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Three Tales in High Dimensional Statistics

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ABSTRACT

In this talk I will present three projects in high dimensional statistics. Inference of high-dimensional varying-coefficient quantile regression: Quantile regression has been successfully used to study heterogeneous and heavy tailed data. In this work, we study high-dimensional varying-coefficient quantile regression model that allows us to capture non-stationary effects of the input variables across time. We develop new tools for statistical inference that allow us to construct valid confidence bands and honest tests for nonparametric coefficient functions of time and quantile. Our focus is on inference in a high-dimensional setting where the number of input variables exceeds the sample size. Performing statistical inference in this regime is challenging due to usage of model selection techniques in estimation. Never the less, we are able to develop valid inferential tools that are applicable to a wide range of data generating processes and do not suffer from biases introduced by model selection. Convergence guarantee for sparse monotone single index model: Single index models (SIMs) is an important semi-parametric extension of linear models. In this ongoing work, we consider a shape constrained high dimensional SIM, where the link function is monotonic (but not necessarily smooth) and the coefficient parameter is high dimensional and sparse. We develop a scalable algorithm and provide theoretical guarantees for the estimation of both the link function and the coefficient parameter. Our theoretical work will be based on very mild assumptions on the design matrix $X$ and error term. In particular, $X$ can be fixed or random, if $X$ is random, it can be asymmetric and the error distribution can depend on $X$. The bias of isotonic regression: We study the bias of the isotonic regression estimator. While there is extensive work characterizing the mean squared error of the isotonic regression, relatively little
is known about the bias. In this work we provide a sharp characterization of the scaling of the bias of isotonic regression when the underlying mean function is strictly increasing and Hölder smooth. Importantly, our analysis only requires the noise distribution to have subexponential tails, without relying on symmetric noise or other restrictive assumptions.