Shrinkage Bayesian Causal Forests for Heterogeneous Treatment Effects Estimation

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Room Benvenuti and live Zoom
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This paper develops a shrinkage-inducing version of Bayesian Causal Forests, a recently proposed nonparametric causal regression model that employs Bayesian Additive Regression Trees and is specifically designed to estimate heterogeneous treatment effects using observational data. The shrinkage-inducing component we introduce is motivated by empirical studies where not all the available covariates are relevant, leading to different degrees of sparsity underlying the surfaces of interest in the estimation of individual treatment effects. The extended version presented in this work, which we name Shrinkage Bayesian Causal Forest, is equipped with an additional pair of priors allowing the model to adjust the weight of each covariate through the corresponding number of splits in the tree ensemble. These priors improve the model's adaptability to sparse data generating processes and allow to perform fully Bayesian feature shrinkage in a framework for treatment effects estimation, and thus to uncover the moderating factors driving heterogeneity. We illustrate the performance of our method in simulated studies, in comparison to Bayesian Causal Forest and other state-of-the-art models, to demonstrate how it scales up with an increasing number of covariates and how it handles strongly confounded scenarios. Finally, we apply the methods to study the effects of early intervention on cognitive abilities in low birth weight infants using the Infant Health and Development Program (IHDP) data.
Joint work with Alberto Caron and Gianluca Baio

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