Estimating Treatment Effect under Additive Hazards Models with High-dimensional Covariates

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Abstract: Estimating causal effects for survival outcomes in the high-dimensional setting is an extremely important topic for many biomedical applications as well as areas of social sciences. We propose a new orthogonal score method for treatment effect estimation and inference that results in asymptotically valid confidence intervals assuming only good estimation properties of the hazard outcome model and the conditional probability of treatment. This guarantee allows us to provide valid inference for the conditional treatment effect under the high-dimensional additive hazards model under considerably more generality than existing approaches. In addition, we develop a new Hazards Difference (HDi) estimator. We showcase that our approach has double-robustness properties in high dimensions: with cross-fitting the HDi estimate is consistent under a wide variety of treatment assignment models; the HDi estimate is also consistent when the hazards model is misspecified and instead the true data generating mechanism follows a partially linear additive hazards model. We further develop a novel sparsity doubly robust result, where either the outcome or the treatment model can be a fully dense high-dimensional model. We apply our methods to study the treatment efect of radical prostatectomy versus conservative management for prostate cancer patients using the SEER-Medicare Linked Data.