Hierarchical Clustering

Importing the libraries

```
In [16]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

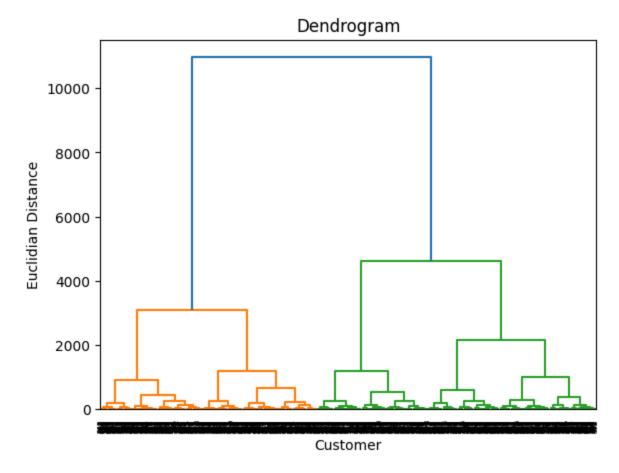
Importing the dataset

```
In [17]: dataset = pd.read csv(r"C:\Users\Admin\Downloads\Synthetic Online Retail.csv
In [18]: dataset.shape
Out[18]: (1000, 6)
In [19]: dataset.info()
        <class 'pandas.core.frame.DataFrame'>
       RangeIndex: 1000 entries, 0 to 999
       Data columns (total 6 columns):
            Column
                               Non-Null Count Dtype
                                -----
           TransactionID
CustomerSegment
        0
                               1000 non-null
                                               int64
                              1000 non-null
                                               object
        2 ProductCategory
                              1000 non-null object
           PurchaseAmount ($) 1000 non-null float64
            Quantity
                               1000 non-null
                                               int64
            PurchaseDate 1000 non-null
        5
                                               object
       dtypes: float64(1), int64(2), object(3)
       memory usage: 47.0+ KB
In [20]: X = dataset.iloc[:,[3,4]].values
In [21]: print(X)
        [[525.95
        [285.85]
                  9. ]
        [301.59
                7. ]
         . . .
        [954.78
                  8. 1
                  5. ]
         [918.93
                     11
        [ 51.76 2.
```

Using the dendrogram to find the optimal number of clusters

```
In [22]: import scipy.cluster.hierarchy as sch
  dendrogram = sch.dendrogram(sch.linkage(X,method = 'ward'))
  plt.title("Dendrogram")
  plt.xlabel("Customer")
  plt.ylabel("Euclidian Distance")
```

Out[22]: Text(0, 0.5, 'Euclidian Distance')



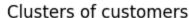
Training the Hierarchical Clustering model on the dataset

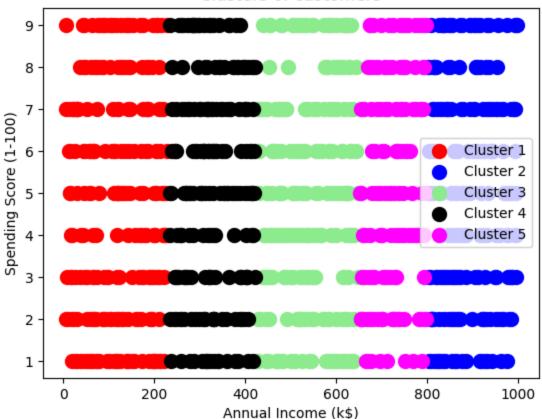
```
In [23]: from sklearn.cluster import AgglomerativeClustering
hc = AgglomerativeClustering (n_clusters = 5, linkage = 'ward')
y_hc = hc.fit_predict(X)
In [24]: print(y_hc)
```

```
[2 3 3 3 4 4 1 1 2 0 0 3 1 2 3 3 2 4 0 1 2 0 1 0 1 1 4 4 3 1 2 4 1 1 1 3 1
\begin{smallmatrix} 2 & 1 & 4 & 3 & 3 & 2 & 4 & 3 & 2 & 3 & 1 & 2 & 0 & 0 & 0 & 2 & 0 & 0 & 1 & 1 & 2 & 1 & 0 & 2 & 2 & 2 & 3 & 2 & 3 & 4 & 0 & 0 & 0 & 3 & 2 & 0 & 1 \\ \end{smallmatrix}
3 0 4 0 2 4 0 0 3 0 0 3 3 2 4 2 0 0 1 2 1 3 2 2 3 2 2 0 3 4 1 3 3 0 4 3 1
3\ 3\ 2\ 1\ 2\ 2\ 1\ 0\ 1\ 0\ 4\ 2\ 3\ 1\ 0\ 0\ 2\ 3\ 2\ 0\ 0\ 0\ 0\ 2\ 4\ 1\ 1\ 0\ 2\ 0\ 3\ 2\ 0\ 0\ 1\ 2\ 2
0\ 3\ 1\ 0\ 3\ 0\ 2\ 0\ 1\ 1\ 4\ 3\ 1\ 2\ 3\ 2\ 0\ 0\ 4\ 3\ 2\ 3\ 1\ 1\ 1\ 3\ 0\ 2\ 0\ 0\ 2\ 2\ 1\ 0\ 3\ 0\ 1
4 1 1 2 2 3 2 2 2 1 1 4 4 4 0 0 4 4 0 1 0 3 4 0 0 3 4 3 4 2 0 1 0 1 2 1 0
2 0 0 2 0 2 0 3 4 2 2 2 1 3 4 1 4 2 2 4 2 0 0 1 3 4 3 2 0 0 1 1 4 2 4 2 2
0 2 4 1 0 4 2 2 0 3 3 3 4 4 2 1 3 3 4 0 3 0 0 1 3 2 0 4 3 4 3 0 2 0 2 3 1
\begin{smallmatrix}0&4&0&3&3&1&3&0&3&0&0&2&0&0&4&3&0&3&2&3&2&0&2&3&2&1&2&3&3&3&0&0&4&3&2&2&2\end{smallmatrix}
0 1 0 4 4 4 2 0 3 2 3 1 3 3 3 3 2 4 4 1 1 1 0 4 0 0 2 3 0 0 0 1 0 0 3 3 1
0 2 4 1 2 1 0 3 3 1 0 0 3 0 0 1 2 2 4 3 0 0 3 2 3 0 2 1 1 1 4 3 4 0 4 2 0
4 1 3 1 0 2 2 2 1 1 4 3 1 0 1 3 0 4 3 3 3 0 0 0 2 0 4 3 1 1 3 4 1 1 2 0 2
2 2 3 1 1 0 0 0 1 4 2 3 2 3 2 4 1 1 1 3 2 4 1 0 3 0 2 3 3 0 3 1 3 4 2 1 0
 1 \; 2 \; 1 \; 1 \; 0 \; 0 \; 3 \; 2 \; 0 \; 0 \; 2 \; 0 \; 0 \; 3 \; 0 \; 3 \; 2 \; 2 \; 1 \; 2 \; 2 \; 3 \; 1 \; 1 \; 1 \; 4 \; 0 \; 3 \; 0 \; 1 \; 4 \; 4 \; 3 \; 1 \; 3 \; 0 \; 3
2 2 1 0 2 2 3 1 4 4 1 4 3 4 3 3 0 4 4 3 4 1 0 3 4 3 2 0 2 4 4 1 1 4 4 0 2
0 1 3 2 3 4 1 3 1 3 2 1 3 1 0 0 1 0 1 1 0 2 0 2 0 0 3 2 1 1 4 2 1 3 4 1 3
4 1 1 4 3 3 0 4 0 1 0 0 2 4 0 2 2 0 0 1 2 0 1 1 2 2 1 1 4 2 2 4 0 2 1 4 3
4 0 3 4 0 0 1 0 3 1 4 4 1 0 4 2 1 2 2 2 2 4 2 2 2 2 4 1 4 1 1 2 4 1 2 1 4
2 3 2 1 4 2 1 2 2 4 4 0 2 2 3 2 3 0 3 0 2 1 4 3 0 0 2 0 2 3 1 3 3 1 3 0 2
2 4 3 2 3 0 1 4 3 2 0 1 0 0 2 2 2 0 3 2 0 1 0 2 4 3 2 1 0 1 2 3 2 3 4 4 1
1 4 2 3 2 0 4 2 0 0 3 2 2 2 2 4 0 0 2 2 0 3 0 2 3 2 1 3 1 2 2 4 4 2 2 0 0
3 3 3 0 4 1 1 2 4 1 3 3 1 2 2 0 0 1 2 3 0 2 2 0 1 0 3 4 3 1 4 4 0 0 3 2 4
1 4 1 4 3 3 4 0 0 2 1 0 4 1 2 0 0 4 4 1 2 0 0 4 0 3 2 0 3 3 3 0 4 1 3 4 3
2\; 1\; 4\; 1\; 0\; 0\; 1\; 3\; 3\; 4\; 1\; 1\; 3\; 1\; 0\; 0\; 2\; 0\; 3\; 4\; 3\; 0\; 3\; 2\; 2\; 4\; 4\; 2\; 1\; 0\; 3\; 1\; 3\; 1\; 2\; 4\; 3
2 3 4 2 1 3 0 3 2 1 3 4 3 2 1 3 3 1 1 2 2 3 2 1 4 3 0 3 0 0 3 0 0 2 0 0 3
0 2 0 4 1 4 2 1 4 0 3 1 3 0 4 1 0 2 0 4 3 3 1 2 4 3 3 2 0 3 0 4 1 1 2 3 2
 1 \; 0 \; 1 \; 3 \; 1 \; 1 \; 1 \; 3 \; 0 \; 3 \; 3 \; 0 \; 2 \; 3 \; 2 \; 2 \; 0 \; 1 \; 0 \; 2 \; 2 \; 1 \; 0 \; 2 \; 2 \; 0 \; 2 \; 1 \; 1 \; 0 \; 3 \; 3 \; 3 \; 0 \; 1 \; 1
01
```

Visualising the clusters

```
In [25]: plt.scatter(X[y_hc == 0, 0], X[y_hc == 0, 1], s = 100, c = 'red', label = '(
    plt.scatter(X[y_hc == 1, 0], X[y_hc == 1, 1], s = 100, c = 'blue', label = '
    plt.scatter(X[y_hc == 2, 0], X[y_hc == 2, 1], s = 100, c = 'lightgreen', late |
    plt.scatter(X[y_hc == 3, 0], X[y_hc == 3, 1], s = 100, c = 'black', label = |
    plt.scatter(X[y_hc == 4, 0], X[y_hc == 4, 1], s = 100, c = 'magenta', label |
    plt.title('Clusters of customers') |
    plt.xlabel('Annual Income (k$)') |
    plt.ylabel('Spending Score (1-100)') |
    plt.legend() |
    plt.show()
```





Internal Evaluation of Cluster

DB Score (lower is better)

```
In [12]: from sklearn.metrics import davies_bouldin_score
davies_bouldin_score(X,y_hc)
```

Out[12]: np.float64(0.5033190522483579)

External Evaluation

Homogenity Score (higher is better)

This notebook was converted with convert.ploomber.io