

Causal Inference

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Roadmap

Counterfactuals and causality

- Causality and models

- Potential outcomes

- Randomization and selection bias

- Randomization inference

Directed Acyclic Graphs

- Graph notation

- Backdoor criterion

- Collider bias

- Front door criterion

- Concluding remarks

Definition 7: Simple difference in mean outcomes (SDO)

A simple difference in mean outcomes (SDO) can be approximated by the sample averages:

$$\begin{aligned} SDO &= E[Y^1|D=1] - E[Y^0|D=0] \\ &= E_N[Y|D=1] - E_N[Y|D=0] \end{aligned}$$

in large samples. I'll usually use expectation operators but we use samples for estimation.

SDO vs. ATE

Notice the subtle difference between the SDO and ATE notation:

$$E[Y|D = 1] - E[Y|D = 0] \quad \begin{matrix} \leq \\ \geq \end{matrix} \quad E[Y^1] - E[Y^0]$$

- The SDO is an *estimate*, whereas ATE is a *parameter*
- SDO is a crank that turns data into numbers
- ATE is a parameter that is unknowable because of the fundamental problem of causal inference
- SDO might line up with the ATE but also might not
- Under what situations is SDO a biased estimate of the ATE?

Potentially biased comparisons

Decomposition of the SDO

The SDO can be decomposed into the sum of three parts:

$$\begin{aligned} E[Y^1|D=1] - E[Y^0|D=0] &= ATE \\ &+ E[Y^0|D=1] - E[Y^0|D=0] \\ &+ (1 - \pi)(ATT - ATU) \end{aligned}$$

Seeing is believing so let's work through this identity!

Decomposition of SDO

Use LIE to decompose ATE into the sum of four conditional average expectations

$$\begin{aligned}\text{ATE} &= E[Y^1] - E[Y^0] \\ &= \{\pi E[Y^1|D=1] + (1-\pi)E[Y^1|D=0]\} \\ &\quad - \{\pi E[Y^0|D=1] + (1-\pi)E[Y^0|D=0]\}\end{aligned}$$

Substitute letters for expectations

$$\begin{aligned}E[Y^1|D=1] &= a \\ E[Y^1|D=0] &= b \\ E[Y^0|D=1] &= c \\ E[Y^0|D=0] &= d \\ \text{ATE} &= e\end{aligned}$$

Rewrite ATE

$$e = \{\pi a + (1-\pi)b\} - \{\pi c + (1-\pi)d\}$$

Move SDO terms to LHS

$$\begin{aligned}
 e &= \{\pi a + (1 - \pi)b\} - \{\pi c + (1 - \pi)d\} \\
 e &= \pi a + b - \pi b - \pi c - d + \pi d \\
 e &= \pi a + b - \pi b - \pi c - d + \pi d + (\mathbf{a} - \mathbf{a}) + (\mathbf{c} - \mathbf{c}) + (\mathbf{d} - \mathbf{d}) \\
 0 &= e - \pi a - b + \pi b + \pi c + d - \pi d - \mathbf{a} + \mathbf{a} - \mathbf{c} + \mathbf{c} - \mathbf{d} + \mathbf{d} \\
 \mathbf{a} - \mathbf{d} &= e - \pi a - b + \pi b + \pi c + d - \pi d + \mathbf{a} - \mathbf{c} + \mathbf{c} - \mathbf{d} \\
 \mathbf{a} - \mathbf{d} &= e + (\mathbf{c} - \mathbf{d}) + \mathbf{a} - \pi a - b + \pi b - \mathbf{c} + \pi c + d - \pi d \\
 \mathbf{a} - \mathbf{d} &= e + (\mathbf{c} - \mathbf{d}) + (1 - \pi)a - (1 - \pi)b + (1 - \pi)d - (1 - \pi)c \\
 \mathbf{a} - \mathbf{d} &= e + (\mathbf{c} - \mathbf{d}) + (1 - \pi)(a - c) - (1 - \pi)(b - d)
 \end{aligned}$$

Substitute conditional means

$$\begin{aligned}
 E[Y^1|D = 1] - E[Y^0|D = 0] &= ATE \\
 &\quad + (E[Y^0|D = 1] - E[Y^0|D = 0]) \\
 &\quad + (1 - \pi)(\{E[Y^1|D = 1] - E[Y^0|D = 1]\} \\
 &\quad - (1 - \pi)\{E[Y^1|D = 0] - E[Y^0|D = 0]\}) \\
 E[Y^1|D = 1] - E[Y^0|D = 0] &= ATE \\
 &\quad + (E[Y^0|D = 1] - E[Y^0|D = 0]) \\
 &\quad + (1 - \pi)(ATT - ATU)
 \end{aligned}$$

Decomposition of difference in means

$$\underbrace{E_N[y_i|d_i = 1] - E_N[y_i|d_i = 0]}_{\text{SDO}} = \underbrace{E[Y^1] - E[Y^0]}_{\text{Average Treatment Effect}} + \underbrace{E[Y^0|D = 1] - E[Y^0|D = 0]}_{\text{Selection bias}} + \underbrace{(1 - \pi)(ATT - ATU)}_{\text{Heterogenous treatment effect bias}}$$

where $E_N[Y|D = 1] \rightarrow E[Y^1|D = 1]$, $E_N[Y|D = 0] \rightarrow E[Y^0|D = 0]$ and $(1 - \pi)$ is the share of the population in the control group.