

The background of the slide is a dark green color with a complex, abstract network pattern. This pattern consists of numerous small, light green dots (nodes) connected by thin, light green lines (edges), creating a web-like structure that fills the entire background. The text is centered in the middle of the slide.

COURSE NOTES: CLUSTER ANALYSIS

Cluster analysis

Cluster analysis

Cluster analysis is a multivariate statistical technique that groups observations on the basis some of their features or variables that they are described by.



The goal of clustering is to maximize the similarity of observations within a cluster and maximize the dissimilarity between clusters.

Euclidean distance

The most intuitive way to measure the distance between them is by drawing a straight line from one to the other. That's also known as Euclidean distance.

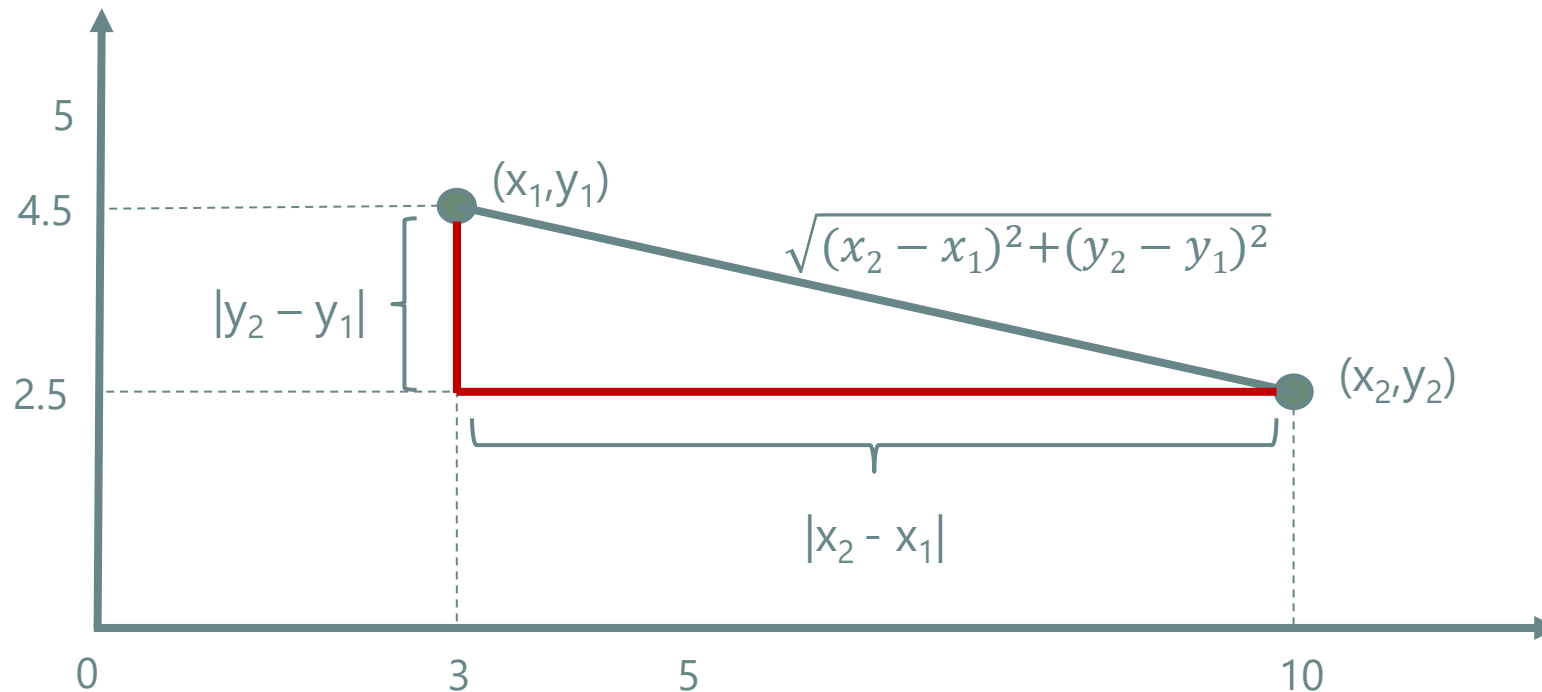
$$\text{2D space: } d(A,B) = d(B,A) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

$$\text{3D space: } d(A,B) = d(B,A) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}$$

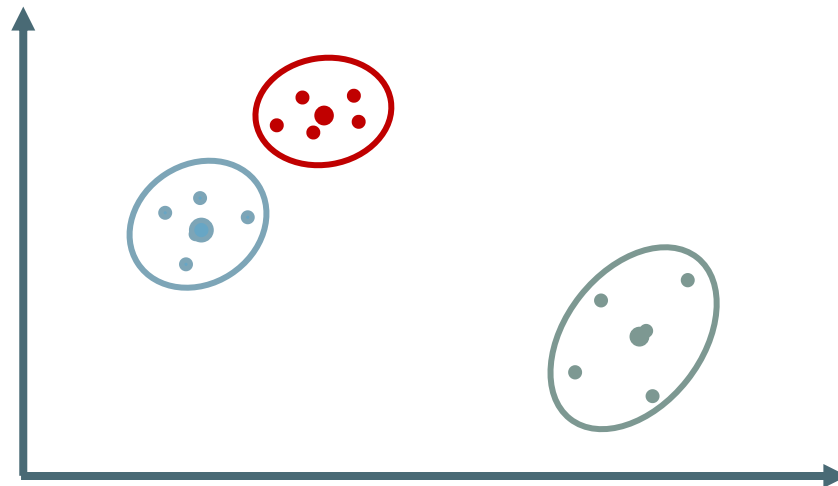
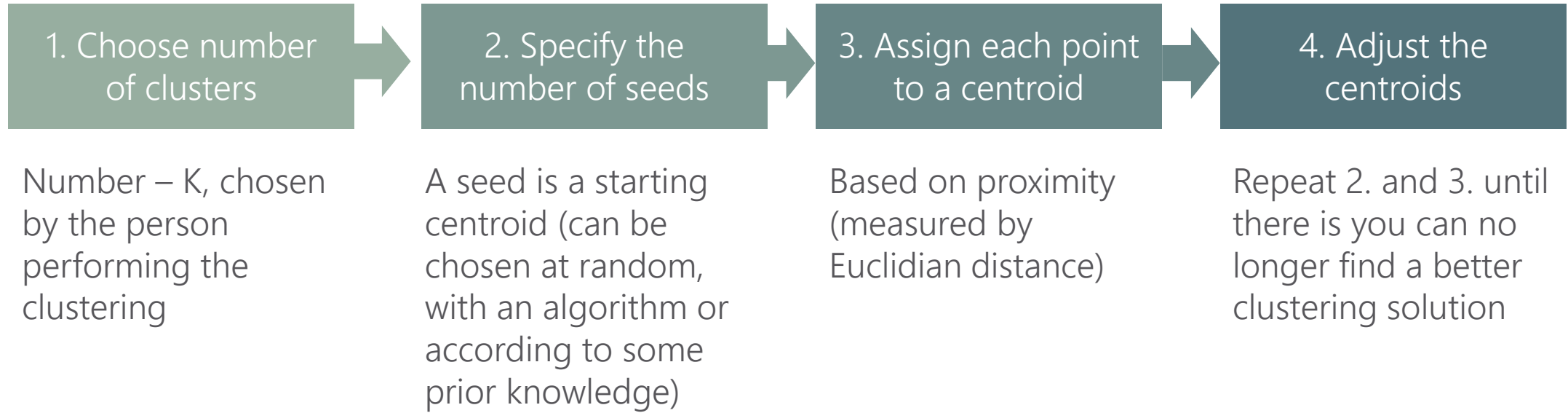
If the coordinates of A are (a_1, a_2, \dots, a_n) and of B are (b_1, b_2, \dots, b_n)

N-dim space:

$$d(A,B) = d(B,A) = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + \dots + (a_n - b_n)^2}$$



K-means clustering



K-means clustering - pros and cons

PROS

- Simple to implement
(so many people can use it)
- Computationally efficient
(it takes considerably less time than any hierarchical clustering model)
- Widely used
(popular, therefore, in demand)
- Always yields a result
(also a con as it may be deceiving)

CONS

- We need to pick K
(often, we don't know how many clusters we need)
- Sensitive to initialization
(but we can use methods such as kmeans++ to determine the seeds)
- Sensitive to outliers
(by far the biggest downside of k-means)
- Produces spherical solutions
(thus, not as generalizable)

Classification

vs

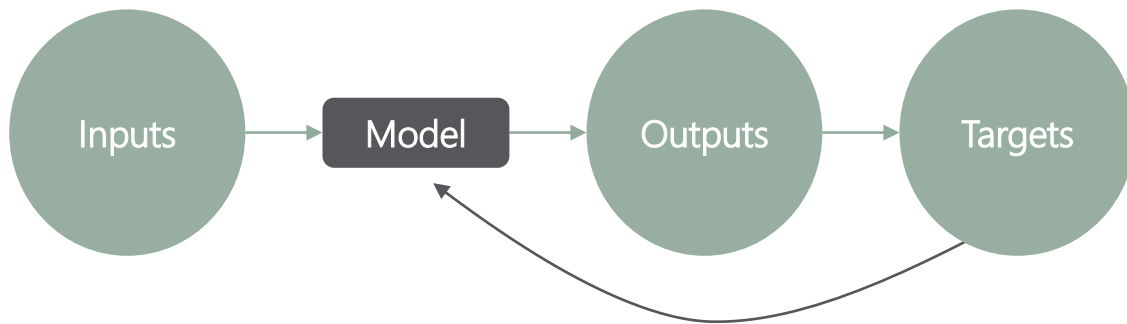
Clustering

Classification is a typical example of **supervised learning**.

It is used whenever we have input data and the desired correct outcomes (targets). We train our data to find the patterns in the inputs that lead to the targets.

With classification we essentially need to know the correct class of each of the observations in our data, in order to apply the algorithm.

A logistic regression is a typical example of classification.

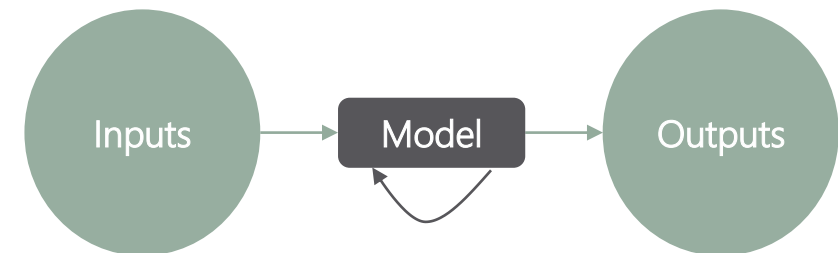


We use the targets (correct values) to adjust the model to get better outputs.

Cluster analysis is a typical example of **unsupervised learning**.

It is used whenever we have input data but have no clue what the correct outcomes are.

Clustering is about grouping data points together based on similarities among them and difference from others.



There is no feedback loop, therefore, the model simply finds the outputs it deems best.

Types of clustering

Clustering

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graph TD; Clustering --> Flat; Clustering --> Hierarchical; Hierarchical --> Divisive["Divisive (top-down)"]; Hierarchical --> Agglomerative["Agglomerative (bottom-up)"]
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Flat

With flat methods there is no hierarchy, but rather the number of clusters are chosen prior to clustering.

Flat methods have been developed because hierarchical clustering is much slower and computationally expensive.

Nowadays, flat methods are preferred because of the volume of data we typically try to cluster.

Hierarchical

Historically, clustering was developed first. An example hierarchical of clustering with hierarchy is taxonomy of the animal kingdom.

It is superior to flat clustering in the fact that it explores (contains) all solutions.

Divisive (top-down)

With divisive clustering we start from a situation where all observations are in the same cluster, e.g. from the dinosaurs. Then we split this big cluster into 2 smaller ones. Then we continue with 3, 4, 5, and so on, until each observation is its separate cluster.

To find the best split, **we must explore all possibilities at each step.**

Agglomerative (bottom-up)

When it comes to agglomerative clustering, the approach is bottom up. We start from different dog and cat breeds, cluster them into dogs and cats respectively, and then we continue pairing up species, until we reach the animal cluster.

To find the combination of observations into a cluster, **we must explore all possibilities at each step.**