

# Data Mining:

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# Concepts and Techniques

— Chapter 7 —

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# Cluster Analysis

1. What is Cluster Analysis?
2. Types of Data in Cluster Analysis
3. A Categorization of Major Clustering Methods
4. Partitioning Methods
5. Hierarchical Methods
6. Density-Based Methods

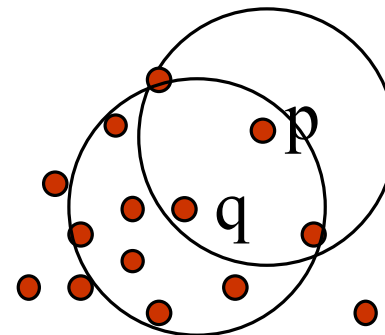
# Density-Based Clustering Methods

- Clustering based on density (local cluster criterion), such as density-connected points
- Major features:
  - Discover clusters of arbitrary shape
  - Handle noise
  - One scan
  - Need density parameters as termination condition
- Several interesting studies:
  - DBSCAN: Ester, et al. (1996)
  - OPTICS: Ankerst, et al (1999).
  - DENCLUE: Hinneburg & D. Keim (1998)

# Density-Based Clustering: Basic Concepts

- Two parameters:
  - *Eps*: Maximum radius of the neighborhood
  - *MinPts*: Minimum number of points in an *Eps*-neighborhood of that point
- $N_{Eps}(p)$ :  $\{q \text{ belongs to } D \mid d(p,q) \leq Eps\}$
- **Directly density-reachable**: A point  $p$  is directly density-reachable from a point  $q$  w.r.t.  $Eps$ ,  $MinPts$  if
  - $p$  belongs to  $N_{Eps}(q)$
  - core point condition:

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



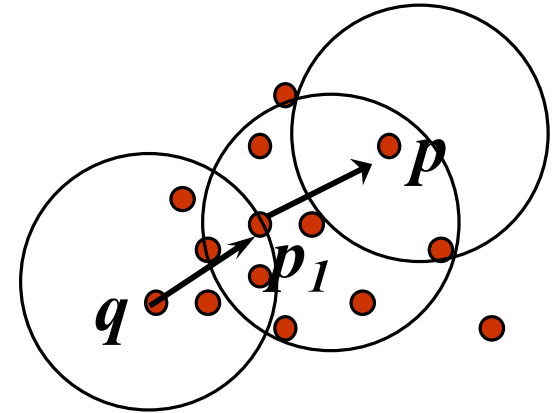
$MinPts = 5$

$Eps = 1 \text{ cm}$

# Density-Based Clustering: Basic Concepts

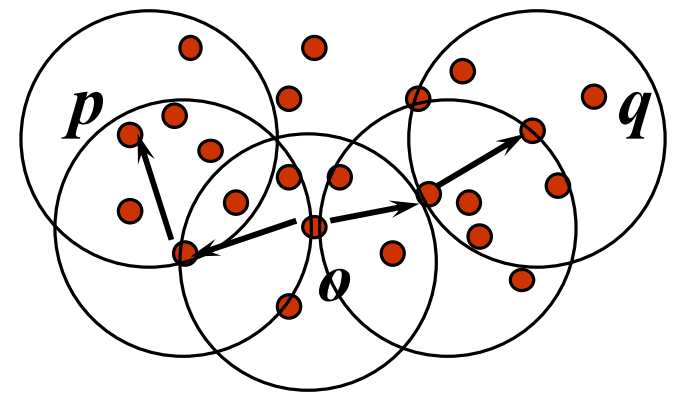
## ■ Density-reachable:

- A point  $p$  is **density-reachable** from a point  $q$  w.r.t.  $Eps$ ,  $MinPts$  if there is a chain of points  $p_1, \dots, p_n$ ,  $p_1 = q$ ,  $p_n = p$  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.  $Eps$ ,  $MinPts$  if there is a point  $o$  such that both,  $p$  and  $q$  are density-reachable from  $o$  w.r.t.  $Eps$  and  $MinPts$

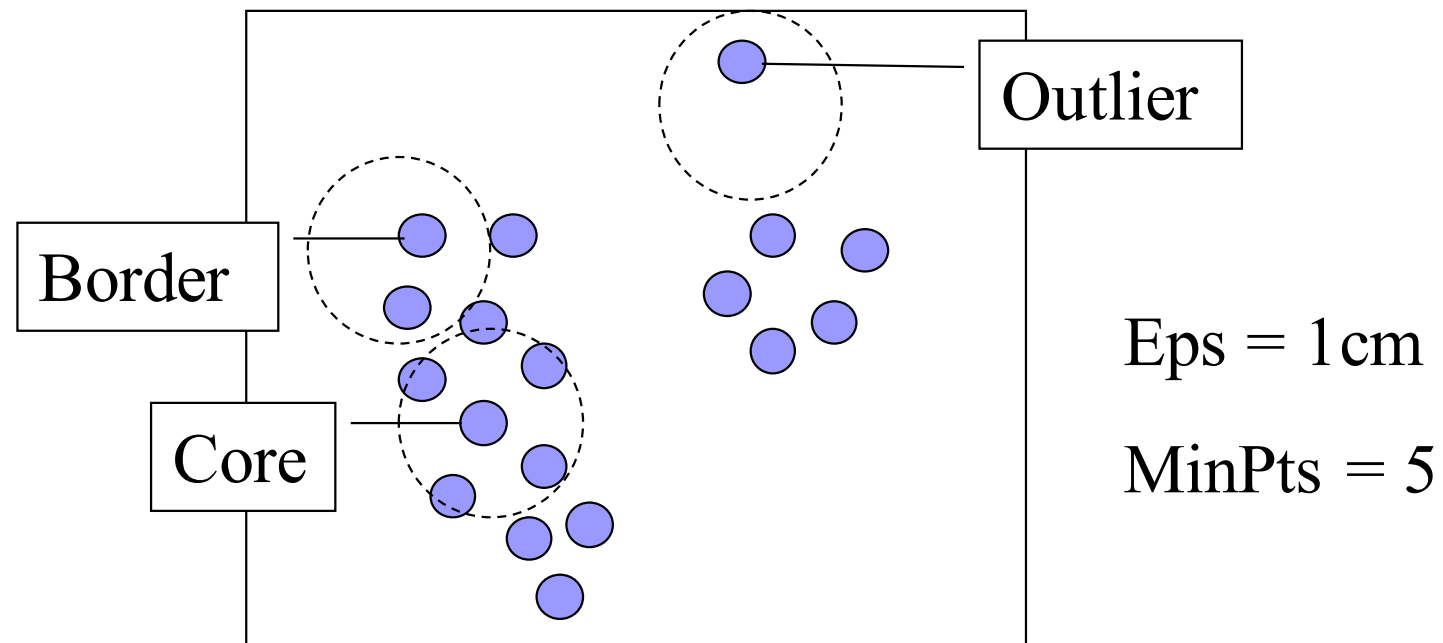




# *Explanation on whiteboard*

# 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

- Arbitrary select a point  $p$
- Retrieve all points density-reachable from  $p$  w.r.t.  $Eps$  and  $MinPts$ .
- If  $p$  is a core point, a cluster is formed containing  $p$  and all the density-reachable points from  $p$ . Mark these points as processed.
- Mark  $p$  as processed.
- Continue this process until all of the points have been processed.



# DBSCAN: Sensitive to Parameters

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

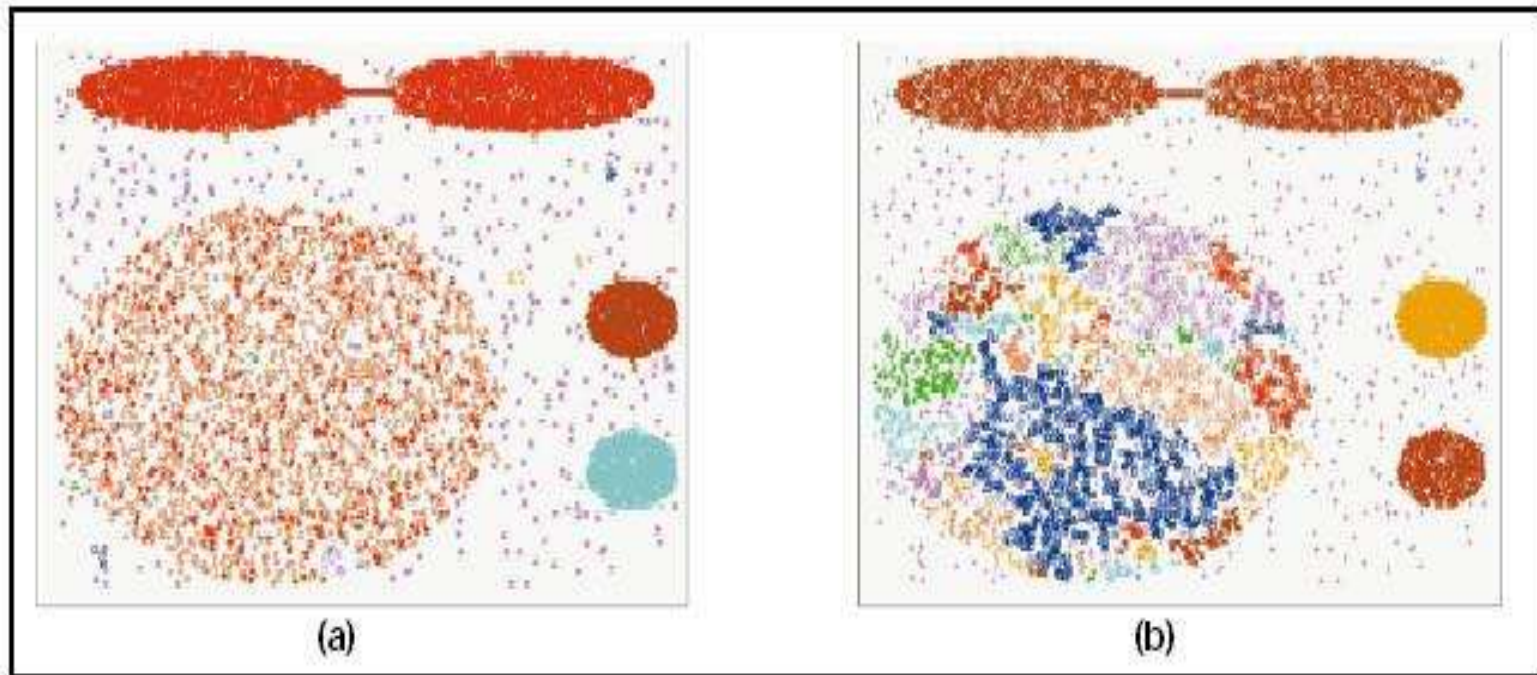
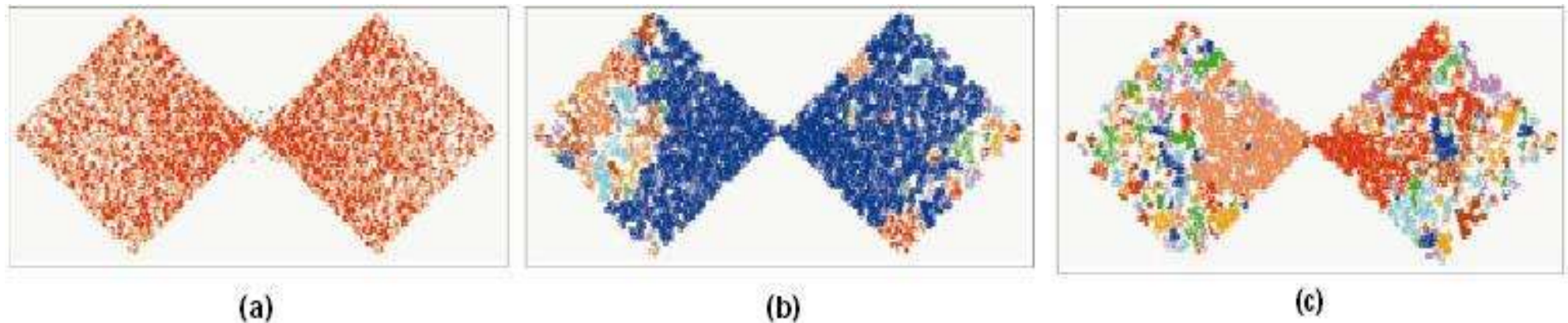


Figure 9. DBScan results for DS2 with MinPts at 4 and Eps at (a) 5.0, (b) 3.5, and (c) 3.0.

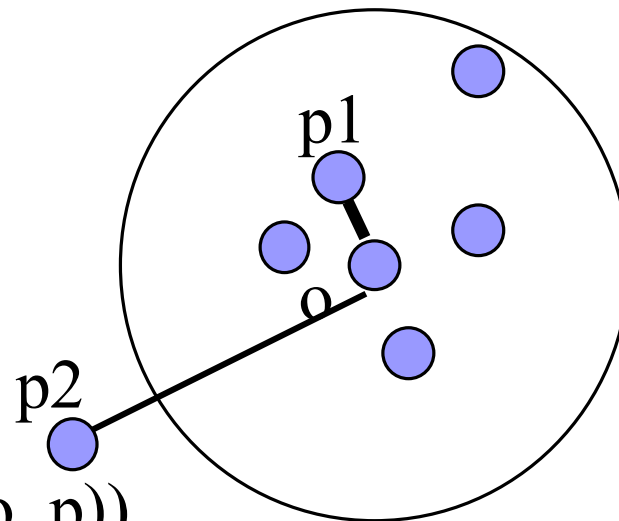


# OPTICS: A Cluster-Ordering Method

- OPTICS: Ordering Points To Identify the Clustering Structure
  - Ankerst, Breunig, Kriegel, and Sander (1999)
  - 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

# OPTICS basic concepts

- Core Distance of  $p$  wrt MinPts: smallest distance  $\epsilon$ ' between  $p$  and an object in its  $\epsilon$ -neighborhood such that  $p$  would be a core object for  $\epsilon$ ' and MinPts. Otherwise, undefined.
- Reachability Distance of  $p$  wrt  $o$ :  
Max (core-distance ( $o$ ),  $d(o, p)$ ) if  $o$  is core object.  
Undefined otherwise



Max (core-distance ( $o$ ),  $d(o, p)$ )

$r(p1, o) = 1.5\text{cm}$ .  $r(p2, o) = 4\text{cm}$

MinPts = 5

$\epsilon = 3\text{ cm}$

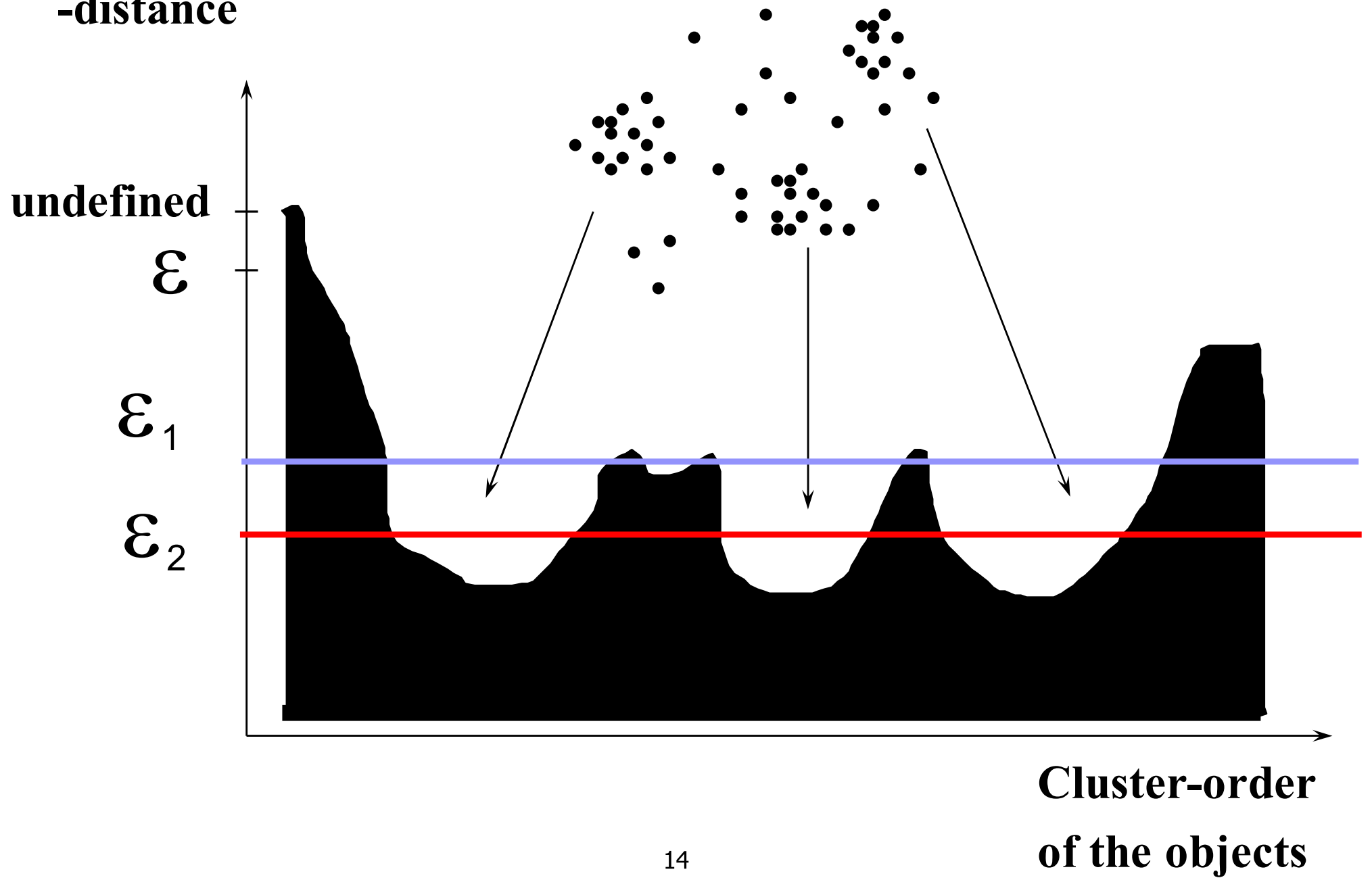
# OPTICS

- (1) Select non-processed object  $o$
- (2) Find neighbors (eps-neighborhood)
- Compute core distance for  $o$
- Write object  $o$  to ordered file and mark  $o$  as processed
- If  $o$  is not a core object, restart at (1)
- ( $o$  is a core object ...)
- Put neighbors of  $o$  in Seedlist and order
  - If neighbor  $n$  is not yet in SeedList then add ( $n$ , reachability from  $o$ )  
else if reachability from  $o <$  current reachability, then update reachability + order SeedList wrt reachability
- Take new object from Seedlist with smallest reachability and restart at (2)



*Example on whiteboard*

# Reachability -distance



# DENCLUE: Using Statistical Density Functions

- DENsity-based CLUstEring by Hinneburg & Keim (1998)
- Using statistical density functions
- 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
  - Significant faster than DBSCAN
  - But needs a large number of parameters

# Denclue: Technical Essence

- Uses grid cells but only keeps information about grid cells that do actually contain data points and manages these cells in a tree-based access structure

- Influence function: describes the impact of a data point within its neighborhood

$$f_{Gaussian}(x, y) = e^{-\frac{d(x, y)^2}{2\sigma^2}} \quad \text{OBS: minus}$$

- Overall density of the data space can be calculated as the sum of the influence function of all data points

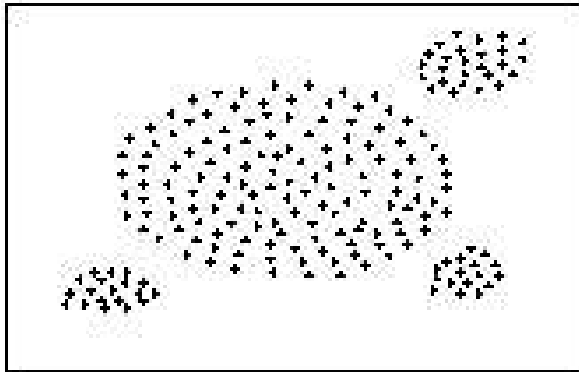
$$f_{Gaussian}^D(x) = \sum_{i=1}^N e^{-\frac{d(x, x_i)^2}{2\sigma^2}} \quad \text{OBS: minus}$$

- Clusters can be determined mathematically by identifying density attractors. Density attractors are local maxima of the overall density function

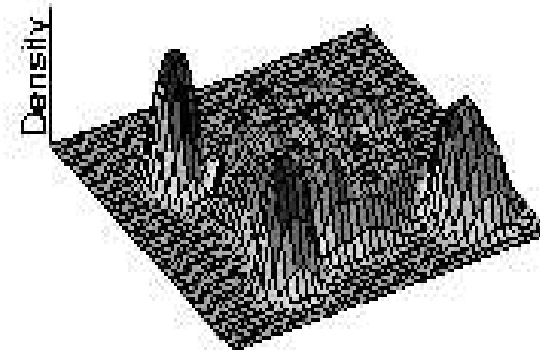
$$\nabla f_{Gaussian}^D(x, x_i) = \sum_{i=1}^N (x_i - x) \cdot e^{-\frac{d(x, x_i)^2}{2\sigma^2}} \quad \text{OBS: minus}$$



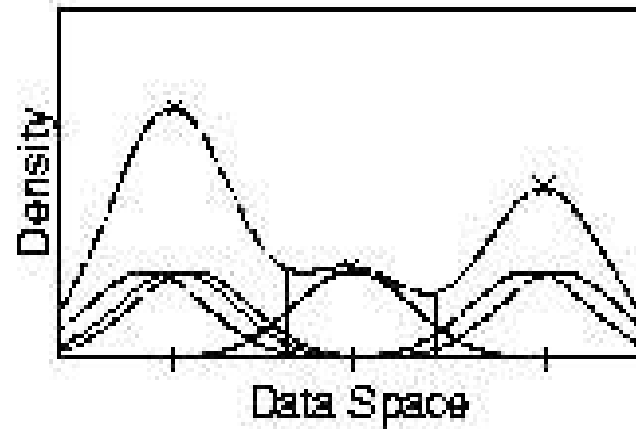
# Density Attractor



(a) Data Set



(c) Gaussian



# Denclue: Technical Essence

- Significant density attractor for threshold  $k$ : density attractor with density larger than or equal to  $k$
- Center-defined cluster for a significant density attractor  $x$  for threshold  $k$ : points that are density attracted by  $x$ 
  - Points that are attracted to a density attractor with density less than  $k$  are called outliers
- Set of significant density attractors  $X$  for threshold  $k$ : for each pair of density attractors  $x_1, x_2$  in  $X$  there is a path from  $x_1$  to  $x_2$  such that each point on the path has density larger than or equal to  $k$
- Arbitrary-shape cluster for a set of significant density attractors  $X$  for threshold  $k$ : points that are density attracted to some density attractor in  $X$

# Center-Defined and Arbitrary-shape clusters

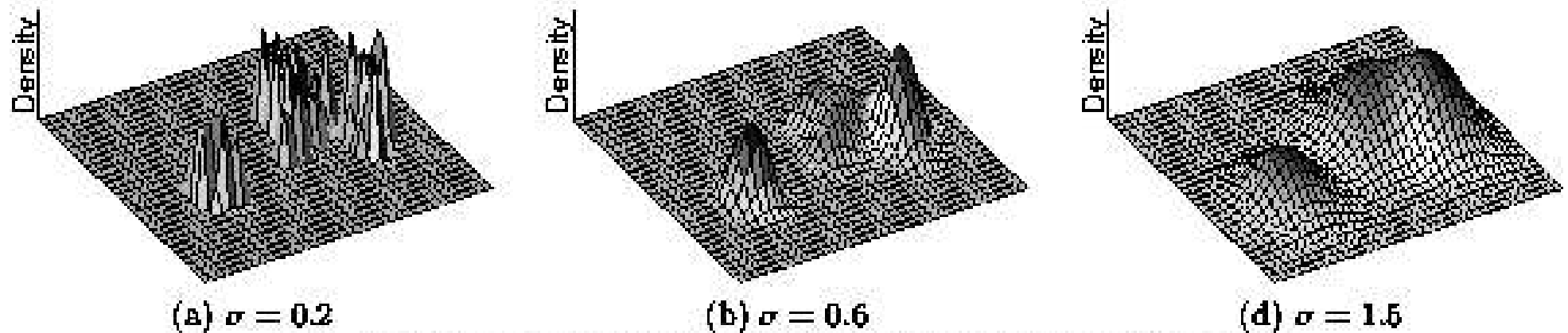


Figure 3: Example of Center-Defined Clusters for different  $\sigma$

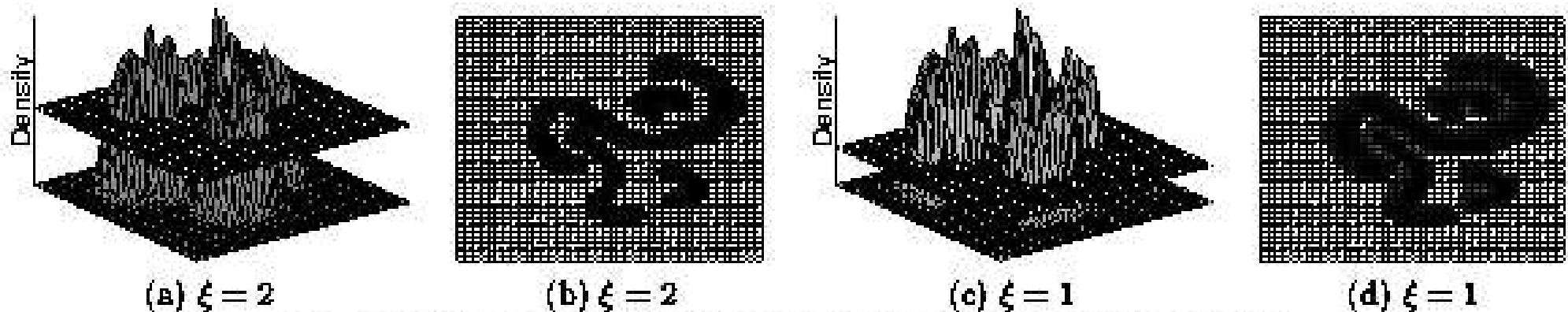


Figure 4: Example of Arbitrary-Shape Clusters for different  $\xi$

