Double machine learning for sample selection models

We consider the evaluation of discretely distributed treatments when outcomes are only observed for a subpopulation due to sample selection or outcome attrition. For identification, we combine a selection-on-observables assumption for treatment assignment with either selection-on-observables or instrumen- tal variable assumptions concerning the outcome attrition/sample selection process. We also consider dynamic confounding, meaning that covariates that jointly affect sample selection and the outcome may (at least partly) be influenced by the treatment. To control in a data-driven way for a potentially high dimensional set of pre- and/or post-treatment covariates, we adapt the double machine learning framework for treatment evaluation to sample selection problems. We make use of (a) Neyman-orthogonal, doubly robust, and efficient score functions, which imply the robustness of treatment effect estimation to moderate regularization biases in the machine learning-based estimation of the outcome, treatment, or sample selection models and (b) sample splitting (or cross-fitting) to prevent overfitting bias. We demonstrate that the proposed estimators are asymptotically normal and root-n consistent under specific regularity conditions concerning the machine learners and investigate their finite sample properties in a simulation study. We also apply our proposed methodology to the Job Corps data for evaluating the effect of training on hourly wages which are only observed conditional on employment. The estimator is available in the causalweight package for the statistical software R.