Causality: Approaches and Pitfalls

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The Problem

Consider an outcome $Y$, treatment $T$, covariate vector $X$

- Example: job training on wages, low fat diet on heart disease, etc.
- $y_{i1}$: outcome for person $i$ if they get $T = 1$
- $y_{i0}$: outcome for person $i$ if they get $T = 0$

- What is the impact of $T$ on $Y$?
- Object of Interest

$$E(y_{i1} - y_{i0})$$
The Problem

- Observe $y_{i1}$ or $y_{i0}$ for a given person
  - You cannot see the same person at the same moment with and without the treatment
- What can you see?
  \[ \bar{y}_1 - \bar{y}_0 \]
- What is the problem?
  - People with $T = 1$ may be systematically different from those with $T = 0$
- How can we figure out the causal impact of $T$?
Example and Outline

- Does eating a low fat diet lower your risk of mortality?
  - Y: Did you die?
  - T: Did you eat a low fat diet?
  - X: Other stuff about you

- Gold Standard
- Options with no special data requirements
- Options with special data requirements
Gold Standard: RCT

- Randomized Controlled Trial
- How to do?
  - Recruit people
  - Randomly tell half of them to eat a low fat diet
  - Follow over time, observe mortality
  - Compare mortality in treatment, control groups
- Why does this work?
- Downsides: expensive, hard to do.
Options with Common Data

- Example: NHANES Data
  - Dietary information
  - Good demographic data (education, income, etc)
  - Other health data
  - Can link to later mortality

- Selection on observables
- Selection on unobservables
Selection on Observables

Consider:

\[ E(y_{i1} | T = 1, X_i) - E(y_{i0} | T = 0, X_i) \]

i.e. a regression of \( Y \) on \( T \) which controls for observed covariates \( X \)

Uncovers causal effect if \( T \) is random conditional on \( X \)

In example: \( T \) diet, \( X \) education, income, race, age, gender.

Pitfalls?
Selection on Unobservables

- There are controls we are important in determining treatment which we do not observe
  - Without further assumptions, can say nothing
- Assume relationship between $X$ and $T$ is informative about relationship between $T$ and unobserved variables $W$
- May be able to bound effect size.
These techniques can work with limited data requirements

- It is easy to look for heterogeneity across people
- Very transparent
- May not (probably does not) generate causal effect.
- Very difficult to figure out how far you are from causal.
Imagine some variable $Z$ which (randomly) pushes some people into treatment.

Imagine isolating variation in treatment which is due to variation in $Z$

Use that part of the variation to estimate the impact of $T$

Examples:

- Regression discontinuity
- Instrumental Variables
- Propensity Score
Regression Discontinuity

(Fake) Example.

Doctors adopt new rule: BMI over 25, told to go on low-fat diet. BMI under 25, not told.

Two individuals
- BMI 24.9: Not told to go on low-fat diet
- BMI 25.1: Told to go on low fat diet

Otherwise similar (before/after breakfast)

“Random” determination of diet advice

If anyone listens to diet advice, can use this
- Graph
Regression Discontinuity: Minuses

- Effects are specific to the characteristics off of which you estimate them
  - What if low fat diet matters more if you are at a BMI of 40?
- Very strong data requirements
- Must be sure other things do not vary across the threshold
  - Why did they put the rule there in the first place?
Instrumental Variables

- (Fake) Example.
- Religion $Z$ requires being a vegetarian; on average, vegetarians eat less fat
  - Key assumption (“exclusion restriction”): religion does not otherwise affect mortality
- Relate $Z$ to $T$, calculate $\hat{T}$
- Relate $Y$ to $\hat{T}$
  - Effect is driven only by the variation in $T$ that is driven by $Z$.
  - $Z$ only impacts $Y$ through $T$. 
Instrumental Variables: Minuses

- Effects local to people impacted by the instrument
- Stringent data requirements
  - Exclusion restriction often implausible.
Propensity Score

- I know full set of variables that determine $T$. Actual $T$ contains some random-ness.
- I do not know how variables enter to determine $T$
  - polynomials, interactions, etc
- Entering all variables in regression over fits
- Generate $Pr(T)$ by regressing $T$ on all variables and combinations and predicting
  - Note on LASSO
- Control for $Pr(T)$, $T$.
- Pitfalls
Final Thoughts

- Causality is hard to show.
- Tension between strength of causality and locality of effect.
- I am in some ways more bullish than most on the first set of things,
  - Especially in the era of big data.