

# Machine learning with kernel methods

## Homework n°1

### Exercise 1. Kernels

1.  $\mathcal{X} = \mathbb{R}_+$ ,  $K(x, x') = \min(x, x')$

- $K$  is obviously symmetric.
- Let  $n \in \mathbb{N}^*$ ,  $(x_1, \dots, x_n) \in \mathbb{R}_+^n$ ,  $(a_1, \dots, a_n) \in \mathbb{R}^n$ .

Note that for  $x, x' \geq 0$ ,  $\min(x, x') = \int_0^{\min(x, x')} 1 \, dt = \int_0^{+\infty} \mathbb{1}_{t \leq \min(x, x')} \, dt = \int_0^{+\infty} \mathbb{1}_{t \leq x} \mathbb{1}_{t \leq x'} \, dt$ ,  
so:

$$\begin{aligned} \sum_{i=1}^n a_i a_j K(x_i, x_j) &= \sum_{i=1}^n a_i a_j \int_0^{+\infty} \mathbb{1}_{t \leq x_i} \mathbb{1}_{t \leq x_j} \, dt = \int_0^{+\infty} \left( \sum_{i=1}^n a_i a_j \mathbb{1}_{t \leq x_i} \mathbb{1}_{t \leq x_j} \right) \, dt \\ &= \int_0^{+\infty} \left( \sum_{i=1}^n a_i \mathbb{1}_{t \leq x_i} \right)^2 \, dt \\ &\geq 0. \end{aligned}$$

Therefore  $\boxed{K \text{ is positive definite}}.$

**Remark:** We essentially just said that  $K(x, x') = \langle \mathbb{1}_{[0, x]}, \mathbb{1}_{[0, x']} \rangle_{L^2(\mathbb{R})}$ , and we can then use the easy implication of Aronszajn's theorem.

2.  $\mathcal{X} = \mathbb{R}_+$ ,  $K(x, x') = \max(x, x')$

Take  $n = 2$ ,  $x_1 = 1$ ,  $x_2 = 2$ ,  $a_1 = 1$ ,  $a_2 = -1$ , then:

$$\begin{aligned} \sum_{1 \leq i, j \leq 2} a_i a_j K(x_i, x_j) &= a_1^2 x_1 + a_2^2 x_2 + 2a_1 a_2 K(x_1, x_2) \\ &= 1 + 2 - 4 \\ &= -1 \\ &< 0, \end{aligned}$$

so  $\boxed{K \text{ is **not** positive definite}}.$

3.  $\mathcal{X}$  a set,  $f, g : \mathcal{X} \rightarrow \mathbb{R}_+$ ,  $K(x, y) = \min(f(x)g(y), f(y)g(x))$ .

First note that  $K(x, y) = \begin{cases} 0 & \text{if } f(x) = 0 \text{ or } f(y) = 0 \\ f(x)f(y) \min\left(\frac{g(x)}{f(x)}, \frac{g(y)}{f(y)}\right) & \text{if } f(x) \neq 0 \text{ and } f(y) \neq 0. \end{cases}$

Let  $n \in \mathbb{N}^*$ ,  $(x_1, \dots, x_n) \in \mathcal{X}^n$ ,  $(a_1, \dots, a_n) \in \mathbb{R}^n$ . Then:

$$\begin{aligned} \sum_{1 \leq i, j \leq n} a_i a_j K(x_i, x_j) &= \sum_{\substack{1 \leq i, j \leq n \\ f(x_i) \neq 0, f(x_j) \neq 0}} a_i a_j K(x_i, x_j) \\ &= \sum_{\substack{1 \leq i, j \leq n \\ f(x_i) \neq 0, f(x_j) \neq 0}} a_i a_j f(x_i) f(x_j) \min\left(\frac{g(x_i)}{f(x_i)}, \frac{g(x_j)}{f(x_j)}\right) \\ &= \sum_{\substack{1 \leq i, j \leq n \\ f(x_i) \neq 0, f(x_j) \neq 0}} b_i b_j \min(y_i, y_j), \end{aligned}$$

where we set, for  $i \in \llbracket 1, n \rrbracket$  such that  $f(x_i) \neq 0$ ,  $b_i = a_i f(x_i)$  and  $y_i = \frac{g(x_i)}{f(x_i)}$ .

Using the fact that  $\min$  is a positive definite kernel (see question 1.), we deduce that

$$\sum_{1 \leq i, j \leq n} a_i a_j K(x_i, x_j) = \sum_{\substack{1 \leq i, j \leq n \\ f(x_i) \neq 0, f(x_j) \neq 0}} b_i b_j \min(y_i, y_j) \geq 0,$$

so  $\boxed{K \text{ is positive definite}}.$

## Exercise 2. Non-expansiveness of the Gaussian kernel

For  $x \in \mathbb{R}^p$ ,  $\|\varphi(x)\|_{\mathcal{H}}^2 = K(x, x) = 1$ .

For  $x, x' \in \mathbb{R}^p$ , we have:

$$\begin{aligned}\|\varphi(x) - \varphi(x')\|_{\mathcal{H}}^2 &= \|\varphi(x)\|_{\mathcal{H}}^2 + \|\varphi(x')\|_{\mathcal{H}}^2 - 2\langle \varphi(x), \varphi(x') \rangle_{\mathcal{H}} \\ &= 1 + 1 - 2K(x, x') \\ &= 2(1 - K(x, x')).\end{aligned}$$

Now, we use the fact that  $\forall t \in \mathbb{R}, e^t \geq 1 + t$  (exp is convex, so its graph is above its tangents), so  $K(x, x') = \exp\left(-\frac{\alpha}{2}\|x - x'\|^2\right) \geq 1 - \frac{\alpha}{2}\|x - x'\|^2$ , and:

$$\|\varphi(x) - \varphi(x')\|_{\mathcal{H}}^2 \leq 2\left(1 - \left(1 - \frac{\alpha}{2}\|x - x'\|^2\right)\right) = \alpha\|x - x'\|^2.$$

So  $\boxed{\forall x, x' \in \mathbb{R}^p, \|\varphi(x) - \varphi(x')\|_{\mathcal{H}} \leq \sqrt{\alpha}\|x - x'\|}$ .

### Exercise 3. RKHS

1. For  $f_1, g_1 \in \mathcal{H}_1, f_2, g_2 \in \mathcal{H}_2$ , we would be tempted to define  $\langle f_1 + f_2, g_1 + g_2 \rangle_{\mathcal{H}_1 + \mathcal{H}_2} = c_1 \langle f_1, g_1 \rangle_{\mathcal{H}_1} + c_2 \langle f_2, g_2 \rangle_{\mathcal{H}_2}$  for some constants  $c_1, c_2 > 0$ . However, the decomposition  $f = f_1 + f_2$  ( $f_1 \in \mathcal{H}_1, f_2 \in \mathcal{H}_2$ ) for  $f \in \mathcal{H}_1 + \mathcal{H}_2$  is not necessarily unique, so  $\langle \cdot, \cdot \rangle_{\mathcal{H}_1 + \mathcal{H}_2}$  is ill-defined.

We consider  $\mathcal{H}_1 \times \mathcal{H}_2$ , which is a Hilbert space when equipped with  $\langle (f_1, f_2), (g_1, g_2) \rangle_{\mathcal{H}_1 \times \mathcal{H}_2} = \frac{1}{\alpha} \langle f_1, g_1 \rangle_{\mathcal{H}_1} + \frac{1}{\beta} \langle f_2, g_2 \rangle_{\mathcal{H}_2}$ . Consider the linear mapping

$$u : \begin{cases} \mathcal{H}_1 \times \mathcal{H}_2 & \rightarrow \mathcal{H}_1 + \mathcal{H}_2 \\ (h_1, h_2) & \mapsto h_1 + h_2. \end{cases}$$

Its kernel  $\ker(u) := u^{-1}(\{0\})$  is closed.

Indeed, if  $(f_n, g_n)_{n \geq 0}$  is a sequence in  $\ker(u)$  which converges to  $(f, g) \in \mathcal{H}_1 \times \mathcal{H}_2$ , we have, by definition of  $\ker(u)$ ,  $\forall n \geq 0, f_n + g_n \stackrel{(*)}{=} 0$ .

And  $f_n \xrightarrow[n \rightarrow +\infty]{\mathcal{H}_1} f, g_n \xrightarrow[n \rightarrow +\infty]{\mathcal{H}_2} g$ , and the converge in a RKHS implies pointwise convergence.

So for each  $x \in \mathcal{X}$ ,  $\lim_{n \rightarrow +\infty} f_n(x) = f(x), \lim_{n \rightarrow +\infty} g_n(x) = g(x)$ , and  $(*)$  implies  $f(x) + g(x) = 0$ . Therefore  $f + g = 0$ , i.e.,  $(f, g) \in \ker(u)$ .

We thus know that  $\mathcal{H}_1 \times \mathcal{H}_2 = \ker(u) \oplus (\ker(u))^\perp$ .

Then, the restriction of  $u$  to  $(\ker(u))^\perp$ , which we denote by  $v = u|_{(\ker(u))^\perp} : (\ker(u))^\perp \rightarrow \mathcal{H}_1 + \mathcal{H}_2$ , is an isomorphism.

For  $f, g \in \mathcal{H}_1 + \mathcal{H}_2$ , define  $\langle f, g \rangle_{\mathcal{H}_1 + \mathcal{H}_2} = \langle v^{-1}(f), v^{-1}(g) \rangle_{\mathcal{H}_1 \times \mathcal{H}_2}$ . Since  $\mathcal{H}_1 \times \mathcal{H}_2$  is a Hilbert space, and  $v^{-1}$  is an isomorphism,  $(\mathcal{H}_1 + \mathcal{H}_2, \langle \cdot, \cdot \rangle_{\mathcal{H}_1 + \mathcal{H}_2})$  is a Hilbert space.

Let us check that  $\mathcal{H}_1 + \mathcal{H}_2$  endowed with the above scalar product is the RKHS of  $K := \alpha K_1 + \beta K_2$ .

- For  $x \in \mathcal{X}$ ,  $K_x = \underbrace{\alpha K_{1,x}}_{\in \mathcal{H}_1} + \underbrace{\beta K_{2,x}}_{\in \mathcal{H}_2} \in \mathcal{H}_1 + \mathcal{H}_2$ .

- Let  $f \in \mathcal{H}_1 + \mathcal{H}_2$ , and let  $x \in \mathcal{X}$ .

Define  $(f_1, f_2) = v^{-1}(f), (A_x, B_x) = v^{-1}(\alpha K_{1,x} + \beta K_{2,x})$ . Then:

$$\begin{aligned} \langle f, \alpha K_{1,x} + \beta K_{2,x} \rangle_{\mathcal{H}_1 + \mathcal{H}_2} &= \langle (f_1, f_2), (A_x, B_x) \rangle_{\mathcal{H}_1 \times \mathcal{H}_2} \\ &= \langle (f_1, f_2), (\alpha K_{1,x}, \beta K_{2,x}) \rangle_{\mathcal{H}_1 \times \mathcal{H}_2} \\ &\quad + \langle (f_1, f_2), (A_x - \alpha K_{1,x}, B_x - \beta K_{2,x}) \rangle_{\mathcal{H}_1 \times \mathcal{H}_2} \end{aligned}$$

Then, we notice that:

$$\begin{aligned} \langle (f_1, f_2), (\alpha K_{1,x}, \beta K_{2,x}) \rangle_{\mathcal{H}_1 \times \mathcal{H}_2} &= \frac{1}{\alpha} \langle f_1, \alpha K_{1,x} \rangle_{\mathcal{H}_1} + \frac{1}{\beta} \langle f_2, \beta K_{2,x} \rangle_{\mathcal{H}_2} \text{ (definition of } \langle \cdot, \cdot \rangle_{\mathcal{H}_1 \times \mathcal{H}_2}) \\ &= f_1(x) + f_2(x) \text{ (reproduction property for } \mathcal{H}_1 \text{ and } \mathcal{H}_2) \\ &= f(x). \end{aligned}$$

And  $u(A_x - \alpha K_{1,x}, B_x - \beta K_{2,x}) = (A_x + B_x) - (\alpha K_{1,x} + \beta K_{2,x}) = 0$  because of the definition of  $A_x, B_x$ . So  $(A_x - \alpha K_{1,x}, B_x - \beta K_{2,x}) \in \ker(u)$ , and  $(f_1, f_2) \in (\ker(u))^\perp$ , and therefore  $\langle (f_1, f_2), (A_x - \alpha K_{1,x}, B_x - \beta K_{2,x}) \rangle_{\mathcal{H}_1 \times \mathcal{H}_2} = 0$ .

Finally,  $\langle f, \alpha K_{1,x} + \beta K_{2,x} \rangle_{\mathcal{H}_1 + \mathcal{H}_2} = f(x)$ , and the reproduction property holds.

So  $\mathcal{H}_1 + \mathcal{H}_2$  is the RKHS of  $\alpha K_1 + \beta K_2$ .

In fact, for  $f \in \mathcal{H}_1 + \mathcal{H}_2$ , let  $f_1 \in \mathcal{H}_1, f_2 \in \mathcal{H}_2$  be such that  $f_1 + f_2 = f$ .  
Then:

$$\begin{aligned} \|(f_1, f_2)\|_{\mathcal{H}_1 \times \mathcal{H}_2}^2 &= \left\| \underbrace{((f_1, f_2) - v^{-1}(f))}_{\in \ker(u)} + \underbrace{v^{-1}(f)}_{\in (\ker(u))^\perp} \right\|_{\mathcal{H}_1 \times \mathcal{H}_2}^2 \\ &= \|(f_1, f_2) - v^{-1}(f)\|_{\mathcal{H}_1 \times \mathcal{H}_2}^2 + \|v^{-1}(f)\|_{\mathcal{H}_1 \times \mathcal{H}_2}^2 \\ &\geq \|v^{-1}(f)\|_{\mathcal{H}_1 \times \mathcal{H}_2}^2 \\ &= \|f\|_{\mathcal{H}_1 + \mathcal{H}_2}^2. \end{aligned}$$

Therefore  $\|f\|_{\mathcal{H}_1 + \mathcal{H}_2} = \inf \{ \|(f_1, f_2)\|_{\mathcal{H}_1 \times \mathcal{H}_2} \mid f_1 \in \mathcal{H}_1, f_2 \in \mathcal{H}_2, f = f_1 + f_2 \}$  or

$$\|f\|_{\mathcal{H}_1 + \mathcal{H}_2}^2 = \inf \left\{ \frac{1}{\alpha} \|f_1\|_{\mathcal{H}_1}^2 + \frac{1}{\beta} \|f_2\|_{\mathcal{H}_2}^2 \mid f_1 \in \mathcal{H}_1, f_2 \in \mathcal{H}_2, f = f_1 + f_2 \right\}.$$

**2.** Let  $K$  be a p.d. kernel on  $\mathcal{X}$ , and  $f : \mathcal{X} \rightarrow \mathbb{R}$ . Let  $\mathcal{H}$  be the RKHS with kernel  $K$ .

- First, assume that  $f \in \mathcal{H}$ .

It is clear that  $(x, x') \mapsto K(x, x') - \lambda f(x)f(x')$  is symmetric for any  $\lambda$  (due to the symmetry of  $K$ ).

For  $n \in \mathbb{N}^*$ ,  $(x_1, \dots, x_n) \in \mathcal{X}^n, (a_1, \dots, a_n) \in \mathbb{R}^n$ :

$$\begin{aligned} \sum_{1 \leq i, j \leq n} a_i a_j f(x_i) f(x_j) &= \left( \sum_{i=1}^n a_i f(x_i) \right)^2 \\ &= \left( \sum_{i=1}^n a_i \langle f, K_{x_i} \rangle_{\mathcal{H}} \right)^2 \\ &= \left( \left\langle f, \sum_{i=1}^n a_i K_{x_i} \right\rangle_{\mathcal{H}} \right)^2 \\ &\leq \|f\|_{\mathcal{H}}^2 \left\| \sum_{i=1}^n a_i K_{x_i} \right\|_{\mathcal{H}}^2 \quad (\text{Cauchy-Schwarz}) \\ &= \|f\|_{\mathcal{H}}^2 \sum_{1 \leq i, j \leq n} a_i a_j \langle K_{x_i}, K_{x_j} \rangle_{\mathcal{H}} \\ &= \|f\|_{\mathcal{H}}^2 \sum_{1 \leq i, j \leq n} a_i a_j K(x_i, x_j). \end{aligned}$$

This shows that  $(x, x') \mapsto K(x, x') - \lambda f(x)f(x')$  is p.d. for  $\lambda = 1/\|f\|_{\mathcal{H}}^2 > 0$  if  $f \neq 0$ .

If  $f = 0$ , then the above kernel (for  $\lambda > 0$ ) is just  $K$ , so it is p.d. for any  $\lambda > 0$ .

- We now assume that  $K_1 : (x, x') \mapsto K(x, x') - \lambda f(x)f(x')$  is p.d. for some  $\lambda > 0$ .

It is easy to check that  $K_2 : (x, x') \mapsto \lambda f(x)f(x')$  is also p.d. (the symmetry is obvious, and

$$\sum_{i,j} a_i a_j \lambda f(x_i) f(x_j) = \left( \sum_i \sqrt{\lambda} a_i f(x_i) \right)^2 \geq 0).$$

Moreover,  $K = K_1 + K_2$ . Using question 1.,  $\mathcal{H}$  is the sum of the RKHS of  $K_1$ , denoted by  $\mathcal{H}_1$ , and the RKHS of  $K_2$ , denoted by  $\mathcal{H}_2$ :  $\mathcal{H} = \mathcal{H}_1 + \mathcal{H}_2$ .

And  $f \in \mathcal{H}_2$  (if  $f \neq 0$ , take  $a$  such that  $f(a) \neq 0$ , then  $f = \frac{1}{\lambda f(a)} K_{2,a} \in \mathcal{H}_2$ ; if  $f = 0$ , it is obvious); and  $0 \in \mathcal{H}_1$ .

So  $f = 0 + f \in \mathcal{H}_1 + \mathcal{H}_2 = \mathcal{H}$ .

We have shown that:

$f \in \mathcal{H}$  if and only if there exists  $\lambda > 0$  such that  $(x, x') \mapsto K(x, x') - \lambda f(x)f(x')$  is p.d. .