# Homework <br> Due February 7th 

## 1 Combination rules for kernels

Consider a set $\mathcal{X}$ and two positive definite (p.d.) kernels $K_{1}, K_{2}: \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$.

1. For all scalars $\alpha, \beta \geq 0$, show that the sum kernel $\alpha K_{1}+\beta K_{2}$ is p.d.
2. Show that the product kernel $(x, y) \mapsto K_{1}(x, y) K_{2}(x, y)$ is p.d. (Be careful, this is a pointwise multiplication, not a matrix multiplication)
3. Given a sequence $\left(K_{n}\right)_{n \geq 0}$ of p.d. kernels such that for all $x, y$ in $\mathcal{X}, K_{n}(x, y)$ converges to a value $K(x, y)$ in $\mathbb{R}$ (pointwise convergence). Show that $K$ is a p.d. kernel.
4. Show that $e^{K_{1}}$ is p.d.

## 2 Positive definite kernels

Which of these kernels are positive definite? You need to provide proofs for all cases.

- $K(x, y)=1 /(1-x y)$ with $\mathcal{X}=(-1,1)$.
- $K(x, y)=2^{x y}$ with $\mathcal{X}=\mathbb{N}$.
- $K(x, y)=\log (1+x y)$ with $\mathcal{X}=\mathbb{R}_{+}$.
- $K(x, y)=e^{-(x-y)^{2}}$ with $\mathcal{X}=\mathbb{R}$.
- $K(x, y)=\cos (x+y)$ with $\mathcal{X}=\mathbb{R}$.
- $K(x, y)=\cos (x-y)$ with $\mathcal{X}=\mathbb{R}$.
- $K(x, y)=\min (x, y)$ with $\mathcal{X}=\mathbb{R}_{+}$.
- $K(x, y)=\max (x, y)$ with $\mathcal{X}=\mathbb{R}_{+}$.
- $K(x, y)=\min (x, y) / \max (x, y)$ with $\mathcal{X}=\mathbb{R}_{+}$.
- $K(x, y)=G C D(x, y)$ (greatest common divisor) with $\mathcal{X}=\mathbb{N}$.
- $K(x, y)=\operatorname{LCM}(x, y)$ (least common multiple) with $\mathcal{X}=\mathbb{N}$.
- $K(x, y)=G C D(x, y) / \operatorname{LCM}(x, y)$ (least common multiple) with $\mathcal{X}=\mathbb{N}$.


## 3 Covariance Operators in RKHS

Given two sets of real numbers $X=\left(x_{1}, \ldots, x_{n}\right) \in \mathbb{R}^{n}$ and $Y=\left(y_{1}, \ldots, y_{n}\right) \in \mathbb{R}^{n}$, the covariance between $X$ and $Y$ is defined as

$$
\operatorname{cov}_{n}(X, Y)=\mathbb{E}_{n}(X Y)-\mathbb{E}_{n}(X) \mathbb{E}_{n}(Y)
$$

where $\mathbb{E}_{n}(U)=\left(\sum_{i=1}^{n} u_{i}\right) / n$. The covariance is useful to detect linear relationships between $X$ and $Y$. In order to extend this measure to potential nonlinear relationships between $X$ and $Y$, we consider the following criterion:

$$
C_{n}^{K}(X, Y)=\max _{f, g \in \mathcal{B}_{K}} \operatorname{cov}_{n}(f(X), g(Y)),
$$

where $K$ is a positive definite kernel on $\mathbb{R}, \mathcal{B}_{K}$ is the unit ball of the RKHS of $K$, and $f(U)=\left(f\left(u_{1}\right), \ldots, f\left(u_{n}\right)\right)$ for a vector $U=\left(u_{1}, \ldots, u_{n}\right)$.

1. Express simply $C_{n}^{K}(X, Y)$ for the linear kernel $K(a, b)=a b$.
2. For a general kernel $K$, express $C_{n}^{K}(X, Y)$ in terms of the Gram matrices of $X$ and $Y$.

## 4 Some upper bounds for learning theory

Let $K$ be a positive definite kernel on a measurable set $\mathcal{X},\left(\mathcal{H}_{K},\|\cdot\|_{\mathcal{H}_{K}}\right)$ denote the corresponding reproducing kernel Hilbert space, $\lambda>0$, and $\phi: \mathbb{R} \rightarrow \mathbb{R}$ a function. We assume that:

$$
\kappa=\sup _{\mathbf{x} \in \mathcal{X}} K(\mathbf{x}, \mathbf{x})<+\infty,
$$

and we note $B_{R}=\left\{f \in \mathcal{H}_{K},\|f\|_{\mathcal{H}_{K}} \leq R\right\}$. Let us define, for all $f \in \mathcal{H}$ and $\mathbf{x} \in \mathcal{X}$,

$$
R_{\phi}(f, \mathbf{x})=\phi(f(\mathbf{x}))+\lambda\|f\|_{\mathcal{H}_{K}}^{2} .
$$

1. $\phi$ is said to be Lipschitz if there exists a constant $L>0$ such that, for all $u, v \in \mathbb{R}$, $|\phi(u)-\phi(v)| \leq L|u-v|$. Show that, in that case, there exists a constant $C_{1}$ to be determined such that, for all $\mathbf{x} \in \mathcal{X}$ and $f, g \in B_{R}$ :

$$
\left|R_{\phi}(f, \mathbf{x})-R_{\phi}(g, \mathbf{x})\right| \leq C_{1}\|f-g\|_{\mathcal{H}_{K}} .
$$

2. $\phi$ is said to be convex if for all $u, v \in \mathbb{R}$ and $t \in[0,1], \phi(t u+(1-t) v) \leq t \phi(u)+(1-$ t) $\phi(v)$. We assume that $\phi$ is convex, and that for all $\mathbf{x} \in \mathcal{X}$, there exists $f_{\mathbf{x}} \in \mathcal{H}$ which minimizes $f \mapsto R_{\phi}(f, \mathbf{x})$. Show that there exists a constant $C_{2}>0$ to be determined, such that:

$$
\psi(f, \mathbf{x}) \triangleq R_{\phi}(f, \mathbf{x})-R_{\phi}\left(f_{\mathbf{x}}, \mathbf{x}\right) \geq C_{2}\left\|f-f_{\mathbf{x}}\right\|_{\mathcal{H}_{K}}^{2} .
$$

3. Under the hypothesis of questions 2.1 and $\mathbf{2 . 2}$, show that there exists a constant $C$, to be determined, such that if $X$ is a random variable with values in $\mathcal{X}$, then:

$$
\forall f \in B_{R}, \quad \mathbb{E} \psi(f, X)^{2} \leq C \mathbb{E} \psi(f, X)
$$

