Statistics Seminar

Department of Mathematics and Statistics

DATE:	Thursday, March 21, 2024
TIME:	1:15pm – 2:15pm
LOCATION:	WH 100E
SPEAKER:	Jingze Liu, Binghamton University
TITLE:	Continuous Treatment Effect Estimation via Generative Adversarial De-confounding

Abstract

One fundamental problem in causal inference is the treatment effect estimation in obser- vational studies, and its key challenge is to handle the confounding bias induced by the associations between covariates and treatment variable. This paper study the prob- lem of effect estimation on continuous treatment from observational data, going beyond previous work on binary treatments. Previous work for binary treatment focuses on de- confounding by balancing the distribution of covariates between the treated and control groups with either propensity score or confounder balancing techniques. In the continuous setting, those methods would fail as we can hardly evaluate the distribution of covariates under each treatment status. To tackle the case of continuous treatments, this paper propose a novel Generative Adversarial De-confounding (GAD) algorithm to eliminate the associa- tions between covariates and treatment variable with two main steps: (1) generating an "calibration" distribution without associations between covariates and treatment by ran- dom perturbation; (2) learning sample weight that transfer the distribution of observed data to the "calibration" distribution for de-confounding with a Generative Adversarial Network. Extensive experiments on both synthetic and real-world datasets demonstrate that our algorithm outperforms the state-of-the-art methods for effect estimation of con- tinuous treatment with observational data.