Adaptive Minimum Confidence Region Rule with Bootstrap for Multivariate Initialization Bias Truncation

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Abstract

Initial bias truncation is critically important for system performance assessment and warm-up length estimation in discrete-event simulations. A vast majority of existing methods are limited to univariate signals, while multivariate truncation has been rarely studied. Adaptive minimal confidence region rule (AMCR) was proposed in the literature for multivariate initial bias truncation. However, AMCR has a number of limitations. First, if the covariance matrix is ill-conditioned, sample generalized variance cannot be computed reliably. Second, the algorithmic complexity of existing AMCR implementations increases rapidly as the space dimension and/or sample size grow. We propose a new computationally efficient method, referred to as adaptive minimal confidence region rule with bootstrap (AMCR-B), for initial bias truncation in multivariate systems. The log-transformation of the covariance is used to avoid matrix inversion and the sample generalized variance is calculated correspondingly. An order preserving bootstrap resampling technique is used to draw data substreams to obtain the bootstrap distribution of the sample generalized variance. Appropriately selected empirical quantile of the sample variance as a function of truncation point is further estimated. The tuning parameter is then automatically selected applying the elbow method to the former quantile curve. The efficacy and superiority of the AMCR-B rule over the leading existing approaches is demonstrated through extensive simulation studies and a real-world application example.

Keywords: Bootstrap; steady state; minimum confidence region; generalized variance; machine learning