

## KERNEL METHODS IN M.L.

Homework 1 - by David SOTO -

### Exercise 1: Kernels

1. We have  $\mathcal{X} = \mathbb{R}_+$  and the kernel  $K$  defined by:

$$\forall (x, y) \in \mathbb{R}_+^2, \quad K(x, y) = \min(x, y).$$

\*  $\forall (x, y) \in \mathbb{R}_+^2, \quad K(x, y) = \min(x, y) = \min(y, x) = K(y, x)$   
 $\Rightarrow K$  is symmetric.

\* Now, let's rewrite the kernel  $K$ . Indeed, we notice that  $\forall (x, y) \in \mathbb{R}_+^2$ :

$$K(x, y) = \min(x, y) = \int_{\mathbb{R}_+} \mathbf{1}_{\{t \leq x\}} \mathbf{1}_{\{t \leq y\}} dt. \quad (*)$$

From this we can prove the second point of the definition of a p.d. kernel.

Let  $N \in \mathbb{N}$ , let  $(x_1, \dots, x_N) \in \mathbb{R}_+^N$  and let  $(a_1, \dots, a_N) \in \mathbb{R}^N$ . We have:

$$A = \sum_{i=1}^N \sum_{j=1}^N a_i a_j K(x_i, x_j) = \sum_{i=1}^N \sum_{j=1}^N a_i a_j \min(x_i, x_j)$$

$$A \stackrel{(*)}{=} \sum_{i=1}^N \sum_{j=1}^N a_i a_j \int_{\mathbb{R}_+} \mathbf{1}_{\{t \leq x_i\}} \mathbf{1}_{\{t \leq x_j\}} dt$$

by the linearity of the integral (since the summations are finite)  
we have:

$$A = \int_{\mathbb{R}_+} \sum_{i=1}^N \sum_{j=1}^N a_i a_j \mathbf{1}_{\{t \leq x_i\}} \mathbf{1}_{\{t \leq x_j\}} dt$$

$$A = \int_{\mathbb{R}_+} \sum_{i=1}^N a_i \mathbf{1}_{\{t \leq x_i\}} \sum_{j=1}^N a_j \mathbf{1}_{\{t \leq x_j\}} dt$$

$$A = \int_{\mathbb{R}_+} \left( \sum_{i=1}^N a_i \mathbf{1}_{\{t \leq x_i\}} \right)^2 dt \geq 0$$

$$\text{That is } \sum_{i=1}^N \sum_{j=1}^N a_i a_j K(x_i, x_j) \geq 0$$

Hence we can conclude that  $K$  is a positive definite kernel.

1.2  $X = \mathbb{R}_+$  and we have  $\forall (x, y) \in \mathbb{R}_+^2, K(x, y) = \max(x, y)$

If we take  $N = 2, (x_1, x_2) = (5, 4) \in \mathbb{R}_+^2$   
and  $(a_1, a_2) = (1, -1) \in \mathbb{R}^2$ , we have:

$$A = \sum_{i=1}^2 \sum_{j=1}^2 a_i a_j K(x_i, x_j)$$

$$A = 1 \times \max(5, 5) - 1 \times \max(5, 4) - 1 \times \max(4, 5) \\ + (-1) \times (-1) \times \max(4, 4)$$

$$A = 5 - 5 - 5 + 4$$

$$A = -1 < 0$$

Thanks to this counterexample we can conclude that the kernel  $K$  is not a positive definite kernel.

3. Let  $X$  be a set and  $f, g: X \rightarrow \mathbb{R}_+$  be two non-negative functions:

$$\forall (x, y) \in X^2, K(x, y) = \min(f(x)g(y), f(y)g(x))$$

$$*\forall (x, y) \in X^2,$$

$$K(x, y) = \min(f(x)g(y), f(y)g(x))$$

$$K(x, y) = \min(f(y)g(x), f(x)g(y))$$

$$K(x, y) = K(y, x)$$

$\Rightarrow K$  is symmetric!

\* Now, we notice that  $\forall (x, y) \in X^2$  such that  
 $g(x) > 0$  and  $g(y) > 0$ , we have :

$$K(x, y) = \min(g(x)g(y), g(y)g(x)) \\ = \min\left(g(x)g(y) \cdot \frac{g(x)}{g(x)}, g(y)g(x) \cdot \frac{g(y)}{g(y)}\right)$$

$$\boxed{K(x, y) = g(x)g(y) \min\left(\frac{g(x)}{g(x)}, \frac{g(y)}{g(y)}\right)} \quad (*)$$

Let  $N \in \mathbb{N}$ , let  $(x_1, \dots, x_N) \in X^N$  and let  $(a_1, \dots, a_N) \in \mathbb{R}^N$ .  
We have :

$$A = \sum_{i=1}^N \sum_{j=1}^N a_i a_j K(x_i, x_j)$$

$$A = \sum_{i=1}^N \sum_{j=1}^N a_i a_j \min(g(x_i)g(x_j), g(x_j)g(x_i))$$

$$A = 0 + \sum_{\substack{1 \leq i, j \leq N \\ g(x_i) > 0 \\ g(x_j) > 0}} a_i a_j g(x_i)g(x_j) \min\left(\frac{g(x_i)}{g(x_i)}, \frac{g(x_j)}{g(x_j)}\right)$$

It is patent that  $\frac{g(x_i)}{g(x_i)} \geq 0 \forall i$  and  $\frac{g(x_j)}{g(x_j)} \geq 0 \forall j$

(when  $g(x_i) > 0$  and  $g(x_j) > 0$ )

Moreover, we have seen that the kernel  $\bar{K}: \mathbb{R}_+^2 \rightarrow \mathbb{R}$   
 $(x, y) \mapsto \min(x, y)$

is a positive definite kernel (see question 1),

therefore  $\bar{K}$  verifies that  $\forall m \in \mathbb{N}$ ,  $\forall (y_1, \dots, y_m) \in \mathbb{R}_+^m$   
and  $\forall (b_1, \dots, b_m) \in \mathbb{R}^m$ :

$$B = \sum_{i=1}^m \sum_{j=1}^m b_i b_j \min(y_i, y_j) \geq 0.$$

If we denote:

$$\forall i=1, \dots, N, \quad b_i = a_i g(x_i)$$

and  $\forall i=1, \dots, N, \quad y_i = \begin{cases} g(x_i) & \text{if } g(x_i) > 0 \\ 0 & \text{otherwise} \end{cases}$

$\in \mathbb{R}_+$

We have:

$$A = \sum_{i=1}^N \sum_{j=1}^N a_i a_j K(x_i, x_j)$$

$$A = \sum_{i=1}^N \sum_{j=1}^N b_i b_j \min(y_i, y_j) \geq 0$$

(from question 1!)

that is  $A = \sum_{i=1}^N \sum_{j=1}^N a_i a_j K(x_i, x_j) \geq 0$

Hence, we can conclude that  $K$  is a positive definite kernel

2

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

**Setting:** We consider the Gaussian kernel  $K: \mathbb{R}^p \times \mathbb{R}^p \rightarrow \mathbb{R}$  such that for all pair of  $(x, y) \in \mathbb{R}^p \times \mathbb{R}^p$ :

$$K(x, y) = e^{-\frac{\alpha}{2} \|x-y\|^2} \quad (\text{where } \|\cdot\| \text{ is the Euclidean norm on } \mathbb{R}^p)$$

We call  $\mathcal{H}$  the RKHS of  $K$  and consider its RKHS mapping  $\varphi: \mathbb{R}^p \rightarrow \mathcal{H}$  such that  $\forall (x, y) \in \mathbb{R}^p \times \mathbb{R}^p$

$$K(x, y) = \langle \varphi(x), \varphi(y) \rangle_{\mathcal{H}}$$

\* Let's show that  $\|\varphi(x) - \varphi(y)\|_{\mathcal{H}} \leq \sqrt{\alpha} \|x-y\|$ .

Let  $(x, y) \in \mathbb{R}^p \times \mathbb{R}^p$ , we have:

$$\begin{aligned} \|\varphi(x) - \varphi(y)\|_{\mathcal{H}}^2 &= \langle \varphi(x) - \varphi(y), \varphi(x) - \varphi(y) \rangle_{\mathcal{H}} \\ &= \langle \varphi(x), \varphi(x) - \varphi(y) \rangle_{\mathcal{H}} - \langle \varphi(y), \varphi(x) - \varphi(y) \rangle_{\mathcal{H}} \\ &= \langle \varphi(x), \varphi(x) \rangle_{\mathcal{H}} - \langle \varphi(x), \varphi(y) \rangle_{\mathcal{H}} \\ &\quad - (\langle \varphi(y), \varphi(x) \rangle_{\mathcal{H}} - \langle \varphi(y), \varphi(y) \rangle_{\mathcal{H}}) \end{aligned}$$

$$\|\varphi(x) - \varphi(y)\|_{\mathcal{H}}^2 = K(x, x) - K(x, y) - K(y, x) + K(y, y)$$

We notice that  $\forall (x, y) \in \mathbb{R}^p \times \mathbb{R}^p$ ,

$$K(x, y) = \langle \varphi(x), \varphi(y) \rangle_{\mathcal{H}} = \langle \varphi(y), \varphi(x) \rangle_{\mathcal{H}} = K(y, x)$$

i.e  $K$  is symmetric. Therefore, we have:

$$\|\varphi(x) - \varphi(y)\|_{\mathcal{H}}^2 = K(x, x) + K(y, y) - 2K(x, y)$$

$$\|\varphi(x) - \varphi(y)\|_{\mathcal{H}}^2 = e^0 + e^0 - 2e^{-\frac{\alpha}{2} \|x-y\|^2}$$

$$\|\varphi(x) - \varphi(y)\|_{\mathcal{H}}^2 = 2 - 2e^{-\frac{\alpha}{2} \|x-y\|^2}$$

$$\text{that is } \|\Psi(x) - \Psi(y)\|_{\text{Hilb}}^2 = 2(1 - e^{-\frac{\alpha}{2}\|x-y\|^2})$$

Now, we use the convexity inequality which states  
that  $\forall u \in \mathbb{R}$ ,  $e^u \geq 1+u$ .

$$\Rightarrow \forall (x,y) \in \mathbb{R}^p \times \mathbb{R}^p \quad e^{-\frac{\alpha}{2}\|x-y\|^2} \geq 1 + \left(-\frac{\alpha}{2}\|x-y\|^2\right)$$

$$\Rightarrow \forall (x,y) \in \mathbb{R}^p \times \mathbb{R}^p \quad -e^{-\frac{\alpha}{2}\|x-y\|^2} \leq -1 + \frac{\alpha}{2}\|x-y\|^2.$$

Moreover, by noticing that  $\forall (x,y) \in \mathbb{R}^p \times \mathbb{R}^p$   $\boxed{-\frac{\alpha}{2}\|x-y\|^2 \leq 0}$   
(because  $\alpha > 0$ ), we have:

$$\Rightarrow \forall (x,y) \in \mathbb{R}^p \times \mathbb{R}^p :$$

$$\|\Psi(x) - \Psi(y)\|_{\text{Hilb}}^2 \leq 2(1 - 1 + \frac{\alpha}{2}\|x-y\|^2)$$

$$\leq 2 \times \frac{\alpha}{2}\|x-y\|^2$$

$$\|\Psi(x) - \Psi(y)\|_{\text{Hilb}}^2 \leq \alpha\|x-y\|^2$$

$$\Rightarrow \|\Psi(x) - \Psi(y)\|_{\text{Hilb}} \leq \sqrt{\alpha} \|x-y\| \quad \forall (x,y) \in \mathbb{R}^p \times \mathbb{R}^p$$

□

(3)

### Exercise 3. Uniqueness of the RKHS

Let us prove that if  $K: X \times X \rightarrow \mathbb{R}$  is a positive definite kernel, then it is the r.k of a UNIQUE RKHS

Let  $K: X \times X \rightarrow \mathbb{R}$  be a positive definite kernel.

Then, we know from the course that  $K$  is a r.k!

Now let us prove that  $K$  is the r.k of a unique RKHS!

\* Let us first consider a RKHS  $\mathcal{H}$  with r.k  $K$ .

By definition of a r.k, we have that:

$$\forall x \in X, K_x \in \mathcal{H}$$

Therefore the linear space spanned by the functions

$K_x: t \mapsto K(x, t) \quad \forall x \in X$ , which we denote

$$\mathcal{F} = \left\{ \sum_{i=1}^m \alpha_i K_{x_i}, m \in \mathbb{N}, (\alpha_1, \dots, \alpha_m) \in \mathbb{R}^m, (x_1, \dots, x_m) \in X^m \right\}$$

is clearly a subspace of  $\mathcal{H}$

Let  $v \in \mathcal{H}$  be a vector orthogonal to all vectors in  $\mathcal{F}$ .

In particular we have that  $\forall x \in X$ ,

$$v(x) \stackrel{*}{=} \langle v, K_x \rangle_{\mathcal{H}} = 0 \quad (* \text{ reproducing property})$$

that is  $v = 0_{\mathcal{H}}$  and since  $\mathcal{H}$  is a Hilbert

space and  $\mathcal{F} \subset \mathcal{H}$  a linear subspace of  $\mathcal{H}$

then we can deduce that  $\mathcal{F}$  is dense in  $\mathcal{H}$ .

Moreover the  $\mathcal{H}$  norm for functions in  $\mathcal{F}$  only depends on the r.k  $K$ , because it is given for a function

$$f = \sum_{i=1}^m \alpha_i K_{x_i} \in \mathcal{F} \text{ by:}$$

$$\|f\|_{\mathcal{H}}^2 = \sum_{i=1}^m \sum_{j=1}^m \alpha_i \alpha_j \langle K_{x_i}, K_{x_j} \rangle_{\mathcal{H}}$$

$$\|f\|_{\mathcal{H}}^2 = \sum_{i=1}^m \sum_{j=1}^m \alpha_i \alpha_j K(x_i, x_j).$$

\* Now we suppose that  $\mathcal{H}'$  is also a RKHS with rk  $K$ .

Let us prove that  $\mathcal{H} = \mathcal{H}'$ .

By using the same arguments as in the first point \*

we obtain that  $\mathcal{F}$  (the linear space spanned by the functions  $K_x: F \rightarrow K(x, \cdot)$   $\forall x \in X$ ) is dense in  $\mathcal{H}'$ , and that the  $\mathcal{H}'$  norm in  $\mathcal{F}$  is given by:  $\forall f = \sum_{i=1}^m \alpha_i K_{x_i} \in \mathcal{F}$

$$\|f\|_{\mathcal{H}'}^2 = \sum_{i=1}^m \sum_{j=1}^m \alpha_i \alpha_j K(x_i, x_j).$$

We have in particular that  $\forall f \in \mathcal{F}$ ,  $\|f\|_{\mathcal{H}'} = \|f\|_{\mathcal{H}}$ .

Let  $f \in \mathcal{H}$ . By definition of  $\mathcal{F}$  being dense in  $\mathcal{H}$ ,  $\exists (f_n)_n$  a sequence in  $\mathcal{F}$  such that  $f_n \xrightarrow{n \rightarrow \infty} f$ , i.e. such that  $\|f_n - f\|_{\mathcal{H}} \xrightarrow{n \rightarrow \infty} 0$ .

In particular, we notice that the converging sequence  $(f_n)_n$  is a Cauchy sequence for the  $\mathcal{H}$  norm, and since  $\mathcal{H}$  norm coincides with the  $\mathcal{H}'$  norm on  $\mathcal{F}$ , we can deduce that  $(f_n)_n$  is also a Cauchy sequence for the  $\mathcal{H}'$  norm and that  $(f_n)_n$  converges in  $\mathcal{H}'$  to a function  $h \in \mathcal{H}'$ .

Then, by using the "convergence in a RKHS implies pointwise convergence" corollary of the course, applied to  $\mathcal{H}$  and  $\mathcal{H}'$ , we have that  $\forall x \in X$ ,  $\lim_{n \rightarrow \infty} f_n(x) = f(x) = h(x)$ . i.e.,  $\forall x \in X$ ,  $f(x) = h(x) \Rightarrow f = h$ .

and therefore we have  $\mathcal{H} \subseteq \mathcal{H}'$ .

$$\Rightarrow \mathcal{H} \subseteq \mathcal{H}'$$

\* By using the same arguments (but the other way around!) we obtain  $\mathcal{H}' \subseteq \mathcal{H}$ .

$$\Rightarrow \mathcal{H} = \mathcal{H}', \quad \mathcal{H} \text{ and } \mathcal{H}' \text{ are the same RKHS!}$$

$\Rightarrow K$  is the r.k of a unique RKHS!  $\square$