Causal Inference with Networked Treatment Diffusion

Causal inference under treatment interference (i.e., one unit’s potential outcomes depend on other units’ treatment) is a challenging but important problem. Past studies usually make strong assumptions on the structure of treatment interference. In this study, I highlight the importance of collecting data on actual treatment interference in order to make more accurate causal inference. I show that with accurate measures of treatment interference, one can identify and estimate a series of causal effects that are previously unavailable, including the direct treatment effect, the treatment interference effect, and the treatment effect on interference. Lastly, I use exponential random graph models to model treatment diffusion networks in order to reveal covariates and network processes that significantly correlate with treatment interference. I illustrate the methods through a case study of a smoking prevention intervention. The findings provide an empirical basis to evaluate previous assumptions on the structure of treatment interference, are informative for imputing treatment interference when necessary, and help improve designs of future interventions that aim to optimize treatment diffusion.