Master Internship 2024

Observational Causal Discovery: Stability as a necessary condition for Identifiability

Topic: Causal Inference, Neural Network Identifiability of Causal Graph
Team: AO/TAU, CNRS – INRIA – LISN, Université Paris-Saclay
Advisors: Michèle Sebag (sebag@lri.fr)
Alessandro Leite (alessandro.leite@inria.fr)
Johanne Cohen (jcohen@lri.fr)
Duration: 6 months
Location: LISN, Paris-Saclay University – Building 660 – Shannon
Level: Master M2

1 Context & Motivation

While artificial intelligence (AI) is acknowledged a source of major scientific and technological breakthroughs, some strong reservations are increasingly made about its robustness, its means, its cost, and last but not least its notoriously toxic effects if used carelessly.

However, the principled methodology of causal modeling has the potential to significantly contribute to the soundness of the artificial intelligence (AI) cycle: from data to models, from models to decisions, from decisions to data.

Causal modeling preferably relies on Randomized Controlled Trials (e.g. inferring the effect of a drug based on randomized interventions). These are unfortunately hardly usable in many real-world problems due to ethical or practical difficulty, which is the reason why *Observational Causal Discovery* [3] emerged as a hot topic in Machine Learning.

Among the difficulties of observational causal discovery is the presence of hidden confounders, possibly biasing the causal relationships among the observed variables. Another issue is that the sought models are learned in a small n large p context (few samples, many variables). Lastly, the causal theory focuses on the identifiability property (existence and uniqueness) of the sought model.

We have shown that adversarial learning [1] can be used to jointly identify the local causal relations among a variable and all other variables (Structural Agnostic Modeling, SAM [2]). Locally, a generative adversarial network is learned to estimate the distribution of each variable conditionally to its causes.

2 Goal of the Internship

The main objective of the internship is to revisit the identifiability property in a fixed point perspective:

Initial dataset $\mathcal{D}$	→	Graph $\mathcal{G}$ discovered from $\mathcal{D}$	→	Augmented dataset $\mathcal{D}'$ from $\mathcal{G}$	→	Graph $\mathcal{G}'$ estimated from $\mathcal{D}'$ and compared with $\mathcal{G}$

In step-1, a first estimate of the causal graph $\mathcal{G}$ is learned from the available data $\mathcal{D}$. In step-2, this graph is used as a generative model to augment the dataset and form a new dataset $\mathcal{D}'$. In step-3, this augmented dataset is exploited to learn a new causal graph $\mathcal{G}'$. In step-4, the two causal graphs $\mathcal{G}$ and $\mathcal{G}'$ are compared. This empirical fixed-point scheme will advance the state of the art in two ways. Firstly: if models $\mathcal{G}$ and $\mathcal{G}'$ are "sufficiently" similar, then the stability of the causal discovery algorithm is empirically established. This property is a necessary condition for identifiability. The key point is that it does not depend on specific assumptions on the domain or the data, but mostly on the causal discovery algorithm itself. Secondly: if, on the contrary, both graphs are dissimilar, the comparison will shed light on the indeterminacies of the initial model, and the biases of the causal discovery algorithm, possibly opening to fruitful discussions with domain experts [2].

3 Profile

The internship requires some curiosity about causality, besides excellent mathematical and machine learning skills + programming expertise. PhD grant available to continue the study.

References

[1] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative adversarial networks. *Communications of the ACM*, 63(11):139–144, 2020.

[2] D. Kalainathan, O. Goudet, I. Guyon, D. Lopez-Paz, and M. Sebag. Structural agnostic modeling: Adversarial learning of causal graphs. *Journal of Machine Learning Research*, 23(219):1–62, 2022.

[3] J. Peters, D. Janzing, and B. Schoelkopf. *Elements of Causal Inference*. The MIT Press, 2017.