Causal Thinking

Or how I learned to love the multiverse

Carolina Torreblanca

DDDI Summer Hangouts • 23 June 2026

High social media use increases mental health risks for adolescents

Vijayakumar et al., *Medical Journal of Australia*, 2026

Does social media cause depression?

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Results: Teens who use SM for two hours a day or more are at higher risk of depression than lighter users

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And an inherent comparison

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A statement of probability: SM makes depression more likely

And an inherent comparison but between what?

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The potential outcomes framework is how we conceptualize causality

Call Y the crop yield. Every unit (plot of land) i has two potential outcomes:

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How much would crop yield differ if we compared a fertilized plot i to plot i had it been unfertilized?

The fundamental problem of causal inference

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The fundamental problem of causal inference: We can only observe one of the potential outcomes $\rightarrow$ we can never recover individual causal effects

Causality is a Missing Data Problem

Four fields. The effect of fertilizer on A is $Y_A(\text{fert}) - Y_A(\text{not})$.

	fertilized	not	effect
A	32	?	?
B	?	40	?
C	25	?	?
D	?	33	?

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Now we only need two averages!

Can we use the observed averages?

We observe the yield in the fertilized fields and yield in the unfertilized fields. So we can compute two averages:

$$\overline{Y}_{\text{fertilized}} \qquad \overline{Y}_{\text{unfertilized}}$$

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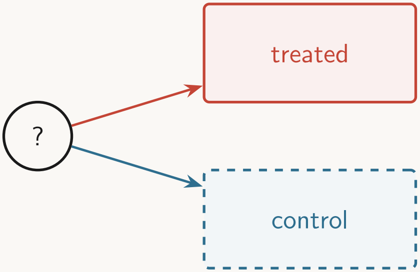
That is a claim about a world we never observe!

Causal social science is the art of making that claim plausible.

A very compelling reason to believe the claim is randomization: Flip a coin



Two groups, alike but for chance

Some questions cannot, or ought not, be randomized

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And yet these are questions we care about

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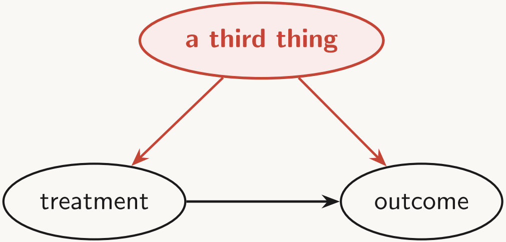
Two common ways it fails:

Confounding Selection

Confounding



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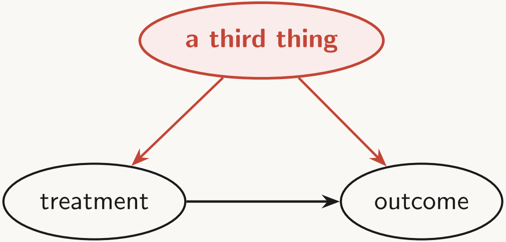
Confounding



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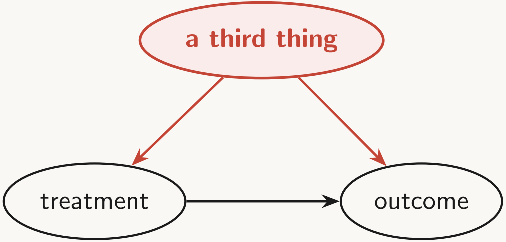

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Spot the confounder

News > Health

Wine drinkers may live longer than beer and spirit drinkers, study finds

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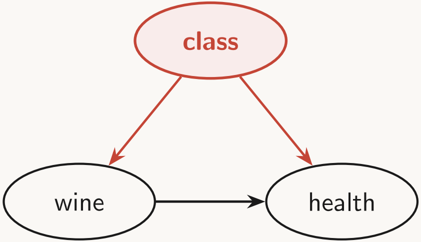

Wine drinkers may differ before the first glass.

Spot the confounder

Another Benefit to Going to Museums? You May Live Longer

Researchers in Britain found that people who go to museums, the theater and the opera were less likely to die in the study period than those who didn't.

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Who goes to museums?

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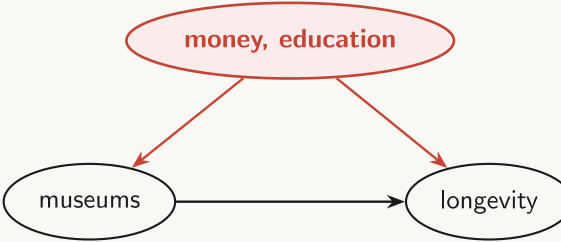
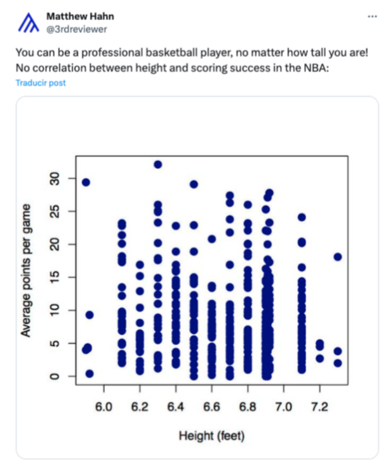
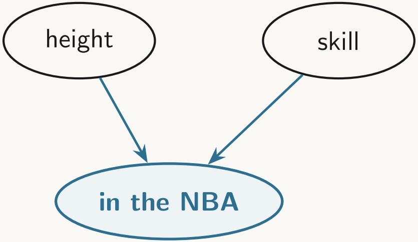


Museum-goers may differ before the visit.

Find the confounder



There is no confounder



Height and skill both help you get into the NBA.

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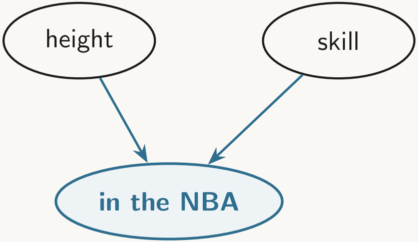

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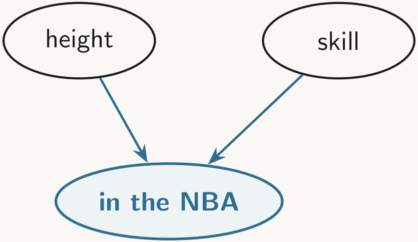

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Selection. Looking only at NBA players distorts the relationship between height and skill.

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The 1969 draft lottery drew birthdays at random.

Chance shifted who was likely to serve.

Angrist, Joshua D. 1990. "Lifetime Earnings and the Vietnam Era Draft Lottery: Evidence from Social Security Administrative Records." *American Economic Review* 80(3): 313–336.

Back to the teenagers and mental health

The ideal comparison is the same teenager in two worlds:

$$Y_i(\text{heavy use}) - Y_i(\text{light use})$$

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When is that comparison credible?

What could break the comparison?

Maybe heavy users were already different.

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- sleeping less

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Maybe heavy users were already different.

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- more isolated
- less supervised
- sleeping less
- using social media because they were already struggling

Keep your secrets

Causality is a comparison to a world we cannot observe.

Keep your secrets

Causality is a comparison to a world we cannot observe.

The work is making the comparison we *can* observe a credible stand-in for the one we cannot.

Thank you

Don't let the universe keeps its counterfactuals

https://carolina-torreblanca.github.io/