

HOMEWORK - 1

Question 1

- ① Let $x \in \mathbb{R}$ be a random variable with mean $E[x] = \mu$. Then, the variance of x ,

$$\begin{aligned} E[(x-\mu)^2] &= E[x^2 - 2x\mu + \mu^2] \\ &= E[x^2] - E[2x\mu] + E[\mu^2] \\ &= E[x^2] - 2\mu \cdot E[x] + E[\mu^2] \\ &= E[x^2] - 2\mu \cdot \mu + \mu^2 \\ &= E[x^2] - 2\mu^2 + \mu^2 \end{aligned}$$

$$\therefore E[(x-\mu)^2] = E[x^2] - \mu^2$$

- ② Let $x \in \mathbb{R}^n$ be an n -dimensional random vector with mean $E[x] = \mu$. Then, the covariance matrix of x ,

$$\begin{aligned} E[(x-\mu)(x-\mu)^T] &= E[x \cdot x^T - \mu x^T - x \mu^T + \mu \mu^T] \\ &= E[x \cdot x^T] - E[\mu x^T] - E[x \mu^T] + E[\mu \mu^T] \\ &= E[x \cdot x^T] - \mu E[x^T] - \mu^T E[x] + \mu \mu^T \\ &= E[x \cdot x^T] - \mu \cdot \mu^T - \mu^T \cdot \mu + \mu \mu^T \\ &= E[x \cdot x^T] - \mu \cdot \mu^T \end{aligned}$$

Question 2

- ① Let the normalization factor be 'N'. Since the pdfs integrate to 1 along the real axis,

$$\therefore P_X(x|L=1) = \int_{-\infty}^{\infty} N \cdot e^{\frac{-|x-a_1|}{b_1}} \cdot dx = 1 \quad \text{for } 1 \in 1, 2 \text{ and } b_1 > 0$$

Due to the modulus involved, the integral is divided as:

$$2 \int_{a_1}^{\infty} N \cdot e^{\frac{-|x-a_1|}{b_1}} \cdot dx = 1$$

$$2N \int_{a_1}^{\infty} e^{\frac{-|x-a_1|}{b_1}} \cdot dx = 1$$

$$2N \left[\frac{1}{-1/b_1} \cdot e^{\frac{-|x-a_1|}{b_1}} \right]_{a_1}^{\infty} = 1$$

$$-2Nb_1 \left[e^{-\infty} - e^0 \right] = 1$$

$$-2Nb_1 [0 - 1] = 1$$

$$\therefore 2Nb_1 = 1$$

$$\therefore N = \frac{1}{2b_1} \Rightarrow P_X(x|L=1) = \frac{1}{2b_1} e^{\frac{-|x-a_1|}{b_1}}$$

- ② The log-likelihood ratio ~~function~~ ~~for the case~~ between class labels 1 and 2 evaluated at a given x ,

$$\lambda(x) = \ln p(x|L=1) - \ln p(x|L=2)$$

$$= \ln \left(\frac{1}{2b_1} \cdot e^{\frac{-|x-a_1|}{b_1}} \right) - \ln \left(\frac{1}{2b_2} \cdot e^{\frac{-|x-a_2|}{b_2}} \right)$$

$$= \ln \left(\frac{1}{2b_1} \right) + \ln \left(e^{\frac{-|x-a_1|}{b_1}} \right) - \ln \left(\frac{1}{2b_2} \right) - \ln \left(e^{\frac{-|x-a_2|}{b_2}} \right)$$

$$l(x) = -\ln(2b_1) - \frac{|x-a_1|}{b_1} + \ln(2b_2) + \frac{|x-a_2|}{b_2}$$

$$l(x) = \ln\left(\frac{b_2}{b_1}\right) + \frac{|x-a_2|}{b_2} - \frac{|x-a_1|}{b_1}$$

③ Log-likelihood-ratio function for the case $a_1=0$, $b_1=1$, $a_2=1$, $b_2=2$ is,

$$l(x) = \ln\left(\frac{b_2}{b_1}\right) + \frac{|x-a_2|}{b_2} - \frac{|x-a_1|}{b_1}$$

$$= \ln\left(\frac{2}{1}\right) + \frac{|x-1|}{2} - \frac{|x-0|}{1}$$

$$= \ln(2) + \frac{|x-1|}{2} - |x|$$

NOTE: Plot of data-set along with its code is on GitHub. The link is:

github.com/nandayvk/Intro-to-Machine-Learning-HW-1

Question 3

For a two-class classification,

$$\frac{P(x|L=1)}{P(x|L=2)} \sum_{D=1}^{D=1} \sum_{D=2}^{D=2} \gamma \text{ --- (1)} \quad \text{where} \quad \gamma = \frac{\lambda_{12} - \lambda_{22}}{\lambda_{21} - \lambda_{11}} \cdot \frac{P(L=2)}{P(L=1)}$$

If $P(L=1) = P(L=2)$, then $\gamma = 1$.

For the given classes, $P(x|L=1) = \frac{1}{b-a}$

and $P(x|L=2) = \frac{1}{t-r}$

Therefore, substituting in (1),

$$\frac{\frac{1}{b-a}}{\frac{1}{t-r}} \sum_{D=1}^{D=1} \sum_{D=2}^{D=2} 1$$

$$\therefore t-r \sum_{D=2}^{D=1} b-a$$

~~Since~~ This is the minimum probability of error classification rule for the given distributions.

Question 4

① Let class 1 have pdf of $\mathcal{N}(0, 1)$ and let class 2 have a pdf of $\mathcal{N}(\mu, \sigma^2)$.

According to the classification rule for a two-class setting,

$$\frac{P(X|L=1)}{P(X|L=2)} \underset{D=2}{\overset{D=1}{>}} \gamma$$

When the classes have equal ^{class}priors, $\gamma = 1$.

Therefore,

$$\frac{P(X|L=1)}{P(X|L=2)} \underset{D=2}{\overset{D=1}{>}} 1$$

$$\begin{aligned} P(X|L=1) &= (2\pi)^{-n/2} |\Sigma|^{-1/2} \cdot e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)} \\ &= (2\pi)^{-n/2} \cdot 1 \cdot e^{-\frac{1}{2}x^T \cdot x} \end{aligned}$$

$$\begin{aligned} P(X|L=2) &= (2\pi)^{-n/2} |\Sigma|^{-1/2} \cdot e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)} \\ &= (2\pi)^{-n/2} \cdot \sigma^{-1} \cdot e^{-\frac{1}{2}(x-\mu)^T \cdot \sigma^{-2} \cdot (x-\mu)} \end{aligned}$$

Therefore, substituting in the classification rule,

$$\frac{(2\pi)^{-n/2} \cdot e^{-\frac{1}{2}x^T \cdot x}}{(2\pi)^{-n/2} \cdot \sigma^{-1} \cdot e^{-\frac{1}{2}(x-\mu)^T \cdot \sigma^{-2} \cdot (x-\mu)}} \underset{D=2}{\overset{D=1}{>}} 1$$

$\therefore e^{-\frac{1}{2}x^T \cdot x} \underset{D=2}{\overset{D=1}{>}} e^{-\frac{1}{2}(x-\mu)^T \cdot \sigma^{-2} \cdot (x-\mu)}$ Therefore, taking $\ln(\log)$ on both sides,

$$-\frac{1}{2} \cdot x^T \cdot x + \ln(\sigma) - \left(-\frac{1}{2}(x-\mu)^T \cdot \sigma^{-2} \cdot (x-\mu)\right) \underset{D=2}{\overset{D=1}{>}} 0$$

$$\therefore \ln(\sigma) - \frac{1}{2} \left(x^T \cdot x + \frac{(x-\mu)^T (x-\mu)}{\sigma^2} \right) \underset{D=2}{\overset{D=1}{>}} 0$$

$$\therefore \ln(\sigma) \approx \sum_{D=2}^{D=1} \frac{\sigma^2 \cdot x^T \cdot x + (x-\mu)^T (x-\mu)}{2\sigma^2}$$

$$\therefore 2\sigma^2 \ln(\sigma) \sum_{D=2}^{D=1} \sigma^2 \cdot x^T \cdot x + (x-\mu)^T (x-\mu)$$

Question 5

① Given: $x = Az + b$

$$A \in \mathbb{R}^{n \times m}, b \in \mathbb{R}^n, z \sim \mathcal{N}(0, I)$$

$$\begin{aligned} E[x] &= E[Az + b] \\ &= E[Az] + E[b] \\ &= A E[z] + b \\ &= A \cdot (0) + b \\ E[x] &= b = \mu_x \end{aligned}$$

$$\text{Var}[x] = \text{Var}[Az + b]$$

$$\text{Var}[x] = E[(x - \mu)(x - \mu)^T]$$

$$\begin{aligned} &= E[(Az + b - \mu_x)(Az + b - \mu_x)^T] \\ &= E[(Az + b - b)(Az + b - b)^T] \\ &= E[(Az)(Az)^T] \\ &= A \cdot E[z \cdot z^T] \cdot A^T \\ &= A \sum_z A^T \\ &= A I A^T \end{aligned}$$

$$\text{Var}[x] = AA^T = \cancel{\sigma_x^2} \sigma_x^2$$

$$\therefore x \sim \mathcal{N}(\mu_x, \sigma_x^2)$$

$$\therefore x \sim \mathcal{N}(b, AA^T)$$

② Let $x = Az + b \Rightarrow z = A^{-1}(x - b)$

$$\therefore \frac{\partial x}{\partial z} = A$$

We know that, while transforming from one PDF to another,

$$P_x(x) = \frac{P_z(z)}{\left| \frac{\partial x}{\partial z} \right|} = \frac{1}{|A|} \cdot (2\pi)^{-n/2} \cdot |\Sigma|^{-1/2} e^{-\frac{1}{2}(z-M)^T \Sigma^{-1}(z-M)}$$

Substituting value of z in eqn.,

$$\begin{aligned} P_x(x) &= \frac{1}{|A|} \cdot (2\pi)^{-n/2} \cdot |\Sigma_z|^{-1/2} \cdot e^{-\frac{1}{2}(A^{-1}(x-b) - \mu_z)^T \Sigma_z^{-1}(A^{-1}(x-b) - \mu_z)} \\ &= \frac{1}{|A|} \cdot (2\pi)^{-n/2} \cdot |\Sigma_z|^{-1/2} \cdot e^{-\frac{1}{2}(x-b - \frac{\mu_z}{A^{-1}})^T (A^{-1})^T \Sigma_z^{-1} (A^{-1})(x-b - \frac{\mu_z}{A^{-1}})} \\ &= \frac{1}{|A|} \cdot (2\pi)^{-n/2} \cdot |\Sigma_z|^{-1/2} \cdot e^{-\frac{1}{2}(x-b - A\mu_z)^T (A^T \Sigma_z A)^{-1} (x-b - A\mu_z)} \end{aligned}$$

Comparing with PDF of x , we can

$$P_x(x) = (2\pi)^{-n/2} \cdot |\Sigma|^{-1/2} \cdot e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)}$$

we can see that, $b + A\mu_z = \mu$ and $A\Sigma_z A^T = \Sigma$

$$\Rightarrow A = \frac{\mu - b}{\mu_z} \quad \text{or}$$

$$\Rightarrow b = \mu - A\mu_z$$