Discussion on hypothetical strategies: a causal inference perspective

UNIVERSITEIT GENT

Kelly Van Lancker

FACULTY OF SCIENCES

Causal inference road map

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  3. **Estimation** method(s) along with statistical assumptions
- Despite the many positive steps, statisticians often tend to go straight to Step 3.
- In my opinion, we should strive to fully follow this road map to achieve the most benefits.

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- By using **counterfactual outcomes** notation, one can uniquely define the estimand. [Jonathan]
  - Controlled direct effect: $E\left[Y_2(Z=1, Sym=0) - Y_2(Z=0, Sym=0)\right]$ [Florian]
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- Importantly, the estimand should target the **scientific question** and be **model-free**.

Identification assumptions for hypothetical estimands

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- Different assumptions exist; e.g., **instrumental variable** conditions.
  - What is the role for instrumental variable assumptions/methods to correct for non-compliance?

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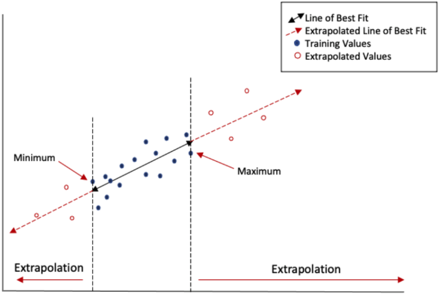
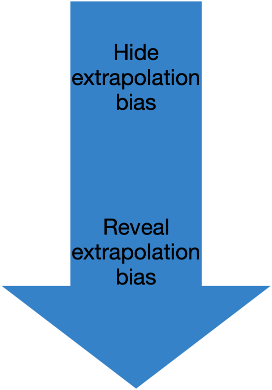
- This brings serious **concers for extrapolation**, and means that trade-offs need to be made between relevant and feasible estimands. [Jinglin]



Estimation of hypothetical estimands (2)



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- **G-estimation**[Florian]
  - Less clear how to use them for other type of endpoints (e.g., binary).
- **Inverse weighting**
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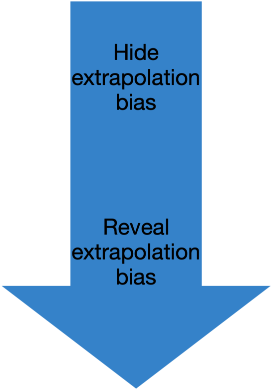

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- **Augmented inverse weighting** / **targeted learning** deserves much more attention. (Van der Laan et al., 2011)
  - More efficient than inverse weighting.
  - Less assumptions than G-estimation, thus usually less efficient.

Friendly criticism towards causal inference community

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I believe that, together, the two communities can push each other forward!

kelly.vanlancker@ugent.be

References I

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