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Causal Graphs: Addressing the Confounding Problem Without Instruments or Ignorability

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1. INTRODUCTION

I wish to congratulate Professor Imbens on a lucid and erudite review of the instrumental variable literature. The paper contrasts an econometric view of instrumental variable models, where treatment confounding is due to agents rationally choosing an optimal treatment for their situation, and the statistical view, where treatment confounding arises due to noncompliance, unobserved baseline differences between individuals, or other such issues.

While the paper does an admirable job describing the statistics view of the instrumental variables based on the potential outcome model of Neyman and Rubin, it does not much discuss the growing statistics literature on causal graphical models, except to mention that causal graphs are a useful tool for displaying the exclusion restriction assumption crucial for the use of instrumental variables.

I would like to give a brief and hopefully complementary account of how causal graphical models serve to clarify and help address the issues of confounding (what Heckman calls the selection problem) that make causal inference from observational data such a challenging endeavor.

2. GRAPHS AS A GENERAL METHOD FOR DEALING WITH CONFOUNDING

Causal inference in statistics has been greatly influenced by Neyman's idea of explicitly representing interventions or forced treatment assignments on the outcome (Neyman, 1923), and by Rubin's idea of using the stable unit treatment value assumption (SUTVA) and ignorability assumptions to equate potential outcome parameters with functionals of the observed data (Rubin, 1974). Professor Imbens discusses these ideas at length in the paper. The essence of Rubin's method is that assumptions on potential outcome random variables allow one to properly adjust for the presence of confounding. Unfortunately, in complex, possibly longitudinal settings it is not easy to see what assumptions are needed, or whether it is even possible to identify parameters of interest as functionals of observed data. For this task, graphical causal models, first used by Wright in the context of animal genetics (Wright, 1921), and expanded into a general methodology for causal inference by Spirtes, Glymour and Scheines (1993), Pearl (2000), Robins (1986, 1997), and others have proven to be invaluable.

Consider Figure 1(a), where vertices represent random variables of interest: a treatment A, an outcome Y, and a source of unobserved confounding C (lightly shaded in the graph to represented unobservability). Following Neyman, we quantify the causal effect of A on Y by means of a function of the distribution of the potential outcome $Y(a)$ (Y after we force A to a value a). For instance, we may use the average causal effect (ACE): $E[Y(a)] - E[Y(a')]$, where a is the active treatment value, and a' is the baseline treatment value. We are interested in using observed data to make inferences about such effects, which entails dealing with confounding in some way. The assumptions underlying this graph which we will use can be expressed in terms of potential outcomes if desired. For example, the *finest fully randomized causally interpretable structured tree graph* (FFRCISTG) model of Robins (1986) corresponding to this graph states that for all value assignments a and c to A and C, random variables C, $A(c)$ and $Y(a, c)$ are mutually independent, while the *nonparametric structural equation model with independent errors* (NPSEM-IE) of Pearl (2000) corresponding to this graph states that for all value assignments a, c and c' to A and C, random variables C, $A(c)$ and $Y(c', a)$ are mutually independent. Note that the former set of assumptions can be viewed as a kind of

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