Recent Advances in Causal Inference under Limited Domain Knowledge

Adèle H. Ribeiro

https://adele.github.io/ | adele.ribeiro@uni-marburg.de

Faculty of Mathematics and Computer Science
Philipps-Universität Marburg

Institute for Machine Learning for Medical Data,
Heinrich-Heine University Düsseldorf

Institut d'Informatique et Mathématiques Appliquées de Grenoble (IMAG)
October 15th, 2024

Artificial Intelligence (AI) & Machine Learning (ML)

AI and ML have achieved remarkable success in **pattern recognition** and **predictive tasks.**

AI's success translates into a wide range of applications, such as:

- Identifying disease-related risk factors,
- Translating languages,
- Optimizing treatment strategies and workflow scheduling,
- Automating financial fraud detection,
- Supporting precision agriculture,
- And many more…

Current Challenges in AI & ML

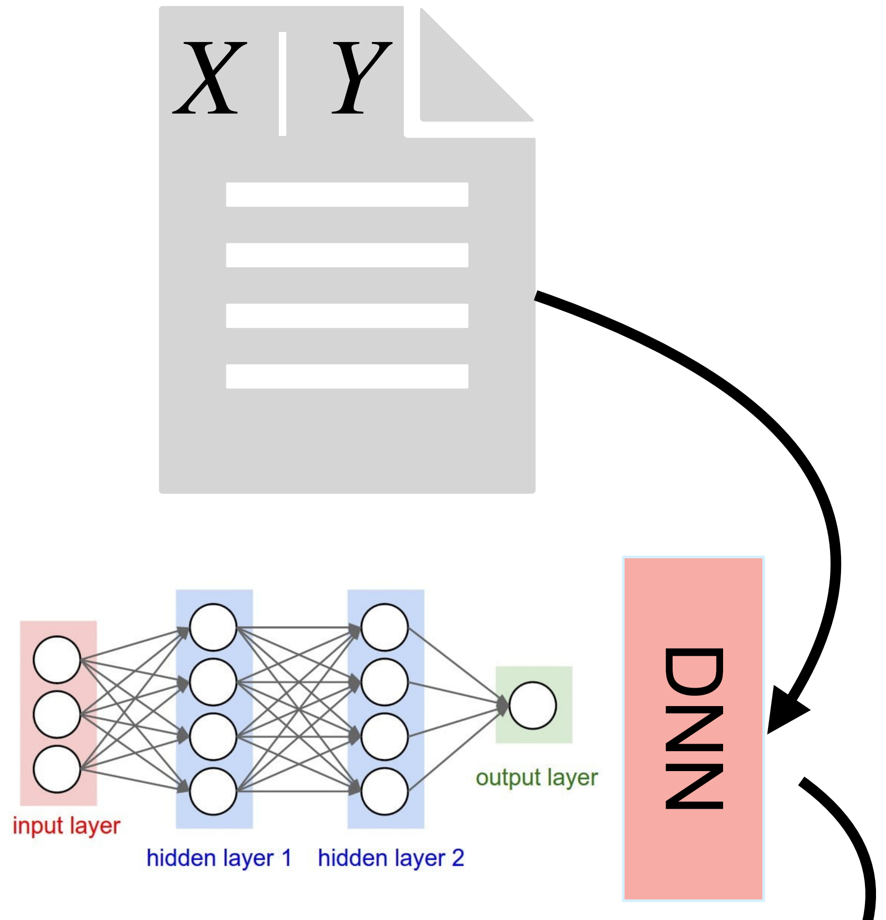
These techniques are extremely **data-intensive,** typically requiring advanced techniques to leverage **multiple, heterogeneous datasets.**

Additionally, challenges emerge in more complex tasks that demand careful consideration of **biases** and **underlying mechanisms**, including:

- Providing **explanations** of underlying processes
- Optimizing treatment / strategy **effectiveness**
- Identifying **personalized** treatments / strategies
- Ensuring **fairness** in clinical decision support systems
- Achieving **generalizability** across diverse domains and populations

Why does model explainability fail to establish causality?

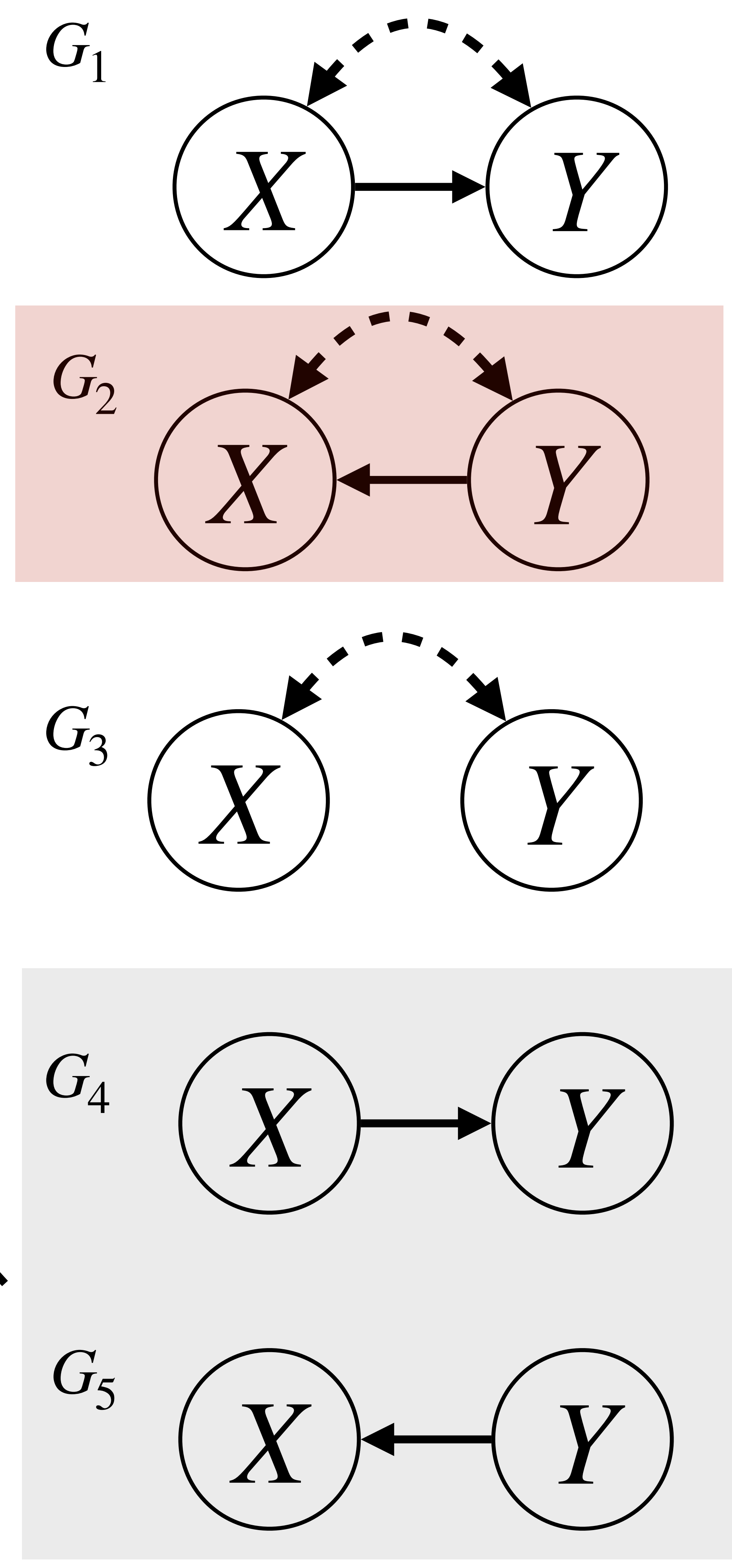
Observational



$\hat{P}(Y \mid X = x)$

X: Number of Doctor Visits
Y: Overall Health Status

$$P(Y \mid X = x) \neq P(Y)$$
$\Rightarrow X$ improves prediction of Y



$\mathcal{M}_{11} = \langle \mathbf{V}, \mathbf{U}_1, \mathcal{F}_{11}, P_{11}(\mathbf{u}_1) \rangle$
$\vdots$
$\mathcal{M}_{1k_1} = \langle \mathbf{V}, \mathbf{U}_1, \mathcal{F}_{1k_1}, P_{1k_1}(\mathbf{u}_1) \rangle$ Fitted Model

$\mathcal{M}_{21} = \langle \mathbf{V}, \mathbf{U}_2, \mathcal{F}_{21}, P_{21}(\mathbf{u}_2) \rangle$
$\vdots$
$\mathcal{M}_{2k_2} = \langle \mathbf{V}, \mathbf{U}_2, \mathcal{F}_{2k_2}, P_{2k_2}(\mathbf{u}_2) \rangle$ True Model

$\mathcal{M}_{31} = \langle \mathbf{V}, \mathbf{U}_3, \mathcal{F}_{31}, P_{31}(\mathbf{u}_3) \rangle$
$\vdots$
$\mathcal{M}_{3k_3} = \langle \mathbf{V}, \mathbf{U}_3, \mathcal{F}_{3k_3}, P_{3k_3}(\mathbf{u}_3) \rangle$

$\mathcal{M}_{41} = \langle \mathbf{V}, \mathbf{U}_4, \mathcal{F}_{41}, P_{41}(\mathbf{u}_4) \rangle$
$\vdots$
$\mathcal{M}_{4k_4} = \langle \mathbf{V}, \mathbf{U}_4, \mathcal{F}_{4k_4}, P_{4k_4}(\mathbf{u}_4) \rangle$

$\mathcal{M}_{51} = \langle \mathbf{V}, \mathbf{U}_5, \mathcal{F}_{51}, P_{51}(\mathbf{u}_5) \rangle$
$\vdots$
$\mathcal{M}_{5k_5} = \langle \mathbf{V}, \mathbf{U}_5, \mathcal{F}_{5k_5}, P_{5k_5}(\mathbf{u}_5) \rangle$

No unobserved confounders

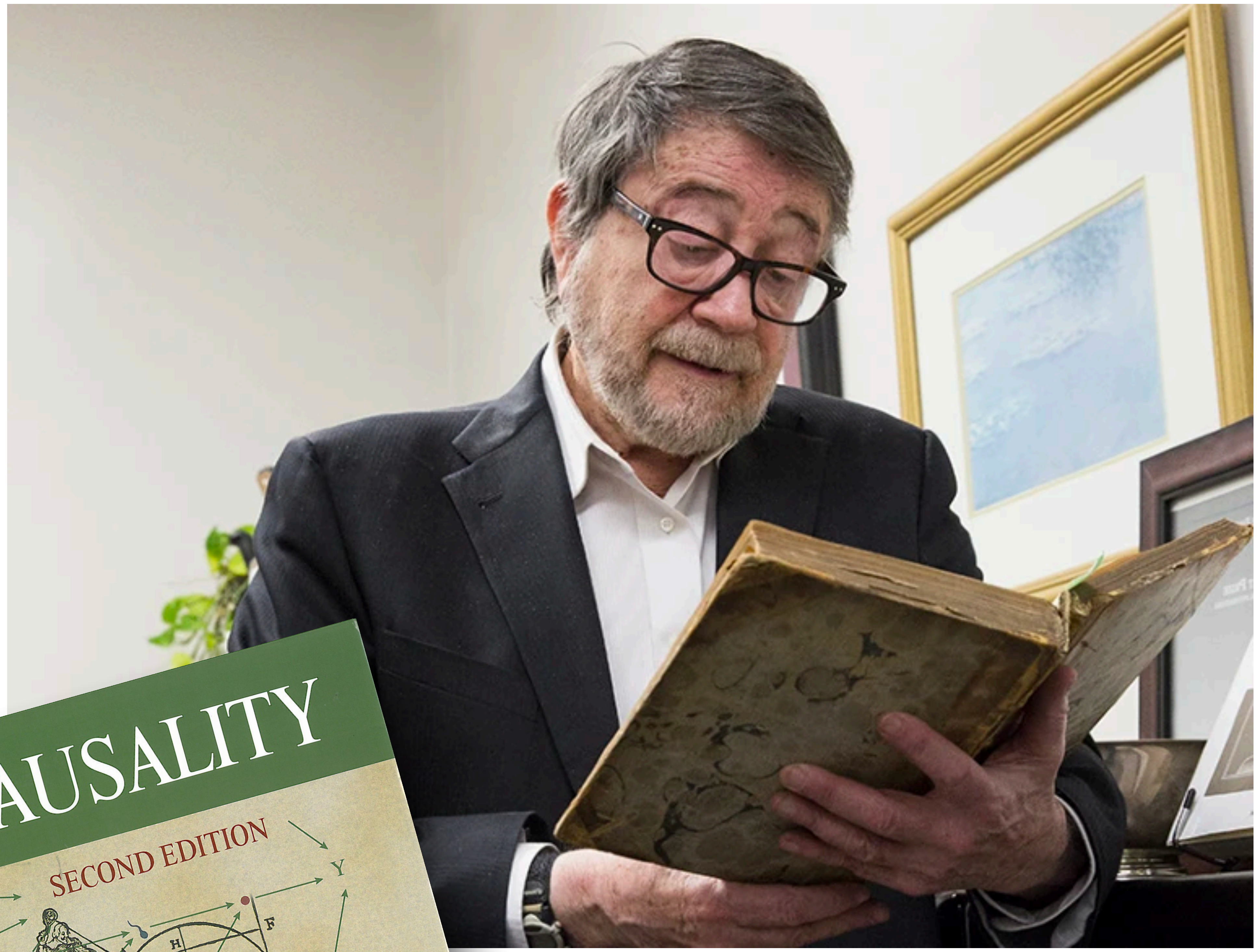
Encoded Knowledge / Assumptions

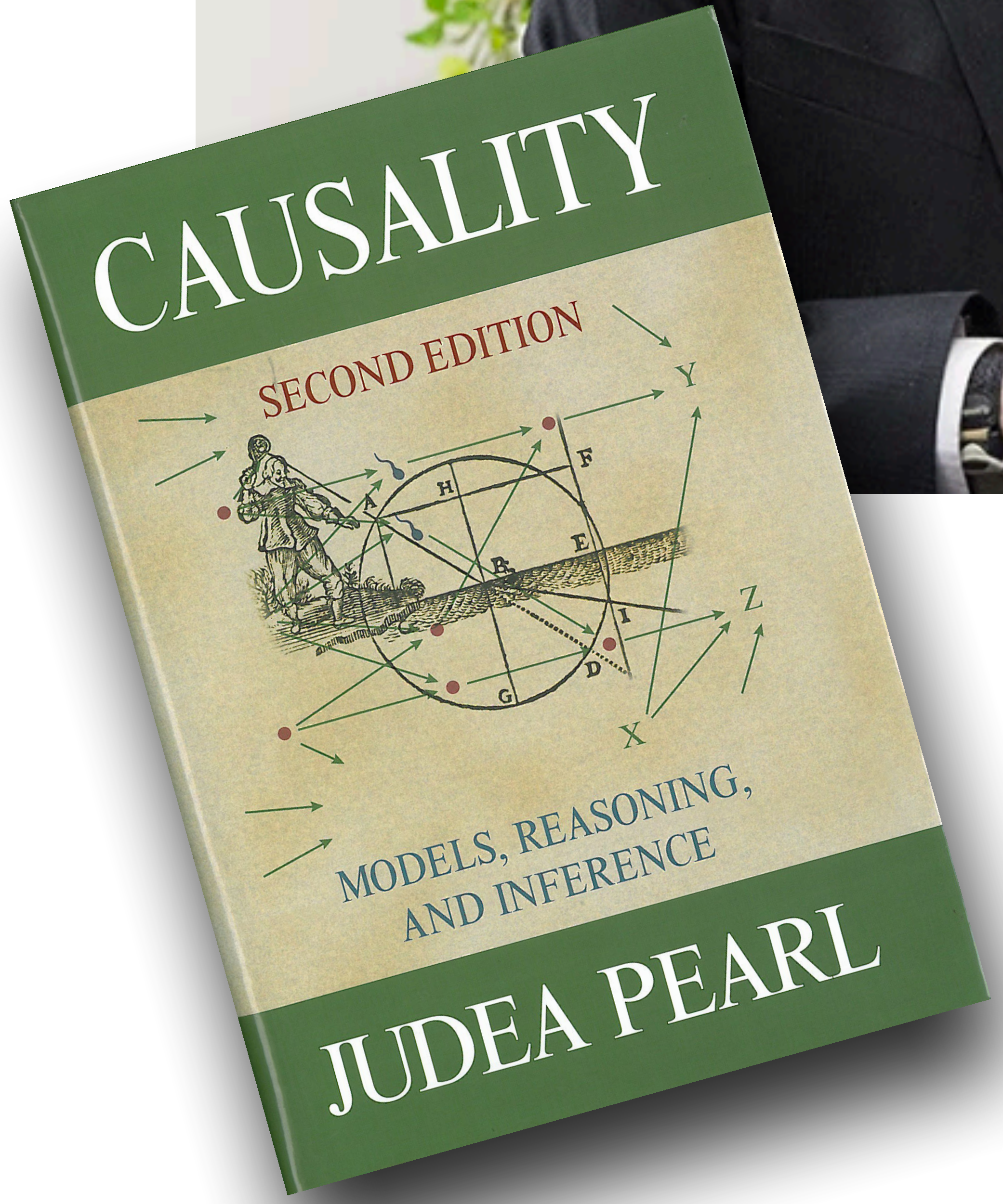
Why does model explainability fail to establish causality?

Even with numerous variables and vast amounts of data, model equivalence persists:

Multiple models (e.g., DNNs) fit the data equally well, but lead to different causal explanations!

Causal Artificial Intelligence by Judea Pearl





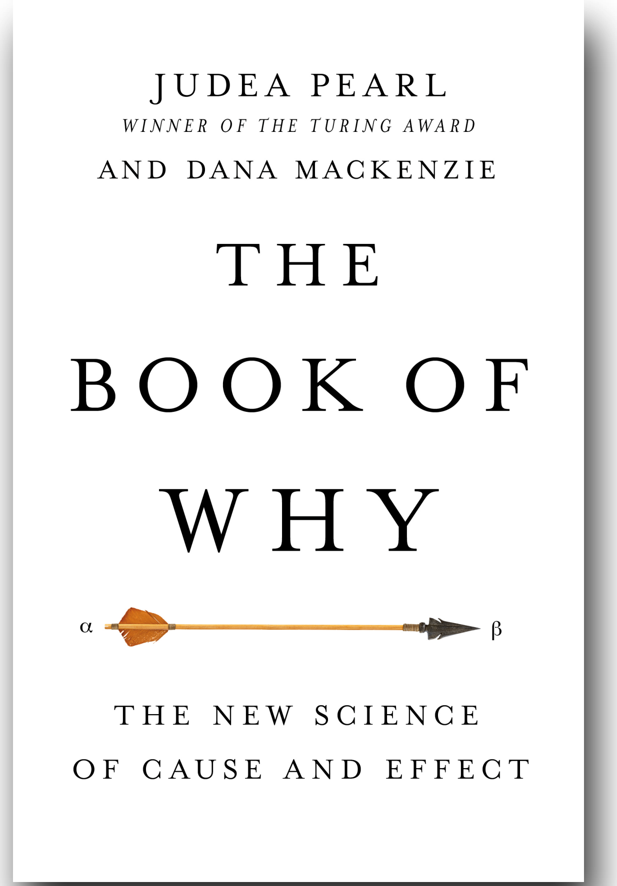
Director of the Cognitive Systems Laboratory at UCLA, received the 2011 A. M. Turing Award

“for fundamental contributions to artificial intelligence through the development of a calculus for probabilistic and causal reasoning.”

— Association for Computing Machinery (ACM)

“Deep learning has instead given us machines with truly impressive abilities but no intelligence. The difference is profound and lies in the absence of a model of reality.”

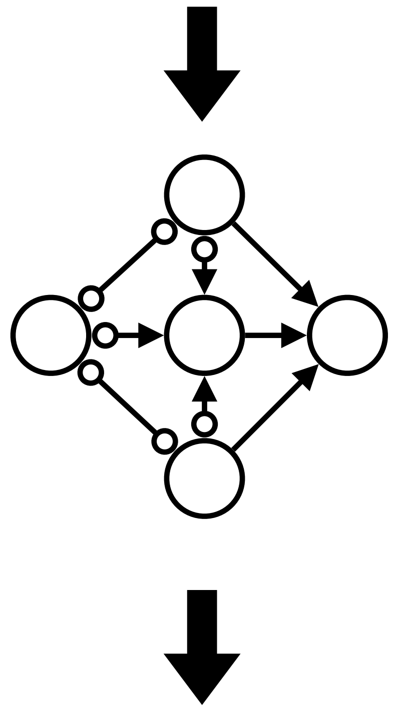
— The Book of Why: The New Science of Cause and Effect



Why causality is so important?

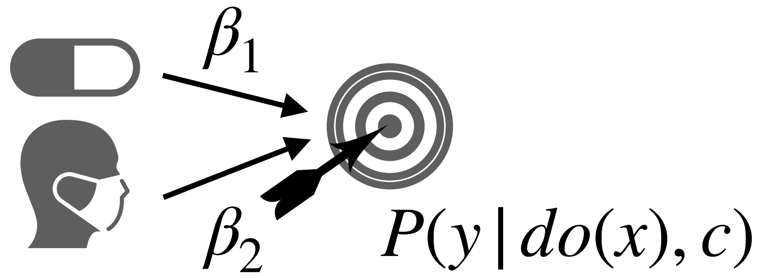
Data Fusion: Provides language and inferential machinery to cohesively combine prior knowledge and data from multiple and heterogeneous studies.

- **Causal Modeling, Causal Representation Learning and Causal Abstraction**



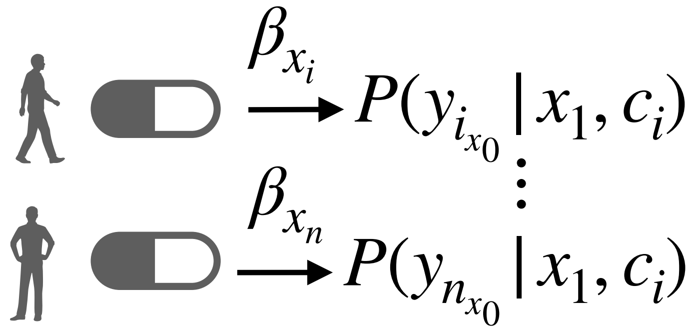
Explainability: Provides a better understanding of the true underlying mechanisms

- **Causal Discovery**

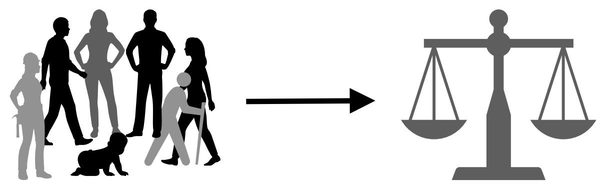


Optimal Decision Making: Can determine the *unbiased* effect of *unrealized* interventions, distinguishing between association and causation, rather than just predicting outcomes.

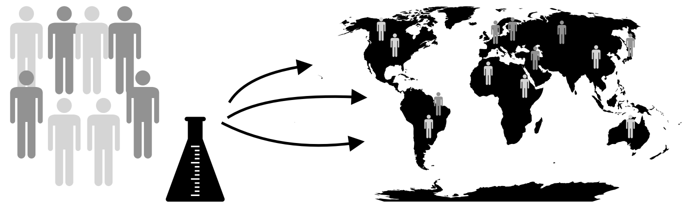
- **Causal Effect Identification and Estimation**



Personalized Inferences: Enables ***counterfactual reasoning*** by considering alternate scenarios and individual variability.



Fairness: Identifies and disentangles any mechanisms of discrimination, whether direct or indirect (potentially mediated or confounded).



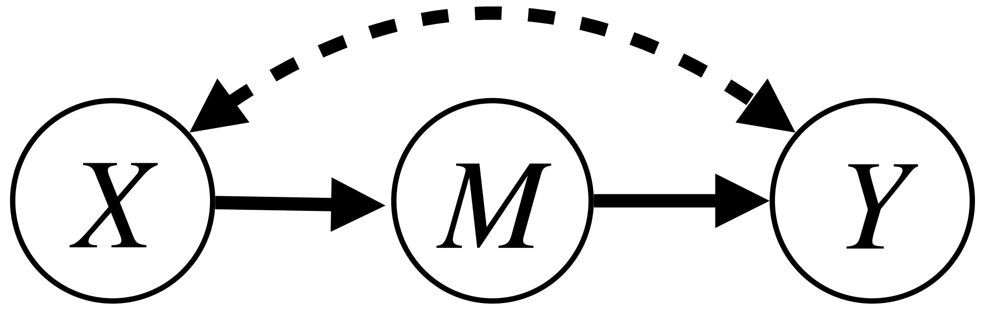
Generalizability: Enables effect *transportability* across different populations.

Causal Effect Identification - Judea Pearl's framework

1 **Query**

$P(y \mid do(x))$

2 **Causal Contraints**



3 **Probability Distributions**

$P(x, m, y)$ **Observational Distribution**

Inference Engine

Solution

yes / no

$$P(y \mid do(x)) = \sum_{m} P(m \mid x) \sum_{x'} P(y \mid m, x') P(x')$$

Interventional Distribution ← Available Distributions

Pearl, J. 1995. Causal diagrams for empirical research. Biometrika, 82(4): 669–688.

Tian, J. and Pearl, J. (2002) A General Identification Condition for Causal Effects. In Proceedings of the Eighteenth National Conference on Artificial Intelligence (AAAI 2002), pp. 567–573, Menlo Park, CA. AAAI Press/MIT Press.

Advances on Effect Identification given a Causal Diagram

Identification from observational and experimental data:

Lee, S., Correa, J., and Bareinboim, E. (2019). General identifiability with arbitrary surrogate experiments. In *Proceedings of the 35th Conference on Uncertainty in Artificial Intelligence*, volume 35, Tel Aviv, Israel. AUAI Press.

J. Correa, S. Lee, E. Bareinboim. (2021) Nested Counterfactual Identification from Arbitrary Surrogate Experiments. In Proceedings of the 35th Annual Conference on Neural Information Processing Systems

Identification of stochastic/soft (and possibly imperfect) interventions:

Correa, J. and Bareinboim, E. (2020). A calculus for stochastic interventions: Causal effect identification and surrogate experiments. In *Proceedings of the 34th AAAI Conference on Artificial Intelligence*, New York, NY. AAAI Press.

Identification and Estimation via Deep Neural Networks:

Xia, K., Lee, K.-Z., Bengio, Y., and Bareinboim, E. (2021). The causal-neural connection: Expressiveness, learnability, and inference. *Advances in Neural Information Processing Systems*, 34.

Xia, K., Pan, Y.,and Bareinboim, E. (2023) Neural Causal Models for Counterfactual Identification and Estimation. In Proceedings of the 11th International Conference on Learning Representations.

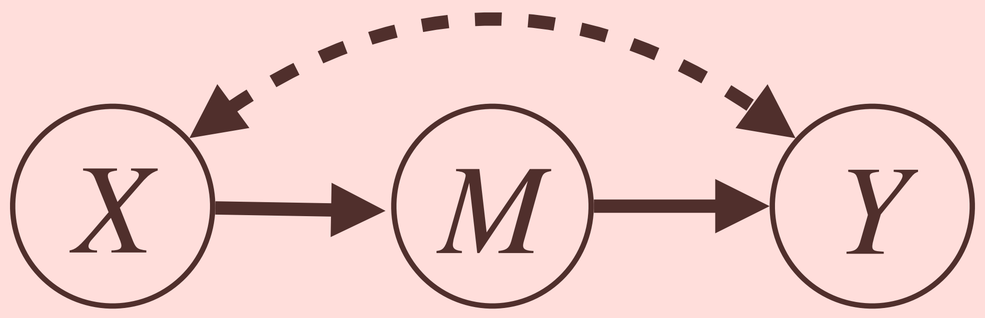
Causal Effect Identification - Judea Pearl's framework

Requires structural causal knowledge
for **every pair** of variables!

1 Query

$P(y \mid do(x))$

2 Causal Contraints



3 Probability Distributions

$P(x, m, y)$ **Observational Distribution**

Inference Engine

Solution

yes / no

$$P(y \mid do(x)) = \sum_{m} P(m \mid x) \sum_{x'} P(y \mid m, x')P(x')$$

Interventional Distribution ← Available Distributions

👍

Pearl, J. 1995. Causal diagrams for empirical research. Biometrika, 82(4): 669–688.

Tian, J. and Pearl, J. (2002) A General Identification Condition for Causal Effects. In Proceedings of the Eighteenth National Conference on Artificial Intelligence (AAAI 2002), pp. 567–573, Menlo Park, CA. AAAI Press/MIT Press.

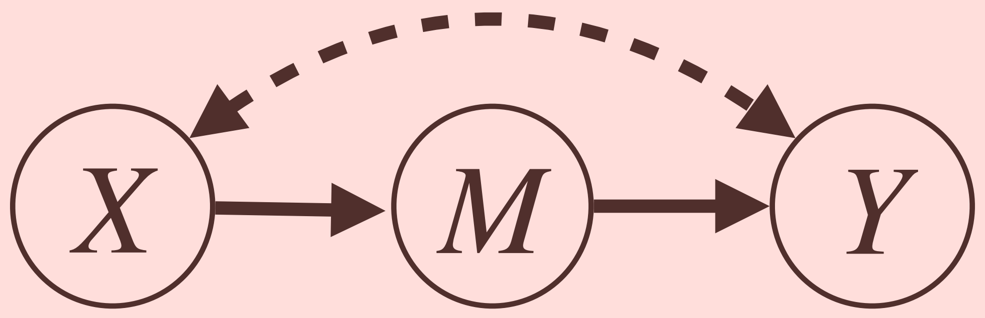
Causal Effect Identification - Judea Pearl's framework

Usually hard to be fully specified.
Can we relax some constraints?

1 **Query**

$P(y \mid do(x))$

2 **Causal Contraints**



3 **Probability Distributions**

$P(x, m, y)$ **Observational Distribution**

Inference Engine

Solution

yes / no

$$P(y \mid do(x)) = \sum_{m} P(m \mid x) \sum_{x'} P(y \mid m, x') P(x')$$

Interventional Distribution ← Available Distributions 👍

Pearl, J. 1995. Causal diagrams for empirical research. Biometrika, 82(4): 669–688.

Tian, J. and Pearl, J. (2002) A General Identification Condition for Causal Effects. In Proceedings of the Eighteenth National Conference on Artificial Intelligence (AAAI 2002), pp. 567–573, Menlo Park, CA. AAAI Press/MIT Press.

Main Research Question

Can we facilitate the application of causality to
complex real-world scenarios, such as those in medicine,
by **relaxing certain assumptions**
while ensuring **robustness**, data **privacy**, and
flexible integration of **domain expertise**?

Causal Inference with Partial Structure Knowledge using Cluster Causal Diagrams (C-DAGs)

Anand, T. V.*, **Ribeiro A. H.*,** Tian, J., & Bareinboim, E. (2023). Causal Effect Identification in Cluster DAGs. In Proceedings of the Thirty-Seventh AAAI Conference on Artificial Intelligence, AAAI-23 (Link).

* Equal contribution

Causal Effect Identification in Cluster DAGs (C-DAGs)

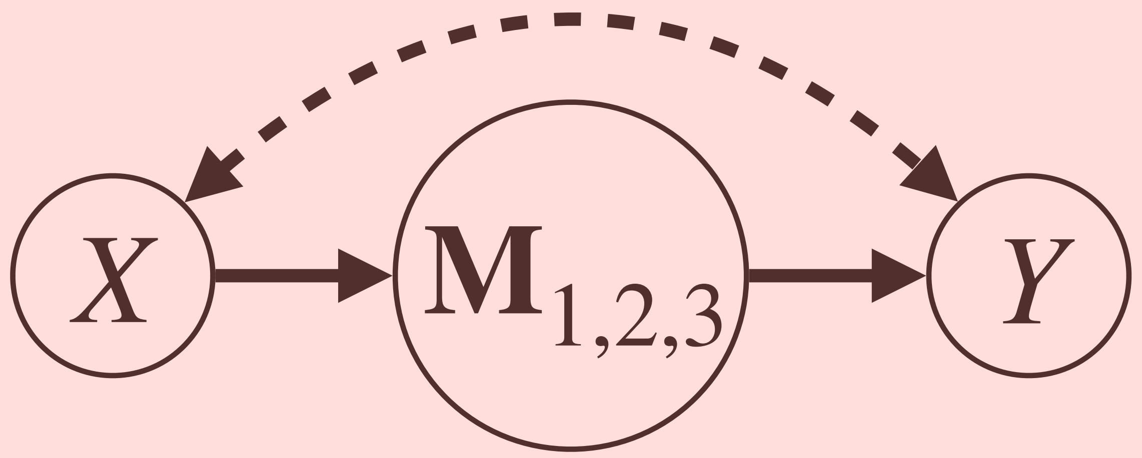
Requires specification only between clusters, leaving the within-cluster relationships

Extension of ID and Ctf-ID algorithms to C-DAGs.

1 **Query**

$P(y \mid do(x))$

2 **C-DAG**



3 **Data**

$P(x, m_1, m_2, m_3, y)$

Inference Engine

Solution

yes / no

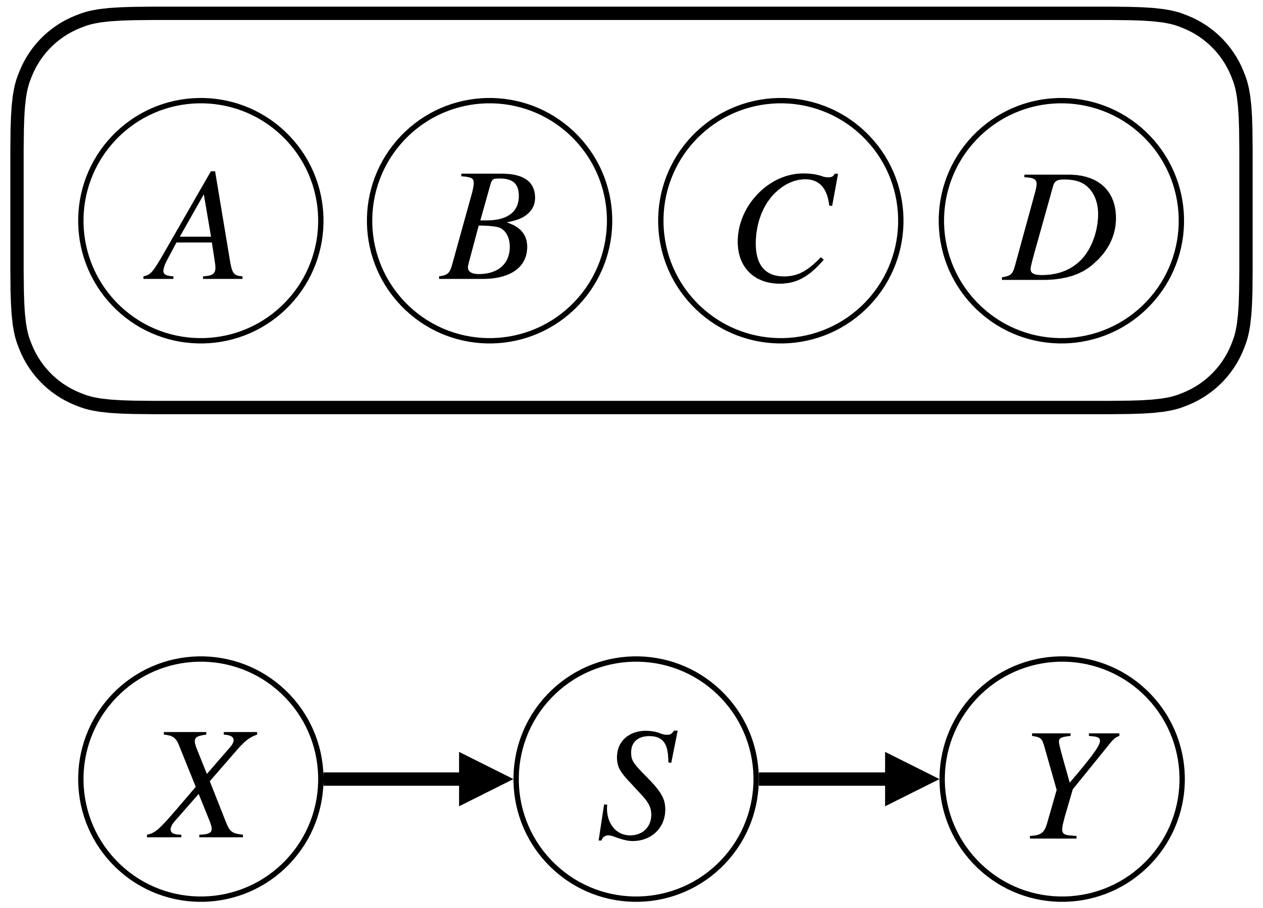
$$P(y \mid do(x)) = \sum_{\mathbf{m}_{123}} P(\mathbf{m}_{123} \mid x) \sum_{x'} P(y \mid \mathbf{m}_{123}, x')P(x')$$

Inferred (Interventional) Distribution ← Available (Observational) Distribution 👍

Anand, T. V.*, **Ribeiro A. H.*,** Tian, J., & Bareinboim, E. (2023). Causal Effect Identification in Cluster DAGs. In Proceedings of the Thirty-Seventh AAAI Conference on Artificial Intelligence, AAAI-23 (Link).

Partially Understood Systems

(A) Age
(B) Blood pressure
(C) Comorbidities
(D) Medication history
(X) Lisinopril
(S) Sleep Quality
(Y) Stroke

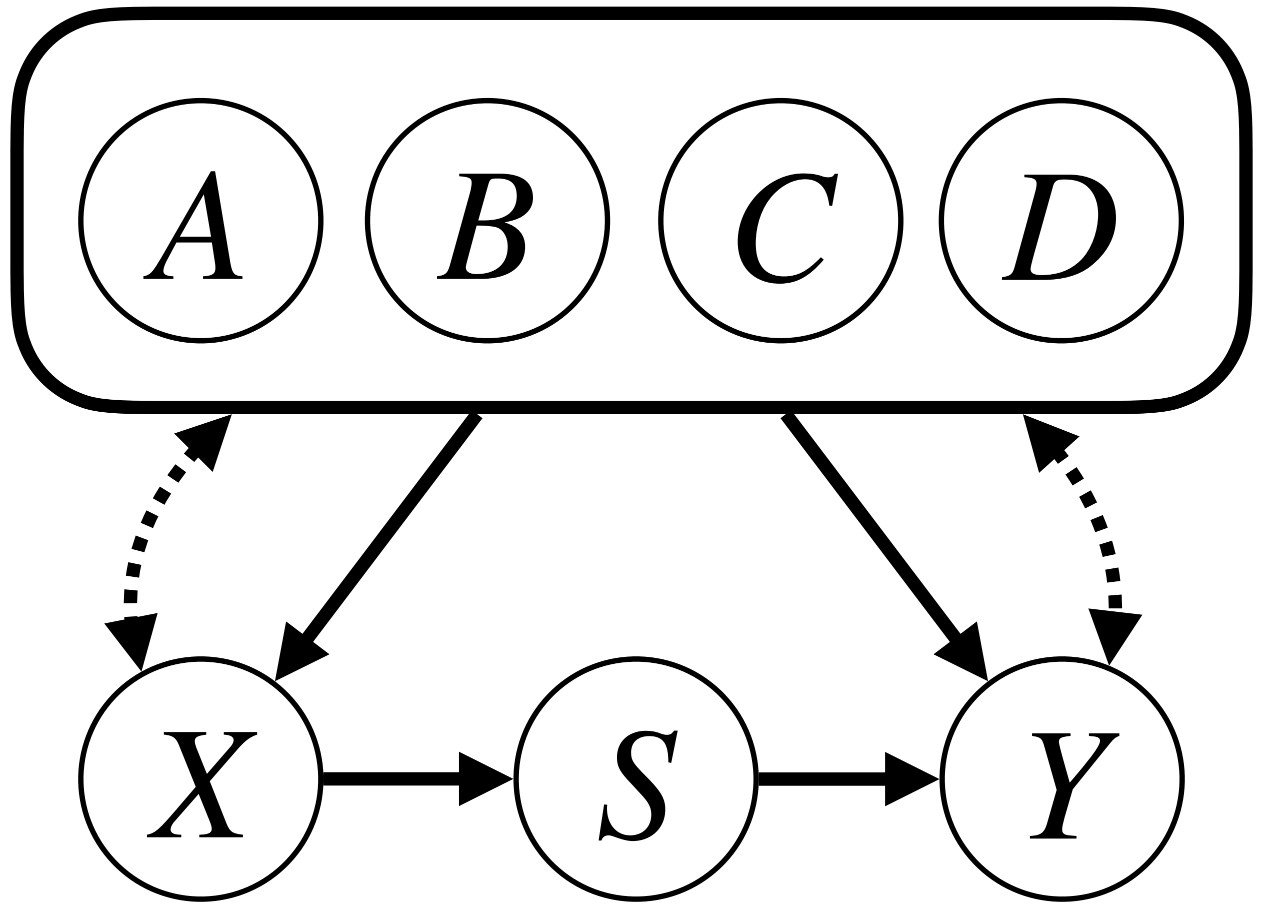


A causal diagram cannot be specified given the existing knowledge!

Can we identify $P(y \mid do(x))$ in this case?

Cluster DAGs (C-DAGs)

A) Age
(B) Blood pressure
(C) Comorbidities
(D) Medication history
(X) Lisinopril
(S) Sleep Quality
(Y) Stroke



$\{\{X\}, \{S\}, \{Y\}, \{A, B, C, D\}\}$

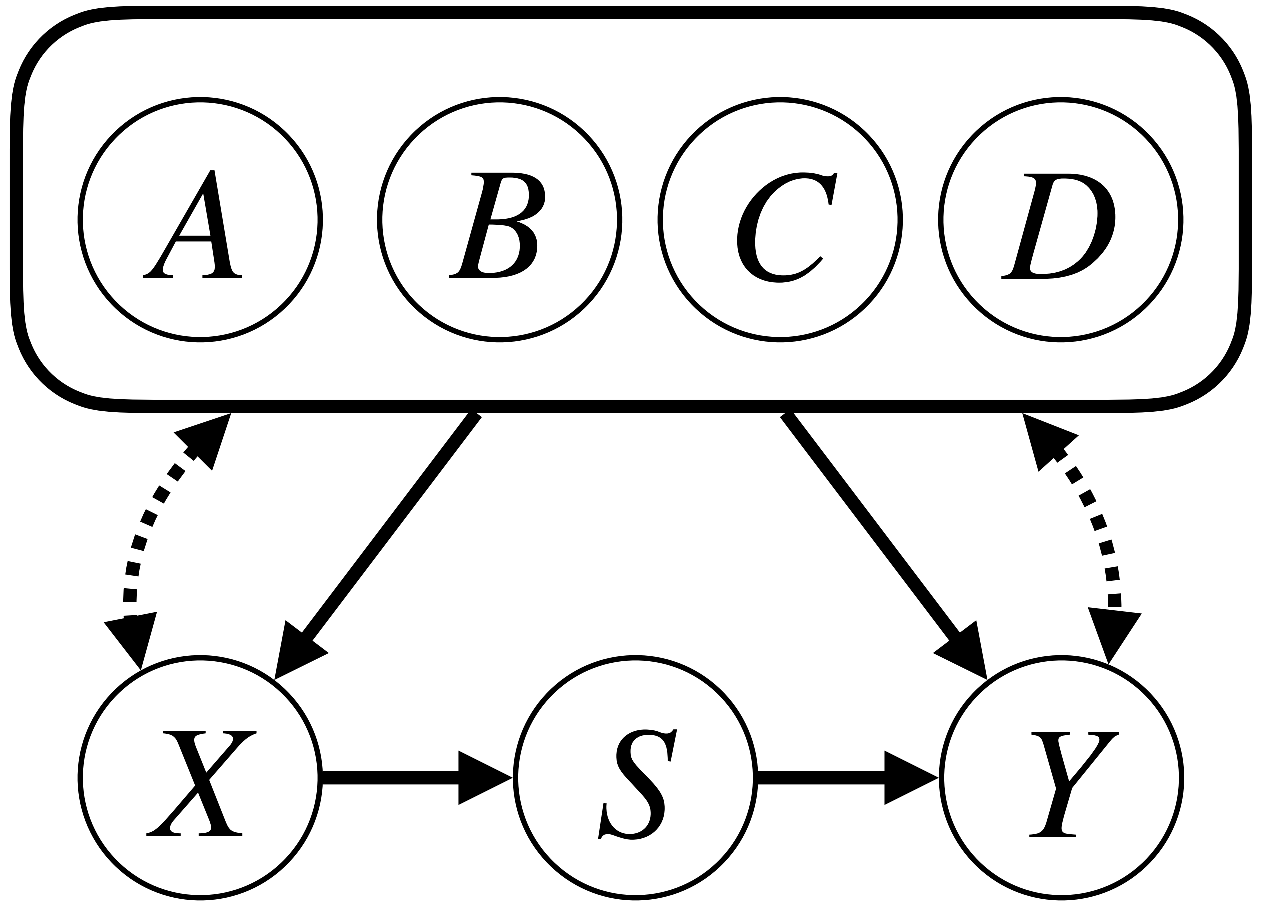
A *cluster DAG* $G_{\mathbf{C}}$ over a given partition $\mathbf{C} = \{\mathbf{C}_1, \ldots, \mathbf{C}_k\}$ of $\mathbf{V}$ is compatible with a causal diagram G over $\mathbf{V}$ if **for every $\mathbf{C}_i, \mathbf{C}_j \in \mathbf{C}$**:

- $\mathbf{C}_i \rightarrow \mathbf{C}_j$ if $\exists V_i \in \mathbf{C}_i$ and $V_j \in \mathbf{C}_j$ such that $V_i \rightarrow V_j$
- $\mathbf{C}_i \dashleftarrow\dashrightarrow \mathbf{C}_j$ if $\exists V_i \in \mathbf{C}_i$ and $V_j \in \mathbf{C}_j$ such that $V_i \dashleftarrow\dashrightarrow V_j$

and $G_{\mathbf{C}}$ contains no cycles.

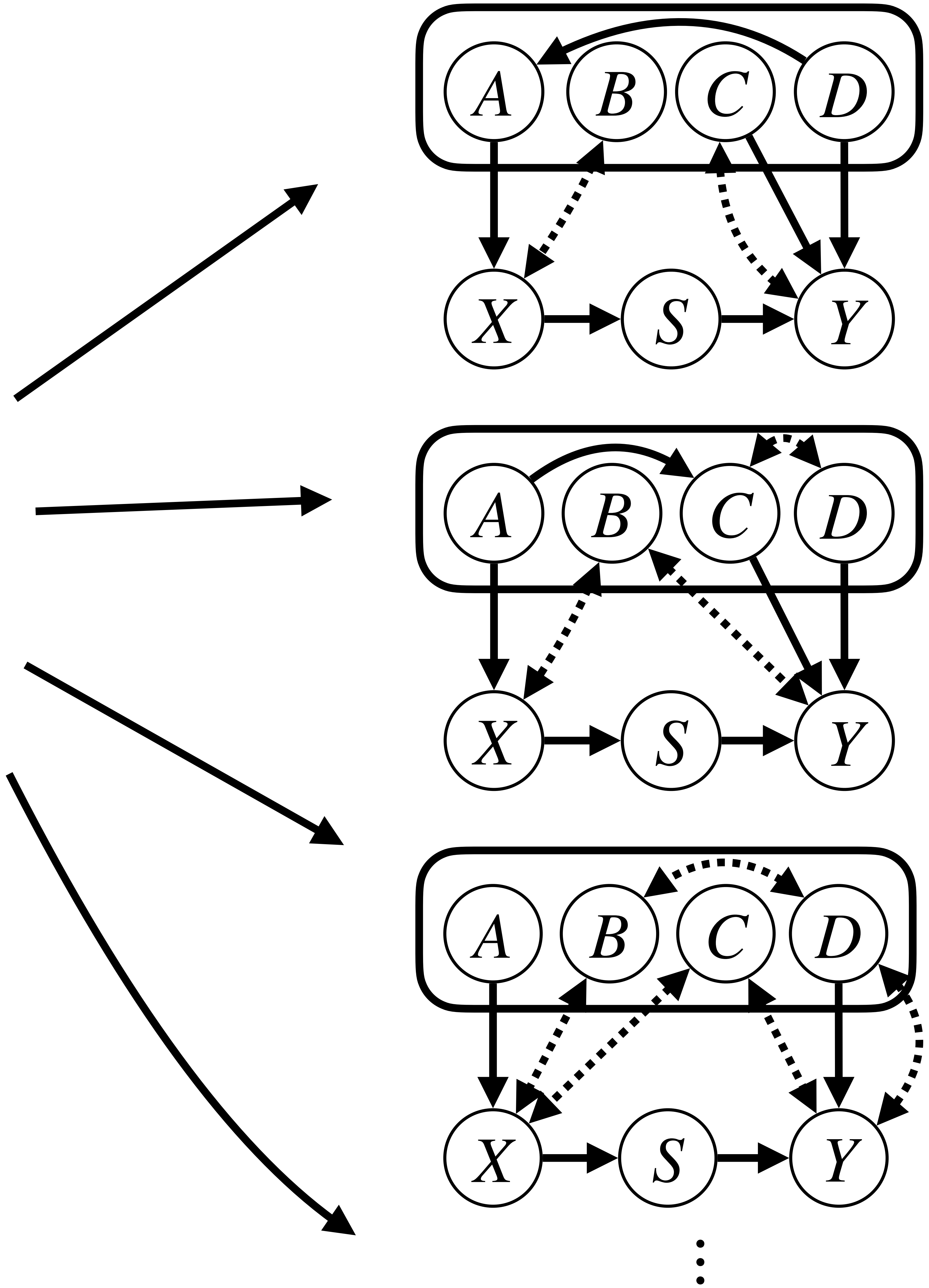
Effect Identification in Partially Understood Systems

Many causal diagrams are compatible with the current knowledge!

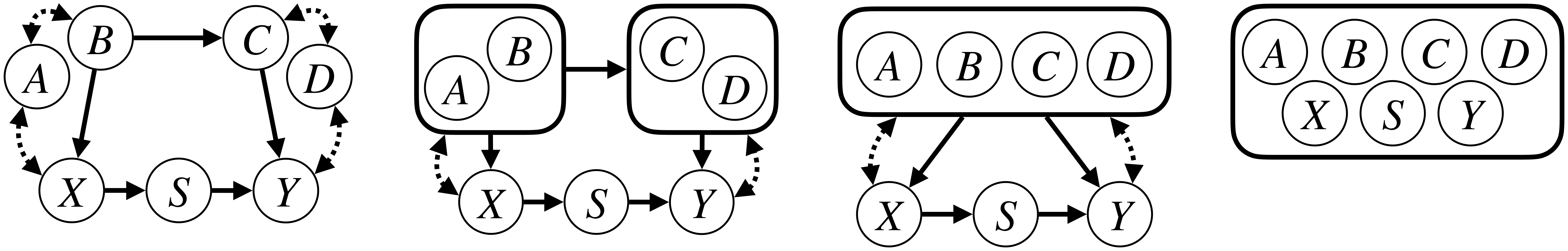


Can be seen as an *equivalence class* of causal diagrams, where any relationships are allowed among the variables within each cluster.

Causal effects are identified without deciding on any particular causal diagram!



C-DAG: Flexible Encoder of Model Assumptions

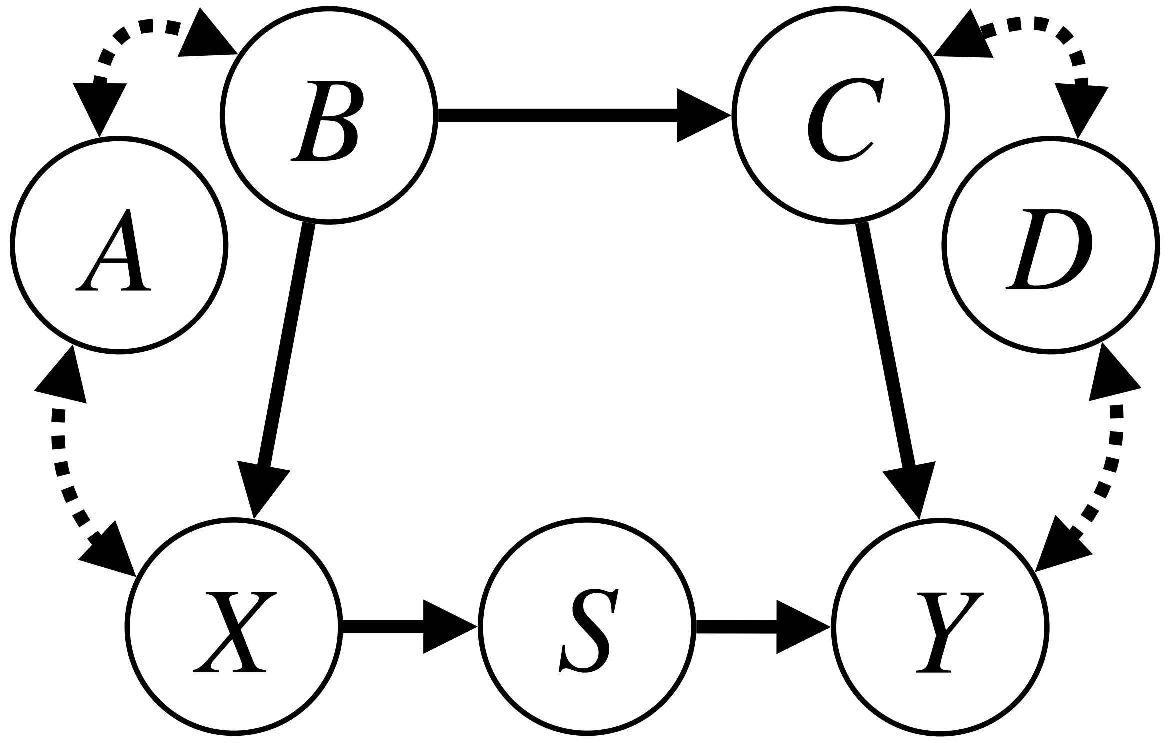


N clusters of size one
(full knowledge - DAG)

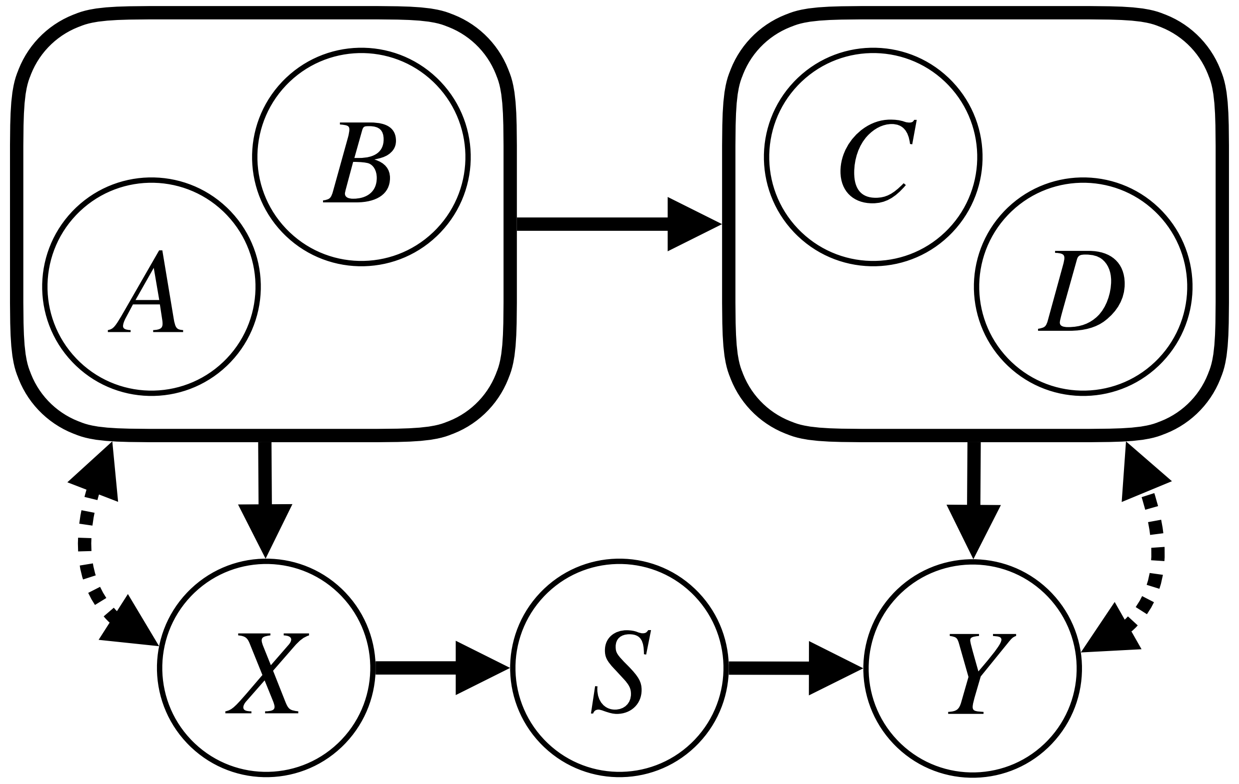
…
(partial knowledge - C-DAG)

One cluster of size N
(no knowledge)

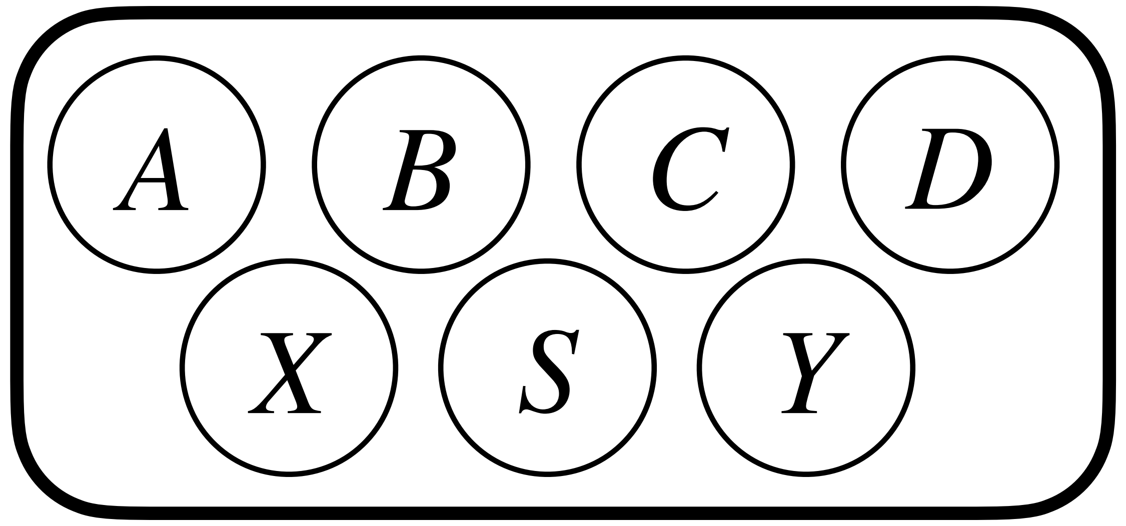
C-DAG: Flexible Encoder of Model Assumptions



N clusters of size one
(full knowledge - DAG)



…
(partial knowledge - C-DAG)



One cluster of size N
(no knowledge)

Clusters are manually created by domain experts:

- due to lack of knowledge, consensus, or interest on the internal causal structure;
- to communicate relationships among semantically meaningful entities.

Associational, Interventional, and Counterfactual Inference

D-Separation ($\mathscr{L}_1$), do-calculus, ID ($\mathscr{L}_2$), and Ctf-ID ($\mathscr{L}_3$) are sound and complete:

- Applicable to C-DAG $G_C \implies$ Applicable in ***every*** G compatible to G_C
- Not applicable to $G_C \implies$ Not applicable in ***at least one*** G compatible to G_C

C-DAGs act as Bayesian Networks ($\mathscr{L}_1$) and Causal Bayesian Networks ($\mathscr{L}_2$).

Moreover, if G is induced by SCM $\mathscr{M}$

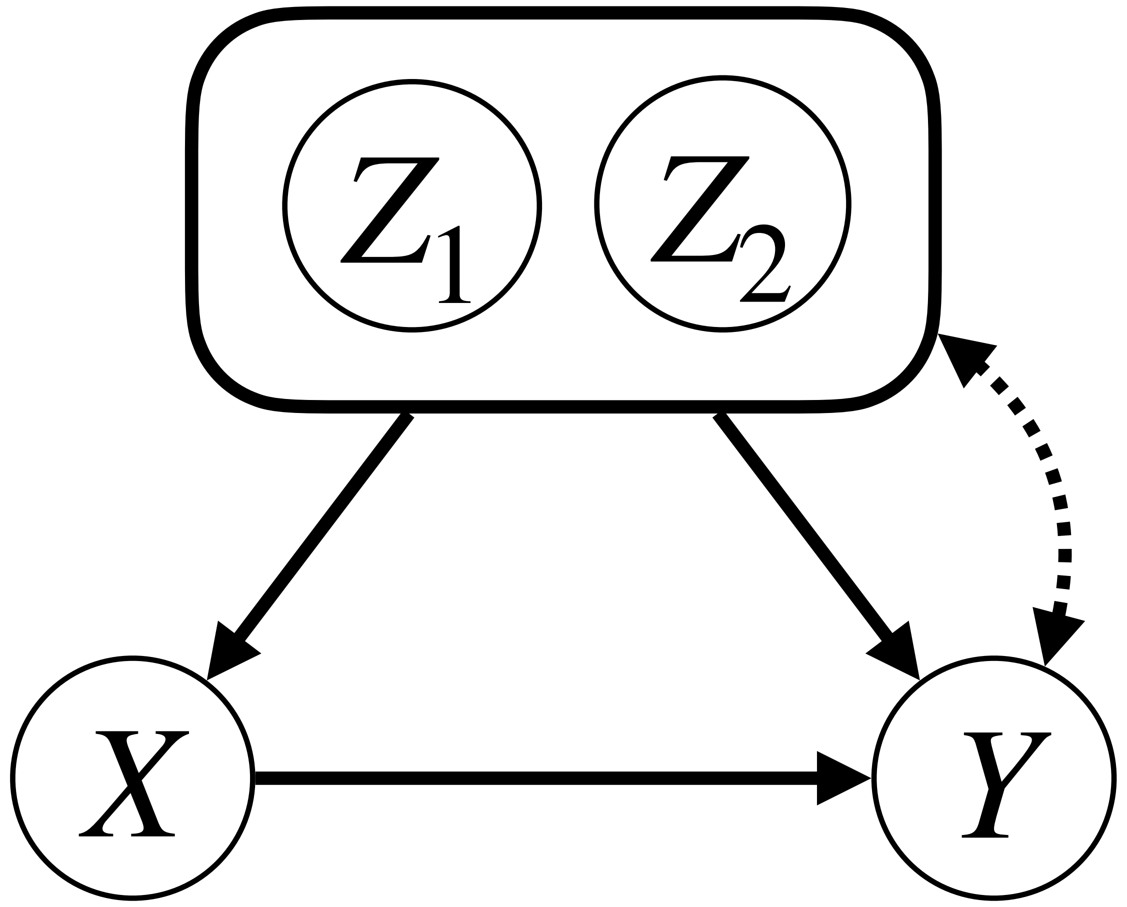
$\implies \exists$ SCM $\mathscr{M}_C$ inducing $G_{\mathbf{C}}$ and $P_{\mathscr{M}}(\mathbf{y}_{\mathbf{x}}, \ldots, \mathbf{z}_{\mathbf{w}}) = P_{\mathscr{M}_{\mathbf{C}}}(\mathbf{y}_{\mathbf{x}}, \ldots, \mathbf{z}_{\mathbf{w}})$

C-DAGs generalized DAGs and causal diagrams for all three layers of inference.

Effect Identifiabiliy given a C-DAG

Simple evaluation of the **validity** of the Backdoor Criterion / Conditional Exchangeability

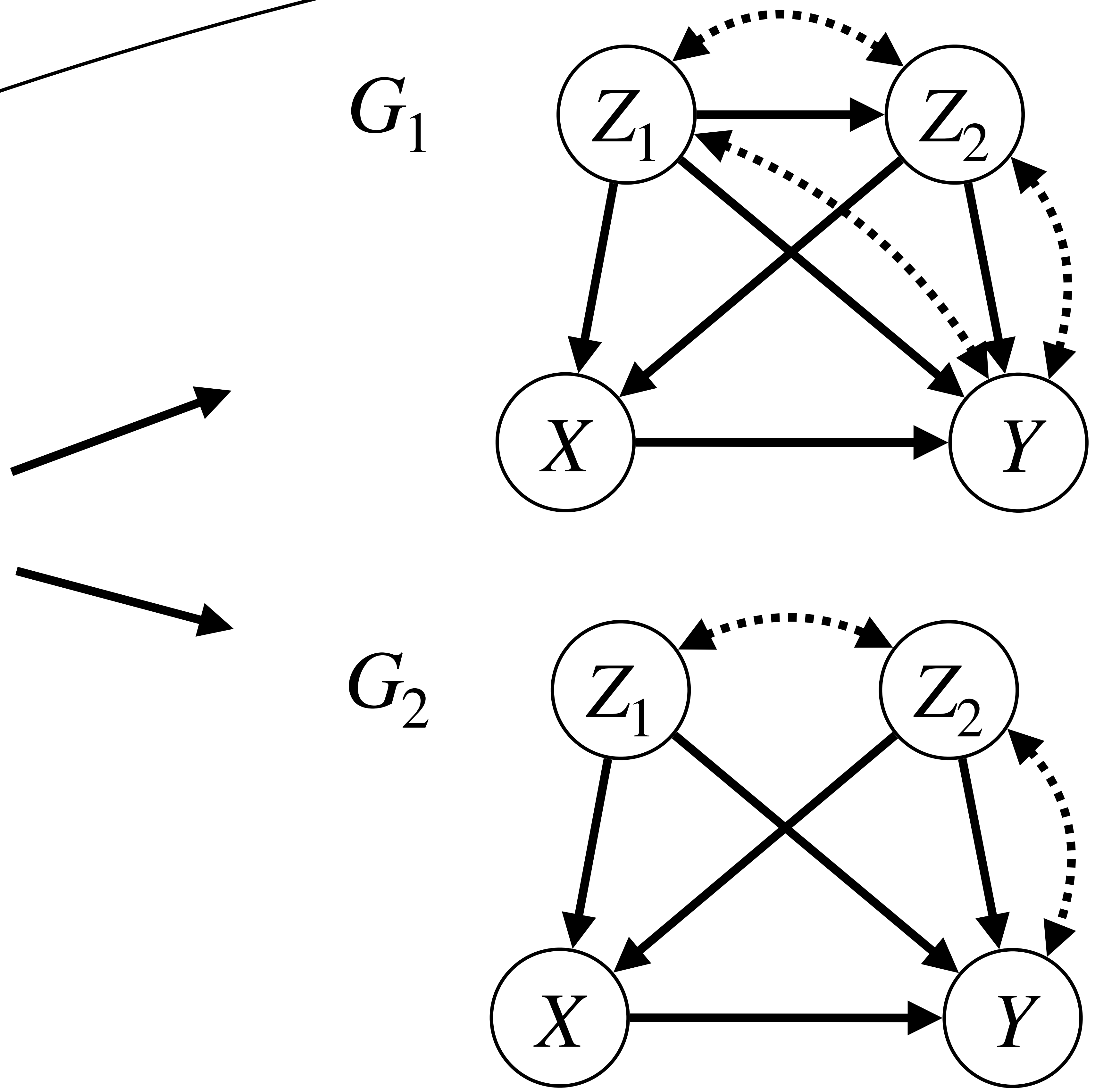
$G_{\mathbf{C}}$



$$P(y \mid do(x)) = \sum_{\mathbf{z}} P\left(y \mid x, \mathbf{z}\right) P\left(\mathbf{z}\right)$$

G_1

G_2



$$P(y \mid do(x)) = \sum_{z_1, z_2} P(y \mid x, z_1, z_2) P(z_1, z_2)$$

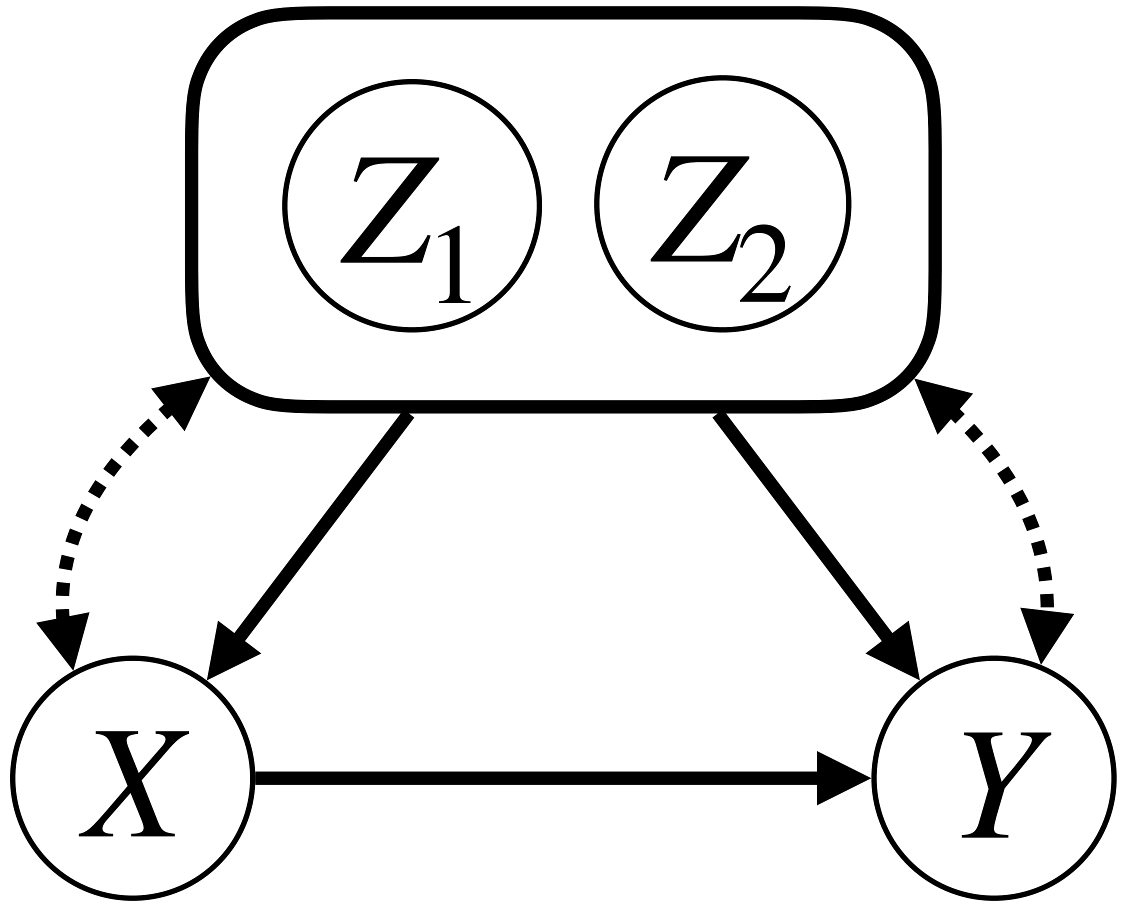
$$P(y \mid do(x)) = \sum_{z_1, z_2} P(y \mid x, z_1, z_2) P(z_1, z_2)$$

An identifiable effect in a C-DAG $G_{\mathbf{C}}$ is identifiable in all compatible causal diagrams G using the same identification formula!

Effect Non-Identifiabiliy given a C-DAG

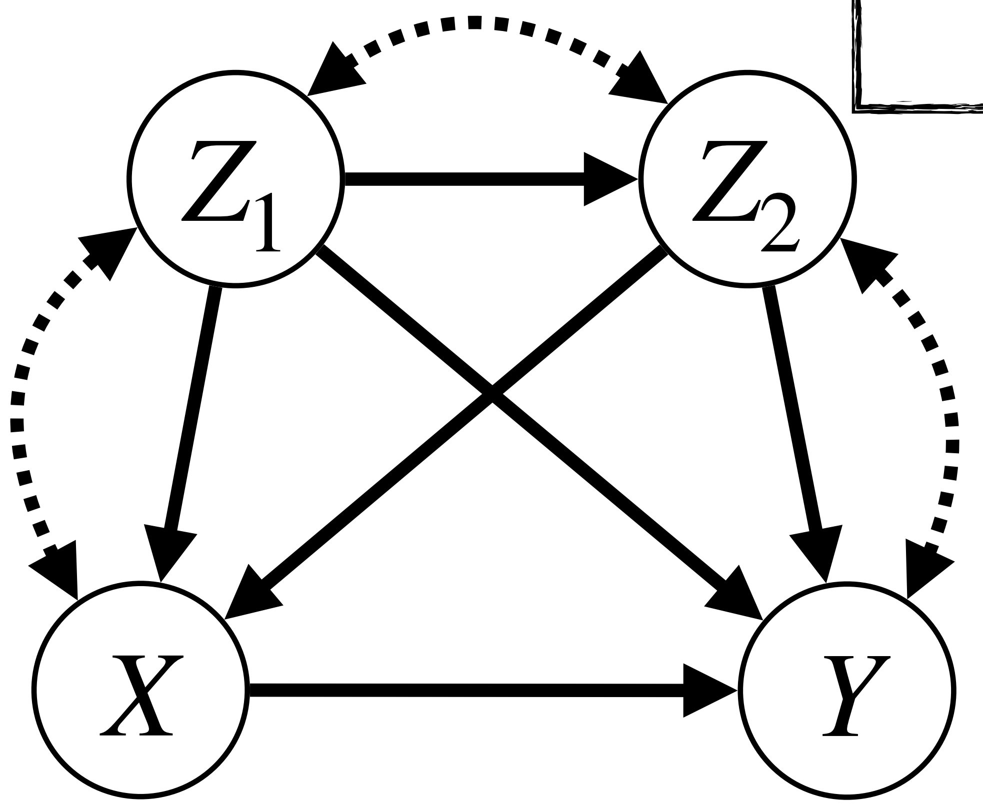
Simple evaluation of a **violation** of the Backdoor Criterion / Conditional Exchangeability

$G_{\mathbf{C}}$



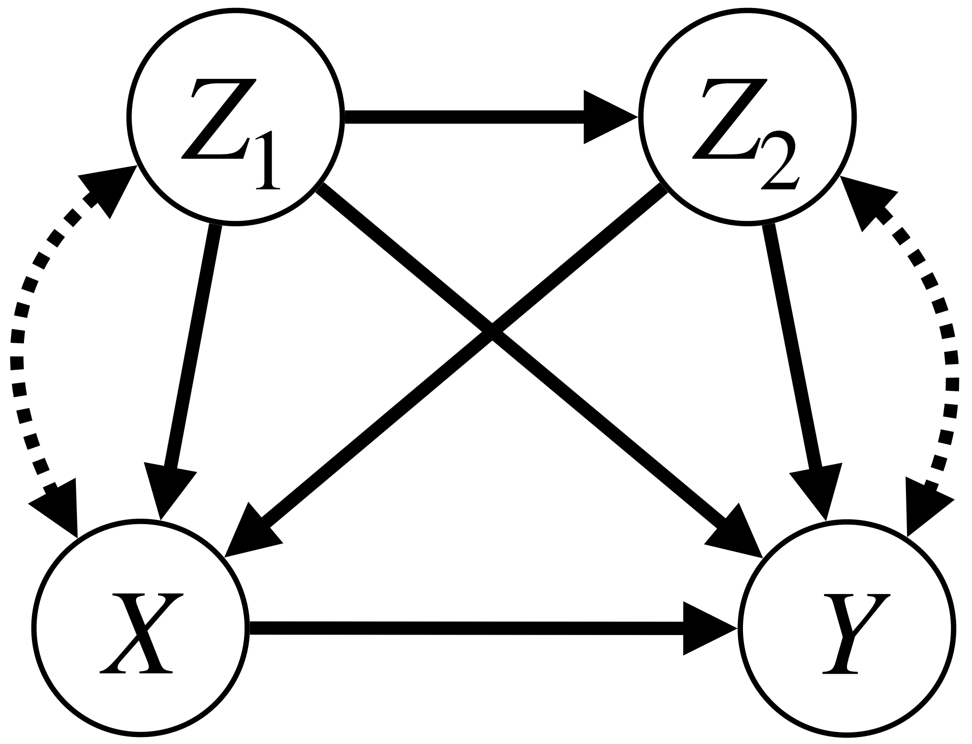
$P(y \mid do(x))$ is not identifiable

G_1



$P(y \mid do(x))$ is not identifiable

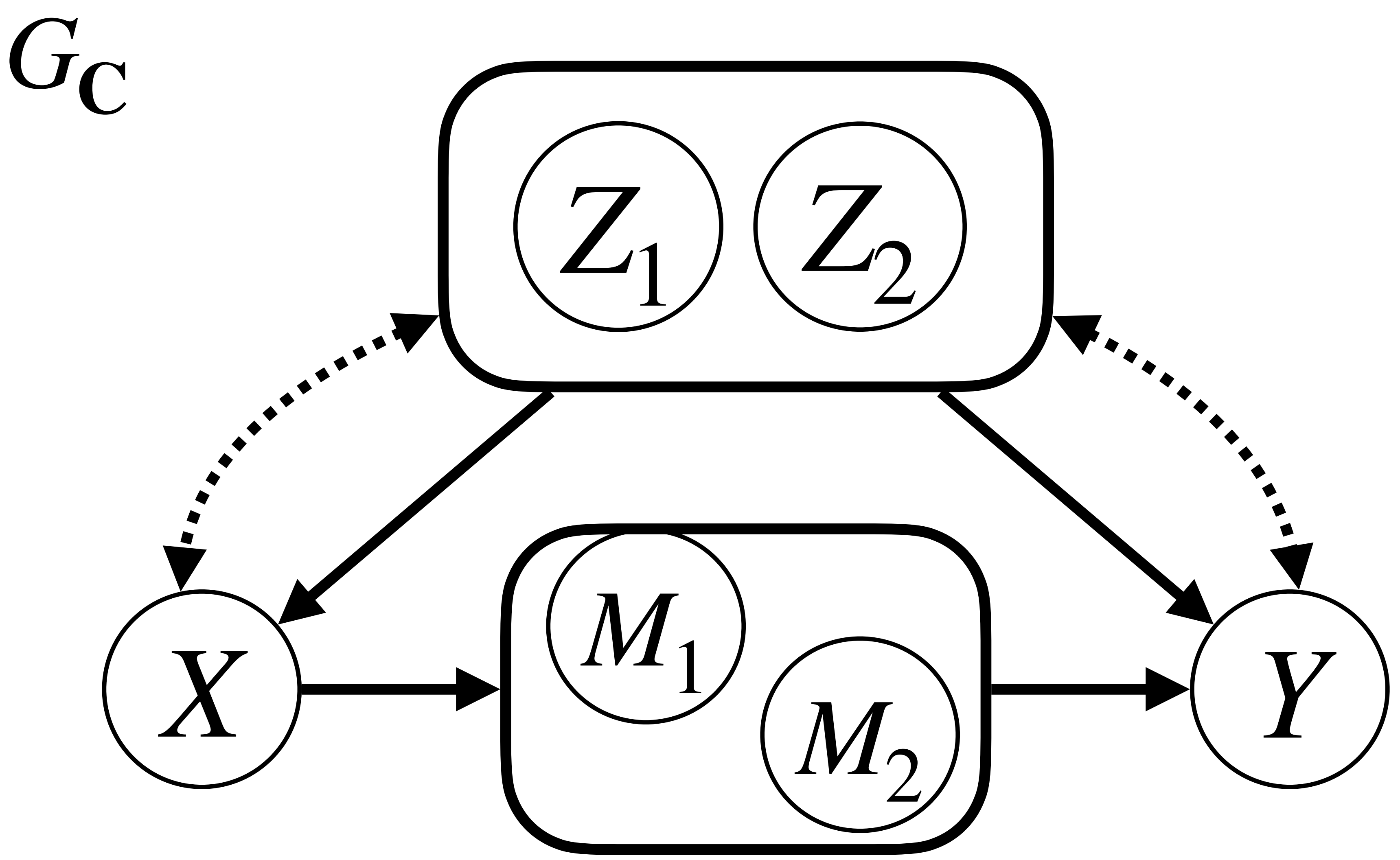
G_2



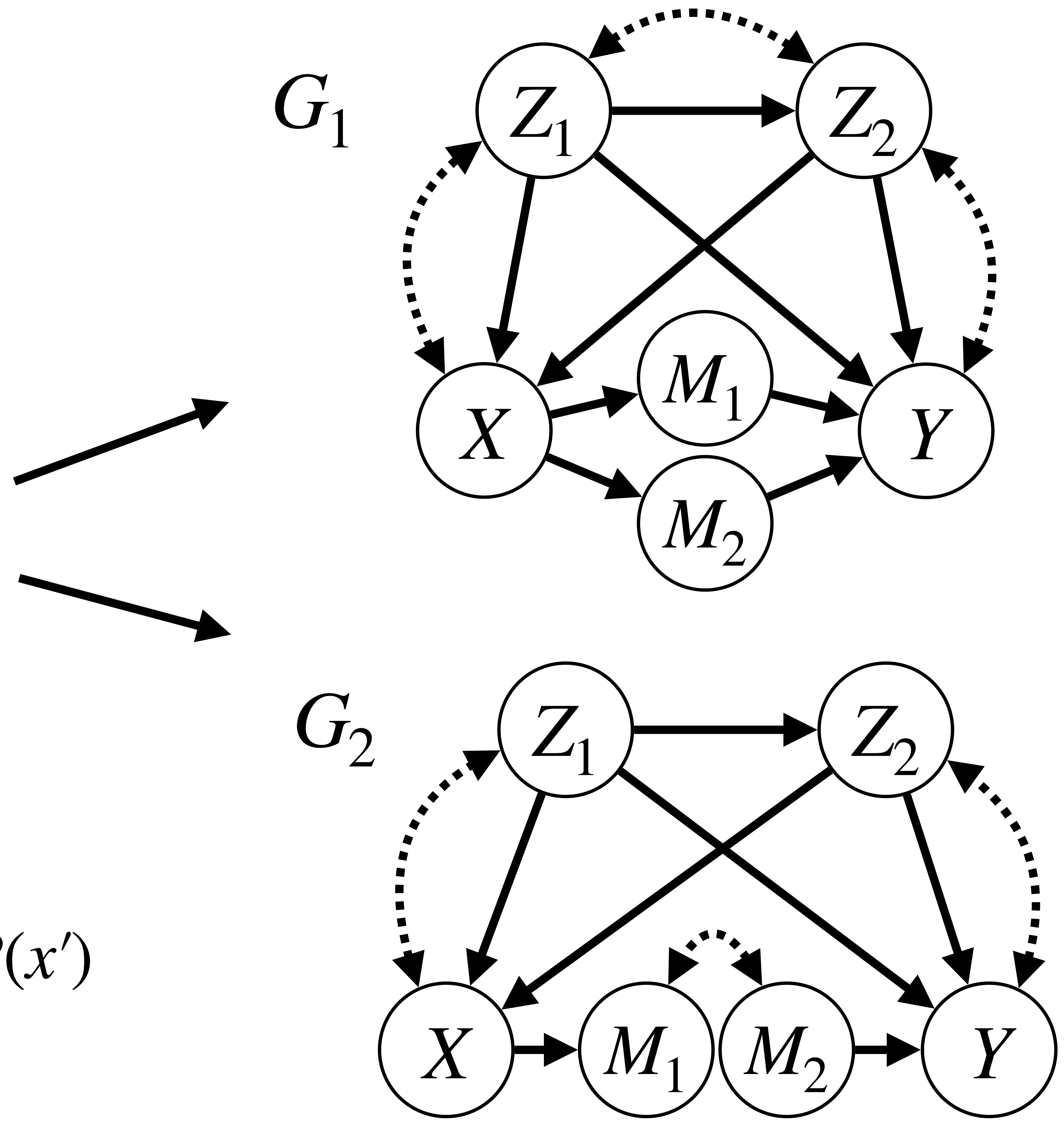
$$P(y \mid do(x)) = \sum_{z_1, z_2} P(y \mid x, z_1, z_2) P(z_1, z_2)$$

A non-identifiable effect in a C-DAG $G_{\mathbf{C}}$ implies that there exists at least one compatible causal diagrams G in which the effect is non-identifiable.

Beyond Backdoor Adjustment



$$P(y \mid do(x)) = \sum_{\mathbf{m}} P(\mathbf{m} \mid x) \sum_{x'} P(y \mid \mathbf{m}, x') P(x')$$

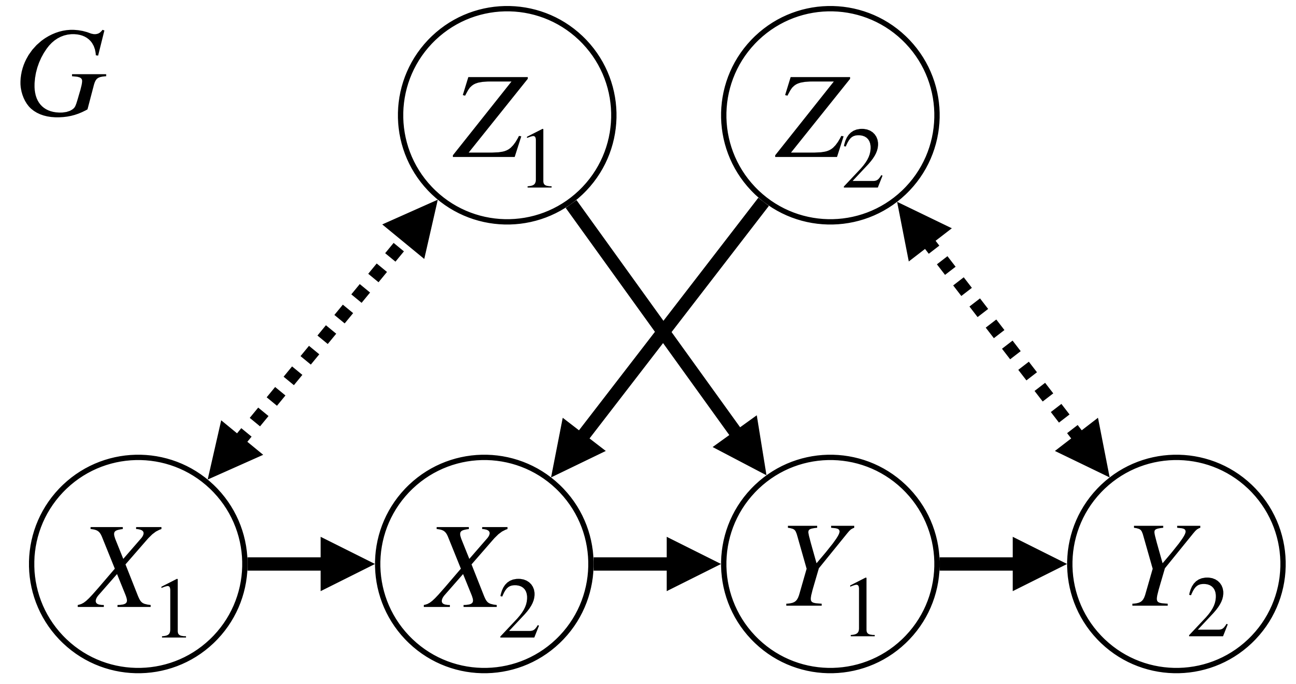


$$P(y \mid do(x)) = \sum_{m_1, m_2} P(m_1, m_2 \mid x) \sum_{x'} P(y \mid m_1, m_2, x') P(x')$$

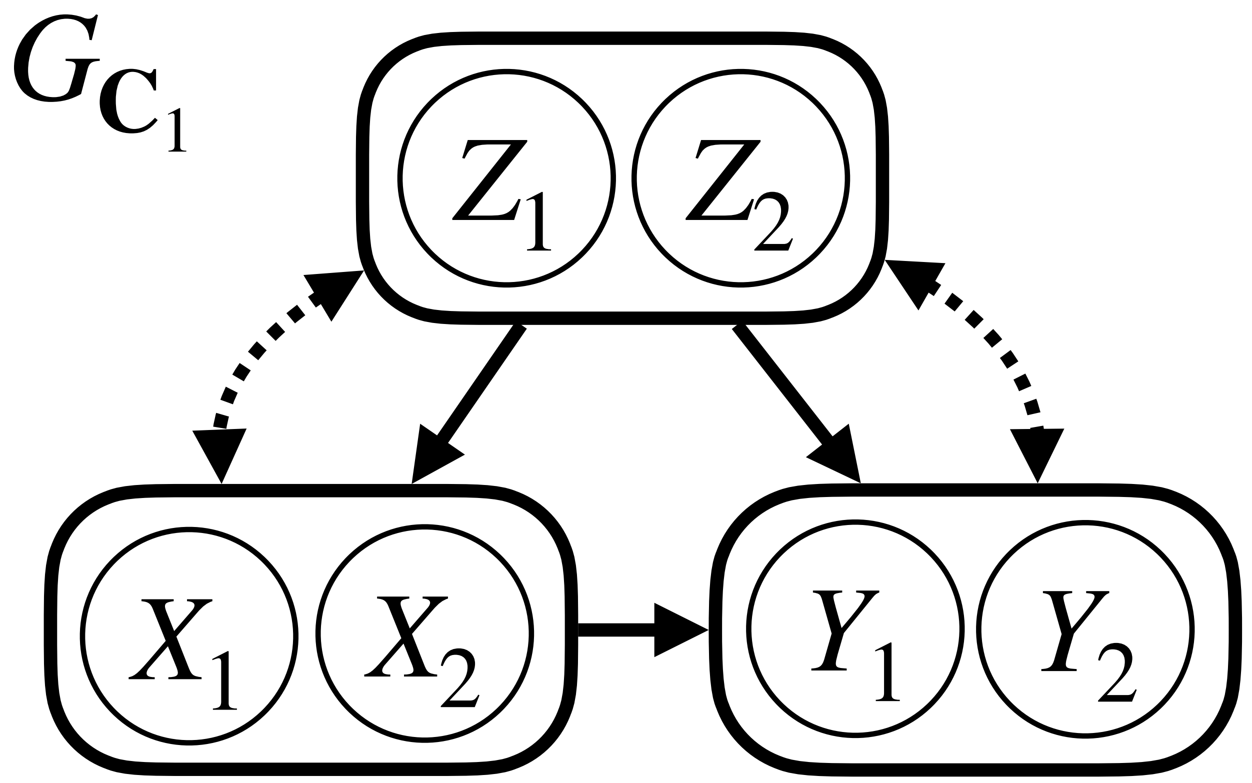
$$P(y \mid do(x)) = \sum_{m_1, m_2} P(m_1, m_2 \mid x) \sum_{x'} P(y \mid m_1, m_2, x') P(x')$$

Again, an effect identifiable in a C-DAG $G_{\mathbf{C}}$ is identifiable in all compatible causal diagrams G using the same identification formula!

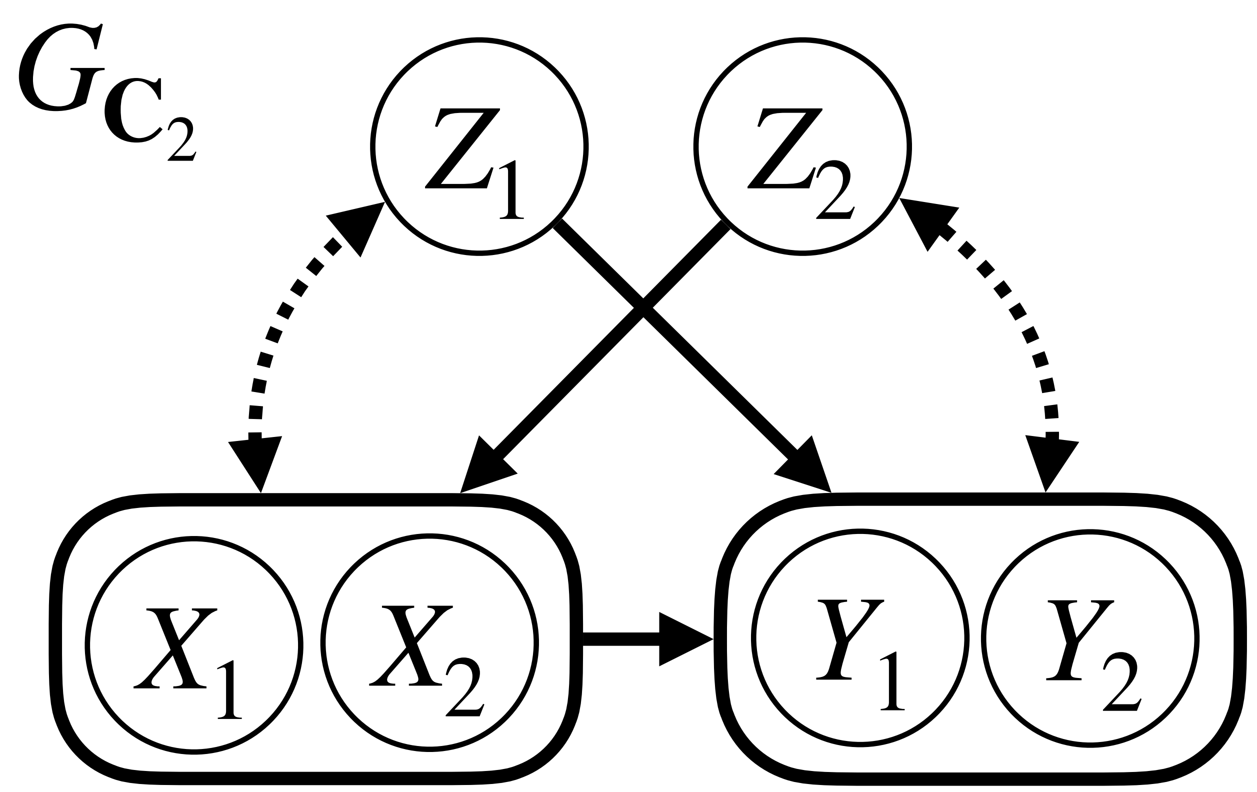
Identifiability under Different Clusterings



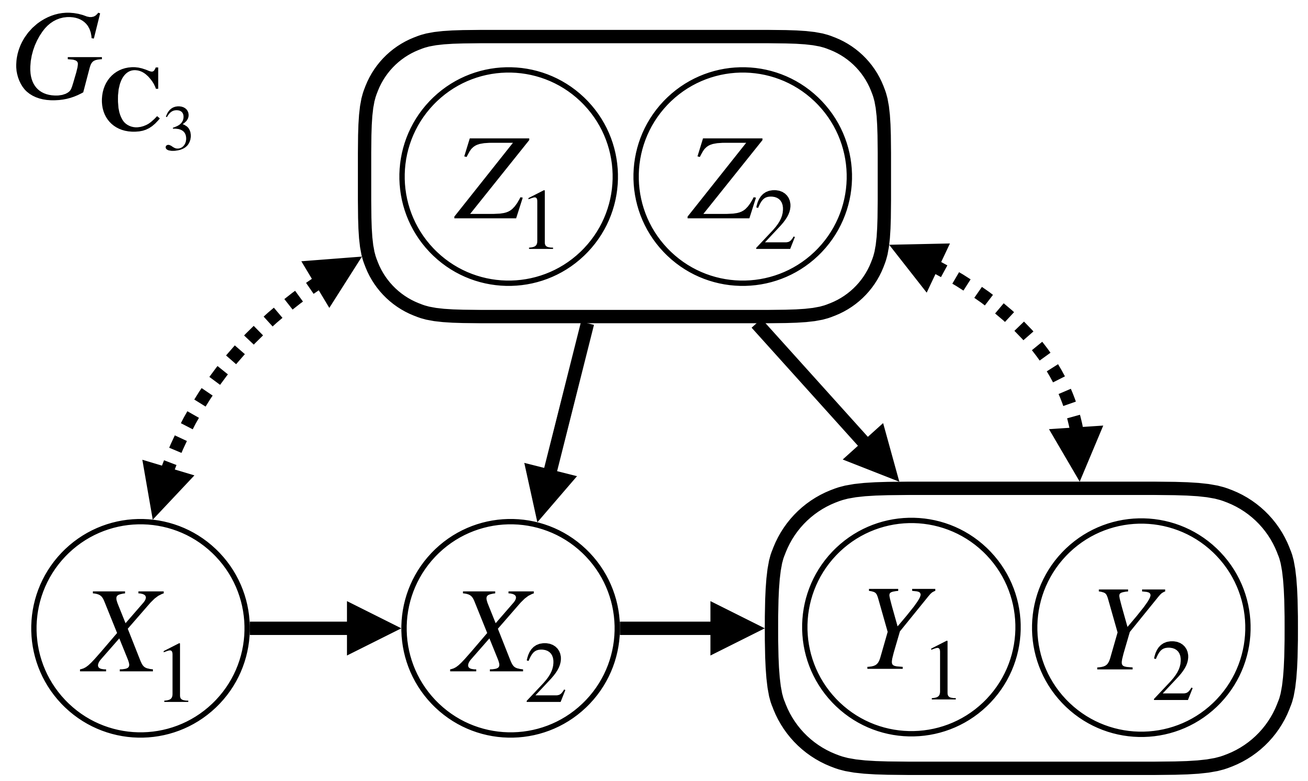
$$P(y_1, y_2 \mid do(x_1, x_2)) = \sum_{z_1, z_2} P(y_1, y_2 \mid x_1, x_2, z_1, z_2) P(z_1, z_2)$$



$P(\mathbf{y}_{1,2} \mid do(\mathbf{x}_{1,2}))$ is not identifiable



$$P(\mathbf{y}_{1,2} \mid do(\mathbf{x}_{1,2})) = \sum_{z_1, z_2} P(\mathbf{y}_{1,2} \mid \mathbf{x}_{1,2}, z_1, z_2) P(z_1, z_2)$$



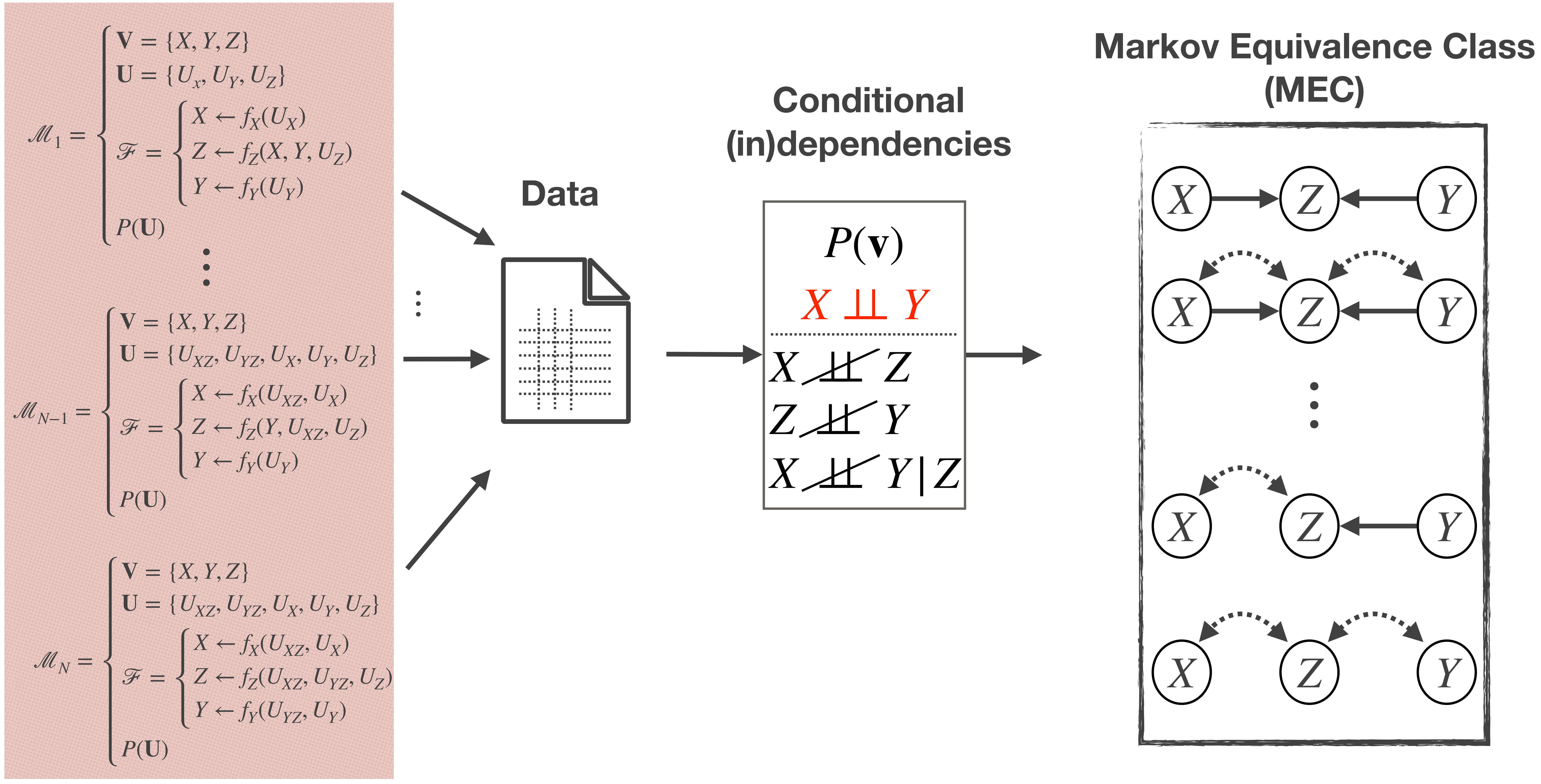
$$P(\mathbf{y}_{1,2} \mid do(x_1, x_2)) = \sum_{\mathbf{z}_{1,2}, x'_1} P(\mathbf{y}_{1,2} \mid x'_1, x_2, \mathbf{z}_{1,2}) P(x'_1, \mathbf{z}_{1,2})$$

The identifiability of an effect in a C-DAG is sensible to the clustering.

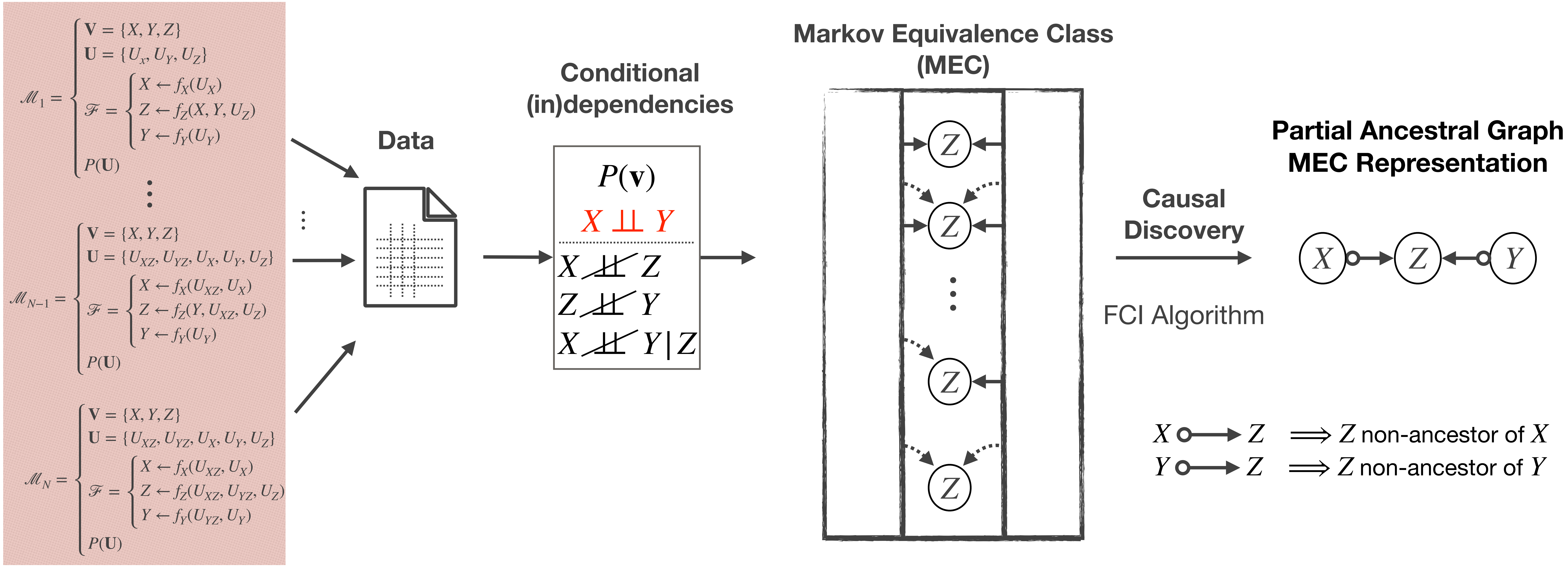
Causal Inference with No Prior Structure Knowledge using FCI and PAG-ID Algorithm

Jaber, A.*, **Ribeiro, A. H.***, Zhang, J., Bareinboim, E. (2022). Causal Identification under Markov equivalence: Calculus, Algorithm, and Completeness. *In Adv. Neural Inf Process Systems, 35, 3679-3690. (NeurIPS-22).* (Link)

Causal Discovery: Learning Structural Invariances



Causal Discovery: Learning Structural Invariances

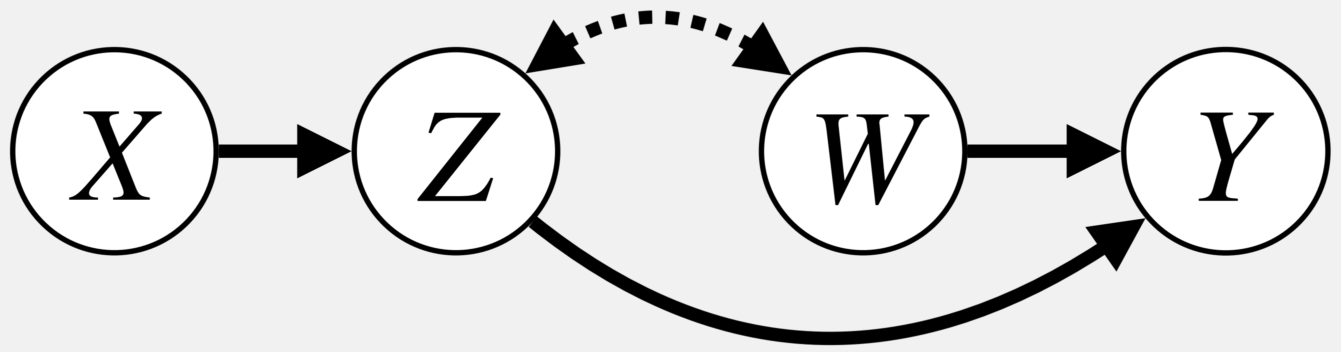


Zhang, J. (2008). On the completeness of orientation rules for causal discovery in the presence of latent confounders and selection bias. *Artificial Intelligence*, 172(16):1873–1896. Link

FCI Algorithm - Pipeline

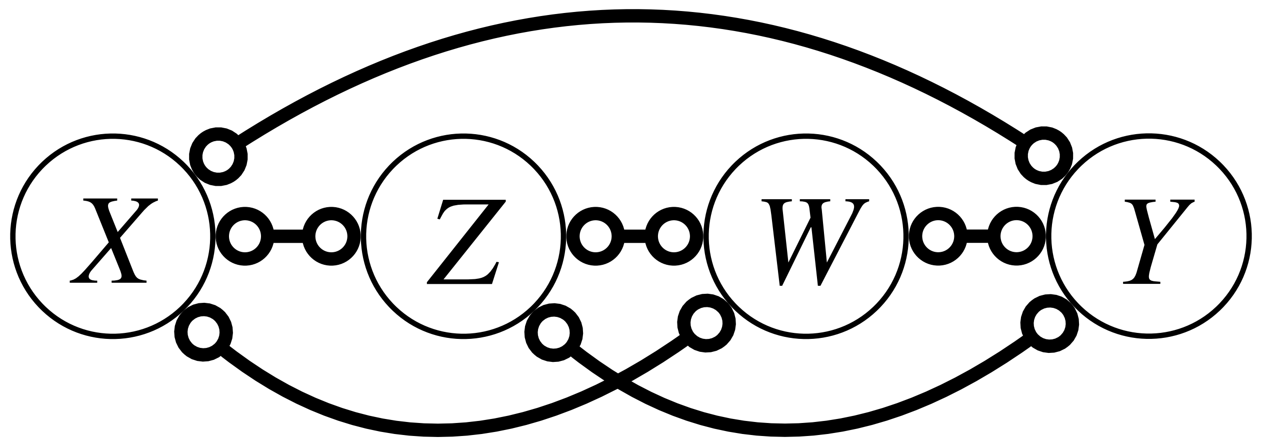
Unknown Reality

True causal diagram



$X \perp\!\!\!\perp W$
$X \perp\!\!\!\perp Y \mid Z, W$

Implied by the ADMG using d-separation

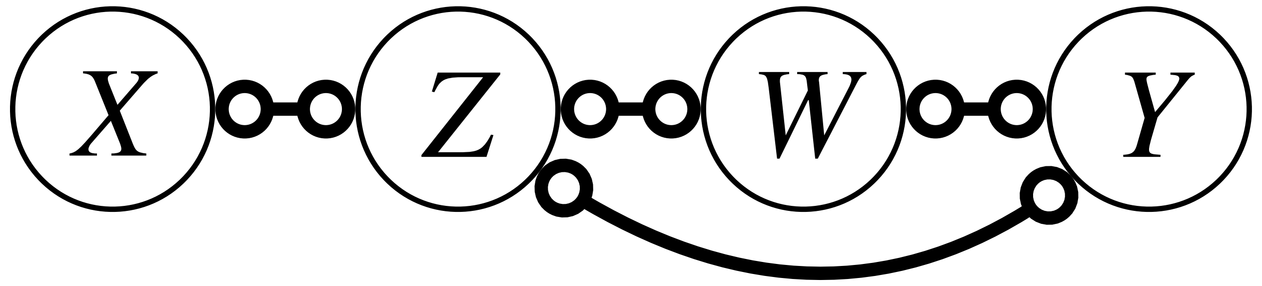


Complete Graph

Conditional Independence Tests

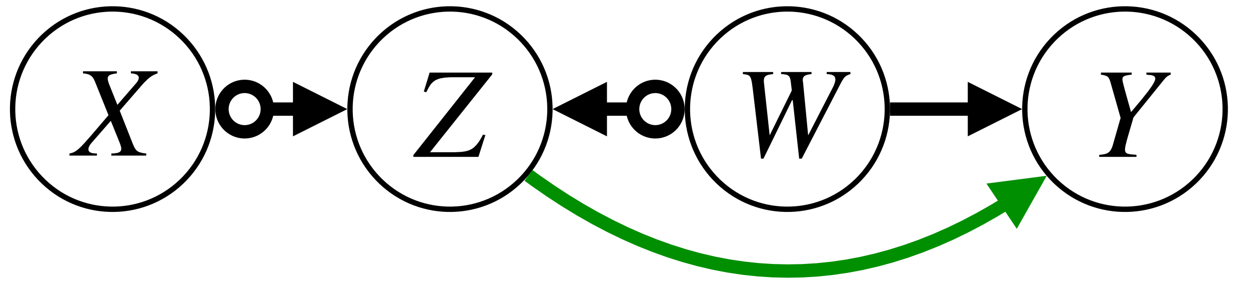
$X \perp\!\!\!\perp W$
$X \perp\!\!\!\perp Y \mid Z, W$

By faithfulness, are observed in the data



Skeleton

FCI Rules
$(R1) - (R10)$



V

Partial Ancestral Graph (PAG)

Implied by the PAG using m-separation

$X \perp\!\!\!\perp W$
$X \perp\!\!\!\perp Y \mid Z, W$

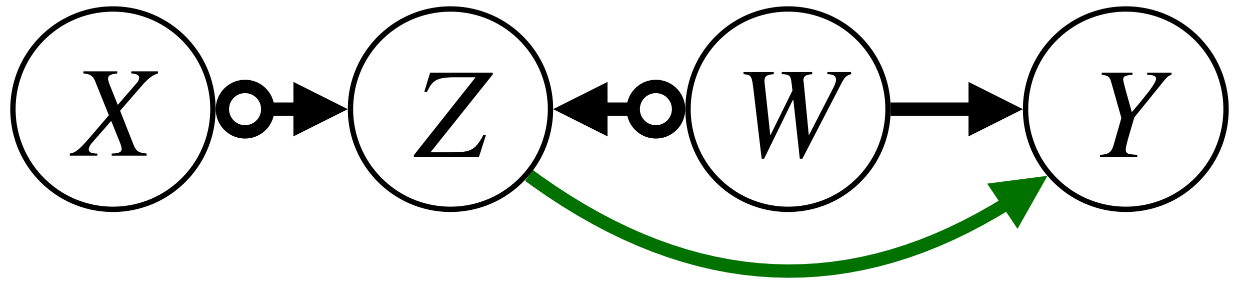
$A \circ\!\!\longrightarrow B \implies$ B non-ancestor of A
$A \longrightarrow B \implies$ A ancestror of B
$A \longleftrightarrow B \implies$ spurious association
A —— $B \implies$ selection bias

Z is not an ancestor of X or W.

Z and W are ancestors of Y.

Z is not confounded with Y.

PAG: Representation of the Markov Equivalence Class



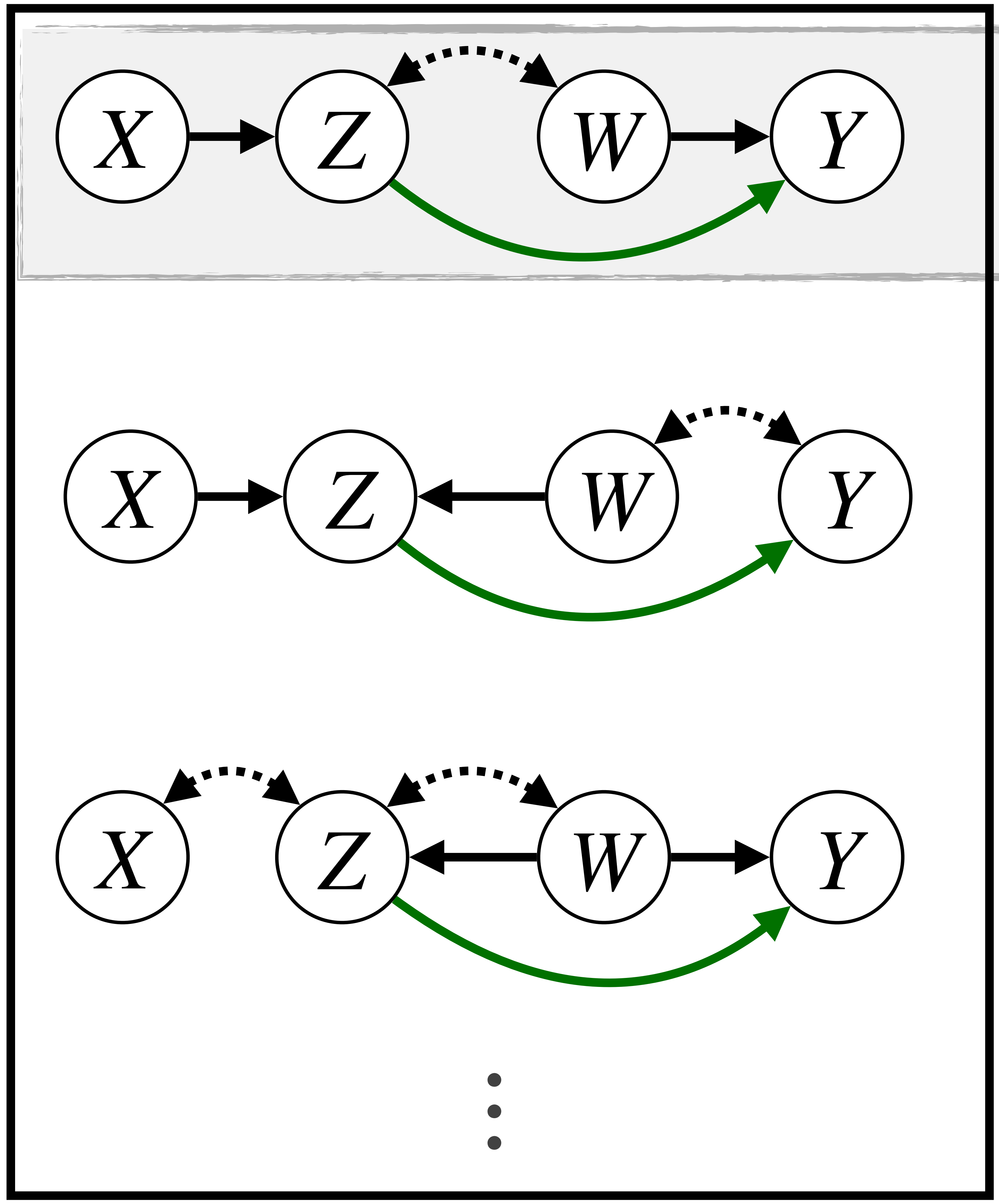
V

Partial Ancestral Graph
(PAG)

Z is not an ancestor of X or W.

Z and W are ancestors of Y.

Z is not confounded with Y.



True
(unknown)
causal diagram

$X \perp\!\!\!\perp W$

$X \perp\!\!\!\perp Y \mid Z, W$

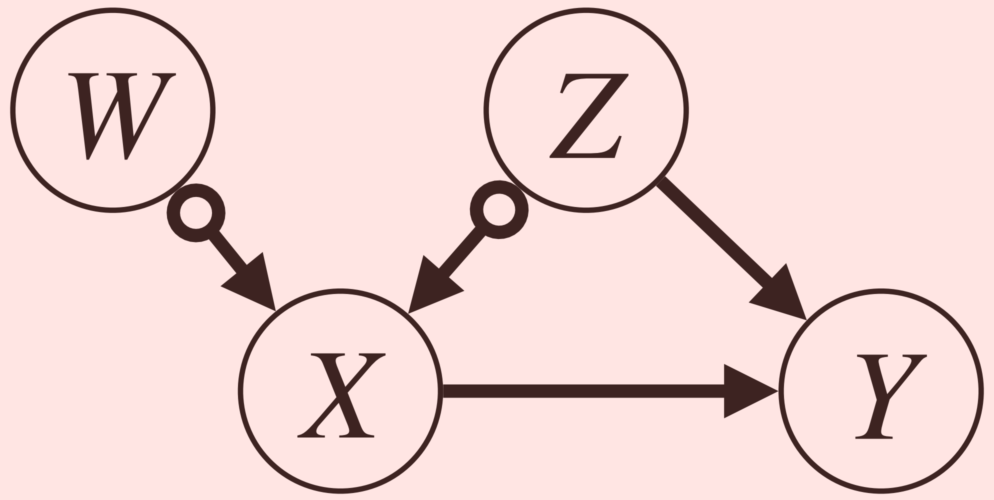
Effect Identification in Markov Equivalence Classes

Can be constructed in a fully data-driven way!

1 **Query**

$P(y \mid do(x))$

2 **PAG**



3 **Data**

$P(x, y, z, w)$ **Observational Distribution**

Inference Engine

Solution

yes / no

$$P(y \mid do(x)) = \sum_{z} P\left(y \mid x, z\right) P\left(z\right)$$

Inferred (Interventional) Distribution ← Available (Observational) Distribution

👍

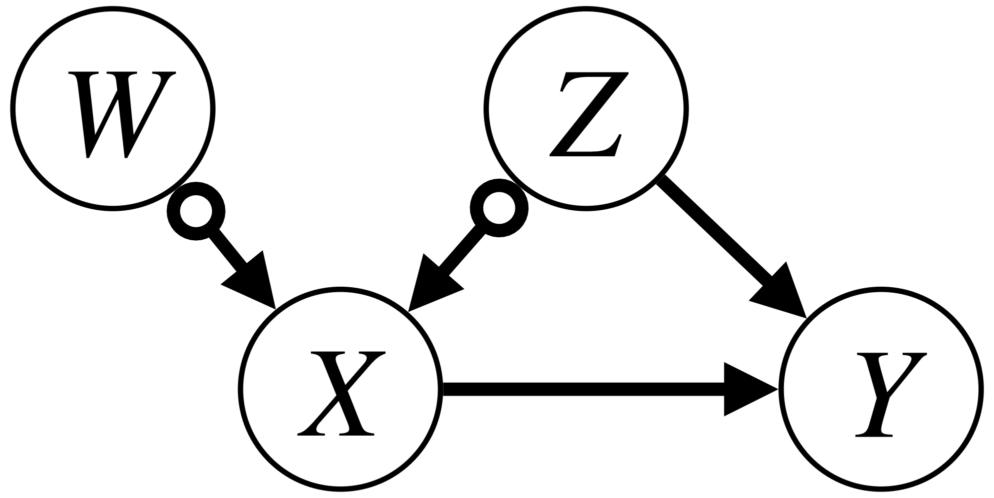
Identification via Adjustment in Markov Equivalence Classes

Identification is possible only when the Generalized Adjustment Criterion applies.

1 **Query**

$P(y \mid do(x))$

2 **PAG**



3 **Data**

$P(x, y, z, w)$ **Observational Distribution**

Adjustment Criterion

Solution

yes / no

$$P(y \mid do(x)) = \sum_{z} P\left(y \mid x, z\right) P\left(z\right)$$

Inferred (Interventional) Distribution ← Available (Observational) Distribution

Perkovic, E., Textor, J. C., Kalisch, M., & Maathuis, M. H. (2018). Complete graphical characterization and construction of adjustment sets in Markov equivalence classes of ancestral graphs. Journal of Machine Learning Research 18 (2018) 1-62

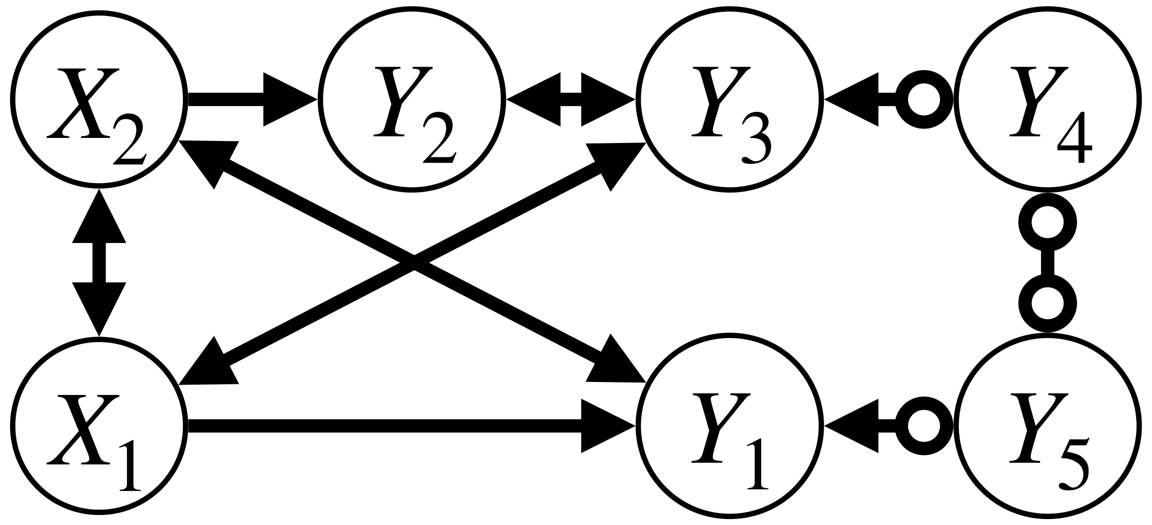
General Identification in Markov Equivalence Classes

Complete algorithms,
available at the *PAGId* R package:
https://github.com/adele/PAGId

1 **Query**

$P(y\,|\,do(x))$

2 **PAG**



3 **Data**

$P(x, y, z, w)$ **Observational Distribution**

IDP / CIDP

Solution

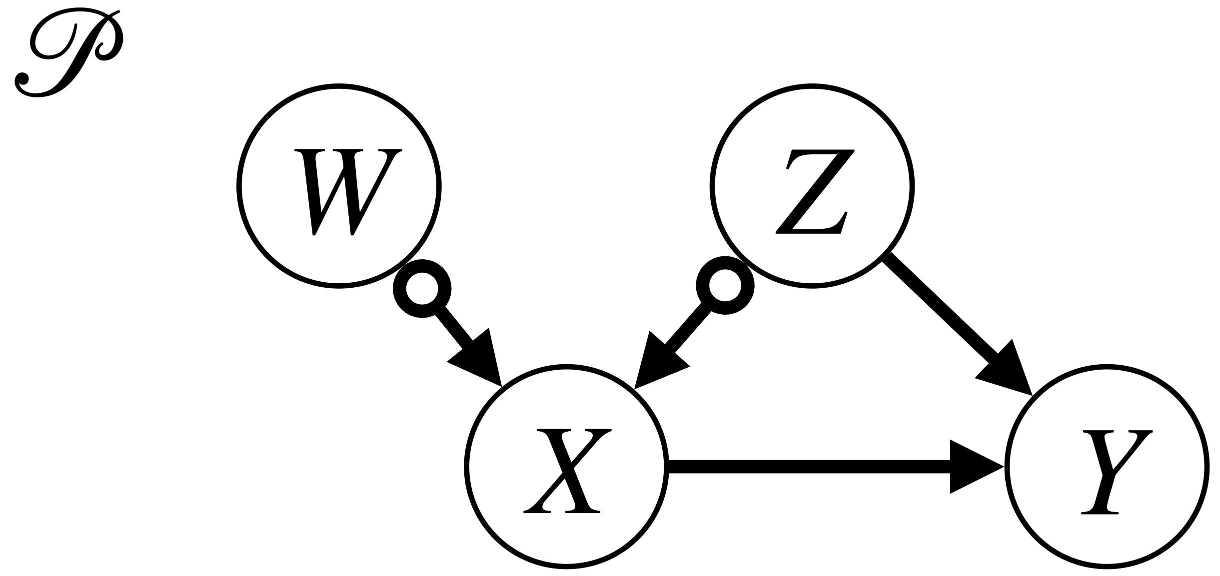
yes / no

$$P(y\,|\,do(x)) = \frac{P(y_1, y_4, y_5\,|\,x_1)\,.\,P(y_2 y_3, y_4, y_5\,|\,x_2)}{P(y_4, y_5)}$$

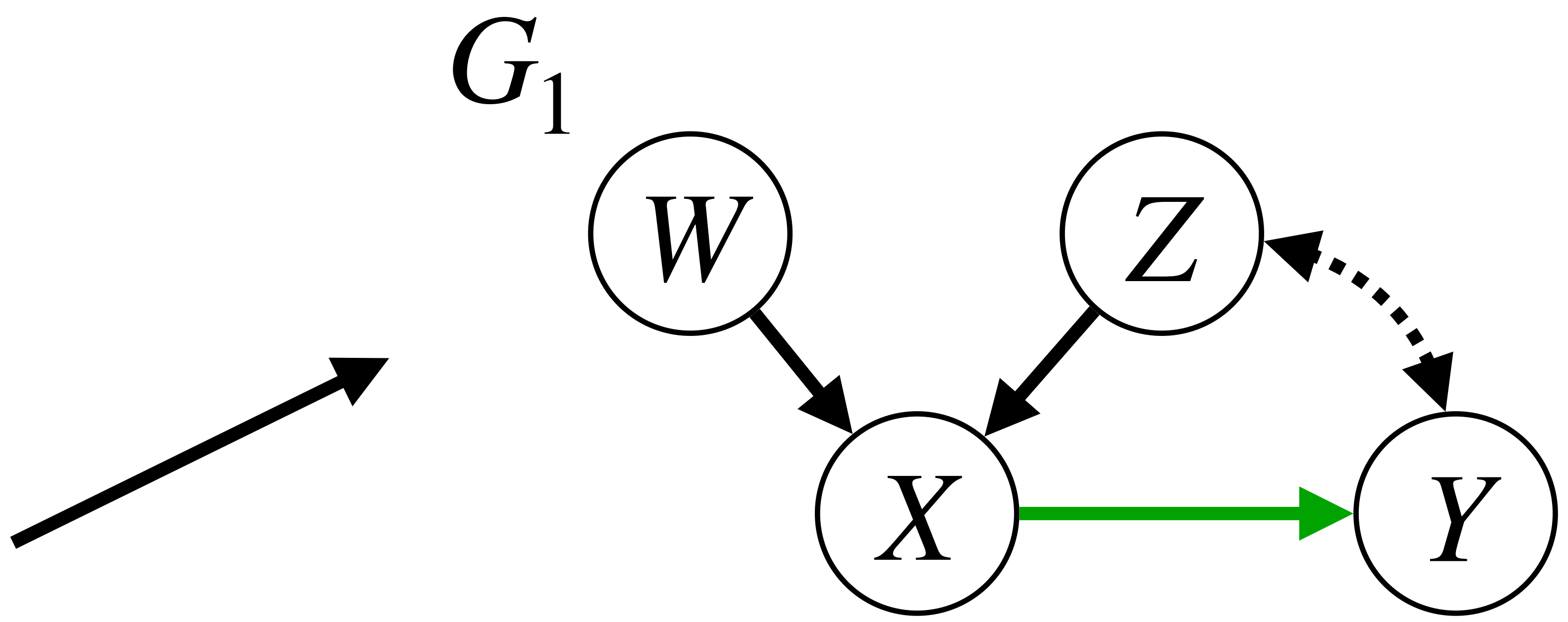
Inferred (Interventional) Distribution ← Available (Observational) Distribution 👍

Jaber A., **Ribeiro A. H.,** Zhang, J., Bareinboim, E. (2022) Causal Identification under Markov Equivalence - Calculus, Algorithm, and Completeness. In Proceedings of the 36th Annual Conference on Neural Information Processing Systems (NeurIPS 2022).

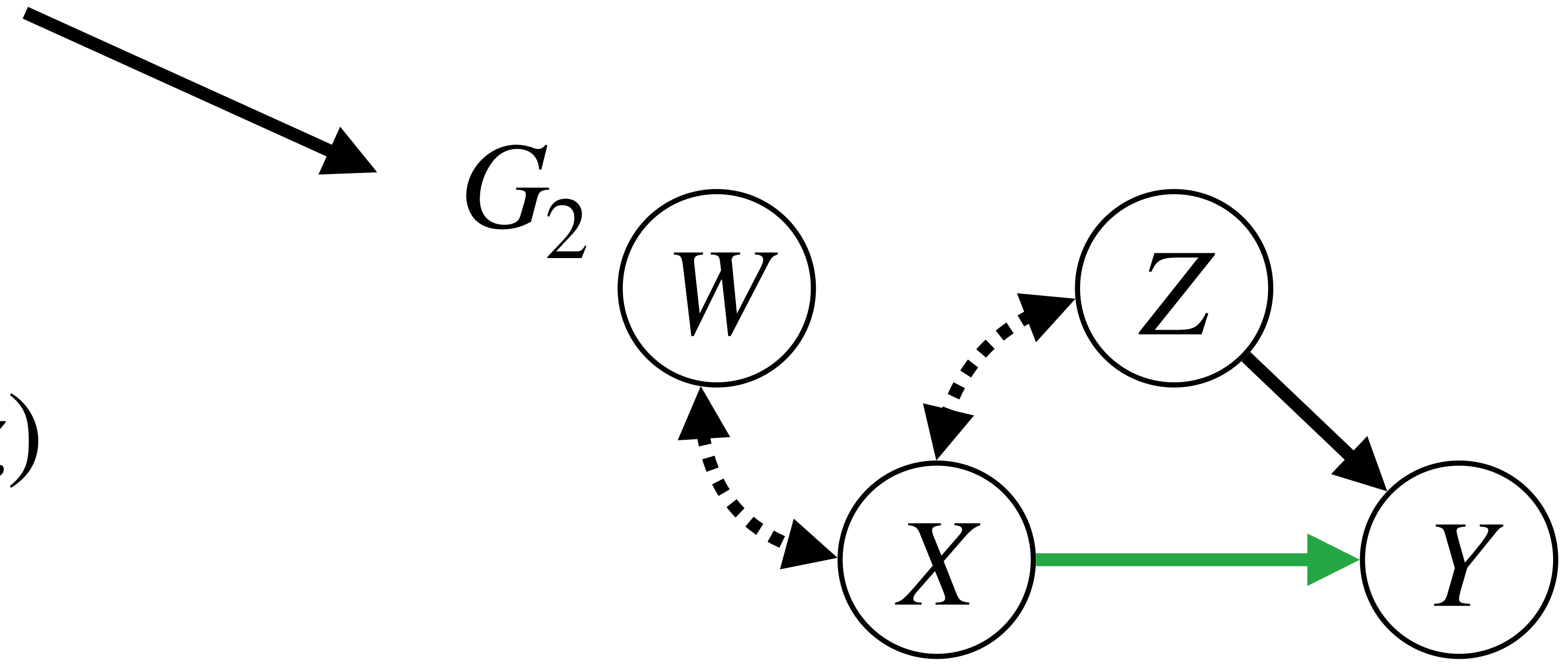
Effect Identifiabiliy given a PAG



$$P(y \mid do(x)) = \sum_z P\left(y \mid x, z\right) P\left(z\right)$$



$$P(y \mid do(x)) = \sum_z P(y \mid x, z) P(z)$$

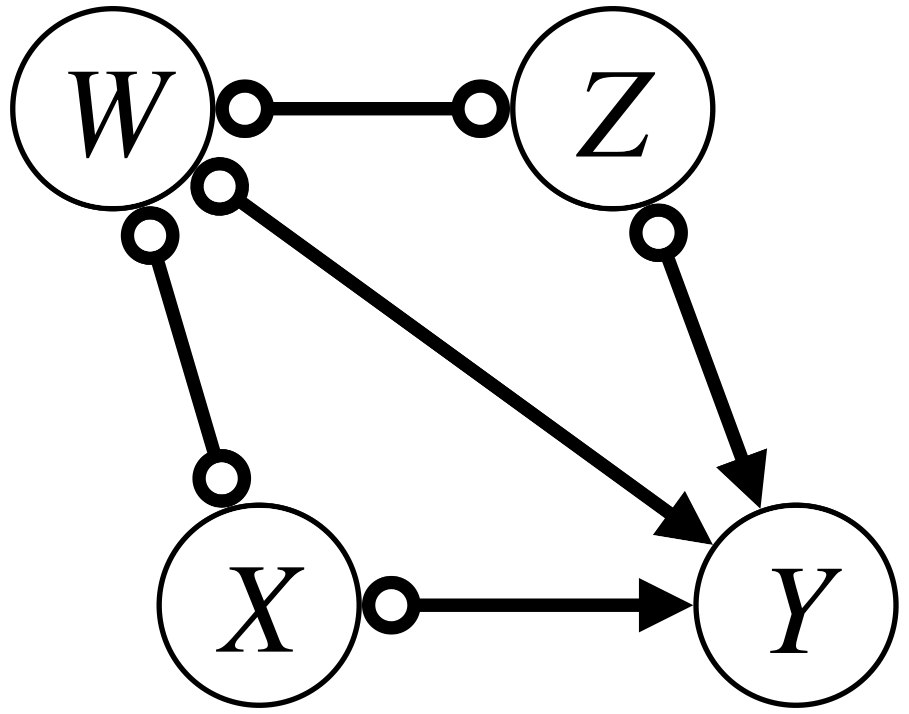


$$P(y \mid do(x)) = \sum_z P(y \mid x, z) P(z)$$

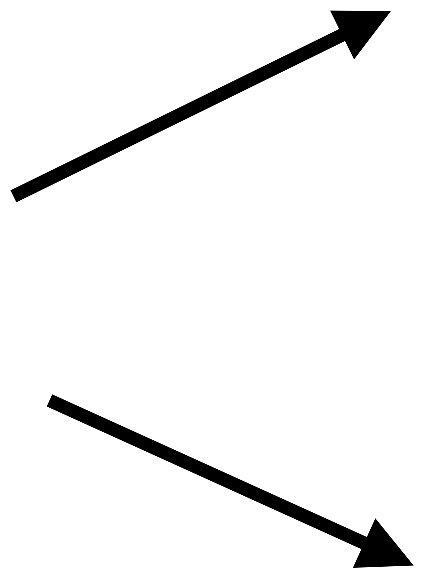
An effect identifiable in a PAG $\mathscr{P}$ is identifiable in all causal diagrams G in the Markov Equivalence Class using the same identification formula!

Effect Non-Identifiabiliy given a PAG

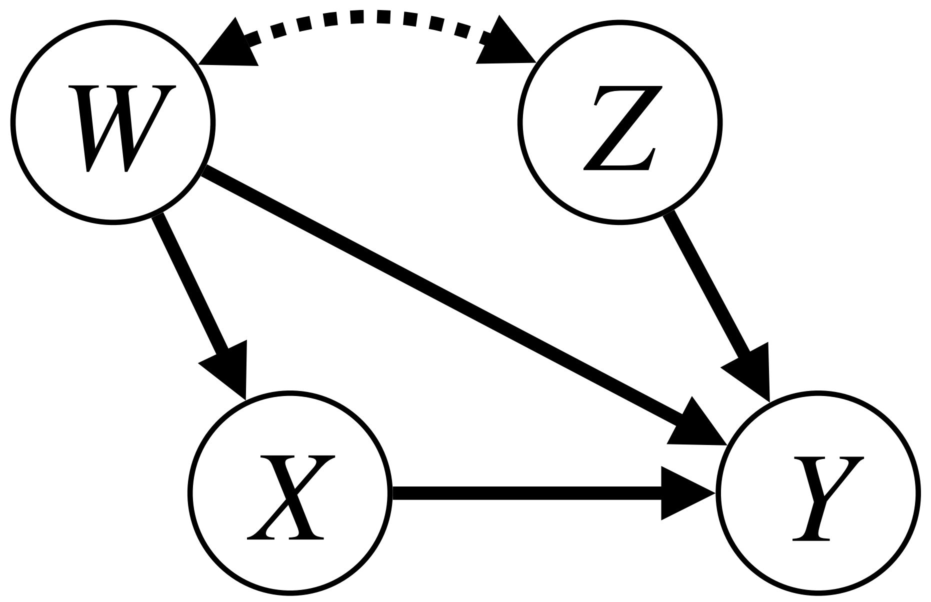
$\mathscr{P}$



$P(y \mid do(x))$ is
not identifiable

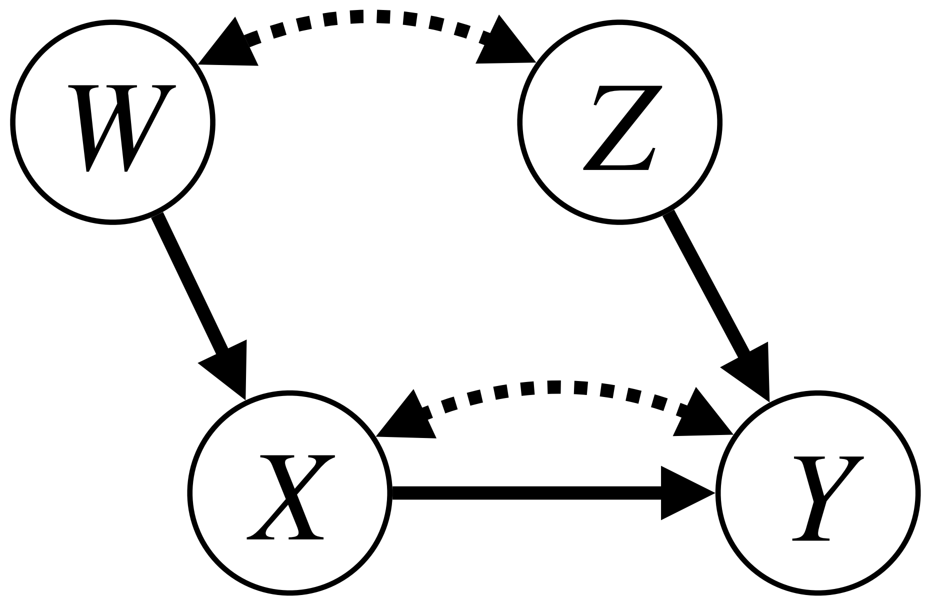


G_1



$$P(y \mid do(x)) = \sum_z P(y \mid x, z)P(z)$$

G_2



$P(y \mid do(x))$ is
not identifiable

An effect not identifiable in a PAG $\mathscr{P}$ is not identifiable in at least one causal diagrams G in the Markov Equivalence Class

Gut Microbiota's Causal Role in Major Depressive Disorder

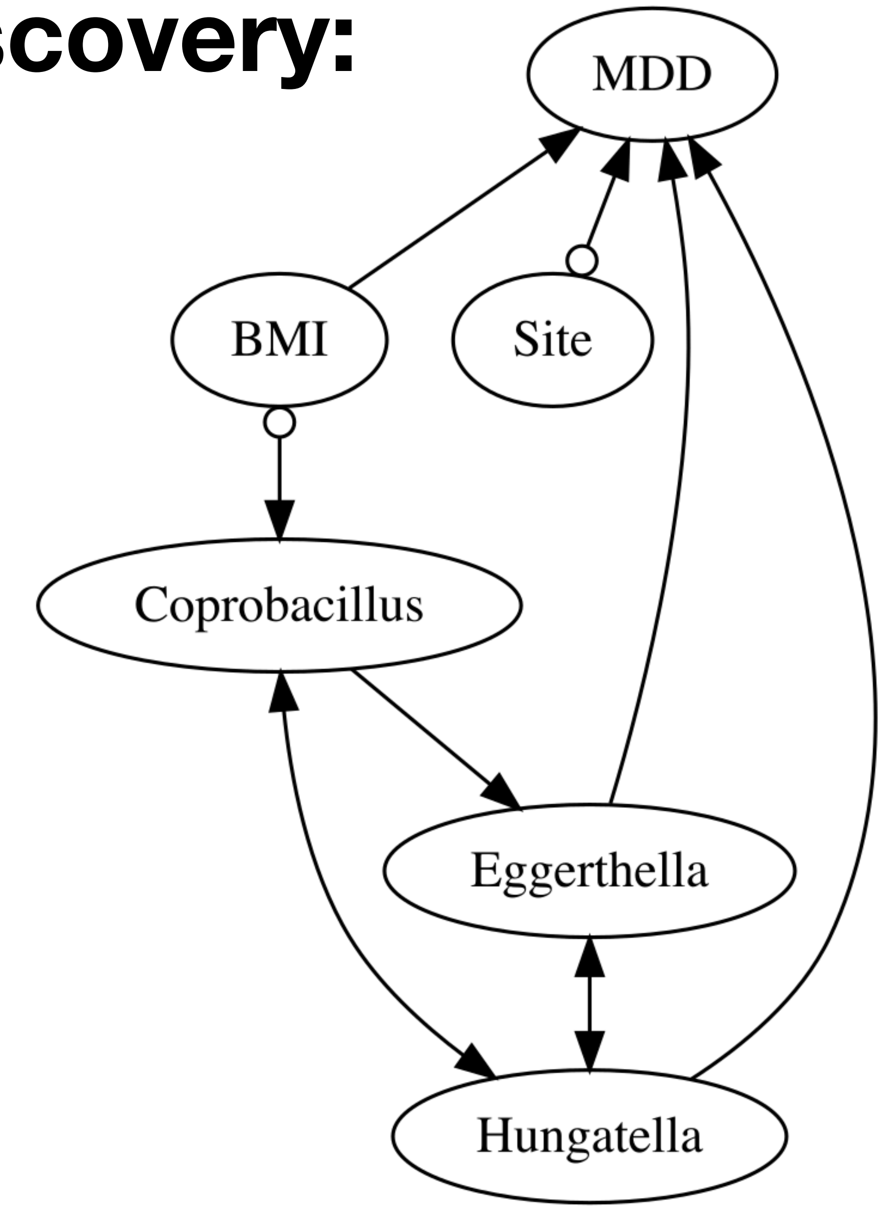
DFG FOR2107 dataset, including microbiome and clinical data from 1,269 patients.

Differential Abundance Analysis:

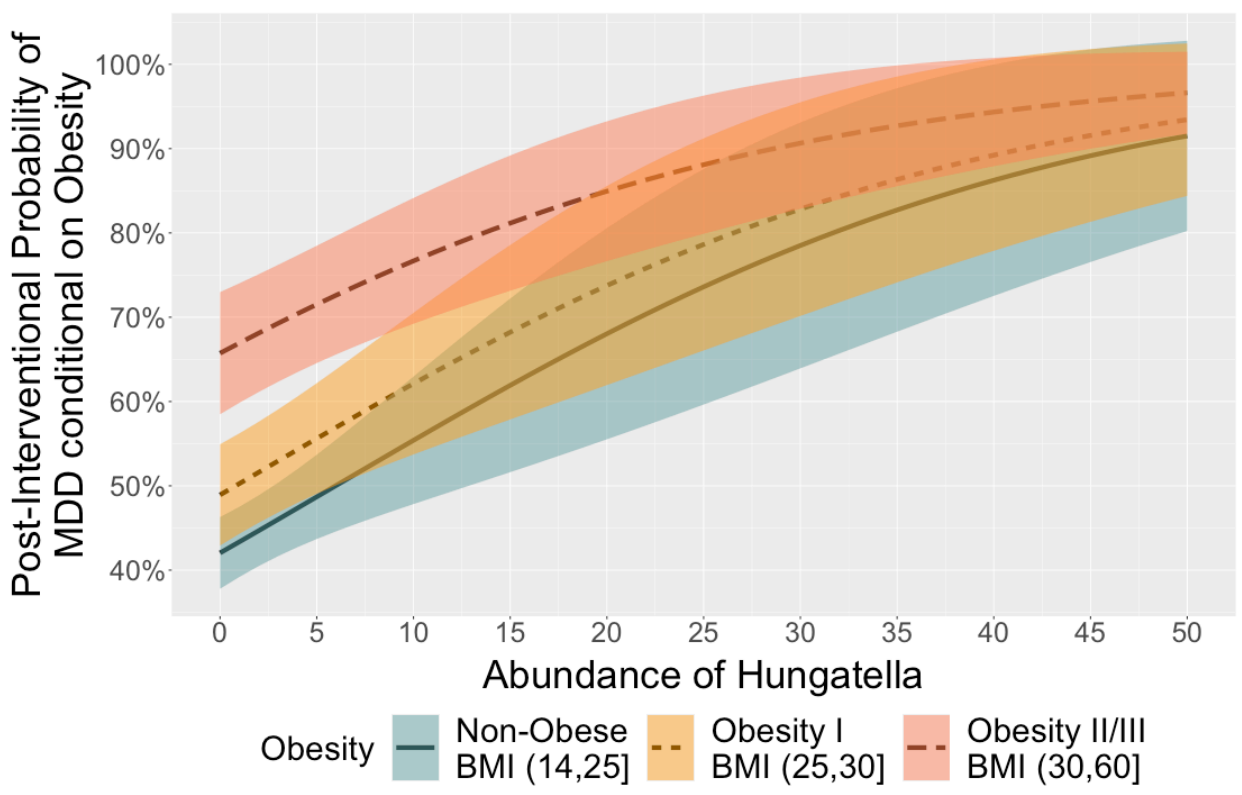
Genus	FDR-corr. p-values	
	LinDA	ZicoSeq
Hungatella	0.0002	0.0071
Eggerthella	0.0063	0.0071
Coprobacillus	0.0070	0.0071
Lachnospiraceae FCS020 group	0.0063	0.011

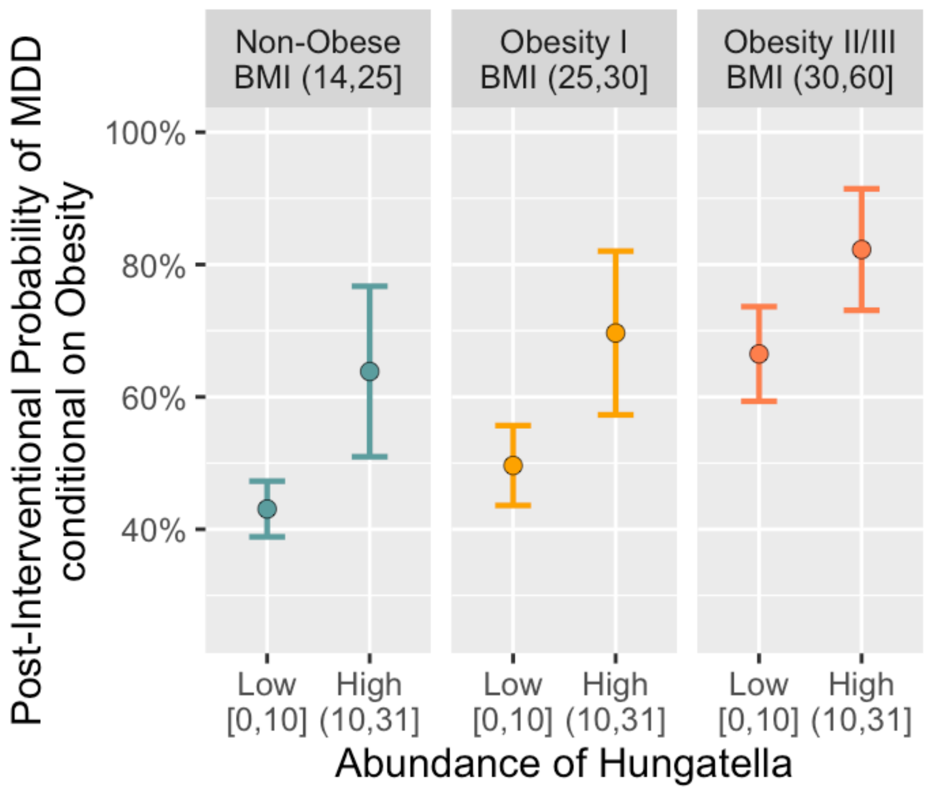
Causal Discovery:

FCI with a robustness-enhancing strategy.



Obesity-specific causal effect of *Hungatella* on MDD

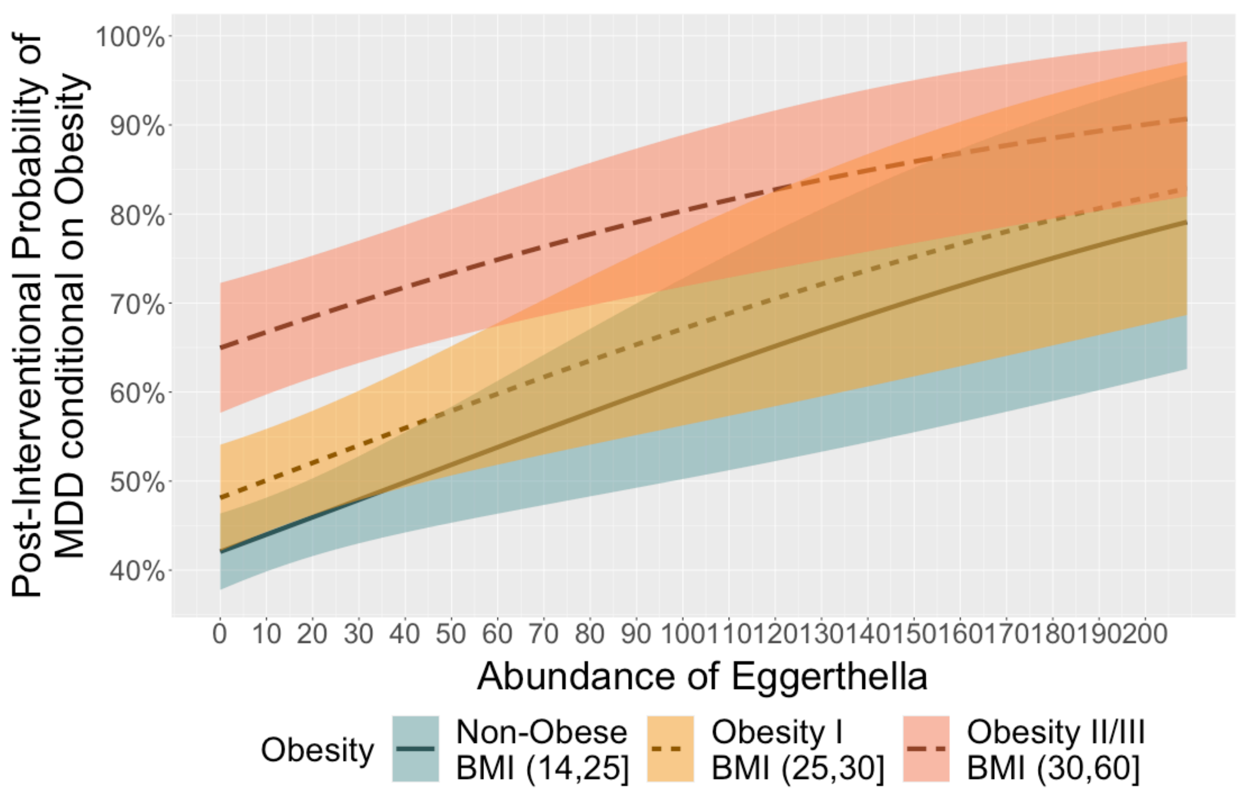


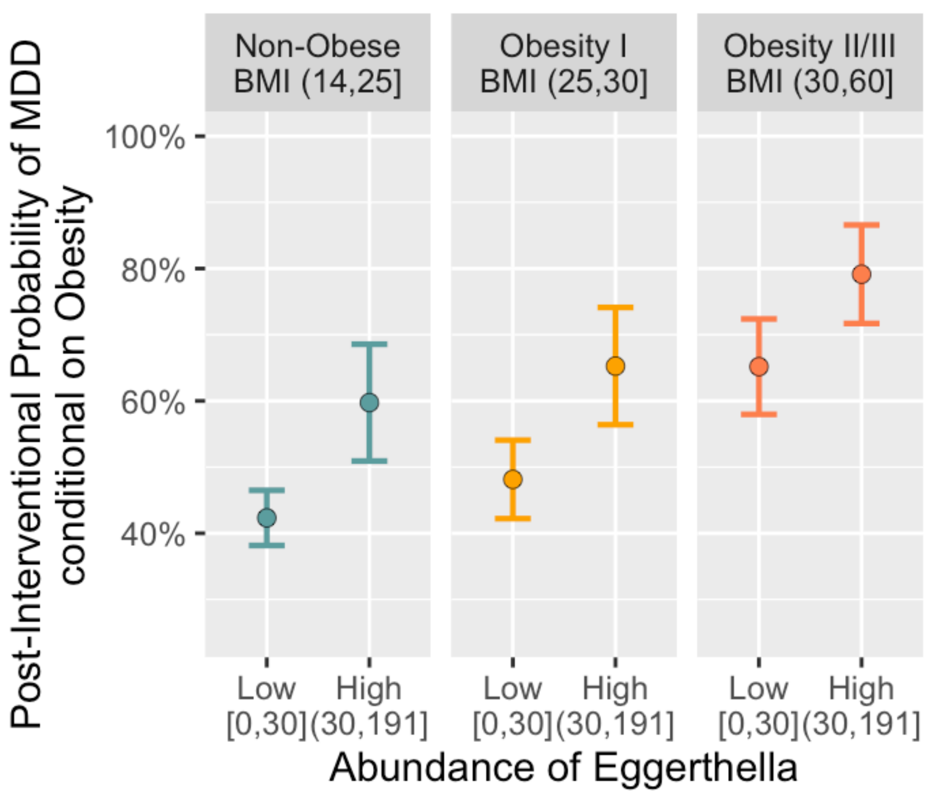


Obesity	Effect	95% C.I.	
No	0.2078	0.07230	0.3433
I	0.2002	0.06261	0.3379
II/II	0.1577	0.04138	0.2741

ACE: 0.1984
95% CI: [0.06607, 0.3307]

Obesity-specific causal effect of *Eggerthella* on MDD





Obesity	Effect	95% C.I.	
No	0.1742	0.07659	0.2718
I	0.1712	0.06460	0.2778
II/II	0.1397	0.03607	0.2433

ACE: 0.1683
95% CI: [0.06812, 0.2684]

Fehse L.*, **Ribeiro, A.H.***, Winter, N. R.*, …, Dominik Heider, Tim Hahn. (2024) From Gut to Mind: Dissecting the Causal Contribution of Gut-Microbiota to Major Depressive Disorder in Humans. *Forthcoming*.

* Equal contribution

FCI — Importance and Key Limitations

Importance

- The FCI stands out by its **foundational principles** and **minimal reliance** on assumptions compared to other causal discovery methods.
  - Provides complete results, even in the presence of ***unobserved confounding, selection bias, and feedback loops***.
  - Extensive theoretical frameworks have been developed to characterize the Markov equivalence class of the output PAG, facilitating its **use in downstream causal inference analyses**.
- Moreover, it provides the basis for the majority of the existing causal discovery algorithms in the presence of unobserved confounding

Key Limitations

- The FCI lacks **robustness** in low-data scenarios, effective **uncertainty** quantification, integration of **background knowledge**, **scalability**, and the ability to handle **multi-modal** data.

Enhancing Robustness and Effectiveness of the FCI Algorithm in Real-World Scenarios

Enabling Multi-Center Data Integration, Data Privacy, Uncertainty Modeling, Human-AI Collaboration, and Applicability in Genetics.

Multi-Center Data Integration & Data Privacy

- Hahn M.*, Zajak, A.*, Heider, D., **Ribeiro A. H.** (2024). fedFCI: Federated Causal Discovery from Multi-Center Datasets with Unobserved Confounders — *Forthcoming.*

Supervised Bachelor's Thesis:

Zajak, A. (2024) *Privacy-Preserving Causal Discovery from Multiple Overlapping Observational Datasets.* Bachelor's Thesis. Department of Computer Science, Heinrich Heine University of Düsseldorf.

R package:

Zajak, A. and **Ribeiro A. H.** (2024) rIOD: A Privacy-Preserving Implementation in R of the IOD Algorithm for Causal Discovery from Multiple Overlapping Observational Datasets.
GitHub repository: @adele/rIOD

- Tajabadi, M, Grabenhenrich, L., **Ribeiro, A. H.**, Leyer, M., Heider D. (2023). Sharing Data With Shared Benefits: Artificial Intelligence Perspective. *J Med Internet Res 2023;25:e47540* (Link)

* Equal contribution

rIOD: An R Package for Privacy-Preserving Causal Discovery

GitHub Repository: @adele/rIOD

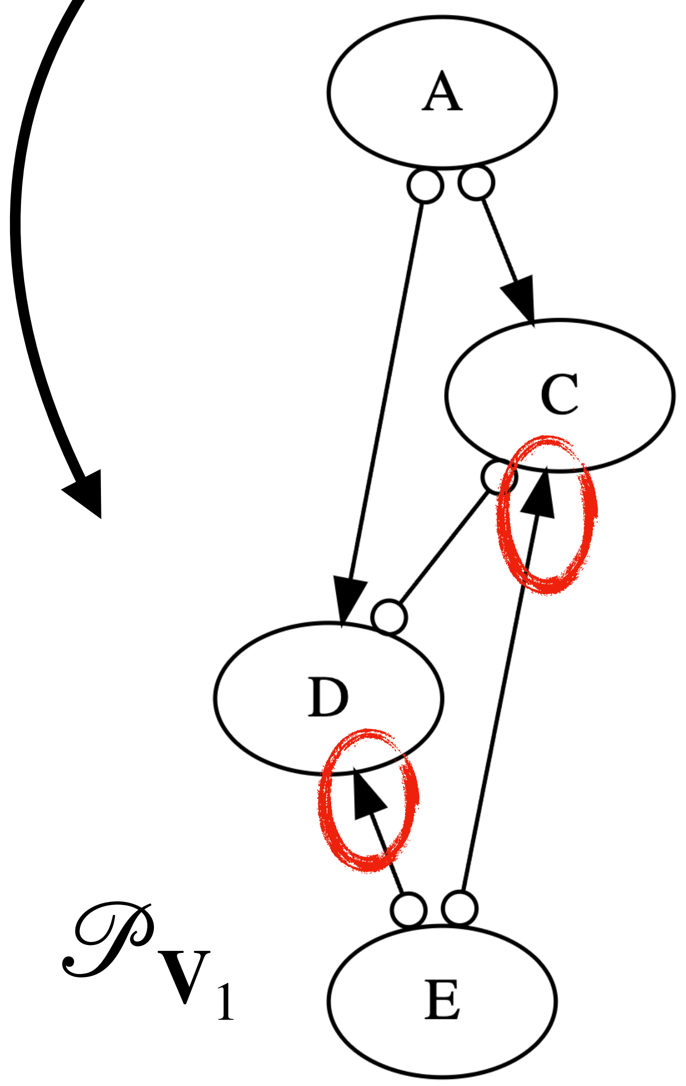
Node 1

	A	C	D	E
1	-0,691	0,981	2,502	-0,431
2	2,396	0,788	-0,185	0,323
3	0,263	-0,158	-0,013	0,415
4	-1,265	0,656	-0,092	-0,600
5	1,429	-1,037	2,221	-1,126
6	-0,612	-1,886	0,946	0,939
...				
5,000	0,142	0,369	-0,108	0,463

$A \perp\!\!\!\perp E \quad (p = 0.076)$

$A \perp\!\!\!\perp E \,|\, C, D \; (p = 0.934)$

FCI



Inaccurate Marginal

Node 2

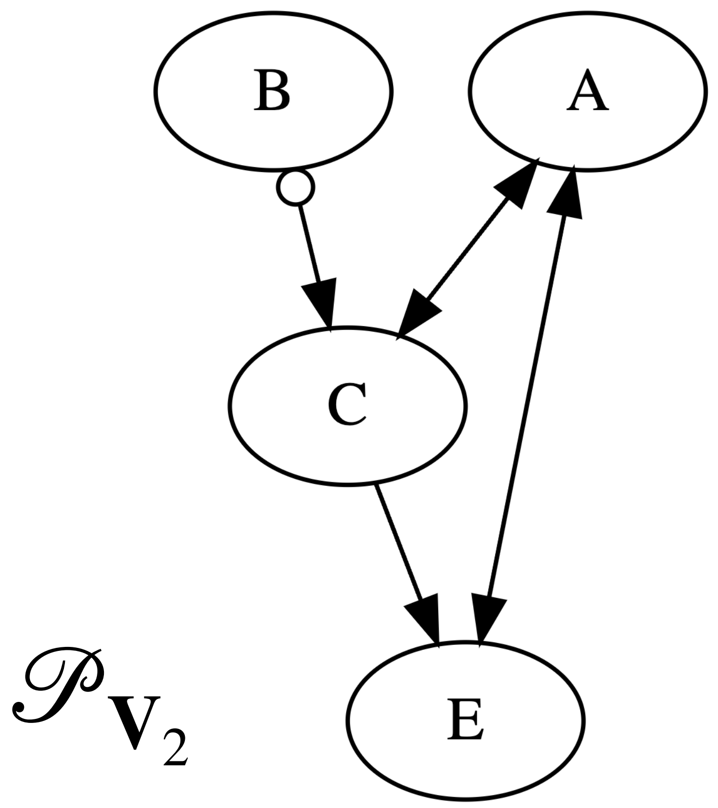
	A	B	C	E
1	1,885	-1,420	-0,932	0,915
2	-0,820	-1,305	-0,404	0,508
3	-0,265	0,054	-0,186	0,919
4	2,900	-0,029	0,106	-0,483
5	-0,662	0,835	-0,171	1,039
6	-0,058	-2,203	0,428	-1,362
...				
10,000	0,175	0,327	-0,064	1,278

$A \not\!\perp\!\!\!\perp E \quad (p = 1.83 \times 10^{-12})$

$A \perp\!\!\!\perp B \; (p = 0.380)$

$B \perp\!\!\!\perp E \,|\, C \; (p = 0.964)$

FCI



Accurate Marginal

Transferring only statistics / p-values

Server

Combined p-values, by a privacy-preserving strategy:

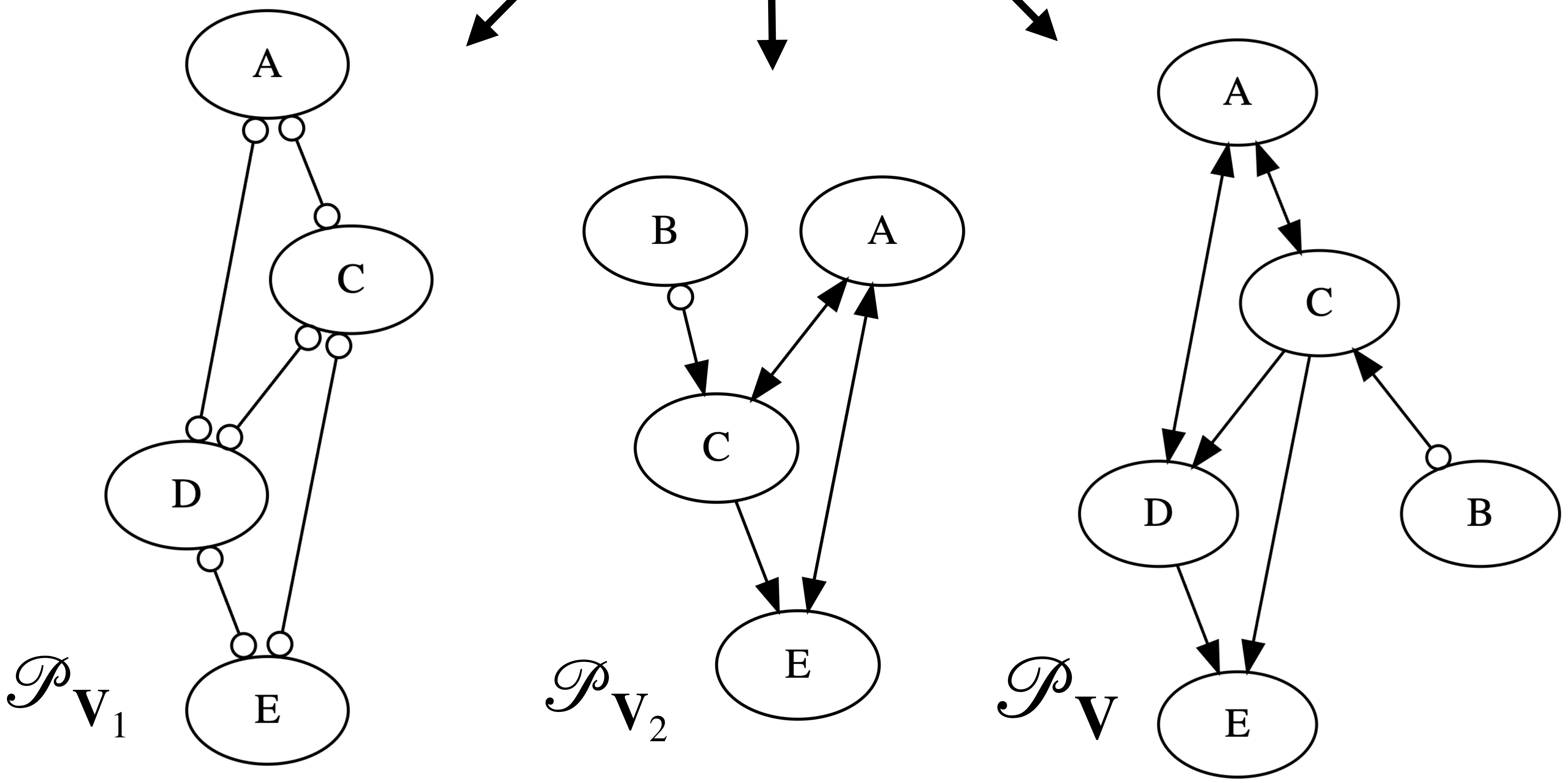
$A \not\!\perp\!\!\!\perp E \quad (p = 4.27 \times 10^{-12})$

$A \perp\!\!\!\perp E \,|\, C, D \; (p = 0.934)$

$A \perp\!\!\!\perp B \; (p = 0.380)$

$B \perp\!\!\!\perp E \,|\, C \; (p = 0.964)$

rIOD



Accurate Marginals and True PAG

fedFCI: A Federated Causal Discovery Algorithm

GitHub Repository: @adele/rIOD

Node 1

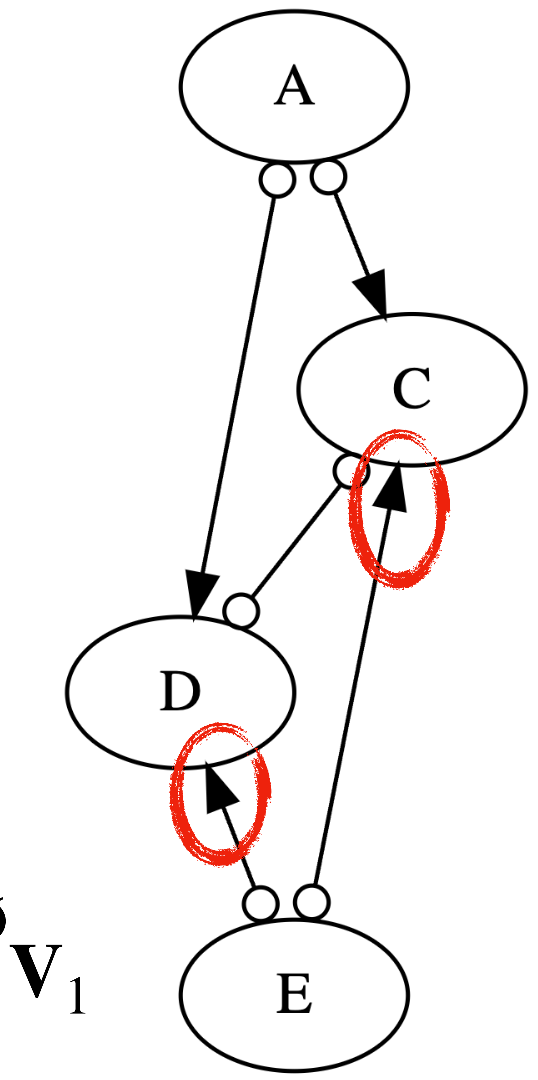
	A	C	D	E
1	-0,691	0,981	2,502	-0,431
2	2,396	0,788	-0,185	0,323
3	0,263	-0,158	-0,013	0,415
4	-1,265	0,656	-0,092	-0,600
5	1,429	-1,037	2,221	-1,126
6	-0,612	-1,886	0,946	0,939
...				
5,000	0,142	0,369	-0,108	0,463

$A \perp\!\!\!\perp E \quad (p = 0.076)$

$A \perp\!\!\!\perp E \,|\, C, D \; (p = 0.934)$

FCI

$\mathscr{P}_{\mathbf{V}_1}$



Inaccurate Marginal

Node 2

	A	B	C	E
1	1,885	-1,420	-0,932	0,915
2	-0,820	-1,305	-0,404	0,508
3	-0,265	0,054	-0,186	0,919
4	2,900	-0,029	0,106	-0,483
5	-0,662	0,835	-0,171	1,039
6	-0,058	-2,203	0,428	-1,362
...				
10,000	0,175	0,327	-0,064	1,278

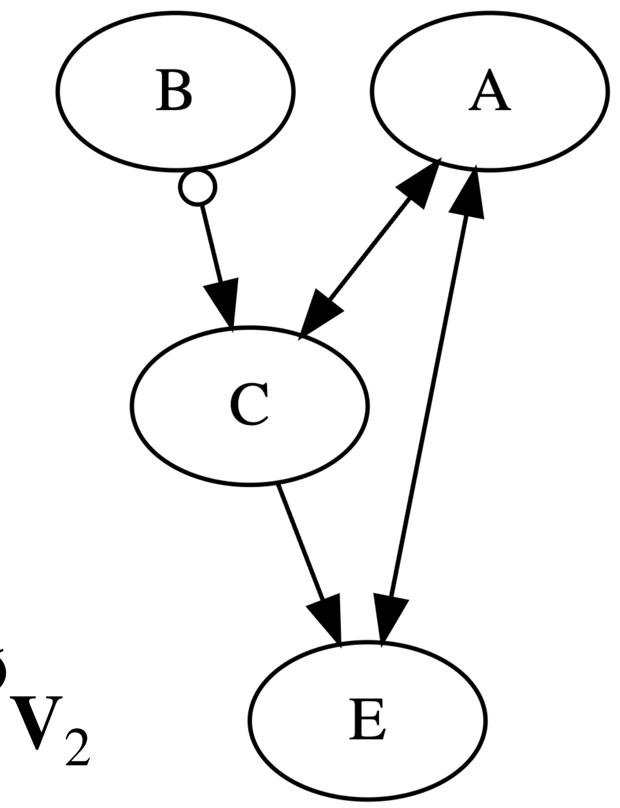
$A \not\perp\!\!\!\perp E \quad (p = 1.83 \times 10^{-12})$

$A \perp\!\!\!\perp B \; (p = 0.380)$

$B \perp\!\!\!\perp E \,|\, C \; (p = 0.964)$

FCI

$\mathscr{P}_{\mathbf{V}_2}$



Accurate Marginal

fedFCI

Enhanced accuracy by using **Federated Conditional Independence Tests** (only model parameters are shared)

Server

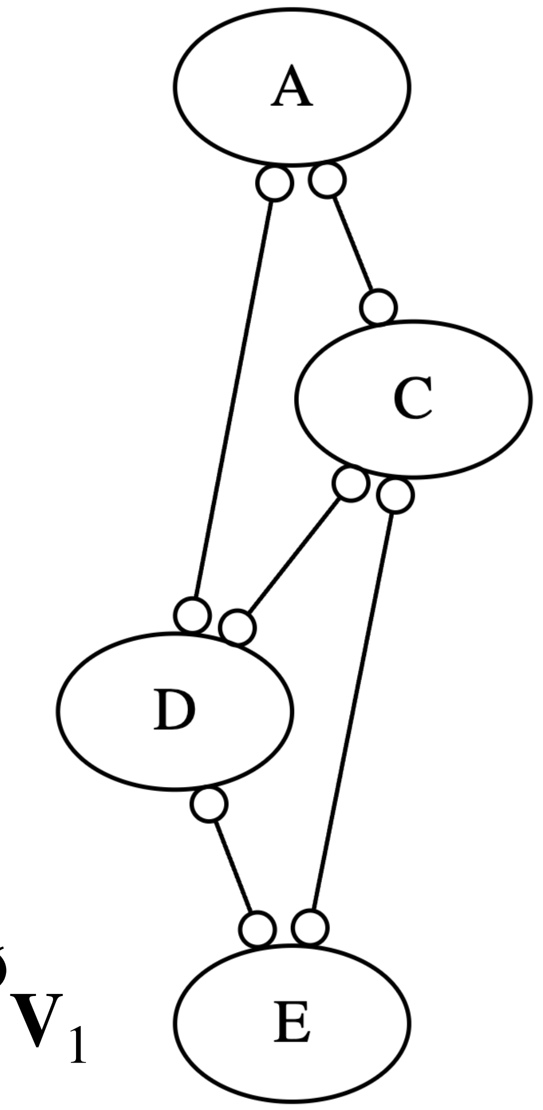
$A \not\perp\!\!\!\perp E \quad (p = 4.27 \times 10^{-12})$

$A \perp\!\!\!\perp E \,|\, C, D \; (p = 0.934)$

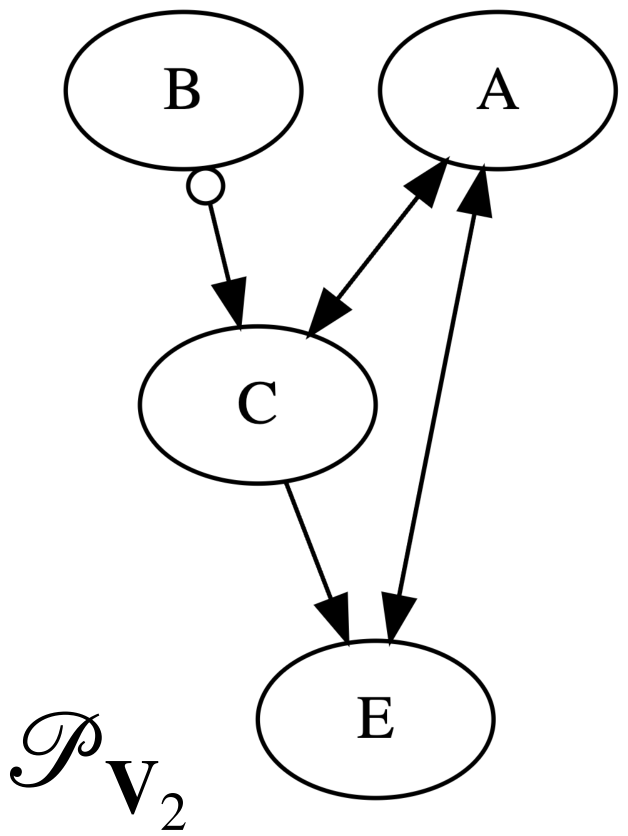
$A \perp\!\!\!\perp B \; (p = 0.380)$

$B \perp\!\!\!\perp E \,|\, C \; (p = 0.964)$

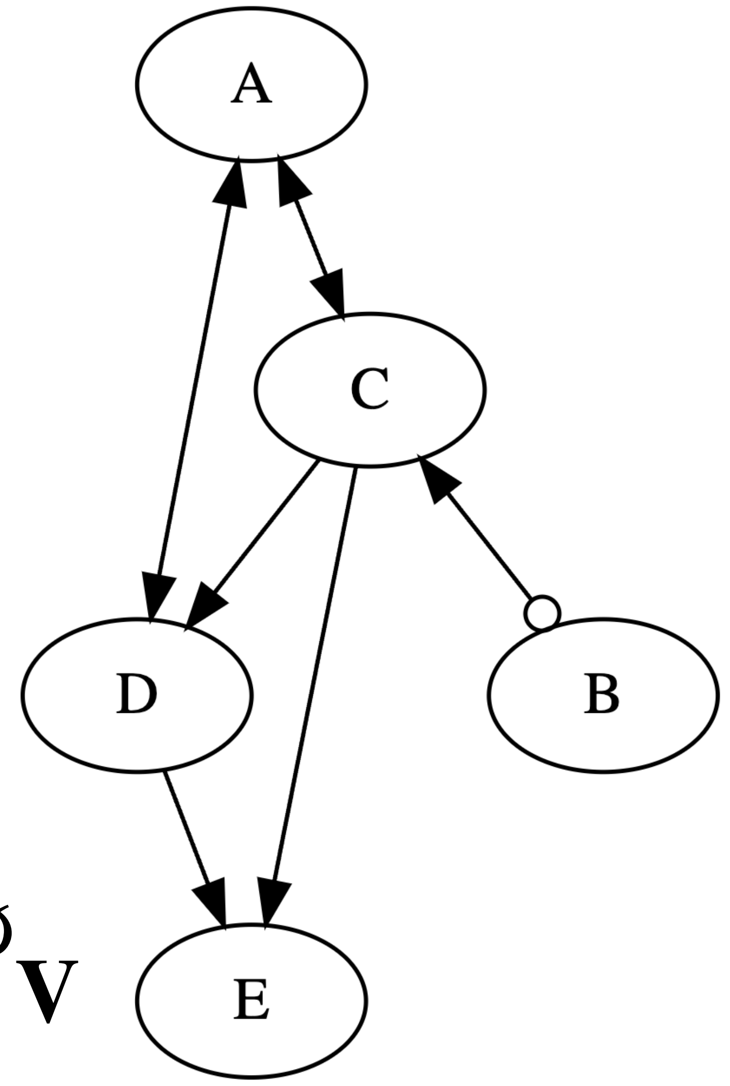
$\mathscr{P}_{\mathbf{V}_1}$



$\mathscr{P}_{\mathbf{V}_2}$



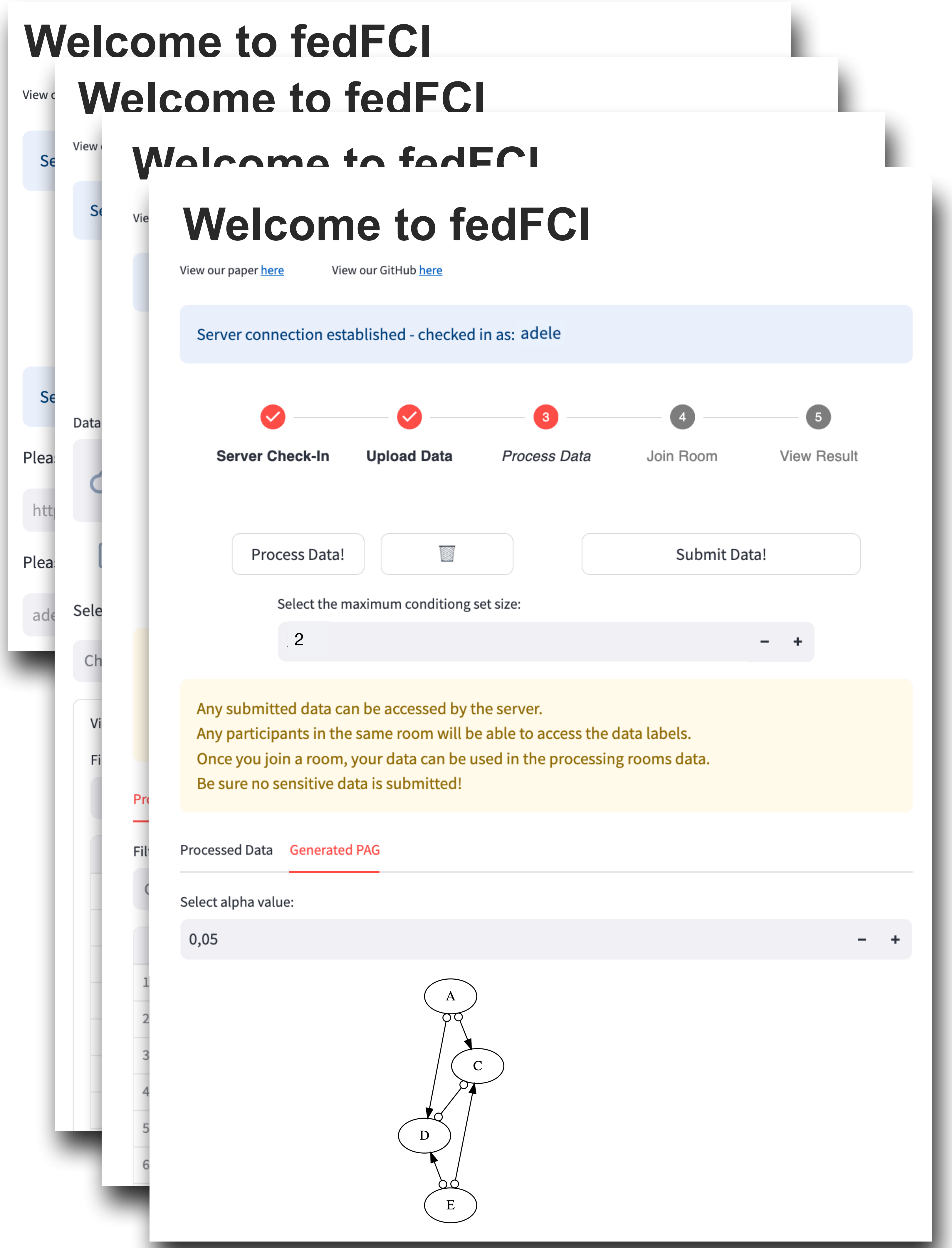
$\mathscr{P}_{\mathbf{V}}$



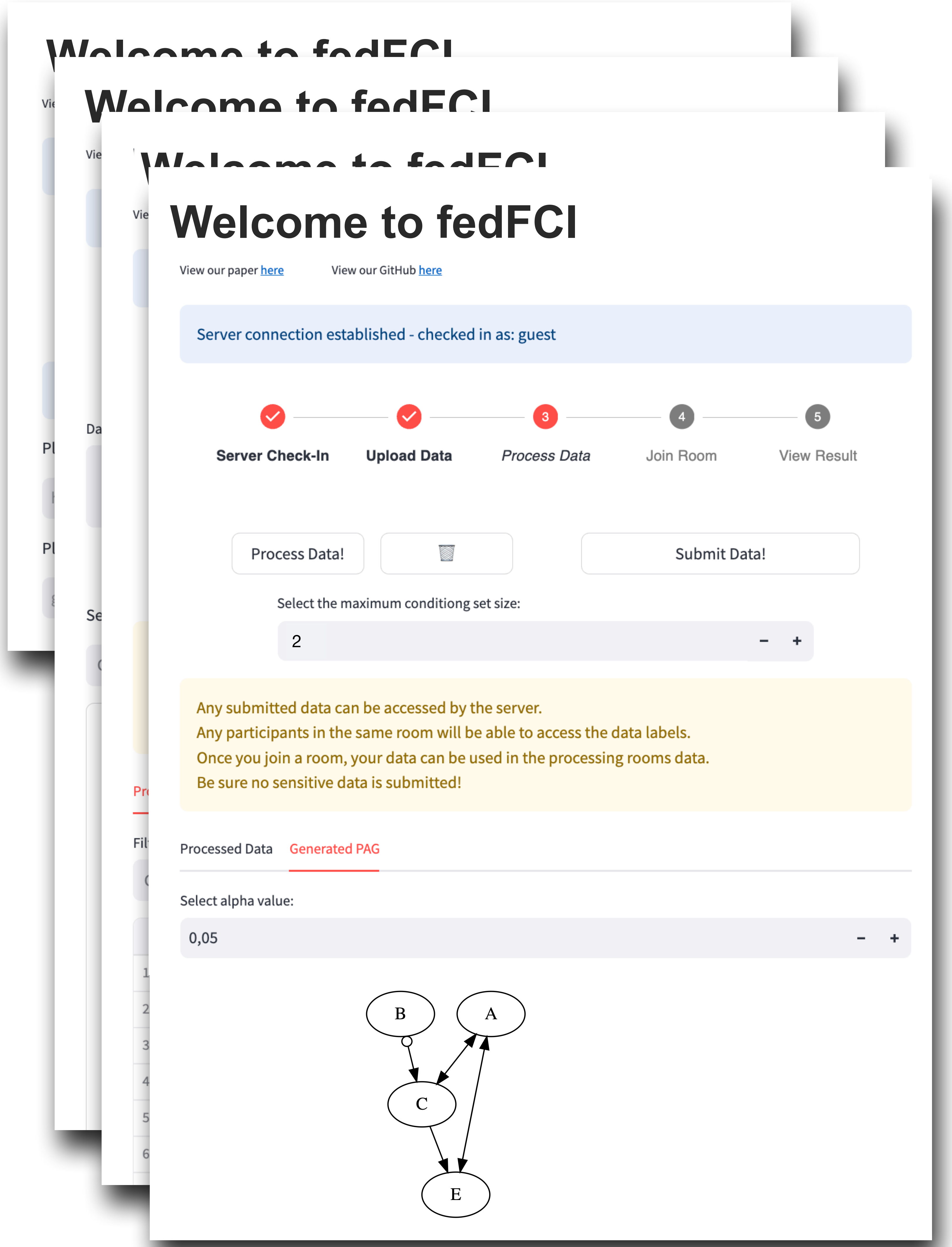
Accurate Marginals and True PAG

fedFCI: User-Friendly Web Application

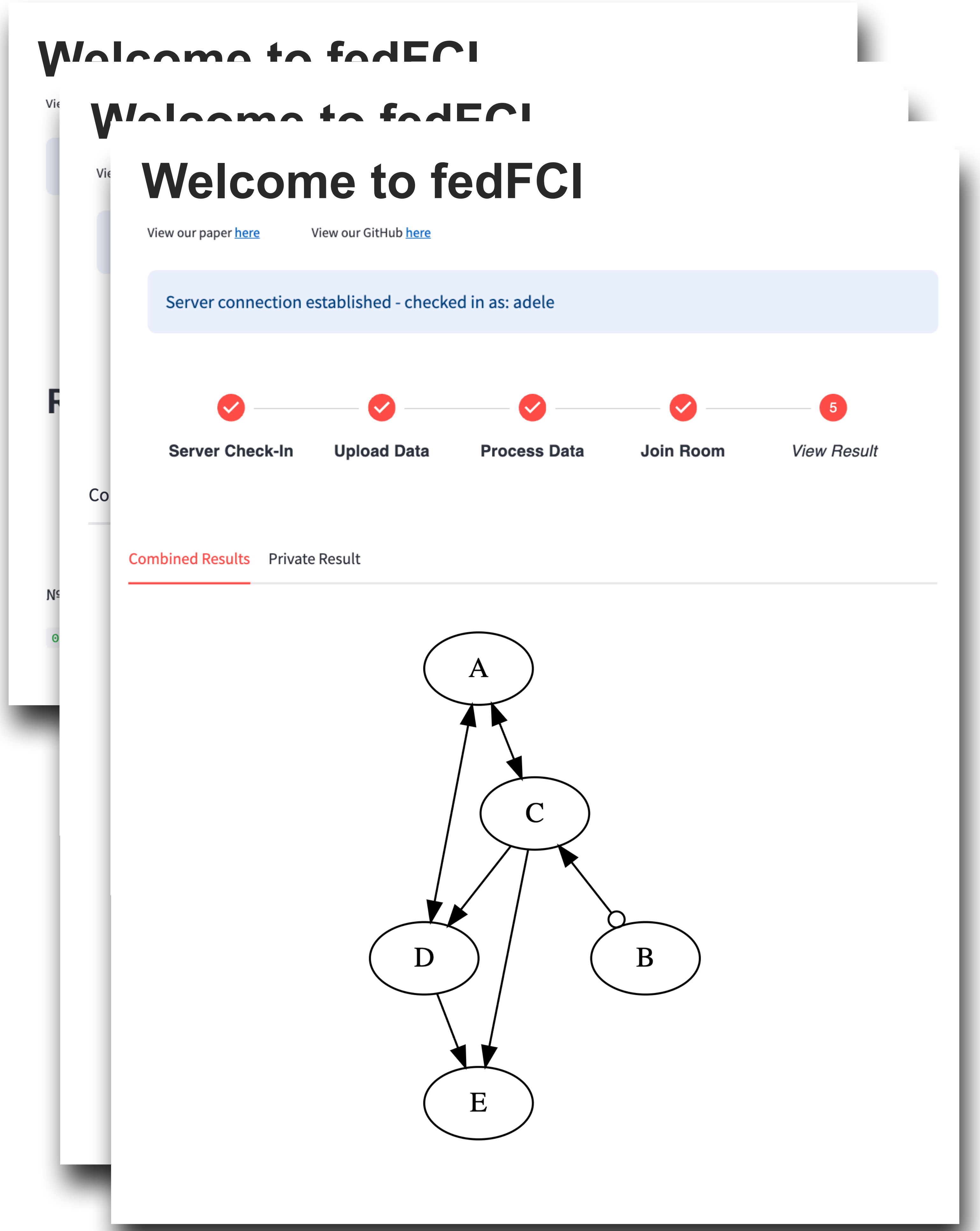
Node 1



Node 2



Server

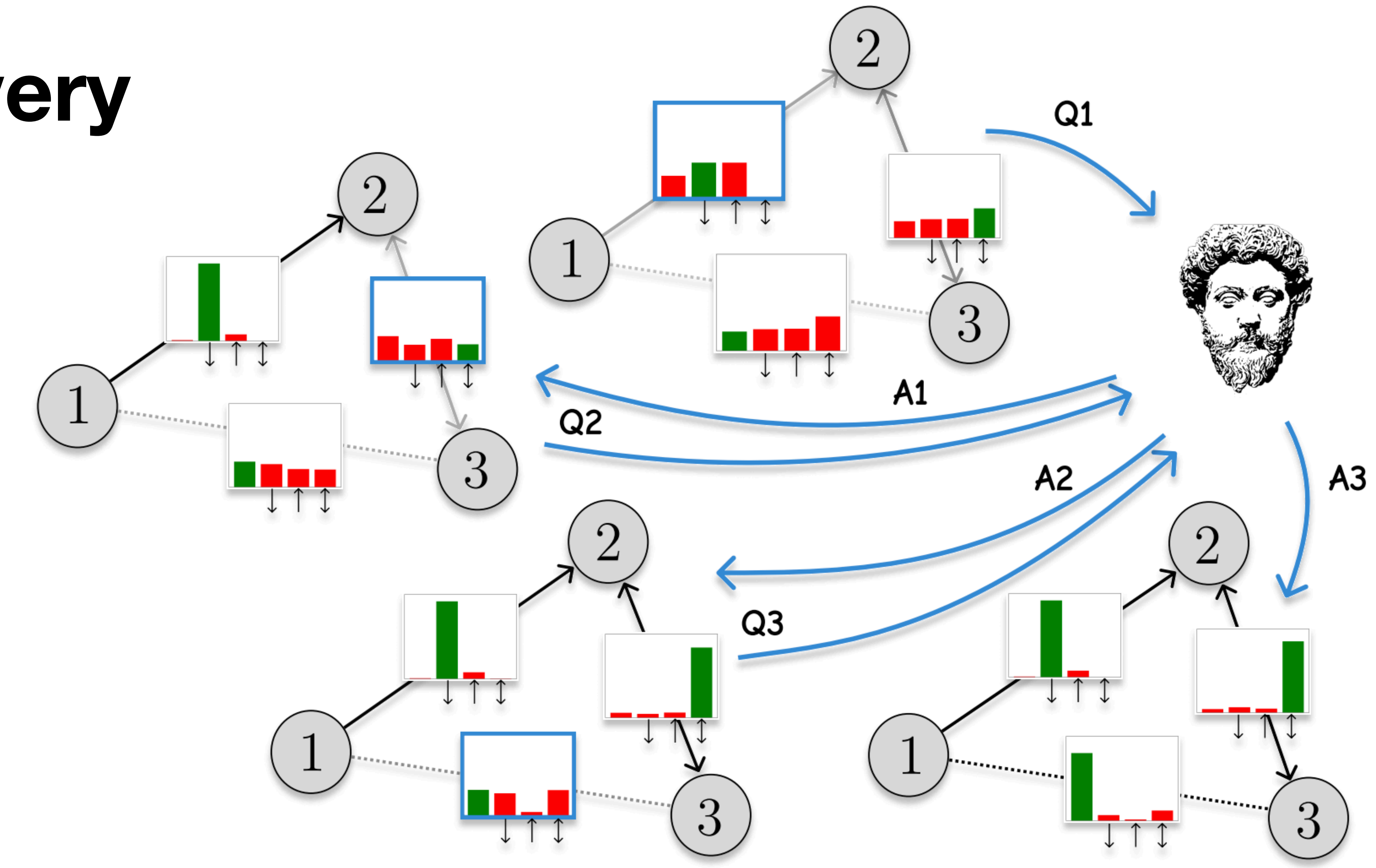


Hahn M.*, Zajak, A.*, Heider, D., **Ribeiro A. H.** (2024). fedFCI: Federated Causal Discovery from Multi-Center Datasets with Unobserved Confounders — *Forthcoming.*

Uncertainty Modeling and Human-AI Collaboration

Human-in-the-Loop Probabilistic Causal Discovery

- da Silva, T., Silva, E.*, **Ribeiro, A.H.***, Góis, A., Heider, D., Kaski, S., & Mesquita, D. (2024). Human-in-the-Loop Causal Discovery under Latent Confounding using Ancestral GFlowNets. *arXiv:2309.12032* (Link) — Under Review.



Robust & Data-Compatible Causal Discovery

- **Ribeiro, A. H.** and Heider, D. (2024). dcFCI: Enhancing Causal Discovery Amid Unobserved Confounders with a Non-Parametric Score for Data-PAG Compatibility — *Forthcoming.*

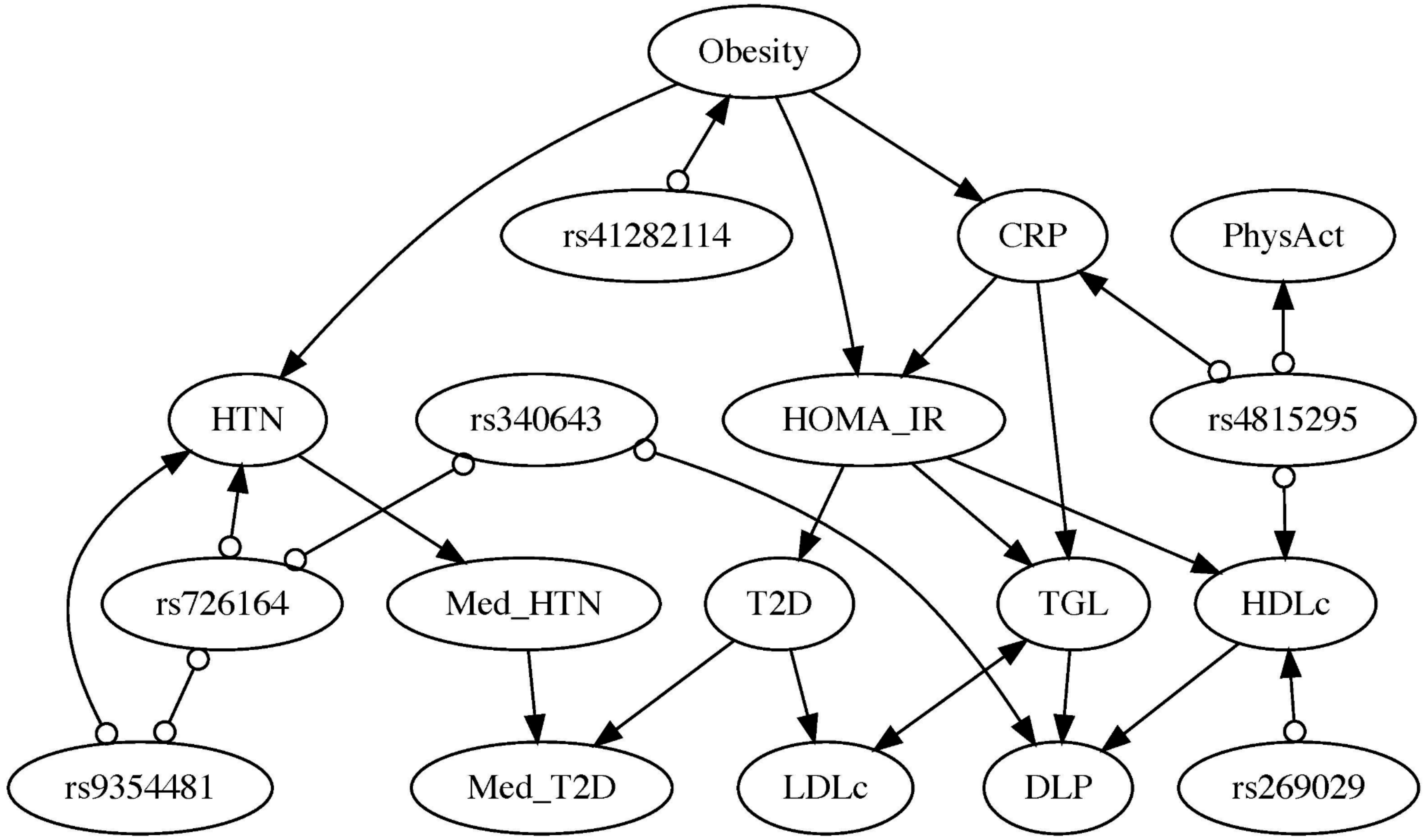
* Equal contribution

Enhancing Applicability of Causality in Genetics

Causal Discovery Using Genetic Anchors

Using Partial Order: Genotypes $\prec$ Phenotypes

- **Ribeiro, A. H.** Crnkovic, M., … Heider, D.*, Cerqueira, A.*(2024). Harnessing Genetic Anchors for Causal Inference: A Data-Driven Method Applied to Cardiometabolic Disease Pathways — *Under Review.*



Health Survey of São Paulo, 2015 ISA-Nutrition Study

Using Partial Order and Mendelian Randomization Approaches

- **Ribeiro, A. H.,** Soler, J. M. P., Chaibub Neto, E., and Fujita, A. (2016). Causal inference and structure learning of genotype-phenotype networks using genetic variation. In *Big Data Analytics in Genomics*. Springer, New York. (Link)

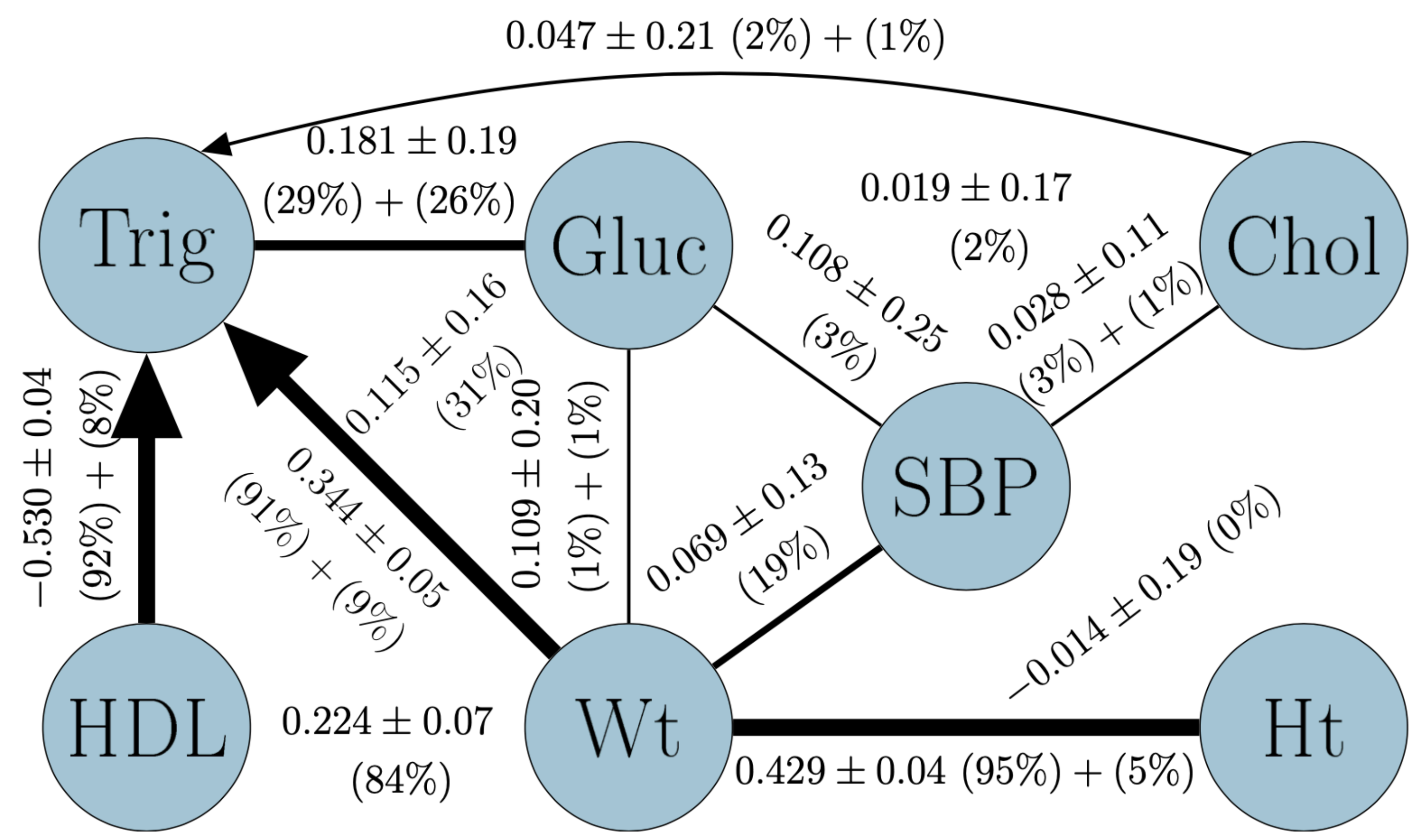
Enhancing Applicability of Causality in Genetics

Causal Discovery from Genetically Related Samples

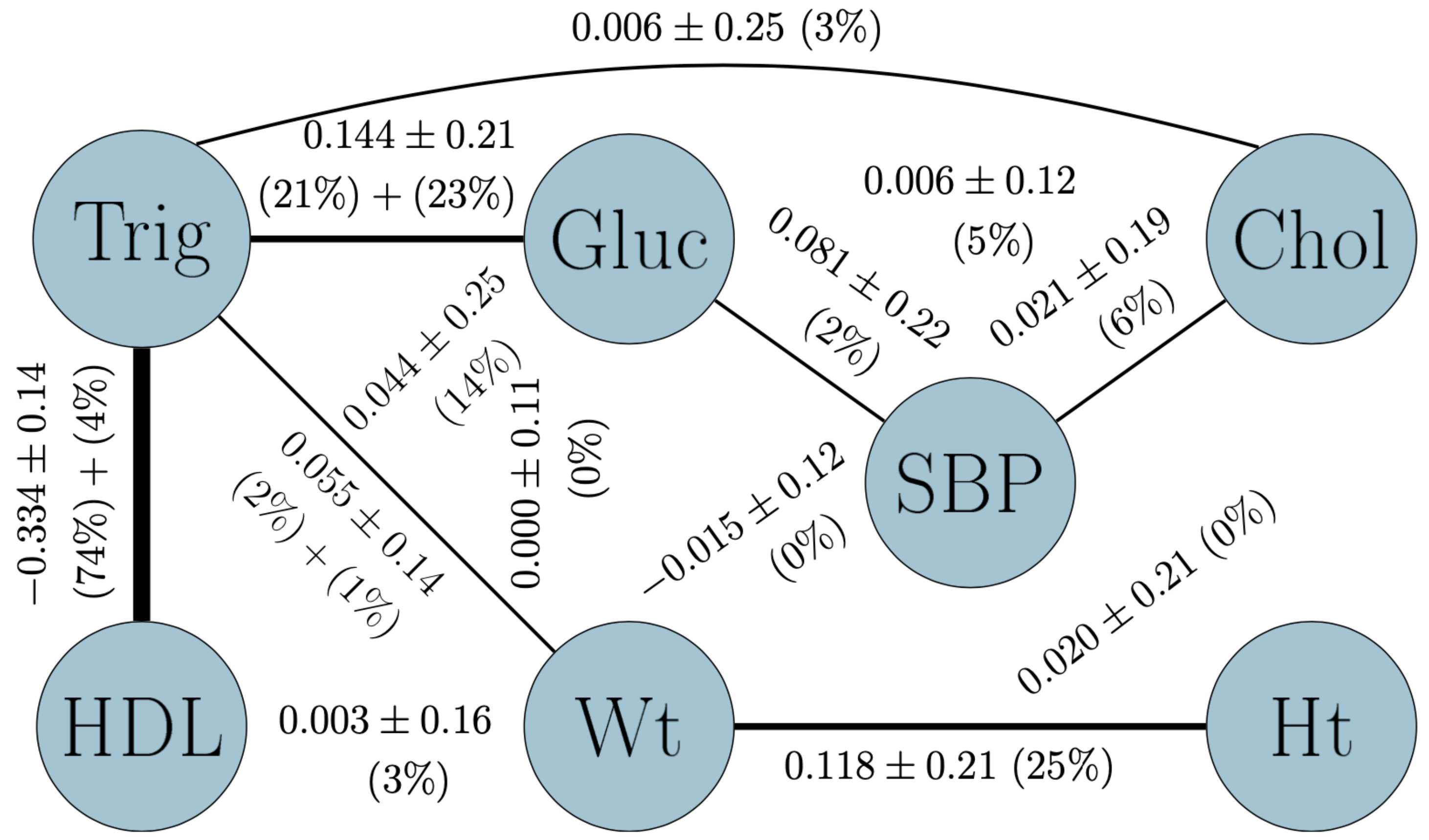
- **Ribeiro, A. H.**, Soler, J. M. P. (2020). Learning Genetic and Environmental Graphical Models from Gaussian Family Data. *Statistics in Medicine.* 39: 2403– 2422. (Link)

R package:

- **Ribeiro, A. H.** (2019). FamilyBasedPGMs: An R package for learning genetic and environmental graphical models from family data. *GitHub repository:* @adele/FamilyBasedPGMs



Genetic Causal Graph



Environmental Causal Graph

GAW13, Framingham Heart Study

Conclusions

Causal inference can address critical challenges in Artificial Intelligence, such as ***robustness, generalizability, explainability,*** and ***fairness***. However, it often relies on impractical assumptions.

My research focuses on bridging the gap between the theory and practice of causal discovery and inference, with a particular emphasis on health research.

- We introduced ***Cluster Causal Diagrams (C-DAGs)*** and provided inferential machinery for all three layers of the causal hierarchy, enabling causal inference in partially understood domains.
- To address situations with no prior knowledge, we developed **PAG-ID**, a sound and complete algorithm for (conditional) ***effect identification from PAGs***. When combined with causal discovery tools such as FCI, this enables a fully data-driven pipeline for causal inference.
- I am currently developing ***robust and adaptive causal discovery methods***, focusing on uncertainty quantification, expert knowledge integration, multi-modal data inference, and privacy-preserving tools for multi-center databases.

Thank you! :)

Feel free to reach out if you have any questions:

adele.ribeiro@uni-marburg.de