Addressing **Instrument-Outcome Confounding** in **Mendelian Randomization** through **Representation Learning**

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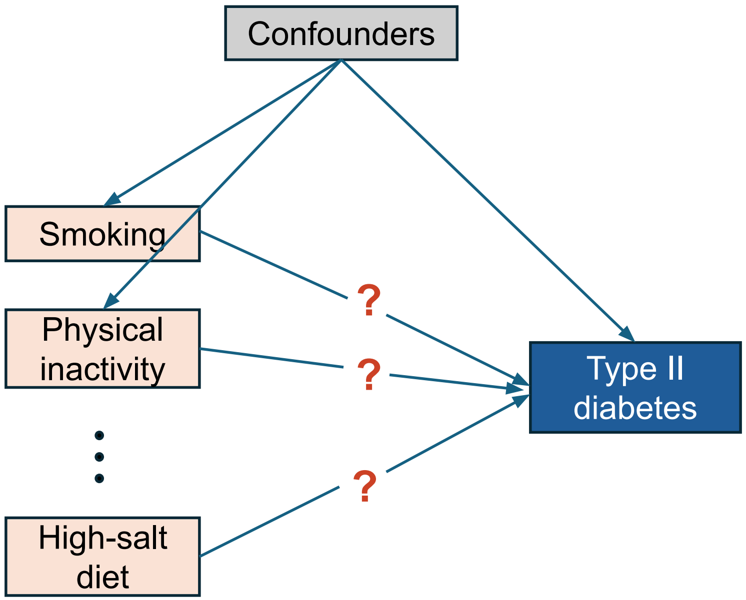
Background: Causality in Epidemiology



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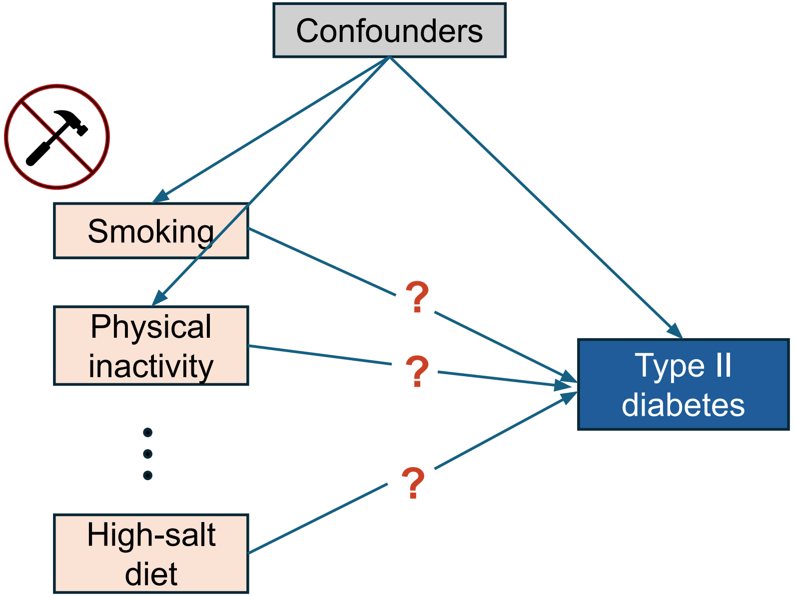

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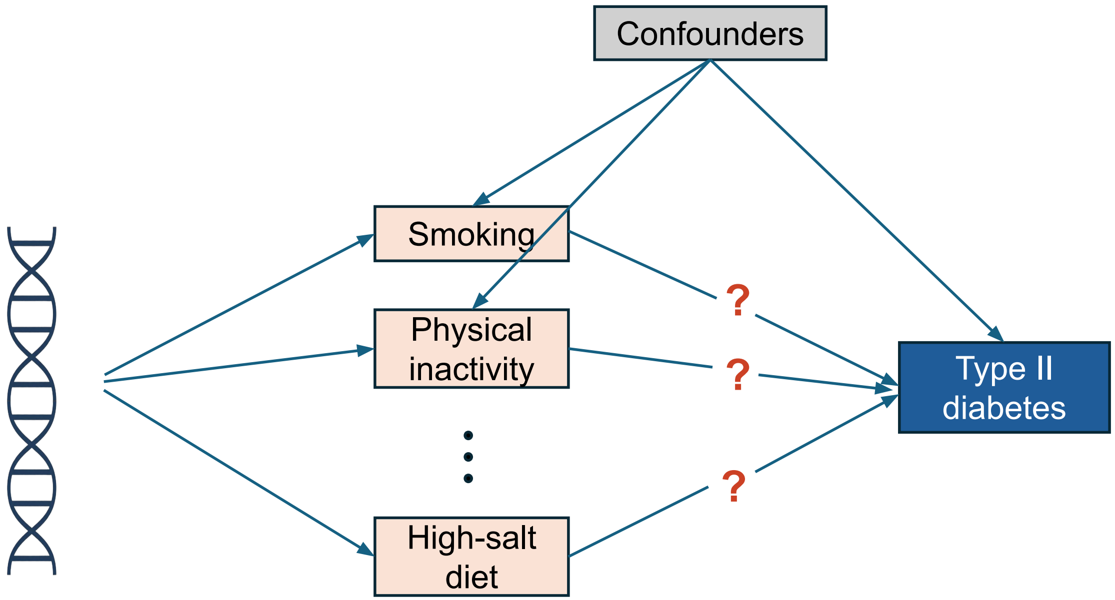
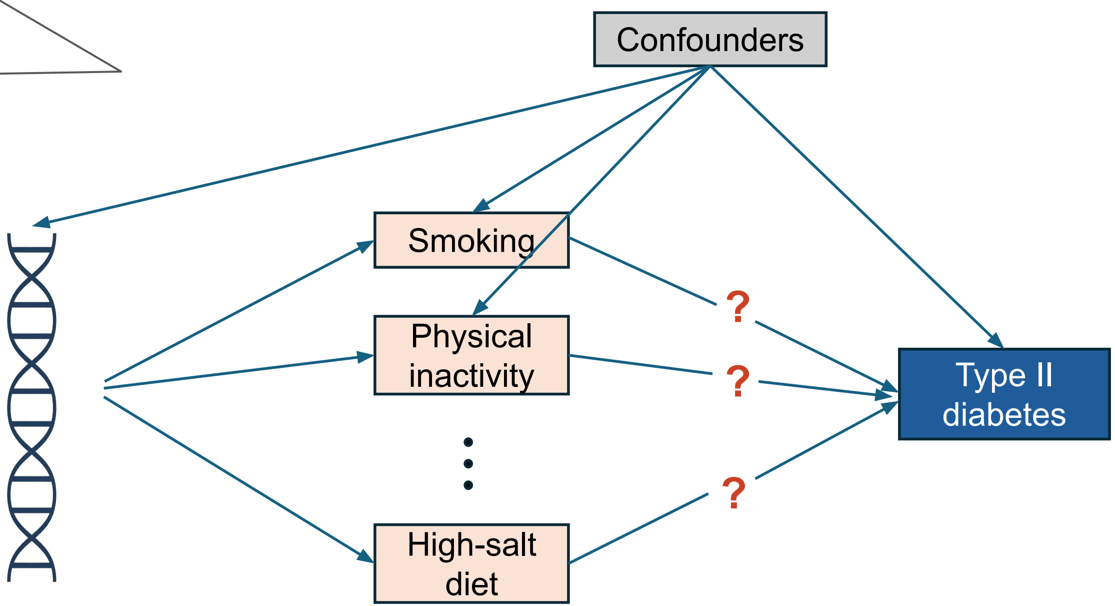


Background: Causality in Epidemiology

Instrument-outcome confounding is common in Mendelian Randomization studies

⟶Violates IV assumptions

⟶Biased causal effect



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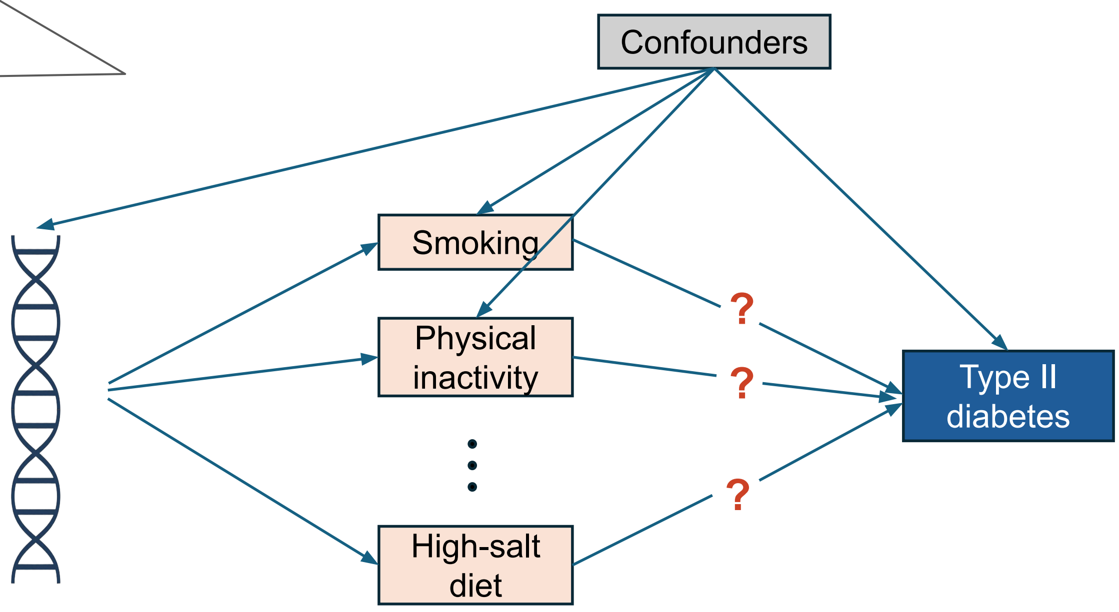
Is it possible to remove this confounding?



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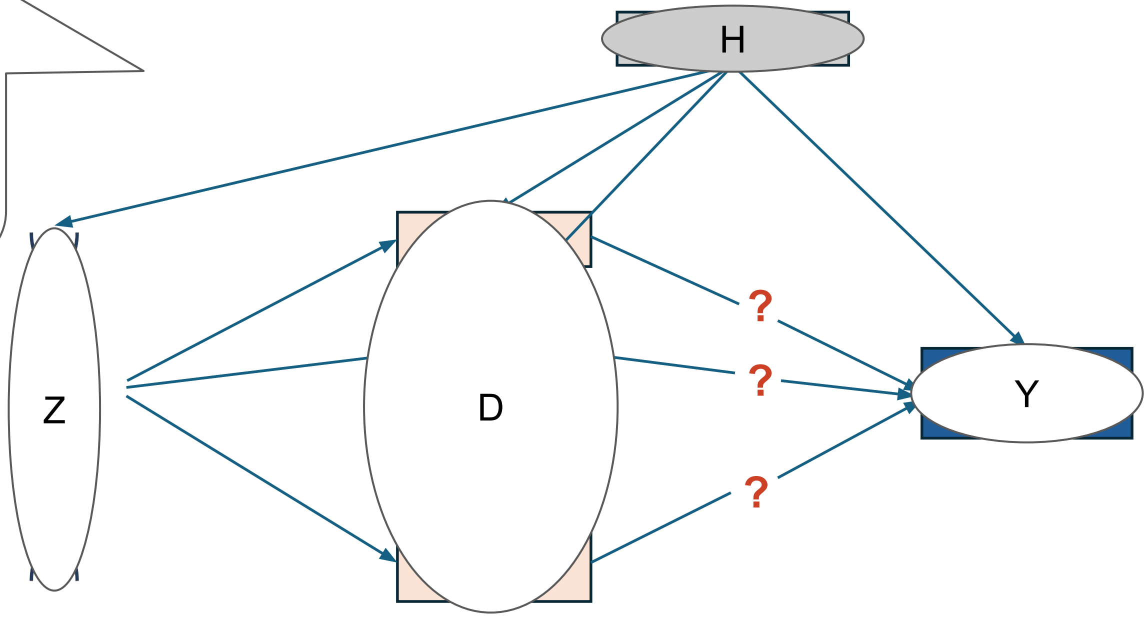
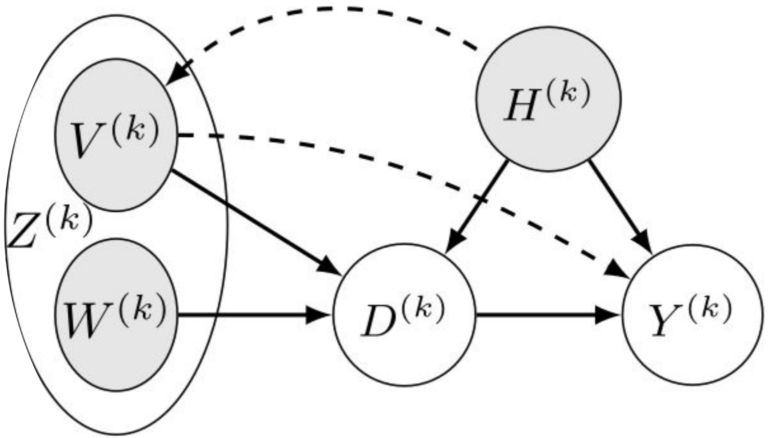


Method: Contrastive Learning using Multi-Population Data

Suppose we can decompose Z into two parts, V and W…



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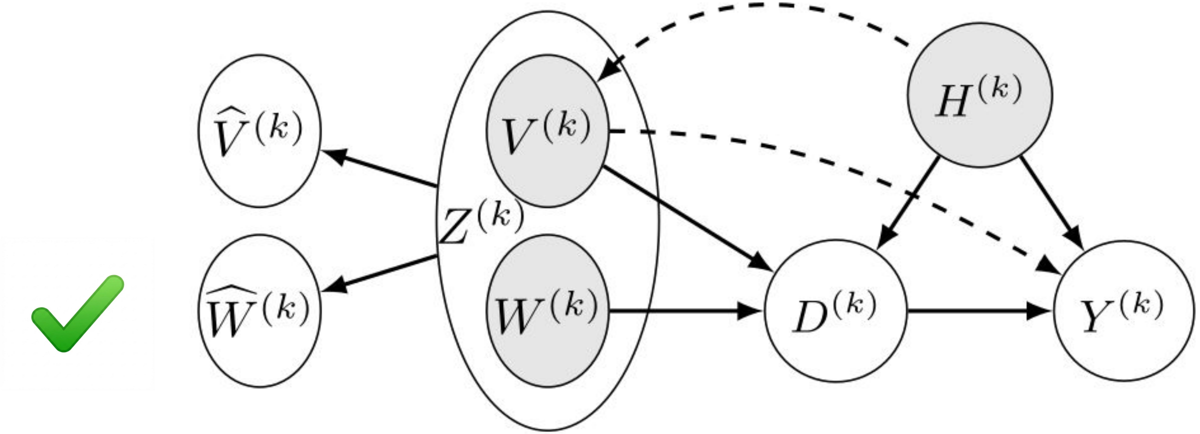

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Key Findings

Identifiability of W and V: Under certain assumptions

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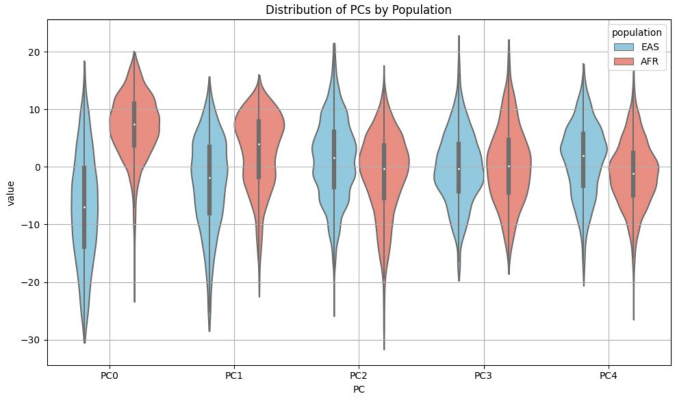
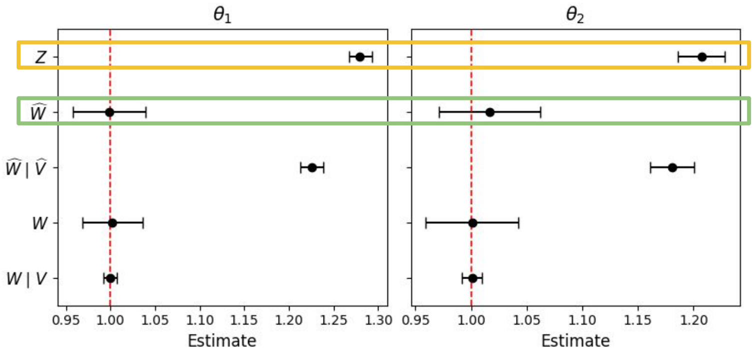
Average causal effect (ACE) estimation: $\hat{W}$ can identify the ACE as long as W can, and it *may* be helpful to control $\hat{V}$.

Results and Conclusion





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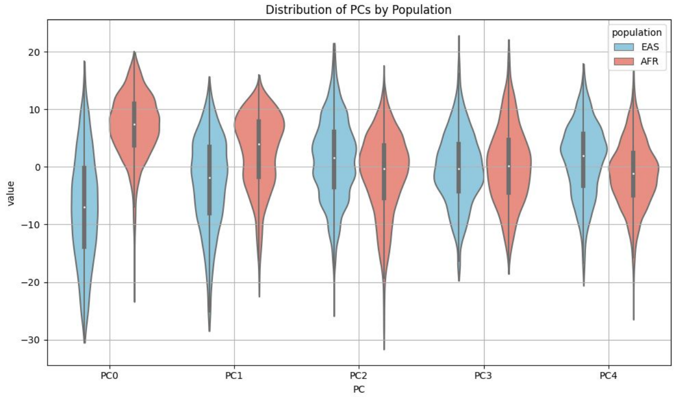

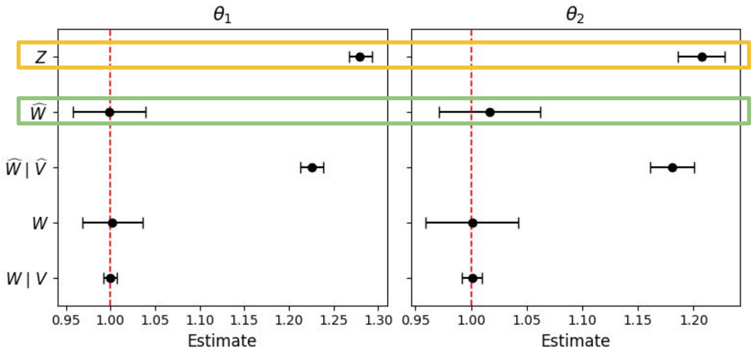

We leverage representation learning in MR under violation of **instrument-outcome confounding**.

We adapt and extend the theoretical results of **contrastive learning** for identifying the invariant component of the instruments.

We show empirically that autoencoders satisfying the **invariance constraint** can identify a valid instrument for MR.

Thank you for your attention!

Please feel free to reach out to shimeng.huang@ista.ac.at

My website