Causal Discovery from Temporal Data

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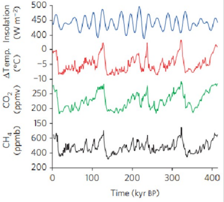
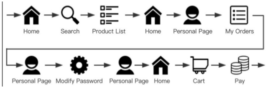
Temporal Data

- It records the status changing of complex systems.
- It consists of attribute sequences ordered by time.
- According to whether the data is calibrated, it can be categorized into two groups, *i.e.*, multivariate time series (MTS) and event sequences.



MTS



Event Sequence

Temporal Data

- It is widely collected by various application domains, such as social networks, bioinformatics, neuroscience and finance.

- Different approaches have been proposed for different tasks such as classification[1], clustering[2], prediction[3].

[1] Hassan Ismail Fawaz, Germain Forestier, Jonathan Weber, Lhassane Idoumghar, and Pierre-Alain Muller. *Deep learning for time series classification: a review*. DMKD, 2009.

[2] Saeed Aghabozorgi, Ali Seyed shirkhorshidi, and Teh Ying Wah. *Time-series clustering-a decade review*. INFORM. SYST., 2015.

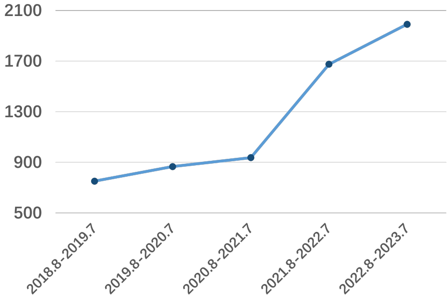
[3] Andreas S Weigend. *Time series prediction: forecasting the future and understanding the past*. Routledge, 2018

Causal Discovery for Temporal Data

- Causal discovery for temporal data recognizing the causal relations between many temporal components has become a challenging yet critical task for temporal data analysis.
- The learned causal structures could be beneficial for explaining the data generation process and guiding the design of data analysis methods.
- The wide applications in many fileds:
  - Scientific endeavours: Earth science, neuroscien, bioinformatics...
  - Industrial implementations: Anomaly detection, root cause analysis, urban data analysis, ...

Causal Discovery for Temporal Data

- The heat of causal discovery has increased rapidly in the past five years[4].

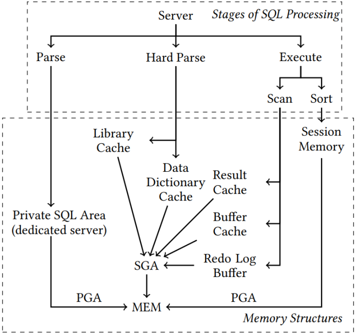


[4] https://trends.google.com

Causal Discovery for Temporal Data

Application in root cause analysis[5].

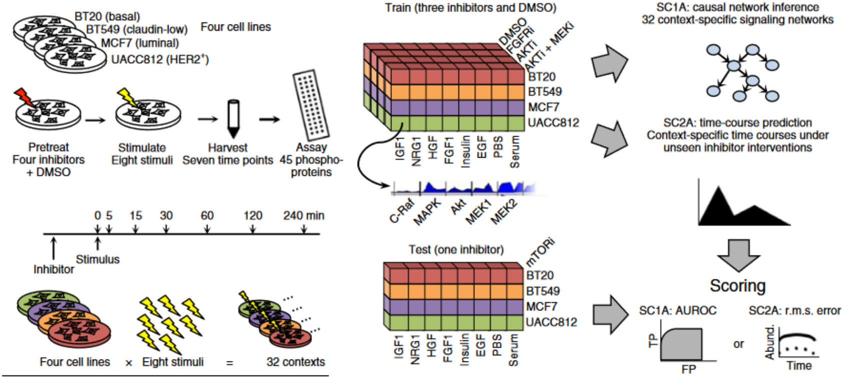
- Most applications use lots of sub-components that interact with each other in the form of a complex graph.
- Causal discovery can help to construct this graph and find the root cause of the failures in a timely fashion.



[5] Mingjie Li, Xiaohui Nie, Dan Pei. *Causal inference-based root cause analysis for online service systems with intervention recognition*. KDD, 2022

Causal Discovery for Temporal Data

- Discovering causal structures of molecular networks helps elucidate the genetic and biological mechanisms of diseases [6] [7].



[6] Jack Kelly, Carlo Berzuini, Bernard Keavney, Maciej Tomaszewski, Hui Guo. *A review of causal discovery methods for molecular network analysis.* Mol Genet Genomic Med. 2022

[7] Steven M Hill, Laura M Heiser, Thomas Cokelaer et al. *Inferring causal molecular networks: empirical assessment through a community-based effort.* Nat. Methods 2016.

Overview

This tutorial is organized as follows:

- Preliminaries (15 mins)
- Causal Discovery for Multivariate Time Series (60 mins)
- Causal Discovery for Event Sequence (60 mins)
- Discussion about Applications and New perspectives (15 mins)

1. Background
2. **Basic Concepts**
3. Assumptions
4. Problem Definitions

Basic Concepts

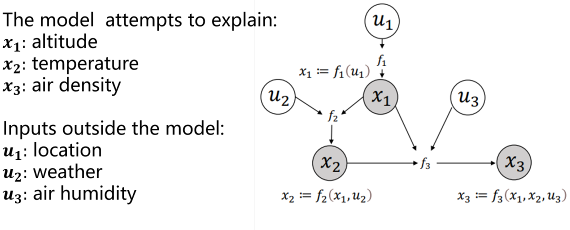
To formalize causal relationships and the task of causal discovery, these basic concepts about causality will be introduced:

- Structural Causal Model (SCM)
- Causal Markov Condition

Structural Causal Model

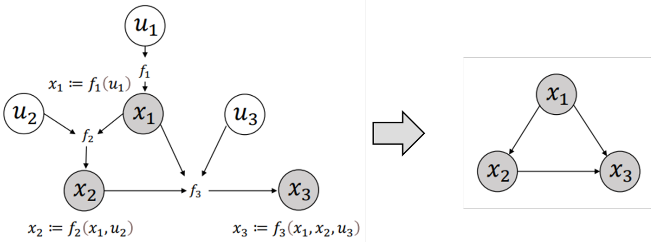
SCM is defined as a graphical representation of causal relationships, it can be represented in a 4-tuple $< V, U, F, P(U) >$

- V, U denote the set of endogenous and exogenous variables.
- $P(U)$ is the distribution of exogenous variables.
- F represents the set of the mapping function. For $f_i \in F$, the model $x_i := f_i(pa_i, u_i)$ indicates the assignment of the value x_i.



Structural Causal Model

For each SCM, we can yield a causal graph DAG G by adding one vertex for each X_i and directing edges from each parent variable in pa_i (the causes) to child X_i (the effect).



Causal Markov Condition

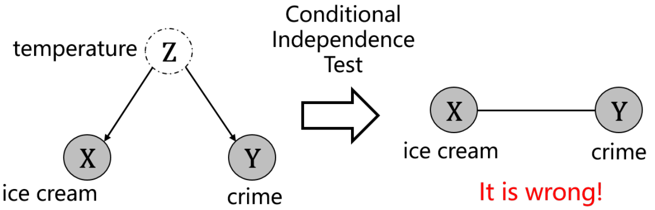
In the causal graph of SCM, each variable is conditionally independent of its non-effects (i.e., variables that do not directly cause it) given its parents. Formally, the causal Markov condition implies the joint distribution can be factorized according to the following decomposition:

$$P(\mathbf{X}) = \prod_{i}^{d} P(X_i|pa_i)$$

This condition plays an essential role in causal inference. It enables the identification of causal effects from observed data.

Causal Sufficiency

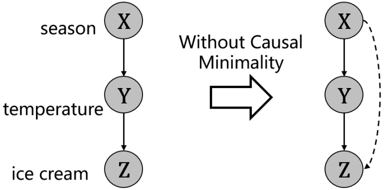
- A set of variables is causally sufficient if all common causes of all variables are observed.
- Without this assumption, the causal structure discovered by Conditional Independence Test is not credible.



- This assumption greatly simplifies the problem of causal discovery, but it does not always hold in reality.

Causal Minimality

- Consider a DAG $\mathcal{G}$ and a probability distribution P, P is said to satisfy the causal minimality with respect to $\mathcal{G}$ if P is Markovian with respect to $\mathcal{G}$ but not to any subgraph of $\mathcal{G}$.
- A distribution is not minimal with respect to the causal graph, if and only if some parents are "inactive".



- It is reasonable since a causal graph without this assumption does not provide more information than the minimal graph.

Causal Faithfulness

- Faithfulness asserts that all conditional independence relations of P that hold in the observed data are entailed by the causal model $\mathcal{G}$.
- This assumption is essential to Conditional Independence test, and it always holds except for some special cases.
- Note that faithfulness implies causal minimality. If P is faithful and Markovian with respect to $\mathcal{G}$, then the causal minimality is satisfied.

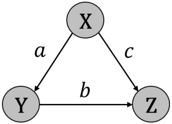
Causal Faithfulness

An example that violates this causal faithfulness assumption

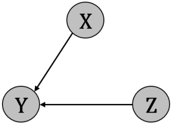
- the generation process of $\mathcal{G}_1$ as a linear Gaussian SCM:

$$\begin{aligned} X &:= N_X \\ Y &:= aX + N_Y \\ Z &:= bY + cX + N_Z \end{aligned}$$

  where the noise variables N_X, N_Y and N_Z are jointly independent and conform $\mathcal{N}(0, \sigma^2)$, and $a \cdot b + c = 0$.
- X and Z are independent, and it looks like the data was generated by $\mathcal{G}_2$



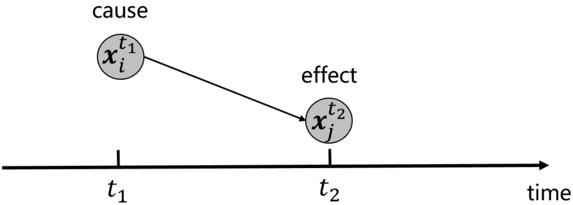
$\mathcal{G}_1$



$\mathcal{G}_2$

Temporal priority

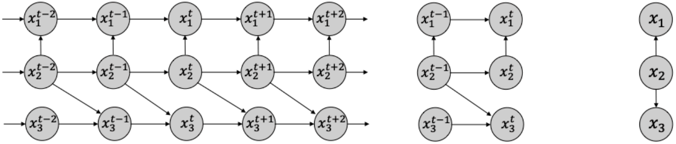
- For two variables, temporal priority means that the cause must have occurred before its effect.
- It is a foundation assumption of causal discovery from temporal data and creates an asymmetric time relationship in causal processes. It helps us to establish the direction of a causal relationship when two variables are causally linked.



Causal Structure for MTS

Given d-variate time series $\mathbf{x} = (x_1^t, \ldots, x_d^t)$:

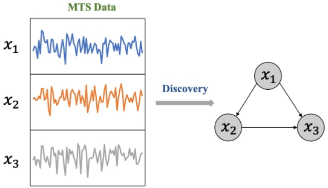
- Full-time causal graph represents a complete graph of the dynamic systems. Each variate at each time point is a vertex in the graph.
- Window causal graph is a partial full-time graph within a given time window.
- Summary causal graph ignores timestamps in the graph that each time series component is collapsed into a node.



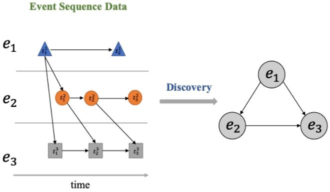
(a) Full time causal graph **(b) Window causal graph** **(c) Summary causal graph**

Causal Discovery from Temporal Data

Given a multivariate time series, causal discovery from MTS aims to find one of the causal structures, *i.e.* summary causal graph or window causal graph.



Given an event sequence: $\{(t_1, e_1), (t_2, e_2), \ldots\}$, causal discovery for event sequences aims to discover the causal relationships between different event types.



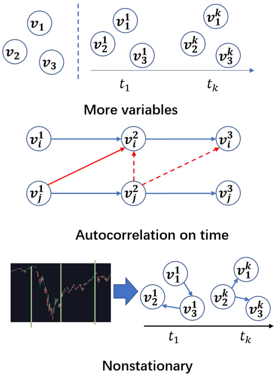
Challenges

General causal discovery is challenging due to the following reasons:

- hidden confounder, nonlinear, heterogeneity

In addition to the above challenges, there are more challenges in temporal causal discovery:

- more variables,
- autocorrelation on time
- nonstationary



What's Next?

- Causal Discovery from Multivariate Time Series (60 mins)
- Causal Discovery from Event Sequence (60 mins)
- Discussion about Applications and New perspectives (15 mins)

Thanks!