Bayesian Nonparametric Adjustment of Confounding

In observational studies, confounder selection is a crucial task in estimation of causal effect of an exposure. Wang et al. (2012, 2015) propose Bayesian adjustment methods for confounding (BAC) to account for the uncertainty in confounder selection by jointly fitting parametric models for exposure and outcome, in which Bayesian model averaging (BMA) is utilized to obtain the causal effect averaged across all potential models according to their posterior weights. In this work, we propose a Bayesian nonparametric approach to select confounders and estimate causal effects without assuming any model structures for exposure and outcome. With the Bayesian additive regression trees (BART) method, the causal model can capture complex data structure flexibly and select a subset of true confounders by specifying a common prior on the selection probabilities in both exposure and outcome models. The proposed model does not require a separate BMA process to average effects across many models as, in our method, selection of confounders and estimation of causal effects based on the selected confounders are processed simultaneously within each MCMC iteration. A set of extensive simulation studies demonstrates that the proposed method outperforms in a variety of situations.