

STATISTICS SEMINAR

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PhD Defense

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Dickens 109, 1:00 pm (Central Time)



Causal inference under the K-nearest neighbors interference model

In causal inference, an experiment exhibits treatment interference when the treatment status of one unit affects the response of other units. While traditional causal inference methods often assume no interference between units, there has been a recent abundance of work on the design and analysis of experiments under treatment interference—for example, those conducted on social networks. Failure to account for interference may lead to biased estimates of treatment effects and wrong conclusions.

In this dissertation, we propose the K-nearest neighbors interference model (KNNIM)---a model of treatment interference where the response of a unit depends only on its treatment status and the statuses of units within its K-neighborhood. Current methods for detecting interference include carefully designed randomized experiments and conditional randomization tests on a set of focal units. We give guidance on how to choose focal units under KNNIM. We then conduct a simulation study to evaluate the efficacy of existing methods for detecting arbitrary network interference under KNNIM with this choice of focal units. We show that this choice of focal units leads to powerful tests of treatment interference which outperform experimental methods drastically.

Then, we extend the potential outcomes approach and the K-neighborhood interference framework to define causal estimands for direct and K-nearest neighbors indirect effects where interference is allowed within K-neighborhoods of individuals. Under completely-randomized and Bernoulli-randomized designs, we provide a closed-form solution to compute the marginal and joint probabilities of units being exposed to treatment exposures of interest. We then propose Horvitz-Thompson unbiased estimators for the defined estimands under K-neighborhood interference assumption. We derive properties of the proposed estimators and provide conservative variance estimators. We then demonstrate how an assumption of no interaction between direct and indirect effects can improve estimates. To demonstrate the proposed causal methods, we perform a simulation study and apply our proposed methods on an anti-conflict study from a randomized experiment among middle schools students in New Jersey.

Finally, we develop additional estimators of the defined estimands under an assumption of no interaction between the indirect effects. This may enhance the estimation standard errors by increasing the number of units under this assumption. Properties of the developed estimators are derived as well as conservative variance estimators of the defined estimands.