CAUSAL INFERENCE FOR SPATIAL TREATMENTS

ABSTRACT:

Many events and policies (treatments) occur at specific spatial locations, with researchers interested in their effects on nearby units of interest. I approach the spatial treatment setting from an experimental perspective: What ideal experiment would we design to estimate the causal effects of spatial treatments? This perspective motivates a comparison between individuals near realized treatment locations and individuals near counterfactual (unrealized) candidate locations, which differs from current empirical practice. I derive design-based standard errors that are straightforward to compute irrespective of spatial correlations in outcomes. Furthermore, I propose machine learning methods to find counterfactual candidate locations and show how to apply the proposed methods to observational data. I apply the proposed methods to study the causal effects of grocery stores on foot traffic to nearby businesses during COVID-19 shelter-in-place policies, finding a substantial positive effect at a very short distance, with no effect at larger distances.