Machine learning methods for causal inference from complex observational data

Alexander Volfovsky, Harvard University

A classical problem in causal inference is that of matching treatment units to control units in an observational dataset. This problem is distinct from simple estimation of treatment effects as it provides additional practical interpretability of the underlying causal mechanisms that is not available without matching. Some of the main challenges in developing matching methods arise from the tension among (i) inclusion of as many covariates as possible in defining the matched groups, (ii) having matched groups with enough treated and control units for a valid estimate of average treatment effect in each group, (iii) computing the matched pairs efficiently for large datasets, and (iv) dealing with complicating factors such as non-independence among units. We propose the Fast Large-scale Almost Matching Exactly (FLAME) framework to tackle these problems for categorical covariates. At its core this framework proposes an optimization objective for match quality that captures covariates that are integral for making causal statements while encouraging as many matches as possible. We demonstrate that this framework is able to construct good matched groups on relevant covariates and further extend the methodology to incorporate continuous and other complex covariates.