

A brief introduction to causal inference

Outline

Causal effects and where to find them

Spurious correlations

Simpson's paradox

Randomised Controlled Trials (RCTs)

Causal effects without RCTs - Adjustment

What if we don't have the graph? - Causal discovery

Instrumental variables

Prediction

Causal effects and where to find them

the effectiveness of a 'treatment' or 'intervention' on an outcome.

Seen in:

- Pharmaceuticals

- Economic policy

- Epidemiology/Public health policy

- Nutrition

- Product testing

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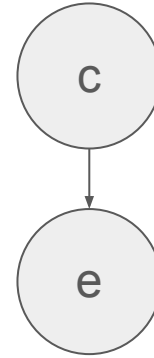
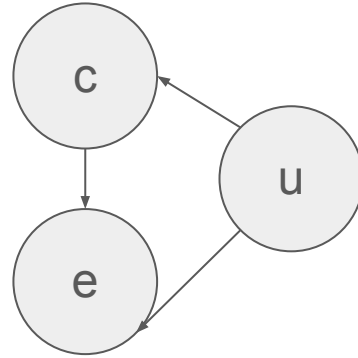
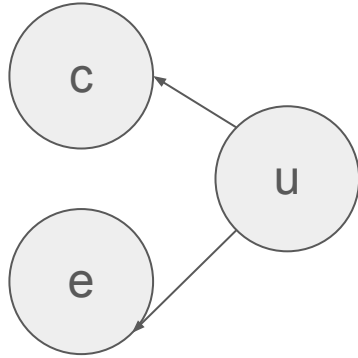
Prediction

Spurious correlations (and conclusions)

1. Mozzarella consumption per capita vs Civil engineering doctorates
2. Income vs marriage status
3. Fires vs. fire fighters

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Simpson's paradox - 1

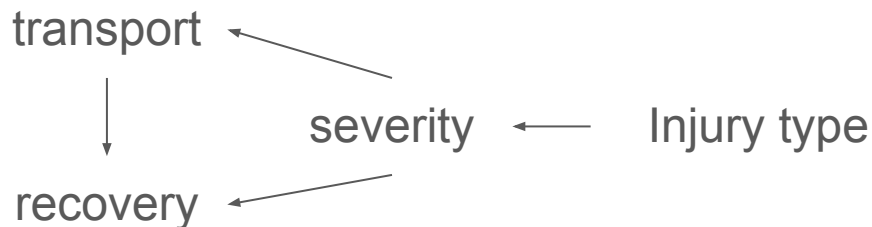
Does using an air ambulance improve chances of full recovery?

Injury type / Transport	Air Ambulance	Ambulance
Sport injury	$81/87 = 93\%$	$234/270 = 87\%$
Motor injury	$192/263 = 73\%$	$55/80 = 69\%$
Total	$273/350 = 78\%$	$289/350 = 83\%$

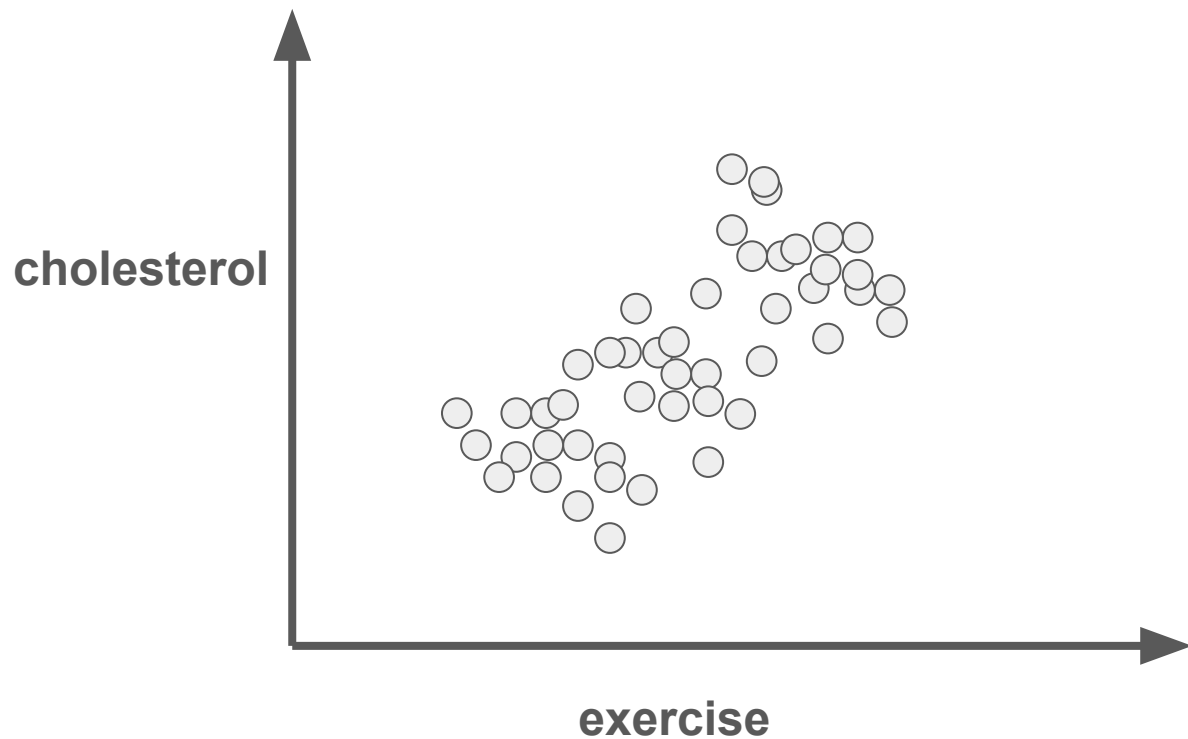
Simpson's paradox - 1

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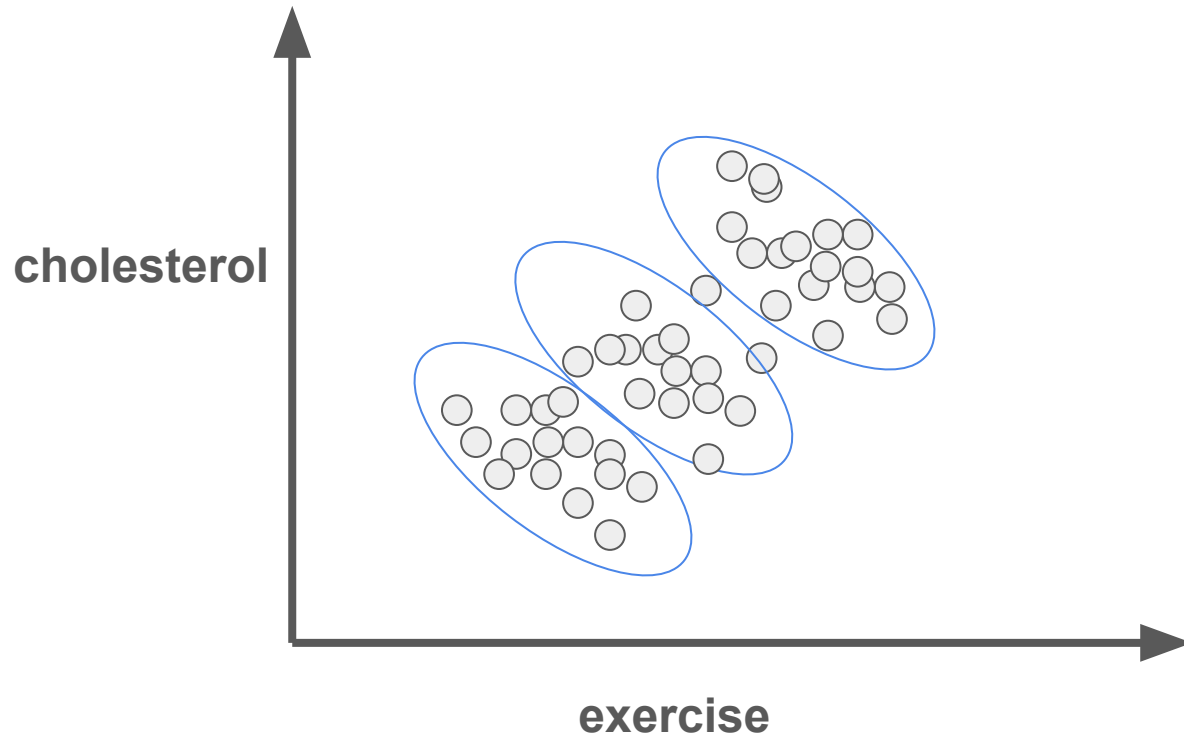
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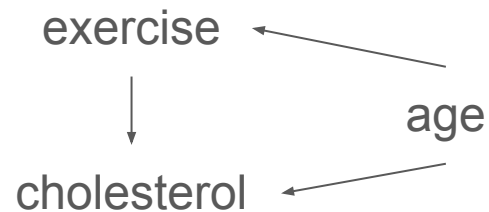
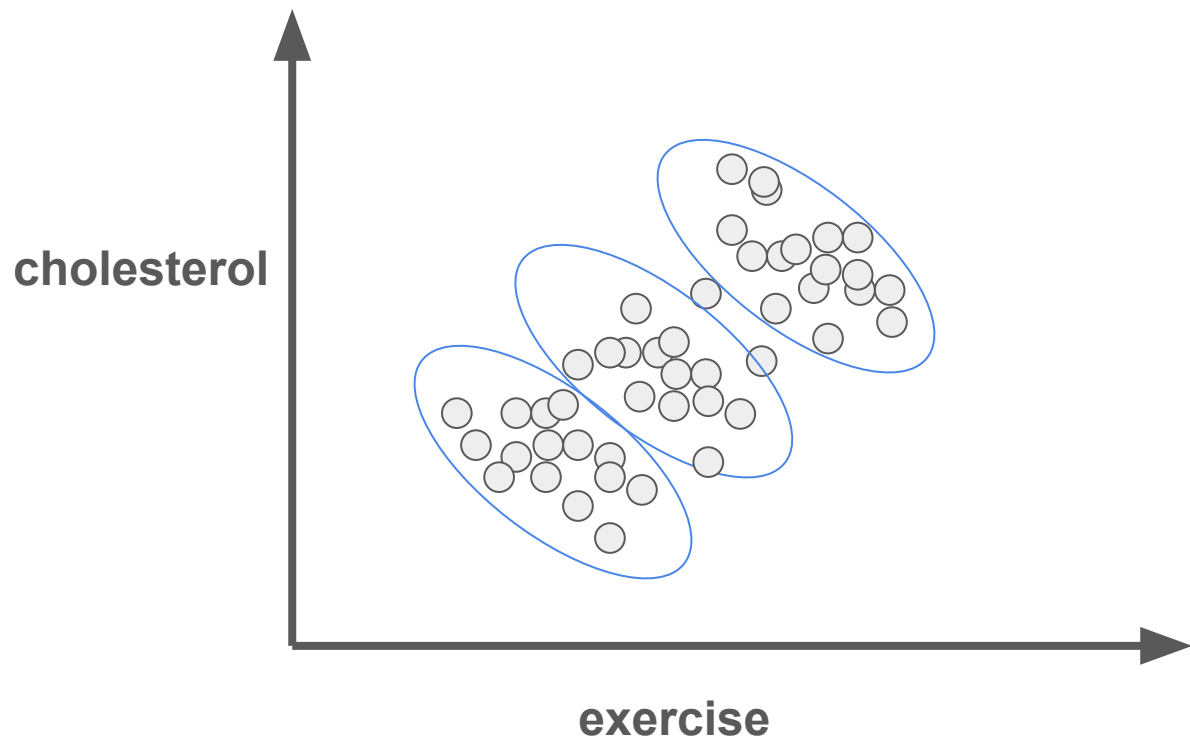
Simpson's paradox - 2



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Randomised controlled trials

Used to measure the effectiveness of an intervention on an outcome - i.e the causal effect.

“Solves the problem of observed and unobserved confounding”

1. Take a large sample from the population
2. Randomly assign the intervention to half of the sampled units
3. Compare the difference in the average outcomes of the two groups

RCTs - why does it give us the causal effect?

$$Y = \begin{cases} Y_1 & \text{if } I = 1 \\ Y_0 & \text{if } I = 0 \end{cases}$$

$$\mathbb{E}[Y_1 - Y_0] \quad (1)$$

$$\mathbb{E}[Y|I = 1] - \mathbb{E}[Y|I = 0] \quad (2)$$

$$= \mathbb{E}[Y_1|I = 1] - \mathbb{E}[Y_0|I = 0] \quad (3)$$

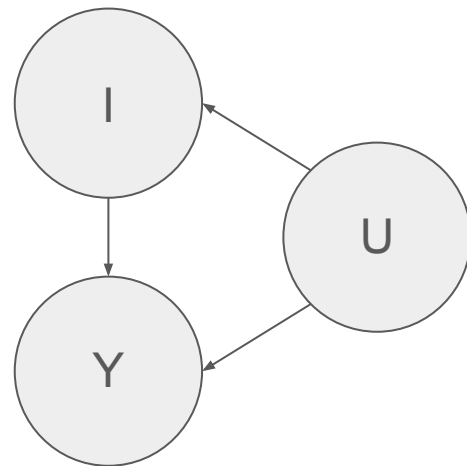
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Randomised controlled trials - the gold standard (?)

1. Population shift
2. Non-representative samples

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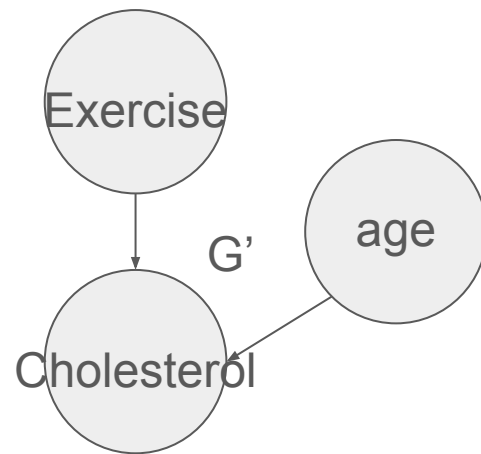
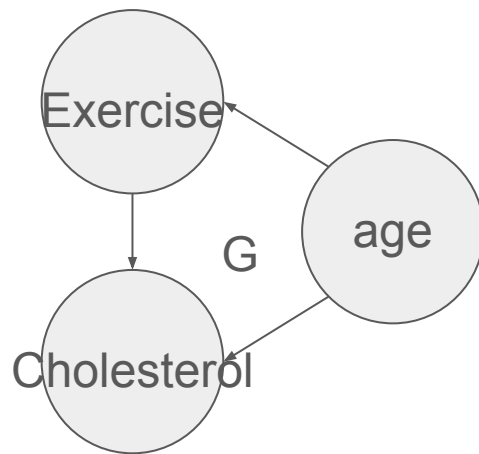
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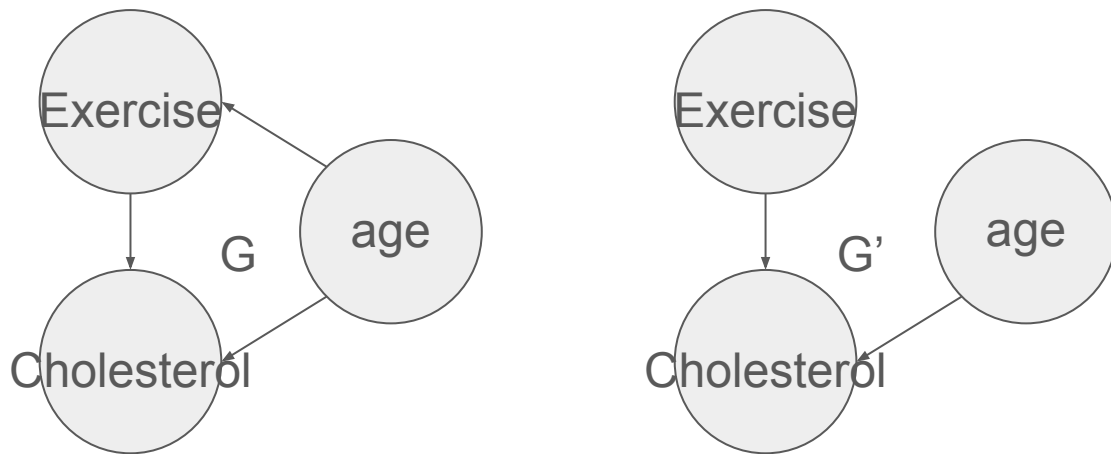
Causal effects without RCTs - Adjustment

If we have data that doesn't come from an RCT,
can we find the causal effect?

Causal effects without RCTs - Adjustment

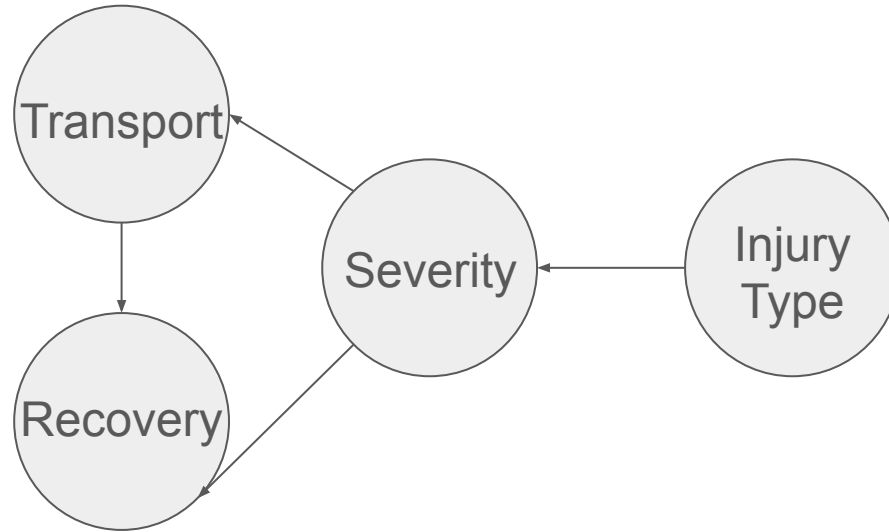


Causal effects without RCTs - Adjustment



$$\begin{aligned} Pr_{G'}(C|E) &= \sum_a Pr_{G'}(C|E, A) Pr_{G'}(A|E) \\ &= \sum_a Pr_{G'}(C|E, A) Pr_{G'}(A) \\ &= \sum_a Pr_G(C|E, A) Pr_G(A) \end{aligned}$$

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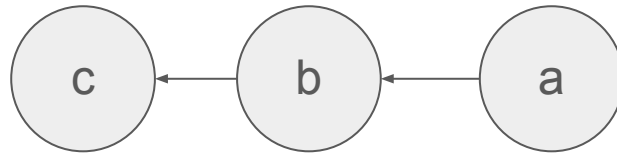
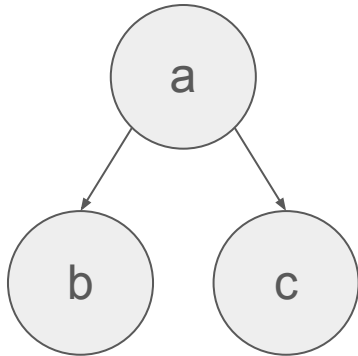
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Causal discovery

1. Given set of variables X_1, X_2, \dots, X_n
2. Start with the fully connected graph
3. Test independence between variables to remove some edges
4. Test conditional independence between variables to remove edges ...



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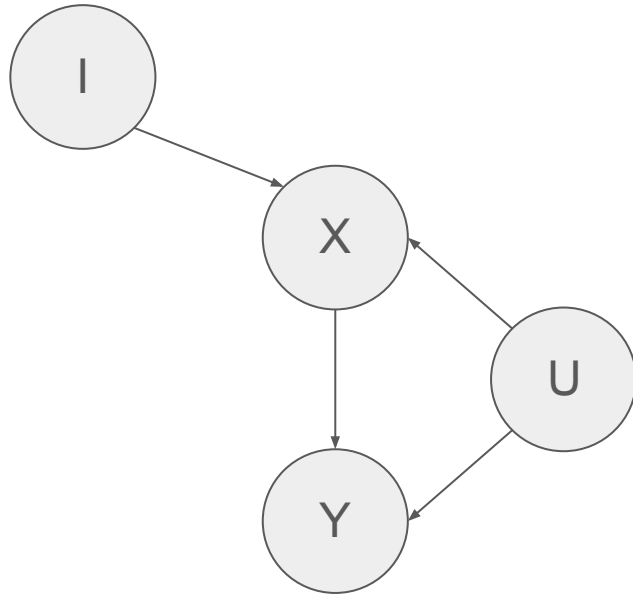
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Instrumental variables



1. The instrument (I) must influence X
2. The instrument (I) does not affect the outcome (Y) in any way other than through the intervention (X)
3. There is no common cause of the instrument (I) and the outcome (Y)

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Take care when using spurious variables for prediction

The causal variables should be robust under most interventions

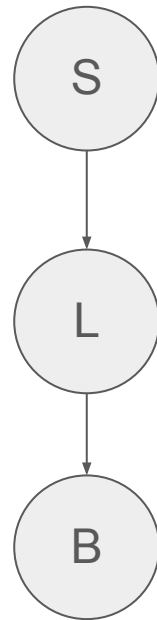
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