L'inférence causale en présence de dépendance et de structure de réseau
« Atelier sur la découverte de la structure causale à haute dimension »
25 au 27 juin 2018

Causal Inference in the Presence of Dependence and Network Structure
"Workshop on Discovery of causal structure in high dimensions"
June 25-27, 2018

Quasi-oracle estimation of heterogeneous causal effects

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Many scientific and engineering challenges, ranging from personalized medicine to customized marketing recommendations, require an understanding of treatment effect heterogeneity. In this paper, we develop a class of two-step algorithms for heterogeneous treatment effect estimation in observational studies. We first estimate marginal effects and treatment propensities to form an objective function that isolates the heterogeneous treatment effects, and then optimize the learned objective. This approach has several advantages over existing methods. From a practical perspective, our method is very flexible and easy to use: In both steps, we can use any method of our choice, e.g., penalized regression, a deep net, or boosting; moreover, these methods can be fine-tuned by cross-validating on the learned objective. Meanwhile, in the case of penalized kernel regression, we show that our method has a quasi-oracle property, whereby even if our pilot estimates for marginal effects and treatment propensities are not particularly accurate, we achieve the same regret bounds as an oracle who has a-priori knowledge of these nuisance components. We implement variants of our method based on both penalized regression and convolutional neural networks, and find promising performance relative to existing baselines.

Joint work with Xinkun Nie.

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