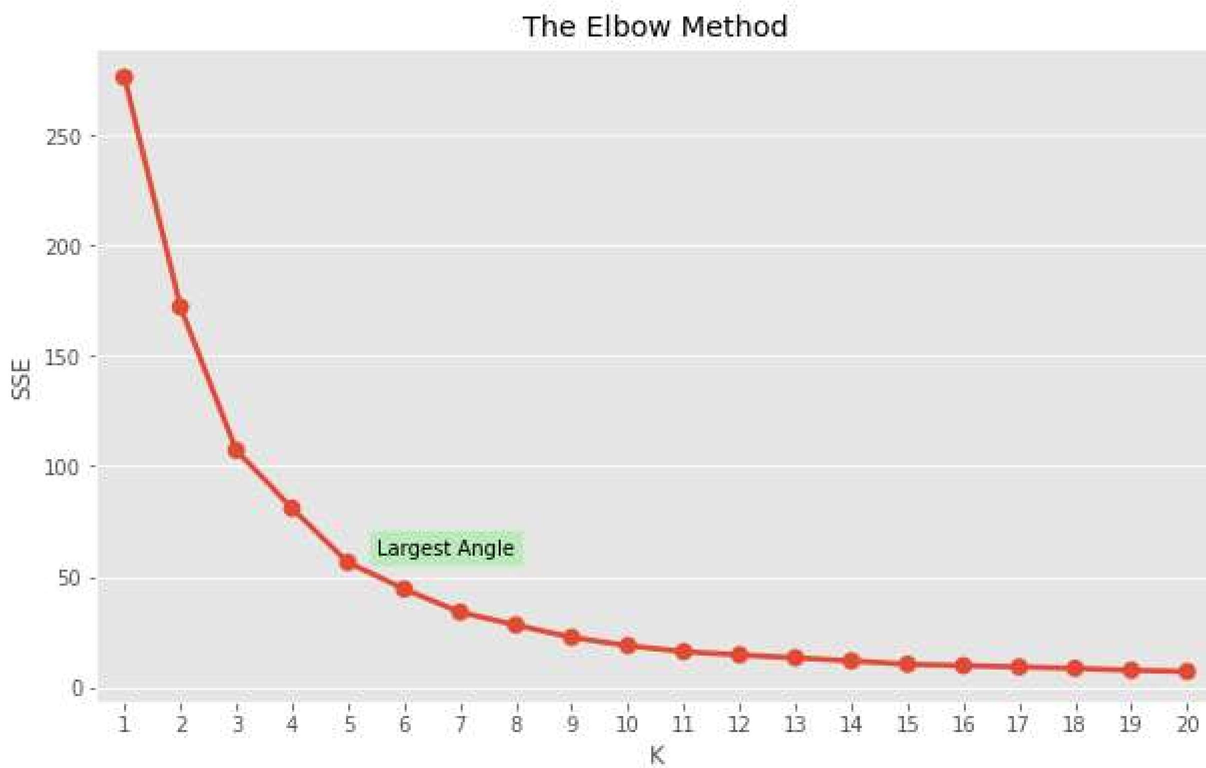
Out[34]:

	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
max	1.12	4.03	3.92

In [35]:
```
#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_
```

```
C:\Users\Lenovo\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1036: UserWarni
ng: KMeans is known to have a memory leak on Windows with MKL, when there are less chu
nks than available threads. You can avoid it by setting the environment variable OMP_N
UM_THREADS=1.
  warnings.warn(
```

In [36]:
```
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()
```



In [37]:
```
# 5 number of clusters seems good
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()
```

Out[37]:

	Recency	Frequency	MonetaryValue	Cluster
CUSTOMERNAME				
AV Stores, Co.	196	51	157807.81	3
Alpha Cognac	65	20	70488.44	0
Amica Models & Co.	265	26	94117.26	0
Anna's Decorations, Ltd	84	46	153996.13	3
Atelier graphique	188	7	24179.96	2

In [ ]: