A Theory on Reproducing Kernel Hilbert Space for Machine Learning

 $\verb|https://github.com/Shena| 4746/RKHS-for-ML| \\ 2020/05/14$

What's this?

This document collects basic results on Reproducing Kernel Hilbert Space that are useful in the context of machine learning, aimed at readers with a basic knowledge of functional analysis. The content relies heavily on the existing literature listed in the bibliography, in particular [1] [2]. [3] [4] [5]

Overview

Contents

1	Bas	ic Property of RKHS	2
	1.1	Properties of Reproducing Kernel	2
		RKHS of a kernel	
	1.3	Basic Properties of Kernel	12
2	Reconstruction of RKHS		12
	2.1	Reconstruction via Restriction	12
	2.2	Reconstruction via Operator	14
	2.3	Reconstruction via Sum and Product	14
3	Inheritance from Kernel to RKHS		1 4
	3.1	Measurability of RKHS	14
	3.2	Separability of RKHS	14
	3.3	Continuity of RKHS	14
4	Me	rcer Representation	14

1 Basic Property of RKHS

1.1 Properties of Reproducing Kernel

Definition 1.1 (Reproducing kernel). Let E be a nonempty set. A function K defined by

$$K: E \times E \ni (x, y) \mapsto K(x, y) \in \mathbb{F}$$

is called a reproducing kernel of a Hilbert space H of functions on E if it satisfies the following conditions:

- (a) $K(\cdot, x) \in H$ for every $x \in E$
- (b) $\langle f, K(\cdot, x) \rangle_H = f(x)$ for every $x \in E$ and every $f \in H$.

Such a Hilbert space, associated with its reproducing kernel, is called a reproducing kernel hilbert space, and is denoted by (H, K).

Remark 1.2. (b) is called the textitreproducing property, and the identity is called the textitreproducing identity.

Theorem 1.3 (Characterization of RKHS). A Hilbert space H of functions on a nonempty set E admits a reproducing kernel K if and only if all evaluation functionals $\{ev_x\}_{x\in E}$ are continuous on H.

Proof. Suppose (H, K) is a RKHS. For $x \in E$ and for $f \in H$ we have

$$|ev_x(f)| = |f(x)| = |\langle f, K(\cdot, x) \rangle| \le ||f|| \, ||K(\cdot, x)|| \le ||f|| \, K(x, x)^{1/2} \to 0$$

as $||f|| \to 0$. Thus, ev_x is continuous linear functional (with norm $K(x,x)^{1/2}$). Conversely, if $\operatorname{ev}_x: H \ni f \mapsto f(x) \in \mathbb{F}$ is continuous, then, by Riesz's representation theorem, there exists $r_x \in H$ such that

$$\langle f, r_x \rangle = f(x)$$

for every $f \in H$. If this happens for every $x \in E$, then $K(x,y) := r_x(y)$ is a reproducing kernel of H.

Corollary 1.4. Every convergent sequence in RKHS converges pointwise to the same limit.

Proof. $|f_n(x) - f(x)| = |\operatorname{ev}_x(f_n - f)| \to 0$ when $f_n \to f$ in norm by continuity of evaluation functional.

Proposition 1.5. (Uniqueness of H and K)

- (a) Let (H, K) be a RKHS. The subspace H_0 spanned by $\{K(\cdot, x)\}_{x \in E}$ is dense in H.
- (b) A Hilbert space admits at most one reproducing kernel.
- (c) A function $K: E \times E \to \mathbb{F}$ is a reproducing kernel for at most one Hilbert space. In particular, there is at most one RKHS that has H_0 as a dense subspace.

Proof. For density of H_0 , observe $f \in H$ fulfills $f \perp H_0$ if and only if

$$\langle f, K(\cdot, x) \rangle_H = f(x) = 0$$

for every $x \in E$, which is the case precisely when $f \equiv 0$. (b) is an immediate consequence of (a) and Corollary1.4. To check (b), suppose K_1 and K_2 qualify as a reproducing kernel of H. By definition,

$$f(x) = \langle f, K_1(\cdot, x) \rangle_H = \langle f, K_2(\cdot, x) \rangle_H$$

for every $x \in E$, and hence

$$\langle f, K_1(\cdot, x) - K_2(\cdot, x) \rangle_H = 0$$

for every $f \in H$ and $x \in E$. From this we conclude $K_1 = K_2$. Finally suppose that (H_1, K) and (H_2, K) are two RKHSs. Pick $f \in H_1$. By (a), there is $\{f_n\} \subset H_0 \subset H_1 \cap H_2$ such that $f_n \to f$ in H_1 -norm. Since $\{f_n\}$ is also an Cauchy sequence in H_2 , it admits a limit $g \in H_2$. But Corollary1.4 implies f = g, and hence $f \in H_2$. We then have

$$||f||_{H_1} = \lim_{n \to \infty} ||f_n||_{H_1} = \lim_{n \to \infty} ||f_n||_{H_0} = \lim_{n \to \infty} ||f_n||_{H_2} = ||f||_{H_2}.$$

Therefore, H_1 is isometrically included in H_2 . Symmetry thus shows that both Hilbert spaces coincide. Exactly the same argument also works for the last claim.

Proposition 1.6. (Representation of RK in terms of evaluation functional) In arbitrary RKHS (H, K), the reproducing kernel $K : E \times E \to \mathbb{F}$ always fulfills the identity

$$K(x,y) = \langle \operatorname{ev}_y, \operatorname{ev}_x \rangle_{H^*}$$

for all $x, y \in E$, where H^* is the dual space of H.

Proof. It suffices to show that a function K defined by the above equation is also a reproducing kernel. Let a mapping $I: H^* \to H$ be the isometric anti-linear surjection, guaranteed by Riesz's Representation Theorem, that assigns to every functional in H^* the corresponding representor in H, i.e., $g^*(f) = \langle f, Ig^* \rangle_H$ for all $f \in H$ and $g \in H^*$, where g^* is the adjoint of g. Then we have

$$K(x,y) = \langle \operatorname{ev}_y, \operatorname{ev}_x \rangle_{H^*} = \langle I \operatorname{ev}_y, I \operatorname{ev}_x \rangle_H = \operatorname{ev}_x (\operatorname{ev}_y) = (I \operatorname{ev}_y)(x),$$

for all $x, y \in E$, and hence $K(\cdot, y) = Iev_y \in H$. From this it follows that

$$f(y) = \operatorname{ev}_{y}(f) = \langle f, I \operatorname{ev}_{y} \rangle_{H} = \langle f, K(\cdot, y) \rangle$$

for all $y \in E$. Thus, K is a reproducing kernel.

Definition 1.7. (Kernel, Feature Space, Feature Map) A function $K : E \times E \to \mathbb{F}$ is called a kernel if there is a \mathbb{F} -Hilbert space H and a mapping $\varphi : E \to H$ such that

$$K(x,y) = \langle \varphi(y), \varphi(x) \rangle_H$$

for all $x, y \in E$. Such a φ is called a feature map, and H a feature space.

Remark 1.8. Proposition 1.6 tells us that every RK is indeed a kernel, and that the map $E \ni x \mapsto \operatorname{ev}_x \in H^*$ is a feature map with a feature space H^* . Every RKHS (H, K) also admits a more simple feature map φ_K , called a canonical feature map, given by

$$\varphi_K: E \ni x \mapsto K(\cdot, x) \in H.$$

This clearly shows that, given a kernel, neither feature space nor feature map are uniquely determined.

1.2 RKHS of a kernel

Definition 1.9. (Positive definite function) Let E be a nonempty set. A function $K: E \times E \to \mathbb{C}$ is called positive definite if for any $n \in \mathbb{N}$ and for any $a \in \mathbb{C}^n$ and $x \in E^n$ there holds

$$\sum_{i=1}^{n} \sum_{j=1}^{n} a_i \overline{a_j} K(x_i, x_j) \ge 0, \tag{1}$$

where \bar{c} is the complex conjugate of c.

Proposition 1.10. (Characterization of real positive definite function) A real function $K: E \times E \to \mathbb{R}$ is positive definite if and only if it has the following properties:

- (a) K is symmetric.
- (b) The defining inequality (1) holds for any $\alpha \in \mathbb{R}^n$ instead of \mathbb{C}^n .

Proposition 1.11. Every positive definite function $K: E \times E \to \mathbb{C}$ satisfies

- (a) $K(x,x) \ge 0$ for every $x \in E$
- (b) $K(x,y) = \overline{K(y,x)}$ for every $x,y \in E$
- (c) \overline{K} is also positive definite, and conversely
- (d) $|K(x,y)| \le K(x,x)K(y,y)$ for every $x,y \in E$.

Proof. (a) and (c) clearly hold. For $\alpha, \beta \in \mathbb{C}$ and $x, y \in E$, we have

$$g(\alpha, \beta) := |\alpha|^2 K(x, x) + \alpha \overline{\beta} K(x, y) + \overline{\alpha} \beta K(y, x) + |\beta|^2 K(y, y) \ge 0.$$

Choose $\alpha = \beta = 1$ and $\alpha = i$, $\beta = 1$ to get

$$K(x,y) + K(y,x) = g(1,1) - K(x,x) - K(y,y) =: A \in \mathbb{R}$$

 $iK(x,y) - iK(y,x) = g(i,1) - K(x,x) - K(y,y) =: B \in \mathbb{R}$

Therefore,

$$2K(y,x) = A + iB$$
$$2K(x,y) = A - iB,$$

which proves (b). Finally, for $x, y \in E$ with $K(x, y) \neq 0$ and for $r \in \mathbb{R}$, (b) gives

$$0 \ge g(r, K(x, y)) = r^2 K(x, x) + 2r |K(x, y)|^2 + |K(x, y)|^2 K(y, y).$$

As RHS is quadratic in r, it must satisfy

$$|K(x,x)|^4 - |K(x,y)|^2 K(x,x)K(y,y) \le 0,$$

from which (d) follows.

Corollary 1.12. (Kernel is positive definite) A kernel is positive definite.

Proof. For the case $\mathbb{F} = \mathbb{C}$, we have

$$\sum_{i=1}^{n} \sum_{j=1}^{n} a_i \overline{a_j} \overline{K(x_i, x_j)} = \sum_{i=1}^{n} \sum_{j=1}^{n} a_i \overline{a_j} \langle \varphi(x_i), \varphi(x_j) \rangle = \left\| \sum_{i=1}^{n} a_i \varphi(x_i) \right\|^2 \ge 0,$$

and hence \overline{K} as well as K are positive definite.

Theorem 1.13. (RKHS generated by inner product space) Let H_0 be the subspace of \mathbb{F}^E , equipped with an inner product $\langle \cdot, \cdot \rangle_{H_0}$ with norm $\|\cdot\|_{H_0}$. Then there exists unique RKHS (H, K) that extends H_0 in the sense that

(a) $H_0 \subset H \subset \mathbb{F}^E$ and the subspace topology of H_0 in H coincides with the topology of $(H_0, \|\cdot\|_{H_0})$

if and only if H_0 satisfies the following conditions:

- (b) every evaluation functional ev_x is continuous in $(H_0, \|\cdot\|_{H_0})$
- (c) any Cauchy sequence $\{f_n\} \subset H_0$ converging pointwise to 0 converges to 0 also in H_0 -norm.

Consequently, H is isomorphic to the completion of H_0 .

Proof. Suppose such an extension H exists. H satisfies (b) by Theorem1.3. Since H is complete, a Cauchy sequence $\{f_n\} \subset H_0$ tends to some f, for which we have

$$f(x) = \operatorname{ev}_x(f) = \lim_{n \to \infty} \operatorname{ev}_x(f_n) = \lim_{n \to \infty} f_n(x) = 0$$

for every $x \in E$. Therefore, f is identically 0.

Conversely, suppose (b)(c) hold. Let H be the set of all functions $f \in \mathbb{F}^E$ for which there exists a Cauchy sequence $\{f_n\} \subset H_0$ converging pointwise to f. Clearly, $H_0 \subset H \subset \mathbb{F}^E$. The rest of proof consists of the following Lemmas.

Lemma 1.14. Let $f, g \in H$ and let $\{f_n\}$ and $\{g_n\}$ be two Cauchy sequences in H_0 that converge pointwise to f and g respectively.

- (A) The sequence $\langle f_n, g_n \rangle_{H_0}$ is convergent.
- (B) The limit $\lim_{n\to\infty} \langle f_n, g_n \rangle_{H_0}$ depends solely on f and g, independent of the choice of f_n and g_n .
- (C) $\langle f, g \rangle_H := \lim_{n \to \infty} \langle f_n, g_n \rangle_{H_0}$ is an inner product on H.

Proof. It follows from the definition of f_n and g_n that

$$\begin{aligned} \left| \langle f_n, g_n \rangle_{H_0} - \langle f_m, g_m \rangle_{H_0} \right| &= \left| \langle f_n - f_m, g_n \rangle - \langle f_m, g_n - g_m \rangle \right| \\ &\geq \|g_n\| \|f_n - f_m\| + \|f_m\| \|g_n - g_m\| \to 0, \end{aligned}$$

which proves (A). In order to verify (B), suppose $\{f'_n\}$ and $\{g'_n\}$ are also such approximating sequences. We then similarly deduce that

$$|\langle f_n, g_n \rangle - \langle f'_n, g'_n \rangle| \le ||g_n|| ||f_n - f'_n|| + ||f'_n|| ||g_n - g'_n||.$$

 $\{f_n - f_n'\}$ and $\{g_n - g_n'\}$ are Cauchy sequences tending pointwise to 0. Thus, assumption (c) gives $||f_n - f_n'|| \to 0$ and $||g_n - g_n'|| \to 0$. So, (A) and (B) show that $\langle f, g \rangle_H$ is well-defined. Note that if $\langle f, f \rangle_H = 0$, then for every $x \in E$

$$f(x) = \operatorname{ev}_x(f) = \lim_{n \to \infty} \operatorname{ev}_x(f_n) = \lim_{n \to \infty} f_n(x) = 0,$$

and hence $f \equiv 0$. As the symmetry, positivity, linearity are quite obvious, we conclude that (C) is true.

Lemma 1.15. (A) Let $f \in H$ and let $\{f_n\} \subset H_0$ be a Cauchy sequence converging pointwise to f. Then $f_n \to f$ also in H-norm.

(B) H_0 is dense in H.

Proof. (A): Fix $\epsilon > 0$. Choose $N \in \mathbb{N}$ large enough so that

$$\|f_n - f_m\|_{H_0} < \epsilon$$

for all n, m > N. For fixed n, $\{f_n - f_m\}_{m \in \mathbb{N}}$ is a Cauchy sequence converging pointwise to $f_n - f$. Therefore, by definition of $\langle \cdot, \cdot \rangle_H$,

$$||f - f_n||_H = \lim_{n \to \infty} ||f_n - f_m||_{H_0} \le \epsilon.$$

(B) is obvious from (A).

Lemma 1.16. Every evaluation functional ev_x is continuous on H.

Proof. Fix $x \in E$. As a linear functional ev_x is assumed to be continuous on H_0 , it admits unique continuous extension T_x onto the closure of H_0 in H, that is, onto whole H, where we use the assumption (a) and Lemma2(B). T_x is also the evaluation functional on H. Indeed, for f and f_n as in Lemma1.15, we have

$$T_x(f) = \lim_{n \to \infty} \operatorname{ev}_x(f_n) = \lim_{n \to \infty} f_n(x) = f(x).$$

Lemma 1.17. H is a RKHS satisfying (a) in Theorem1.13. Consequently, H is isomorphic to the completion of H_0 and thus unique RKHS that meets the requirement.

Proof. We first prove that H is actually a RKHS. In light of Theorem1.3 and Lemma1.16, it suffices to show that H is complete. Let $\{f_n\}$ be a Cauchy sequence in H. Let $x \in E$. $\{f_n(x)\}$ is also a Cauchy in \mathbb{F} , and hence converges to some f(x). By Lemma1.15, for every $n \in \mathbb{N}$, there is $g_n \in H_0$ such that $||f_n - g_n||_H < n^{-1}$. In view of the inequality

$$||f - f_n||_H \le ||f - g_n||_H + ||g_n - f_n||_H$$

it suffices to prove that $||f - g_n||_H \to 0$. To this end, we show that $\{g_n\}$ is a Cauchy sequence converging pointwise to f (and then apply Lemma1.15).

For fixed $x \in E$, we have

$$|g_n(x) - f(x)| \le |g_n(x) - f_n(x)| + |f_n(x) - f(x)|$$

= $|\operatorname{ev}_x(g_n - f_n)| + |f_n(x) - f(x)| \to 0$

as $n \to \infty$, since ev_x is continuous and $f_n(x) \to f(x)$ pointwise. Moreover,

$$||g_n - g_m||_{H_0} = ||g_n - g_m||_H$$

$$\leq ||g_n - f_n|| + ||f_n - f_m|| + ||g_m - f_m||$$

$$= n^{-1} + ||f_n - f_m|| + n^{-1} \to 0$$

when $n, m \to \infty$, as required. H is isomorphic to the completion of H_0 since H_0 is dense in H. Uniqueness of (H, K) comes from Proposition1.5.

Theorem 1.18. (Moore-Aronszajn) For arbitrary positive definite function $K: E \times E \to \mathbb{F}$, there exists unique RKHS H that has K as its reproducing kernel. Moreover, the subspace H_0 spanned by $\{K(\cdot,x)\}_{x\in E}$ is dense in H.

Proof. Define an inner product $\langle \cdot, \cdot \rangle_{H_0}$ on H_0 by setting

$$\langle f, g \rangle_{H_0} := \sum_{i=1}^n \sum_{j=1}^n \alpha_i \beta_i K(y_i, x_i),$$

where $f = \sum_{i=1}^{n} \alpha_i K(\cdot, x_i)$ and $g = \sum_{j=1}^{n} \alpha_i K(\cdot, y_i)$. Let us observe

$$\sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \beta_i K(y_i, x_i) = \sum_{i=1}^{n} \alpha_i \overline{g(x_i)} = \sum_{j=1}^{n} \overline{\beta_i} f(y_j),$$

and therefore that the value $\langle f, g \rangle_{H_0}$ is determined by solely by f and g, independent of the choice of representing linear combination. Choosing $g = K(\cdot, x)$ yields

$$\langle f, K(\cdot, x) \rangle_{H_0} = \sum_{i=1}^n \alpha_i \overline{h(x_i)} = \sum_{i=1}^n \alpha_i K(x, x_i) = f(x).$$

So, K fulfills the reproducing identity under $\langle \cdot, \cdot \rangle_{H_0}$. In particular,

$$||K(\cdot, z)||_{H_0} = \langle K(\cdot, x), K(\cdot, x) \rangle_{H_0} = K(x, x) \ge 0.$$

From this definiteness of $\langle \cdot, \cdot \rangle_{H_0}$ follows; indeed, if $\langle f, f \rangle_{H_0} = 0$, then we have

$$|f(x)| = |\langle f, K(\cdot, x) \rangle| \le \langle f, f \rangle^{1/2} K(x, x)^{1/2} = 0,$$

for every $x \in E$, implying $f \equiv 0$. We then conclude that $\langle \cdot, \cdot \rangle_{H_0}$ is in fact an inner product on H_0 as the other requirements are easy to check.

We now show that H_0 fulfills the conditions of Theorem1.13. First, each ev_x is continuous on H_0 ; in fact, for $f, g \in H_0$,

$$|\operatorname{ev}_x(f) - \operatorname{ev}_x(g)| = |\langle f - g, K(\cdot, x) \rangle_{H_0}| \le ||f - g||_{H_0} K(x, x)^{1/2}$$

for every $x \in E$. To verify the other condition, let $\{f_n\}$ be a Cauchy sequence in H_0 converging pointwise to 0. Let B > 0 be an upper bound for $||f_n||_{H_0}$. For $\epsilon > 0$ and large $N \in \mathbb{N}$ we have

$$||f_n - f_N|| < \frac{\epsilon}{B}$$

for all $n \geq N$. We may write

$$f_N = \sum_{i=1}^k K(\cdot, x_i)$$

for some $\alpha_i \in \mathbb{F}$ and $x_i \in E$, and for some fixed k. It then follows that

$$||f_n||_{H_0}^2 = \langle f_n - f_N, f_n \rangle_{H_0} + \langle f_N, f_n \rangle_{H_0} \le \epsilon + \sum_{i=1}^k f(x_i)$$

for $n \geq N$, and hence $||f_n|| \to 0$ as $n \to 0$. Therefore, there is a RKHS H that has H_0 as a dense subspace. Furthermore, for each $f \in H$ there is $\{f_n\} \subset H_0$ such that $f_n \to f$ pointwise as well as in H-norm, for which we have

$$f(x) = \lim_{n \to \infty} f_n(x) = \lim_{n \to \infty} \langle f_n, K(\cdot, x) \rangle_{H_0} = \langle f, K(\cdot, x) \rangle_H,$$

for every $x \in E$. Thus, K is a reproducing kernel of H. Uniqueness follows from Proposition 1.5.

Theorem 1.19. (Characterization of positive definite function) A function $K: E \times E \to \mathbb{F}$ is positive definite (and thus a reproducing kernel of some RKHS) if and only if K is a kernel, that is, if and only if there exists some mapping φ of E into some \mathbb{F} -Hilbert space H such that

$$K(x,y) = \langle \varphi(y), \varphi(x) \rangle_H$$

for all $x, y \in E$.

Proof. If (H, K) is the RKHS generated by positive definite function K, then the canonical feature map $\varphi_K : E \ni x \mapsto K(\cdot, x) \in H$ obviously qualifies. The converse follows from Corollary1.12.

Remark 1.20. Theorem1.19 implies that RKHS (H, K) is a natural feature space.

Theorem1.19 is a powerful tool to construct a positive definite function as well as to prove a given function is a kernel if we can find an appropriate feature space, as the following example illustrates.

Example 1.21. Let us show that $K(x,y) = \min(x,y), x,y \in \mathbb{R}_+$ is positive definite. Let $H:=L^2(\mathbb{R}_+,\mu)$ be the space of all square integrable functions on \mathbb{R}_+ with respect to a σ -finite measure μ . It is well-known that H is a Hilbert space with the inner product $\langle f,g\rangle_H:=\int_{\mathbb{R}_+}f\overline{g}d\mu$. Then we have

$$K(x,y) = \int_{\mathbb{R}} 1_{[0,y]}(t) 1_{[0,x]}(t) d\mu(t) = \langle \varphi(y), \varphi(x) \rangle_H,$$

where $\varphi: E \ni x \mapsto 1_{[0,x]}(\cdot) \in H$ is the feature map, and $1_A(\cdot)$ is the indicator function of A. Therefore, K is positive definite.

The next Theorem relates a feature map (therefore a kernel) and the RKHS the corresponding positive definite function generates.

Theorem 1.22. (RKHS generated by feature map) Let $E \neq \emptyset$. Suppose K is a positive definite kernel with a feature space H_0 and a feature map $\varphi_0: E \to H_0$. Then the Hilbert space

$$H:=\{f:E\to\mathbb{F}\mid\exists w\in H_0\,:\,f(x)=\langle w,\varphi_0(x)\rangle_{H_0}\;\forall x\in E\}$$

equipped with the norm

$$||f||_H := \inf\{||w||_{H_0} : w \in H_0, f = \langle w, \varphi_0(\cdot) \rangle_{H_0}\}$$
 (2)

is the RKHS with the reproducing kernel K, and H and $\|\cdot\|_H$ are determined independent of the choice of feature space H_0 and feature map φ_0 . Moreover, the function

$$V: H_0 \ni w \mapsto \langle w, \varphi_0(\cdot) \rangle_{H_0} \in H$$

is an isometric isomorphism on $(\ker V)^{\perp}$.

Proof. In light of Theorem1.18, it suffices to prove that H is RKHS with reproducing kernel K. The property of V are automatically obtained in the process. It is easy to verify that $\|\cdot\|_H$ is actually a norm on H. As $\ker V$ is closed subspace of H_0 , we get the orthogonal decomposition $H_0 = \ker V \oplus (\ker V)^{\perp}$. Let $H_1 := (\ker V)^{\perp}$ and the restriction of V onto H_1 be denoted by V_1 . Since every $f \in H$ can be written as $f = V(w_0 + w_1) = V_1 w_1$, with $w_0 \in \ker V$, $w_1 \in H_1$, we see that $V_1 : H_1 \to H$ is an isomorphism. Similarly, we have

$$||f||_{H} = \inf\{||w_{0} + w_{1}||_{H_{0}}^{2} : w_{0} \in \ker V, w_{1} \in H_{1}, w_{0} + w_{1} \in V^{-1}(\{f\})\}$$

$$= \inf\{||w_{0}||_{H_{0}}^{2} + ||w_{1}||_{H_{0}}^{2} : w_{0} \in \ker V, w_{1} \in H_{1}, w_{0} + w_{1} \in V^{-1}(\{f\})\}$$

$$= \inf\{||w_{1}||_{H_{0}}^{2} : w_{1} \in H_{1}, w_{1} \in V^{-1}(\{f\})\}$$

$$= ||V_{1}^{-1}(f)||_{H_{1}} \left(:= ||V_{1}^{-1}(f)||_{H_{0}} \right).$$

From this equation, we conclude that $V_1: H_1 \to H$ is an isometric isomorphism, as required, and that H is a Hilbert space.

It remains to show that K qualifies as the reproducing kernel. Observe

$$K(\cdot, x) = \langle \varphi_0(x), \varphi_0(\cdot) \rangle_{H_0} = V \varphi_0(x) \in H.$$

Moreover, the fact $\langle w, \varphi_0(x) \rangle_{H_0} = 0$ for all $w \in \ker V$ implies

$$f(x) = \langle V_1^{-1} f, \varphi_0(x) \rangle_{H_0} = \langle f, V \varphi_0(x) \rangle_H = \langle f, K(\cdot, x) \rangle_H$$

for all $f \in H$ and $x \in E$.

Remark 1.23. (Infimum in the norm $\|\cdot\|_H$ at (2) is attainable) We continue with the notation in The Theorem1.22. The isometric relation $\|f\|_H = \|V_1^{-1}(f)\|_{H_1}$ clearly shows that the infimum is achievable within the domain of V_1 , namely within the subspace $D := (\ker V)^{\perp}$ of H_0 . From this it follows that the infimum of norm $\|f\|_H$ of $f \in H$ is attained at the D-orthogonal-component of $V^{-1}(\{f\})$.

1.3 Basic Properties of Kernel

Proposition 1.24. (\mathbb{R} -valued \mathbb{C} -kernel admits a \mathbb{R} -feature space) Let $K: E \times E \to \mathbb{C}$ be a kernel with a \mathbb{C} -feature space H and a feature map $\varphi: E \to H$. Assume $K(x,y) \in \mathbb{R}$ for all $x,y \in E$. Then $H_0 := H$ equipped with an inner product

$$\langle f, g \rangle_{H_0} := \operatorname{Re} \langle f, g \rangle_{H_0}$$

is an \mathbb{R} -Hilbert space, and $\varphi_0: E \to H_0$ is a feature map of K.

Proposition 1.25. Let $K : E \times E \to \mathbb{F}$ be a kernel.

(a) For an arbitrary map $T: E_1 \to E$, the function

$$K_T: E_1 \times E_1 \ni (x,y) \mapsto K(T(x),T(y)) \in \mathbb{F}$$

is also a kernel. In particular, the restriction of K to $E_1 \times E_1$ is a kernel if $E_1 \subset E$.

(b) For an arbitrary map $S: E \to \mathbb{F}$, the function $E \times E \ni (x,y) \mapsto S(x)K(x,y)\overline{S(y)}$ is also an kernel.

2 Reconstruction of RKHS

2.1 Reconstruction via Restriction

Corollary 2.1. (RKHS of a Restricted Kernel) Let (H, K) be a RKHS of functions on E. Let $\emptyset \neq E_1 \subset E$. The restriction K_1 of K to $E_1 \times E_1$ is the RK of the Hilbert space

$$H_1 := \{ f|_{E_1} \mid f \in H \}$$

equipped with the norm

$$||f_1||_{H_1} := \inf\{||f||_H : f \in H, f|_{E_1} = f_1\} = ||f1_{E_1}||_H,$$

where $f|_A$ stands for the restriction of f to the set A, and 1_A is the indicator function of A.

Proof. Define a feature map

$$\varphi: E_1 \ni x \mapsto K(\cdot, x) 1_{E_1}(x) \in H$$
,

and apply Theorem1.22 to see (H_1, K_1) is the RKHS generated by the feature map φ . Moreover, Remark1.23 tells us that the infimum of $||f_1||_{H_1}$ is achievable at $f \in H$ that should necessarily satisfy

$$f_1 = \langle f, K(\cdot, x) 1_{E_1}(x) \rangle_H$$

that is, at $f = f_1 1 E_1(x)$.

Proposition 2.2. Let $K: E \times E \to \mathbb{C}$ be a kernel and H its corresponding \mathbb{C} -RKHS.

(a) If $K(x,y) \in \mathbb{R}$ for all $x,y \in E$ then

$$H_1 := \{ f : E \to \mathbb{R} \mid \exists g \in H, \operatorname{Re} g = f \}$$

equipped with the norm

$$||f||_{H_1} := \inf\{||g||_H : g \in H, \operatorname{Re} g = f\}$$

is the \mathbb{R} -RKHS of the kernel $K: E \times E \to \mathbb{R}$.

(b) Suppose $E = \mathbb{C}^d$ of the kernel $K : E \times E \to \mathbb{R}$. Then

$$H_2 := \{ f \in \mathbb{R}^d \to \mathbb{R} \mid \exists g \in \mathbb{C}^d \to \mathbb{C} : g \in H, \operatorname{Re} g|_{\mathbb{R}^d \times \mathbb{R}^d} = f \}$$

equipped with the norm

$$||f||_{H_2} := \inf\{||g||_H : g \in H, \operatorname{Re} g|_{\mathbb{R}^d} = f\}$$

is the \mathbb{R} -RKHS of the restricted kernel $K|_{\mathbb{R}^d \times \mathbb{R}^d}$.

Proof. Proposition 1.24 tells us that $H_0 := H$ with an inner product

$$\langle f, g \rangle_{H_0} := \operatorname{Re} \langle f, g \rangle_H$$

is an \mathbb{R} -feature space of a \mathbb{R} -feature map

$$\varphi: E \ni x \mapsto K(\cdot, x) \in H_0.$$

For all $f \in H_0$ and $x \in E$, we have

$$f(x) = \langle f, \varphi(x) \rangle_H = \operatorname{Re} \langle f, \varphi(x) \rangle_H + \operatorname{Im} \langle f, \varphi(x) \rangle_H$$
$$= \langle f, \varphi(x) \rangle_{H_0} + \operatorname{Im} \langle f, \varphi(x) \rangle_H,$$

which implies $\langle f, \varphi(x) \rangle_{H_0} = \operatorname{Re} f(x)$. Applying Theorem1.22 then proves (a). (b) is an immediate consequence of (a) and Corollary2.1.

- 2.2 Reconstruction via Operator
- 2.3 Reconstruction via Sum and Product
- 3 Inheritance from Kernel to RKHS
- 3.1 Measurability of RKHS
- 3.2 Separability of RKHS
- 3.3 Continuity of RKHS
- 4 Mercer Representation

References

- [1] Alain Berlinet and Christine Thomas-Agnan. Reproducing Kernel Hilbert Spaces in Probability and Statistics. Springer, 1st edition, 2004.
- [2] Andreas Christmann and Ingo Steinwart. Support vector machines. Springer, 1st edition, 2008.
- [3] Felipe Cucker and Ding Xuan Zhou. Learning theory: An approximation theory viewpoint. Cambridge University Press, 1st edition, 2007.
- [4] Vern I. Paulsen and Mrinal Raghupathi. An Introduction to the Theory of Reproducing Kernel Hilbert Spaces. Cambridge University Press, 1st edition, 2016.
- [5] Bernhard Schlkopf and Alexander J. Smola. Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond. The MIT Press, 1st edition, 2001.