Neural Network Sieve Bootstrap for Nonlinear Time Series

Michele La Rocca*
University of Salerno, Salerno Italy - larocca@unisa.it

Cira Perna
University of Salerno, Salerno Italy - larocca@unisa.it
Francesco Giordano
University of Salerno, Salerno Italy - larocca@unisa.it

Sieve bootstrap schemes have proved to be effective resampling techniques with applications in a wide range of fields. These methods are easy to implement (since they retain the simplicity of the classical residual bootstrap) and are robust to model misspecification (since they should be viewed as nonparametric techniques).

In this talk, we discuss a bootstrap scheme suitable for nonlinear processes, developed in the same spirit as the AR-sieve bootstrap which uses the class of feedforward neural networks as sieve approximators. This seems to be justified for several reasons. First, feedforward neural networks are popular models in nonlinear time series analysis for their good forecasting accuracy. Secondly, this approach does not suffer for the so-called curse of dimensionality, since the approximation form does not appear to be so sensitive to the increasing dimension, at least within the confines of par- ticular classes of functions. Therefore, extension of the neural network sieve bootstrap procedure to high-dimensional models is expected to be more straightforward than that of other nonparametric approaches. Moreover, neural networks are global nonparametric methods, and their use could stress different features and data structures when compared with the local nonparametric methods such as the kernel one. Finally and most importantly, under quite general conditions, this class of models provides an arbitrarily accurate approximation to an unknown target function of interest. If the network model is fitted to the data in such a way that the complexity of the network is allowed to increase at a proper rate with the sample size, the resulting function estimator can then be viewed as a nonparametric sieve estimator. The resampling scheme from the residuals of feedforward neural networks is shown to be asymptotically justified. Moreover, a Monte Carlo study shows that it has comparable performances to the AR-sieve bootstrap, when the process is linear, but it delivers better results when the process is nonlinear, both in terms of bias and variability.

As a main drawback, the use of feedforard neural networks makes the computational burden of the proposed sieve bootstrap scheme quite heavy, being both resampling and neural networks computer intensive techniques. As an effective solution to this problem, we propose and discuss the use of a sieve bootstrap scheme based on Extreme Learning Machines, a class of neural networks that are becoming more and more popular in the neural network community. The novel approach shows perfomance comparable with that of the classical neural network sieve bootstrap with a much lighter computational burden, comparable with that of the AR-sieve bootstrap in the linear case.

Keywords: sieve bootstrap; neural networks; extreme learning machines; nonlinear time series.