Sensitivity Analysis of Linear Structural Causal Models

Carlos Cinelli UCLA

Joint work with Daniel Kumor, Bryant Chen, Judea Pearl and Elias Bareinboim

ICML, Long Beach, June 2019

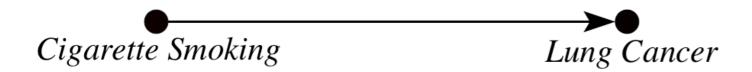
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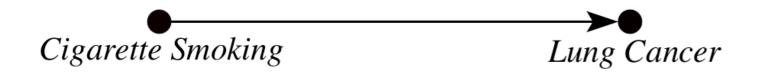
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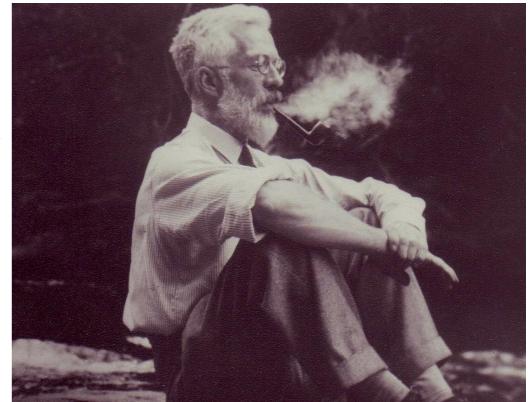
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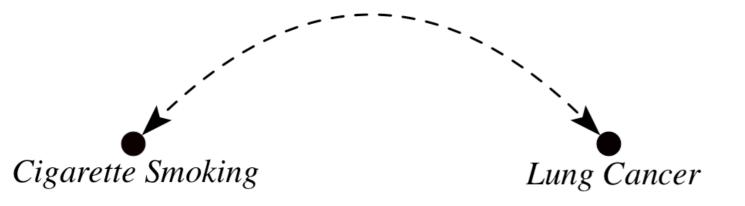
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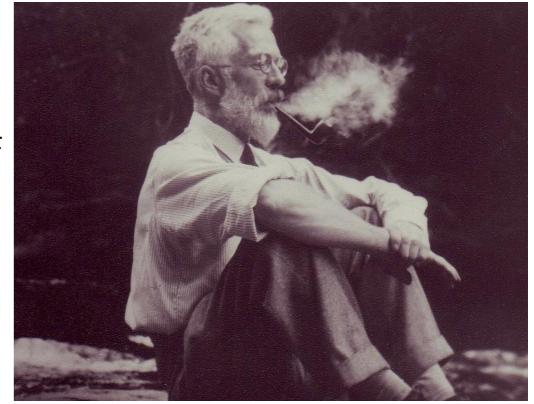
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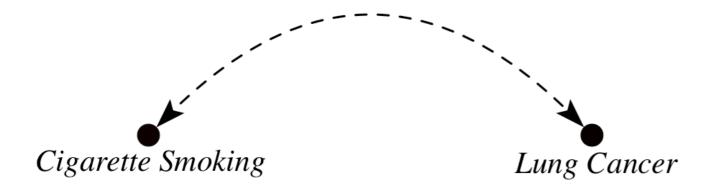


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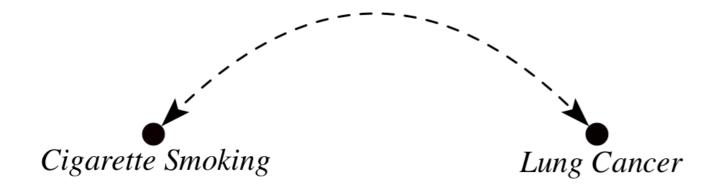
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Observational data alone cannot distinguish both models.

Let's suppose for a moment that Fisher's hypothesis were true.

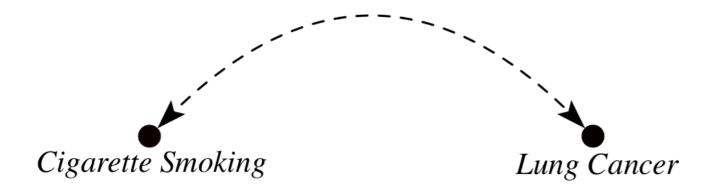


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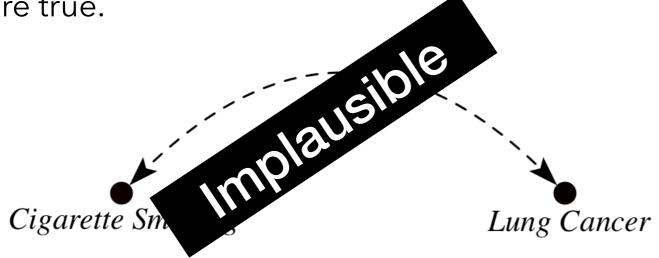
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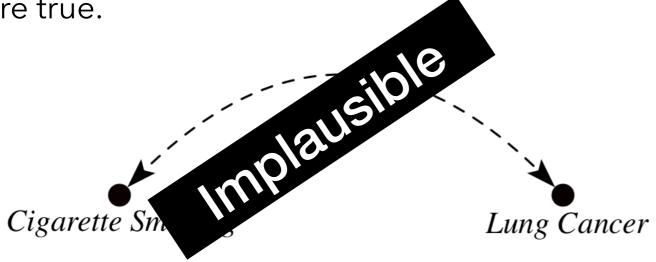
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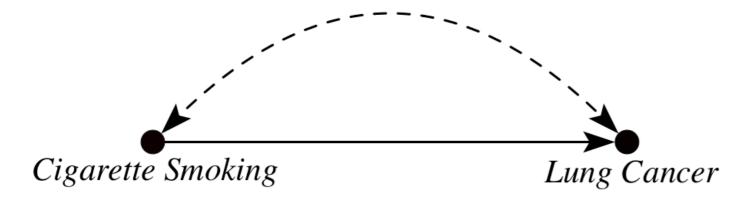
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Sensitivity analysis + plausibility judgments = there must be a causal path between cigarette smoking and lung cancer.



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These results can then be *submitted to expert judgment*, to decide whether problematic degrees of violation are plausible.

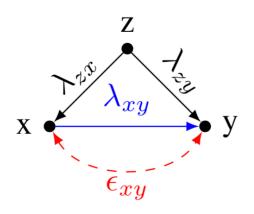
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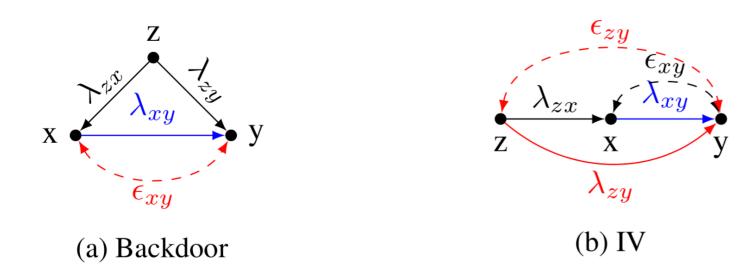
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(a) Backdoor

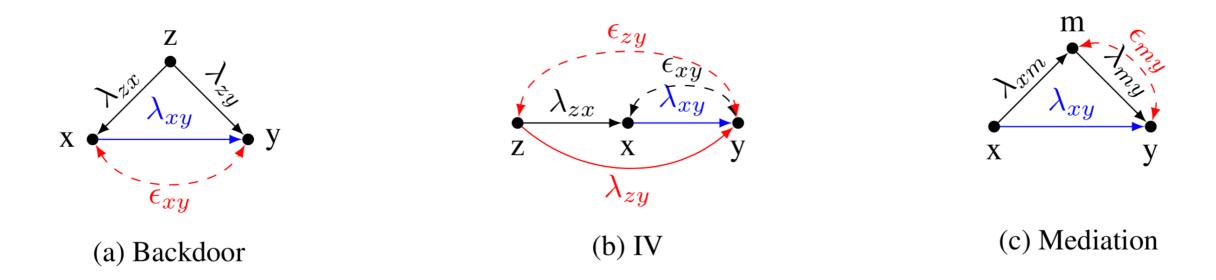
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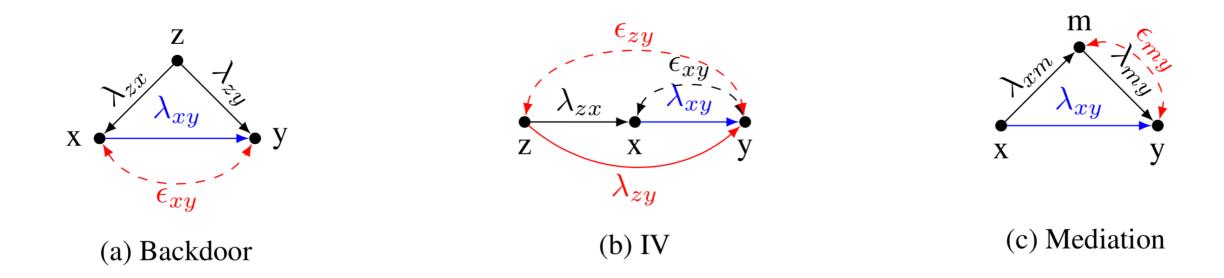
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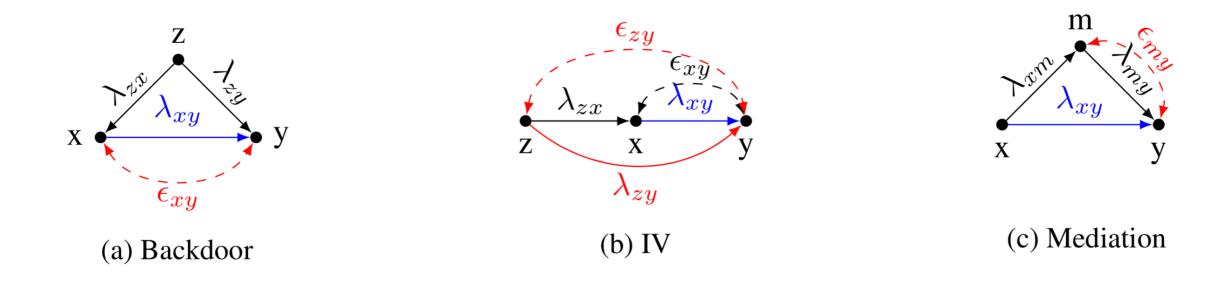
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Can we have a *general-purpose, algorithmic framework* that captures all these canonical cases – and many more?

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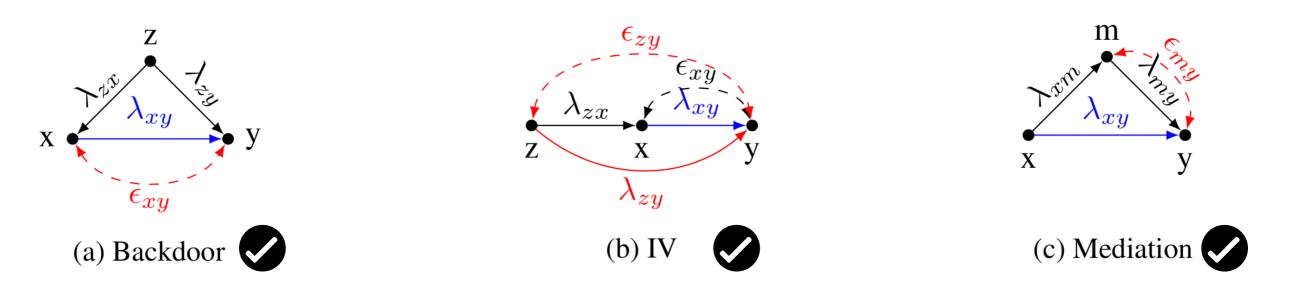
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...canonical cases are a small subset of all possible sensitivity analyses covered by our framework.

For details, come to our poster session:

Wed, Jun 12th 6:30pm–9:00pm @ Pacific Ballroom #78

Or see paper: https://tinyurl.com/y5urlwqs

Thank you!

Contact carloscinelli@ucla.edu twitter: @analisereal