

# Chapter VII: Cluster analysis

## Knowledge Discovery in Databases

Luciano Melodia M.A.

Evolutionary Data Management, Friedrich-Alexander University Erlangen-Nürnberg

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## Chapter VII: Cluster analysis

### **Cluster analysis: basic concepts.**

Partitioning methods.

Hierarchical methods.

Density-based methods.

Grid-based methods.

Evaluation of clustering.

Summary.

## What is cluster analysis?

**Cluster:** A collection of data objects within a larger set that are.

Similar (or related) to one another within the same group and,  
dissimilar (or unrelated) to the objects outside the group.

**Cluster analysis (or clustering, data segmentation, . . .).**

Define similarities among data based on the characteristics found in the data (input from user!).  
Group similar data objects into clusters.

**Unsupervised learning:**

No predefined classes.

I.e., learning by observation (vs. learning by examples: supervised).

**Typical applications:**

As a stand-alone tool to get insight into data distribution.

As a preprocessing step for other algorithms.

## Clustering for data understanding and applications

### **Biology:**

Taxonomy of living things: kingdom, phylum, class, order, family, genus, and species.

### **Information retrieval:**

Document clustering.

### **Land use:**

Identification of areas of similar land use in an earth-observation database.

### **Marketing:**

Help marketers discover distinct groups in their customer bases, and then use this knowledge to develop targeted marketing programs.

### **City planning:**

Identifying groups of houses according to their house type, value, and geographical location.

### **Earthquake studies:**

Observed earthquake epicenters should be clustered along continent faults.

### **Climate:**

Understanding earth climate, find patterns of atmosphere and ocean.

## Quality: what is good clustering?

**A good clustering method will produce high-quality clusters.**

**High intra-class similarity:**

Cohesive within clusters.

**Low inter-class similarity:**

Distinctive between clusters.

**The **quality** of a clustering method depends on:**

the **similarity measure** used by the method,  
its implementation, and  
its ability to discover some or all of the hidden patterns.

## Measure the quality of clustering

### Dissimilarity/similarity metric:

Similarity is expressed in terms of a distance function, typically a metric:  $d(x, y)$ .

The definitions of distance functions are usually rather different for interval-scaled, Boolean, categorical, ordinal, ratio, and vector variables (see chapter 2).

**Weights** should be associated with different variables based on applications and data semantics.

### Quality of clustering:

There is usually a separate **"quality" function** that measures the "goodness" of a cluster. It is hard to define "similar enough" or "good enough."

The answer is typically highly subjective.

## Considerations for cluster analysis

### **Partitioning criteria:**

Single level vs. hierarchical partitioning.

Often, multi-level hierarchical partitioning is desirable.

### **Separation of clusters:**

Exclusive (e.g., one customer belongs to only one region) vs.

Non-exclusive (e.g., one document may belong to more than one class).

### **Similarity measure:**

Distance-based (e.g., Euclidian, road network, vector) vs.

Connectivity-based (e.g., density or contiguity).

### **Clustering space:**

Full space (often when low-dimensional) vs.

Subspaces (often in high-dimensional clustering).

## Requirements and challenges

### **Scalability:**

Clustering all the data instead of only on samples.

### **Ability to deal with different types of attributes:**

Numerical, binary, categorical, ordinal, linked, and mixture of these.

### **Constraint-based clustering:**

User may give inputs on constraints.

Use domain knowledge to determine input parameters.

### **Interpretability and usability.**

### **Others:**

Discovery of clusters with arbitrary shape.

Ability to deal with noisy data.

Incremental clustering and insensitivity to input order.

High dimensionality.



## Major clustering approaches

### Partitioning approach:

Construct various partitions and then evaluate them by some criterion.

E.g., minimizing the sum of square errors.

Typical methods: k-means, k-medoids, CLARA, CLARANS.

### Hierarchical approach:

Create a hierarchical decomposition of the set of data (or objects) using some criterion.

Typical methods: AGNES, DIANA, BIRCH, CHAMELEON.

### Density-based approach:

Based on connectivity and density functions.

Typical methods: DBSCAN, OPTICS, DENCLUE.

### Grid-based approach:

Based on a multiple-level granularity structure.

Typical methods: STING, WaveCluster, CLIQUE.

## Major clustering approaches (II)

### **Model-based approach:**

A model is hypothesized for each of the clusters and tries to find the best fit of that model to each other.

Typical methods: EM, SOM, COBWEB.

### **Frequent-pattern-based approach:**

Based on the analysis of frequent patterns.

Typical methods: p-Cluster.

### **User-guided or constraint-based approach:**

Clustering by considering user-specified or application-specific constraints.

Typical methods: COD (obstacles), constrained clustering.

### **Link-based clustering:**

Objects are often linked together in various ways.

Massive links can be used to cluster objects: SimRank, LinkClus.

## Chapter VII: Cluster analysis

Cluster analysis: basic concepts.

### **Partitioning methods.**

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## Partitioning algorithms: basic concept

### Partitioning method:

Partition a database  $D$  of  $n$  objects  $o_j, j \in \{1, \dots, n\}$  into a set of  $k$ -clusters  $C_i, 1 \leq i \leq k$  such that the sum of squared distances to  $c_i$  is minimized (where  $c_i$  is the **centroid** or **medoid** of cluster  $C_i$ ):

$$\min \sum_{i=1}^k \sum_{o \in C_i} d(o, c_i)^2. \quad (1)$$

**Given  $k$ , find a partition of  $k$  clusters that optimizes the chosen partitioning criterion.**

Globally optimal: exhaustively enumerate all partitions.

Heuristic methods: k-means and k-medoids algorithms.

**k-means** (MacQueen'67, Lloyd'57/'82):

Each cluster is represented by the center of the cluster.

**k-medoids** or PAM (Partition around medoids) (Kaufman & Rousseeuw'87):

Each cluster is represented by one of the objects in the cluster.

## The $k$ -means clustering method

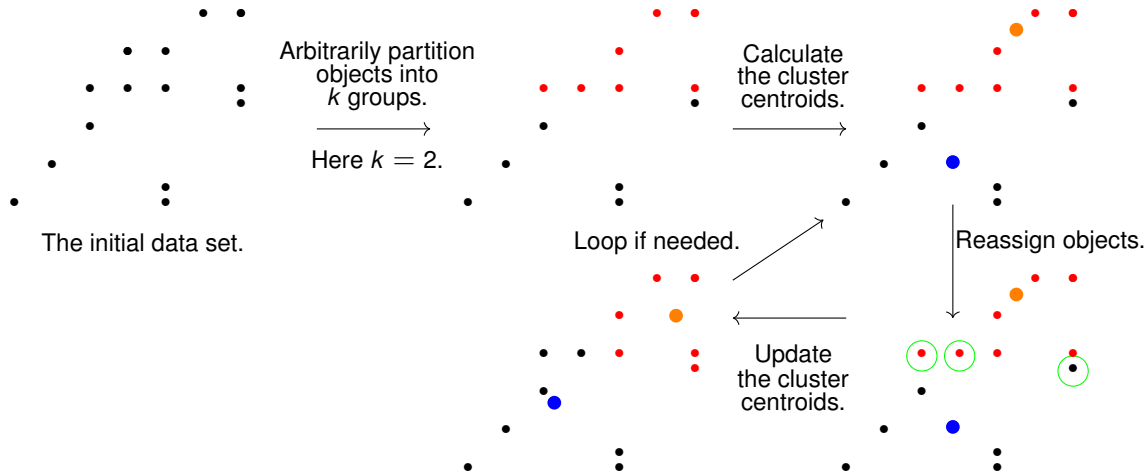
**Given  $k$ , the  $k$ -means algorithm is implemented in four steps:**

1. Partition the database into  $k$  non-empty subsets.  
E.g. the first  $\frac{n}{k}$  objects, then the next  $\frac{n}{k}$  objects, . . .
2. Compute the centroids of the **clusters** of the current partitioning.  
The centroid is the center, i.e. mean point, of the cluster.  
For each attribute (or dimension), calculate the average value.
3. Assign each object to the cluster with the nearest centroid.  
That is, for each object calculate distance to each of the  $k$  centroids and pick the one with the smallest distance.
4. If any object has changed its cluster, go back to step 2. Otherwise stop.

**Variant:**

Start with arbitrarily chosen  $k$  objects as initial centroids in step 1.  
Continue with step 3.

## An example of $k$ -means clustering



## Comments on the $k$ -means method

### Strength:

Efficient:  $\mathcal{O}(tkn)$ , where  $n$  is # objects,  $k$  is # of clusters, and  $t$  is the # of iterations.

Normally,  $k, t \ll n$ .

Comparing: PAM:  $\mathcal{O}(k(n-k)^2)$ , CLARA:  $\mathcal{O}(ks^2 + k(n-k))$ .

Comment: Often terminates at a local optimum.

### Weakness:

Applicable only to objects in a continuous  $n$ -dimensional space.

Using the  $k$ -modes method for categorical data.

In comparison,  $k$ -medoids can be applied to a wide range of data.

Need to specify  $k$ , the number of clusters, in advance.

There are ways to automatically determine the best  $k$  (see Hastie et al., 2009).

Sensitive to noisy data and outliers.

Not suitable to discover clusters with non-convex shapes.

## Variations of the $k$ -means method

### Most of the variants of the $k$ -means differ in:

- Selection of the initial  $k$  subsets (or centroids).
- Dissimilarity calculations.
- Strategies to calculate cluster centroids.

### Handling categorical data: $k$ -modes:

- Replacing centroids with modes.

See Chapter 2: mode = value that occurs most frequently in the data.

Using new dissimilarity measures to deal with categorical objects.

Using a frequency-based method to update modes of clusters.

A mixture of categorical and numerical data:  $k$ -prototype method.



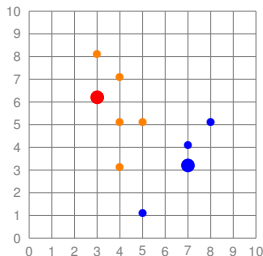
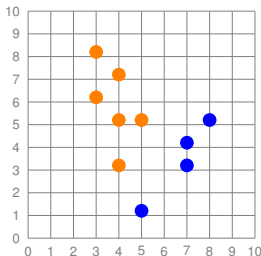
## What is the problem of the $k$ -means method?

The  $k$ -means algorithm is **sensitive to outliers!**

Since an object with an extremely large value may substantially distort the distribution of the data.

**$k$ -medoids:**

Instead of taking the mean value of the objects in a cluster as a reference point, medoids can be used, which is the most centrally located object in a cluster.



## The $k$ -medoids clustering method

### $k$ -medoids clustering:

Find representative objects (medoids) in clusters.

**PAM** (Partitioning Around Medoids, Kaufmann & Rousseeuw, 1987):

Starts from an initial set of  $k$  medoids and iteratively replaces one of the medoids by one of the non-medoids, if it improves the total distance of the resulting clustering.

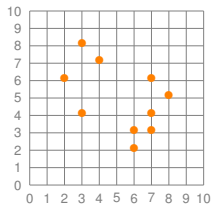
PAM works effectively for small data sets, but does not scale well for large data sets (due to the computational complexity).

### Efficiency improvement on PAM:

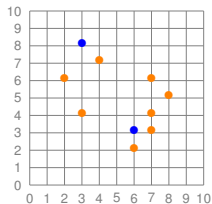
CLARA (Kaufmann & Rousseeuw, 1990): PAM on samples.

CLARANS (Ng & Han, 1994): Randomized re-sampling.

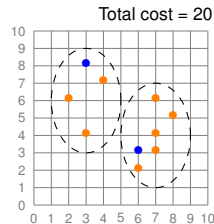
## PAM: A typical $k$ -medoids algorithm



Arbitrarily  
choose  $k$   
object as  
initial  
medoids  
for  $k = 2$

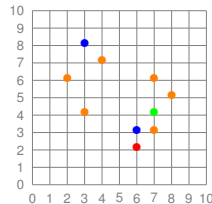


Assign  
each  
remaining  
object to  
nearest medoid



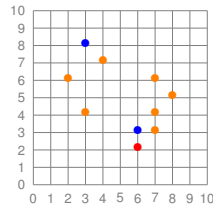
Randomly  
select  
nonmedoid  
object  $o_{\text{random}}$

Total cost = 26



Swapping  $o$   
and  $o_{\text{random}}$   
if quality is  
improved

Compute  
total cost of  
swapping



## PAM (Partitioning Around Medoids)

**Use real objects to represent the clusters.**

**Algorithm:**

1. Arbitrarily choose  $k$  objects as the initial mediods.
2. Repeat.
3. Assign each remaining object to the cluster with the nearest mediod  $o_i$ .
4. Randomly select a non-medoid object  $o_h$ .
5. Compute the total cost  $TC_{ih}$  of swapping  $o_i$  with  $o_h$ .
6. If  $TC_{ih} < 0$  then swap  $o_i$  with  $o_h$  to form the new set of  $k$  medoids.
7. Until no change.

$$TC_{ih} = \sum_j C_{jih}$$

with  $C_{jih}$  as the cost for object  $o_j$  if  $o_i$  is swapped with  $o_h$ .

That is, distance to new medoid minus distance to old medoid.

## PAM Clustering (II)

### Case 1:

$o_j$  currently belongs to medoid  $o_i$ . If  $o_i$  is replaced with  $o_h$  as a medoid, and  $o_j$  is closest to  $o_h$ , then  $o_j$  is reassigned to  $o_h$  (same cluster, different distance).

$$C_{jih} = d(o_j, o_h) - d(o_j, o_i). \quad (2)$$

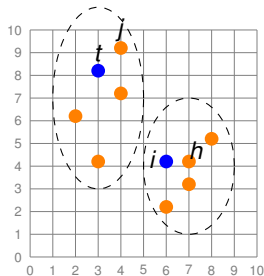


## PAM Clustering (III)

### Case 2:

$o_j$  currently belongs to medoid  $o_t$ ,  $t \neq j$ . If  $o_i$  is replaced with  $o_h$  as a medoid, and  $o_j$  is still closest to  $o_t$ , then the assignment does not change.

$$C_{jih} = d(o_j, o_h) - d(o_j, o_i) = 0. \quad (3)$$

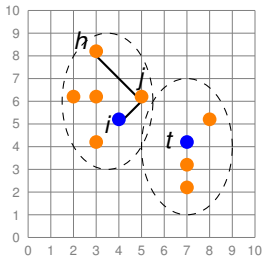


## PAM Clustering (IV)

### Case 3:

$o_j$  currently belongs to medoid  $o_i$ . If  $o_i$  is replaced with  $o_h$  as a medoid, and  $o_j$  is closest to medoid  $o_t$  of one of the other clusters, then  $o_j$  is reassigned to  $o_t$  (new cluster, different distance).

$$C_{jih} = d(o_j, o_t) - d(o_j, o_i). \quad (4)$$

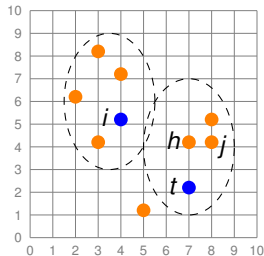


## PAM Clustering (V)

### Case 4:

$o_j$  currently belongs to medoid  $o_t$ ,  $t \neq j$ . If  $o_i$  is replaced with  $o_h$  as a medoid (from a different cluster!), and  $o_j$  is closest to  $o_h$ , then  $o_j$  is reassigned to  $o_h$  (new cluster, different distance).

$$C_{jih} = d(o_j, o_t) - d(o_j, o_i). \quad (5)$$





## CLARA (Clustering Large Applications)

**(Kaufmann and Rousseeuw, 1990)**

**Built in statistical-analysis packages, such as S+.**

**Draws multiple samples of the data set, applies PAM on each sample, and gives the best clustering as the output.**

**Strength:**

Deals with larger data sets than PAM.

**Weakness:**

Efficiency depends on the sample size.

A good clustering based on samples will not necessarily represent a good clustering of the whole data set if the sample is biased.

## CLARANS ("Randomized" CLARA)

**A Clustering Algorithm based on Randomized Search** (Ng & Han, 1994)

**Samples:**

Drawn dynamically with some randomness in each step of the search.

**Clustering process:**

Can be presented as searching a graph where each node is a potential solution, that is, a set of  $k$  medoids.

**If local optimum found,**

start with new randomly selected node in search for a new local optimum.

**More efficient and scalable than both PAM and CLARA.**

**Focusing techniques and spatial access structures may further improve its performance.**  
(Ester et al., 1995)

## Chapter VII: Cluster analysis

Cluster analysis: basic concepts.

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## Hierarchical clustering

Does not require the number of clusters  $k$  as an input,  
but needs a termination condition.



## AGNES (Agglomerative Nesting)

**Introduced in (Kaufmann & Rousseeuw, 1990)**

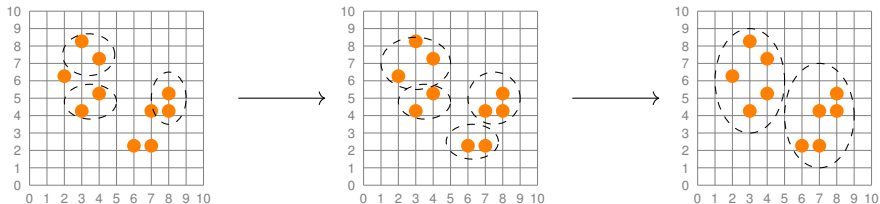
**Implemented in statistical packages, e.g., S+.**

**Use the single-link method. (see below)**

**Merge nodes that have the least dissimilarity.**

**Go on in a non-descending fashion.**

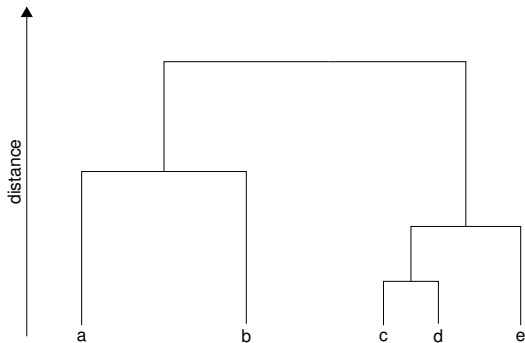
**Eventually all nodes belong to the same cluster.**



## Dendrogram: shows how clusters are merged

Decompose data objects into a several levels of nested partitioning (tree of clusters), called a **dendrogram**.

A clustering of the data objects is obtained by **cutting** the dendrogram at the desired level, then each connected component forms a cluster.



## DIANA (Divisive Analysis)

Introduced in (Kaufmann & Rousseeuw, 1990)

Implemented in statistical analysis packages, e.g., S+.

Inverse order of AGNES.

Eventually each node forms a cluster of its own.



## Distance between clusters

### Minimum distance:

Smallest distance between an object in one cluster and an object in the other, i.e.,  
$$\text{dist}_{\min}(C_i, C_j) = \min_{o_{ip} \in C_i, o_{jq} \in C_j} d(o_{ip}, o_{jq}).$$

### Maximum distance:

Largest distance between an object in one cluster and an object in the other, i.e.,  
$$\text{dist}_{\max}(C_i, C_j) = \max_{o_{ip} \in C_i, o_{jq} \in C_j} d(o_{ip}, o_{jq}).$$

### Average distance:

Average distance between an object in one cluster and an object in the other, i.e.,  
$$\text{dist}_{\text{avg}}(C_i, C_j) = \frac{1}{n_i \cdot n_j} \sum_{o_{ip} \in C_i, o_{jq} \in C_j} d(o_{ip}, o_{jq}).$$

### Mean distance:

Distance between the centroids of two clusters, i.e.,  $\text{dist}_{\text{mean}}(C_i, C_j) = d(c_i, c_j).$



## Distance between clusters (II)

### Nearest-neighbor clustering algorithm:

Uses **minimum distance** to measure distance between clusters.

### Single-linkage algorithm:

Terminates if distance between nearest clusters exceeds user-defined threshold.

### Minimal spanning-tree algorithm:

View objects (data points) as nodes of a graph.

Edges form a path between nodes in a cluster.

Merging of two clusters corresponds to adding an edge between the nearest pair of nodes.

Because edges linking clusters always go between distinct clusters,  
resulting graph will be a tree.

Thus, agglomerative hierarchical clustering that uses minimum distance produces minimal spanning tree.

## Distance between clusters (III)

### Farthest-neighbor clustering algorithm:

Uses **maximum distance** to measure distance between clusters.

### Complete-linkage algorithm:

Terminates if maximum distance between nearest clusters exceeds user-defined threshold.

Good if true clusters are rather compact and approx. equal in size.

## Extensions to hierarchical clustering

### Major weakness of agglomerative clustering methods:

- Can never undo what was done previously.

- Do not scale well: Time complexity of at least  $\mathcal{O}(n^2)$ , where  $n$  is the number of objects.

### Integration of hierarchical and distance-based clustering:

- BIRCH (1996): Uses CF-tree and incrementally adjusts the quality of sub-clusters.

- CHAMELEON (1999): Hierarchical clustering using dynamic modeling.

## BIRCH (Balanced Iterative Reducing and Clustering Using Hierarchies)

(Zhang, Ramakrishnan & Livny, SIGMOD'96)

### **Incrementally construct a CF (Clustering Feature) tree:**

A hierarchical data structure for multiphase clustering.

Phase 1: Scan DB to build an initial in-memory CF-tree.

A multi-level compression of the data that tries to preserve the inherent clustering structure of the data.

Phase 2: Use an arbitrary clustering algorithm to cluster the leaf nodes of the CF-tree.

### **Scales linearly:**

Finds a good clustering with a single scan and improves the quality with a few additional scans.

### **Weakness:**

Handles only numerical data, and sensitive to the order of the data records.

## Clustering feature in BIRCH

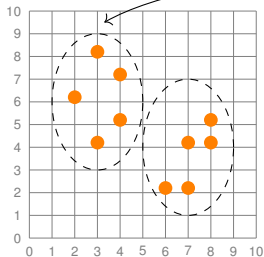
**Clustering Feature CF = (n, LS, SS):**

3D vector summarizing statistics about clusters.

$n$ : number of data points.

LS: linear sum of  $N$  points  $\sum_{i=1}^n x_i$ .

SS: square sum of  $N$  points  $\sum_{i=1}^n x_i^2$ .



$CF = (5, (16, 30), (54, 190))$

(3,4)

(2,6)

(4,5)

(4,7)

(3,8)

## Clustering feature in BIRCH (II)

**Allows to derive many useful statistics of a cluster:**

E.g. centroid:  $c_i = \frac{\sum_{i=1}^n o_i}{n} = \frac{LS}{n}$ .

**Additive:**

For two disjoint clusters  $C_1$  and  $C_2$  with clustering features  $CF_1 = (n_1, LS_1, SS_1)$  and  $CF_2 = (n_2, LS_2, SS_2)$ , the clustering feature of the cluster that is formed by merging  $C_1$  and  $C_2$  is simply:  $CF_1 + CF_2 = (n_1 + n_2, LS_1 + LS_2, SS_1 + SS_2)$ .

## CF-Tree in BIRCH

**Height-balanced tree.**

**Stores the clustering features for a hierarchical clustering.**

Non-leaf nodes store sums of the CFs of their children.

**Two parameters:**

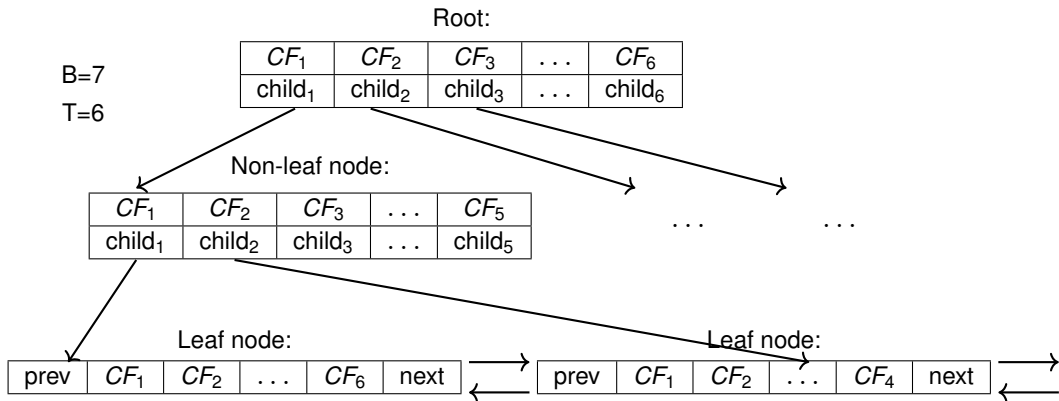
**Branching factor  $B$ :** max # of children.

**Threshold  $T$ :** maximum diameter of sub-clusters stored at leaf nodes.

Diameter  $D$ : average pairwise distance within a cluster,  
reflects the tightness of the cluster around the centroid:

$$D = \sqrt{\frac{\sum_{i=1}^n \sum_{j=1}^n (o_i - o_j)^2}{n(n-1)}} = \sqrt{\frac{2nSS - 2LS^2}{n(n-1)}}. \quad (6)$$

## CF-Tree structure





## The BIRCH algorithm

### Phase 1:

#### For each point in the input:

Find closest leaf-node entry.

Add point to leaf-node entry and update CF.

If  $entry\_diameter > max\_diameter$ , then split leaf node, and possibly parents.

Information about new point is passed toward the root of the tree.

**Algorithm is  $\mathcal{O}(n)$  and incremental.**

#### Concerns:

Sensitive to insertion order of data points.

Since we fix the size of leaf nodes, clusters may not be so natural.

Clusters tend to be spherical given the radius and diameter measures.

## CHAMELEON: hierarchical clustering using dynamic modeling

(Karypis, Han & Kumar, 1999)

### **Measures the similarity based on a dynamic model:**

Two clusters are merged only if the **interconnectivity** and **closeness (proximity)** between two clusters are high relative to the internal interconnectivity of the clusters and the closeness of items within the clusters.

### **Graph-based, and a two-phase algorithm.**

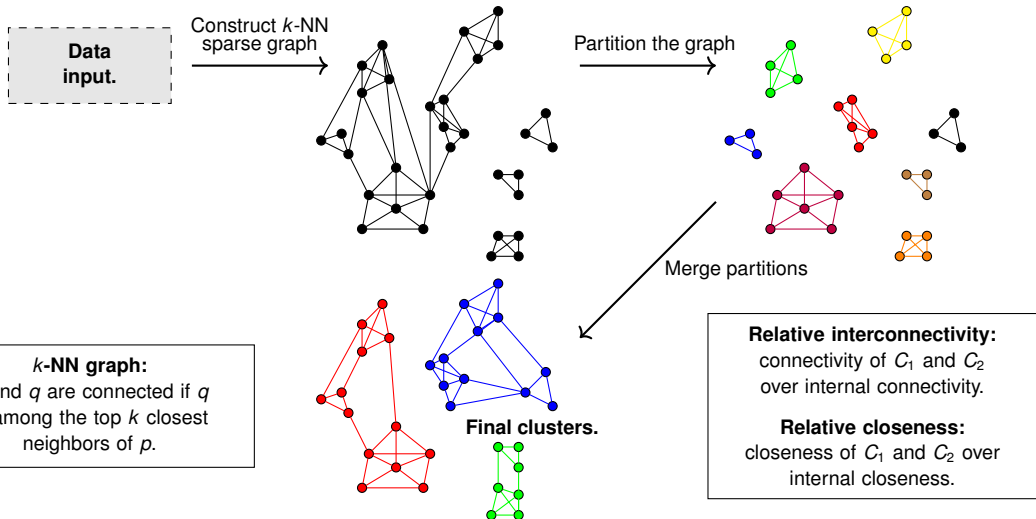
Use a graph-partitioning algorithm:

Cluster objects into a large number of relatively small sub-clusters.

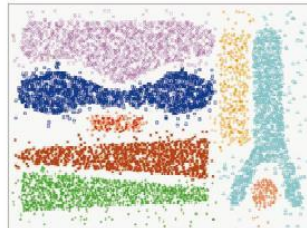
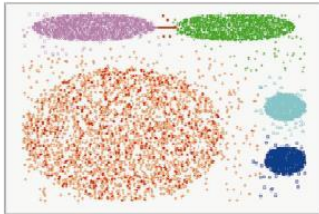
Use an agglomerative hierarchical clustering algorithm:

Find the genuine clusters by repeatedly combining these sub-clusters.

## Overall framework of CHAMELEON



## CHAMELEON (Clustering Complex Objects)



## Probabilistic hierarchical clustering

### Algorithmic hierarchical clustering.

- Nontrivial to choose a good distance measure.

- Hard to handle missing attribute values.

- Optimization goal not clear: heuristic, local search.

### Probabilistic hierarchical clustering.

- Use probabilistic models to measure distances between clusters.

#### Generative model:

- Regard the set of data objects to be clustered as a sample of the underlying data-generation mechanism to be analyzed.

- Easy to understand, same efficiency as algorithmic agglomerative clustering method, can handle partially observed data.

- In practice, assume the generative models adopt **common distribution functions**, e.g., Gaussian distribution or Bernoulli distribution, governed by parameters.

## Generative model

Given a set of 1-D points  $X = \{x_1, \dots, x_n\}$  for clustering analysis and assuming they are generated by a Gaussian distribution:

$$N(\mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right). \quad (7)$$

The probability that a point  $x_i \in X$  is generated by the model:

$$P(x_i|\mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_i - \mu)^2}{2\sigma^2}\right). \quad (8)$$

## Generative model (II)

The likelihood that  $X$  is generated by the model:

$$L(N(\mu, \sigma)|X) := P(X|\mu, \sigma) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_i - \mu)^2}{2\sigma^2}\right). \quad (9)$$

The task of learning the generative model: find the parameters  $\mu$  and  $\sigma$ , such that

$$N(\mu_0, \sigma_0) = \arg \max (L(N(\mu, \sigma)|X)). \quad (10)$$

## A probabilistic hierarchical clustering algorithm

For a set of objects partitioned into  $m$  clusters  $C_1, \dots, C_m$ , the quality can be measured by:

$$Q(\{C_1, \dots, C_m\}) = \prod_{i=1}^m P(C_i), \quad (11)$$

where  $P(C_i)$  is the maximum likelihood of  $C_i$ .

Distance between clusters  $C_i$  and  $C_j$  can be computed as a proximity measure:

$$d(C_i, C_j) = -\log \frac{P(C_i \cup C_j)}{P(C_i)P(C_j)}. \quad (12)$$



## A probabilistic hierarchical clustering algorithm (II)

### Algorithm: Progressively merge points and clusters

Input:  $D = \{o_1, \dots, o_n\}$ : a dataset containing  $n$  objects.

Output: A hierarchy of clusters.

Method:

Create cluster for each object  $C_i = \{o_i\}$ , for  $1 \leq i \leq n$ .

**For**  $i = 1$  **to**  $n$ :

Find a pair of clusters  $C_i$  and  $C_j$ , such that

$$C_i, C_j = \arg \max_{i \neq j} \left( \log \left( \frac{P(C_i \cup C_j)}{P(C_i)P(C_j)} \right) \right).$$

**If**  $\log \left( \frac{P(C_i \cup C_j)}{P(C_i)P(C_j)} \right) > 0$  **then** merge  $C_i$  and  $C_j$ ,

**Else stop.**

## Chapter VII: Cluster analysis

Cluster analysis: basic concepts.

Partitioning methods.

Hierarchical methods.

**Density-based methods.**

Grid-based methods.

Evaluation of clustering.

Summary.

## Chapter VII: Cluster analysis

**Clustering based on density (local cluster criterion), such as density-connected points.**

**Major features:**

- Discover clusters of arbitrary shape.

- Handle noise.

- One scan.

- Need density parameters as termination condition.

**Several interesting studies:**

- DBSCAN (Ester et al., KDD'96).

- OPTICS (Ankerst et al., SIGMOD'99).

- DENCLUE (Hinneburg & Keim, KDD'98).

- CLIQUE (Agrawal et al., SIGMOD'98) (more grid-based).

## Density-based clustering: basic concepts

### Two parameters:

**Eps:** Maximum radius of a neighborhood.

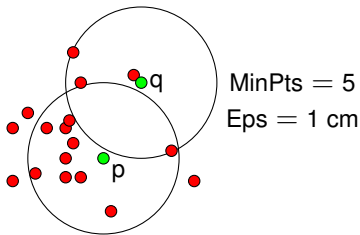
Defines the neighborhood of a point  $p$ :  $N_{\text{Eps}}(p) := \{q \in D \mid d(p, q) \leq \text{Eps}\}$ .

Distance function is still needed.

**MinPts:** Minimum number of points in an Eps-neighborhood of a point  $p$ .

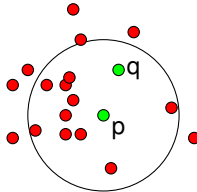
**Core-point condition:**  $|N_{\text{Eps}}(p)| \geq \text{MinPts}$ .

Only these neighborhoods are considered.



## Directly density-reachable

A point  $q$  is said to be directly density-reachable from a point  $p$  w.r.t.  $\text{Eps}$ ,  $\text{MinPts}$ , if  $q$  belongs to  $N_{\text{Eps}}(p)$ .

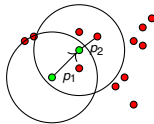


MinPts = 5  
Eps = 1 cm

## Density-reachable and density-connected

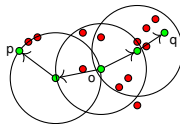
### Density-reachable:

A point  $q$  is density-reachable from a point  $p$  w.r.t. Eps, MinPts, if there is a **chain of points**  $p_1, \dots, p_n$ ,  $p_1 = p$ ,  $p_n = q$  such that  $p_i + 1$  is directly density-reachable from  $p_i$ .



### Density-connected:

A point  $p$  is density-connected to a point  $q$  w.r.t. Eps, MinPts, if there is a point  $o$  such that both  $p$  and  $q$  are density-reachable from  $o$ .

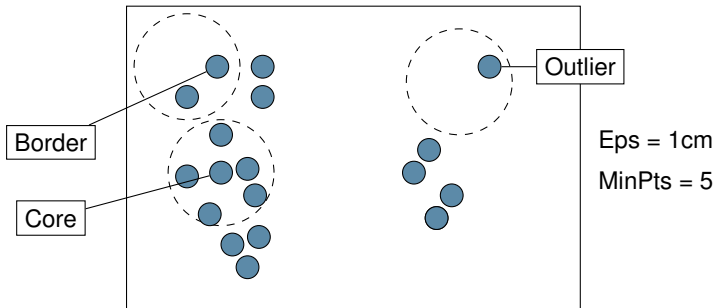


## DBSCAN: density-based spatial clustering of applications with noise

**Relies on a density-based notion of cluster:**

A cluster is defined as a maximal set of density-connected points.

**Discovers clusters of arbitrary shape in spatial databases with noise.**



## DBSCAN: the algorithm

All objects in database  $D$  are marked unvisited.

Randomly select unvisited object  $p$  and mark as visited.

If Eps-neighborhood of  $p$  contains less than MinPts objects:

    Mark  $p$  as noise.

Otherwise (that is,  $p$  is core point):

    Create new cluster  $C$  for point  $p$ .

    Add all objects in Eps-neighborhood of  $p$  to candidate set  $N$ .

    For each  $p'$  in  $N$  that does not yet belong to a cluster:

        Add  $p'$  to  $C$ .

        If  $p'$  is unvisited, mark as visited.

        If  $p'$  is core point, add all objects in its Eps-neighborhood to  $N$ .

    Ends when  $N$  is empty, that is,  $C$  can no longer be expanded.

Continue the process (randomly select next unvisited object in  $D$ ) until all points have been visited.



## DBSCAN: sensitive to parameters

Figure 8. DBScan results for DS1 with MinPts at 4 and Eps at (a) 0.5 and (b) 0.4.

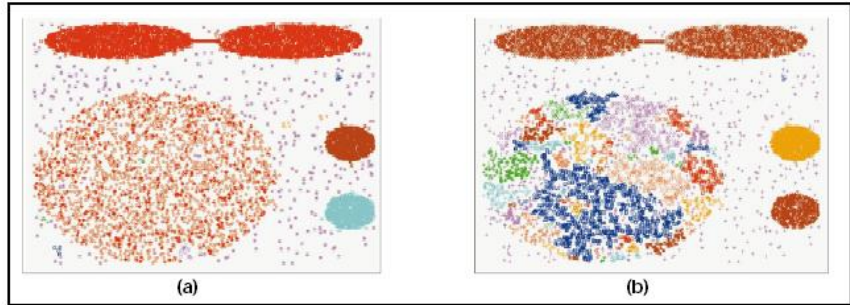
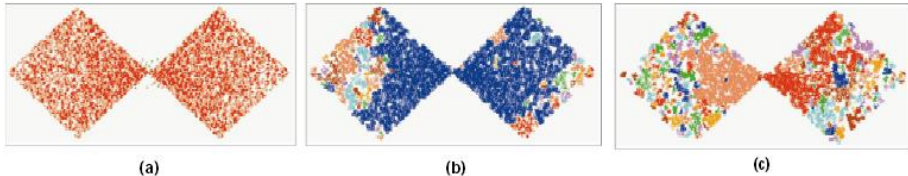


Figure 9. DBScan results for DS2 with MinPts at 4 and Eps at (a) 5.0, (b) 3.5, and (c) 3.0.



## OPTICS: a cluster-ordering method

### OPTICS: Ordering Points To Identify the Clustering Structure.

(Ankerst, Breunig, Kriegel & Sander, SIGMOD'99)

Avoid difficulty of finding the right parameters:

Only MinPts must be given, Eps remains open.

Produces a special **order of the database** w.r.t. its density-based clustering structure.

This cluster-ordering contains info equivalent to the density-based clusterings corresponding to a broad range of parameter settings.

Good for both automatic and interactive cluster analysis, including finding intrinsic clustering structure.

Can be represented graphically or using visualization techniques.

Process point in order: Select a point that is density-reachable w.r.t. the lowest Eps value, so that clusters with higher density (lower Eps) will be finished first.

## OPTICS: Some Extension of DBSCAN

### Core distance:

of a point  $p$ .

Min Eps s.t.  $p$  is core point.

### Reachability Distance $r$ :

of a point  $p$  from  $q$ .

Minimum radius value that makes  $p$

directly density-reachable from  $q$ .

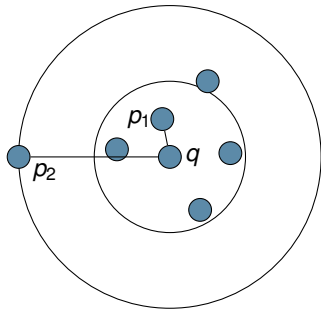
That is,  $r(q, p) := \max\{\text{core-distance}(q), d(q, p)\}$ .

### Example:

MinPts = 5,  $\text{core\_distance}(q) = 3\text{cm}$ .

$d(q, p_1) = 2.8\text{cm} \implies r(q, p_1) = 3\text{cm}$ .

$d(q, p_2) = 4\text{cm} \implies r(q, p_2) = 4\text{cm}$ .



## OPTICS: algorithm

### Maintains a list of **OrderSeeds**:

Points sorted by **reachability-distance** from their resp. closest core points.

### Begin with arbitrary point from input DB.

### For each point $p$ under consideration:

Retrieve the closest MinPts points of  $p$ , determine core-distance, set reachability-distance to undefined.

Write  $p$  to output.

If  $p$  is core point, for each point  $q$  in the Eps-neighborhood of  $p$ :

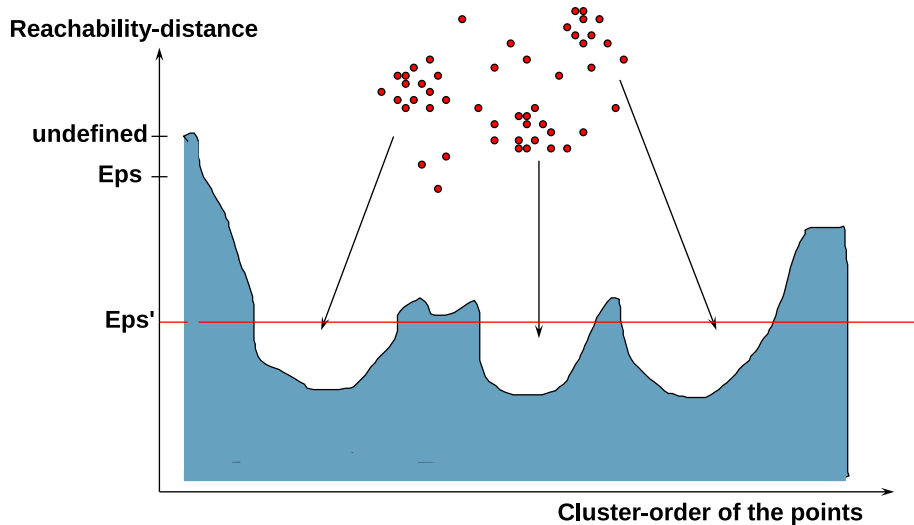
Update reachability-distance from  $p$ .

Insert  $q$  into OrderSeeds (if  $q$  has not yet been processed).

Move to next object in OrderSeeds list with smallest reachability-distance (or input DB if OrderSeeds is empty).

### Continue until input DB fully consumed (and OrderSeeds empty).

## OPTICS: visualization



## DENCLUE: using statistical density functions

**DENSity-based CLUstEring** (Hinneburg & Keim, KDD'98)

**Using statistical density functions:**

$f_{\text{Gaussian}}(x, y) = \exp\left(\frac{d(x, y)^2}{2\sigma^2}\right)$ , influence of  $y$  on  $x$ .

$f_{\text{Gaussian}}^D(x, x_i) = \sum_{i=1}^N \exp\left(\frac{d(x, y)^2}{2\sigma^2}\right)$ , total influence on  $x$ .

$\nabla_{x_i} f_{\text{Gaussian}}^D(x, x_i) = \sum_{i=1}^N (x_i - x) \cdot \exp\left(\frac{d(x, y)^2}{2\sigma^2}\right)$ , gradient of  $x$  in direction  $x_i$ .

**Major features:**

- Solid mathematical foundation.

- Good for data sets with large amounts of noise.

- Allows a compact mathematical description of arbitrarily shaped clusters in high-dimensional data sets.

- Significantly faster than existing algorithms (e.g., DBSCAN).

- But needs a large number of parameters.

## DENCLUE: technical essence

### Density estimation:

Estimation of an unobservable underlying probability density function based on a set of observed data.

Regarded as a sample.

### Kernel density estimation:

Treat an observed object as an indicator of high-probability density in the surrounding region.  
Probability density at a point depends on the distances from this point to the observed objects.

### Density attractor:

Local maximum of the estimated density function.

Must be above threshold  $\xi$ .

## DENCLUE: technical essence (II)

### **Clusters:**

Can be determined mathematically by identifying density attractors.  
That is, local maxima of the overall density function.

### **Center-defined clusters:**

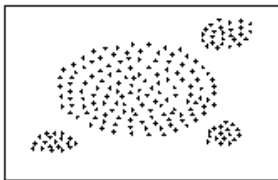
Assign to each density attractor the points density-attracted to it.

### **Arbitrary shaped cluster:**

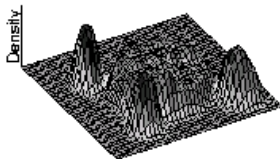
Merge density attractors that are connected through paths of high density ( $>$  threshold).



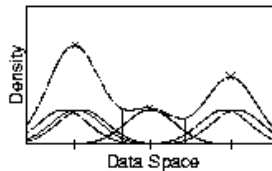
## Density attractor



(a) Data Set



(c) Gaussian



## Density attractor

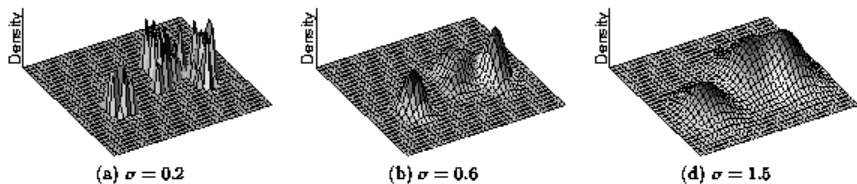


Figure 3: Example of Center-Defined Clusters for different  $\sigma$

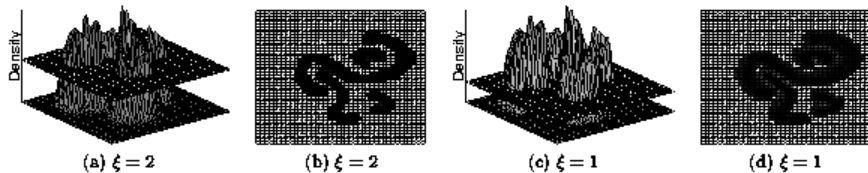


Figure 4: Example of Arbitrary-Shape Clusters for different  $\xi$

## Chapter VII: Cluster analysis

Cluster analysis: basic concepts.

Partitioning methods.

Hierarchical methods.

Density-based methods.

**Grid-based methods.**

Evaluation of clustering.

Summary.

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Thank you for your attention.  
**Any questions about the seventh chapter?**

Ask them now, or again, drop me a line:  
✉ [luciano.melodia@fau.de](mailto:luciano.melodia@fau.de).