From experiments to observational data

STSCI / INFO / ILRST 3900

16 Sep 2025

Learning goals for today

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

- Tie analysis of observational data to an idealized experiment
- Ask good questions which
  - involve treatments that exist (positivity assumption)
  - involve precise treatments (consistency assumption)

After class:

- Optional: Hernán, M. 2016.
  "Does water kill? A call for less casual causal inferences."
  Annals of Epidemiology 26(10):674–680.

Linking observational data to an experiment

- Marginal exchangeability: $Y_i^{a=1}, Y_i^{a=0} \perp\!\!\!\perp A_i$ holds in conditionally experiments
- Is almost never true in observational data

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- Conditional exchangeability: $Y_i^{a=1}, Y_i^{a=0} \perp\!\!\!\perp A_i \mid L$ holds in conditionally randomized experiments
- We've typically discussed L being a single variable, but it could also be a set of variables
- But does it ever hold in observational data?

Linking observational data to an experiment

What is the effect of college degree on income at age 35

- $A_i = 1$ if four year college degree; $A_i = 0$ if no college degree
- Suppose we have information on parental income
  - $L_i = 0$: parents have high income
  - $L_i = 1$: parents have low income
- Does conditional exchangeability hold given parental income?

Linking observational data to an experiment

What is the effect of college degree on income at age 35

- $A_i = 1$ if four year college degree; $A_i = 0$ if no college degree
- Suppose we have information on parental income
  - $L_i = 0$: parents have high income
  - $L_i = 1$: parents have low income
- Does conditional exchangeability hold given parental income?
- What additional information would you gather to make conditional exchangeability plausible?

Conditional exchangeability in observational data

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Conditional exchangeability in observational data

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- Is it reasonable?

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- Requires expert knowledge

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?
- In observational data, conditional exchangeability is an assumption we make (but can't typically verify)
- Requires expert knowledge
- Causal claims are data + outside knowledge

Formulating causal questions

Asking "good" causal questions involve

- Positivity condition: Treatments that exist
- Consistency: Treatments that are precise
- Accounts for interference

Good causal questions involve **treatments that exist**

1. Treatments that exist

Employer 1	Employer 2
100 employees	200 employees
Face-to-face interaction	Work in individual offices
75% randomized to vaccine 25% randomized to no vaccine	50% randomized to vaccine 50% randomized to no vaccine

How do you estimate the average effect over all 300 employees?

1. Treatments that exist

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100 employees	200 employees
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How do you estimate the average effect over all 300 employees?

1. Treatments that exist

If units are exchangeable given a confounder L,
then to estimate $E(Y^a)$ we need **positivity** to hold

$$\mathrm{P}(A = a \mid \vec{L} = \vec{\ell}) > 0$$

Some treatments simply do not exist in some populations.

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Source: Wikimedia A, B, C

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Would the bulbs in Ithaca bloom if it did not freeze all winter?

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Would the bulbs in Ithaca bloom if it did not freeze all winter?

Confounder L	Ithaca
Treatment a	Did not freeze
Outcome Y^a	Blooms?

Some treatments simply do not exist in some populations.

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Sarah has no MD training.
Would Sarah earn more money if she were a surgeon?

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Treatment a	Did not freeze
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Sarah has no MD training. Would Sarah earn more money if she were a surgeon?

Confounder L	No MD training
Treatment a	Surgeon
Outcome Y^a	Earnings

1. Treatments that exist

We can choose causal questions so that positivity holds.

$$\mathrm{P}(A = a \mid \vec{L} = \vec{\ell}) > 0$$

- in each population subgroup $\vec{L} = \vec{\ell}$
- only study treatment values a that can actually happen

Good causal questions involve
precise treatments

Consistency.

$$Y = Y^A$$

1. holds for precise treatments
2. holds with clarity about interference among units

2. Precise treatments

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
>
> $$\text{P}\left(\text{BA}^{\text{Enroll in SUNY}}\right) > \text{P}\left(\text{BA}^{\text{Enroll in Community College}}\right)$$

How would you advise students?

2. Precise treatments

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6-year graduation rate	
Binghamton University, State University of New York	83%
	78%
University at Buffalo, The State University of New York	74%
University at Albany, State University of New York	66%

2. Precise treatments

The treatment value

`Enroll in SUNY`

is not sufficiently precise

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$$\text{BA}^{\text{Binghamton}} \neq \text{BA}^{\text{Stony Brook}} \neq \text{BA}^{\text{Buffalo}} \neq \text{BA}^{\text{Albany}}$$

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To advise the student,
a precise treatment
is more helpful

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2. Precise treatments

Consistency assumption: $Y = Y^A$

More credible when A is very precise

- it is clear how to run a hypothetical experiment
- is 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.
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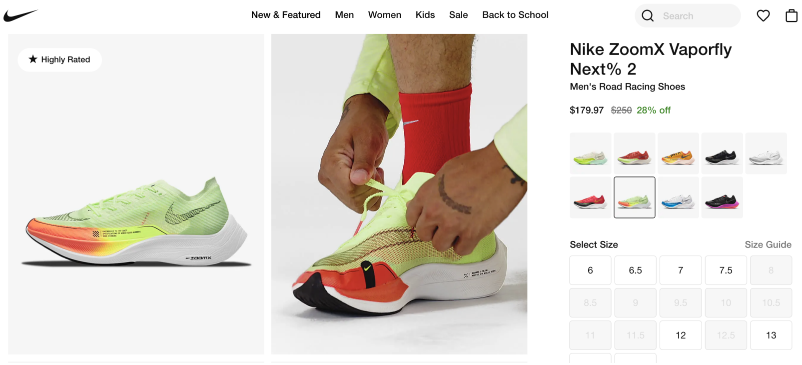
Good causal questions involve **clarity about interference**

3. With clarity about interference



[1]

[1] Image source: Nike

3. With clarity about interference

You and a friend race in your normal shoes.

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$$Y_{\text{You}}^{\text{You wear springy shoes}} = \text{Win}$$

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It is extremely close.
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What if you had the springy shoes?

$$Y_{\text{You}}^{\text{You wear springy shoes}} = \text{Win}$$

But what if your friend also wears them?

$$Y_{\text{You}}^{\text{You wear springy shoes, Your friend wears springy shoes}} = \text{Lose}$$

$$Y_{\text{You}}^{\text{You wears springy shoes, Your friend wear normal shoes}} = \text{Win}$$

Good causal questions: In math

We should study treatments that exist (positivity)

$$\mathrm{P}(A = a \mid \vec{L} = \vec{\ell}) > 0$$

with potential outcomes that are well-defined (consistency)

$$Y = Y^A$$

Well-defined potential outcomes involve precise treatments

$$\text{BA}^{\text{Binghamton}} \quad \text{instead of} \quad \text{BA}^{\text{SUNY}}$$

and incorporate interference when it exists

$$Y^{a_{\text{you}}, a_{\text{your friend}}} \quad \text{instead of} \quad Y^{a_{\text{you}}}$$

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