

# Machine Learning - Theoretical exercise 1

Téo Bouvard

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## Problem 1

a) According to the sum rule,

$$\begin{aligned}\iint_X \rho(x) dx &= 1 \\ \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \rho(x_1, x_2) dx_1 dx_2 &= 1 \\ \int_{a_2}^{b_2} \int_{a_1}^{b_1} c dx_1 dx_2 &= 1 && \text{p.d.f is zero outside of these bounds} \\ c(b_1 - a_1)(b_2 - a_2) &= 1 \\ \frac{1}{(b_1 - a_1)(b_2 - a_2)} &= c\end{aligned}$$

b) Using the formula to compute the expected value,

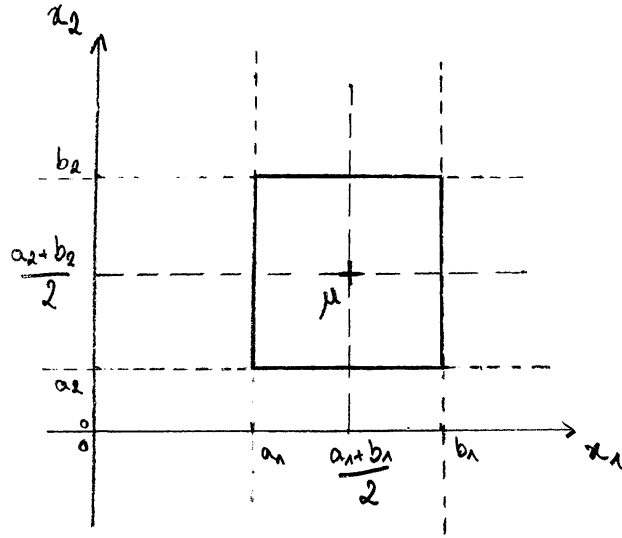
$$\begin{aligned}E(x) &= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \rho(x_1, x_2) dx_1 dx_2 \\ &= c \int_{a_2}^{b_2} \int_{a_1}^{b_1} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} dx_1 dx_2 \\ &= c \int_{a_2}^{b_2} \begin{bmatrix} \frac{b_1^2 - a_1^2}{2} \\ x_2(b_1 - a_1) \end{bmatrix} dx_2 \\ &= c \begin{bmatrix} \frac{b_1^2 - a_1^2}{2} (b_2 - a_2) \\ \frac{b_2^2 - a_2^2}{2} (b_1 - a_1) \end{bmatrix}\end{aligned}$$

Using  $a^2 - b^2 = (a - b)(a + b)$ , we can factor factor this expression as

$$E(x) = c \begin{bmatrix} \frac{(b_1 - a_1)(b_1 + a_1)(b_2 - a_2)}{2} \\ \frac{(b_1 - a_1)(b_2 + a_2)(b_2 - a_2)}{2} \end{bmatrix}$$

Substituting  $c$  with the value computed in the previous question, we can simplify it further as

$$\begin{aligned}E(x) &= \frac{1}{(b_1 - a_1)(b_2 - a_2)} \begin{bmatrix} \frac{(b_1 - a_1)(b_1 + a_1)(b_2 - a_2)}{2} \\ \frac{(b_1 - a_1)(b_2 + a_2)(b_2 - a_2)}{2} \end{bmatrix} \\ &= \frac{1}{2} \begin{bmatrix} b_1 + a_1 \\ b_2 + a_2 \end{bmatrix}\end{aligned}$$



c) We compute the covariance matrix, defined as follows

$$\begin{aligned}\text{Cov}(x) &= E((x - \mu)(x - \mu)^T) \\ &= E(xx^T) - \mu\mu^T\end{aligned}$$

Let's compute each term independently.

$$\begin{aligned}E(xx^T) &= E\left(\begin{bmatrix} x_1^2 & x_1x_2 \\ x_1x_2 & x_2^2 \end{bmatrix}\right) \\ &= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \begin{bmatrix} x_1^2 & x_1x_2 \\ x_1x_2 & x_2^2 \end{bmatrix} \rho(x_1, x_2) dx_1 dx_2 \\ &= c \int_{a_2}^{b_2} \int_{a_1}^{b_1} \begin{bmatrix} x_1^2 & x_1x_2 \\ x_1x_2 & x_2^2 \end{bmatrix} dx_1 dx_2 \\ &= c \int_{a_2}^{b_2} \begin{bmatrix} \frac{b_1^3 - a_1^3}{3} & x_2 \frac{b_1^2 - a_1^2}{2} \\ x_2 \frac{b_1^3 - a_1^3}{2} & x_2^2 (b_1 - a_1) \end{bmatrix} dx_2 \\ &= c \begin{bmatrix} \frac{b_1^3 - a_1^3}{3} (b_2 - a_2) & \frac{b_2^2 - a_2^2}{2} \frac{b_1^2 - a_1^2}{2} \\ \frac{b_2^3 - a_2^3}{3} \frac{b_1^3 - a_1^3}{2} & \frac{b_2^3 - a_2^3}{3} (b_1 - a_1) \end{bmatrix}\end{aligned}$$

Substituting  $c$  by its value and using  $a^3 - b^3 = (a - b)(a^2 + ab + b^2)$ ,

$$\begin{aligned}E(xx^T) &= \frac{1}{(b_1 - a_1)(b_2 - a_2)} \begin{bmatrix} \frac{(b_1 - a_1)(a_1^2 + a_1b_1 + b_1^2)(b_2 - a_2)}{3} & \frac{(b_2 - a_2)(b_2 + a_2)(b_1 - a_1)(b_1 + a_1)}{4} \\ \frac{(b_2 - a_2)(b_2 + a_2)(b_1 - a_1)(b_1 + a_1)}{4} & \frac{(b_2 - a_2)(a_2^2 + a_2b_2 + b_2^2)(b_1 - a_1)}{3} \end{bmatrix} \\ &= \begin{bmatrix} \frac{a_1^2 + a_1b_1 + b_1^2}{3} & \frac{(b_2 + a_2)(b_1 + a_1)}{4} \\ \frac{(b_2 + a_2)(b_1 + a_1)}{4} & \frac{a_2^2 + a_2b_2 + b_2^2}{3} \end{bmatrix}\end{aligned}$$

And

$$\begin{aligned}\mu\mu^T &= \frac{1}{2} \begin{bmatrix} a_1 + b_1 \\ a_2 + b_2 \end{bmatrix} \times \frac{1}{2} \begin{bmatrix} a_1 + b_1 & a_2 + b_2 \end{bmatrix} \\ &= \frac{1}{4} \begin{bmatrix} (a_1 + b_1)^2 & (a_1 + b_1)(a_2 + b_2) \\ (a_1 + b_1)(a_2 + b_2) & (a_2 + b_2)^2 \end{bmatrix}\end{aligned}$$

Using the previous results to find the covariance,

$$\begin{aligned}\text{Cov}(x) &= E(xx^T) - \mu\mu^T \\ &= \begin{bmatrix} \frac{a_1^2 + a_1 b_1 + b_1^2}{3} & \frac{(b_2 + a_2)(b_1 + a_1)}{4} \\ \frac{(b_2 + a_2)(b_1 + a_1)}{4} & \frac{a_2^2 + a_2 b_2 + b_2^2}{3} \end{bmatrix} - \frac{1}{4} \begin{bmatrix} (a_1 + b_1)^2 & (a_1 + b_1)(a_2 + b_2) \\ (a_1 + b_1)(a_2 + b_2) & (a_2 + b_2)^2 \end{bmatrix} \\ &= \frac{1}{12} \begin{bmatrix} 4(a_1^2 + a_1 b_1 + b_1^2) - 3(a_1 + b_1)^2 & 3(b_2 + a_2)(b_1 + a_1) - 3(b_2 + a_2)(b_1 + a_1) \\ 3(b_2 + a_2)(b_1 + a_1) - 3(b_2 + a_2)(b_1 + a_1) & 4(a_2^2 + a_2 b_2 + b_2^2) - 3(a_2 + b_2)^2 \end{bmatrix} \\ &= \frac{1}{12} \begin{bmatrix} a_1^2 - 2a_1 b_1 + b_1^2 & 0 \\ 0 & a_2^2 - 2a_2 b_2 + b_2^2 \end{bmatrix} \\ &= \frac{1}{12} \begin{bmatrix} (a_1 - b_1)^2 & 0 \\ 0 & (a_2 - b_2)^2 \end{bmatrix}\end{aligned}$$

- d)  $\text{Cov}(x) = \begin{bmatrix} \sigma_{x_1}^2 & \sigma(x_1, x_2) \\ \sigma(x_2, x_1) & \sigma_{x_2}^2 \end{bmatrix}$ , so identical elements on the diagonal  $\implies \sigma_{x_1} = \sigma_{x_2}$ . In other terms,  $x_1$  and  $x_2$  spread in a similar manner around their respective expected value.  
In this problem, having identical elements on the diagonal would mean that  $a_1 - b_1 = a_2 - b_2$ , or that the probability density function is a square.

- e)  $\text{Cov}(x)$  diagonal  $\implies \sigma(x_1, x_2) = 0$  and  $\sigma(x_2, x_1) = 0$ , which means that  $x_1$  and  $x_2$  are uncorrelated.

## Problem 2

- a) We first find the eigenvalues by computing the characteristic equation.

$$\begin{aligned}\det(\Sigma - \lambda I) &= 0 \\ \begin{vmatrix} 5 - \lambda & 3 \\ 3 & 5 - \lambda \end{vmatrix} &= 0 \\ (5 - \lambda)^2 &= 3^2\end{aligned}$$

Which implies

$$\begin{cases} 5 - \lambda_1 = -3 \\ 5 - \lambda_2 = 3 \\ \lambda_1 = 8 \\ \lambda_2 = 2 \end{cases}$$

Let  $u_1 = \begin{bmatrix} e_{11} \\ e_{21} \end{bmatrix}$  and  $u_2 = \begin{bmatrix} e_{12} \\ e_{22} \end{bmatrix}$  be the two eigenvectors of  $\Sigma$ .

$$\begin{aligned}\Sigma u_1 &= \lambda_1 u_1 \\ (\Sigma - \lambda_1 I) u_1 &= 0 \\ \begin{bmatrix} -3 & 3 \\ 3 & -3 \end{bmatrix} \begin{bmatrix} e_{11} \\ e_{21} \end{bmatrix} &= 0\end{aligned}$$

Which leads to the following system of equations

$$\begin{cases} -3e_{11} + 3e_{21} = 0 \\ 3e_{11} - 3e_{21} = 0 \end{cases} \implies e_{11} = e_{21} \implies u_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

We use the same process to find  $u_2$ .

$$\begin{aligned} \Sigma u_2 &= \lambda_2 u_2 \\ (\Sigma - \lambda_2 I) u_2 &= 0 \\ \begin{bmatrix} 3 & 3 \\ 3 & 3 \end{bmatrix} \begin{bmatrix} e_{12} \\ e_{22} \end{bmatrix} &= 0 \end{aligned}$$

Which leads to the following system of equations

$$\begin{cases} 3e_{12} + 3e_{22} = 0 \\ 3e_{12} + 3e_{22} = 0 \end{cases} \implies e_{12} = -e_{22} \implies u_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

Therefore, we have

$$\begin{aligned} \Phi &= \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \\ \Lambda &= \begin{bmatrix} 8 & 0 \\ 0 & 2 \end{bmatrix} \end{aligned}$$

We can check our results by verifying that  $\Phi \Lambda \Phi^T = \Sigma$ .

$$\begin{aligned} \Phi \Lambda \Phi^T &= \frac{1}{\sqrt{2}} \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 8 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \\ &= \frac{1}{2} \begin{bmatrix} 8 & 2 \\ 8 & -2 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \\ &= \frac{1}{2} \begin{bmatrix} 10 & 6 \\ 6 & 10 \end{bmatrix} \\ &= \begin{bmatrix} 5 & 3 \\ 3 & 5 \end{bmatrix} \\ &= \Sigma \end{aligned}$$

Let  $v_1$  and  $v_2$  be the principal axes of the probability density function. According to the previous decomposition, we have  $v_1 = \sqrt{\lambda_1} u_1$  and  $v_2 = \sqrt{\lambda_2} u_2$ .

$$\begin{aligned} v_1 &= 2\sqrt{2} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\ v_2 &= \sqrt{2} \begin{bmatrix} 1 \\ -1 \end{bmatrix} \end{aligned}$$

b)

