香港中文大學統計學系
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SEMINAR

DEPARTMENT OF STATISTICS
THE CHINESE UNIVERSITY OF HONG KONG

New Strategies for Inference on High-Dimensional Data

INVITED SPEAKER

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TIME

January 30, 2024 (Tue) · 2:00 pm - 3:00 pm

VENUE

LSB LT1 · Lady Shaw Building LT1 · CUHK

ABSTRACT

How can we conduct inference on high-dimensional data when classical asymptotic theory fails because noise accumulates faster than at root-n rate and function classes are non-Donsker? In this talk, I discuss two complementary approaches to address this problem: First, I introduce a new framework for inference on regression functions in the presence of high-dimensional nuisance parameters. At its core is a convex program that aims to minimize the mean squared prediction error of the regression function by trading off bias and variance optimally. The resulting regression function is asymptotically normal and semiparametric efficient "in a weak sense". I will focus on a specific implementation of this framework for estimating the conditional mean when outcomes are missing at random. Second, I discuss recent advances on the high-dimensional bootstrap. I propose a new bootstrap procedure that takes the correlation structure of the data into account and, under assumption on the correlation structure, allows consistent bootstrapping of the sampling distribution of supremum-type statistics. These theoretical results generalize the existing Gaussian multiplier bootstrap and broaden its applicability for inference on high-dimensional data. They also provide new intuition for why the high-dimensional bootstrap works or doesn't.