Identification conditions for the effect of treatment in the treated

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We can target different parameters of interest in causal inference, including the average treatment effect (ATE) and the average treatment effect in the treated (ATT)

- The "identification conditions" of causal consistency, exchangeability, and positivity are sufficient to point-identify the ATE.[1]

This presentation will:

1. Describe conditions sufficient to point-identity the ATE and the ATT.
2. Provide an example where the ATE and ATT differ.
3. Demonstrate a simulation study where we vary the identification conditions.

Identification conditions

A = treatment (1: treated, 0: untreated), W = set of measured confounders, Y^a = potential outcome under treatment $A = a$

Average treatment effect (ATE)

1. Causal consistency: If $A_i = a, Y_i = Y_i^a$
2. Conditional exchangeability: $Y^a \perp A|W$
3. Positivity: $Pr(A = a|W = w) > 0$, for all w where $f(w) > 0$

Average treatment effect in the treated (ATT)

1. Causal consistency: If $A_i = a, Y_i = Y_i^a$
2. Partial conditional exchangeability: $Y^{a=0} \perp A|W$
3. Partial positivity: $Pr(A = a|W = w) > 0$, for all w where $f(w|A = 1) > 0$

Results of Multivariable Logistic Regression, Propensity Matching, Propensity Adjustment, and Propensity-based Weighting under Conditions of Nonuniform Effect[2]

Tobias Kurth, Alexander M. Walker, Robert J. Glynn, K. Arnold Chan, J.Michael Gaziano, Klaus Berger, and James M. Robins

- Investigated the effect of tissue-type plasminogen activator therapy (tPA) on in-hospital mortality in ischemic stroke patients.
- Utilized the Stroke Registry of Northwest Germany, 2000-2001
- Compared 5 methods of treatment effect estimation

Motivating example

To motivate our simulation, we updated Kurth and colleagues' analyses using 2020-2021 data from the same stroke registry.

We made a few updates:

1. Focused on risk ratios
2. Only two methods: inverse probability of treatment and standardized mortality ratio weighted effect estimates.
3. Propensity score model coefficients, weighted risks, risk ratios, odds ratios, and corresponding standard errors estimated using M-estimation.

Motivating example: results

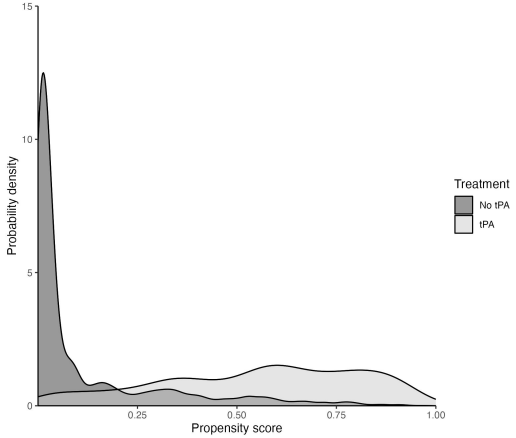

Figure 1: Probability density function of the propensity score by treatment status

Table 1: tPA treatment effect on in-hospital mortality by propensity score percentile.

Percentile	RR
95 to 100	0.67
90 to <95	0.63
75 to <90	0.71
50 to <75	1.24
25 to <50	1.04
10 to <25	3.08
5 to <10	13.59
0 to <5	

Motivating example: results cont'd

Table 2: Comparison of estimated treatment effect of tPA on in-hospital mortality using IPT and SMR weighted risk ratios

	Risk Ratio	95% CI
Crude	1.51	1.17, 1.95
IPT weighted	2.27	0.89, 5.76
SMR weighted	0.82	0.55, 1.21

Simulation

- We define three populations, each with a treatment (A) prevalence of 0.2.
- Each population has a different prevalence of confounder W: 0.25, 0.5, 0.75
- Treatment assignment:
  - Under "complete" conditional exchangeability with positivity, the prevalence of treatment does not depend on W.
  - Under "partial" conditional exchangeability with positivity for the treated, prevalence of treatment does depend on W, i.e.:

$$P(A = 1|W = 0) = 0$$

$$P(A = 1|W = 1) = 0.8, 0.4, 0.267$$

Simulation

- Generated potential outcomes under each treatment strategy assuming a treatment effect corresponding to a risk ratio of 0.8.
  - Outcome incidence in the untreated ranged from 0.01 (W=0) to 0.08 (W=1).
- Propensity score model coefficients, weighted risks, risk ratios, odds ratios, and corresponding standard errors estimated using M-estimation.

Simulation Results

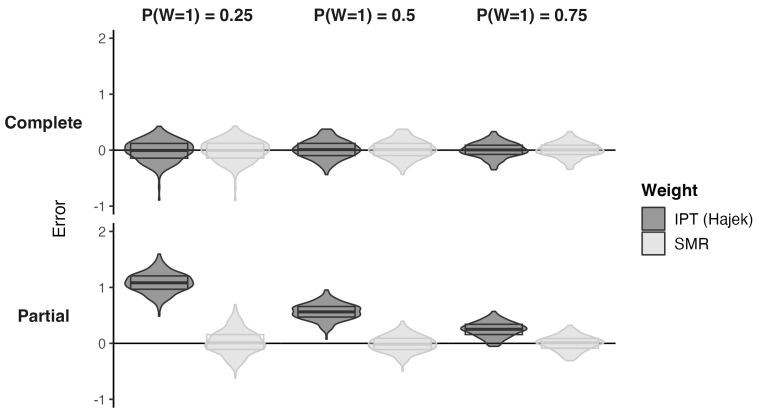

Figure 2: Bias of the log risk ratio in simulated populations under complete exchangeability and partial exchangeability with varying marginal distributions of W.

Conclusions

- The effect of tPA on in-hospital mortality continues to show considerable treatment effect heterogeneity.
- Targeting the ATE when causal identification conditions are not met results in biased effect estimates.
- If partial causal identification conditions are met for one treatment group, the treatment effect for that group can be consistently estimated.

Still working on:

- Understanding discrepancies by weighted risk estimators (Hajek vs. Horvitz-Thompson)
- Running all 5,000 simulations

References

1. Hernán MA, Robins JM. Estimating causal effects from epidemiological data. *Journal of Epidemiology and Community Health*. 2006;60(7):578-586. doi:10.1136/jech.2004.029496

2. Kurth T, Walker AM, Glynn RJ, et al. Results of multivariable logistic regression, propensity matching, propensity adjustment, and propensity-based weighting under conditions of nonuniform effect. *American Journal of Epidemiology*. 2006;163(3):262-270. doi:10.1093/aje/kwj047