Statistics Seminar

Department of Mathematics and Statistics

DATE:	Thursday, February 2nd, 2022
TIME:	1:15pm – 2:15pm
LOCATION:	WH 100E
SPEAKER:	Xinhai Zhang, Binghamton University
TITLE:	Estimating individual treatment effects under unobserved confounding using binary instruments

Abstract

Estimating conditional average treatment effects (CATEs) from observational data is relevant in many fields such as personalized medicine. However, in practice, the treatment assignment is usually confounded by unobserved variables and thus introduces bias. A remedy to remove the bias is the use of instrumental variables (IVs). Such settings are widespread in medicine (e.g., trials where the treatment assignment is used as binary IV). In this paper, the authors propose a novel, multiply robust machine learning framework, called MRIV, for estimating CATEs using binary IVs and thus yield an unbiased CATE estimator. Different from previous work for binary IVs, the framework in this paper estimates the CATE directly via a pseudo outcome regression. (1) the authors provide a theoretical analysis where they show that their framework yields multiple robust convergence rates: their CATE estimator achieves fast convergence even if several nuisance estimators converge slowly. (2) the authors further show that their framework asymptotically outperforms state-of-the-art plug-in IV methods for CATE estimation, in the sense that it achieves a faster rate of convergence if the CATE is smoother than the individual outcome surfaces. (3) the authors build upon their theoretical results and propose a tailored deep neural network architecture called MRIV-Net for CATE estimation using binary IVs. Across various computational experiments, the authors demonstrate empirically that their MRIV-Net achieves state-of-theart performance. Their MRIV seems to be the first multiply robust machine learning framework tailored to estimating CATEs in the binary IV setting.