

# Clustering with the $k$ -means algorithm I

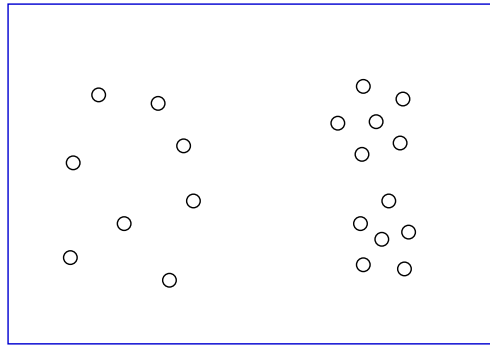
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## Topics we'll cover

- ① The clustering problem
- ② Two uses of clustering
- ③ The  $k$ -means cost function and algorithm
- ④ Initializing Lloyd's algorithm

# Clustering in $\mathbb{R}^d$



Two common uses of clustering:

- **Vector quantization**  
Find a finite set of representatives that provides good coverage of a complex, possibly infinite, high-dimensional space.
- **Finding meaningful structure in data**  
Finding salient grouping in data.

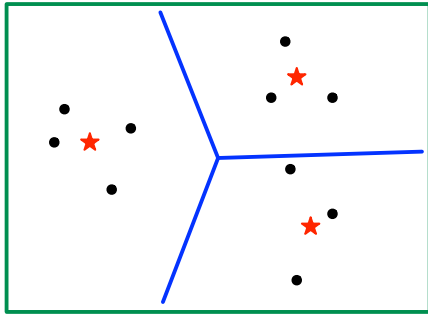
## Widely-used clustering methods

- ① **K-means and its many variants**
- ② **EM for mixtures of Gaussians**
- ③ **Agglomerative hierarchical clustering**

## The $k$ -means optimization problem

- Input: Points  $x_1, \dots, x_n \in \mathbb{R}^d$ ; integer  $k$
- Output: “Centers”, or representatives,  $\mu_1, \dots, \mu_k \in \mathbb{R}^d$
- Goal: Minimize average squared distance between points and their nearest representatives:

$$\text{cost}(\mu_1, \dots, \mu_k) = \sum_{i=1}^n \min_j \|x_i - \mu_j\|^2$$

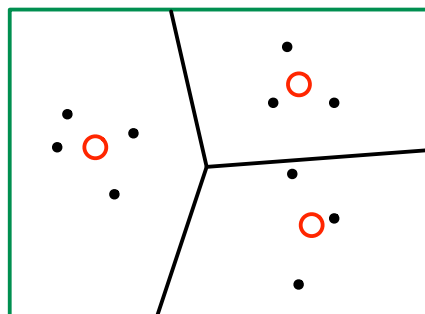


The centers partition  $\mathbb{R}^d$  into  $k$  convex regions:  $\mu_j$ 's region consists of points for which it is the closest center.

## Lloyd's $k$ -means algorithm

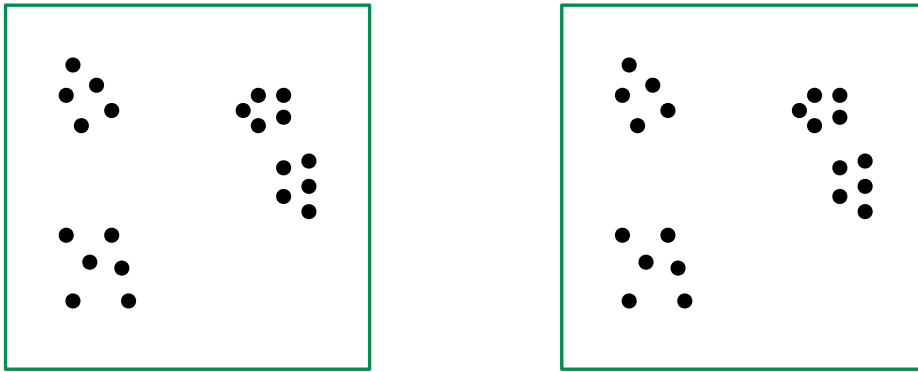
The  $k$ -means problem is NP-hard. Most popular heuristic: “ $k$ -means algorithm”.

- Initialize centers  $\mu_1, \dots, \mu_k$  in some manner.
- Repeat until convergence:
  - Assign each point to its closest center.
  - Update each  $\mu_j$  to the mean of the points assigned to it.



Each iteration reduces the cost  $\Rightarrow$  convergence to a local optimum.

## Initialization matters



## Initializing the $k$ -means algorithm

Typical practice: choose  $k$  data points at random as the initial centers.

Another common trick: start with extra centers, then prune later.

A particularly good initializer:  **$k$ -means++**

- Pick a data point  $x$  at random as the first center
- Let  $C = \{x\}$  (centers chosen so far)
- Repeat until desired number of centers is attained:
  - Pick a data point  $x$  at random from the following distribution:

$$\Pr(x) \propto \text{dist}(x, C)^2,$$

where  $\text{dist}(x, C) = \min_{z \in C} \|x - z\|$

- Add  $x$  to  $C$