L'inférence causale en présence de dépendance et de structure de réseau
« Atelier sur la découverte de la structure causale à haute dimension »
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Causal Inference in the Presence of Dependence and Network Structure
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Reliable decision-support using counterfactual models

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In real-time environments, decision-makers are faced with the challenge of quickly integrating high-dimensional data to inform their actions. For instance, physicians in a hospital's intensive care unit must process long histories of vital signals, laboratory test results, and treatments in order to decide whether a patient is at risk and what future interventions might be necessary to prevent undesirable outcomes. To aid in this process, machine learning practitioners commonly use supervised learning algorithms to fit models that predict outcomes given the high-dimensional history, but this approach can produce biased models that may lead to dangerous downstream decisions. The key issue is that supervised learning algorithms are highly sensitive to the policy used to choose actions in the training data, which causes the model to capture relationships that do not generalize. We propose using a different learning objective that predicts counterfactuals instead of predicting outcomes under an existing action policy as in supervised learning. To support decision-making in temporal settings, we introduce the Counterfactual Gaussian Process (CGP) to predict the counterfactual future progression of continuous-time trajectories under sequences of future actions, and describe a rich family of probabilistic models based on the theory of linear time-invariant systems that can flexibly learn treatment effects on high-dimensional, time-varying processes.

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