MACHINE LEARNING FOR HEALTH

Causal Inference: From Correlation to Effect

DAGs, confounding, and the limits of observational evidence

TECHNICAL HANDOUT · SESSION 12

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Academic teaching material based exclusively on the PDFs available in the project

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Introduction

Predicting what usually occurs after observing X is not the same as estimating what would occur if X were changed. This distinction is central to questions about interventions, treatments, and policy. [1]

This session introduces causal relationships, confounding, directed graphs, and strategies for comparability. Because the local PDFs do not cover every technique planned in the slides in detail, the text maintains a level of depth consistent with the available evidence. [1]

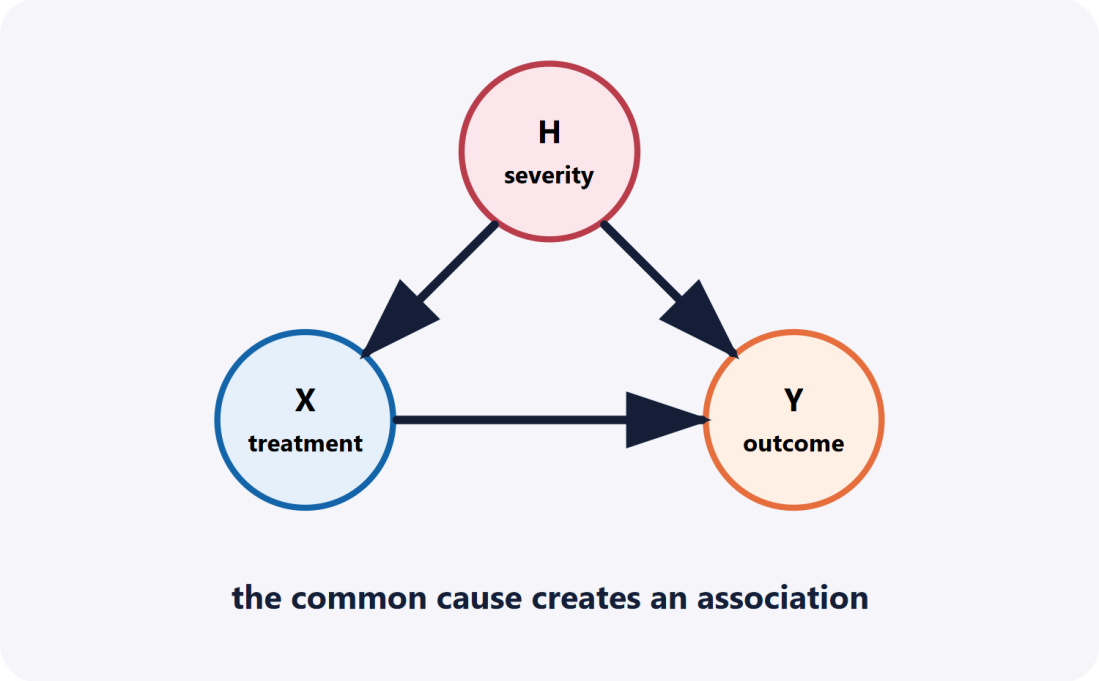

Figure 1 — Confounding represented in a DAG. Source: original illustration based on [1] and [2].

1. Observation and intervention

Predictive models estimate variables after observing other variables. Causal inference seeks relationships that make it possible to predict consequences after setting or intervening on a variable. Diagnosis with existing information is an observational prediction; choosing a therapy requires a prediction about the consequences of actions [1].

KEY CONCEPT
Predictive models estimate variables after observing other variables.

2. Confounding and DAGs

Confounding occurs when a common cause influences both exposure and outcome, creating or changing an association. If the factor is not measured, observational data may support incompatible explanations. A larger sample size does not automatically remove this problem [2].

Directed acyclic graphs represent hypotheses about causal relationships. They help make common causes, mediators, and colliders explicit and support discussion of which variables should be controlled. The graph is not discovered from correlation alone: it depends on knowledge and assumptions [1].

3. Comparability in real-world data

Randomized trials use allocation to create expected comparability. In observational data, stratification, matching, and weighting seek to balance measured covariates. The propensity score summarizes the probability of receiving an exposure given observed covariates; it does not resolve unmeasured confounding [2].

Confounding by indication occurs when prognosis and the treatment decision are related. Direct comparisons may then attribute to treatment differences that actually reflect the clinical indication [2].

4. Evidence, perturbation, and learning systems

Interventions or external variations can provide causal information that correlation alone does not supply. In translational biology, perturbing a variable and observing changes helps establish direction between mechanisms [3].

A learning health system combines care data, analysis, implementation, and renewed evaluation. The cycle produces reliable evidence only when the question, treatment, time, outcome, and causal assumptions are specified before analysis [4].

SOURCE LIMITATION
Target trial emulation, Mendelian randomization, and propensity-score formulas are not covered in detail by the local PDFs.

Session summary

Observation and intervention: predictive models estimate variables after observing other variables.
Confounding and DAGs: confounding occurs when a common cause influences both exposure and outcome, creating or changing an association.
Comparability in real-world data: randomized trials use allocation to create expected comparability.
Evidence, perturbation, and learning systems: interventions or external variations can provide causal information that correlation alone does not supply.

References

[1] Visweswaran, S.; King, A. J.; Cooper, G. F. Integration of AI for Clinical Decision Support. In: Intelligent Systems in Medicine and Health. Springer, 2022. External link

Local file: pdfs/3-Intelligent Systems/X-Integration of AI for Clinical Decision Support.pdf · PDF pages used: 7, 8, 9, 22.

[2] Friedman, C. P.; Wyatt, J. C. Evaluation of Biomedical and Health Information Resources. In: Biomedical Informatics. Springer, 2021. External link

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[3] Butte, A. J. et al. Translational Bioinformatics. In: Biomedical Informatics. Springer, 2021. External link

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[4] Brixey, J. J.; Burningham, Z. Evidence-Based Informatics. In: Health Informatics. 2021.

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