Estimating causal treatment effects using observational data holds great interest in various research fields. Propensity score is one of the most frequently used methods to address the estimation bias in observational data. In this study, we propose using propensity score to expand interaction trees (IT) (Su et al., 2009) for the estimation of optimized causal effects interaction trees (OCEIT). Each interaction tree recursively partitions the data into two subgroups with greatest heterogeneity of treatment effect. By integrating propensity score into tree growing process, subgroups in OCEIT not only have maximized treatment effect differences, but also similar baseline covariates. Thus, it allows for causal effects analysis using observational data. Three different approaches incorporating propensity score in the tree growing process are discussed in the study: propensity score as covariance (Covariance); propensity score used in stratified sampling (Stratified); and inverse probability of treatment weighting (IPTW). In addition, an optimization algorithm using nonparametric Kolmogorov–Smirnov statistic is added to optimize the subgroup homogeneity. Simulation results show that all methods are able to improve estimation accuracy, with IPTW delivering the best results.

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