Seminar on Causal Inference

Winter Semester 25/26

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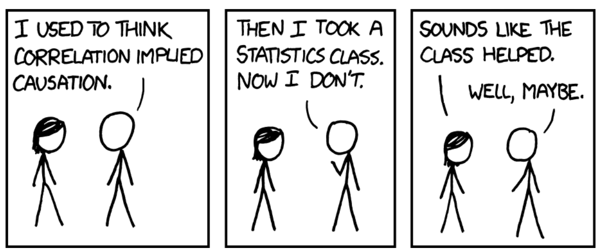
Introduction

Understanding *cause-and-effect* relationships is a fundamental goal across all scientific disciplines. Causal Inference provides a rigorous mathematical and computational framework to distinguish causation from correlation.



This seminar introduces the core concepts of causality, including counterfactual reasoning, graphical models (e.g., DAGs), structural causal models, and connections with stochastic differential equations. We will start by giving a brief introduction to causality and its classical representations as mentioned above (mostly from [SPJ17]). Depending on interest, we also aim to explore some theoretical and real-world applications ranging from measure theory [PBSM23], invariant prediction [PBM15], to dynamical systems [PBP20], machine learning [KLL+22] [LKS23] [CS16] [VP13] [Sch19] [LSR+22], [SLB+21], optimal transport [CE23] [Gun25], or computational biology [BLL+20].

No prior background in causal inference is assumed, though familiarity with probability theory might be helpful for getting started.

First Meeting: 10.11.2025 @ 1400hrs (Raum: EG 0/200)

In the first meeting, we will discuss the dates and give a brief introduction to causal inference. (If you are unable to attend the first meeting but would still like to participate, please send us an email).

There will be a total of 5 sessions, two in December (kw50, k251) two in Jan (kw3, kw5), and one more in Feb (kw8/9) if required.

References

[BLL+20] Philippe Brouillard, Sébastien Lachapelle, Alexandre Lacoste, Simon Lacoste-Julien, and Alexandre Drouin. Differentiable causal discovery from interventional data, 2020.

[CE23] Patrick Cheridito and Stephan Eckstein. Optimal transport and wasserstein distances for causal models, 2023.

[CS16] Fabio Costa and Sally Shrapnel. Quantum causal modelling. *New Journal of Physics*, 18(6):063032, June 2016.

[Gun25] Florian F Gunsilius. A primer on optimal transport for causal inference with observational data, 2025.

[KLL+22] Jean Kaddour, Aengus Lynch, Qi Liu, Matt J. Kusner, and Ricardo Silva. Causal machine learning: A survey and open problems, 2022.

[LKS23] Lars Lorch, Andreas Krause, and Bernhard Schölkopf. Causal modeling with stationary diffusions, 2023.

[LSR+22] Lars Lorch, Scott Sussex, Jonas Rothfuss, Andreas Krause, and Bernhard Schölkopf. Amortized inference for causal structure learning, 2022.

[PBM15] Jonas Peters, Peter Bühlmann, and Nicolai Meinshausen. Causal inference using invariant prediction: identification and confidence intervals. 2015.

[PBP20] Jonas Peters, Stefan Bauer, and Niklas Pfister. Causal models for dynamical systems, 2020.

[PBSM23] Junhyung Park, Simon Buchholz, Bernhard Schölkopf, and Krikamol Muandet. A measure-theoretic axiomatisation of causality, 2023.

[Sch19] Bernhard Schölkopf. Causality for machine learning. 2019.

[SLB+21] Bernhard Schölkopf, Francesco Locatello, Stefan Bauer, Nan Rosemary Ke, Nal Kalchbrenner, Anirudh Goyal, and Yoshua Bengio. Towards causal representation learning, 2021.

[SPJ17] Bernhard Scholkopf, Jonas Peters, and Dominik Janzing. *Elements of causal inference*. Adaptive Computation and Machine Learning series. MIT Press, London, England, November 2017.

[VP13] Tom S. Verma and Judea Pearl. On the equivalence of causal models, 2013.