

Statistics II

Week 2: **Foundations**

The potential outcomes framework and experiments

Content for today

1. Review of core concepts from lecture
2. R refresher
3. Calculating NATE, ATT, ATU and ATE with in R using `dplyr`

Lecture Review

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

Remember these to make sense of every method we will see in the class.

Potential Outcomes Framework

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

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**).

But we can understand them theoretically...

Getting familiar with POF notation

- Don't panic. Don't avoid the equations.
- Break down the equation into parts.
- Practice reading them *in English*.

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


The diagram illustrates the components of the NATE equation. A red arrow points from the first term $E[y_{1i}|d_i = 1]$ to the text 'The expected outcome when treated'. A purple arrow points from the variable y_{1i} to the word 'treated'. A green arrow points from the second term $E[y_{0i}|d_i = 0]$ to the phrase 'for those in the treatment group'.

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

Key definitions (in POF notation)

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

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

$$\text{ATU} = E[\underline{y_{1i}|d_i = 0}] - E[y_{0i}|d_i = 0]$$

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

Unattainable: we cannot observe
counterfactuals.

ATE, ATT, ATU

If we could observe counterfactuals...

...we could know:

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



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

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

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

NATE

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

Student (<i>i</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.

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

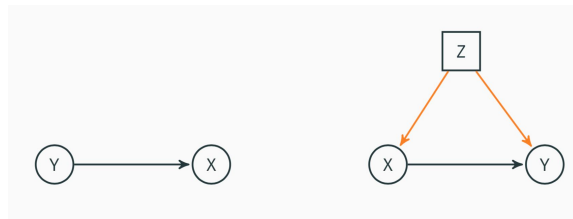
NATE and biases

Student (i)	Prejudice		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

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

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



Estimating Bias

Total bias of NATE = $\text{NATE} - \text{ATE}$

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

Heterogeneous 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 the **same potential outcomes** (average)

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

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

Because, when randomly assigned, the expected outcomes of each group are the same as those of the entire population.

Questions?