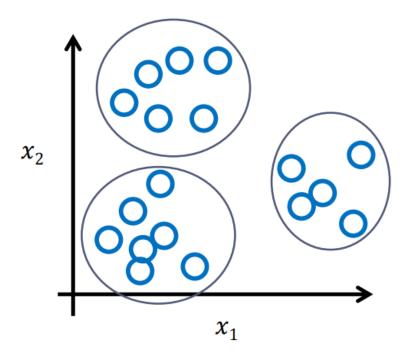
Clustering

Outline

- Clustering Definition
- Clustering main approaches
 - Partitional (flat)

Definition

- We have a set of unlabeled data points and we intend to find groups of similar objects (based on the observed features)
 - high intra-cluster similarity
 - o low inter-cluster similarity



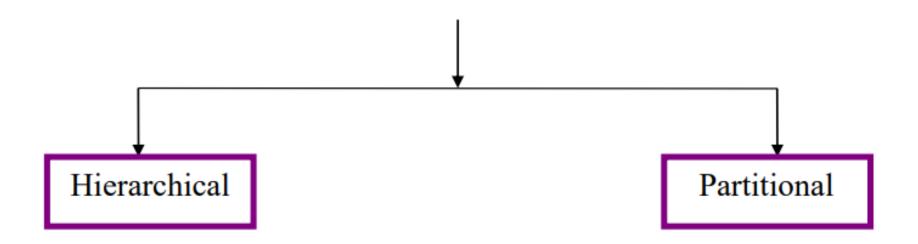
Clustering Purpose

- Preprocessing stage to index, compress, or reduce the data
- Representing high-dimensional data in a low-dimensional space

Clustering Applications

- Information retrieval (search and browsing)
- Cluster users of social networks by interest (community detection).
- Bioinformatics
- Market segmentation

Categorization of Clustering Algorithms



Partitional Algorithms

- Objective based clustering

 - © EM-style algorithm for clustering for mixture of Gaussians

Partitional Clustering

$$\mathcal{X} = \left\{ \mathbf{x}^{(i)} \right\}_{i=1}^{N}$$

$$\mathcal{C} = \left\{ \mathcal{C}_{1}, \mathcal{C}_{2}, \dots, \mathcal{C}_{K} \right\}$$

- $\vdash \forall j, \mathcal{C}_j \neq \emptyset$
- $\forall i, j, \ \mathcal{C}_i \cap \mathcal{C}_j = \emptyset$

Objective Based Clustering

- k-median: find center pts c1, c2, ..., cK to minimize
- k-means: find center pts c1, c2, ..., cK to minimize

$$\sum_{i=1}^{N} \min_{j \in 1, \dots, K} d^2(\boldsymbol{x}^{(i)}, \boldsymbol{c}_j)$$

• k-center: find partition to minimize the maxim radius

K means

- Input: a set x 1 , ... , x N of data points (in a d-dim feature space) and an integer k
- Output: a set of K representatives c1, c2, ..., $cK \in \mathbb{R}$ as the cluster representatives
- Objective: choose c1, c2, ..., cK to minimize:

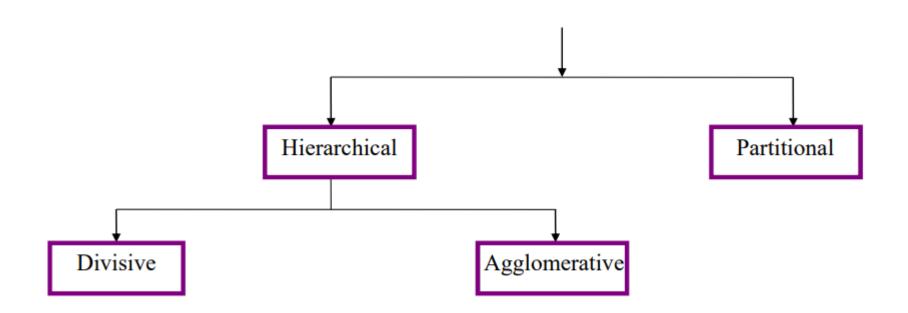
$$\sum_{i=1}^{N} \min_{j \in 1, \dots, K} d^2(\boldsymbol{x}^{(i)}, \boldsymbol{c}_j)$$

Advantages and disadvantages

- Strength
 - It is a simple method
 - Relatively efficient: O(tKNd), where t is the number of iterations
- Weakness
 - Need to specify K, the number of clusters, in advance
 - Works for numerical data. What about categorical data?

Hierarchical Clustering

• Hierarchical Clustering: Clusters contain sub-clusters and subclusters themselves can have sub-sub-clusters, and so on

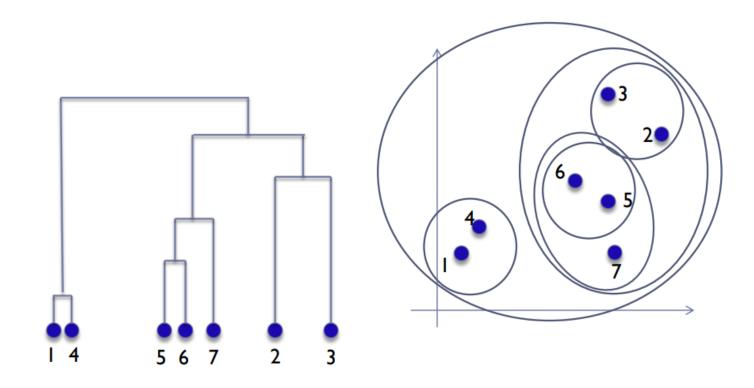


Hierarchical Clustering

- Agglomerative (bottom up):
 - Starts with each data in a separate cluster
 - @ Repeatedly joins the closest pair of clusters, until there is only one cluster
- Divisive (top down):
 - Starts with the whole data as a cluster
 - Repeatedly divide data in one of the clusters until there is only one data in each cluster

Example

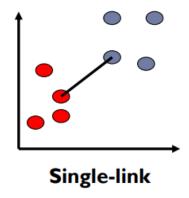
• Hierarchical Agglomerative Clustering (HAC)

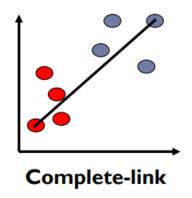


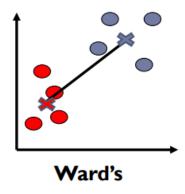
Distances between Cluster Pairs

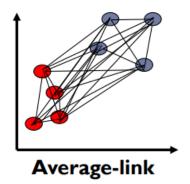
- Single-link
- Complete-link
- Centroid
- Average-link

Distances between Cluster Pairs







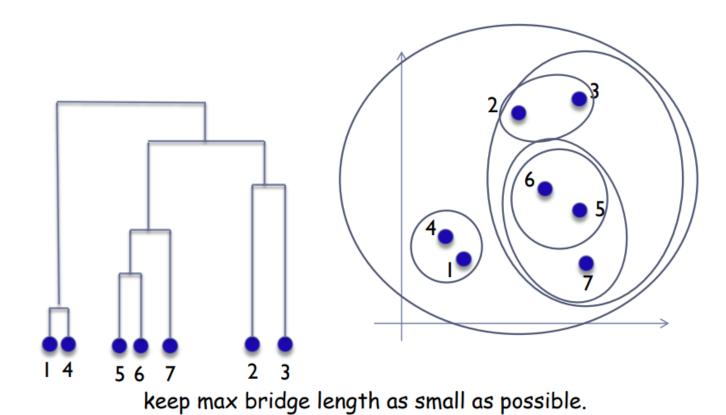


Single Linkage

• The minimum of all pairwise distances between points in the two clusters:

$$dist_{SL}(\mathcal{C}_i, \mathcal{C}_j) = \min_{\mathbf{x} \in \mathcal{C}_i, \mathbf{x}' \in \mathcal{C}_j} dist(\mathbf{x}, \mathbf{x}')$$

Single-Link

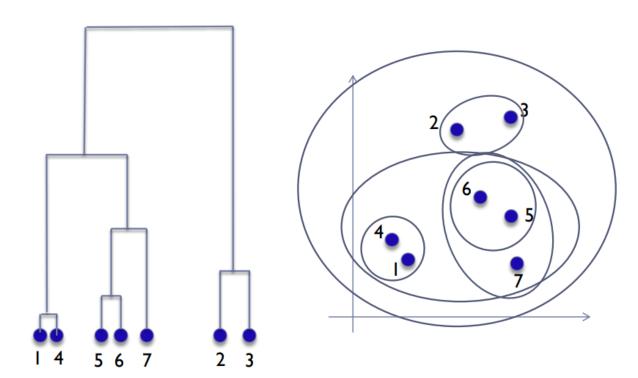


Complete Linkage

• The maximum of all pairwise distances between points in the two clusters:

$$dist_{CL}(\mathcal{C}_i, \mathcal{C}_j) = \max_{\mathbf{x} \in \mathcal{C}_i, \mathbf{x}' \in \mathcal{C}_j} dist(\mathbf{x}, \mathbf{x}')$$

Complete Link



Ward's method

• The distances between centers of the two clusters

$$dist_{Ward}(\mathcal{C}_i, \mathcal{C}_j) = \frac{|\mathcal{C}_i| |\mathcal{C}_j|}{|\mathcal{C}_i| + |\mathcal{C}_j|} dist(\mathbf{c}_i, \mathbf{c}_j)$$

- Merge the two clusters such that the increase in k-means cost is as small as possible
- Works well in practice.

K-means vs Hierarchical

- Time cost:
 - K-means is usually fast while hierarchical methods do not scale well
- Human intuition
- Choosing of the number of clusters
 - There is no need to specify the number of clusters in advance for hierarchical methods