

# OPTICS

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## OPTICS: A Cluster-Ordering Method (1999)

- ❖ **OPTICS: Ordering Points To Identify the Clustering Structure**
  - ▶ Ankerst, Breunig, Kriegel, and Sander (SIGMOD'99)
  - ▶ 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,
  - ▶ Cluster ordering can be used to extract basic clustering information,
  - ▶ Good for both automatic and interactive cluster analysis, including finding intrinsic clustering structure,
  - ▶ Can be represented graphically or using visualization techniques,

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## OPTICS

- ❖ It addresses one of DBSCAN's major weaknesses: **the problem of detecting meaningful clusters in data of varying density.**
- ❖ The similarity between OPTICS and DBSCAN:
  - ▶ two parameters are required, i.e.:  $\epsilon$  and  $MinPts$ .
  - ▶ A point  $p$  is a *core point* if at least  $MinPts$  points are found within its  $\epsilon$ -neighborhood.
- ❖ The Difference between OPTICS and DBSCAN:
  - ▶ Contrary to DBSCAN, OPTICS also considers points that are part of a more densely packed cluster, so each point is assigned a *core distance* that basically describes the distance to its  $MinPts$ -th point.
  - ▶ The *reachability-distance* of a point  $p$  from another point  $r$  is the distance between  $p$  and  $r$ , or the core distance of  $r$ .

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## OPTICS - Main idea

- ❖ In DBSCAN, for constant  $MinPts$ , clusters with high density (lower  $\epsilon$ ) are completely contained in **density-connected** sets obtained with lower density.
- ❖ in order to produce a set or ordering of density-based clusters, DBSCAN is extended to process a set of distance parameter  $\epsilon$  at the same time.
- ❖ in order to produce a set or ordering of density-based clusters, the objects need to be processed in a specific order.
- ❖ This order selects an object that is density reachable w.r.t. lowest  $\epsilon$  so that clusters of higher density (lower  $\epsilon$ ) will be finished first.

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## OPTICS - Main idea

- ❖ Based on this idea, 2 values need to be stored for each object:
  - ▶ *Core distance*
  - ▶ *Reachability distance*

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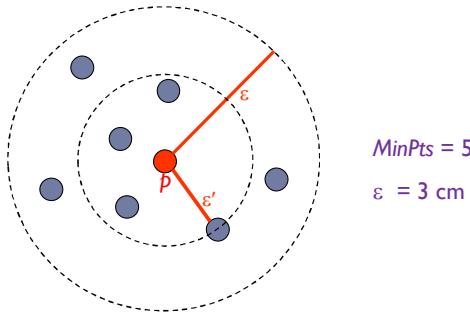
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## OPTICS - Main idea

- ❖ *Core distance*: smallest radius ( $\varepsilon$ ) that makes it a core object. If  $p$  is not core, it is undefined.

$$\text{core-distance}_{\varepsilon, \text{MinPts}}(p) = \begin{cases} \text{distance to the } (\text{MinPts}-1)\text{thNN} & \text{otherwise} \\ \text{undefined} & \text{if } |N_\varepsilon(p)| < \text{MinPts} \end{cases}$$

- ▶ Core Distance of  $p$  or  $\varepsilon'$ : distance between  $p$  and its 4-thNN.



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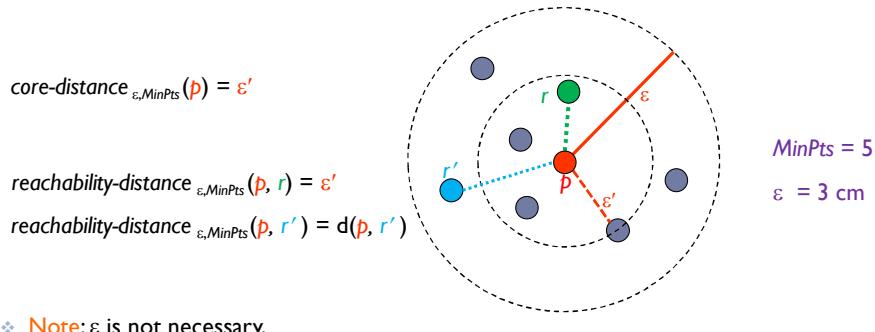
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## OPTICS - Main idea

- ❖ **Reachability distance** of  $r$  w.r.t.  $p$  is the greater value of the core distance of  $p$  and the Euclidean distance between  $p$  &  $r$ . If  $p$  is not a core object, distance reachability between  $p$  &  $q$  is undefined.

$$\text{reachability-distance}_{\varepsilon, \text{MinPts}}(p, r) = \begin{cases} \max(\text{core-distance}_{\varepsilon, \text{MinPts}}(p), \text{dist}(p, r)) & \text{otherwise} \\ \text{undefined} & \text{if } |N_\varepsilon(p)| < \text{MinPts} \end{cases}$$



- ❖ Note:  $\varepsilon$  is not necessary.

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## OPTICS - Main idea

- ❖ Intuitively, the reachability-distance of an object  $r$  w.r.t. another object  $p$  is the smallest distance such that  $r$  is *directly density-reachable (DDR)* from  $p$  if  $p$  is a core object.
- ❖ Basically, if  $r$  and  $p$  are nearest neighbors, this is the  $\varepsilon' < \varepsilon$  we need to assume in order to have  $r$  and  $p$  belong to the same cluster.

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## OPTICS - Main idea

- ❖ Both the core-distance and the reachability-distance are undefined if no sufficiently dense cluster (w.r.t.  $\varepsilon$ ) is available.
  - ▶ Given a sufficiently large  $\varepsilon$ , this will never happen, but then every  $\varepsilon$ -neighborhood query will return the entire database, resulting in an untractable runtime cost. Hence, the  $\varepsilon$  parameter is required to cut off the density of clusters that is no longer considered to be interesting.
- ❖ The parameter  $\varepsilon$  is strictly speaking not necessary. It can be set to a maximum value. It often claimed that OPTICS abstract from DBSCAN by removing this parameter. It does however play a practical role when it comes to **complexity** (i.e. time complexity).

## Extracting the Clusters

- ❖ The ordering information produced by OPTICS, is sufficient for the extraction of all density-based clusterings w.r.t. any distance  $\varepsilon' < \varepsilon$  used in generating the order.
- ❖ Using a *reachability-plot* (a special kind of dendrogram, i.e. from Greek *dendron* "tree", *-gramma* "drawing", or a *tree diagram*), the hierarchical structure of the clusters can be obtained easily.

## Extracting the Clusters

- ❖ **Reachability-plot:** a 2D plot, with the ordering of the points on the x-axis and the reachability distance on the y-axis.
  - ▶ Since points belonging to a cluster have a low reachability distance to their nearest neighbor, the clusters show up as **valleys** in the reachability plot. The deeper the valley, the denser the cluster.



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## Pseudocode

- ❖ OPTICS hence outputs the points in a particular ordering, annotated with their *smallest reachability distance* (in the original algorithm, the core distance is also exported, but this is not required for further processing).

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## Pseudocode

```
OPTICS (SetOfObjects,  $\epsilon$ , MinPts, OrderedFile)
    OrderedFile.open();
    for i = 1 to SetOfObjects.size do
        Object := SetOfObjects.get(i); // get an object from database
        if NOT Object.Processed then
            ExpandClusterOrder(SetOfObjects, Object,  $\epsilon$ , MinPts, OrderedFile)
        OrderedFile.close();
    end; // OPTICS
```

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## Pseudocode

```
ExpandClusterOrder (SetOfObjects, Object,  $\epsilon$ , MinPts, OrderedFile);
    neighbors := SetOfObjects.neighbors(Object,  $\epsilon$ ); // retrieve the  $\epsilon$ -neighborhood of Object
    Object.Processed := TRUE;
    Object.reachability_distance := UNDEFINED;
    Object.setCoreDistance(neighbors,  $\epsilon$ , MinPts); // determine the core distance for Object
    OrderedFile.write(Object); // write Object into the OrderFile with its c.d. and r.d.
    if Object.core_distance != UNDEFINED then // if Object is core, then collect its DDR to expand
        OrderSeeds.update(neighbors, Object); // sort objects by their r.d. to the closest core ★
        while NOT OrderSeeds.empty() do
            currentObject := OrderSeeds.next(); // get the object with the smallest r.d.
            neighbors := SetOfObjects.neighbors(currentObject,  $\epsilon$ );
            currentObject.Processed := TRUE;
            currentObject.setCoreDistance(neighbors,  $\epsilon$ , MinPts);
            OrderedFile.write(currentObject); // write current Object into the OrderFile with its ...
            if currentObject.core_distance != UNDEFINED then
                OrderSeeds.update(neighbors, currentObject);
    end; // ExpandClusterOrder
```

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## Pseudocode

```
OrderSeeds::update(neighbors, centerObj):
    d = centerObj.coreDistance
    for each unprocessed obj in neighbors:
        newRdist = max(d, dist(obj, centerObj))
        if obj.reachability == NULL then
            obj.reachability = newRdist
            insert(obj, newRdist)
        elseif newRdist < obj.reachability then
            obj.reachability = newRdist
            decrease(obj, newRdist)
```



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## Pseudocode

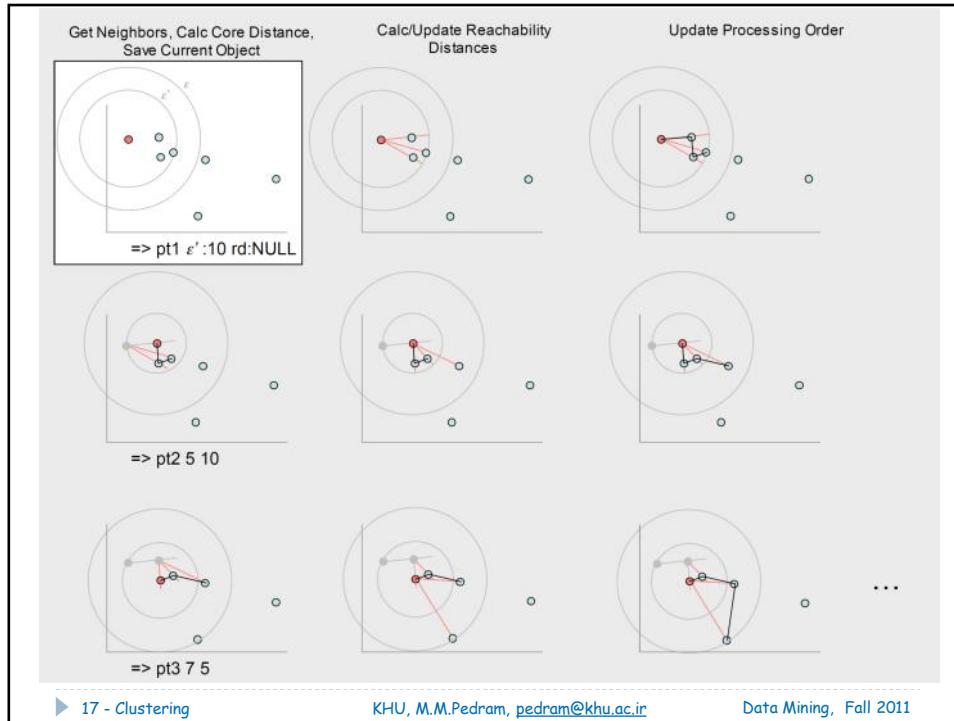
```
ExtractDBSCAN-Clustering (ClusterOrderedObjs, ε', MinPts)
    // Precondition: ε' ≤ generating dist ε for ClusterOrderedObjs
    ClusterId := NOISE;
    for i=1 to ClusterOrderedObjs.size do
        Object := ClusterOrderedObjs.get(i);
        if Object.reachability_distance > ε' then
            // UNDEFINED > ε
            if Object.core_distance ≤ ε' then
                ClusterId := nextId(ClusterId);
                Object.clusterId := ClusterId;
            else
                Object.clusterId := NOISE;
            else // Object.reachability_distance ≤ ε'
                Object.clusterId := ClusterId;
        end; // ExtractDBSCAN-Clustering
```

▶ 16 - Clustering

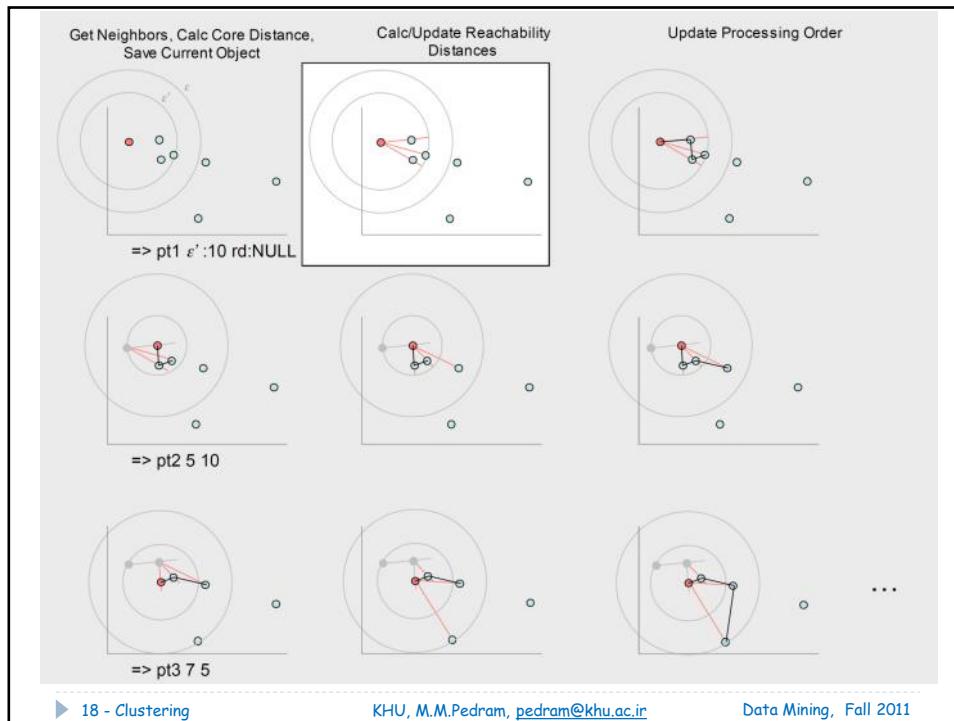
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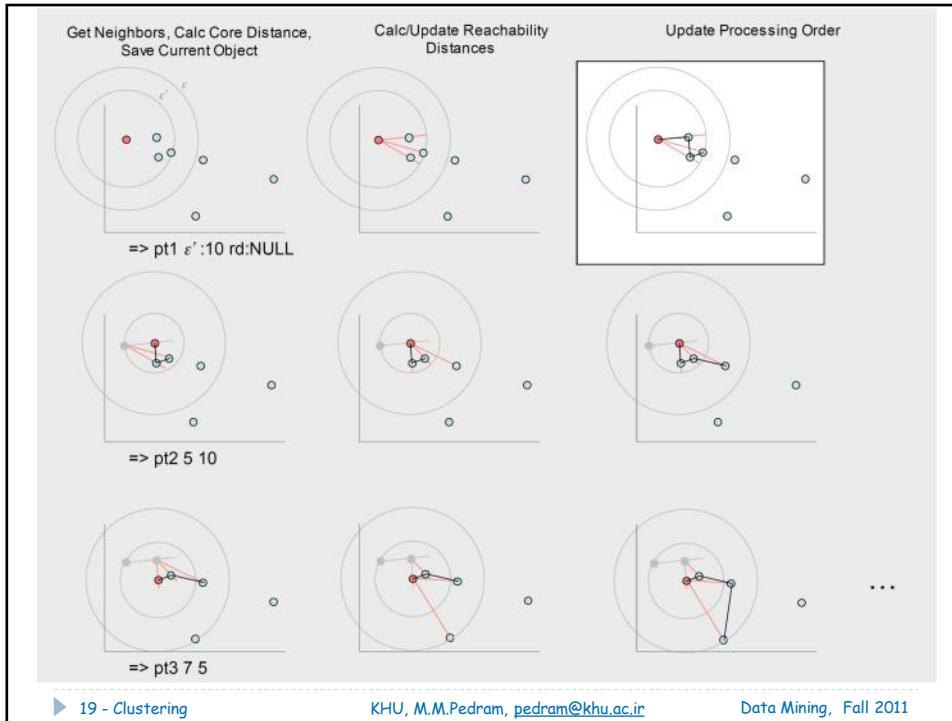
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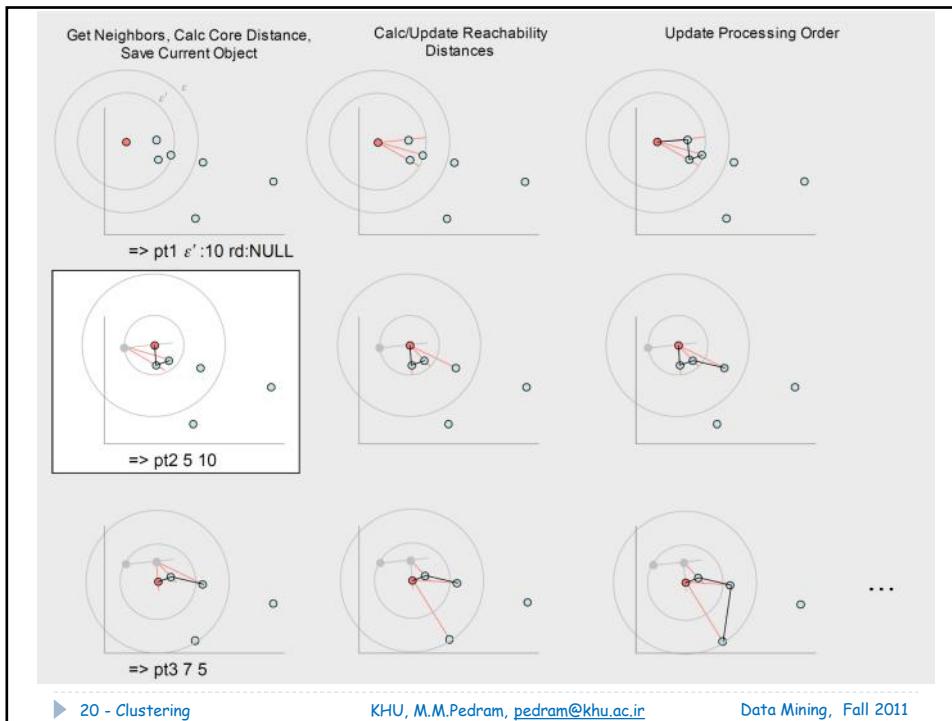
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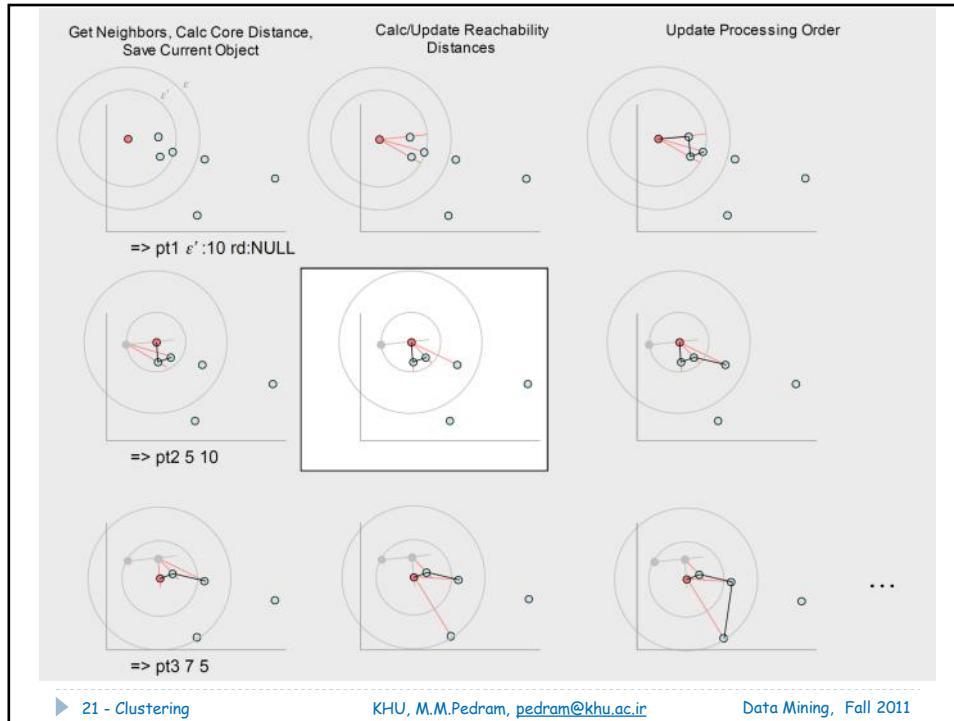
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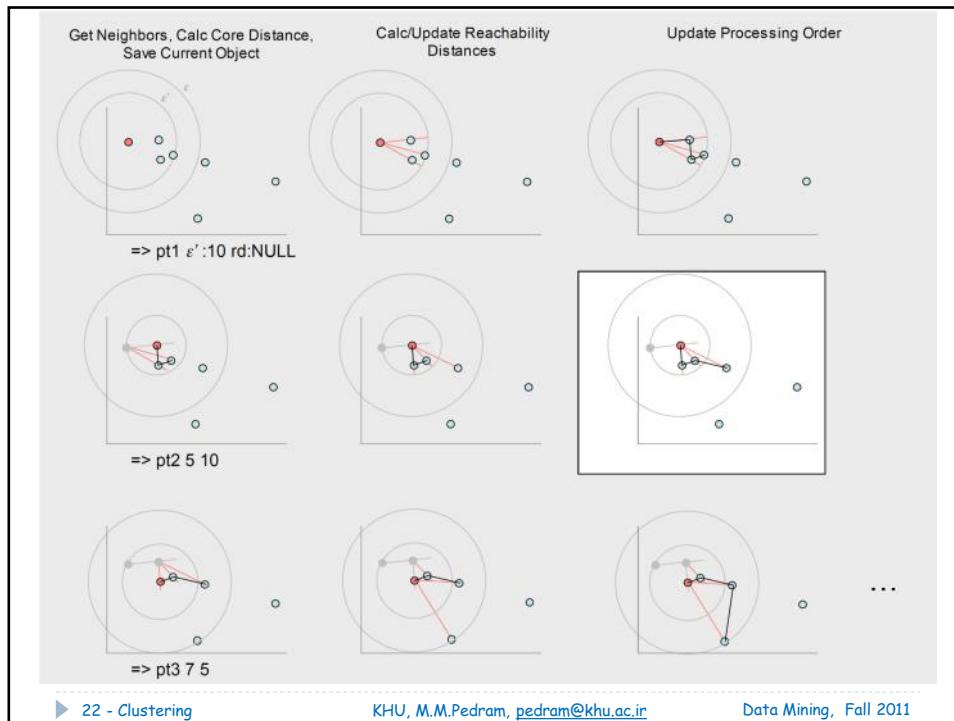
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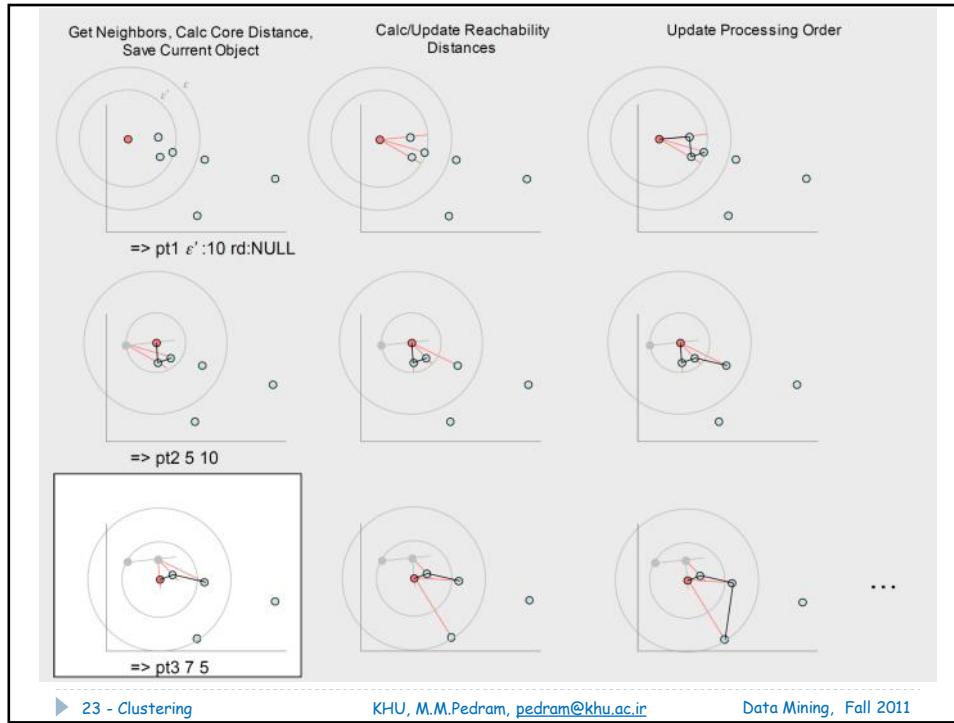
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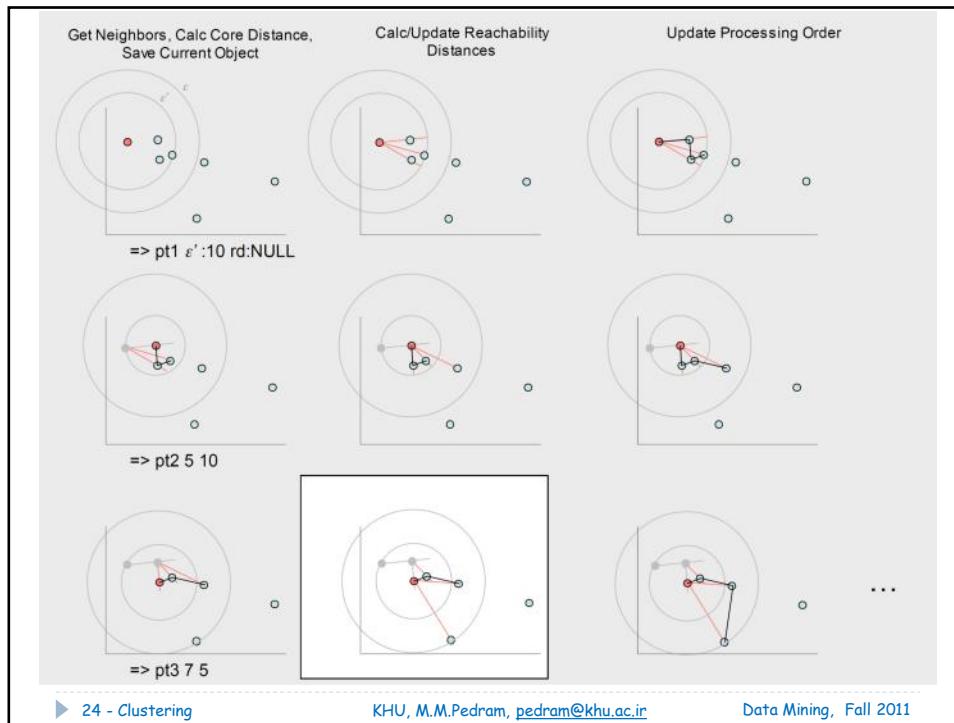
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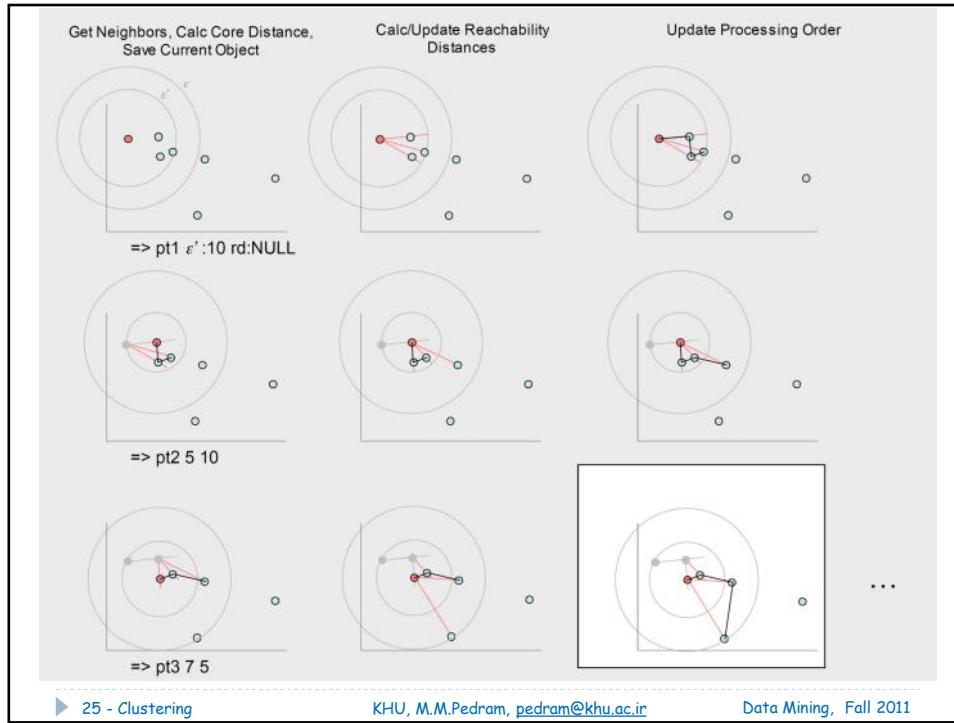
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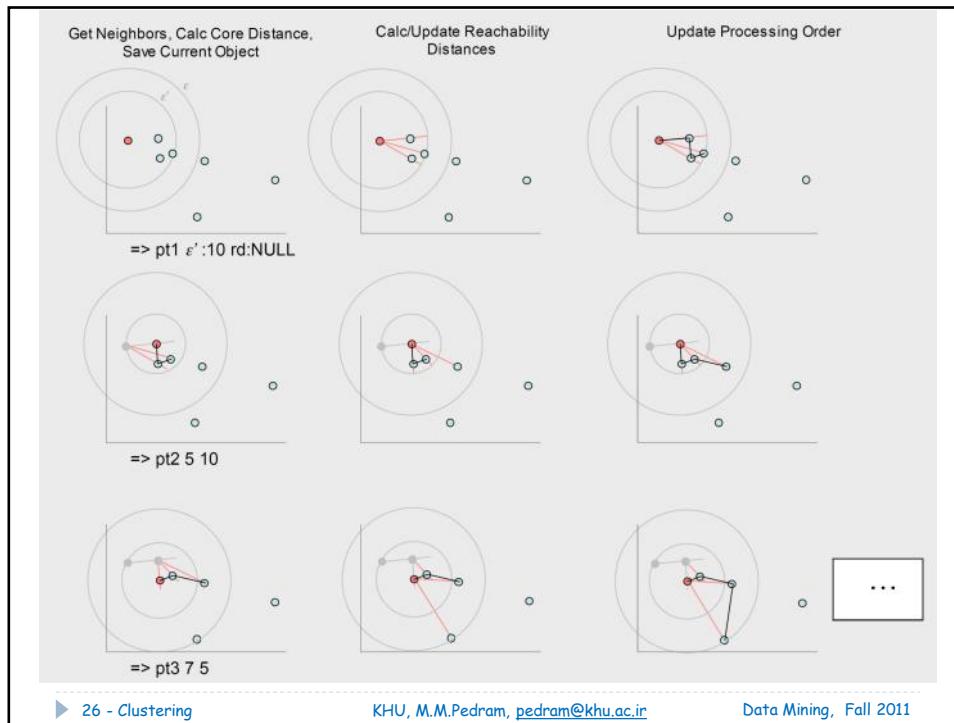
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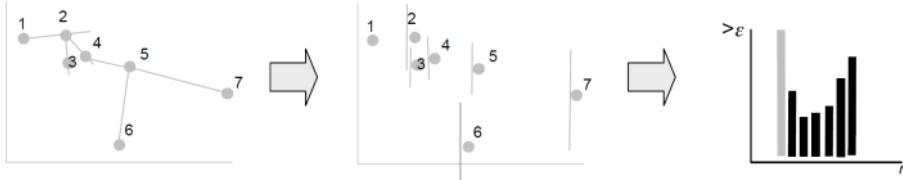
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## Reachability Plots

- ❖ A **reachability plot** is a bar chart that shows each object's reachability distance in the order the object was processed.



▶ 27 - Clustering

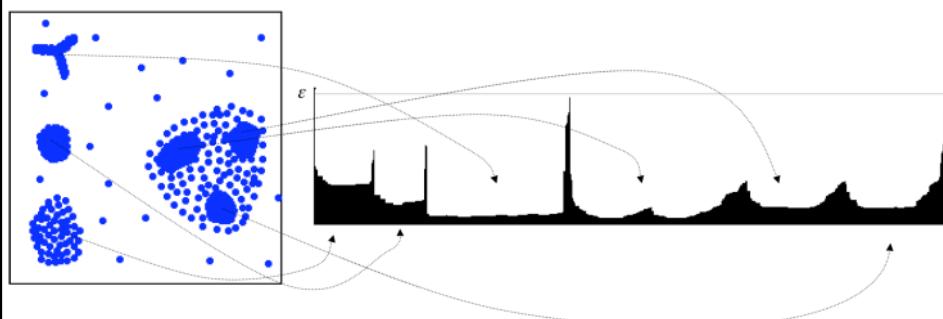
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## Reachability Plots

- ❖ Reachability plots clearly show the cluster structure of the data.

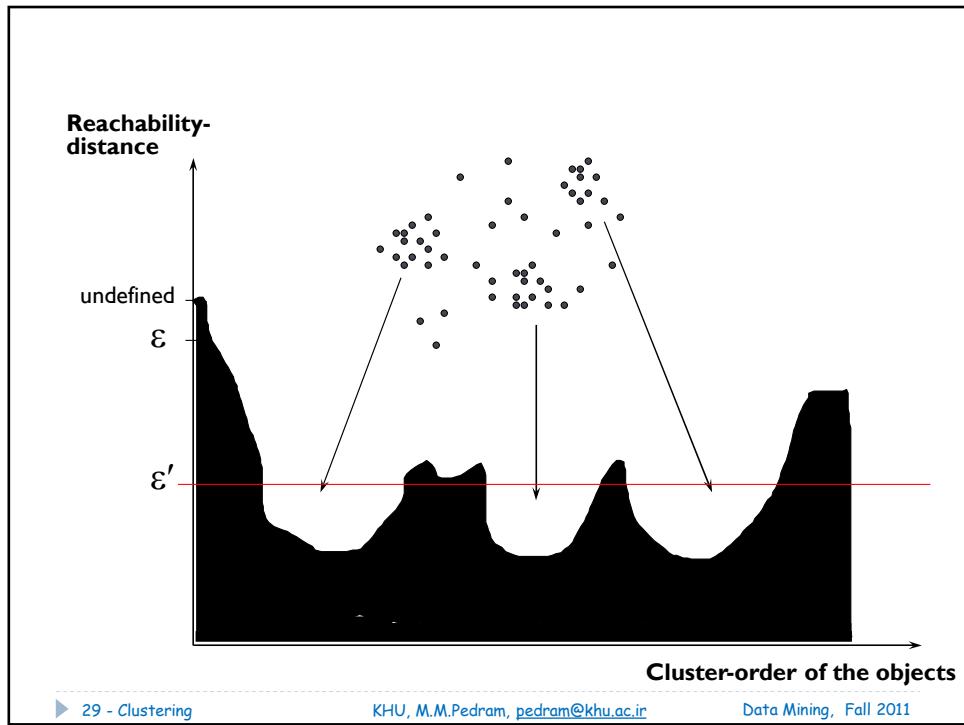


▶ 28 - Clustering

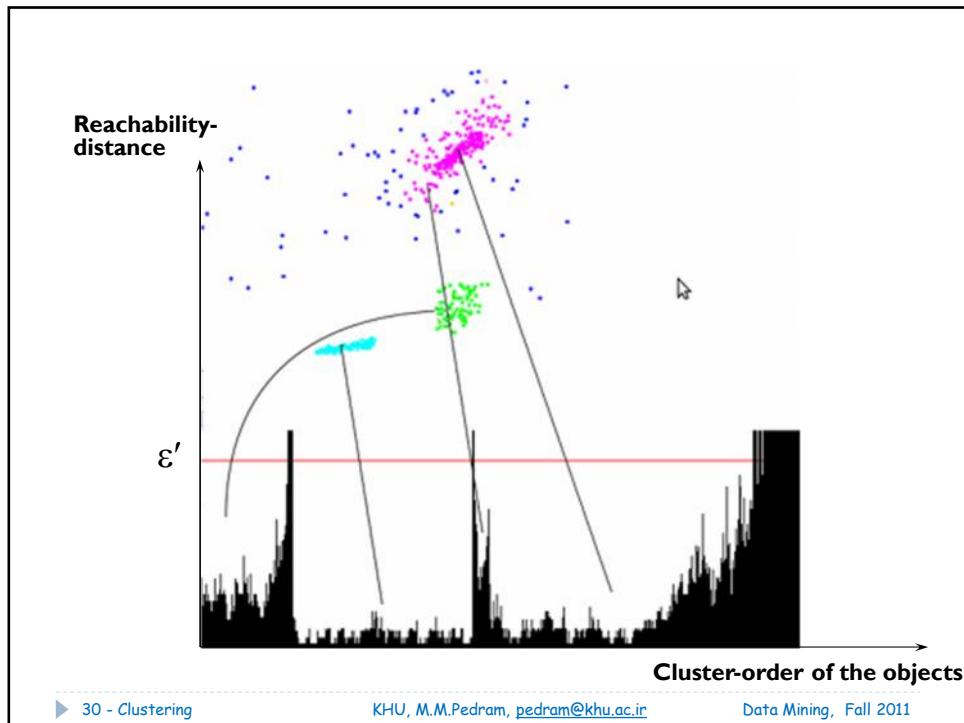
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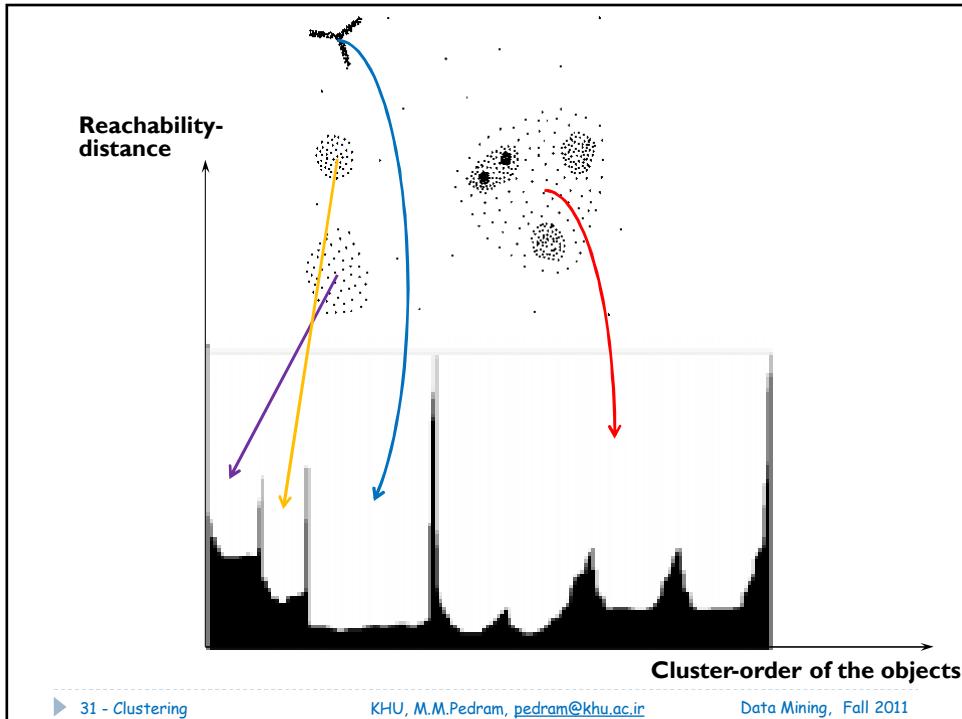
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## Conclusion

- ❖ It addresses one of DBSCAN's major weaknesses: the problem of detecting meaningful clusters in data of varying density. In order to do so:
  - ▶ The points of the database are (linearly) ordered such that points which are spatially closest become neighbors in the ordering.
  - ▶ Additionally, a special distance is stored for each point that represents the density that needs to be accepted for a cluster in order to have both points belong to the same cluster. This is represented as a dendrogram.
- ❖ Because of the structural equivalence of the OPTICS algorithm to DBSCAN, the OPTICS algorithm has the same runtime complexity as that of DBSCAN, that is,  $O(n \cdot \log n)$  if a spatial index is used, where  $n$  is the number of objects.

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