Agenda

Motivation

Balancing score property of propensity scores (PS) assumes that:

1. all confounders are observed and
2. measured without error.

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- In reality, covariate measurement error may be the rule rather than the exception.
  - self-reported measures: household income, weight, age of parents.
  - imperfect instruments: blood pressure, cortisol levels.
  - latent constructs: depression, disability.

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- Covariate measurement error may compromise the bias-reduction potential of propensity scores if treatment assignment depends on the true, unobserved covariate.
- Researchers left with the choice: exclude mismeasured covariates from PS model or ignore the measurement error.

Previous Research

Focus has been on classical measurement error

$W = X + U$, $E(U|X) = 0$, with constant variance
$U|X \sim Normal(0, \sigma_u^2)$

where X is the correctly measured covariate, and W is the mismeasured version of X.

Previous Research

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- Lockwood, McCaffrey. 2014: Argue that PS matching using covariates measured with error (only) will not work, but suggest that using the covariates measured with error in conjunction with treatment status may work in some scenearios.

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- Raykov. 2012: Propose latent variable approach to address covariate measurement error in propensity score methods. Assumes have congeneric measures for each covariate

Research Gap

Non-classical measurement error: differential by treatment status.

- Systematic differential measurement error that affects the mean.
  - Example: Adolescents in disadvantaged neighborhoods ('treatment' group) tend to overestimate their mothers' age when the adolescents were born.
- Heteroscedastic differential measurement error that affects the variance.
  - Example: Adolescents in disadvantaged neighborhoods are less accurate in knowing their mothers' age when the adolescents were born.

Goal

Approach that can flexibly handle covariate measurement error that is differential by treatment status.

Bayesian approach

- Most flexible approach for addressing measurement error (Carroll et al., 2006). Especially useful for measurement error model involving heteroscedasticity.
- Propogates uncertainty.
- Appropriate when validation data are external to the study sample instead of internal (Cole et al., 2006).
- Maximum likelihood approach has similar advantages, but Bayesian is simpler to implement (Hossain, Gustafson, 2009).

Notation

Let observed data $O = (W, Y, A, Z)$ and complete data $C = (W, Y, A, X, Z)$, where:

- Y = observed, continuous outcome of interest.
- A = observed, binary $(0/1)$ variable indicating treatment.
- Z = observed, continuous covariate.
- X = unobserved, continuous covariate.
- W = observed, mismeasured version of X, where the mismeasurement depends on the tratment.
  $W \sim Normal(f(X, A), \sigma^2 f(X, A)^2)$