Nonparametric causal inference by the kernel method

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Abstract. Rubin causal model is a statistical model to estimate the effect of a treatment on the outcome based on the framework of potential outcomes. To estimate a causal effect based on Rubin causal model, propensity score plays a central role. In particular, matching and weighting methods like Inverse Probability Weighted Estimator (IPWE) and Doubly-Robust estimator based on the estimated propensity score are widely used. Despite its popularity, it was pointed out that model misspecification of the propensity score can result in substantial bias of the resulting estimators of a causal effect and potential outcomes. It is possible to estimate propensity score in nonparametric ways or machine learning methods to avoid model misspecification. However, it doesn't work well in most situations due to following reasons: 1) Curse of dimensionality. 2) They only aim at an accuracy of classification and don't optimize the covariate balancing. To overcome the problems above, we propose a new estimator of propensity score using kernel mean embeddings of conditional distributions. Although our proposal is completely nonparametric, our estimator has a dimensionality-independent rate of convergence. Using kernel measures of conditional independence for model selection, our estimator can also correct the bias that arises from the imbalance of covariates. In numerical simulations, we confirm that our method can reduce the bias in misspecified settings. We also describe several asymptotic properties of our estimator.

Keywords. Rubin causal model, Propensity score, Kernel method, Kernel mean embedding, Hilbert-Schmidt Independence Criterion