



Data Mining and Information Retrieval Laboratory, DMIR Lab

# Non-linear Causal Discovery for Additive Noise Models with Multiple Latent Confounders

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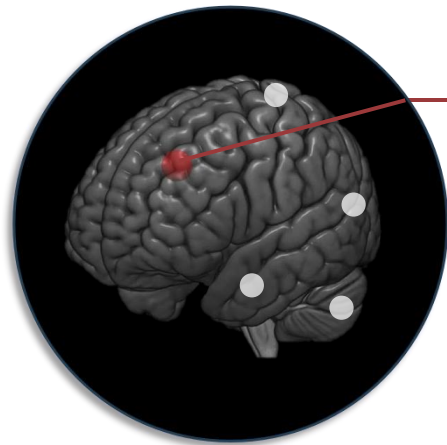
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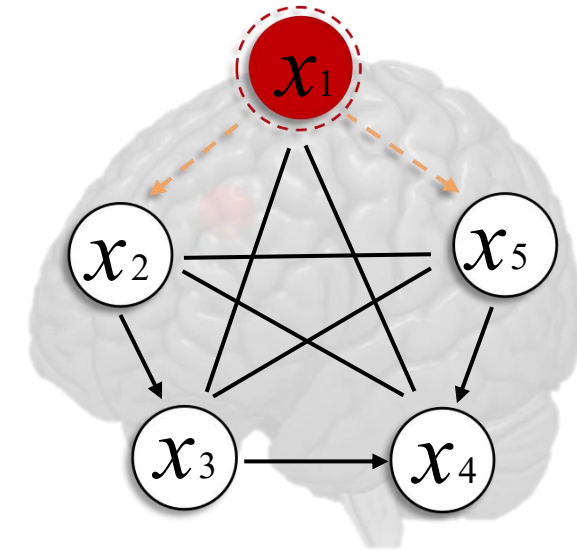
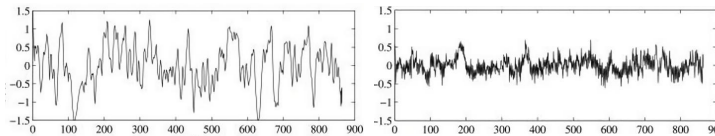
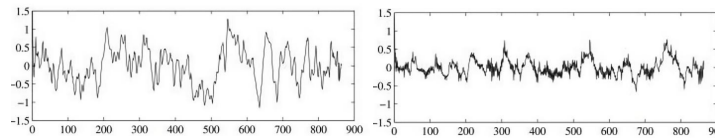
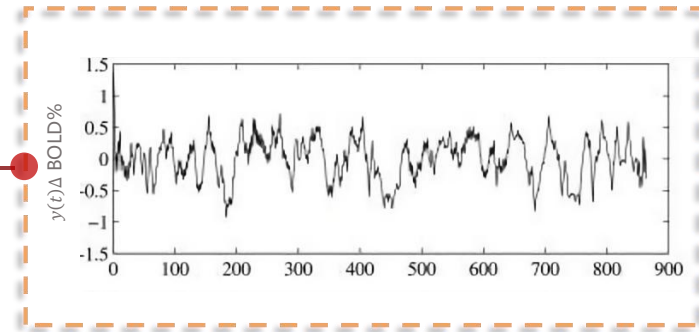
**What specific questions as to **causal networks learning**  
do you care about?**



# Non-linear Causal Discovery with Latent Confounders



Regions of Interest  
(ROI)



Brain "Networks"

[1] Introduction to FSL, [Andrew Jahn](#)

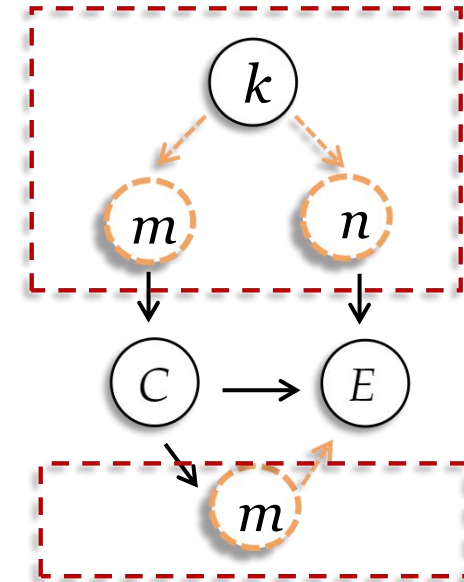
[2] Minati, Ludovico, et al. "Synchronization, non-linear dynamics and low-frequency fluctuations: analogy between spontaneous brain activity and networked single-transistor chaotic oscillators." *Chaos: An Interdisciplinary Journal of Nonlinear Science* 25.3 (2015).

**What assumptions and methodology give rise to  
the causal identification?**



## Related Work, Issues, and Motivation

- **Probabilistic Graphical Models (GPMs)**
  - Constraint-based method: the **PC** algorithm  
*Spirtes, C. N. Glymour, et al. (2000)*
- **Structure Causal Models (SCMs)**
  - Functional-based methods: **LiNGAM, CAM**  
*Shimizu, P. O. Hoyer, et al. (2006)*
- **Methods for Latent Confounders (Variables)**
  - Hybrid-based approach: **MLC-LiNGAM**  
*Chen et al. (2021)*
  - Define “**latent variables paths**” by the **CAM-UV** approach  
*Maeda and Shimizu (2021)*

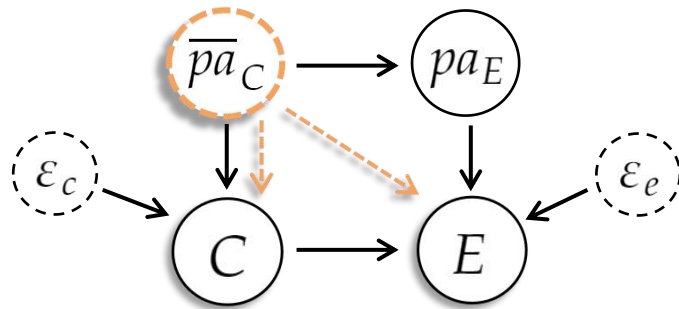


**Illustration of**  
“**Latent Variables Paths**”

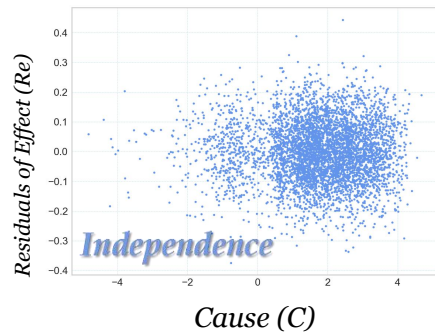


# Related Work, Issues, and Motivation

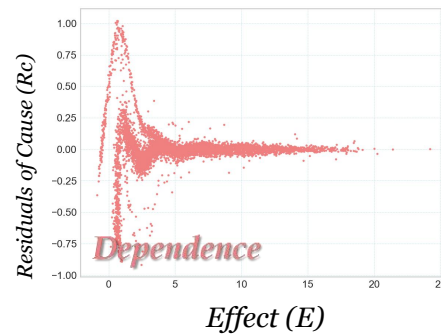
*Unobserved Indirected Confounding*



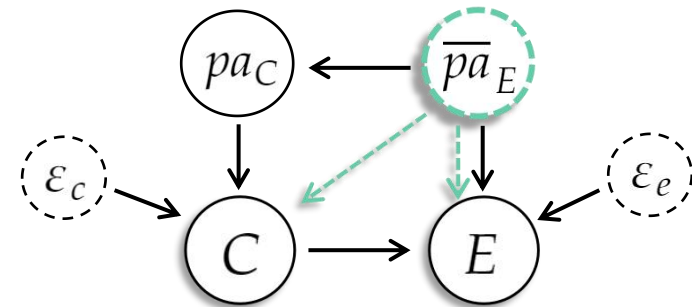
*Regressing Effect on Cause*



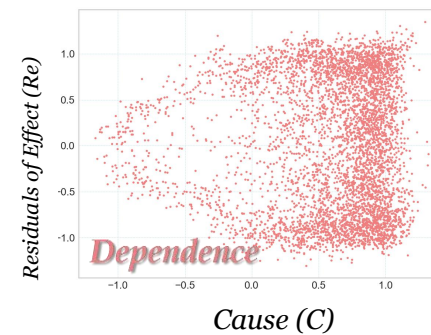
*Regressing Cause on Effect*



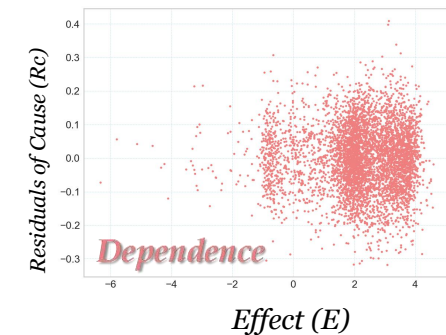
*Unobserved Indirected Confounding*



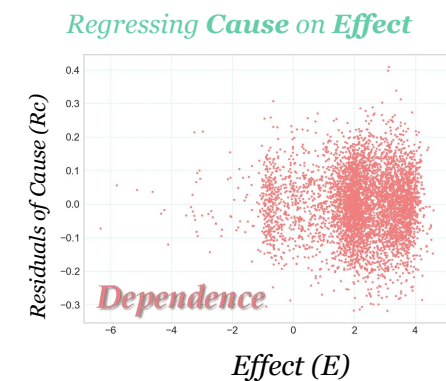
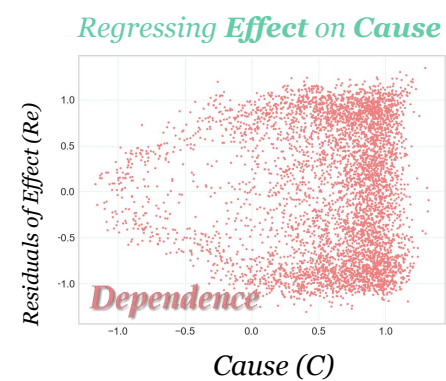
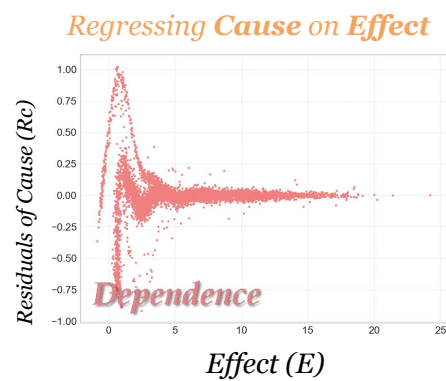
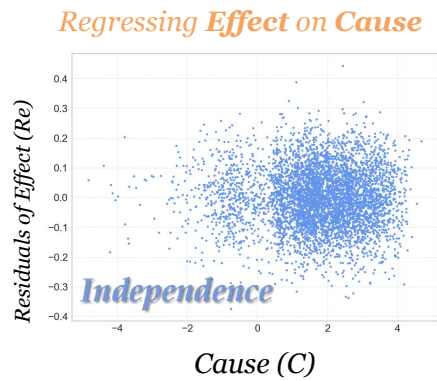
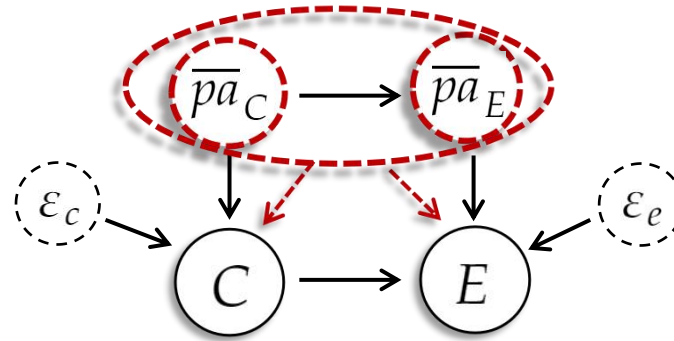
*Regressing Effect on Cause*



*Regressing Cause on Effect*



# Related Work, Issues, and Motivation



In order to make it more clear,  
What is the **most important idea for modeling** this case?





## Causal Models: **Latent Additive-Noise-Models (L-ANMs)**

Nonlinear causal discovery with additive noise models. Hoyer et al. (2008)

### ➤ Model Definition (Theory)

➤ Directed acyclic graphs (DAG):  $\mathbf{X} = \{x_1, x_2, \dots, x_d\}$ ,  $\boldsymbol{\varepsilon} = \{\varepsilon_1, \varepsilon_2, \dots, \varepsilon_d\}$ .

➤ Data generation procedure:

$$x_i := \sum_{x_j \in \mathbf{pa}_i} f_{ij}(x_j) + \xi_i. \quad (\xi_i := \varepsilon_i \cup \mathbf{f}(\overline{\mathbf{pa}}_i).)$$

### ➤ Empirical Regressor (Algorithm)

➤ Non-linear **Identifiable Condition** as to  $x_j$  and  $\xi_i$ :

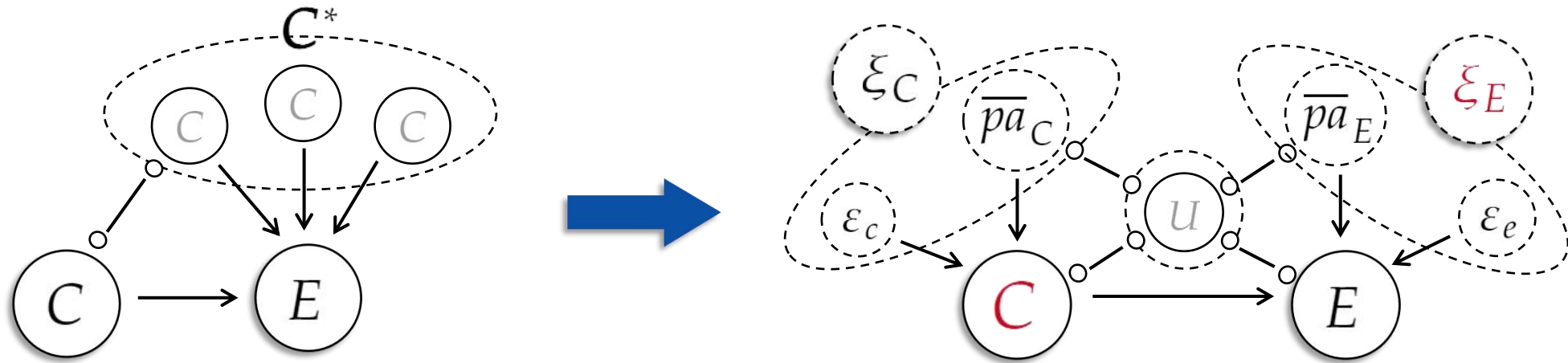
$$x_i - \underbrace{\sum_{x_h \in \mathbf{pa}_i \setminus \{x_j\}} f_{ih}(x_h)}_{\mathcal{R}_i} = f(x_j) + \underbrace{\left( \sum_{x_k \in \overline{\mathbf{pa}}_i} f_{ik}(x_k) + \varepsilon_i \right)}_{\xi_i}.$$



**Based on this model,**  
**what is the intuition for the new causal identification**



## Contribution-1: The **Latent-ANM** Condition

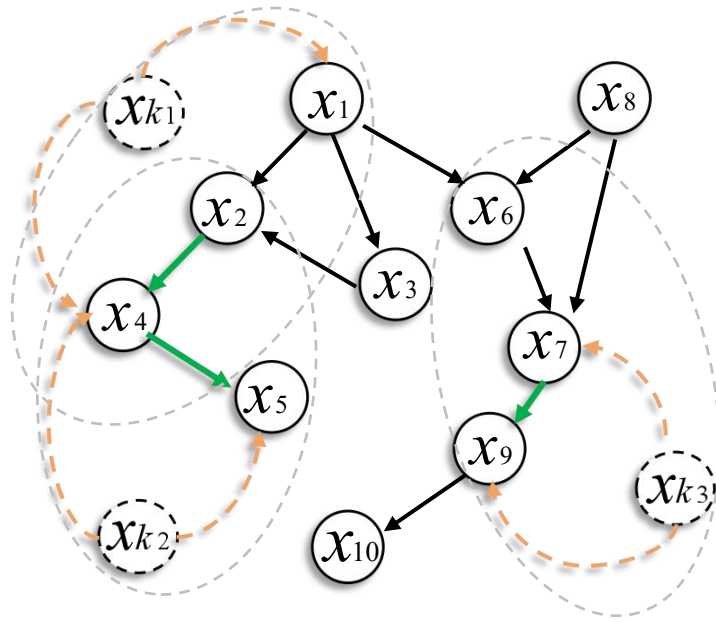


**Nonlinear Identifiable Condition:**

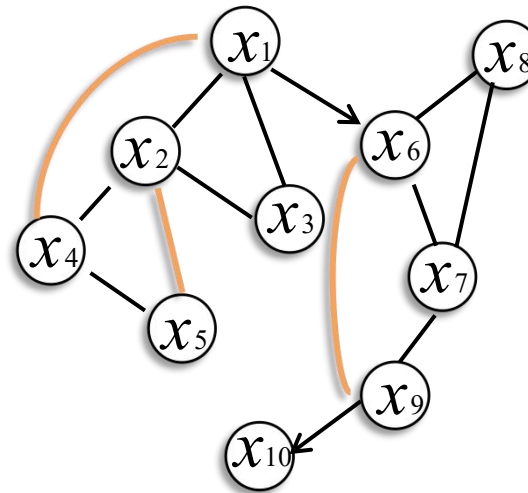
$$(\xi_E \perp\!\!\!\perp C) \wedge (\xi_E := \epsilon_E \cup f(C^*))$$



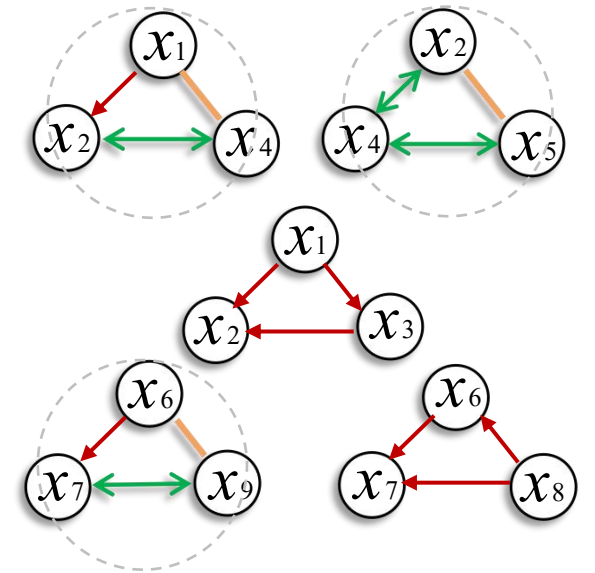
## Contribution-2: The **Nonlinear-MLC** Algorithm



**Unidentifiable Non-linear Causation**



**Spurious Edges**



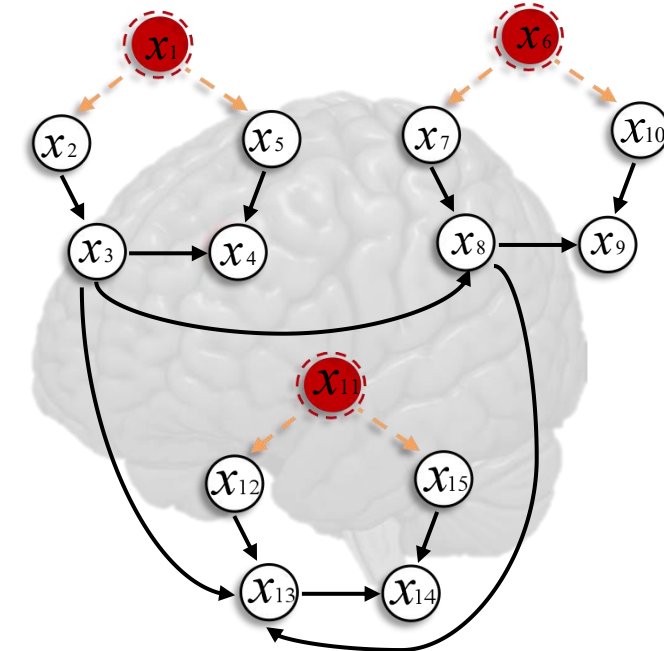
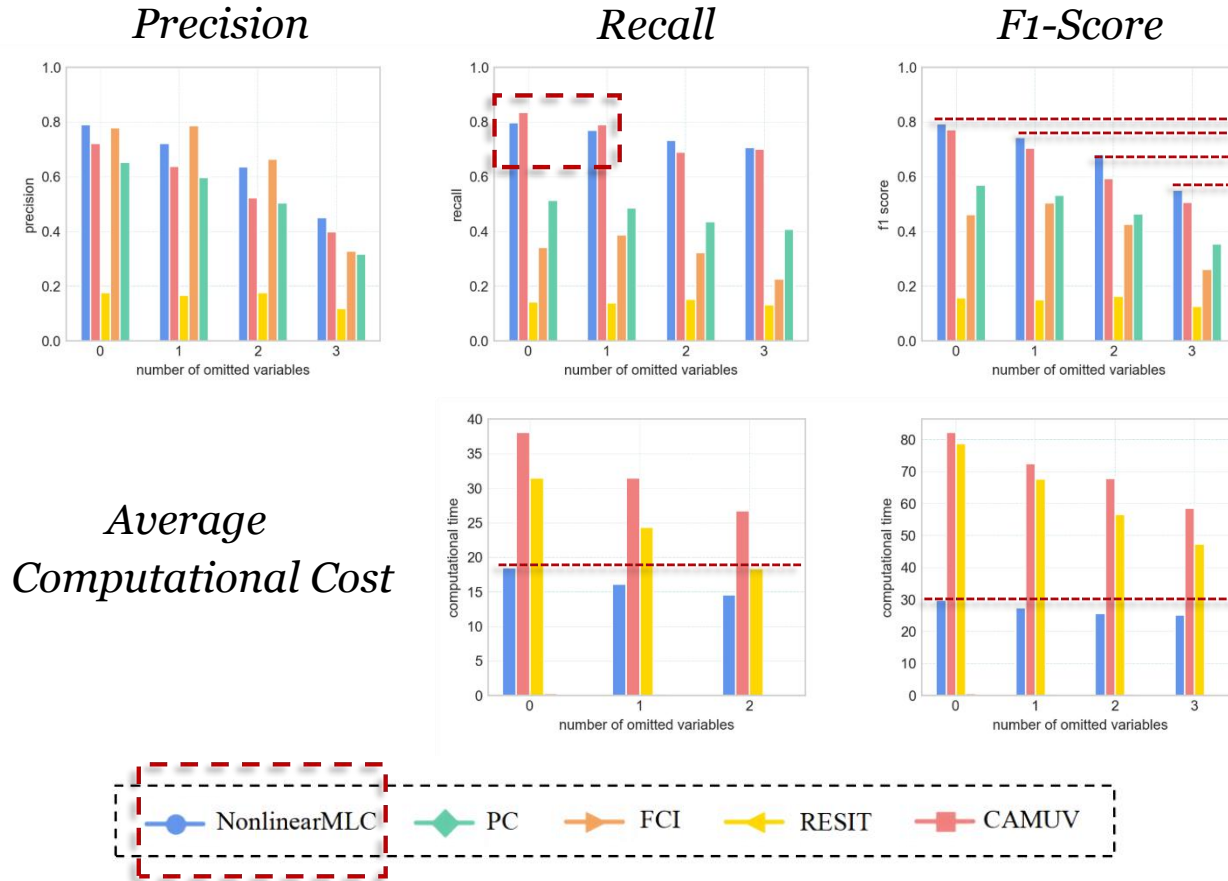
**Causal Inference**  
Based on L-ANMs Identification



How did you **evaluate** your approach?  
(the “Nonlinear-MLC” algorithm)



# Performance on **F**unctional **M**agnetic **R**esonance **I**maging Data



**Brain "Networks"**  
from fMRI Data (**NetSim-3**)



[1] <https://www.fmrib.ox.ac.uk/datasets/netstim/index.html>

[2] Smith, Stephen M., et al. "Network modelling methods for FMRI." *Neuroimage* 54.2 (2011): 875-891.

**Finally, how can I **get start** to apply the approach?  
(for general non-linear causal discovery)**



## Source

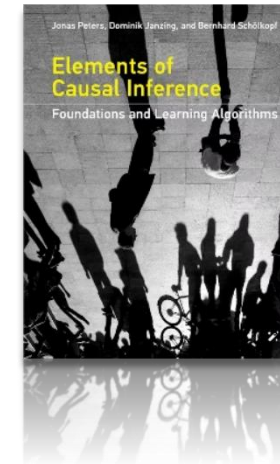
- **caudimlc: Light Python Package for Hybrid-Based Causal Discovery**
  - Provide easy-to-use **Python APIs** to learn an empirical causal graph with relative efficiency
  - Integrate implementations of **hybrid-based approaches** and micro workflow of causal discovery
  - **Github:** <https://github.com/xuanzhichen/cadimulc>

- **A Quote from *Elements of Causal Inference***

Jonas Peters, Dominik Janzing, and Bernhard Schölkopf

*“Statistical causal methods do not need to be motivated by the proofs of the identifiability results.”*

*“Causal methods that follow the proofs closely are often inefficient in making use of the data.”*







**Thanks for Watching**

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