

Biostatistics 201a - Lecture 17

11/2/11

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Confounding, Adjustment & Mediation

Confounding occurs if you get a significant difference in your interpretation of the relationship between X and Y depending on whether or not variable Z is in your model.

Confounding can do several things:

- (i) Make an apparent $X \leftrightarrow Y$ relationship go away ("classical")
 - usual reason for "adjustment" (including additional variables in model to see if results remain significant)
- (ii) Make a relationship appear where there originally wasn't one.
- (iii) Change the sign or the magnitude of a relationship

Examples:

(1) X = treatment for cancer

e.g. - wait and see

- mild intervention

- aggressive intervention

Y = years of survival

Z = severity of illness

Z affects both the choice of treatment and the outcome,

e.g. It's possible (likely) that people with more advanced illness get the more aggressive tx but also have worse outcomes - so if we don't adjust for Z the aggressive tx might look really bad.

(2)

X = breast feeding rate

Y = infant mortality

Z = GDP (average SES) /

If you just look at correlation of X and Y it's positive
⇒ more breast feeding goes with higher mortality rates

Underlying cause - access to clean water, good food, etc. is worse in undeveloped countries where formula is not an option. Once you account for this, breast-feeding actually has a ~~positive~~ ^{good} result on infant outcomes

(3) X = ice cream sales / week
 Y = number of drawings / week

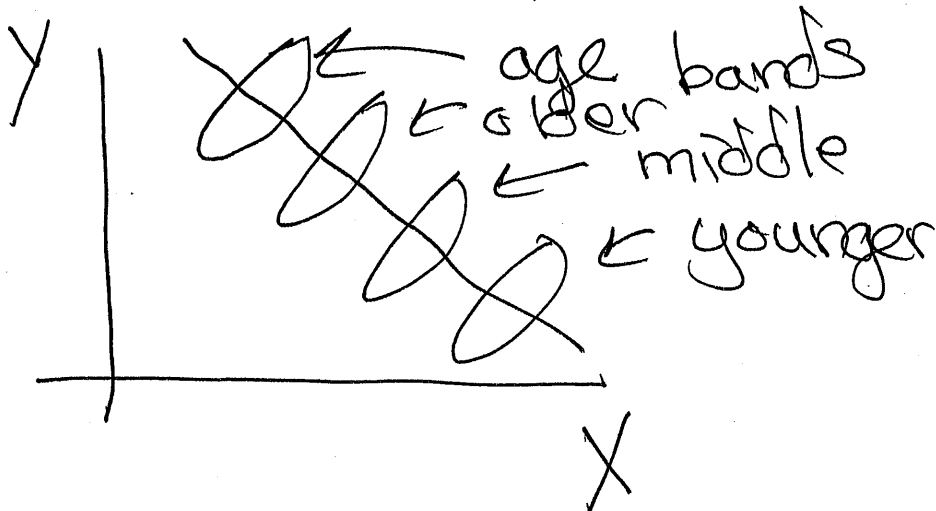
There's a strong positive relation!
I don't believe ice cream makes you draw or vice versa!

Z = temperature / season.

(4) X = smoking rate
 Y = death rate

Turns out that X and Y have a negative relationship if you do raw correlation suggests smoking is protective!

$Z = \text{age}$ - as people get older they are more likely to die but also less likely to smoke



Within each age band higher smoking rates are associated higher death rates

(5)

$X = \text{age}$

$Y = \text{depression index}$ } positive relationship

$Z = \text{social network support}$
illness severity

Here if you adjust for Z the relationship between X and Y might be reduced or go away all together.

Adjustment: Just the process of including potential confounders in a MLR model and seeing if they change the effect of the predictors of interest. Usual variables to control for are things like age, gender, education, SES, etc. Frequently the goal is to be sure that a significant relationship between a predictor of interest and outcome couldn't be accounted for by the adjustment variables - particularly an issue in observational studies.

Note: This is one reason you may leave in your model variables that aren't significant - to show they haven't affected the result.

Mediation: Idea is that you are trying to trace a causal path - you have a theory about causes the outcome and you want to see data are consistent with that theory

Diagram for mediation



X = predictor

Y = outcome

M = potential mediator

We believe that X (or is related to Y) through its effect on M which is the direct cause of what happens to Y.

e.g. Example 5 - X = age

Y = depression

Z = health / social support

Social support / health "mediates" the observed relationship between age and depression.

Is mediation the same as confounding?

No. Mediation \Rightarrow causal path.

for example $X =$ ice cream sales

$Y =$ drownings

$Z =$ temp, season

Z is a confounder (it explains or accounts for the relationship between X and Y) but it is not a mediator. We don't believe that ice cream sales affect temperature thereby leading to drowning which is what mediation would mean

cigarette lighter example:

Carrying a cigarette lighter is related to death rate - a classic corr \neq cause example. The real culprit is smoking - people who carry lighters

are more likely to smoke -
but this isn't mediation
either since carrying a
lighter doesn't make you
smoke, nor does carrying
the lighter cause cancer -
smoking → both.