Mendelian randomization with pharmaceutically modifiable biomarkers

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Overview



Background:

Mendelian randomization (MR) studies of biomarkers

Objectives:



1. Describe the sources of bias that arise when using conventional methods to adjust for medication use.



2. Describe the causal estimands that can be targeted.



3. Demonstrate the use of g-methods to adjust for medication use.

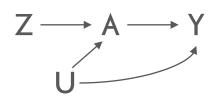


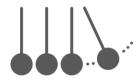
Mendelian randomization (MR) is an increasingly popular application of instrumental variable analysis



Genetic variants used as proposed instruments

➤ Three instrumental conditions





Estimate the effect of a non-genetic exposure on outcome

Even with unmeasured confounding

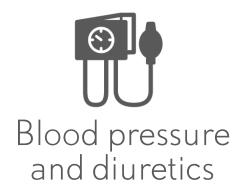


Exposures in MR studies

No Biomarkers that affect and are affected by medication use



LDL cholesterol and statins



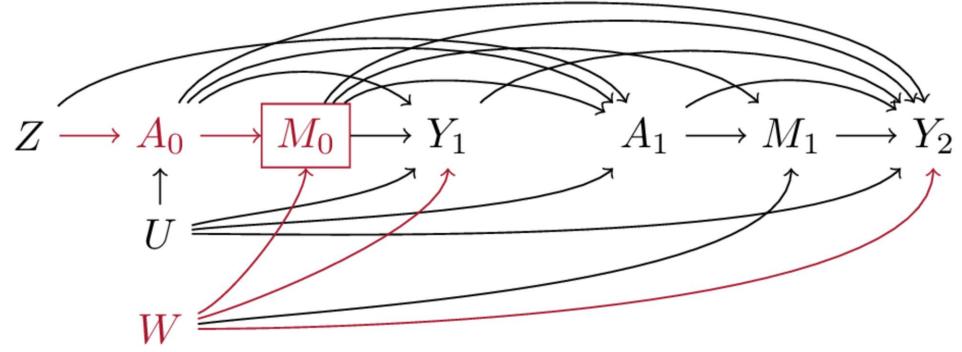


Adjusting for medication use or restricting to non-users introduces bias



Objective 1: Bias of conventional methods

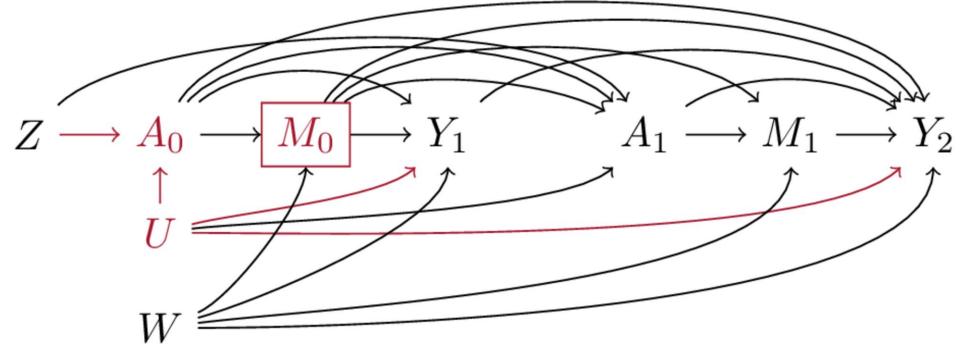
Genetic variant (Z) LDL cholesterol over time (A_k) Statin use over time (M_k) Coronary heart disease incidence (Y_{k+1}) LDL cholesterol-CHD confounders (U)Statin-CHD confounders (W)





Objective 1: Bias of conventional methods

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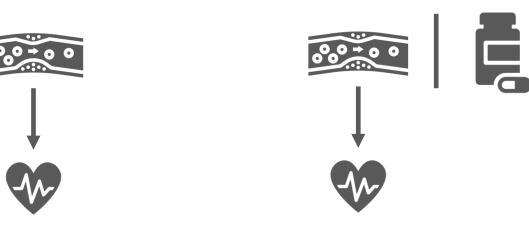
Objective 2: Potential causal estimands of interest

Total lifetime effect of LDL cholesterol

 $E[Y^{\bar{a}_K+1}] - E[Y^{\bar{a}_K}]$

Unbiased

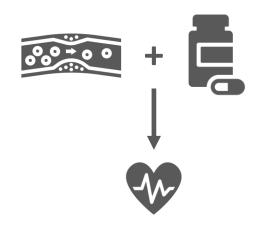
Lifetime effect of LDL cholesterol, conditional on statin use



$$\mathrm{E}\big[Y^{\bar{a}_K+1}|M_k\big] - \mathrm{E}\big[Y^{\bar{a}_K}|M_k\big]$$

Conditioning creates bias

Lifetime effect of a joint intervention on LDL cholesterol and statin use



$$E[Y^{\bar{a}_K+1,\bar{m}_K}] - E[Y^{\bar{a}_K,\bar{m}_K}]$$

Proposed approach



Proposed approach



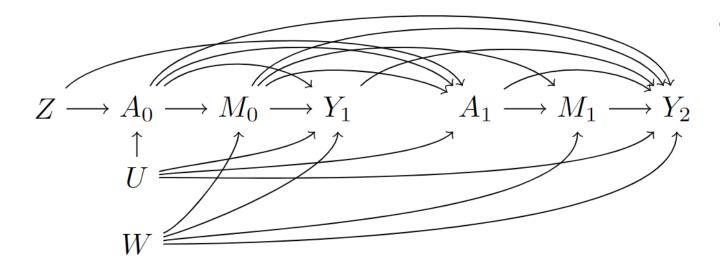
G-methods to model an intervention on statin use

- ➤ Without conditioning on statin use
- Generate data under a hypothetical statin intervention (e.g., never take statins)
- Conduct MR analysis (to assess the effect of an LDL cholesterol intervention) in the counterfactual data
- Estimating lifetime effect of a joint intervention



Objective 3: Data simulations

Data on LDL cholesterol (A_k) , statin use (M_k) and CVD (Y_{k+1}) generated according to the DAG:



Three scenarios:

- 1. A_k and M_k under the null
- 2. A_k only under the null
- 3. Neither under the null



Analysis

Conventional MR design

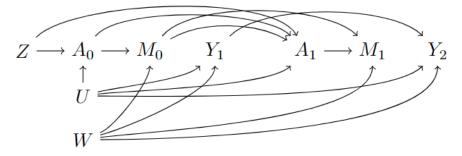
- 2SLS (single measurement of the exposure)
- Varying age of participants at start of follow-up

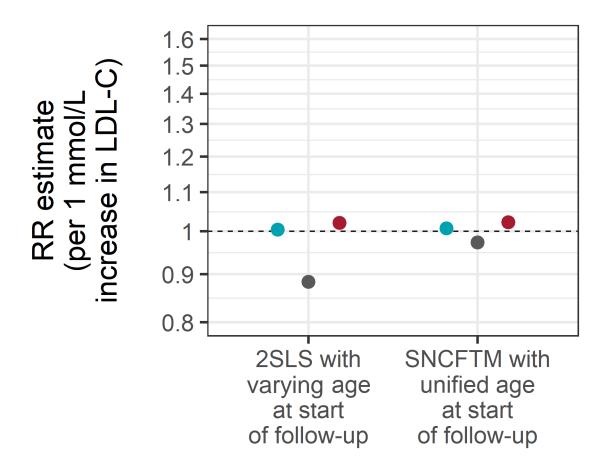
Ideal/proposed MR design

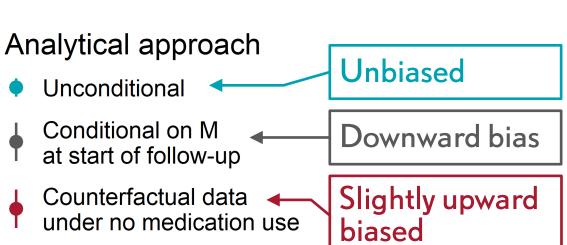
- ➤ G-estimation of SNCFTM^a (longitudinal)
- Same age of participants at start of follow-up



Simulation results for data generated under the null for A and M



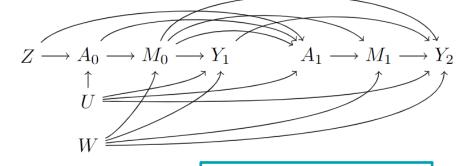




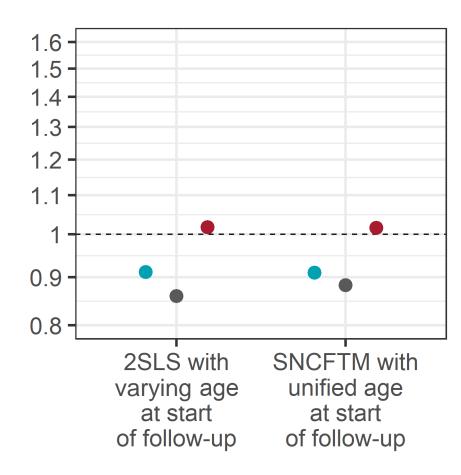
MR Design



Simulation results for data generated under the null for A only







Analytical approach

Unconditional

Conditional on M at start of follow-up

Counterfactual data under no medication use

Combined effect of A+M

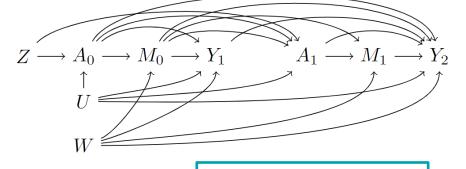
Downward bias

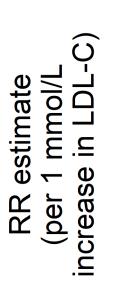
Direct effect of A only

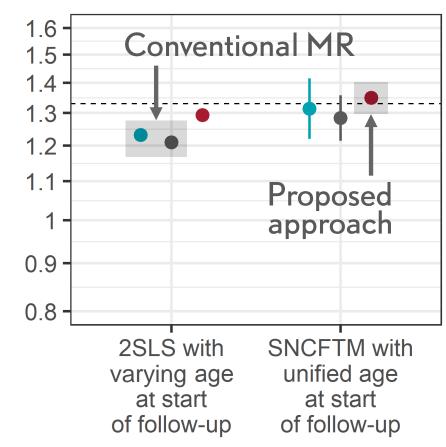
MR Design



Simulation results for data generated not under the null for A or M







Analytical approach

Unconditional

Conditional on M at start of follow-up

Counterfactual data under no medication use

Combined effect of A+M

Downward bias

Direct effect of A only

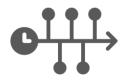
MR Design



Conclusions



Conditioning on variables downstream of the exposure can introduce bias



Need to consider time-varying nature of the exposure in MR (and other IV) studies



Combining g-methods and IV can mitigate bias of conventional approaches



Future steps: real data analysis in the Million Veterans Program



Acknowledgements



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- **** CAUSALab
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Questions

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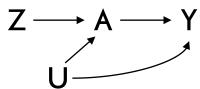




Supplementary Slides

Instrumental conditions

1. Relevance: the instrument (genetic variant) is associated with the exposure



- 2. Exclusion restriction: the instrument (genetic variant) does not affect the outcome except through its potential effect on the exposure
- 3. No confounding for Z: The instrument (genetic variant) and the outcome do not share common causes

To estimate a point effect, need a fourth assumption of homogeneity or monotonicity.

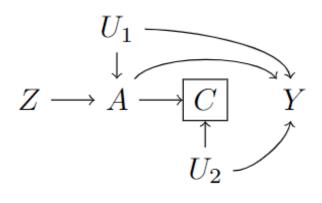


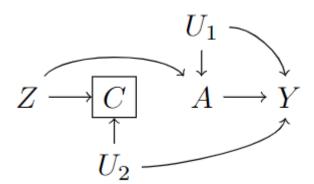
Selection bias in instrumental variable analyses

The instrumental conditions are violated in the presence of selection bias. For example, for a time-fixed exposure:

Loss to follow-up:

Misalignment of t₀:





Conditioning on the exposure:

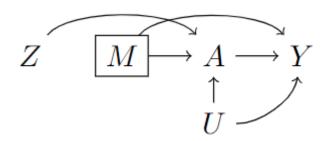
$$Z \longrightarrow A \longrightarrow C \qquad Y$$

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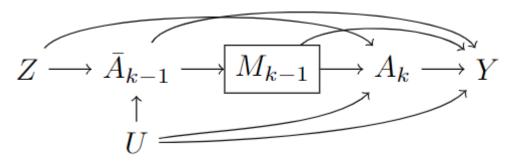


Mendelian randomization studies are often conditioning on variables downstream of the exposure without realizing it

- Most MR studies are interested in the effects of a time-varying exposure, but
 - o Consider only a single measure of the exposure in the analysis
 - o Conceptualize the exposure as time-fixed
- ➤ Conditioning on a "pre-baseline" variable could introduce selection bias
 - o If this variable is affected by prior exposure
- i.e., the DAG is not:

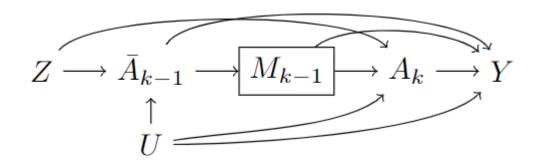


but rather more like:





Consider a MR study of LDL cholesterol and CVD



Z: LDL cholesterol-related genetic variant

 \bar{A}_{k-1} : history of LDL cholesterol

 M_{k-1} : statin use at time k-1

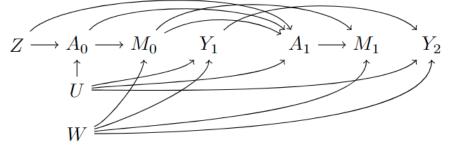
 A_k : LDL cholesterol at time k

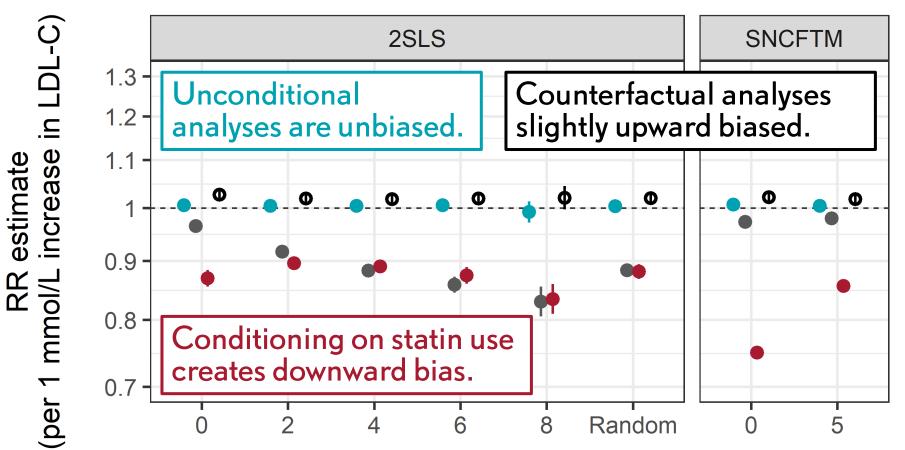
Y: CVD

A MR analysis of LDL cholesterol which conditions on statin use will introduce selection bias.



Simulation results for data generated under the null for A and M





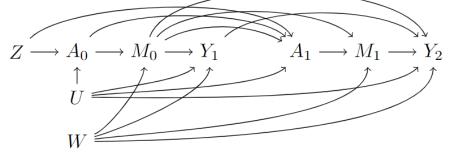
Analytical approach

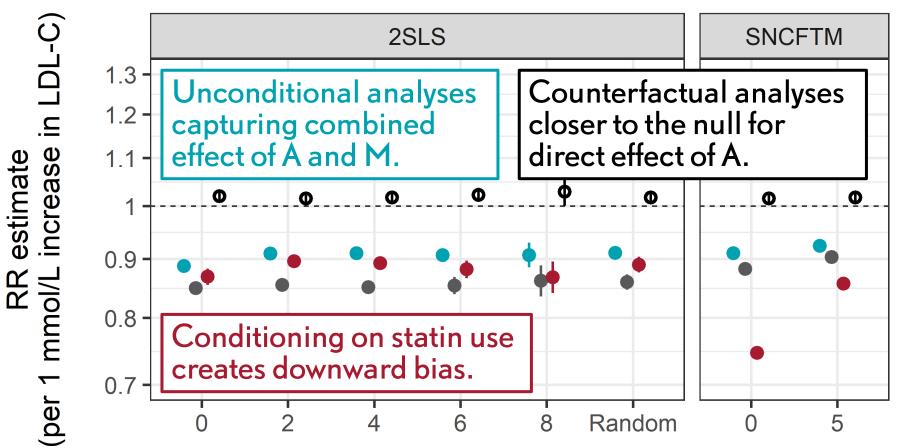
- Unconditional
- Conditional on M at start of follow-up
- Conditional on M over follow-up
- Counterfactual data under no medication use

Start of follow-up



Simulation results for data generated $z \rightarrow A_0 \rightarrow M_0 \rightarrow Y_1$ under the null for A only





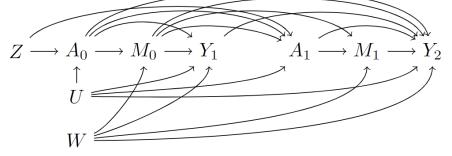
Analytical approach

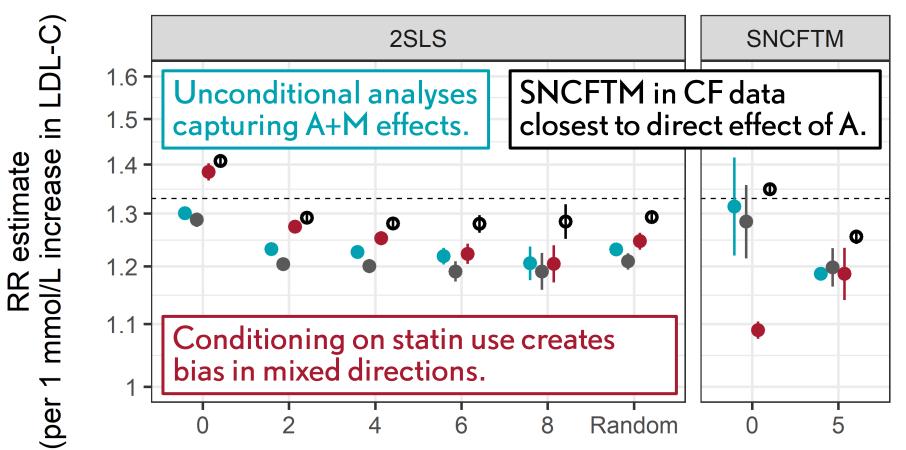
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Simulation results for data generated $z \rightarrow A_0 \rightarrow M_0 \rightarrow Y_1$ not under the null for A or M





Analytical approach

- Unconditional
- Conditional on M at start of follow-up
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- Counterfactual data under no medication use

Start of follow-up

