

PhD position – INSERM U1136 CIPHOD team, Paris

Abstractions of Causal Graphs for Transportability and Fairness

Project summary: Causal inference has become a cornerstone of modern epidemiology, providing a principled framework to estimate the effects of interventions from observational data. Directed Acyclic Graphs (DAGs) [Pearl, 2009, Greenland and Robins, 1986, Savitz and Wellenius, 2016] offer a powerful way to represent assumptions about causal structure and guide the identification of causal effects via tools such as the do-calculus.

However, in real-world epidemiological applications, data heterogeneity across populations often limits the generalizability of causal findings. The theory of causal transportability [Bareinboim and Pearl, 2012] formally characterizes when and how causal effects can be validly transferred across populations using DAGs or their augmented versions. Yet, in practice, it is often more feasible for epidemiologists and clinical experts to specify abstract, macro-level causal structures, such as cluster graphs, summary causal graphs, or difference graphs, rather than complete, fine-grained DAGs.

Recent advances show that these causal abstractions support sound causal reasoning [Assaad et al., 2024, Ferreira and Assaad, 2025a,b, Assaad, 2025b,a]. Nevertheless, how to perform causal transportability within such abstract representations remains an open question. Addressing this gap constitutes the first main aim of this thesis: to develop a framework for causal transportability that operates directly at the level of abstractions, accommodating partial knowledge, and heterogeneous data typical of epidemiological studies.

Beyond transportability, the augmented DAGs used in existing transportability frameworks have also been applied to fairness analysis [Plečko and Bareinboim, 2024] in decision-making. In this context, difference graphs (which capture causal discrepancies between two populations) offer a principled tool to analyze how interventions or societal factors affect causal relations differently across groups (e.g., by gender, ethnicity, or country). Understanding how causal effects change or fail to generalize across populations is central both to equitable policy design and to responsible data-driven decision-making. Hence, the second objective of this thesis is to leverage difference graphs to analyze fairness in decision making across different populations.

In summary, the objectives of this project are the following:

- Define transportability semantics (e.g., selection nodes) for abstract causal graphs;
- Extend the theory of causal transportability to cluster graphs, summary causal graphs, and difference graphs;
- Apply and validate the proposed framework on real-world epidemiological data.
- Investigate the usability of difference graphs for studying fairness and causal disparities across populations.

Lab location and description: The Pierre Louis Institute of Epidemiology and Public Health (co-accredited by Inserm and Sorbonne University) is located at the Sorbonne University Faculty of Medicine - Hôpital Saint Antoine in Paris. It is composed of six teams, in addition to the recently established CIPHOD “Causal Inference in Public Health using large Observational health Databases” team. The general research objectives of CIPHOD are to put forth novel theoretical findings and develop innovative methodologies in the realm of causal inference, with a focus on their applicability and utility for epidemiologists.

Contract: The thesis contract will start in September 2026, for a duration of 36 months and after registration with the ED393 Doctoral School Pierre Louis of Public Health: Epidemiology and biomedical information sciences. The monthly doctoral allowance will be around €2,131 gross, subject to annual revaluation.

The doctoral student will be supervised by Dr. Charles Assaad (CIPHOD team). The student will also collaborate with other teams in IPLESP and will have access to the resources and infrastructure available at INSERM/IPLESP and Sorbonne Université.

Candidat profile: 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.

Contact: Candidates are requested to send their CV (including a list of publications, research experiences, and references) to Charles Assaad (charles.assaad@inserm.fr) by June 01 2026. For additional details, please reach out to the same email address.

References

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- E. Bareinboim and J. Pearl. Transportability of causal effects: Completeness results. *Proceedings of the AAAI Conference on Artificial Intelligence*, 26(1):698–704, Sep. 2012. doi: 10.1609/aaai.v26i1.8232.
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