Predicting Customer Segmentation

An unsupervised learning algorithm can be trained on a dataset of customer behavior and demographic information to segment customers into different groups.

Criteria	Particular
Algorithm	K-Means Clustering
Evaluation Parameters	Within-Cluster Sum of Squares Silhouette Score Calinski-Harabasz Index Davies-Bouldin Index

1. Importing Dependencies

In [31]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
import warnings
warnings.filterwarnings('ignore')
```

2. Loading the Dataset

In [4]:
```
%%time
df = pd.read_excel("/content/drive/MyDrive/SEM VIII/ADS/Experiment 4/Online Retail.xlsx")
```

```
CPU times: user 1min 16s, sys: 301 ms, total: 1min 16s
Wall time: 1min 17s
```

In [46]:
```
df.head(3)
```

Out[46]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom

In [6]:
```
df.describe()
```

Out[6]:

	Quantity	UnitPrice	CustomerID
count	541909.000000	541909.000000	406829.000000
mean	9.552250	4.611114	15287.690570
std	218.081158	96.759853	1713.600303
min	-80995.000000	-11062.060000	12346.000000
25%	1.000000	1.250000	13953.000000
50%	3.000000	2.080000	15152.000000
75%	10.000000	4.130000	16791.000000
max	80995.000000	38970.000000	18287.000000

3. EDA & Data Cleaning

In [7]:
```
df.dtypes
```

Out[7]:
```
InvoiceNo              object
StockCode              object
Description            object
Quantity                int64
InvoiceDate    datetime64[ns]
UnitPrice             float64
CustomerID            float64
Country                object
dtype: object
```

In [8]:
```
df.duplicated().sum()
```

Out[8]:
```
5268
```

In [9]:
```
df1 = df.drop_duplicates()
df1.duplicated().sum()
```

Out[9]:
```
0
```

In [10]:
```
df1.isna().sum()
```

Out[10]:
```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135037
Country             0
dtype: int64
```

In [11]:
```
df1['Description'] = df1['Description'].replace(np.nan, 'NA')
```

Dropping ALL those rows where the `CustomerID` is null, because the number is huge (135037 - almost 25% of the dataset). This will result in the most accurate clustering.

In [ ]:
```
df2 = df1.dropna(subset=['CustomerID'])
```

4. Selecting the optimal number of clusters

In [13]:
```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

```python
from sklearn.metrics import silhouette_score, calinski_harabasz_score, davies_bouldin_score
```

Mapping the `Country` column to a unique number for each Country.

In [17]:
```python
df2['Country'].unique()
```

Out[17]:
```
array(['United Kingdom', 'France', 'Australia', 'Netherlands', 'Germany',
       'Norway', 'EIRE', 'Switzerland', 'Spain', 'Poland', 'Portugal',
       'Italy', 'Belgium', 'Lithuania', 'Japan', 'Iceland',
       'Channel Islands', 'Denmark', 'Cyprus', 'Sweden', 'Austria',
       'Israel', 'Finland', 'Greece', 'Singapore', 'Lebanon',
       'United Arab Emirates', 'Saudi Arabia', 'Czech Republic', 'Canada',
       'Unspecified', 'Brazil', 'USA', 'European Community', 'Bahrain',
       'Malta', 'RSA'], dtype=object)
```

In [18]:
```python
value_map = {value: index for index, value in enumerate(df2['Country'].unique())}

# Map the values in the 'category' column to numbers
df2['Country'] = df2['Country'].map(value_map)
```

In [19]:
```python
X = df2[['Quantity', 'UnitPrice', 'CustomerID', 'Country']]
```

In [20]:
```python
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Determining the optimal number of clusters using the `within-cluster sum of squares (WCSS)`, `Silhouette Score`, `Calinski-Harabasz Index` and `Davies-Bouldin Index`

In [19]:
```python
%%time
wcss = []

for i in range(2, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=0)
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)
```

```
CPU times: user 31.5 s, sys: 10.8 s, total: 42.4 s
Wall time: 24.8 s
```

In [20]:
```python
%%time
silhouette_scores = []

for i in range(2, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=0)
    kmeans.fit(X_scaled)
    silhouette_scores.append(silhouette_score(X_scaled, kmeans.labels_))
```

```
CPU times: user 4h 54min 59s, sys: 1h 32min, total: 6h 27min
Wall time: 5h 16min 29s
```

In [21]:
```python
%%time
ch_scores = []

for i in range(2, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=0)
    kmeans.fit(X_scaled)
    ch_scores.append(calinski_harabasz_score(X_scaled, kmeans.labels_))
```

```
CPU times: user 34.1 s, sys: 11.6 s, total: 45.7 s
Wall time: 27.8 s
```

In [22]:
```python
%%time
db_scores = []

for i in range(2, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=0)
```

```
    kmeans.fit(X_scaled)
    db_scores.append(davies_bouldin_score(X_scaled, kmeans.labels_))
```

```
CPU times: user 34.1 s, sys: 12 s, total: 46.2 s
Wall time: 27.4 s
```

Plot the results

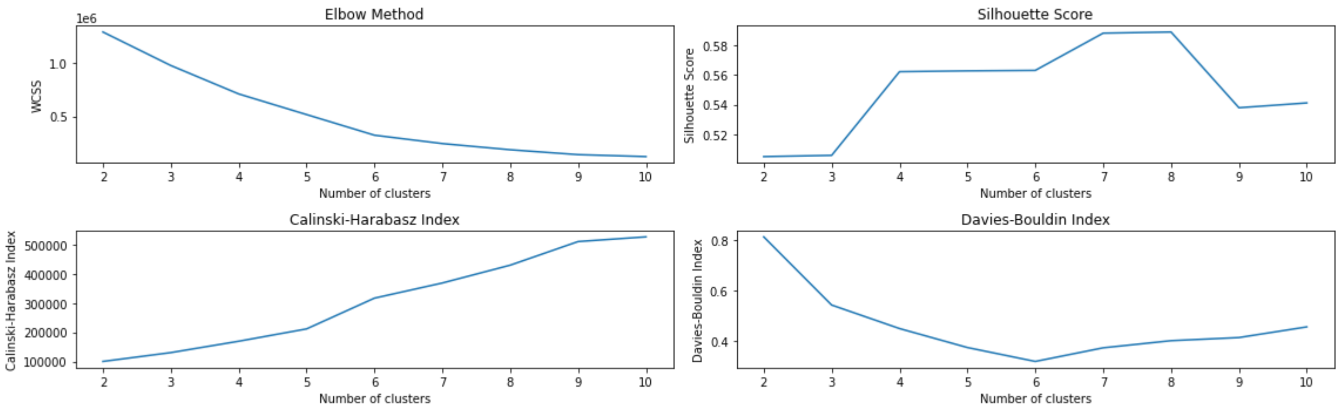
In [26]:
```
fig, ax = plt.subplots(2, 2, figsize=(16, 5))
ax[0, 0].plot(range(2, 11), wcss)
ax[0, 0].set_title('Elbow Method')
ax[0, 0].set_xlabel('Number of clusters')
ax[0, 0].set_ylabel('WCSS')

ax[0, 1].plot(range(2, 11), silhouette_scores)
ax[0, 1].set_title('Silhouette Score')
ax[0, 1].set_xlabel('Number of clusters')
ax[0, 1].set_ylabel('Silhouette Score')

ax[1, 0].plot(range(2, 11), ch_scores)
ax[1, 0].set_title('Calinski-Harabasz Index')
ax[1, 0].set_xlabel('Number of clusters')
ax[1, 0].set_ylabel('Calinski-Harabasz Index')

ax[1, 1].plot(range(2, 11), db_scores)
ax[1, 1].set_title('Davies-Bouldin Index')
ax[1, 1].set_xlabel('Number of clusters')
ax[1, 1].set_ylabel('Davies-Bouldin Index')

plt.tight_layout()
plt.show()
```



4. Optimal Clusters Conclusion : 6

Parameter	Clusters	Score
WCSS	6	0.5
Silhouette Score	6	0.56
Calinski-Harabasz Index	6	3,00,000
Davies-Bouldin Index	6	0.38

5. Implementing Clustering

In [22]:
```
%%time
kmeans = KMeans(n_clusters=6, init='k-means++', n_init=10, max_iter=300, random_state=None)
labels = kmeans.fit_predict(X)
```

```
CPU times: user 6.55 s, sys: 1.11 s, total: 7.66 s
Wall time: 4.96 s
```

6. Evaluating the model

In [27]:

```
%%time
w = kmeans.inertia_
c = calinski_harabasz_score(X, labels)
d = davies_bouldin_score(X, labels)
```

```
CPU times: user 130 ms, sys: 41.8 ms, total: 172 ms
Wall time: 129 ms
```

In [28]:

```
print(f'WCSS: {w}')
print(f'Silhoutte Score: 0.56')
print(f'Calinski-Harabasz Index: {c}')
print(f'Davies-Bouldin Index: {d}')
```

```
WCSS: 57396299545.58153
Silhoutte Score: 0.56
Calinski-Harabasz Index: 1608721.3965428101
Davies-Bouldin Index: 0.49500741104792817
```

7. Plotting the Cluster Scatter Graph

In [42]:

```
plt.figure(figsize=(16, 5))
plt.scatter(X.iloc[:, 2], X.iloc[:, 3], c=labels)
plt.scatter(kmeans.cluster_centers_[:, 2], kmeans.cluster_centers_[:, 3], marker='*', s=300,
plt.xlabel('Customer ID')
plt.ylabel('Country')
plt.show()
```