Bayesian nonparametric model for heterogeneous treatment effects with zero-inflated data

Chanmin Kim*
Sungkyunkwan University
Yisheng Li
MD Anderson Cancer Center
Ting Xu
MD Anderson Cancer Center
Zhongxing Liao
MD Anderson Cancer Cente

Abstract

One goal of precision medicine is to develop effective treatments for patients by tailoring to their individual demographic, clinical, and/or genetic characteristics. To achieve this goal, statistical models must be developed that can identify and evaluate potentially heterogeneous treatment effects in a robust manner. The of-cited existing methods for assessing treatment effect heterogeneity are based upon parametric models with interactions or conditioning on covariate values, the performance of which are sensitive to the omission of important covariates and/or the choice of their values. We pro- pose a new Bayesian nonparametric (BNP) method for estimating heterogeneous causal effects in studies with zero-inflated outcome data which arise commonly in health-related studies. Our BNP approach, using the enriched Dirichlet process (EDP) mixture, connects an outcome model to covariate clustering models and jointly estimates posterior distributions to allow inference on group-specific causal effects, where groups are determined by applying partitioning around medoids (PAM) to the posterior distribution of similarity matrices. We show in In a simulation study hat the proposed method outperforms two other BNP methods in terms of bias and mean squared error (MSE) of the group-specific causal effect estimates, and adjusted Rand index, which measures the similarity between the true data grouping and grouping identified by the methods. We apply the proposed method to a study of the relationship between heart radiation dose parameters and the blood level of high-sensitivity cardiac troponin T (hs-cTnT) to examine if the effect of a high mean heart radiation dose on hs-cTnT varies by individual characteristics.