

Computational Intelligence

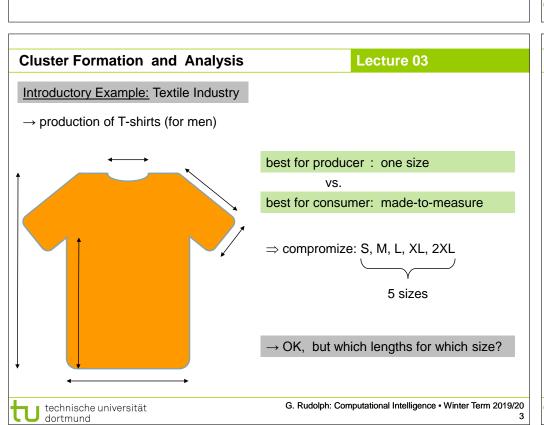
Winter Term 2019/20

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Plan for Today

lay Lecture 03

Fuzzy Clustering

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Cluster Formation and Analysis

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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

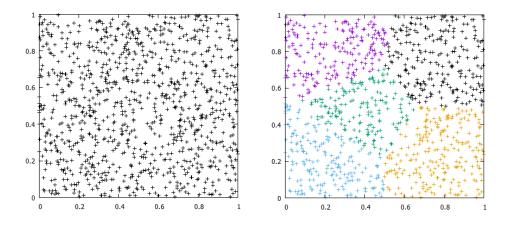
- elements within a cluster are as homogeneous as possible
- elements across clusters are as heterogeneous as possible

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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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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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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: $\forall k = 1, \dots, K : |C_k| \ge 1$ hence $1 \le K \le N$

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Lecture 03 Hard / Crisp Clustering

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

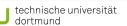
$$D(C^*) = \min \{ D(C) \, : \, C \in P(\mathsf{N}, K) \, \}$$

where P(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 $D(C) = \sum_{j=1}^K \sum_{i \in C_j} d(x_i, \bar{x}_j)^2 \to \min!$

 \rightarrow 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

$$t = t + 1$$

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

$$\forall i = 1, ..., N$$
: $d_{ik} = d(x_i, \bar{x}_k)$ 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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Lecture 03

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

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

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

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

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

at least one element belongs to some extent to a certain cluster, but not all elements to a single cluster

Fuzzy K-Means Clustering

Lecture 03

two questions:

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

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

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

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

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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 $ightarrow u_{ij}^* = 0$

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

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

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

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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

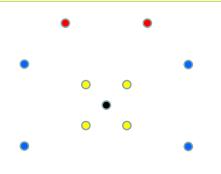
repeat
$$\forall j=1,\ldots,K \colon \text{calculate centers } \bar{x}_j \\ \forall i=1,\ldots,N \colon \\ \text{let } J_i=\{j:x_i=\bar{x}_j\} \\ \text{if } J_i=\emptyset \text{ determine memberships } u_{ij} \\ \text{else} \\ \text{choose } u_{ij} \text{ such that } \sum_{j\in J_i} u_{ij}=1 \\ \text{and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

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?)

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Measures for Cluster Quality

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• Partition Coefficient

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

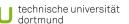
$$\begin{array}{c} \text{maximum if } u_{ij} \in \{0,1\} \to \text{crisp partition} \\ \text{minimum if } u_{ij} = \frac{1}{K} & \to \text{entirely fuzzy} \end{array} \right\} \qquad \frac{1}{K} \leq \text{PC}(C_1,\ldots,C_K) \leq 1$$

Partition Entropy

PE(
$$C_1, \ldots, C_K$$
) = $-\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^K u_{ij} \cdot \log_2(u_{ij})$ ("smaller is better")

maximum if $u_{ij} = \frac{1}{K} \longrightarrow \text{entirely fuzzy}$

minimum if $u_{ij} \in \{0,1\} \longrightarrow \text{crisp partition}$ $0 \le \text{PE}(C_1, \ldots, C_K) \le \log_2(K)$



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Measures for Cluster Quality

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• Silhouette Values (crisp version)

$$\mathsf{PC}(C_1, \dots, C_K) = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{K} u_{ij}^2$$

("larger is better")

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