# Homework Assignment 2 – [30 points]

STAT437 Unsupervised Learning – Spring 2025

Due: Friday, February 7 on Canvas

**Questions #1-#3:** Refer to the attached Jupyter notebook to complete questions #1-#3 of this assignment.

Problem	Points
1	6.5
2	4.5
3	12
4	1.5
5	2.5
6	3

#### **Question #4: Video**

Summarize what you learned when going through questions #1-#3. Specifically, what are some potential ways in which the following missing value cleaning techniques might negatively impact your ability to detect meaningful, practically relevant clusters in your dataset:

- Dropping rows with missing values
- Imputing missing values with 0
- Imputing missing values with the column mean?

Share your screen and go through your Jupyter notebook results as you give your explanation.

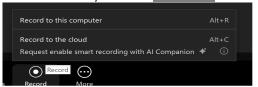
### Questions #5-6 (See below)

#### **IMPORTANT Video Element of ALL Homework Assignments:**

- In order to receive points for each video submission, you need to do ALL of the following.
  - Have your camera on.
  - O Show your FULL screen in Zoom (not just a particular application).
  - We should be able to hear the audio. Make sure to turn your mic on.
  - O You should give a good faith attempt to answer the prompt.
  - O Your video meet the minimum time requirement.
  - It should not sound like you are just reading off a script.
  - It's ok if your video recording is not the most eloquent. What's important is that you are putting together YOUR authentic thoughts on your particular understanding of the assignment and the lecture content.

#### **How to Submit Videos:**

- You should record your videos in your UIUC Zoom client.
- You should record your videos To the Cloud.



- You can find your recording link at <a href="https://illinois.zoom.us/recording/">https://illinois.zoom.us/recording/</a>.
- Click on the corresponding video and Copy shareable link to paste

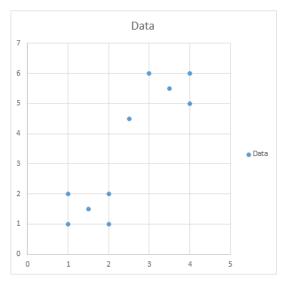
**Question #5: [3 pt]** Plotted and shown below is a two-dimensional dataset with 10 objects. Your two **initial medoids** have been randomly initialized to be **object 1** and **object 2**. What will be the NEXT two medoids in the k-medoids algorithm? Show your work.

<u>Note 1:</u> In this k-medoids algorithm, we will be using the Euclidean distance metric. A pairwise Euclidean distance matrix for each pair of objects in the dataset is also given below.

Note 2: Many algorithms that we will learn in this class may encounter a "tie" scenario for certain datasets. For instance, when it comes to assigning a particular object to a particular cluster based on the rules stipulated by the *general algorithm*, the object could *technically* be assigned to more than one cluster. In scenarios such these, it's often useful to designate a "tie-breaker" rule. For instance, let's designate the following "tie-breaker rule" for the cluster assignment step of the k-Medoids algorithm.

<u>Tie-Breaker Rule:</u> If an observation is equally close to two or more centroids (medoids), assign it to the centroid with the "lowest index" (ie. "object 3" < "object 4").

	Data			
	x	у		
Object 1	1	1		
Object 2	2	2		
Object 3	1	2		
Object 4	2	1		
Object 5	1.5	1.5		
Object 6	2.5	4.5		
Object 7	3	6		
Object 8	4	5		
Object 9	4	6		
Object 10	3.5	5.5		



## **Euclidean Distance Between Each Pair of Objects**

	Object 1	Object 2	Object 3	Object 4	Object 5	Object 6	Object 7	Object 8	Object 9	Object 10
Object 1	0.00	1.41	1.00	1.00	0.71	3.81	5.39	5.00	5.83	5.15
Object 2	1.41	0.00	1.00	1.00	0.71	2.55	4.12	3.61	4.47	3.81
Object 3	1.00	1.00	0.00	1.41	0.71	2.92	4.47	4.24	5.00	4.30
Object 4	1.00	1.00	1.41	0.00	0.71	3.54	5.10	4.47	5.39	4.74
Object 5	0.71	0.71	0.71	0.71	0.00	3.16	4.74	4.30	5.15	4.47
Object 6	3.81	2.55	2.92	3.54	3.16	0.00	1.58	1.58	2.12	1.41
Object 7	5.39	4.12	4.47	5.10	4.74	1.58	0.00	1.41	1.00	0.71
Object 8	5.00	3.61	4.24	4.47	4.30	1.58	1.41	0.00	1.00	0.71
Object 9	5.83	4.47	5.00	5.39	5.15	2.12	1.00	1.00	0.00	0.71
Object										
10	5.15	3.81	4.30	4.74	4.47	1.41	0.71	0.71	0.71	0.00

## Question #6 [3 pt]

### Designing our Own Clustering Algorithms

Suppose that we'd like to design ourselves three different types of clustering algorithms.

- <u>Clustering Algorithm A</u>: a clustering algorithm that is designed to detect density-based clusters
- Clustering Algorithm B: a clustering algorithm that is designed to detect contiguity-based clusters
- Clustering Algorithm C: a clustering algorithm that is designed to detect prototype-based clusters

### Three Datasets and their *Desired* Clusters

Four datasets are shown in the scatterplots below. The clusters of observations that we'd ideally *like* for the chosen clustering algorithm to find are color-coded.

(One exception to this is dataset 2. We can assume that the observations represented with green points (ie. label 2) actually represent "noise" that we would NOT like for the algorithm to put in an "official cluster" and simply just label as "noise".)

### Match the Algorithm to the Dataset

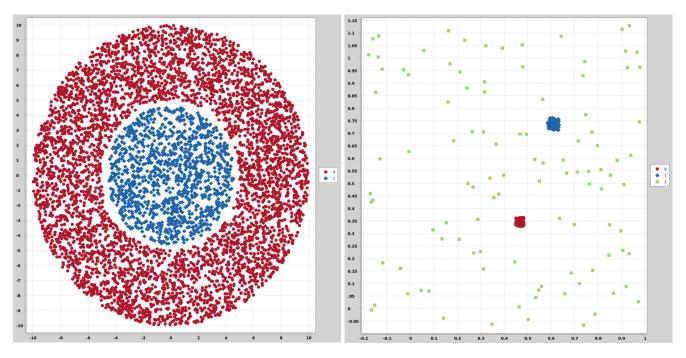
- 1. Select the algorithm (from the A,B,C above) that would be the best at detecting the cluster that we're looking for in **dataset 1.**
- 2. Select the algorithm (from the A,B,C above) that would be the best at detecting the cluster that we're looking for in **dataset 2.**
- 3. Select the algorithm (from the A,B,C above) that would be the best at detecting the cluster that we're looking for in dataset 3.

### Match the Algorithm to the Dataset

For questions (1, 2, and 3) above also answer the following.

- If you selected a clustering algorithm designed to detect **density-based clusters** for a given dataset, how might you specifically determine if a point should belong to a **density-based cluster** as opposed to being considered as **noise** in this given dataset?
- If you selected a clustering algorithm designed to detect **contiguity-based clusters** for a given dataset, how might you specifically determine if two points are **connected** in this given dataset? (We can also assume that if A and B connect, and B and C connected, then A and C connect as well).
- If you selected a clustering algorithm designed to detect **prototype-based clusters** for a given dataset, what prototype might you use for this given dataset?

Dataset 1 Dataset 2



# Dataset 3

