Collider Bias

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Plan

- → Why care about collider bias?
- → 'Explaining away' in probabilities (and in your head)
- → Album charts
- → Selection on the dependent variable
- → Learning in (and from) social networks
- → Policing data

Colliders everywhere

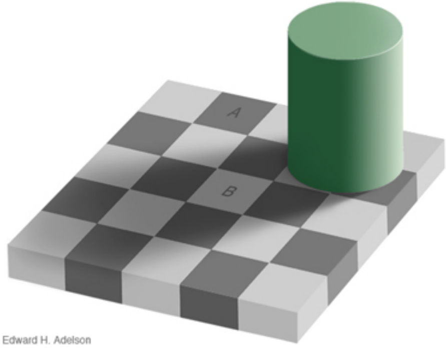
The social sciences have huge numbers of names for apparently distinct forms of bias

- Confounding bias
- Sample selection bias
- Ascertainment bias
- Truncation bias
- Sampling on the dependent variable
- Attrition bias
- Overcontrol

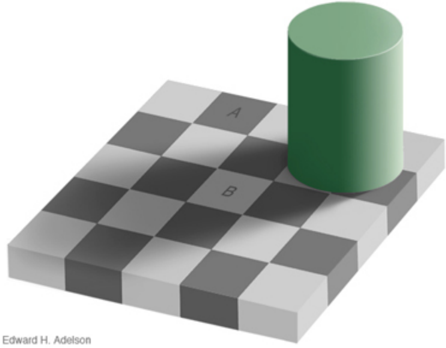
This can give them impression that there are this many ways to go wrong. We'll see that the list could be reduced to two:

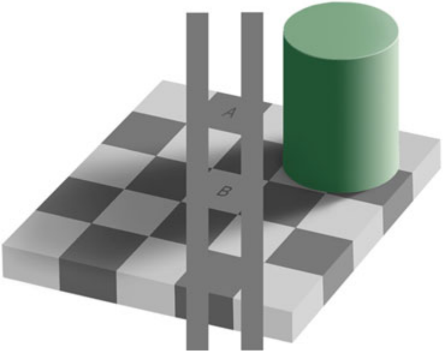
- Confounding bias (conditioning on a common cause)
- Collider bias (conditioning on a common effect)

Explaining away



Explaining away





Explaining away

How bright a surface looks is the product of

→ surface *illumination* (less in shadow)
→ intrinsic *reflectance* (greater for lighter colours)

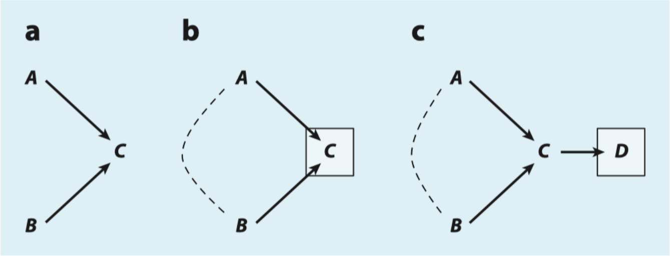
Physically identical 'input' from A and B needs parsing by your visual system in the context of the scene

The pillar's shadow suggests that the B is under *lower* illumination, so it 'must' have *higher* reflectance if it's to match A

→ So *we* perceive it as having greater reflectance, i.e. being lighter than A.

Smart causal reasoning at the sub-perceptual level!

Conditioning on a collider



(Elwert & Winship, 2014, Fig.4)

C is the collider

→ Conditioning on C generates non-causal association between its causes

→ Conditioning on any *consequence* of C generates non-causal association between C's causes

Two ways to condition

Reminder: Conditioning is at least one of:

- → making C an explanatory variable in a regression model
- → analyzing data where $C = k$ (or $C > k$)

In the latter case C either is, or drives a *sample-inclusion indicator*

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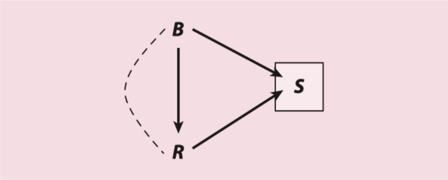
Recall that regression is a more efficient (and potentially more biased) way to do stratification

→ if C were a confounder, you'd *want* to do this, e.g. using the *adjustment formula*
→ Here it woud be a bad idea

Albums



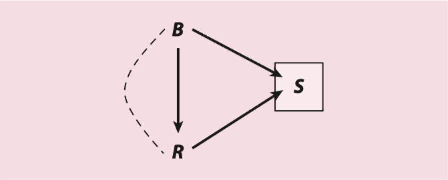
(Elwert & Winship, 2014, Fig.7)

Why are albums that reach Rolling Stone's list of 500 best albums (R=1), *less likely* to be top the Billboard charts (B=1)?

Data collection:

- → Pick all the 'Rolling Stone 500' albums and 1200 Billboard topping comparisons
- → S is a sample selection indicator

Albums



Contrast:

- → *positive* (causal) association between B and R
- → *negative* (non-causal) association between B and R due to conditioning on S
- → B 'explains away' R, and vice versa

The *sign* of the final association depends on all three causal effects

Case control

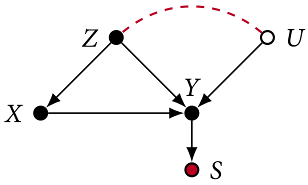
Note: done right, this would be a *case control design*

→ In case control designs the explanatory variables (B) must do not affect sample inclusion

Lots of work in epidemiology on this (see Hernán & Robins, 2020; Mansournia et al., 2013, for details)

Selecting on the dependent variable

A reminder of our old friend from week 1



Controlling for Z is good, until we selected on S. That caused our sample to be unbalanced with respect to U and Z (equivalently: errors are now correlated with X)

Case control designs can allow us to select on Y, but not like this…

Contagion vs homophily

Do fat friends make you fat? Is smoking contagious? (Christakis & Fowler, 2007)

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Maybe! But for most research designs you'd never be able to tell (Shalizi & Thomas, 2011) Helpful precis as a blog post: [link]

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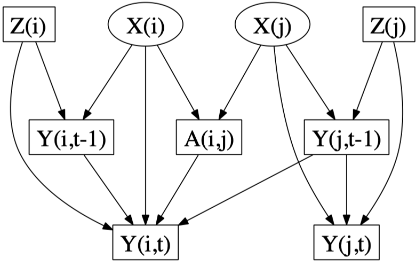
> *If your friend Joey jumped off a bridge, would you jump too?"*
> *yes: Joey inspires you (social contagion or influence)*
> *yes: Joey infects you with a parasite which suppresses fear of falling (actual contagion)*
> *yes: you're friends because you both like to jump off bridges (manifest homophily)*
> *yes: you're friends because you both like roller-coasters, and have a common risk-seeking propensity (latent homophily)*
> *yes: because you're both on it when it starts collapsing and that's the only way off (external causation)*
>
> *(Shalizi & Thomas, 2011)*

Contagion vs homophily

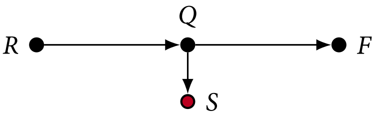


(Fig.1 Shalizi & Thomas, 2011)

Having data on friends ($A_{i,j}$) but not latent preferences (X_i and X_j) makes non-parametrically estimating $Y_{j,t-1} \longrightarrow Y_{i,t}$ *impossible*, even with Z

Post treatment bias: policing

A stylized setup: Race (R) causes questioning (Q) which generates a report (S), which may lead to use of force (F)



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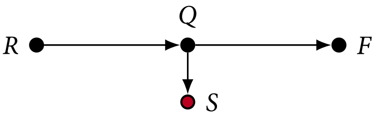


If we conditioned on Q then we would make the ATE of R on F zero.

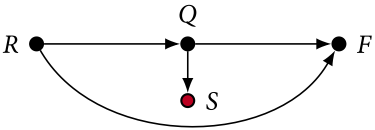
However, S *measures* Q.

→ If it measures it very well, then it's almost as good as observing Q directly

Conditioning on S makes the ATE estimate of R on F depend on the measurement error (and we may be able to recover from it too Kuroki & Pearl, 2014)

Post treatment bias: policing

Now race (R) affects both stages of the process



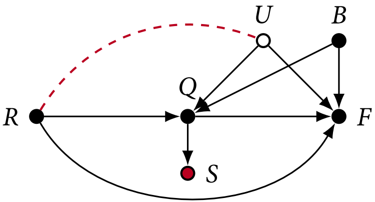
Can we get the ATE of R on F for S- or Q-selected data?

- → Not in general, no.

Can we get the *direct* effect of R on F for S- or Q-selected data?

- → Up to measurement error, yes, in exactly this graph
- → But when $Q \longrightarrow V$ has confounders, no.

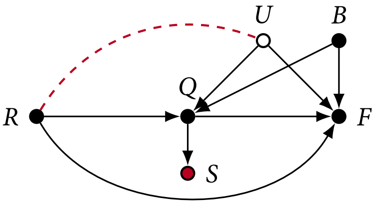
Post treatment bias: policing



Race (R), behaviour (B), and unobserved factors (U) cause questionings (Q) which are recorded (S); they also affect use of force (F), conditional on Q.

Controlling for B still leaves U to generate collider bias

Post treatment bias: covid



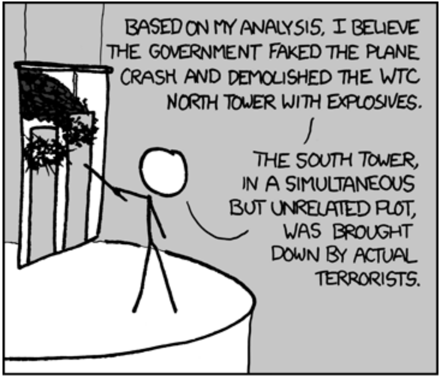
Infection (R) puts you in hospital (Q), but so does smoking (B) and other risk factors (U) which also cause bad outcome (F). (Griffith et al., 2020)

Solutions

We'll talk about sensitivity testing a bit later, but non-parametrically speaking, not so much…

Boooo.

Different colliders



THE 9/11 TRUTHERS RESPONDED POORLY TO MY COMPROMISE THEORY.

There is only one good cartoon about collider bias, and this is it.

→ Why would it be rational to respond poorly?

Spoiling this joke by over-explaining it will be the class task for Tuesday

References

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