

FUZZY CLUSTERING

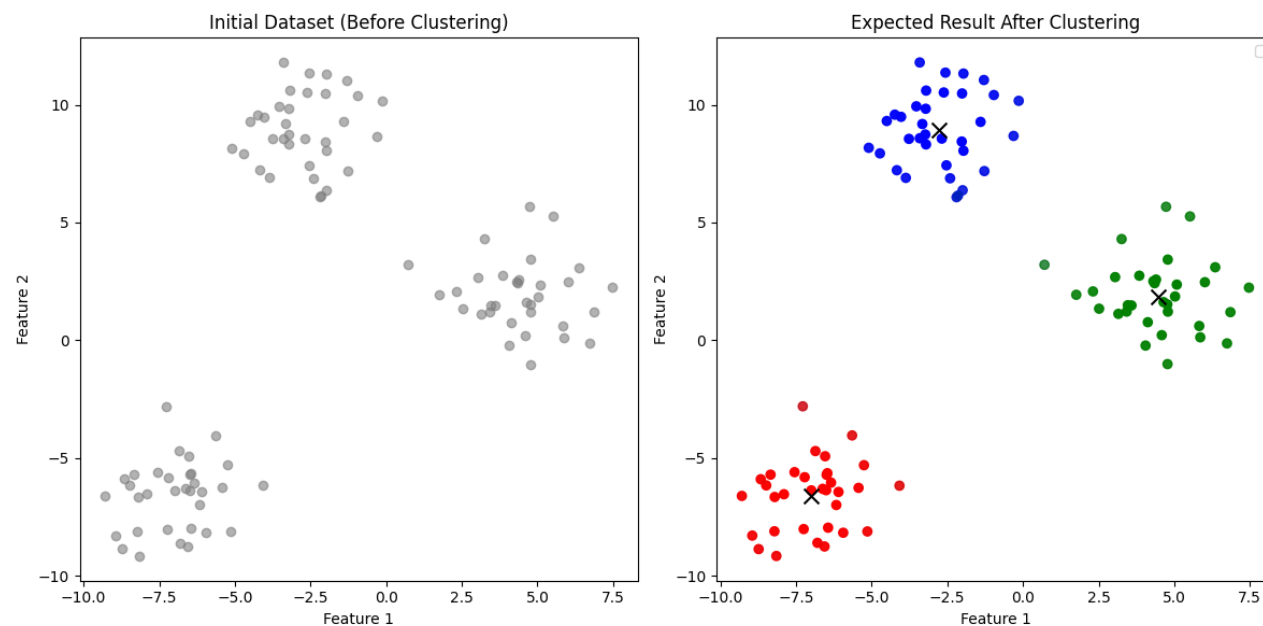
By Alessandro Gentili and Jakub Swistak

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What is clustering?

- › Clustering is the task of partitioning a set of elements into groups (clusters) such that the elements belonging to the same group are similar (in some way)
- › Elements are represented as **vectors**
- › We can compare elements using **distance**



Preliminaries

› Set of vectors:

$$x = \{x_1, x_2, \dots, x_n\}$$

› Centroid:

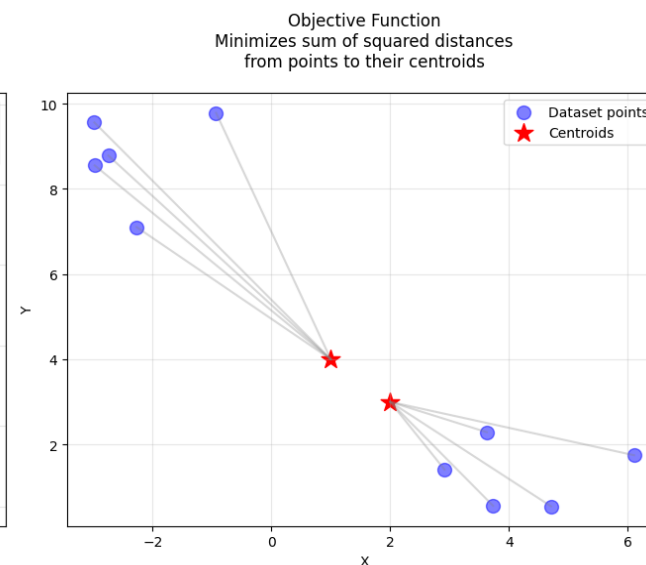
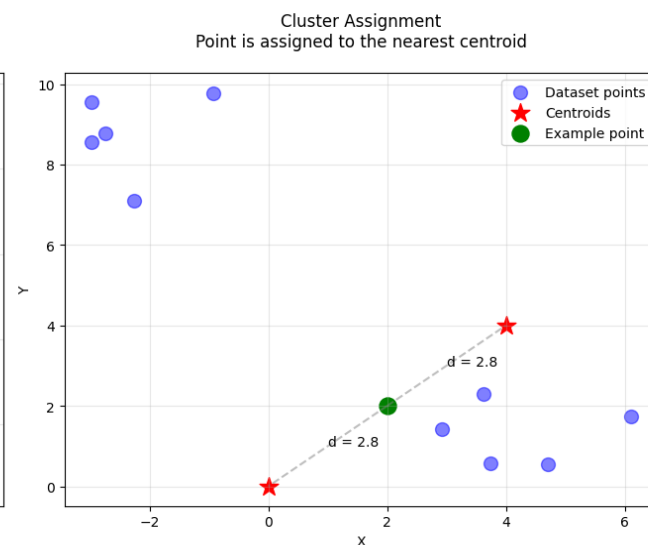
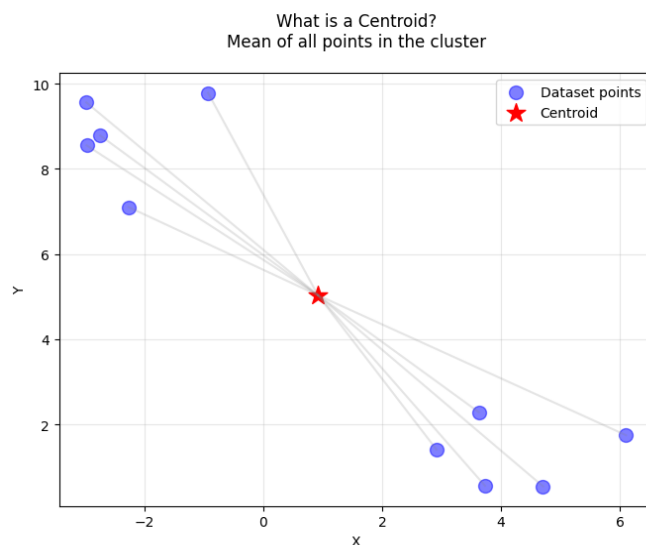
$$\mathbf{c} = \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i$$

› Distance:

$$d_{Euclidean}(\mathbf{a}, \mathbf{b}) = \sqrt{\sum_{i=1}^n (a_i - b_i)^2} \quad d_{Manhattan}(\mathbf{a}, \mathbf{b}) = \sum_{i=1}^n |a_i - b_i|$$

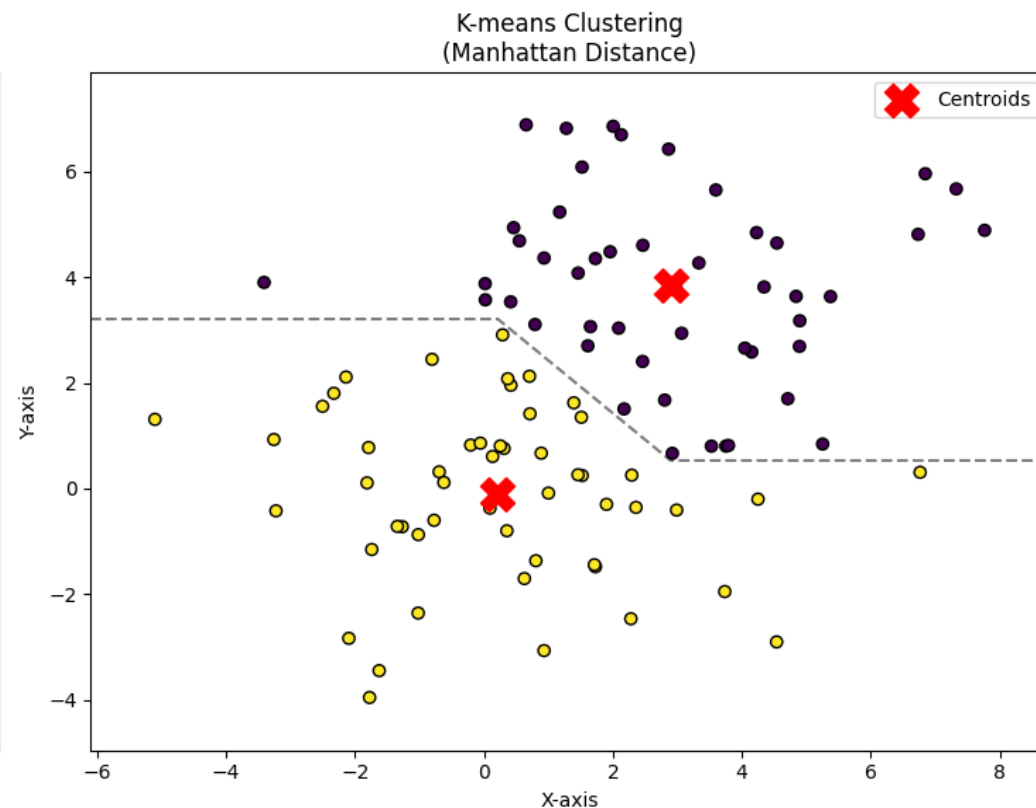
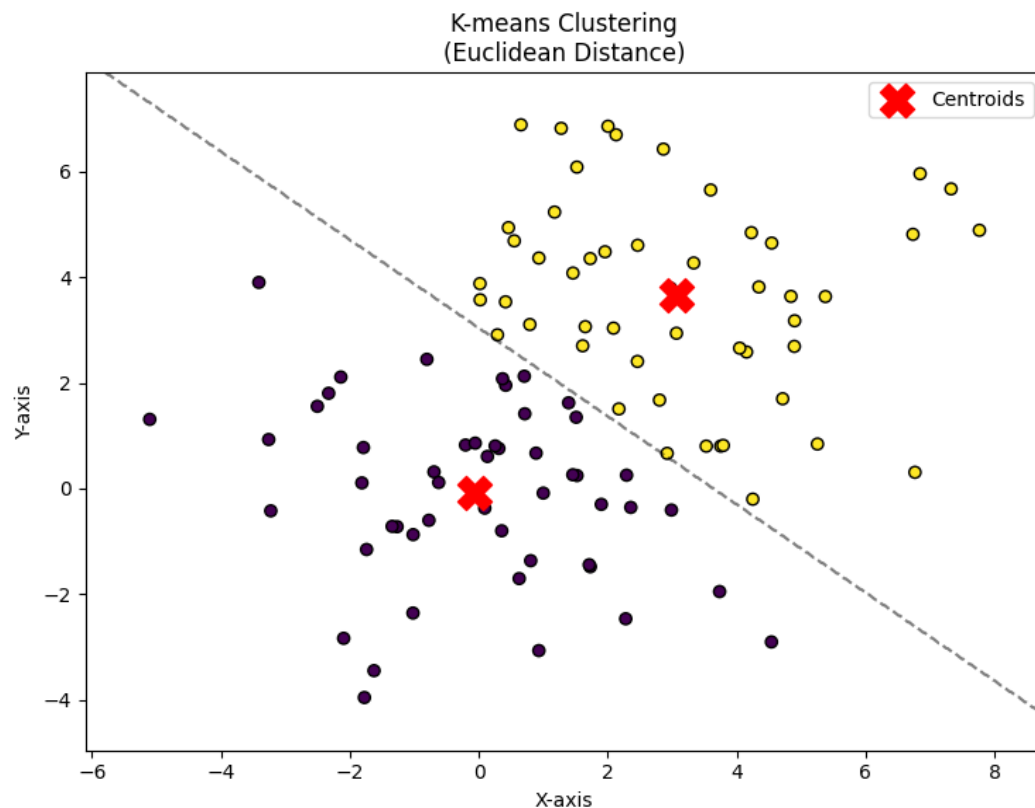
› Loss function:

$$\mathcal{L}(x, c) = \sum_{k=1}^K \sum_{i=1}^n \|x_i - c_k\|^2$$

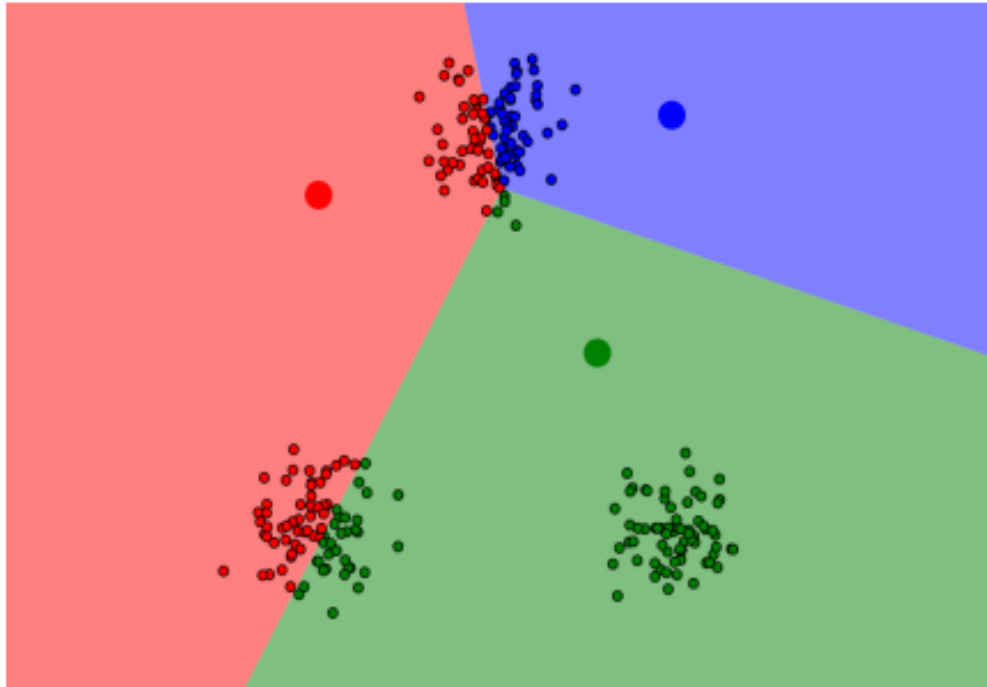


Distance matter

If we change the distance we change the **decision boundaries**, therefore we get different clustering results

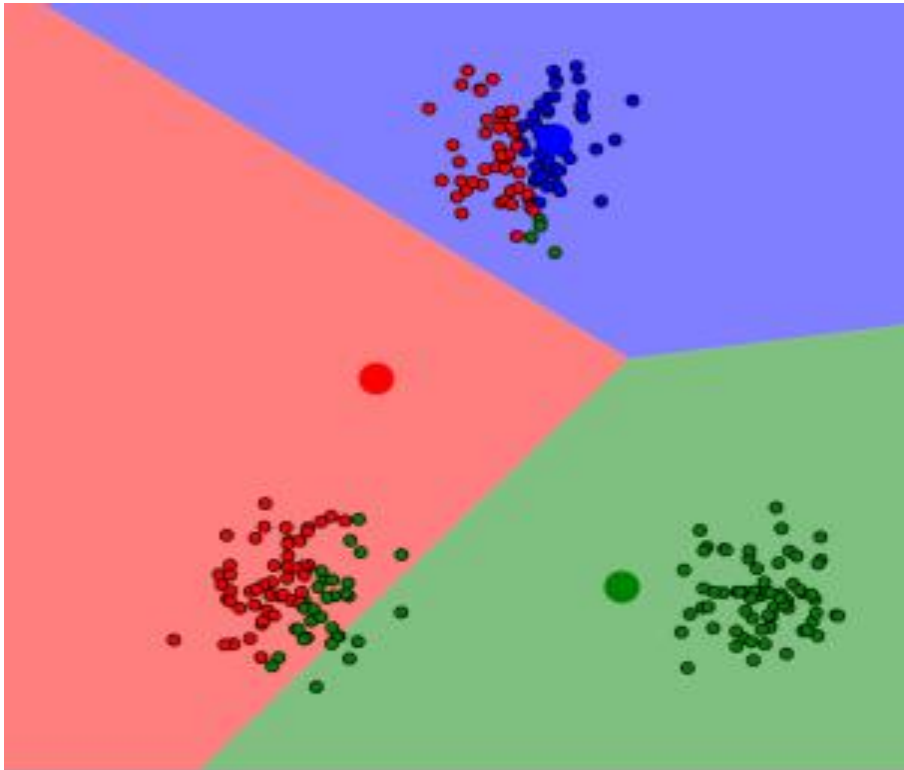


K-Means Algorithm – step 1



- › Select k the number of clusters
- › Assign k random centroids
- › Assign each point to the closest centroid and create the clusters

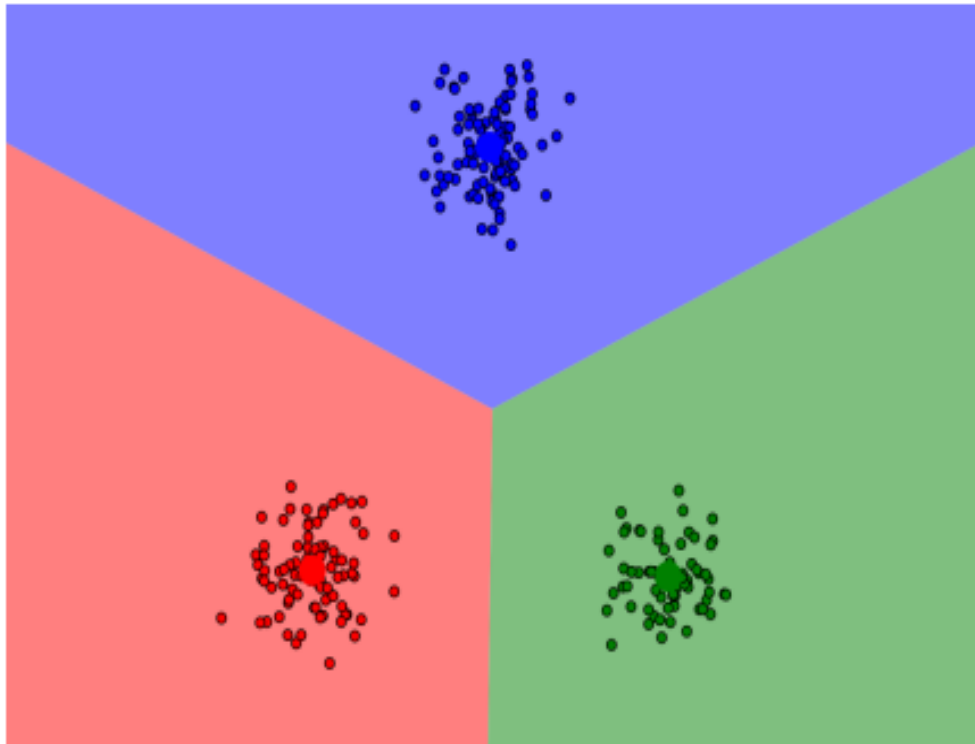
K-Means Algorithm – step 2



- › Compute centroids for the new clusters
- › Reassign each point to the closest centroid

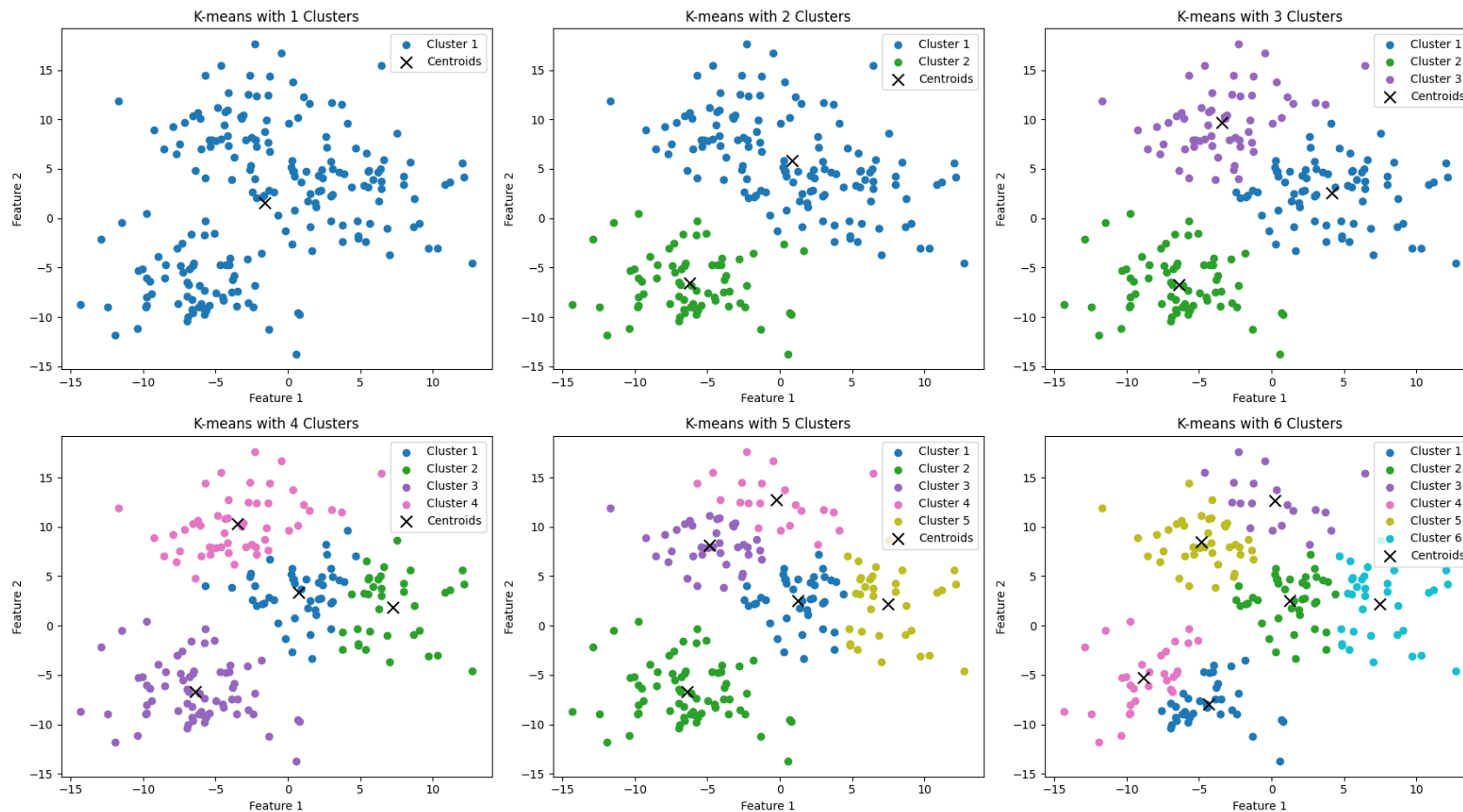
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K-Means Algorithm – step 3



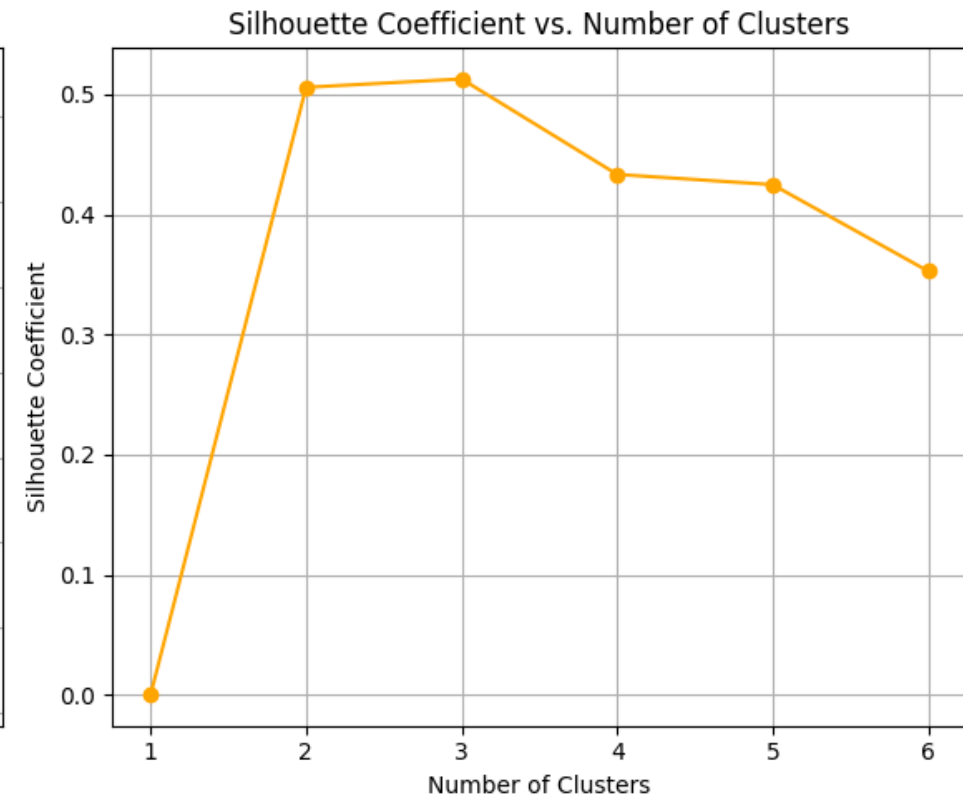
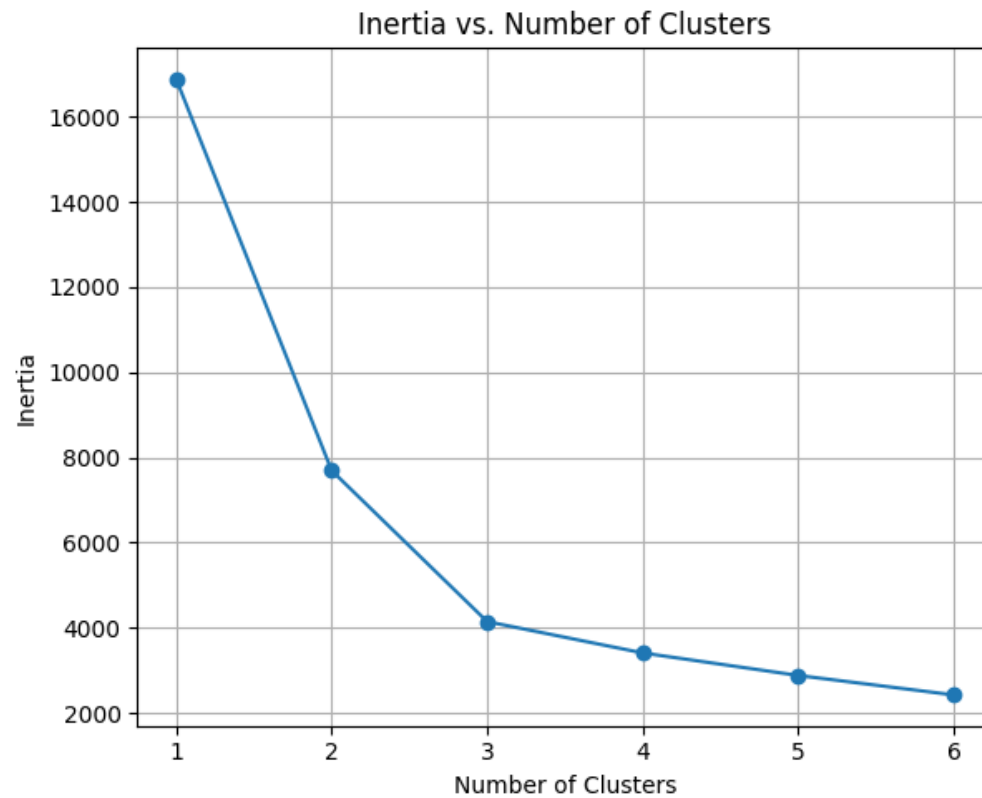
- › Repeat the process until **convergence**, meaning that the loss does not improve significantly any more

K-Means Algorithm – parameter tuning



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K-Means Algorithm – parameter tuning



Fuzzy C-Means – additional elements

- › We need a new data structure:

$$U = [u_{ij}] \quad 0 \leq u_{ij} \leq 1, \quad \sum_{j=1}^k u_{ij} = 1, \quad \forall i$$

- › For each cluster the centroid is computed as follows:

$$c_j = \frac{\sum_{i=1}^N u_{i,j}^m x_i}{\sum_{i=1}^N u_{i,j}^m}$$

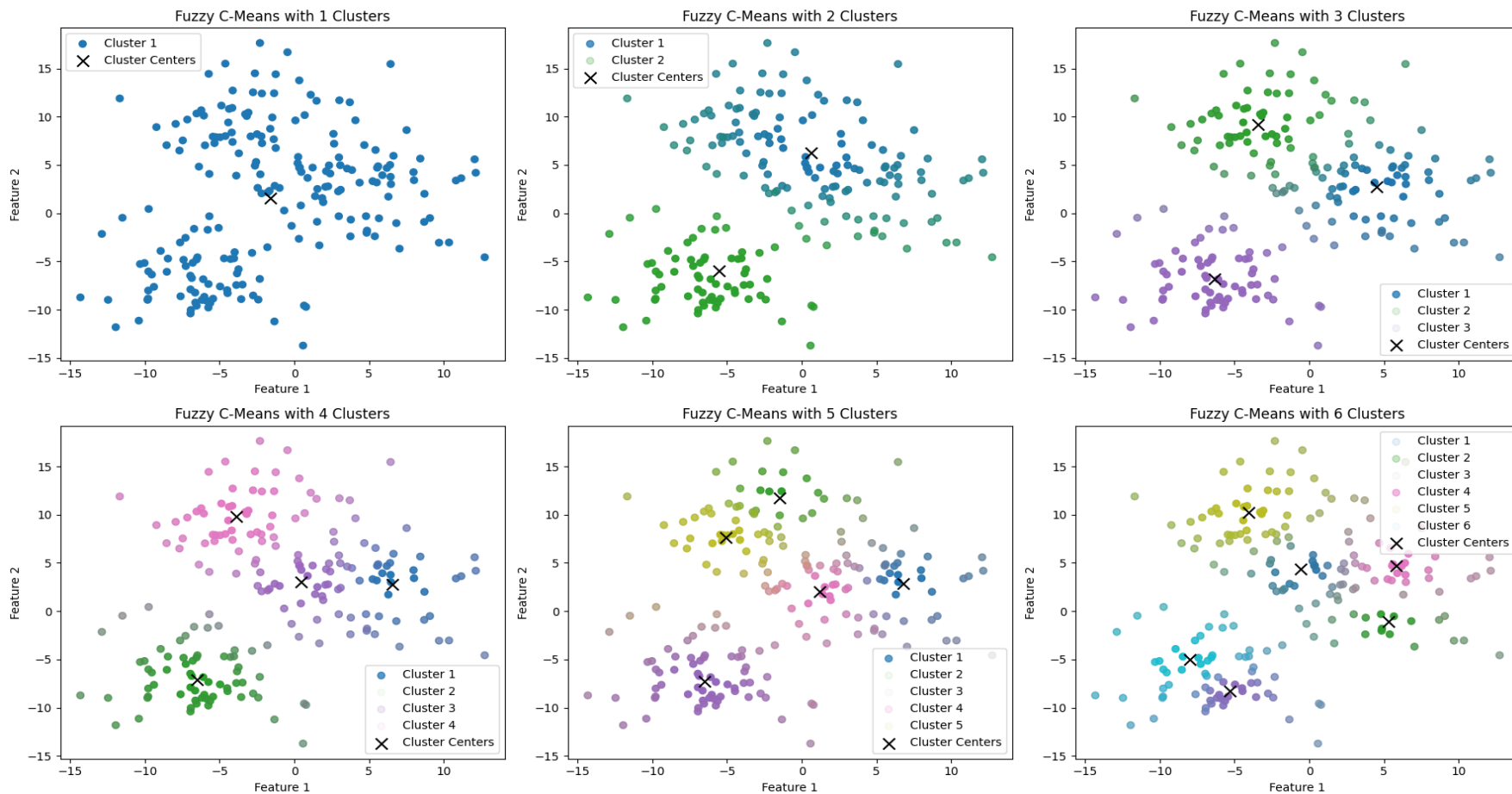
- › For each element the degree of membership is updated as follows:

$$u_{i,j} = \left(\sum_{k=1}^c \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}} \right)^{-1}$$

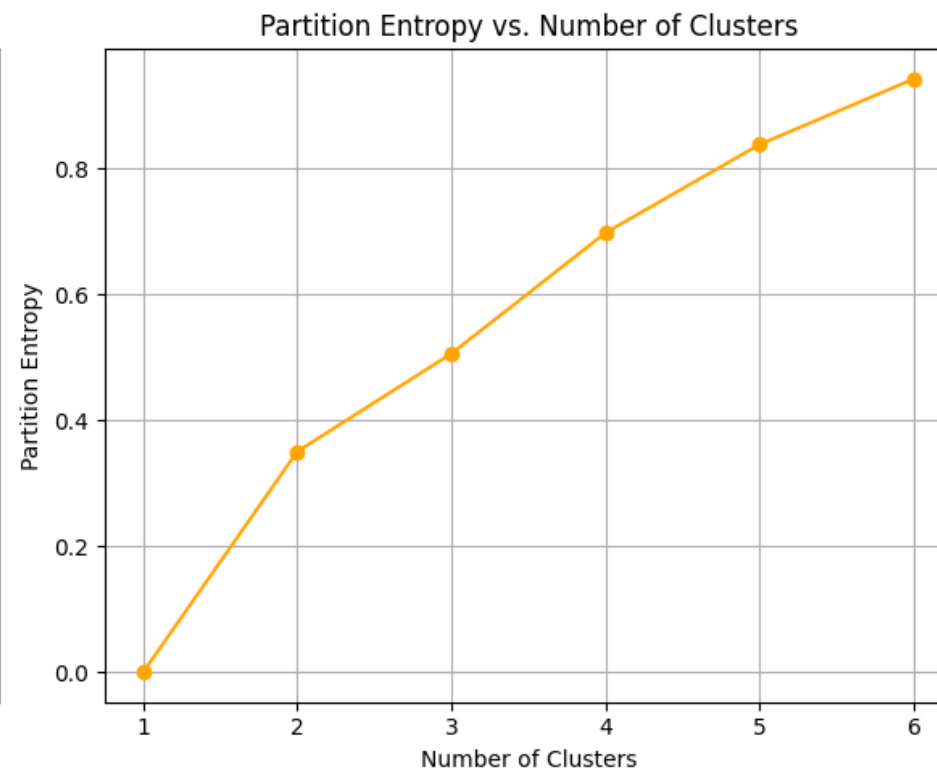
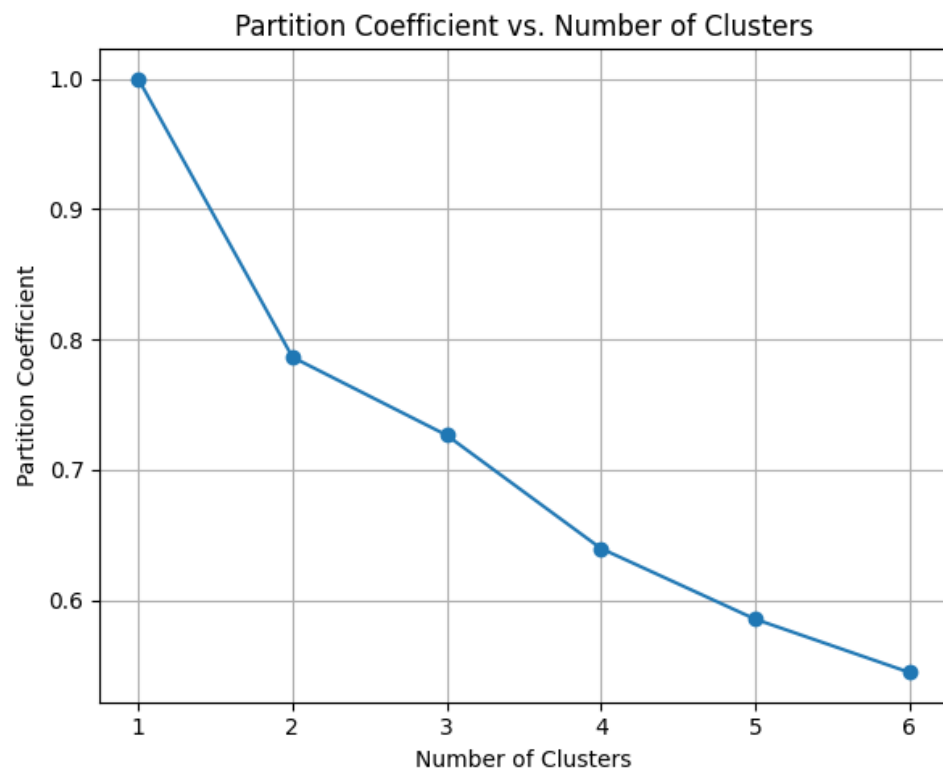
Fuzzy C-Means - algorithm

- › Select the number of clusters to detect
- › Assign centroids randomly
- › Assign to each point a **degree of membership** to each cluster
- › Repeat until convergence:
 - Compute the new centroids
 - Assign each point a new degree of membership to each cluster

Fuzzy C-Means – parameter tuning

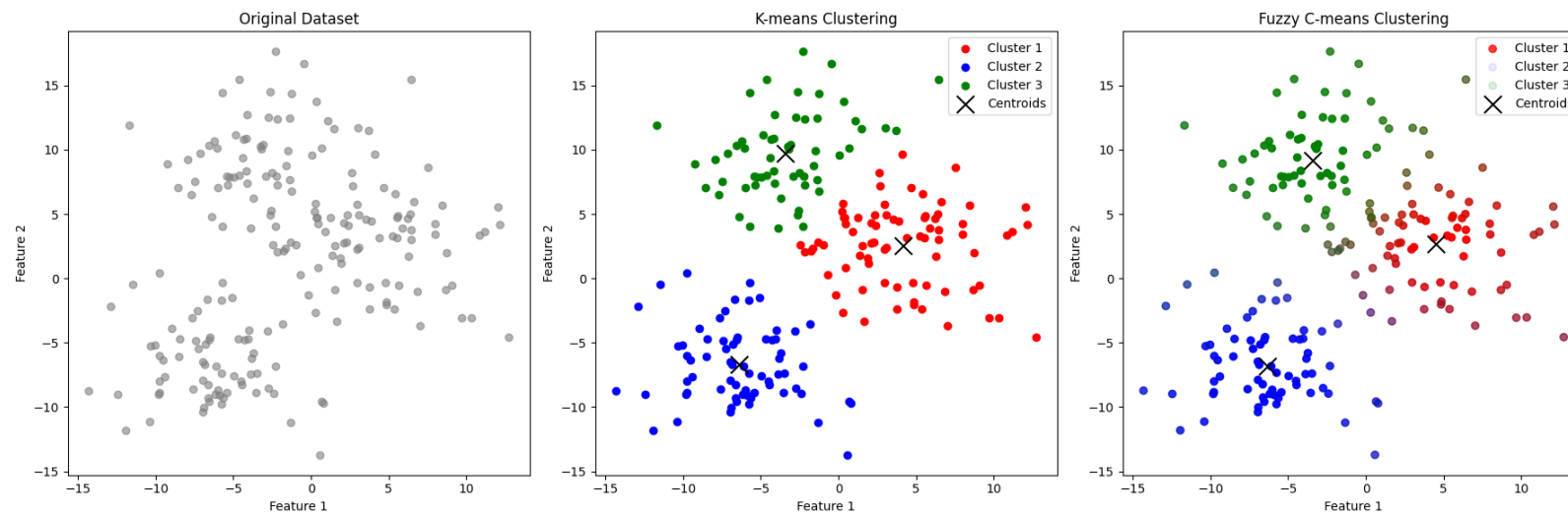


Fuzzy C-Means – parameter tuning



Fuzzy C-Means – pros and cons

- › Computationally more expensive
- › Possible overlapping clusters
- › Choosing the right number of clusters is hard
- › Difficulty in handling outliers



Possibilistic Fuzzy C-Means – additionalities

- › We introduce a new parameter $t_{i,j}$, called **typicality**, that measure how much each elements fits each cluster, without consider the others (it is not require that them sum to 1).
- › **a** and **b** are additional hyperparameters. They define the relative importance of fuzzy membership and typicality.
- › An additional hyperparameters defined for each clusters: δ_j

Possibilistic Fuzzy C-Means – steps

- › Compute centroids:

$$c_j = \frac{\sum_{i=1}^N (au_{i,j}^m + bt_{i,j}^\eta) x_i}{\sum_{i=1}^N (au_{i,j}^m + bt_{i,j}^\eta)}$$

- › Compute membership values based on new clusters:

$$u_{i,j} = \left(\sum_{k=1}^c \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}} \right)^{-1}$$

- › Compute typicality values based on new centroids:

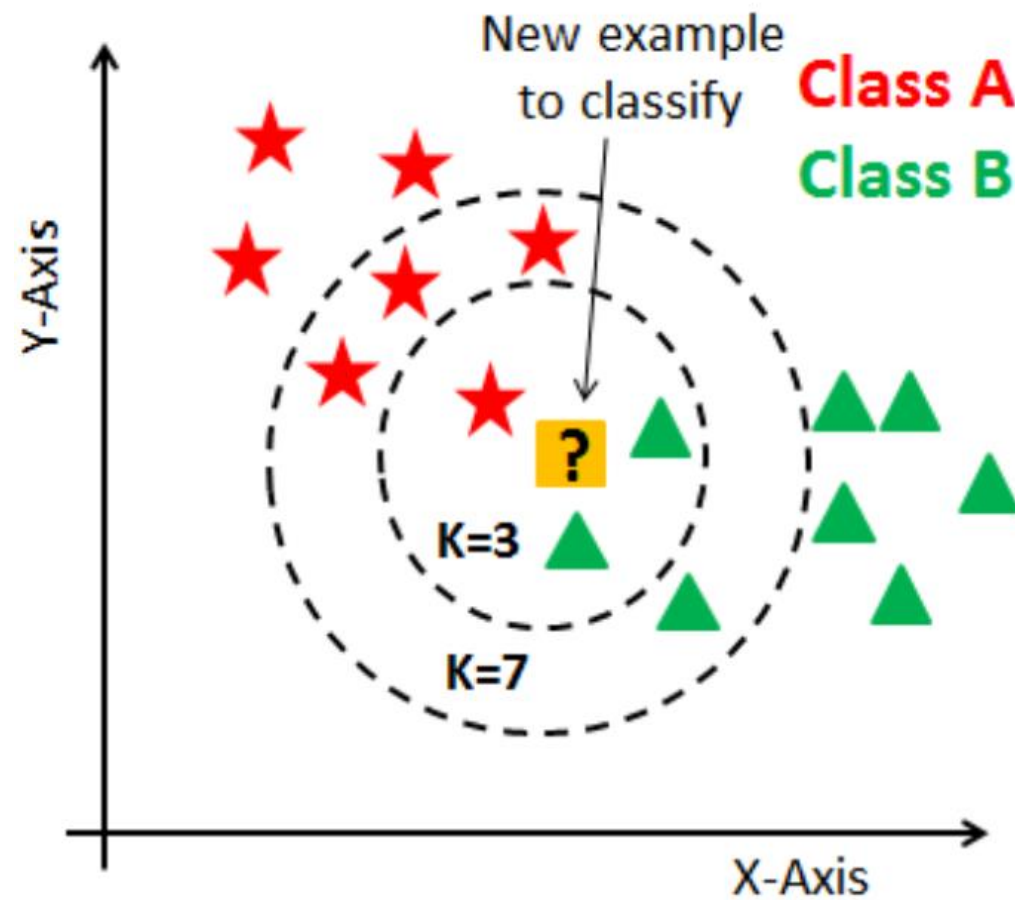
$$t_{i,j} = \left(1 + \left(\frac{b\|x_i - c_j\|^2}{\delta_j} \right)^{\frac{1}{\eta-1}} \right)^{-1}$$

Possibilistic Fuzzy C-Means – Pros and Cons

- › Requires carefully choosing more hyperparameters
- › Able to detect more patterns in the data
- › Handles outliers better than the fuzzy c-means clustering

kNN clustering

- › Red stars and green triangles are classified
- › Calculate distances and find k nearest neighbours
- › Assign label to the unknown points based on k-closest labels



kNN clustering – How to Compute

| Point | X | Y | Class |
|-----------|-----|-----|-------|
| A | 1.0 | 1.0 | Red |
| B | 2.0 | 1.0 | Red |
| C | 4.0 | 4.0 | Red |
| D | 5.0 | 5.0 | Blue |
| E | 4.5 | 3.5 | Blue |
| New Point | 3.0 | 2.0 | ? |

$$\triangleright \sqrt{(3.0 - 1.0)^2 + (2.0 - 1.0)^2} = 2.24$$

$$\triangleright \sqrt{(3.0 - 2.0)^2 + (2.0 - 1.0)^2} = 1.41$$

$$\triangleright \sqrt{(3.0 - 4.0)^2 + (2.0 - 4.0)^2} = 2.24$$

$$\triangleright \sqrt{(3.0 - 5.0)^2 + (2.0 - 5.0)^2} = 3.61$$

$$\triangleright \sqrt{(3.0 - 4.5)^2 + (2.0 - 3.5)^2} = 2.12$$

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Fuzzy kNN (K = 3)

| Point | X | Y | Class |
|-----------|-----|-----|-------|
| A | 0.8 | 0.8 | A |
| B | 0.8 | 1.2 | A |
| C | 3.8 | 2.8 | B |
| D | 4.2 | 3.2 | B |
| E | 4.5 | 3.5 | A |
| New Point | 3.0 | 2.0 | ? |

$\sqrt{(3.0 - 0.8)^2 + (2.0 - 0.8)^2} = 2.50$
 $\sqrt{(3.0 - 0.8)^2 + (2.0 - 1.2)^2} = 1.23$
 $\sqrt{(3.0 - 3.8)^2 + (2.0 - 2.8)^2} = 2.16$
 $\sqrt{(3.0 - 4.2)^2 + (2.0 - 3.2)^2} = 2.34$
 $\sqrt{(3.0 - 4.5)^2 + (2.0 - 3.5)^2} = 1.96$

π

Fuzzy kNN (K = 3, m=2)

| Point | X | Y | Class |
|-----------|-----|-----|-------|
| A | 0.8 | 0.8 | A |
| B | 0.8 | 1.2 | A |
| C | 3.8 | 2.8 | B |
| D | 4.2 | 3.2 | B |
| E | 4.5 | 3.5 | A |
| New Point | 3.0 | 2.0 | ? |

$$\sqrt{(3.0 - 0.8)^2 + (2.0 - 0.8)^2} = 2.50$$

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$$\sqrt{(3.0 - 4.5)^2 + (2.0 - 3.5)^2} = 1.96$$

Fuzzy kNN (K = 3, m=2)

$$\mu_i(P) = \frac{\sum_{j=1}^k \mu_{ij} \left(\frac{1}{d(P_i, X_j)^{\frac{2}{m-1}}} \right)}{\sum_{j=1}^k \left(\frac{1}{d(P_i, X_j)^{\frac{2}{m-1}}} \right)}$$

| Point | X | Y | Class |
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| B | 0.8 | 1.2 | A |
| C | 3.8 | 2.8 | B |
| D | 4.2 | 3.2 | B |
| E | 4.5 | 3.5 | A |
| New Point | 3.0 | 2.0 | ? |

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$$\mu_A(P) = \frac{\frac{1}{1.23^2} + \frac{0}{2.16^2} + \frac{1}{1.96^2}}{\frac{1}{1.23^2} + \frac{1}{2.16^2} + \frac{1}{1.96^2}} \approx 0.811$$

$$\mu_B(P) = \frac{\frac{0}{1.23^2} + \frac{1}{2.16^2} + \frac{0}{1.96^2}}{\frac{1}{1.23^2} + \frac{1}{2.16^2} + \frac{1}{1.96^2}} \approx 0.189$$

Fuzzy kNN (K = 3, m=2)

$$\mu_i(P) = \frac{\sum_{j=1}^k \mu_{ij} \left(\frac{1}{d(P_i, X_j)^{\frac{2}{m-1}}} \right)}{\sum_{j=1}^k \left(\frac{1}{d(P_i, X_j)^{\frac{2}{m-1}}} \right)}$$

| Point | X | Y | Class |
|-----------|-----|-----|-------|
| A | 0.8 | 0.8 | A |
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| New Point | 3.0 | 2.0 | ? |

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$$\mu_B(P) = \frac{\frac{0}{1.23^2} + \frac{1}{2.16^2} + \frac{0}{1.96^2}}{\frac{1}{1.23^2} + \frac{1}{2.16^2} + \frac{1}{1.96^2}} \approx 0.189$$

Fuzzy Scaling Process – Main Idea

- › The most basic algorithm for fuzzy clustering:
- › For each pair x_i, x_j *determine their similarity* $s_{i,j}$
- › Define a matrix $S = (s_{i,j})_{n \times n}$
- › Calculate the transitive closure $R = tc(S)$
- › *Calculate* the α – cut R_α
- › If i–th and j–th rows of R_α are equal x_i and x_j are in the same cluster

Fuzzy Scaling Process – Example

- › Let's take 3 colors sky blue, light blue and green

Fuzzy Scaling Process – Example

- › Let's take 3 colors sky blue, light blue and green
- › Let's pick some distance metric which will return the distance between two colors

Fuzzy Scaling Process – Example

- › Let's take 3 colors sky blue, light blue and green
- › Let's pick some distance metric which will return the distance between two colors
- › Let's fill the matrix with the distances between colors

$$S = \begin{bmatrix} 1 & 0.9 & 0.2 \\ 0.9 & 1 & 0.3 \\ 0.2 & 0.3 & 1 \end{bmatrix}$$

Fuzzy Scaling Process – Pros and Cons

› We have to obtain R

$$R = \begin{bmatrix} 1.0 & 0.9 & 0.3 \\ 0.9 & 1.0 & 0.3 \\ 0.3 & 0.3 & 1.0 \end{bmatrix}$$

Fuzzy Scaling Process – Pros and Cons

- › We have to obtain R

$$R = \begin{bmatrix} 1.0 & 0.9 & 0.3 \\ 0.9 & 1.0 & 0.3 \\ 0.3 & 0.3 & 1.0 \end{bmatrix}$$

- › We have to perform alpha-cut (let's take 0.5)

Fuzzy Scaling Process – Pros and Cons

- › We have to obtain R

$$R = \begin{bmatrix} 1.0 & 0.9 & 0.3 \\ 0.9 & 1.0 & 0.3 \\ 0.3 & 0.3 & 1.0 \end{bmatrix}$$

- › We have to perform alpha-cut (let's take 0.5)

$$R_{\alpha} = \begin{bmatrix} 1.0 & 0.9 & 0 \\ 0.9 & 1.0 & 0 \\ 0 & 0 & 1.0 \end{bmatrix}$$

THANK YOU FOR YOUR ATTENTION!

