Editorial
Special Issue on Causality: Fundamental Limits and Applications

CAUSAL determinism, is deeply ingrained with our ability to understand the physical sciences and their explanatory ambitions. Besides understanding phenomena, identifying causal networks is important for effective policy design in nearly any avenue of interest, be it epidemiology, financial regulation, management of climate, etc. This special issue covers several areas where causal inference research intersects with information theory and machine learning.

We focus on foundational topics such as network causal structure learning and applications of causality to facilitate predictions in unseen environments. Specifically, a number of the papers focus on causal structure learning and how information-theoretic and optimization methods can be used to recover the causal structure both in case of random variables as well as time series. In the case of time series, in one paper, the authors cast the causal discovery problem as a general convex optimization by harnessing recently developed stochastic monotone variational inequality formulation. While in another paper, the authors detect nonlinear relationships in a network through an information-theoretic measure based on modified Granger causality from observational data. In the case of random variables, two paper study an important setting of linear Gaussian structural models. In one case, a scalable local approach to learn the causal structure in linear Gaussian polytree from interventional experiments is introduced. In the other, the limit of structure learning under partial homoscedasticity of noise is studied. Finally, one manuscript identifies forms of causal invariance to facilitate prediction in unseen environments.

The editorial team (the lead and guest editors) would like to thank the authors of all submitted manuscripts and our dedicated referees who provided timely and high-quality reviews. We are excited about our issue and hope our readers will share our enthusiasm for this special issue.

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APPENDIX: RELATED ARTICLES

[A1] D. Tramontano, L. Waldmann, M. Drton, and E. Duarte, "Learning linear Gaussian Polytree models with interventions," *IEEE J. Sel. Areas Inf. Theory*, vol. 4, pp. 569–578, 2023, doi: 10.1109/JSAIT.2023.3328429.

[A2] J. Wu and M. Drton, "Partial homoscedasticity in causal discovery with linear models," *IEEE J. Sel. Areas Inf. Theory*, vol. 4, pp. 639–650, 2023, doi: 10.1109/JSAIT.2023.3328476.

[A3] S. Wei, Y. Xie, C. S. Josef, and R. Kamaleswaran, "Causal graph discovery from self and mutually exciting time series," *IEEE J. Sel. Areas Inf. Theory*, vol. 4, pp. 747–761, 2023, doi: 10.1109/JSAIT.2023.3342569.

[A4] K. Du and Y. Xiang, "Learning invariant representations under general interventions on the response," *IEEE J. Sel. Areas Inf. Theory*, vol. 4, 2023, doi: 10.1109/JSAIT.2023.3328651.

[A5] M.-A. Divernois, J. Etesami, D. Filipovic, and N. Kiyavash, "Analysis of large market data using neural networks: A causal approach," *IEEE J. Sel. Areas Inf. Theory*, vol. 4, 2023, doi: 10.1109/JSAIT.2023.3351549.

Digital Object Identifier 10.1109/JSAIT.2024.3350468