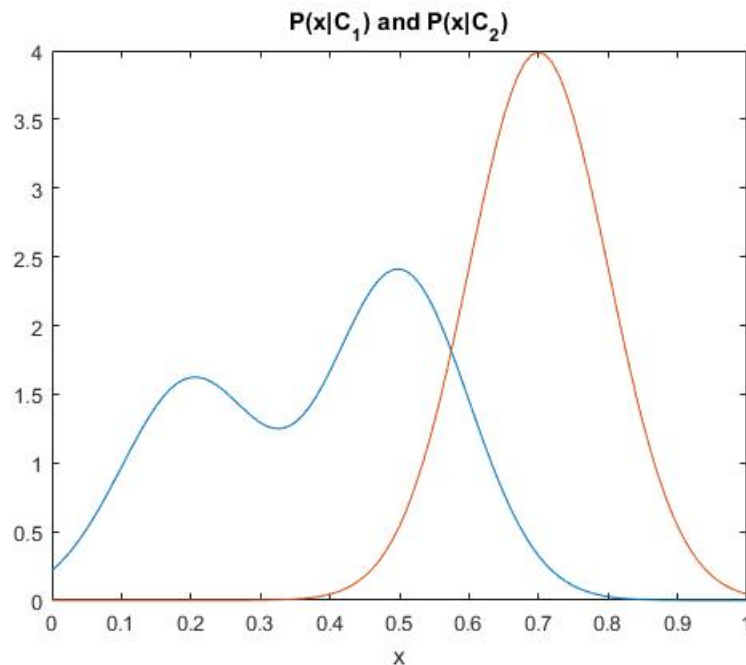


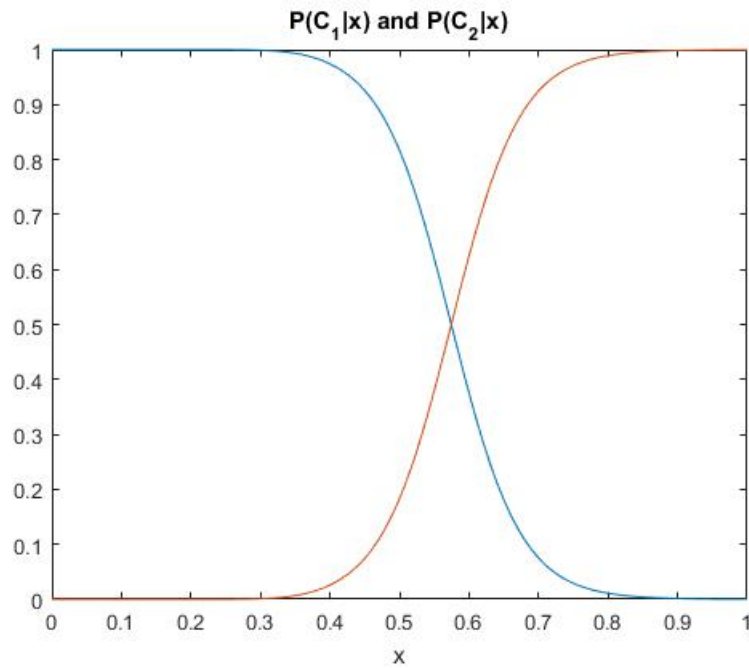
1. More about Discriminative v.s. Generative

Let $p(x|C_1) \sim 0.4\mathcal{N}(0.2, 0.1) + 0.6\mathcal{N}(0.5, 0.1)$. Let $p(x|C_2) \sim \mathcal{N}(0.7, 0.1)$. In MATLAB, plot the two class conditional distribution and find the decision boundary. Let $P(C_1) = P(C_2) = 0.5$, what is the equation to find the posterior distribution for C_1 and C_2 . Find and plot the posterior distribution for C_1 and C_2 .

Find the maximum likelihood decision boundary using both the class conditional distribution and the posterior distribution. Comment on your observation.

Solution:





We notice that the bi-modal shape of the class conditional distribution is lost after we compute the posterior distribution.

2. We are given a training set $\{(x^{(i)}, y^{(i)}); i = \{1, \dots, m\}\}$, where $x^{(i)} \in R^n$ and $y^{(i)} \in \{0, 1\}$. We consider the Gaussian Discriminant Analysis (GDA) model, which models $P(x|y)$ using multivariate Gaussian. Writing out the model, we have:

$$P(y = 1) = \phi = 1 - P(y = 0)$$

$$P(x|y = 0) = \frac{1}{(2\pi)^{n/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu_0)^T \Sigma^{-1}(x - \mu_0)\right)$$

$$P(x|y = 1) = \frac{1}{(2\pi)^{n/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu_1)^T \Sigma^{-1}(x - \mu_1)\right)$$

The log-likelihood of the data is given by:

$$L(\phi, \mu_0, \mu_1, \Sigma) = \ln P(x^{(1)}, \dots, x^{(m)}, y^{(1)}, \dots, y^{(m)}) = \ln \prod_{i=1}^m P(x^{(i)}|y^{(i)})P(y^{(i)}).$$

In this exercise, suppose we already find μ_0 and μ_1 , we want to maximize $L(\phi, \mu_0, \mu_1, \Sigma)$ with respect to Σ .

- (a) Write down the explicit expression for $P(x^{(1)}, \dots, x^{(m)}, y^{(1)}, \dots, y^{(m)})$ and $L(\phi, \mu_0, \mu_1, \Sigma)$.

Solution:

$$P(x^{(1)}, \dots, x^{(m)}, y^{(1)}, \dots, y^{(m)})$$

$$= \prod_{i=1}^m \left[\frac{1 - \phi}{(2\pi)^{n/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x^{(i)} - \mu_0)^T \Sigma^{-1}(x^{(i)} - \mu_0)\right) \right]^{1-y^{(i)}}$$

$$\times \left[\frac{\phi}{(2\pi)^{n/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x^{(i)} - \mu_1)^T \Sigma^{-1}(x^{(i)} - \mu_1)\right) \right]^{y^{(i)}}$$

$$L(\phi, \mu_0, \mu_1, \Sigma)$$

$$= \sum_{i=1}^m \left\{ (1 - y^{(i)}) \left[\ln(1 - \phi) - \frac{n}{2} \ln(2\pi) - \frac{1}{2} \ln(|\Sigma|) - \frac{1}{2}(x^{(i)} - \mu_0)^T \Sigma^{-1}(x^{(i)} - \mu_0) \right] \right.$$

$$\left. + y^{(i)} \left[\ln(\phi) - \frac{n}{2} \ln(2\pi) - \frac{1}{2} \ln(|\Sigma|) - \frac{1}{2}(x^{(i)} - \mu_1)^T \Sigma^{-1}(x^{(i)} - \mu_1) \right] \right\}.$$

- (b) Differentiate $L(\phi, \mu_0, \mu_1, \Sigma)$ with respect to Σ and set it to 0. Show that the maximum likelihood result for Σ is:

$$\Sigma = \frac{1}{m} \sum_{i=1}^m (x^{(i)} - \mu_{y^{(i)}})(x^{(i)} - \mu_{y^{(i)}})^T.$$

Hints: You may use the following properties without proof: $a = \text{Tr}(a)$ for scalar a ; $\text{Tr}(A) + \text{Tr}(B) = \text{Tr}(A + B)$; $\frac{\partial \ln|A|}{\partial A} = A^{-T}$; $\frac{\partial \text{Tr}(A^{-1}B)}{\partial A} = -(A^{-1}BA^{-1})^T$.

Solution: We pick out the terms in $L(\phi, \mu_0, \mu_1, \Sigma)$ and treat other terms as constant:

$$\begin{aligned}
L(\phi, \mu_0, \mu_1, \Sigma) &= -\frac{m}{2} \ln(|\Sigma|) - \frac{1}{2} \sum_{i=1}^m (x^{(i)} - \mu_{y^{(i)}})^T \Sigma^{-1} (x^{(i)} - \mu_{y^{(i)}}) + \text{const} \\
&= -\frac{m}{2} \ln(|\Sigma|) - \frac{1}{2} \sum_{i=1}^m \text{Tr} \left((x^{(i)} - \mu_{y^{(i)}})^T \Sigma^{-1} (x^{(i)} - \mu_{y^{(i)}}) \right) + \text{const} \\
&= -\frac{m}{2} \ln(|\Sigma|) - \frac{1}{2} \sum_{i=1}^m \text{Tr} \left(\Sigma^{-1} (x^{(i)} - \mu_{y^{(i)}}) (x^{(i)} - \mu_{y^{(i)}})^T \right) + \text{const} \\
&= -\frac{m}{2} \ln(|\Sigma|) - \frac{m}{2} \text{Tr} \left(\Sigma^{-1} \frac{1}{m} \sum_{i=1}^m (x^{(i)} - \mu_{y^{(i)}}) (x^{(i)} - \mu_{y^{(i)}})^T \right) + \text{const} \\
&= -\frac{m}{2} \ln(|\Sigma|) - \frac{m}{2} \text{Tr} (\Sigma^{-1} S) + \text{const},
\end{aligned}$$

where

$$S = \frac{1}{m} \sum_{i=1}^m (x^{(i)} - \mu_{y^{(i)}}) (x^{(i)} - \mu_{y^{(i)}})^T.$$

We then take the derivative with respect to Σ and set to 0:

$$-\Sigma^{-T} + (\Sigma^{-1} S \Sigma^{-1})^T = 0.$$

We find $\Sigma = S$ which is the desired result.