

## HW3

**Q3:**

**Parts A, C and D)**

**Answer:**

(a)  $p(\omega_i|\mathbf{x}) = \frac{p(\mathbf{x}|\omega_i)P(\omega_i)}{p(\mathbf{x})}$ . Since  $P(\omega_1) = P(\omega_2) = P(\omega_3) = 1/3$ , we just need to compare the likelihood  $p(\mathbf{x}|\omega_i)$ .

$$\begin{aligned} p(\mathbf{x}|\omega_1) &= \frac{1}{2\pi} \exp\left[-\frac{1}{2}[0.3, 0.3][0.3, 0.3]^t\right] = 0.1455 \\ p(\mathbf{x}|\omega_2) &= \frac{1}{2\pi} \exp\left[-\frac{1}{2}[-0.7, -0.7][-0.7, -0.7]^t\right] = 0.0975 \end{aligned}$$

$$\begin{aligned} p(\mathbf{x}|\omega_3) &= \frac{1}{4\pi} \exp\left[-\frac{1}{2}[-0.2, -0.2][-0.2, -0.2]^t\right] \\ &\quad + \frac{1}{4\pi} \exp\left[-\frac{1}{2}[0.8, -0.2][0.8, -0.2]^t\right] \\ &= 0.1331 \end{aligned}$$

Since  $p(\mathbf{x}|\omega_1)$  is the largest likelihood,  $\mathbf{x}$  is classified to be from class 1.

(b) Assume that  $\mathbf{x} = [x_1, x_2]^t$ ,

$$p(\omega_i|x_2) = \frac{\int p(x_1, x_2|\omega_i)P(\omega_i)dx_1}{p(x_2)}$$

Still since  $P(\omega_1) = P(\omega_2) = P(\omega_3) = 1/3$ , we just need to compare  $\int p(x_1, x_2|\omega_i)dx_1$ .

$$\begin{aligned} \int p(x_1, x_2|\omega_1)dx_1 &= \frac{1}{2\pi} \int \exp\left[-\frac{1}{2}(x_1^2 + 0.09)\right] dx_1 \\ &= \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{0.09}{2}\right) = 0.3813 \\ \int p(x_1, x_2|\omega_2)dx_1 &= \frac{1}{2\pi} \int \exp\left[-\frac{1}{2}((x_1 - 1)^2 + 0.49)\right] dx_1 \\ &= \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{0.49}{2}\right) = 0.3122 \\ \int p(x_1, x_2|\omega_3)dx_1 &= \frac{1}{4\pi} \int \exp\left[-\frac{1}{2}((x_1 - 0.5)^2 + 0.04)\right] dx_1 \\ &\quad + \frac{1}{4\pi} \int \exp\left[-\frac{1}{2}((x_1 + 0.5)^2 + 0.04)\right] dx_1 \\ &= \frac{1}{2\sqrt{2\pi}} \exp\left(-\frac{0.04}{2}\right) + \frac{1}{2\sqrt{2\pi}} \exp\left(-\frac{0.04}{2}\right) \\ &= 0.3910 \end{aligned}$$

Thus  $\mathbf{x}$  is classified to be from class 3.

(c) Still  $\mathbf{x} = [x_1, x_2]^t$ ,

$$p(\omega_i|x_1) = \frac{\int p(x_1, x_2|\omega_i)P(\omega_i)dx_2}{p(x_1)}$$

We need to compare  $\int p(x_1, x_2|\omega_i)dx_2$ .

$$\begin{aligned}\int p(x_1, x_2|\omega_1)dx_2 &= \frac{1}{2\pi} \int \exp\left[-\frac{1}{2}(x_2^2 + 0.09)\right] dx_2 \\ &= \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{0.09}{2}\right) = 0.3813 \\ \int p(x_1, x_2|\omega_2)dx_2 &= \frac{1}{2\pi} \int \exp\left[-\frac{1}{2}((x_2 - 1)^2 + 0.49)\right] dx_2 \\ &= \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{0.49}{2}\right) = 0.3122 \\ \int p(x_1, x_2|\omega_3)dx_2 &= \frac{1}{4\pi} \int \exp\left[-\frac{1}{2}((x_2 - 0.5)^2 + 0.04)\right] dx_2 \\ &\quad + \frac{1}{4\pi} \int \exp\left[-\frac{1}{2}((x_2 - 0.5)^2 + 0.64)\right] dx_2 \\ &= \frac{1}{2\sqrt{2\pi}} \exp\left(-\frac{0.04}{2}\right) + \frac{1}{2\sqrt{2\pi}} \exp\left(-\frac{0.64}{2}\right) \\ &= 0.3403\end{aligned}$$

$x$  belongs to class 1.

Part B) Bayes Error =  $\frac{1}{3}(0.097) + \frac{1}{3}(0.133) = 0.077$

#### Q4:

##### Part A.

In general:  $(M_2 - M_1)^T \Sigma^{-1} X + \frac{1}{2}(M_1^T \Sigma^{-1} M_1 - M_2^T \Sigma^{-1} M_2) \geq_{w_2}^{w_1} \ln \frac{P_2(\lambda_{21} - \lambda_{22})}{P_1(\lambda_{12} - \lambda_{11})}$  if  $P_2 = P_1 = \frac{1}{2}$ :

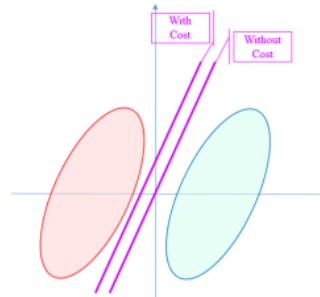
$$[-2 \ 0]^T \frac{4}{3} \begin{bmatrix} 1 & -0.5 \\ -0.5 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \frac{1}{2} \left( [1 \ 0]^T \frac{4}{3} \begin{bmatrix} 1 & -0.5 \\ -0.5 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} - [-1 \ 0]^T \frac{4}{3} \begin{bmatrix} 1 & -0.5 \\ -0.5 & 1 \end{bmatrix} \begin{bmatrix} -1 \\ 0 \end{bmatrix} \right) = 0$$

$$\frac{4}{3}(-2x_1 + x_2) + \frac{1}{2} \left( \frac{4}{3} - \frac{4}{3} \right) = 0 \rightarrow 2x_1 = x_2,$$

Part B. considering cost:  $\frac{4}{3}(-2x_1 + x_2) = \ln \frac{1}{2} = -0.7 \rightarrow 2x_1 - 0.5 = x_2$

The borders are given in this image:

Blue is class  $w_1$  and red is class  $w_2$ .



##### Part C.

$$\text{Bayes Error} = \frac{1}{2}(2\lambda_{21}) \int \int N(M_1, \Sigma) dX + \frac{1}{2}(\lambda_{21}) \int \int N(M_2, \Sigma) dX$$

**Q5:**

**Part A)**

$$p(x|w_1) = \frac{1}{\sqrt{2\pi}\sigma_n^2} \exp\left(-\frac{1}{2}x^t\Sigma_1^{-1}x\right) = \frac{1}{\sqrt{2\pi}\sigma_n^2} \exp\left(-\frac{1}{2\sigma_n^4}[x_1 \ x_2] \begin{bmatrix} \sigma_n^2 & 0 \\ 0 & \sigma_n^2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right) = \frac{1}{\sqrt{2\pi}\sigma_n^2} \exp\left(-\frac{1}{2\sigma_n^4}(x_1^2\sigma_n^2 + x_2^2\sigma_n^2)\right) =$$

$$p(x|w_2) = \frac{1}{\sqrt{2\pi\sigma_n^2(\sigma_n^2+\sigma_s^2)}} \exp\left(-\frac{1}{2}x^t\Sigma_2^{-1}x\right) = \frac{1}{\sqrt{2\pi\sigma_n^2(\sigma_n^2+\sigma_s^2)}} \exp\left(-\frac{1}{2\sigma_n^2(\sigma_n^2+\sigma_s^2)}[x_1 \ x_2] \begin{bmatrix} \sigma_n^2 & 0 \\ 0 & \sigma_n^2 + \sigma_s^2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right) =$$

$$\frac{1}{\sqrt{2\pi\sigma_n^2(\sigma_n^2+\sigma_s^2)}} \exp\left(-\frac{1}{2\sigma_n^2(\sigma_n^2+\sigma_s^2)}(x_1^2\sigma_n^2 + x_2^2(\sigma_n^2 + \sigma_s^2))\right)$$

$$p(x|w_3) = \frac{1}{\sqrt{2\pi\sigma_n^2(\sigma_n^2+\sigma_s^2)}} \exp\left(-\frac{1}{2}x^t\Sigma_3^{-1}x\right) = \frac{1}{\sqrt{2\pi\sigma_n^2(\sigma_n^2+\sigma_s^2)}} \exp\left(-\frac{1}{2\sigma_n^2(\sigma_n^2+\sigma_s^2)}[x_1 \ x_2] \begin{bmatrix} \sigma_n^2 + \sigma_s^2 & 0 \\ 0 & \sigma_n^2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right) =$$

$$\frac{1}{\sqrt{2\pi\sigma_n^2(\sigma_n^2+\sigma_s^2)}} \exp\left(-\frac{1}{2\sigma_n^2(\sigma_n^2+\sigma_s^2)}(x_1^2(\sigma_n^2 + \sigma_s^2) + x_2^2\sigma_n^2)\right)$$

$$e_1 = \lambda_{11}p(w_1)p(x|w_1) + \lambda_{12}p(w_2)p(x|w_2) + \lambda_{13}p(w_3)p(x|w_3) = pp(x|w_2) + (1-2p)p(x|w_3)$$

$$e_2 = \lambda_{21}p(w_1)p(x|w_1) + \lambda_{22}p(w_2)p(x|w_2) + \lambda_{23}p(w_3)p(x|w_3) = pp(x|w_1) + a(1-2p)p(x|w_3)$$

$$e_2 = \lambda_{31}p(w_1)p(x|w_1) + \lambda_{32}p(w_2)p(x|w_2) + \lambda_{33}p(w_3)p(x|w_3) = pp(x|w_1) + app(x|w_2)$$

$w_1$  vs.  $w_2, w_3$ :

$$e_1 < e_2: pp(x|w_2) + (1-2p)p(x|w_3) < pp(x|w_1) + a(1-2p)p(x|w_3):$$

$$\frac{\textcolor{violet}{p}}{\sqrt{2\pi\sigma_n^2(\sigma_n^2+\sigma_s^2)}} \exp\left(-\frac{1}{2\sigma_n^2(\sigma_n^2+\sigma_s^2)}(x_1^2\sigma_n^2 + x_2^2(\sigma_n^2 + \sigma_s^2))\right)$$

$$+ \frac{1-2p}{\sqrt{2\pi\sigma_n^2(\sigma_n^2+\sigma_s^2)}} \exp\left(-\frac{1}{2\sigma_n^2(\sigma_n^2+\sigma_s^2)}(x_1^2(\sigma_n^2 + \sigma_s^2) + x_2^2\sigma_n^2)\right)$$

$$< \frac{\textcolor{violet}{p}}{\sqrt{2\pi\sigma_n^2}} \exp\left(-\frac{1}{2\sigma_n^2}(x_1^2 + x_2^2)\right) + \frac{a(1-2p)}{\sqrt{2\pi\sigma_n^2(\sigma_n^2+\sigma_s^2)}} \exp\left(-\frac{1}{2\sigma_n^2(\sigma_n^2+\sigma_s^2)}(x_1^2(\sigma_n^2 + \sigma_s^2) + x_2^2\sigma_n^2)\right)$$

Use natural logarithm:

$$\ln \textcolor{violet}{a} - \frac{1}{2\sigma_n^2(\sigma_n^2+\sigma_s^2)}(x_1^2\sigma_n^2 + x_2^2(\sigma_n^2 + \sigma_s^2)) + \ln \textcolor{blue}{b} - \frac{1}{2\sigma_n^2(\sigma_n^2+\sigma_s^2)}(x_1^2(\sigma_n^2 + \sigma_s^2) + x_2^2\sigma_n^2)$$

$$< \ln \textcolor{teal}{c} - \frac{1}{2\sigma_n^2}(x_1^2 + x_2^2) + \ln \textcolor{brown}{d} - \frac{1}{2\sigma_n^2(\sigma_n^2+\sigma_s^2)}(x_1^2(\sigma_n^2 + \sigma_s^2) + x_2^2\sigma_n^2)$$

$$2\sigma_n^2(\sigma_n^2 + \sigma_s^2) \ln a - (x_1^2\sigma_n^2 + x_2^2(\sigma_n^2 + \sigma_s^2)) + 2\sigma_n^2(\sigma_n^2 + \sigma_s^2) \ln b - (x_1^2(\sigma_n^2 + \sigma_s^2) + x_2^2\sigma_n^2)$$

$$< 2\sigma_n^2(\sigma_n^2 + \sigma_s^2) \ln c - (\sigma_n^2 + \sigma_s^2)(x_1^2 + x_2^2) + 2\sigma_n^2(\sigma_n^2 + \sigma_s^2) \ln d - (x_1^2(\sigma_n^2 + \sigma_s^2) + x_2^2\sigma_n^2)$$

$$\dot{a} - (x_1^2\sigma_n^2 + x_2^2(\sigma_n^2 + \sigma_s^2)) + \dot{b} - (x_1^2(\sigma_n^2 + \sigma_s^2) + x_2^2\sigma_n^2) < \dot{c} - (\sigma_n^2 + \sigma_s^2)(x_1^2 + x_2^2) + \dot{d} - (x_1^2(\sigma_n^2 + \sigma_s^2) + x_2^2\sigma_n^2)$$

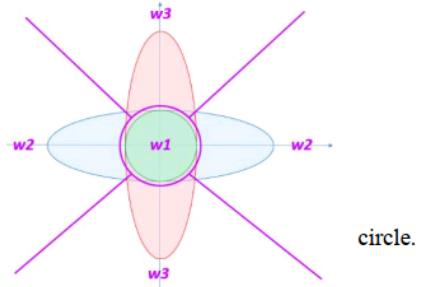
$$\begin{aligned} \acute{a} - x_1^2 \sigma_n^2 - x_2^2 \sigma_n^2 - x_2^2 \sigma_s^2 + \acute{b} - x_2^2 \sigma_n^2 - x_2^2 \sigma_s^2 - x_2^2 \sigma_n^2 \\ < \acute{c} - x_1^2 \sigma_n^2 - x_1^2 \sigma_s^2 - x_2^2 \sigma_n^2 - x_2^2 \sigma_s^2 + \acute{d} - x_2^2 \sigma_n^2 - x_2^2 \sigma_s^2 - x_2^2 \sigma_n^2 \end{aligned}$$

$$\acute{a} + \acute{b} < \acute{c} - x_1^2 \sigma_s^2 + \acute{d} \quad \rightarrow \quad x_1^2 < \acute{f} \quad \rightarrow \quad \textcolor{blue}{A}x_1^2 < \textcolor{orange}{C}$$

$$\rightarrow \left( \frac{\sigma_s^2}{\sigma_n^2(\sigma_s^2 + \sigma_n^2)} \right) x_1^2 < \ln(a^2 \frac{\sigma_s^2 + \sigma_n^2}{\sigma_n^2})$$

$$\begin{aligned} e_1 < e_3: pp(x|w_2) + (1 - 2p)p(x|w_3) &< pp(x|w_1) + \\ app(x|w_2) \quad \rightarrow \quad \left( \frac{\sigma_s^2}{\sigma_n^2(\sigma_s^2 + \sigma_n^2)} \right) x_2^2 &< \ln\left(\frac{a^2}{(1-2p)^2} \times \frac{\sigma_s^2 + \sigma_n^2}{\sigma_n^2}\right) \end{aligned}$$

$$\textcolor{blue}{A}x_1^2 < \textcolor{orange}{C} \text{ and } \textcolor{blue}{A}x_2^2 < \textcolor{green}{D}: \quad Ax_1^2 + Ax_2^2 < C + D \rightarrow x_1^2 + x_2^2 < B : A$$



If we calculate like above for  $w_2$  and  $w_3$  we will get:  $x_2 = \pm x_1$

Final borders are plotted here:

Green area belongs to class  $w_1$ . Blue and red areas belong to

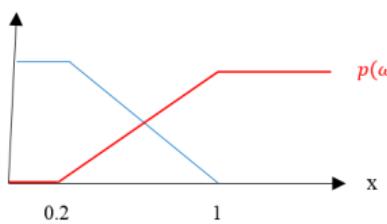
Classes  $w_2$  and  $w_3$ , respectively.

## Part B)

$$\begin{aligned} \text{Error} = \int_{R_1} [pp(x|w_2) + (1 - 2p)p(x|w_3)]dx + \int_{R_2} [pp(x|w_1) + a(1 - 2p)p(x|w_3)]dx + \\ \int_{R_3} [pp(x|w_1) + app(x|w_2)]dx \end{aligned}$$

**Q6:**

**Part A)** Considering the shape, posterior is defined just for positive xs.



$$\begin{aligned} p(\omega_1|x) &= \begin{cases} 1 & 0 \leq x \leq 0.2 \\ \frac{-5}{4}x + \frac{5}{4} & 0.2 < x \leq 1 \end{cases} \\ p(\omega_2|x) &= \begin{cases} 0 & 1 \leq x \\ \frac{1}{4}x - \frac{1}{4} & 0.2 < x < 1 \end{cases} \end{aligned}$$

**Part B)**  $p(\omega_1|x) \leq_{\omega_1}^{\omega_2} p(\omega_2|x)$  Therefore,  $R_2 = \{x|x > 0.6\}$  and  $R_1 = \{x|x < 0.6\}$  where 0.6 is the Bayes boundary:

$$\frac{-5}{4}x + \frac{5}{4} = \frac{1}{4}x - \frac{1}{4} \quad \rightarrow \quad x = 0.6$$

**Part C)**  $R(t) = \{x|r(x) \geq t\}$

$$r(x) = \min\{p(\omega_1|x), p(\omega_2|x)\} = \begin{cases} 0 & x \leq 0.2 \cup 1 < x \\ \frac{5}{4}x - \frac{1}{4} & 0.2 < x \leq 0.6 \\ \frac{-5}{4}x + \frac{5}{4} & 0.6 < x \leq 1 \end{cases}$$

$$\text{in } 0.2 < x \leq 0.6: \quad \frac{5}{4}x - \frac{1}{4} \geq t \quad \rightarrow \quad \frac{5}{4}x - \frac{1}{4} \geq \frac{1}{4} \quad \rightarrow \quad x > 0.4$$

$$\text{in } 0.6 < x \leq 1: \quad \frac{-5}{4}x + \frac{5}{4} \geq t \quad \rightarrow \quad \frac{-5}{4}x + \frac{5}{4} \geq \frac{1}{4} \quad \rightarrow \quad x < 0.8$$

$$\text{So, } R\left(\frac{1}{4}\right) = \{0.4 < x < 0.8\}$$

**Part D)** We classify  $x$  to class  $i$  if  $c_i(x)$  is smaller than  $\lambda$ . Considering the costs:

$$\text{in } 0.2 < x \leq 0.6, \text{ we have } c_1(x) = \frac{5}{4}x - \frac{1}{4} \quad \frac{5}{4}x - \frac{1}{4} \leq \lambda \quad x \leq \frac{4}{5}\lambda + \frac{1}{5}$$

$$\text{in } 0.6 < x \leq 1, \text{ we have } c_2(x) = \frac{-5}{4}x + \frac{5}{4} \quad \frac{-5}{4}x + \frac{5}{4} \leq \lambda \quad x \geq \frac{-4}{5}\lambda + 1$$

$$d(x) = \begin{cases} 1 & x \leq \frac{4}{5}\lambda + \frac{1}{5} \\ 2 & x \geq \frac{-4}{5}\lambda + 1 \\ 0 & \frac{4}{5}\lambda + \frac{1}{5} < x < \frac{-4}{5}\lambda + 1 \end{cases}$$

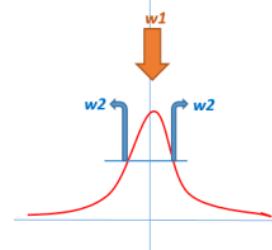
$$\text{Part E)} \text{ considering } d(x) \text{ above and } \lambda = \frac{1}{4}: \quad \frac{4}{5}\left(\frac{1}{4}\right) + \frac{1}{5} < x < \frac{-4}{5}\left(\frac{1}{4}\right) + 1 \quad \rightarrow \quad 0.4 < x < 0.8$$

We get the same reject region from part C and part D.

**Q7:**

$$\text{Part A)} p(\omega_1|x) \leq_{\omega_1}^{\omega_2} p(\omega_2|x) \quad \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) = \frac{1}{4} \quad \rightarrow \quad x = \pm 1.36$$

The borders are specified in the image:



**Part B)** let  $p(\omega_1) = p$

$$pp(x|\omega_1) > (1-p)p(x|\omega_1) \quad \rightarrow \quad \frac{p}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) > \frac{1-p}{4}$$

$$p\left(\frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) + \frac{1}{4}\right) > \frac{1}{4} \quad \rightarrow \quad p > \frac{\frac{1}{4}}{\frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) + \frac{1}{4}}$$

$$x = \pm 2 \text{ in it. Then, } p > \frac{\frac{1}{4}}{\frac{1}{\sqrt{2\pi}} \exp(-2) + \frac{1}{4}} \quad \rightarrow \quad p > 0.82$$

This inequality should be correct for all  $x$ . Therefore I put

**Part C)** It is impossible! The domain of  $p(x|\omega_2)$  is in range [-2 2]. Changing its prior does not extend the domain so there is always some areas out of this range that  $p(x|\omega_1)$  is greater than  $p(x|\omega_2) = 0$  for them.

**Q10:**

$$p(\omega_2|x) = \frac{1}{2}x \quad p(\omega_1|x) = -\frac{1}{2}x + 1$$

**Part A)**

$$\varepsilon = \int_0^1 P(\omega_2|x)p(x)dx + \int_1^2 P(\omega_1|x)p(x)dx = \int_0^1 0.5xp(x)dx + \int_1^2 0.5(1 - 0.5x)p(x)dx$$

**Part B)**

Let's re-arrange the table:

تشخيص	عدم وجود خرابی	وجود خرابی
ادامه کار با ظرفیت کامل	0	$2\epsilon$
ادامه کار با ظرفیت محدود	$2\epsilon$	$\epsilon$
توقف کامل	$4\epsilon$	0

$$D_1 \text{ vs. } D_2: 0 \times p(\omega_2|x) + 2\epsilon \times p(\omega_1|x) \geq_{D_1}^{D_2} 2\epsilon \times p(\omega_2|x) + \epsilon \times p(\omega_1|x)$$

$$2 \left( -\frac{1}{2}x + 1 \right) \geq_{D_1}^{D_2} 2 \left( \frac{1}{2}x \right) + \left( -\frac{1}{2}x + 1 \right) \rightarrow \frac{2}{3} \geq_{D_1}^{D_2} x$$

$$D_1 \text{ vs. } D_3: 0 \times p(\omega_2|x) + 2\epsilon \times p(\omega_1|x) \geq_{D_1}^{D_3} 4\epsilon \times p(\omega_2|x) + 0 \times p(\omega_1|x)$$

$$2 \left( -\frac{1}{2}x + 1 \right) \geq_{D_1}^{D_3} 4 \left( \frac{1}{2}x \right) \rightarrow 1 \geq_{D_1}^{D_3} x$$

$$D_2 \text{ vs. } D_3: 2\epsilon \times p(\omega_2|x) + \epsilon \times p(\omega_1|x) \gtrless_{D_2}^{D_3} 4\epsilon \times p(\omega_2|x) + 0 \times p(\omega_1|x)$$

$$2\left(\frac{1}{2}x\right) + \left(-\frac{1}{2}x + 1\right) \gtrless_{D_2}^{D_3} 4\left(\frac{1}{2}x\right) \rightarrow \frac{2}{3} \gtrless_{D_2}^{D_3} x$$

Therefore:  $\begin{cases} D_1 & \text{if } x > 1 \\ D_2 & \text{if } \frac{2}{3} < x < 1 \\ D_3 & \text{if } \frac{2}{3} > x \end{cases} \rightarrow \begin{array}{ll} \text{full capacity} & \\ \text{Limited capacity} & \\ \text{stop working} & \end{array}$

**Q11:**

$$P(C_1) = P(C_2) = 0.5$$

$X_1 =$	Class	$C_1$	$C_2$
-1		0.2	0.3
0		0.4	0.6
1		0.4	0.1

$X_2 =$	Class	$C_1$	$C_2$
-1		0.4	0.1
0		0.5	0.3
1		0.1	0.6

**Part A)**

$$P(C_1|X_1 = -1, X_2 = -1) = \frac{P(X_1 = -1, X_2 = -1|C_1)P(C_1)}{P(X_1 = -1, X_2 = -1)} = \frac{P(X_1 = -1|C_1)P(X_2 = -1|C_1)P(C_1)}{P(X_1 = -1, X_2 = -1)} = \frac{0.2 \times 0.4 \times 0.5}{(0.2 \times 0.4 \times 0.5) + (0.3 \times 0.1 \times 0.5)} = \frac{0.08}{0.11} = \frac{8}{11}$$

**Part B)**

$$\text{Error: } P(C_2|X_1 = -1, X_2 = -1) = 1 - P(C_1|X_1 = -1, X_2 = -1) = \frac{3}{11}$$

## Q12-

A) This is wrong for several reasons. First, to get the Bayes risk, you would need to scale each curve by its prior. Second, some of the shaded area has to be counted twice; e.g., the area under A where B and C are both above A.

B and C) The only way for something like this to occur is if the prior for a class is significant enough that its joint distribution raises above the other classes' joint distribution for all  $x$ . Class C can't do that, as it does not span all of the  $x$ -space. Class B can, as it covers the whole number line and its variance is greater than Class A's.

## Q14-

$$p(w1) = p(w2) = \frac{1}{2} \rightarrow \ln(p(x|w1)) - \ln(p(x|w2)) = 0 \rightarrow$$

$$D = \ln \left( \frac{1}{2 \times \pi^{\frac{1}{2} \times |\Sigma|^2}} \times e^{-\frac{1}{2}(x-\mu_1)^T \times \Sigma^{-1} \times (x-\mu_1)} \right) - \ln \left( \frac{1}{2 \times \pi^{\frac{1}{2} \times |\Sigma|^2}} \times e^{-\frac{1}{2}(x-\mu_2)^T \times \Sigma^{-1} \times (x-\mu_2)} \right)$$

$$D = (\mu_1 - \mu_2)^T \Sigma^{-1} x - \frac{1}{2} \mu_1 \Sigma^{-1} \mu_1 + \frac{1}{2} \mu_2^T \Sigma^{-1} \mu_2$$

یک متغیر تصادفی گوسی تحت هر تبدیل خطي به یک متغیر تصادفی گوسی دیگر با پارامتر های متفاوت تبدیل می شود.

$$\mu'_1 = E\{D|w_1\} = E\{(\mu_1 - \mu_2)^T \Sigma^{-1} x - \frac{1}{2} \mu_1 \Sigma^{-1} \mu_1 + \frac{1}{2} \mu_2^T \Sigma^{-1} \mu_1\} = \frac{1}{2} (\mu_1 - \mu_2)^T \Sigma^{-1} (\mu_1 - \mu_2) = \frac{1}{2} dm^2$$

$$\mu'_2 = E\{D|w_2\} = -\frac{1}{2} (\mu_1 - \mu_2)^T \Sigma^{-1} (\mu_1 - \mu_2) = -\frac{1}{2} dm^2$$

$$\sigma_1^2 = \sigma_2^2 = (\mu_1 - \mu_2)^T \Sigma^{-1} (\mu_1 - \mu_2) = dm^2$$

$$p_e = \frac{1}{2} \int_{-\infty}^0 \frac{1}{\sqrt{2\pi} dm} e^{-\frac{(D - \frac{1}{2} dm^2)^2}{2dm^2}} dD + \frac{1}{2} \int_0^\infty \frac{1}{\sqrt{2\pi} dm} e^{-\frac{(D + \frac{1}{2} dm^2)^2}{2dm^2}} dD$$

$$p_e = \frac{1}{\sqrt{2\pi} dm} \int_{-\infty}^0 e^{-\frac{1}{2} \left( \frac{D - \frac{1}{2} dm^2}{dm} \right)^2} dD$$

حالا کافی است تغییر متغیر بدهیم تا به عبارت مورد نظر برسیم.

$$z = \frac{D - \frac{1}{2} dm^2}{dm} \rightarrow dz = \frac{dD}{dm}$$

$$P_e=\frac{1}{\sqrt{2\Pi}}\int_{-\infty}^{\frac{1}{2}d_m}e^{-\frac{z^2}{2}}dz=\frac{1}{\sqrt{2\Pi}}\int_{\frac{1}{2}dn}^0e^{-\frac{z^2}{2}}dz$$