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IPS Paper

Generalized outcome-adaptive lasso: Variable selection for high dimensional causal inference

Author: Ismaïla Baldé

Coauthors: Archer Yi Yang, Geneviève Lefebvre

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Brief Description

Shortreed and Ertefaie introduced a clever propensity score variable selection approach for estimating average causal effects, namely, the outcome adaptive lasso (OAL).

OAL aims to select desirable covariates, confounders, and predictors of outcome, to build an unbiased and statistically efficient propensity score estimator.

Due to its design, a potential limitation of OAL is how it handles the collinearity problem, which is often encountered in high-dimensional data.

As seen in Shortreed and Ertefaie, OAL's performance degraded with increased correlation between covariates.

In this note, we propose the generalized OAL (GOAL) that combines the strengths of the adaptively weighted L1 penalty and the elastic net to better handle the selection of correlated covariates.

Two different versions of GOAL, which differ in their procedure (algorithm), are proposed.

We compared OAL and GOAL in simulation scenarios that mimic those examined by Shortreed and Ertefaie.

Although all approaches performed equivalently with independent covariates, we found that both GOAL versions were more performant than OAL in low and high dimensions with correlated covariates.

Abstract

Shortreed and Ertefaie introduced a clever propensity score variable selection approach for estimating average causal effects, namely, the outcome adaptive lasso (OAL). OAL aims to select desirable covariates, confounders, and predictors of outcome, to build an unbiased and statistically efficient propensity score estimator. Due to its design, a potential limitation of OAL is how it handles the collinearity problem, which is often encountered in high-dimensional data. As seen in Shortreed and Ertefaie, OAL's performance degraded with increased correlation between covariates. In this note, we propose the generalized OAL (GOAL) that combines the strengths of the adaptively weighted L1 penalty and the elastic net to better handle the selection of correlated covariates. Two different versions of GOAL, which differ in their procedure (algorithm), are proposed. We compared OAL and GOAL in simulation scenarios that mimic those examined by Shortreed and Ertefaie. Although all approaches performed equivalently with independent covariates, we found that both GOAL versions were more performant than OAL in low and high dimensions with correlated covariates.