Approaches to deal with confounding

Alternatives to traditional regression adjustment

ERHS 732

Conditional models

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  - where γ' represents a vector of parameter coefficients for each of our covariates C_i

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  - We could look at effect estimates in strata defined by C_i and take the weighted average across the strata

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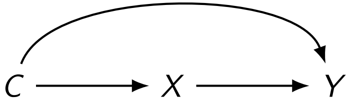

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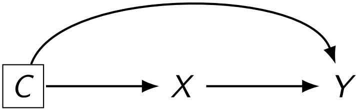

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- Approaches that minimize the amount of parameters in the model, could therefore be advantageous

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- Since we no longer have to worry about covariates given the PS this is a dimension reduction procedure

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- Have to weigh limitations against advantages in each case

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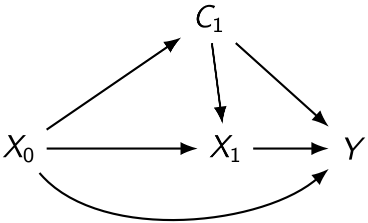

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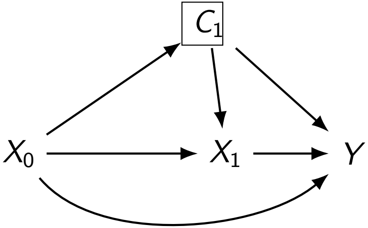

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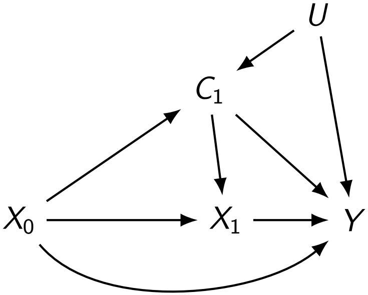

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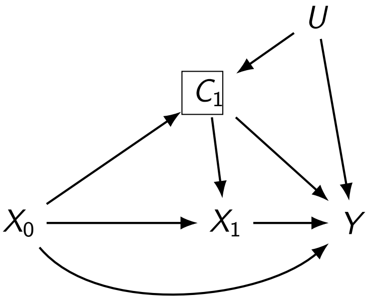

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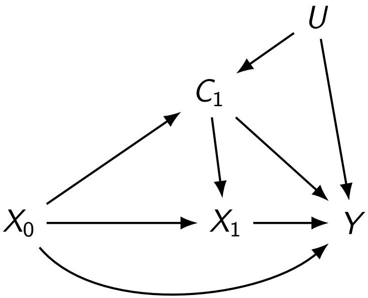

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