CS685: Data Mining Density-Based Clustering Methods

Arnab Bhattacharya arnabb@cse.iitk.ac.in

Computer Science and Engineering, Indian Institute of Technology, Kanpur http://web.cse.iitk.ac.in/~cs685/

> 1st semester, 2020-21 Mon 1030-1200 (online)

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- Density-Based Spatial Clustering of Applications with Noise (DBSCAN)
- Ordering Points to Identify the Clustering Structure (OPTICS)
- Density-based Clustering (DENCLUE)

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- Uses notions of density-reachability and density-connectivity

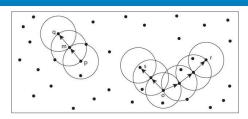
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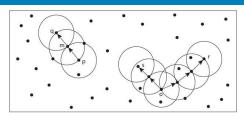
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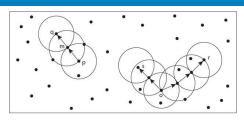
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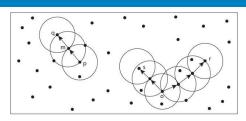
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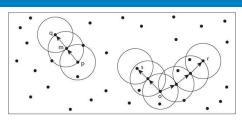
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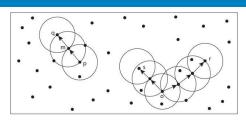
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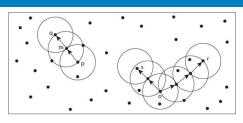
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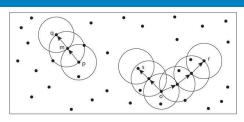
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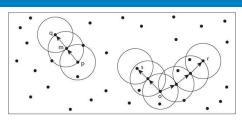
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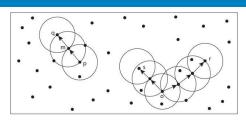
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- ullet Depends heavily on the parameters ϵ and au

OPTICS

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- ullet Tries to overcome the difficulty of choosing ϵ in DBSCAN
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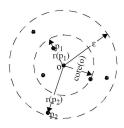
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Core Distance and Reachability Distance

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- The reachability distance of point p to point q is the minimum radius that makes q directly density-reachable from p
- p must become a core point
- It is, therefore, the maximum of core distance of p and distance of p to q
 - If p is not a core point with respect to ϵ , it is considered *undefined*

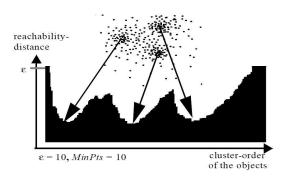


Reachability Plot

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- Still uses parameters: au, ϵ

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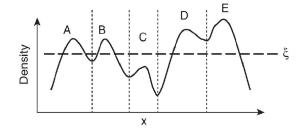
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- Local peaks denote cluster centres
- Points are attracted towards the nearest peak

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- Cluster corresponding to C is discarded
- Clusters A and B remain separated
- Clusters D and E get merged



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- Uses the gradient of the Gaussian kernel

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- Influence function constrained to a range
- May use grids where each point influences its own cell and the neighboring cells only