Data 102 Lecture 15:

Causal inference III

Lecture 15 overview

- Why observational studies?
- What goes wrong when we don’t have randomized treatment?
- The unconfoundedness assumption offers a way back
- Three methods for estimating the ATE
    - Outcome regression
    - Inverse propensity score weighting
    - Matching

Drawbacks about randomized experiments

Experiments may have low power

- Usually have small sample sizes because they are expensive to run

Some experiments are infeasible

- Too expensive
- Unethical

E.g. Cannot design an experiment to test whether smoking causes lung cancer, because it is unethical to randomize people into smoking vs non-smoking

A lot of observational (non-experimental) data…

Credit card transaction information

Website/app user logs

Electronic Health Records

Census, tax returns

Satellite images

…

Can we do causal inference using observational data?

What goes wrong when we don’t have randomized treatment?

A superpopulation model...

Z_i = Treatment indicator

$Y_i(1)$, $Y_i(0)$ = Potential outcomes

X_i = *Covariate vector [age, gender, etc.]*

We usually assume that we observe i.i.d. Samples (X_i, Z_i, $Y_i(1)$, $Y_i(0)$) drawn from a superpopulation [i.e. a density over (x,z,y(1),y(0))]

The average treatment effect (ATE) is now an expectation:

$$\tau = \mathbb{E}[Y(1) - Y(0)]$$

A superpopulation model...

More details in whiteboard notes...

Simpson's paradox / kidney stones example revisited

Z = 1(Treatment B)

Y(1) = 1(Recovery under Treatment B)

Y(0) = 1(Recovery under Treatment A)

X = 1(small kidney stones)

Then we get E[Y(0)|Z=0] = 0.83, E[Y(1)|Z=1] = 0.78

	Treatment A helps	Treatment B helps
Large kidney stones	69% (55 / 80)	**73%** (192 / 263)
Small kidney stones	87% (234 / 270)	**93%** (81 / 87)
All patients	**83%** (289 / 350)	78% (273 / 350)

From Charig et al. (1986)

Simpson's paradox / kidney stones example revisited

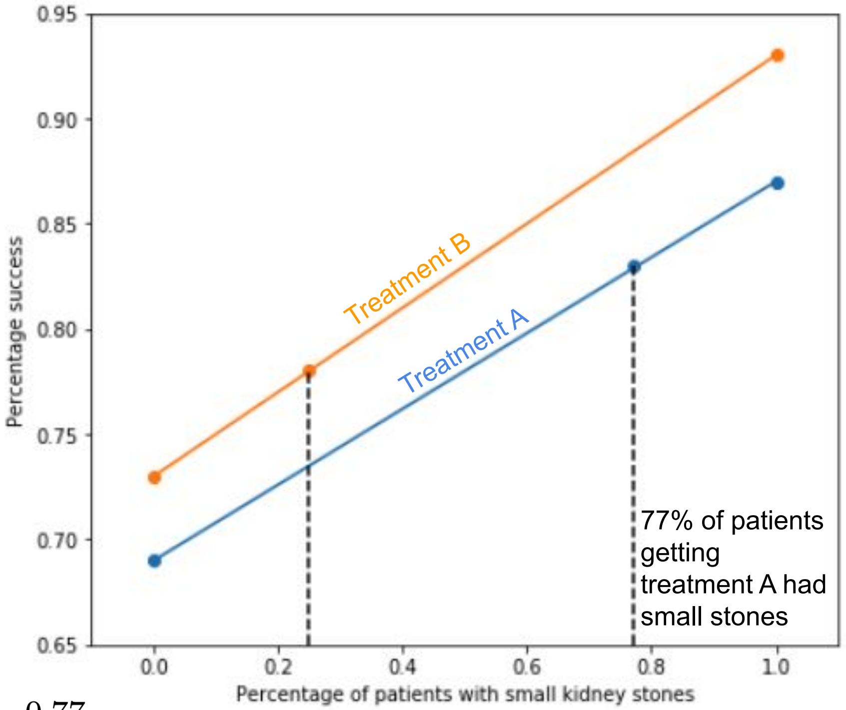
The prima facie causal effect is

$$\tau_{PF} = \mathbb{E}[Y(1)|Z=1] - \mathbb{E}[Y(0)|Z=0]$$
$$= 0.78 - 0.83 = -0.05$$

This is not equal to the ATE because of **selection bias**:

$$\mathbb{E}[Y(1)|Z=1] \neq \mathbb{E}[Y(1)]$$
$$\mathbb{E}[Y(0)|Z=0] \neq \mathbb{E}[Y(0)]$$

The treated and control groups are different: $\mathbb{P}(X=1|Z=1) = 0.25, \quad \mathbb{P}(X=1|Z=0) = 0.77$



Overcoming this with the unconfoundedness assumption

Unconfoundedness assumption

See whiteboard notes

Methods for estimating ATE under confoundedness

1. Outcome regression
2. Inverse propensity score weighting
3. Matching

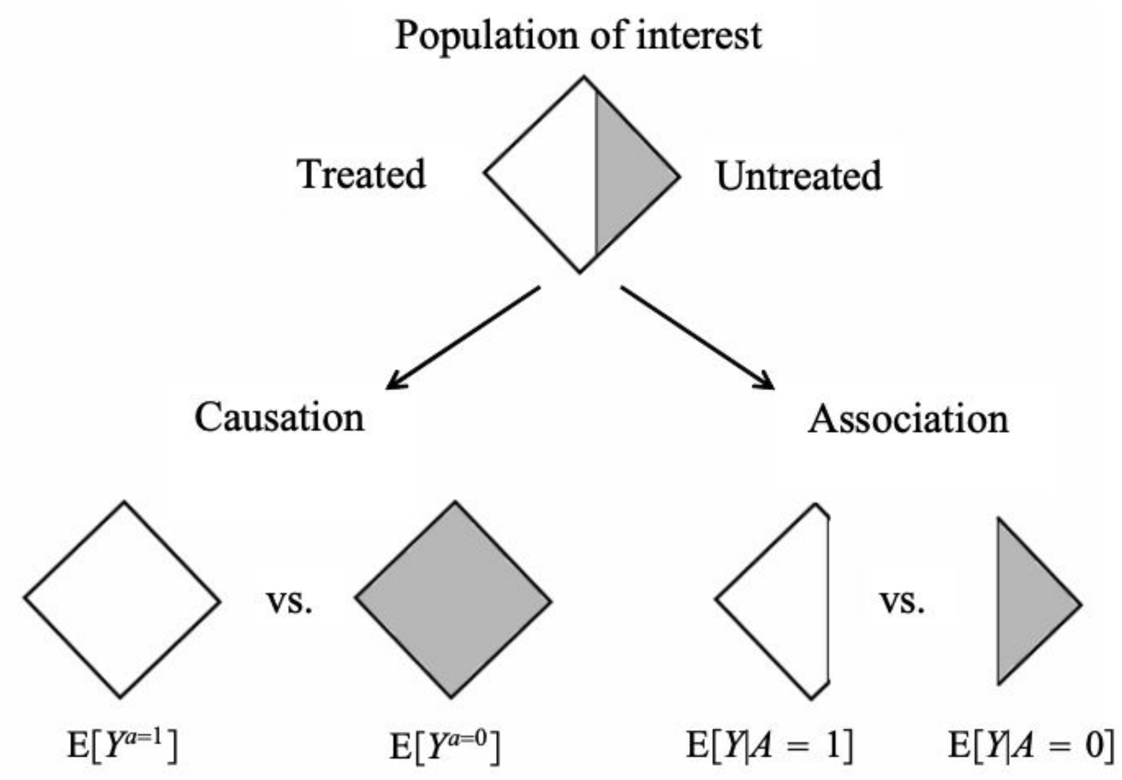
See whiteboard notes

Method 1: Outcome regression

See whiteboard notes

Method 2: Inverse propensity score weighting

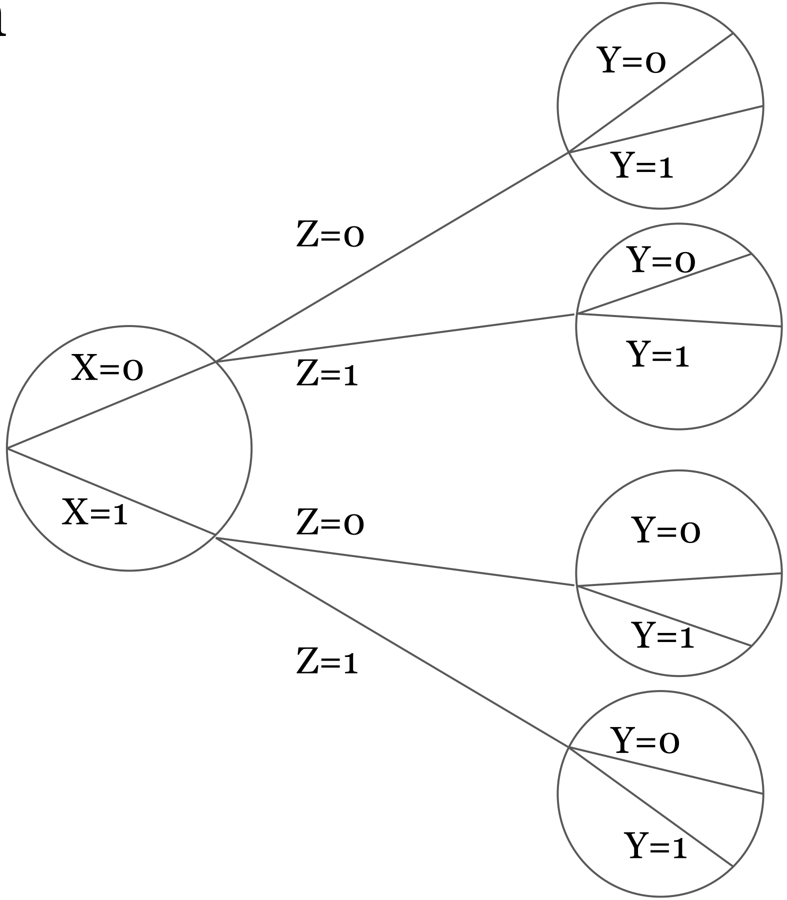
Another way to think about observational studies…



Propensity score is the probability of being treated

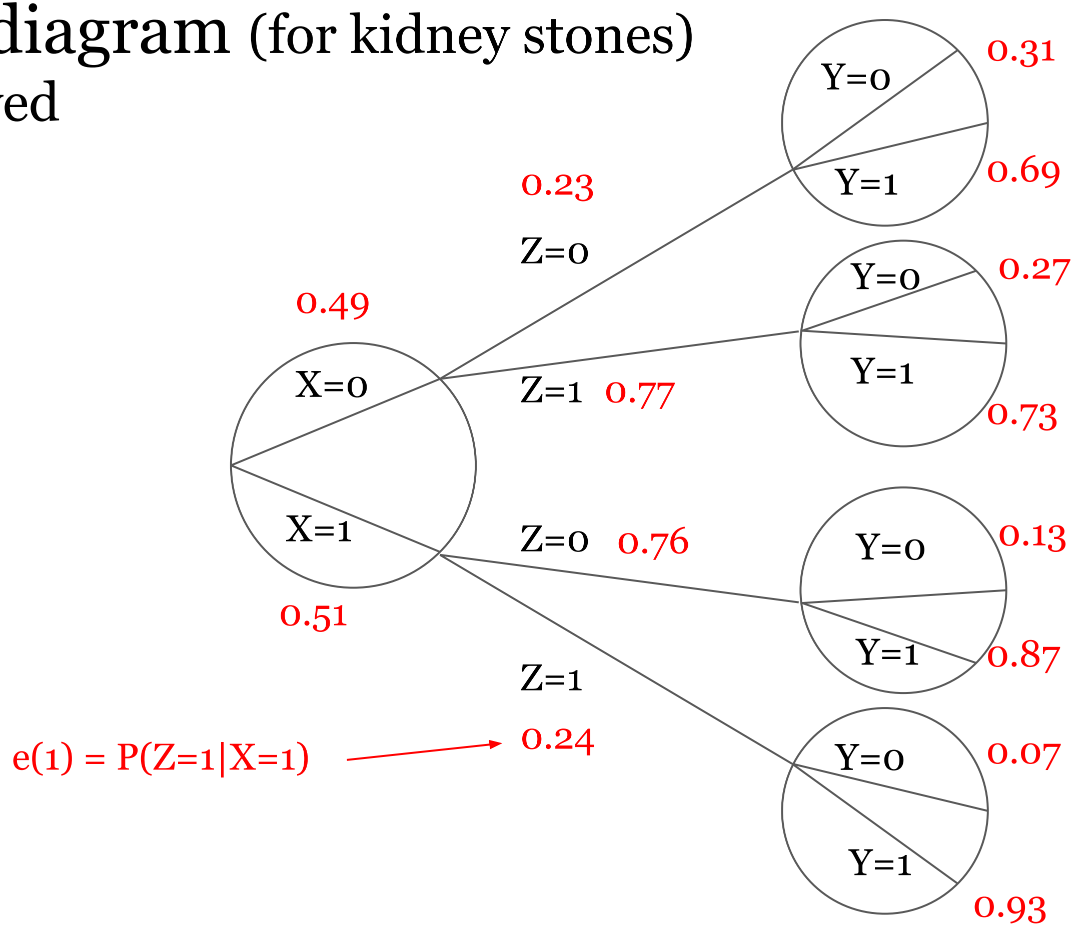
$$e(x) = \mathbb{P}(Z = 1 | X = x)$$

Tree diagram



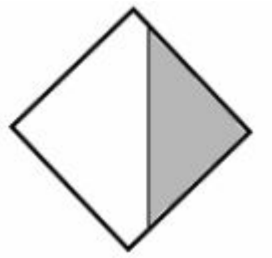
Tree diagram (for kidney stones)

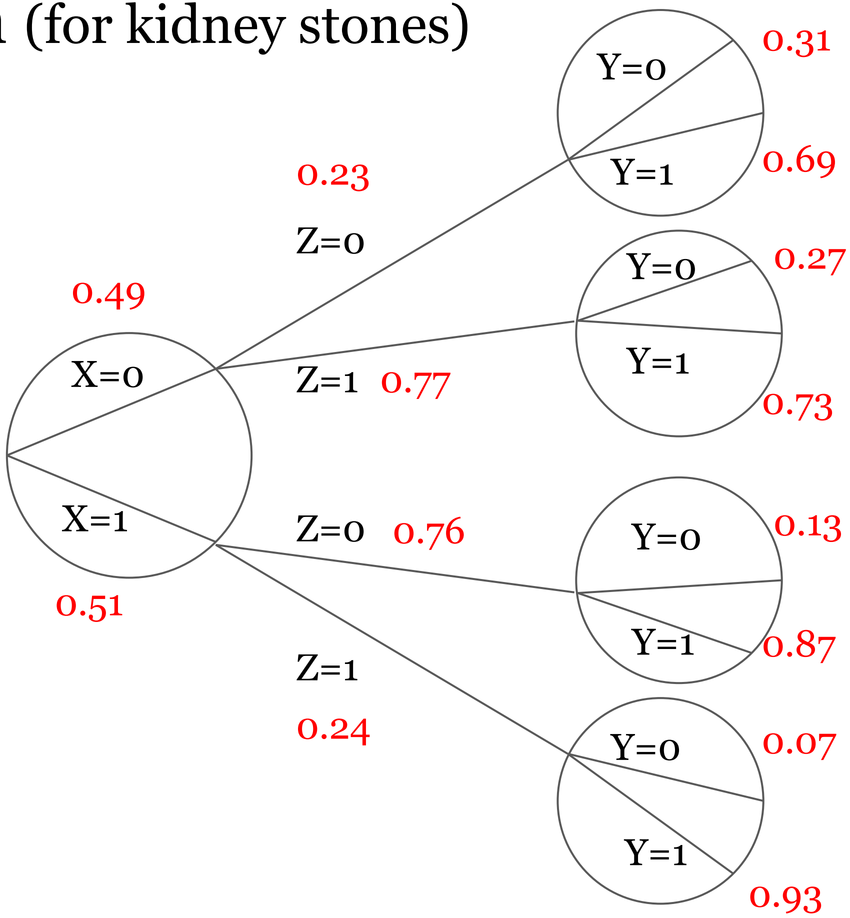
Observed



Tree diagram (for kidney stones)

Observed





No. of patients

25

55

71

192

36

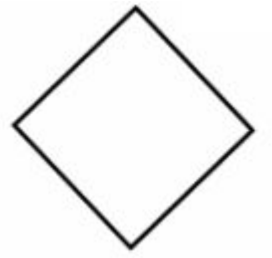
234

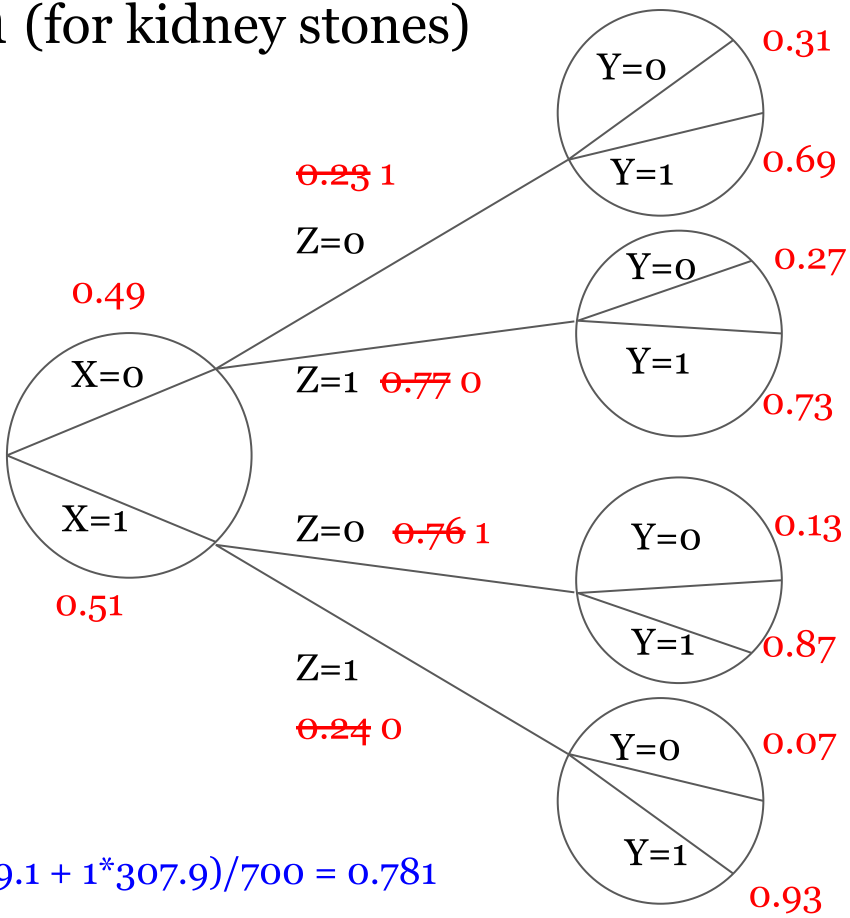
6

81

Tree diagram (for kidney stones)

World A





<u>No. of patients</u>

25 * 1/0.23 = 108.7

55 * 1/0.23 = 239.1

0

0

36 * 1/0.76 = 47.4

234 * 1/0.76 = 307.9

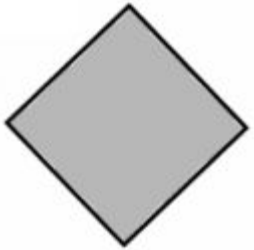
0

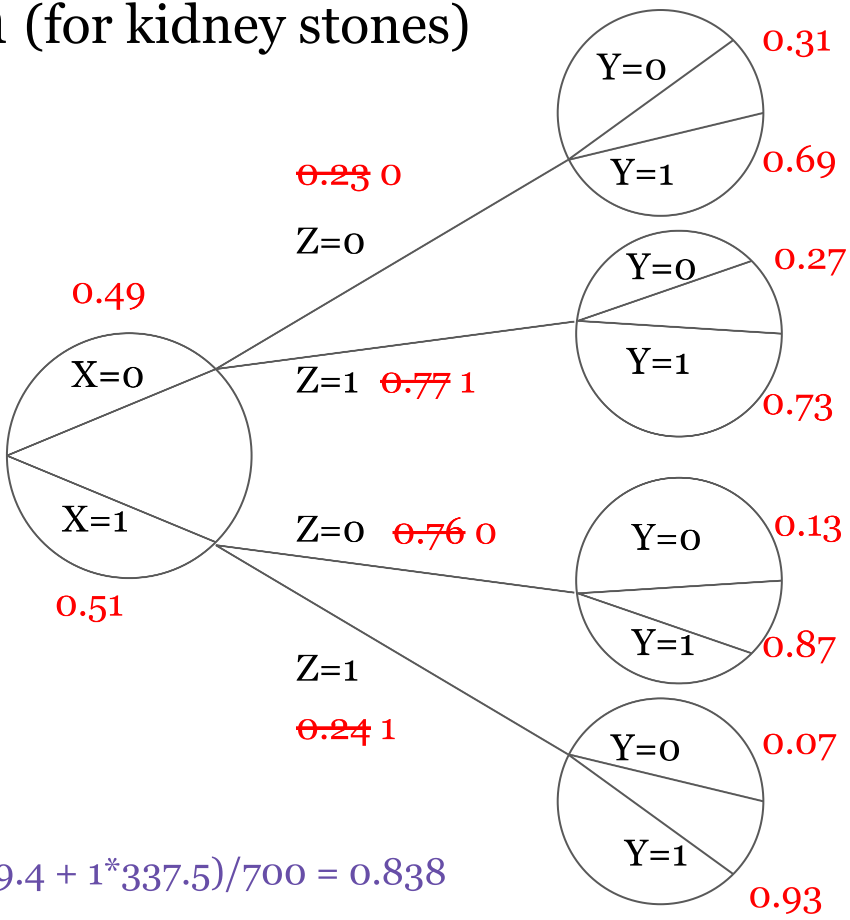
0

Average outcome = (1*239.1 + 1*307.9)/700 = 0.781

Tree diagram (for kidney stones)

World B





No. of patients

0

0

71 * 1/0.77 = 92.2

192 * 1/0.77 = 249.4

0

0

6 * 1/0.24 = 25

81 * 1/0.24 = 337.5

Average outcome = (1*249.4 + 1*337.5)/700 = 0.838

ATE calculation with IPW

ATE = Average outcome in World B - Average outcome in World A

= 0.838 - 0.781

= 0.057

Should be the same as the answer gotten from earlier in lecture, but different because of rounding...

Propensity score theorems

See whiteboard notes