

KMML Final homework !

Mahdi Kallel

TOTAL POINTS

17.75 / 20

QUESTION 1

1 Exercise 1 2 / 3

- 0 pts Correct
- ✓ - 0.5 pts Error
- ✓ - 0.5 pts Missing
- 1 pts 2 errors

💡 K5 : you can not take $x' = -1$ (kernel defined on R^+). K6 missing

QUESTION 2

2 Exercise 2 2.5 / 3

- 0 pts Correct
- 0.5 pts Error in "K pd implies $(K(x,x')=1 \text{ iff } K(x',x)=1)$ "
- 1 pts Error in "K pd implies $(K(x,x')=K(x',x'')=1 \Rightarrow K(x',x'')=1)$ "
- 1 pts Proof of the converse (that K is pd if ...)
imcomplete
 - 1.5 pts Proof that "K pd implies the two properties" missing
 - 1 pts Lacks clarity
 - 2 pts Incomplete
- ✓ - 0.5 pts Lacks details
- 1.5 pts Error

💡 You did not prove that K is symmetric (to prove that it is pd)

QUESTION 3

3 3.1 2 / 2

- ✓ - 0 pts Correct
- 0.5 pts Lacks information
- 1 pts Unclear
- 1.5 pts Not correct
- 2 pts Not correct

QUESTION 4

4 3.2 1 / 1

- ✓ - 0 pts Correct
- 0.5 pts Small error
- 1 pts Not finished
- 1 pts Error in the proof
- 1 pts Not solved

QUESTION 5

5 3.3 0.5 / 1

- 0 pts Correct
 - ✓ - 0.5 pts Expression of MMD as a function of kernel missing or wrong
 - 0.5 pts Expression of MMD as a sup missing or wrong
- 💡 almost good... a "-2" missing though

QUESTION 6

6 3.4 2 / 2

- ✓ - 0 pts Correct
- 2 pts Not done or wrong
- 1.5 pts Not solved, but some effort...
- 1 pts Small error
- 0.5 pts Small error

QUESTION 7

7 4.1 1 / 1

- ✓ - 0 pts Correct
- 1 pts wrong argument or missing answer
- 0.25 pts missing details

QUESTION 8

8 4.2 0.75 / 1

- 0 pts Correct
- 1 pts major argument is missing
- ✓ - 0.25 pts need to be a bit more rigorous to handle

the cases when $x_i = 0$

- **0.5 pts** missing argument
- **1 pts** missing answer

QUESTION 9

9 4.3 2 / 2

✓ - **0 pts** Correct

- **0.5 pts** missing minor argument
- **1 pts** there is a wrong argument but part of the proof is ok
- **2 pts** the proof relies on a wrong statement
- **1 pts** missing major argument
- **2 pts** missing answer

QUESTION 10

10 4.4 2 / 2

✓ - **0 pts** Correct

- **0.5 pts** missing details or minor mistake
- **2 pts** missing or wrong answer
- **1 pts** not exactly the right answer
- **0 pts** Click here to replace this description.

QUESTION 11

11 4.5 2 / 2

✓ - **0 pts** Correct

- **2 pts** missing or too incomplete answer
- **1 pts** inaccurate or incomplete statement
- **1.5 pts** the sufficient condition is too strong (only leads to a trivial case)
- **0.5 pts** minor details missing

Kernel Methods HW#5:

Mahdi KALLEL

Exercice 1 :

$K_1(x, x') = 2^{x-x'}$ is not symmetric : $K(1, 0) = 2 / K(0, 1) = 0.5$ and therefore is not p.d

$K_2(x, x') = 2^{x+x'}$ is symmetric, $K(x, x') = 2^{x+x'} = 2^{x'+x} = K(x', x)$

and $\forall A, X \in (\mathbb{R}^n, \mathbb{R}^n)$ $A^T K A = \sum a_i a_j K(x_i, x_j) = \sum a_i 2^{x_i} 2^{x_j} a_j =$
 $(a_1 2^{x_1} \dots a_n 2^{x_n})^T (a_1 2^{x_1} \dots a_n 2^{x_n}) \geq 0$

$K_3(x, x') = 2^{xx'} = e^{xx' \log(2)},$

$\kappa(x, x') = \log(2)xx'$ is p.d a p.d kernel scaled by the positive factor $\log(2)$.

We know that if K is p.d then e^K is p.d and thus K_3 is p.d.

$K_4(x, x') = \log(1 + xx')$, if we take $x = 1, x' = 2$. and $A = (-2, 1)$.

then $K = \begin{pmatrix} \log(5) & \log(3) \\ \log(3) & \log(2) \end{pmatrix}$ and $A^T K A = 4 \log 2 - 4 \log 3 + \log 5 = \log \left(\frac{80}{81}\right) < 0$.

$K_5(x, x') = \max(x, x')$ is not pd for $A = (-1, 1), X = (-1, 1)$, then

$A^T K_{XX} A = (-1 \ 1) \begin{pmatrix} -1 & 1 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} -1 \\ 1 \end{pmatrix} = (-1 \ 1) \begin{pmatrix} 2 \\ 0 \end{pmatrix} = -2$.

1 Exercise 1 2 / 3

- 0 pts Correct
- ✓ - 0.5 pts Error
- ✓ - 0.5 pts Missing
- 1 pts 2 errors

 K5 : you can not take $x' = -1$ (kernel defined on R^+). K6 missing

Exercice 2 :

← If $K(x, x') = K(x', x)$ and $K(x, x') = K(x', x'') = 1 \implies K(x, x'') = 1$:

Let's denote by $x \sim y$ the relationship $K(x, y) = 1$. We now show it's an equivalence relationship :

\sim is reflexive since $K(x, x) = 1 \implies x \sim x$

\sim is symmetric since if $K(x, y) = 1$ then $K(y, x)$ meaning $x \sim y \implies y \sim x$

\sim is transductive since if $K(x, y) = K(y, z) = 1$ then $K(x, z) = 1$ meaning if $x \sim y$ and $y \sim z$ then $x \sim z$.

Now let's take $(X, A) \in (X^n, \mathbb{R}^n)$, thus $X = (x_1, \dots, x_n) / x_i \in X$

Now we prove that the order in which we take the elements does not affect the eigenvalues of the Kernel matrix.

Now by the Cayley – Hamilton theorem, the eigenvalues are the solutions of the polynomial

$H(K) = \det(XI_n - K)$. We show that this determinant is independant of the order of the points. We illustrate the reasoning for 3 points. But this holds for any n .

Performing a permutation of two rows or two columns changes the determinant by -1 .

And thus performing two of these operations does not change the determinant.

$$H[K_{(x_1, x_2, x_3)}] = \begin{pmatrix} X - K(x_1, x_1) & -K(x_2, x_2) & -K(x_3, x_3) \\ -K(x_2, x_1) & X - K(x_2, x_2) & -K(x_2, x_3) \\ -K(x_3, x_1) & -K(x_3, x_2) & X - K(x_3, x_3) \end{pmatrix} \implies (\text{Switch rows } x_1, x_2) \implies$$

$$\begin{pmatrix} -K(x_2, x_1) & X - K(x_2, x_2) & -K(x_2, x_3) \\ X - K(x_1, x_1) & -K(x_2, x_2) & -K(x_3, x_3) \\ -K(x_3, x_1) & -K(x_3, x_2) & X - K(x_3, x_3) \end{pmatrix} \implies (\text{Switch columuns } x_1, x_2) \implies$$

$$\begin{pmatrix} X - K(x_2, x_2) & -K(x_2, x_1) & -K(x_2, x_3) \\ -K(x_2, x_2) & X - K(x_1, x_1) & -K(x_3, x_3) \\ -K(x_3, x_2) & -K(x_3, x_1) & X - K(x_3, x_3) \end{pmatrix} = H[K_{(x_2, x_1, x_3)}]$$

And thus changing the order of two elements does not affect the Cayley Hamilton determinant.

Therefore it does not affect the eigenvalues of K .

Now since the equivalence classes form a partition of X , we can find an ordering of our vector X such that elements in the same equivalence classes are adjacent.

Now since for all elements in an equivalence class $[x]$ we have $K(x, y) = 1 \forall (y, z) \in [x]^2$

and if $x'' \notin [x]$ then $K(x', x'') = 0 \forall (x', x'') \in \{[x], \overline{[x]}\}$, the kernel matrix will be block diagonal with each block elements filled by ones.

If a block B_i has size $|B_i|$ then it will have one eigenvalue of $|B_i|$ and the remaining eigenvalues are 0.

Thus $\text{Spec}(K) = \cup \text{Spec}(B_i) = \cup \{|B_i|, 0\} = \{|B_i|_{B \text{ is block}}, 0\}$ which elements are all positive.

And thus K is a positive definite matrix whatever elements (x_1, \dots, x_n) we take and whatever the ordering.

#####

Exercice 2 (suite) :

$\rightarrow K$ is pd and $K(x, x) = 1 \forall x$

Since K is p.d then it's associated kernel is symmetric $\implies K(x, y) = K(y, x)$ and thus

$K(x, y) = 1 \implies K(y, x) = 1$.

Let's take 3 elements x, x', x'' . and denote by K their kernel matrix.

Without loss of generality let's suppose $K(x, x') = K(x', x'') = 1$.

With the information we have we know that $K_{(x, x', x'')}$ looks like this and is symmetric ($x = K(x, x'')$)

$$K = \begin{pmatrix} 1 & 1 & x \\ 1 & 1 & 1 \\ x & 1 & 1 \end{pmatrix}, \text{ if } K(x, x'') = 0 \text{ then : } \det(K) = 0 - 1 + 0 = -1 = \prod_{i=1}^3 \lambda_i$$

$\implies K$ has a negative eigenvalue $\implies K$ is not p.d.

Therefore $K(x, x'') = 1$. And thus we conclude our proof.

2 Exercise 2 2.5 / 3

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- **1 pts** Proof of the converse (that K is pd if ...) incomplete
- **1.5 pts** Proof that "K pd implies the two properties" missing
- **1 pts** Lacks clarity
- **2 pts** Incomplete

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- **1.5 pts** Error

 You did not prove that K is symmetric (to prove that it is pd)

Exercice 3.1 :

$$L : \mathcal{H} \rightarrow \mathbb{R}$$

$$f \rightarrow E_{X \sim P}[f(X)]$$

$$\begin{aligned} |L(f)| &= |E_{X \sim P}[f(X)]| \leq (\text{Jensen, } |\cdot| \text{ convex}) E_{X \sim P}[|f(X)|] \leq E_{X \sim P}[|\langle f, K_x \rangle_{\mathcal{H}}|] \\ &\leq E_{X \sim P}[||f||_{\mathcal{H}} * ||K_x||_{\mathcal{H}}] \leq ||f||_{\mathcal{H}} * E_{X \sim P}[||K_x||_{\mathcal{H}}] \leq E_{X \sim P}\left[\sqrt{K(X, X)}\right] * ||f||_{\mathcal{H}} \end{aligned}$$

Since K is a bounded operator $E_{X \sim P}\left[\sqrt{K(X, X)}\right] \leq \text{Max}_{x \in X}(K(x, x)) < \infty$

And thus L is a linear bounded operator on the hilbert space \mathcal{H}

$$\implies \text{By Riesz theorem, } \exists! g \in \mathcal{H} \text{ s.t. } \forall f \in \mathcal{H} : L(f) = \langle f, g \rangle.$$

$$\begin{aligned} \implies \exists! g \in \mathcal{H}, \text{ st. } \forall y \in X : L(K_y) &= E_{X \sim P}[K_y(X)] = E_{X \sim P}[\langle K_x, K_y \rangle] \\ &= E_{X \sim P}[K(x, y)] = \mu(P)(y) = \langle K_y, g \rangle \end{aligned}$$

This shows that $\forall y \in \mathcal{H}, z g(y) = \mu(P)(y)$ and therefore $\mu = g \in \mathcal{H}$.

3 3.1 2 / 2

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Exercice 3.2 :

$$\mathbb{E}_S[|\mu(P) - \mu(P_s)|] \leq \mathbb{E}_{x_i \sim S} [|\mu(P) - \mu(P_s)|]$$

$$\begin{aligned} &\leq \mathbb{E}_{x_i \sim S} [|\mu(P) - \mu(P_s)|] \leq \mathbb{E}_{x_i \sim S} \left[|\mu(P) - \frac{1}{n} \sum f(x_i)|\right] \\ &\leq \mathbb{E}_{x_i \sim S} \left[|\mu(P) - \frac{1}{n} \sum f(\tilde{x}_i)|\right] \\ &\leq \mathbb{E}_{x_i \sim S} \left[|\mu(P) - \frac{1}{n} \sum f(\tilde{x}_i) - \frac{1}{n} \sum f(x_i)|\right] \end{aligned}$$

[We show that $\mathbb{E}(\mu(P)) \leq \mathbb{E}(\mu(P_s))$ below.]

$$\leq \mathbb{E}_{(X_i) \sim P} \mathbb{E}_{(\tilde{X}_i) \sim P} \left[|\mu(P) - \frac{1}{n} \sum (f(\tilde{x}_i) - f(x_i))|\right]$$

(The two variables follow the same distribution it does not matter in which order we take

$$f(\tilde{x}_i) \& f(x_i))$$

$$\begin{aligned} &\leq \mathbb{E}_{(X_i) \sim P} \mathbb{E}_{(\tilde{X}_i) \sim P} \mathbb{E}_\sigma \left[|\mu(P) - \frac{1}{n} \sum \sigma_i (f(\tilde{x}_i) - f(x_i))|\right] \\ &\leq \mathbb{E}_{(X_i) \sim P} \mathbb{E}_{(\tilde{X}_i) \sim P} \mathbb{E}_\sigma |\mu(P) - \frac{1}{n} \sum \sigma_i (|f(\tilde{x}_i)| + |f(x_i)|)| \end{aligned}$$

(X and \tilde{X} are independant and follow the same distribution)

$$\leq \mathbb{E}_{(X_i) \sim P} \mathbb{E}_{(\tilde{X}_i) \sim P} \mathbb{E}_\sigma |\mu(P) - \frac{1}{n} \sum \sigma_i (|f(\tilde{x}_i)| + |f(x_i)|)|$$

$$\leq 2 \mathbb{E}_{(X_i) \sim P} \mathbb{E}_\sigma |\mu(P) - \frac{1}{n} \sum \sigma_i |f(x_i)||$$

$$\leq 2 \mathbb{E}_{(X_i) \sim P} \mathbb{E}_\sigma |\mu(P) - \frac{1}{n} \sum \sigma_i |f(x_i)||$$

$$\leq 2 \mathbb{E}_{(X_i) \sim P} \mathbb{E}_\sigma |\mu(P) - \frac{1}{n} \sum \sigma_i |f(x_i)||$$

$$\leq 2 \mathcal{R}_n(|f|) \quad (\text{from the course}) : \leq \frac{4 * \sqrt{\mathbb{E} K(X, X)}}{\sqrt{n}}$$

We show that $\text{Sup}(\mathbb{E}) \leq \mathbb{E}(\text{Sup})$:

$$\begin{aligned}
& \forall f \text{ s.t } \|f\|_{\mathcal{H}} \leq 1, \quad \frac{1}{n} \sum f(\tilde{x}_i) - f(x_i) \leq \text{Sup}_{\|f\|_{\mathcal{H}} \leq 1} \left(\frac{1}{n} \sum f(\tilde{x}_i) - f(x_i) \right) \\
& \Rightarrow E_{(\tilde{X}_i) \sim P} \left[\frac{1}{n} \sum f(\tilde{x}_i) - f(x_i) \right] \leq E_{(\tilde{X}_i) \sim P} \left[\text{Sup}_{\|f\|_{\mathcal{H}} \leq 1} \left(\frac{1}{n} \sum f(\tilde{x}_i) - f(x_i) \right) \right] \\
& \Rightarrow \text{Sup}_{\|f\|_{\mathcal{H}} \leq 1} E_{(\tilde{X}_i) \sim P} \left[\frac{1}{n} \sum f(\tilde{x}_i) - f(x_i) \right] \\
& \leq \text{Sup}_{\|f\|_{\mathcal{H}} \leq 1} E_{(\tilde{X}_i) \sim P} \left[\text{Sup}_{\|f\|_{\mathcal{H}} \leq 1} \left(\frac{1}{n} \sum f(\tilde{x}_i) - f(x_i) \right) \right] \\
& = E_{(\tilde{X}_i) \sim P} \left[\text{Sup}_{\|f\|_{\mathcal{H}} \leq 1} \left(\frac{1}{n} \sum f(\tilde{x}_i) - f(x_i) \right) \right]
\end{aligned}$$

$$\begin{aligned}
& \text{Therefore we have : } \text{Sup}_{\|f\|_{\mathcal{H}} \leq 1} E_{(\tilde{X}_i) \sim P} \left[\frac{1}{n} \sum f(\tilde{x}_i) - f(x_i) \right] \\
& \leq E_{(\tilde{X}_i) \sim P} \left[\text{Sup}_{\|f\|_{\mathcal{H}} \leq 1} \left(\frac{1}{n} \sum f(\tilde{x}_i) - f(x_i) \right) \right]
\end{aligned}$$

4 3.2 1 / 1

✓ - 0 pts Correct

- 0.5 pts Small error

- 1 pts Not finished

- 1 pts Error in the proof

- 1 pts Not solved

Exercice 3.3 :

3) $MMD(S1, S2)$:

$\mu(P_s)??$ we know that $\forall f \in H, \langle f, \mu(P_s) \rangle = \mathbb{E}_{x \sim P_s} [f(X)]$

And thus for $P_s = \left(\frac{1}{n} \sum \delta_{x_i} \right), \langle f, \mu(P_s) \rangle = \frac{1}{n} \sum f(x_i)$

$$\| \mu(P_{s1}) - \mu(P_{s2}) \|_{\mathcal{H}}^2 = \text{Sup}_{f \in \mathcal{H}} \langle f, \mu(P_s) \rangle = \frac{1}{n} \sum f(x_i)$$

**:

$$\langle f, \mu(P_{s1}) - \mu(P_{s2}) \rangle \leq \| f \|_{\mathcal{H}} \| \mu(P_{s1}) - \mu(P_{s2}) \|_{\mathcal{H}}$$

And by cauchy schwarz the maximum is achieved for $f = \alpha [\mu(P_{s1}) - \mu(P_{s2})]$

$$= \text{Sup}_{\|f\|_{\mathcal{H}} \leq 1} \langle f, \mu(P_{s1}) - \mu(P_{s2}) \rangle^2 = \text{Sup}_{\|f\|_{\mathcal{H}} \leq 1} \left\{ \frac{1}{n} \sum f(x_i) - \frac{1}{m} \sum f(y_j) \right\}^2$$

$$\| \mu(P_{s1}) - \mu(P_{s2}) \|_{\mathcal{H}}^2 = \| \mu(P_{s1}) \|_{\mathcal{H}}^2 + \| \mu(P_{s2}) \|_{\mathcal{H}}^2 - 2 \langle \mu(P_{s1}), \mu(P_{s2}) \rangle$$

$$\langle \mu(P), \mu(P') \rangle = E_{X' \sim P'} [\mu(P)(x')] = E_{X' \sim P'} E_{X \sim P} [K(x, x')]$$

$$\langle \mu(P_{s1}), \mu(P_{s2}) \rangle = E_{X \sim P_{s1}} \left[\frac{1}{n} \sum_{y_i \in S_2} K(x, y_i) \right] = \frac{1}{m} \sum_{x_i \in S_1} \left[\frac{1}{n} \sum_{y_i \in S_2} K(x_i, y_i) \right]$$

$$= \frac{1}{nm} \sum_{(x_i, y_i) \in S_1 \times S_2} K(x_i, y_i)$$

$$\| \mu(P_{s1}) - \mu(P_{s2}) \|_{\mathcal{H}}^2 = \frac{1}{n^2} \sum_{(x_i, y_i) \in S_1 \times S_1} K(x_i, y_i) + \frac{1}{m^2} \sum_{(x_i, y_i) \in S_2 \times S_2} K(x_i, y_i) - \frac{1}{nm} \sum_{(x_i, y_i) \in S_1 \times S_2} K(x_i, y_i)$$

5 3.3 0.5 / 1

- 0 pts Correct
- ✓ - 0.5 pts Expression of MMD as a function of kernel missing or wrong
- 0.5 pts Expression of MMD as a sup missing or wrong
- 💬 almost good... a "-2" missing though

Exercice 3.4 :

$$MMD(S_1, S_2) = \text{Sup}_{\|f\|_{\mathcal{H}} \leq 1} \left\{ \frac{1}{n} \sum f(x_i) - \frac{1}{m} \sum f(y_j) \right\}^2$$

$$\text{We know for } x \in \mathbb{R} \text{ for } f(x) = \frac{1}{\sigma} \exp\left(\frac{-x^2}{2\sigma^2}\right) \implies \hat{f}(\epsilon) = \sqrt{2\pi} \exp\left(\frac{-\sigma^2 \epsilon^2}{2}\right)$$

$$\begin{aligned} \text{for } x \in \mathbb{R}^d \quad f(x) &= \sigma^{-d} \exp\left(\frac{-\|x\|^2}{2\sigma^2}\right) = \prod_i^d \frac{1}{\sigma} \exp\left(\frac{-x_i^2}{2\sigma^2}\right) \\ \implies \hat{f}(\epsilon) &= \prod_i^d \sqrt{2\pi} \sigma \exp\left(\frac{-\sigma^2 \epsilon_i^2}{2}\right) = (\sqrt{2\pi})^d \exp\left(\frac{-\sigma^2 \|\epsilon\|^2}{2}\right) \end{aligned}$$

$$\text{For } K_\sigma(x, y) = \exp\left(\frac{-\|x-y\|^2}{2\sigma^2}\right) \text{ we know that is RKHS is } \mathcal{H}_\sigma : \left\{ f : \int |\hat{f}(w)|^2 \exp\left(\frac{\sigma^2 \|w\|^2}{2}\right) < \infty \right\}$$

$$\text{For } \sigma' > \sigma \text{ if } \int |\hat{f}(w)|^2 \exp\left(\frac{\sigma'^2 \|w\|^2}{2}\right) < \infty \implies \int |\hat{f}(w)|^2 \exp\left(\frac{\sigma^2 \|w\|^2}{2}\right) < \infty$$

And thus $\mathcal{H}_{\sigma'} \in \mathcal{H}_\sigma$.

If we call $A_1 = \{f : \|f\|_{\mathcal{H}_\sigma} \leq 1\} / A_2 = \{f : \|f\|_{\mathcal{H}_{\sigma'}} \leq 1\} (A_2 \in A_1)$

$$\implies \text{Sup}_{f \in A_1} \left\{ \frac{1}{n} \sum f(x_i) - \frac{1}{m} \sum f(y_j) \right\}^2 \geq \text{Sup}_{f \in A_2} \left\{ \frac{1}{n} \sum f(x_i) - \frac{1}{m} \sum f(y_j) \right\}^2$$

$$\implies MMD_\sigma(S_1, S_2) \geq MMD_{\sigma'}(S_1, S_2)$$

And thus for $K(x, y) = \sigma^{-d} \exp\left(\frac{-\|x-y\|^2}{2\sigma^2}\right)$ $MMD(S_1, S_2)$ is a decreasing function of σ .

6.3.4 2 / 2

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Exercice 4 :

$$1) K_1(x, x') = \sum a_i \langle x, x' \rangle^i, a_i \geq 0.$$

We know that $K(x, x') = \langle x, x' \rangle$ is a p.d kernel.

And the product of p.d kernels is p.d, and multiplying by $\alpha \geq 0$ keeps it p.d

Thus $\forall_i a_i \langle x, x' \rangle^i$ is p.d

Then $K_1(x, x')$ is p.d as the (infinite) sum of p.d kernels.

$$2) \|x\| \|x'\| \kappa \left(\frac{\langle x, x' \rangle}{\|x\| \|x'\|} \right) =$$

If we take $K_3(x, x') = \|x\| \|x'\|$ then K_3 is p.d since

$$(x_1, \dots, x_n) \in (\mathbb{S}^{p-1})^n \text{ for } a \text{ in } \mathbb{R}^n, \quad \sum a_i K_3(x_i, x_j) a_j = \sum a_i \|x_i\| \|x_j\| a_j$$

$$= a'^T a' \geq 0 \text{ where } a' = (a_1 \|x_1\|, \dots, a_n \|x_n\|)$$

$$\text{If we take } K_1' = \kappa \left(\frac{\langle x, x' \rangle}{\|x\| \|x'\|} \right) = \kappa \left(\langle \frac{x}{\|x\|}, \frac{x'}{\|x'\|} \rangle \right) \text{ (if } \|x\| \text{ & } \|x'\| \neq 0)$$

and 0 if $\|x\|$ or $\|x'\| = 0$

then $K_1'(x, x')$ can be seen as $K_1(\tilde{x}, \tilde{x}')$ where $\tilde{x}, \tilde{x}' \in (\mathbb{S}^{p-1})^2$, therefore K_1' is p.d

And thus K_2 is the product of K_1' and K_3 which are two p.d kernels and thus it is p.d.

$$3) \kappa(u) = \kappa(1) - \int_u^1 \kappa'(u) du$$

$$\text{Since } u \leq 1, \kappa'(u) = \sum_i i a_i u^i \leq \sum_i i a_i = \kappa'(1).$$

$$\implies \int_u^1 \kappa'(u) du \leq \int_u^1 \kappa'(1) du \leq \kappa'(1) \int_u^1 du = \kappa'(1)(1-u) = (1-u)$$

$$\implies \kappa(u) \geq 1 - (1-u) \geq u$$

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

$$= K(x, x) + K(x', x') - 2 K(x, x') = 2(1 - \kappa(\langle x, x' \rangle)) \{x, x' \in \mathbb{S}^{p-1}\}$$

$$\implies \|\phi(x) - \phi(x')\|_{\mathcal{H}}^2 \leq \|x\|^2 + \|x'\|^2 - \langle x, x' \rangle \leq \|x - x'\|^2$$

7 4.1 1 / 1

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Exercice 4 :

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We know that $K(x, x') = \langle x, x' \rangle$ is a p.d kernel.

And the product of p.d kernels is p.d, and multiplying by $\alpha \geq 0$ keeps it p.d

Thus $\forall_i a_i \langle x, x' \rangle^i$ is p.d

Then $K_1(x, x')$ is p.d as the (infinite) sum of p.d kernels.

$$2) \|x\| \|x'\| \kappa \left(\frac{\langle x, x' \rangle}{\|x\| \|x'\|} \right) =$$

If we take $K_3(x, x') = \|x\| \|x'\|$ then K_3 is p.d since

$$(x_1, \dots, x_n) \in (\mathbb{S}^{p-1})^n \text{ for } a \text{ in } \mathbb{R}^n, \quad \sum a_i K_3(x_i, x_j) a_j = \sum a_i \|x_i\| \|x_j\| a_j$$

$$= a'^T a' \geq 0 \text{ where } a' = (a_1 \|x_1\|, \dots, a_n \|x_n\|)$$

$$\text{If we take } K_1' = \kappa \left(\frac{\langle x, x' \rangle}{\|x\| \|x'\|} \right) = \kappa \left(\langle \frac{x}{\|x\|}, \frac{x'}{\|x'\|} \rangle \right) \text{ (if } \|x\| \text{ & } \|x'\| \neq 0)$$

and 0 if $\|x\|$ or $\|x'\| = 0$

then $K_1'(x, x')$ can be seen as $K_1(\tilde{x}, \tilde{x}')$ where $\tilde{x}, \tilde{x}' \in (\mathbb{S}^{p-1})^2$, therefore K_1' is p.d

And thus K_2 is the product of K_1' and K_3 which are two p.d kernels and thus it is p.d.

$$3) \kappa(u) = \kappa(1) - \int_u^1 \kappa'(u) du$$

$$\text{Since } u \leq 1, \kappa'(u) = \sum_i i a_i u^i \leq \sum_i i a_i = \kappa'(1).$$

$$\implies \int_u^1 \kappa'(u) du \leq \int_u^1 \kappa'(1) du \leq \kappa'(1) \int_u^1 du = \kappa'(1)(1-u) = (1-u)$$

$$\implies \kappa(u) \geq 1 - (1-u) \geq u$$

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

$$= K(x, x) + K(x', x') - 2 K(x, x') = 2(1 - \kappa(\langle x, x' \rangle)) \{x, x' \in \mathbb{S}^{p-1}\}$$

$$\implies \|\phi(x) - \phi(x')\|_{\mathcal{H}}^2 \leq \|x\|^2 + \|x'\|^2 - \langle x, x' \rangle \leq \|x - x'\|^2$$

8 4.2 0.75 / 1

- **0 pts** Correct
- **1 pts** major argument is missing
- ✓ - **0.25 pts** need to be a bit more rigorous to handle the cases when $x_i = 0$
- **0.5 pts** missing argument
- **1 pts** missing answer

Exercice 4 :

$$1) K_1(x, x') = \sum a_i \langle x, x' \rangle^i, a_i \geq 0.$$

We know that $K(x, x') = \langle x, x' \rangle$ is a p.d kernel.

And the product of p.d kernels is p.d, and multiplying by $\alpha \geq 0$ keeps it p.d

Thus $\forall_i a_i \langle x, x' \rangle^i$ is p.d

Then $K_1(x, x')$ is p.d as the (infinite) sum of p.d kernels.

$$2) \|x\| \|x'\| \kappa \left(\frac{\langle x, x' \rangle}{\|x\| \|x'\|} \right) =$$

If we take $K_3(x, x') = \|x\| \|x'\|$ then K_3 is p.d since

$$(x_1, \dots, x_n) \in (\mathbb{S}^{p-1})^n \text{ for } a \text{ in } \mathbb{R}^n, \quad \sum a_i K_3(x_i, x_j) a_j = \sum a_i \|x_i\| \|x_j\| a_j$$

$$= a'^T a' \geq 0 \text{ where } a' = (a_1 \|x_1\|, \dots, a_n \|x_n\|)$$

$$\text{If we take } K_1' = \kappa \left(\frac{\langle x, x' \rangle}{\|x\| \|x'\|} \right) = \kappa \left(\langle \frac{x}{\|x\|}, \frac{x'}{\|x'\|} \rangle \right) \text{ (if } \|x\| \text{ & } \|x'\| \neq 0)$$

and 0 if $\|x\|$ or $\|x'\| = 0$

then $K_1'(x, x')$ can be seen as $K_1(\tilde{x}, \tilde{x}')$ where $\tilde{x}, \tilde{x}' \in (\mathbb{S}^{p-1})^2$, therefore K_1' is p.d

And thus K_2 is the product of K_1' and K_3 which are two p.d kernels and thus it is p.d.

$$3) \kappa(u) = \kappa(1) - \int_u^1 \kappa'(u) du$$

$$\text{Since } u \leq 1, \kappa'(u) = \sum_i i a_i u^i \leq \sum_i i a_i = \kappa'(1).$$

$$\implies \int_u^1 \kappa'(u) du \leq \int_u^1 \kappa'(1) du \leq \kappa'(1) \int_u^1 du = \kappa'(1)(1-u) = (1-u)$$

$$\implies \kappa(u) \geq 1 - (1-u) \geq u$$

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

$$= K(x, x) + K(x', x') - 2 K(x, x') = 2(1 - \kappa(\langle x, x' \rangle)) \{x, x' \in \mathbb{S}^{p-1}\}$$

$$\implies \|\phi(x) - \phi(x')\|_{\mathcal{H}}^2 \leq \|x\|^2 + \|x'\|^2 - \langle x, x' \rangle \leq \|x - x'\|^2$$

9 4.3 2 / 2

✓ - 0 pts Correct

- 0.5 pts missing minor argument
- 1 pts there is a wrong argument but part of the proof is ok
- 2 pts the proof relies on a wrong statement
- 1 pts missing major argument
- 2 pts missing answer

Exercice 4. 4 :

If we take the mapping $\mu(x) = (\sqrt{a_i} x^{\otimes i})_{i \in \mathbb{N}}$

Then we have that $\langle \mu(x), \mu(y) \rangle = \sum a_i \langle x, y \rangle^i$

But $\mu(x)$ is not really in l^2 as each $X^{\otimes i}$ has a different dimension.

To go around this we can bring this expression into a suite of reals.

We know that $X^{\otimes i} \in \mathbb{R}^{d^i}$.

We create the following functions :

$$\psi(i) = \mathbf{1}_{i > p} + \mathbf{1}_{i > p+p^2} + \mathbf{1}_{i > p+p^2+p^3} = \sum_k^{\infty} \mathbf{1}_{i > \sum_{j=1}^k p^j}$$

(to keep the same index (i) over the tensor $x^{\otimes i}$)

$$\Gamma(i) = i \text{ modulo } \sum_{j=1}^{\psi(i)} p^j \quad (\text{all the indexes of the tensor } x^{\otimes i}, i \text{ from 1 to } P^i)$$

If we take $\phi(x) = (\sqrt{a_{\psi(i)}} (x^{\otimes \psi(i)})_{\Gamma(i)})_{i \in \mathbb{N}}$ then we get a suite of reals.

$$\begin{aligned} \phi(x) \in l_2 \text{ since } \langle \phi(x), \phi(x) \rangle &= \sum a_i \langle x^{\otimes i}, x^{\otimes i} \rangle = \sum a_i \langle x, x \rangle^i \\ &= \{x \in S^{p-1}\} \sum a_i = \kappa(1) \end{aligned}$$

$$\begin{aligned} \langle \phi(x), \phi(y) \rangle &= \sum_i a_{\psi(i)} (x^{\otimes \psi(i)})_{\Gamma(i)} (y^{\otimes \psi(i)})_{\Gamma(i)} = \sum_i a_i \langle x^{\otimes i}, y^{\otimes i} \rangle \\ &= \sum a_i \langle x, y \rangle^i = K(x, y) \end{aligned}$$

10 4.4 2 / 2

✓ - 0 pts Correct

- 0.5 pts missing details or minor mistake
- 2 pts missing or wrong answer
- 1 pts not exactly the right answer
- 0 pts Click here to replace this description.

Exercice 4.5 :

$$H : \left\{ f_w \mid x \rightarrow \langle w, \phi(x) \rangle_{l^2} : w \in l^2 \right\} / \phi(x) = \left(\sqrt{a_{\psi(i)}} (x^{\otimes \psi(i)})_{\Gamma(i)} \right)_{i \in \mathbb{N}}$$

$$f_w = \langle w, \phi(x) \rangle_{l^2} = \sum w_i \sqrt{a_{\psi(i)}} (x^{\otimes \psi(i)})_{\Gamma(i)}$$

$$g_z = \sum b_i \langle z, x \rangle^i = \sum b_i \langle z^{\otimes i}, x^{\otimes i} \rangle = \sum b_{\psi(i)} (x^{\otimes \psi(i)})_{\Gamma(i)} (z^{\otimes \psi(i)})_{\Gamma(i)}$$

We want $g(z)$ to be written as f_w :

$$\sum b_{\psi(i)} (x^{\otimes \psi(i)})_{\Gamma(i)} (z^{\otimes \psi(i)})_{\Gamma(i)} = \sum w_i \sqrt{a_{\psi(i)}} (x^{\otimes \psi(i)})_{\Gamma(i)}.$$

We can make the terms of the sums equal to get equality :

$$\frac{b_{\psi(i)}}{\sqrt{a_{\psi(i)}}} (z^{\otimes \psi(i)})_{\Gamma(i)} = w_i \quad \{ (w)_i \in l^2 \}$$

A sufficient condition is : $\frac{b_{\psi(i)}}{\sqrt{a_{\psi(i)}}} \in l^2$ which can be rewritten as : $\frac{b_i}{\sqrt{a_i}} \in l^2$,

this requires all $a_i > 0$.

If $(U)_i = \left(\frac{b_{\psi(i)}}{\sqrt{a_{\psi(i)}}} \right)_{i \in N}$ in l^2 then $(V)_i = \left(\frac{b_{\psi(i)}}{\sqrt{a_{\psi(i)}}} (z^{\otimes \psi(i)})_{\Gamma(i)} \right)_{i \in N} \in l_2$ because :

$$\|V\|_{l^2} = \sum \frac{b_{\psi(i)}^2}{a_{\psi(i)}} \langle z^{\otimes i}, z^{\otimes i} \rangle = \sum \frac{b_i^2}{a_i} \langle z, z \rangle^i = \sum \frac{b_i^2}{a_i} = \|U\|_{l^2} \quad \{ z \in S^{P-1} \}$$

Now $g_z(x)$ can be written as $\langle V, \phi(x) \rangle$ where $V \in l^2$. And thus $g_z \in \mathcal{H}$.

11 4.5 2 / 2

✓ - 0 pts Correct

- 2 pts missing or too incomplete answer
- 1 pts inaccurate or incomplete statement
- 1.5 pts the sufficient condition is too strong (only leads to a trivial case)
- 0.5 pts minor details missing