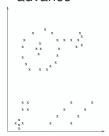


Machine Learning 1: Foundations

Marius Kloft (TUK)

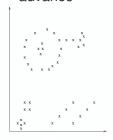
Big problem in *k*-means: do not know the number of clusters in advance

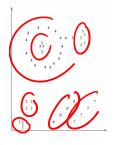
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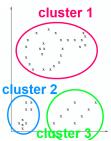




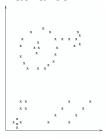
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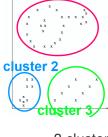




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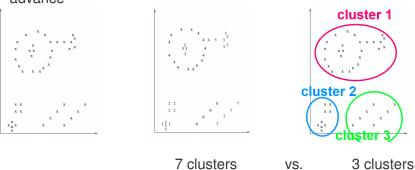
cluster 1

7 clusters

VS.

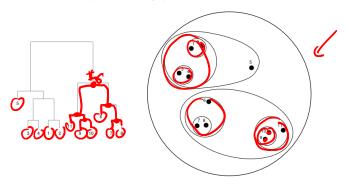
3 clusters

Big problem in *k*-means: do not know the number of clusters in advance

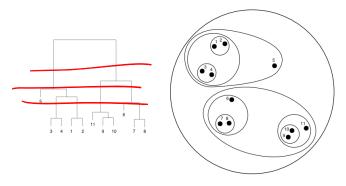


Quiz: what to do?

► Generates a tree ("hierarchy") of clusters



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do not need to specify number of clusters

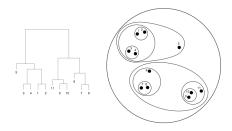
1: function Hierarchical Clustering (inputs  $\mathbf{x}_1, \dots, \mathbf{x}_n \in \mathbb{R}^d$ )

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- 2: assign each input to a cluster

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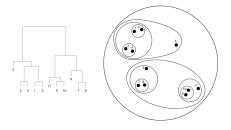
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5: until only a single root cluster left

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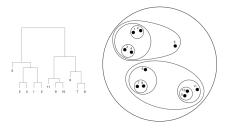
3: repeat

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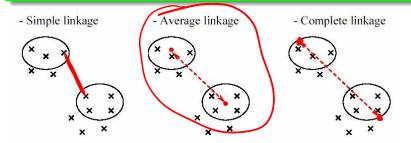
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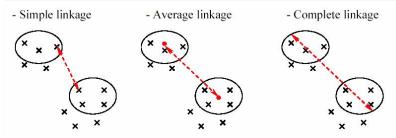
7: end function



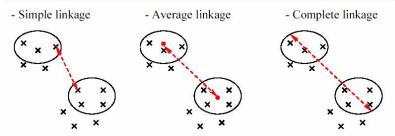
How to measure distance between two clusters?



Quiz: How to measure distance d(i,j) between two clusters i and j?



▶ Let  $S_j \subseteq \{\mathbf{x}_1, \dots, \mathbf{x}_n\}$  be the set of inputs contained in the jth cluster



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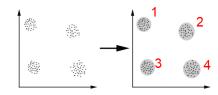
- Simple linkage Average linkage Complete linkage
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- ▶ Complete linkage:  $d(i,j) := \max_{\mathbf{x} \in S_i, \tilde{\mathbf{x}} \in S_i} \|\mathbf{x} \tilde{\mathbf{x}}\|$

- Simple linkage - Average linkage - Complete linkage
- ▶ Let  $S_i \subseteq \{\mathbf{x}_1, \dots, \mathbf{x}_n\}$  be the set of inputs contained in the ith cluster
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- ► Complete linkage:  $d(i,j) := \max_{\mathbf{x} \in S_i, \tilde{\mathbf{x}} \in S_i} \|\mathbf{x} \tilde{\mathbf{x}}\|$
- Note: again, all this can be kernelized...

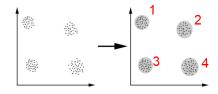
#### Clustering:

Organizing data into groups



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Organizing data into groups

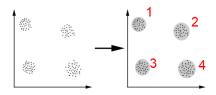


#### k-means:

 Alternatingly, assign inputs to closest cluster center and re-compute centers

#### Clustering:

Organizing data into groups

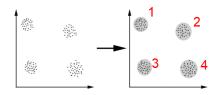


#### k-means:

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- Can be kernelized
- Can be deepified using transfer learning

#### Clustering:

Organizing data into groups



#### k-means:

- Alternatingly, assign inputs to closest cluster center and re-compute centers
- Can be kernelized
- Can be deepified using transfer learning

- Consider clusters at various scales
- ► Helpful when the number of clusters is unknown

#### Refs I