Causal Inference

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Randomized experiments

How can we learn the average causal effect from an experiment?

Randomized experiments vs observational studies

Randomized experiments

Review: Core elements of a randomized experiment

- You have a treatment.
- *You randomly assign treatment to units.*
- You compare the outcomes for the units that were assigned to treatment to outcomes for those that were not.

What can you learn from an experiment?

The *average causal effect* of the treatment T on an outcome Y for the units that you have in your study.

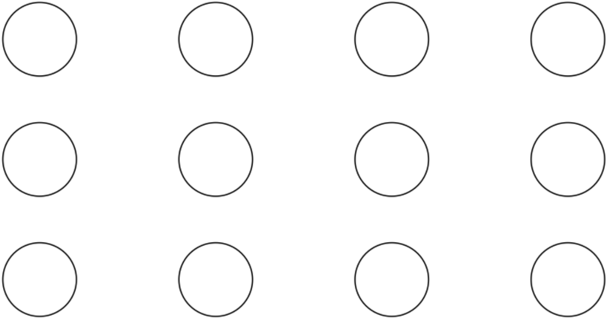
- You have to clearly define what the treatment means and what it means to not have the treatment.
- The units in your study might or might not be representative of a larger population.

What do we mean by "T causes Y"?

- We're going to take the counterfactual approach.
- "T causes Y" is a claim about what didn't happen.
  - "If T had not occurred, then Y would not have occurred."
  - "With T, the probability of Y is higher than would be without T."
- "T causes Y" requires a *context*
  - Matches cause flame but require oxygen.
  - Small classrooms improve test scores but require experienced teachers and funding.
- "T causes Y" doesn't mean "W does not cause Y."

How can we learn the average causal effect from an experiment?

We have 12 units

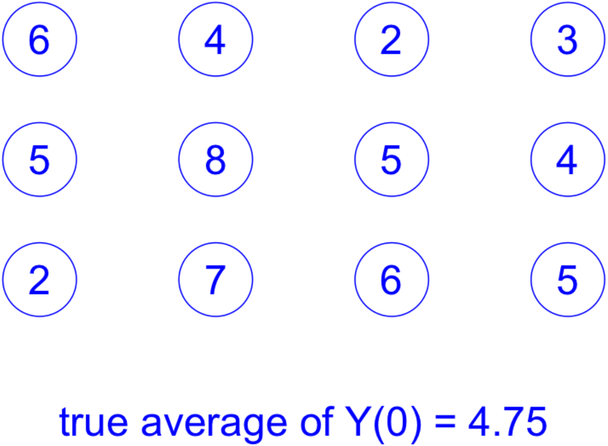


$Y_i(1)$, the outcome each unit would have if treated

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 $Y_i(0)$

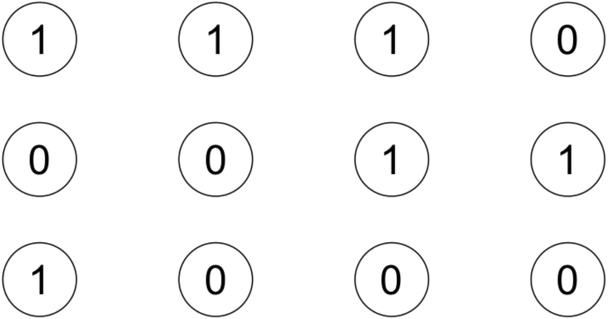
7	5	3	3
5	8	6	5
3	7	6	5

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



true average treatment effect = 0.5

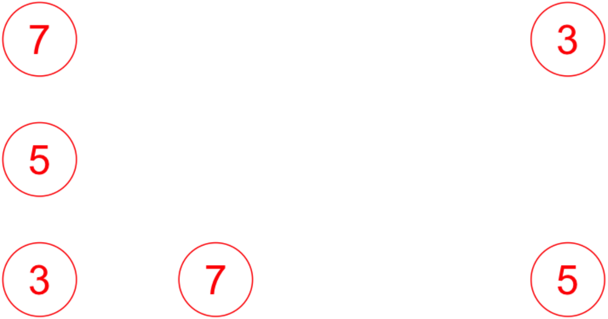
The *causal effect* of treatment is $\tau_i = Y_i(1) - Y_i(0)$

1. Each individual unit i has its own causal effect τ_i.
2. But 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. This is known as the *fundamental problem of causal inference*.

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 $Y_i(1)$

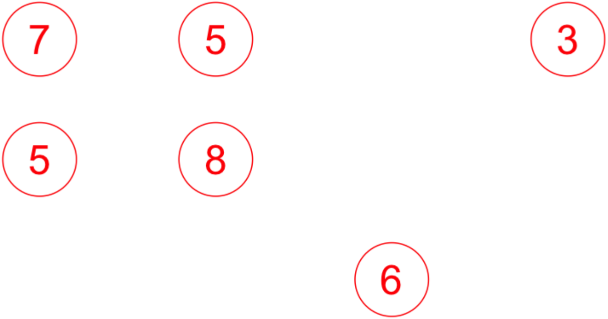


average Y(1) of sample #1 = 5

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

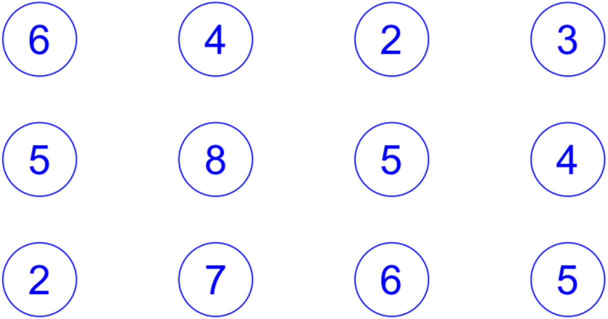
average Y(1) of sample #2 = 5.5

And another!



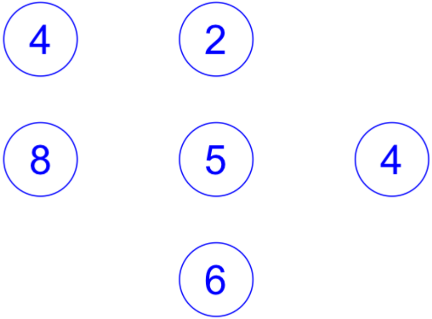
average Y(1) of sample #3 = 5.67

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



true average of Y(0) = 4.75

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



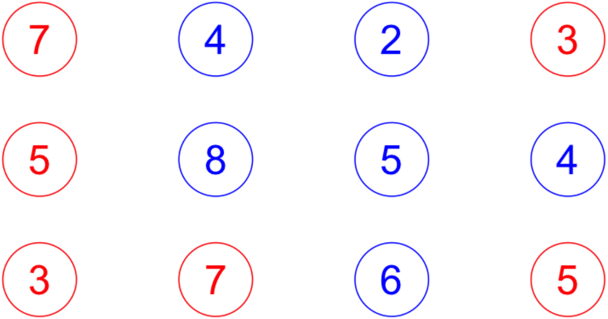
average Y(0) of sample #1 = 4.83

A random assignment

average Y(1) of sample #1 = 5

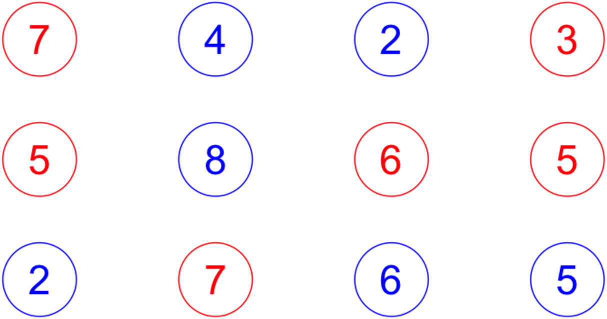
average Y(0) of sample #1 = 4.83

Put them together



5 - 4.83 = 0.17

A different random assignment



5.5 - 4.5 = 1

Randomization is powerful

- Randomization creates groups that are similar except that one will receive the treatment and the other will not.
- So when we compare the two groups after one has received treatment, we can attribute the difference to (1) the effect of the treatment and (2) chance.
- Without randomization, it's hard to tell whether differences in the outcome are due to (1) treatment or (2) some other factor correlated with it.

Let's be more precise about randomization

- It doesn't mean haphazard or having no control!
- 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 $= 0$).

Core assumptions

We need to make sure we don't violate two core assumptions behind our theoretical infrastructure as we design our randomized experiments:

- Excludability.
- Stable unit treatment value assumption (SUTVA).

Core assumption 1: 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 $Y_i(0)$!

Core assumption 1: 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 take. We would have two different $Y_i(1)$!

Core assumption 2: Excludability

- Treatment assignment has no effect on outcomes except through its effect on whether treatment was received.
  - Important to define receiving treatment precisely.
  - Treatment and control groups should be treated the same, except for the actual treatment.

Randomized experiments vs observational studies

Different types of studies

- Randomized studies
  - Randomize treatment, then go measure outcomes.
  - We can attribute differences in outcomes to the treatment (plus noise).
- Observational studies
  - Treatment is not randomly assigned. It is observed, but not manipulated.
  - Differences might be due to underlying differences (selection bias) or the treatment (plus noise). It's often very hard to tell.

What is the advantage of randomization?

- If the intervention is randomized, then who receives or doesn't receive the intervention is not related to the characteristics of the potential recipients.
- With randomization, those who were randomly selected to not receive the intervention are good stand-ins for the counterfactuals for those who were randomly selected to receive the treatment, and vice versa.
- This is not assured in observational studies.

Internal validity

- Randomized studies have high internal validity – confidence that we have learned the causal effect of a treatment on an outcome.
- An advantage over observational studies that have to invoke other strong assumptions to make the same claim.

Generalizability

- The finding from a particular study in one particular place and at one particular time may not hold in other settings (i.e., not have external validity).
- This is a general concern for observational studies as well, 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.