Placy - Power law causal Discovery

Robust Causal Discovery in Real-World Time Series with Power-Laws

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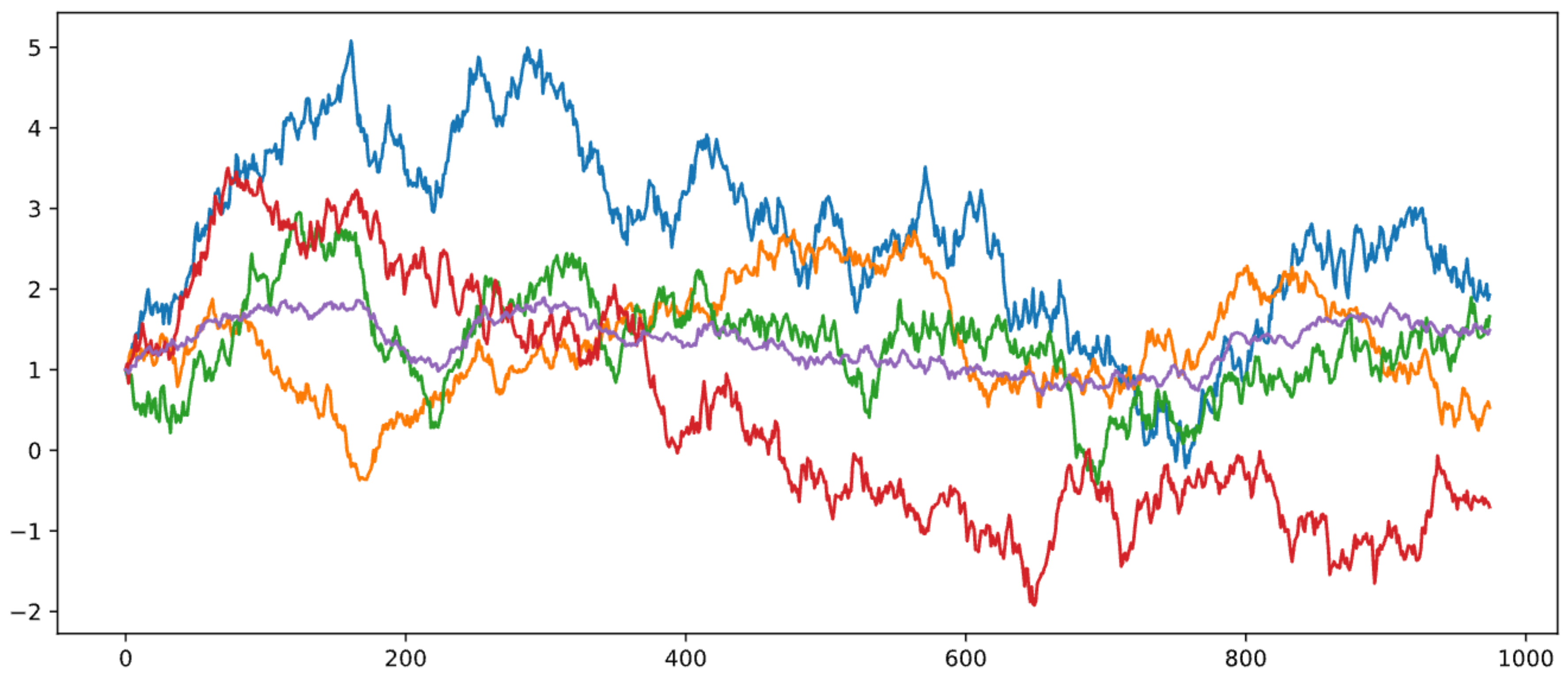
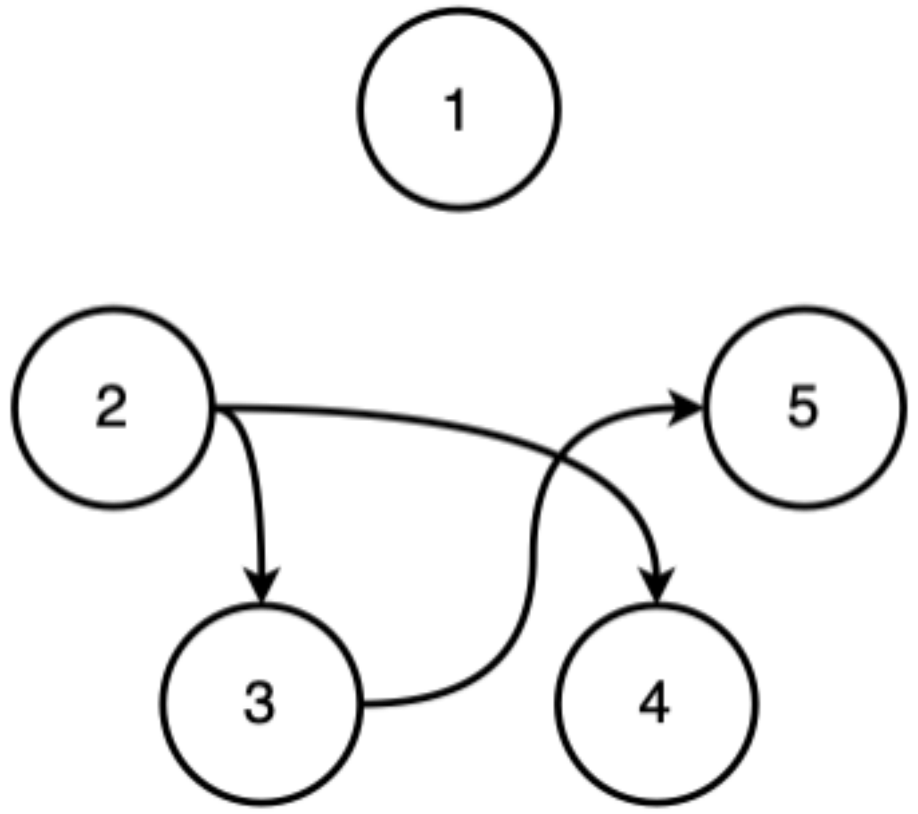
Motivation



Causal Discovery algorithm



Observational causality

Identifying **statistical patterns**:

- Temporal precedence (cause precedes effect),
- conditional dependencies
- predictive improvement

Problem

Extraordinary difficult in presence of **noise** and **non-stationarity**

Question

Can spectral properties of time series make causal discovery more reliable?

Power-Law Behaviour in Real-World Systems

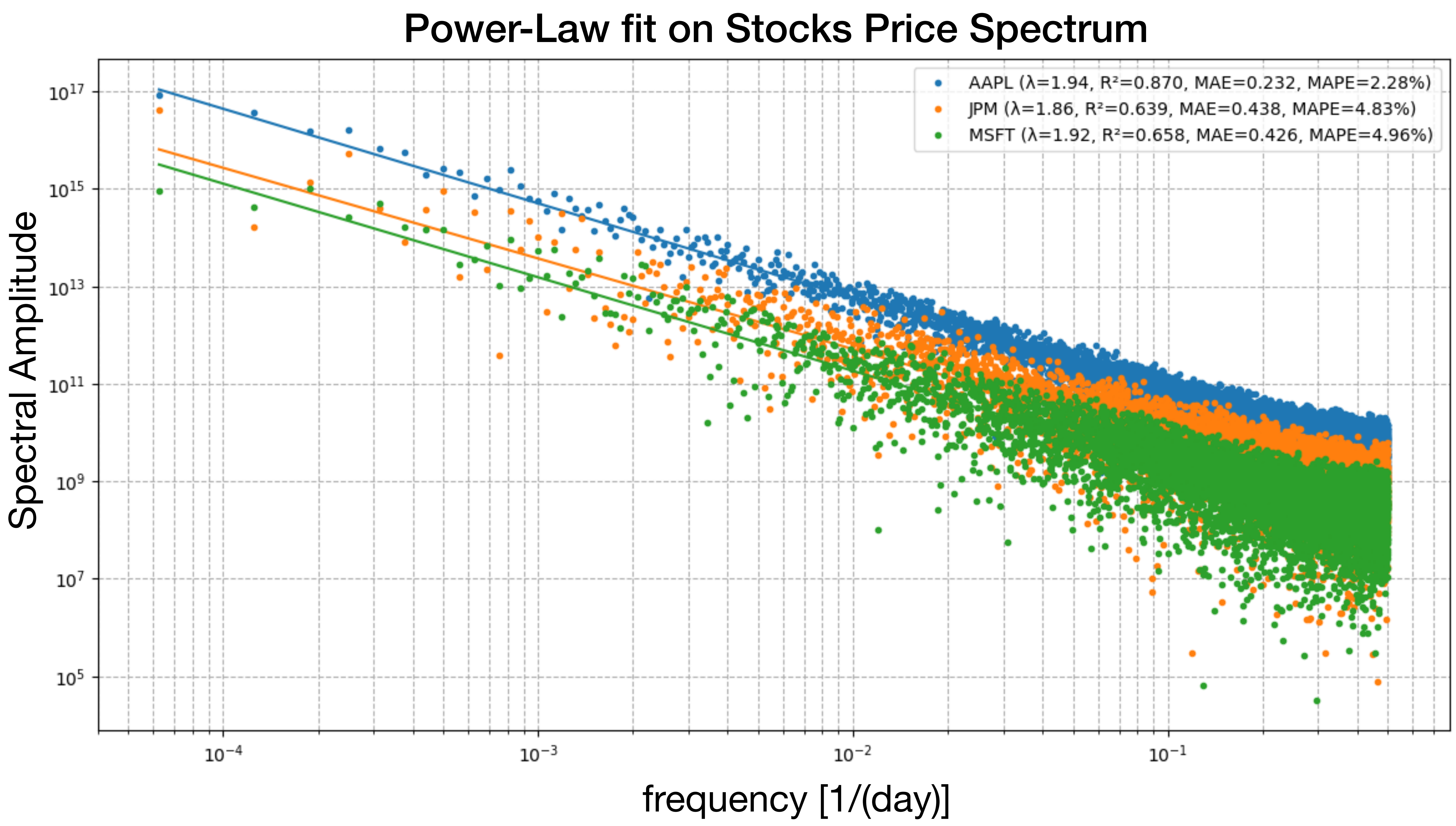
$$\log A(f) = a - \lambda \log f$$

Exhibit

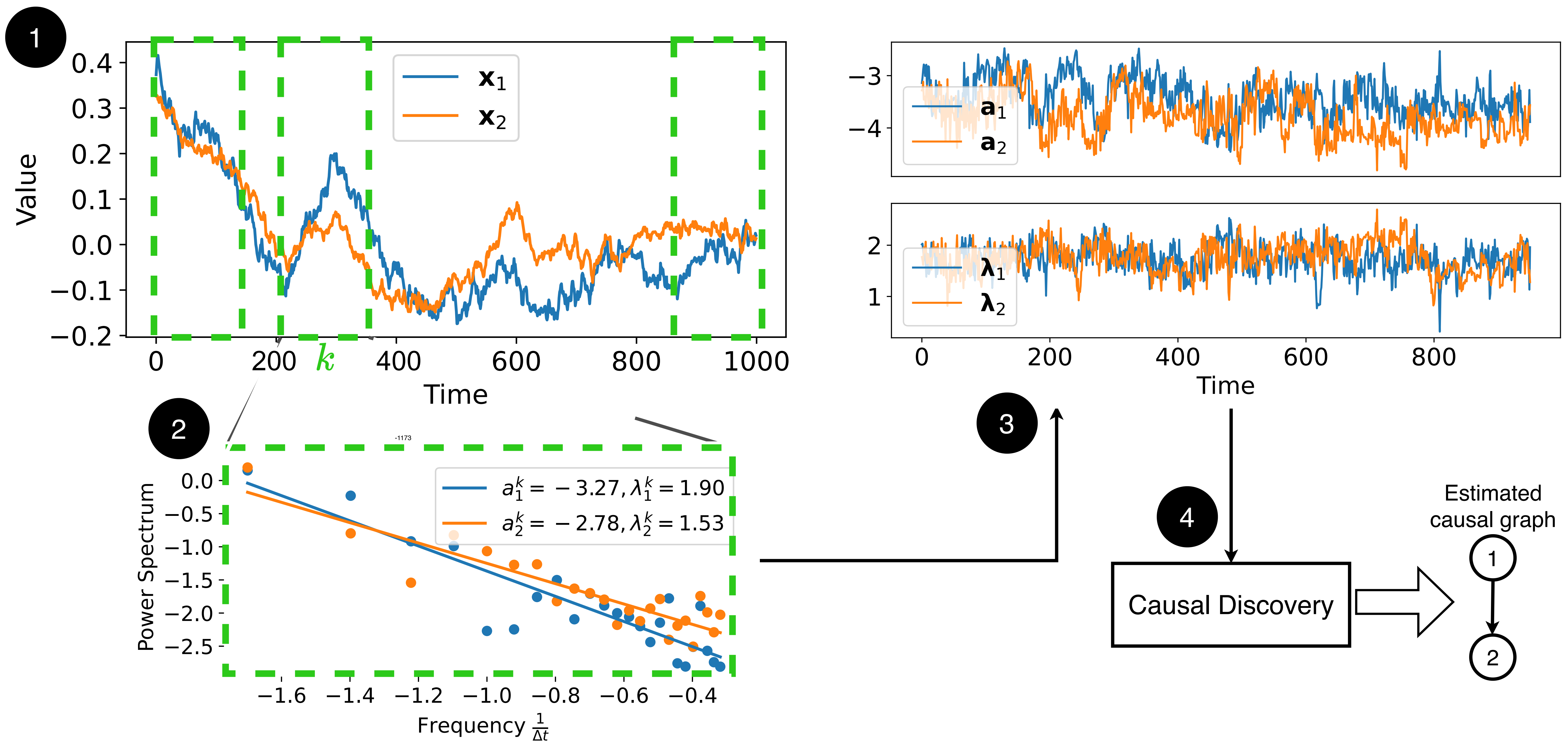
Scale-free behaviour
Self-organized criticality

Observed in

Finance
Climate science
Networks
Neuroscience



Placy : Algorithm Description



1. Time series $\mathbf{x}_1$ and $\mathbf{x}_2$ are fragmented into overlapping windows
2. For each window k, compute amplitudes (a_1^k,a_2^k) and exponents (λ_1^k,λ_2^k) of the power-law spectra
3. Obtain new, multi-dimensional, time series: ($\mathbf{a}_1$,$\boldsymbol{\lambda}_1$) for $\mathbf{x}_1$ and ($\mathbf{a}_2$,$\boldsymbol{\lambda}_2$) for $\mathbf{x}_2$
4. Apply multi-variate Granger Causality tests to construct causal graph

OU-process

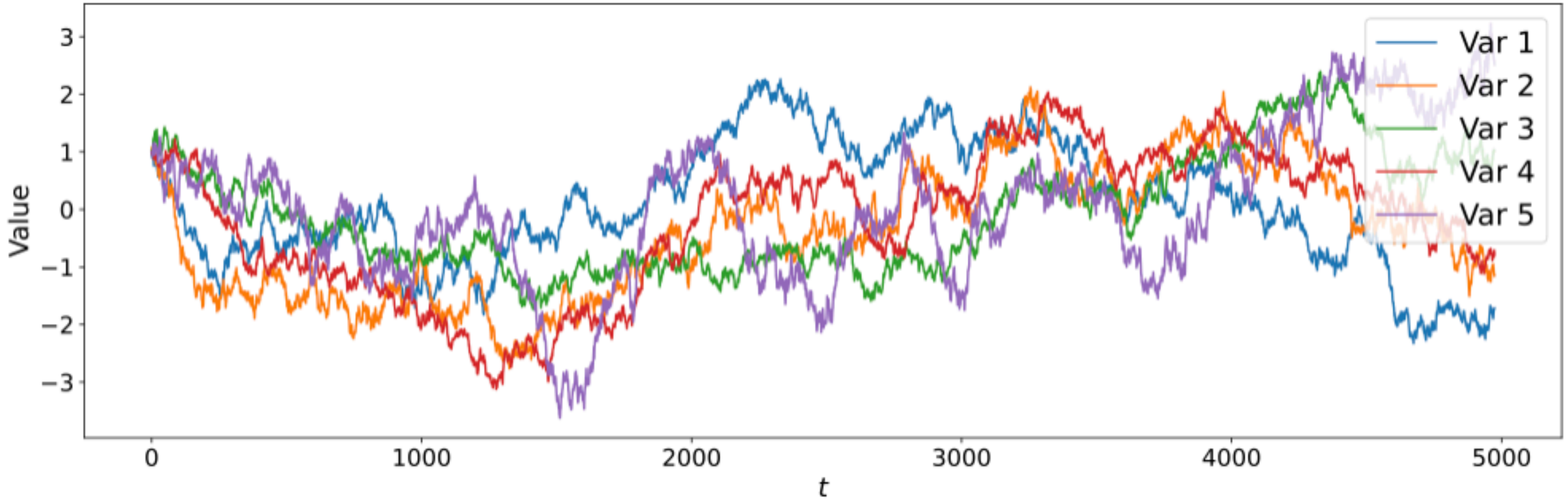
Data generation

- Ornstein-Uhlenbeck (OU) processes:

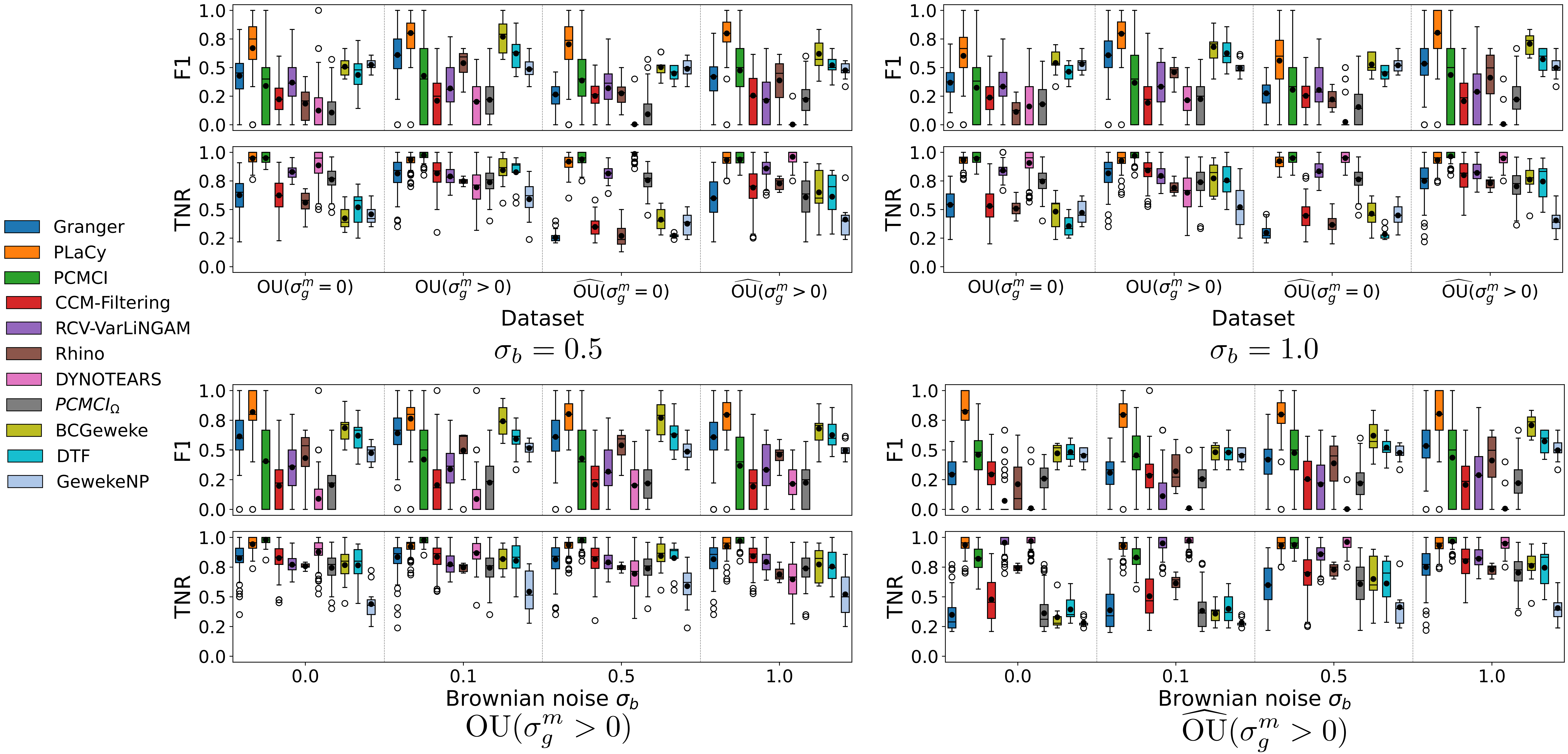
$$x(t+\Delta t) = x(t) + \frac{\Delta t}{\tau_c}(\mu - x(t)) + \left(\sigma_b \epsilon_b(t) + \sigma_g^a \epsilon_g^a(t) + \sigma_g^m \epsilon_g^m(t) \cdot x(t)\right)\sqrt{\Delta t}$$

- Causality introduced linearly after the data generation process

$$\forall t,\ x_j(t) \leftarrow x_j(t) + C \cdot x_i(t-\tau)$$



Results on Synthetic datasets



Results on Real world datasets

Rivers

Data from three hydrological stations located in southern Germany, namely Dillingen, Kempten, and Lenggries

Airquality

Pollution measurements collected over one year from N = 36 monitoring stations across various Chinese cities

	Rivers		AirQuality	
Algorithm	**F1**	**TNR**	**F1**	**TNR**
Granger	0.47 ± 0.07	0.64 ± 0.09	0.41 ± 0.02	0.22 ± 0.05
PLaCy	$\mathbf{0.51} \pm 0.10$	$\mathbf{0.75} \pm 0.13$	$\mathbf{0.45} \pm 0.04$	0.66 ± 0.07
PCMCI	0.47 ± 0.07	0.74 ± 0.05	0.25 ± 0.03	$\mathbf{0.95} \pm 0.02$
CCM	0.28 ± 0.01	0.19 ± 0.00	0.40 ± 0.00	0.04 ± 0.00
RCV	0.16 ± 0.12	0.51 ± 0.12	—	—
Rhino	0.29 ± 0.03	0.35 ± 0.05	0.44 ± 0.01	0.23 ± 0.04
DYNO.	0.12 ± 0.07	0.53 ± 0.06	0.37 ± 0.08	0.92 ± 0.03
$\mathbf{PCMCI_{\Omega}}$	0.10 ± 0.09	0.57 ± 0.05	0.36 ± 0.04	0.69 ± 0.07
BCGeweke	0.41 ± 0.06	0.61 ± 0.08	0.39 ± 0.02	0.16 ± 0.07
DTF	0.36 ± 0.05	0.42 ± 0.12	0.43 ± 0.02	0.36 ± 0.09
GewekeNP	0.26 ± 0.05	0.31 ± 0.06	0.40 ± 0.02	0.13 ± 0.07

Conclusion

- **Power-law spectra are common in real-world time series**
- **Spectral descriptors improve robustness to noise and non-stationarity**
- **Placy achieves competitive or state-of-the-art causal discovery performance**

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