

Causality

Talk 1: Introduction

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Note: The following slides are primarily adapted from the course materials¹.

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¹C. 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

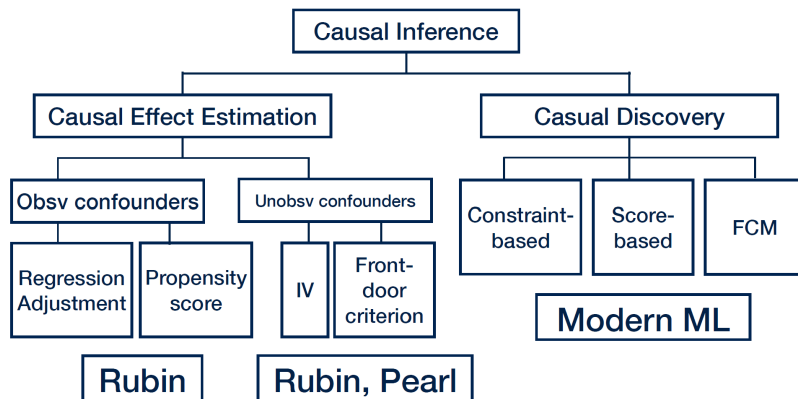


Figure 2: Big Picture².

²Ava Khamseh. Causality in Biomedicine. URL: <https://edbiomed.ai/teaching/>.

Causal Inference

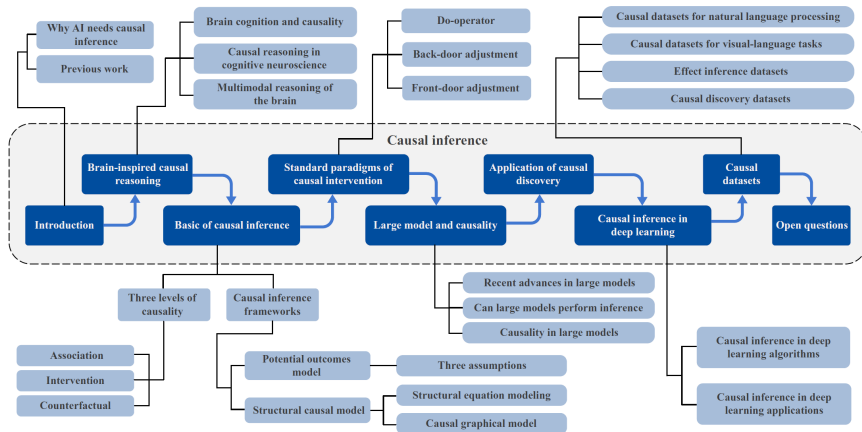


Figure 3: The overview of the survey³.

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



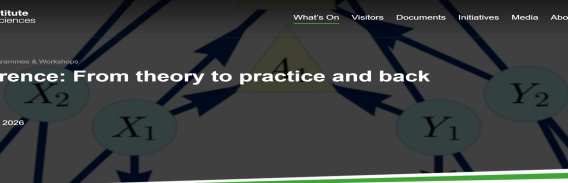
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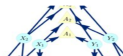
Causal inference: From theory to practice and back again

CIF
12 January 2026 to 26 June 2026



Programme theme

As new technologies emerge and the amount of data explode in our time, an increasing number of scientific and industrial problems, from drug discovery and approval to economic policies and social programs, require new methodologies to draw credible causal conclusions from observational and experimental data. Causal inference is a rapidly developing field at the



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

Long Programs

Programs > Long Programs > Machine Learning for Physics and the Physics of Learning

Machine Learning for Physics and the Physics of Learning

SEPTEMBER 4 - DECEMBER 8, 2019

OVERVIEW PARTICIPANT LIST SEMINAR SERIES ACTIVITIES

Overview

Machine Learning (ML) is quickly providing new powerful tools for physicists and chemists to extract essential information from large amounts of data, either from experiments or simulations. Significant steps forward in every branch of the physical sciences could be made by embracing, developing and applying the methods of machine learning to interrogate high-dimensional complex data in a way that has not been possible before.



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



Introduction

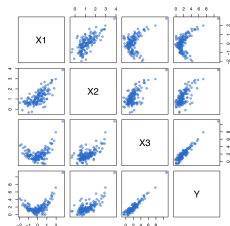
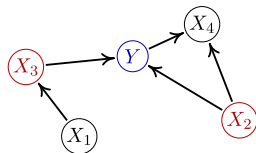
Causality

Christina Heinze-Deml

Spring 2021

Tentative course outline

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

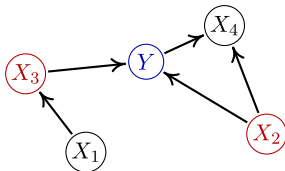


Tentative course outline

- 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
 - ...



$$Y = f_Y(\text{parents}(Y), \text{noise}_Y)$$

$$X_1 = f_1(\text{parents}(X_1), \text{noise}_1)$$

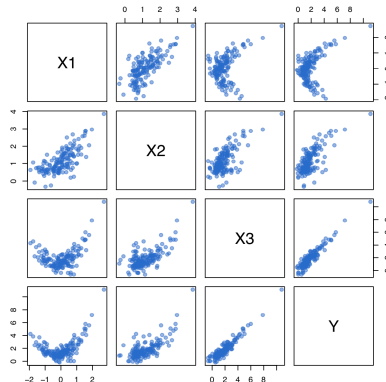
$$X_2 = f_2(\text{parents}(X_2), \text{noise}_2)$$

...

$$X_p = f_p(\text{parents}(X_p), \text{noise}_p)$$

Tentative course outline

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



Observational studies

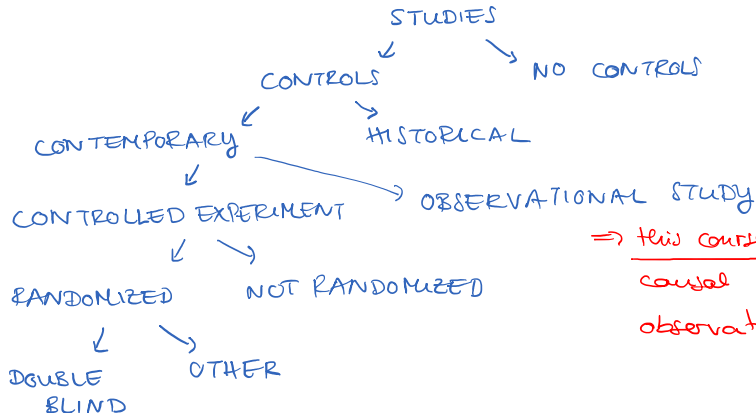
- **Example:**

- 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



⇒ this course: study
causal inference based on
observational data

⇨ gold standard for causal inference

Simpson's paradox

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

⇓ 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:
"The treatment can hardly be rejected as valueless to the race when it is beneficial when applied to males and to females."

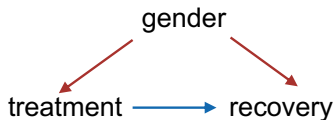
⇒ control for gender, use the treatment

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

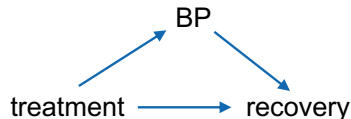
⇒ don't control for BP, don't use the treatment

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.