LAB No 11

Agglomerative Hierarchical Clustering

In this lab, students will learn how to perform Agglomerative Hierarchical Clustering (AHC), a method used to group similar data points into clusters. The lab involves:

- Understanding hierarchical clustering and dendrograms.
- Performing clustering on datasets using Python (scikit-learn, scipy).
- Visualizing clusters using dendrograms.
- Interpreting the clustering results for practical data analysis.

Objectives:

1. Understand hierarchical clustering concepts and linkage methods.
2. Perform agglomerative clustering on sample datasets.
3. Visualize the clustering process using dendrograms.
4. Analyze cluster assignments and validate results.

Theory

1. Introduction to Hierarchical Clustering

Hierarchical clustering is an **unsupervised learning** method that builds a hierarchy of clusters. It can be:

- **Agglomerative (bottom-up)**:
  Each observation starts as its own cluster, and pairs of clusters are merged step by step until only one cluster remains.
- **Divisive (top-down)**:
  Start with all observations in one cluster and recursively split them into smaller clusters.

2. Agglomerative Hierarchical Clustering

- Start with each data point as a separate cluster.
- Compute a **distance matrix** between all clusters.
- Merge the **two closest clusters** at each step.

- Repeat until all points belong to a single cluster.

Distance Metrics:

- **Euclidean Distance:** Most common for continuous data.
- **Manhattan Distance:** Sum of absolute differences.
- **Cosine Distance:** Measures angular distance for high-dimensional data.

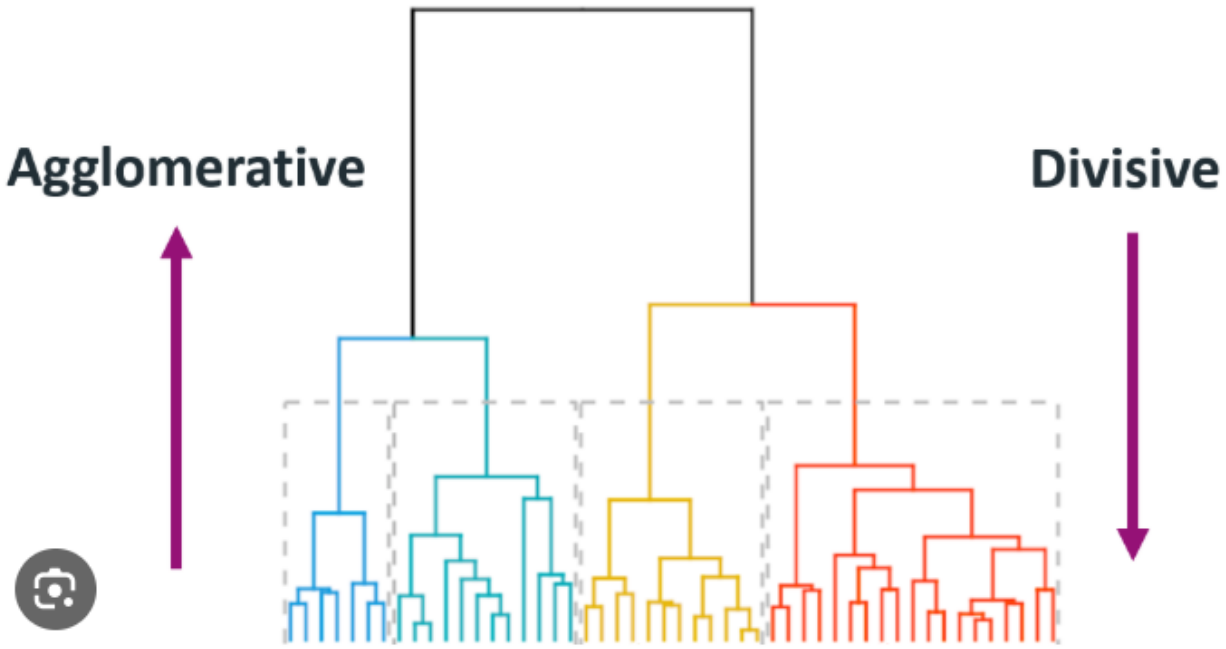
Linkage Methods:

- **Single Linkage:** Distance between closest points of two clusters.
- **Complete Linkage:** Distance between farthest points of two clusters.
- **Average Linkage:** Average distance between all points in two clusters.
- **Ward's Method:** Minimizes variance within clusters.

3. Dendrogram

A **dendrogram** is a tree-like diagram showing the order of cluster merges. It helps to:

- Visualize the hierarchy of clusters.
- Decide the optimal number of clusters by cutting the dendrogram.



4. Applications

- Customer segmentation in marketing.
- Document clustering in NLP.
- Gene expression analysis in bioinformatics.
- Image segmentation.

Python Libraries Required

```
import numpy as np
import pandas as pd
from scipy.cluster.hierarchy import dendrogram, linkage, fcluster
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
```

Solved Examples

Example 1: Clustering Simple 2D Points

Dataset:

```
data = np.array([[1, 2], [2, 3], [5, 8], [6, 9], [10, 12]])
```

Solution

```
# Step 1: Import libraries
from scipy.cluster.hierarchy import linkage, dendrogram, fcluster
import matplotlib.pyplot as plt

# Step 2: Linkage matrix
Z = linkage(data, method='ward')  # Using Ward's method

# Step 3: Plot dendrogram
plt.figure(figsize=(6,4))
dendrogram(Z)
plt.title("Dendrogram - Example 1")
plt.show()

# Step 4: Form clusters (choose 2 clusters)
clusters = fcluster(Z, t=2, criterion='maxclust')
print("Cluster assignments:", clusters)
```

Output:

```
less
Cluster assignments: [1 1 2 2 2]
```

Explanation: The first two points are grouped together; the last three points form the second cluster.

Example 2: Agglomerative Clustering on Random Dataset

Solution

```
from sklearn.datasets import make_blobs
from scipy.cluster.hierarchy import linkage, dendrogram, fcluster

# Generate random data
X, _ = make_blobs(n_samples=8, centers=3, random_state=42)

# Linkage
Z = linkage(X, method='complete')

# Dendrogram
plt.figure(figsize=(6,4))
dendrogram(Z)
plt.title("Dendrogram - Example 2")
plt.show()

# Form clusters
clusters = fcluster(Z, t=3, criterion='maxclust')
print("Cluster assignments:", clusters)
```

Explanation: The dendrogram shows three distinct clusters; cluster labels indicate the group each point belongs to.

Example 3: Agglomerative Clustering on Iris Dataset (subset)

Solution

```
from sklearn.datasets import load_iris
```

```
from sklearn.preprocessing import StandardScaler
from scipy.cluster.hierarchy import linkage, dendrogram, fcluster
import matplotlib.pyplot as plt

# Load Iris dataset
iris = load_iris()
X = iris.data[:, :2]  # Use only sepal length and width
X = StandardScaler().fit_transform(X)

# Linkage
Z = linkage(X, method='average', metric='euclidean')

# Plot dendrogram
plt.figure(figsize=(8,5))
dendrogram(Z)
plt.title("Dendrogram - Iris Example")
plt.show()

# Form clusters (3 clusters)
clusters = fcluster(Z, t=3, criterion='maxclust')
print("Cluster assignments:", clusters)
```

Explanation:

- Standardization is important to normalize features.
- The dendrogram helps to visualize clusters of similar iris species.
- fcluster assigns each data point to a cluster.

LAB Assignment No. 11

Question 1:

Perform Agglomerative Clustering with Different Linkages.

Task:

Load the "shopping-data.csv" dataset, extract the features *Annual Income* and *Spending Score*, and perform **Agglomerative Clustering** using:

- linkage = "ward"
- linkage = "complete"
- linkage = "average"

Instructions:

1. Perform clustering using AgglomerativeClustering.
2. Plot the clusters using matplotlib.
3. Compare how the cluster structure changes with each linkage method.

Question 2:

Draw a Dendrogram and Identify the Optimal Number of Clusters

Task:
Using the same dataset or any synthetic dataset, draw a **dendrogram** using:

```
from scipy.cluster.hierarchy import dendrogram, linkage
```

Instructions:

1. Fit the data using linkage(method='ward').
2. Plot a dendrogram.
3. From the dendrogram, visually determine:
    - The optimal number of clusters
    - The height at which clusters merge
4. Explain why hierarchical clustering may be preferred over K-Means.

Question 3: Compare Agglomerative vs Divisive Hierarchical Clustering

Task:
Using a small synthetic dataset (e.g., 10–12 points), perform:

- Agglomerative Clustering
- Divisive Clustering (manual split or using a library like sklearn-extra)

Instructions:

1. Plot dendrograms for both methods.
2. Compare the merge/split patterns.
3. Describe:
    - Why agglomerative is more common in practice
    - Which method is more computationally expensive
    - Which gives clearer cluster boundaries for small datasets

LAB Assessment

Student Name		**LAB Rubrics**	CLO3 , P5, PLO5

		Total Marks	10
Registration No		**Obtained Marks**	
		Teacher Name	Dr. Syed M Hamedoon
Date		**Signature**	