Unconfounded Treatment Assignment

Lorenzo Lagos
February 27, 2017

I want to take this opportunity to lay out two terms from the potential outcomes framework that have been causing much confusion, and try to relate these to causal graphs.

The first is **unconfoundedness**—the assumption that treatment is conditional independent from potential outcomes given a set of covariates. In other words, the conditional distribution of the missing potential outcomes (not in the data) is equal to that of the observed potential outcomes (in the data). In the economics literature this is also known as the conditional independence or selection on observables assumption. It relates to the assignment mechanism, since unconfoundedness basically states that treatment is as random within fixed values of a set of covariates. I believe the analog in causal graphs is satisfying the back-door criterion of the treatment relative to the outcome. In fact, we test the back-door criterion through the Bayes ball algorithm, which essentially gives us a set on conditional independence assumptions. A notable difference is that satisfying the back-door criterion is posed as an issue of identification, while unconfoundedness is framed as a selection into treatment question. Does this mean that dealing with selection gives us identification? My response is NO. For example, the back-door criterion covers more than selection issues since it accounts for mediators, which have nothing to do with selection into treatment. Therefore, there is something misleading in looking at W is conditionally independent of $(Y(0), Y(1))$ given X as simply about the selection mechanism.

The second is **ignorability**—a feature of the study design whereby the missing data patterns supply no information. In the missing data literature, it is known as the missing at random assumption (which unfortunately is also a term for unconfoundedness in the econometrics literature). However, according to Chapter 8 of Gelman's textbook, there are two conditions that ensure ignorability of the missing data mechanism in Bayesian analysis: 1) Missing at random—given the observed data, missingness is a function of ϕ only; and 2) Distinct parameters—when the parameters of the missing data process ϕ are independent of those from the data generating process θ. The important thing is that ignorability is about study design, which makes it hard to relate to causal graphs since the latter are about our model of the world. Nonetheless, ignorability and unconfoundedness are somewhat related. When the dependence of missing patterns is only on observed covariates—$p(I|x, y, \phi) = p(I|x)$—we have a strongly ignorable design (aka. unconfounded design). How is an unconfounded design similar to unconfoundedness? An unconfounded design relates to the model of the inclusion matrix I. This matrix determines which data we see as researchers. Beyond classical missing data issues, this also includes the missing potential outcomes (if seen from an Imbens and Rubin perspective). Hence, if whether I observe $Y(0)$ or $Y(1)$ is solely dependent on observables, controlling for these covariates suggests "as if random" treatment. No wonder the degree of confusion in econometrics. The important distinctive factor is that while unconfoundedness is about the selection mechanism, ignorability is about the data collection process.