6. Population inference from samples

Ian Lundberg
Cornell Info 6751: Causal Inference in Observational Settings
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Comments on Problem Set 1

Definition of potential outcomes

- $\{Y_i^1, Y_i^0\}$ are potential outcomes.
  When $A_i = 1$, then Y_i^1 is factual and Y_i^0 is counterfactual.
  When $A_i = 0$, then these are reversed.
  This is why potential, not necessarily counterfactual.
- Y^a is the outcome of a randomly sampled unit assigned to treatment value a. In itself, it is not an average over a group—that would be $\mathrm{E}(Y^a)$.

Comments on Problem Set 1

$\mathrm{E}(Y \mid A = 1) > \mathrm{E}(Y \mid A = 0)$

- Descriptive
- Outcomes were higher, on average, for those who got the treatment

$\mathrm{E}(Y^1) > \mathrm{E}(Y^0)$

- Causal
- The treatment (1 vs 0) increases outcomes, on average

$Y_i^1 > Y_i^0$ for all i

- Causal
- The treatment (1 vs 0) increases the outcome for every unit

Comments on Problem Set 1

Observational Claims	Causal Claims
Observational Evidence	Causal Evidence

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"...all causal inference is based on assumptions that cannot be derived from observations alone," (Greenland, Pearl, & Robins 1999, p. 47)

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"...all causal inference is based on assumptions that cannot be derived from observations alone," (Greenland, Pearl, & Robins 1999, p. 47)

There is no causal evidence.
There is only observational evidence,
which speaks to causal claims under assumptions.

Learning goals for today

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

1. Understand DAGs more fully
   - DAGs are nonparametric
   - DAGs are hard to learn from data
2. Generalize from a sample to a population
   - Encode sampling assumptions in DAGs

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This does **not** mean

$$Y = \beta_0 + \beta_1 X + \beta_2 A + \epsilon$$

DAGs are nonparametric

$$X \longrightarrow A \longrightarrow Y$$

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This **does** mean

- $A = f(X, U_A)$ for some function $f()$
- $Y = g(X, A, U_Y)$ for some function $g()$

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- $Y = g(X, A, U_Y)$ for some function $g()$

which allows that

- The effect of A may depend on X (heterogeneity)
- $\mathrm{E}(Y \mid X, A)$ may be a nonlinear function of each input

DAGs are nonparametric: Why this is really great

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- Among everyone with $X = x$,
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These are two **different sets** of people

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- $\{\beta, \gamma\}$ are "main effects"
- η is an "interaction": the effect of A varies by X
- Key assumption: $A \perp\!\!\!\perp \epsilon$, or A is "exogenous"

That requires us to do **both** causal reasoning **and** statistical reasoning simultaneously.

DAGs support causal reasoning **before** statistical reasoning

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Let's pause to discuss this.

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   - DAGs are hard to learn from data
2. Generalize from a sample to a population
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Causal Discovery[1]: DAGs are hard to learn from data

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\begin{tikzcd}
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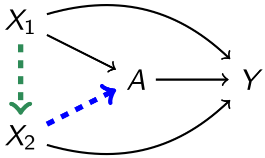

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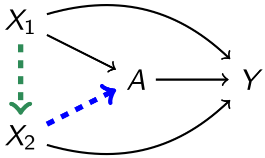

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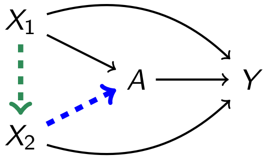

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- In the absence of both edges,

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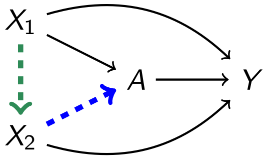

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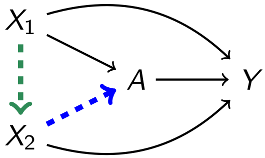

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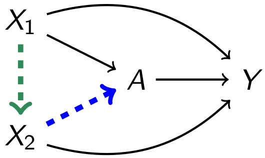

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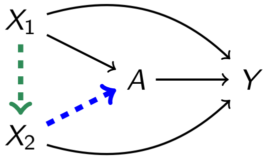

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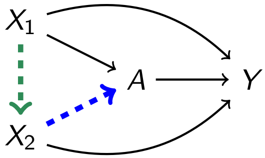

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- In the absence of the blue edge, $X_2 \perp\!\!\!\perp A \mid X_1$
- In the absence of the green edge, $X_1 \perp\!\!\!\perp X_2$ and $X_1 \not\!\perp\!\!\!\perp X_2 \mid A$

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Causal Discovery[2]: DAGs are hard to learn from data

Will data replace human researchers?

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Will data replace human researchers?

I think not.

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Often, what we want to know cannot be answered by the data.

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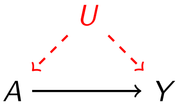
Example: Does the unobserved U confound treatment assignment?



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$$\begin{tikzcd}
& \color{red}{U} \arrow[dl, dashed, red] \arrow[dr, dashed, red] & \\
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A and Y are associated either way.

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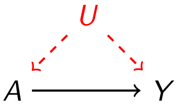

A and Y are associated either way.
The absence of U is a completely untestable assumption.

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As a general rule, the DAG encodes
substantive theory (made by a human)

rather than **data** (crunched by a computer)

Some academic history of DAGs

- Historical roots in path models in the 1920s
  - Wright, S. (1921). Correlation and causation. Part I: Method of path coefficients. Journal of Agricultural Research, 20(7), 557-585.
- Linear path models in the 1960s
  - Duncan, O. D. (1966). Path analysis: Sociological examples. American Journal of Sociology, 72(1), 1-16.
- Landmark contributions: Pearl, Greenland, Robins
  - **(assigned)** Greenland, S., Pearl, J., & Robins, J. M. (1999). Causal diagrams for epidemiologic research. Epidemiology, 37-48.
  - Pearl, J. (2000). Causality. Cambridge University Press.
  - Pearl, J., & Mackenzie, D. (2018). The Book of Why: The New Science of Cause and Effect. Basic Books.
- More accessible introduction for social scientists
  - Morgan, S. L., & Winship, C. (2015). Counterfactuals and Causal Inference. Cambridge University Press.

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Sample $\rightarrow$ Population

Fun example

Wang, Rothschild, Goel, & Gelman

Survey of **Xbox users** to forecast the 2012 election![3]

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[3]Wang, W., Rothschild, D., Goel, S., & Gelman, A. (2015). Forecasting elections with non-representative polls. International Journal of Forecasting, 31(3), 980-991.

Fun example

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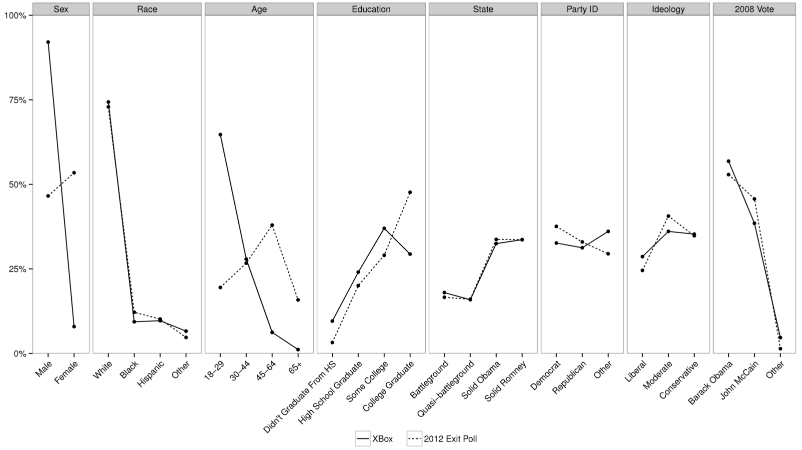

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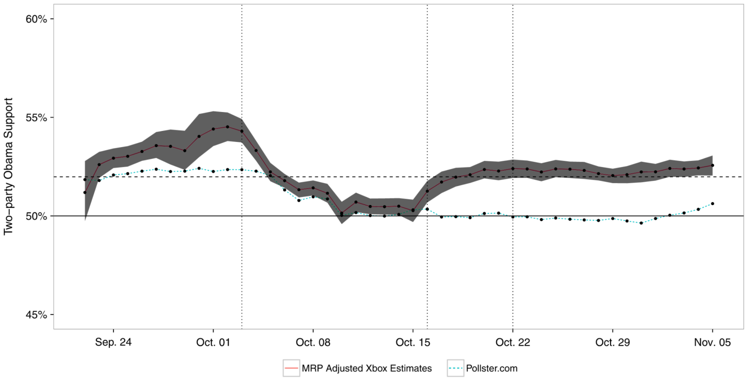

Today we will formalize the conditions under which this works

Imagine a study:

Imagine a study:

- We randomly sample 1,000 voters from the U.S. voter file.

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- **100%** respond.

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Yes! A probability sample

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Iffy. Almost a probability sample

Imagine another study:

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Can we draw conclusions about the population of U.S. voters?

Big worry:

Do we believe that selection into the sample is independent of Obama support?

$$S = 1$$

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Thinks Obama
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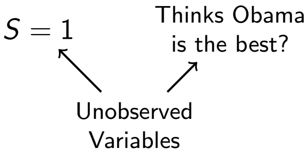
Unobserved
Variables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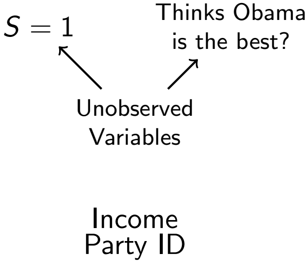
Unobserved Variables

Income


$S = 1$
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Income
Party ID

$S = 1$

Thinks Obama is the best?

Unobserved Variables

Income
Party ID
Age

$S = 1$

Thinks Obama is the best?

Unobserved Variables

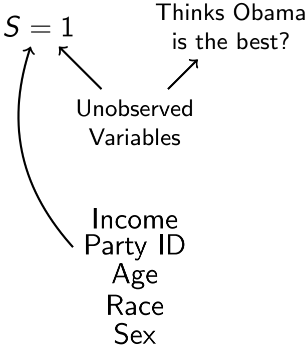
Income
Party ID
Age
Race

$S = 1$

Thinks Obama is the best?

Unobserved Variables

Income
Party ID
Age
Race
Sex



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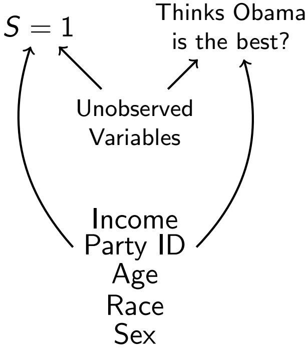
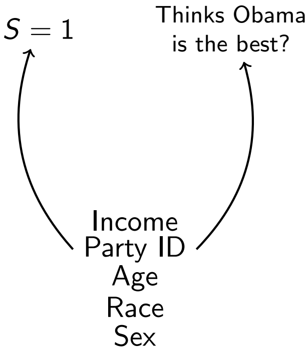
Race
Sex


$S = 1$
Thinks Obama is the best?
Unobserved Variables
Income
Party ID
Age
Race
Sex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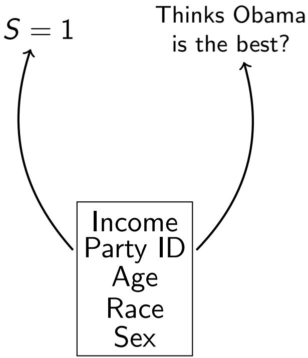

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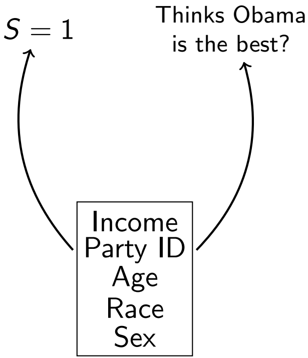
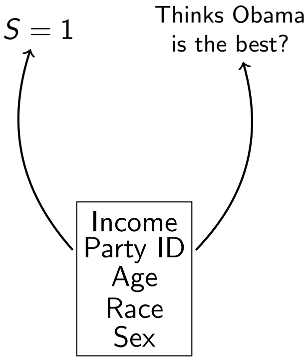
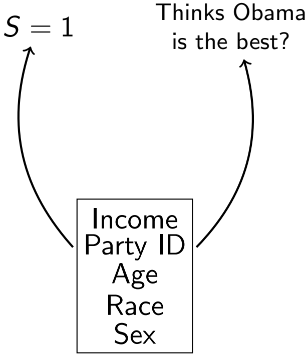


If this is the case:



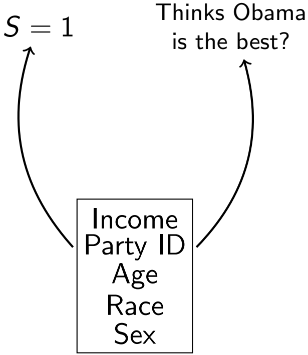
If this is the case:

1. Split into sample subgroups (in sample)



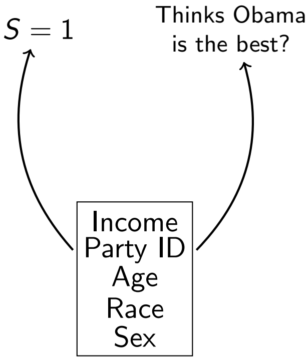
If this is the case:

1. Split into sample subgroups (in sample)
2. Take the mean Obama support (in sample)



If this is the case:

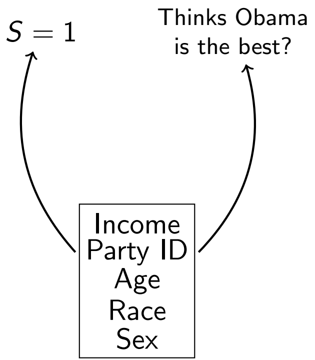
1. Split into sample subgroups (in sample)
2. Take the mean Obama support (in sample)
3. Find each subgroup size in all voter records (in population)



If this is the case:

1. Split into sample subgroups (in sample)
2. Take the mean Obama support (in sample)
3. Find each subgroup size in all voter records (in population)
4. Average over subgroups, weighted by the population size (population estimate!)

Post-Stratification



If this is the case:

1. Split into sample subgroups (in sample)
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A step further: No probability sample.

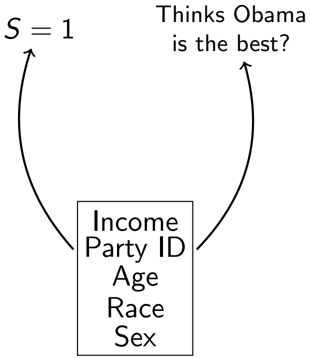
A step further: No probability sample.

We sample random passers-by on the streets of Chicago.

A step further: No probability sample.

We sample random passers-by on the streets of Chicago.

- Was Barack Obama the best president
  of the past 20 years?



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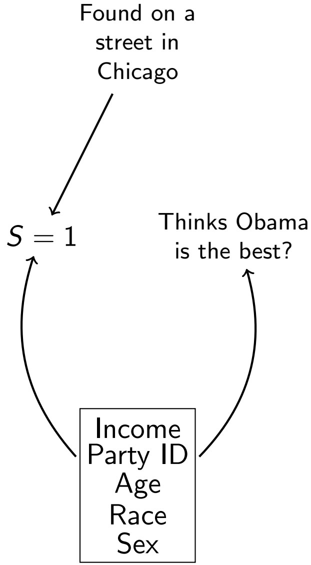
Found on a street in Chicago
$S = 1$
Thinks Obama is the best?
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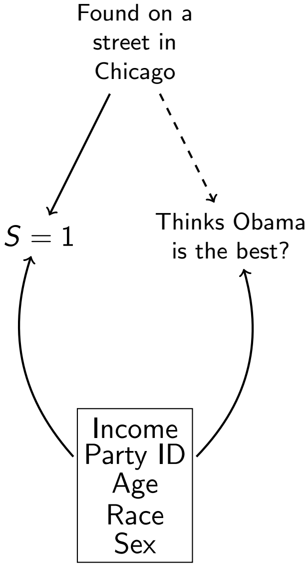
Party ID
Age
Race
Sex



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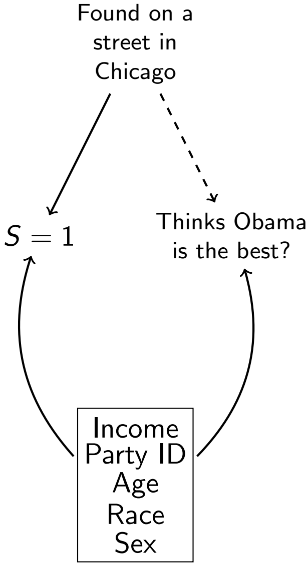
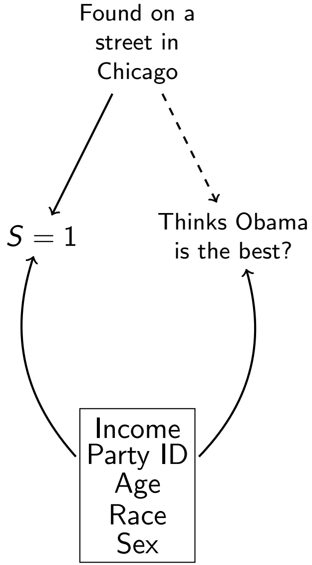
Post-stratification is not a cure-all



Post-stratification is not a cure-all

Credibility depends on causal assumptions
— what causes sample inclusion?
— what causes the outcome?
Need conditional independence.



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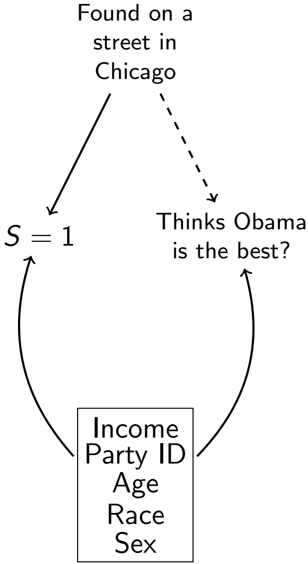
These assumptions belong in a DAG



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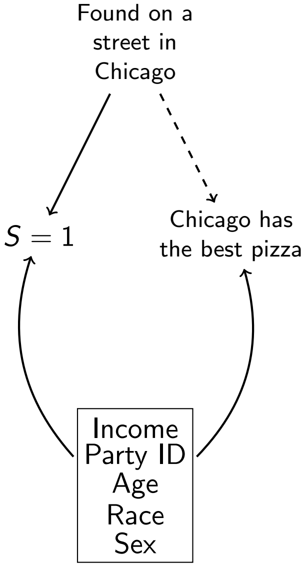
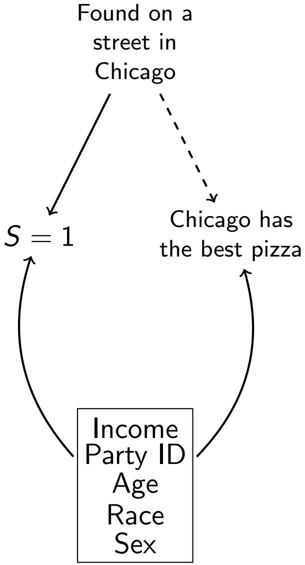


Post-stratification is not a cure-all

Credibility depends on causal assumptions
— what causes sample inclusion?
— what causes the outcome?
Need conditional independence.

These assumptions belong in a DAG

The DAG requires theory
about the particular question



Westreich et al. 2019

Westreich et al. 2019

We often care about **internal validity**

Westreich et al. 2019

We often care about **internal validity**

- Have I identified the causal effect well in my sample?

Westreich et al. 2019

We often care about **internal validity**

- Have I identified the causal effect well in my sample?

and also about **external validity**

Westreich et al. 2019

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- Does my sample speak to the population of interest?

Westreich et al. 2019

We often care about **internal validity**

- Have I identified the causal effect well in my sample?

and also about **external validity**

- Does my sample speak to the population of interest?

The authors combine these to discuss **target validity**

Westreich et al. 2019, Fig 1 (modified)

Nonexchangeability
for **internal** validity
due to **confounding**

$$
\begin{tikzcd}
 & Z \arrow[dl] \arrow[dr] & \\
A \arrow[rr] & & Y
\end{tikzcd}
$$

Nonexchangeability
for **external** validity
due to **sampling bias**

$$
\begin{tikzcd}
\boxed{S = 1} & & Z \arrow[ll] \arrow[dr] & \\
 & A \arrow[rr] & & Y
\end{tikzcd}
$$

Learning goals for today

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

1. Understand DAGs more fully
   - DAGs are nonparametric
   - DAGs are hard to learn from data
2. Generalize from a sample to a population
   - Encode sampling assumptions in DAGs

Let me know what you are thinking

tinyurl.com/CausalQuestions

Office hours TTh 11am-12pm and at
calendly.com/ianlundberg/office-hours
Come say hi!