Causality

Talk 1: Introduction

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Note: The following slides are primarily adapted from the course materials[1].

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[1] C. Heinze-Deml. Causality. URL: https://stat.ethz.ch/lectures/ss21/causality.php.

Causal Inference

Causal Inference the science of why. They invented the language of Causality roughly 30 years ago.

(a) J. Pearl, SCM

(b) D. Rubin, RCM(POF)

Figure 1: Mr. Bigs

Causal Inference

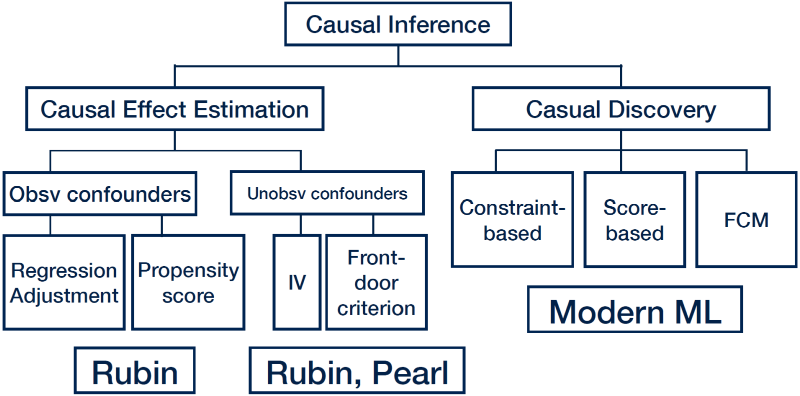


Figure 2: Big Picture[2].

[2] Ava Khamseh. Causality in Biomedicine. URL: https://edbiomed.ai/teaching/.

ETH zürich

Introduction

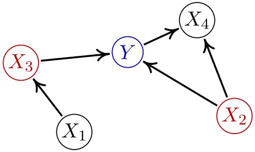
Causality

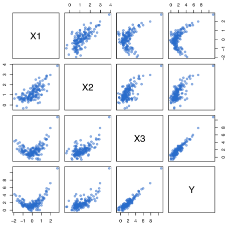
Christina Heinze-Deml

Spring 2021

Tentative course outline

- Background and frameworks
- Methods using the known causal structure
- Learning the causal structure





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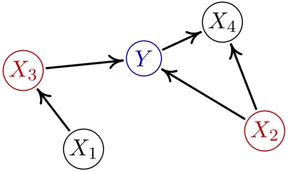
Tentative course outline

- Background and framework
  - Controlled experiments vs. observational studies
  - Simpson's paradox
  - Graphical models
  - Causal graphical models
  - Structural equation models
  - Interventions
  - …

Tentative course outline

- Methods using the known causal structure
  - Covariate adjustment
  - Instrumental variables
  - Counterfactuals
  - ...



$$
\begin{aligned}
Y &= f_Y(\text{parents}(Y), \text{noise}_Y) \\
X_1 &= f_1(\text{parents}(X_1), \text{noise}_1) \\
X_2 &= f_2(\text{parents}(X_2), \text{noise}_2) \\
&\dots \\
X_p &= f_p(\text{parents}(X_p), \text{noise}_p)
\end{aligned}
$$

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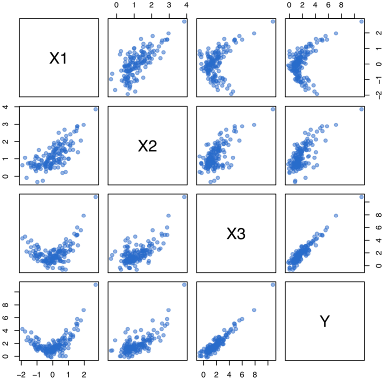
Tentative course outline

- Learning the causal structure
  - Constraint-based methods
  - Score-based methods
  - Invariant causal prediction
  - …



Observational studies

- Example:
  - Smoking is associated with disease
  - But does it cause diseases?
  - Cannot force people to smoke
  - Potential confounders: Gender, age, …
- What to do?
  - Compare similar subgroups
    - i.e. males who smoke vs. males who don't
    - "Controlling for confounders"
  - What should we control for?
    - Covered in detail later

Controlled experiments vs. observational studies

STUDIES

CONTROLS

NO CONTROLS

CONTEMPORARY

HISTORICAL

CONTROLLED EXPERIMENT

OBSERVATIONAL STUDY

⇒ this course: study causal inference based on observational data

RANDOMIZED

NOT RANDOMIZED

DOUBLE BLIND

OTHER

↳ gold standard for causal inference

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Simpson's paradox

	Treatment	Placebo
Male	50/100	150/500
Female	50/500	0/100
Total	100/600	150/600

Simpson (1951), in an example similar to this one: "*The treatment can hardly be rejected as valueless to the race when it is beneficial when applied to males and to females.*"

⇒ control for gender, use the treatment

⇓ replace gender by blood pressure (BP); numbers stay the same

	Treatment	Placebo
High BP	50/100	150/500
Low BP	50/500	0/100
Total	100/600	150/600

Simpson (1951), in an example similar to this one: "*…, yet it is the combined table which provides what we would call the sensible answer…*"

⇒ don't control for BP, don't use the treatment

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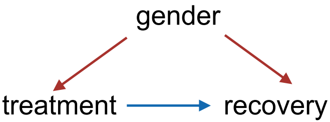
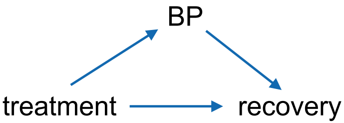
Simpson’s paradox and causal diagrams

- Same numbers, different conclusions….
  - Must use additional information: “story behind the data”, causal assumptions
- Consider total causal effect of treatment on recovery
  - Possible scenarios:



gender is a confounder;
control for gender



BP is an intermediate variable;
don’t control for BP

Or…..

Discussion

Any comments or questions?

We may not always find an answer, and since we're not very familiar with causality, we will need to dedicate more time to this topic.