

Elastic-Net for Instrumental Variables Regression

This paper contributes to the literature on estimation of treatment effects in a non-experimental setting with many instrumental variables (IV). While the use of many instruments improves estimation accuracy, dealing with high-dimensional sets of instrumental variables may be complicated, and often requires instrument selection or regularization of the first-stage regression. Currently, lasso is established as the most popular method to simultaneous variable selection and regularization.

I advocate the use of elastic-net (EN) methods in place of lasso in the first-stage regression. The motivation is twofold. First, elastic-net combines lasso regularization with ridge penalization, therefore it generally improves upon lasso in finite samples if correlations among the instrumental variables are significant. Second, by attaining a balance between lasso and ridge penalties, elastic-net accommodates deviations of the first-stage equation from a sparse structure, thus being a robust alternative to lasso that heavily relies on the sparsity assumption.

I show the asymptotic equivalence of the IV estimators that employ the lasso and elastic-net first-stage predictions. Via a Monte Carlo study I demonstrate the robustness to correlation among the instruments and deviations from sparsity of the sample-split IV estimation based on elastic-net first-stage estimates. The cross-fitted EN IV estimator tends to perform similarly to the sample-split version, though sometimes resulting in minor test size distortions. Finally, I provide an empirical example that employs the proposed methods for estimation of return to schooling. The example demonstrates the cross-fitted EN IV estimator resulting in the point estimate without a clear bias towards the OLS estimate, while delivering the smallest standard errors. As expected, the sample-split EN IV estimator appears to be more vulnerable to random splits of the real data. However, similarly to the cross-fitted EN IV estimator, it continues to produce the reasonable estimates even in the cases when its lasso-based counterpart does not select any variables into the first-stage regression, and thus fails to deliver any estimates.