

Deadline: Th. January 23th, 14:00 Drop your printed or legible handwritten submissions into the boxes at Samelsonplatz. Alternatively upload a .pdf file via LearnWeb. (e.g. exported Jupyter notebook)

1. K Means Clustering

(10 points)

A. [2p] Compute the (squared) **distance matrix** $D_{ij} = \text{dist}_{\text{eucl.}}(x_i, x_j)^2$, given the data from Table 1.

x_1	x_2
0	0
0	1
-1	2
2	0
3	0
4	-1

B. [4p] Perform K-means clustering on the dataset from Table 1. Use the first and last datapoints as initial centers ($K = 2$). Given the final parameters, which cluster would $x^* = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$ belong to?

C. [1p] For a set of points $(x_n)_{n=1:N}$ in \mathbb{R}^m , show that the **mean** $\hat{\mu} = \frac{1}{N} \sum_{n=1}^N x_n$ is the solution to the optimization problem

Table 1

$$\hat{\mu} = \underset{\mu \in \mathbb{R}^m}{\text{argmin}} \sum_{i=1}^N \text{dist}_{\text{eucl.}}(x_n, \mu)^2 \quad (1)$$

I.e. for a set of points, their mean can be characterized as the point which is, on average, closest to all the other points with respect to the **squared euclidean distance**.

D. [3p] For a set of points $(x_n)_{n=1:N}$ in \mathbb{R}^m , the **geometric median** is defined as the point

x_1	x_2
-1	-1
-1	1
1	-1
1	1
10	0

$$\hat{\mu} = \underset{\mu \in \mathbb{R}^m}{\text{argmin}} \sum_{n=1}^N \text{dist}_{\text{eucl.}}(x_n, \mu) \quad (2)$$

Note that in contrast to the mean, (2) does not have a closed form solution. However, the minimum can be found numerically by a fixed point iteration scheme (algorithm 1). Given the dataset from Table 2 (rows are datapoints!), compute both the mean and the geometric median. What happens to both if we change the last datapoint to $\begin{pmatrix} 100 \\ 0 \end{pmatrix}$?

Table 2

Algorithm 1: Weiszfeld’s algorithm

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1  $\mu^{(0)} = \frac{1}{N} \sum_{n=1}^N x_n$  ;
2 for  $t = 0, 1, 2, \dots, \text{max\_iter}$  do
3    $\mu^{(t+1)} = \left( \sum_{n=1}^N x_n \|x_n - \mu^{(t)}\|^{-1} \right) / \left( \sum_{n=1}^N \|x_n - \mu^{(t)}\|^{-1} \right)$  ;
4   if converged then
5     return  $\mu$ 

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2. Gaussian Mixture Models (GMMs)

(8 points)

Two datasets ("MOONS" and "STRIPES") were each clustered by 3 different methods: K-means clustering, Gaussian-Mixture-Models and Hierarchical Clustering (single link). The results are shown in Table 3.

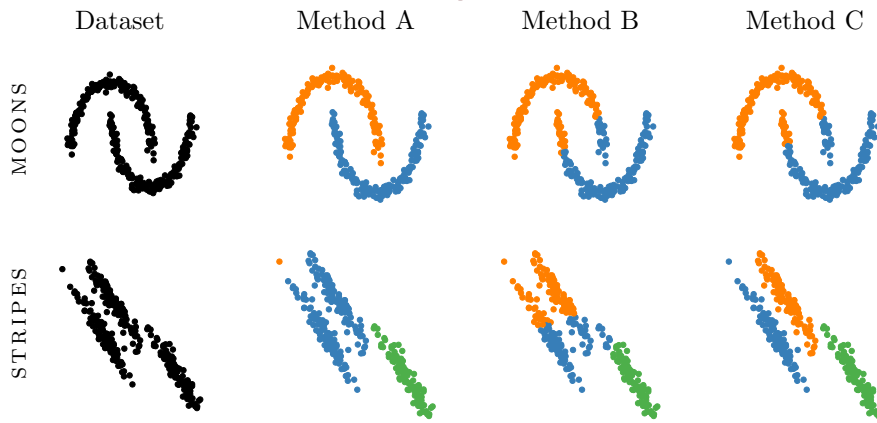


Table 3: Different Clustering Methods

A. [2p] Decide which method corresponds to A, B and C. Explain your decision.

B. [6p] Given the data from Table 1, and the initial configuration $\pi_1, \pi_2 = \frac{1}{2}$, $\mu_1 = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$, $\mu_2 = \begin{pmatrix} 3 \\ 0 \end{pmatrix}$, $\Sigma_1, \Sigma_2 = \mathbb{I}$, perform 1 iteration of the (soft partition) EM algorithm to fit a GMM. Which cluster would $x^* = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$ belong to according to the initial/final parameters?

3. Hierarchical Clustering

(6 points)

A. [2p] Compute the **distance matrix** $D_{ij} = \text{dist}(x_i, x_j)$, using the **Manhattan distance** (i.e. L^1), given the data from Table 4.

x_1	x_2
0	0
1	0
2	0
-0.5	-1
0.5	-1
0	-1.5

B. [4p] Perform **agglomerative Hierarchical Clustering** using **single linkage** as the cluster distance measure. Draw the associated tree (as in slides 26/27).

Table 4