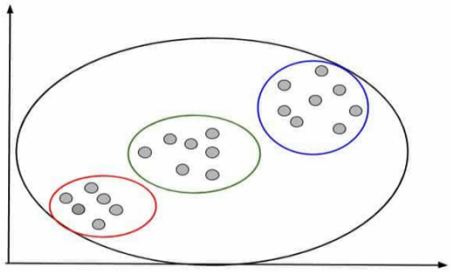
Exercise-9

AIM: Implementation of Hierarchical Agglomerative Clustering Algorithm

DESCRIPTION:

Hierarchal Clustering: Hierarchical Clustering groups similar objects into one cluster. The final cluster in the Hierarchical cluster combines all clusters into one cluster.

An example of Hierarchical clustering is **Dendrogram.** Hierarchical clustering cluster the **data points based on its similarity.** Hierarchical clustering continues clustering until one single cluster left. you can see in this image. Hierarchical clustering combines all three smaller clusters into one final cluster.



Type of Hierarchical Clustering

Hierarchical Clustering is of 2 types-

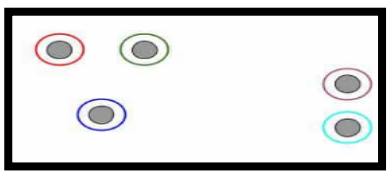
1. **Agglomerative Hierarchical Clustering.**
2. **Divisive Hierarchical Clustering.**

1. Agglomerative Hierarchical Clustering.

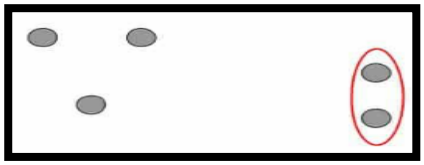
Agglomerative Hierarchical Clustering uses a **bottom-up approach** to form clusters. That means it starts from single data points. Then it clusters the closer data points into one cluster. The same process repeats until it gets one single cluster.

Steps to Perform Hierarchical Clustering:

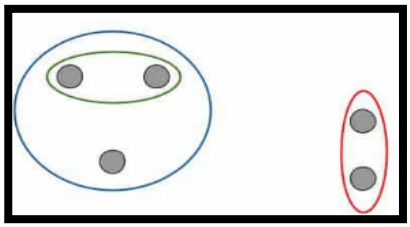
Step 1- Make each data point a single cluster. Suppose that forms n clusters.



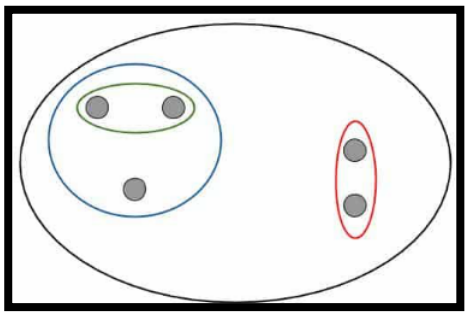
Step 2- Take the 2 closet data points and make them one cluster. Now the total clusters become n-1.



Step 3-Take the 2 closet clusters and make them one cluster. Now the total clusters become n-2.



Step 4- Repeat Step 3 until only one cluster is left.



Python Implementation of Aggloramative Hierarchical Clustering Algorithm:

We have a dataset of **Mall_Customers_dataset.csv**, which is the data of customers who visit the mall and spend there. In the given dataset, we have **Customer_Id, Gender, Age, Annual Income ($), and Spending Score** (which is the calculated value of how much a customer has spent in the mall, the more the value, the more he has spent). **From this dataset**, we need to **calculate some patterns**, as it is an **unsupervised method**, so we don't know what to calculate exactly.

The **steps to be followed for the implementation** are given below:

- Data Pre-processing
- Finding the optimal number of clusters using the elbow method
- Training the K-means algorithm on the training dataset
- Visualizing the clusters

1. Data Pre-processing:

(a) Importing Libraries: firstly, we will import the libraries for our model, which is part of data pre-processing. The code is given below:

```
# importing libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

(b) Importing the Dataset: Next, we will import the dataset that we need to use. So here, we are using the **Mall_Customer_data.csv** dataset. It can be imported using the below code:

```
# Importing the dataset
dataset = pd.read_csv('Mall_Customers_dataset.csv')
```

(c) Extracting Independent Variables: Here we don't need any dependent variable for data pre-processing step as it is a clustering problem, and we have no idea about what to determine. So we will just add a line of code for the matrix of features.

```
x = dataset. iloc [:, [3, 4]].values
```

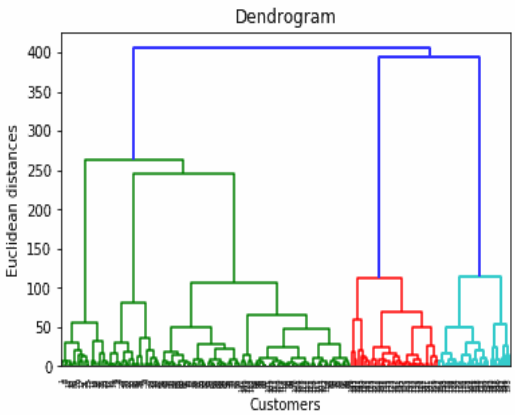
Step-2: We have loaded dataset. Now it's time to find the optimal number of clusters. And for that we need to create a Dendrogram

Create Dendrogram to find the Optimal Number of Clusters

scipy.cluster.hierarchy as sch dendro = sch.dendrogram(sch.linkage(X, method = 'ward'))

Here in the code **"sch"** is the short code for **scipy.cluster.hierarchy**."
"dendro" is the variable name. It may be anything. And **"Dendrogram"** is the function name.

So, after implementing this code, we will get our Dendrogram.



As I discussed that cut the **horizontal line with longest line** that **traverses maximum distance** up and down **without intersecting the merging points**. In that dendrogram, the optimal number of clusters are 5.

Step- 3: Training the Aggloramative Hierarchical Clustering algorithm on the training dataset:

```
from sklearn.cluster import AgglomerativeClustering
hc = AgglomerativeClustering(n_clusters = 5, affinity = 'euclidean', linkage = 'ward')
y_hc = hc.fit_predict(X)
```

Step-4: Visualizing the Clusters:

The last step is to visualize the clusters. As we have 5 clusters for our model, so we will visualize each cluster one by one. To visualize the clusters will use scatter plot using **plt.scatter() function** of matplotlib.

#visulaizing the clusters

```
plt.scatter(X[y_hc == 0, 0], X[y_hc == 0, 1], s = 100, c = 'red', label = 'Cluster 1')
plt.scatter(X[y_hc == 1, 0], X[y_hc == 1, 1], s = 100, c = 'blue', label = 'Cluster 2')
plt.scatter(X[y_hc == 2, 0], X[y_hc == 2, 1], s = 100, c = 'green', label = 'Cluster 3')
plt.scatter(X[y_hc == 3, 0], X[y_hc == 3, 1], s = 100, c = 'cyan', label = 'Cluster 4')
plt.scatter(X[y_hc == 4, 0], X[y_hc == 4, 1], s = 100, c = 'magenta', label = 'Cluster 5')
plt.title('Clusters of customers') plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```

In above **lines of code,** we have written code for each clusters, ranging from 1 to 5. The first coordinate of the **plt.scatter, i.e., x[y_hc == 0, 0]** containing the x value for the showing the matrix of features values, and the y_predict is ranging from 0 to 1.

The output image is clearly showing **the five different clusters** with **different colors**. The clusters are formed between **two parameters of the dataset**; **Annual income of customer** and **Spending**. We can change the colors and labels as per the requirement or choice. We can also observe some points from the above patterns, which are given below:

- **Cluster1 shows the customers with average salary** and **average spending** so we can categorize these customers as

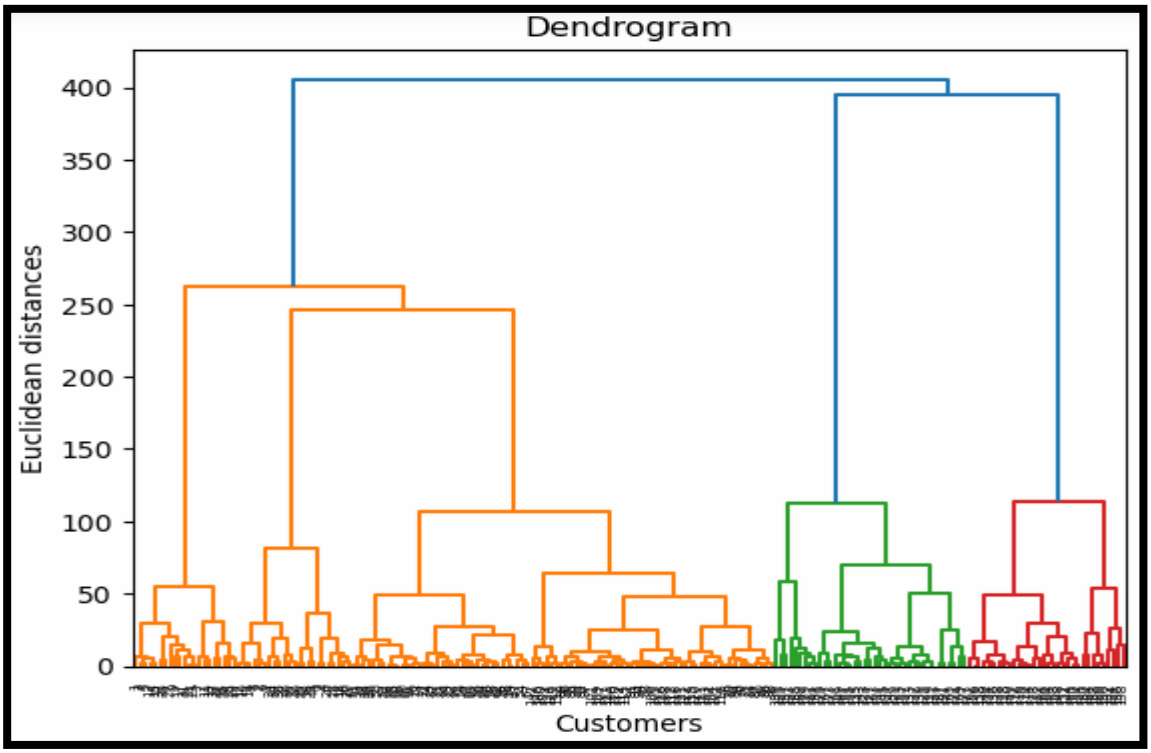
- **Cluster2 shows the customer has a high income** but **low spending**, so we can categorize them as careful.
- **Cluster3** shows the **low income** and also **low spending** so they can be categorized as sensible.
- **Cluster4** shows the customers with **low income** with **very high spending** so they can be categorized as careless.
- **Cluster5** shows the customers with **high income and high spending** so they can be categorized as target, and these customers can be the most profitable customers for the mall owner.

PROGRAM:

```
# importing libraries
import numpy as nm
import matplotlib.pyplot as plt
import pandas as pd
# Loading the dataset
dataset = pd.read_csv('Mall_Customers_dataset.csv')
print(dataset)
x = dataset.iloc[:, [3, 4]].values
print(x)
#Create Dendrogram to find the Optimal Number of Clusters
import scipy.cluster.hierarchy as sch
dendro = sch.dendrogram(sch.linkage(X, method = 'ward'))
plt.title('Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Euclidean distances')
plt.show()
#Fitting Agglomerative Hierarchical Clustering to the dataset
from sklearn.cluster import AgglomerativeClustering
hc = AgglomerativeClustering(n_clusters = 5, affinity = 'euclidean', linkage = 'ward')
y_hc = hc.fit_predict(X)
y_hc
#Visualise the clusters
plt.scatter(X[y_hc == 0, 0], X[y_hc == 0, 1], s = 100, c = 'red', label = 'Cluster 1')
plt.scatter(X[y_hc == 1, 0], X[y_hc == 1, 1], s = 100, c = 'blue', label = 'Cluster 2')
plt.scatter(X[y_hc == 2, 0], X[y_hc == 2, 1], s = 100, c = 'green', label = 'Cluster 3')
plt.scatter(X[y_hc == 3, 0], X[y_hc == 3, 1], s = 100, c = 'cyan', label = 'Cluster 4')
plt.scatter(X[y_hc == 4, 0], X[y_hc == 4, 1], s = 100, c = 'magenta', label = 'Cluster 5')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```

INPUT/OUTPUT:

 # Creating Dendrogram



 # Optimal No. of Clusters

CONCLUSION: **Program is executed successfully without any error.**