

# Top-down and bottom-up causal reasoning: when higher-level causal estimates inform lower-level ones (and vice versa)

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## 1 Context and description

By modeling the underlying data generation processes with an SCM, causal inference can attain deeper reasoning that transcends mere associations [Pearl, 2009]. Causal questions like "why" and "what would have happened if" can now be answered.

Causal questions can also arise in settings where there is a hierarchical structure in the data in addition to the causal structure, i.e., subunits are nested within units such as students in schools, or cities in states. In these settings, higher-level variables may affect lower-level outcomes, and lower-level characteristics may aggregate to influence higher-level outcomes [Weinstein and Blei, 2026]. However, most causal inference methods are designed to consider only one level of the hierarchy [Chernozhukov et al., 2018, Künzel et al., 2019, Nie and Wager, 2021, Curth and Van der Schaar, 2021]. As a result, they do not take advantage of the mutual information shared across hierarchies. The goal of this project is to exploit the hierarchical structure in the data by using causal estimates done at the level of one hierarchy to inform estimates that could be made about another hierarchy.

More formally, we assume that the data generation process can be represented by a Hierarchical Causal Model (HCM) [Weinstein and Blei, 2026]. We furthermore suppose that we have some oracle causal estimators (of Average Treatment Effects or Conditional Average Treatment Effects) on a hierarchy (unit or subunit). The research question is to what extent (i.e., under which assumptions on the HCM) these estimators can improve the estimations on the other hierarchy (for example, by making them more robust, using less data, relaxing identification assumptions, etc.).

## 2 Internship Goals

During the internship, **the objectives** will be the following:

- Deepen knowledge of hierarchical causal modeling, particularly through a review of the literature
- Explore toy examples (with specific graph structures, hierarchies and parametric forms) to get intuitions
- Based on the results obtained in the previous step, construct an estimator that incorporates information from another hierarchy (for example, in the form of regularization).
- Demonstrate the value of the proposed estimator and the added value of incorporating information from the other hierarchy
  - Through empirical experiments using synthetic and/or semi-synthetic data
  - Through identification guarantees (if time allows)

### 3 Candidate profile

The ideal candidate is passionate about artificial intelligence and motivated by applied research issues. He has a solid background in machine learning, statistics, applied mathematics, computer science, modeling, and optimization, and good scientific writing and oral communication skills. Proven experience and taste in computer programming (Python) and data analysis are expected. Past experience in Causal Inference would be a major advantage.

Applicants must be in their final year of Master (M2 or Msc) or last year of engineering school (3A) in one of the following fields: Applied Mathematics, Machine Learning, AI, Computer Science, Statistics or related fields. A good command of the English language will be appreciated.

### 4 Supervision team, Funding and location

The internship will be in an academical and industrial research environment as it is the result of a collaboration between the [Eki.Lab](#) (the AI research lab of [Ekimetrics](#)), the CRAN (Centre de Recherche en Automatique de Nancy, Université de Lorraine and CNRS) and the the LIG (Laboratoire d'Informatique de Grenoble, Université Grenoble Alpes).

The internship duration will be **5 or 6 months**, with an expected start in February or March 2027. The remuneration will be higher than a classical university internship gratification. More details will be given during the interview. The intern will officially be hired by **Ekimetrics**. The internship will therefore take place in **Paris**.

Finally, this internship offers the **opportunity to pursue a Ph.D. in causal inference** within these research labs.

### 5 Application

Application must be sent to [emilie.devijver@univ-grenoble-alpes.fr](mailto:emilie.devijver@univ-grenoble-alpes.fr), [marianne.clausel@univ-lorraine.fr](mailto:marianne.clausel@univ-lorraine.fr) and [audrey.poinsot@ekimetrics.com](mailto:audrey.poinsot@ekimetrics.com) as soon as possible and must include:

- Cover letter (can be the email itself);
- Resume / CV ;
- GitHub link containing projects completed during their studies (optional but recommended)
- Transcript for the most recent academic year

Incomplete applications will not be considered.

### References

- [Chernozhukov et al., 2018] Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., and Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal*, 21(1).
- [Curth and Van der Schaar, 2021] Curth, A. and Van der Schaar, M. (2021). Nonparametric estimation of heterogeneous treatment effects: From theory to learning algorithms. In *International conference on artificial intelligence and statistics*. PMLR.
- [Künzel et al., 2019] Künzel, S. R., Sekhon, J. S., Bickel, P. J., and Yu, B. (2019). Metalearners for estimating heterogeneous treatment effects using machine learning. *Proceedings of the national academy of sciences*, 116(10).

- [Nie and Wager, 2021] Nie, X. and Wager, S. (2021). Quasi-oracle estimation of heterogeneous treatment effects. *Biometrika*, 108(2).
- [Pearl, 2009] Pearl, J. (2009). *Causality: Models, Reasoning, and Inference*. Cambridge University Press, 2nd edition.
- [Weinstein and Blei, 2026] Weinstein, E. N. and Blei, D. M. (2026). Hierarchical causal models. *Journal of Machine Learning Research*, 27(37):1–73.