Day 02: Basics of experimental design

Erin Rossiter

January 18, 2022

Today's plan

1. Tidy up
   - Peitong, will you:
     - » remind me to take a break at 4:30
     - » jot notes on typos & email after class
   - Questions on syllabus, homework logistics, etc.
   - More Github skills
2. Lecture
3. Lab
   - Reinforce new concepts

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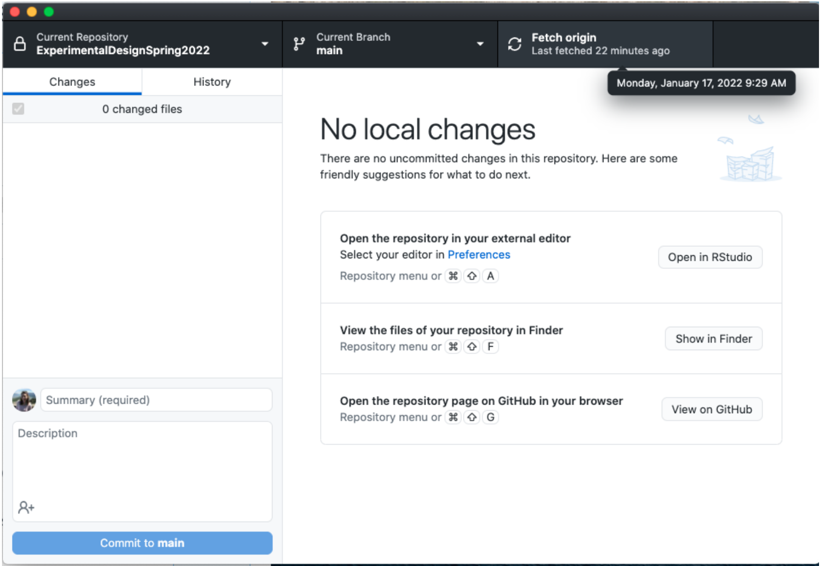
GitHub

Grabbing my changes

- "Fetch origin" – Grab changes to the repo that I've made
- Check that they appear locally for you (Day02, HW1, etc.)



Workflow

1. Fetch any changes I might have made (If needed, like before class)
2. Each time you sit down to work:
   - Make edits locally
   - Commit changes
   - Repeat...
3. Push online (when you want me/classmates to be able to see)

We'll try later with the lab

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- We're interested in testing causal questions
- **Causal effect** difference in outcome(s) *caused by* an intervention.
  - Compares units under two hypothetical situations: when they take an intervention and when they go without it (i.e., **counterfactuals**)
- Potential outcomes are a **formal way to discuss counterfactuals**
  - Remember, you must use your imagination!

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Notation recap

- Finite population of units: $i \in 1, 2, ...N$
- Observed outcomes: Y_i
- Binary treatment:
  - $D_i = 1$ if unit i is treated
  - $D_i = 0$ if unit i is untreated (control)
  - (note this D_i a random variable; unit might be treated in a hypothetical study or not)
- Potential outcomes:
  - $Y_i(d_i)$ is the potential outcome for unit i, so:
    - $Y_i(1)$ is the outcome if unit i is exposed to treatment
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  - Both versions of history
    - what would happen if a treatment were or were not administered
- For each unit, we want to know the causal effect of treatment
  - $\tau_i = Y_i(1) - Y_i(0)$
- **Fundamental problem of causal inference: we can only observe one potential outcome**

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Treatment effects

- We can't observe *both* potential outcomes, we can only observe one.
- Formally, the relationship between **potential outcomes** and the **observed outcome** is:

$$Y_i = d_i Y_i(1) + (1 - d_i) Y_i(0)$$

- "switching equation"
- one term will always be 0
- we can only observe one potential outcome for each unit!!!!
- let's confirm on the board

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Estimand vs. estimator vs. estimate

Estimand parameters that we aim to estimate, often written with greek letters (μ, β, τ)

Estimator rules for calculating an estimate; function of the observed sample data; used to learn about estimands ($\hat{\beta}$, $\hat{\tau}$)

Estimate particular values of estimators that are realized in a given sample

Example:

- What's the average weight of newborns?
  - Population mean (estimand)
  - Sample mean (estimator)
  - 7.5lb (estimate)
- Board?

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Our estimand today

An important parameter, or **estimand** is the **average treatment effect (ATE)**

- Why is it important, interesting, useful, etc?
- Can you think of other estimands we might want to use instead?
- In terms of potential outcomes:

$$
\begin{aligned}
ATE &= \frac{1}{N}\sum_{i=1}^{N}\tau_i \\
&= \frac{1}{N}\sum_{i=1}^{N}[Y_i(1) - Y_i(0)] \\
&= \frac{1}{N}\sum_{i=1}^{N}Y_i(1) - \frac{1}{N}\sum_{i=1}^{N}Y_i(0)
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- Can we observe this?

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&= \frac{1}{N}\sum_{i=1}^{N} Y_i(1) - \frac{1}{N}\sum_{i=1}^{N} Y_i(0)
\end{aligned}
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- Can we observe this?

ATE as our estimand

- We can't observe the ATE (or any other estimand)... we need an **estimator**
- How do we estimate it? You already know the answer!
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An aside on expectations

Why do we need this aside on expectations?

Design process (so far)

- Establish estimand, or population parameter of interest
  - ATE
- Draw a *random sample*
  - selection procedure for inclusion in sample
  - each unit in population equally likely to be included
  - randomly assign units to treatment and control; observe one potential outcome
- Potential outcomes vary for each unit, so our estimate of ATE will vary across samples
  - this means ATE is a **random variable**
    - **expected value** is average outcome of a random variable
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Expectations

How should we think about expectations in terms of experiments?

Recall the definition of expectation $E[X] = \sum xPr[X = x]$

What is the expected value of random variable τ_i in Table 2.1?
Board?

Village	τ_i
1	5
2	0
3	10
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Notation and interpretation

$E[Y_i(0)]$

- "expected value of $Y_i(0)$ when one subject sampled at random"

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Conditional expectations

$$E[Y|X=x] = \sum yPr[Y=y|X=x] = \sum y \frac{Pr[Y=y|X=x]}{Pr[X=x]}$$

- Now, we're after the expected value of the random variable Y given a certain condition occurs ($X=x$)
- Today, we're interested in conditional expectations like
  - $E[Y_i(1)|D_i=0]$
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Conditional expectations, potential outcomes, and random assignment

(This is an important slide! pg. 33 of GG)

Under what conditions is this true?

$$E[Y_i(1)|D_i = 1] = E[Y_i(1)]$$

Is this true, too?

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What about this?

$$E[Y_i(1)|D_i = 1] = E[Y_i(1)|D_i = 0]$$

D_i **conveys no information about values of** $Y_i(0)$ **and** $Y_i(1)$ ***under random assignment***

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Expected potential outcomes and the ATE

When one subject sampled at random, what is the expected value of their treatment effect?

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- Recall, the ATE is our **estimand**
- Next we want an **estimator** s.t. $E[A\hat{T}E] = ATE$. Why?

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Estimating the ATE

1. Design

- Randomize D_i with probability p
  - first m units assigned to treatment
  - remaining $N - m$ units assigned to control
- Assume two potential outcomes $Y_i(1)$, $Y_i(0)$
  - (more on this later)
- Observed outcome is Y_i

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2. Estimator

How do we write the DIM estimator? Struggle with it for a minute.

$$\hat{ATE} = ???$$

Then, let's prove $E[\hat{ATE}] = ATE$ *under certain assumptions*

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Technical details on random assignment

In practice

- Beware "random" being using to mean abritrary or haphazard–not here!
- Random assignment procedures:
  - Simple random assignment
    - Ex: Flip a coin for each unit
  - Complete random assignment
    - Ex: Randomly permute N units, assign first m units to treatment and $N - m$ to control
- Usually, we'll use computational tools to accomplish random assignment, unless you're limited in the field
- Ensures treatment assignment is **statistically independent** of all observed *and unobserved* covariates

$$Y_i(0), Y_i(1), \mathbf{X} \perp\!\!\!\perp D_i$$

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- Without random assignment, we have no idea if covariates (observed and unobserved) that explain the outcome are independent of treatment assignment.
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  - Examples?
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Assumptions we're making about potential outcomes

Key assumptions

Experiments provide unbiased estimates of the average treatment effect (ATE) under the following assumptions:

1. **Random assignment**
2. **Excludability** treatment is *solely* responsible for the outcome
3. **Non-interference (aka SUTVA)** potential outcomes are defined over the set of treatments that subject *itself* receives

Assumptions #2 and #3 are assumptions about how units respond to treatment allocation.

- Important to be clear about the causal effect of interest and assess assumptions in light of how the causal effect is defined.
- Example: effect of new vaccine on contagious disease
  - Do we want to know effectiveness on just person i?
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Experiments provide unbiased estimates of the average treatment effect (ATE) under the following assumptions:

1. **Random assignment**
2. **Excludability** treatment is *solely* responsible for the outcome
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Assumptions #2 and #3 are assumptions about how units respond to treatment allocation.

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- We are assuming random assignment does not set in motion causes of Y_i *other than* d_i
- Where? Defining only $Y_i(0)$ and $Y_i(1)$ implicitly assumes the only "causal agent" is the receipt of the treatment
  - Ex: In a vaccine clinical trial, we must assume that the manipulation only affects illness through the effect of the vaccine. Jeopardized if the administrator gave extra encouragement for other precautions to treatment group while giving dose.
  - What about if getting the vaccine (even if I didn't know it) caused me to stay at home for an extra few days because I felt icky $\rightarrow$ less exposure than control?
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Excludability in practice

- Research activity should not be correlated with treatment assignment!
- Be careful to avoid measurement asymmetries
  - Ex: different research teams measuring outcomes in control and treatment groups
  - DIM estimator is biased if measurement errors have different expected values (see pg. 41 in GG)
- Safeguards:
  - double-blind
  - parallelism in administration (same time, interviewers, questionnaires, etc.)
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Non-interference assumption

- We're assuming potential outcomes depend only on if unit i is treated

$$Y_i(\mathbf{d}) = Y_i(d_1, d_2, ..., d_i, ..., d_n) = Y_i(d)$$

- Where? Again, by only defining $Y_i(0)$ and $Y_i(1)$
- Problems arise if one unit's treatment status affects another unit!
- Ex: We could write four potential outcomes per unit:
  - $Y(d_i, d_5)$
    - d_i is a unit's own treatment assignment
    - d_j is treatment assignment of unit 5

Unit	$Y_i(0,0)$	$Y_i(0,1)$	$Y_i(1,0)$	$Y_i(1,1)$
1	1	1	4	4
2	2	-1	6	0
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- Also called "spillovers"
- Violations:
  - subjects are aware of treatments of other subjects
  - treatments may be transmitted from treated to untreated subjects
  - resources used to treat one set of subjects diminish resources that would otherwise be available to other subjects
- Examples from Alex Coppock's EGAP 10 Things to Know:
  - providing an vaccine to some individuals may decrease the probability that nearby individuals become ill.
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- Be on the look out for networks in your context:
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  - We talked about the critical role of randomization of treatment when estimating ATEs.
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