Case Studies of Causal Discovery from IT Monitoring Time Series

Ali Aït-Bachir, Charles K. Assaad, Christophe de Bignicourt, Emilie Devijver, **Simon Ferreira**, Eric Gaussier, Hosein Mohanna and Lei Zan

Outline

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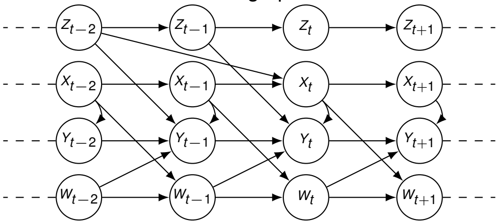
Temporal causal graphs and abstractions

Full time graph: $\mathcal{G}^f$



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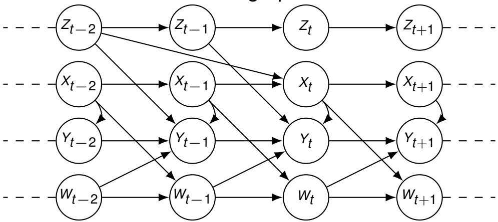

Additional assumption: consistency throughout time

$\gamma_{\max}$: maximal lag between causes and their effets

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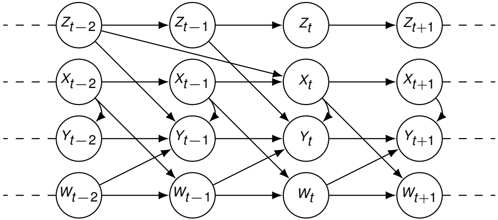

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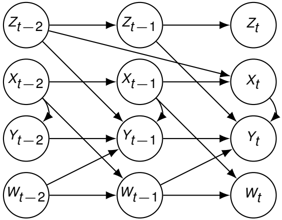

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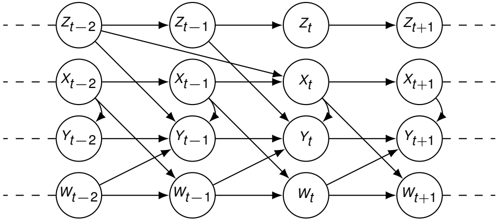

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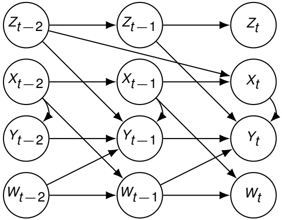

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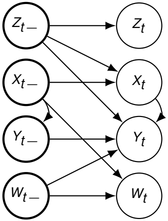

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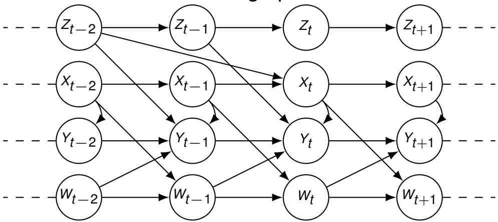

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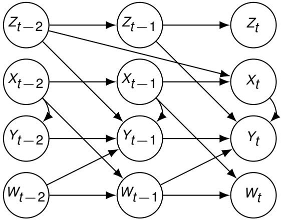

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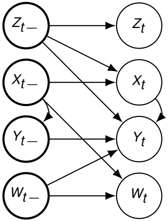
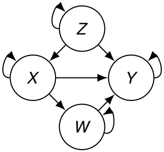


Summary graph (SCG): $\mathcal{G}^s$



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Additional assumption on causal relations

- Stationary and linear dynamic structural causal model

$$\forall Y_t \in \mathcal{V}_w$$

$$Y_t = \sum_{X_{t-\gamma_{xy}} \in Parents(Y_t, \mathcal{G}_w)} \alpha_{XY\gamma_{xy}} X_{t-\gamma_{xy}} + \xi_t^y,$$

where $\alpha_{XY\gamma_{xy}} \neq 0$ is the direct effect of $X_{t-\gamma_{xy}}$ on Y_t

Rajen D. Shah, Jonas Peters. *The hardness of conditional independence testing and the generalised covariance measure.* Ann. Statist. 2020.

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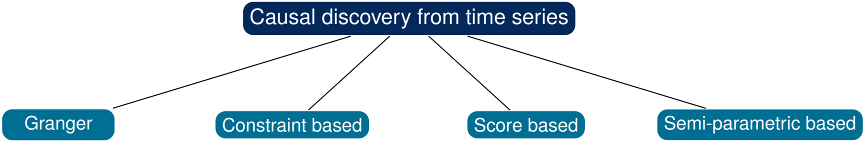

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Causal discovery from time series

- Causal discovery from time series
  - Granger
    - GCMVL (Arnold, 2007)
  - Constraint based
    - PCMCI^{+} (Runge, 2020)
    - PCGCE (Assaad, 2022)
  - Score based
    - Dynotears (Pamfil, 2020)
  - Semi-parametric based
    - VLiNGAM (Hyvärinen, 2010)
    - TiMINo (Peters, 2010)

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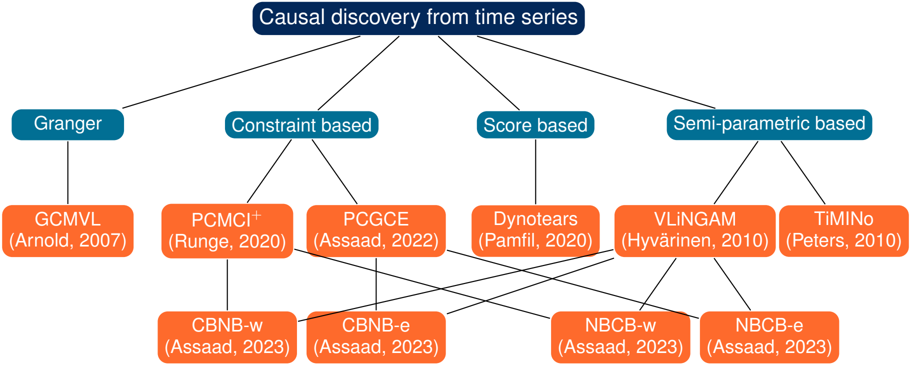

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Summary of the main characteristics

Family	Algorithm	Causal graph	Instantaneous relations	Faithfulness	Non-Gaussianity	Equal noise variances
Granger	GCMVL	SCG	✗	✗	✗	✗
Constraint-based	PCMCI^{+}	WCG	✓	✓	✗	✗
	PCGCE	ECG	✓	✓	✗	✗
Score-based	DYNOTEARS	WCG	✓	✗	✗	✓
Semi-parametric-based	VarLiNGAM	WCG	✓	✗	✓	✗
	TiMINo	SCG*	✓	✗	✓	✗
Hybrid-based	CBNB-w	WCG	✓	✗	✓	✗
	CBNB-e	ECG	✓	✗	✓	✗
	NBCB-w	WCG	✓	✗	✓	✗
	NBCB-e	ECG	✓	✗	✓	✗

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Pre-Processing

Alignment issues and missing values:

- Strategy 1: Re-sample according to the lowest sampling rate by taking the closest value.

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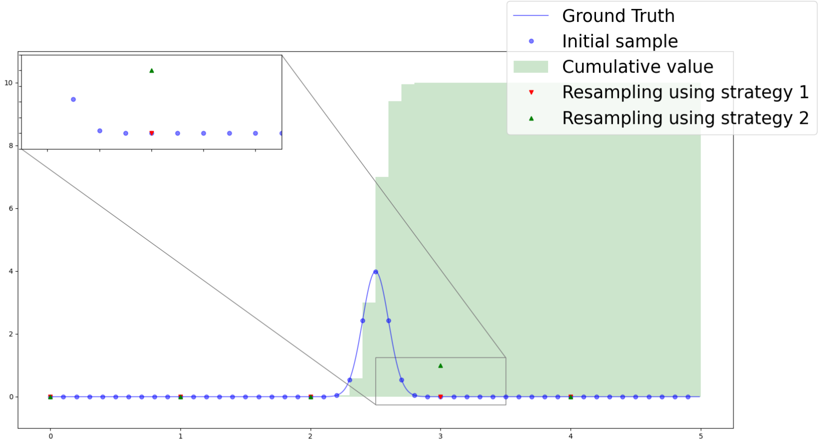
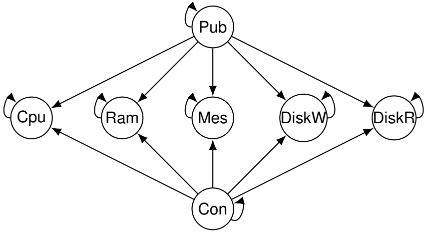


The use case of MoM activity

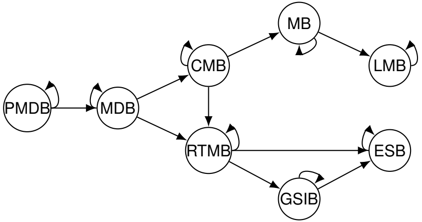
Message ingestion activity based on Publish/Subscribe architecture



Two datasets of 288 and 364 timestamps with a sampling rate of 1 seconde.

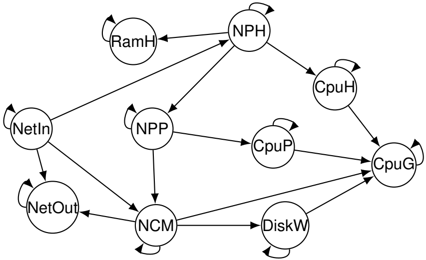
The use case of Ingestion activity

Message ingestion activity based on Storm architecture



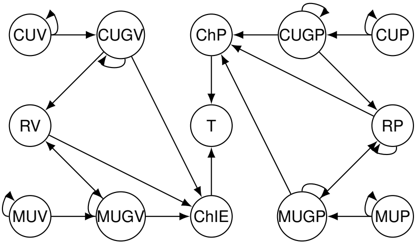
A dataset of 991 timestamps with a sampling rate of 1 minute.

The use case of Web activity



A dataset of 3000 timestamps with a sampling rate of 1 minute.
The data was misaligned so the two pre-processing strategies were used.

The use case of Antivirus activity



A dataset of 1321 timestamps with a sampling rate of 1 and 5 minutes.
The data was misaligned so the two pre-processing strategies were used.

IT monitoring case studies: results

Estimation

- Partial correlation
- ...

Hyper-parameters

- $\gamma_{max} = 15$ for MoM and Ingestion, $\gamma_{max} = 3$ for other datasets
- Significance level $= 0.05$
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Evaluation measure

- F1-score on orientations in the SCG.

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Results

	MoM 1	MoM 2	Ingestion	Web 1	Web 2	Antivirus 1	Antivirus 2
GCMVL	0.0	0.0	0.2	0.2	0.0	0.08	0.0
Dynotears	0.26	0.2	0.14	0.23	0.3	0.18	0.19
PCMCI^{+}	**0.4**	0.0	0.0	0.23	0.3	0.04	0.11
PCGCE	0.0	0.12	0.12	0.22	0.15	0.3	**0.45**
VLiNGAM	0.0	0.0	0.19	**0.29**	0.18	0.15	0.22
TiMINo	0.0	0.17	0.18	0.0	0.0	0.0	0.0
NBCB-w	**0.4**	0.0	0.13	0.23	0.3	0.14	0.24
NBCB-e	0.13	**0.29**	**0.27**	0.19	**0.42**	**0.31**	**0.45**
CBNB-w	**0.4**	0.0	0.15	0.23	0.3	0.17	0.16
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Not satisfactory for real applications!

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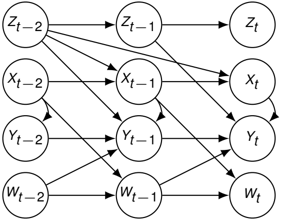

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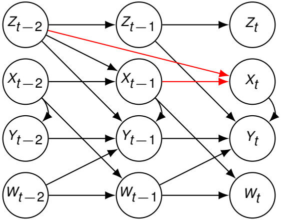

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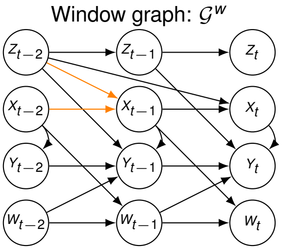

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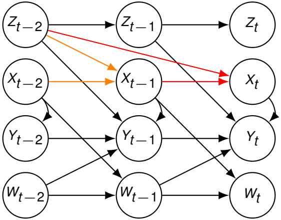

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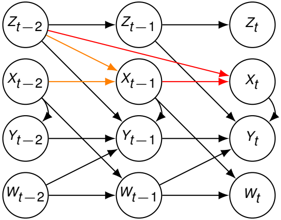

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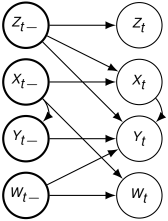

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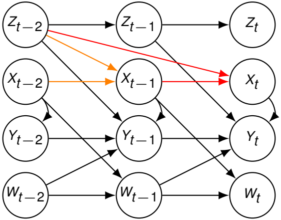

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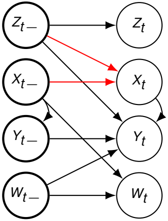

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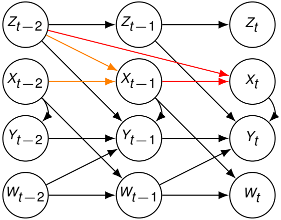

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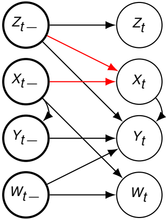

$\Longrightarrow$ NBCB-e performs better.

Prespectives

Many things to improve for causal discovery in time series:

- non-stationarity
- regime-change
- measurement errors
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Thank you for your attention, feel free to ask questions.

References

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Thank you !

Hybrid-based Methods

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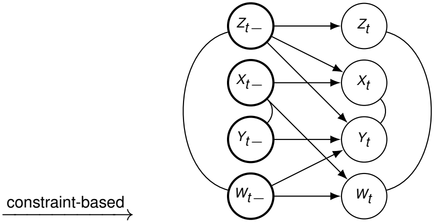

Hybrid-based Methods

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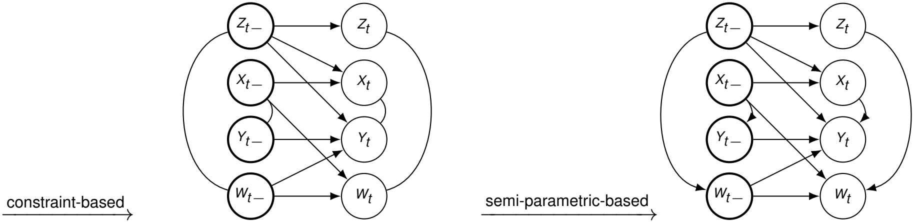
- Step 1: Use the first part of a constraint-based algorithm (PCMCI+ or PCGCE) to discover the skeleton.
- Step 2: Use a semi-parametric-based algorithm (VarLiNGAM) on relevant vertices to orient the edges.



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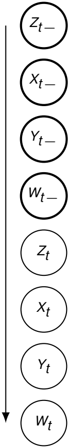

semi-parametric-based

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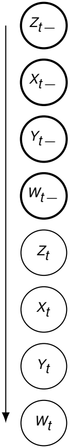
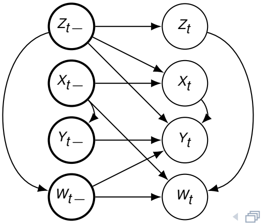
- Step 2: Use a constraint-based algorithm (PCMCI+ or PCGCE) with the knowledge of parents to eliminate some remaining edges.

semi-parametric-based $\longrightarrow$



constraint-based $\longrightarrow$



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CBNB:

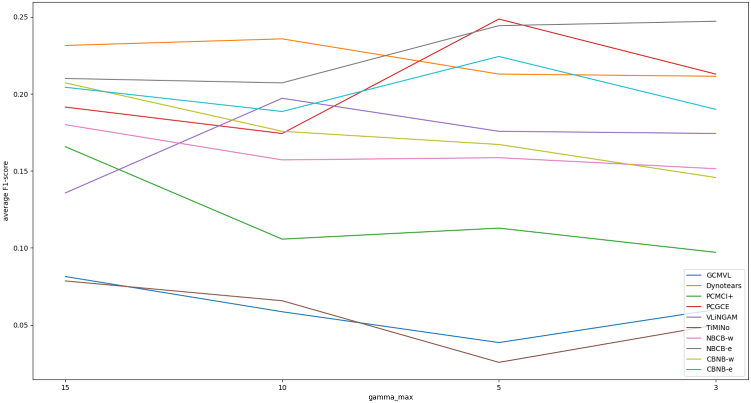
- Step 1: Use the first part of a constraint-based algorithm (PCMCI+ or PCGCE) to discover the skeleton.
- Step 2: Use a semi-parametric-based algorithm (VarLiNGAM) on relevant vertices to orient the edges.

NBCB:

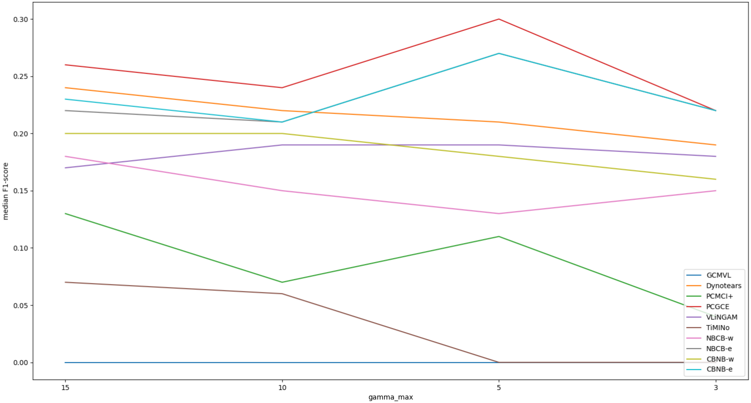
- Step 1: Use the first part of a semi-parametric-based algorithm (VarLiNGAM) an order in the vertices.
- Step 2: Use a constraint-based algorithm (PCMCI+ or PCGCE) with the knowledge of parents to eliminate some remaining edges.

Advantages:
In theory both need the same assumptions. However, CBNB algorithms are robust regarding the semi-parametric assumption and NBCB algorithms are robust regarding the faithfulness assumption.

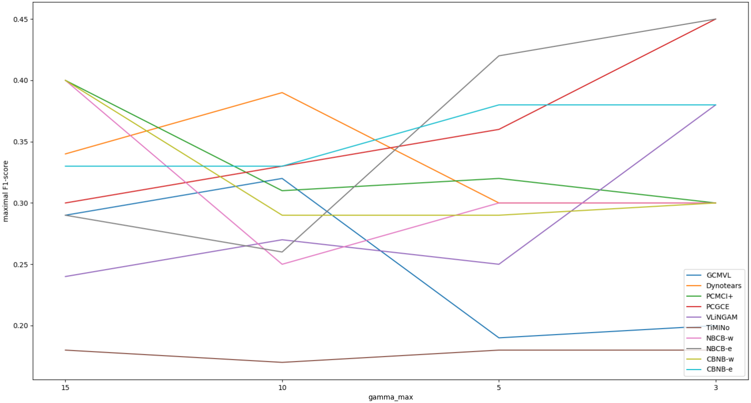
Average F1-Score



Median F1-Score



Maximal F1-Score



Minimal F1-Score