IQB
Forschungsdatenzentrum

Introduction to Graphical Causal Inference

FDZ Frühjahrsakademie / Spring Academy 2026

- Dozierende*r / Lecturer: Moritz Ketzer, Humboldt-Universität zu Berlin
- Termin / Date and Time: Teil 1 / Part 1: Montag/Monday, 09.03.2026, 9:00 – 13:00 h
  Teil 2 / Part 2: Dienstag/Tuesday, 10.03.2026, 9:00 – 13:00 h

Abstract

I will provide an accessible introduction to graphical approaches to causal inference. In Part 1, we build up the basic concepts of causal reasoning. We learn what distinguishes association from causation and how we can formalize causal reasoning with Pearl's structural causal models (SCMs) and directed acyclic graphs (DAGs). We express interventions using the do-operator and turn informal scientific questions into precise causal quantities that our analyses can meaningfully target. Once we have these concepts in place, we introduce the graphical language of confounders, colliders, mediators and backdoor paths, and use them to decide when a causal question can be answered from observational data alone. We practice recognizing these structures and identifying suitable covariate adjustment sets by visual inspection and by using the online tool DAGitty. Between the two sessions, participants are encouraged to apply their new knowledge to their own research. In Part 2, we will discuss participants' graphs and related questions. We then extend the framework to multilevel and longitudinal data, drawing on my current research on how causal graphs can be used to understand confounding due to structured heterogeneity in parametric multilevel models such as cross-sectional and dynamic panel models.

Inhalte / Contents

Part 1 (4 hours): Foundations of graphical causal inference

- Welcome and introduction round
- Framing Causal Thinking
    - The ladder of causation: association, intervention, and counterfactuals

- The Causal Roadmap (for the workshop): informal question → formal causal query → estimand → identification → estimation
- Introduction to structural causal models (SCMs)
    - Structural Equations and directed acyclic graphs (DAGs)
    - The do-operator
    - Defining causal estimands
    - Brief comparison to the Rubin–Holland causal model (potential outcomes)
- Reading and working with causal graphs
    - Basic patterns:
        - fork (confounder)
        - collider
        - chain (mediator)
    - Understand open vs blocked paths (d-separation)
    - Identify backdoor paths and valid adjustment sets
    - Practice: "Which variables should we adjust for?"
    - Using DAGitty to draw DAGs, check backdoor paths, and find adjustment sets

Part 2 (4 hours): Multilevel and longitudinal causal graphs and causal implications of structured heterogeneity

- Recap and connection to participants' work
    - Short recap of key ideas from Part 1
    - Optional space for participants' DAGs
- Representing contexts and structured heterogeneity
    - Two ways to represent contexts (schools, clinics, etc.):
        - as single "context nodes" (long-format models)
        - as indices and repeated units (wide-format models)
        - a brief introduction to plate notation
- Revealing heterogeneity induced backdoor paths with wide-format graphs for parametric models
    - Graphical representation of cross-sectional multilevel models (persons nested in schools)
    - Introduction to the causal implications of structured heterogeneity in time-ordered models
        - What happens in a univariate dynamic model?
        - Outlook to more complex dynamic models (such as cross-lagged panel models)
- Recap, discussion and open questions

Voraussetzungen / Previous knowledge required

Basic familiarity with quantitative methods is required (introductory statistics and linear regression at the level of interpreting coefficients and covariates). Prior knowledge of causal inference, directed acyclic graphs (DAGs), or structural equation modeling is not required. Familiarity with multilevel/mixed models is helpful for Part 2 but not a prerequisite.

Literatur / Literature

Short conceptual pieces (framing the "C-word" and the roadmap)

Ahern, J. (2018). Start With the "C-Word," Follow the Roadmap for Causal Inference. American *Journal of Public Health, 108*(5), 621–621. https://doi.org/10.2105/AJPH.2018.304358

Hernán, M. A. (2018). The C-Word: Scientific Euphemisms Do Not Improve Causal Inference From Observational Data. *American Journal of Public Health, 108*(5), 616–619. https://doi.org/10.2105/AJPH.2018.304337

The popular scientific book (also available on audible)

Pearl, J., & Mackenzie, D. (2018). *The book of why: The new science of cause and effect* (First edition). Basic Books.

Introduction to graphical causal models in psychology

Rohrer, J. M. (2018). Thinking clearly about correlations and causation: Graphical causal models for observational data. *Advances in Methods and Practices in Psychological Science, 1*(1), 27–42.

Bailey, D. H., Jung, A. J., Beltz, A. M., Eronen, M. I., Gische, C., Hamaker, E. L., Kording, K. P., Lebel, C., Lindquist, M. A., & Moeller, J. (2024). Causal inference on human behaviour. *Nature Human Behaviour, 8*(8), 1448–1459.

Special topics (multilevel: causal inference in clustered and longitudinal data)

Rohrer, J. M., & Murayama, K. (2023). These Are Not the Effects You Are Looking for: Causality and the Within-/Between-Persons Distinction in Longitudinal Data Analysis. *Advances in Methods and Practices in Psychological Science, 6*(1), 251524592211408. https://doi.org/10.1177/25152459221140842

Gische, C., West, S. G., & Voelkle, M. C. (2021). Forecasting Causal Effects of Interventions versus Predicting Future Outcomes. *Structural Equation Modeling: A Multidisciplinary Journal, 28*(3), 475–492. https://doi.org/10.1080/10705511.2020.1780598

Ketzer, M., Gische, C., & Voelkle, M. C. (2025). From path diagrams to causal graphs: A structural causal perspective on cross-sectional multilevel models. *Structural Equation Modeling: A Multidisciplinary Journal*. Advance online publication. https://doi.org/10.1080/10705511.2025.2592071

Introductory and foundational textbooks for deeper study

Pearl, J. (2009). *Causality: Models, Reasoning, and Inference* (2nd ed.). Cambridge University Press.

Pearl, J., Glymour, M., & Jewell, N. P. (2016). *Causal Inference in Statistics: A Primer* (1. edition). Wiley.

Imbens, G. W., & Rubin, D. B. (2015). *Causal Inference for Statistics, Social, and Biomedical Sciences.* Cambridge University Press.

Morgan, S. L., & Winship, C. (2015). *Counterfactuals and causal inference: Methods and principles for social research* (Second Edition). Cambridge University Press.

Hernán MA, Robins JM (2020). *Causal Inference: What If.* Chapman & Hall/CRC.

Software / Software requirements

A computer or laptop with a modern web browser to use DAGitty (https://dagitty.net), an online tool for drawing and analyzing causal DAGs