

# Detecting direct influences in complex systems from observational time series

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#### **IHPCSS '18 Poster**

## Causal Graphs<sup>1</sup>



#### Causal Graphs

- Directed graphs
- A link denotes a causal relationship



#### Important Question

How do we detect direct causal relationships from observed data (in particular, observational time series)?

<sup>1</sup>Judea Pearl. "Causality. Cambridge". In: *New York* (2000).



$$\mathbb{P}(x_2, x_3 | x_1) = \mathbb{P}(x_2 | x_1) \mathbb{P}(x_3 | x_1)$$

 $\mathbb{P}(x_2, x_3) = \mathbb{P}(x_2) \mathbb{P}(x_3)$ 

<sup>2</sup>Peter Spirtes, Clark N Glymour, and Richard Scheines. *Causation, prediction, and search.* MIT press, 2000.

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## Granger Causality<sup>3</sup> Temporal causal discovery in time series







- A cause precedes its effect
- A direct cause should significantly contribute for the prediction of its effects, given all the information from the past: regress x<sub>1</sub> on past of every signal in the system.

<sup>3</sup>Clive WJ Granger. "Testing for causality: a personal viewpoint". In: *Journal of Economic Dynamics and control* (1980).

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## MD Algorithm<sup>4</sup> Combining PC and Granger



#### Step 1: $x_i^- \rightarrow x_j(t)$ ?

Search for S s.t.  $regress(x_i, \{x_i^- \cup S\})$  leads to zero coeff. in front of  $x_i^-$ .

#### Step 2: $x_i(t) \rightarrow x_j(t)$ ?

Search for S s.t.  $regress(x_i, \{x_i \cup S\})$  leads to zero coeff. in front of  $x_i$ .



#### **Computational Challenges**

- Combinatorial search for a separating set.
- Size of regression increases by increasing the number of lags we consider.

<sup>4</sup>Mihaela Dimovska and Donatello Materassi. "Granger-causality meets causal inference in graphical models". In: *CDC, IEEE 56th Annual Conference*. IEEE. 2017.