

Causal Inference, Self Selection and Identification

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Outline

- ▶ What is causality?
- ▶ Objective of causal inference
- ▶ Self-selection
- ▶ Identification methods

What is Causality? (My Understanding)

- ▶ Holding all factors save one at a constant level, the change in the outcome associated with manipulation of the varied factor is called a causal effect of the manipulated factor.
- ▶ What is the object that bears the “causal effect”? (In this talk, human being)
- ▶ Unit of causal effect: individual vs population
- ▶ Key feature:
 - ▶ *ceteris paribus*
 - ▶ hypothetical

Examples

- ▶ (In Ehsan's talk) Does participating in a training program *cause* an increase in earnings?
- ▶ (Epidemiological topic?) Does smoking *cause* a deterioration in health?
- ▶ (Labor economics) Does education *cause* an increase/decrease in labor supply?
- ▶ (Political science topic?) Does migration to Canada *cause* an increase/decrease in salary?
- ▶ (Business problem) Will a price increment of SMS decrease the usage of SMS?

If I know A cause B, so what?

- ▶ (My understanding) The final purpose of causal inference is to evaluate policy intervention.
 - ▶ Historical policy intervention
 - ▶ Policy intervention in new environment
 - ▶ New policy intervention

(Ehsan's) Example

- ▶ Two treatments: participation ($X = 1$) vs non-participation ($X = 0$)
- ▶ Interested outcome: earnings (Y)
- ▶ Objective: Does participation cause a higher earning?

Individual Causal Effect

- ▶ Population: Ω . Individual: $\omega \in \Omega$.
- ▶ Individual causal effect:

$$Y(X = 1, \omega) - Y(X = 0, \omega).$$

- ▶ They are called “counterfactuals”.
- ▶ The ideas of “ceteris paribus” and “hypothetical” are embedded.

Population Causal Effects

- ▶ Suppose we could observe Y_1 and Y_0 for everyone.
- ▶ We have the population distribution $f_{Y_1, Y_0}(y_1, y_0)$.
- ▶ In principle, one could define various causal effects/parameters based on f_{Y_1, Y_0} .
- ▶ Example:

$$E_{\omega} \{Y_1 - Y_0\} \text{ or } E_{\omega} \{Y_1 - Y_0 | X = 0\}.$$

Causal Inference

- ▶ Why do we need “inference”?
- ▶ Main problem: we don't observe Y_1 and Y_0 for the same person!
- ▶ Define $Y = XY_1 + (1 - X) Y_0$. We observe Y and X .
- ▶ The general task of causal inference is to estimate f_{Y_1, Y_0} from $f_{Y, X}$.
- ▶ More specifically: estimate $E_{\omega} \{Y_1 - Y_0\}$ from $\{Y, X\}$.

Self Selection

- ▶ A key feature: X is NOT independent of Y .
- ▶ This is generally true for many social science and epidemiological problems.
- ▶ In contrast with non-random sampling, self selection problem is from the perspective of the individuals, not the researchers.
- ▶ Even though we could observe the population data, self selection problem is still there.

Additive Assumption (Only for Simplification)

- ▶ Assume

$$\begin{cases} Y_{1\omega} = \mu_1 + U_{1\omega} \\ Y_{0\omega} = \mu_0 + U_{0\omega} \end{cases}, E(U_{1\omega}) = E(U_{0\omega}) = 0.$$

- ▶ What is U_1 and U_2 ?
- ▶ So the causal parameter of interest becomes

$$E_{\omega} \{Y_1 - Y_0\} = \mu_1 - \mu_0 + E(U_{1\omega}) - E(U_{0\omega}) = \mu_1 - \mu_0.$$

Bias From STAT200 Analysis

- ▶ Recall what we observe: $\{Y, X\}$.
- ▶ Suppose we observe the whole population.
- ▶ Does a linear regression “estimate” give what we want?
- ▶ Linear regression “estimate”

$$\begin{aligned} & E(Y_1|X=1) - E(Y_0|X=0) \\ = & \mu_1 - \mu_0 + [E(U_1|X=1) - E(U_0|X=0)]. \end{aligned}$$

Essentials of Bias

- ▶ The dependence between the “outcome process” and the “selection process”.
- ▶ Emphasis again: not from any biased-sampling procedure.
- ▶ Why randomization in the design context is so important?

Identification

- ▶ Without further assumptions, one could not (I think!!) identify the causal parameter from the observed data.
- ▶ Difference identification methods essentially require
 - ▶ Different identification assumptions
 - ▶ Different knowledge about the outcome process, the selection process and the relationship between them.
- ▶ Focus on a general survey of different identification methods.

Matching (Propensity Score)

- ▶ In addition to $\{Y_\omega, X_\omega\}$, we also observe $\{W_\omega\}$.
- ▶ Rosenbaum and Rubin (1983) showed that

$$(Y_1, Y_0) \perp X \mid P(W),$$

under assumptions

$$(A1) \quad (Y_1, Y_0) \perp X \mid W$$

and

$$(A2) \quad 0 < Pr(X = 1|W) = P(W) < 1.$$

Matching Cont.

- ▶ Under the assumptions, we have

$$\begin{aligned}E(Y_1|X = 1, P(W)) &= E(Y_1|P(W)) \\E(Y_0|X = 0, P(W)) &= E(Y_0|P(W)).\end{aligned}$$

- ▶ So the causal parameter could be obtained as

$$E(Y_1 - Y_0) = \int \{E(Y_1|X = 1, P(w)) - E(Y_0|X = 0, P(w))\} f_W(w) dw.$$

Why Can Matching Help?

- ▶ What do the following mean?
 - ▶ $(Y_1, Y_0) \perp X | W$
 - ▶ $(Y_1, Y_0) \perp X | P(W)$
- ▶ Conditional on the observed information W , the reason that two observationally equivalent individuals make different choices is purely due to randomization!
- ▶ Can we justify it? What does it imply for the requirement of W ?

Instrumental Variable

- ▶ Re-write the observed Y as

$$\begin{aligned} Y &= XY_1 + (1 - X)Y_0 \\ &= \mu_0 + \Delta \cdot X + U_0, \end{aligned}$$

where $\Delta = \mu_1 - \mu_0 + U_1 - U_0$.

- ▶ To illustrate a fundamental idea of IV, assume $U_1 = U_0$.
- ▶ In this case, does a linear regression of Y on X give us a consistent estimate of Δ ?

IV Cont.

- ▶ The problem of linear regression is the dependence between X and U_0 .
- ▶ If we can find such an instrument Z that satisfies

$$E(U_0|Z) = E(U_0),$$

and

$Pr(X = 1|Z)$ is a nontrivial function of Z .

- ▶ The IV estimator could be defined as

$$\Delta^{IV} = \frac{E(Y|Z = z) - E(Y|Z = z')}{Pr(X = 1|Z = z) - Pr(X = 1|Z = z')}.$$

Other Identification Methods

- ▶ Control function
- ▶ MLE

Miscellaneous

- ▶ The definition of causal effects could be very different in other fields.
- ▶ We don't have to focus on the mean!!
- ▶ When use different identification methods, I urge one to critically evaluate the invoked assumptions under the specific subject area context.

Reference

James Heckman, “The Scientific Model of Causality,” *Sociological Methodology*, 35: 1–97, 2005.