Causal discovery

Further perspectives

Christine Winther Bang,
Department of Mathematical Sciences, October 21 2025

UNIVERSITY OF COPENHAGEN

Applications of TPC and TFCI

Petersen, Osler & Ekstrøm (2021): Data-driven model building for life-course epidemiology. American Journal of Epidemiology.

Andersen et al. (2023). Nighttime smartphone use, sleep quality, and mental health: investigating a complex relationship. Sleep.

Foraita et al. (2024): A longitudinal causal graph analysis investigating modifiable risk factors and obesity in a European cohort of children and adolescents. Scientific Reports.

Lee et al. (2023): Causal determinants of postoperative length of stay in cardiac surgery using causal graphical learning. The Journal of Thoracic and Cardiovascular Surgery.

Applicability of causal discovery

Petersen, Ekstrøm, Spirtes & Osler (2023). Constructing Causal Life-Course Models: Comparative Study of Data-Driven and Theory-Driven Approaches. American Journal of Epidemiology.

Didelez (2024). Invited Commentary: Where Do the Causal DAGs Come From?. American Journal of Epidemiology.

Textor (2025). Invited Commentary: When will causal structure learning become practical?. International Journal of Epidemiology.

Gururaghavendran & Murray (2025). Can algorithms replace expert knowledge for causal inference? A case study on novice use of causal discovery. American journal of epidemiology.

Alternative algorithms

Score-based methods: Heuristic search through possible (CP)DAGs, score each model according to fit. Examples: GES (Chickering 2002), GRASP (Lam et al. 2022), BOSS (Andrews et al. 2023).

Optimization-based methods: Try to estimate the global DAG structure at once. Examples: LiNGAM (Shimizu et al. 2006), NOTEARS (Zheng et al. 2018), DAG-GNN (Yu et al. 2019).

Fast-paced research field with many new algorithms being proposed each year, these are only a very few.

Finite sample and realistic real world data performance receives much less focus (see e.g. Bang et al. 2024).

Software

R packages: pcalg, bnlearn, tpc, micd

Python: causal-learn

TETRAD: Point-and-click software (also available in commandline (in Java), or via Python (py-tetrad))

See also the overview and introduction:
Andrews, Foraita, Didelez & Witte (2021). A practical guide to causal discovery with cohort data. arXiv preprint arXiv:2108.13395

Estimating causal effects

We can use the estimated graph for identifying causal effects, but it is not straightforward.

Find an adjustment set that is valid for covariate adjustment in every DAG: Perković et al. (2017, 2018), Henckel et al (2022).

Intervention calculus when the DAG is Absent (IDA) algorithm: Bounding causal effects from a CPDAG (Maathuis, Kalisch & Bühlmann 2009) or MPDAG (Perković et al. 2017, Fang & He 2020), or optimal (Witte et al. 2020).

One should be aware of post-selection issues. Ongoing research but generally a difficult problem: Strieder & Drton (2023), Chang et al. (2024), and Gradu et al. (2025).

Course day evaluation

https://forms.gle/eU4XEfNT4bvSzKPB9

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Andrews, Foraita, Didelez & Witte (2021). A practical guide to causal discovery with cohort data. arXiv preprint arXiv:2108.13395

Andrews, Ramsey, Romero, Camchong & Kummerfeld (2023). Fast Scalable and Accurate Discovery of DAGs Using the Best Order Score Search and Grow Shrink Trees. Advances in Neural Information Processing Systems.

Bang, Witte, Foraita, & Didelez (2024). Improving finite sample performance of causal discovery by exploiting temporal structure. arXiv preprint arXiv:2406.19503.

Chang, Guo & Malinsky (2024). Post-selection inference for causal effects after causal discovery. arXiv preprint arXiv:2405.06763.

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Foraita, Witte, Börnhorst, Gwozdz, Pala, Lissner, Lauria, Reisch, Molnár, De Henauw, Moreno, Veidebaum, Tornaritis, Pigeot & Didelez (2024): A longitudinal causal graph

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Shimizu, Hoyer, Hyvarine, Kermine & Jordan (2006). A linear non-gaussian acyclic model for causal discovery. Journal of Machine Learning Research.

Strieder & Drton (2023). Confidence in causal inference under structure uncertainty in linear causal models with equal variances. Journal of Causal Inference.

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Zheng, Aragam, Ravikumar & Xing (2018). DAGs with NOTEARS: Continuous optimization for structure learning. Advances in neural information processing systems.