Foundations of causality | R

Agenda

- Revisiting lecture
  - Causality
  - Potential Outcomes Framework
  - NATE and biases

- Getting started with R
  - Data-wrangling with `dplyr`

Causal Inference

The *reasoning* process of

- ruling out non-causal explanations of the observed association
- pointing out the assumptions necessary to rule out such sources

plus

- providing evidence to support or refute these assumptions

Potential Outcomes Framework

Key concept: Every individual has a potential outcome (Y_i) both under treatment and under control (no treatment).

The difference between these states for an individual is the (ITE)

The fundamental problem of causal inference: we can only ever observe one of these states.

Potential Outcomes Framework

Key concept: Every individual has a potential outcome (Y_i) both under treatment and under control (no treatment).

The difference between these states for an individual is the (ITE)

The fundamental problem of causal inference: we can only ever observe one of these states.

So, we cannot observe the individual treatment effect (ITE), nor directly observe the average treatment effect (ATE).

POF Notation

NATE $= E[y_{1i}|d_i = 1] - E[y_{0i}|d_i = 0]$

"The expected outcome when treated, for those in the treatment group"

$E[y_{0,i}]$ / $E[y_{0,i}]$ "expected outcomes"

$y_{0,i}$ / $y_{1,i}$ "potential outcomes"

POF Logic

ATE $= E[y_{1i} - y_{0i}] = E[y_{1i}] - E[y_{0i}]$

ATT $= E[y_{1i}|d_i = 1] - E[y_{0i}|d_i = 1]$

ATC $= E[y_{1i}|d_i = 0] - E[y_{0i}|d_i = 0]$

Unattainable: we cannot observe counterfactuals.

NATE $= E[y_{1i}|d_i = 1] - E[y_{0i}|d_i = 0]$

Example

- Contact hypothesis (Allport, 1954)

Inter-group contact (X) $\longrightarrow$ Prejudice (Y)

Each individual *i* in a student sample is exposed (di = 1) to the cause, or not exposed (di = 0) (here: contact with member of different ethnic group).

$y_{0,i}$ = non-exposure $y_{1,i}$ = exposure

Example

Student (i)	Prejudice			Contact
	y_{0i}	y_{1i}	δ_i	
1	6	5	-1	0
2	4	2	-2	1
3	4	4	0	0
4	6	7	1	0
5	3	1	-2	1
6	2	2	0	1
7	8	7	-1	0
8	4	5	1	0

- Contact hypothesis (Allport, 1954)

In our example, we have eight students who were either in contact, or not, with members of other ethnic groups.

We also have information of their potential outcomes under each state.

$y_{0,i}$ = non-exposure $y_{1,i}$ = exposure

ATE, ATT, ATC

If we could observe counterfactuals…

Student (i)	Prejudice y_{0i}	y_{1i}	δ_i	Contact
1	6	5	-1	0
2	4	2	-2	1
3	4	4	0	0
4	6	7	1	0
5	3	1	-2	1
6	2	2	0	1
7	8	7	-1	0
8	4	5	1	0

→

…we could know:

$$ATE = E[\delta_i] = \frac{-1 + (-2) + 0 + 1 + (-2) + 0 + (-1) + 1}{8} = -0.5 \quad (5)$$

$$ATT = \frac{-2 + (-2) + 0}{3} = -1.333$$

$$ATC = \frac{-1 + 0 + 1 + (-1) + 1}{5} = 0$$

NATE

We can only observe half of the potential outcomes we need to get to the ATE…

Student (i)	Prejudice			Contact
	y_{0i}	y_{1i}	δ_i	
1	6			0
2		2		1
3	4			0
4	6			0
5		1		1
6		2		1
7	8			0
8	4			0

Information we *do* have

…so we can only calculate a naïve average treatment effect.

$$
\begin{aligned}
NATE &= E[y_{1i}|d_i = 1] - E[y_{0i}|d_i = 0] \\
&= \frac{2+1+2}{3} - \frac{6+4+6+8+4}{5} \\
&= 1.666 - 5.6 \\
&= -3.933
\end{aligned}
$$

NATE and biases

Student (i)	Prejudice y_{0i}	y_{1i}	δ_i	Contact
1	6			0
2		2		1
3	4			0
4	6			0
5		1		1
6		2		1
7	8			0
8	4			0

Information we *do* have

The treated and untreated groups may differ in more ways than just being treated or not and, therefore, have different potential outcomes.

$$NATE = ATE + \underbrace{E[Y_0|D=1] - E[Y_0|D=0]}_{\text{selection bias}} + \underbrace{(1-p)(ATT - ATU)}_{\text{HTE bias}}$$

baseline bias

heterogeneous / differential treatment effect bias

NATE and biases

$$NATE = ATE + \underbrace{E[Y_0|D=1] - E[Y_0|D=0]}_{\text{Baseline bias}} + \underbrace{(1-p)(ATT - ATU)}_{\text{Differential treatment effect}}$$

Baseline bias: difference in average outcome without treatment for the treatment and control groups.

Differential treatment effect bias: the difference in the average treatment effect between the treatment and control groups, weighted by the proportion of the population in the control group.

Tackling biases

Randomization: randomly assigning subjects to D=0 or D=1.

- The probability of being assigned to treatment is the same for all subjects.
- Being assigned to treatment does not depend of any characteristic of the subjects.
- The treatment and control groups have (on average) the same potential outcomes

- Key point: *when using random assignment* (and the SUTVA holds), then ATE = NATE

$$ATE = E[Y_{1i}] - E[Y_{0i}] \longrightarrow ATE = E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0]$$

Picking up the lecture discussion again…

You are part of the newly established EU Policy Impact Evaluation Unit.

- **Your mission** is to evaluate a brand new policy that allocates funds to EU regions to combat climate change by fostering green energy, industry, housing, etc.
- To qualify for the funding regions have to be above 125% of the EU average of CO2 emissions per capita.
- **You are given full control** in the pilot phase (i.e., you alone can decide how funds are allocated).
- **What design do you propose** to evaluate the impact of the policy on CO2 emission reduction at the regions level?

Coding with `dplyr`

We'll often use the pipe operator (`%>%`) to string together commands, and rely on the `dplyr` "verbs". For example:

`select`: subset columns
`filter`: subset rows
`arrange`: reorder rows
`mutate`: add columns to existing data
`summarize`: summarize values in the dataset
`group_by`: defines groups within dataset

Further Resources

R basics: https://tinyurl.com/vkebh2f

RMarkdown: The definitve guide https://tinyurl.com/y4tyfqmg

Dplyr: https://tinyurl.com/vyrv596

Dplyr video tutorial: https://www.youtube.com/watch?v=jWjqLW-u3hc

Summary of lab materials – Lab homepage

For any coding issues – Stackoverflow

Hertie's Data Science Lab – Research Consulting