

Convergence rates for kernel regression in infinite-dimensional spaces

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Received: 17 September 2016 / Revised: 2 October 2018 / Published online: 17 November 2018 © The Institute of Statistical Mathematics, Tokyo 2018

Abstract

We consider a nonparametric regression setup, where the covariate is a random element in a complete separable metric space, and the parameter of interest associated with the conditional distribution of the response lies in a separable Banach space. We derive the optimum convergence rate for the kernel estimate of the parameter in this setup. The small ball probability in the covariate space plays a critical role in determining the asymptotic variance of kernel estimates. Unlike the case of finite-dimensional covariates, we show that the asymptotic orders of the bias and the variance of the estimate achieving the optimum convergence rate may be different for infinite-dimensional covariates. Also, the bandwidth, which balances the bias and the variance, may lead to an estimate with suboptimal mean square error for infinite-dimensional covariates. We describe a data-driven adaptive choice of the bandwidth and derive the asymptotic behavior of the adaptive estimate.

Keywords Adaptive estimate \cdot Bias-variance decomposition \cdot Gaussian process \cdot Maximum likelihood regression \cdot Mean square error \cdot Optimal bandwidth \cdot Small ball probability $\cdot t$ process

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s10463-018-0697-2) contains supplementary material, which is available to authorized users.

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