An introduction to causality

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Contents

What does ‘X caused Y’ mean?

How can we decide if ‘X caused Y’?

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Definitions of causality

'...*we may define a cause to be* an object, followed by another, and where all the objects similar to the first are followed by objects similar to the second. *Or in other words* where, **if the first object had not been, the second never had existed**.'

— D Hume (1748)

Definitions of causality

*'We think of a cause as **something that makes a difference**, and the difference it makes must be a **difference from what would have happened without it**. Had it been absent, its effects — some of them, at least, and usually all — would have been absent as well.'*

*— D Lewis (1973), J Phil **70**(17)*

What does 'X caused Y' mean?

Y is present

but

Y would not have been present if X were not present

Counterfactual approach to causality

Contribution, not attribution

- Interest is in figuring out the **effect of** X, not the cause of Y
- No notion that X is 'responsible' (i.e. the main or even the only reason) for Y
- Causes are not rivals: no point in 'apportioning' outcomes

✗	✓
What is the cause of Y?	How much does X affect Y?

Example: National Rifle Association

'Guns don't kill people, people kill people'

Questions

Take away...

- Guns
- People

...do you still have deaths from gunshot wounds?

Fundamental problem of causal inference

Causal effects are statements about differences between:

- What happened
- What **could have** happened

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…and so cannot be measured!

Potential outcomes

$Y_i(1)$

denotes the outcome for i observed under condition 1 (e.g. treatment)

$Y_i(0)$

denotes the outcome for i that would be observed, all else held constant, under condition 0 (e.g. control)

Causal effect

$$\tau_i = Y_i(1) - Y_i(0)$$

Example: usefulness of this course

Assume that...

X You take this course

Y You are hired as Principal Data Scientist

Questions

- What is the counterfactual?
- Can you conclude that X caused Y?

Average causal effects

We cannot conclude whether X caused Y in any given case, but...

Average causal effects

We cannot conclude whether X caused Y
in any given case, but...

We can still figure out if X causes Y **on average**

$$\mathbb{E}[\tau_i] = \mathbb{E}[Y_i(1) - Y_i(0)] = \mathbb{E}[Y_i(1)] - \mathbb{E}[Y_i(0)]$$

Average causal effects are not transitive

If $A \rightarrow B$ and $B \rightarrow C$ **on average**, does it follow that $A \rightarrow C$?

Average causal effects are not transitive

If $A \to B$ and $B \to C$ **on average**, does it follow that $A \to C$?

No!

To see why, imagine that...

- $A \to B$ for men only (so $A \to B$ **on average**)
- $B \to C$ for women only (so $B \to C$ **on average**)

...so there is no one for whom $A \to C$ through B!

Correlation is not causation

A correlation is a statement about relations between **actual outcomes**, not between actual and counterfactual outcomes

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Example

Taking cough syrup:

- Is **positively correlated** with coughing
- Has a **negative causal effect** on coughing (hopefully)

How can we decide if ‘X caused Y’?

There is no causation without manipulation…

…because we need to be able to think how things might look in different conditions

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Problems

- Some counterfactuals are not specified clearly: 'The recession was caused by bankers'
- Some cannot even be imagined: 'He got the job because he is a man'

How can we decide if ‘X caused Y’?

Try it and find out!

How can we decide if 'X caused Y'?

- Randomisation
- Natural experiments (as-if randomisation)
- Before/after comparisons
- Ex-post controlling:
    - Regression
    - Matching and weighting
    - Instrumental variables

Confounding variables

- Associated with both exposure and outcome
- May explain presumed causal relationships that have no direct causal connection

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Example
'Grey hair causes heart disease'