The Causal Inference Toolbox

A Gentle Introduction

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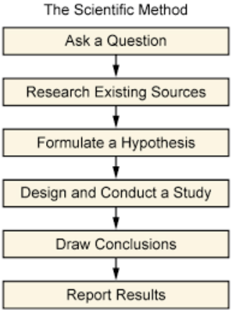
Motivation

Scientific Enterprise

- Scientists try to answer questions about the world with data.
- Focus on empirical questions.
- Science can help answer normative questions, but can never answer them by itself.



Scientific Questions

- Not all empirical questions are created equal.

1. Description: Summarize data, investigate facts, discover hidden patterns.
2. Prediction: Forecast future events from data.
3. Causation: Inferring why X affects Y from data.

- Causal inference is the most difficult of the three.

- Data alone can never tell you what causes what!
- Strong correlation is not a sufficient condition for causality.
- No correlation does not imply lack of causation either.
- Observed correlation could be due to a hidden third variable.

Causation

- Multiple views on causality:
  1. Regularity: causation as constant conjunction of events.
  2. Probabilistic: causation as increasing the likelihood of an outcome.
  3. Process-Mechanism: causation as a series of events/interactions/steps linking cause and effect.
  4. Counterfactual: causation as what would happen if the cause were absent.

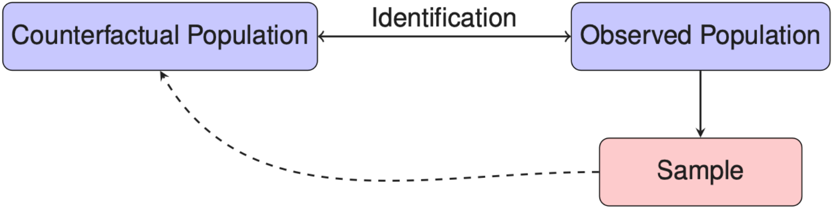
Counterfactual Reasoning

- If it had been the case that C (or not C), it would have been the case that E (or not E).
- Transform "Why" questions into "What If" questions.
- It goes beyond the comparison of current cases $\longrightarrow$ Thought Experiments.

- Hallmarks of Causal Empiricism:
  1. Research design is much more important than statistical modeling.
  2. Most convincing causal studies require deep knowledge of context and institutional details(qualitative knowledge to identify opportunities and fully exploit them).
  3. Research designs typically allow us to make inference only about specific populations.

Identification

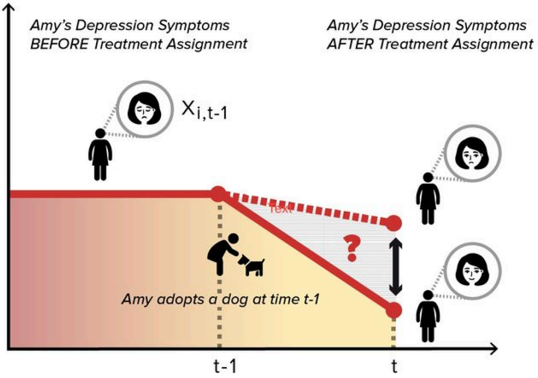
- Causal Inference is about connecting counterfactuals to observed data.



- The process of figuring out what part of the data has your answer in it.

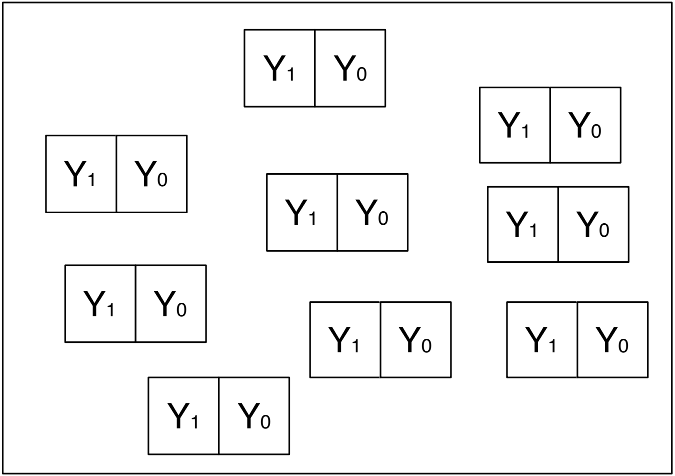
Potential Outcomes

- Causality is about "what-if's" or counterfactuals – you must compare what happened with what actually did not happen.
- Fact is we can only analyze what we observe. We cannot observe what didn't happen.



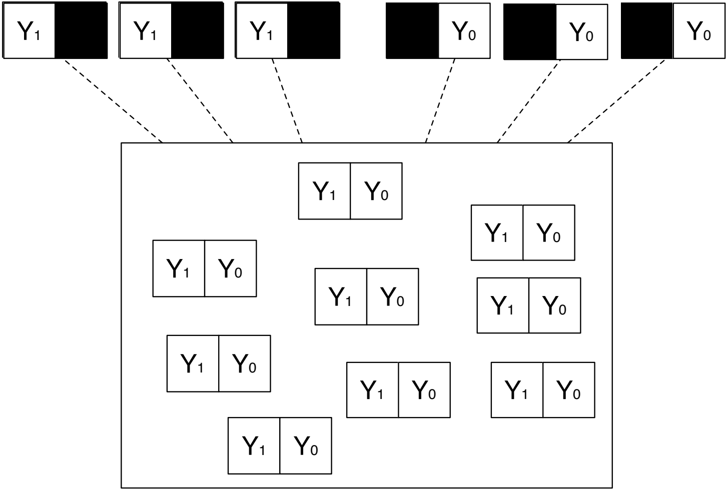
"Two-Sided Card" Model

Imagine the true world is like this...



"Two-Sided Card" Model

But what we can actually observe is...



Language of Potential Outcomes

- Treatment: $D_i = \begin{cases} 1 & \text{if person } i \text{ received the treatment} \\ 0 & \text{otherwise} \end{cases}$
- Observed outcome: Y_i
- The subscript "i" indicates person, or "unit."
- The true world consists of the two potential outcomes:

$$Y_{di} = \begin{cases} Y_{1i} & \text{Potential outcome for unit } i \text{ with treatment} \\ Y_{0i} & \text{Potential outcome for unit } i \text{ without treatment} \end{cases}$$

- That is, Y_{di} = Value of the outcome that would be realized if unit i received the treatment d, where $d = 0$ or 1

Causal Effects

- The causal effect of the treatment on the outcome for unit i:

$$\tau_i = Y_{1i} - Y_{0i}$$

- Note that we can never identify τ_i from what we observe! $\longrightarrow$ Fundamental Problem of Causality.
- In fact, the observed outcomes are realized from potential outcomes as

$$Y_i = Y_{D_i i} = D_i Y_{1i} + (1 - D_i) Y_{0i} \quad \text{so} \quad Y_i = \begin{cases} Y_{1i} & \text{if } D_i = 1 \\ Y_{0i} & \text{if } D_i = 0 \end{cases}$$

- Two solutions:
  - Assume unit homogeneity: $\tau_i = \tau$ for all i
  - Statistical solution $\longrightarrow$ focus on averages. $\tau_{ATE} = \frac{1}{N} \sum_{i=1}^{N} \{Y_{1i} - Y_{0i}\}$

An Illustration

Suppose we observe a population of 4 units:

i	D_i	Y_i
1	1	3
2	1	1
3	0	0
4	0	1

What is $\tau_{ATE} = [Y_{1i} - Y_{0i}]$?

An Illustration

Suppose we observe a population of 4 units:

i	D_i	Y_i
1	1	3
2	1	1
3	0	0
4	0	1
$[Y_i \mid D_i = 1]$		2
$[Y_i \mid D_i = 0]$		0.5
$[Y_i \mid D_i = 1] - [Y_i \mid D_i = 0]$		1.5

What is $\tau_{ATE} = [Y_{1i} - Y_{0i}]$?

A naïve calculation:

$$\begin{aligned} \tilde{\tau} &= [Y_i \mid D_i = 1] - [Y_i \mid D_i = 0] \quad \text{(observed difference in means)} \\ &= \frac{3+1}{2} - \frac{0+1}{2} = 1.5 \quad \text{Could this be wrong?} \end{aligned}$$

An Illustration

Suppose we observe a population of 4 units:

i	D_i	Y_i	Y_{1i}	Y_{0i}	τ_i
1	1	3	3	?	?
2	1	1	1	?	?
3	0	0	?	0	?
4	0	1	?	1	?

What is $\tau_{ATE} = [Y_{1i} - Y_{0i}]$? We need potential outcomes that we do not observe!

An Illustration

Suppose we observe a population of 4 units:

i	D_i	Y_i	Y_{1i}	Y_{0i}	τ_i
1	1	3	3	0	?
2	1	1	1	1	?
3	0	0	1	0	?
4	0	1	1	1	?

Suppose hypothetically: $Y_{01} = 0, Y_{02} = Y_{13} = Y_{14} = 1$.

An Illustration

Suppose we observe a population of 4 units:

i	D_i	Y_i	Y_{1i}	Y_{0i}	τ_i
1	1	3	3	0	3
2	1	1	1	1	0
3	0	0	1	0	1
4	0	1	1	1	0
$[Y_{1i}]$			1.5		
$[Y_{0i}]$				0.5	
$[Y_{1i} - Y_{0i}]$					1

$$\tau_{ATE} = [Y_{1i} - Y_{0i}] = [\tau_i] = \frac{3+0+1+0}{4} = 1.$$

An Illustration

Suppose we observe a population of 4 units:

i	D_i	Y_i	Y_{1i}	Y_{0i}	τ_i
1	1	3	3	0	3
2	1	1	1	1	0
3	0	0	1	0	1
4	0	1	1	1	0
$[Y_{1i}]$			1.5		
$[Y_{0i}]$				0.5	
$[Y_{1i} - Y_{0i}]$					1

$$\tau_{ATE} = [Y_{1i} - Y_{0i}] = [\tau_i] = \frac{3+0+1+0}{4} = 1.$$

Why $\tau_{ATE} \neq \tilde{\tau}$? When would they be equal?

The Ideal Solution: Experiments

- Controlled setting and controlled intervention.

Experiments I

Social Pressure and Voter Turnout: Evidence from a Large-Scale Field Experiment

ALAN S. GERBER *Yale University*
DONALD P. GREEN *Yale University*
CHRISTOPHER W. LARIMER *University of Northern Iowa*

Voter turnout theories based on rational self-interested behavior generally fail to predict significant turnout unless they account for the utility that citizens receive from performing their civic duty. We distinguish between two aspects of this type of utility, intrinsic satisfaction from behaving in accordance with a norm and extrinsic incentives to comply, and test the effects of priming intrinsic motives and applying varying degrees of extrinsic pressure. A large-scale field experiment involving several hundred thousand registered voters used a series of mailings to gauge these effects. Substantially higher turnout was observed among those who received mailings promising to publicize their turnout to their household or their neighbors. These findings demonstrate the profound importance of social pressure as an inducement to political participation.

Experiments II

Does Political Oversight of the Bureaucracy Increase Accountability? Field Experimental Evidence from a Dominant Party Regime

PIA J. RAFFLER *Harvard University, United States*

Concerned with poor service delivery, a large literature studies accountability of politicians to voters. This article instead considers accountability relationships within *governments—the ability of politicians to implement policies by holding bureaucrats responsible for their actions. In collaboration with the Ugandan government, I conducted a field experiment across 260 local governments. The objective of the reform was to empower local politicians to exercise closer oversight over the bureaucracy through training and the dissemination of financial information. Lowered oversight costs increase politicians' monitoring effort and the quality of services, but only in areas where the political leadership is not aligned with the dominant party. In areas under ruling-party control, politicians fear uncovering mismanagement of funds. In contrast to scholars arguing that insulating bureaucrats allows them to do their jobs more effectively, these findings imply that increased political oversight can improve government responsiveness in settings with a modicum of party competition.*

Experiments III

An Experimental Test of the Effects of Fear in a Coordination Game

Abraham Aldama[1*], Deshawn Sambrano[2], Mateo Vásquez-Cortés[3] and Lauren E. Young[4]

[1]Vote Rev, New York, NY, USA, [2]Department of Psychology, Harvard University, Cambridge, MA, USA, [3]Department of Political Science, Instituto Tecnológico Autónomo de México, Mexico City, Mexico and [4]Department of Political Science, University of California, Davis, CA, USA
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Abstract
Cognitive appraisal theory predicts that emotions affect participation decisions around risky collective action. However, little existing research has attempted to parse out the mechanisms by which this process occurs. We build a global game of regime change and discuss the effects that fear may have on participation through pessimism about the state of the world, other players' willingness to participate, and risk aversion. We test the behavioral effects of fear in this game by conducting 32 sessions of an experiment in two labs where participants are randomly assigned to an emotion induction procedure. In some rounds of the game, potential mechanisms are shut down to identify their contribution to the overall effect of fear. Our results show that in this context, fear does not affect willingness to participate. This finding highlights the importance of context, including integral versus incidental emotions and the size of the stakes, in shaping effect of emotions on behavior.

Selection Bias

- Comparisons of observed outcomes for the treated and the untreated do not usually give the right answer:

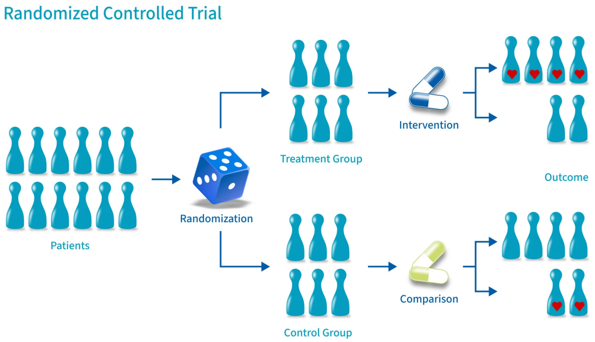
$$
\begin{aligned}
\tilde{\tau} &= [Y_i | D_i = 1] - [Y_i | D_i = 0] \\
&= [Y_{1i} | D_i = 1] - [Y_{0i} | D_i = 0] \\
&= \underbrace{[Y_{1i} - Y_{0i} | D_i = 1]}_{\tau_{ATT}} + \underbrace{[Y_{0i} | D_i = 1] - [Y_{0i} | D_i = 0]}_{\text{Bias}}
\end{aligned}
$$

- Bias term $\neq 0$ if selection into treatment is associated with potential outcomes

Example: Church attendance and election turnout

- churchgoers differ from individuals who do not attend church in many ways
- turnout for churchgoers would be higher than for non-churchgoers even if churchgoers never attended church ($[Y_{0i} | D_i = 1] - [Y_{0i} | D_i = 0] > 0$)

Experimental Logic



- Design of the intervention: Random Assignment $\{Y_{1i}, Y_{0i}\} \perp\!\!\!\perp D_i$
- Extra Assumption $\longrightarrow$ SUTVA (No interference between units + No different versions of treatment).

A Gold Standard?

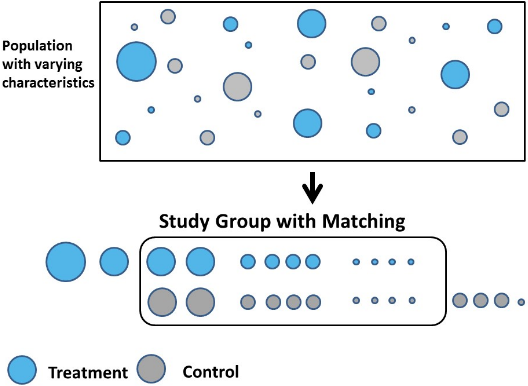
- Experiments are fantastic, but they are not without problems:
  - Definition of the treatment.
  - Compliance.
  - Selection of Sample.
  - Statistical Power.
  - External Validity.
  - Ethical Concerns.

- You don't have to get obsessed with them either or they can become a straitjacket:

  $\longrightarrow$ Big Questions + Creativity

  What alternatives do we have?: Use a research design that either
  - mimics a randomized experiment, or
  - simulates counterfactual comparisons.

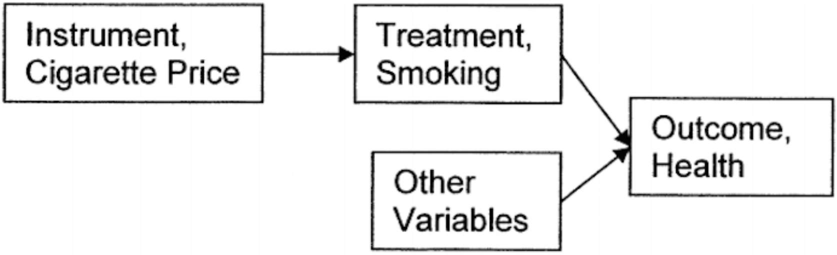
Matching and Regression



Intuition: Trim and/or adjust observations so that the two groups are as similar as possible in terms of observed characteritics.

If those characteristics are all that matter, the difference between the groups can be called a causal effect.

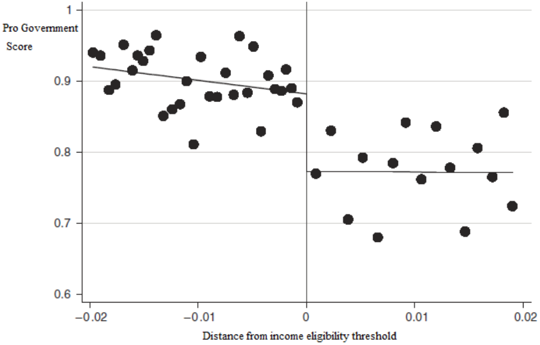
Instrumental Variables



Intuition: Find a random or haphazard natural event (instrument) that affects the outcome only through the treatment of interest.

If the instrument is correlated with outcome, then it must be because of the causal relationship between treatment and the outcome.

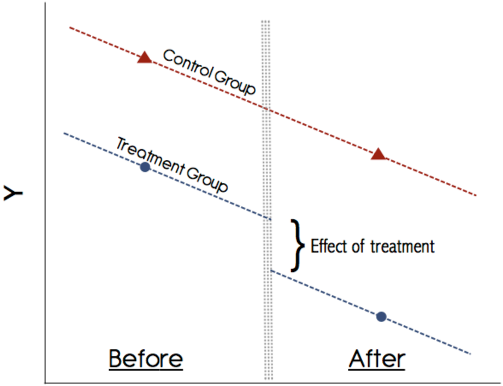
Regression Discontinuity



Intuition: Find a natural or administrative "rule" that sets an arbitrary threshold for the treatment of interest.

Whether a unit falls just below the threshold or above is almost random, so the difference between the two groups is a causal effect.

Difference-in-Differences



Intuition: Collect data on two groups over time, of which one received the treatment during the period but not the other.

If the two groups would have followed parallel trends in the absence of the treatment, then the "difference in differences" identifies a causal effect.

Conclusions

- Causal questions are difficult.
- There are several ways to approach them. A very fruitful solution is based on counterfactual logic.
- Potential Outcomes Model: the observed reality is only one of the possibilities (What If).
- Variety of Tools:
  - Experiments
  - Selection on Observables
  - Instrumental Variables
  - Regression Discontinuity Design
  - Difference in Differences
- Focus on your interests/concerns, not on the methods.