# Estimating network-mediated causal effects via spectral embeddings

Alex Hayes, Mark M. Fredrickson, Keith Levin
Presented at ACIC 2023

Causal inference for network data is an area of active interest in the social sciences. Unfortunately, the complicated dependence structure of network data presents an obstacle to many causal inference procedures. We consider the task of mediation analysis for network data, and present a model in which mediation occurs in a latent embedding space. Under this model, node-level interventions have causal effects on nodal outcomes, and these effects can be partitioned into a direct effect independent of the network, and an indirect effect induced by homophily. To estimate network-mediated effects, we embed nodes into a low-dimensional space and fit two regression models: (1) an outcome model describing how nodal outcomes vary with treatment, controls, and position in latent space; and (2) a mediator model describing how latent positions vary with treatment and controls. We prove that the estimated coefficients are asymptotically normal about the true coefficients under a sub-gamma generalization of the random dot product graph, a widely-used latent space model. We show that these coefficients can be used in product-of-coefficients estimators for causal inference. Our method is easy to implement, scales to networks with millions of edges, and can be extended to accommodate a variety of structured data.