POLI 273: Causal Inference

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Lecture 01 | Introduction

Causal Inference

Causal Inference

- This class will teach Intro to Causal Inference
- You will learn what is causal inference:
    - Experimental x Observational research
    - Fundamentals of Experimental research
    - Observational methods:
        - Dif-in-Dif, RDD, Matching, Dif-in-Disc, Syntetic Control, Distributional Effects, and Causal Learning.

Bureaucracy

Bureaucracy

- It is meant for PoliSci Grad Students
  - All are welcome, but I assume you have the pre-reqs that PoliSci students have learned
- What are those:
  - Some calculus
  - Some stats
  - Some linear algebra
  - Some exposure to coding
- Can you follow the class without these? Yes, but you have to be willing to learn them now.

Bureaucracy

- This class is going to mix:
  - Causal Inference theory (medium level of difficulty)
  - with Causal Inference concepts (a lot of them)
  - and some knowledge on how to implement these concepts
- It is going to be a fun, but hard, class. I'm sure you are going to enjoy!

Bureaucracy

- The math for the class:
  - It is not hard, but you should be willing to bypass the initial shock of seeing it
  - After that, you will see that the concepts repeat themselves.
    - They form some sort of elementary algebra, you will see.
- The stats: We can go as deep as we want. No need to go excessively deep, but we need to be able to understand what is under the hood and why it works.
- The coding: This is the easiest part. You can get the coding done in whatever language you want. More on that later.

Bureaucracy

Grading:

1. Office hours
2. Experimental Projects
3. Replication Projects
4. Final paper

Bureaucracy

- GitHub page: https://github.com/umbertomig/POLI273
- Will post today the readings and the final version of the syllabus.
- The partial version is on Canvas.

Causal Inference

Causal Inference

- What is causal inference?
  - You all learned that correlation is not causation.
  - We don't know what causation is, but we also have little idea of what correlation is.
- What is correlation?
  - It relates to covariance.
  - The hell! What is covariance?

$$Cov(X, Y) = \mathbb{E}\left[(X - \mathbb{E}(X))(Y - \mathbb{E}(Y))\right]$$

Causal Inference

- What does this mean? It means that things vary together.

As X Rises, Y…	Type of Covariance (or Correlation)	Value of Covariance
Rises	Positive	$\text{Cov}(X,Y) > 0$
Does Not Change	None (variables are uncorrelated or independent)	$\text{Cov}(X,Y) = 0$
Falls	Negative	$\text{Cov}(X,Y) < 0$

Causal Inference

- And then, what is correlation? (where $Std(X) = \sqrt{\mathbb{E}(X - \mathbb{E}(X))^2}$)

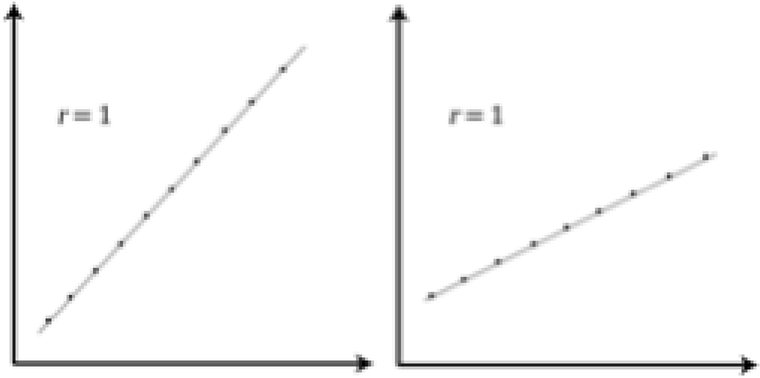
$$Corr(X, Y) = \frac{Cov(X, Y)}{Std(X)Std(Y)}$$

Causal Inference

- Measures the *linear association* between two variables.
- And it is a good summary for a binary relation. For instance, you cannot bullshit it:
  - To have correlation, you need variation (imagine if $Std(X) = 0$?!)
- It nicely varies between -1 and 1. All good.

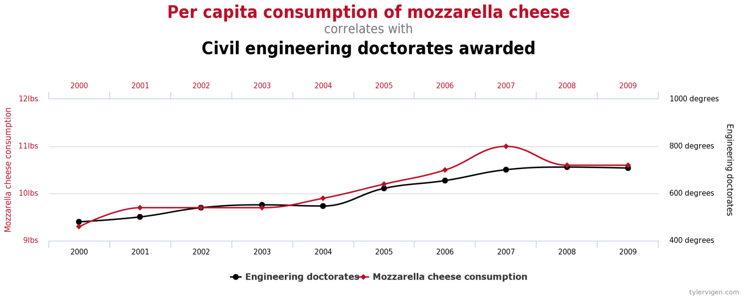
Causal Inference

- But it is incomplete (statistically):



Causal Inference

- Conceptually: $Cov(X, Y) = Cov(Y, X)$. And you find these beauties:



Causal Inference

- In the end, we want to make claims about cause and effect. We want to say things like:
  - If you do X, Y is going to *cause* a τ change in Y.
- What does that mean?
  - It **is** a statement about what did **not** happen!
  - Lewis (1973): "something that makes a difference, and the difference it makes must be a difference from what would have happened without it.''

Causal Inference

- **Problem:** Correlation without Causation
  - Reverse Causality:
    - Spinning Windmills and Wind, Mother's Day Card and Mothers day
    - Direction.
  - Common Cause: Omitted Variable, Confounders, Selection
    - Dressing for Success, Job Training Programs, Elite Colleges and income, etc

Causal Inference

- Causal Inference relies on what we call *counterfactual dependence*:
  - X causes Y if, and only if, Y occurs when X occurs and would not have occurred in the counterfactual world where X did not occur
- This poses a lot of problems:
  - Observables x unobservables
  - Comparison
  - Phantom causal effects

Causal Inference

- Causal inference and counterfactual dependence: Rubin Causal Model.
  - Causal Inference is a problem of missing data.
  - This makes it impossible to recover individual causal effects.
- But what if we abstract away from individuals, and look at aggregates?
  - If some hypothesis are fulfilled, we can do that!
- This is what we are going to learn in this class!

Causal Inference

Week	Content
01	Causal Inference and Tooling
02	Background (Rubin Causal Models and Causal Diagrams)
03	Regression for Causal Inference
04	Matching and Experiments
05	More Experiments

Causal Inference

Week	Content
06	Panel data and differences in differences
07	Regression Discontinuity Design
08	Synthetic Control Methods
09	Distributional Effects
10	Machine Learning Meets Causal Inference

Questions?

See you in the next class