

# Causality

## Talk 1: Introduction

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Note: The following slides are primarily adapted from the course materials<sup>1</sup>.

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<sup>1</sup>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

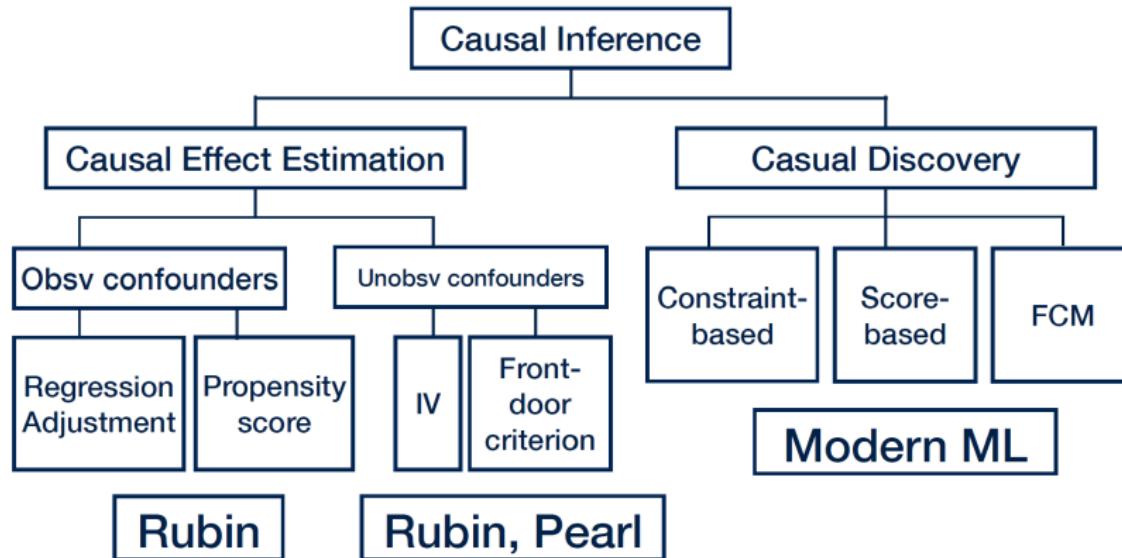


Figure 2: Big Picture<sup>2</sup>.

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

# Causal Inference

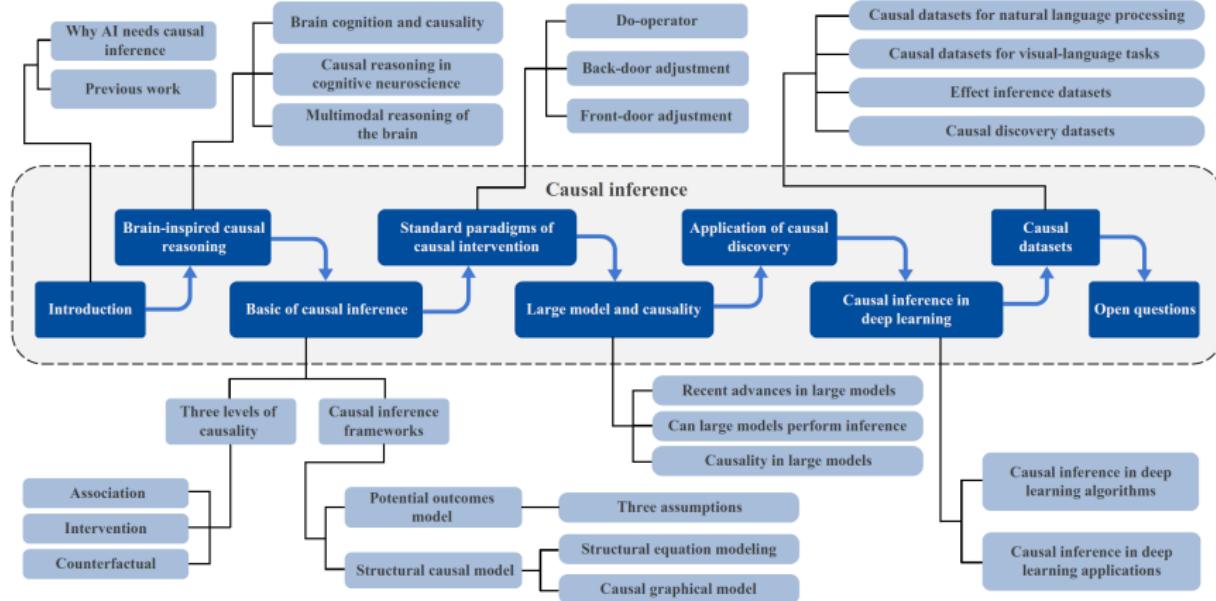


Figure 3: The overview of the survey<sup>3</sup>.

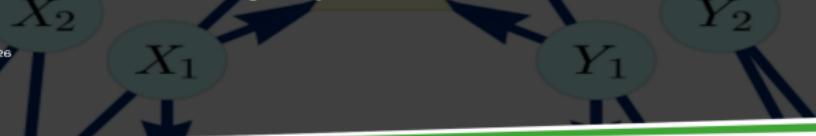
<sup>3</sup>L. Jiao et al. "Causal Inference Meets Deep Learning: A Comprehensive Survey". In: *Research* 7 (2024), pp. 1–41.

Home > What's On > Programmes & Workshops

## Causal inference: From theory to practice and back again

CIF

12 January 2026 to 26 June 2026



### Programme theme

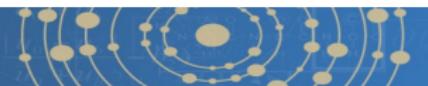
As new technologies emerge and the amount of data explode in our time, an increasing number of scientific and industrial problems, from drug discovery and approval to economic policies and social programs, require new methodologies to draw credible causal conclusions from observational and experimental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

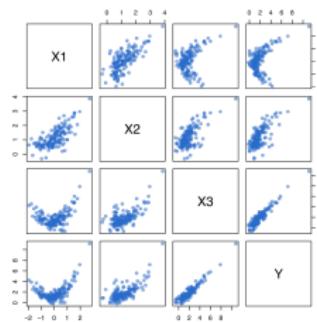
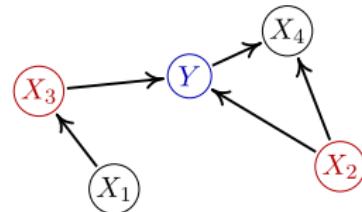
Causality

Christina Heinze-Deml

Spring 2021

## Tentative course outline

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

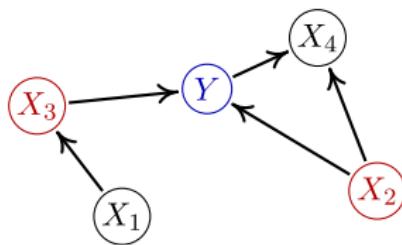


# Tentative course outline

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

## Tentative course outline

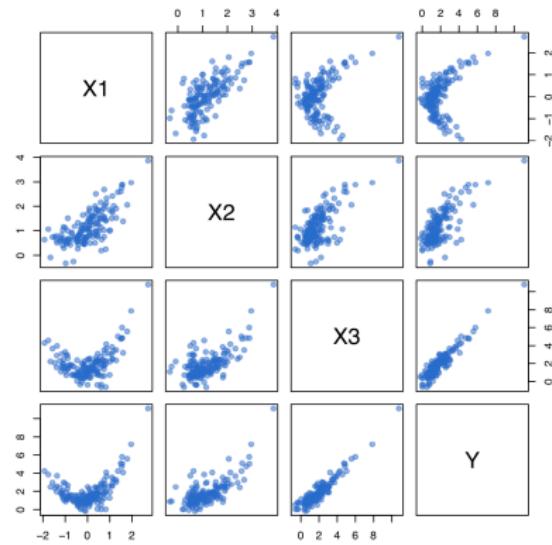
- Methods using the known causal structure
  - Covariate adjustment
  - Instrumental variables
  - Counterfactuals
  - ...



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

# Tentative course outline

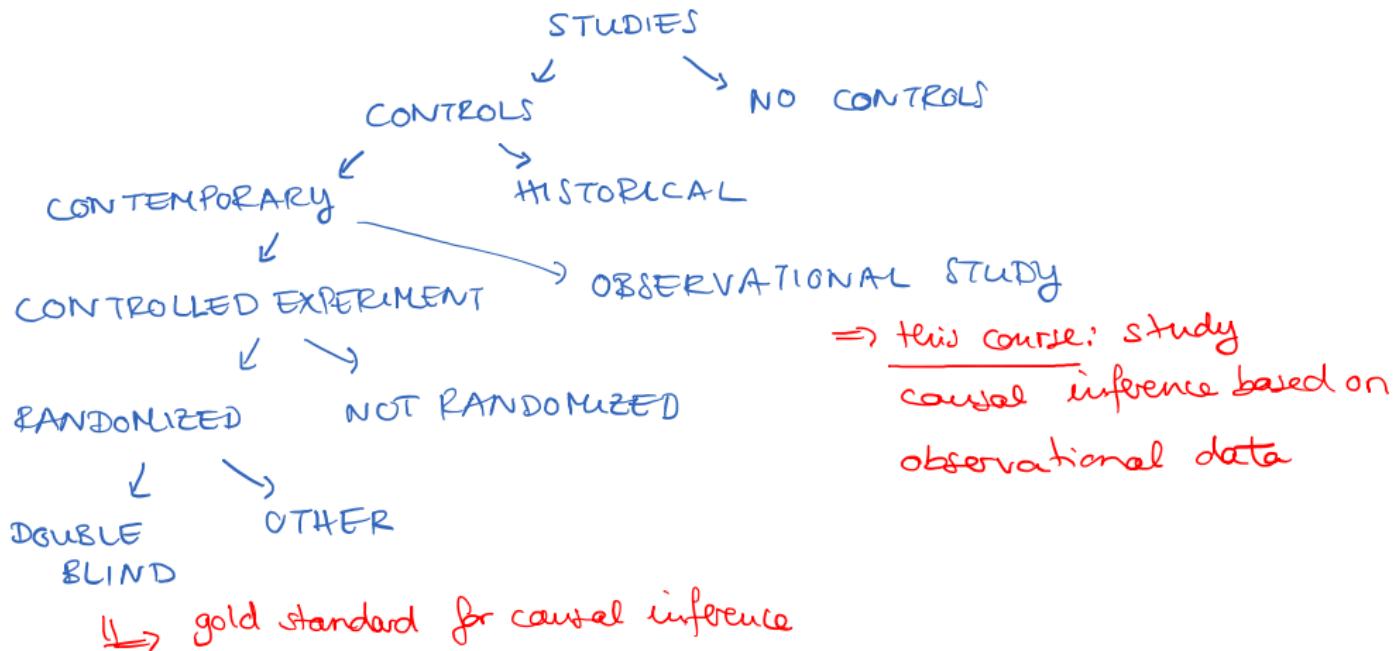
- Learning the causal structure
  - Constraint-based methods
  - Score-based methods
  - Invariant causal prediction
  - ...



# 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



## 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."*

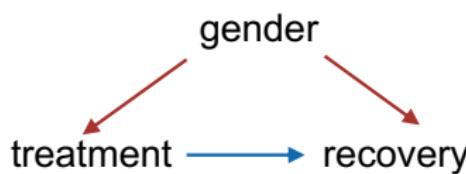
⇒ control for gender, use the treatment

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

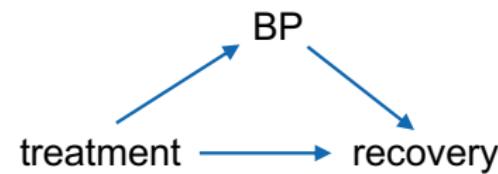
⇒ don't control for BP, don't use the treatment

## 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.