THE UNIVERSITY OF CHICAGO | DEPARTMENT OF STATISTICS

PhD Dissertation Proposal Presentation

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"Beyond Classical Assumptions: Hardness and Hope in Adaptive Statistical Inference"

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Abstract

In many modern statistical applications, the comforting ideal of "classical assumptions" is simply false. Fundamental hardness emerges as we try to adapt textbook procedures to broader, more realistic models. Nevertheless, certain robust structures remain and can serve as anchors for principled adaptivity.

In this talk, I will instantiate this viewpoint mainly through two examples. First, I will show how the classical spectral method for top-K ranking can adapt beyond the Bradley–Terry model to general pairwise comparison models under strong stochastic transitivity (SST). Although any algorithm fails with nontrivial probability on a fixed comparison graph, we prove that the spectral method remains consistent under SST when the comparison graph is resampled in each round, by exploiting the robustness of the stationary distribution of an associated (possibly nonreversible) Markov chain against perturbations. Second, I will discuss an adaptive construction of confidence intervals for the null mean in large-scale inference under Efron's Gaussian two-groups model, where a small and typically unknown fraction of observations come from an arbitrarily shifted nonnull population. We show a sharp hardness result: any valid confidence interval must suffer a non-negligible inflation in length to adapt to unknown contamination proportion and variance, in stark contrast to the absence of such a cost in point estimation. To attain the optimal length, we design an efficient Fourier-based procedure that leverages a trigonometric analogue of the sum-of-squares proof to certify the feasibility of candidate null means. Our contributions thus illustrate how the spectrum of Markov chains and Fourier series can function as robust anchors for adaptive inference well beyond the classical settings.
