Protecting causal effects

April 22, 2016

Consider a scenario under which the causal graph generating a dataset is considered known - but may contain unmeasured variables.

Assume we add noise to the dataset via a single point crossover process (see paper). The goal is to prevent reliable estimation of causal effects without effecting our ability to predict a particular target variable. Some specific questions:

- Under what circumstances (graph structures) it is possible to disrupt inference of a particular causal effect
- How can we maxiumully disrupt this inference (ie is there a cut that adds more noise for a given amount of shuffling of the data)
- What about if we want to disrupt a specific set of causal inference questions
- What about if we want to disrupt as many causal queries as possible.

The single point crossover process divides the variables into two groups and makes estimates of the form $P(X_1|X_2)$ unreliable if X_1 and X_2 are in different partitions. We can think of the process as drawing a cut through the graph.