Statistical Considerations in Multilevel Mediation Analysis

William Ruth

Collaborators: Rado Ramasy, Rowin Alfaro, Ariel Mundo, Bruno Remillard, Bouchra Nasri





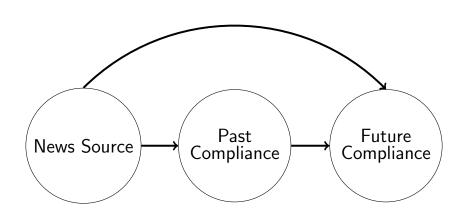
Outline

- 1) The Problem
- 2) Multilevel Causal Mediation Analysis
- 3) Uncertainty Quantification

Example

- Goal: Understand adherence to restrictive measures
 - E.g. Lockdowns
 - Both past and future
- Influence of news source
 - How trustworthy?
- Disentangle influence on future from influence on past

Example

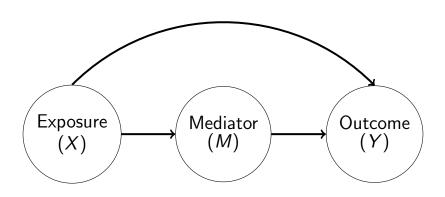


Example

Terminology

- Top path: Direct effect
- Center path: Indirect effect
- Combined: Total effect

- Exposure: *X*
- Outcome: Y
- Mediator: M



- Separate **Total Effect** of *X* on *Y* into
 - Direct Effect
 - Indirect Effect
- Define mediation effects using counterfactuals
- Differences, ratios, odds-ratios

- We only observe one outcome per individual
- Explore population-level effects by averaging
- Identify expected counterfactuals with conditional expectations
 - Now it's a regression problem

- Fit two regression models
 - Mediator given exposure
 - Outcome given mediator and exposure
 - Both may include confounders
- Linear vs Logistic
- Fixed- vs Mixed-Effects
 - Single- vs Multi-Level

- Fit two regression models
 - Mediator given exposure
 - Outcome given mediator and exposure
 - Both may include confounders
- Linear vs Logistic
- Fixed- vs Mixed-Effects
 - Single- vs Multi-Level

- Model fitting involves intractable integrals over unobserved random effects
 - Evaluate using quadrature
- Estimated mediation effects depend on coefficients and RE covariances
- Uncertainty quantification:
 - Quasi-Bayesian Monte Carlo
 - δ -method

- Quasi-Bayesian Monte Carlo
 - Monte Carlo δ -Method
- Estimate sampling distribution of regression parameters
- Simulate from estimated sampling distribution
- Compute mediation effects for simulated parameters

- Quasi-Bayesian Monte Carlo
 - Monte Carlo δ -Method
- Advantage: Flexible
- Disadvantage: Computational
- Existing implementation in R: mediation
 - Limited

• δ -Method

- Estimate (asymptotic) sampling distribution of regression parameters
- Compute Jacobian of map from regression parameters to mediation effects
- Multiply asymptotic covariance by Jacobian

- δ -Method
- Advantage: Analytical
- Disadvantage: Asymptotic
- No existing R implementation
 - Until now!
 - Use glmmTMB, not lme4

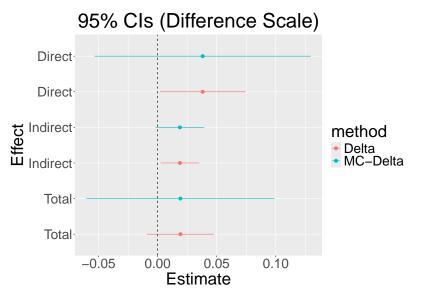
- Simulate 200 datasets
 - 100 groups, 500 individuals per group
- Build confidence intervals using δ and MC δ -methods
- Also build Wald interval using Monte Carlo (empirical) covariance matrix

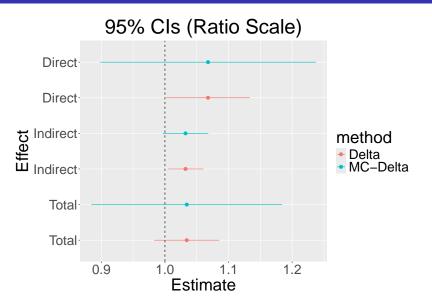
Effect	Scale	δ	$MC \delta$	Empirical
Total	Diff	0.940	0.940	0.940
	Ratio	0.935	0.930	0.955
	OR	0.955	0.960	0.950
Direct	Diff	0.960	0.960	0.960
	Ratio	0.935	0.930	0.945
	OR	0.970	0.970	0.950
Indirect	Diff	0.950	0.955	0.965
	Ratio	0.955	0.955	0.960
	OR	0.955	0.955	0.960

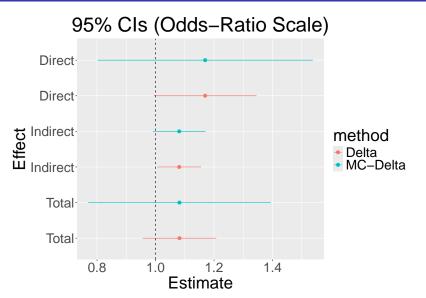
- Simulate 200 datasets
 - 10 groups, 1000 individuals per group
- Build confidence intervals using δ and MC δ -methods
- Also build Wald interval using Monte Carlo (empirical) covariance matrix

Effect	Scale	δ	$MC \delta$	Empirical
Total	Diff	0.935	0.928	0.954
	Ratio	0.961	0.974	0.967
	OR	0.935	0.928	0.967
Direct	Diff	0.948	0.928	0.941
	Ratio	0.928	0.935	0.967
	OR	0.954	0.935	0.948
Indirect	Diff	0.974	0.967	0.961
	Ratio	0.980	0.974	0.961
	OR	0.948	0.928	0.948

- Applying our method to the trust study dataset
 - Compare low-high trustworthiness
- Cls for all effect-scale pairs
 - 9 Intervals
- \bullet δ and MC δ







Next Steps

- Compare with Imai et al. (mediation package)
- Sensitivity to values of confounders
- Parametric bootstrap
- Group-specific effects

Acknowledgements

Collaborators:

- Rado Ramasy
- Rowin Alfaro
- Ariel Mundo
- Bruno Remillard
- Bouchra Nasri

Funding:

Canadian Statistical Sciences Institute

Thank You