Causal Inference in AI for Complexity

with applications in the Humanities and the Social Sciences

Identifying causal relationships between variables has been a subject of investigation in a variety of (if not all) scientific fields for a long time. It has recently taken a new turn thanks to novel methods, in particular graphical models such as Bayesian networks. Contemporaneously, new statistical methods based on machine and deep learning, and other methods within the broader AI toolbox, have sometimes led to causal relationships being blurred or more difficult to identify, let alone establish. All the more so when dealing with systems that may be harder to bring into controlled experiments, such as social or economical systems. Such systems often exhibit complexity, i.e. interactions between entities within the system that lead to properties emerging at the macro/collective level while being absent or hard to predict at the micro/individual level. Dynamical systems ranging from financial markets to the Ising model in statistical physics or the Schelling model of urban segregation in geography belong to this category of complex systems.

Being of very broad interest, results on causal inference tend to be scattered across the literature in many different disciplines, and sometimes lack a general, robust mathematical framework – especially one that would be geared toward applications in the social sciences and the humanities. Hence there is a strong need for mathematical work to be carried out at the interface between mathematics and AI, with an eye to questions in geography, economics, sociology...

The proposed postdoc will aim at filling this gap by providing as comprehensive a framework as possible, establishing new results, in particular robust methods for the investigation of causal relationships in complex systems. The postdoc will be based at Centre Borelli (UMR9010), ENS Paris-Saclay, along with the “Chaire *Modélisations mathématiques & Sciences humaines et sociales*”. Anyone with a PhD in the mathematical sciences, quantitative social sciences or other related disciplines is encouraged to apply.

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