

Internship proposal

Cost-effective interventional design for identifying causal effects in summary causal graphs

Context: Epidemiology critically depends on understanding causal relationships to effectively address public health challenges. Theoretical advancements, such as those derived from Pearl's do-calculus [Pearl, 2000], have laid a strong foundation for identifying causal effects from observational data. However, when effects are non-identifiable due to latent variables or complex causal mechanisms, strategically designed interventions become necessary. These interventions, however, often involve significant costs. In response to this challenge, recent research has focused on formulating these interventions more cost-effectively. Notably, studies have shown that the problem of designing minimum-cost interventions is NP-hard [Akbari et al., 2022], indicating the complexity and computational demand of these solutions.

Current research primarily focuses on fully specified causal graphs; however, real-world epidemiological studies often deal with partially specified graphs, such as summary causal graphs (SCGs) [Assaad et al., 2024, Ferreira and Assaad, 2024b,a]. These graphs represent a simplification of complex causal relationships by encapsulating clusters of variables or interactions that might not be fully understood or observed. The use of SCGs presents a unique opportunity for designing cost-effective interventions in situations where the complete causal architecture cannot be explicitly detailed.

The successful design of cost-effective interventions for identifying causal effects in epidemiology using SCGs can revolutionize how researchers address complex public health issues, leading to more effective and economically feasible health interventions.

Proposal: This internship is dedicated to investigating innovative methodologies for designing cost-effective interventions essential for identifying causal effects, especially in epidemiological settings characterized by significant resource constraints and where the primary background knowledge is encapsulated in an SCG.

Candidate: Highly motivated candidate with an M2 degree and strong background in probability, machine learning, and causal inference, along with a keen interest in epidemiology. Proficiency in programming is also required.

Location: The intern will work at IPLESP (<https://iplesp.fr/>), located in Paris. They will be supervised by Charles Assaad.

Dates: Starting date: To be discussed, early 2025, for a duration of 5-6 months.

Contact: To apply, please send a CV and a cover letter to Charles Assaad charles.assaad@inserm.fr

References

- S. S. Akbari, J. Etesami, and N. Kiyavash. Minimum cost intervention design for causal effect identification. In *International Conference on Machine Learning*, 2022. URL <https://api.semanticscholar.org/CorpusID:263876713>.
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- S. Ferreira and C. K. Assaad. Identifying macro conditional independencies and macro total effects in summary causal graphs with latent confounding, 2024a. URL <https://arxiv.org/abs/2407.07934>.
- S. Ferreira and C. K. Assaad. Identifiability of direct effects from summary causal graphs. *Proceedings of the AAAI Conference on Artificial Intelligence*, 38(18):20387–20394, Mar. 2024b. doi: 10.1609/aaai.v38i18.30021.

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