# Homework 7

## Exercise 1

Since class  $\omega_1$  is modeled by the normal distribution N(0,1) we have that:

$$p(x|\omega_1) = \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-x^2}{2}\right)$$

Similarly, since class  $\omega_2$  is modeled by the normal distribution N(0,5) we have that:

$$p(x|\omega_2) = \frac{1}{\sqrt{2\pi}\sqrt{5}} \exp\left(\frac{-x^2}{10}\right)$$

We know that if x lies in the decision region  $R_1$ , then it holds that:

$$p(x|\omega_1)P(\omega_1) > p(x|\omega_2)P(\omega_2)$$
 (1)

But  $P(\omega_1) = P(\omega_2)$ , because classes are equiprobable.

$$(1) \Rightarrow p(x|\omega_1) > p(x|\omega_2) \Rightarrow$$

$$\frac{1}{\sqrt{2\pi}} \exp\left(\frac{-x^2}{2}\right) > \frac{1}{\sqrt{2\pi}\sqrt{5}} \exp\left(\frac{-x^2}{10}\right) \Rightarrow$$

$$\exp\left(\frac{-x^2}{2}\right) > \frac{1}{\sqrt{5}} \exp\left(\frac{-x^2}{10}\right) \Rightarrow$$

$$ln\left(\exp\left(\frac{-x^2}{2}\right)\right) > ln\left(\frac{1}{\sqrt{5}} \exp\left(\frac{-x^2}{10}\right)\right) \Rightarrow$$

$$-\frac{x^2}{2} > -\frac{1}{2}\ln(5) - \frac{x^2}{10} \Rightarrow$$

$$x^2 < \ln(5) + \frac{x^2}{5} \Rightarrow$$

$$x^2 < \ln(5) + \frac{x^2}{5} \Rightarrow$$

$$x^2 < \frac{5}{4}\ln(5)$$

$$\Rightarrow -\sqrt{5/4 \ln(5)} < x < \sqrt{5/4 \ln(5)}$$

Therefore, decision regions are:

$$R_1: \{x: -\sqrt{5/4 \ln{(5)}} < x < \sqrt{5/4 \ln{(5)}} \} \text{ and } R_2: \{x: x < -\sqrt{\frac{5}{4} \ln{(5)}} \ \cup \ x > \sqrt{5/4 \ln{(5)}} \}$$

#### Exercise 2

According to the Bayesian classifier, the border between two classes is given by the equation:  $p(x|\omega_1)P(\omega_1)=p(x|\omega_2)P(\omega_2)$ . Since the two classes are equiprobable it holds that  $P(\omega_1)=P(\omega_2)$ . Combining the two equations we get:

$$\begin{split} p(x|\omega_{1}) &= p(x|\omega_{2}) \\ \Rightarrow \frac{1}{(2\pi)^{\frac{-1}{2}}} exp\left(-\frac{(x-\mu_{1})^{T} \Sigma^{-1}(x-\mu_{1})}{2}\right) = \frac{1}{(2\pi)^{\frac{-1}{2}}} exp\left(-\frac{(x-\mu_{2})^{T} \Sigma^{-1}(x-\mu_{2})}{2}\right) \\ \Rightarrow exp\left(-\frac{(x-\mu_{1})^{T} \Sigma^{-1}(x-\mu_{1})}{2}\right) &= exp\left(-\frac{(x-\mu_{2})^{T} \Sigma^{-1}(x-\mu_{2})}{2}\right) \\ \Rightarrow -\frac{1}{2}(x-\mu_{1})^{T} \Sigma^{-1}(x-\mu_{1}) &= -\frac{1}{2}(x-\mu_{2})^{T} \Sigma^{-1}(x-\mu_{2}) \\ \Rightarrow -\frac{1}{2}(x-\mu_{1})^{T} \Sigma^{-1}(x-\mu_{1}) &= -\frac{1}{2}(x-\mu_{2})^{T} \Sigma^{-1}(x-\mu_{2}) \\ \Rightarrow -\frac{1}{2}(x^{T} \Sigma^{-1} x - 2x^{T} \Sigma^{-1} \mu_{1} + \mu_{1}^{T} \Sigma^{-1} \mu_{1}) &= -\frac{1}{2}(x^{T} \Sigma^{-1} x - 2x^{T} \Sigma^{-1} \mu_{2} + \mu_{2}^{T} \Sigma^{-1} \mu_{2}) \\ \Rightarrow -\frac{1}{2}x^{T} \Sigma^{-1} x + \mu_{1}^{T} \Sigma^{-1} x - \frac{1}{2}\mu_{1}^{T} \Sigma^{-1} \mu_{1} &= -\frac{1}{2}x^{T} \Sigma^{-1} x + \mu_{2}^{T} \Sigma^{-1} x - \frac{1}{2}\mu_{2}^{T} \Sigma^{-1} \mu_{2} \\ \Rightarrow \mu_{1}^{T} \Sigma^{-1} x - \frac{1}{2}\mu_{1}^{T} \Sigma^{-1} \mu_{1} &= \mu_{2}^{T} \Sigma^{-1} x - \frac{1}{2}\mu_{2}^{T} \Sigma^{-1} \mu_{2} \\ \Rightarrow \mu_{1}^{T} \left[ \frac{1}{\sigma^{2}} \quad 0 \\ 0 \quad 1/\sigma^{2} \right] x - \frac{1}{2}\mu_{1}^{T} \left[ \frac{1}{\sigma^{2}} \quad 0 \\ 0 \quad 1/\sigma^{2} \right] \mu_{1} \\ &= \mu_{2}^{T} \left[ \frac{1}{\sigma^{2}} \quad 0 \\ 0 \quad 1/\sigma^{2} \right] x - \frac{1}{2}\mu_{2}^{T} \left[ \frac{1}{\sigma^{2}} \quad 0 \\ 0 \quad 1/\sigma^{2} \right] \mu_{2} \end{split}$$

$$\Rightarrow \sigma^{2} \mu_{1}^{T} \begin{bmatrix} 1/\sigma^{2} & 0 \\ 0 & 1/\sigma^{2} \end{bmatrix} x - \sigma^{2} \frac{1}{2} \mu_{1}^{T} \begin{bmatrix} 1/\sigma^{2} & 0 \\ 0 & 1/\sigma^{2} \end{bmatrix} \mu_{1}$$

$$= \sigma^{2} \mu_{2}^{T} \begin{bmatrix} 1/\sigma^{2} & 0 \\ 0 & 1/\sigma^{2} \end{bmatrix} x - \sigma^{2} \frac{1}{2} \mu_{2}^{T} \begin{bmatrix} 1/\sigma^{2} & 0 \\ 0 & 1/\sigma^{2} \end{bmatrix} \mu_{2}$$

$$\Rightarrow \mu_{1}^{T} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} x - \frac{1}{2} \mu_{1}^{T} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \mu_{1} = \mu_{2}^{T} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} x - \frac{1}{2} \mu_{2}^{T} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \mu_{2}$$

$$\Rightarrow (\mu_{1}^{T} - \mu_{2}^{T}) x - \frac{1}{2} \mu_{1}^{T} \mu_{1} + \frac{1}{2} \mu_{2}^{T} \mu_{2} = 0$$

 $\Rightarrow (\mu_1 - \mu_2)^T x - \frac{1}{2} ||\mu_1||^2 + \frac{1}{2} ||\mu_2||^2 = 0$ , which is the perpendicular bisector of the line segment whose endpoints are  $\mu_1$  and  $\mu_2$ .

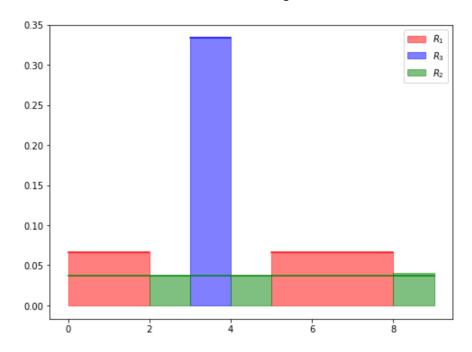
#### Exercise 3

I. Classes are equiprobable:  $P(\omega_1) = P(\omega_2) = P(\omega_3) = \frac{1}{3}$ 

(i) 
$$p(x|\omega_1) = \begin{cases} \frac{1}{5}, & x \in (0,2) \cup (5,8) \\ 0, otherwise \end{cases}$$
$$p(x|\omega_2) = \begin{cases} \frac{1}{9}, & x \in (0,9) \\ 0, otherwise \end{cases}$$
$$p(x|\omega_3) = \begin{cases} 1, & x \in (3,4) \\ 0, otherwise \end{cases}$$

In the diagram bellow, horizontal lines are the probabilities  $p(x|\omega_1)P(\omega_1)$  (red),  $p(x|\omega_2)P(\omega_2)$  (green),  $p(x|\omega_3)P(\omega_3)$  (blue).

The blocks under the lines are the decision regions of the classes.



(ii) 
$$P_{e} = \left( \int_{R_{1}} (p(x|\omega_{2}) + p(x|\omega_{3})) dx + \int_{R_{2}} (p(x|\omega_{1}) + p(x|\omega_{3})) dx + \int_{R_{3}} (p(x|\omega_{1}) + p(x|\omega_{2})) dx \right) \frac{1}{3} = \left( \int_{0}^{2} (p(x|\omega_{2}) + p(x|\omega_{3})) dx + \int_{5}^{8} (p(x|\omega_{2}) + p(x|\omega_{3})) dx + \int_{4}^{5} (p(x|\omega_{1}) + p(x|\omega_{3})) dx + \int_{4}^{5} (p(x|\omega_{1}) + p(x|\omega_{3})) dx + \int_{8}^{6} (p(x|\omega_{1}) + p(x|\omega_{3})) dx + \int_{4}^{6} (p(x|\omega_{1}) + p(x|\omega_{2})) dx \right) \frac{1}{3} = \left( \int_{0}^{2} \left( \frac{1}{9} + 0 \right) dx + \int_{5}^{8} \left( \frac{1}{9} + 0 \right) dx + \int_{2}^{3} (0 + 0) dx + \int_{4}^{5} (0 + 0) dx + \int_{8}^{9} (0 + 0) dx + \int_{4}^{6} (0 + \frac{1}{9}) dx \right) \frac{1}{3} = \left( \frac{1}{9} (2 - 0) + \frac{1}{9} (8 - 5) + 0 + 0 + 0 + \frac{1}{9} (4 - 3) \right) \frac{1}{3} = \left( \frac{2}{9} + \frac{3}{9} + \frac{1}{9} \right) \frac{1}{3}$$

$$\Rightarrow P_{e} = 0.2222$$

Error classification probability is  $P_e = 0.2222$ .

(iii) To classify the point x' = 3.5 we will use the Bayes classifier:

- $p(3.5|\omega_1)\frac{1}{3} = 0$   $p(3.5|\omega_2)\frac{1}{3} = \frac{1}{27}$   $p(3.5|\omega_3)\frac{1}{3} = \frac{1}{3}$ , which is the greatest value

Thus, x' = 3.5 is classified to class  $\omega_3$ .

Classes are not equiprobable. II.

(i)

#### • Case $\omega_2$ over $\omega_1$

x'=3.5 can never be assigned to class  $\omega_1$  since  $p(3.5|\omega_1)=0$ . Thus, for every value of  $P(\omega_1)$ ,  $P(\omega_2)$  the point will be assigned to  $\omega_2$ .

### Case $\omega_2$ over $\omega_3$

For x'=3.5 to be assigned to  $\omega_2$  over  $\omega_3$  it needs to hold that

$$p(3.5|\omega_2)P(\omega_2) > p(3.5|\omega_3)P(\omega_3) \Rightarrow \frac{1}{9}P(\omega_2) > 1P(\omega_3)$$
$$\Rightarrow P(\omega_2) > 9P(\omega_3)$$

Thus,  $P(\omega_2)$  needs to be 9 times greater than  $P(\omega_3)$ .

(ii)  $p(3.5|\omega_1) = 0$  then  $p(\omega_1|3.5) = 0$  for every  $P(\omega_1), P(\omega_2), P(\omega_3)$ . In conclusion, there is no combination of the a priori probabilities that guarantees that it will be assigned to  $\omega_1$ .