

Marginal Structural Models

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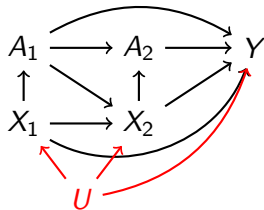
17 Nov 2023

Learning goals for today

1. define causal estimands
2. make causal assumptions with Directed Acyclic Graphs
3. estimate with inverse probability weights
 - ▶ in one period
 - ▶ in two periods
4. estimate with a marginal structural model

Running example

- ▶ at time 1,
 - ▶ a student receives a midterm test score X_1
 - ▶ they decide whether to study more A_1
- ▶ at time 2,
 - ▶ a student receives a midterm test score X_2
 - ▶ they decide whether to study more A_2
- ▶ they get a final exam score Y



Defining causal effects

Effect of studying at time 2

Expected outcome $E(Y^{a_2})$ if assigned to the value a_2 for studying at time 2

Student	$Y^{a_2=0}$	$Y^{a_2=1}$
1	80	95
2	70	95
3	90	90
\vdots	\vdots	\vdots

Defining causal effects

Effect of studying at time 2

Expected outcome $E(Y^{a_2})$ if assigned to the value a_2 for studying at time 2

Student	$Y^{a_2=0}$	$Y^{a_2=1}$
1	80	?
2	70	?
3	?	90
\vdots	\vdots	\vdots

Defining causal effects

Effect of studying at time 1 and 2

Expected outcome $E(Y^{a_1, a_2})$ if assigned
to the value (a_1, a_2) for studying at time 1 and time 2

Student	$Y^{a_1=0, a_2=0}$	$Y^{a_1=0, a_2=1}$	$Y^{a_1=1, a_2=0}$	$Y^{a_1=1, a_2=1}$
1	70	80	75	90
2	80	95	80	95
3	90	90	90	90
\vdots	\vdots	\vdots	\vdots	\vdots

Defining causal effects

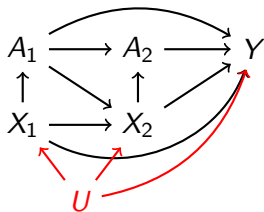
Effect of studying at time 1 and 2

Expected outcome $E(Y^{a_1, a_2})$ if assigned
to the value (a_1, a_2) for studying at time 1 and time 2

Student	$Y^{a_1=0, a_2=0}$	$Y^{a_1=0, a_2=1}$	$Y^{a_1=1, a_2=0}$	$Y^{a_1=1, a_2=1}$
1	?	?	?	90
2	?	95	?	?
3	?	?	90	?
\vdots	\vdots	\vdots	\vdots	\vdots

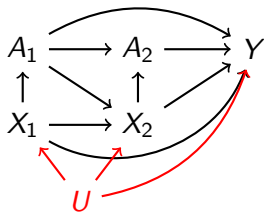
Causal assumptions

We observe data from this model

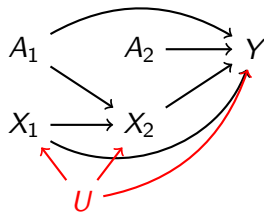


Causal assumptions

We observe data from this model

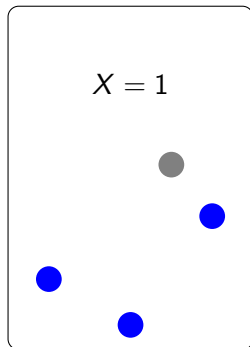
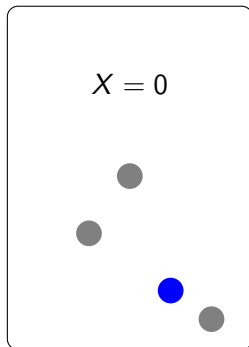


We want this

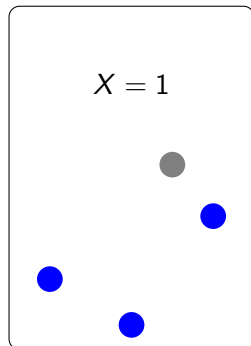
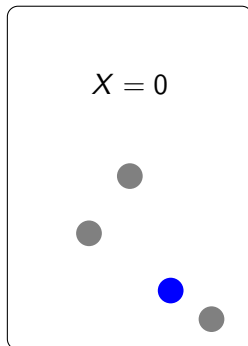
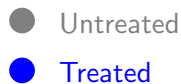


Inverse probability of treatment weighting

- Untreated
- Treated

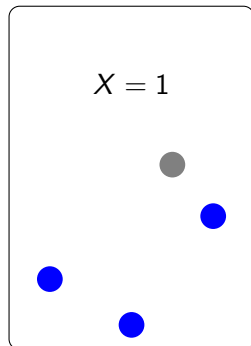
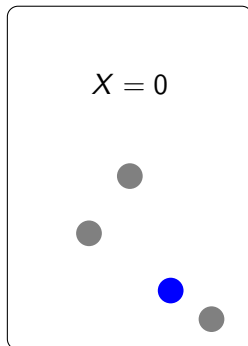
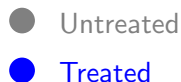


Inverse probability of treatment weighting



Propensity score: $\pi_i = P(A = A_i \mid X = X_i)$

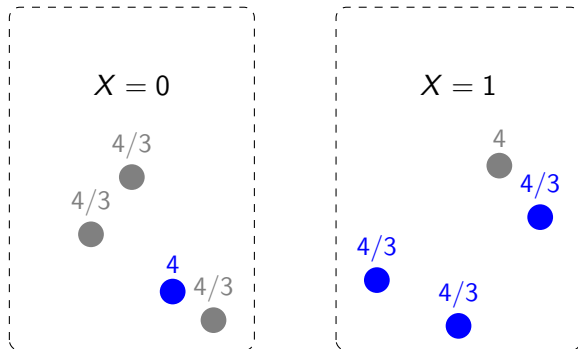
Inverse probability of treatment weighting



Propensity score: $\pi_i = P(A = A_i \mid X = X_i)$

Inverse probability weight: $w_i = \frac{1}{\pi_i}$

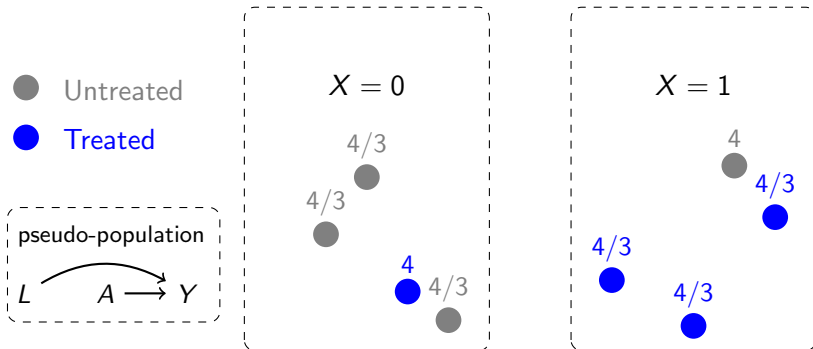
Inverse probability of treatment weighting



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Inverse probability of treatment weighting



Propensity score: $\pi_i = P(A = A_i \mid X = X_i)$

Inverse probability weight: $w_i = \frac{1}{\pi_i}$

Inverse probability weighting

At every time t , define an inverse probability of treatment weight given the measured past confounders and treatments

$$W^{A_t} = \frac{1}{P(A_t \mid \bar{A}_{t-1}, \bar{L}_t)}$$

Inverse probability weighting

At every time t , define an inverse probability of treatment weight given the measured past confounders and treatments

$$W^{A_t} = \frac{1}{P(A_t \mid \bar{A}_{t-1}, \bar{L}_t)}$$

Define the overall weight as the product

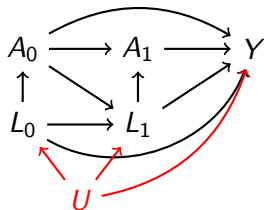
$$W^{\bar{A}} = \prod_{k=1}^K \frac{1}{P(A_k \mid \bar{A}_{k-1}, \bar{L}_k)}$$

Inverse probability weighting

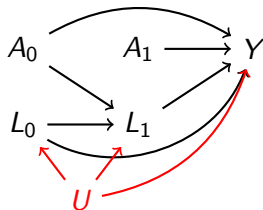
The weight

$$w^{\bar{A}} = \prod_{k=1}^K \frac{1}{P(A_k \mid \bar{A}_{k-1}, \bar{L}_k)}$$

Takes us from this



to this pseudo-population



Marginal structural models

- ▶ inverse probability weighting estimates by weighted means

$$E(Y^{a_1=1, a_2=1}) = \frac{1}{\sum_{i:\vec{A}=1} w_i} \sum_{i:\vec{A}=1} Y_i w_i$$

- ▶ marginal structural model estimates by a weighted regression

$$E(Y^{a_1, a_2}) = \beta_0 + \beta_1 a_1 + \beta_2 a_2$$

Let's try it

- ▶ logistic regression for treatment at each time
- ▶ predict the propensity score
- ▶ create inverse probability weights
- ▶ estimate by IPW and MSM

A1	A2	estimate
0	0	$\hat{E}(Y^{00})$
0	1	$\hat{E}(Y^{01})$
1	0	$\hat{E}(Y^{10})$
1	1	$\hat{E}(Y^{11})$

