

# STAT/BIOST 572: Intro Student Presentation

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Title of paper

**Transparent Parametrizations of  
Models for Potential Outcomes**

- Richardson, T., Robins, J.M. and Evans, R.J. (2011)

# Background

- Potential Outcomes Models
  - Models for estimating causal effects for inference [Rubin, 1974]
  - Estimands of interest involve comparisons of *potential outcomes*
  - Outcomes that would have been observed under different exposures of units to treatment [Rubin, 2004]
  - Well-established framework for formalizing causal assumptions

# Background

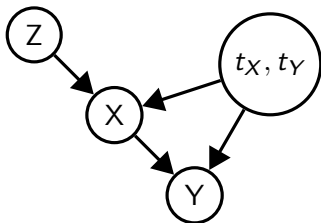
- Problem of non-compliance
  - Each unit's compliance with assigned treatment is not perfect
  - Even if assignment to a treatment was ignorable, the exposure to treatment is not
  - Lee et al. [1991] proposed Intention-To-Treat (ITT) Analysis
  - Angrist et al. [1996] made use of Instrumental Variables

# Motivation

- How to identify causal effects?
  - Hirano et al. [2000] use a hidden variable model for the distribution of the compliance and response types
  - Pearl [2000] derives bounds for causal effects
  - Stable (invariant to changes in compliance behaviour)
  - Can yield information on marginal and subject-specific effects
  - Bayesian approach - put a prior on it

# Motivation

- Observed
  - $Z$  = Assignment to treatment (Instrument)
  - $X$  = Receipt/Exposure to treatment
  - $Y$  = Response
- Unobserved (describing *potential outcomes*)
  - $t_X$  = Underlying compliance "type"
  - $t_Y$  = Underlying response "type"

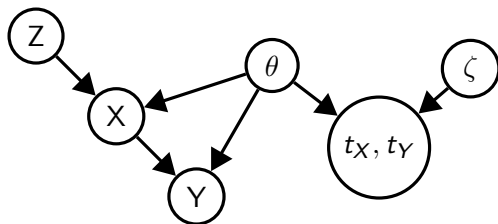


# Introduction to Methods

- Non-identifiability
  - Distribution over potential outcomes  $p(t_X, t_Y)$  may only be partially-identified [Richardson et al., 2011]
  - Causal estimands of interest would hence depend on parameters that are not fully-identified.
- Transparent Parametrizations
  - Re-parameterize the model such that the complete parameter vector may be divided into point-identified and entirely non-identified subvectors
  - Parts of the analysis which have been informed by the data become clear and distinct ("transparent")

# Introduction to Methods

- Re-parameterize  $p(t_X, t_Y)$  into  $f(\theta, \zeta)$ 
  - $\theta$  = identifiable parameter (estimable from observed  $(X, Y, Z)$ )
  - $\zeta$  = non-identifiable parameter





# Introduction to Methods

- Inference without the latent-variable model
  - Derive the distribution of the observed data implied by the potential outcomes model
  - Compute the posterior distribution of the instrumental variables
  - Apply inequality restrictions ("truncate") by Monte-Carlo rejection sampling
- Further extensions
  - Include baseline covariates
  - Build in robustness under mis-specification under the Intent-To-Treat null hypothesis (that  $Z$  and  $Y$  are independent)

## References

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- Y.J. Lee, J.H. Ellenberg, D.G. Hirtz, and K.B. Nelson. Analysis of clinical trials by treatment actually received: is it really an option? *Statistics in medicine*, 10(10):1595–1605, 1991.
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