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Testing Predictive Accuracy with Penalized Regression

Supervised Machine Learning (ML) algorithms have become an integral part of forecasting. To assess the out-of-sample performance of these algorithms relative to standard benchmark models like the Autoregressive (AR) model, forecasters routinely rely on predictive ability tests like the classical Diebold-Mariano test. In this paper, we document the limiting behaviour of various predictive ability tests when the series of forecast errors is based on a penalized regression such as Lasso, Ridge or Elastic Net regression. Under squared error loss and certain regularity conditions, we show that when the number of predictors is finite, Parameter Estimation Error (PEE) does not contribute to the asymptotic variance of the test like in the non-penalized case, but may lead to non-zero bias in the limiting distribution. Moreover, depending on the degree of sparsity in the data, the contribution of PEE to the variance may not vanish when the number of predictors grows with the sample size, and can in fact also lead to a non-centered limiting distribution. This casts doubt on the use of standard normal critical values for inference. We illustrate this issue via a set Monte Carlo simulations and find that inference based on the standard normal distribution can be highly misleading. We propose a suitable block bootstrap procedure to mitigate this shortcoming. An empirical illustration showcases the usefulness of the latter procedure.