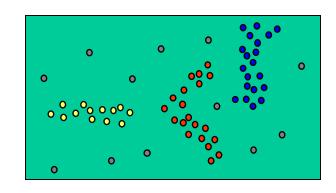
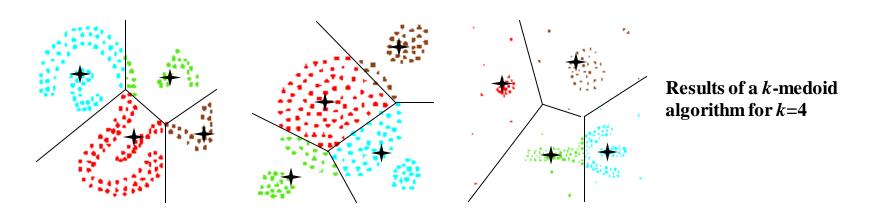
Data Mining Cluster Analysis

Density-based clustering: DBSCAN

* Basic Idea:

Clusters are dense regions in the data space, separated by regions of lower object density

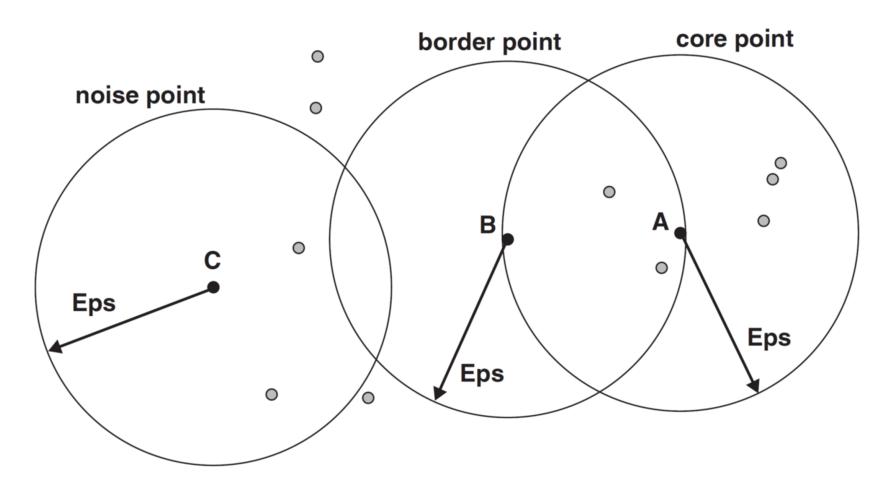




- DBSCAN is a density-based algorithm.
 - Density = number of points within a specified radius (Eps)
 - A point is a core point if it has at least a specified number of points (MinPts) within Eps
 - These are points that are at the interior of a cluster
 - Counts the point itself
 - A border point is not a core point, but is in the neighborhood of a core point
 - A noise point is any point that is not a core point or a border point

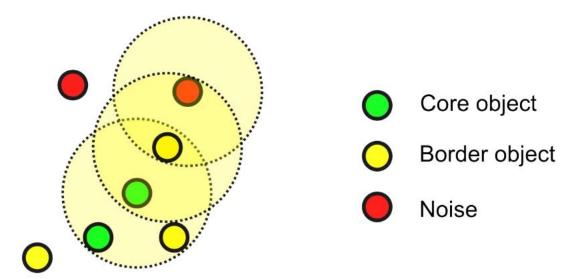
DBSCAN: Core, Border, and Noise Points

MinPts = 7

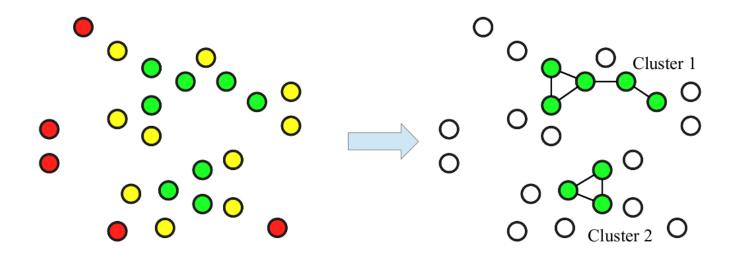


Step 1: label points as core (dense), border and noise

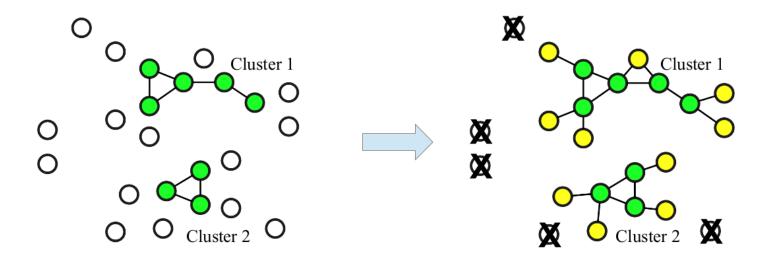
 Based on thresholds R (radius of neighborhood) and min_pts (min number of neighbors)



Step 2: connect core objects that are neighbors, and put them in the same cluster

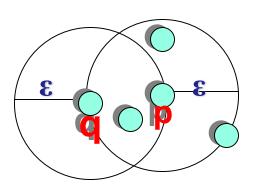


Step 3: associate border objects to (one of) their core(s), and remove noise



Density-Reachability

- **Directly density-reachable**
 - **Δn** object q is directly density-reachable from object p if p is a core object and q is in p's ε-neighborhood.

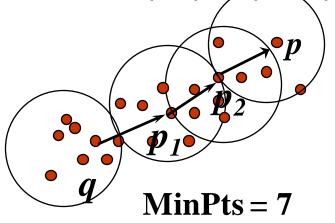


- **q** is directly density-reachable from **p**
- p is not directly density- reachable from q?
- **■** Density-reachability is asymmetric.

MinPts = 4

Density-Reachability

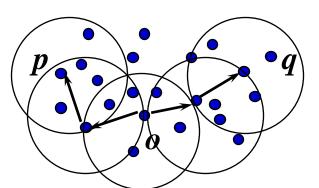
- Density-Reachable (directly and indirectly):
 - □ A point p is directly density-reachable from p2;
 - p2 is directly density-reachable from p1;
 - □ p1 is directly density-reachable from q;
 - \square p \leftarrow p2 \leftarrow p1 \leftarrow q form a chain.



- p is (indirectly) density-reachable from q
- **q** is not density- reachable from p?

Density-Reachability

- **Density-reachable is not symmetric**
 - □ not good enough to describe clusters
- **Density-Connected**
 - ☐ A pair of points p and q are density-connected if they are commonly density-reachable from a point o.



Density-connectivity is symmetric

DBSCAN Algorithm

```
Input: The data set D

Parameter: ε, MinPts

For each object p in D

if p is a core object and not processed then

C = retrieve all objects density-reachable from p

mark all objects in C as processed

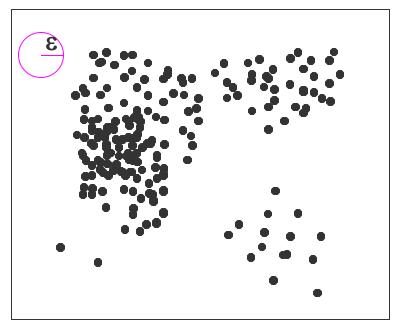
report C as a cluster

else mark p as outlier

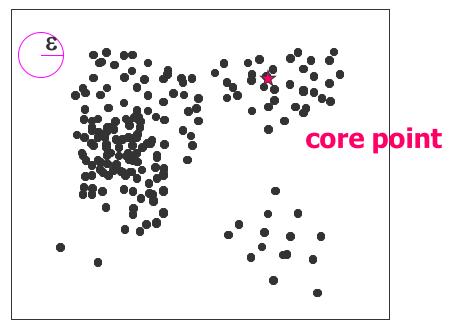
end if

End For
```

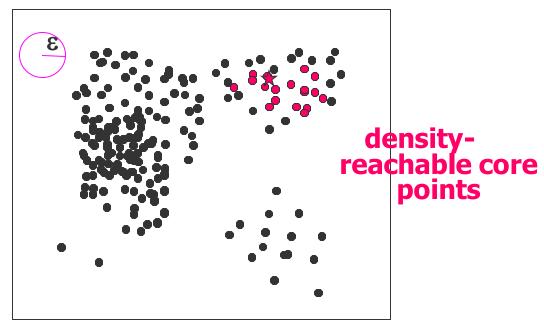
- \diamond Radius ϵ as shown below (Euclidean distance).
- ♦ Minimum support m = 7.
- What are the clusters?



- \diamond Radius ϵ as shown below (Euclidean distance).
- ♦ Minimum support m = 7.
- What are the clusters?



- \diamond Radius ϵ as shown below (Euclidean distance).
- ♦ Minimum support m = 7.
- What are the clusters?

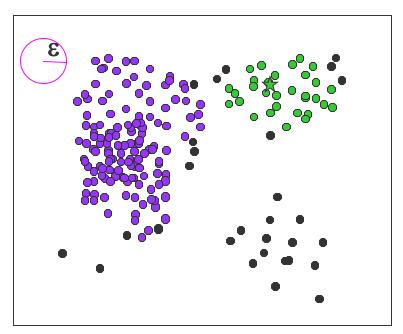


Example:

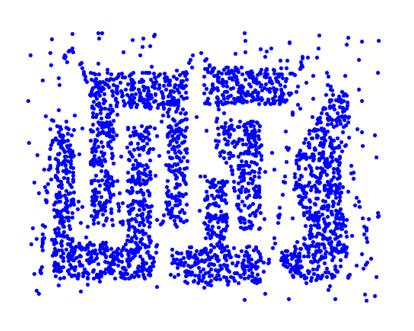
- \diamond Radius ϵ as shown below (Euclidean distance).
- ♦ Minimum support m = 7.
- What are the clusters?

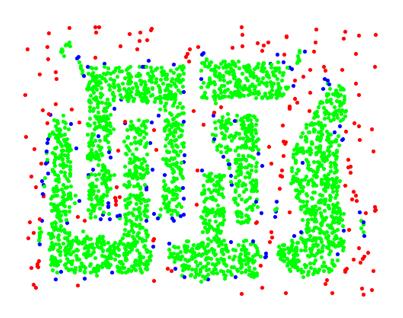
density-reachable noncore points densityreachable core points

- \diamond Radius ϵ as shown below (Euclidean distance).
- ♦ Minimum support m = 7.
- ♦ 2 clusters in this example.
- ♦ Lower-right grouping not dense enough to form a cluster.



DBSCAN: Core, Border and Noise Points



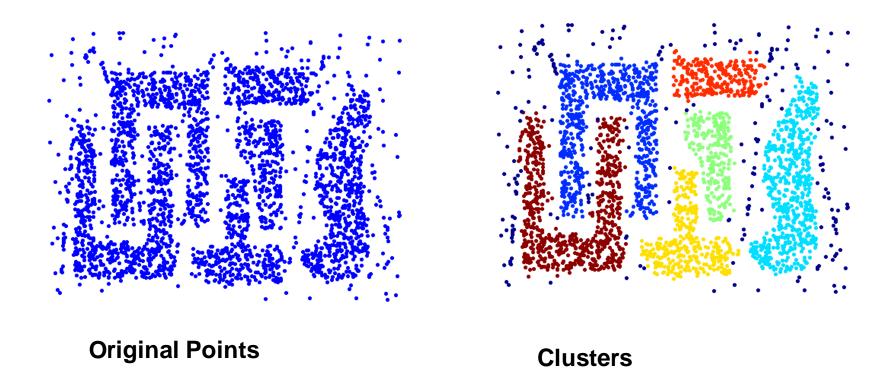


Original Points

Point types: core, border and noise

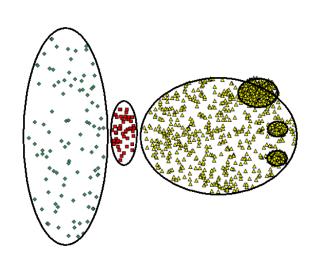
Eps = 10, MinPts = 4

When DBSCAN Works Well



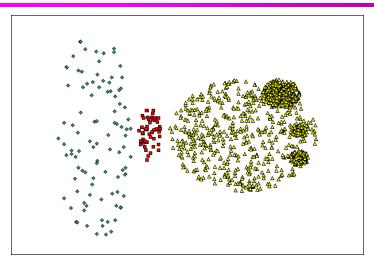
- Resistant to Noise
- Can handle clusters of different shapes and sizes

When DBSCAN Does NOT Work Well

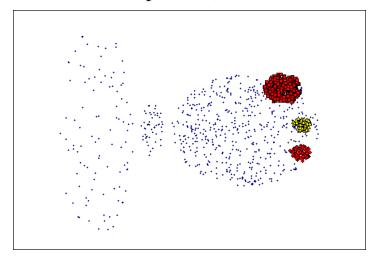


Original Points

- Varying densities
- High-dimensional data



(MinPts=4, Eps=9.75).



(MinPts=4, Eps=9.92)

DBSCAN: Determining EPS and MinPts

- Idea is that for points in a cluster, their kth nearest neighbors are at roughly the same distance
- Noise points have the kth nearest neighbor at farther distance
- So, plot sorted distance of every point to its kth nearest neighbor

