

# Machine Learning - Theoretical exercise 2

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## Problem 1

a) In the following, we use the notation  $\lambda(\alpha_i | \omega_j) \Leftrightarrow \lambda_{ij}$

$\lambda_{11} = 0$	correct classification of toxic container
$\lambda_{21} = 10^5$	incorrect classification of toxic container
$\lambda_{22} = 0$	correct classification of non-toxic container
$\lambda_{12} = 250$	incorrect classification of non-toxic container

b)

$$\begin{aligned}R(\alpha_1 | x) &= \lambda_{11}P(\omega_1 | x) + \lambda_{12}P(\omega_2 | x) \\R(\alpha_2 | x) &= \lambda_{21}P(\omega_1 | x) + \lambda_{22}P(\omega_2 | x)\end{aligned}$$

As  $\lambda_{11} = 0$  and  $\lambda_{22} = 0$ ,

$$\begin{aligned}R(\alpha_1 | x) &= \lambda_{12}P(\omega_2 | x) \\R(\alpha_2 | x) &= \lambda_{21}P(\omega_1 | x)\end{aligned}$$

c) To determine the decision boundary that minimizes the average cost, we solve the equality of conditional loss functions.

$$\begin{aligned}R(\alpha_1 | x) &= R(\alpha_2 | x) \\ \lambda_{12}P(\omega_2 | x) &= \lambda_{21}P(\omega_1 | x) \\ \frac{\lambda_{12}}{\lambda_{21}} \frac{P(\omega_2)P(x | \omega_2)}{P(x)} &= \frac{P(\omega_1)P(x | \omega_1)}{P(x)} && \text{(Bayes Rule)} \\ \frac{\lambda_{12}P(\omega_2)}{\lambda_{21}P(\omega_1)} P(x | \omega_2) &= P(x | \omega_1)\end{aligned}$$

Let  $K = \frac{\lambda_{12}P(\omega_2)}{\lambda_{21}P(\omega_1)}$ . Furthermore, we know that  $P(x | \omega_1) \sim \mathcal{N}(\mu_1, \sigma^2)$  and  $P(x | \omega_2) \sim \mathcal{N}(\mu_2, \sigma^2)$ .

$$\begin{aligned}
K \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu_1)^2}{2\sigma^2}} &= \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu_2)^2}{2\sigma^2}} \\
\ln(K e^{-\frac{(x-\mu_1)^2}{2\sigma^2}}) &= \ln(e^{-\frac{(x-\mu_2)^2}{2\sigma^2}}) \\
\ln K - \frac{(x-\mu_1)^2}{2\sigma^2} &= -\frac{(x-\mu_2)^2}{2\sigma^2} \\
\ln K + \frac{1}{2\sigma^2}((x-\mu_2)^2 - (x-\mu_1)^2) &= 0 \\
\ln K + \frac{1}{2\sigma^2}(x^2 - 2\mu_2x + \mu_2^2 - x^2 + 2\mu_1x - \mu_1^2) &= 0 \\
\ln K + \frac{1}{2\sigma^2}(2x(\mu_1 - \mu_2) + \mu_2^2 - \mu_1^2) &= 0 \\
\ln K + \frac{\mu_1 - \mu_2}{\sigma^2}x + \frac{\mu_2^2 - \mu_1^2}{2\sigma^2} &= 0 \\
\frac{\mu_1 - \mu_2}{\sigma^2}x &= \frac{\mu_1^2 - \mu_2^2}{2\sigma^2} - \ln K \\
x &= \frac{\mu_1^2 - \mu_2^2}{2(\mu_1 - \mu_2)} - \sigma^2 \ln K \\
x &= \frac{\mu_1 + \mu_2}{2} - \frac{\sigma^2}{\mu_1 - \mu_2} \ln K
\end{aligned}$$

Numerically solving this equation gives us the decision boundary (CHECK STRANGE RESULT?)

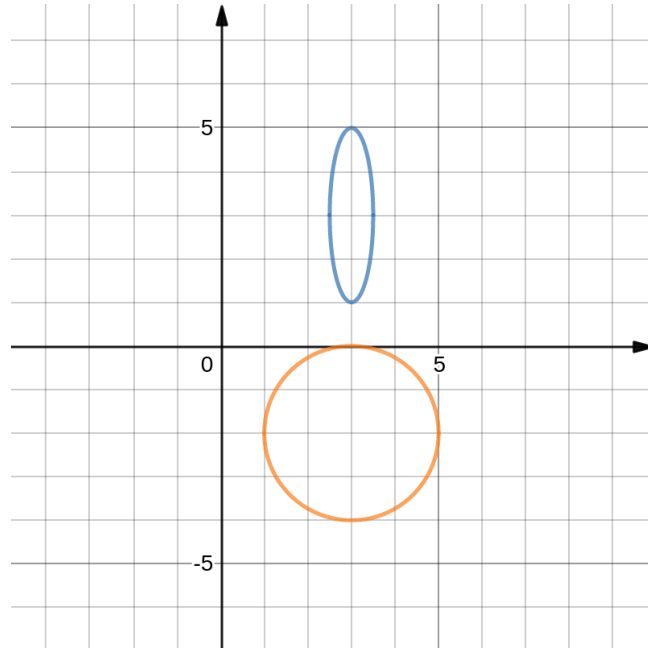
$$\begin{aligned}
x_{lim} &= \frac{0.4 + 0.2}{2} - \frac{10^{-4}}{0.4 - 0.2} \times \ln\left(\frac{25 \times 250}{10^5}\right) \\
x_{lim} &= 0.3014
\end{aligned}$$

- d) To determine the minimum average cost  $R_{min}$  upon classification, we can use both equations derived in question b). Or P(error) with integral ?

$$\begin{aligned}
R_{min} &= \lambda_{12}P(\omega_2 | x_{lim}) \\
&= \lambda_{12} \frac{P(\omega_2)P(x_{lim} | \omega_2)}{P(x_{lim})}
\end{aligned}$$

## Problem 2

a)



- b) The risk function  $g$  can be defined as  $g_i(x) = \ln P(\omega_i) + \ln P(x | \omega_i)$  for  $i = 1, 2$ . In this exercise, priors are equal so they can be omitted when solving the equality of risk for both classes.

$$\begin{aligned} g_1(x) &= g_2(x) \\ \ln P(\omega_1) + \ln P(x | \omega_1) &= \ln P(\omega_2) + \ln P(x | \omega_2) \\ \ln P(x | \omega_1) &= \ln P(x | \omega_2) \end{aligned}$$

Furthermore, the feature vectors of the two classes are normally distributed, meaning that

$$P(x | \omega_i) = \frac{1}{(2\pi)^{\frac{d}{2}} |\Sigma_i|^{\frac{1}{2}}} e^{-\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1} (x-\mu_i)} \quad i = 1, 2$$

So the previous equality becomes

$$\begin{aligned} -\frac{d}{2} \ln 2\pi - \frac{1}{2} \ln |\Sigma_1| - \frac{1}{2} (x - \mu_1)^T \Sigma_1^{-1} (x - \mu_1) &= -\frac{d}{2} \ln 2\pi - \frac{1}{2} \ln |\Sigma_2| - \frac{1}{2} (x - \mu_2)^T \Sigma_2^{-1} (x - \mu_2) \\ -\frac{1}{2} \ln |\Sigma_1| - \frac{1}{2} (x - \mu_1)^T \Sigma_1^{-1} (x - \mu_1) &= -\frac{1}{2} \ln |\Sigma_2| - \frac{1}{2} (x - \mu_2)^T \Sigma_2^{-1} (x - \mu_2) \end{aligned}$$

The covariance matrices  $\Sigma_i$  have nice properties allowing us to simplify this equation.

$$|\Sigma_1| = \begin{vmatrix} \frac{1}{2} & 0 \\ 0 & 2 \end{vmatrix} = 1 \implies \frac{1}{2} \ln |\Sigma_1| = 0 \quad (1)$$

$$|\Sigma_2| = \begin{vmatrix} 2 & 0 \\ 0 & 2 \end{vmatrix} = 4 \implies \frac{1}{2} \ln |\Sigma_2| = \ln 2 \quad (2)$$

$$\Sigma_1^{-1} = \begin{bmatrix} \frac{1}{2} & 0 \\ 0 & 2 \end{bmatrix}^{-1} = \begin{bmatrix} 2 & 0 \\ 0 & \frac{1}{2} \end{bmatrix} \quad \text{because } \Sigma_1 \text{ is diagonal} \quad (3)$$

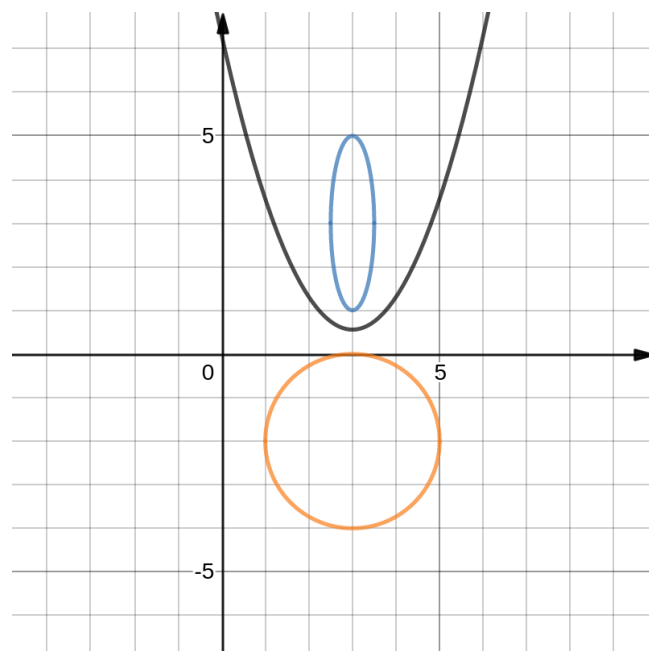
$$\Sigma_2^{-1} = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}^{-1} = \begin{bmatrix} \frac{1}{2} & 0 \\ 0 & \frac{1}{2} \end{bmatrix} \quad \text{because } \Sigma_2 \text{ is diagonal} \quad (4)$$

This allows us to write the previous equality as

$$\begin{aligned}
& -\frac{1}{2}(x - \mu_1)^T \Sigma_1^{-1}(x - \mu_1) + \frac{1}{2}(x - \mu_2)^T \Sigma_2^{-1}(x - \mu_2) + \ln 2 = 0 \\
& -\frac{1}{4} \begin{bmatrix} x_1 - 3 \\ x_2 - 3 \end{bmatrix}^T \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 - 3 \\ x_2 - 3 \end{bmatrix} + \frac{1}{4} \begin{bmatrix} x_1 - 3 \\ x_2 + 2 \end{bmatrix}^T \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 - 3 \\ x_2 + 2 \end{bmatrix} + \ln 2 = 0 \\
& -\frac{1}{4}[(4x_1 - 12)(x_1 - 3) + (x_2 - 3)^2] + \frac{1}{4}[(x_1 - 3)^2 + (x_2 + 2)^2] + \ln 2 = 0 \\
& -\frac{1}{4}(4x_1^2 - 24x_1 + 36 + x_2^2 - 6x_2 + 9) + \frac{1}{4}(x_1^2 - 6x_1 + 9 + x_2^2 + 4x_2 + 4) + \ln 2 = 0 \\
& \qquad \qquad \qquad \frac{3}{4}x_1^2 + \frac{9}{2}x_1 - 8 + \ln 2 = x_2
\end{aligned}$$

Thus, the decision border is a parabola.

c)



### Problem 3

$$\begin{aligned}
g_i(x) &= g_j(x) \\
-\frac{\|x - \mu_i\|^2}{2\sigma^2} + \ln P(\omega_1) &= -\frac{\|x - \mu_j\|^2}{2\sigma^2} + \ln P(\omega_2) \\
\frac{\|x - \mu_j\|^2 - \|x - \mu_i\|^2}{2\sigma^2} + \ln \frac{P(\omega_1)}{P(\omega_2)} &= 0 \\
\frac{(\mu_i - \mu_j)(2x - (\mu_i + \mu_j))}{2\sigma^2} + \ln \frac{P(\omega_1)}{P(\omega_2)} &= 0 \\
\frac{2x(\mu_i - \mu_j) - (\mu_i + \mu_j)(\mu_i - \mu_j)}{2\sigma^2} + \ln \frac{P(\omega_1)}{P(\omega_2)} &= 0 \\
\frac{x(\mu_i - \mu_j)}{\sigma^2} - \frac{(\mu_i + \mu_j)(\mu_i - \mu_j)}{2\sigma^2} + \ln \frac{P(\omega_1)}{P(\omega_2)} &= 0 \\
x(\mu_i - \mu_j) - \frac{1}{2}(\mu_i + \mu_j)(\mu_i - \mu_j) + \sigma^2 \ln \frac{P(\omega_1)}{P(\omega_2)} &= 0 \\
(\mu_i - \mu_j)\left(x - \frac{1}{2}(\mu_i + \mu_j) + \frac{\sigma^2}{\mu_i - \mu_j} \ln \frac{P(\omega_1)}{P(\omega_2)}\right) &= 0 \\
(\mu_i - \mu_j)\left(x - \frac{1}{2}(\mu_i + \mu_j) + \frac{\sigma^2}{\|\mu_i - \mu_j\|^2} \ln \frac{P(\omega_1)}{P(\omega_2)}(\mu_i - \mu_j)\right) &= 0
\end{aligned}$$

Assigning  $\theta = \mu_i - \mu_j$  and  $x_0 = \frac{1}{2}(\mu_i + \mu_j) - \frac{\sigma^2}{\|\mu_i - \mu_j\|^2} \ln \frac{P(\omega_1)}{P(\omega_2)}(\mu_i - \mu_j)$ , we get

$$\theta^T(x - x_0) = 0$$