
Causal Inference

a summary

Contents

1	General	3	3	Longitudinal Data	5
2	Models	4			

1 General

Causal Roadmap (Petersen and van der Laan, 2014)

systematic approach linking causality to statistical procedures

1. Specifying Knowledge. structural causal model (unifying counterfactual language, structural equations, & causal graphs): a set of possible data-generating processes, expresses background knowledge and its limits

2. Linking Data. specifying measured variables and sampling specifics (latter can be incorporated into the model)

3. Specifying Target. define hypothetical experiment: decide

1. variables to intervene on: one (point treatment), multiple (longitudinal, censoring/missing, (in)direct effects)
2. intervention scheme: static, dynamic, stochastic
3. counterfactual summary of interest: absolute or relative, marginal structural models, interaction, effect modification
4. population of interest: whole, subset, different population

4. Assessing Identifiability. are knowledge and data sufficient to derive estimand and if not, what else is needed?

5. Select Estimand. current best answer: knowledge-based assumptions + which minimal convenience-based assumptions (transparency) gets as close as possible

6. Estimate. choose estimator by statistical properties, nothing causal here

7. Interpret. hierarchy: statistical, counterfactual, feasible intervention, randomized trial

Notation chapter 1.1

average causal effect chapter 1.2 and 1.3 and 1.4 and 1.5

randomized experiments (target trial) 2.1 and 2.2; 3.6

standardization 2.3

IP Weighting 2.4 (adjust for surrogate confounders)

identifiability conditions most of 3

effect modification chapter 4

interaction chapter 5

causal diagrams chapter 6, include swigs from 7.5 and that one technical point

confounding chapter 7

selection bias chapter 8

measurement bias chapter 9

random variability chapter 10

2 Models

Modeling data are a sample from the target population

estimand: quantity of interest, e. g. $E[Y|A = a]$

estimator: function to use, e. g. $\hat{E}[Y|A = a]$

estimate: apply function to data, e. g. 4.1

model: a priori restriction of joint distribution/dose-response curve; *assumption*: no model misspecification (usually wrong)

non-parametric estimator: no restriction (saturated model) = *Fisher consistent estimator* (entire population data \rightarrow true value)

parsimonious model: few parameters estimate many quantities

bias-variance trade-off:

wiggleness $\uparrow \rightarrow$ misspecification bias \downarrow , CI width \uparrow

IP Weighting / marginal structural models

(comparison at 13.4) (maybe censoring as own paragraph)

standardization / parametric g-formula chapter 13

g-estimation chapter 14

Outcome regression chapter 15

instrumental variable estimation chapter 16

causal survival analysis chapter 17

variable selection beginning of chapter 18

machine learning in CI end of chapter 18

3 Longitudinal Data

time-varying treatments beginning chapter 19

identifiability middle chapter 19

treatment-confounder feedback end chapter 19 and chapter 20

g-formula chapter 21.1

IP weighting chapter 21.2

doubly robust estimators chapter 21.3

g-estimation chapter 21.4

censoring chapter 21.5

target trial chapter 22 (does that even really fit in here, maybe push to 3rd paragraph in without models)

References

If no citation is given, the source is (Hernán and Robins, 2023)

Hernán, M. A. and Robins, J. M. (2023). *Causal inference: what if*. Boca Raton: Chapman & Hall/CRC.

Petersen, M. L. and van der Laan, M. J. (2014). Causal models and learning from data: integrating causal modeling and statistical estimation. *Epidemiology (Cambridge, Mass.)*, 25(3):418–426.

