Revisiting Treatment Effects with Causal Forests

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Abstract

This thesis focuses on the application of Causal Forests, a prominent causal machine learning algorithm, to estimate heterogeneous treatment effects in complex socio-economic phenomenon. Causal Forests leverage the capabilities of random forests to partition the high-dimensional covariate space and identify subgroups where the effect of an intervention remains constant. This approach is particularly valuable when dealing with heterogeneous causal effects, where a uniform measure of gains for all is an unrealistic assumption. Unlike traditional manual methods that are susceptible to p-hacking, the algorithm objectively uncovers nuanced treatment effect variations through data-driven analysis. The thesis demonstrates the algorithm's potential in exploring causal effects and providing valuable policy insights. An empirical illustration showcases the modeling of a complex socio-economic phenomenon, such as the gender wage gap, and leverages Causal Forests to extract policy learning from the identified heterogeneity. The study highlights the algorithm's contribution to credible and robust causal inference, bridging the gap between traditional decomposition methods and data-informed heterogeneity analysis.

Keywords: Causal machine learning, heterogeneity, policy learning, policy targeting, gender gap