

Cyclic Causality: D-separation and Nonlinearity

David Reber
3/24 - 3/30 update

Past To-Do's

- 3/24 - 3/25
 - ✓ ○ Relate problem to the literature
 - ✓ ○ Writeup, submit mid-semester report
- 3/27 - 3/30
 - Come up with an example for each of the following:
 - ✓ ■ Cyclic SCMs
 - ✓ ■ Loss of d-separation
 - ✓ ■ Intrinsic SCMs
 - Validity of d-separation via numerics

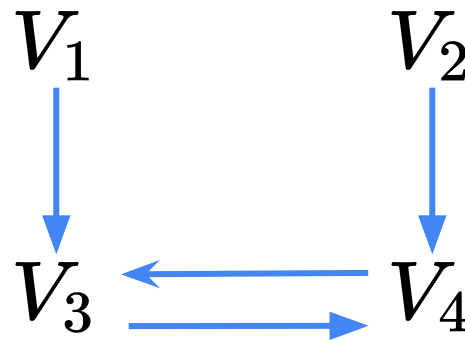
(It'll be a short week for me as I'll be out of town 3/31 - 4/3)

Example: Cyclic SCM

$$M \left\{ \begin{array}{l} \mathbf{u}, \mathbf{v} \in \mathbb{R}^4 \\ U_i \sim \mathcal{N}(0, 1) \quad iid. \\ f_1 : V_1 \leftarrow U_1 \\ f_2 : V_2 \leftarrow U_2 \\ f_3 : V_3 \leftarrow V_1 V_4 + U_3 \\ f_4 : V_4 \leftarrow V_2 V_3 + U_4 \end{array} \right.$$

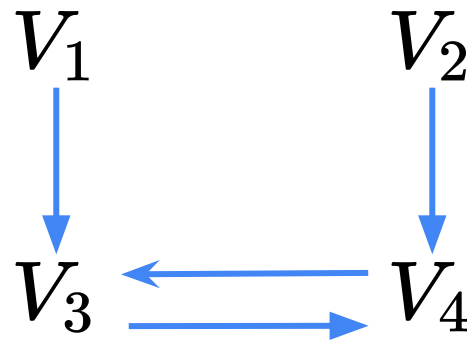
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Not latent confounder:



Example: Observational Distribution

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Potential Responses

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$$U_i \sim \mathcal{N}(0, 1) \quad iid.$$

$$P(U_i = u_i) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u_i^2}$$

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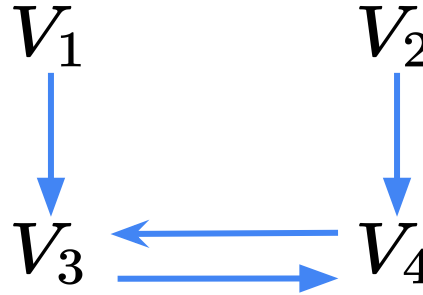
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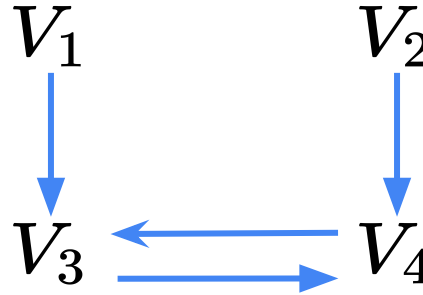
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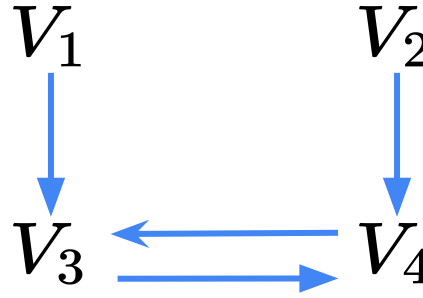
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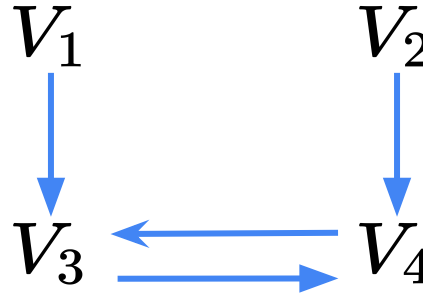


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2 edges means 2 paths

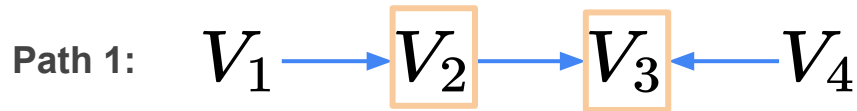
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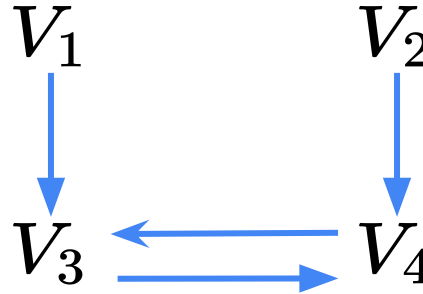
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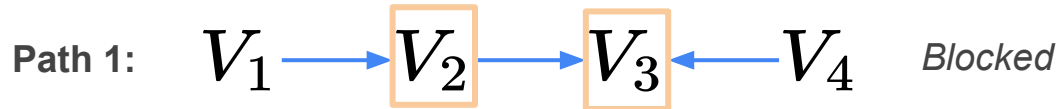
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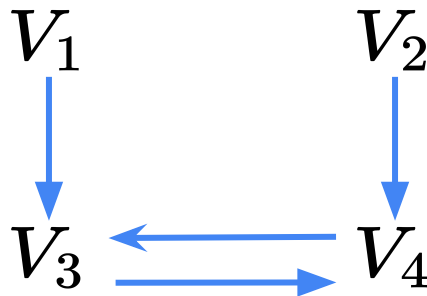
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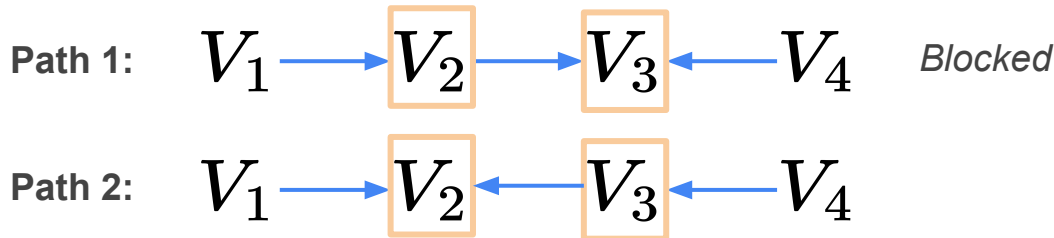
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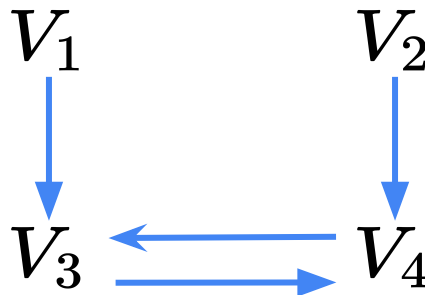
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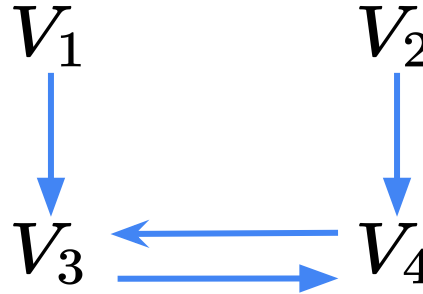
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Path 1: $V_1 \rightarrow V_2 \rightarrow V_3 \leftarrow V_4$ *Blocked*

Path 2: $V_1 \rightarrow V_2 \leftarrow V_3 \leftarrow V_4$ *Blocked*

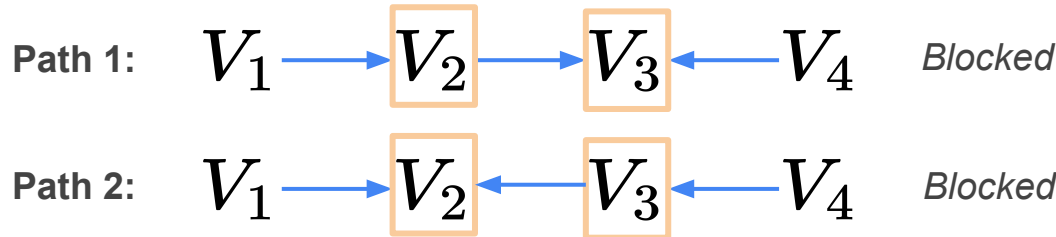
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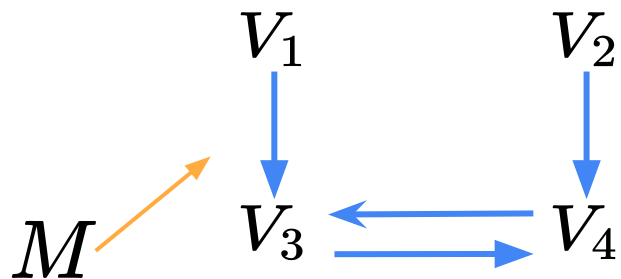


$$(V_1 \perp\!\!\!\perp V_2 | V_3, V_4)_G \checkmark$$

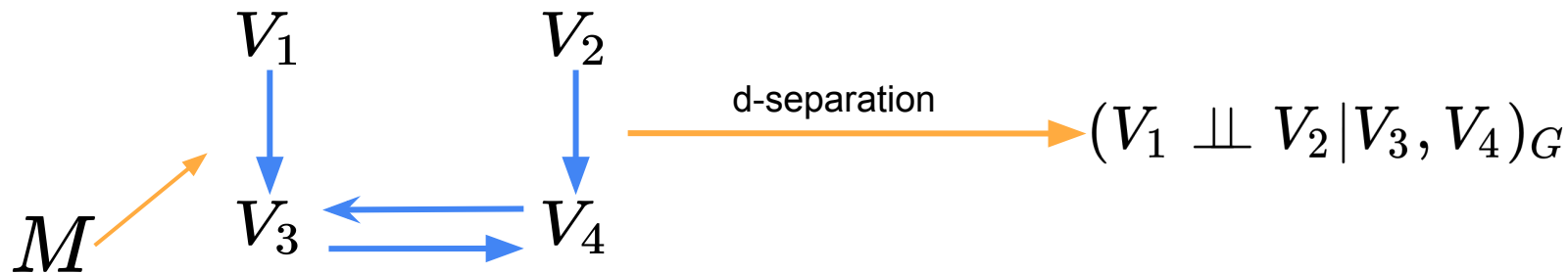
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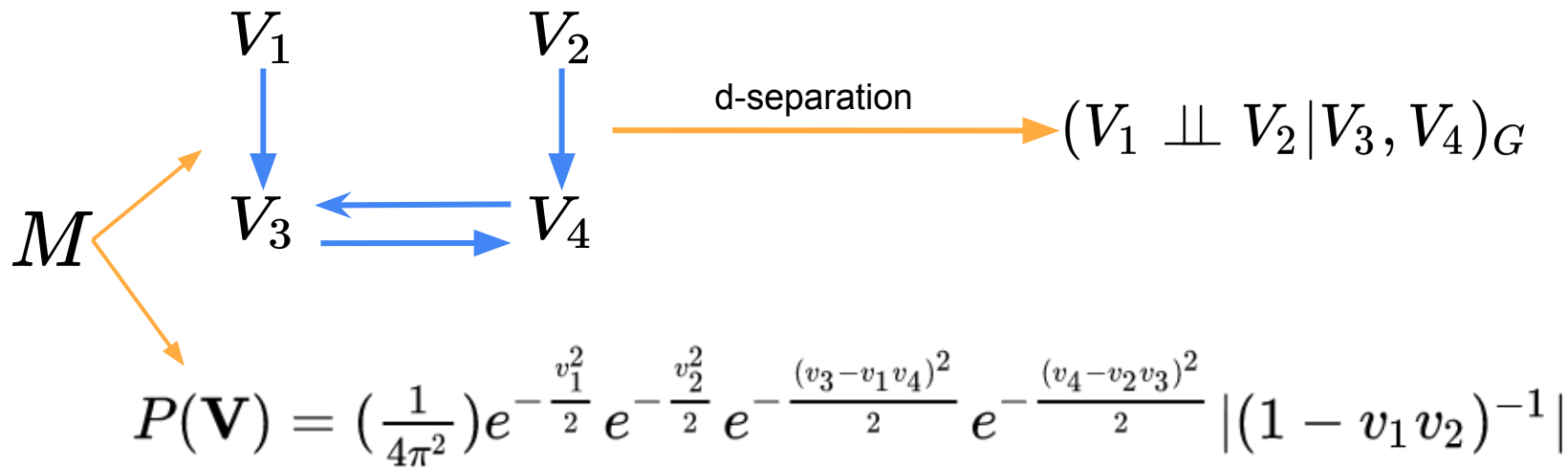
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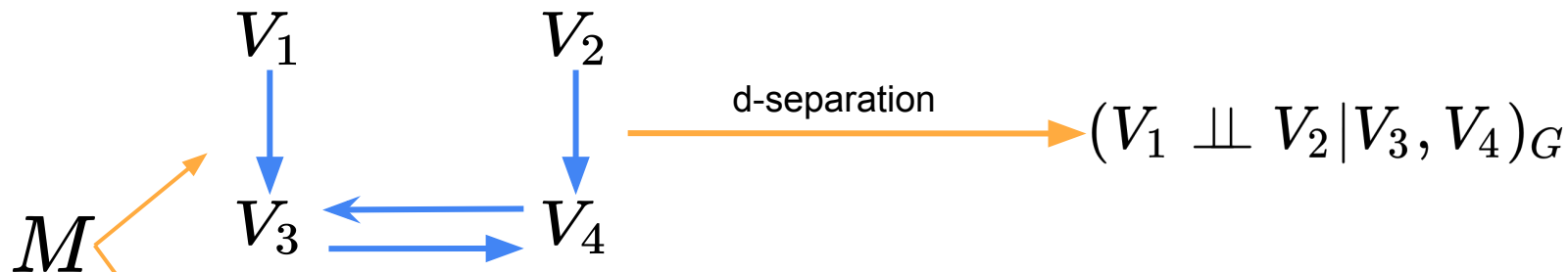
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Let's double check with numerics...

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- Test $(V_1 \perp\!\!\!\perp V_2 | V_3, V_4)_P$ numerically...



Conditional independence + continuous domain? That's hard...

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← (a fast independence test which tries to predict V_1 from V_2 after V_3 and V_4 are provided)

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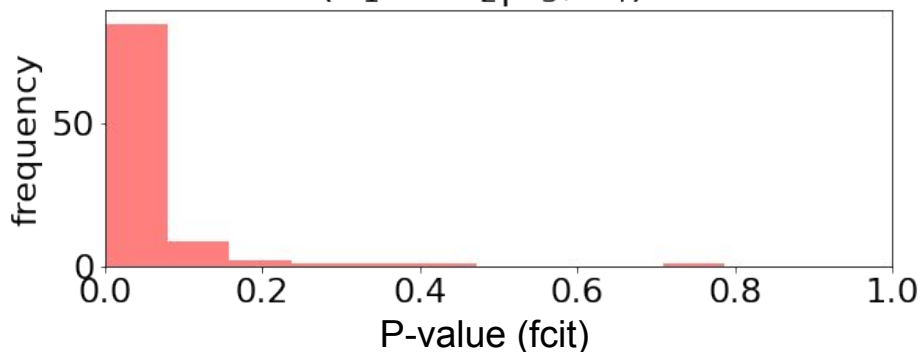


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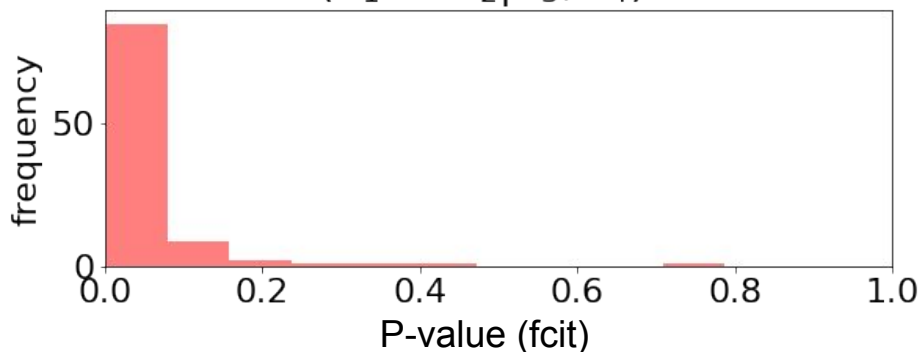


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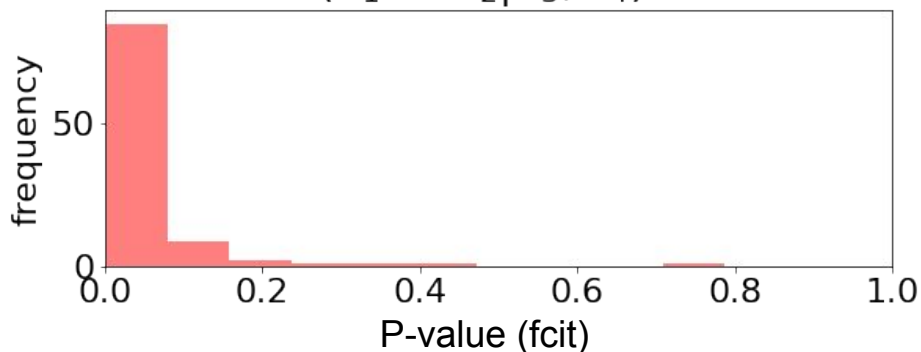


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- What happens if we try to bound this example??

*If $P(\mathbf{V}) > 0$ everywhere, and there's no trivial dependencies

Example: Linear Bounding

Bound each f_i by

$$g_i = \left(\sum_j a_{ij} V_j\right) + U_i \qquad a_{ij} = \max_{\mathbf{v}} \left| \frac{\partial f_i}{\partial V_j}(\mathbf{v}, \mathbf{u}) \right|$$

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$$g_1 : V_1 \leftarrow U_1$$

$$g_2 : V_2 \leftarrow U_2$$

$$g_3 : V_3 \leftarrow \boxed{a_{31}} V_1 + \boxed{a_{34}} V_4 + U_3$$

$$g_4 : V_4 \leftarrow \boxed{a_{42}} V_2 + \boxed{a_{43}} V_3 + U_4$$

Example: Linear Bounding

Bound each f_i by $g_i = (\sum_j a_{ij} V_j) + U_i$ $a_{ij} = \max_{\mathbf{v}} |\frac{\partial f_i}{\partial V_j}(\mathbf{v}, \mathbf{u})|$

$$f_1 : V_1 \leftarrow U_1 \xrightarrow{\text{blue}} a_{1j} = 0 \xrightarrow{\text{blue}} g_1 : V_1 \leftarrow U_1$$

$$f_2 : V_2 \leftarrow U_2 \xrightarrow{\text{blue}} a_{2j} = 0 \xrightarrow{\text{blue}} g_2 : V_2 \leftarrow U_2$$

$$f_3 : V_3 \leftarrow V_1 V_4 + U_3 \xrightarrow{\text{red}} g_3 : V_3 \leftarrow \boxed{a_{31}} V_1 + \boxed{a_{34}} V_4 + U_3$$

$$f_4 : V_4 \leftarrow V_2 V_3 + U_4 \xrightarrow{\text{red}} g_4 : V_4 \leftarrow \boxed{a_{42}} V_2 + \boxed{a_{43}} V_3 + U_4$$

$$a_{31} = \max_{\mathbf{v}} |V_4| \quad a_{34} = \max_{\mathbf{v}} |V_1| \quad a_{42} = \max_{\mathbf{v}} |V_3| \quad a_{43} = \max_{\mathbf{v}} |V_2|$$

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 - (these correspond directly to unboundedness of the potential response function)

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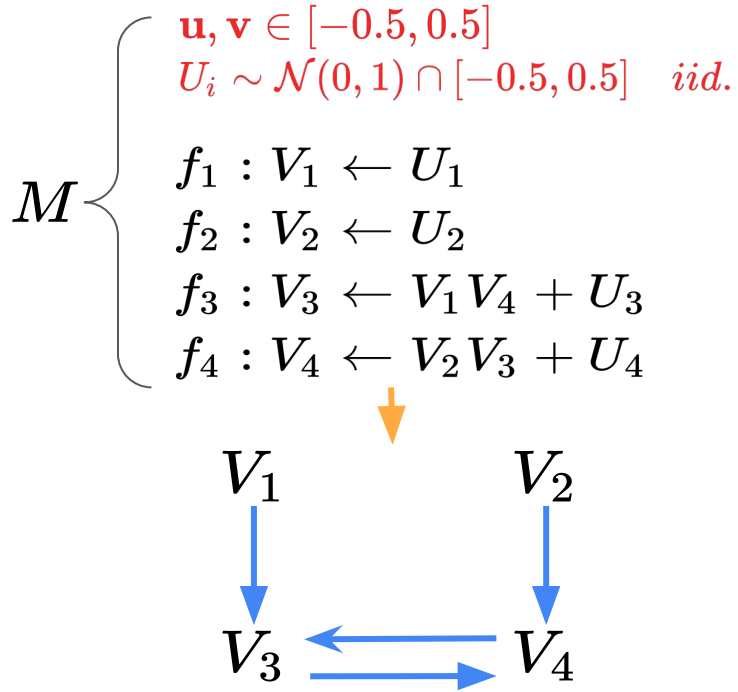
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- Some terms go to infinity, so we can't bound this example!
 - (these correspond directly to unboundedness of the potential response function)
- What if we tweak the example?

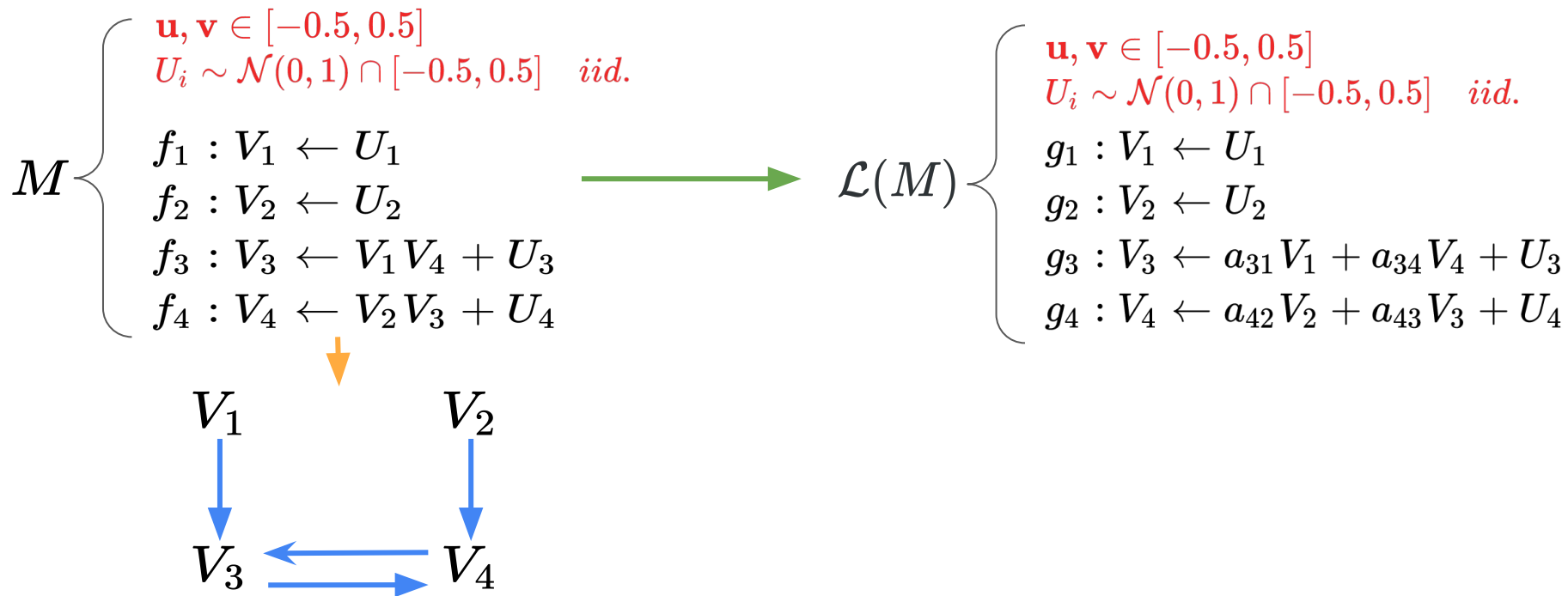
Example: Intrinsic SCM

$$M \left\{ \begin{array}{l} \mathbf{u}, \mathbf{v} \in [-0.5, 0.5] \\ U_i \sim \mathcal{N}(0, 1) \cap [-0.5, 0.5] \quad iid. \\ f_1 : V_1 \leftarrow U_1 \\ f_2 : V_2 \leftarrow U_2 \\ f_3 : V_3 \leftarrow V_1 V_4 + U_3 \\ f_4 : V_4 \leftarrow V_2 V_3 + U_4 \end{array} \right.$$

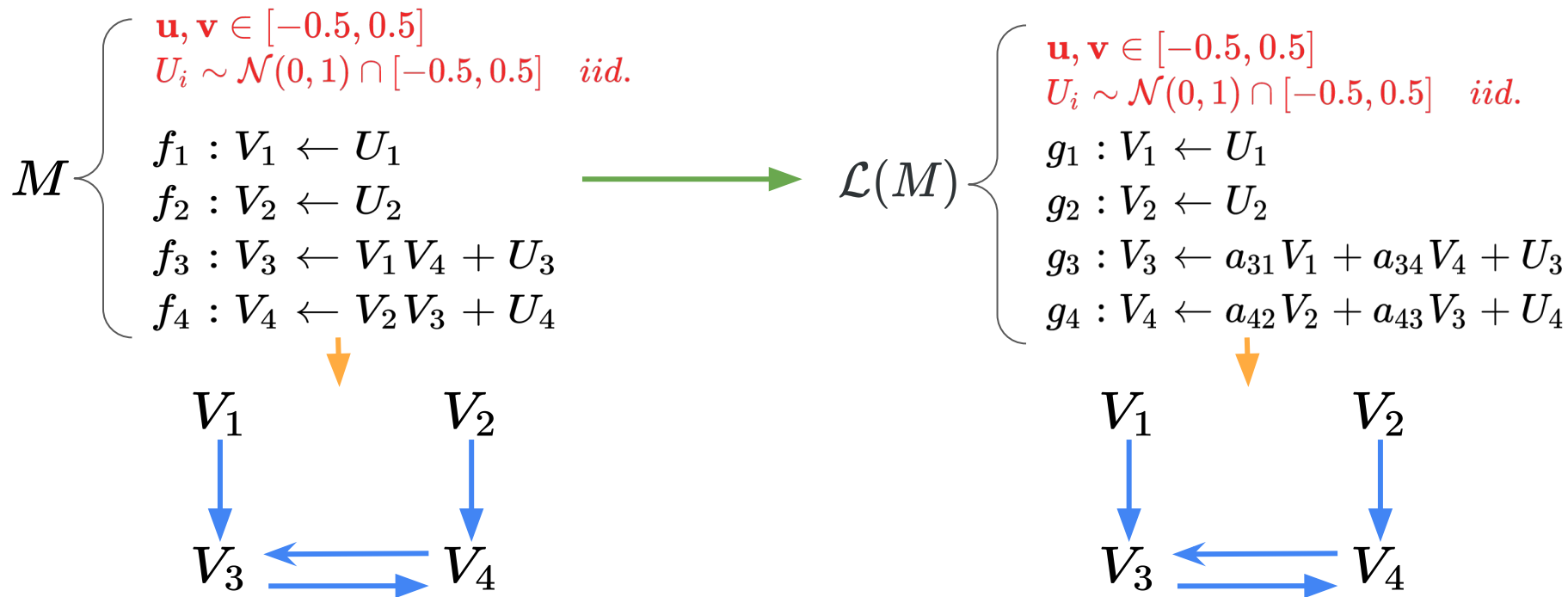
Example: Intrinsic SCM



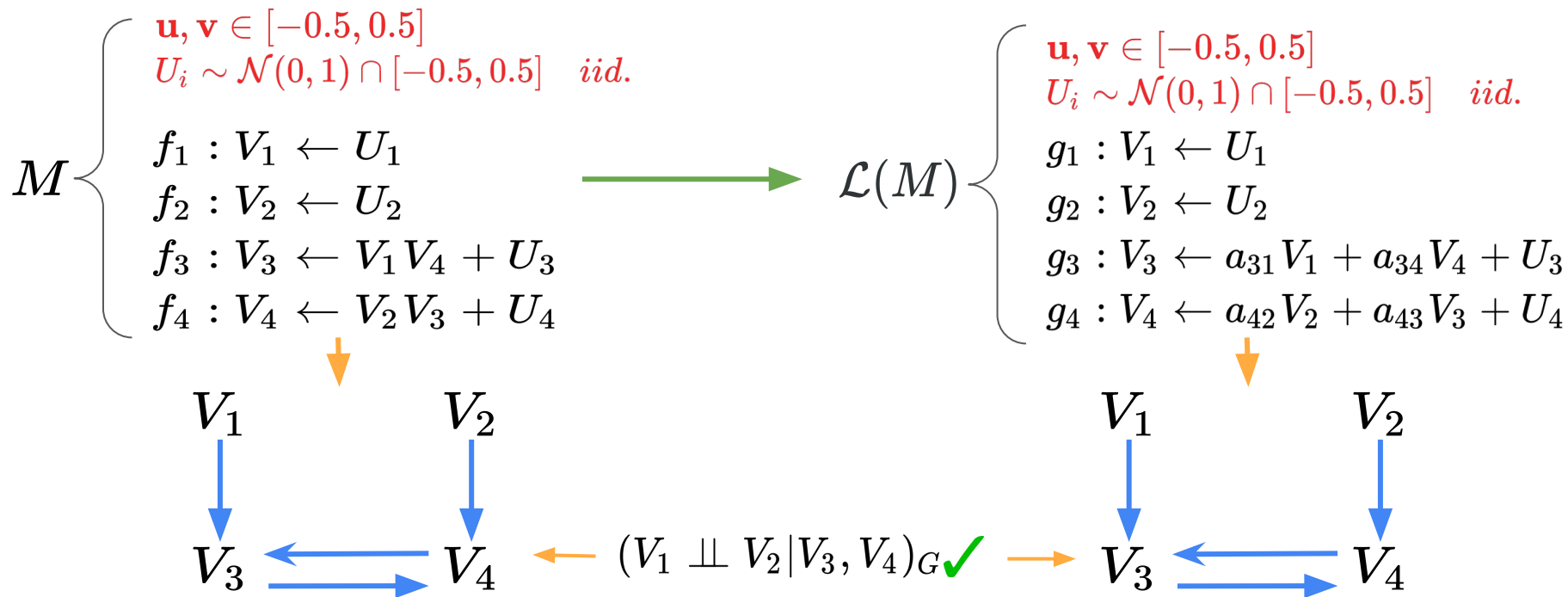
Example: Intrinsic SCM



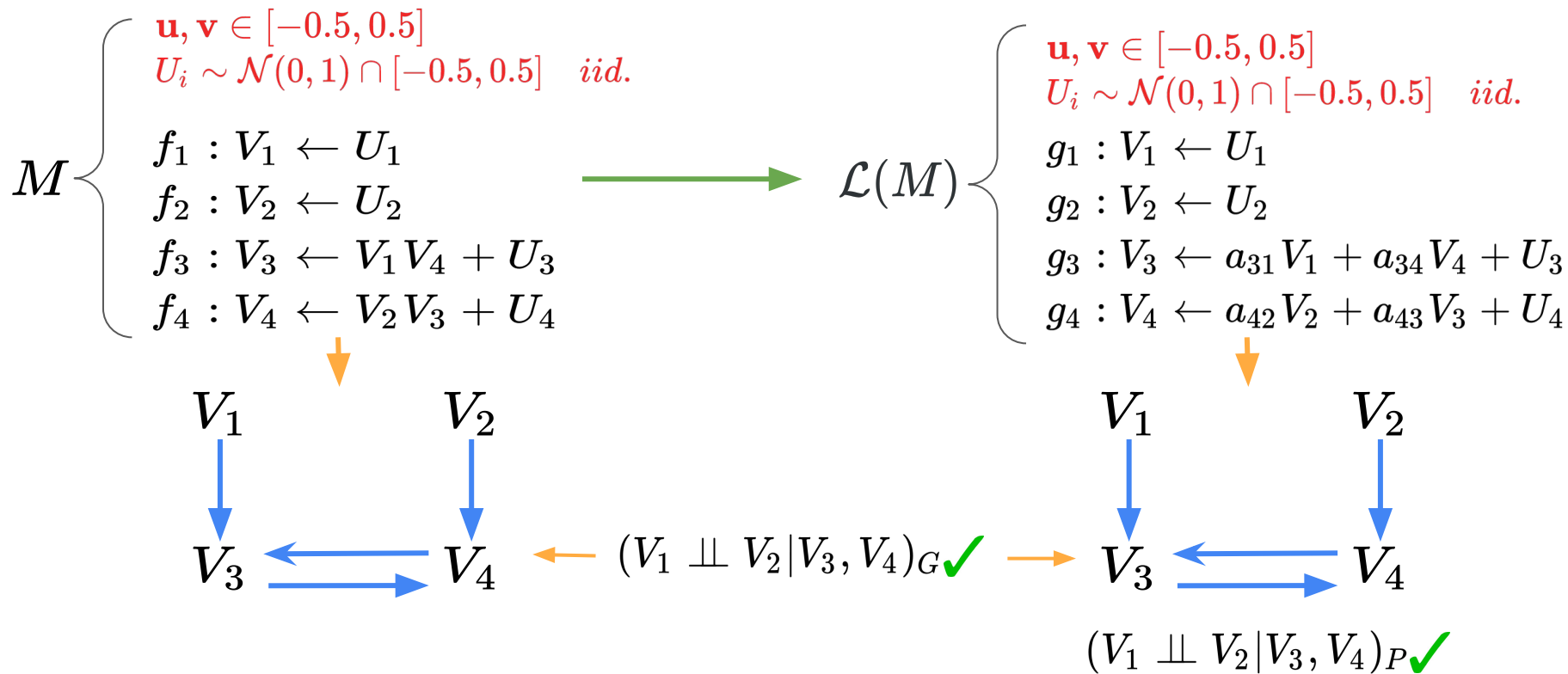
Example: Intrinsic SCM



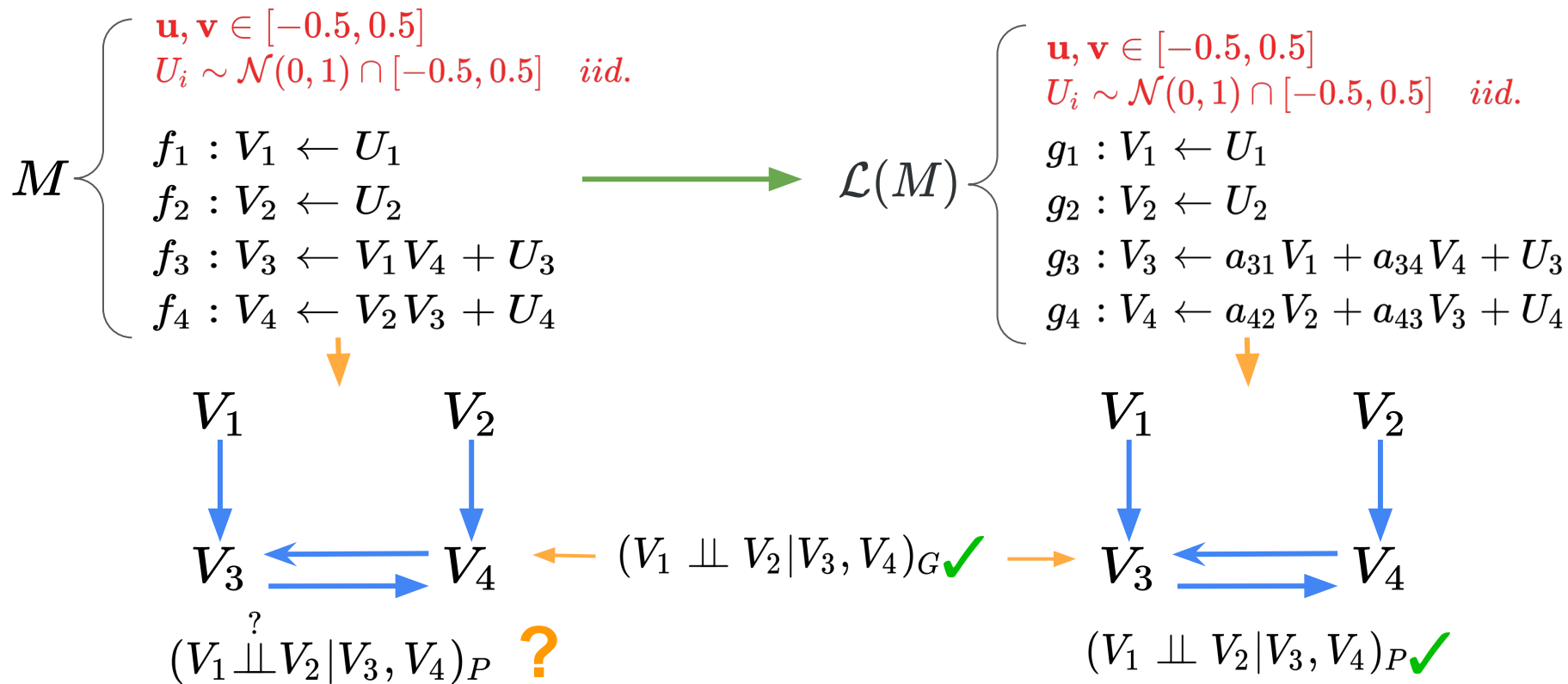
Example: Intrinsic SCM



Example: Intrinsic SCM



Example: Intrinsic SCM



Numerics: Intrinsic SCM

$U_i \sim \mathcal{N}(0, 1) \cap [-0.5, 0.5]$ *iid.*

$$\begin{aligned} V_1(\mathbf{U}) &= U_1 \\ V_2(\mathbf{U}) &= U_2 \\ V_3(\mathbf{U}) &= \frac{U_1 U_4 + U_3}{1 - U_1 U_2} \\ V_4(\mathbf{U}) &= \frac{U_1 U_4 + U_3}{1 - U_1 U_2} U_2 + U_4 \end{aligned}$$

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Test $(V_1 \overset{?}{\perp\!\!\!\perp} V_2 | V_3, V_4)_P$ again, numerically

- Using $P(\mathbf{U}) \xrightarrow{V_i(\mathbf{U})} P(\mathbf{V})$ but with restricted domain

Numerics: Intrinsic SCM

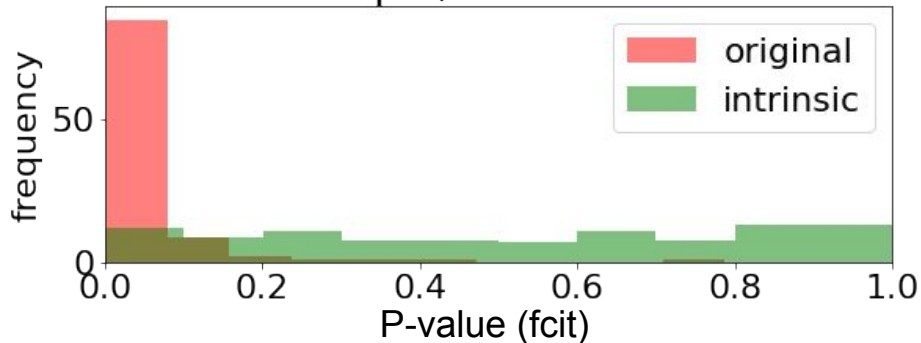
$U_i \sim \mathcal{N}(0, 1) \cap [-0.5, 0.5]$ *iid.*

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 \end{aligned}$$

Test $(V_1 \overset{?}{\perp\!\!\!\perp} V_2 | V_3, V_4)_P$ again, numerically

- Using $P(\mathbf{U}) \xrightarrow{V_i(\mathbf{U})} P(\mathbf{V})$ but with restricted domain

Counterexample, w/ domain restriction



Uniform p-values \longrightarrow conditional independence

Numerics: Intrinsic SCM

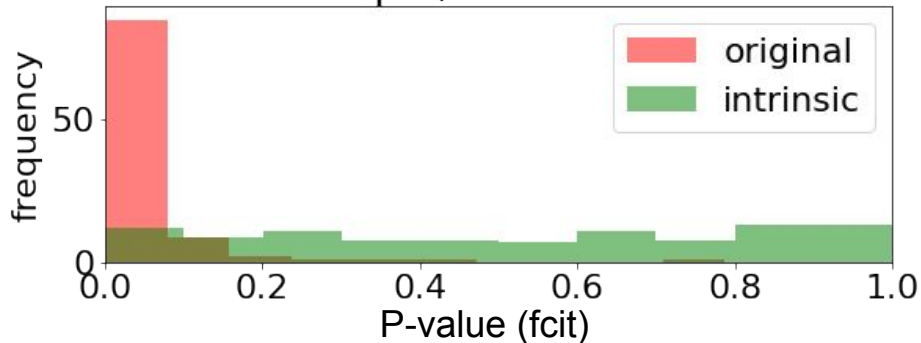
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 V_1(\mathbf{U}) &= U_1 \\
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 V_4(\mathbf{U}) &= \frac{U_1 U_4 + U_3}{1 - U_1 U_2} U_2 + U_4
 \end{aligned}$$

Test $(V_1 \overset{?}{\perp\!\!\!\perp} V_2 | V_3, V_4)_P$ again, numerically

- Using $P(\mathbf{U}) \xrightarrow{V_i(\mathbf{U})} P(\mathbf{V})$ but with restricted domain

Counterexample, w/ domain restriction



Uniform p-values \longrightarrow conditional independence

$$(V_1 \perp\!\!\!\perp V_2 | V_3, V_4)_P$$

Numerics: Intrinsic SCM

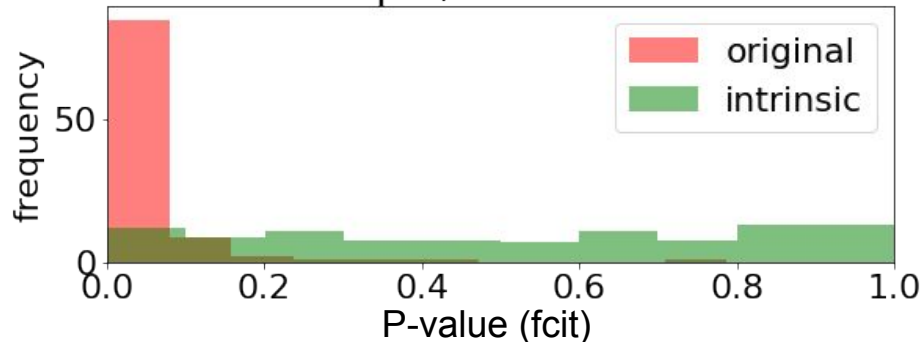
$U_i \sim \mathcal{N}(0, 1) \cap [-0.5, 0.5]$ *iid.*

$$M \begin{cases} V_1(\mathbf{U}) = U_1 \\ V_2(\mathbf{U}) = U_2 \\ V_3(\mathbf{U}) = \frac{U_1 U_4 + U_3}{1 - U_1 U_2} \\ V_4(\mathbf{U}) = \frac{U_1 U_4 + U_3}{1 - U_1 U_2} U_2 + U_4 \end{cases}$$

Test $(V_1 \perp\!\!\!\perp V_2 | V_3, V_4)_P$ again, numerically

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Counterexample, w/ domain restriction



Uniform p-values \longrightarrow conditional independence

$$(V_1 \perp\!\!\!\perp V_2 | V_3, V_4)_P$$

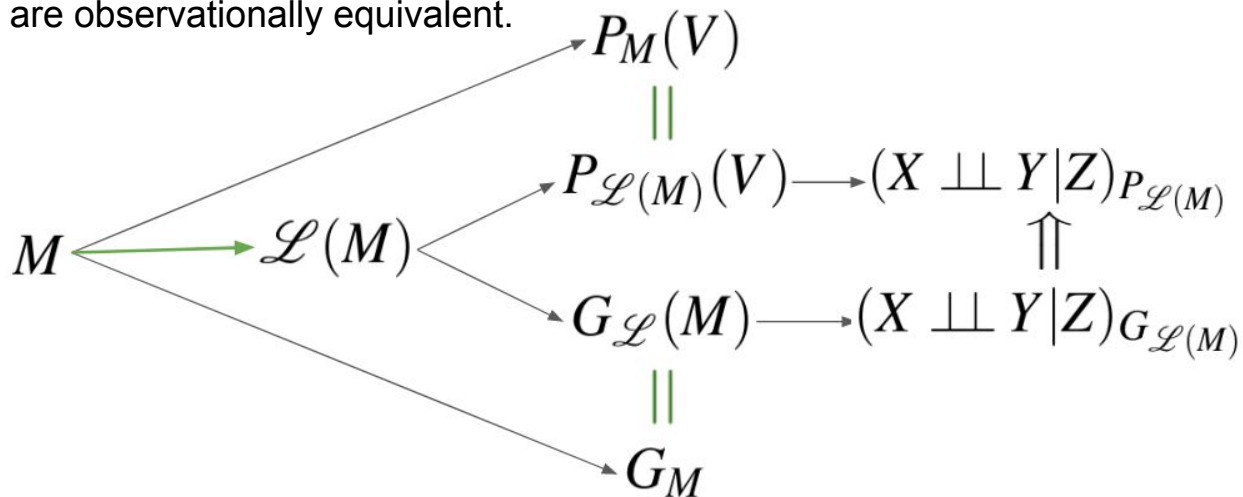
$(V_1 \perp\!\!\!\perp V_2 | V_3, V_4)_G \Rightarrow (V_1 \perp\!\!\!\perp V_2 | V_3, V_4)_P$
was inherited by the linear bound!

Next week's directions

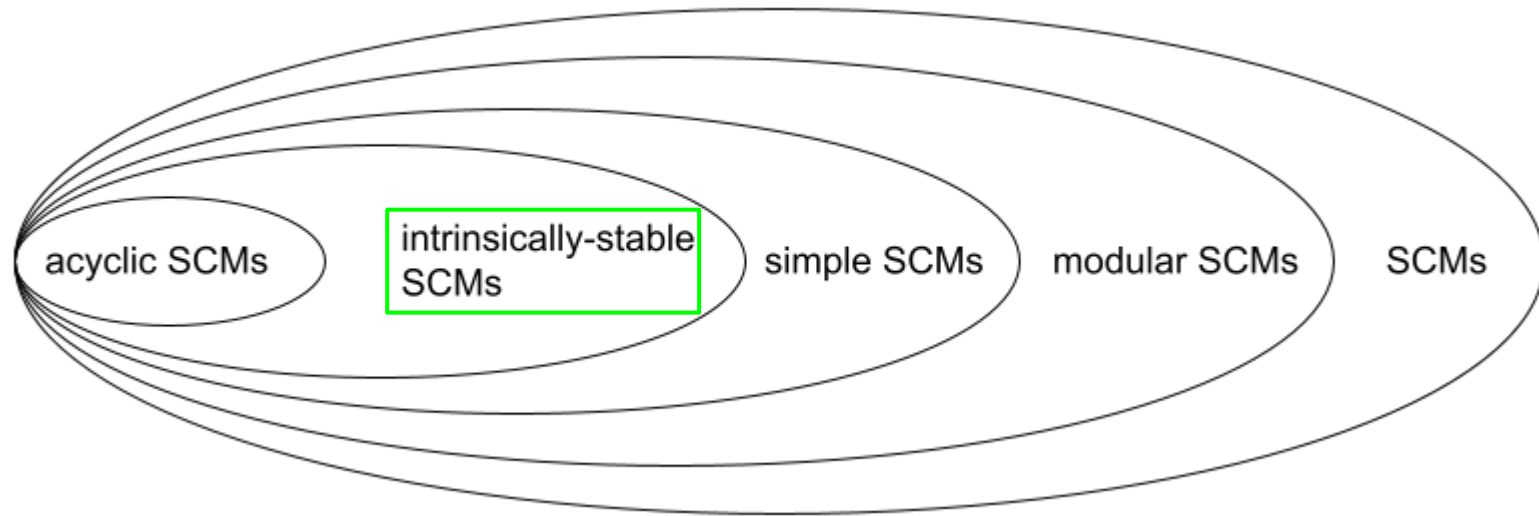
Observational Case: Proof Sketch

Strategy:

- Relate M to a linear SCM $L(M)$ which satisfies the directed global Markov property.
- Show that M and $L(M)$:
 - respect the same graph
 - are observationally equivalent.



Conjectured relation to other spaces of cyclic SCMs



Continuing Discussions: Game Theory + Causality

- Lewis Hammond (Oxford, Computer Science: Dphil student)
 - Extending Pearl's causal hierarchy to the game-theoretic domain
- Christian Kroer (Columbia, IOER department: Assistant professor)
 - Research: Game Theory, scalable optimization methods (for finding the potential responses)
- How relates:
 - Game theory is a primary motivation for cyclic causality
 - Local intrinsic stability

Next To-do's

- Prove Observational Equivalence
 - Get examples for each lemma
- Example of finding proper $P(U)$ for linear bound
 - show numerically as well
 - Also an example of when it fails
- Prove (or disprove):
 - $\text{acyclic SCMs} \subset \text{intrinsic SCMs} \subset \text{simple SCMs}$
 - Example of each:
 - Linear bound for acyclic
 - Demonstrating unique solvability for each subset of intrinsic example
 - Example of simple SCM that's not intrinsic
- Meet with Christian Kroer, see if worth collaborating

References

- Krzysztof Chalupka, Pietro Perona, and Frederick Eberhardt. Fast conditional independence test for vector variables with large sample sizes, 2018.
- Patrick Forré and Joris M. Mooij. Markov properties for graphical models with cycles and latent variables. arXiv:Statistics Theory, 2017.
- Peter Spirtes. Directed cyclic graphical representations of feedback models. CoRR, abs/1302.4982, 2013.
- Stephan Bongers, Patrick Forré, Jonas Peters, and Joris M. Mooij. Foundations of structural causal models with cycles and latent variables. The Annals of Statistics, 49(5):2885 – 2915, 2021.