Applied Causality Reading Assignment 8

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This reading response summarizes Chapter 9 of [1].

1 Why use IV

We are still interested in estimate the causal effect of D on Y. We know that there are some variable U that satisfies back-door criteria and that we are able to estimate consistent causal effect of D on Y conditioning on U. However, U is not observed. In this case, a fourth variable Z, the instrumental variable, comes into play: when Z is binary, we can estimate the effect δ by

$$\hat{\delta} = \frac{E[Y|Z=1] - E[Y|Z=0]}{E[D|Z=1] - E[D|Z=0]}$$

and when Z is continuous:

$$\hat{\delta} = \frac{Cov(Y,Z)}{Cov(D,Z)}$$

2 Two important assumptions

In order for the above estimates to be consistent, two ky assumptions are (1). U and Z are independent; (2). Z and D satisfy ignorability assumption. The first assumption is obvious. If it is violated, the above formulas cannot be derived because there is always one term that involves $E[U|Z]$ left. What is worse is when $Cov(D,Z)- > 0$, i.e., the prediction of D on Z is weak. When this is the case, the remaining bias induced by $E[U|Z]$ will be greatly amplified by the small denominator of $Cov(D,Z)$. I wonder, however, if both candidate IVs Z_1 and Z_2 are independent of U but Z_1 predicts D better than Z_2, will that happen and if so, which IV should be choose?
The second assumption is an analogy to the "ignorability" assumption between D and Y that we encounter in the first reading assignment. Notice that both the numerator and the denominator take the form of the Naive estimate introduced in the first reading assignment. We discussed in class that in order to infer the effect of $D- > Y$ by Naive estimate, we need the equivalence between $Y|D = d$ and $Y|do(D = d)$. Here is the same: we need the equivalence of $D|Z = z$ and $D|do(Z = z)$. When this does not hold, just like in the first reading assignment that we fail to estimate ATE but ATT, we are only able to estimate LATE but not ATE. This is especially interesting to me, and I think the importance is that it gives us a warning message anytime we want to use estimates that take similar form of the Naive estimate: is the association estimate by the sample the association in the do graph?

References

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