

# Clustering

## CSC 461: Machine Learning

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Prof. Marco Alvarez  
University of Rhode Island

## Unsupervised learning

- Algorithms/methods for **uncovering** latent structure in the data

- ✓ unlabeled data

- Observations / data instances / data points:

$$\mathcal{D} = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n\}$$

usually  $\mathbf{x}_i \in \mathbb{R}^d$

**Labels** may be available with the data, but should be ignored if unsupervised learning is applied.

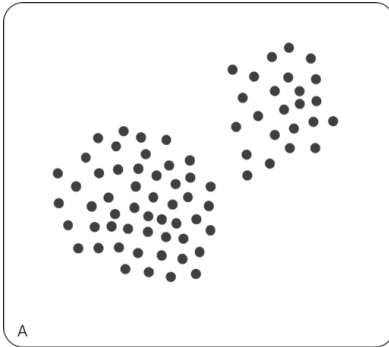
## Cluster Analysis

## Not this type of clusters ...



Credit: <https://blogs.nvidia.com/blog/2021/06/22/tesla-a100-training-supercomputer-nvidia-a100-gpus/>

## Clustering unlabeled data



Given  $n$  feature vectors group them into  $K$  clusters based on pairwise similarities

Credit: <https://towardsdatascience.com/a-step-by-step-guide-for-clustering-images-4b45f9906128>

## Subjective nature



(a) Original points.

(b) Two clusters.



(c) Four clusters.

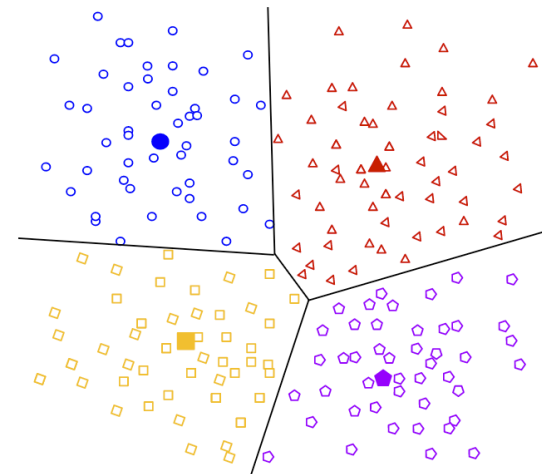
(d) Six clusters.

Credit: <https://www-users.cse.umn.edu/~kumar001/dmbook/index.php>

## Types of clustering

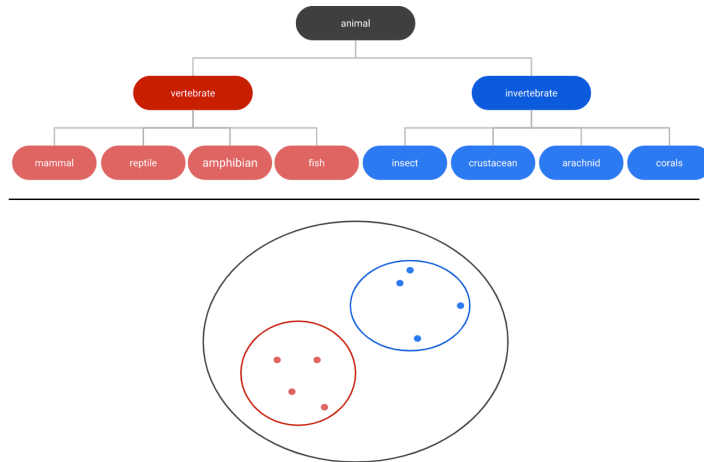
- ▶ **Partitioning** clustering (centroid-based)
  - ✓ each observation belongs to one partition (centroid)
  - ✓ each partition has a centroid
  - ✓ observations are assigned iteratively to the cluster with the closest centroid
- ▶ **Hierarchical** clustering
  - ✓ defines a hierarchy (tree) of clusters
  - ✓ sensitive to the definition of distance between observations

## Partition clustering



Credit: <https://developers.google.com/machine-learning/clustering/clustering-algorithms>

# Hierarchical clustering



Credit: <https://developers.google.com/machine-learning/clustering/clustering-algorithms>

# Types of clustering

## ► Density-based

- ✓ clusters are formed in high-density areas
- ✓ can form arbitrary-shaped clusters
- ✓ difficult to deal with varying densities and high dimensions

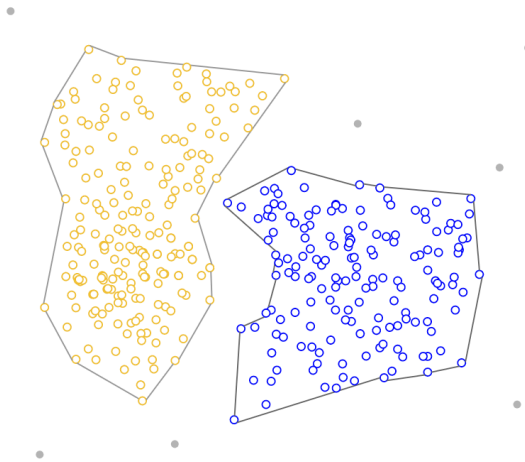
## ► Distribution-based

- ✓ assumes clusters are generated by underlying distributions (e.g. gaussian distribution)
- ✓ requires defining the proper distribution

## ► and more

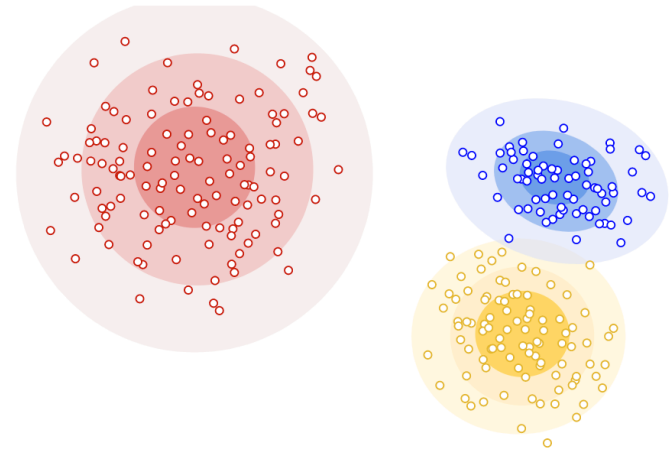
- ✓ fuzzy clustering, spectral clustering, etc.

# Density-based



Credit: <https://developers.google.com/machine-learning/clustering/clustering-algorithms>

# Distribution-based



Credit: <https://developers.google.com/machine-learning/clustering/clustering-algorithms>

# K-Means

## K-means clustering

- ▶ Given  $n$  observations (feature vectors) ...

$$\mathcal{D} = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n\} \quad \mathbf{x}_i \in \mathbb{R}^d$$

- ▶ ... partition the data into  $K$  clusters such that the **within-cluster-distance** is minimized for all clusters  $C_i$ :

$$\arg \min_{C_1, \dots, C_K} \sum_{k=1}^K WCD(C_k)$$

## Formally

- ▶ Each cluster is denoted by  $C_i \subseteq \{1, \dots, n\}$

✓ if  $\mathbf{x}_i$  is assigned to cluster  $j$  then  $i \in C_j$

✓ subject to:

$$\bigcup_i C_i = \{1, \dots, n\} \quad \text{and} \quad C_i \cap C_j = \emptyset, \text{ for } i \neq j$$

- ▶ Defining the clustering goal:

$$\arg \min_{C_1, \dots, C_K} \sum_{k=1}^K \frac{1}{2|C_k|} \sum_{i,j \in C_k} \|\mathbf{x}_i - \mathbf{x}_j\|_2^2$$

Credit: <https://www.cs.cornell.edu/courses/cs4780/2022fa/lectures/UnsupervisedLearning.html>

## Using centroids

- ▶ A **centroid**  $\mu_k$  is the mean of all observations (datapoints) in cluster  $C_k$

$$\mu_k = \frac{1}{|C_k|} \sum_{i \in C_k} \mathbf{x}_i$$

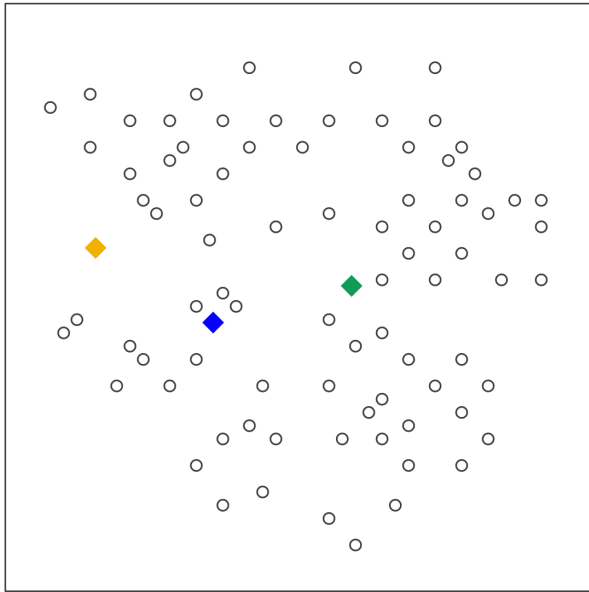
- ▶ The clustering goal can also be defined using centroids:

$$\arg \min_{C_1, \dots, C_K} \sum_{k=1}^K \sum_{i \in C_k} \|\mathbf{x}_i - \mu_k\|_2^2$$

Credit: <https://www.cs.cornell.edu/courses/cs4780/2022fa/lectures/UnsupervisedLearning.html>

## How to minimize the goal?

- ▶ Trying a brute-force approach for an optimal solution would be computationally infeasible
  - ✓ i.e. calculating all possible partitions of  $n$  observations into  $K$  clusters
  - ✓  $n = 25$ ,  $K = 4$  gives  $5 \times 10^{13}$  possible partitions
- ▶ Relaxing our minimization goal
  - ✓ instead of an optimal we can settle with an approximate solution, using an efficient iterative method (Lloyd's algorithm)

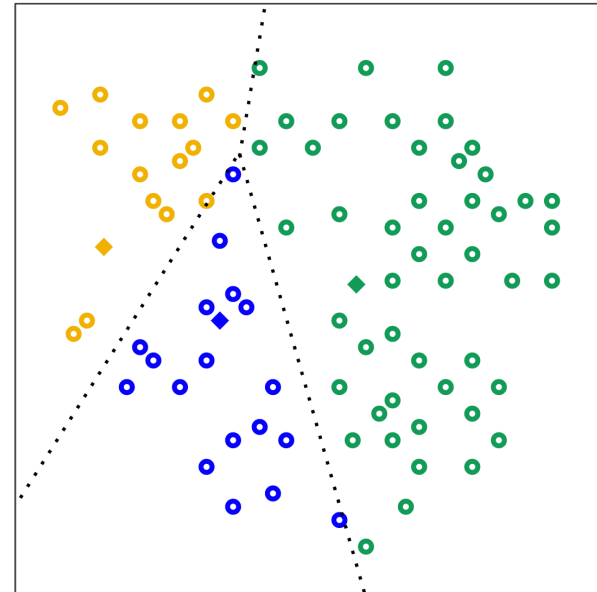


Credit: <https://developers.google.com/machine-learning/clustering/clustering-algorithms>

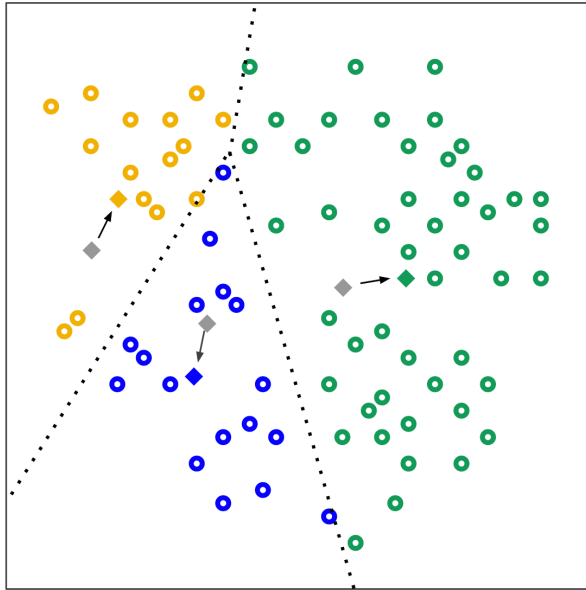
## k-Means algorithm

- ▶ Randomly **assign** observations to clusters
- ▶ Repeat
  - ✓ compute all cluster **centroids**
  - ✓ **assign** each observation to their closest centroid
  - ✓ stop if observations stop changing clusters

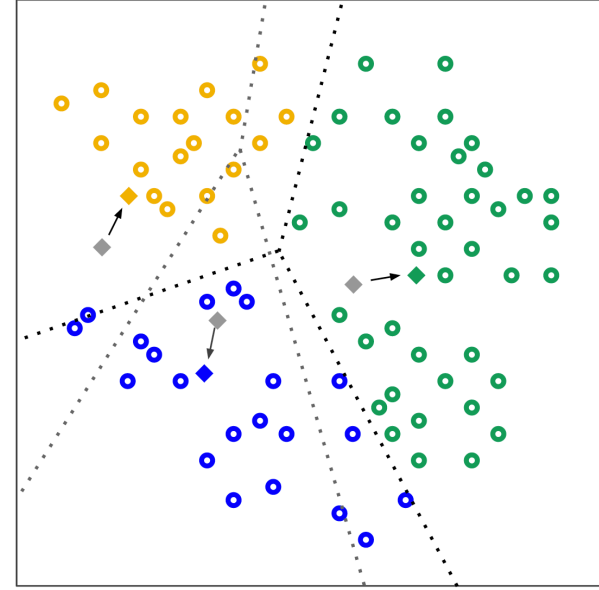
can also use different stopping criteria for large datasets



Credit: <https://developers.google.com/machine-learning/clustering/clustering-algorithms>



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## Online demo

<https://user.ceng.metu.edu.tr/~akifakkus/courses/ceng574/k-means/>