

# Adjusting for confounders

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Tyler Tuan

Without the needs  
for intervention, we  
can infer causality  
by adjusting for  
confounders.

# Propensity-based methods

- Assignment Mechanism
    - Randomized (intervention)
    - Propensity (observation)
  - Propensity grouping
  - IP-weighting
  - G-formula
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# Assignment Mechanism

## 1. Intervention

- a. Randomized trials
- b. Independent from confounders

## 2. Observation

- a. Propensity
- b. Depend on confounders

# Data of choice:

- 1) Set of treatments  $A$
- 2) Set of responses  $Y$
- 3) Find all possible  
causal relationships

$$E[Y^{A=a}]$$

# Propensity grouping

- Treatment is independent from confounders given propensity score  $e(L) = \Pr(A = 1|L)$
- By stratifying on propensity score, we are approximating a randomized trial within the subpopulation
- $A \perp L \mid e(L)$ , confounders are adjusted within the strata of propensity
- $E[Y^{A=a}] = E[Y|A = a, e(L)]$
- Problem: Continuous treatments... Move to IP-weighting and G-formula, which use the propensity score as numerical value instead of stratification

# IP-weighting

- Create pseudo-population, which adjusted for confounders, through the use of numerical value of propensity score instead of stratification
- $E[Y^{A=a}] = E[\frac{I(A=a)Y}{f(A=a|L)}]$
- Mean of Y reweighted by the IP-weight  
 $W^A = 1/f(A|L)$
- Fit  $E[Y|A = a] = \theta_0 + \theta_1 a$  with weighted linear regression with weight being IP weight
- Such model is estimation for  $\hat{E}[Y^{A=a}]$
- Weighted non-linear for  $E[Y|A = a]$  ?



# G-formula

- Standardization: Counterfactual distribution given confounders is the same as response distribution given confounders and treatment

- $E[Y^{A=a}]$

$$= \sum_l E[Y^{A=a} | L = l] \Pr[L = l]$$

$$= \sum_l E[Y | A = a, L = l] \Pr[L = l]$$

- The real work here is to estimate  $\hat{E}[Y | A = a, L = l]$  through a ML model of choice

- $\hat{E}[Y^{A=a}] = \frac{1}{N} \sum_i \hat{E}[Y | A = a, L_i]$

# How Machine Learning is incorporated?

- Estimate Propensity Score:  $\Pr[A = a|L]$
- Estimate IP-weighted response:  $E[Y|A = a]$  along with IP weights info
- Estimate G-formula:  $\hat{E}[Y|A = a, L = l]$
- Note that, IP-weighting requires two ML models while G-formula requires only one
- Does overfitting and underfitting matter? It might be true that overfitting is good...