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 (RKHS) 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

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Notation

1 Basic Property of RKHS

1.1 Kernel and Positive Definite Function

Definition 1.1. (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.

Example 1.2. (Kernel admits many different feature spaces and feature maps) Consider the function $K: \mathbb{R} \times \mathbb{R} \ni (x,y) \mapsto xy \in \mathbb{R}$. Clearly, K is a kernel with a feature map $E \ni x \mapsto x \in \mathbb{R}$ with a feature space \mathbb{R} . On the other hand, the map $E \ni x \mapsto (x/\sqrt{2}, x/\sqrt{2}) \in \mathbb{R}^2$ is also a feature map of K. An analogous argument works in order to invent a new feature map of an arbitrary kernel. In other words, neither feature space nor feature map are uniquely determined.

Let us start with an almost trivial remark about codomain of kernel.

Proposition 1.3. (\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.

Proof. It is easy to check that $\langle \cdot, \cdot \rangle_{H_0}$ is indeed an inner product. The proof about φ_0 is quite straightforward.

In the following Proposition, we demonstrate an naive method to prove some elementary transformation of kernels is again a kernel.

Remark 1.4. (An review of tensor product of Hilbert spaces) Let H_1 and H_2 be two \mathbb{F} -Hilbert spaces of functions on E_1 and E_2 , respectively. Consider the vector space $H_1 \bullet H_2$ spanned by the all functions of the form

$$f_1 \otimes f_2 : E_1 \times E_2 \ni (x_1, x_2) \mapsto f_1(x_1) f_2(x_2) \in \mathbb{F},$$

where f_1 and f_2 run through H_1 and H_2 , respectively. We can then introduce an inner product on $H_1 \bullet H_2$ by setting

$$\langle \cdot, \cdot \rangle : (H_1 \bullet H_2) \times (H_1 \bullet H_2) \ni (f_1 \otimes f_2, g_1 \otimes g_2) \mapsto \langle f_1, g_1 \rangle_{H_1} \langle f_2, g_2 \rangle_{H_2}.$$

The smallest complete Hilbert space containing the inner product space $H_1 \bullet H_2$ is called the tensor product of H_1 and H_2 , and is denoted by $H_1 \otimes H_2$. \triangleleft

Proposition 1.5. (Product of kernels) Let K_1 be a kernel on E_1 and K_2 be a kernel on E_2 . Then $K_1 \cdot K_2$ is a kernel on $E_1 \times E_2$.

Proof. Let $\varphi_i: E_i \ni x \mapsto H_i$ be a feature map of K_i . It follows from the definition of tensor product space $H_1 \otimes H_2$ that

$$K_1(x_1, y_1) \times K_2(x_2, y_2) = \langle \varphi_1(y_1), \varphi_1(x_1) \rangle_{H_1} \langle \varphi_2(y_2), \varphi_2(x_2) \rangle_{H_2}$$
$$= \langle \varphi_1(y_1) \otimes \varphi_2(y_2), \varphi_1(x_1) \otimes \varphi_2(x_2) \rangle_{H_1 \otimes H_2},$$

which justifies our claim.

This method is a bit tricky and sometimes even very hard to apply to more complicated situations. The difficulty comes from the heavy requirement that we have to specify an suitable feature space and a feature map, for instance, the tensor product space in the above Proposition. So, we now introduce the concept of positive definite function in order to explore the property of kernel in a more handy way.

Definition 1.6. (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.

Remark 1.7. As we see later in section??, the notion of positive definite function and that of kernel completely coincide. Consequently, all the results stated in the language of positive definite functions turn out to be true for kernels, and vice versa.

We first want to establish that kernel is indeed positive definite. Before we do that, however, we should mention about the concept of positive definite *real* functions.

Proposition 1.8. (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 .

We now state the series of elementary properties of positive definite functions.

Proposition 1.9. 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 1.10. (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.

The following Propositions are easy to deduce.

Proposition 1.11. Let $K_n : E \times E \to \mathbb{F}$ be kernels.

- (a) $aK_1 + bK_2$ is positive definite if $a, b \ge 0$.
- (b) The function defined by the pointwise limit $\lim_{n\to\infty} K_n(x,y)$ of $K_n(x,y)$ is positive definite, provided that limit is well-defined.

In other words, the set of all positive definite functions is a closed cone.

Proposition 1.12. Let $K: E \times E \to \mathbb{F}$ be a positive definite function.

(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 positive definite. In particular, if $E_1 \subset E$, the restriction of K to $E_1 \times E_1$ is positive definite.

(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 positive definite.

1.2 Properties of Reproducing Kernel

Definition 1.13 (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 1.14. (b) is called the *reproducing property*, and the identity is called the *reproducing identity*.

Theorem 1.15 (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 1.16. 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 1.17. (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 $f \equiv 0$. 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 Corollary1.16 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.

Proposition 1.18. (Representation of RK in terms of evaluation functional) In an arbitrary RKHS (H, K), the reproducing kernel $K : E \times E \to \mathbb{F}$ always fulfills the identity

$$K(x,y) = \langle ev_y, ev_x \rangle_{H^*}$$

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 $I: H^* \to H$ 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

$$K(x,y) = \langle ev_y, ev_x \rangle_{H^*} = \langle Iev_y, Iev_x \rangle_H = ev_x (ev_y) = (Iev_y)(x),$$

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.

1.3 RKHS of a positive definite function

Theorem 1.19. (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 , and it consists of pointwise limit of Cauchy sequence in H_0 .

Proof. Suppose such an extension H exists. H satisfies (b) by Theorem1.15. 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. As Proposition 1.17 show the uniqueness of such H, we only have to prove the existence. Let X be the Hilbert space derived by the completion of H_0 . In general, X consists of equivalent classes of Cauchy sequence in H_0 equipped with the inner product

$$\langle \cdot, \cdot \rangle_X : X \times X \ni ([\{f_n\}], [\{g_n\}]) \mapsto \lim_{n \to \infty} \langle f_n, g_n \rangle_{H_0} \in \mathbb{F}.$$

Let $f = [\{f_n\}]$ be an element in X with a representative Cauchy sequence $\{f_n\} \subset H_0$. It follows from (a) that

$$|f_n(x) - f_m(x)| = |\operatorname{ev}_x(f_n - f_m)| \to 0,$$

when $n, m \to \infty$. As this implies $\{f_n(x)\}$ is a Cauchy sequence for every $x \in E$, we can define a function $f: E \to \mathbb{F}$ by setting

$$f(x) := \lim_{n \to \infty} f_n(x).$$

It is easy to see that f is well-defined, independent of the choice of a representative $\{f_n\}$. We then define a linear mapping

$$I: X \ni [\{f_n\}] \mapsto f \in \mathbb{F}^E$$
.

Obviously, $I([\{f\}]) = f$ for $f \in H_0$. Moreover, I is injective; indeed, if $h = [\{f_n\}] \in X$ and $\lim_{n \to \infty} f_n(x) = 0$ for every $x \in E$, then (b) gives $f_n \to 0$ in H_0 -norm and therefore $h \equiv 0$ in X, as required. The isomorphism I induces the Hilbert structure on H := I(X), which makes I isometric on H. Clearly, H_0 is dense in H. Finally, we claim that every evaluation functional ev_x is continuous on H. Fix $x \in E$. As ev_x is assumed in (a) to be (uniformly) continuous on H_0 , it admits unique continuous extension T_x onto the closure of H_0 in H, that is, onto whole H. For $f \in H$ and for $f_n \in H_0$ with $f_n \to f$ pointwise, we have

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

It follows from Theorem 1.15 that H admits a reproducing kernel.

Remark 1.20. Since H is derived as the completion of H_0 , any Hilbert space that include H_0 and is isomorphic to H is identical to H.

Theorem 1.21. (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,

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

This establishes the definiteness of $\langle \cdot, \cdot \rangle_{H_0}$; 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 sufficient conditions of Theorem1.19. 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 1.17.

Theorem 1.22. (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 Corollary1.10.

Remark 1.23. Theorem1.22 implies that RKHS (H, K) is a natural feature space.

Theorem1.22 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 1.24. 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 construct a RKHS as a continuous embedding into a given feature space. We will repeatedly exploit this constructive method later.

Theorem 1.25. (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

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

acts as an isometrical isomorphism on $(\ker V)^{\perp}$.

Proof. In light of Theorem1.21, 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 let 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 isometrical 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 1.26. (Infimum in the norm $\|\cdot\|_H$ at (2) is attainable) We continue with the notation in the Theorem1.25. 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 $V^{-1}(\{f\})$.

Corollary 1.27. (RKHS derived by Fourier transformation) Suppose that $r \in L^1(\mathbb{R}, \mathcal{B}, dt)$ is a bounded continuous function with r(t) > 0 for all t, and write $H_0 := L^2(\mathbb{R}, \mathcal{B}, r(t)dt)$. Then,

$$H := {\{\hat{wr} \mid w \in H_0\}} = {\{f \in L^2(\mathbb{R}, \mathcal{B}, dt) \mid \int_{\mathbb{R}} \frac{|\hat{f}|^2}{r} dt < \infty}}$$

is a RKHS with the inner product

$$\langle f, g \rangle_H := \int_{\mathbb{R}} \frac{\hat{f} \cdot \overline{\hat{g}}}{r} dt,$$

where \hat{f} stands for the Fourier transformation of f, and with the RK

$$K: \mathbb{R} \times \mathbb{R} \ni (x, y) \mapsto \int_{\mathbb{R}} e^{-\sqrt{-1}(x-y)t} r(t) dt \in \mathbb{C}.$$

Proof. Let φ be a feature map that assigns, to each $x \in \mathbb{R}$, the function $\mathbb{R} \ni t \mapsto e^{-\sqrt{-1}xt} \in H_0$. Theorem1.25 tells us that $H = \{\widehat{wr} \mid w \in H_0\}$ is a RKHS with the RK K. We claim that the map

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

is injective. It is easy to deduce from Schwartz inequality that $wr \in L^1(\mathbb{R}, dt)$ for every $w \in H_0$. Suppose $\langle w, \varphi(x) \rangle_{H_0} = 0$, that is, suppose that Fourier transformation of wr is identically zero. This necessarily leads to wr = 0, and hence $w \equiv 0$, as required. It then follows that $V: H_0 \to H$ is an isometrical isomorphism, and consequently that

$$\langle f, g \rangle_H = \langle V^{-1} f, V^{-1} g \rangle_{H_0} = \int \frac{\hat{f}}{r} \frac{\overline{\hat{g}}}{r} r dt = \int \frac{\hat{f} \cdot \overline{\hat{g}}}{r} dt.$$

In order to justify the alternative expression of H, let us note that $wr \in L^2(\mathbb{R}, dt) \cap L^1(\mathbb{R}, dt)$ for $w \in H_0$. We may write $f \in H$ as $f = \widehat{wr}$ for some $w \in H_0$. The well-known result from the theory of Fourier transformation then yields $\widehat{f} = wr$, which implies $w \in H_0 \iff \widehat{f}/r \in H_0$.

1.4 Example of Kernels

Example 1.28. (Normalized kernel)

Example 1.29. (Polynomial kernel) fuga

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Example 1.30. (Taylor type kernel)

Example 1.31. (Exponential kernel)

Example 1.32. (Binomial kernel)

Example 1.33. (Fourier type kernel)

Example 1.34. (Gaussian RBF kernel)

Example 1.35. (Laplacian 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

$$||f_1||_{H_1} := \inf\{||f||_H : f \in H, f|_{E_1} = f_1\} = ||f_{1,0}||_H,$$

where $f|_A$ stands for the restriction of f to the set A, and $f_{1,0}$ the extension of f_1 over H by zero.

Proof. Define a feature map

$$\varphi: E_1 \ni x \mapsto K(\cdot, x) \in H$$
,

and apply Theorem1.25 to see (H_1, K_1) is the RKHS generated by the feature map φ . Moreover, Remark1.26 tells us that the infimum of $||f_1||_{H_1}$ is achievable at the orthogonal projection of $f \in H$ satisfying $f|_{E_1} = f_1$ onto $\ker V^{\perp}$, namely, at $f1_{E_1} \in H$.

Proposition 2.2. (\mathbb{R} -RKHS of a \mathbb{R} -valued \mathbb{C} -kernel) Let $K: E \times E \to \mathbb{C}$ be a kernel and H its corresponding \mathbb{C} -RKHS, and suppose $K(x,y) \in \mathbb{R}$ for all $x,y \in E$.

(a) The space

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

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) In particular, if $E = \mathbb{C}^d$, then the space

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

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 1.3 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 Theorem1.25 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

Theorem 2.3. (Sum of RKHSs) Let (H_1, K_1) and (H_2, K_2) be two \mathbb{F} -RKHSs of functions on the common set E. Then $K := K_1 + K_2$ is the RK of

$$H := H_1 \oplus H_2 := \{ f_1 + f_2 \mid f_1 \in H_1, f_2 \in H_2 \}$$

with the norm

$$||f||_H := \min\{||f_1||_{H_1} + ||f_2||_{H_2} : f = f_1 + f_2, f_1 \in H_1, f_2 \in H_2\}.$$

Proof. Let F be the Hilbert sum of H_1 and H_2 :

$$F := \{ (f_1, f_2) \mid f_1 \in H_1, f_2 \in H_2 \}$$

equipped with an inner product

$$\langle f, g \rangle_F := \langle f_1, g_1 \rangle_{H_1} + \langle f_2, g_2 \rangle_{H_2}.$$

It is easy to see that the map

$$\varphi: E \ni x \mapsto (K_1(\cdot, x), K_2(\cdot, x)) \in F$$

is a feature map of K, and that we have

$$\langle f, \varphi(x) \rangle_F = f_1(x) + f_2(x)$$

for all $f = (f_1, f_2) \in F$ and $x \in E$. Thus, (H, K) is a RKHS by Theorem1.25. For attainability of $\|\cdot\|_H$, see Remark1.26.

Theorem 2.4. (Tensor product of RKHSs) Let K_1 and K_2 be \mathbb{F} -kernels defined on E_1 and E_2 , respectively, and let H_1 and H_2 be the corresponding \mathbb{F} -RKHSs. Set $H := H_1 \otimes H_2$.

- (a) Define the product kernel K of K_1 and K_2 via $K: (E_1 \times E_2) \times (E_1 \times E_2) \ni ((x_1, x_2), (y_1, y_2)) \mapsto K_1(x_1, y_1) K_2(x_2, y_2) \in \mathbb{F}.$ Then (H, K) is a RKHS.
- (b) Assume $(E :=)E_1 = E_2$. The RKHS the kernel $K_E(x, y) := K_1(x, y)K_2(x, y)$ coincides with $H_E := \{f|_{E \times E} \mid f \in H_1 \otimes H_2\}$.

Proof. (a) It is easy to see that

$$\varphi: E_1 \times E_2 \ni (x_1, x_2) \mapsto (K_1(\cdot, x_1)K_2(\cdot, x_2)) \in H$$

is a feature map of K. Let H' be the RKHS generated by φ (and hence by K). Let H_0 be the subspace of H' spanned by $\{K(\cdot,x)\}_{x\in E_1\times E_2}$. Note that $H_0\subset H_1\bullet H_2$ is dense in H', and that H' is isomorphic to the completion of H_0 and hence to that of $H_1\bullet H_2$. It thus follows that H' and $H_1\otimes H_2$ must coincide.

2.4 Examples of RKHSs

Example 2.5. (Finite dimensional RKHS)

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Example 2.6. (RKHS of a linear kernel)

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Example 2.7. (RKHS of functions on a finite set)

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Example 2.8. (RKHS of polynomial a kernel)

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Example 2.9. (RKHS of a Gaussian RBF kernel)

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Example 2.10. (RKHS of a Laplacian kernel)

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3 Inheritance from Kernel to RKHS

- 3.1 Topological Properties of RKHS
- 3.2 Differentiablity of RKHS
- 4 Representor Theorem and its Application

5 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.