Outline

Basics

Motivation, definition, evaluation

Methods

- Partitional
- Hierarchical
- Density-based
- Mixture model
- Spectral methods

Advanced topics

- Clustering ensemble
- Clustering in MapReduce
- Semi-supervised clustering, subspace clustering, co-clustering, etc.

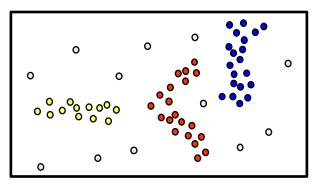
Density-based Clustering

Basic idea

- Clusters are dense regions in the data space,
 separated by regions of lower object density
- A cluster is defined as a maximal set of densityconnected points
- Discovers clusters of arbitrary shape

Method

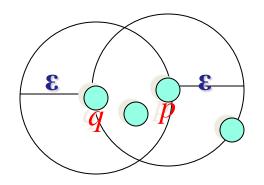
- DBSCAN



Density Definition

• ϵ -Neighborhood – Objects within a radius of ϵ from an object. $N_{\epsilon}(p) : \{q \mid d(p,q) \leq \epsilon\}$

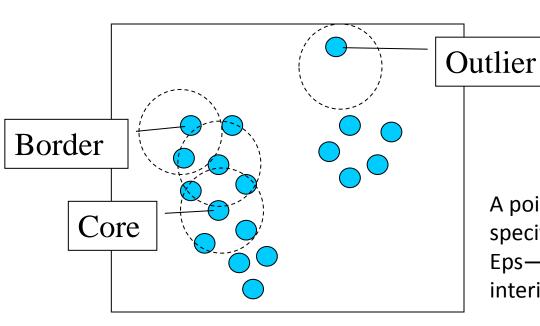
 "High density" - ε-Neighborhood of an object contains at least *MinPts* of objects.



 ϵ -Neighborhood of p ϵ -Neighborhood of qDensity of p is "high" (MinPts = 4)

Density of q is "low" (MinPts = 4)

Core, Border & Outlier



 $\varepsilon = 1$ unit, MinPts = 5

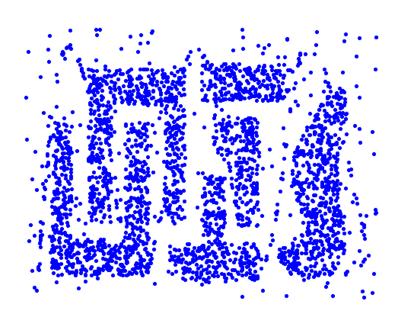
Given ε and *MinPts*, categorize the objects into three exclusive groups.

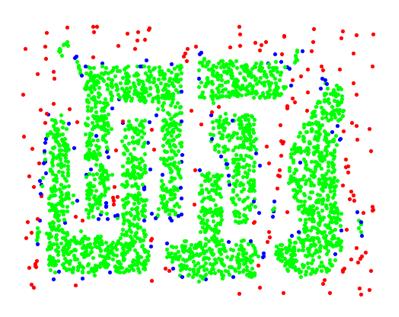
A point is a core point if it has more than a specified number of points (MinPts) within Eps—These are points that are at the interior of a cluster.

A border point has fewer than MinPts within Eps, but is in the neighborhood of a core point.

A noise point is any point that is not a core point nor a border point.

Example





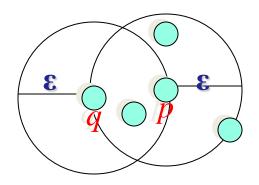
Original Points

Point types: core, border and outliers

 ε = 10, MinPts = 4

Density-reachability

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

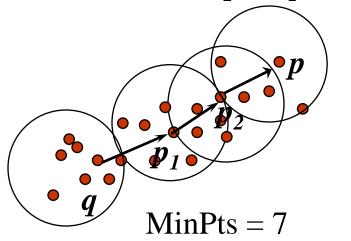


MinPts = 4

- q is directly density-reachable from p
- p is not directly density-reachable from
 q
- Density-reachability is asymmetric

Density-reachability

- Density-Reachable (directly and indirectly):
 - A point p is directly density-reachable from p_2
 - p_2 is directly density-reachable from p_1
 - p_1 is directly density-reachable from q
 - $-p \leftarrow p_2 \leftarrow p_1 \leftarrow q$ form a chain

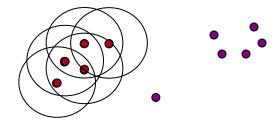


- *p* is (indirectly) density-reachable from *q*
- q is not density-reachable from p

DBSCAN Algorithm: Example

Parameter

- ε = 2 cm
- *MinPts* = 3



```
for each o \in D do

if o is not yet classified then

if o is a core-object then

collect all objects density-reachable from o

and assign them to a new cluster.

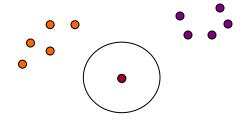
else

assign o to NOISE
```

DBSCAN Algorithm: Example

Parameter

- ε = 2 cm
- *MinPts* = 3



```
for each o \in D do

if o is not yet classified then

if o is a core-object then

collect all objects density-reachable from o

and assign them to a new cluster.

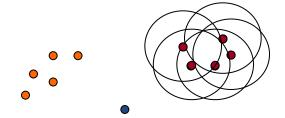
else

assign o to NOISE
```

DBSCAN Algorithm: Example

Parameter

- ε = 2 cm
- *MinPts* = 3



```
for each o \in D do

if o is not yet classified then

if o is a core-object then

collect all objects density-reachable from o

and assign them to a new cluster.

else

assign o to NOISE
```

DBSCAN: Sensitive to Parameters

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

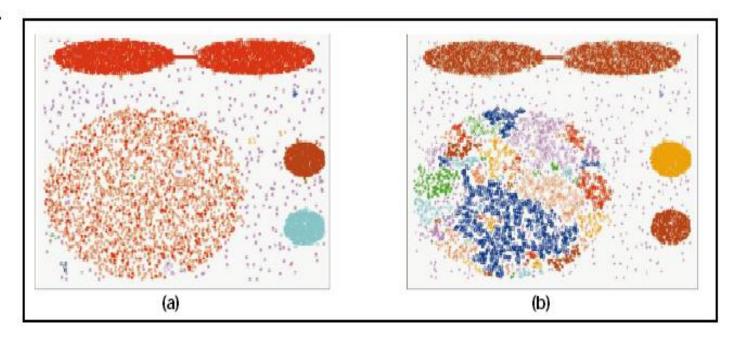
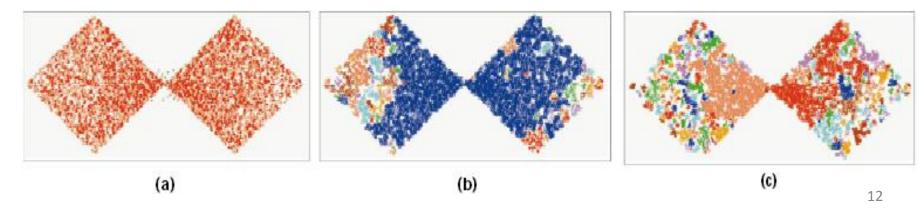
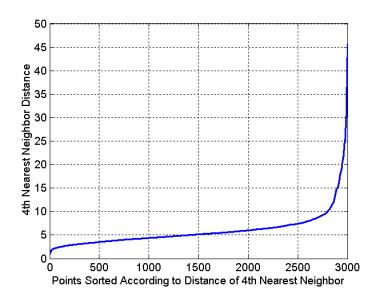


Figure 9. DBScan results for DS2 with MinPts at 4 and Eps at (a) 5.0, (b) 3.5, and (c) 3.0.

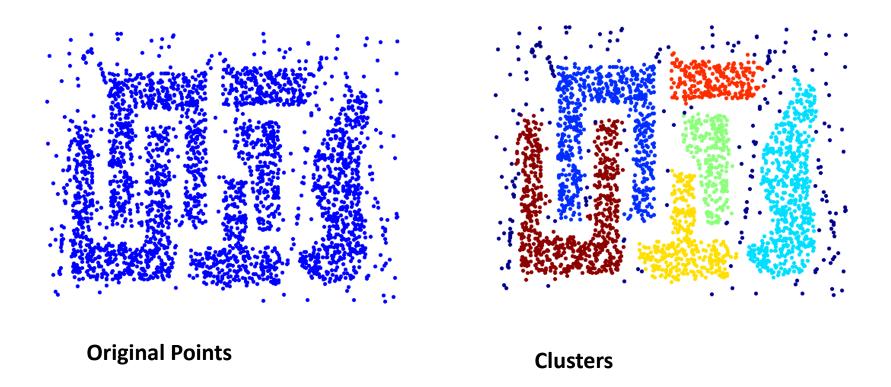


DBSCAN: Determining EPS and MinPts

- 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

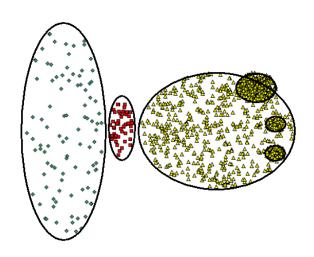


When DBSCAN Works Well



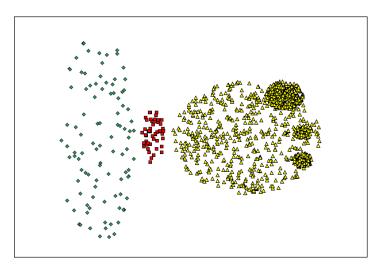
- Resistant to Noise
- Can handle clusters of different shapes and sizes

When DBSCAN Does NOT Work Well

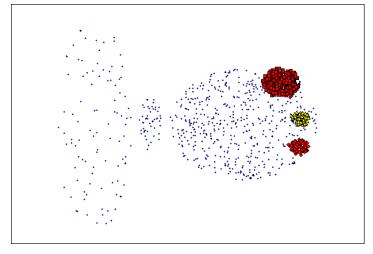


Original Points

- Cannot handle varying densities
- sensitive to parameters—hard to determine the correct set of parameters



(MinPts=4, Eps=9.92).



(MinPts=4, Eps=9.75)