Causal Inference

Introduction to Causality

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What is this course about?

This course is about:

- How (and when) we can use data to learn about cause-effect relationships in the world (***"causal inference"***)
- How can we use causal concepts to make better decisions, particularly in business settings (***"causal reasoning"***)

Big Questions:

- What is “causality”? How is it different from correlation?
- Why does causality matter for decisionmaking?
- What is so special about randomized experiments?
- What do we do if we have data but can’t run an experiment?
- How can we evaluate causal claims made by others?

The New Dot Com Bubble

the Correspondent

Analysis

6 November 2019 • Reading time 21 - 26 minutes

In 2018 $273bn was spent on digital ads globally. We delve into the world of clicks, banners and keywords to find out if any of it is real. What do we really know about the effectiveness of digital advertising?

The new dot com bubble is here: it's called online advertising

Jesse **FREDERIK** + *Maurits* **MARTIJN**

Q: What is your general reaction to the article?

- Do any of you have experience in marketing or want to work in marketing?
- Do you think that online advertising is effective? Why or why not?
- How is advertising effectiveness generally measured?

Measuring Advertising Effectiveness (According to Google)

1. Track "conversions" (e.g. sales, sign-ups, etc.) that occur after an ad is clicked
2. Calculate the "conversion rate" (conversions per ad click)
3. Calculate the Return on Investment (ROI) for the ad campaign as:

$$\text{ROI} = \frac{\text{Revenue} - \text{Cost}}{\text{Cost}}$$

   Where "Revenue" is the total value of conversions and "Cost" is the total cost of the ad campaign.

Q: Is this a good measure of advertising effectiveness? Why or why not?

The article contrasts two main “effects”:

- “*Advertising Effect*”
- “*Selection Effect*”

Let’s talk about each of them.

The “advertising effect”

Q: What do the authors mean by the “advertising effect”?

The “Selection effect”

Q: What do the authors mean by “*selection effect*”? How does it lead companies to lose money on online advertising?

Terminology: We will use the term "*selection bias*" instead of "*selection effect*".

Selection bias is not a causal effect.

Defining "Causal"

In this class, we will define causation in relation to a specific ***intervention*** and a specific ***outcome*** within a system.

- By "system", I mean a collection of variables and relationships between those variables
- An ***intervention*** is a change in the value of a variable that is not driven by the normal dynamics of the system
- A ***causal effect*** is the difference between the outcome with and without the intervention.

Potential Outcomes & Counterfactuals

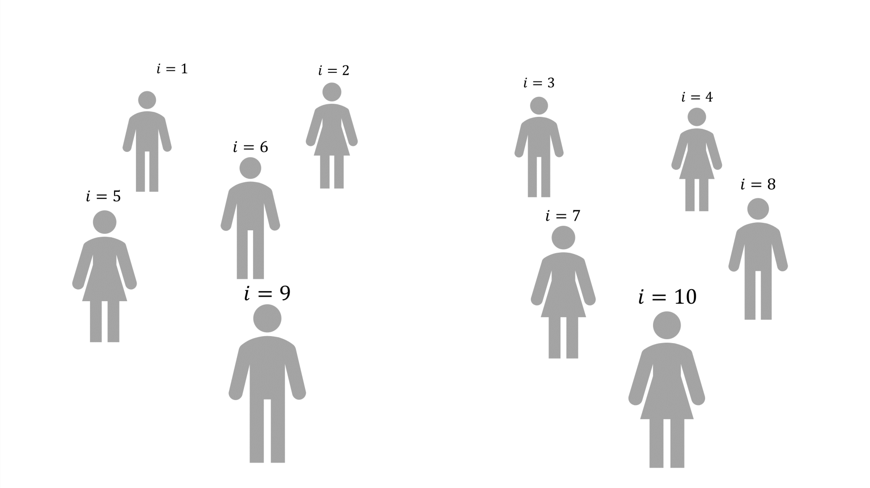
The ***Potential Outcomes Causal Model (PO)*** is a popular framework for analyzing causal relationships.

- The PO model clarifies causal relationships by explicitly describing ***observed*** and ***counterfactual*** outcomes for one variable
- It also builds in some subtle *assumptions* about the nature of those outcomes

Treatment and Outcome

PO considers the causal effect of an intervention (called a "***treatment***") on a specific ***outcome*** variable.

- We assume we can observe a population of units of observation (individuals, organizations, products, etc.) indexed by $i = 1, 2, 3, \ldots, N$
- I will use D_i to indicate the treatment status of unit i, and Y_i to indicate the observed outcome.
- In the simplest case, treatment is binary: each unit is either ***treated*** $(D_i = 1)$ or ***untreated*** $(D_i = 0)$

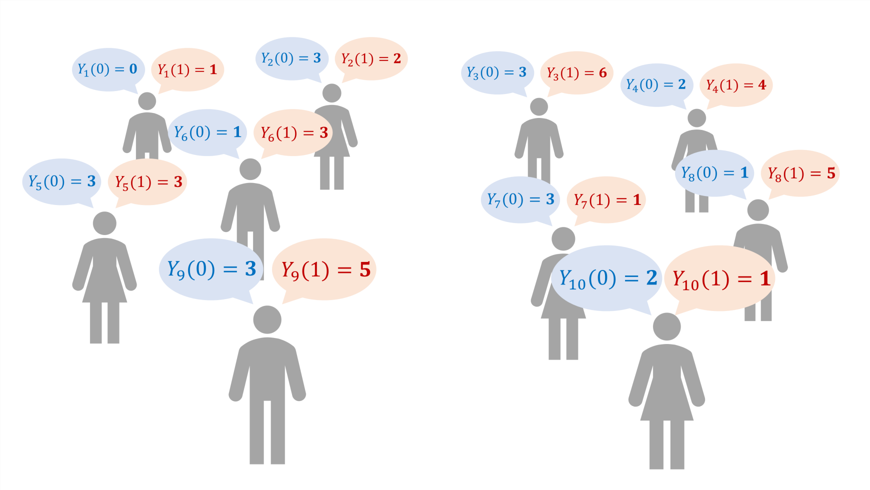


A population of units $i = 1, 2, 3, \ldots, 10$.

Potential Outcomes

- A potential outcome $Y_i(D)$ indicates the outcome that would occur if unit i receives treatment D.
- For example, with binary treatment, we have two potential outcomes:
  - $Y_i(1)$ is the potential outcome that occurs if unit i is treated
  - $Y_i(0)$ is the potential outcome that occurs if unit i is *not* treated

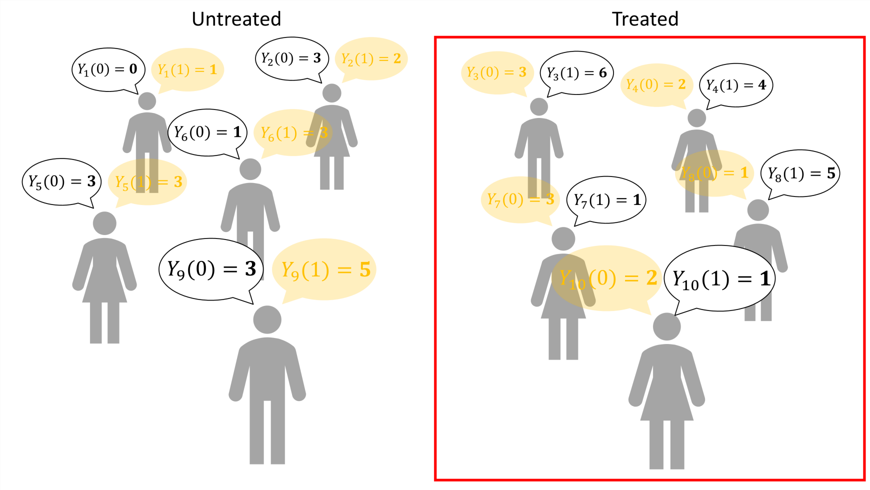
Watch out: "Potential outcomes" does *not* mean "the range of values that Y can take".



With binary treatment, each unit has two potential outcomes (we cannot observe them directly). Every unit can have different potential outcomes.

Observed and Counterfactual Outcomes

- We only ever observe ***one*** potential outcome for each unit
- For example, for unit i, if $D_i = 1$, we observe $Y_i(1)$ but not $Y_i(0)$
- The potential outcomes that we do not observe are called ***counterfactual*** outcomes (or collectively "*counterfactuals*")



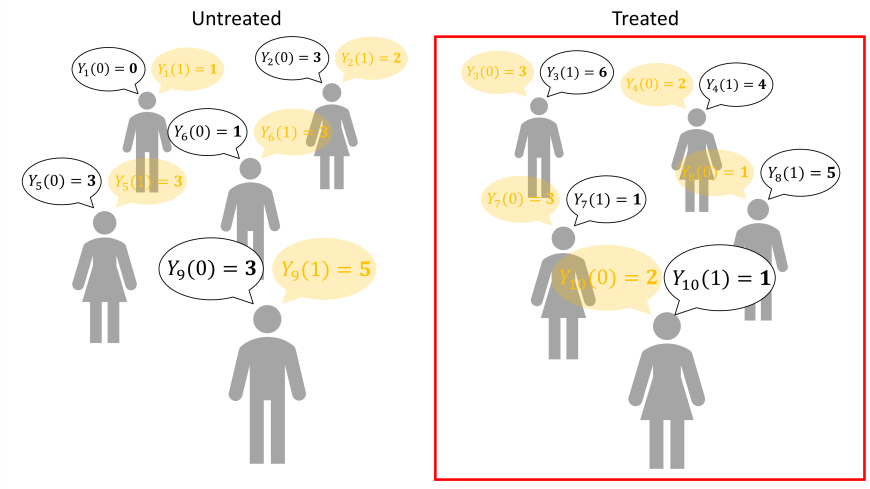
When treatment is assigned, one potential outcome is observed for each unit (black). The others become counterfactuals (orange).

Causal Effects

We define the causal effect of treatment for each unit as the *difference* between the treated and untreated potential outcomes.

I will use δ_i indicate the causal effect of the treatment on unit i, defined as:

$$\delta_i = Y_i(1) - Y_i(0)$$



In this picture, each unit's treatment effect is the difference between its treated and untreated outcome.

The Fundamental Problem of Causal Inference

To directly measure a causal effect we would need to be able to observe both:

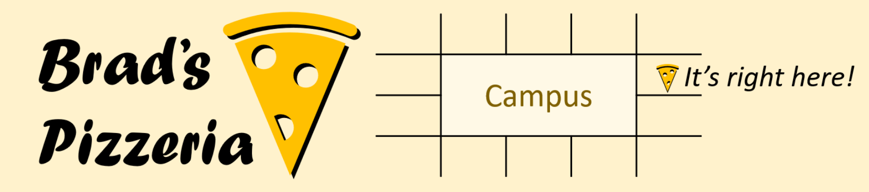
1. What *did* occur (the observed outcome)
2. What *would have* occurred if the treatment were different (the counterfactual).

This can never happen!

Flyers at the Pizzeria

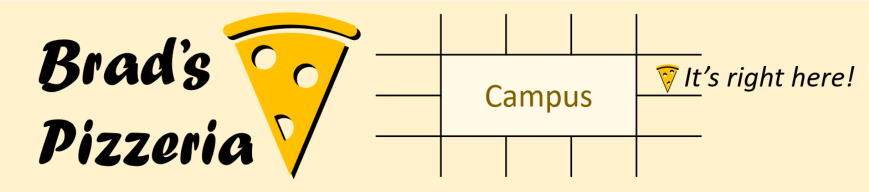
Activity: It's the first week of classes, and I need some help running an marketing campaign for *Brad's Pizzeria*.

- It's located on the edge of campus, so I know there are a lot of potential customers around. The problem is that not many students seem to know it exists.
- I'm going to run a marketing campaign where I have someone hand out paper flyers to students in the area. Each flyer will have a map directing students to the pizzeria.



Any volunteers to help me run my campaign?

Worth it?



Q: Can I tell if the flyer campaign will be worthwhile? What do I need to know?

Potential Outcomes Notation:

Suppose I want to know the effect of *receiving a flyer* on the quantity of *slices of pizza sold*.

- Y_i: Number of slices of pizza you will purchase from Brad's Pizzeria
- D_i: Whether or not you receive a flyer
  - $D_i = 1$: Flyer
  - $D_i = 0$: No Flyer

Q:

- What do $Y_i(0)$ and $Y_i(1)$ mean in this context?
- What is your individual treatment effect?

Some additional assumptions:

- The cost of the flyer campaign is \$1 per flyer
- The profit on each slice of pizza is \$1
- People in the first two rows are "*in line*". This is the only information available when deciding who to give flyers to.
- We will start by computing the ROI of a flyer campaign as:

$$\text{ROI} = \frac{\text{Total Sales to those with Flyers} - \text{Flyers}}{\text{Flyers}}$$

Advertising Strategies

Let's try running some different advertising campaigns and see what happens.

1. Flyers to everyone
2. Flyers to those in line
3. Flyers to those *not* in line

“ROI” vs ROI

Problem: Our (Google’s?) naive ROI calculation assumes that people who receive flyers would not have bought pizza without the flyer.

Q: What do we actually need to know to estimate the true ROI of the flyer campaign?

ROI is fundamentally a *causal* concept

- To know the true benefit of the each campaign we need to know how many *additional* slices of pizza were sold *because of* the flyer campaign.
- We can compute this if we know the *causal effect* of the flyer campaign on each individual.

$$\text{True ROI} = \frac{\sum_{i=1}^{N} \delta_i - \text{Flyers}}{\text{Flyers}}$$

- Equivalently, we can compute total sales that would occur if no flyers were given out, and compare that to the total sales that actually occurred.

Things to think about:

- Can you ever compute the true ROI of a marketing campaign as we just did?
- What happens if advertisers focus on maximizing the naive conversion-based "ROI" instead?

The Stable Unit Treatment Value Assumption (SUTVA)

Defining causal effects as the difference between their potential outcomes requires that the potential outcomes $Y_i(1)$ and $Y_i(0)$ are fixed, regardless of how treatment is assigned.

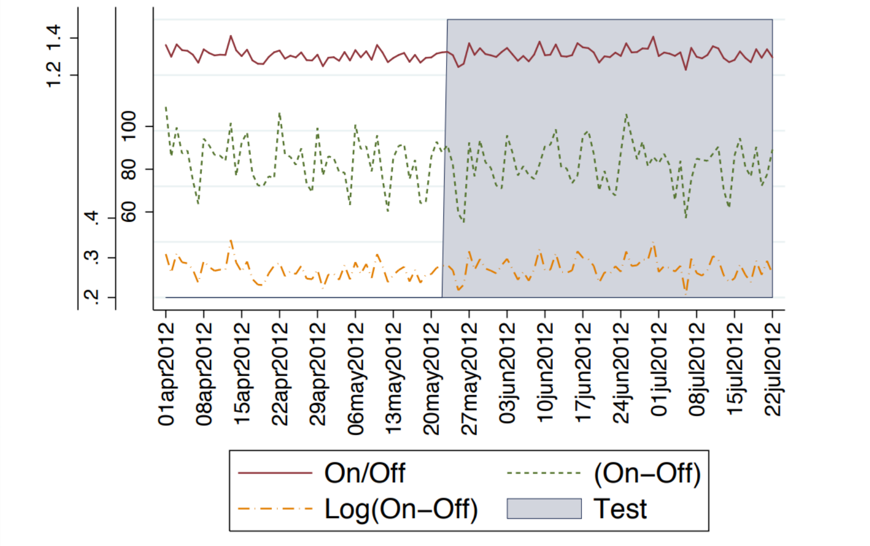
This assumption is called the *Stable Unit Treatment Value Assumption (SUTVA)*

Q: Does SUTVA seem realistic in the Pizzeria example?

Back to Steve Tadelis and eBay

Q: How did Steve Tadelis convince eBay that they were wasting money on keyword ads?

Difference in total sales between treated and untreated regions



Who is using Causal Inference?:

Causal Inference Applications in Business

- **Netflix:** What is the effect of restricting password sharing on total subscription revenue?
- **Tesla:** What is the effect of using the Autopilot feature on the probability of being in an accident?
- **Amazon:** What is the effect of using air-shipping on sales for a particular product?
- **Microsoft:** What is the effect of adding AI to Bing Search on monthly users?
- **Airbnb:** What is the effect of having a professional photo on rental demand?
- **Spotify:** What is the effect of changing the recommendation algorithm on user engagement?
- **TD:** What is the effect of an employee training program on productivity?

Let's take a break

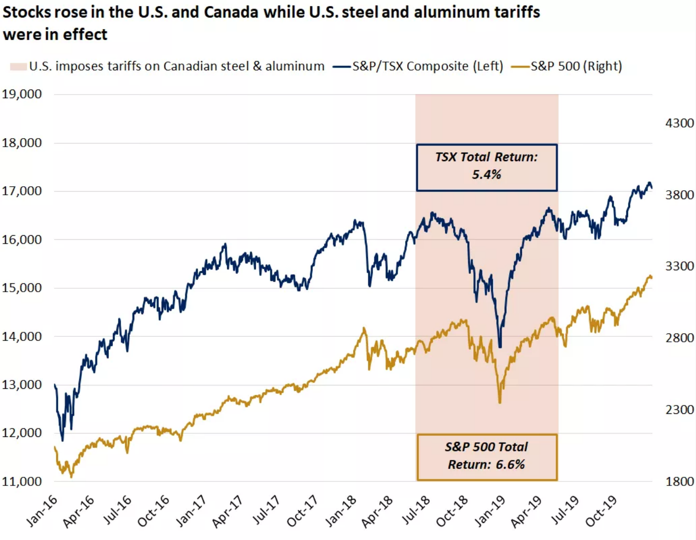
Before the break, we:

- Explored the problem of causality in online advertising
- Defined causality in in terms of an *intervention* and an *outcome*.
- Introduced Potential Outcomes framework:
  - Potential Outcomes
  - Treatment
  - Observed Outcomes
  - Counterfactual Outcomes

Quick Review:

- What is a *"Potential Outcome"*?
- What is an *"individual treatment effect"*?
- What is the *fundamental problem of causal inference*?

Example:



Q: Did the tariffs affect stock prices? What do we need to know?

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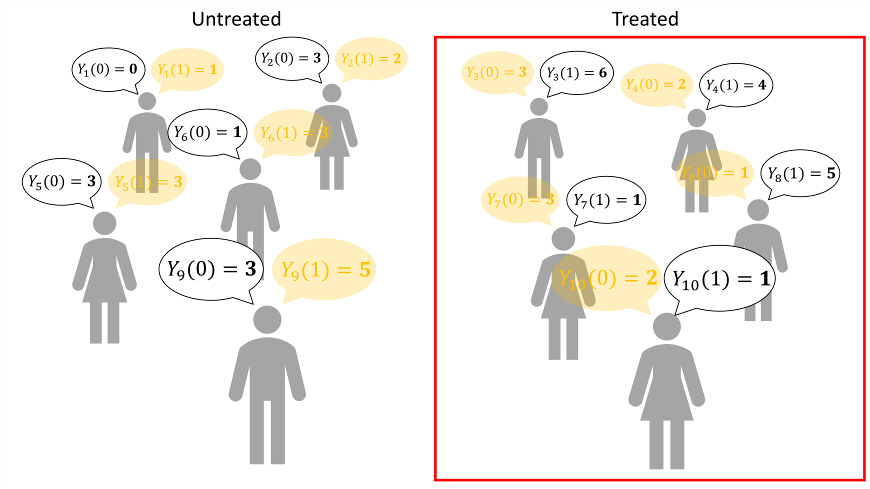

In this picture, each unit's treatment effect is the difference between its treated and untreated outcome. *One of these is always a counterfactual.*

The Fundamental Problem of Causal Inference

To directly measure a causal effect we would need to be able to observe both:

1. What *did* occur (the observed outcome).
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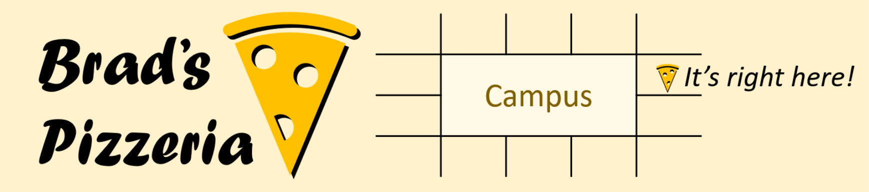
Intro to R

Back to the Pizzeria



let's refresh our memories:

- What was the scenario?
- What did we learn?

R Demo: `PizzeriaDemo.Rmd`

Goals:

- Introduce R, RStudio, and RMarkdown
- Simulate some data that tells a causal story
- Think about how to run a better marketing campaign