Daniel NevoTel-Aviv University

Causal inference with misspecified interference structure

Abstract:
The typical approach towards drawing causal conclusions from observed data starts by defining a causal estimand, for example in terms of potential outcomes or the so-called do operator, and continues by providing conditions for identification of this estimand from the data, followed by statistical estimation and inference. One of the main assumptions is the no-interference assumption, meaning that the treatment assigned to one unit does not affect other units in the sample. However, in many domains such as in the social sciences and infectious disease epidemiology, this assumption is implausible in practice due to social interactions. As an alternative to the no-interference assumption, an interference structure is often represented using a network. Ubiquitously, the network structure is assumed to be known and correctly specified. Nevertheless, correctly encoding the interference structure in a network can be challenging. For example, people may misreport their social connections, or report connections irrelevant to the specific combination of treatment and outcome. Building on the exposure mapping framework, we derive the bias arising from estimating causal effects under a misspecified interference structure. To address this problem, we propose a novel estimator that uses multiple networks simultaneously and is unbiased if one of the networks correctly represents the interference structure, thus providing robustness to the network specification. Additionally, we propose a sensitivity analysis that quantifies the impact of a postulated misspecification mechanism on the causal estimates. Through simulation studies, we illustrate the bias from assuming an incorrect network and show the bias-variance tradeoff of our proposed network-misspecification-robust estimator. We further demonstrate the utility of our methods in two real examples. Joint work with Bar Weinstein