RELIABLE CAUSAL DISCOVERY IN TIME SERIES

Workshop on Artificial Intelligence, Causality and Personalised Medicine (AICPM 2022) - September 8-9, 2022

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Causal Inference group at the DLR-Institute of Data Science

DLR

Goal

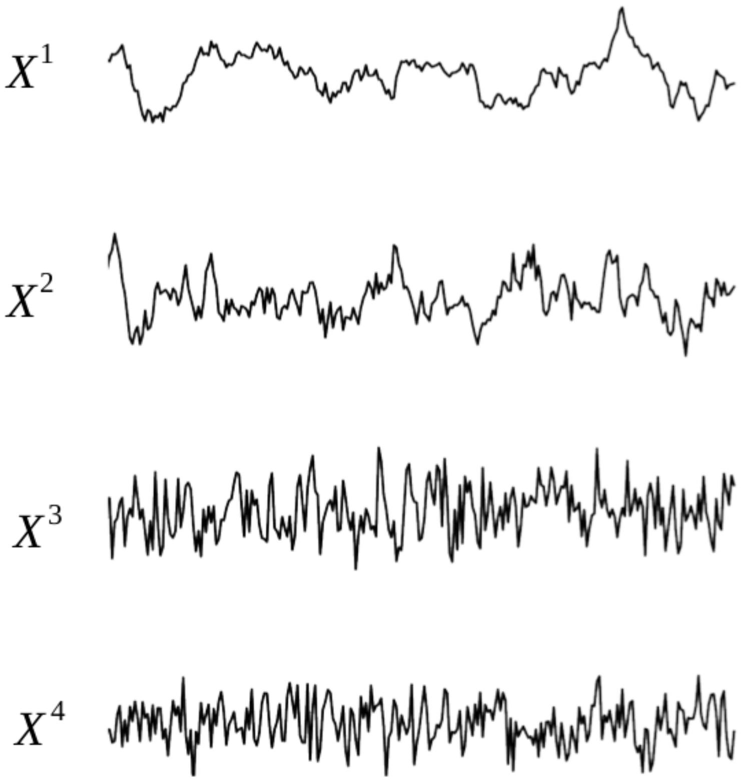
- Contribute to a data-driven understanding of complex dynamical systems

Systems of interest

- Not limited to a particular field of study
- So far majority of application cases from Earth and Climate sciences, but also beyond

Approach

- Development of theory and methods
- Provisioning within the open-source Python package **tigramite** for application by domain scientists
- Focus on the modern **causal inference** framework



What is causation?

Correlation is not causation

- Statistical dependencies in observational data do not necessarily imply causal relationships.

History of causation

- The notion of causation has a long history in philosophy and science that involves strong disputes over its meaning and importance.
- Here, we neither attempt to discuss this at length nor attempt to enter this dispute.

Working definition of causality

- Variable X causes variable Y if an experimental manipulation that changes X and only X, referred to as an **intervention** on X, leads to a change of Y.

→ Experimental / interventional notion of causation

Why is causal knowledge important?

Scientific understanding

- Knowledge of cause and effect relationships is an essential part of the physical understanding of natural processes

Robust prediction & forecasting

- Predictive systems consistent with the underlying causal structures are thought to be more robust under changing environmental conditions (see, e.g., [Schölkopf et al., 2021] and [Arjovsky et al.,. 2019])

Decision making

- Given the current state of affairs, how should I act in order to achieve a certain goal?

Attribution

- Questions of the type *Why did this event happen?* are of causal nature.

The causal inference framework

Causal inference

- Casts notion of causation in a mathematical framework
- Formalizes causal questions such as
  - Does variable X cause Y?
  - How large is the effect of X on Y?
- Specifies assumptions that connect causation and statistical dependence
- Provides methods for **answering causal questions from data**

Key references

- Pearl, J., Causality: Models, Reasoning, and Inference, 2nd edition (Cambridge University Press, 2009)
- Spirtes, P., Glymour, C., and Scheines, R., Causation, Prediction, and Search (MIT Press, 2000)
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Causal discovery

- Learn qualitative cause-and-effect relationships between a set of variables

Causal effect estimation

- Quantify the causal relationships between variables

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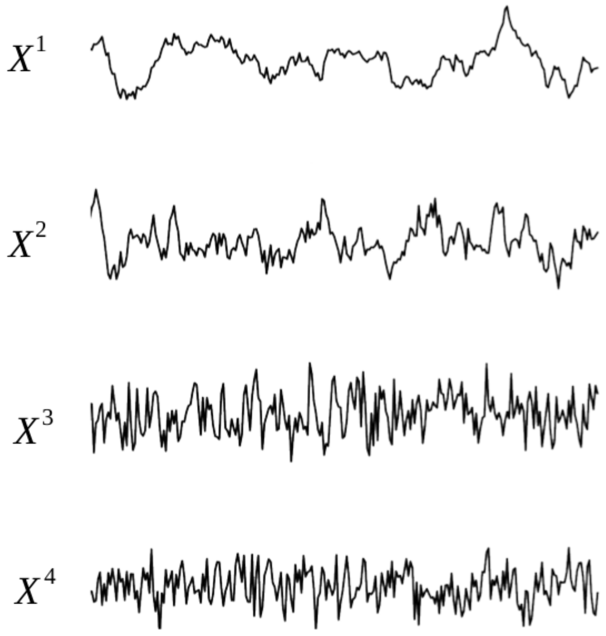
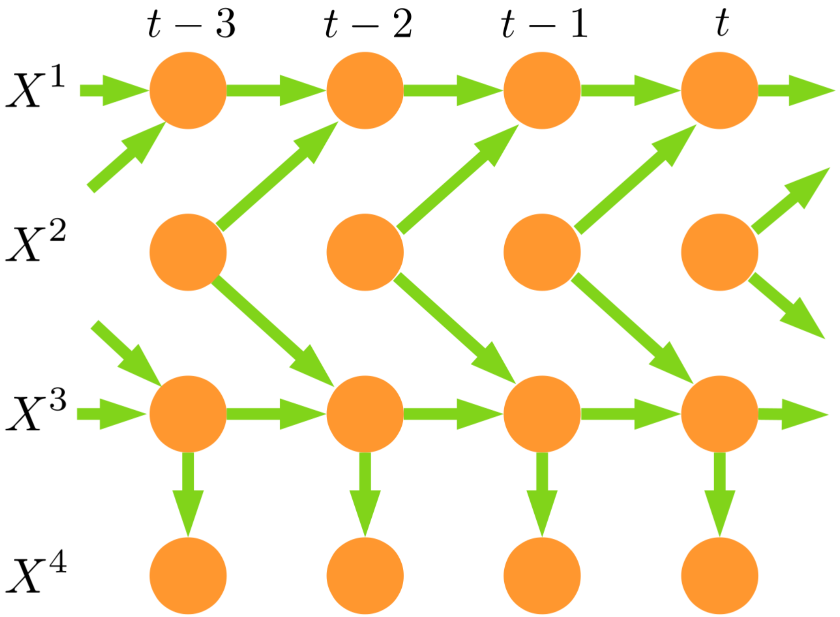
Learning causal relationships in time series data

Task

- Learn qualitative cause-and-effect relationships, i.e., the causal graph of the data-generating process from observational data





Causal discovery based on statistical independencies

Considered approach to causal discovery

- Learn causal graph from (conditional) independencies in the observational data, which are tested statistically (*CI-based causal discovery*)

Intuition

$$X \rightarrow Y \rightarrow Z$$

- X influences Y: $X \not\perp\!\!\!\perp Y$ (dependence)
- Y influences Z: $Y \not\perp\!\!\!\perp Z$ (dependence)
- X influences Z through Y: $X \not\perp\!\!\!\perp Z$ (dependence)
- Knowing Y, X does not say more about Z: $X \perp\!\!\!\perp Z \mid Y$ (conditional independence)

Structure of causal graph imposes pattern of (conditional) dependence and independence

Causal discovery based on statistical independencies

Idea

- Perform statistical tests of (conditional) independence in observational data
- Use test results to constrain the structure of the causal graph

Enabling assumptions

- Data generated by structural causal model (i.e., system is composed of independent mechanisms)
- No „accidental“ independencies (so-called *causal faithfulness*)
- Typical: No cyclic causation (can be avoided)
- Optional: No unobserved confounders

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Example

Test decisions:

$$X \not\perp\!\!\!\perp Y$$
$$Y \not\perp\!\!\!\perp Z$$
$$X \perp\!\!\!\perp Z$$

Possible causal graphs:

$$X \rightarrow Y \leftarrow Z$$

(assuming no unobserved confounders)

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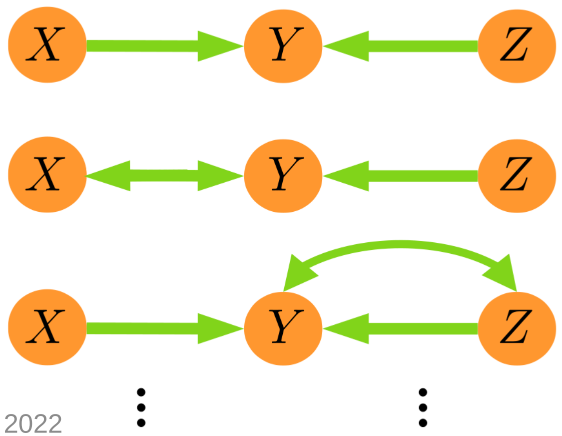

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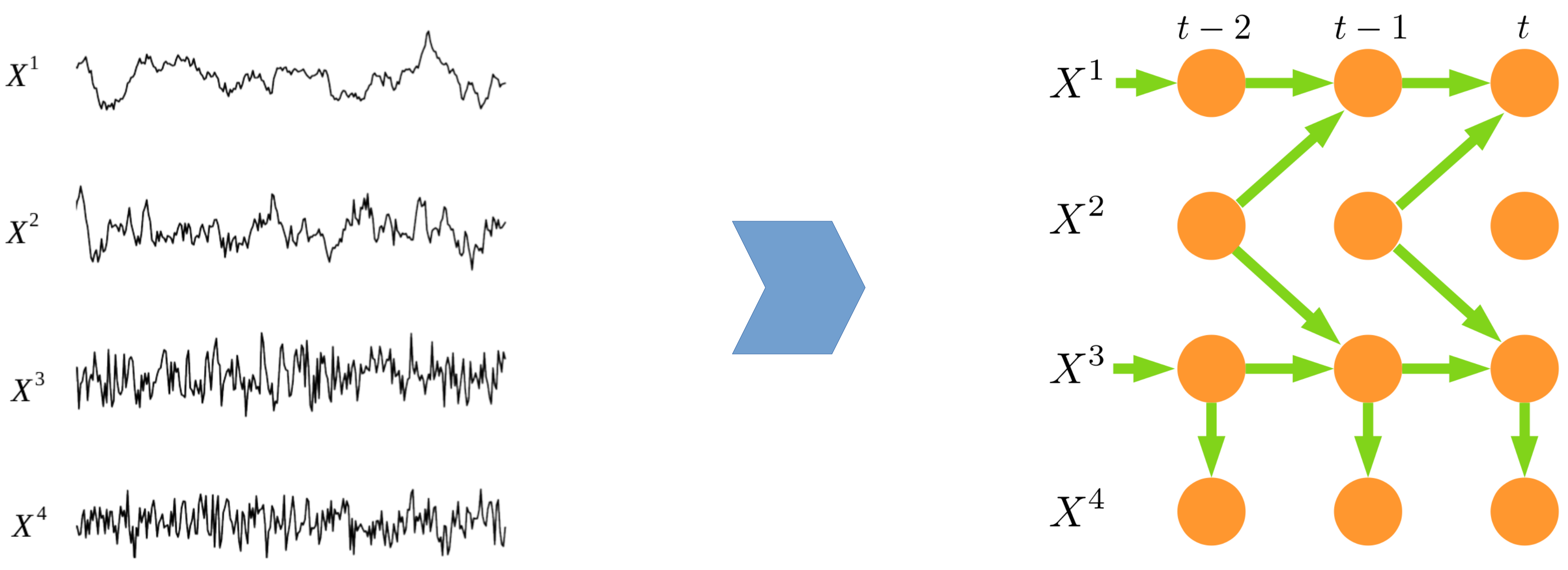
CI based causal discovery for time series



Particularities

- Variables are resolved in time
- Autocorrelation

Additional assumption

- Stationary causal structure (can be avoided)

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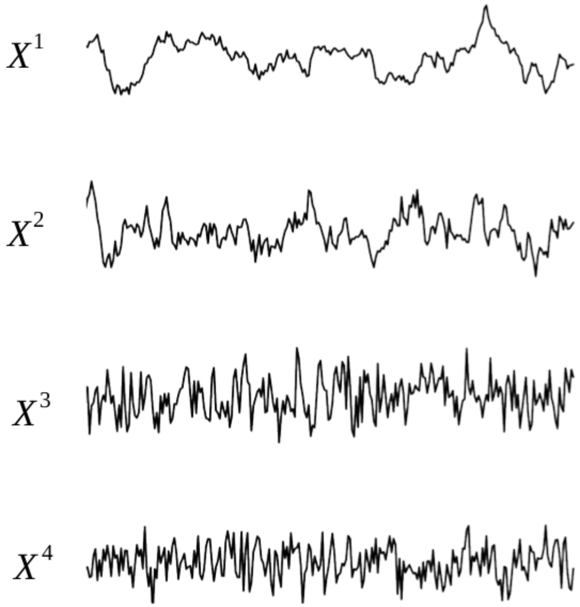

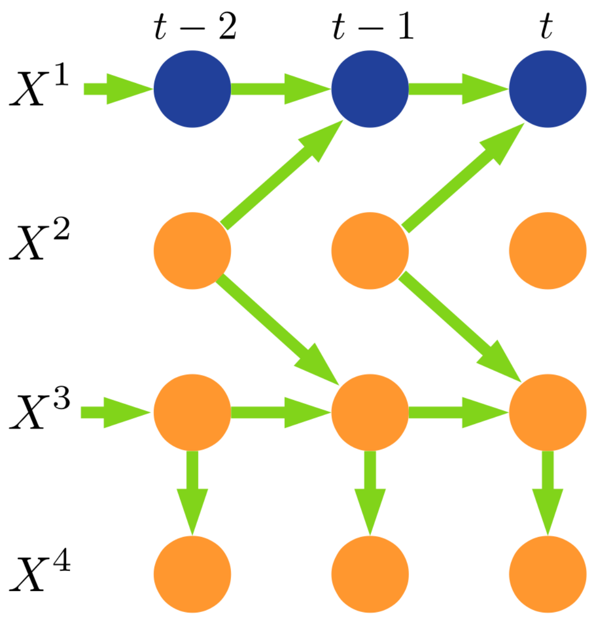

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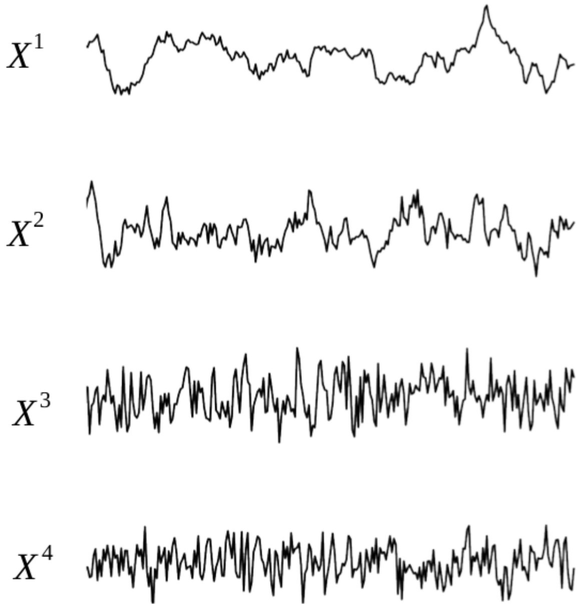

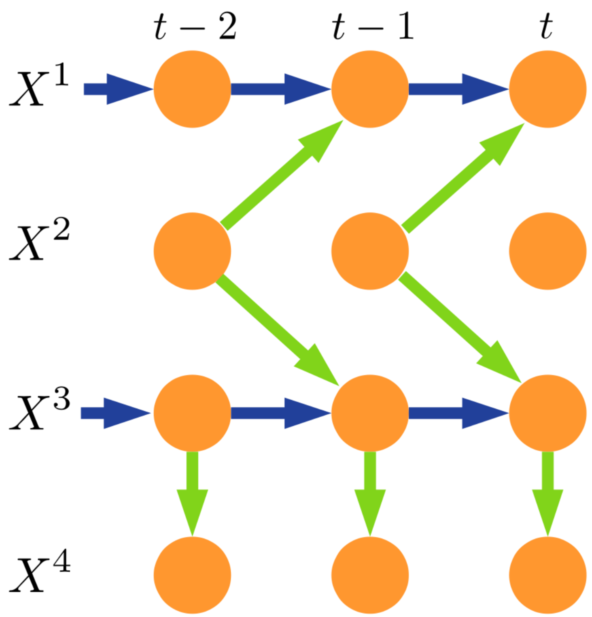

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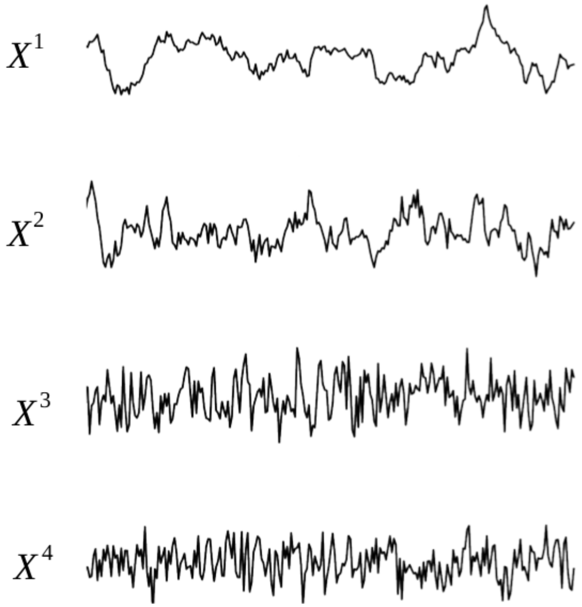

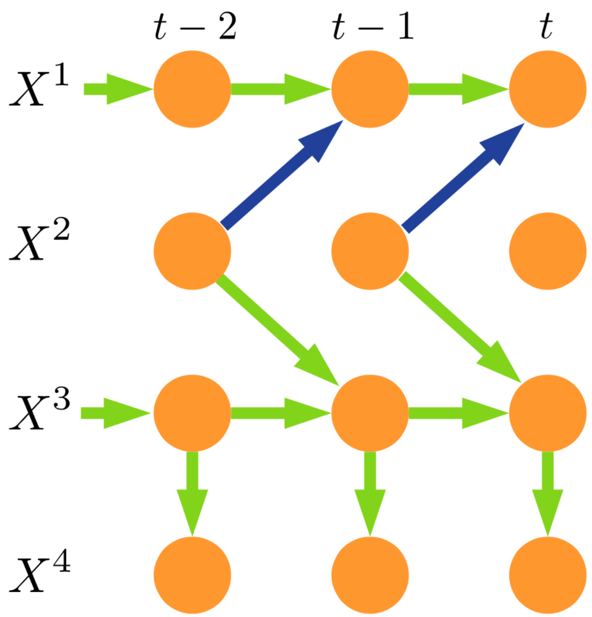

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CI based causal discovery for time series

Statistical challenges due to autocorrelation

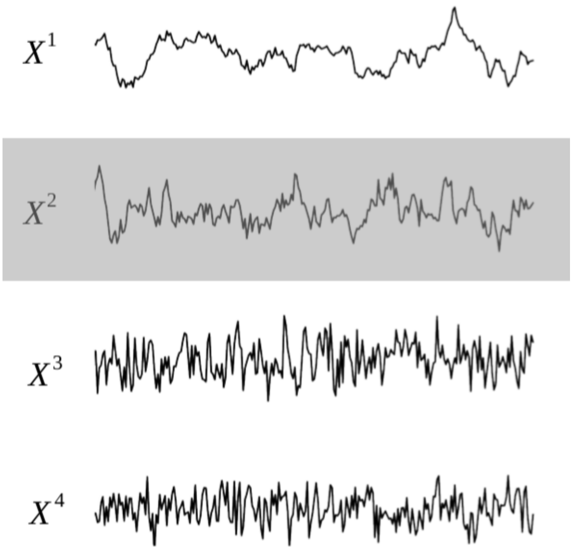
- Ill-calibrated statistical tests of independence
- Low detection power for true causal links

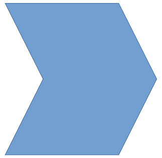
→ Standard algorithms often yield bad statistical performance

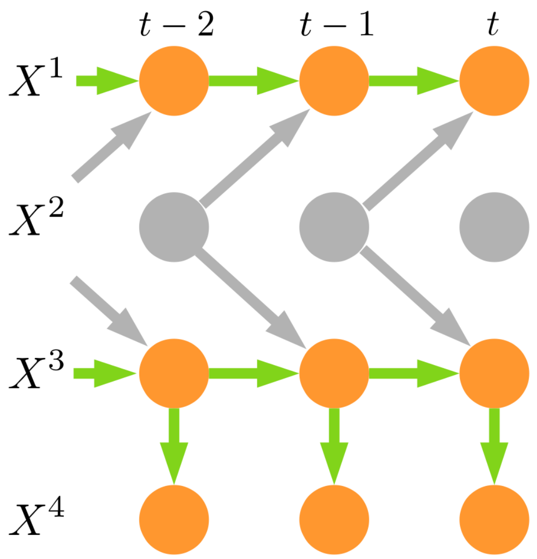
Our contribution

- Statistical problems alleviated by specialized algorithms developed by the Causal Inference group of the DLR-Institute of Data Science in Jena
  - PCMCI (time lagged links only & no unobserved confounders) [Runge et al., 2019]
  - PCMCI+ (no unobserved confounders) [Runge, 2020]
  - Latent-PCMCI [Gerhardus and Runge, 2020]
- All algorithms available within the open-source Python package *tigramite*

Causal discovery with Latent-PCMCI







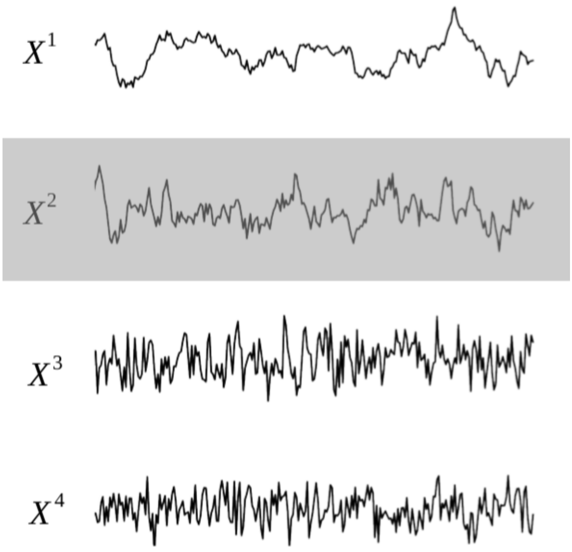
Allows for

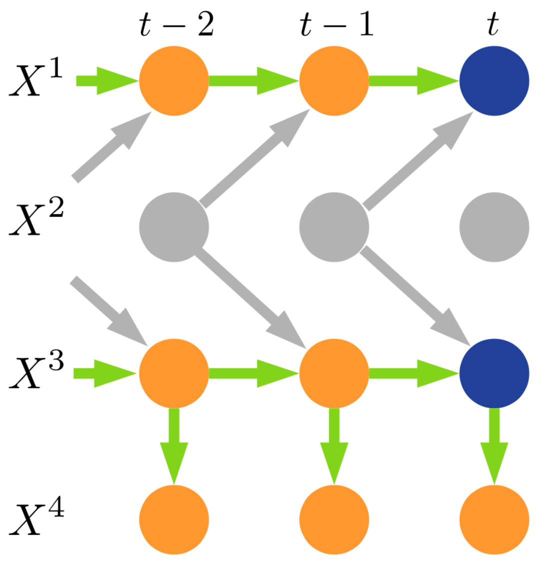
- Contemporaneous causal links (also PCMCI+ does)
- Unobserved confounders

Basic idea

- More powerful CI tests by iterative learning of and subsequent conditioning on direct causes

Causal discovery with Latent-PCMCI





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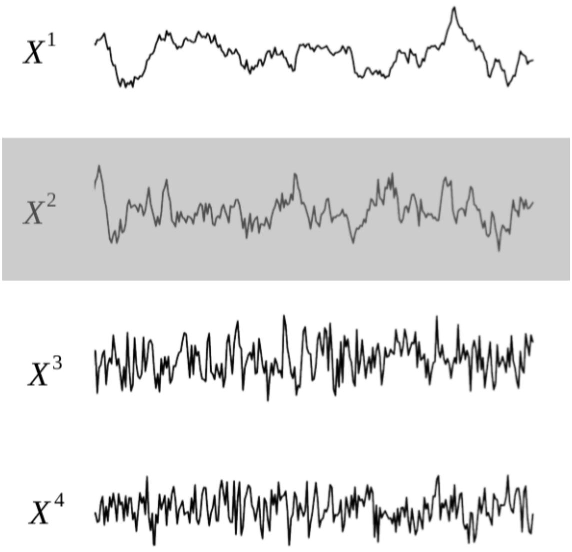

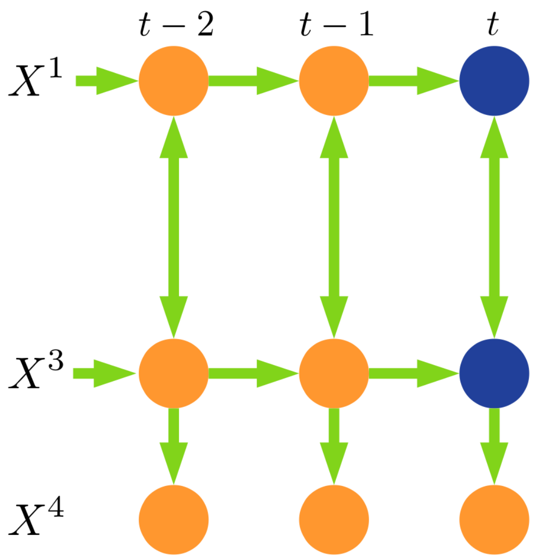

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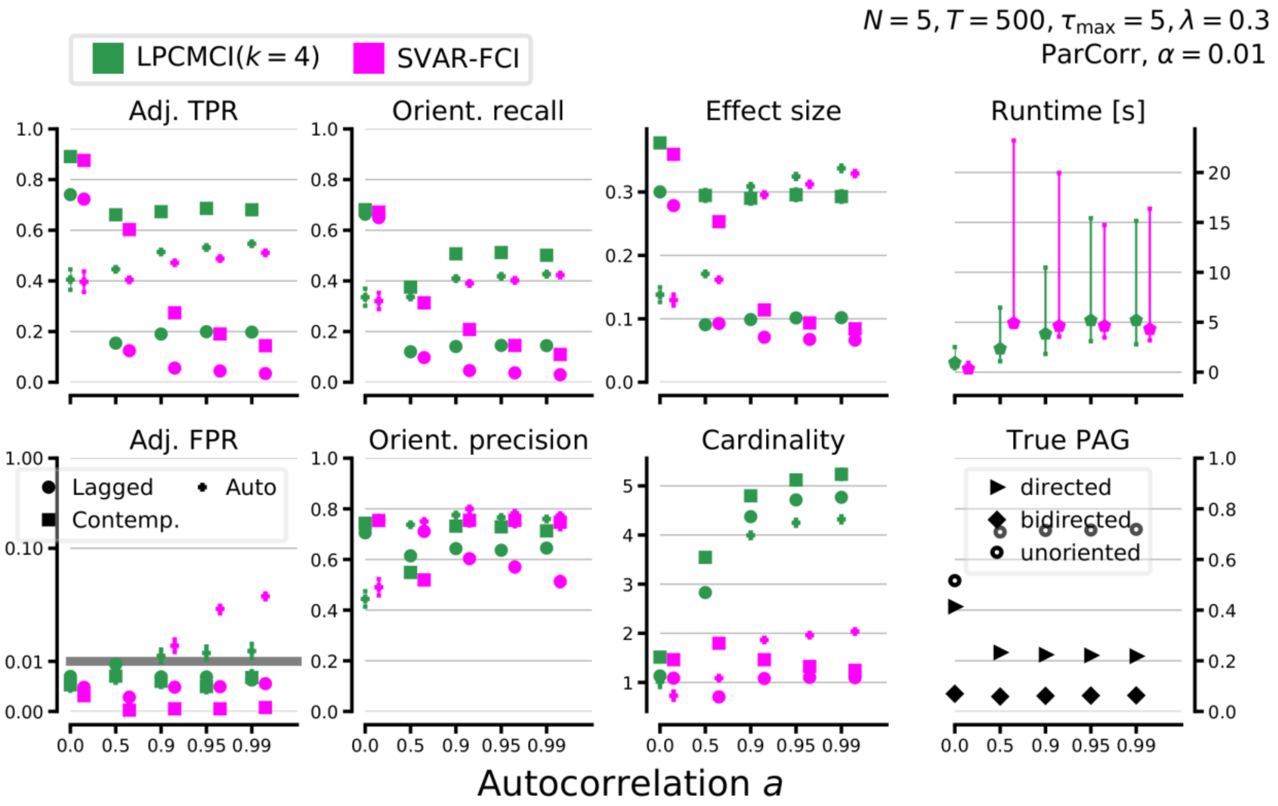
Simulation study: Latent-PCMCI (LPCMCI)

Key finding

- For autocorrelated continues data Latent-PCMCI shows strong gains in recall as compared to the previous state-of-the-art algorithm SVAR-FCI by [Malinsky and Spirtes, 2018]



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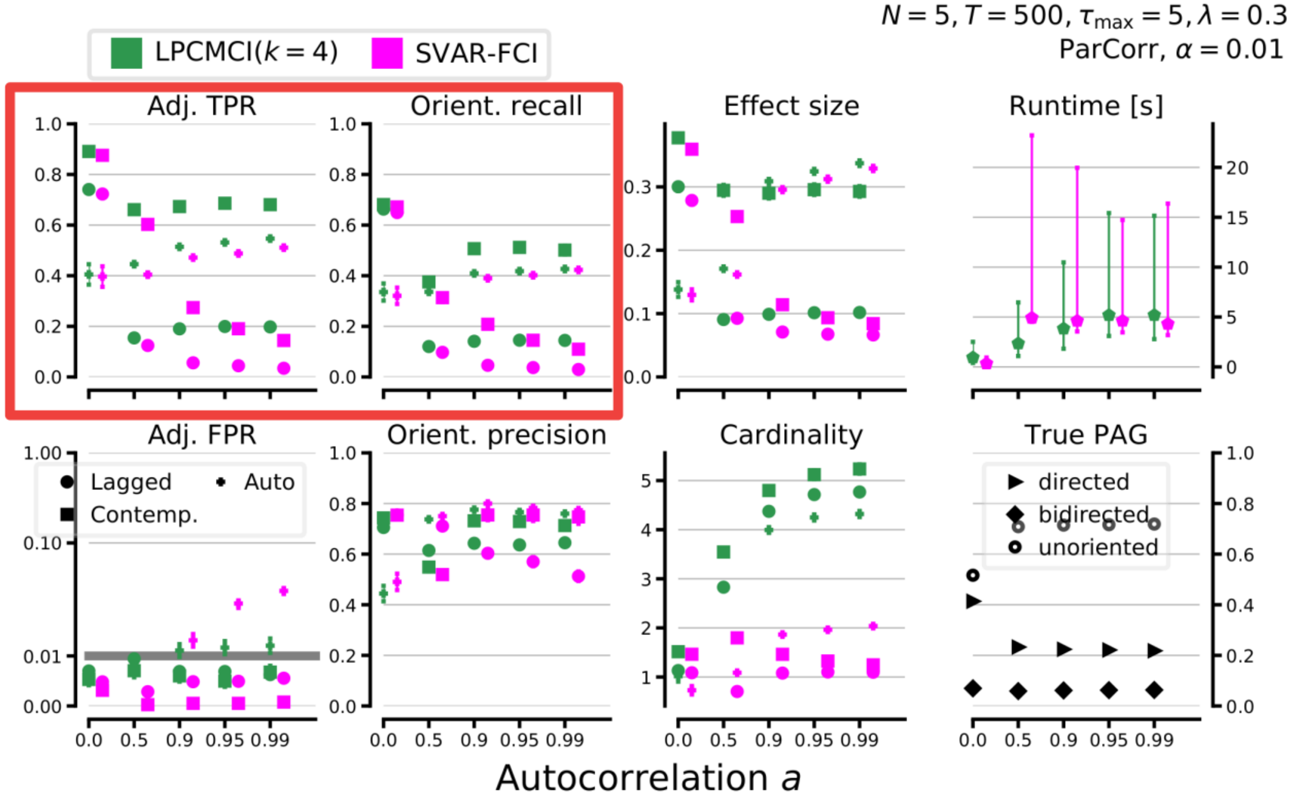

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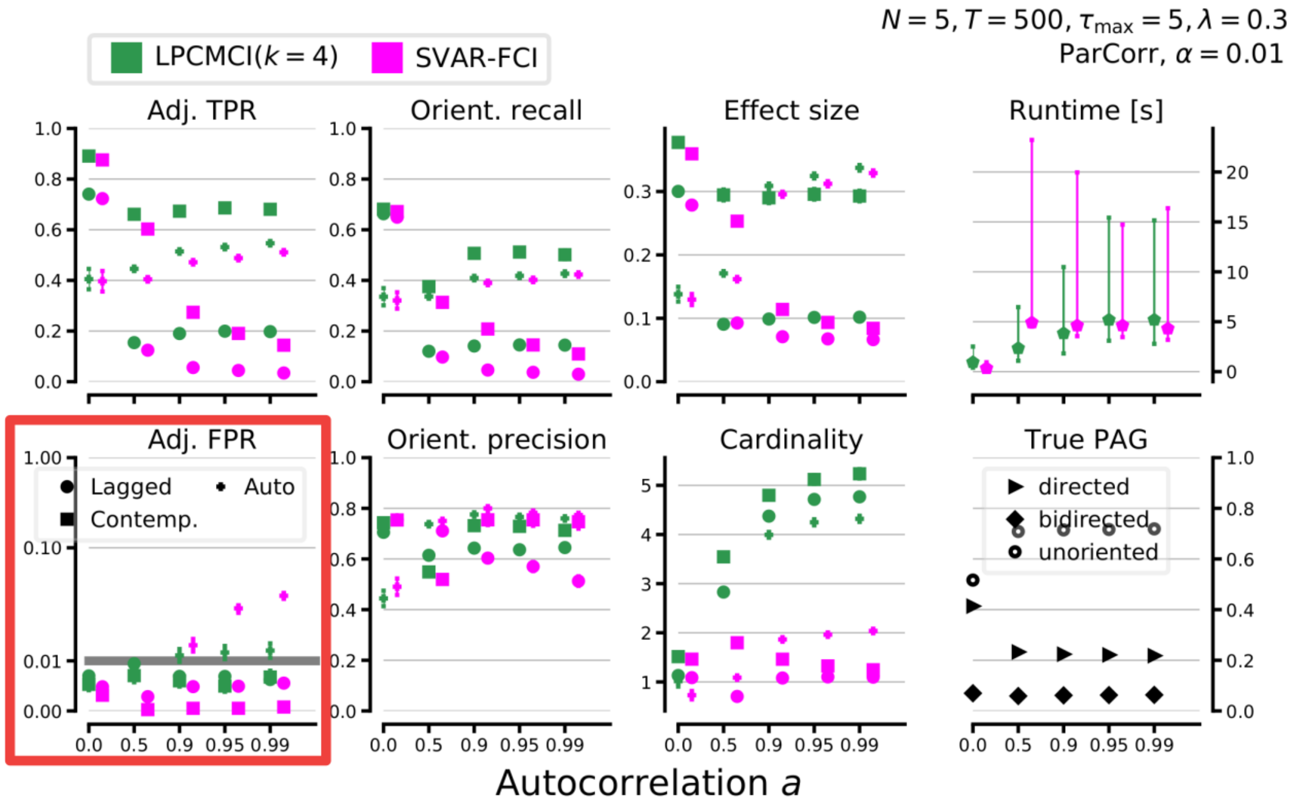

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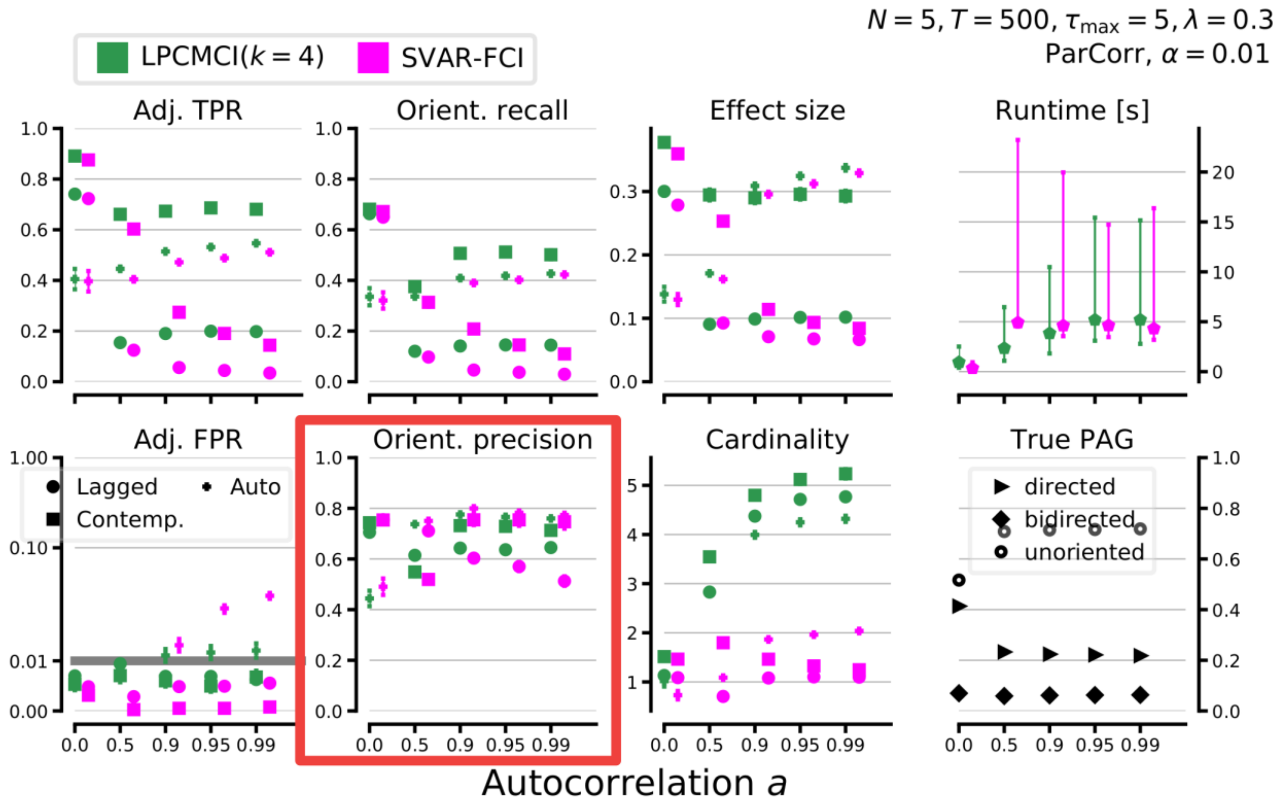


Application examples

- (PCMCI) Reconstruction of the **Walker circulation** from observed surface pressure and surface air temperatur anomalies in the West, Central, and East Pacific

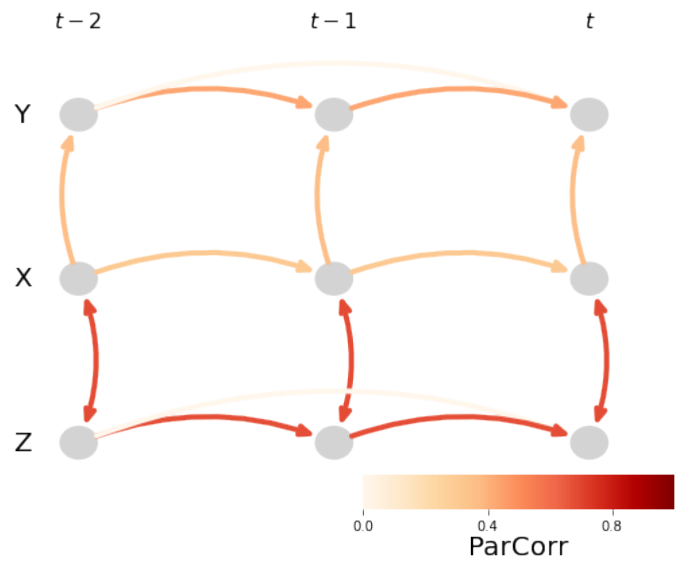
  → see Runge, J., et al., *Inferring causation from time series in earth system sciences*. Nature Communications, 10:2553.

- (PCMCI) Causal graph between different **arctic drivers and midlatitude winter circulation**

  → see Kretschmer, M., Coumou, D., Donges, J. F. & Runge, J. Using causal effect networks to analyze different arctic drivers of midlatitude winter circulation J. Clim. 29, 4069–4081 (2016)

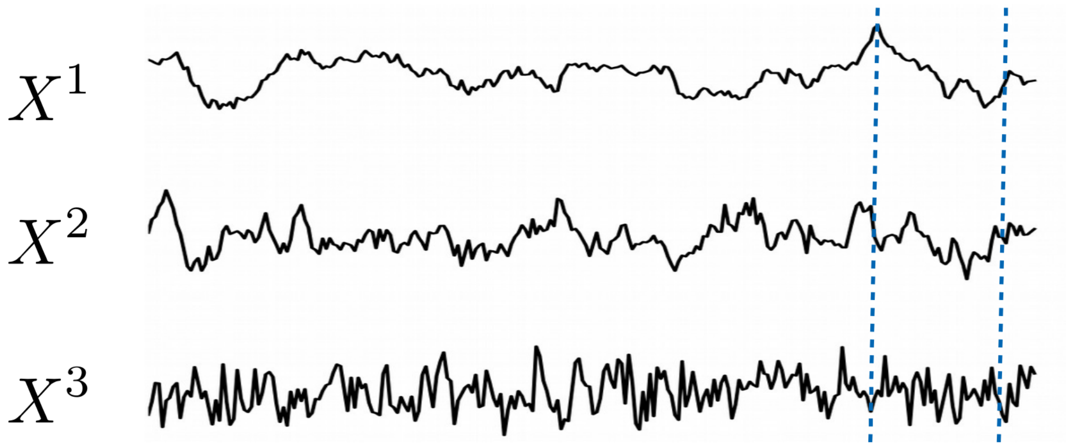
- (Latent-PCMCI) Causal connections between average daily **discharges of three rivers** in the upper Danube basin

  → see Gerhardus, A. & Runge, J. *High-recall causal discovery for autocorrelated time series with latent confounders.* Advances in Neural Information Processing Systems, 2020, 33.



Causal discovery from a single vs. from a collection of time series

From a single time series



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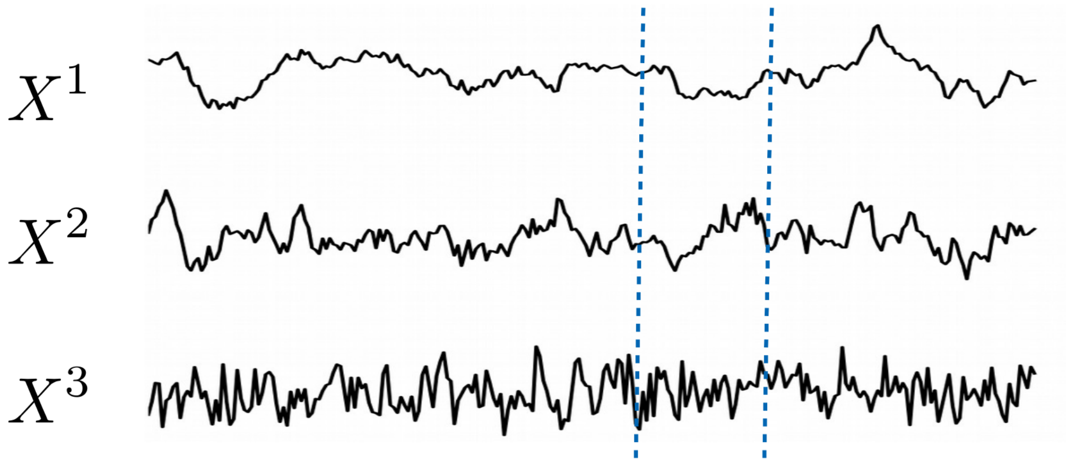

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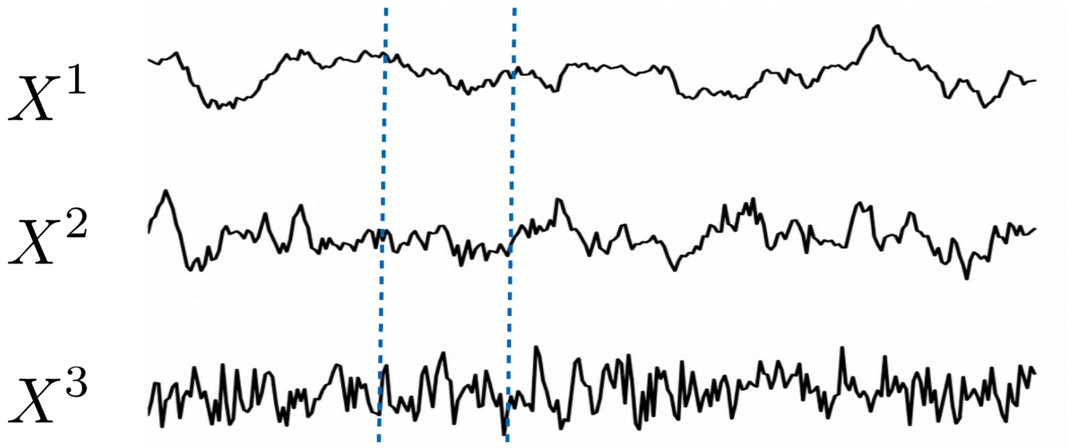

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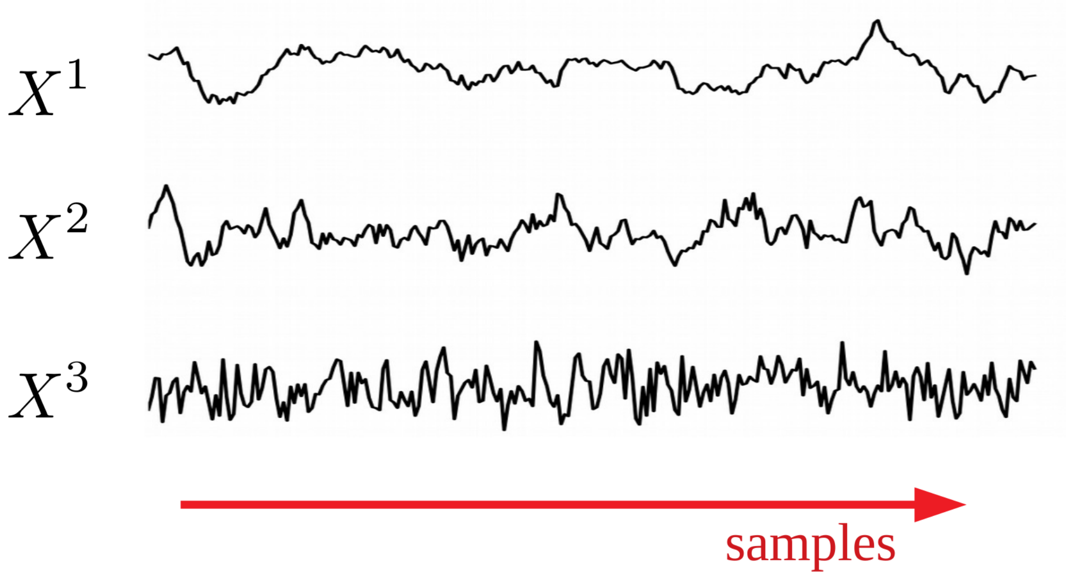

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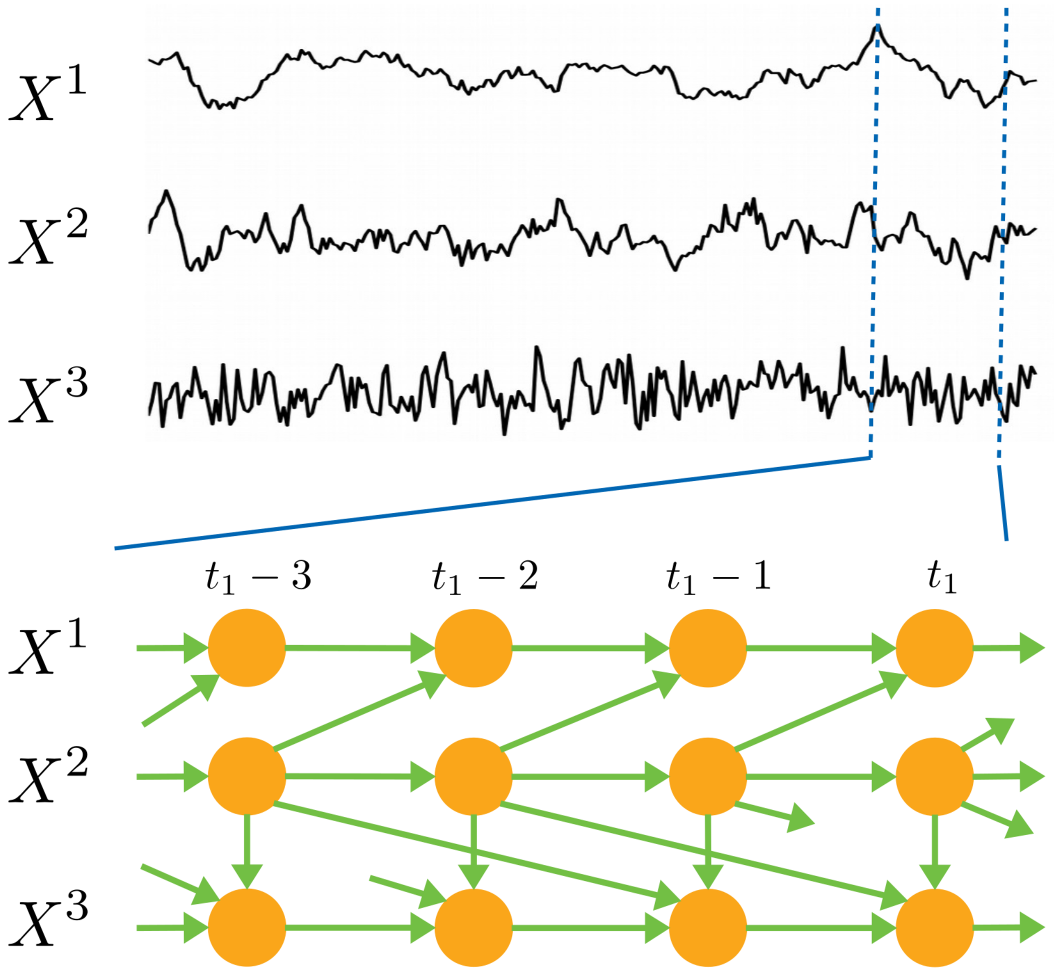

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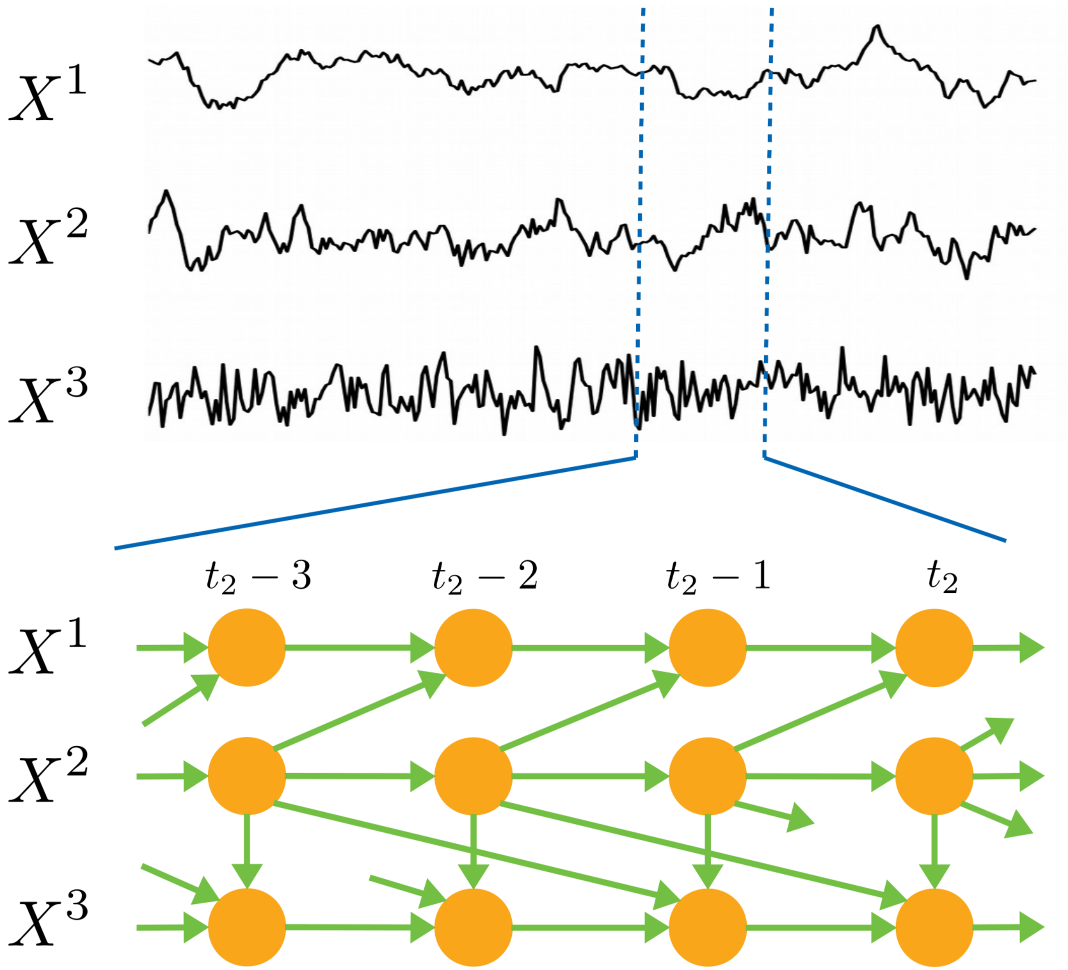

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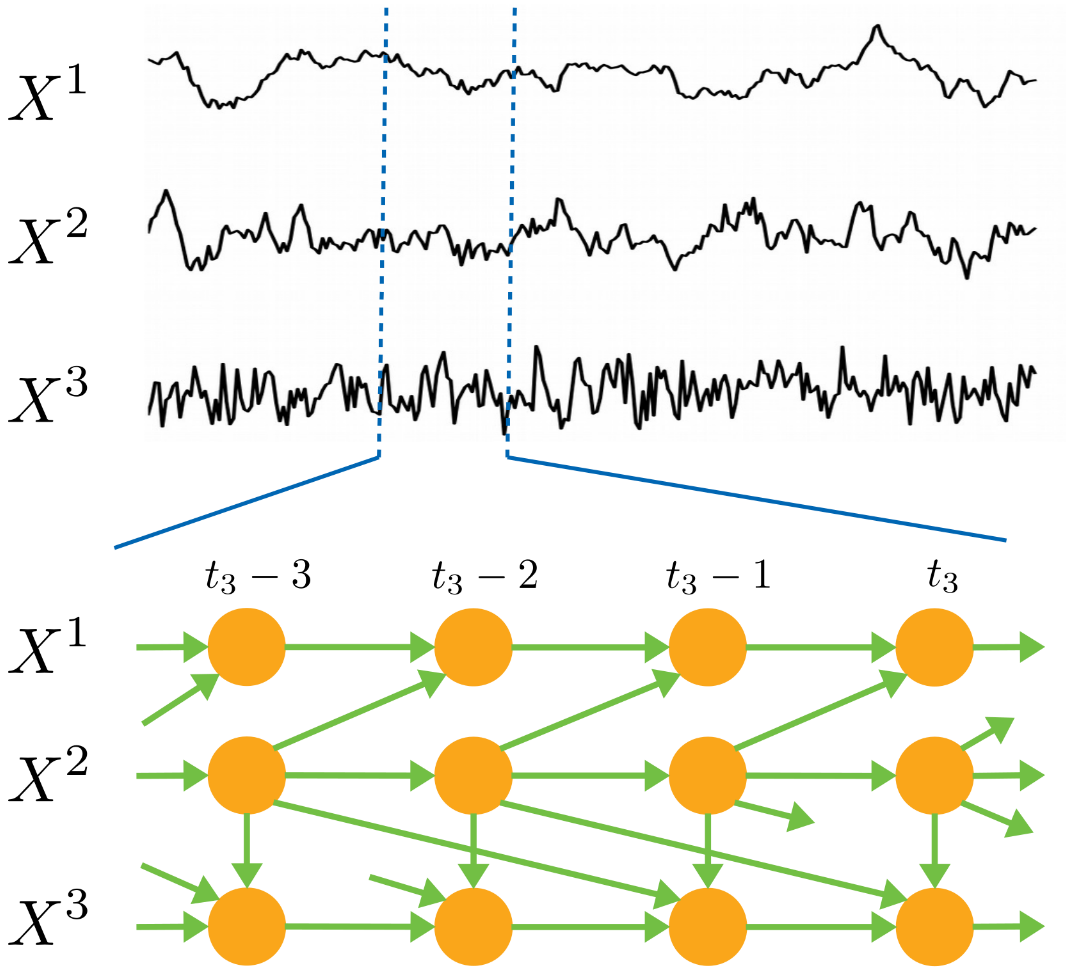

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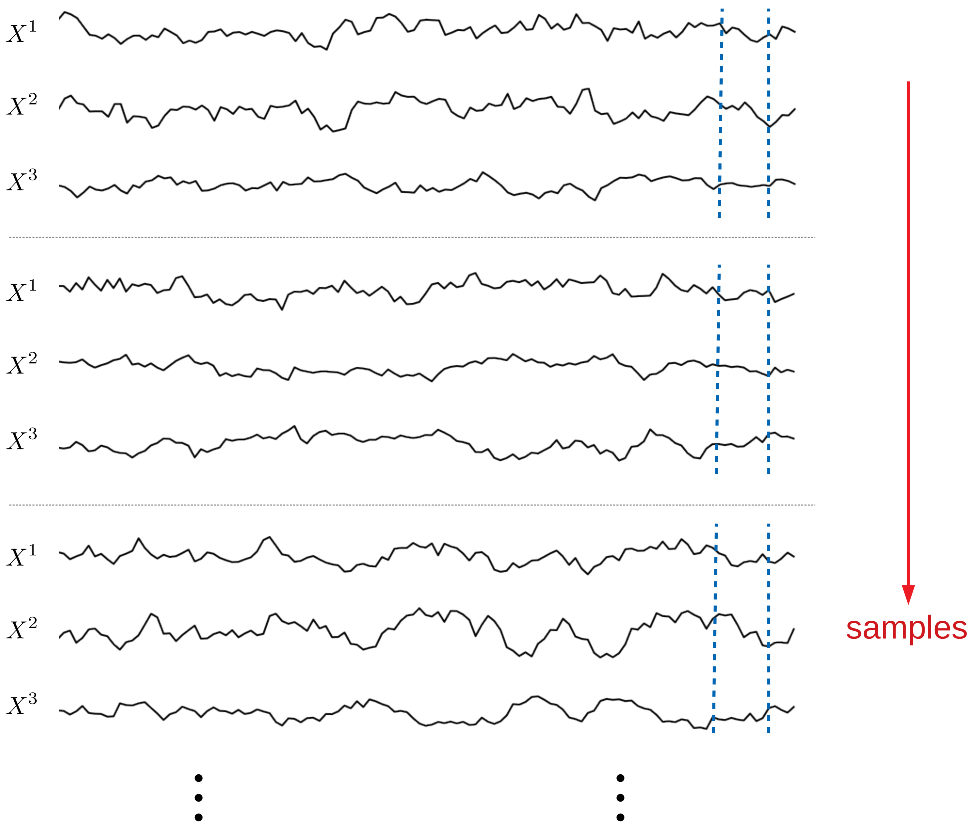

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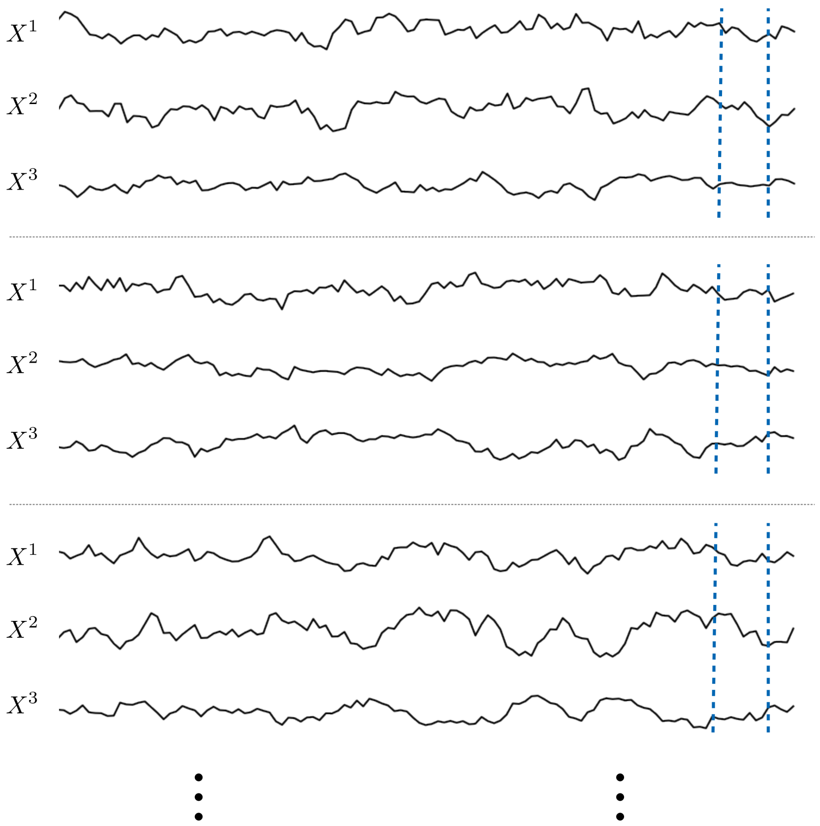

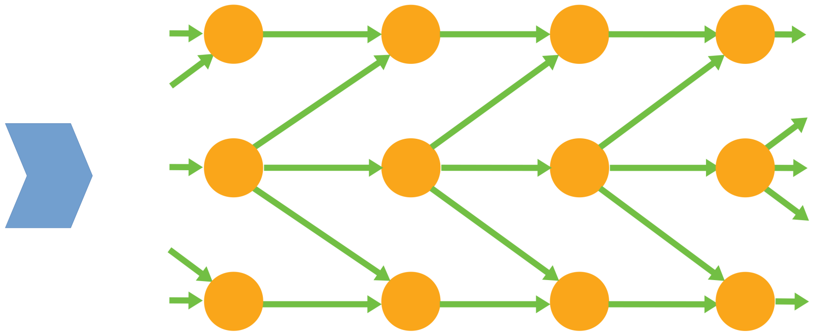

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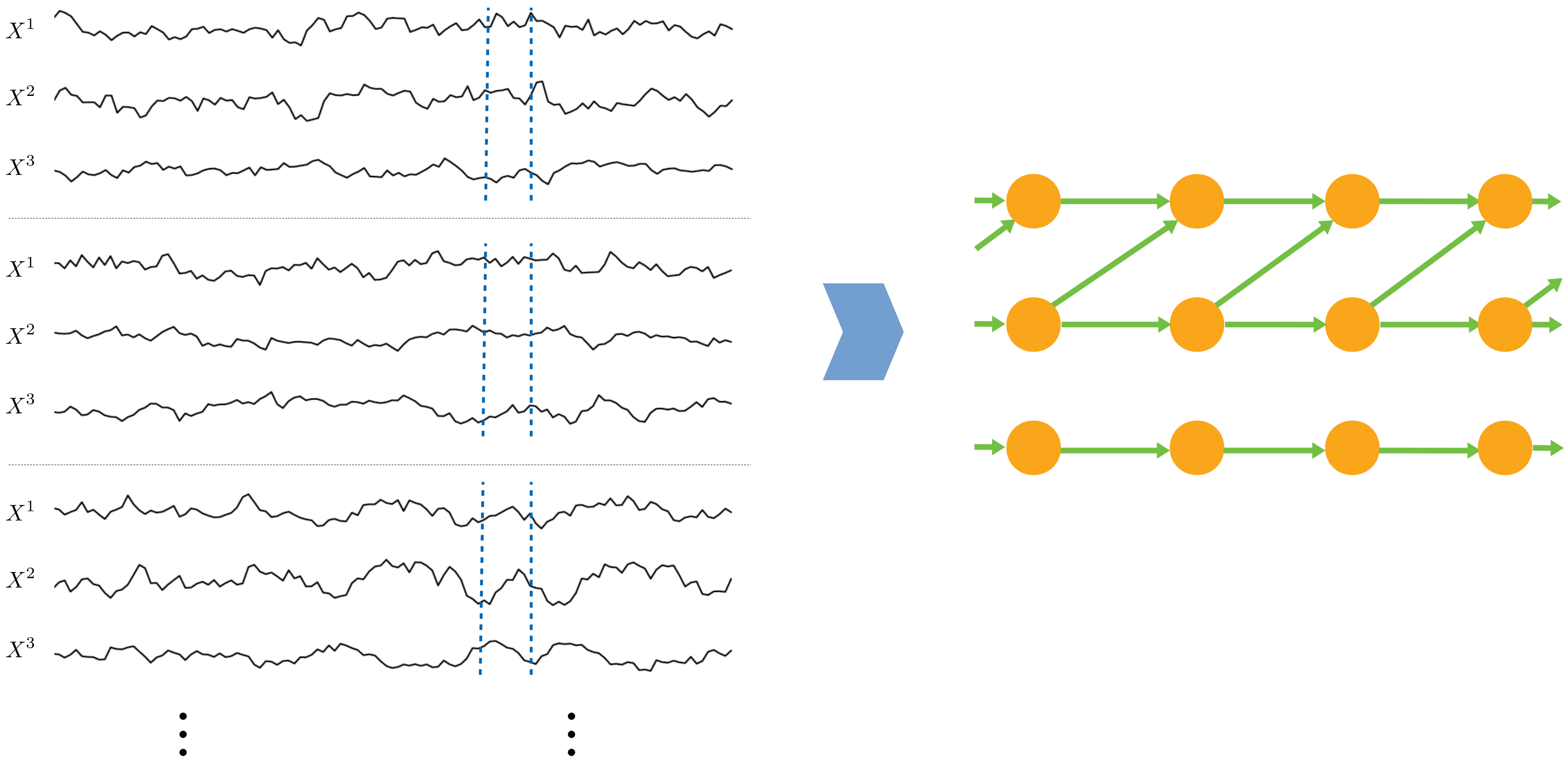

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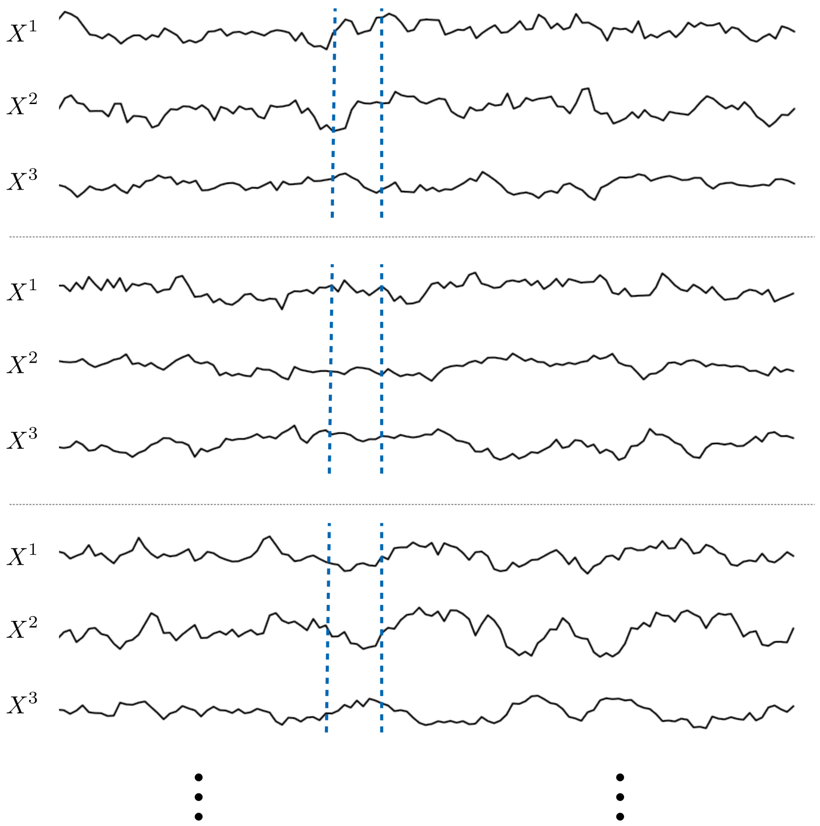

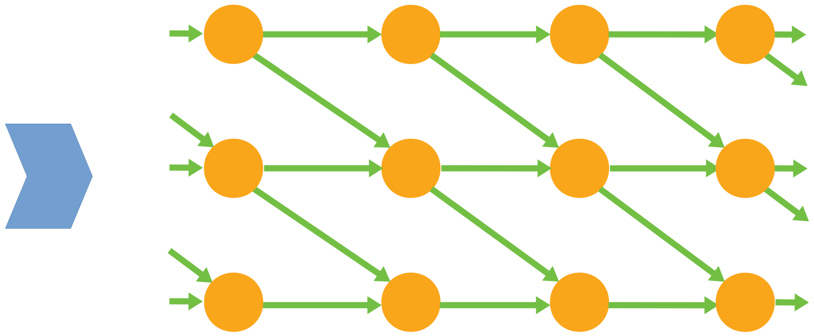

Thank you

- Thanks a lot for your attention!
- Questions? Comments? Feedback?

References

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