



# Cluster Analysis

—Hierarchical Methods—

徐华

清华大学 计算机系 智能技术与系统国家重点实验室

xuhua@tsinghua.edu.cn

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## Cluster Analysis



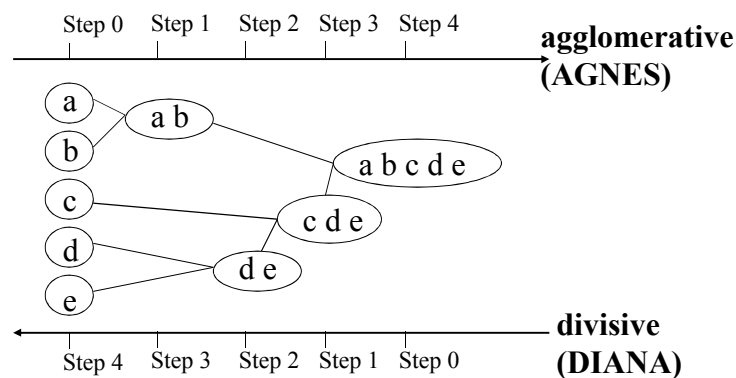
- ◉ What is Cluster Analysis?
- ◉ Types of Data in Cluster Analysis
- ◉ A Categorization of Major Clustering Methods
- ◉ Partitioning Methods
- ◉ Hierarchical Methods
- ◉ Density-Based Methods
- ◉ Grid-Based Methods
- ◉ Model-Based Clustering Methods
- ◉ Outlier Analysis
- 2 ◉ Summary



## Hierarchical Clustering



- Use distance matrix as clustering criteria. This method does not require the number of clusters  $k$  as an input, but needs a termination condition



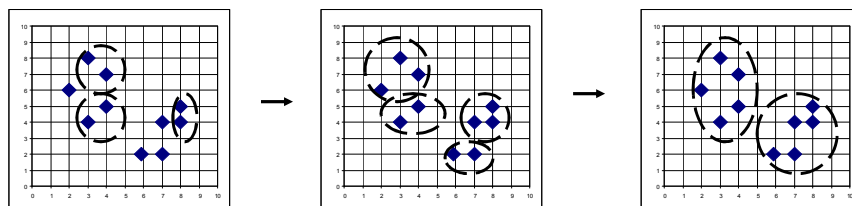
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## AGNES (Agglomerative Nesting)



- Introduced in Kaufmann and Rousseeuw (1990)
- Implemented in statistical analysis packages, e.g., Splus
- Use the Single-Link method and the dissimilarity matrix.
- Merge nodes that have the least dissimilarity
- Go on in a non-descending fashion
- Eventually all nodes belong to the same cluster



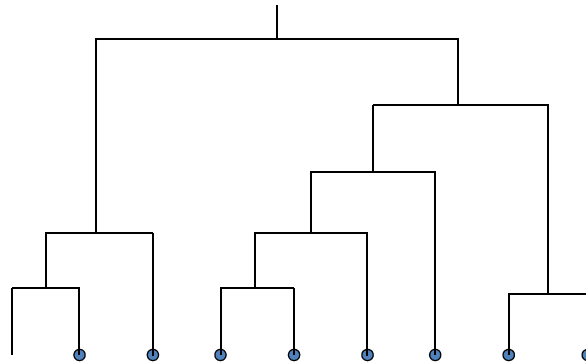
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### A Dendrogram Shows How the Clusters are Merged Hierarchically



- 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.



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### More on Hierarchical Clustering Methods



- Major weakness of agglomerative clustering methods
  - do not scale well: time complexity of at least  $O(n^2)$ , where  $n$  is the number of total objects
  - can never undo what was done previously
- Integration of hierarchical with distance-based clustering
  - BIRCH (1996)**: uses CF-tree and incrementally adjusts the quality of sub-clusters
  - CURE (1998)**: selects well-scattered points from the cluster and then shrinks them towards the center of the cluster by a specified fraction
  - CHAMELEON (1999)**: hierarchical clustering using dynamic modeling

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## BIRCH (1996)



- ◉ Birch: Balanced Iterative Reducing and Clustering using Hierarchies, by 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 numeric data, and sensitive to the order of the data record.

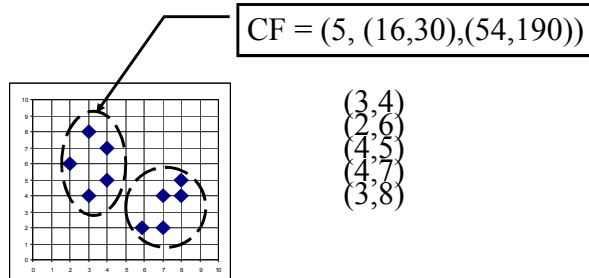
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## Clustering Feature Vector



- ◉ Clustering Feature:  $CF = (N, LS, SS)$
- ◉  $N$ : Number of data points
- ◉  $LS$ :  $\sum Ni = \sum Xi$
- ◉  $SS$ :  $\sum Ni = \sum Xi^2$



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## CF-Tree in BIRCH

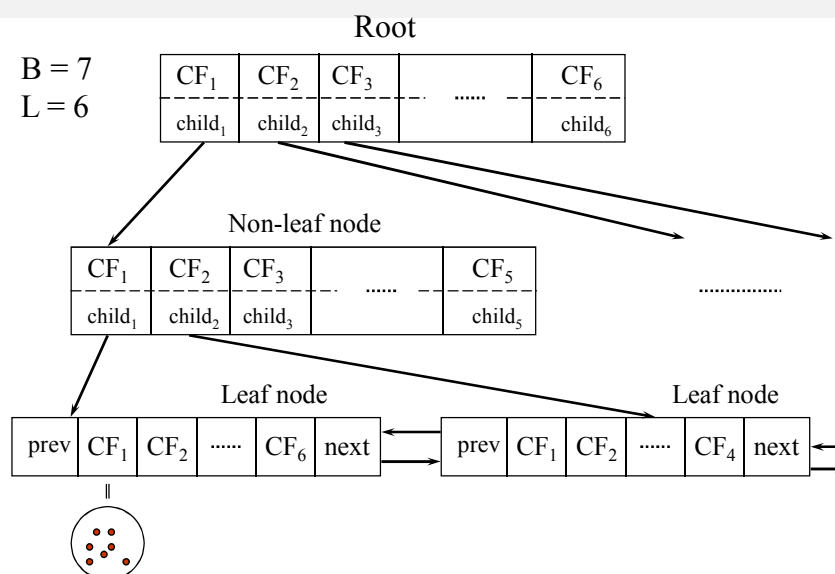


- ◉ **Clustering feature:**
  - ◆ summary of the statistics for a given subcluster: the 0-th, 1st and 2nd moments of the subcluster from the statistical point of view.
  - ◆ registers crucial measurements for computing cluster and utilizes storage efficiently
- ◉ **A CF tree is a height-balanced tree that stores the clustering features for a hierarchical clustering**
  - ◆ A nonleaf node in a tree has descendants or “children”
  - ◆ The nonleaf nodes store sums of the CFs of their children
- ◉ **A CF tree has two parameters**
  - ◆ **Branching factor:** specify the maximum number of children.
  - ◆ **Threshold:** max diameter of sub-clusters stored at the leaf nodes

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## CF Tree



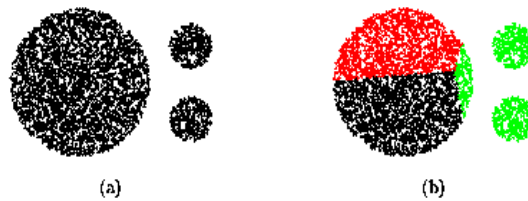
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## CURE (Clustering Using REpresentatives )



- ◉ CURE: proposed by Guha, Rastogi & Shim, 1998
  - ◆ Stops the creation of a cluster hierarchy if a level consists of  $k$  clusters
  - ◆ Uses multiple representative points to evaluate the distance between clusters, adjusts well to arbitrary shaped clusters and avoids single-link effect



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## Cure: The Algorithm



- ◉ Draw random sample  $s$ .
- ◉ Partition sample to  $p$  partitions with size  $s/p$
- ◉ Partially cluster partitions into  $s/pq$  clusters
- ◉ Eliminate outliers
  - ◆ By random sampling
  - ◆ If a cluster grows too slow, eliminate it.
- ◉ Cluster partial clusters.
- ◉ Label data in disk

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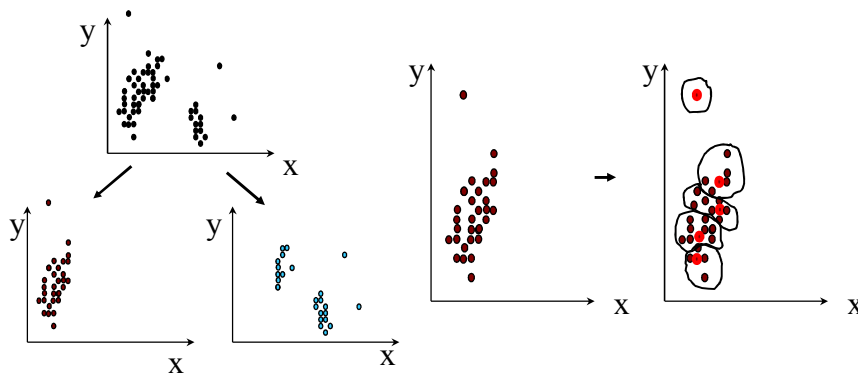


## Data Partitioning and Clustering



$$\begin{aligned}s &= 50 \\ p &= 2 \\ s/p &= 25\end{aligned}$$

$$s/pq = 5$$



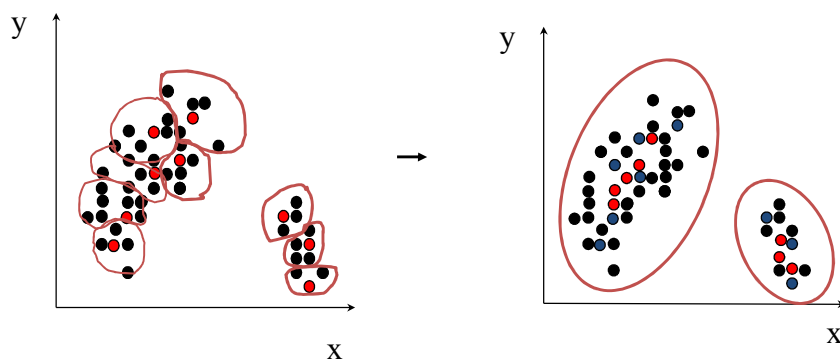
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## Cure: Shrinking Representative Points



- Shrink the multiple representative points towards the gravity center by a fraction of  $\alpha$ .
- Multiple representatives capture the shape of the cluster



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## CHAMELEON (Hierarchical clustering using dynamic modeling)

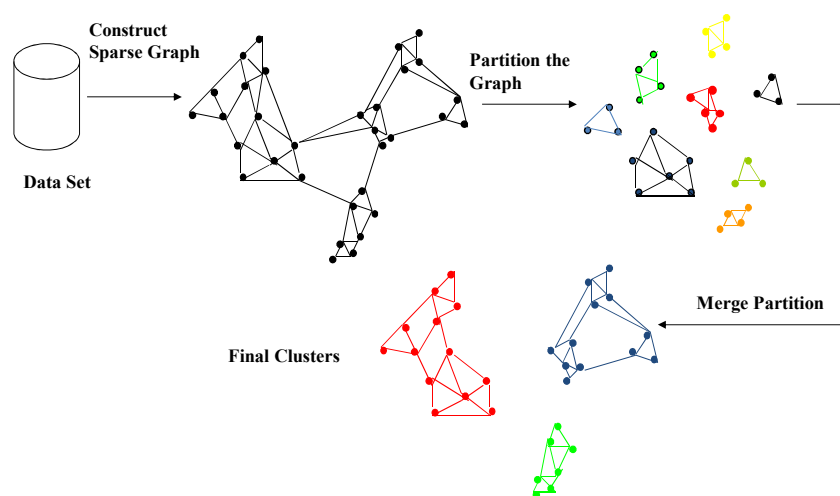


- ◉ CHAMELEON: by G. Karypis, E.H. Han, and V. Kumar'99
- ◉ Measures the similarity based on a dynamic model
  - ◆ Two clusters are merged only if the *interconnectivity* and *closeness (proximity)* between two clusters are high *relative to* the internal interconnectivity of the clusters and closeness of items within the clusters
  - ◆ Cure ignores information about interconnectivity of the objects, Rock ignores information about the closeness of two clusters
- ◉ A two-phase algorithm
  1. Use a graph partitioning algorithm: cluster objects into a large number of relatively small sub-clusters
  2. Use an agglomerative hierarchical clustering algorithm: find the genuine clusters by repeatedly combining these sub-clusters

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## Overall Framework of CHAMELEON



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**Thanks!**

