#### K-means

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### Overview



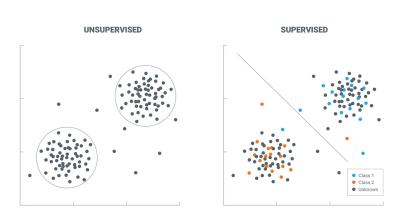
**Unsupervised Learning** 

K-means

Choose k

## **Unsupervised Learning**

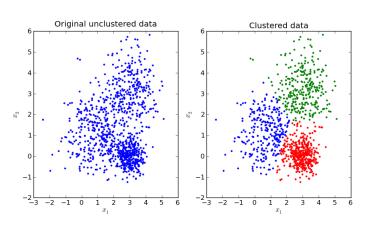




Hình 1: Supervised vs Unsupervised

## Clustering

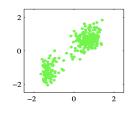




Hình 2: Clustering

# Clustering (cont.)

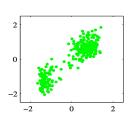


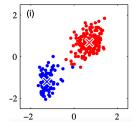


- Given the dataset x<sub>1</sub>, x<sub>2</sub>,...,x<sub>N</sub>, each x<sub>i</sub> ∈ R<sup>D</sup>, partition the dataset into K clusters.
- Intuitively, a cluster is a group of points, which is close together and far from other.

#### Distortion Measure







- Formally, introduce cluster center  $\mu_k \in \mathbb{R}^D$ .
- Use binary  $r_{nk}$ , 1 if point n is in cluster k, 0 otherwise (1 of K coding scheme again).
- Find  $\{\mu_k\}$ ,  $\{r_{nk}\}$  to minimize distortion measure:

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} r_{nk} ||x_n - \mu_k||^2 \qquad (1)$$

e.g. two clusters

$$J = \sum_{x_n \in C_1} \|x_n - \mu_1\|^2 + \sum_{x_n \in C_2} \|x_n - \mu_2\|^2$$
(2)

## Minimizing Distortion Measure



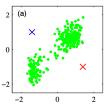
Minimizing J directly is hard. Why?

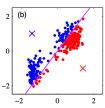
$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} r_{nk} \|x_n - \mu_k\|^2$$
 (3)

However, two things are easy:

- ▶ if we know  $\mu_k$ , minimizing J wrt  $r_{nk}$
- ▶ if we know  $r_{nk}$ , minimizing J wrt  $mu_k$
- ⇒ Iterative procedure
  - ▶ Start with initial guess for  $\mu_k$
  - ► Iteration of two steps:
    - Minimizing J wrt r<sub>nk</sub>
    - Minimizing J wrt muk







Minimizing J wrt r<sub>nk</sub>

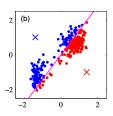
$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} r_{nk} ||x_n - \mu_k||^2 \qquad (4)$$

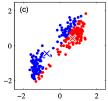
Loss for each item

$$J_n = \sum_{k=1}^{K} r_{nk} ||x_n - \mu_k||^2 \qquad (5)$$

- $\Rightarrow$  find  $r_{nk}$  to minimize J
- ▶ Simply set  $r_{nk} = 1$  for the cluster center  $\mu_k$  with smallest distance







• Minimizing J wrt  $\mu_k$ 

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} r_{nk} ||x_n - \mu_k||^2$$
 (6)

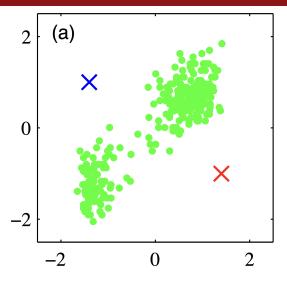
we can minimize wrt each μ<sub>k</sub> separately

$$\frac{\partial J}{\partial \mu_k} = 2\sum_{n=1}^N r_{nk}(x_n - \mu_k) = 0$$

$$\Leftrightarrow \mu_k = \frac{\sum_n r_{nk} x_n}{\sum_n r_{nk}} (7)$$

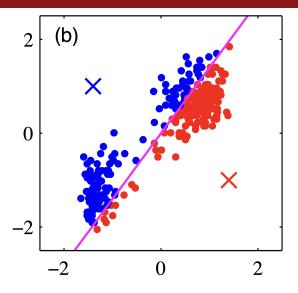
mean of datapoints x<sub>n</sub> assigned to cluster k





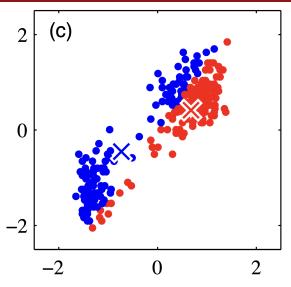
Hình 3: Initialize the cluster center





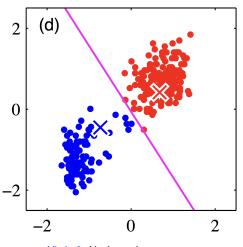
Hình 4: Initialize the cluster center





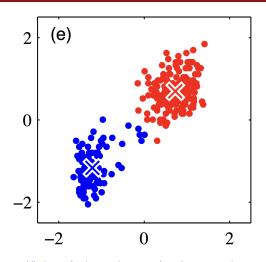
Hình 5: Assign points to the cluster





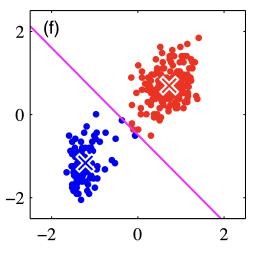
Hình 6: Update cluster center





Hình 7: Assign points to the cluster again



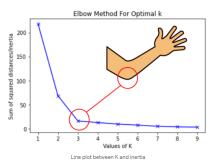


Hình 8: Update cluster center again

#### Elbow method



- ► Calculate the Within-Cluster-Sum of Squared Errors (WSS) for different values of k
- ► Choose the k for which WSS becomes first starts to diminish. In the plot of WSS-versus-k, this is visible as an elbow.



Hình 9: Elbow method

## Silhouette analysis



The silhouette coefficient or silhouette score kmeans is a measure of how similar a data point is within-cluster (cohesion) compared to other clusters (separation)

$$S(i) = \frac{b(i) - a(i)}{\max(\{a(i), b(i)\})}$$
(8)

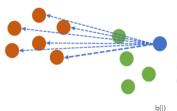
- ► S(i) is the silhouette coefficient of the data point i.
- a(i) is the average distance between i and all the other data points in the cluster to which i belongs.
- ▶ b(i) is the average distance from i to all clusters to which i does not belong.

### Silhouette analysis (cont.)





a(i): avg distance between i and all other datapoints within cluster

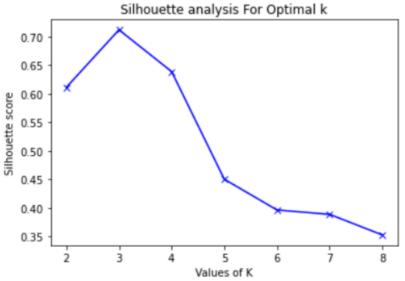


b(i): avg distance between i and all other datapoints outside/neighboring cluster

## Silhouette analysis (cont.)



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Line plot between K and Silhouette score