Identifying Direct Causal Effects Under Unmeasured Confounding

Philippe Boileau[*1], Nima S. Hejazi[*2], Ivana Malenica[*1], Sandrine Dudoit[1], Mark J. van der Laan[1]

[1]University of California, Berkeley; [2]Weill Cornell Medicine

Introduction

This is the background.

Statistical Problem

State the causal and statistical models, and estimand.
The causal target parameter is

$$\Psi^F(P_{U,X,0}) = \int_{w,z} \mathbb{E}[Y(1,z) - Y(0,z) \mid W = w]$$
$$p_Z(z \mid A = 0, w) p_W(w) \, dz \, dw \ .$$

Identification

(A1) Treatment–outcome randomization

(A2) Treatment–mediator randomization

(A3) Mediator–outcome randomization

(A4) No unmeasured endogenous pathways:
$f_Y(Z, A, W, V, U_Y) \equiv f_Y(Z, A, W, U_Y)$.

(A5) Conditional expectation equivalence:
$\mathbb{E}(Y \mid Z, A = 1, W, V) \equiv \mathbb{E}(Y \mid Z, A = 1, W)$
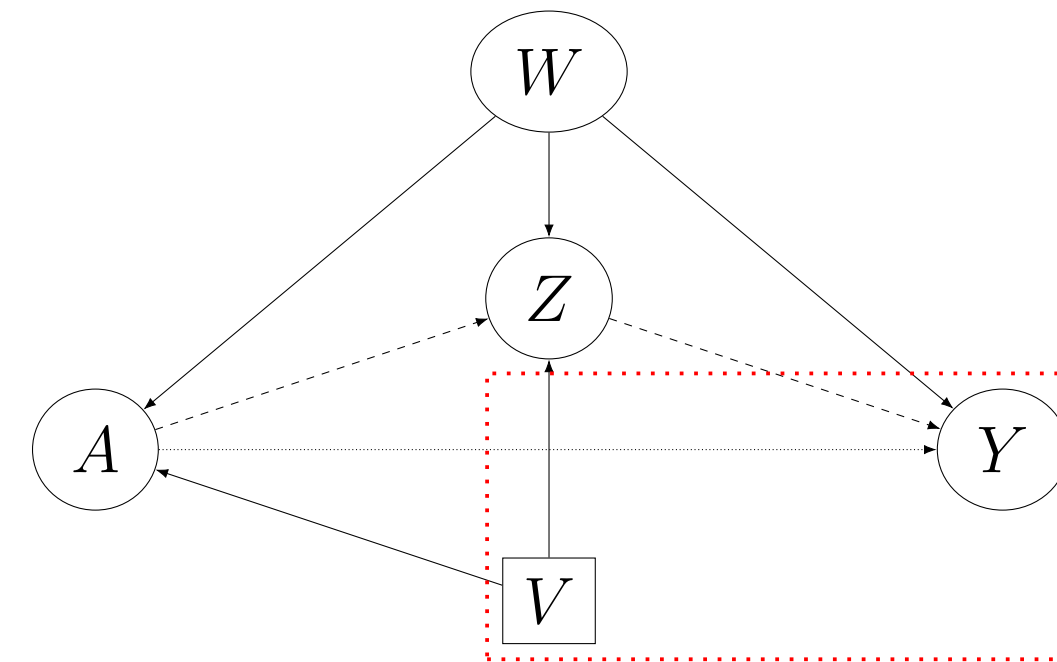
Theorem

Under these assumptions, the corresponding statistical estimand is

$$\Psi(P_0) = \mathbb{E}_{P_0} \mathbb{E}_{P_0} \{ \mathbb{E}_{P_0}(Y \mid W, A = 1, Z)$$
$$- \mathbb{E}_{P_0}(Y \mid W, A = 0, Z) \mid A = 0, W \} \ .$$

Inference

Statistical inference is possible using standard methods.

Simulation Results

Here are the results of our simulation study.

Conclusions

Here are the important takeaways.

References

List of references.

Funding

Thank you for paying my bills.

indicates shared first-authorship