FLS 6441 - Methods III: Explanation and Causation

Week 1 - Review

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Probability Review

$$Pr(A) = \frac{\text{Number of times A occurs}}{\text{Number of Trials}}$$

Joint Probability: $Pr(A \cap B) = P(A, B)$

Conditional Probability: $Pr(A|B) = \frac{Pr(A \cap B)}{Pr(B)}$

Probability Review

Independence: A and B are independent iff

$$Pr(A \cap B) = Pr(A) * Pr(B)$$

Then: $Pr(A|B) = \frac{Pr(A \cap B)}{Pr(B)} = \frac{Pr(A) * Pr(B)}{Pr(B)} = Pr(A)$

Probability Review

- A = It’s raining in Osasco right now
- B = I flip this coin and get Heads
- Are these events independent?

Probability Review

- A = It's raining in Osasco right now
- B = I flip this coin and get Heads
- Are these events independent?
- Yes! One does not affect the other at all
- So $Pr(A \cap B) = Pr(A) * Pr(B)$
- $Pr(A \cap B) = 0.3 * 0.5 = 0.15$

Probability Review

- A = It’s raining in Osasco right now
- B = It’s raining in São Paulo right now
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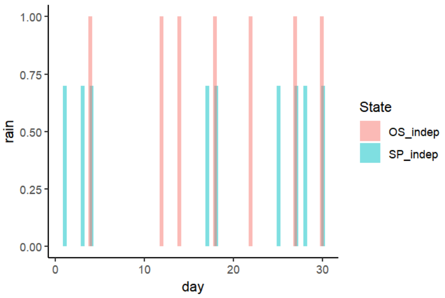
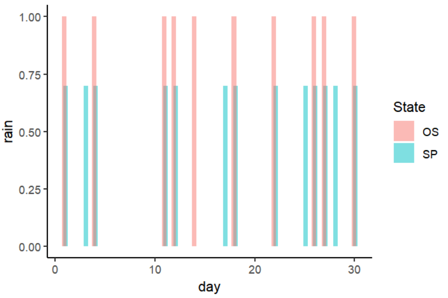
Probability Review

- A = It's raining in Osasco right now
- B = It's raining in São Paulo right now
- Are these events independent?
- No! If you know it's raining in Osasco there's a stronger chance it will be raining in São Paulo
- So $Pr(A \cap B) \neq Pr(A) * Pr(B)$
- $Pr(A \cap B) \neq 0.3 * 0.5 = 0.15$
- $Pr(A \cap B) > 0.15$ (probably)

Probability Review





$Pr(\text{Rain in Osasco}) * Pr(\text{Rain in São Paulo}) = 0.2 * 0.2 = 0.04$

$Pr(\text{Rain in Osasco} \cap \text{Rain in São Paulo}) = 0.05$

$Pr(\text{Rain in Osasco}) * Pr(\text{Rain in São Paulo}) = Pr(\text{Rain in Osasco} \cap \text{Rain in São Paulo})$

$Pr(\text{Rain in Osasco}) * Pr(\text{Rain in São Paulo}) = 0.37 * 0.36 = 0.13$

$Pr(\text{Rain in Osasco} \cap \text{Rain in São Paulo}) = 0.25$

$Pr(\text{Rain in Osasco}) * Pr(\text{Rain in São Paulo}) \neq Pr(\text{Rain in Osasco} \cap \text{Rain in São Paulo})$

Section 1

Explanation

Learning from Data

- What does it mean to explain something?

Learning from Data

- What does it mean to explain something?
- To give an account of what happens, *and why*
  - The ’chain of causation’

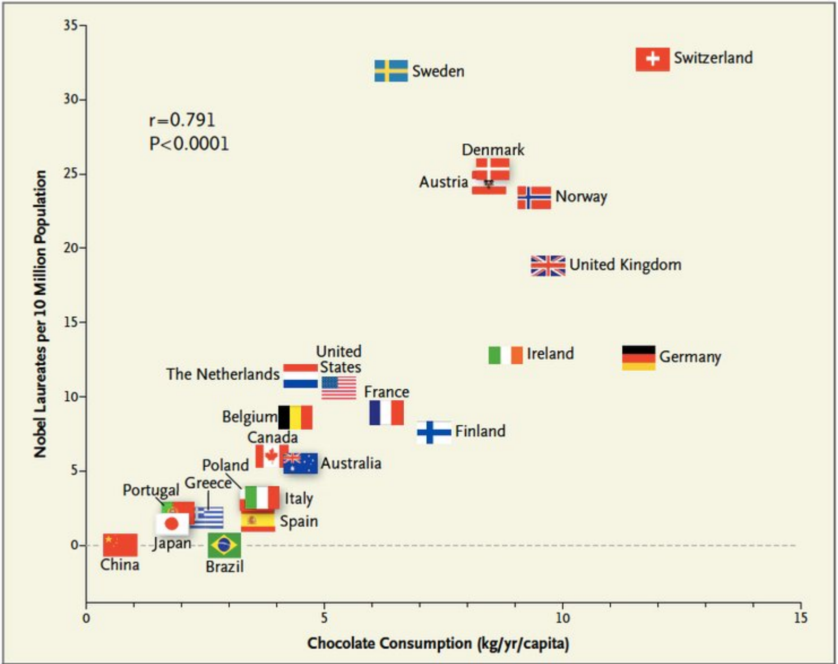


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel

Learning from Data

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Learning from Data

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  - For **prediction**, correlation is fine: If we know a country has chocolate consumption of 10kg/yr/capita we can reasonably predict it will have about 25 Nobel Laureates
  - But for **intervention**, correlation does not help: forcing people to eat more chocolate does nothing on its own to produce more Nobel Laureates
  - For **explanation**, correlation also fails - it is no *explanation* to say that Switzerland has the most Nobel Laureates because it has the highest chocolate consumption

Learning from Data

- Two perspectives on explanation:

Learning from Data

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Causes of Effects	**Effects of Causes**
What caused Y?	Does D cause Y?
Why does Switzerland have so many Nobel laureates?	Does chocolate cause more Nobel laureates?

Learning from Data

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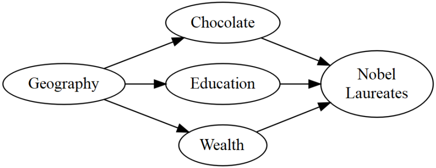

Learning from Data

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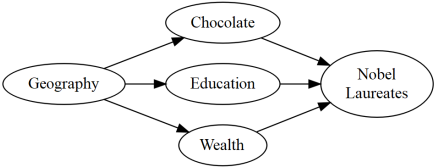

- Identifying the source of **ALL** of the variation in Nobel Laureates

Learning from Data

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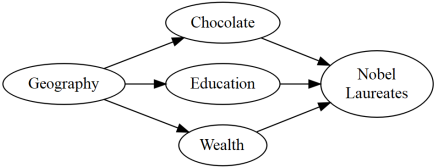

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- An infinite task!

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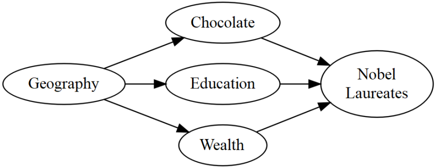

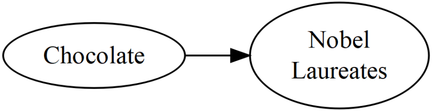

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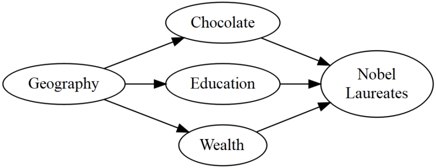

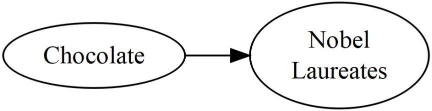

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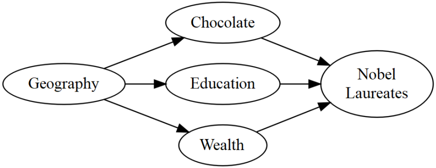
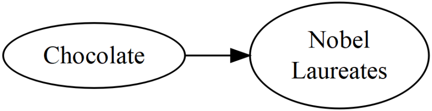




- Identifying the source of **ALL** of the variation in Nobel Laureates
- An infinite task!

- Identifying how much **ONE** variable causes variation in Nobel Laureates
- This we can do!

Explanation

- A focus on a single explanatory variable D requires a clear definition of **'Treatment'**
- AND to clearly define a **'Control'**
  - What is the opposite of investing $1bn in education?
  - No investment, or investing it elsewhere?
- Define treatment:

$$D_i = \begin{cases} 1, \text{ if treated} \\ 0, \text{ if not treated} \end{cases}$$

Causal Inference

- Defining our outcome:
  - Is it the outcome we really care about? Or just what's easy to measure?
  - Tempting to look at many outcomes, but the risk of 'cherry-picking'
    - All outcomes are **probabilistic** (due to all the other factors we haven't accounted for)
    - If we study 20 outcomes, on average one will show a significant effect even with no real causal effect
  - So we also want a **single outcome** usually

Causal Inference

- What are the **units** of our analysis?
- Countries? Political Parties? Individuals?
- eg. How does electoral system affect attitudes to redistribution?
  - Treatment at the national level
  - Outcome at the individual level
  - Measurement needed at the lowest (individual) level
- Units are **time-specific**: the same person 10 minutes later is a different unit

Section 2

Causal Inference

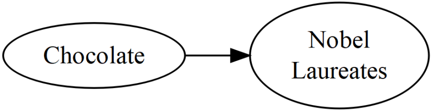
Causal Inference

- Why wasn't regression enough for explanation?
  1. Omitted Variables
  2. Reverse Causation
  3. Selection Bias
  4. Measurement Bias
  5. Lack of Overlap
- In all of these cases the values in our data hid the real causal relationship

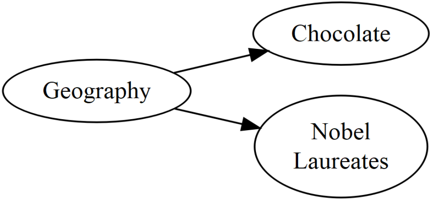
Causal Inference

- Omitted Variables

A real causal relationship:



Being misled by omitted variable bias:



Causal Inference

- Reverse Causation

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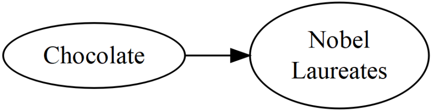

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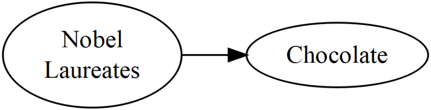

Causal Inference

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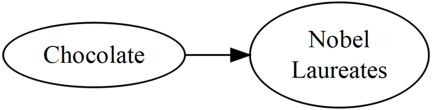
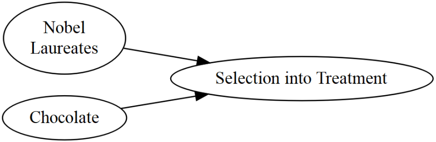


Being misled by Selection Bias:



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- Messy treatment assignment mechanisms are why basic regression is no use for explanation
  - It means our control cases are really misleading
  - South Africa is our counterfactual for Switzerland
  - What would happen if the 'untreated' units got treated?

Causal Inference

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- This means comparing the **Potential Outcomes** for unit i:

$$Y_{Di} = \begin{cases} Y_{1i} \text{ Potential Outcome if unit i treated} \\ Y_{0i} \text{ Potential Outcome if unit i NOT treated} \end{cases}$$

- Individual Treatment Effect for unit $i = Y_{1i} - Y_{0i}$

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$$Y_{Di} = \begin{cases} Y_{1i} \text{ GDP Growth of Brazil in 2010 if a Democracy} \\ Y_{0i} \text{ GDP Growth of Brazil in 2010 if NOT a Democracy} \end{cases}$$

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Causal Inference

Potential Outcomes are just another Variable

	GDP Growth if Democracy	GDP Growth if NOT Democracy	
	Y_1	Y_0	Treatment Effect
Brasil	4	2	2
Argentina	7	3	4
Bolivia	2	4	-2
Colombia	11	11	0
Peru	6	2	4

Causal Inference

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- We know how democracy works in Europe; the question is what will happen if it becomes more common in Africa?
- We want to calculate an **Average Treatment Effect**
- $ATE = \frac{\sum_i (Y_{1i} - Y_{0i})}{N}$

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Colombia	7	7	0
Peru	5	4	1
Average Treatment Effect	**5**	**4**	**1**

Causal Inference

- **The Fundamental Problem of Causal Inference**
  - No units can receive **both** treatment and control
  - So we can never observe both Y_1 and Y_0 for the same unit

Causal Inference

Potential Outcomes Example

	PR System?	Investment in Education if PR system	Investment in Education if FPTP system	
	D_i	Y_1	Y_0	Treatment Effect
Brasil	1	8	?	?
Argentina	1	10	?	?
Bolivia	0	?	4	?
Colombia	0	?	11	?
Peru	0	?	2	?

Causal Inference

- We can’t even look at the change in countries that switch to a PR system
  - What if **all** countries had started to invest more in education at the same time, for different reasons?
  - The potential outcome for Country X in time 1 is different to at time 2
- So we need to consider the **counterfactual** - what would have happened if the country had **not** switched to a PR system?
- So we can only estimate the effect by comparing **across** units
- That is why we are doing causal **inference**, not causal proof

Causal Inference

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Causal Inference

- To compare across units we need counterfactuals: **control** units that do not receive treatment
- Control units can never be perfect substitutes
- Causal Inference is all about identifying a **plausible counterfactual**
  - Plausible means that the potential outcomes of the control unit are the same as those of the treated unit

Causal Inference

- The comparability of treatment and control units depends on how they got to be treated
  - On the **treatement assignment mechanism**
- If we 'treated' an outlier like Búzios in Rio, could we find a comparable control unit?
- Comparisons are easier where the **treatment assignment mechanism is independent of potential outcomes**
  - This makes it more likely that potential outcomes are 'balanced' and comparable

Section 3

Rest of the Course

Causal Inference

- The rest of the course is mostly about the types of treatment assignment mechanisms that **avoid these biases** and provide plausible counterfactuals

Causal Inference

1. **Controlled Experiments** where we **control** the treatment assignment
   - Field Experiments
   - Survey Experiments
   - Lab Experiments

Causal Inference

2. **Natural Experiments** where the assignment mechanism creates balanced potential outcomes
    - Randomized natural experiments
    - Regression Discontinuities
    - Instrumental Variables

Causal Inference

3. **Observable Studies:** What if no suitable treatment assignments are available?
    - No historical examples of natural experiments
    - Not feasible or ethical to run a field experiment

- Remember the purpose of using these specific treatment assignment mechanisms is to achieve **comparable potential outcomes**
- One alternative way of making potential outcomes comparable is to **selectively use Observable Data**
    - Difference-in-Differences
    - Controlling for confouding variables
    - Matching

Causal Inference

Analysis Types and Assumptions

Week	Assumption:	Researcher Controls Treatment Assignment?	Treatment Assignment Independent of Potential Outcomes	SUTVA	Additional Assumptions
	Controlled Experiments				
1	Field Experiments	✓	✓	✓	
2	Survey and Lab Experiments	✓	✓	✓	Controlled Environment for treatment exposure
	Natural Experiments				
3	Randomized Natural Experiments	X	✓	✓	
4	Instrumental Variables	X	✓	✓	First stage and Exclusion Restriction (Instrument explains treatment but not outcome)
5	Regression Discontinuity	X	✓	✓	Continuity of covariates; No manipulation; No compounding discontinuities
	Observational Studies				
6	Difference-in-Differences	X	X	✓	No Time-varying confounders; Parallel Trends
7	Controlling for Confounding	X	X	✓	Blocking all Back-door paths
8	Matching	X	X	✓	Overlap in sample characteristics

Causal Inference

4. **Small-N studies:** Some research questions have few units available

- How do we learn about the political economy of development with few units?
- We can at least avoid some key biases:
  - Comparative Case Studies
  - Process Tracing

Causal Inference

- But **how much** can we learn from a causal analysis?
- Is this an accurate representation of what would happen in the real-world?
  - What was the policy problem (/academic question) you were trying to solve?
  - What details differ? Eg. context of how treatment was applied
- Generalizability to other units (External validity)
  - Would the same thing happen in another country? Next year?
  - Look out for variation in treatment, context, spillovers, learning etc.
- Any generalization requires assumptions

Causal Inference

- We will try to identify abstract, portable processes
  - **Causal Mechanisms**
- **Portable:** If the weather affects election turnout ONLY in Acre, is that a useful causal mechanism?
- **Abstract:** If unions are good at mobilizing support, but so are churches, the mechanism is collective action, not union organization
- We still need to define the **scope conditions** in which we think this causal mechanism will operate as expected

Causal Inference

- Examples of Causal Mechanisms:
  - Citizens
    - Electoral Accountability
    - Client Power
    - Collective Action
    - Social Trust/Sanctioning
    - Wealth Effects
  - Elites
    - Violence/Coercion
    - Brokerage/Patronage
    - Persuasion/Framing
    - Incumbency Power
  - Institutions
    - Power Devolution/Median Voter
    - Network Effects
    - Evolutionary Selection
    - Conversion/Layering/Drift/Replacement

Causal Inference

- Examples of Causal Mechanisms:
  - Citizens
    - Electoral Accountability - Class 5
    - Client Power - Class 6
    - Collective Action - Class 11
    - Social Trust/Sanctioning - Class 4
    - Wealth Effects
  - Elites
    - Violence/Coercion - Class 8
    - Brokerage/Patronage - Class 9
    - Persuasion/Framing
    - Incumbency Power - Class 7
  - Institutions
    - Power Devolution/Median Voter - Class 3
    - Network Effects
    - Evolutionary Selection
    - Conversion/Layering/Drift/Replacement - Class 12