

Computational Intelligence

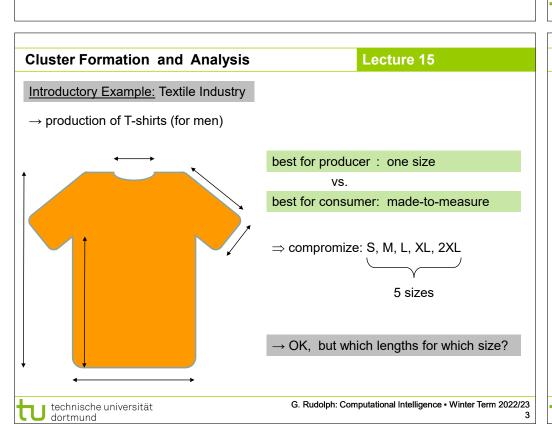
Winter Term 2022/23

Prof. Dr. Günter Rudolph

Lehrstuhl für Algorithm Engineering (LS 11)

Fakultät für Informatik

TU Dortmund



Plan for Today

Fiail Ioi Touay

Fuzzy Clustering

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Lecture 15

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Cluster Formation and Analysis

Lecture 15

idea:

- select, say, 2000 men at random and measure their "body lengths"
- arrange these 2000 men into five disjoint groups



arm's length, collar size, chest girth, ...

- deviations from mean of group as small as possible
- differences between group means as large as possible

in general:

such that

arrange objects into groups / clusters such that

- elements within a cluster are as homogeneous as possible
- elements across clusters are as heterogeneous as possible

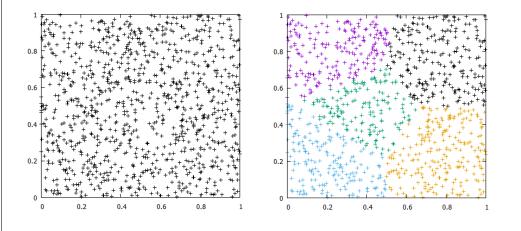
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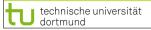
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Cluster Formation and Analysis

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numerical example: 1000 points uniformly sampled in $[0,1] \times [0,1] \rightarrow$ form 5 cluster





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Hard / Crisp Clustering

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given data points $x_1, x_2, ..., x_N \in \mathbb{R}^n$

objective: group data points into cluster such that

- points within cluster are as homogeneous as possible

- points across clusters are as heterogeneous as possible

 \Rightarrow crisp clustering is just a partitioning of data set { $x_1, x_2, ..., x_N$ }, i.e.,

$$\bigcup_{k=1}^K C_k = \{\, \mathbf{x_1}, \mathbf{x_2}, ..., \mathbf{x_N} \,\} \quad \text{ and } \quad \forall j \neq k : C_j \cap C_k \ = \ \emptyset$$

where C_k is Cluster k and K denotes the number of clusters.

Constraint: $\forall k=1,\ldots,K: |C_k|\geq 1$ hence $1\leq K\leq N$



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Hard / Crisp Clustering

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Complexity: How many choices to assign N objects into K clusters?

more precisely:

- → objects are distinguishable / labeled
- → clusters are nondistinguishable / unlabeled **and** nonempty

$$\Rightarrow$$
 Stirling number of 2nd kind $S(N,K) = \frac{1}{K!} \sum_{i=1}^{K} (-1)^{K-i} {K \choose i} \cdot i^{N} \sim \frac{K^{N}}{K!}$

N/K	1	2	3	4	5
10	1	511	9,330	34,105	42,525
11	1	1,023	28,501	145,750	246,730
12	1	2,047	86,526	611,501	1,379,400
13	1	4,095	261,625	2,532,530	7,508,501
14	1	8,191	788,970	10,391,745	40,075,035
15	1	16,383	2,375,101	42,355,950	210,766,920

 $S(100,5) = 6.6 \times 10^{67}$ $S(1000,5) = 7.8 \times 10^{696}$ $S(2000,5) = 7.3 \times 10^{1395}$

⇒ enumeration hopeless! ⇒ iterative improvement procedure required!

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Hard / Crisp Clustering

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define objective function idea:

that measures compactness of clusters and quality of partition

- → elements in cluster C_i should be as homogeneous as possible!
- → sum of squared distances to unknown center y should be as small as possible
- \rightarrow find y with $\sum_{i \in C_i} d(x_i, y)^2 \rightarrow \min!$

typically, $d(x_i, y) = ||x_i - y|| = \sqrt{(x_i - y)'(x_i - y)}$ (Euclidean norm)

$$\frac{d}{dy} \sum_{i \in C_j} (x_i - y)'(x_i - y) = -2 \sum_{i \in C_j} (x_i - y) \stackrel{!}{=} 0$$

$$\Rightarrow \sum_{i \in C_j} x_i \stackrel{!}{=} \sum_{i \in C_j} y = |C_j| \cdot y \qquad \Rightarrow y = \frac{1}{|C_j|} \sum_{i \in C_j} x_i =: \bar{x}_j$$

Hard / Crisp Clustering

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 \rightarrow elements in <u>each</u> cluster C_i should be as homogeneous as possible!

$$ightarrow$$
 find partition $C=(C_1,\ldots,C_K)$ with $D(C)=\sum_{j=1}^K\sum_{i\in C_j}d(x_i,\bar{x}_j)^2
ightarrow \min!$

Definition

A partition C^* is optimal if

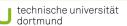
$$D(C^*) = \min \{ D(C) \, : \, C \in P(\mathsf{N}, K) \, \}$$

where $P(\mathsf{N},K)$ denotes all partitions of N elements in K clusters.

Theorem

$$\min_{C \in P(N,K)} D(C) = \max_{C \in P(N,K)} \sum_{j=1}^{K} |C_j| \cdot ||\bar{x}_j - \bar{x}||$$

where \bar{x} is the mean of all x.



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From Crisp to Fuzzy Clustering

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objective for crisp clustering:

find partition
$$C = (C_1, \dots, C_K)$$
 with $D(C) = \sum_{j=1}^K \sum_{i \in C_j} d(x_i, \bar{x}_j)^2 \to \min!$

→ rewrite objective:

find partition
$$C = (C_1, \dots, C_K)$$
 with $D(C) = \sum_{j=1}^K \sum_{i=1}^N u_{ij} \cdot d(x_i, \bar{x}_j)^2 \to \min!$

expresses membership \longrightarrow $u_{ij} = \left\{ \begin{array}{ll} 1 & \text{if } x_i \in C_j \\ 0 & \text{otherwise} \end{array} \right.$

objective for fuzzy clustering:

find partition
$$C=(C_1,\ldots,C_K)$$
 with $D(C)=\sum_{j=1}^K\sum_{i=1}^N u_{ij}^m\cdot d(x_i,\bar{x}_j)^2\to \min!$
$$u_{ij}\in[0,1]\subset\mathbb{R}, m>1$$

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Crisp K-Means Clustering

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$$\forall k = 1, \dots, K$$
: set $C_k = \emptyset$

$$\forall x \in \{x_1, \dots, x_N\}$$
: assign x to some cluster C_k

set
$$t=0$$
 and $D^{(t)}=\infty$

repeat

$$t = t + 1$$

$$\forall k = 1, \dots, K: \ \bar{x}_k = \frac{1}{|C_k|} \sum_{x \in C_k} x$$

$$\forall i=1,\ldots,N \colon d_{ik}=d(x_i,\bar{x}_k)$$
 distance to center of cluster k

let
$$k^*$$
 be such that $d_{ik^*} = \min\{d_{ik} : k = 1, ..., K\}$

assign
$$x_i$$
 to C_{k^*}

$$D^{(t)} = \sum_{k=1}^{K} \sum_{x \in C_k} d(x, \bar{x}_k)$$

$$\text{until } D^{(t-1)} - D^{(t)} < \varepsilon$$

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Fuzzy K-Means Clustering

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find partition $C=(C_1,\ldots,C_K)$ with $D(C)=\sum_{i=1}^K\sum_{j=1}^N u_{ij}^m\cdot d(x_i,\bar{x}_j)^2\to \min!$

where

 $u_{ij} \in [0,1] \subset \mathbb{R}$ denotes membership of x_i to cluster C_i

m>1 denotes a fixed fuzzifier (controls / affects membership function)

subject to

$$\sum_{j=1}^{K} u_{ij} = 1 \qquad \forall i = 1, \dots, N$$

$$0 < \sum_{i=1}^{N} u_{ij} < N \qquad \forall j = 1, \dots, K$$

each x_i distributes membership completely over clusters C_1, \ldots, C_K \rightarrow normalization

Fuzzy K-Means Clustering

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two questions:

- (a) how to define and calculate centers \bar{x}_i ?
- (b) how to obtain optimal memberships u_{ij} ?

ad a) let
$$d(x_i, \bar{x}_j) = ||x_i - \bar{x}_j||_2$$

$$\frac{d}{d\bar{x}_j} \sum_{i=1}^N u_{ij}^m \cdot (x_i - \bar{x}_j)'(x_i - \bar{x}_j) = -2 \sum_{i=1}^N u_{ij}^m \cdot (x_i - \bar{x}_j) \stackrel{!}{=} 0$$

$$\Leftrightarrow \sum_{i=1}^N u_{ij}^m \, x_i \; \stackrel{!}{=} \; \sum_{i=1}^N u_{ij}^m \, \bar{x}_j \qquad \Leftrightarrow \qquad \left| \bar{x}_j \; = \; \frac{\sum\limits_{i=1}^N u_{ij}^m \, x_i}{\sum\limits_{i=1}^N u_{ij}^m} \right| \qquad \to \text{weighted mean!}$$

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let $d(x_i, \bar{x}_i) = ||x_i - \bar{x}_i||_2$

$$\frac{d}{d\bar{x}_j} \sum_{i=1}^N u_{ij}^m \cdot (x_i - \bar{x}_j)'(x_i - \bar{x}_j) = -2 \sum_{i=1}^N u_{ij}^m \cdot (x_i - \bar{x}_j) \stackrel{!}{=} 0$$

$$\bar{x}_{j} = \frac{\sum_{i=1}^{N} u_{ij}^{m} x_{i}}{\sum_{i=1}^{N} u_{ij}^{m}}$$

Fuzzy K-Means Clustering

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ad b) let
$$d_{ij} := d(x_i, \bar{x}_j) = ||x_i - \bar{x}_j||_2$$

apply Lagrange multiplier method:

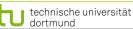
$$\frac{\partial}{\partial u_{ij}} \sum_{j=1}^K \sum_{i=1}^N u_{ij}^m \cdot d_{ij}^2 - \sum_{i=1}^N \lambda_i \left(\sum_{j=1}^K u_{ij} - 1 \right) = m u_{ij}^{m-1} \cdot d_{ij}^2 - \lambda_i \stackrel{!}{=} 0$$

without constraints
$$\rightarrow u_{ij}^* = 0$$

$$u_{ij}^* = \left(\frac{\lambda_i}{m \cdot d_{ij}^2}\right)^{\frac{1}{m-1}} \quad \longleftarrow$$

$$\sum_{j=1}^{K} \stackrel{\downarrow}{u_{ij}} = \sum_{j=1}^{K} \left(\frac{\lambda_i}{m \cdot d_{ij}^2} \right)^{\frac{1}{m-1}} = \sum_{j=1}^{K} \frac{\lambda_i^{\frac{1}{q}}}{(m \cdot d_{ij}^2)^{\frac{1}{q}}} = \lambda_i^{\frac{1}{q}} \sum_{j=1}^{K} \frac{1}{(m \cdot d_{ij}^2)^{\frac{1}{q}}} \stackrel{!}{=} 1$$

$$\Rightarrow \lambda_i^* = \left[\sum_{k=1}^{K} \frac{1}{(m \cdot d_{ik}^2)^{\frac{1}{q}}} \right]^{-q}$$



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Fuzzy K-Means Clustering

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after insertion:

$$u_{ij}^* = \left(\frac{1}{m \cdot d_{ij}^2} \left[\frac{1}{\sum_{k=1}^K \left(\frac{1}{m \cdot d_{ik}^2}\right)^{\frac{1}{m-1}}}\right]^{m-1}\right)^{\frac{1}{m-1}} = \left[\sum_{k=1}^K \left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}\right]^{-1}\right]$$

choose $K \in \mathbb{N}$ and m > 1choose u_{ij} at random (obeying constraints) repeat

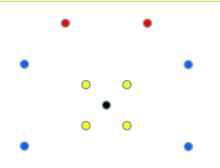
$$\begin{aligned} &\forall j=1,\ldots,K \text{: calculate centers } \bar{x}_j \\ &\forall i=1,\ldots,N \text{:} \\ &\text{let } J_i=\{j:x_i=\bar{x}_j\} \\ &\text{if } J_i=\emptyset \text{ determine memberships } u_{ij} \\ &\text{else} \\ &\text{choose } u_{ij} \text{ such that } \sum_{j\in J_i} u_{ij}=1 \\ &\text{and } u_{ij}=0 \text{ for } j\not\in J_i \\ &\text{until } D(C^{(t)})-D(C^{(t+1)})<\varepsilon \text{ or } t=t_{max} \end{aligned}$$

problems:

- choice of K calculate quality measure for each #cluster: then choose best
- choice of m try some values; typical: m=2; use interval \rightarrow fuzzy type-2

Example: Special Case $|J_i| > 1$

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black dot is center of

- red cluster
- blue cluster
- yellow cluster

in case of equal weights

 $u_{ii} = 1 / |J_i|$ for $j \in J_i$ appears plausible

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but: different values algorithmically better

→ cluster centers more likely to separate again (→ tiny randomization?)

Measures for Cluster Quality

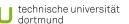
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Partition Coefficient

$$\mathsf{PC}(C_1,\ldots,C_K) = \frac{1}{N}\sum_{i=1}^N\sum_{j=1}^K u_{ij}^2$$
 ("larger is better")

$$\begin{array}{c} \text{maximum if } u_{ij} \in \{0,1\} \to \text{crisp partition} \\ \text{minimum if } u_{ij} = \frac{1}{K} & \to \text{entirely fuzzy} \end{array} \right\} \qquad \frac{1}{K} \leq \operatorname{PC}(C_1,\ldots,C_K) \leq 1$$

Partition Entropy



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Measures for Cluster Quality

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Finding an appropriate number of clusters

Possible approach: (m = max. number of clusters)

```
set score s* to worst possible value
for c = 2 to m
    apply FCM with c clusters (yields membership matrix U)
    determine quality of clustering from U (yield score s)
    if s better than s* then
        s* = s; c* = c
    endif
endfor
output c*
```

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