RUTGERS–NEW BRUNSWICK
School of Arts and Sciences

Department of Statistics

Department of Statistics Seminar Series

Edward Kennedy
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Minimax optimal causal inference in high dimensions

Wednesday, November 4th, 2026
12:10-1:30 PM
Hill Center - 552
Light refreshments will be served in Hill Center 452 at 11:40 AM

Abstract:

In this talk I survey recent work on causal inference in complex yet common settings with high-dimensional confounders, treatments, or outcomes. First we consider high-dimensional discrete confounders, where popular assumptions like sparsity and smoothness do not apply. We give new error bounds for standard estimators and show they are unimprovable in a minimax sense, illustrating fundamental limits of high-dimensional confounding adjustment. We then study the role of effect homogeneity and knowledge of the covariate distribution, showing how this additional structure can mitigate the curse of dimensionality and allow for faster convergence rates. Next we study high-dimensional treatments (both multi- and vector-valued), which bring distinct complications, such as high-dimensional target parameters and positivity violations. We propose and study a framework for constructing estimators based on sparse pseudo-outcome regression, and give new error bounds. We go on to show that resulting methods are minimax optimal in a black-box model with sparsity. I conclude by discussing implications for applications in the social sciences and medicine, as well as open problems and avenues for future work. This talk is mostly based on the papers arxiv.org/abs/2405.00118 with Tiger Zeng, Siva Balakrishnan, and Yanjun Han, and arxiv.org/abs/2602.21423 with Patrick Kramer and Isaac Opper.

Bio:

Edward Kennedy is a professor of Statistics & Data Science at Carnegie Mellon University. He joined the department after graduating with a PhD in biostatistics from the University of Pennsylvania. Edward's research interests lie at the intersection of causal inference, machine learning, and nonparametric theory, especially in settings involving high-dimensional and otherwise complex data. His applied work focuses on problems in criminal justice, health services, medicine, and public policy. Edward is a recipient of the Mortimer Spiegelman Award for outstanding contributions to health statistics, the NSF CAREER Award, and the Thomas Ten Have Award for exceptional research in causal inference.