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?

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

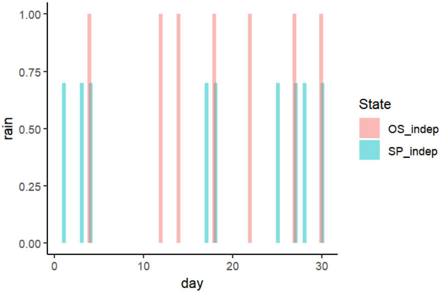
Probability Review

- 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)

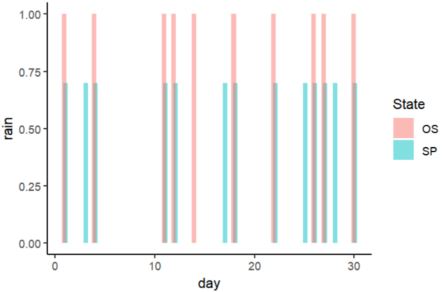
Probability Review



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

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

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



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

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

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

Explanation

- Descriptive Inference
- Predictive Inference
- Causal Inference

Learning from Data

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- But the only way to *confirm* the hypothesis is to verify that:
  1. In other cases, the presence of the condition also produces the same outcome (if not, the explanation is not sufficient)
  2. The absence of the condition does not produce the same outcome (if not, the explanation is not necessary)

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  - But...Costa Rica

Learning from Data

- For example, we could look at India and conclude large Asian countries produce successful democracies
  - But...China
  - But...Costa Rica
- Only by looking at other cases, particularly 'control' cases (small non-Asian countries) can we understand if this explanation is plausible

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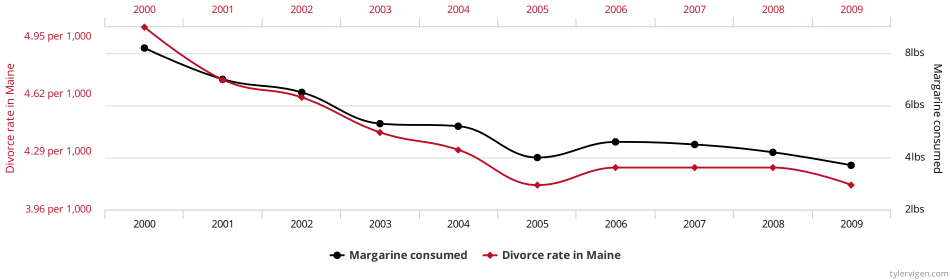
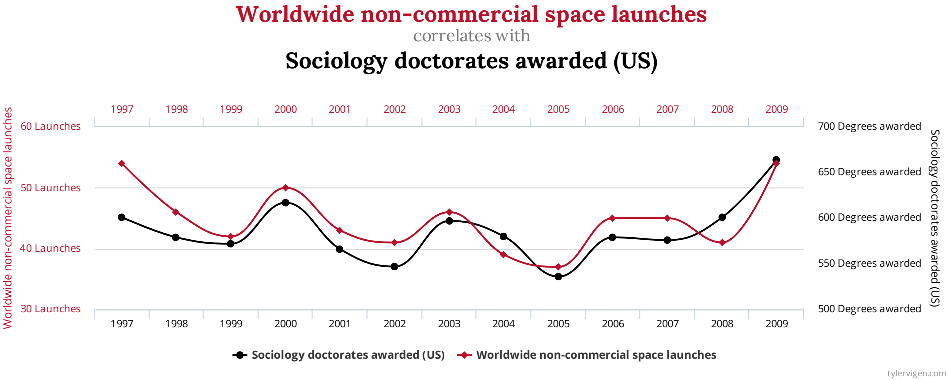
- The problem is the *type* of data; it does not allow us to answer the causal question
- Remember, **regression only buys you correlation**

Divorce rate in Maine
correlates with
Per capita consumption of margarine




Worldwide non-commercial space launches
correlates with
Sociology doctorates awarded (US)
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
60 Launches
50 Launches
40 Launches
30 Launches
Worldwide non-commercial space launches
700 Degrees awarded
650 Degrees awarded
600 Degrees awarded
550 Degrees awarded
500 Degrees awarded
Sociology doctorates awarded (US)
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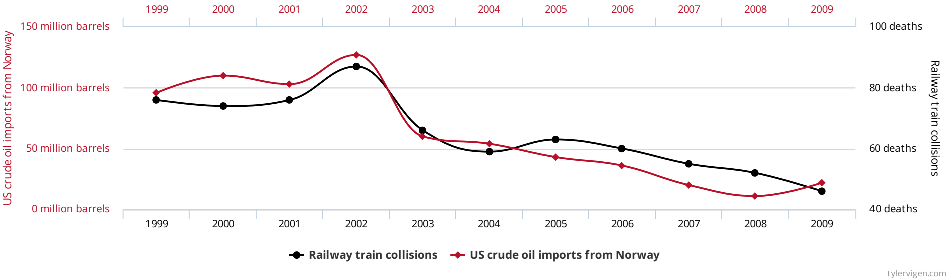
Worldwide non-commercial space launches
tylervigen.com

US crude oil imports from Norway

correlates with

Drivers killed in collision with railway train



Letters in Winning Word of Scripps National Spelling Bee

correlates with

Number of people killed by venomous spiders

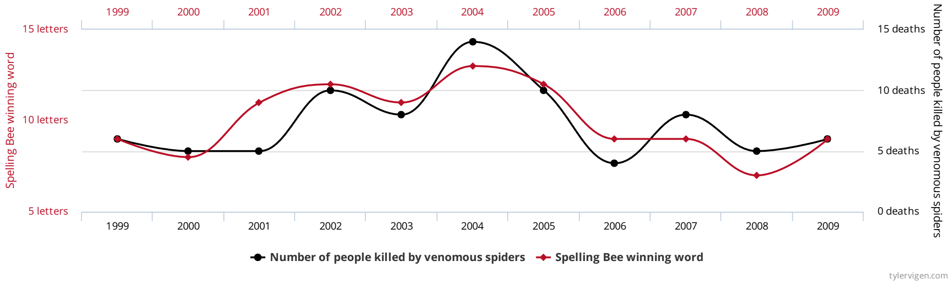


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.

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  - But for *intervention*, correlation does not help: forcing people to eat more chocolate does nothing on its own to produce more Nobel Laureates
- So if we want to provide policy-relevant advice, we need to know more than just correlation

Learning from Data

- Why isn't correlation enough?
    - 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
    - Explanation means identifying the *direct* and *local* factors that generate Nobel Laureates

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  - So let's abandon tax checks; the government wants to save money
  - But reducing checks reduces the chances of getting caught
  - Citizens start to lie on their tax forms
- That means we need to understand what *causes* people to lie on tax forms, so we can better understand their behaviour

Learning from Data

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Causes of Effects	**Effects of Causes**
What caused Y?	Does X cause Y?
Why did the United States grow faster than Bolivia in the twentieth century?	Did the more permanent colonial settlement of the United States compared to Bolivia affect their subsequent growth rates?

Causal Inference

- So we need to learn about the **causal mechanisms** that drive behaviour and shape outcomes
- The problem is not data *quality*, but how the data were generated
- We need data generated in ways that reveal the causal mechanism - what would happen if we changed a variable, keeping everything else the same

Causal Inference

- So the type of questions we are asking are NOT "What caused Y?"
  - eg. Why did the United States grow faster than Bolivia in the twentieth century?
- But "Does X affect Y?"
  - eg. Did the more permanent colonial settlement of the United States compared to Bolivia affect their subsequent growth rates?
- These are called “Effects of Causes” questions (not “Causes of Effects” questions)

Causal Inference

- A focus on a single explanatory variable X requires us to clearly define this '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 also crucial:
  - Can we measure our outcome of interest?
  - Is that outcome the end of the causal chain?
  - Tempting to look at many outcomes, but the risk of cherry-picking
    - All outcomes are probabilistic
    - If we study 20 outcomes, on average one will show a significant effect even with no real causal effect

Causal Inference

- Learning about causal effects requires us to specify the 'unit' - what is being affected?
- Countries? Political Parties? Individuals?
- eg. How does segregation affect attitudes to redistribution?
  - Treatment at the community/societal level
  - Outcome at the individual level
  - Measurement needed at the individual level
- Units are **time-specific**: the same person 10 minutes later is a different unit

Causal Inference

- We want to know how some variable affects another variable
- eg. how a proportional representation electoral system affects investment in education
  - The **unit** here is any political system where both electoral system and education can vary independently of other units, i.e. countries
  - The **treatment** is a change to a PR electoral system (vs FPTP)
  - The **outcome** is the level of (public?) investment in education

Causal Inference

- Causality is complex, eg. for $X \rightarrow Y$:
  1. Many factors influence a single outcome ($X1, X2 \rightarrow Y$)
     - Parliamentarism also influences investment in education
  2. Equifinality: Many routes to the same outcome ($X1 + X2$ or $X3 + x4 \rightarrow Y$)
     - Ghana and Iceland spend the same on education, but in very different ways
  3. Reverse causation ($Y \rightarrow X$)
     - A highly educated population might prefer a PR system
  4. Non-linear impact of one variable on another ($X \Rightarrow Y$)
     - A mixed electoral system may have no effect, but a full PR system might lead to a big jump in investment
  5. General equilibrium effects - treatment affects many other variables ($X \rightarrow Y1, Y2 \rightarrow Y1$)
     - Public investment in education rises, but private investment falls by the same amount

Causal Inference

6. Context matters ($X|Z \rightarrow Y$)
   - PR has a different effect in British vs French legacy education systems
7. Treatments cannot be replicated ($X1 \rightarrow Y1, X2 \rightarrow Y2$)
   - Some countries apply open list PR, others closed list etc.
8. Spillovers between units ($X_T \rightarrow X_C \rightarrow Y$)
   - When New Zealand switched to PR, Australia was a natural comparator, but to compete for students, Australia also raised education investment
9. Learning, demonstration effects and history matter ($X_{t=1} \rightarrow Y1, X_{t=2} \rightarrow Y2$)
   - New Zealand adopted PR *because* it saw that education improved in Japan
10. Social complications eg. emotion, irrationality, chaos theory ($X \rightarrow Y1, X \rightarrow Y2$)
    - New Zealand introduced PR because of an off-hand remark by one person in a campaign

Causal Inference

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Causal Inference

- 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:

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

- Treatment Effect $= Y_{1i} - Y_{0i}$

Causal Inference

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  - Would World War I still have happened if Archduke Franz Ferdinand had not been assassinated in 1914?
  - Would people have voted for Brexit if the campaign had been better regulated?
  - Would Brazil have won the 2014 World Cup if Neymar had not been injured?
- To explain a class of events - not a single event - we need multiple counterfactual comparisons

Causal Inference

Potential Outcomes Example

	Investment in Education if PR	Investment in Education if NOT PR	
	Y_1	Y_0	Treatment Effect
Brasil	8	4	4
Argentina	10	7	3
Bolivia	2	4	-2
Colombia	11	11	0
Peru	6	2	4

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

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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

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