STATISTICS 536B, Lecture #11

April 2, 2015

Thinking about causal inference as a missing data problem

Instead of

C_1	C_2	X	Y
1.2	3.7	1	18.3
1.8	2.5	0	20.6
1.3	4.2	0	10.9

...

Think of

C_1	C_2	X	$Y^{(0}$	$Y^{(1)}$
1.2	3.7	1	?	18.3
1.8	2.5	0	20.6	?
1.3	4.2	0	10.9	?

...

Counterfactuals

Everybody has a pair of outcomes $(Y^{(0)}, Y^{(1)})$.

But we only get to observe one of them:
$Y = Y^{(X)} = (1 - X)Y^{(0)} + XY^{(1)}$.

But would like to estimate targets such as
$E(Y^{(1)} - Y^{(0)}) = E\left(Y^{(1)}\right) - E\left(Y^{(0)}\right)$.

Think of comparing two counterfactual worlds, one where everybody is exposed, and one where everybody is unexposed.

This framework lets us be precise about 'adjusting for confounders'.

Variables C completely control for confounding if
$(Y^{(0)}, Y^{(1)}) \perp\!\!\!\perp X|C$.

Within each stratum of people with the same C value, the potential outcomes and the exposed/unexposed choice/assignment are 'blind' to one another. (think within C, like a randomized trial).

Confounding, continued

Clear how condition can fail?

For example, say that:

- Being older is associated with worse outcomes (whether exposed or not)
- Being male is associated with worse outcomes (whether exposed or not)
- Males are more likely to choose $X = 1$ than females

Say $C = AGE$ only. The requisite condition $X \perp\!\!\!\perp (Y^{(0)}, Y^{(1)})|\text{AGE}$ will not hold.

Connect to what we've done already?

Largely based on intuition, we've eschewed unadjusted comparisons like

$$E(Y|X=1) - E(Y|X=0)$$

in favour of adjusted comparisons like

$$E\{E(Y|X=1,C) - E(Y|X=0,C)\}$$

Reminder: We have multiple strategies for going after this target.

Tie-in with counterfactuals?

Counterfactuals can bring clarity to assumptions and to targets of inference

Example - revisit noncompliance in randomized study story, comparing active treatment to control.

Observe for everybody: binary Z, X, Y.

But think everybody has (latent) $(M, Y^{(0)}, Y^{(1)})$

M is compliance type. To keep things simple, say our population contains only two types of people:

Never-takers ($M = 0$): will not take active treatment, regardless of what they are told to do.

Compliers ($M = 1$): will do what they are told to do.

Then study investigator randomly generates treatment *assignment* Z . Hence Z is independent of $(M, Y^{(0)}, Y^{(1)})$.

And the treatment *received*, X, is a deterministic function of (Z, M).

Observed data tells you some things about the latent variables

Z	X	Y	M	$Y^{(0)}$	$Y^{(1)}$
0	0	1	?	1	?
0	0	0	?	0	?
1	1	1	1	?	1
1	0	1	0	?	1

...

Interpreting $E(Y|Z=1) - E(Y|Z=0)$

Interpreting $E(X|Z=1) - E(X|Z=0)$

So what exactly are we estimating via the instrumental variable technique?

So some targets are identified by the data, others are not

Revisit Vitamin A study

Z	X	Y
1	0	34/2419
1	1	12/9675
0	0	74/11588
0	1	---