

EDAMI laboratory

Clustering

Basic notions

- Object – an entity described by a set of attributes
 - Nominal attributes
 - Numerical attributes
- Data base (DB) – a set of objects.

Clustering

The purpose of clustering is to divide a set of objects into groups including similar objects (objects having similar values of attributes).

In some methods the number of groups has to be given as an input parameter.

A good clustering must have the following property:

- high similarity between objects within groups,
- low similarity between objects belonging to different groups.

Similarity is often defined as a certain distance measure between two objects.

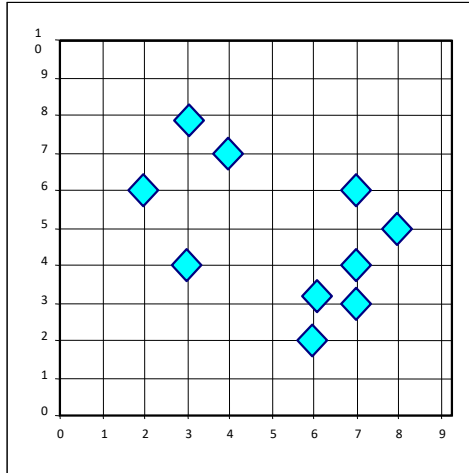
Partitioning algorithms: basic notions

- Partitioning method: create a division of the database D composed of n objects into k clusters, minimize the sum of distances squared

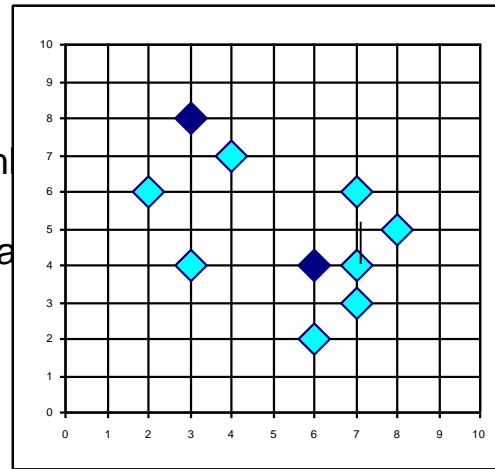
$$\sum_{i=1}^k \sum_{p \in C_i} \text{dist}(p, c_i)^2$$

- Given k find such partitioning into k clusters that optimizes the selected partitioning criterion
 - heuristic methods: k-medoids and k-means algorithms
 - *k-means* (MacQueen'67): each cluster is represented by its center
 - *k-medoids* or PAM (Partition around medoids) (Kaufman & Rousseeuw'87): each cluster is represented by one of the objects in the cluster

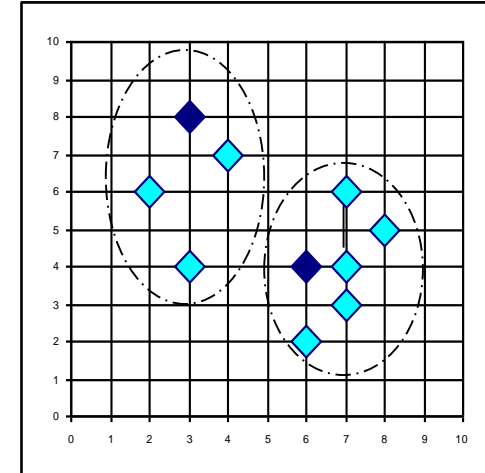
Typical *k*-means algorithm



Random
select k
objects as
initial
centers

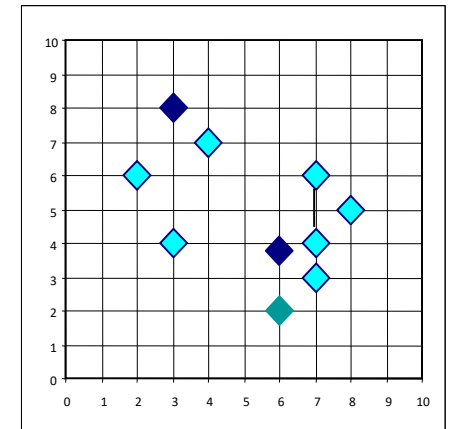


Assign
each of
the remaini
ng objects
to the
closest
center

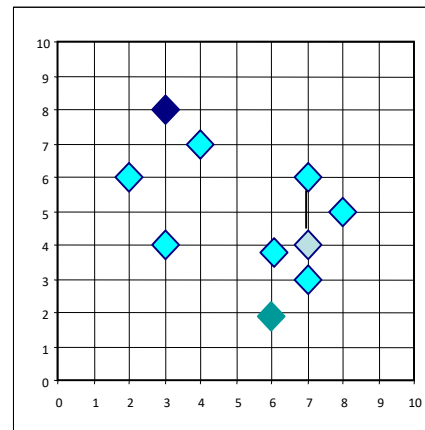


Total cost = 20

Randomly select an
object not being a
center, O_{random}



Compute
the total
cost of a
switch



Total cost = 26

Switch O
and O_{random}

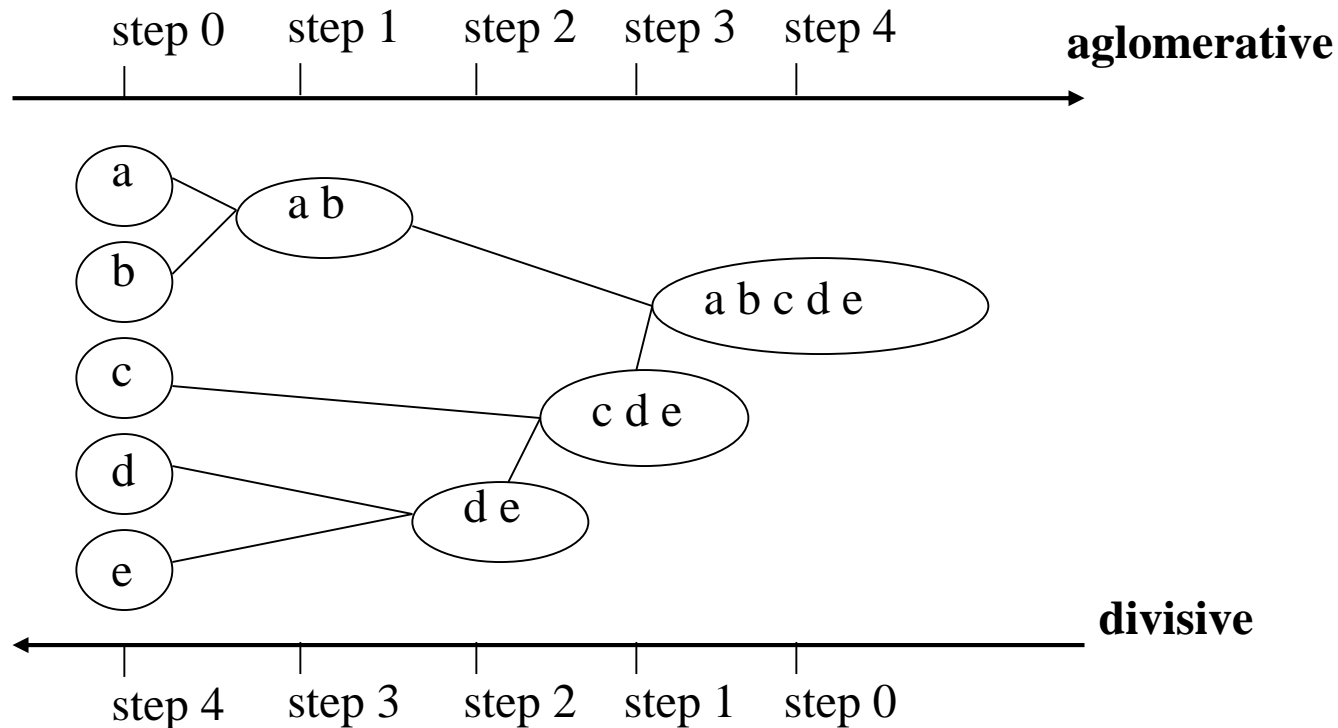
If quality
improves

$K=2$

**Do loop
Until no
changes**

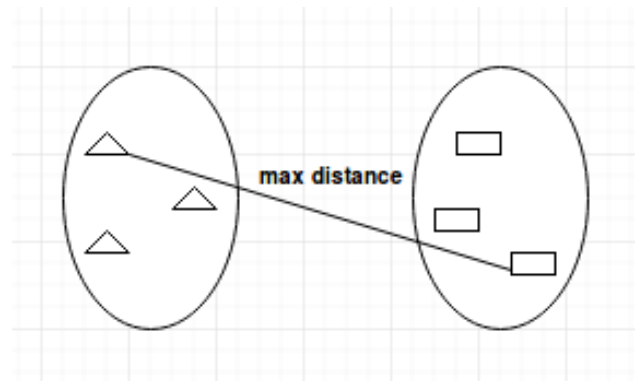
Hierarchical clustering

- Agglomerative (most methods belong to this category)
- Divisive (finish after reaching the stop criterion, e.g. fixed number of clusters, fixed diameter of a cluster)



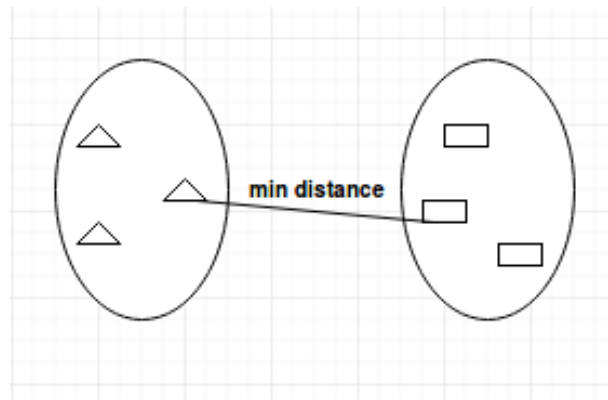
Hierarchical clustering: cluster linkage methods

Maximum or complete linkage: the distance between two clusters is defined as the maximum value of all pairwise distances between the elements in cluster 1 and the elements in cluster 2. It tends to produce more compact clusters.



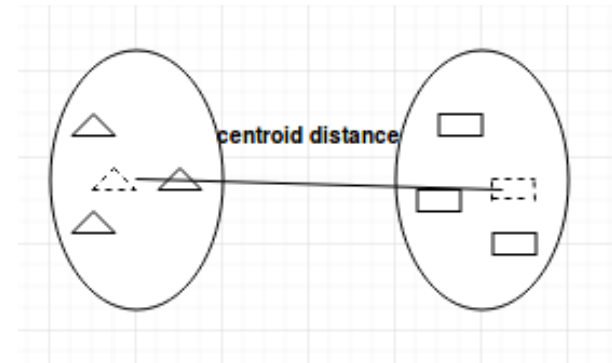
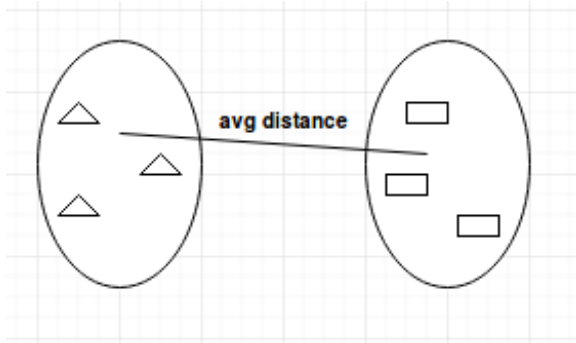
Hierarchical clustering: cluster linkage methods

Minimum or single linkage: the distance between two clusters is defined as the minimum value of all pairwise distances between the elements in cluster 1 and the elements in cluster 2. It tends to produce long, "loose" clusters.



Hierarchical clustering: cluster linkage methods

- Mean or average linkage: The distance between two clusters is defined as the average distance between the elements in cluster 1 and the elements in cluster 2.
- Centroid linkage: The distance between two clusters is defined as the distance between the centroid for cluster 1 (a mean vector of length p variables) and the centroid for cluster 2.

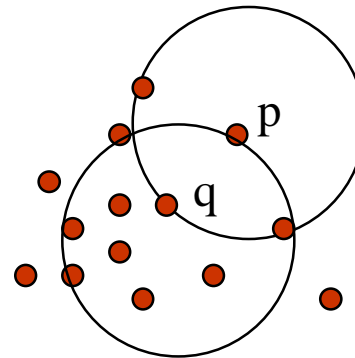


At each stage of the clustering process the two clusters, that have the smallest linkage distance, are linked together.

Density-based clustering: basic notions

- Two parameters:
 - *Eps*: maximum neighborhood diameter
 - *MinPts*: minimum nb of points in the neighborhood *Eps* of the point
- $N_{Eps}(p)$: $\{q \text{ belongs to } D \mid \text{dist}(p, q) \leq Eps\}$
- **Directly density-reachable**: Point p is directly density-reachable from point q with respect to Eps and $MinPts$ if
 - p belongs to $N_{Eps}(q)$
 - conditio of the core point:

$$|N_{Eps}(q)| \geq MinPts$$

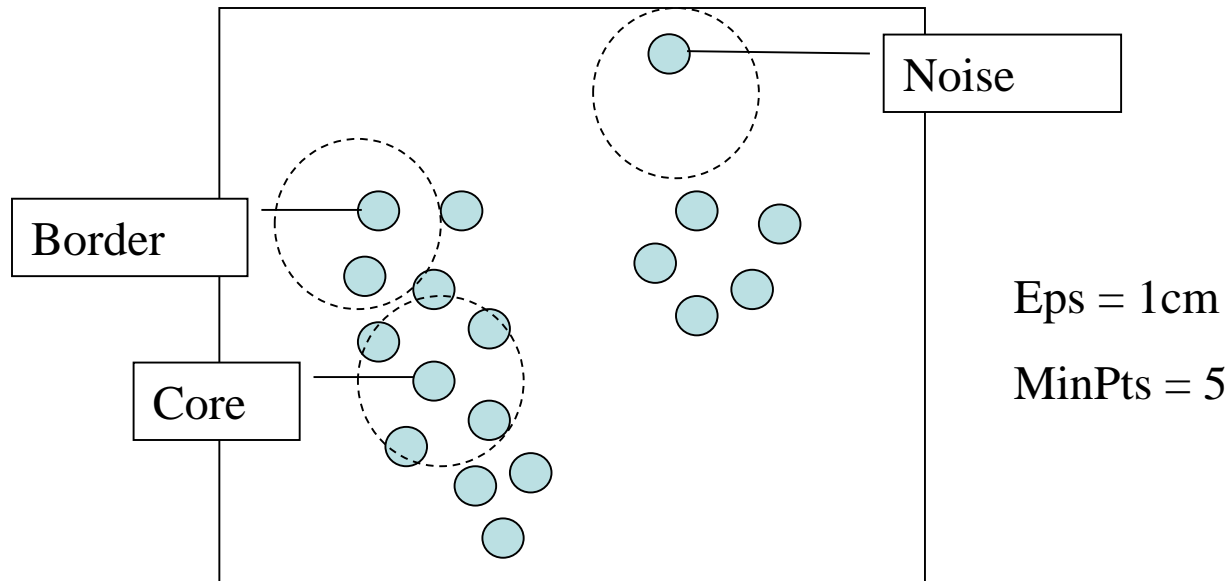


MinPts = 5

Eps = 1 cm

DBSCAN

Based on the notion of a density-based cluster: a cluster is defined as the maximum set of density-reachable points.



Evaluation of clustering quality (1)

Index Silhouette

$$Silhouette(x) = \frac{b(x) - a(x)}{\max(b(x), a(x))}$$

where:

$a(x)$ – the average distance between x and other objects in a group including x

$b(x)$ – the minimum average distance between x and the nearest group not including x .

The index has a value from the range $<-1, 1>$, where 1 means that the object is assigned to the best possible group, 0 - the object is located between two groups, and -1 - wrong assignment of the object.

$$GSilhouette = \frac{1}{N} \sum_{i=1}^N Silhouette(x_i)$$

where: N – number of objects

Evaluation of clustering quality (2)

Rand index

W – reference clustering, G – obtained clustering

A – a number of pairs of objects belonging to the same group in W and G

B – a number of pairs of objects belonging to the different groups in W and G

a – a number of pairs of objects belonging to the same group in W but not in G

b – a number of pairs of objects belonging to the different group in W but in the same in G

$$R = \frac{A+B}{A+B+a+b} = \frac{A+B}{n(n-1)/2}$$

Clustering in R (1)

Standard packages

- `scale()` – for centering and/or scaling the columns of a numeric matrix.
- `kmeans()` - k-Means algorithm, returns a `kmeans` object with a description of clusters.
- `hclust ()` - hierarchical clustering.
- `cutree()` – for cutting trees obtained by the means of `hclust()` function.
- `plot()` – for visualization of the clusters.

Clustering in R(2)

- Package fpc
 - dbscan () - an implementation of the DBScan algorithm
 - plotcluster() – a function for plotting clusters.
- Package cluster
 - Includes implementations of several clustering algorithms