

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

```
In [27]: import pandas as pd
import numpy as np
```

```
In [28]: df = pd.read_csv('./sales_data_sample.csv', encoding='unicode_escape')
```

```
In [29]: df.head()
```

Out[29]:

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

```
In [31]: #Check for null values
df.isnull().sum()
```

Out[31]:

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 [32]: #But territory does not have significant impact on analysis, let it be
```

```
In [33]: df.dtypes
```

```
Out[33]: 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
```

```
In [34]: #ORDERDATE Should be in date time
df['ORDERDATE'] = pd.to_datetime(df['ORDERDATE'])
```

```
In [35]: #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 [36]: df_RFM.head()
```

Out[36]:

	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 [37]: # 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[37]:

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

Out[38]:

	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

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

```
In [39]: 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[39]:

	Recency	Frequency	MonetaryValue	M	R	F	RFM_Score	RFM_Level
CUSTOMERNAME								
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 [40]: # Time to perform KMeans
data = df_RFM[['Recency', 'Frequency', 'MonetaryValue']]
data.head()
```

Out[40]:

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

Out[41]:

	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 [42]: #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[42]:

	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 [43]: #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_

fig, ax = plt.subplots()
ax.plot(sse, 'b-')
ax.set_xlabel('Number of clusters')
ax.set_ylabel('Sum of Squared Errors (SSE)')
plt.show()
```

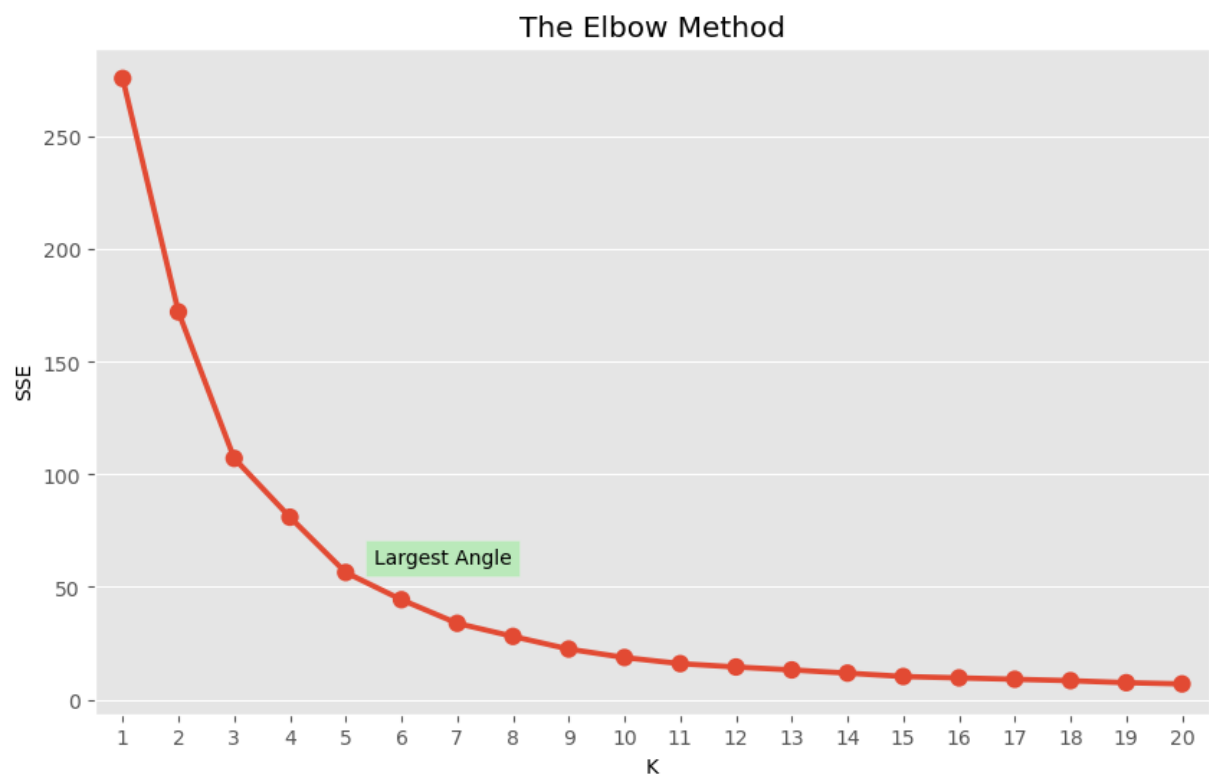
ng. The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning

```
warnings.warn(
C:\ProgramData\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1382: UserWarnin
g: KMeans is known to have a memory leak on Windows with MKL, when there are less chun
ks than available threads. You can avoid it by setting the environment variable OMP_NU
M_THREADS=1.
warnings.warn(
C:\ProgramData\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarni
ng: 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
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ng: 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
```

```
In [44]: 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 [45]: # 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()
```

C:\ProgramData\anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:870: 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
warnings.warn(
C:\ProgramData\anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:1382: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks th
an available threads. You can avoid it by setting the environment variable OMP_NUM_THREA
DS=1.
warnings.warn(

Out[45]:

	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