Data Mining

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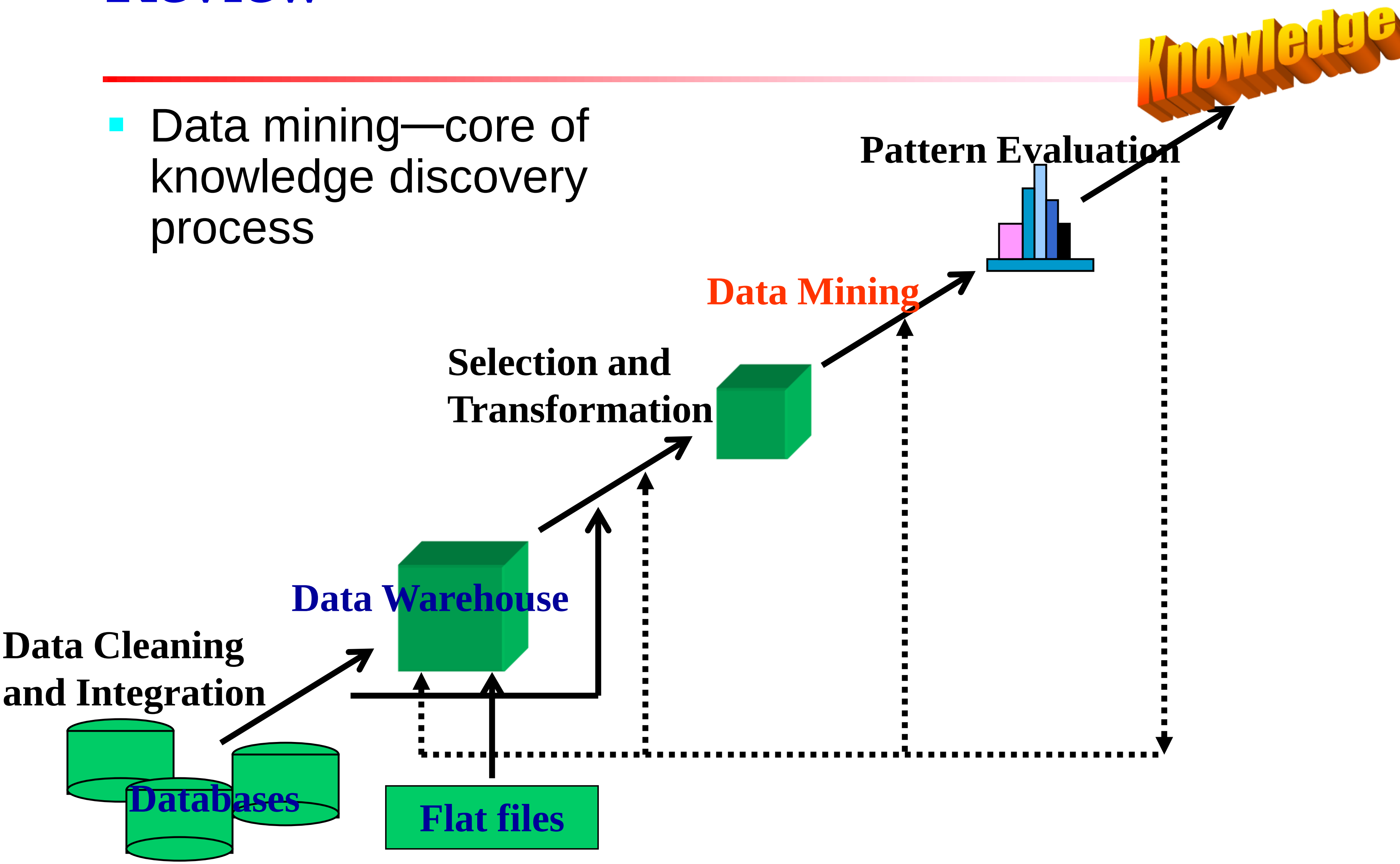
Review

- Data mining—core of knowledge discovery process



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
- Outlier Analysis
- Summary

What is Cluster Analysis?

- Cluster: a collection of data objects
  - Similar to one another within the same cluster
  - Dissimilar to the objects in other clusters
- Cluster analysis
  - Finding similarities between data according to the characteristics in the data and grouping similar data objects into clusters
- Unsupervised learning: no predefined classes
- Typical applications
  - As a stand-alone tool to get insight into data distribution
  - As a preprocessing step for other algorithms

Examples of Clustering Applications

- Marketing: Help marketers discover distinct groups according to their customer databases, and then use this knowledge to develop targeted marketing programs
- Land use: Identification of areas of similar land use in an earth observation database
- Insurance: Identifying groups of motor insurance policy holders with a high average claim cost
- City-planning: Identifying groups of houses according to their house type, value, and geographical location

Examples of Clustering Applications

- Earth-quake studies: Observed earth quake epicenters are clustered along continent faults
- Biology: categorize genes with similar functionality
- WWW
  - Document classification
  - Cluster Weblog data to discover groups of similar accessing patterns

Clustering: Rich Applications and Multidisciplinary Efforts

- Pattern Recognition
- GIS
  - Create thematic maps in GIS by clustering feature spaces
  - Detect spatial clusters or for other spatial mining tasks
- Image Processing
- Economic Science (especially marketing research)
- Software package
  - S-Plus, SPSS, SAS, R

What Is Good Clustering?

- A good clustering method will produce high quality clusters with
  - high intra-class similarity
  - low inter-class similarity
- The quality of a clustering result depends on both the similarity measure used by the method and its implementation
- The quality of a clustering method is also measured by 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 metric: *d*(*i, j*)
- The definitions of distance functions are usually very different for interval-scaled, boolean, categorical, ordinal ratio, and vector variables
- Weights may be assigned to different variables based on applications and data semantics
- It is hard to define “similar enough” or “good enough”
  - The answer is typically highly subjective

Requirements of Clustering

- Scalability
- Ability to deal with different types of attributes
- Ability to handle dynamic data
- Discovery of clusters with arbitrary shape
- Minimal requirements for domain knowledge to determine input parameters
- Able to deal with noise and outliers
- Insensitive to order of input records
- High dimensionality
- Incorporation of user-specified constraints
- Interpretability and usability

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Data Structures

- Data matrix

$$\begin{bmatrix} x_{11} & \cdots & x_{1f} & \cdots & x_{1p} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{i1} & \cdots & x_{if} & \cdots & x_{ip} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{n1} & \cdots & x_{nf} & \cdots & x_{np} \end{bmatrix}$$

- Dissimilarity matrix

$$\begin{bmatrix} 0 & & & & \\ d(2,1) & 0 & & & \\ d(3,1) & d(3,2) & 0 & & \\ \vdots & \vdots & \vdots & & \\ d(n,1) & d(n,2) & \cdots & \cdots & 0 \end{bmatrix}$$

Type of Data in Clustering Analysis

- Interval-scaled variables 区间值
- Binary variables 二进制
- Nominal variables
- Ordinal variables 顺序变量
- Ratio-scaled variables 级数变化
- Variables of mixed types

Interval-valued Variables

- Standardize data
  - Calculate the mean absolute deviation:

$$s_f = \frac{1}{n}(|x_{1f} - m_f| + |x_{2f} - m_f| + ... + |x_{nf} - m_f|)$$

where $m_f = \frac{1}{n}(x_{1f} + x_{2f} + ... + x_{nf})$.

  - Calculate the standardized measurement (*z-score*)

$$z_{if} = \frac{x_{if} - m_f}{s_f}$$

平均绝对离差

- Using mean absolute deviation is more robust than using standard deviation

标准差

Similarity and Dissimilarity Between Objects

- Distances are normally used to measure the similarity or dissimilarity between two data objects
- Some popular ones include: *Minkowski distance*:

$$d(i,j)=\sqrt[q]{(|x_{i_1}-x_{j_1}|^q+|x_{i_2}-x_{j_2}|^q+...+|x_{i_p}-x_{j_p}|^q)}$$

where $i = (x_{i1}, x_{i2}, \ldots, x_{ip})$ and $j = (x_{j1}, x_{j2}, \ldots, x_{jp})$ are two *p*-dimensional data objects, and *q* is a positive integer

- If *q* = *1*, *d* is Manhattan distance

$$d(i,j)=|x_{i_1}-x_{j_1}|+|x_{i_2}-x_{j_2}|+...+|x_{i_p}-x_{j_p}|$$

Similarity and Dissimilarity Between Objects

欧几里得度量

- If *q* = *2*, *d* is Euclidean distance:

$$d(i,j)=\sqrt{(|x_{i_1}-x_{j_1}|^2+|x_{i_2}-x_{j_2}|^2+...+|x_{i_p}-x_{j_p}|^2)}$$

  - Properties
    - $d(i,j) \geq 0$
    - $d(i,i) = 0$
    - $d(i,j) = d(j,i)$
    - $d(i,j) \leq d(i,k) + d(k,j)$
- Also, one can use weighted distance

Binary Variables

- A contingency table for binary data
- Distance measure for symmetric binary variables:

对称

- Distance measure for asymmetric binary variables:

不对称

		Object j		
		1	0	*sum*
Object *i*	1	a	b	$a+b$
	0	c	d	$c+d$
	sum	$a+c$	$b+d$	p

$$d(i,j) = \frac{b+c}{a+b+c+d}$$

$$d(i,j) = \frac{b+c}{a+b+c}$$

D是双方都为0的情况，对于聚类的贡献不大，因此选择不对的计算方法。

Dissimilarity between Binary Variables

- Example

Name	Gender	Fever	Cough	Test-1	Test-2	Test-3	Test-4
Jack	M	Y	N	P	N	N	N
Mary	F	Y	N	P	N	P	N
Jim	M	Y	P	N	N	N	N

  - gender is a symmetric attribute
  - the remaining attributes are asymmetric binary
  - let the values Y and P be set to 1, and the value N be set to 0

$$d(jack, mary) = \frac{0+1}{2+0+1} = 0.33$$

$$d(jack, jim) = \frac{1+1}{1+1+1} = 0.67$$

$$d(jim, mary) = \frac{1+2}{1+1+2} = 0.75$$

Nominal Variables

- A generalization of binary variable in that it can take more than 2 states, e.g., red, yellow, blue, green
- Method 1: Simple matching
  - *m*: # of matches, *p*: total # of nominal variables

$$d(i,j) = \frac{p-m}{p}$$

- Method 2: use a large number of binary variables
  - creating a new binary variable for each of the *M* nominal states

Ordinal Variables

- An ordinal variable can be discrete or continuous
- Order is important, e.g., rank
- Can be treated like interval-scaled
  - replace x_{if} by their rank $r_{if} \in \{1, \ldots, M_f\}$
  - map the range of each variable onto [0, 1] by replacing *i*-th object in the *f*-th variable by

$$z_{if} = \frac{r_{if} - 1}{M_f - 1}$$

  - compute the dissimilarity using methods for interval-scaled variables

级数变化

Ratio-Scaled Variables

- Ratio-scaled variable: a positive measurement on a nonlinear scale, approximately at exponential scale, such as Ae^{Bt} or Ae^{-Bt}
- Methods:

  不能像对待区间变量一样去处理级数变量

  - treat them like interval-scaled variables — *not a good choice!*
  - apply logarithmic transformation

    使用对数来处理

$$y_{if} = log(x_{if})$$

  - treat them as continuous data and treat their rank as interval-scaled

Variables of Mixed Types

- A database may contain all the six types of variables
  - symmetric binary, asymmetric binary, nominal, ordinal, interval and ratio
- One may use a weighted formula to combine their effects

$$d(i,j) = \frac{\sum_{f=1}^{p} \delta_{ij}^{(f)} d_{ij}^{(f)}}{\sum_{f=1}^{p} \delta_{ij}^{(f)}}$$

  - $\delta^{(f)}_{ij} = 0$ if x_{if} or x_{jf} is missing, or $x_{if} = x_{jf} = 0$ and f is asymmetric attribute; otherwise, $\delta^{(f)}_{ij} = 1$
  - *f* is binary or nominal:

    $d_{ij}^{(f)} = 0$ if $x_{if} = x_{jf}$, or $d_{ij}^{(f)} = 1$ otherwise
  - *f* is interval-based: use the normalized distance
  - *f* is ordinal
    - compute ranks r_{if} and treat z_{if} as interval-scaled

$$z_{if} = \frac{r_{if} - 1}{M_f - 1}$$

  - *f* is ratio-scaled
    - Transform *f*, and treat *f* as interval-scaled. $y_{if} = log(x_{if})$

Exercise

1. Please compute the dissimilarity matrix for the data set.

ID	Test-1 (categorical)	Test-2 (ordinal)	Test-3 (ratio-scaled)
1	A	excellent	445
2	B	fair	22
3	C	good	164
4	A	excellent	1,210

Solution

For test-1, use simple matching

0			
d(2,1)	0		
d(3,1)	d(3,2)	0	
d(4,1)	d(4,2)	d(4,3)	0

?

=

0			
1	0		
1	1	0	
0	1	1	0

For test-2

0			
1	0		
0.5	0.5	0	
0	1	0.5	0

Solution

For test-3, use log transformation

- Convert test-3 to 2.65, 1.34, 2.21, 3.08
- Normalize to 0.75, 0, 0.5,1

0			
0.75	0		
0.25	0.5	0	
0.25	1	0.5	0

Dissimilarity matrix

0			
0.92	0		
0.58	0.67	0	
0.08	1	0.67	0

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Major Clustering Approaches (I)

- 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, CLARANS
- Hierarchical approach: 分级聚合
  - Create a hierarchical decomposition of the set of data (or objects) using some criterion
  - Typical methods: Diana, Agnes, BIRCH, ROCK, CHAMELEON

上面这俩rlies on distance

- Density-based approach: 依赖于密度，阈值的确定是一个缺点
  - Based on connectivity and density functions
  - Typical methods: DBSACN, OPTICS, DenClue

Major Clustering Approaches (II)

- Grid-based approach:
  - based on a multiple-level granularity structure
  - Typical methods: STING, WaveCluster, CLIQUE
- Probabilistic Model-based approach:
  - Typical methods: EM

质心

Centroid, Radius and Diameter of a Cluster (for numerical data sets)

- Centroid: the “middle” of a cluster

$$C = \frac{\sum_{i=1}^{N}(t_i)}{N}$$

- Radius: square root of average distance from any point of the cluster to its centroid

$$R = \sqrt{\frac{\sum_{i=1}^{N}(t_i - c)^2}{N}}$$

- Diameter: square root of average mean squared distance between all pairs of points in the cluster

$$D = \sqrt{\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}(t_i - t_j)^2}{N(N-1)}}$$

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Partitioning Algorithms: Basic Concept

- Partitioning method: Construct a partition of a database *D* of *n* objects into a set of *k* clusters, s.t., min sum of squared distance

$$\Sigma_{m=1}^{k}\Sigma_{t_{mi}\in Km}(C_m - t_{mi})^2$$

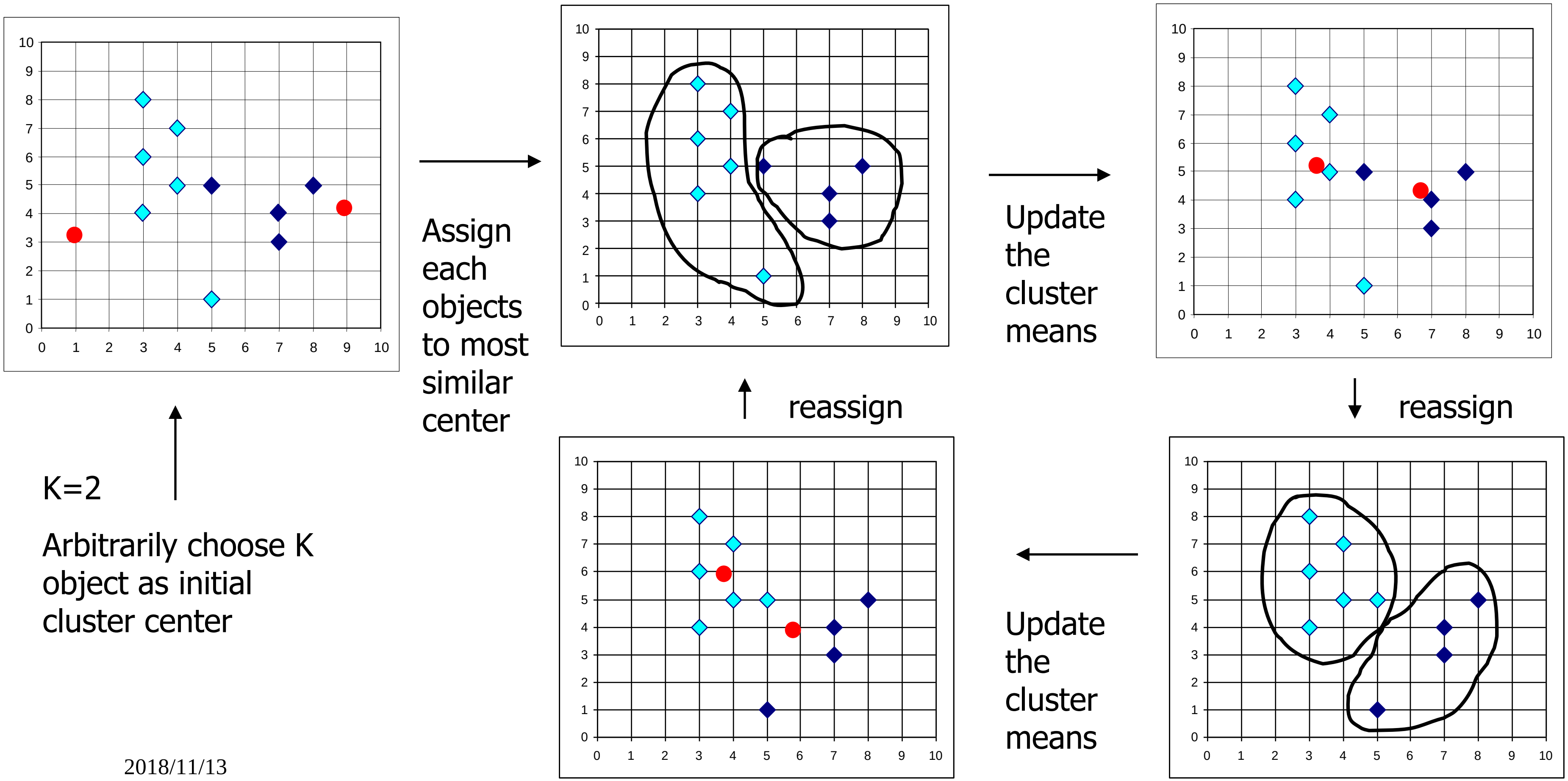
- Given a *k*, find a partition of *k clusters* that optimizes the chosen partitioning criterion
  - *k-means* (MacQueen'67): Each cluster is represented by the center of the cluster
  - *k-medoids* or PAM (Partition around medoids) (Kaufman & Rousseeuw'87): Each cluster is represented by one of the objects in the cluster

The *K-Means* Clustering Method

- Given a *k*, the *k-means* algorithm is implemented in four steps:
  - Give *k* random seeds as the initial centroids
  - Compute the centroid of each cluster of the current partition (the centroid is the center, i.e., *mean point*)
  - For each object, compute its distance to the centroids
    - Assign it to the cluster with the nearest centroid
  - Go back to Step 2, stop when no more new assignment

The *K-Means* Clustering Method

- Example



K=2

Arbitrarily choose K object as initial cluster center

Assign each objects to most similar center

Update the cluster means

reassign

Update the cluster means

reassign

Comments on the *K-Means* Method

- Strength: Relatively efficient: *O*(*tkn*), where *n* is # objects, *k* is # clusters, and *t* is # iterations. Normally, *k*, *t* << *n*
- Comment: Often terminates at a *local optimum*. The *global optimum* may be found using techniques such as: *deterministic annealing* and *genetic algorithms*

模拟退火和遗传算法

- Weakness
  - Applicable only when *mean* is defined, then what about categorical data?
  - Need to specify *k,* the number of clusters, in advance
  - Unable to handle noisy data and outliers
  - Not suitable to discover clusters with *non-convex shapes*

非凸

Variations of the *K-Means* Method

- Handling categorical data: *k-modes*

modes -众数

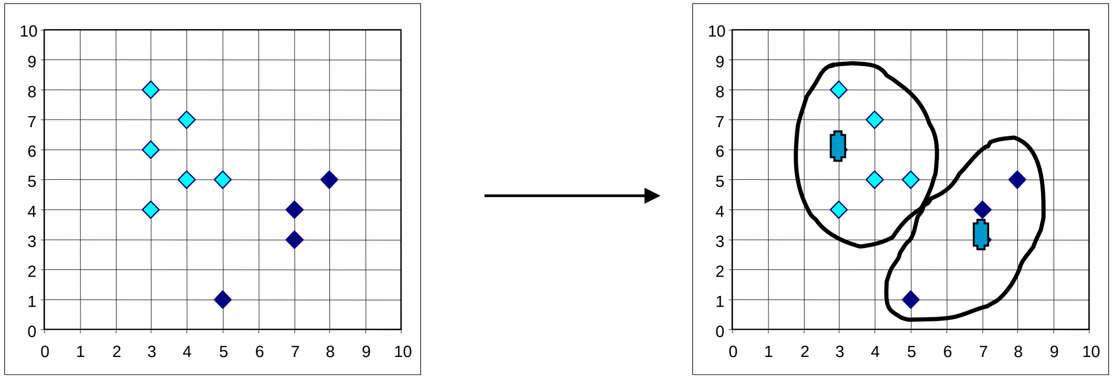
  - Replacing means of clusters with modes
  - Using new dissimilarity measures to deal with categorical objects
  - Using a frequency-based method to update modes of clusters
  - A mixture of categorical and numerical data: *k-prototype* method

原型

- Expectation Maximization: an extension to k-means
  - Assign each object to a cluster according to a weight (prob.)
  - New means are computed based on weighted measures

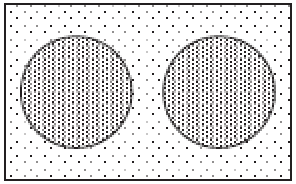
What Is the Problem of the K-Means Method?

- 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 枚举算法 复杂度：O n^2

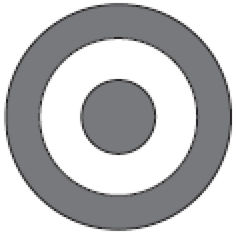


Exercise

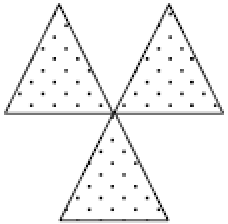
1. Identify the clusters using the K-means (using squared error as the objective function). Note that darkness or the number of dots indicates density.



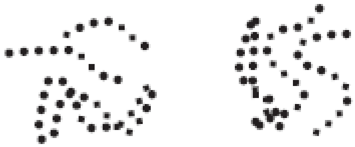
(a)



(b)



(c)



(d)

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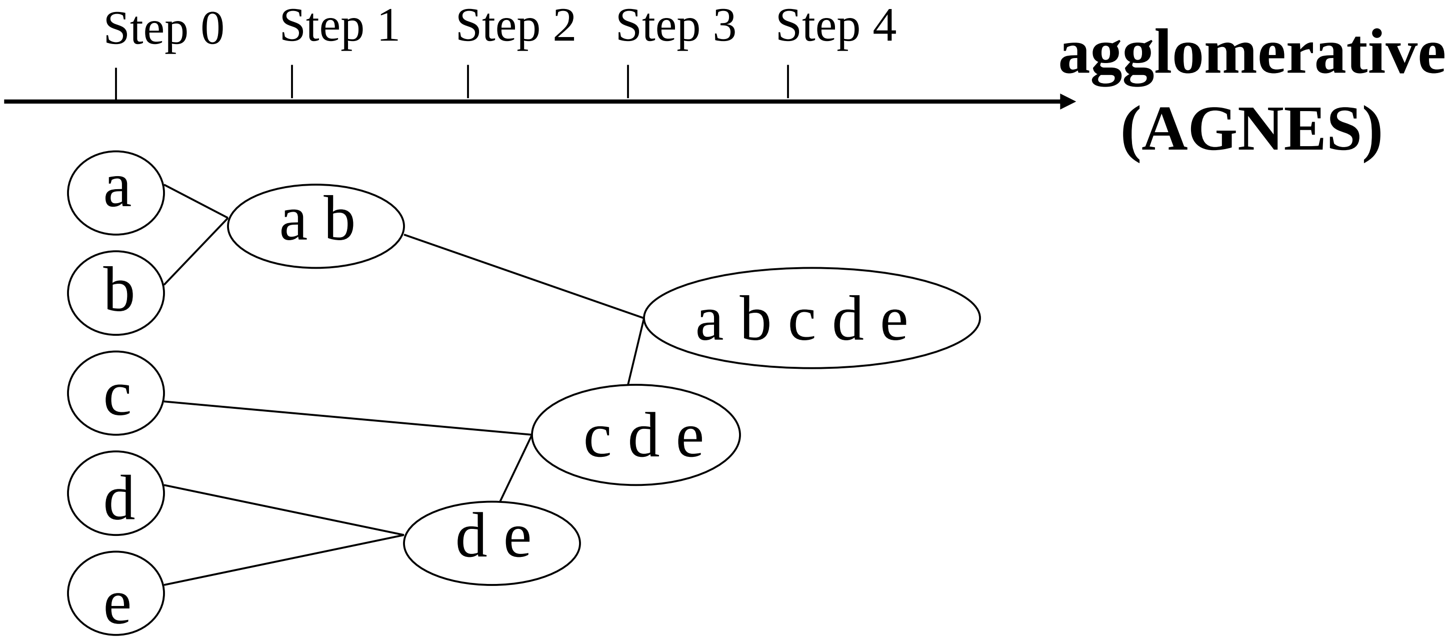
Hierarchical Clustering

- This method does not require the number of clusters ***k*** as an input, but needs a termination condition



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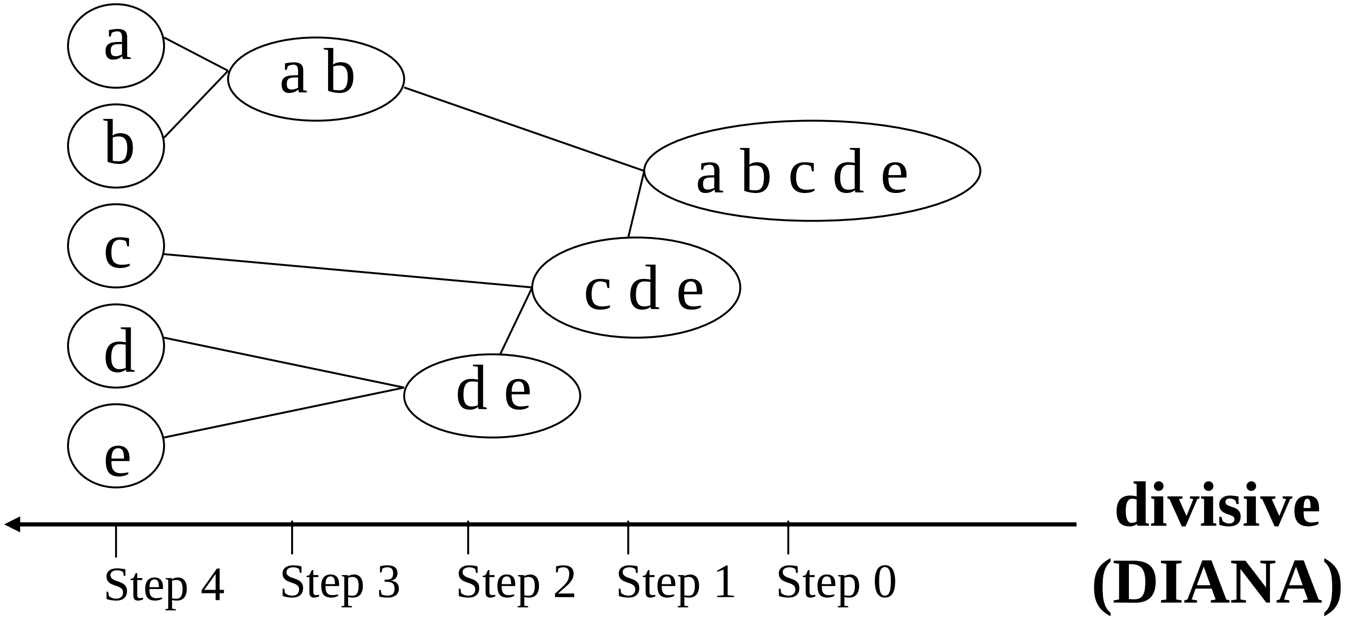
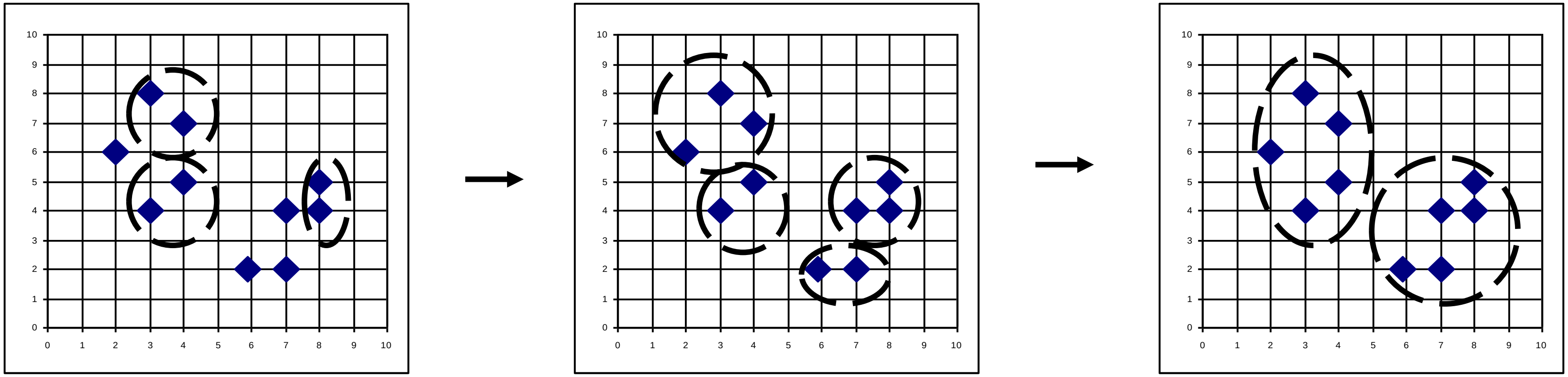


AGNES (Agglomerative Nesting)

- Introduced by Kaufmann and Rousseeuw (1990)
- 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

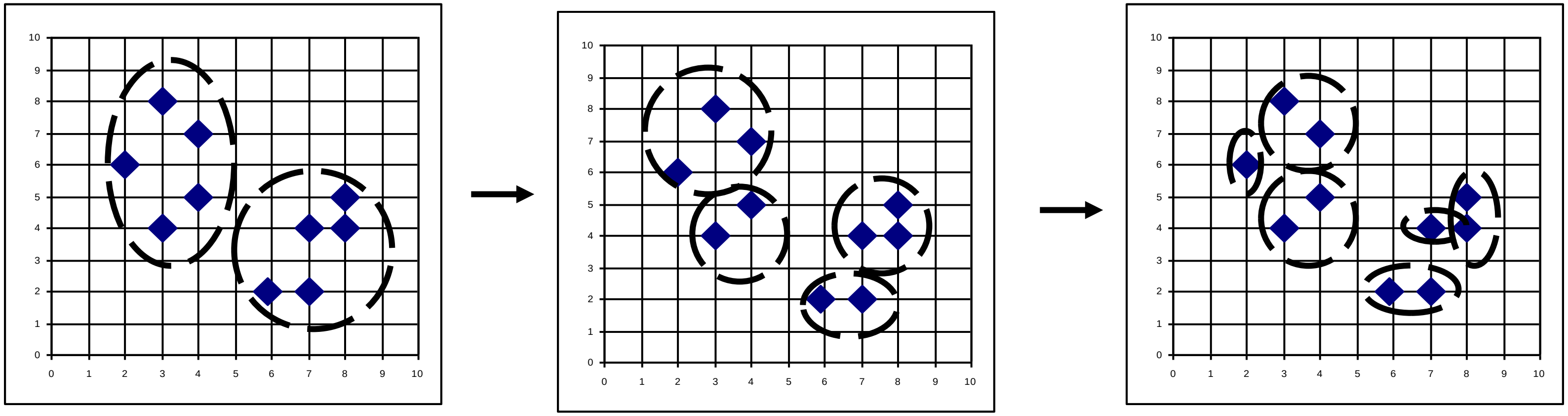


DIANA (Divisive Analysis)

- Introduced by Kaufmann and Rousseeuw (1990)
- Inverse order of AGNES
- Eventually each node forms a cluster on its own

如何去切割是一个难点

复杂度至少是n^2



Recent Hierarchical Clustering Methods

- Major weakness of hierarchical 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
  - ROCK (1999): clustering categorical data by neighbor and link analysis
  - CHAMELEON (1999): hierarchical clustering using dynamic modeling

BIRCH (1996)

- BIRCH: integrated hierarchical clustering
- Clustering feature, Clustering feature tree
- Incrementally construct a CF (Clustering Feature) tree, a hierarchical data structure for multiphase clustering
  - 阶段
    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 a clustering algorithm to cluster the leaf nodes of the CF-tree

Clustering Feature Vector in BIRCH

Clustering Feature: ***CF* = (*N*, $\overrightarrow{LS}$, *SS*),** summarize the cluster members

N: **Number of data points**

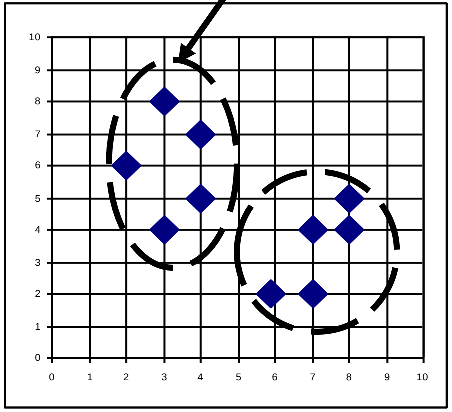
$LS: \sum^{N}_{i=1} = \overrightarrow{X_i}$

线性和：所有横纵坐标加起来

$SS: \sum^{N}_{i=1} = \overline{X_i^2}$

平方和：横纵坐标的平方加起来

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



(3,4)

(2,6)

(4,5)

(4,7)

(3,8)

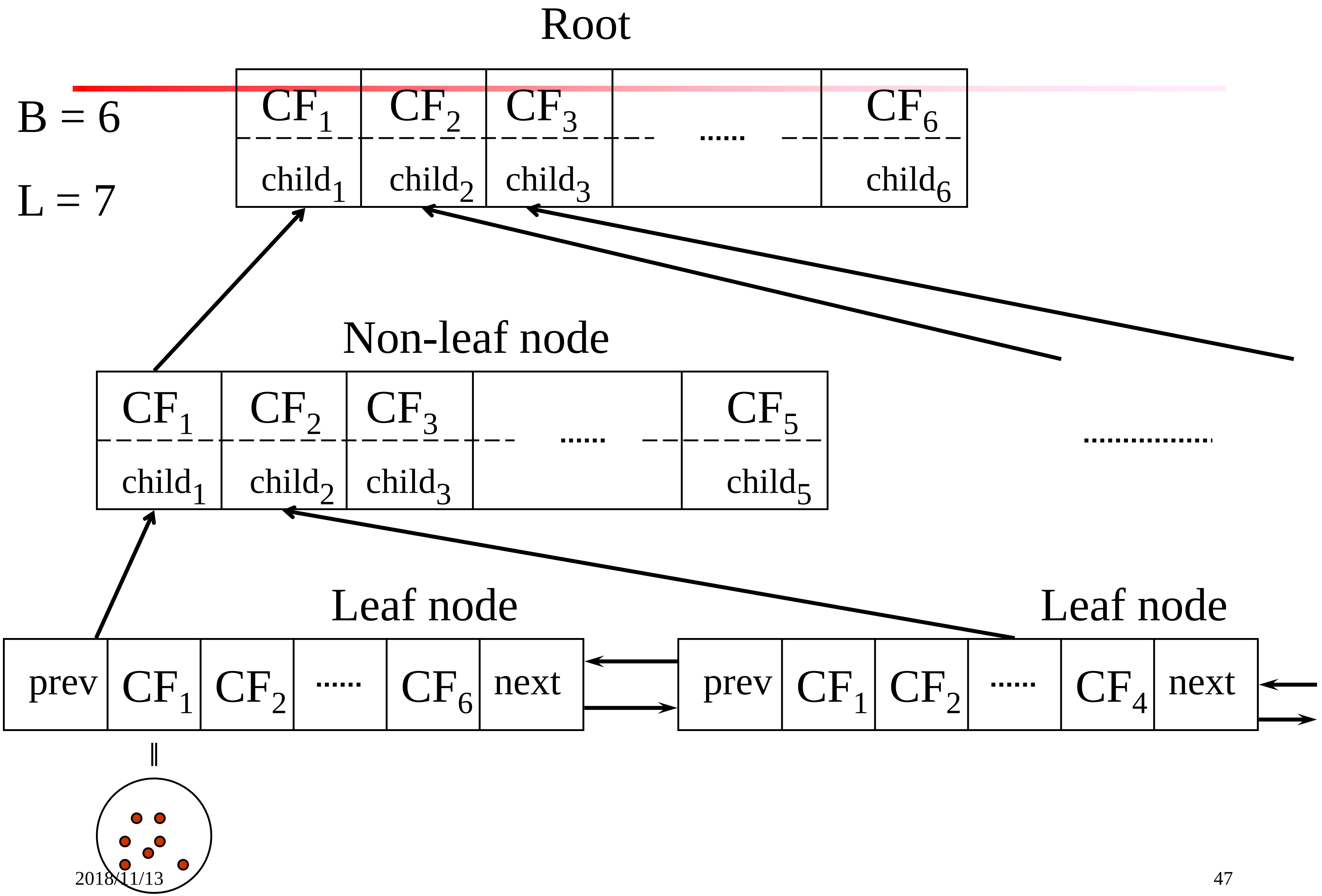
CF-Tree in BIRCH

- Clustering feature:
  - summary of the statistics for a given subcluster
  - registers crucial measurements for computing cluster and utilizes storage efficiently 为计算集群注册重要的度量并有效地利用存储
- 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

The CF Tree Structure

B = 6

L = 7


Root
CF_1 CF_2 CF_3 ...... CF_6
$child_1$ $child_2$ $child_3$ $child_6$
Non-leaf node
CF_1 CF_2 CF_3 ...... CF_5
$child_1$ $child_2$ $child_3$ $child_5$
....
Leaf node
prev CF_1 CF_2 ...... CF_6 next
Leaf node
prev CF_1 CF_2 ...... CF_4 next
||

BIRCH

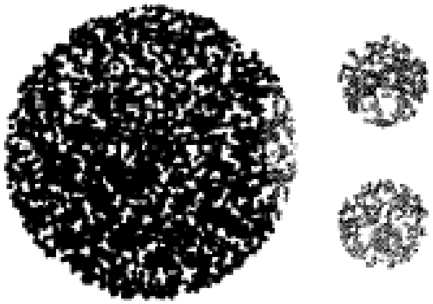
- Phase 1
  - Insert each object to its closest leaf entry
  - If the diameter of a leaf is larger than a threshold, the leaf will be split
  - Update the CF and its ancestor's CF
  - If the size of the CF tree is too big, re-build the tree from the leaf node, no re-scan the original objects
  - Two parameters (branching factor, threshold), control the size of the tree

BIRCH

- Scales linearly
  - Complexity: O(*n*)
  - Scalable for large database
  - Incremental clustering
  - Finds a good clustering with a single scan, I/O cost small
- Weakness
  - Handles only numeric data, and sensitive to the order of the data record
  - Not good at arbitrary shaped cluster

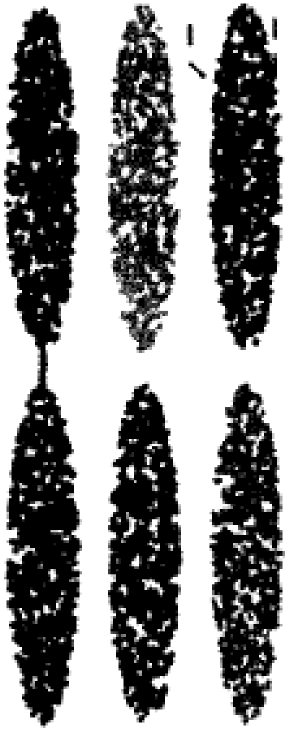
CURE: Clustering Using Representatives

Centroid-based clustering



一个中心点

All-points agglomerative clustering



一对中心点

CURE: middle ground between centroid-based clustering and all-points agglomerative clustering

CURE: Clustering Using Representatives

- Start with each individual point as a separate cluster
- Merge closest clusters till each cluster contains more than *c* points
- For each cluster, use *c* scattered points as representatives
- If more than *k* clusters
  - Clusters with the closest pair of representative points are merged
  - Update the representative points of merged clusters

CURE: Clustering Using Representatives

- Choose representatives
  - the point farthest from the mean of the cluster
  - for 2 to *c* do

        the point farthest from the previously chosen point
  - Shrink the scattered points toward the mean by a fraction α

      for each scattered point *p* do

          representative = $p + \alpha * (\text{mean} - p)$
- Merge

$$dist(u, v) = \min_{p \in u.\mathrm{rep}, q \in v.\mathrm{rep}} dist(p, q)$$

  - Euclidian distance 欧式距离
  - Closest clusters –- minimum distance between representative points from two clusters

CURE: Clustering Using Representatives

- Multiple representative points allow CURE to discover arbitrary shaped clusters
- Less sensitive to outliers
  - Shrink scattered points toward the mean, weaken the effects of outliers

- Time complexity O($n^2 log(n)$)
- For large-scale database, do sampling and partitioning

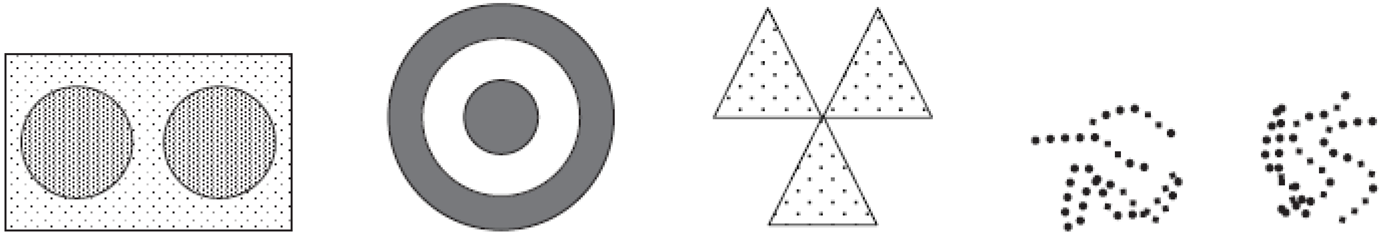
CURE: Clustering Using Representatives

- Draw a random sampling *S* from original objects
- Cluster the sampled objects (basic *CURE*)
- Eliminate outliers
- Each unsampled original object is assigned to the cluster containing the closest representative point to it

? ? ?

Exercise

1. Identify the clusters using the Single-Link method. Note that darkness or the number of dots indicates density.



(a) (b) (c) (d)

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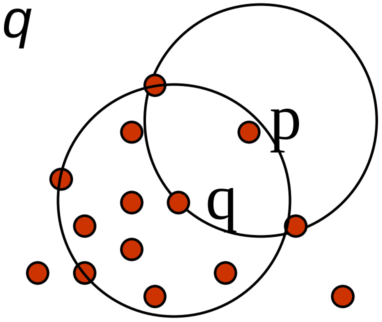
Density-Based Clustering Methods

- Clustering based on density (local cluster criterion), such as density-connected points
- Major features:
  - Discover clusters of arbitrary shape
  - Handle noise
  - Need density parameters as termination condition
  - Complexity is O(n^2)

Density-Based Clustering: Basic Concepts

- Two parameters*:*
  - *ε-neighborhood*: neighborhood within a radius ε of a point
  - *MinPts*: Min number of points in ε-neighborhood of a point
- core object: If the number of points in ε-neighborhood of point *p* exceeds *MinPts*
- Directly density-reachable: A point *p* is directly density-reachable from a point *q* w.r.t. , ε , *MinPts* if
  - *p* belongs to ε-neighborhood of *q*
  - *q* is core object

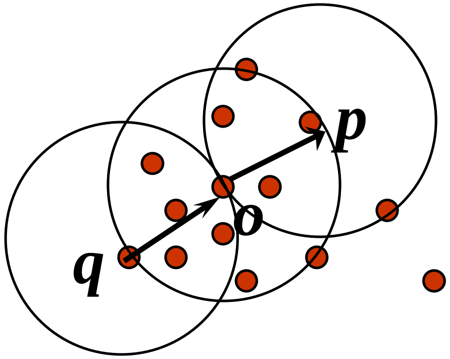


$MinPts = 5$

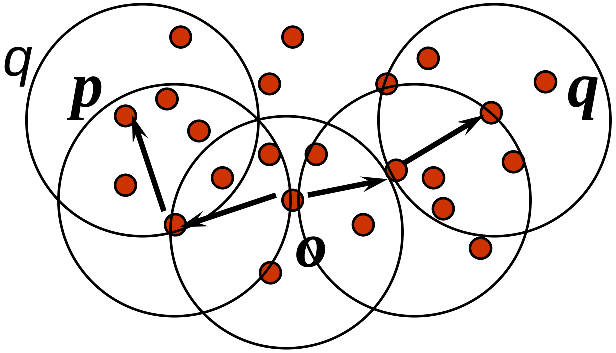
$\varepsilon = 1$ cm

Density-Reachable and Density-Connected

- Density-reachable:
  - A point *p* is density-reachable from a point *q* w.r.t. ε, *MinPts* if there is a chain of points $p_1, \ldots, p_n$, $p_1 = q$, $p_n = p$ such that p_{i+1} is directly density-reachable from p_i



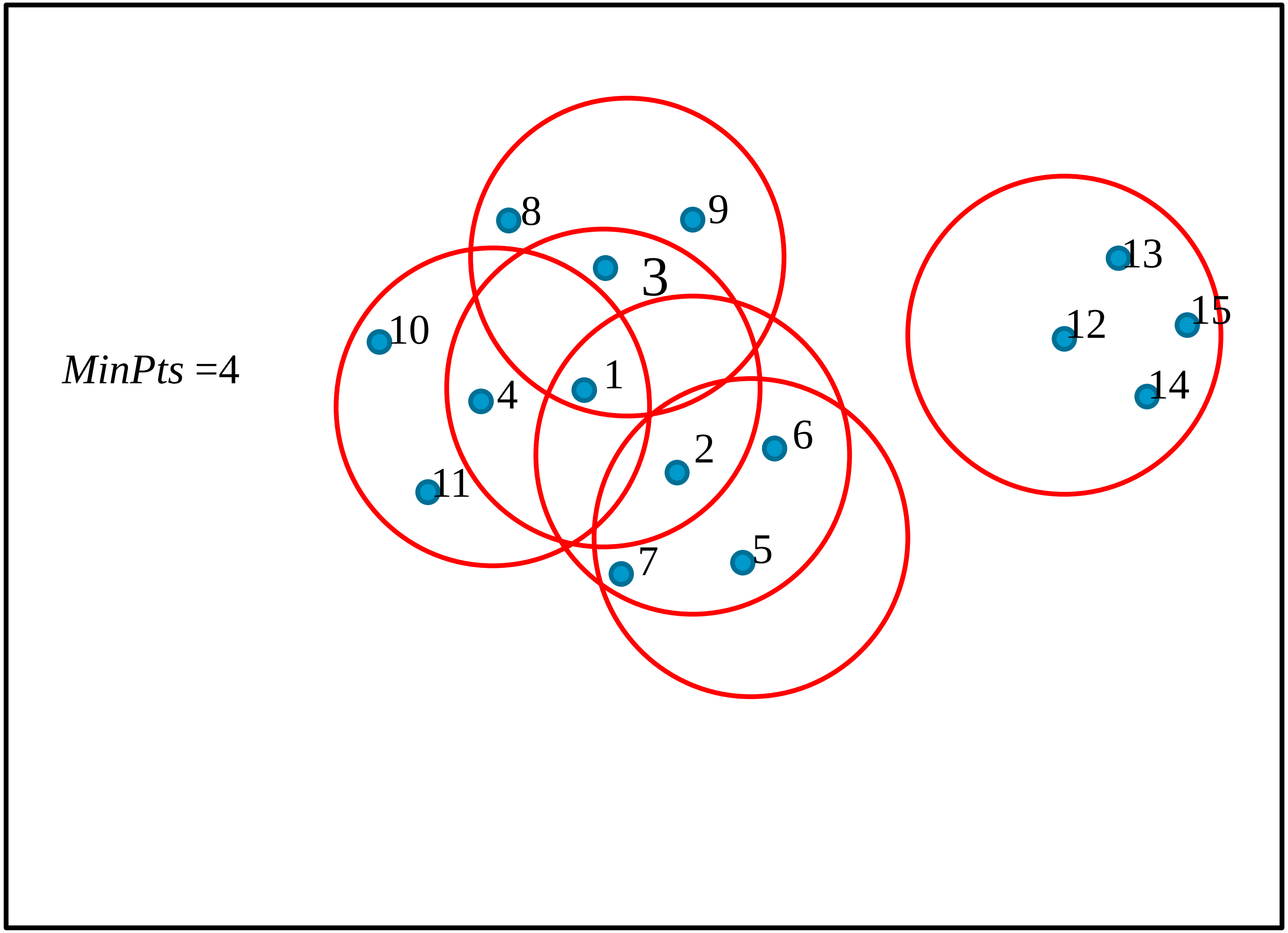
- Density-connected
  - A point *p* is density-connected to a point *q* w.r.t. ε, *MinPts* if there is a point *o* such that both *p* and *q* are density-reachable from *o* w.r.t. ε and *MinPts*



DBSCAN: The Algorithm

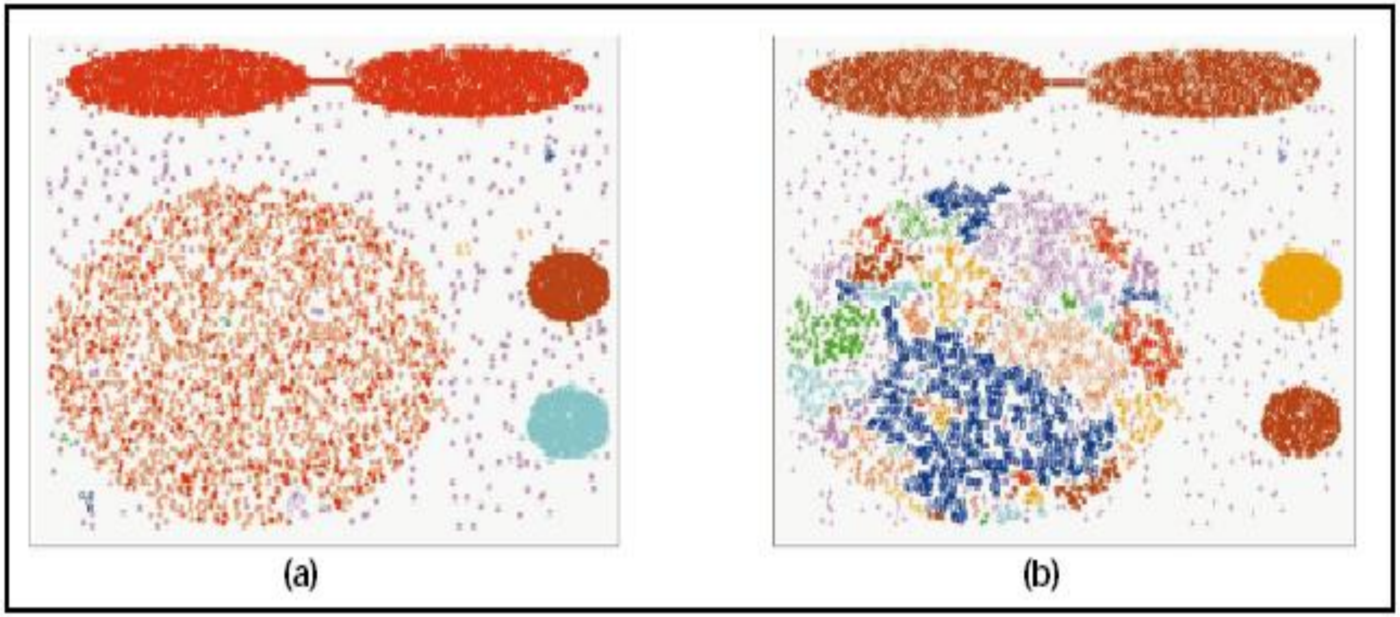
```
mark all the objects as unvisited;
do
    randomly select an unvisited object p;
    mark p as visited;
    if the $\varepsilon$-neighborhood of p has at least MinPts objects
        create a new cluster C, and add p to C;
        let N be the set of objects in the $\varepsilon$-neighborhood of p;
        for each point p' in N
            if p' is unvisited
                mark p' as visited;
                if the $\varepsilon$-neighborhood of p' has at least MinPts points, add those points to N;
            if p' is not yet a member of any cluster, add p' to C;
        end for
        output C;
    else mark p as noise;
until no object is unvisited.
```

DBSCAN: The Algorithm

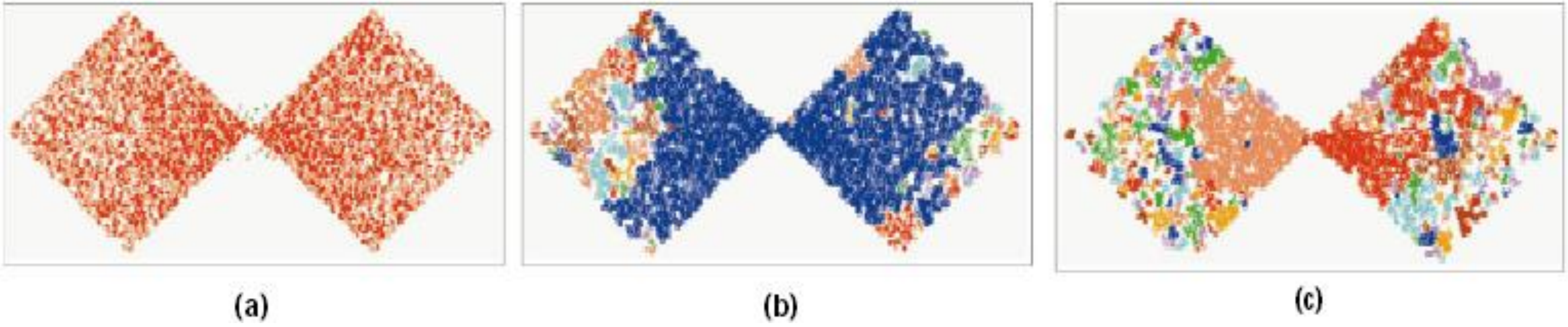


DBSCAN: Sensitive to Parameters

DBScan results with MinPts = 4 and ε= (a) 0.5, (b) 0.4

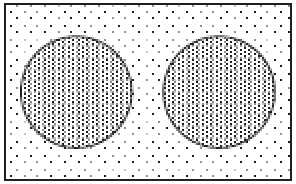


DBScan results with MinPts = 4 and ε= (a) 5.0, (b) 4.0, (c) 3.0

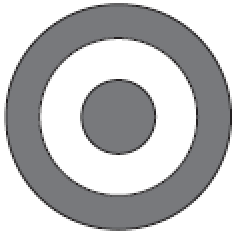


Exercise

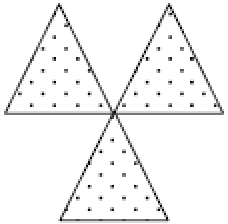
1. Identify the clusters using DBSCAN. Note that darkness or the number of dots indicates density.



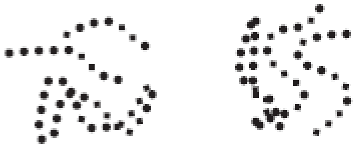
(a)



(b)



(c)



(d)

Cluster Analysis

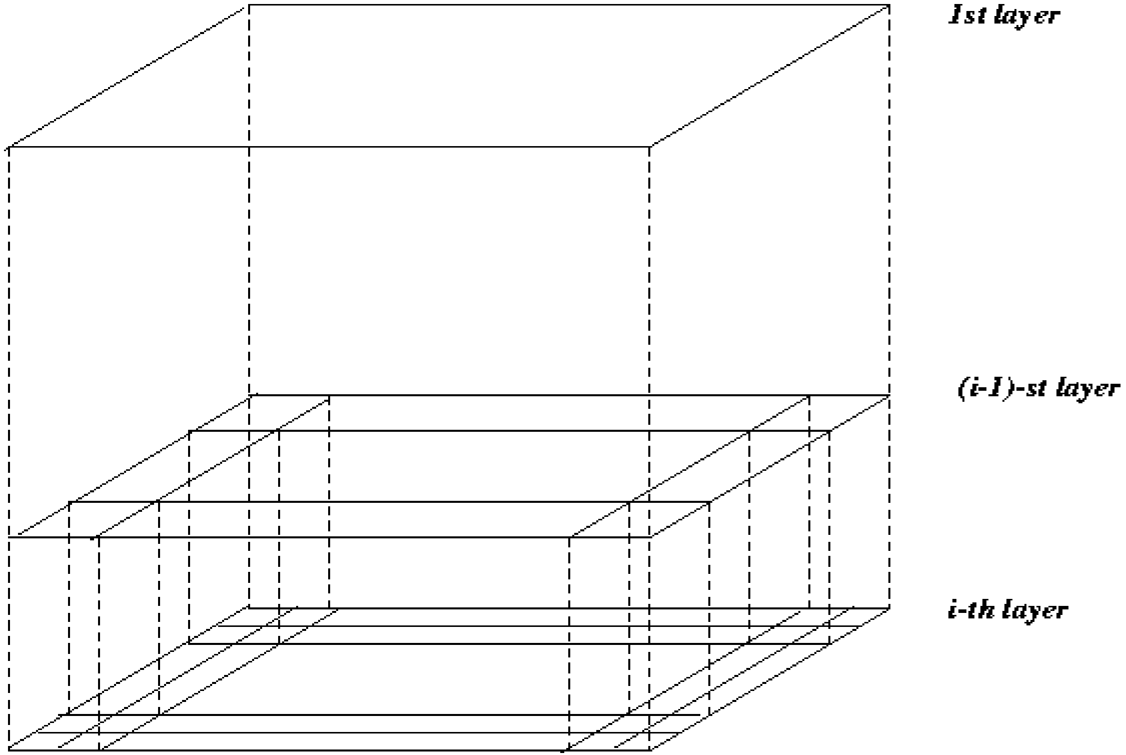
- What is Cluster Analysis?
- Types of Data in Cluster Analysis
- A Categorization of Major Clustering Methods
- Partitioning Methods
- Hierarchical Methods
- Density-Based Methods
- Grid-Based Methods
- Outlier Analysis
- Summary

Grid-Based Clustering Method

- Using multi-resolution grid data structure
- Several interesting methods
  - STING (a STatistical INformation Grid approach) by Wang, Yang and Muntz (1997)
  - WaveCluster by Sheikholeslami, Chatterjee, and Zhang (VLDB’98)
    - A multi-resolution clustering approach using wavelet method
  - CLIQUE: Agrawal, et al. (SIGMOD’98)
    - On high-dimensional data

STING: A Statistical Information Grid Approach

- The spatial area is divided into rectangular cells
- There are several levels of cells corresponding to different levels of resolution
- Each cell at a high level is partitioned into a number of smaller cells in the next lower level



The STING Clustering Method

- Statistical info of each cell is calculated and stored beforehand and is used to answer queries
  - *count*, *mean*, *s*, *min*, *max*
  - type of distribution—normal, uniform, NONE, etc.
- Parameters of higher level cells can be easily calculated from parameters of lower level cells
- Clusters are identified based on *count*, *cell size*, etc.

$$n = \sum_i n_i$$

$$m = \frac{\sum_i m_i n_i}{n}$$

$$s = \sqrt{\frac{\sum_i (s_i^2 + m_i^2) n_i}{n} - m^2}$$

$$min = \min_i(min_i)$$

$$max = \max_i(max_i)$$

The STING Query Method

- Use a top-down approach to answer spatial data queries
- Start from a pre-selected layer — typically with a small number of cells
- For each cell in the current level compute the confidence interval
- Remove the irrelevant cells from further consideration
- When finish examining the current layer, proceed to the next lower level of the relevant cells
- Repeat this process until the bottom layer is reached

Exercise

1. Please give some comments on STING in the following aspects:

(1) cluster shape

(2) computational complexity

(3) cluster quality

(4) incremental clustering

Comments on STING Clustering

- Advantages:
  - Query-independent
  - incremental update
  - *O(K)* for query, where *K* is the number of grid cells at the lowest level
  - O(*n*) for generating clusters
- Disadvantages:
  - All the cluster boundaries are either horizontal or vertical, and no diagonal boundary is detected
  - Processing time depends on the size of each grid

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What Is Outlier Discovery?

- What are outliers?
  - The set of objects are considerably dissimilar from the remaining of the data
  - Caused by
    - Measurement or execution errors
    - Result of inherent variability
- Mining outliers is valuable
- Applications:
  - Credit card fraud detection
  - Customer segmentation
  - Medical analysis

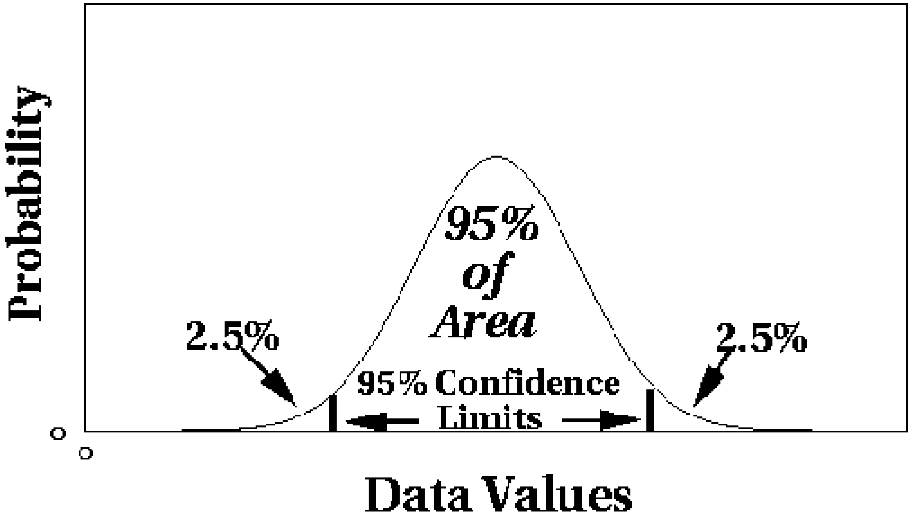
Outlier Detection

- Visualization
  - Weak in data with categorical data, high dimensional data
  - Good at numerical data of 2 or 3 dimensions
- Clustering
  - Byproduct of clustering may be outliers
- Computer-based methods
  - Statistical-based outlier detection
  - Distance-based outlier detection
  - Deviation-based outlier detection

Outlier Detection: Statistical Approaches

- Assume a distribution (e.g. normal distribution) for the data set and then use discordancy test to find outliers
- Discordancy tests depends on knowledge
  - data distribution
  - two hypothesis
  - distribution parameter (e.g., mean, variance)
  - number of expected outliers

Outlier Detection: Statistical Approaches



- Drawbacks
  - Most tests are for single attribute
  - In many cases, data distribution may not be known
  - Require input parameters

Outlier Detection: Distance-Based Approach

- Introduced to overcome the main limitations imposed by statistical methods
  - We need multi-dimensional analysis without knowing data distribution, no statistical test
- Distance-based outlier: A DB(*p*, *d*)-outlier is an object O in a dataset T such that at least a fraction *p* of the objects in T lies at a distance greater than *d* from O
- Algorithms for mining distance-based outliers
  - Index-based algorithm
  - Cell-based algorithm

Index-based Algorithm

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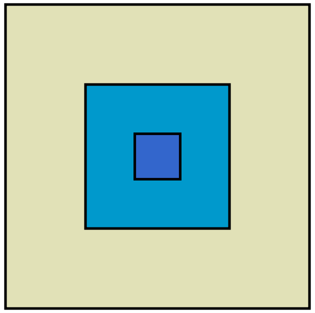
- Search for neighbors of each object O within radius *d* around the object
- Multi-dimensional index structure, e.g. kd tree
- Max number of objects within *d*-neighborhood of each outlier
- The worst case $O(kn^2)$

  k dimensionality, *n* number of objects
- Drawbacks：
  - Tree building is computational intensive

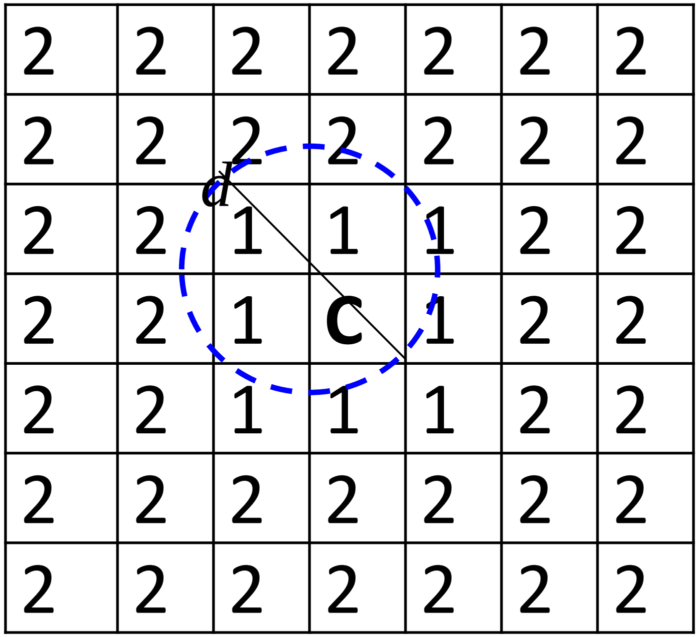
Cell-based Algorithm

- Cell partition
  - Partition data space into cells, side length d/2k$^{1/2}$
  - Each cell has two layers around it
    - First layer one cell thick
    - Second layer (2k$^{1/2}$ –1) cells thick



- Outlier detection
  - If count of the first layer >M, no outlier in this cell
  - If count of the second layer<=M, all objects are outliers
  - Otherwise, examine every object in the cell
- Good for large-scale data set

Cell-based Algorithm



2	2	2	2	2	2	2
2	2	2	2	2	2	2
2	2	1	1	1	2	2
2	2	1	C	1	2	2
2	2	1	1	1	2	2
2	2	2	2	2	2	2
2	2	2	2	2	2	2

- *k*=2, *k* dimensionality
- Layer-1 property: given any point *x* in cell *C*, and any point *y* in layer-1 cell, *dist*(*x*,*y*) ≤ *d*

Outlier Detection: Deviation-Based Approach

- Identifies outliers by examining the main characteristics of objects in a group
- Objects that “deviate” from this description are considered outliers
- Sequential exception technique
  - Simulates the way in which humans can distinguish unusual objects from among a series of supposedly like objects
  - A sequence of subsets, $\{S_1, S_2, \ldots, S_m\}$, $S_{j-1} \subset S_j$
  - Calculate the dissimilarity difference between the current subset with the proceeding subset in the sequence

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Summary

- Cluster analysis groups objects based on their similarity and has wide applications
- Measure of similarity can be computed for various types of data
- Clustering algorithms can be categorized into partitioning methods, hierarchical methods, density-based methods, grid-based methods
- Outlier detection and analysis are very useful for fraud detection, etc. and can be performed by statistical, distance-based or deviation-based approaches

Summary

- Considerable progress has been made in scalable clustering methods
    - Partitioning: k-means, k-medoids, CLARANS
    - Hierarchical: BIRCH, ROCK, CHAMELEON
    - Density-based: DBSCAN, OPTICS, DenClue
    - Grid-based: STING, WaveCluster, CLIQUE
    - Model-based: EM, Fuzzy K-Means
    - Frequent pattern-based: pCluster
    - Constraint-based: COD, constrained-clustering