An Instrumental Variable Tree Approach for Detecting Heterogeneous Treatment Effects in Observational Studies

No two people are exactly alike, especially when it comes to health care. Patients differ not only in their demographics and medical conditions but also in their responses to a medical treatment. While some patients respond positively to a particular treatment, others may see little response or even experience serious negative effects from the same treatment. However, most studies of treatment effects have focused on the average effect across all patients in a sample. The lack of an effective methodology for analyzing heterogeneous treatment effects has led to “one-size-fits-all” approaches that may not help, or may even harm, some patients. Recognizing this, a number of public and private organizations have called for “personalized medicine” (also termed “precision medicine”). Most prominently, in 2015, the US government announced a $215-million national Precision Medicine Initiative that aims to prevent diseases and treat patients taking into account individual differences in people's genes, environment, and lifestyles.¹

Recent advances in machine learning techniques may help promote personalized medicine by providing new ways to evaluate heterogeneous treatment effects. For example, Athey and Imbens (2016) proposed a causal tree for analyzing heterogeneous treatment effects when patients are randomly assigned to receive a treatment. This approach partitions patients into groups such that patients in the same group have similar treatment effects and those in different groups have different treatment effects. In random experiments like clinical trials, because treatment assignment is not confounded with

¹ https://obamawhitehouse.archives.gov/the-press-office/2015/01/30/fact-sheet-president-obama-s-precision-medicine-initiative
features, it is straightforward to estimate the treatment effect using the average outcome difference between the treatment and control groups.

While random experiments are ideal for causal inference, it is often unethical, uneconomical or impossible to carry out large-scale random experiments. It is obviously unethical to assign patients to a treatment that is potentially harmful, but ethical concerns may also arise when a patient is prevented from receiving a better and/or more suitable treatment. There are also cases when random experiments are infeasible due to legal issues or unavailability of participants. For example, it would be illegal to recruit adolescents to study the impact of smoking at a young age on the development of a lung cancer. Finally, even when ethical concerns are not an issue, random experiments can be very costly and take a long time to conduct.

In situations where random experiments are not practical, researchers and policy makers have turned to observational data. Ideally, observational data can be mined to uncover patient-specific differences in responses to medical treatment. However, observational sources are subject to potential endogeneity issues because the data often do not include all features that affect treatment assignment and outcome. In the context of health care, there are patient features such as diagnostic details that physicians or patients themselves observe but we as researchers do not. If these features affect both the treatment assignment and medical outcome, simply taking the average outcome difference between the treatment and control groups will lead to biased estimates of the treatment effects.

An approach has been widely used in the health care operations management literature to correct for potential endogeneity issues is the instrumental variable method. A valid
instrument induces changes in treatment assignment but has no independent effect on the outcomes, which allows a researcher to uncover the causal effect of the treatment on the outcome. However, use of the instrumental variable method has been limited to regression models. It has not been applied to tree-based approaches.

We address the gap by developing a new instrumental variable tree that combines the tree-based approach with the instrumental variable method to study heterogeneous treatment effects using observational data. This approach partition subjects into groups such that subjects in the same group have similar treatment effects and those in different groups have different treatment effects. We prove that estimates from the instrumental variable tree are asymptotically consistent under very general assumptions. Also, using simulation with synthetic data, we show that the instrumental variable tree has better coverage rates and smaller mean-squared errors than the conventional causal tree, and a random forest constructed using instrumental variable trees has a better accuracy and interpretability than the generalized random forest (Athey et al., 2017). Finally, we apply the instrumental variable tree to identify patient groups that exhibit significant differences between 35 hospitals for six cardiovascular surgeries in New York State and find that outcome differences between hospitals are heterogeneous not only across procedure types, but also along other dimensions such as patient age and comorbidities.

Reference
