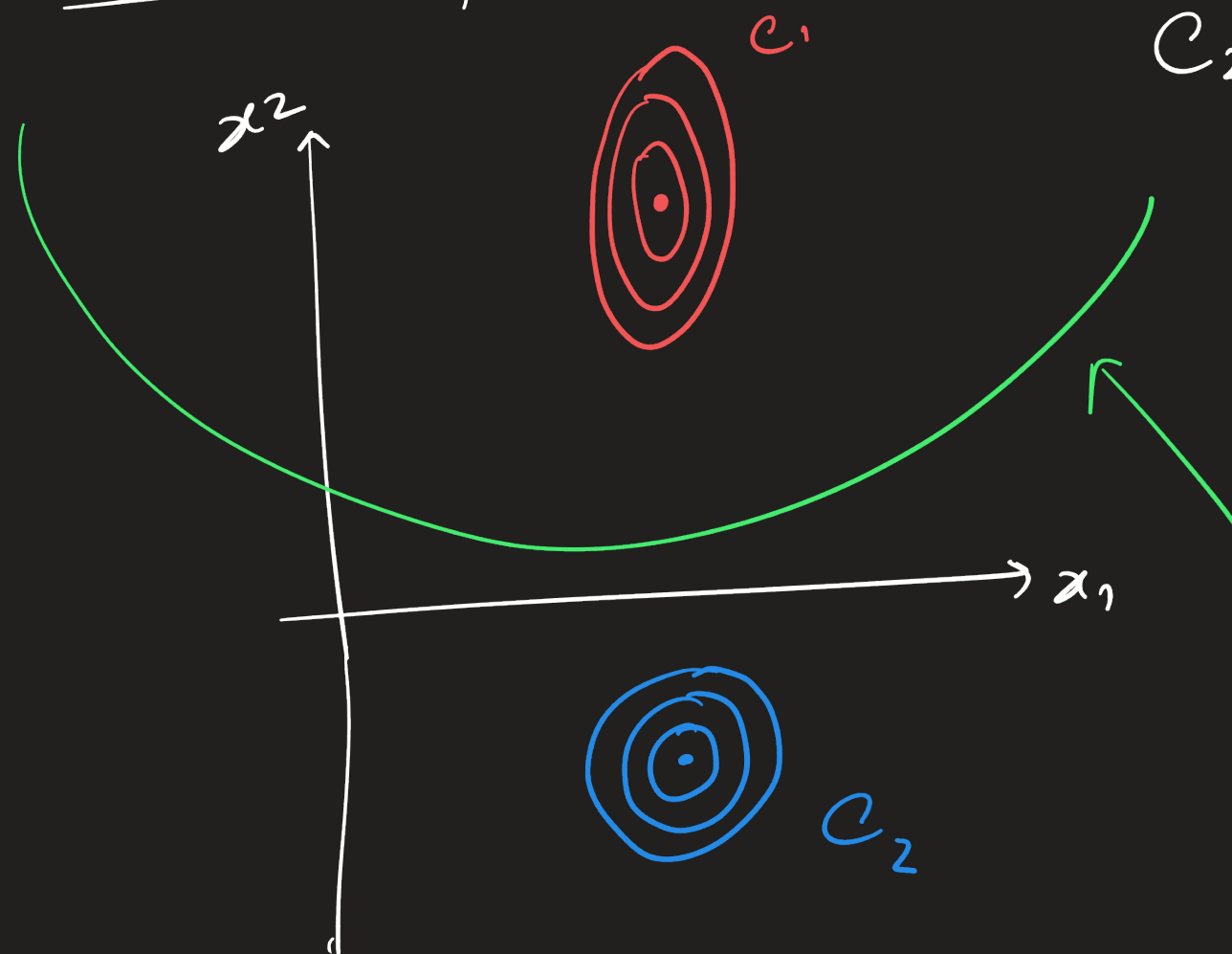


Two-class problem



$$C_1 \sim G(\mu_1, \Sigma_1)$$

$$C_2 \sim G(\mu_2, \Sigma_2)$$

$$P(C_1) = P(C_2) = \frac{1}{2}$$

discriminant
function
 $g(x)$

$$\frac{P(C_1|x)}{P(C_2|x)} > 1, \quad x \in C_1$$

otherwise $x \in C_2$

$$\frac{\frac{P(x|C_1) \cdot P(C_1)}{\cancel{P(x)}}}{\frac{P(x|C_2) \cdot P(C_2)}{\cancel{P(x)}}} > 1$$

$$\frac{P(x|C_1) \cdot P(C_1)}{P(x|C_2) \cdot P(C_2)} > 1$$

$$\ln \left(\frac{P(x|C_1) \cdot P(C_1)}{P(x|C_2) \cdot P(C_2)} \right) > \ln(1)$$

$y(x) \equiv$ discriminant function.

$$\underbrace{\ln(P(x|C_1) \cdot P(C_1))}_{g_1(x)} - \underbrace{\ln(P(x|C_2) \cdot P(C_2))}_{g_2(x)} > 0$$

$$\underbrace{g_1(x) - g_2(x)}_{y(x)}$$

$$P(x|C_1) = \frac{1}{(2\pi)^{d/2} |\Sigma_1|} \cdot \exp \left\{ -\frac{1}{2} (x - \mu_1)^T \Sigma_1^{-1} (x - \mu_1) \right\}$$

$$\mu_1 = \begin{bmatrix} 3 \\ 6 \end{bmatrix}, \Sigma_1 = \begin{bmatrix} 1/2 & 0 \\ 0 & 2 \end{bmatrix}, |\Sigma_1| = \frac{1}{2} \times 2 = 1, \Sigma_1^{-1} = \frac{1}{|\Sigma_1|} \begin{bmatrix} 2 & 0 \\ 0 & 1/2 \end{bmatrix} = \begin{bmatrix} 2 & 0 \\ 0 & 1/2 \end{bmatrix}$$

$$\mu_2 = \begin{bmatrix} 3 \\ -2 \end{bmatrix}, \Sigma_2 = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}, |\Sigma_2| = 4, \Sigma_2^{-1} = \begin{bmatrix} 1/2 & 0 \\ 0 & 1/2 \end{bmatrix}$$

$$P(C_1) = P(C_2) = \frac{1}{2}$$

$$g_1(x) = \ln(P(x|C_1) \cdot P(C_1))$$

$$= -\frac{d}{2} \cdot \ln(2\pi) - \frac{1}{2} \cdot 1 - \frac{1}{2} \left\{ \begin{bmatrix} x_1 - 3 \\ x_2 - 6 \end{bmatrix}^T \begin{bmatrix} 2 & 0 \\ 0 & 1/2 \end{bmatrix} \begin{bmatrix} x_1 - 3 \\ x_2 - 6 \end{bmatrix} \right\} + \ln$$

$d=2$
features

$$= -\ln(2\pi) - \frac{1}{2} + \ln\left(\frac{1}{2}\right) - \frac{1}{2} \left(2(x_1 - 3)^2 + \frac{1}{2}(x_2 - 6)^2 \right)$$

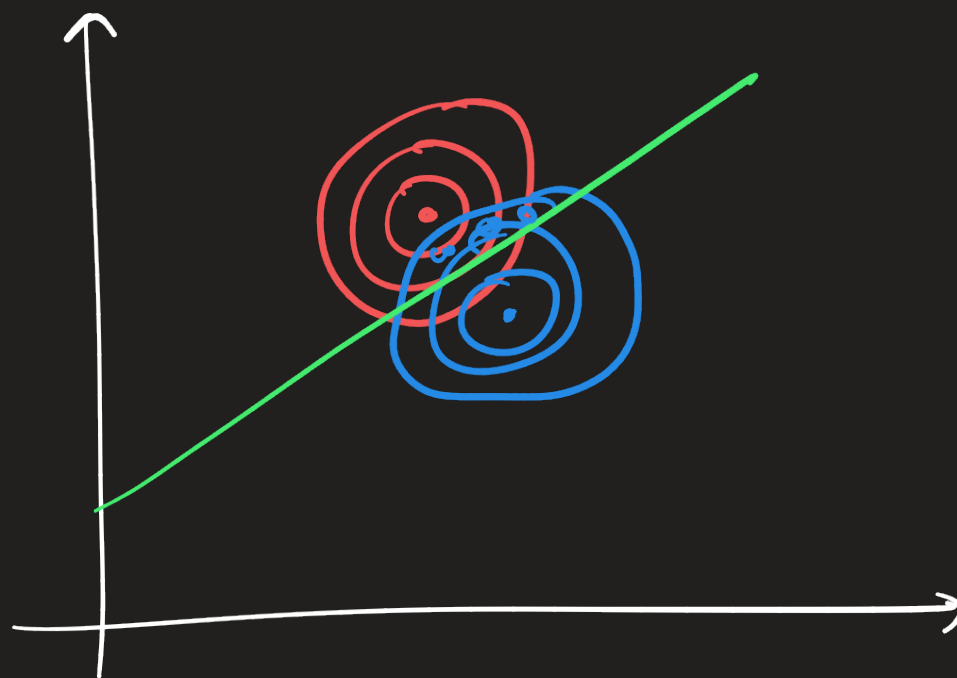
Repeat for $g_2(x) = \ln(P(x|C_2) \cdot P(C_2))$. EXERCISE

$$y(x) = g_1(x) - g_2(x)$$

Simplify to: (EXERCISE)

$$x_2 - 0.1875 \cdot x_1^2 + 1.125 \cdot x_1 - 3.514 = 0$$

$\nearrow c_1$
 $\searrow c_2$



$$\Sigma_1 = \Sigma_2$$

Mixture Model

hyperparameter

$$P(x|\theta) = \sum_{k=1}^K \pi_k \cdot P_k(x|\theta_k)$$

where $\sum_{k=1}^K \pi_k = 1$

and $0 \leq \pi_k \leq 1$

$\theta \equiv$ parameters
of the mixture
model

$K \equiv$ # components
in the mixture

$\pi_k \equiv$ weight for k^{th}
component

$P_k \equiv$ probabilistic
model for
 k^{th} component

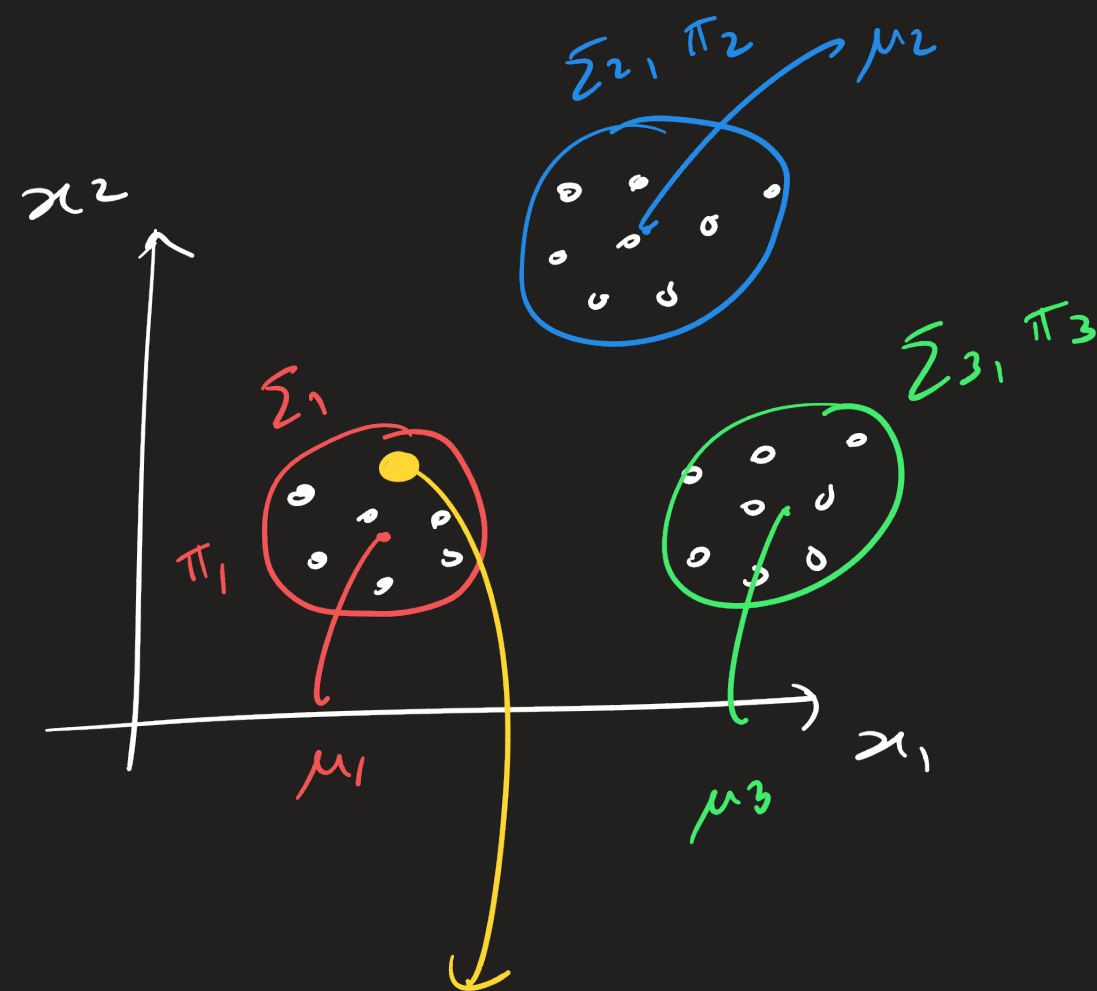
Gaussian Mixture Model (GMM)

$$P(x|\theta) = \sum_{k=1}^K \pi_k \cdot G(x|\mu_k, \Sigma_k)$$

$$\theta = \left\{ \pi_k, \mu_k, \Sigma_k \right\}_{k=1}^K$$

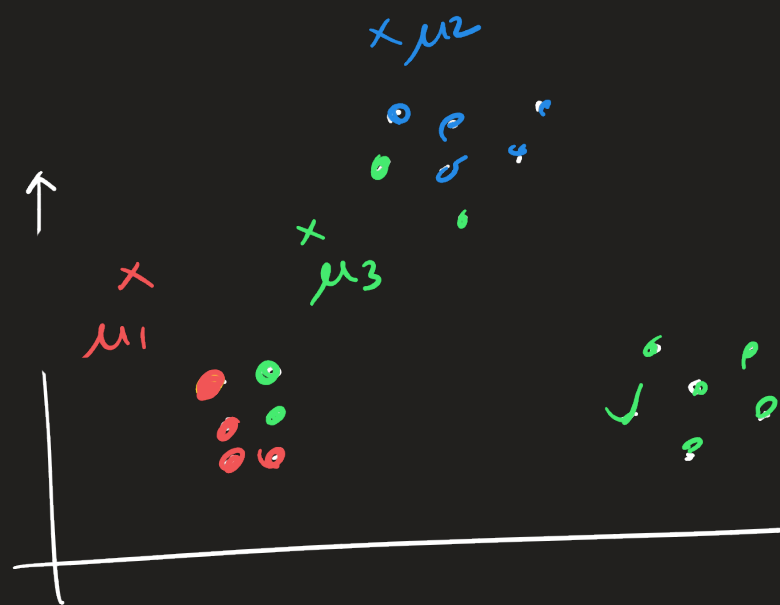
where $\sum_{k=1}^K \pi_k = 1$

and $0 \leq \pi_k \leq 1$



Each sample is assumed to
have been modeled by one
component.

x_i will be a member of
component k .



①

$$\Sigma_1 = \Sigma_2 = \Sigma_3 = I$$

$$\pi_1 = \pi_2 = \pi_3 = \frac{1}{3}$$

② Memberships for Each sample

$$U = \begin{bmatrix} & & \textcircled{1} \\ & & \\ & & \\ & & \\ & & \\ & & \end{bmatrix}_{N \times K} \rightarrow \frac{P(x_1 | C_3) \cdot \pi_3}{\sum_{j=1}^3 P(x_1 | C_j) \cdot \pi_j}$$

③ Now, fix U . Update the parameters,

$$\theta = \{\mu_k, \Sigma_k, \pi_k\}_{k=1}^K$$

④ go back to step ② until convergence.