FLS 6441 - Methods III: Explanation and Causation

Week 1 - Review

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Probability Review

$$Pr(A) = \frac{\text{Number of times A occurs}}{\text{Number of Trials}}$$
$$\text{Joint Probability: } Pr(A \cap B) = P(A, B)$$
$$\text{Conditional Probability: } Pr(A|B) = \frac{Pr(A \cap B)}{Pr(B)}$$

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
- ▶ Are these events independent?

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
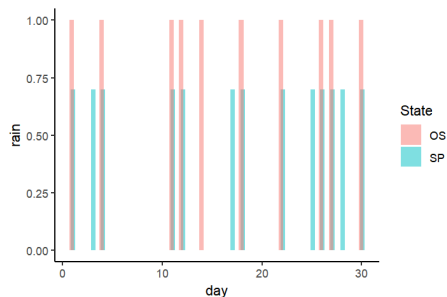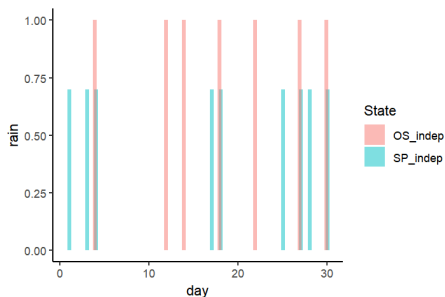
Pr(Rain in Osasco) $*$
Pr(Rain in São Paulo) $= 0.2 * 0.2 =$
0.04
Pr(Rain in Osasco $\cap$
Rain in São Paulo) $= 0.05$
Pr(Rain in Osasco) $*$
Pr(Rain in São Paulo) $=$
Pr(Rain in Osasco $\cap$ Rain in São Paulo)

Pr(Rain in Osasco) $*$
Pr(Rain in São Paulo) $= 0.37 * 0.36 =$
0.13
Pr(Rain in Osasco $\cap$
Rain in São Paulo) $= 0.25$
Pr(Rain in Osasco) $*$
Pr(Rain in São Paulo) $\neq$
Pr(Rain in Osasco $\cap$ 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'
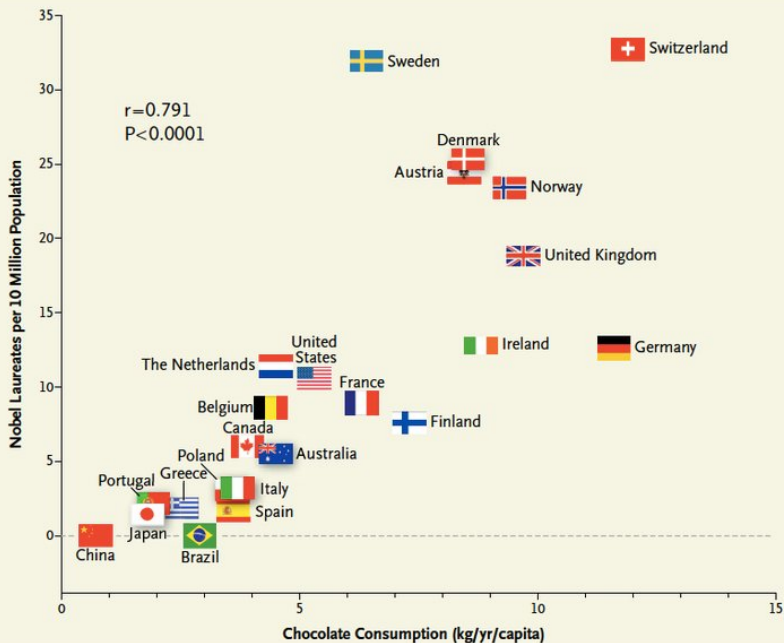
r=0.791
P<0.0001

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

Learning from Data

- Why isn't correlation enough?

Learning from Data

- ▶ Why isn't correlation enough?
  - ▶ 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

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
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Learning from Data

- ► Why isn't correlation enough?
  - ► 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:

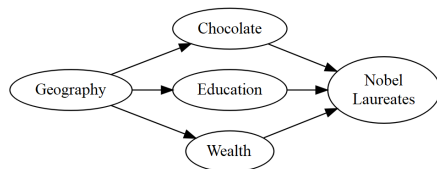Learning from Data

▶ Two perspectives on explanation:

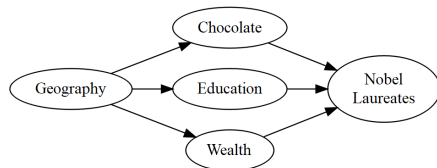| **Causes of Effects**	**Effects of Causes**
What caused Y?	Does D cause Y?
Why does Switzerland have so many Nobel laureates?	Does chocolate cause more Nobel laureates?

Learning from Data

► Two perspectives on explanation:

Learning from Data

- ▶ Two perspectives on explanation:

- ▶ Identifying the source of
  ALL of the variation in
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Learning from Data

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- ► An infinite task!

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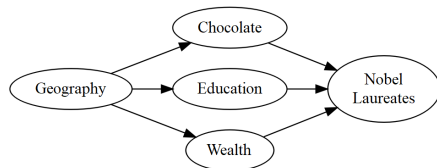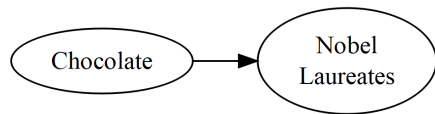- Identifying how much **ONE** variable causes variation in Nobel Laureates

Learning from Data

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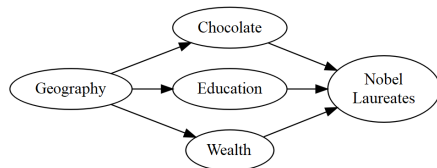- Identifying the source of **ALL** of the variation in Nobel Laureates
- An infinite task!

- 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:
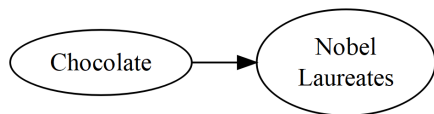
Being misled by omitted variable bias:
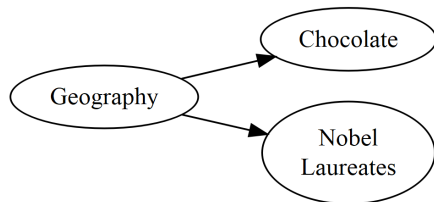
Causal Inference

- Reverse Causation
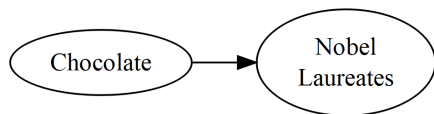
A real causal relationship: Being misled by reverse causation:
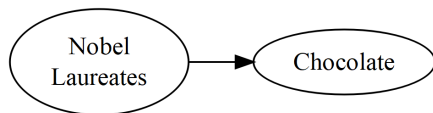
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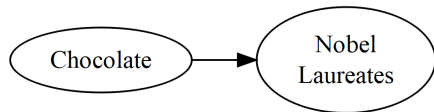
A real causal relationship: Being misled by Selection Bias:
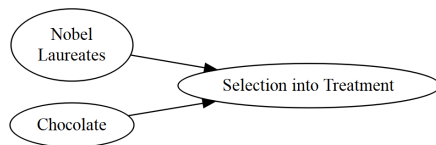
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- Messy treatment assignment mechanisms are why basic regression is no use for explanation
    - It means our control cases are really misleading
    - South Africa is our counterfactual for Switzerland
    - What would happen if the 'untreated' units 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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- ▸ The **causal effect** of treatment is how each unit's outcome differs when it is treated and not treated
- ▸ This means comparing the **Potential Outcomes** for unit i:

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

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

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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

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We want to calculate an **Average Treatment Effect**

$$ATE = \frac{\sum_i (Y_{1i} - Y_{0i})}{N}$$

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	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
- ▶ *Individual* Treatment Effects are **Impossible to Estimate**

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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  - That is why we are doing causal **inference**, not causal proof

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