Causal Inference

Mixtape Session

MIXTAPE SESSIONS

Roadmap

- Counterfactuals and causality
  - Causality and models
  - Potential outcomes
  - Randomization and selection bias
  - Randomization inference
- Directed Acyclic Graphs
  - Graph notation
  - Backdoor criterion
  - Collider bias
  - Front door criterion
  - Concluding remarks

Sidebar: bootstrapping is different

- Sometimes people confuse randomization inference with bootstrapping
- Bootstrapping randomly draws a percent of the total observations for estimation; “uncertainty over the sample”
- Randomization inference randomly reassigns the treatment; “uncertainty over treatment assignment”

(Thanks to Jason Kerwin for helping frame the two against each other)

6-step guide to randomization inference

The following is from Imbens and Rubin's textbook on causal inference, as well as Matthew Blackwell's helpful lectures

1. Choose a sharp null hypothesis (e.g., no treatment effects)
2. Calculate a test statistic (T is a scalar based on D and Y)
3. Then pick a randomized treatment vector $\tilde{D}_1$
4. Calculate the test statistic associated with $(\tilde{D}, Y)$
5. Repeat steps 3 and 4 for all possible combinations to get $\tilde{T} = \{\tilde{T}_1, \ldots, \tilde{T}_K\}$
6. Calculate exact p-value as $p = \frac{1}{K}\sum_{k=1}^{K} I(\tilde{T}_k \geq T)$