Causal Discovery from Temporal Data

Applications and New Perspectives

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Applications

- Scientific endeavors
  - Earth science
  - Neuroscience
  - Bioinformatics
  - ...
- Industrial implementations
  - Anomaly detection
  - Root cause analysis
  - Urban data analysis
  - ...

Earth science

- Motivations:
  - Climate is a complex and chaotic system, incorporating spatiotemporal information
    - Forward simulations have limitations due to uncertainties, simplifications, and discrepancies from observed data
    - Commonly used data-centric methods may lead to ambiguous conclusions in the field
- Main applications:
  - Climate change attribution[1]
  - Climate interactions quantification[2]
  - Latent driving force detection[3]
  - Causality validation[4]

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[1] Lozano, Li, Niculescu-Mizil, Liu, Perlich, Hosking and Abe. *Spatial-temporal Causal Modeling for Climate Change Attribution*. SIGKDD, 2009.

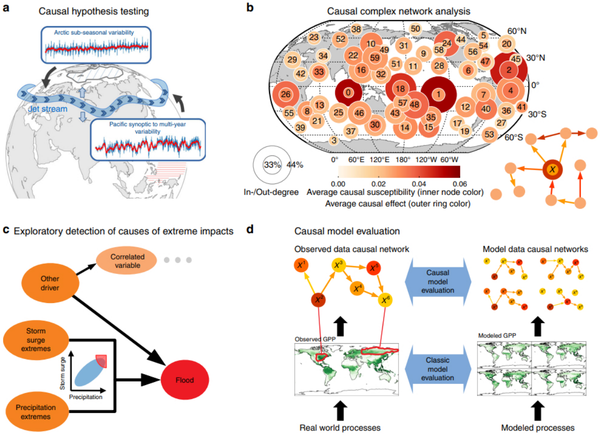
[2] Runge, Petoukhov and Kurths. *Quantifying the strength and delay of climatic interactions: The ambiguities of cross correlation and a novel measure based on graphical models*. Journal of climate, 2014.

[3] Trifunov, Shadaydeh, Runge, Eyring, Reichstein and Denzler. *Quantifying the strength and delay of climatic interactions: The ambiguities of cross correlation and a novel measure based on graphical models*. DAGM, 2019.

[4] Nes, Scheffer, Brovkin, Lenton, Ye, Deyle and Sugihara. *Causal feedbacks in climate change*. Nature climate change, 2015.

Earth science

- A roadmap[1]:



[1] Runge, Bathiany, Bollt, Camps-Valls, Coumou, Deyle, Glymour, Kretschmer, Mahecha, Muñoz-Marí, et al. *Inferring causation from time series in earth system sciences*. Nature communications, 2019.

Anomaly detection

- Motivations:
  - In industrial systems, detecting anomalies in massive temporal data, which is derived from sensors, logs, physical measurements, system settings, etc, is meaningful while challenging
  - Challenges mainly come from high dimensions and complex dependency on data
  - Temporal causal discovery has played a nonnegligible role by providing **efficient, robust** and **interpretable** results
- Main applications:
  - Causal structure as **detection reference & interpretation**
  - e.g., GGM[1], Heterogeneous Anomaly Detection[2], GC-Anomaly[3], TCCL[4]

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[1] Qiu, Liu, Subrahmanya and Li. *Granger Causality for Time-Series Anomaly Detection*. ICDM, 2012.

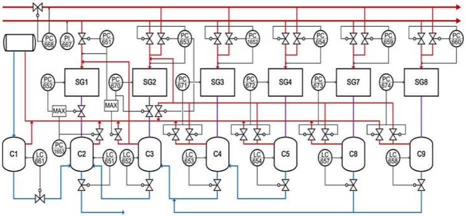
[2] Behzadi, Hlavaťckova-Schindler and Plant. *Dependency anomaly detection for heterogeneous time series: A Granger-Lasso approach*. ICDM Workshops, 2017.

[3] Apte, Vaishampayan and Palshikar. *Detection of causally anomalous time-series*. IJDSA, 2021.

[4] Huang, Xu, Yoo, Yan, Wang and Xue. *Imbalanced Time Series Classification for Flight Data Analyzing with Nonlinear Granger Causality Learning*. CIKM, 2020.

Root cause analysis
Manufacturing process

- Motivations:
  - Manufacturing processes are temporal and complex scenarios usually composed of multiple process units and a large number of feedback control loops[1]
  - Traditional ML methods are hindered due to **FAT principle** especially in sensitive-use cases
  - It's paramount to extract knowledge such as causal relationships



[1] Landman, Kortela, Sun and Jämsä-Jounela. *Fault propagation analysis of oscillations in control loops using data-driven causality and plant connectivity*. Computers and Chemical Engineering, 2014.

Root cause analysis

Manufacturing process

- Main applications:
  - Oscillation propagation tracing in the control loop[1,2]
  - Alarm flood reduction[3]
  - Industrial knowledge combined analysis[4]

[1] Lindner, Chioua, Groenewald, Auret and Bauer. *Diagnosis of Oscillations in an Industrial Mineral Process Using Transfer Entropy and Nonlinearity Index*. IFAC, 2018.

[2] Chen, Yan, Zhang, Liu and Yao. *Root Cause Diagnosis of Process Faults Using Conditional Granger Causality Analysis and Maximum Spanning Tree*. IFAC, 2018.

[3] Rodrigo, Chioua, Hagglund and Hollender. *Causal analysis for alarm flood reduction*. IFAC, 2016.

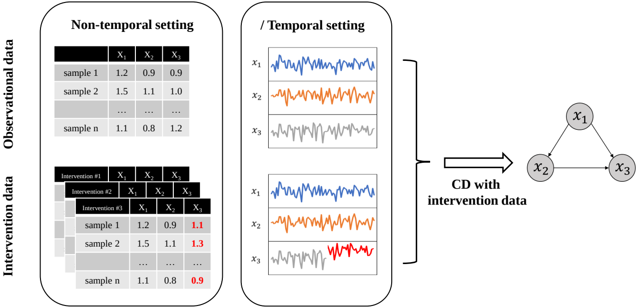
[4] Cao, Su, Wang, Cao, Siang, Li, Saddler and Gopaluni. *Causal discovery based on observational data and process knowledge in industrial processes*. Industrial & Engineering Chemistry Research, 2022.

New Perspectives

- Multivariate Time-series
  - Causal Discovery with Intervention data
  - Causal Discovery with Adaption
  - Causal Discovery under Supervision
- Event sequence
  - Causal Discovery with Graph Event Model(GEM)

Causal discovery with intervention data

- Additional information from interventional data can enhance identifiability in CD. Widely applied in non-temporal settings[1].
- e.g., IDYNO[2]

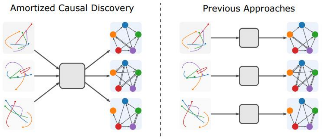


[1] Brouillard, Lachapelle, Lacoste, Lacoste-Julien and Drouin. *Differentiable Causal Discovery from Interventional Data*. NeurIPS, 2020.

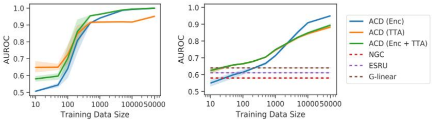
[2] Gao, Bhattacharjya, Nelson, Liu, and Yu. *IDYNO: learning nonparametric dags from interventional dynamic data*. ICML, 2022.

Adaptive causal discovery

- The causal structures of the same set of variables may changes in different samples and different time period.
- Learn a global causal discovery model for different dataset and output different causal structures, e.g., InGRA[1], ACD[2]



(a)



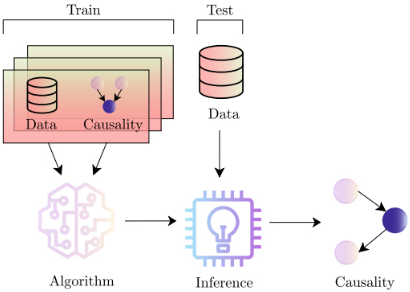
(b)

[1] Chu, Wang, Ma, Jia, Zhou, and Yang. *Inductive Granger causal modeling for multivariate time series.* ICDM, 2020.

[2] Löwe, Madras, Shilling, and Welling. *Amortized causal discovery: Learning to infer causal graphs from time-series data.* CLeaR, 2022.

Supervised causal discovery

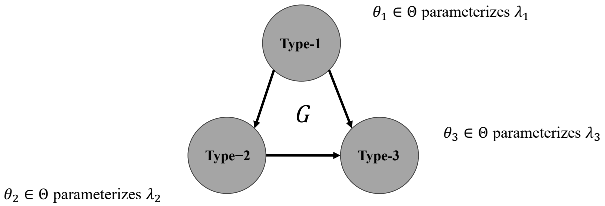
- The label information is causal structures and can be easily accessed in synthetic datasets
- 'Domain shift' issue: synthetic data *to* real-world dataset [1] [2]



[1] Benozzo, Olivetti and Avesani. *Supervised estimation of granger-based causality between time series*. Frontiers in Neuroinformatics, 2017.

[2] Wang and Kording. *Meta-learning Causal Discovery*. Arxiv, 2022.

Causal Discovery with GEM



- Similar with SCM for MTS data, GEM is promising to be the new perspective for event sequences causal discovery. [1]
- **Score-based** and **Constrain-based** approaches can be adapted for GEM

[1] Debarun Bhattacharjya et al. *Process independence testing in proximal graphical event models.* PMLR. 2022

1. Applications
2. New Perspectives
3. Summary

Summary

- Formally define causal discover task and introduce some common concepts. (Part I)
- Causal Discovery from Multivariate Time Series (Part II)
  - Constraint-based, Score-based, Granger causality-based, and Model-based Methods
- Causal Discovery from Event Sequences (Part III)
  - Granger causality-based, Constraint-based, and Score-based Methods
- Discussion about Applications and New Perspectives (Part IV)

More information can be found in our survey paper [1].

[1] Chang Gong et al. *Causal Discovery from Temporal Data: An Overview and New Perspectives*. ArXiv. 2023

Thanks!