Conditional Exchangeability in Observational Studies

INFO/STSCI/ILRST 3900: Causal Inference

17 Sep 2024

Logistics

- ► Peer reviews for pset 1 due today by 5pm
- ► Pset 2 Due Tue (9/24) @ 5pm
- ▶ Post questions on Ed Discussion or come to office hours!
- ► After class, read 3.4 and 3.5 of Hernán & Robins

Learning goals for today

At the end of class, you will be able to:

- 1. Explain the challenge of satisfying conditional exchangeability in observational data
- 2. Explain part one the consistency assumption
 - ► Well-defined, precise treatments

What could go wrong?

- ▶ What does $Y_i^{a=1}$, $Y_i^{a=0} \perp A_i$ (exchangeability) mean?
- ► Effect of college degree (A) on income level (Y) at age 30
 - ▶ $A_i = 1$ if college degree, $A_i = 0$ if no college degree
- ightharpoonup Suppose we have information on parental income (L)
 - $ightharpoonup L_i = 1$: parents have high income
 - ► $L_i = 0$: parents have low income
- ► *L* associated with the outcome $L \not\perp Y_i^{a=1}, Y_i^{a=0}$

Check Your Understanding: Exchangeability

Discuss in groups, then submit your response individually to PollEverywhere. Your response won't be graded.

Recall the of definition (marginal) exchangeability:

$$Y_i^{a=1}, Y_i^{a=0} \perp A_i$$

If exchangeability holds, which of the following are true?



https://pollev.com/causal3900

PollEverywhere: Possible Answers

Recall the of definition (marginal) exchangeability:

$$Y_i^{a=1}, Y_i^{a=0} \perp A_i$$

If exchangeability holds, which of the following must be true?

- (A) Your potential outcome under treatment would be the same regardless of the treatment observed
 - $ightharpoonup E(Y_{Y_{OU}}^{a=1} \mid A_{Y_{OU}} = 1) = E(Y_{Y_{OU}}^{a=1} \mid A_{Y_{OU}} = 0)$
- (B) Your potential outcome depends on what treatment is observed
- (C) Your potential outcome under no treatment would be the same regardless of the treatment observed

$$ightharpoonup E(Y_{Y_{OU}}^{a=0} \mid A_{Y_{OU}} = 1) = E(Y_{Y_{OU}}^{a=0} \mid A_{Y_{OU}} = 0)$$

(D) Your observed outcome depends on what treatment is observed

Conditional Exchangeability in Observational Studies

- ► Conditional exchangeability lets us estimate causal effects
- ► Stratification: conditional average treatment effects
- ► Standardization or inverse probability weighting: population average treatment effect
- By design, conditional exchangeability holds in conditionally randomized experiments
- Conditional exchangeability more reasonable in observational data than marginal exchangeability

What could go wrong?

- ► Effect of college degree (A) on income level (Y) at age 30
 - ▶ $A_i = 1$ if college degree, $A_i = 0$ if no college degree
- ightharpoonup Suppose we have information on parental income (L)
 - ▶ L = 1: parents have high income
 - ► L = 0: parents have low income
- ▶ L associated with the outcome $L \not\perp \!\!\! \perp Y_i^{a=1}, Y_i^{a=0}$
- ► Are your own education level and your parents' income the only two factors that influence your income level?
- ► What additional information would you gather to make conditional exchangebaility plausible?

$$Y_i^{a=1}, Y_i^{a=0} \perp A_i \mid L_1, L_2, \cdots, L_k$$

Conditional exchangeability in observational data

- ► Even if gathering data was possible for every covariate we want, when do we stop?
- ► Never 100% sure that conditional exchangeability holds
- ► Is it reasonable?
- ► Causal inference with observational data requires expert knowledge!

Indentification Assumptions

- Exchangeability is an identification assumption
- ► Identification assumptions take us from observable quantities to causal effects (which deal with unobservable potential outcomes)
- ► In randomized experiments, often take identification assumptions for granted
- ► The rest of the class will mostly deal with observational settings!
- ► This means we have to think more critically about the implicit assumptions we often make

Activity

- ► Looking at data to analyze the effectiveness of a medication on relieving headaches
- ► "What is the effect of taking HeadacheRelief" on a person's headache within one hour of taking it?"
- ► Info collected for each study participant:
 - ▶ whether or not they took HeadacheRelief[™] $(A_i = 1 \text{ or } A_i = 0)$
 - whether or not their headache was relieved within one hour of taking the medication $(Y_i = 1 \text{ or } Y_i = 0)$
- ► With the people around you, discuss the following:
 - ► Thinking about how treatment is defined here, could there be any potential issues in this study?
 - ► How do you interpret "take headache medication"?

The consistency assumption

- ► holds for precise treatments (today)
- ► holds with clarity about interference among units (next lecture)

If $A_i = a$, then $Y_i^a = Y_i$

 $Y_i^{\mathsf{Treatment}}$

 Y_i^{Control}

Potential Outcomes

 Y_i

Factual Outcomes

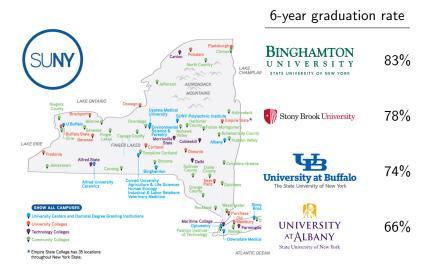
Imagine you are a high school counselor.

A statistician tells you

The probability of receiving a BA in 6 years would be higher if a student initially enrolled in the State University of New York instead of a community college

$$\mathsf{P}\bigg(\mathsf{B}\mathsf{A}^{\mathsf{Enroll} \ \mathsf{in} \ \mathsf{SUNY}}\bigg) > \mathsf{P}\bigg(\mathsf{B}\mathsf{A}^{\mathsf{Enroll} \ \mathsf{in} \ \mathsf{Community} \ \mathsf{College}}\bigg)$$

How would you advise students?



The treatment value Enroll in SUNY is not sufficiently precise

 $\mathsf{BA}^{\mathsf{Binghamton}}
eq \mathsf{BA}^{\mathsf{Stony}\ \mathsf{Brook}}$ $eq \mathsf{BA}^{\mathsf{Buffalo}}$ $eq \mathsf{BA}^{\mathsf{Albany}}$

To advise the student, a precise treatment is more helpful

6-year graduation rate

BINGHAMTON
UNIVERSITY
STATE UNIVERSITY OF NEW YORK

83%

Stony Brook University 78%

University at Buffalo
The State University of New York
The State University of New York



66%

Consistency assumption: $Y = Y^A$

More credible when A is very precise

- ▶ it is clear how to run a hypothetical experiment
- ► it is clear how to inform policy

Example:

- ▶ if a = SUNY, then Y^a is vague. To which SUNY should you send the student?
- ▶ if a = Binghamton, then Y^a is clearer

A good read:

Hernán, M. 2016.

"Does water kill? A call for less casual causal inferences."

Annals of Epidemiology 26(10):674–680.

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