Causal Inference

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Why Should Social Scientists and Policymakers Care about Causality?

Counterfactual Approach to Causal Inference

Learning the Average Causal Effect from an Experiment

Randomized vs. observational studies

Why Should Social Scientists and Policymakers Care about Causality?

Why should social scientists and policymakers care about causality?

- Maybe you know the answer by now! Please let us know what you think :)

Counterfactual Approach to Causal Inference

Recent changes in social science research

- Historically, reverse causality and omitted variable bias have been problematic for a lot of social science research aimed at making causal claims.
- Recently, the counterfactual approach has been embraced in the social sciences as a framework for causal inference.
- This represents a big shift in research:
  - Being more precise about what we mean by causal effects.
  - Using randomization or designs with as-if randomization.
  - More partnerships between researchers and practitioners.

"X causes Y" is a claim about what didn't happen

- In the counterfactual approach: "If X had not occurred, then Y would not have occurred."
- Experiments help us learn about counterfactual and manipulation-based claims about causation.
- It's not wrong to *conceptualize* "cause" in another way. But it has been productive to work in this counterfactual framework (Brady 2008).

How to interpret “X causes Y” in this approach

1. “X causes Y” need not imply that W and V do not cause Y: X is a part of the story, not the whole story. (The whole story is not necessary in order to learn about whether X causes Y).
2. “X causes Y” requires a **context**: matches cause flame but require oxygen; small classrooms improve test scores but require experienced teachers and funding (Cartwright and Hardie 2012).
3. “X causes Y” can mean “With X, the probability of Y is higher than would be without X.” or “Without X there is no Y.” Either is compatible with the counterfactual idea.

How to interpret "X causes Y" in this approach

4. It is not necessary to know the mechanism to establish that X causes Y. The mechanism can be complex, and it can involve probability: X causes Y sometimes because of A and sometimes because of B.
5. Counterfactual causation does not require "a spatiotemporally continuous sequence of causal intermediates".
6. Correlation is not causation.

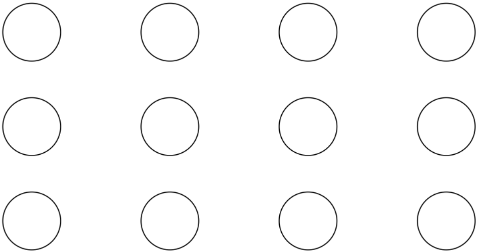
Exercise: Aspirin

- Your friend says taking aspirin reduces the duration of colds.
- If we take a counterfactual approach, what does this statement implicitly claim about the counterfactual? What other counterfactuals might be possible and why?

Learning the Average Causal Effect from an Experiment

EVIDENCE IN GOVERNANCE AND POLITICS

We have 12 units

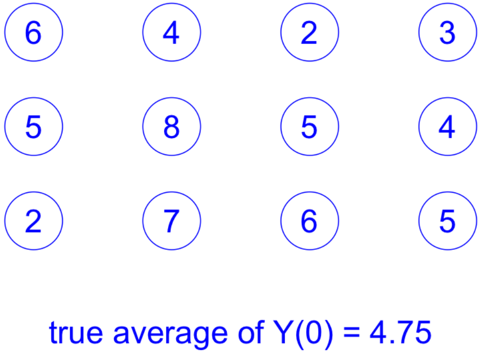


$Y_i(1)$, the outcome each unit would have if treated

7	5	3	3
5	8	6	5
3	7	6	5

true average of Y(1) = 5.25

$Y_i(0)$, the outcome each unit would have if not treated



Each unit has both $Y_i(1)$ and $Y_i(0)$

7	5	3	3
5	8	6	5
3	7	6	5

true average of Y(1) = 5.25

6	4	2	3
5	8	5	4
2	7	6	5

true average of Y(0) = 4.75

So each unit has a treatment effect $\tau_i = Y_i(1) - Y_i(0)$

1	1	1	0
0	0	1	1
1	0	0	0

true average treatment effect = 0.5

Potential outcomes

- For each unit we assume that there are two **post-treatment** outcomes: $Y_i(1)$ and $Y_i(0)$.
- $Y_i(1)$ is the outcome that **would** obtain **if** the unit received the treatment ($T_i = 1$).
- $Y_i(0)$ is the outcome that **would** obtain **if** the unit received the control ($T_i = 0$).

Fundamental problem of causal inference

- We can't measure the individual-level causal effect, because we can't observe both $Y_i(1)$ and $Y_i(0)$ at the same time.
- But not all is lost.
- We can estimate the **average treatment effect** with a randomized experiment.

$$\overline{\tau_i} = \frac{1}{N}\sum_{i=1}^{N}(Y_i(1) - Y_i(0)) = \overline{Y_i(1) - Y_i(0)}$$

Estimands and causal questions

- Note that the ATE is only **one type of estimand**.
- An estimand is a quantity you want to learn about (from your data). It's the target of your research that *you* set.
- Being precise about your research question means being precise about your estimand. For causal questions, this means specifying:
  - The outcome
  - The treatment and control conditions
  - The study population
- Say $T = 1$ means a community meeting to discuss public health. Is $T = 0$ no meeting at all? Is $T = 0$ a community meeting on a different subject? Is $T = 0$ a flyer on public health?
- The phrase "causal effect of T on Y'' doesn't make sense without knowing what is means to not have T.

Other types of estimands you may be interested in

- The ATE for a particular subgroup, aka conditional average treatment effect (CATE)
- Differences in CATEs: differences in the average treatment effect for one group as compared with another group.
- The ATE for just the treated units, aka ATT (average treatment effect on the treated)
- The local ATE (LATE). "Local" = those whose treatment status would be changed by an encouragement in an encouragement design (aka CACE, complier average causal effect) or those in the neighborhood of a discontinuity for a regression discontinuity design.
- Estimands will be discussed in detail in the next sessions.

Randomization of Treatment Assignment

- Randomization means that every observation has a known probability of assignment to experimental conditions *between* 0 and 1.
  - No unit in the experimental sample is assigned to treatment with certainty (probability $= 1$) or to control with certainty (probability $= 0$).
- Units can vary in their probability of treatment assignment.
  - For example, the probability might vary by group: women might have a 25% probability of being assigned to treatment while men have a different probability.
  - It can even vary across individuals, though that would complicate your analysis.

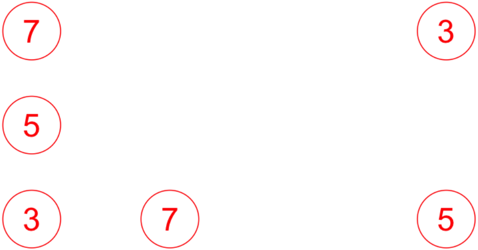
Random assignment vs. random sampling

- Randomization (of treatment): assigning subjects with known probability to experimental conditions.
  - This random assignment of treatment can be combined with any kind of sample (random sample, convenience sample, etc.).
  - But the size and other characteristics of your sample will affect your power and your ability to extrapolate from your finding to other populations.
- Random sampling (from population): selecting subjects into your sample from a population with known probability.

Let's go back to the $Y_i(1)$

7	5	3	3
5	8	6	5
3	7	6	5

We can take a random sample of these $Y_i(1)$

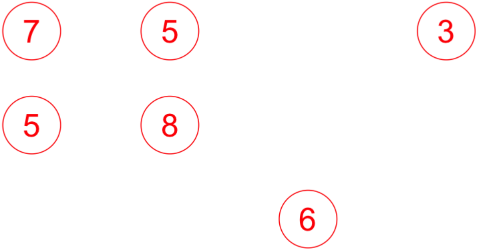


average Y(1) of sample #1 = 5

We can take another random sample of these $Y_i(1)$

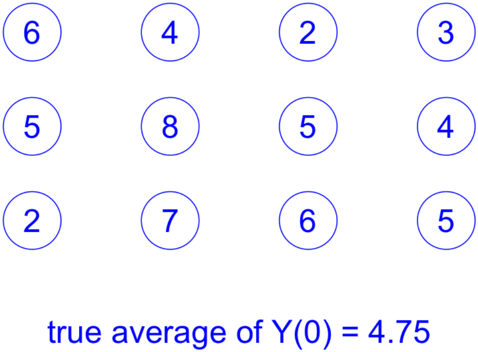
average Y(1) of sample #2 = 5.5

And another!

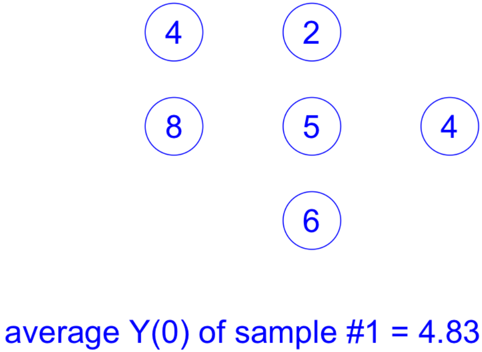


average Y(1) of sample #3 = 5.67

Let's get back to the $Y_i(0)$



And we can take a random sample of these $Y_i(0)$

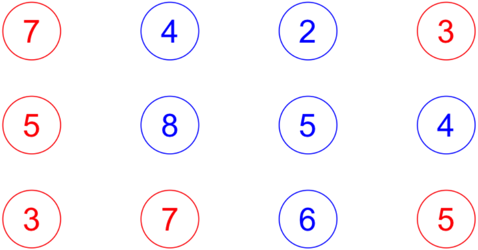


A random assignment

average Y(1) of sample #1 = 5

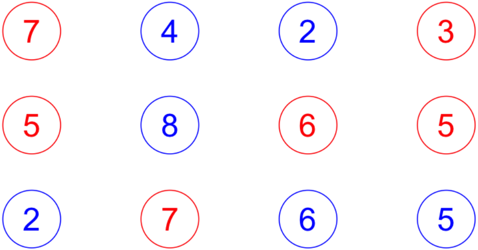
average Y(0) of sample #1 = 4.83

Put them together



5 - 4.83 = 0.17

A different random assignment



$$5.5 - 4.5 = 1$$

Randomization is powerful

- We want the ATE, $\overline{\tau_i} = \overline{Y_i(1) - Y_i(0)}$.
- We will make use of the fact that the average of differences equals the difference of averages:

$$\text{ATE} = \overline{Y_i(1) - Y_i(0)} = \overline{Y_i(1)} - \overline{Y_i(0)}$$

Three key assumptions

To make causal claims with an experiment (or to judge whether we believe a study's claims), we need three core assumptions:

- Random assignment of subjects to treatment, which implies that receiving the treatment is statistically independent of subjects' potential outcomes.
- Stable unit treatment value assumption (SUTVA).
- Excludability, which means that a subject's potential outcomes respond only to the defined treatment, not other extraneous factors that may be correlated with treatment.

Key assumption: SUTVA, part 1

1. No interference – A subject's potential outcome reflects only whether that subject receives the treatment himself/herself. It is not affected by how treatments happen to be allocated to other subjects.
   - A classic violation is the case of vaccines and their spillover effects.
   - Say I am in the control condition (no vaccine). If whether I get sick ($Y_i(0)$) depends on other people's treatment status (whether they take the vaccine), it's like I have two different $Y_i(0)$!
   - SUTVA (= stable unit treatment value assumption)

Key assumption: SUTVA, part 2

2. No hidden variations of the treatment

    - Say treatment is taking a vaccine, but there are two kinds of vaccines and they have different ingredients.
    - An example of a violation is when whether I get sick when I take the vaccine ($Y_i(1)$) depends on which vaccine I got. We would have two different $Y_i(1)$!

Key assumption: Excludability

- Treatment assignment has no effect on outcomes except through its effect on whether treatment was received.
  - Important to define the treatment precisely.
  - Important to also maintain symmetry between treatment and control groups (e.g., through blinding, having the same data collection procedures for all study subjects, etc.), so that treatment assignment only affects the treatment received, not other things like interactions with researchers that you don't want to define as part of the treatment.

Randomization is powerful (4)

- If the intervention is randomized, then who receives or doesn't receive the intervention is not related to the characteristics of the potential recipients.
- Randomization makes those who were randomly selected to not receive the intervention to be good stand-ins for the counterfactuals for those who were randomly selected to receive the treatment, and vice versa.
- We have to worry about this if the intervention were not randomized (= an observational study).

Randomized vs. observational studies

Different types of studies

- Randomized studies
  - Randomize treatment, then go measure outcomes
- Observational studies
  - Treatment is not randomly assigned. It is observed, but not manipulated.

Generalizability and external validity

- Randomization brings high internal validity to a study – confidence that we have learned the causal effect of a treatment on an outcome.
- But the finding from a particular study in one particular place and at one particular time may not hold in other settings (i.e., external validity).
- This is a general concern, not just a concern for randomized studies.
- EGAP's Metaketa Initiative works to accumulate knowledge by pre-planning a meta-analysis of multiple studies that have high internal validity due to randomization.

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