Estimation of controlled direct effects

Stijn Vansteelandt[1], Sylvie Goetgeluk[1], Els Goetghebeur[1,2] and Christoph Lange[2]

[1] Department of Applied Mathematics and Computer Science, Ghent University, Belgium
[2] Department of Biostatistics, Harvard School of Public Health, Boston, USA

When regression models adjust for mediators on the causal path from exposure to outcome, the regression coefficient of exposure is commonly viewed as a measure of the direct exposure effect. This interpretation can be misleading, even with a randomly assigned exposure. This is because adjustment for post-exposure measurements introduces bias whenever their association with outcome is confounded by more than just the exposure. By the same token, adjustment for such confounders stays problematic when these are themselves affected by the exposure. Robins[1] accommodated this by introducing structural nested direct-effect models with direct effect parameters that can be estimated using inverse probability weighting by a conditional distribution of the mediator. The resulting estimators are consistent, but inefficient and can be extremely unstable when the intermediate variable is absolutely continuous. In this talk, I will develop direct effect estimators which are not only more efficient, but also consistent under a less demanding model for a conditional expectation of the outcome. We find the one estimator which avoids inverse probability weighting altogether to perform best. This estimator is intuitive and computationally straightforward. Simulation and application to three genome-wide association studies demonstrates the adequate performance of the estimator and shows that it competes extremely well with ordinary least squares estimators in settings where standard regression is valid.

References

[1] Robins JM (1999) Testing and estimation of direct effects by reparameterizing directed acyclic graphs with structural nested models. In *Computation, Causation, and Discovery*, eds. C. Glymour, and G.F. Cooper, AAAI Press/The MIT Press, pp. 349-405.