ESTIMATING CAUSAL EFFECT

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OVERVIEW

- Difficulties in Estimating Causal Effect
- Causal Assumptions
- Causal Diagrams
- 3 methods for estimating causal effect
  - Outcome Regression
  - Inverse Probability Weighting
  - Doubly Robust Estimator

EXAMPLE

- Data from observation study in 1997
- Took place at Ohio Heart Health
- Data recorded by staff of the Lindner Center

Treatment A:

0: did not receive extra therapy

1: Received extra therapy

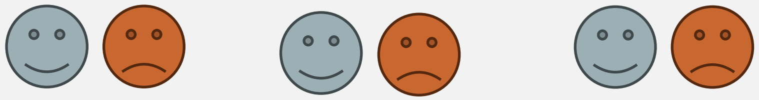
Outcome Y:

0: Survival after 6 months

1: Did not survive after 6 months

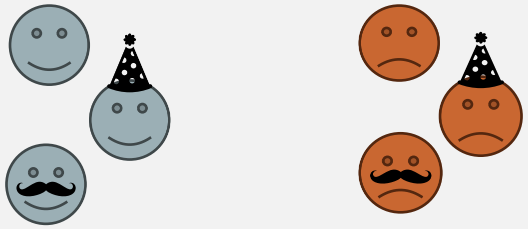
DIFFICULTIES IN ESTIMATING CAUSAL EFFECT

1: Observe both treatment effect in the same individual

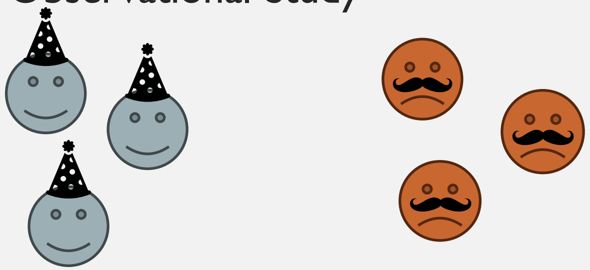


- These are counterfactual outcomes
  - Y^1 and Y^0

2: Perform a Randomized Trial



3: Observational Study



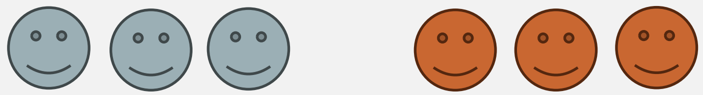
- Confounding

How to estimate causal effect

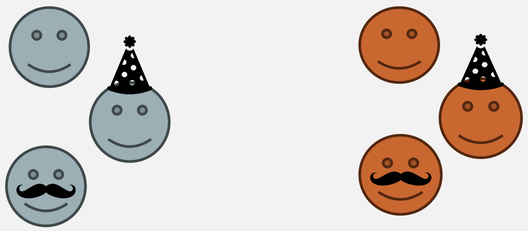
with these difficulties?

CAUSAL ASSUMPTIONS

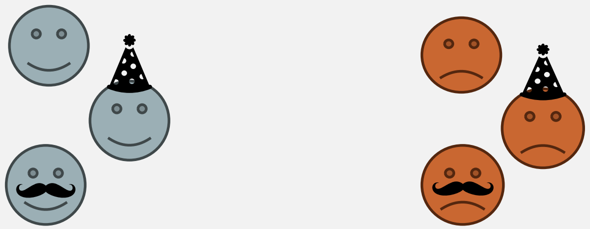
1: Consistency



2: Exchangeability



3: Positivity



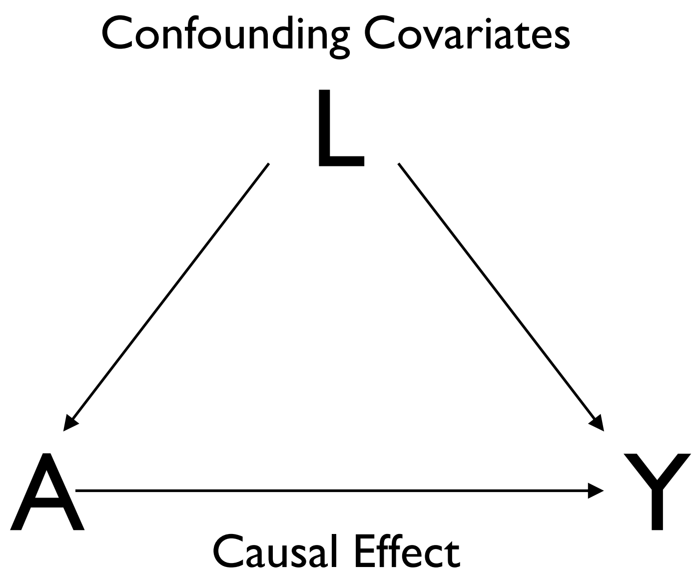
If these assumptions do not hold, you cannot interpret the effect causally

CAUSAL DIAGRAM

Directed Acyclic Graph (DAG)

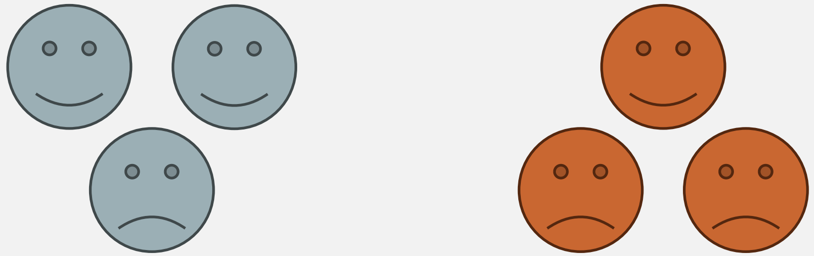
- A = Treatment Variable (augmented therapy ABCIX)
- Y = Outcome Variable (survival after 6 months)
- L = Covariates
  - stent, height, female, diabetic, acutemi, ejecfrac, ves1proc

If you have a DAG that looks like this, you want to condition on the confounding covariates L.



ONE MEASURE OF CAUSAL EFFECT

Risk Difference



$$E[Y^1 - Y^0]$$

0 means no causal effect

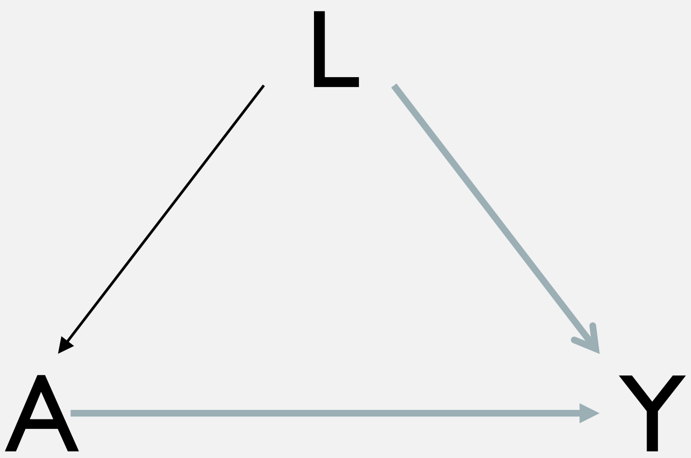
$$\frac{2}{3} - \frac{1}{3}$$

Example: -0.036

$\frac{1}{3} \rightarrow$ Blue causes happy

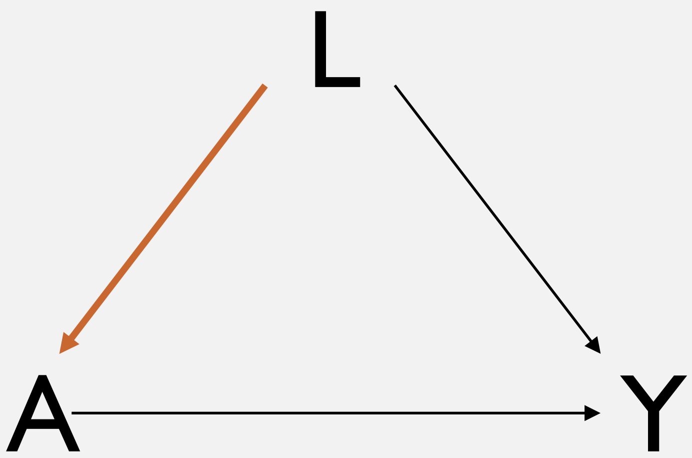
METHOD 1 – OUTCOME REGRESSION

- Predict **outcome Y** from **treatment A** and **covariates L**
- Estimate average predicted outcome Y when A = 1 and when A = 0, calculate risk difference



METHOD 2 – INVERSE PROBABILITY WEIGHTING

- Predict **treatment A** from **covariates L**
- Creates pseudo-population where arrow between L and A is removed
- Adjusts for confounding



METHOD 3 - DOUBLY ROBUST ESTIMATOR

- Combine Outcome Regression and IPW into one model
- Predict **outcome Y** based on **treatment A and covariates L** and **weighted by IPW**
- Only need one method to be correct

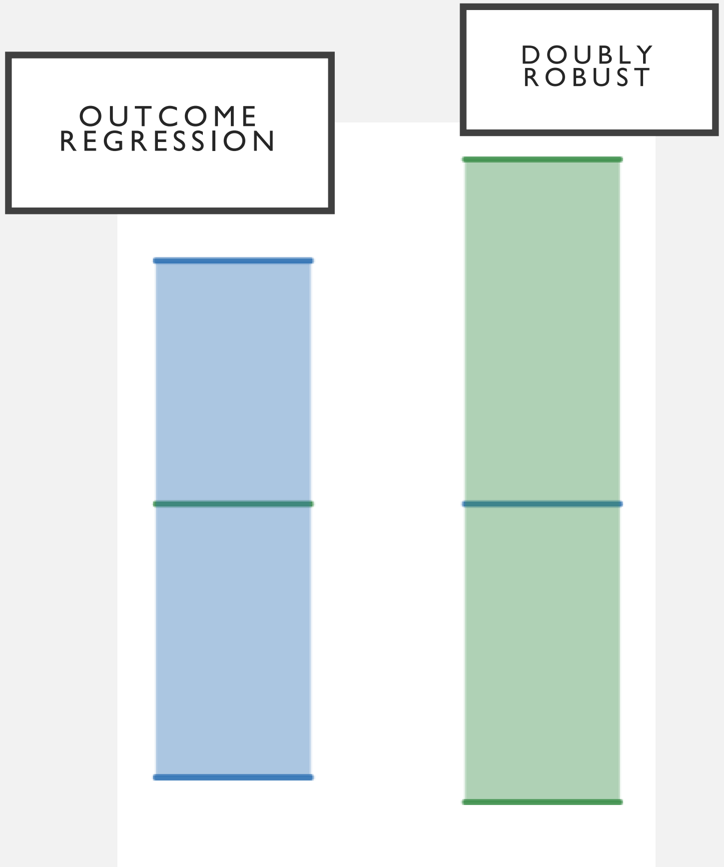
EXAMPLE RESULTS

Risk Reduction Estimates:

Reduction in risk of death after 6 months

- Outcome Regression: -0.049
  - CI: [-0.0774, -0.0105]
- Doubly Robust Estimator: -0.061
  - CI: [-0.1056, -0.0224]

In practice, the CI for the doubly robust estimate is expected to be smaller than CI for outcome regression.



THANK YOU!

References:

Hernán MA, Robins JM (2020). Causal Inference: What If. Boca Raton: Chapman & Hall/CRC

Kereiakes DJ, Obenchain RL, Barber BL, et al. Abciximab provides cost effective survival advantage in high volume interventional practice. Am Heart J 2000; 140: 603-610.