

(Casual) Causality Course 2025

Session 2

Gherardo Varando

27 March 2025

(Casual) Causality Course 2025

Instructors

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Schedule

- ▶ **week 1, Tuesday** Intro and causal inference (GV)
- ▶ **week 1, Thursday** Causal inference and robustness (GV)
- ▶ **week 2, Tuesday** Causal Discovery (ED)
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- ▶ **week 3** Intensive weeek with group projects!

Content week 1

- ▶ **Session 1** Tue 25/03

- Part I Intro to causality and causal methods

- Part II Basics of causal inference

- ▶ **Session 2** Thu 27/03

- ▶ Causal inference methods

Content week 1

► Session 1 Tue 25/03

Part I Intro to causality and causal methods

motivation, causal questions, what is causality?
experiments, interventions and counterfactuals
structural causal models and graphs

Part II Basics of causal inference

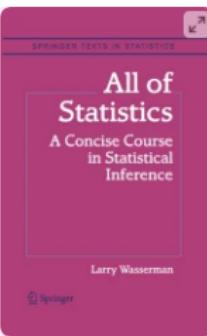
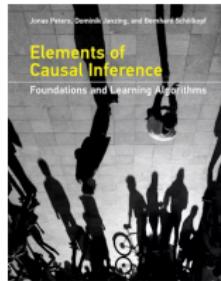
causal effect, randomized experiments
observational studies, identifiability conditions
graphical representation, confounding, selection bias
random variability and measurement error

► Session 2 Thu 27/03

► Causal inference methods

Basic references

- ▶ Elements of causal inference [Peters et al., 2017] [EC]
- ▶ Causal Inference: What If [Hernan and Robins, 2025] [Wif]
- ▶ All of Statistics [Wasserman, 2013] [AoS]



What is causality?

- ▶ Causality in Law

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- ▶ Rethinking Actual Causation in Tort Law

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Rovelli [2022]



Figure: Karditsa Thinker at the National Archaeological Museum, Athens

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Figure: Karditsa Thinker at the National Archaeological Museum, Athens

- ▶ Work in groups and briefly discuss causality in physics or law [15 min], choose a speaker
- ▶ The two speakers present the main ideas [5 min] (whiteboard, slides)

Potential outcomes - Counterfactual model

Hernan and Robins [2025]

Wasserman [2013]

- ▶ consider a binary **treatment variable** A (1: forest management practice (thinning, controlled burns,...) , 0: wild/uncontrolled forest)
- ▶ and a binary **outcome** Y (1: burned area, 0: not burned)
- ▶ A, Y are random variables that take possible different values for each individual



Figure: From <https://www.kunc.org/2024-03-15/long-term-study-finds-combination-of-prescribed-burns>

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- ▶ $Y^{a=1}$ and $Y^{a=0}$ are called **potential outcomes** or **counterfactual outcomes**
- ▶ for each individual, only one of the potential outcomes is actually observed/factual.

$$Y = Y^{a=A} \quad (\text{consistency equation})$$



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Causal effects

Definition

Average causal effects An average causal effect of treatment A on outcome Y is present if

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or equivalently (for binary outcomes)

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- ▶ causal odds ratio $\frac{P(Y^{a=1}=1)/P(Y^{a=1}=0)}{P(Y^{a=0}=1)/P(Y^{a=0}=0)}$

Randomized experiments

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- ▶ We then collect the outcome variable Y (e.g. burned or not after 1 year) for all individuals in the study



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- ▶ can we say something about the causal effect of A on Y ?
- ▶ yes! we can compute the average causal effect ... formally because there is **exchangeability** between the treated ($A = 1$) and untreated ($A = 0$) groups





New problem: the firefighters do not like your randomized study they say that it is too dangerous not to manage some patches at all, and that some areas have a too high fire risk to be left completely untreated

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- ▶ this is called *stratification*
- ▶ moreover we say that this procedure ensure **conditional exchangeability** $Y^a \perp\!\!\!\perp A|L$

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$$P(Y^a = 1) = \sum P(Y^a = 1 | L = I)P(L = I)$$

- ▶ **Inverse Probability Weighting** is an alternative, but equivalent, procedure to compute $P(Y^a = 1)$ by weighting each individual sample by $w_I = 1/P(A = a | L = I)$ and then we compute $P(Y^a = 1) = \sum w_I P(Y | A = a, L = I)$

Observational studies

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- ▶ still under certain conditions and assumptions we can identify the causal effect
- ▶ this conditions *assure that the observational study can be used somehow as a randomized trial*

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If we can assume this three conditions we can use the techniques such as IPW or standardization to compute ATE from observational data

Effect modification

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- ▶ Standardization (or IPW), stratification and matching measure different causal effects: Average effects in the entire population, conditional causal effects (stratification) and usually causal effects in the treated and untreated for matching

Computing interventional distributions in SCM

truncated factorization [Pearl, 1993], G-computation formula [Robins, 1986], manipulation theorem [Spirtes et al., 2000]

Given an SCM \mathcal{C} and an intervened SCM $\tilde{\mathcal{C}}$, obtained from \mathcal{C} by intervening on some X_k with $k \neq j$, we have that

$$P^{\tilde{\mathcal{C}}}(X_j | X_{pa(j)}) = P^{\mathcal{C}}(X_j | X_{pa(j)})$$

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- ▶ Thus in practical terms we will be able sometimes to estimate interventional objects, such as treatment effects, from observational data alone
- ▶ This requires the *knowledge of the causal graph*

Confounding and adjusting

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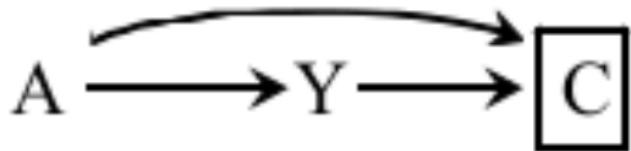
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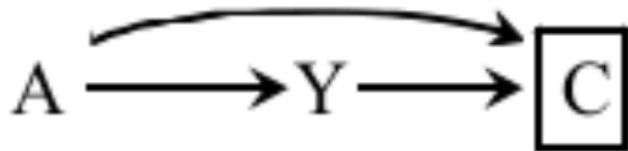
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- ▶ Valid adjustment sets ensure conditional exchangeability, thus we can use standardization or stratification to compute average or conditional causal effect
- ▶ viceversa there are techniques that can handle confounding problems without relying on exchangeability: e.g. difference-in-differences, instrumental variables and the front door criterion

Selection bias



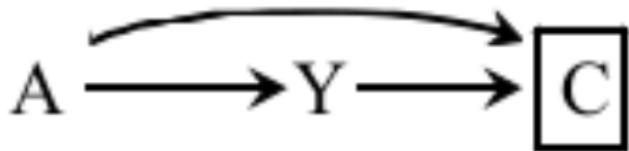
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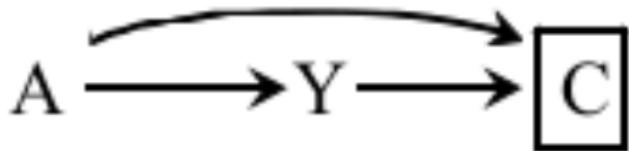
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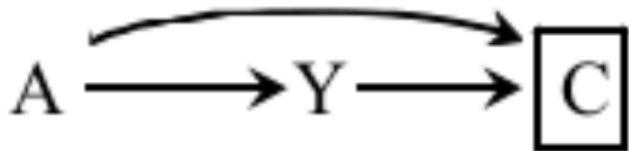
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- ▶ Selection bias leads to a lack of exchangeability
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- ▶ randomization does not protect from selection bias

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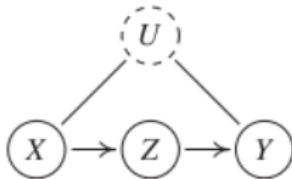
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- ▶ do-calculus is complete, every identifiable interventional distribution can be obtained
- ▶ one corollary of the do-calculus theorem is the **front-door adjustment**

Example 6.46 (Front-door adjustment) Let \mathfrak{C} be an SCM with corresponding graph



If we do not observe U , we cannot apply the backdoor criterion. In fact, there is no valid adjustment set. But still, provided that $p^{\mathfrak{C}}(x, z) > 0$, the *do*-calculus provides us with

$$p^{\mathfrak{C}; \text{do}(X:=x)}(y) = \sum_z p^{\mathfrak{C}}(z|x) \sum_{\bar{x}} p^{\mathfrak{C}}(y|\bar{x}, z) p^{\mathfrak{C}}(\bar{x}). \quad (6.23)$$

The fact that observing Z in addition to X and Y here reveals causal information nicely shows that causal relations can also be explored by observing the “channel” (here Z) that carries the “signal” from X to Y . \square

Bibliography I

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