Mathematical foundations of Infinite-Dim Statistical models ${\it Chap. 2.6.2 \sim} 2.6.3$

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Review of RKHS

Some applications of RKHS

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Reviwe of RKHS

For centred Gaussian Process $X_t, t \in T$, Define $F := span\{X_t : t \in T\} \subset L^2(\Omega, \Sigma, \mathbb{P})$ **Definition 2.6.1(RKHS of GP)** The reproducing kernel Hilbert space of a centered Gaussian process is

$$H = completion(\{\mathbb{E}(hX) : h \in F\})$$

Definition 2.6.4(RKHS of B-valued random variable) Let B be a separable Banach space, and let X be a B-valued centered random variable. Define $F = \{f(X): f \in B^*\} \subset L^2(\Omega, \Sigma, \mathbb{P}) \text{ and } \bar{F} \text{ is its completion. The reproducing kernel hilbert space of X is}$

$$H=\{\mathbb{E} hX:h\in\bar{F}\}\subset B$$
 with inner product $\langle\mathbb{E}(h_1X),\mathbb{E}(h_2X)\rangle_H:=\mathbb{E} h_1h_2$

Review of RKHS

Some applications of RKHS

- ▶ Isoperimetric inequality
- ► Equivalence and Singularity
- ► Small ball estimation

Isoperimetric

Theorem 2.6.12 Let O_H be the unit ball centerd at zero of the RKHS H of X, where X is a centered Gaussian B-valued random variable, B a separable Banach space. Let μ be the probability law of X. Then, for every set $A \in \mathcal{B}_B$ and every $\epsilon > 0$,

$$\mu(A + \epsilon O_H) \le \Phi(\Phi^{-1}(\mu(A)) + \epsilon)$$

Equivalance and Singularity

Theorem 2.6.13 (Cameron-Martin formula) Let B ba a separable Banach space, let μ be a centered Gaussian Borel meaure on B, Let H be its RKHS and let $h \in H$. Then the probability measure $\tau_h \mu$ defined as $\tau_h \mu(A) = \mu(A-h)$, is absolutely continuous with repect to μ , and

$$\frac{d\tau_h \mu}{d\mu}(x) = e^{(\phi^{-1}h(x) - \|h\|_H^2/2}$$

Moreover, if $\nu \notin H$, then $\tau_{\nu}\mu$ and μ are mutually singular.

Remark 2.6.14 $au_h\mu$ and μ are mutually absolutely continuous for any $h\in H$

Equivalance and Singularity

Corollary 2.6.17 Let μ be a centered Gaussian measure on a separable Banach space B, and let H be its RKHS. Then the support of μ is \bar{H} , the closure in B of H

The probability of small ball

Corollary 2.6.18 Let $C \subset B$ be a symmetric Borel set, where B is a separable Banach space, and let X be a centered Gaussian B-valued random variable. Then, for every $h \in H$,

$$\mathbb{P}(X - h \in C) \ge e^{-\|h\|_H^2/2} \mathbb{P}(X \in C)$$

The probability of small ball

Given a centered Gaussian B-valued random variable X with law μ , define its concentration function $\phi_{\mathsf{X}}(\epsilon) = \inf_{h \in H, \|h - \mathsf{X}\| < \epsilon} [\frac{1}{2} \|h\|_{H}^{2} - \log \mathbb{P}(\|\mathsf{X}\| < \epsilon)]$

Proposition 2.6.19 Let X be a centered Gaussian B-valued random variable, where B is a separable Banach space. Let $x \in supp(\mathcal{L}(X)) = \bar{H}(\text{See Cor 2.6.17})$ and $\epsilon > 0$. Then,

$$\phi_{\mathsf{X}}(\epsilon) \leq -log\mathbb{P}(\|\mathsf{X} - \mathsf{x}\| < \epsilon) \leq \phi_{\mathsf{X}}(\frac{\epsilon}{2})$$

Review of RKHS

Some applications of RKHS

Review: Brownian motion

Brownian motion on [0,1] is a centered sample continuous Gaussian process W whose covariance is $\mathbb{E} W_s W_t = s \wedge t$. It can be thought as a B-valued random variable where $\mathsf{B} = \mathcal{C}([0,1])$ endowed with sup norm

▶ The sample paths of W are all in $C^{\alpha}([0,1])$, the space of Hölder continuous of order α on all $0 < \alpha < 1/2$. (Exercise 2.3.2)

Released Process

- ▶ Let $(I_{0+}f)(t) = \int_0^t f(x)dx$ denote the primirive of f which is zero at zero for any continuous function f on [0,1], and let $(I_{0+}^k f)(t) = \int_0^t I_{0+}^{k-1} f(s) ds$
- $I_{0+}^{0}W = W, (I_{0+}^{k}W)(t) = \int_{0}^{t} (I_{0+}^{k-1}W)(s)ds$
- $I_{0+}^k W$ are almost all in $C^{k+\alpha}([0,1])$
- ▶ Released Process Define $W^k(t) = \sum_{j=0} kt^j g_j/j! + (I_{0+}^k W)(t), t \in [0,1], k \ge 0$ where g_i are i.i.d standard normal variables idependent of W

RKHS of W^k

Proposition 2.6.24 For $k \geq 0$, the RKHS of W^k as a $\mathit{C}([0,1])$ -valued random variable is

 $\begin{array}{l} \textit{H}_{W,k} = \{\textit{f}: [0,1] \rightarrow \mathbb{R}: \textit{fisktimesdifferentiable}, \textit{f}^{(k)} \textit{isabs.cont.andf}^{(k+1)} \in L^2([0,1])\} \\ \text{with inner product } \langle \textit{f}, \textit{g} \rangle_{\textit{H}_{W,k}} = \sum_{j=0} \textit{kf}^{(j)}(0) \textit{g}^{(j)}(0) + \int_0^1 \textit{f}^{(k+1)}(s) \textit{g}^{(k+1)}(s) \textit{d}s \end{array}$

Theorem 2.6.26 Let W be Brownian motion on [0,1] Then, there exists $C \in (0,\infty)$ such that, for all $0<\epsilon \leq 1$,

$$-\mathit{C}\epsilon^{-2} \leq \mathit{log}\mathbb{P}\{\mathit{sup}_{t \in [0,1]}|\mathit{W}(t)| < \epsilon\} \leq -\tfrac{1}{\mathsf{C}}\epsilon^{-2}$$

That is, the exact order of small ball concentration function ϕ_0^W of Brownian motion is $\phi_0^W = O(\epsilon^{-2})$ as $\epsilon \to 0$.

Theorem 2.6.29 If there is $\gamma>0$ such that, for $\mathcal{C}_1<\infty$ and $\tau_i>0$,

$$\phi_0(\epsilon) \le C_1 \epsilon^{-\gamma}, 0 < \epsilon \le \tau_1$$

and if

$$\log \mathit{N}(\mathit{H}_1,\epsilon) \leq \mathit{C}_2\epsilon^{-\alpha}, 0 < \epsilon < \tau_2$$

for some $0 < \alpha < 2$, then there exists $C_3 < \infty$ such that for every $0 < \epsilon < \tau_3$,

$$\phi_0(\epsilon) \le C_3 \epsilon^{-2\alpha/(2-\alpha)}$$
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