

# Clustering

classification  $\left[ \mathcal{X} = \{ (x_i, y_i) \}_{i=1}^N \right.$   
 $\swarrow$  class labels  
 $\searrow$  data points

Binary classification

$y_i \in \{0, 1\}$  or  $y_i \in \{-1, +1\}$

Multiclass classification

$y_i \in \{1, 2, \dots, K\}$

clustering  $\left[ \mathcal{X} = \{ x_i \}_{i=1}^N \right.$

NO CLASS LABELS!

## PARAMETRIC CLASSIFICATION

- We assumed that each class follows a certain density

$$p(x | y=c)$$

- we estimated the parameters

$$\hat{\mu}_1, \hat{\Sigma}_1$$

$$\hat{P}(y=1)$$

$$\dots \dots p(x | y=k)$$

$$\hat{\mu}_k, \hat{\Sigma}_k$$

$$P(y=k)$$

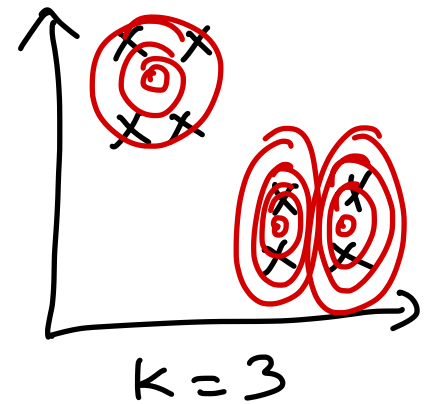
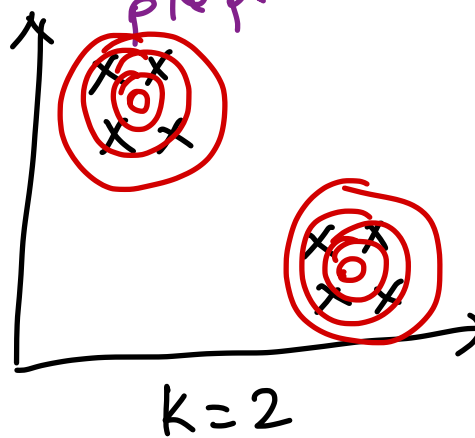
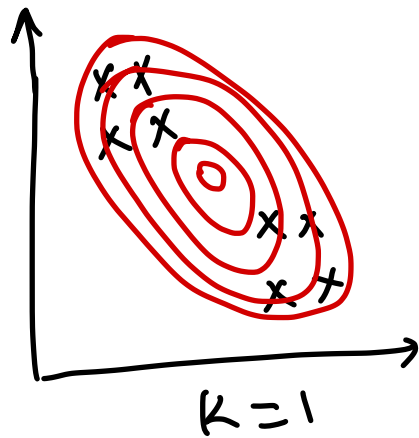
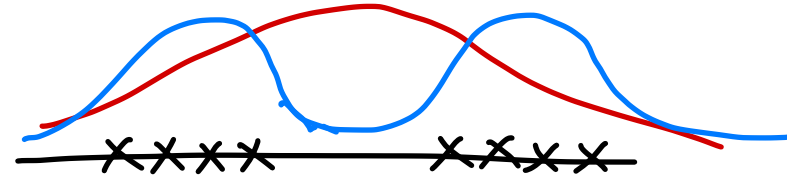
$$\hat{P}(y=k)$$

$$P(y=c | x) = ?$$

Mixture Densities  $K$  different clusters (unknown)

$C_k = \text{cluster \# } k$

$$p(x) = \sum_{k=1}^K \underbrace{p(x | C_k)}_{\text{Component density}} \underbrace{P(C_k)}_{\text{mixture proportions}}$$



$K = \# \text{ of components (clusters) (groups)}$

$$\Phi = \left\{ \hat{P}(C_k), \hat{\mu}_k, \hat{\Sigma}_k \right\}_{k=1}^K$$

$y_{ik} = \begin{cases} 1 & \text{if } x_i \text{ belongs to component / cluster / group } k. \\ 0 & \text{otherwise} \end{cases}$

→ cluster / component / group membership

WE DO NOT KNOW

" $y_{ik}$ " VALUES APRIORI!

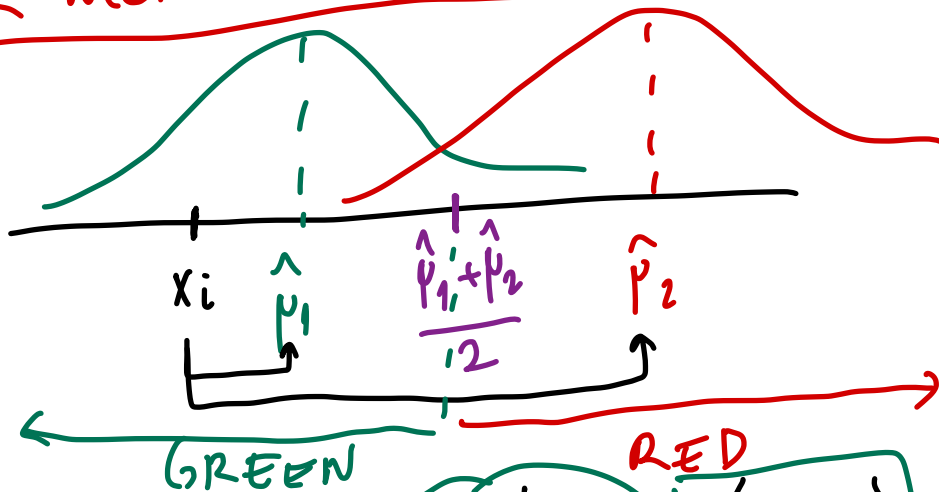
# Iterative Algorithm:

STEP ①: Estimate the cluster memberships ( $\hat{y}_{i:k}$ )

STEP ②: Estimate the parameters.

$$\hat{p}(C_k) = \frac{\sum_{i=1}^N \hat{y}_{i:k}}{N} \quad \hat{\mu}_k = \frac{\sum_{i=1}^N \hat{y}_{i:k} \cdot x_i}{\sum_{i=1}^N \hat{y}_{i:k}} \quad \hat{\Sigma}_k = \frac{\sum_{i=1}^N \hat{y}_{i:k} (x_i - \hat{\mu}_k)(x_i - \hat{\mu}_k)^T}{\sum_{i=1}^N \hat{y}_{i:k}}$$

## K-MEANS CLUSTERING



$$P(y=1|x) = \frac{P(x|y=1)P(y=1)}{p(x)} \approx$$

$$P(y=2|x) = \frac{P(x|y=2)P(y=2)}{p(x)}$$

$$\exp\left[-\frac{(x_i - \hat{\mu}_1)^2}{2\hat{\sigma}_1^2}\right] \cdot \frac{1}{\sqrt{2\pi\hat{\sigma}_1^2}}$$

$$\exp\left[-\frac{(x_i - \hat{\mu}_2)^2}{2\hat{\sigma}_2^2}\right] \cdot \frac{1}{\sqrt{2\pi\hat{\sigma}_2^2}}$$

$$\hat{\sigma}_1^2 = \hat{\sigma}_2^2$$

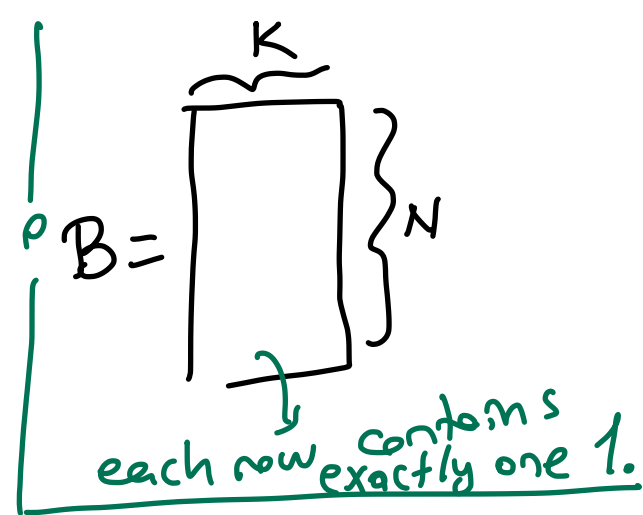
$$\|x_i - \hat{\mu}_1\|_2 \quad \|x_i - \hat{\mu}_2\|_2 \quad \dots \quad \|x_i - \hat{\mu}_k\|_2$$

assume that 2nd distance is minimum.

$$\hat{y}_{i:1}=0 \quad \hat{y}_{i:2}=1 \quad \hat{y}_{i:3}=0 \quad \dots \quad \hat{y}_{i:k}=0$$

$$\text{Error} = \sum_{i=1}^N \sum_{k=1}^K \underbrace{b_{ik}}_{?} \|x_i - \underbrace{\hat{\mu}_k}_{?}\|_2^2$$

$$b_{ik} = \begin{cases} 1 & \text{if } \|x_i - \hat{\mu}_k\|_2 = \min_{c=1}^K \|x_i - \hat{\mu}_c\|_2 \\ 0 & \text{otherwise} \end{cases}$$



MIP  $\left[ \begin{array}{l} \text{minimize } \sum_{i=1}^N \sum_{k=1}^K b_{ik} \|x_i - \hat{\mu}_k\|_2^2 \\ \text{with respect to: } \hat{\mu}_1, \hat{\mu}_2, \dots, \hat{\mu}_K, \{b_{ik}\}_{i=1, k=1}^{N, K} \end{array} \right]$

- Initialize  $\hat{\mu}_1, \hat{\mu}_2, \dots, \hat{\mu}_K$  randomly

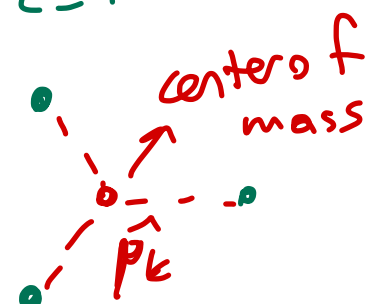
- Repeat  $\xrightarrow{\text{E-STEP } a \rightarrow}$  for all  $x_i$ :  

$$b_{ik} = \begin{cases} 1 & \text{if } \|x_i - \hat{\mu}_k\|_2 = \min_{c=1}^K \|x_i - \hat{\mu}_c\|_2 \\ 0 & \text{otherwise} \end{cases}$$

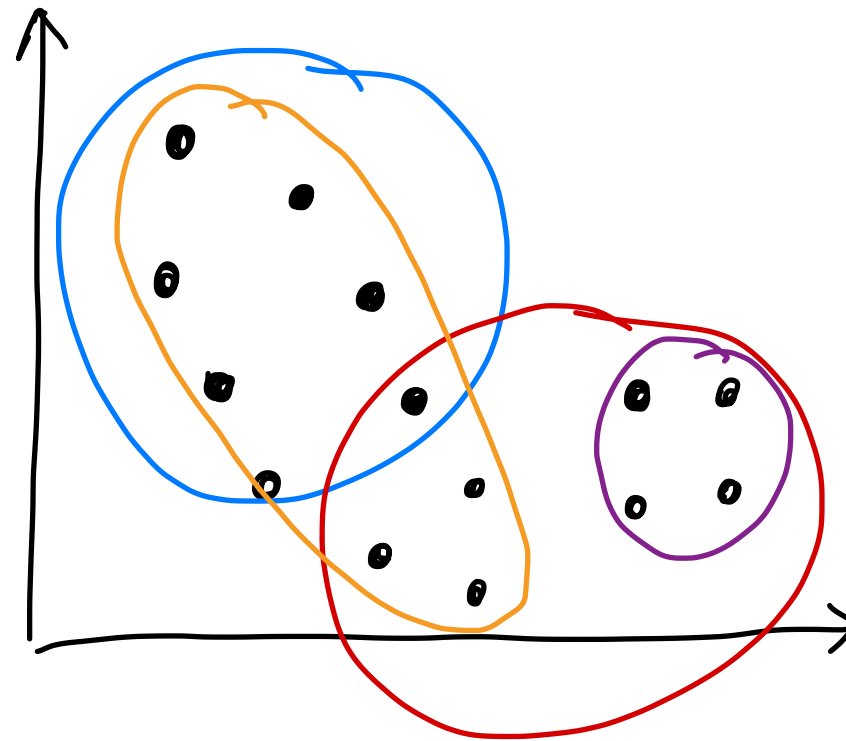
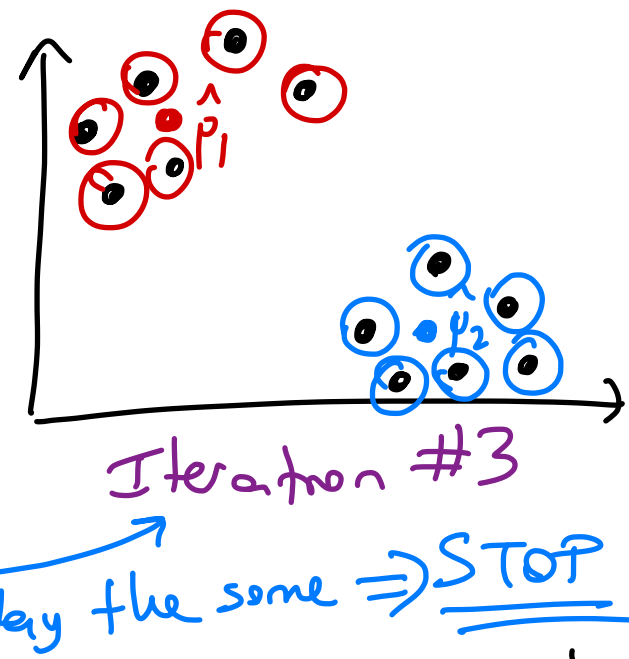
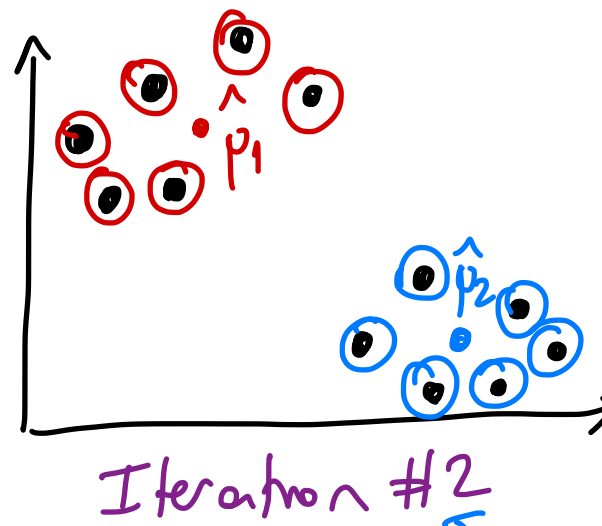
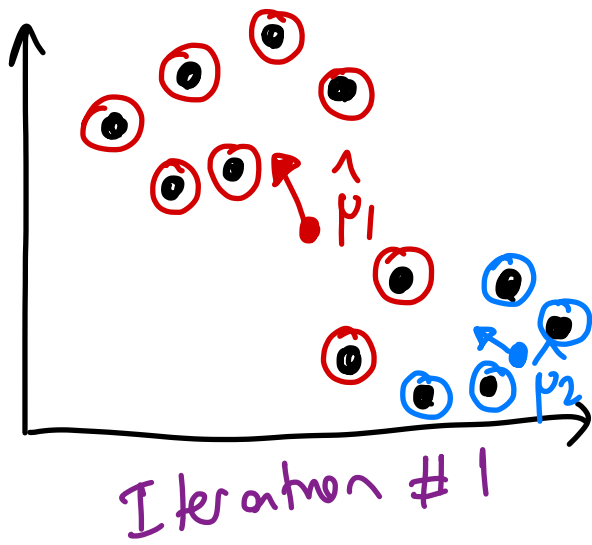
$\xrightarrow{\text{M-STEP } b \rightarrow}$  for all  $\hat{\mu}_k$ :  

$$\hat{\mu}_k = \frac{\sum_{i=1}^N b_{ik} x_i}{\sum_{i=1}^N b_{ik}}$$

- Until convergence [all  $b_{ik}$ 's stay the same] or [all  $\hat{\mu}_k$ 's stay the same]



$K=2$



$\left. \begin{array}{l} \text{---} \\ \text{---} \end{array} \right\}$  assumed shared covariance

$\left. \begin{array}{l} \text{---} \\ \text{---} \end{array} \right\}$  assumed different covariances

Expectation - Maximization Algorithm

$$X = \{x_i\}_{i=1}^N$$

$$\log \text{likelihood} \Rightarrow L(\Phi | X) = \log \left[ \prod_{i=1}^N p(x_i | \Phi) \right]$$

$$\log L(\Phi | X) = \sum_{i=1}^N \log \left[ \underbrace{\sum_{k=1}^k p(x_i | C_k) P(C_k)}_{\text{mixture densities}} \right]$$

two sets of random variables

$Z$  = cluster memberships (hidden variables)

$\Phi$  = parameters  $[\hat{\mu}_1, \hat{\mu}_2, \dots, \hat{\mu}_k, \hat{\Sigma}_1, \hat{\Sigma}_2, \dots, \hat{\Sigma}_k]$

E-STEP :  $E[L_c(\Phi | X, Z) | X, \Phi^{(t)}]$

M-STEP :  $\Phi^{(t+1)} = \arg \max_{\Phi} E[L_c(\Phi | X, Z) | X, \Phi^{(t)}]$

E-STEP:



each row sums up to 1.

$$h_{ik} = E[z_{ik} | \mathcal{X}, \Phi^{(+)}] = \frac{p(x_i | C_k, \Phi^{(+)}). P(C_k)}{\sum_{c=1}^K \underbrace{p(x_i | C_c, \Phi^{(+)})}_{\text{multivariate Gaussian}} P(C_c)}$$

$$h_{ik} \geq 0, \sum_{k=1}^K h_{ik} = 1 \quad \forall i$$

M-STEP:

$$\hat{P}(C_k)^{(t+1)} = \frac{\sum_{i=1}^N h_{ik}}{N}$$

$$\hat{\mu}_k^{(t+1)} = \frac{\sum_{i=1}^N h_{ik} \cdot x_i}{\sum_{i=1}^N h_{ik}}$$

$$\hat{\Sigma}_k^{(t+1)} = \frac{\sum_{i=1}^N h_{ik} (x_i - \hat{\mu}_k^{(t+1)}) (x_i - \hat{\mu}_k^{(t+1)})^T}{\sum_{i=1}^N h_{ik}}$$