Introducing Counterfactual Causal Inference

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Some causal questions asked by some EGAP members

1. Did a new Hausa television station in northern Nigeria change attitudes about violence, the role of women in society, or the role of youth in society?
2. Does empowering voters with information about the performance of their elected officials improve accountability?
3. Does watching candidate debates increase viewer's knowledge, interest, and participation in politics and change which candidate they support?

What do we mean by "cause"?

When someone says "X causes Y" they might mean:

Persistent association (correlation) "We always/mostly see $Y = 1$ when $X = 1$ and see $Y = 0$ when $X = 0$."

Difference-Making "When we change X from one value to another value, then Y changes from one value to another value."

There are also other approaches to causation.

This week, we're going to focus on the difference-making or **counterfactual** approach because this framework has been incredibly useful for empirical research.

What do we mean by "cause"?

A cause is "something that makes a difference, and the difference it makes must be a difference from what would have happened without it" (David Lewis).

Potential outcomes framework:

- Outcome for unit i if treated is $Y_i(1)$
- Outcome for unit i if control is $Y_i(0)$
- Treatment effect for unit i is $\tau_i = Y_i(1) - Y_i(0)$

What this counterfactual approach means/doesn't mean for causal claims

1. This is about contribution of X to Y, not attribution.
   - We focus on what is the effect of X on Y, not what caused Y.
2. X can be a cause of Y, without being necessary nor sufficient.
   - We can think of cause probabilistically or as conditional on some other condition Z.
3. This is not about "actual" cause, which is difficult to define.
   - A boy and a girl each throw a stone at a glass window. The girl's stone hits the window and breaks it. The boy's stone would have broken the window if the glass were still there.
4. In this approach, knowing that A causes B and B causes C doesn't mean that A causes C.
   - A = boulder coming towards you. B = ducking. C = surviving.
5. We need treatments that we can imagine being manipulated.
   - Difficult to conceptualize the "effect" of gender.

Fundamental problem of causal inference (Holland)

We can't observe $Y_i(1)$ and $Y_i(0)$ at the same time!

So we can't measure the individual causal effect τ_i.

HOWEVER we can estimate average causal effects

This is because:

1. the average of the differences is the same as the difference of the averages:
   average treatment effect (ATE)
   $\tau = E[\tau_i] = E[Y_i(1) - Y_i(0)] = E[Y_i(1)] - E[Y_i(0)]$

2. and we can estimate $E[Y_i(1)]$ and $E[Y_i(0)]$.

The ATE is just one type of estimand (something we want to estimate).

Random assignment of treatment is a powerful way to estimate $E[Y_i(1)]$ and $E[Y_i(0)]$

We can estimate an average of a quantity by taking the average value from a random sample of units.

1. Randomly assigning some units to treatment means we get a random sample of $Y(1)$.
2. It also means randomly assigning the other units to control.
3. This means that we get a random sample of $Y(0)$.
4. We calculate the average of each random sample and then take the difference.

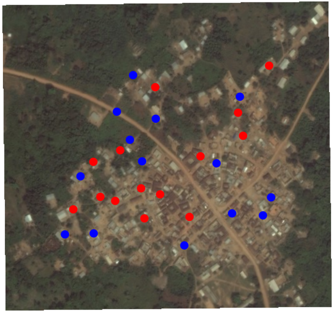
Our random sample

We have a random sample of n households from a community in the Central Region of Ghana.

Potential Outcomes

Each household $i = 1, 2, ..., n$ has a $Y_i(1)$ and $Y_i(0)$.

Random Assignment of Treatment



Random assignment of treatment (red or blue) means we're drawing a random sample from these $Y_i(1)$ and $Y_i(0)$.

Random Assignment of Treatment

Random assignment of treatment (red or blue) means we're drawing a random sample from these $\color{red}{Y_i(1)}$ and $\color{blue}{Y_i(0)}$.

Exercise 1

Unit	$Y_i(1)$	$Y_i(0)$	τ_i
A	1	1	
B	4	1	
C	5	2	
D	3	3	
E	3	1	
F	5	1	

1. Calculate the unit-level treatment effect for each unit.
2. Calculate the true average treatment effect.
3. Imagine that all units have equal probability of being assigned to treatment. In this particular case, A, B, and C were assigned to treatment, and we only observe the potential outcome corresponding to the assigned treatment. Estimate the average treatment effect.

Some subtleties

1. Random assignment doesn't guarantee that the treatment group and the control group will look identical. We're using the fact that the average outcome in a random sample is an unbiased estimate of the average outcome in the population.
   - What if only one person were assigned to treatment?
2. If treatment is randomly assigned to subjects, but without equal probabilities, we have to be careful to calculate weighted averages.
   - This also means if we don't know the probability of treatment assignment, then it's not clear what we're calculating.
3. Random assignment also gives us a basis for characterizing the uncertainty of our conclusions. More on this coming up tomorrow.

Why not just look at correlations?

A correlation between A and B is a statement about the relationship between observed outcomes, not potential outcomes.

A couple examples:

1. A = carrying cough drops. B = coughing.
2. A = years of education. B = income.

Correlation reflects some combination of the treatment effect and selection bias.

Exercise 2

In small groups, take a causal question and sketch out (a) an ideal observational study, with no randomized treatment, and (b) an ideal experimental study, where you do randomize the treatment.

Think ahead: What questions would critical readers ask when you claim that your results reflect a causal relationship?

Three Core Assumptions

Random assignment of subjects to treatment Receiving treatment is statistically independent of subjects' potential outcomes.

Non-interference Subject's potential outcome reflects only whether that subject receives the treatment him/herself. Not affected by how treatments happen to be allocated (to a neighbor..)

Excludability Subject's potential outcome responds only to the defined treatment, not to other factors correlated with treatment. Need symmetry between treated and control groups.

Estimands

The ATE is an example of an estimand (something we want to estimate). Other estimands you might be interested in:

- ATE for the treated (ATT)
- ATE for the control (ATC)
- Conditional ATE (CATE)
- Local ATE (LATE)

What makes a good causal question?

1. Helps make a decision
2. Contributes to an accumulation of knowledge
3. An important outcome
4. A manipulable treatment that specifies the counterfactual condition (what does being in the control condition mean?)
5. A population of interest
6. An estimand (a specific causal effect we want to learn)
7. Others?

The research design is our strategy for estimating the estimand. It will include an estimator (the procedure we apply to our data to produce an estimate).