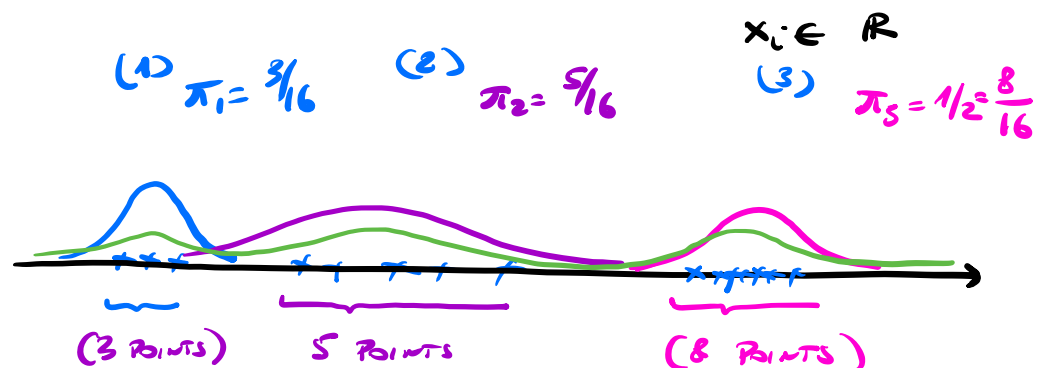


# THE GAUSSIAN MIXTURE MODEL (GMM)

FOR CLUSTERING.



GENERATIVE PROBABILITY MODEL FOR.

THE DATA  $x_i \in \mathbb{R}^d$

$$z_i \in \{1, \dots, K\} \quad K \equiv \# \text{ OF CLUSTERS}$$

$$P(z_i = j) = \pi_j \quad j \in \{1 \dots K\}$$

$$P(x_i | z_i = j) \sim \mathcal{N}(\mu_j, \Sigma_j)$$

GENERATIVE PROCEDURE FOR  $x_i$ .

1. Sample  $z_i \in \{1 \dots K\}$
2. Sample  $x_i$  from  $p(x_i | z_i)$

LET'S COMPUTE THE PROBABILISTIC  
DESCRIPTION OF  $x_i$

$$\begin{aligned} p(x_i) &= \sum_{j=1}^k \underbrace{p(x_i | z_i=j) p(z_i=j)}_{p(x_i, z_i=j)} \\ &= \sum_{j=1}^k \underbrace{p(x_i | z_i=j)}_{\mathcal{N}(\mu_j, \Sigma_j)} \pi_j \end{aligned}$$

- $0 \leq \pi_j \leq 1$
- $\sum_{j=1}^k \pi_j = 1$

### ASSUMPTIONS

$\{x_i\}_{i \in [m]}$  are i.i.d samples

FROM THE UNKNOWN DISTRIBUTION

$$p(x_i) = \sum_{j=1}^k \underbrace{p(x_i | z_i=j)}_{\mu_j, \Sigma_j} \pi_j \quad (1)$$

## PROBLEM # 1

GIVEN DATA  $\{x_i\}_{i \in [m]}$  ESTIMATE  
THE PARAMETERS (UNKNOWN) OF MODEL (1)  
THAT IS  $\Theta = \{\mu_j, \Sigma_j, \pi_j, j=1 \dots K\}$

## PROBLEM # 2

ASSUME  $\Theta$  IS FIXED AND KNOWN.

AND GIVEN A NEW DATA POINT  $x$   
"DECIDE" TO WHICH CLUSTER  $x$  BELONGS TO



GIVEN  $\Theta$  WE KNOW:

$$p(x|z=j) \quad \text{AND} \quad p(z=j) = \pi_j$$

! CAN COMPUTE

$$p(z=j|x) = \frac{p(x|z=j)p(z=j)}{\underbrace{p(x)}_{\text{CAN BE COMPUTED}}}$$

FOR ANY  $x$   
WHEN  $\theta$  IS KNOWN.

## BACK TO PROBLEM 1

SOLVE BY MAXIMUM LIKELIHOOD.

$$\hat{\theta}_{ML} = \arg \max_{\theta \in \Theta} \underbrace{P_{\theta}(x_1 x_2 \dots x_m)}_{\prod_{i=1}^m \underbrace{P_{\theta}(x_i)}_{= (1)}}$$

WE WANT TO INTRODUCE AN ITERATIVE  
PROCEDURE THAT PRODUCES A SEQUENCE  
OF ESTIMATORS  $\hat{\theta}^{(k)}$   $k=1, 2, \dots$

SO THAT (HOPEFULLY)

$$\lim_{k \rightarrow \infty} \hat{\theta}^{(k)} = \hat{\theta}_{ML}$$

WARNING: WE WILL ONLY BE  
ABLE TO PRODUCE A SEQUENCE

$$\hat{\theta}^{(k)}$$

THAT CONVERGES TO

A LOCAL MAXIMUM OF  $P_{\theta}(x_1, x_2, \dots, x_m)$

THE PROCEDURE WE INTRODUCED IS  
CALLED THE EM - ALGORITHM.

EM  $\equiv$  EXPECTATION  
MAXIMIZATION

REMARK: IF WE ALSO KNEW ALL  
THE (HIDDEN) VARIABLES  
 $z_1 \dots z_m$  THEN THE PROBLEM.

$$\hat{\theta} = \arg \max \log P_{\theta}(x_1, z_1, x_2, z_2, \dots, x_m, z_m)$$

IDEA: CONSTRUCT AN ESTIMATE  
OF  $\log P_{\theta}(x_1, z_1, \dots, x_m, z_m)$

□



(2)  $\rightarrow$

$$Q(\theta, \hat{\theta}^{(k)}) = \mathbb{E}_{\substack{p_{\hat{\theta}^{(k)}}(\underline{z} | \underline{x})}} \log p_{\theta}(x_1, z_1, \dots, x_m, z_m) + c$$

↑  
THAT  
DOES NOT  
DEPEND ON

$\theta$

Numbers that  
we can compute

$$= \sum_{z_1=1}^k \dots \sum_{z_m=1}^k \log p_{\theta}(x_1, z_1, \dots, x_m, z_m) \cdot \underbrace{p_{\hat{\theta}^{(k)}}(z_1 | x_1) \dots p_{\hat{\theta}^{(k)}}(z_m | x_m)}_{\text{Numbers that we can compute}}$$

$$z_i \in \{1 \dots k\}$$

THE STEPS OF EM ARE:

INITIALIZATION      FIX  $\hat{\theta}^{(0)}$

FOR  $k = 1, 2, \dots$

(1) COMPUTE

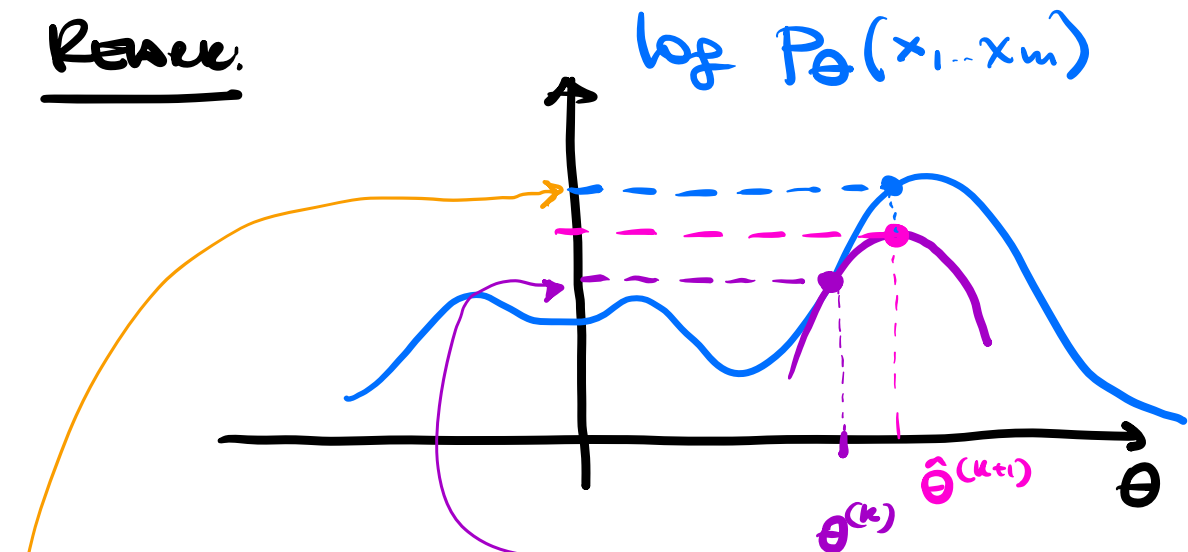
$$Q(\theta, \hat{\theta}^{(k-1)}) \quad \text{AS IN (2)}$$

(EXPECTATION STEP)

$$(2) \quad \hat{\theta}^{(k)} = \arg \max_{\theta} Q(\theta, \hat{\theta}^{(k-1)})$$

MAXIMIZATION STEP

Recall:



$$Q(\theta, \hat{\theta}^{(k)}) \leq \log P_{\theta}(x_1 \dots x_m) + c$$

$$Q(\hat{\theta}^{(k+1)}, \hat{\theta}^{(k)}) = \log P_{\hat{\theta}^{(k+1)}}(x_1 \dots x_m) + c$$

$\Downarrow$

$$\log P_{\hat{\theta}^{(k+1)}}(x_1 \dots x_m)$$

$$\geq \log P_{\hat{\theta}^{(k)}}(x_1 \dots x_m)$$