The Pros and Cons for parametric bootstrap, sieve bootstrap and block bootstrap:

The gain of the **sieve bootstrap** is usually more substantial and performs better than other two bootstrap methods, if the autocovariances of the process exhibit some damped pseudoperiodic decay.

Sieve bootstraps in general resample from a reasonable time series model. This implies two advantages: the plug-in rule is employed for defining and computing the bootstrapped estimator, and the double bootstrap potentially leads to higher order accuracy. Good sieve bootstraps, like the AR- or VLMC-sieve schemes, are expected to adapt to the degree of dependence: their accuracy improves as the degree of dependence decreases; Also, sieve bootstraps seem generally less sensitive to selection of a model in the sieve than the block bootstrap to the blocklength. While for the disadvantages: The disadvantage is the difficulty of doing the resampling: the context algorithm which is used for this task is publicly available in R, which should help to overcome most of the implementational burdens. The algorithm is computationally fast using only O(n log(n)) essential operations. Double bootstrapping was successful in a simulated example.

While the **block bootstrap** method is the most general bootstrap method and its easy to implement, but the disadvantages are as follows: The block bootstrap sample should not be viewed as a reasonable sample mimicking the data-generating process: it is not stationary and exhibits artifacts where resampled blocks are linked together. This implies that the plug-in rule for bootstrapping an estimator θ is not appropriate. A prevectorization of the data is highly recommended, but the bootstrapped estimator and its computing routine may then need to be redesigned. What's more, Second-order accuracy for a confidence interval has been justified with the approach of Studentizing and BCa correction (in the case of noncategorical time series); the latter was found to yield marginal improvement in a simulated example (we did not consider the former). Double bootstrapping does not seem promising since the block bootstrap in the first iteration corrupts dependence where blocks join.

For the parametric bootstrap: we should note that for block bootstrap and the sieve bootstrap, these are non-parametric bootstrap. So In the nonparametric bootstrap, samples are drawn from a discrete set of n observations. This can be a serious disadvantage in small sample sizes because spurious fine structure in the original sample, but absent from the population sampled, may be faithfully reproduced in the simulated data.

Another concern is that because small samples have only a few values, covering a restricted range, nonparametric bootstrap samples underestimate the amount of variation in the population you originally sampled. As a result, statisticians generally see samples of 10 or less as too small for reliable nonparametric bootstrapping.

Small samples convey little reliable information about the higher moments of their population distribution function - in which case, a relatively simple function may be adequate.

Although parametric bootstrapping provides more power than the nonparametric bootstrap, it does so on the basis of an inherently arbitrary choice of model. Whilst the cumulative distribution of even quite small samples deviate little from that of their population, it can be far from easy to select the most appropriate mathematical function *a priori*.

Maximum likelihood estimators are commonly used for parametric bootstrapping despite the fact that this criterion is nearly always based upon their large sample behaviour.

Choosing an appropriate parametric error structure for a statistic based upon small samples can be awkward to justify. Bootstrap *t* statistics present an additional problem, partly because of problems in estimating standard errors analytically, partly because of difficulties in working out a suitable number of degrees of freedom for your pivot's (presumed, but often large-sample-based) distribution.