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

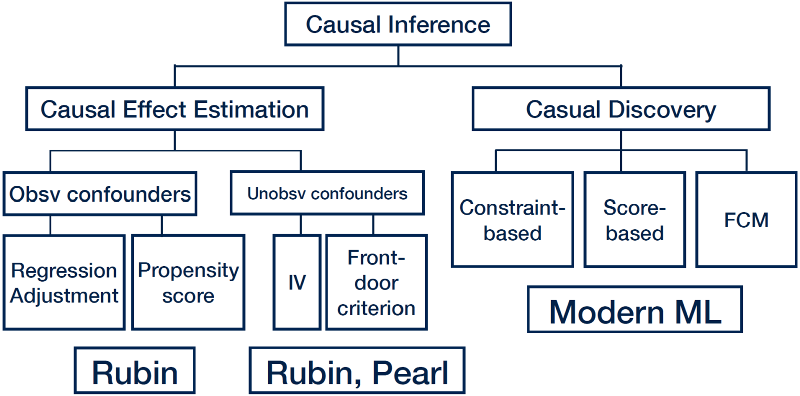


Figure 2: Big Picture[2].

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

Causal Inference

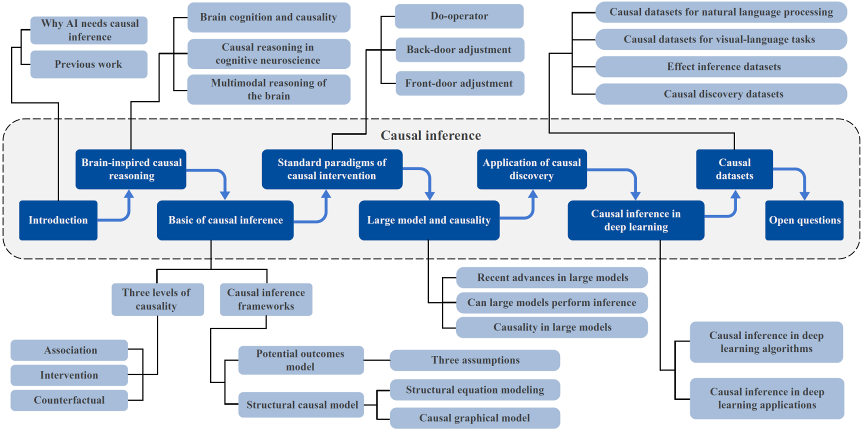
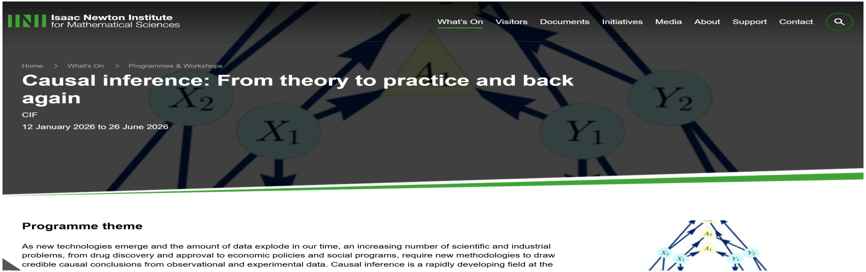


Figure 3: The overview of the survey[3].

[3] L. Jiao et al. "Causal Inference Meets Deep Learning: A Comprehensive Survey". In: Research 7 (2024), pp. 1–41.



(a) Causal Inference: From Theory to Practice and Back Again

(b) Machine Learning for Physics and the Physics of Learning

Introduction

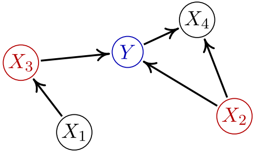
Causality

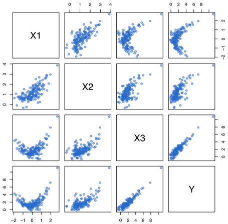
Christina Heinze-Deml

Spring 2021

Tentative course outline

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





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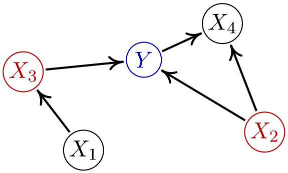
Tentative course outline

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

Tentative course outline

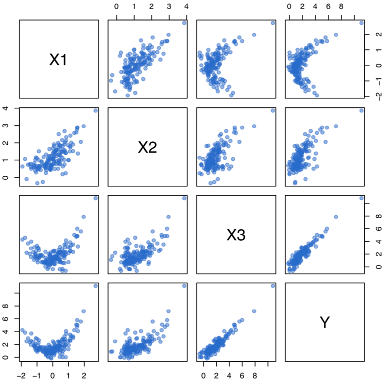
- Methods using the known causal structure
  - Covariate adjustment
  - Instrumental variables
  - Counterfactuals
  - …



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

Tentative course outline

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



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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
    - CONTEMPORARY
      - CONTROLLED EXPERIMENT
        - RANDOMIZED
          - DOUBLE BLIND
            - ↳ gold standard for causal inference
          - OTHER
        - NOT RANDOMIZED
      - OBSERVATIONAL STUDY
        - ⇒ this course: study causal inference based on observational data
    - HISTORICAL
  - NO CONTROLS

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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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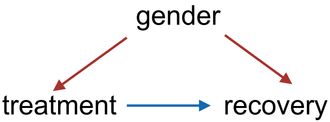
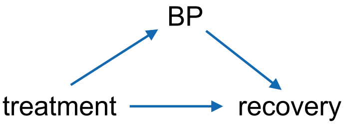
Simpson’s paradox and causal diagrams

- 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…..

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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.