

Bootstrap methods for time series

Part 2: Bootstrap Confidence Interval

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1. Introduction to Bootstrap
2. **Bootstrap Confidence Interval**
3. Block Bootstrap Methods
4. Bootstrap for Data with Periodic Structure

2.1. Bootstrap-t interval

2.2. Percentile confidence intervals

In this lecture, we assume that all bootstrap samples have the same size as an original sample. That is, $m = n$.

2.1. Bootstrap- t interval

Recall that to construct confidence intervals for the mean μ in a normal population with unknown variance, we use the following fact

$$Z = \frac{\bar{X}_n - \mu}{S_n/\sqrt{n}} \sim t_{n-1}.$$

The obtained confidence interval is given

$$[\bar{X}_n - t_{n-1}(1 - \alpha/2) \cdot S_n/\sqrt{n}, \bar{X}_n - t_{n-1}(\alpha/2) \cdot S_n/\sqrt{n}]$$

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In the bootstrap- t approach, we estimate the distribution of

$$Z = \frac{\hat{\theta}_n - \theta}{\hat{\sigma}_n}.$$

Specifically estimate the quantiles of Z to contract the confidence interval in the same way as in the previous slide.

Algorithm

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Additionally, for each bootstrap sample, compute the standard error estimate $\hat{\sigma}_n^{*(b)}$.

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$$Z_b^* = \frac{\hat{\theta}^{*(b)} - \hat{\theta}_n}{\hat{\sigma}^{*(b)}}$$

and let $Z_{(1)}^*, \dots, Z_{(B)}^*$ be the order statistics. Calculate the $\alpha/2$ and $1 - \alpha/2$ sample quantiles of the bootstrap estimators

$$\hat{Z}^{*(\alpha/2)} = Z_{(\lfloor (B+1)\alpha/2 \rfloor)}^*, \quad \text{and} \quad \hat{Z}^{*(1-\alpha/2)} = Z_{(\lfloor (B+1)(1-\alpha/2) \rfloor)}^*.$$

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4. Construct the bootstrap-t equal-tailed confidence interval of the form

$$\left[\hat{\theta}_n - \hat{z}^{*(1-\alpha/2)} \cdot \hat{\sigma}_n, \hat{\theta}_n - \hat{z}^{*(\alpha/2)} \cdot \hat{\sigma}_n \right]$$

2.2. Percentile confidence intervals

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Then

- $\hat{\theta}_{low} = \hat{\theta}_n^*(\alpha/2) = 100 \cdot (\alpha/2)^{th}$ percentile of $\hat{\theta}_n^*$'s distribution
- $\hat{\theta}_{up} = \hat{\theta}_n^*(1 - \alpha/2) = 100 \cdot (1 - \alpha/2)^{th}$ percentile of $\hat{\theta}_n^*$'s distribution

Idea

Assume that we have a dataset X_n^* generated using the bootstrap method and computed bootstrap replications $\hat{\theta}_n^*$.

Let the function \hat{G}_n be the distribution function of $\hat{\theta}^*$.

Then, the $1 - \alpha$ confidence interval is defined as

$$[\hat{\theta}_{\%,low}, \hat{\theta}_{\%,up}] = [\hat{G}_n^{-1}(\alpha/2), \hat{G}_n^{-1}(1 - \alpha/2)]$$

Notice that $\hat{G}_n^{-1}(\alpha) = \hat{\theta}_n^*(\alpha)$ is the $100 \cdot \alpha$ percentile of the bootstrap distribution. Therefore, the percentile confidence interval can be written as:

$$[\hat{\theta}_{\%,low}, \hat{\theta}_{\%,up}] = [\hat{\theta}_n^*(\alpha), \hat{\theta}_n^*(1 - \alpha)]$$

The above situation refers to the case where we have an infinite number of replications.

In practice, we use a finite number B .

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$$\hat{\theta}^{*(\alpha/2)} = \hat{\theta}_{(\lfloor (B+1)\alpha/2 \rfloor)}^*, \quad \text{and} \quad \hat{\theta}^{*(1-\alpha/2)} = \hat{\theta}_{(\lfloor (B+1)(1-\alpha/2) \rfloor)}^*.$$

4. The percentile confidence interval is given by

$$[\hat{\theta}^{*(\alpha/2)}, \hat{\theta}^{*(1-\alpha/2)}]$$



Efron, B., & Tibshirani, R.J. (1994). *An Introduction to the Bootstrap*. Chapman and Hall/CRC.



Simar, L. (2008). *An Invitation to the Bootstrap: Panacea for Statistical Inference?* Institut de Statistique, Université Catholique de Louvain Louvain-la-Neuve, Belgium. [\[link\]](#)

Course materials

Go to my website (<https://home.agh.edu.pl/~bartmaje/>) to the section Teaching.

You can use the QR code below:



Thank you!