Applied Causality Reading Assignment 2

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January 30, 2017

This reading response summarizes Chapter 4 of [1]. Several important messages conveyed in this chapter include (1) Causal graphs can be used as an alternative framework to the potential outcome approach; (2) Using *Back-door criteria*, one can find variables to condition on so that conditioning ignorability can be fulfilled in order to effectively identify and consistently estimate treatment effects. I will break down the logic of this chapter into the following 2 steps of why and how to use causal graphs. At the end, I list several notes that I think interesting.

1 Why causal graphs? Want conditional independence!

The potential outcome framework defines the causal treatment effect of a variable D on an outcome Y. Due to the "potential" or unobserved nature of part of the outcomes, many estimators, such as the Naive estimator, do not generate unbiased and consistent estimation of the causal effect unless the "ignorability" assumption holds, i.e., $Y^0, Y^1 \perp\!\!\!\perp D$, which is valid through randomization of the experiments. However, in observational studies, this assumption is rarely satisfied, so one hopes to establish the "conditional ignorability" assumption, i.e., $Y^0, Y^1 \perp\!\!\!\perp D|S$. Causal graphs help to find this S variable, through the "*Back-door criteria*".

2 How to use causal graphs? By Back-door criteria and conditioning!

So the goal, now, is to find a set of variables S that blocks all the information flow between D and Y except the true causal effect of D on Y, so that conditioning on S gives the independence between the potential outcomes and the treatment assignment, and many estimators can be drawn from there. To find such set, one can use the Back-door criteria, in 3 steps:
(1) draw the graph with directed edges among the variables;
(2) within *ONLY* the "*back-door paths*", search for the nodes that "*block*" *ALL* the paths from D to Y simultaneously, either "in chains of mediation", or in "forks of mutual dependence", and *NEVER* in "inverted forks of mutual causation";
(3) double check all directed paths from D to Y to make sure that the blockers found in (2) are NOT in these paths.
Here, the keywords of back-door criteria are (1). "*block*", or "*d-seperation*", means that the variables emit some arrows along the path and are not collider or its descendants; (2). "*back-door path*", means that the first arrow along the path from D to Y points *TO* D, not *FROM* D.
Once, the set S is found, one can condition on it and use, say, the Naive estimator, to consistently infer causal estimates.

3 Several notes

Apart from the main discussions above, several notes that are worthy keeping in mind is that (1). Be aware of colliders! Conditioning on them induces or unblocks back-door paths; (2). Structural equations are just writing the descendants as flexible functions of parents plus errors. (3). When drawing causal inference, one hopes to control mechanism of treatment assignment: in randomized design, one can fully control $Pr(D)$; in other studies, one maybe able to partially control the propensity scores $Pr(D|S)$; in the worst case, such as observational studies, one has NO control over those probabilities, but one could model $Pr(D|S) = f(S)$, where S is completely observed.

References

[1] Winship and Morgan *Counterfactuals and Causal Inference*. Cambridge University Press (2014).