Bootstrap resampling

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What is the bootstrap?

The bootstrap is a method for estimating standard errors and computing confidence intervals.

Bootstrap (B. Efron 1979)

"To pull oneself up by one's own bootstraps"

To estimate the variability of an estimator $\widehat{\theta}$, you need to observe many possible values and/or use probability calculations to approximate its distribution. But

- ullet we only see ONE value of $\widehat{ heta}$ from ONE observed sample;
- in complex models, probability calculations are intractable.

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How do we sample from an *unknown* population?

we cannot do this exactly!

Observation: an i.i.d. sample X_1, \ldots, X_n \hookrightarrow we simulate sampling from the population by sampling from the sample = resampling

- The resamples are drawn with replacement from X_1, \ldots, X_n ,
- each resample has the same sample size *n* as the original sample.

(model-free resampling=basic bootstrap)

bootstrap samples

 θ parameter, $\widehat{\theta} = g(X_1, \dots, X_n)$: estimator from the sample.

- draw n observations with replacement from X_1,\ldots,X_n $\hookrightarrow X_1^*,\ldots,X_n^*$ bootstrap sample
- ullet equivalently: $X_1^*,\ldots,X_n^*\sim F_n$, where F_n is the ECDF of X_1,\ldots,X_n

 F_n is an estimator of the unknown CDF of $X_1, \ldots, X_n : X_1^*, \ldots, X_n^*$ is as similar as possible to the original sample.

Bootstrap sampling distribution

 n^n different bootstrap samples \hookrightarrow in practice, simulate B resamples

- In the real world, compute $\widehat{\theta} = g(X_1, \dots, X_n)$;
- In the bootstrap world, compute $\hat{\theta}^* = g(X_1^*, \dots, X_n^*)$;
- Repeat B times

$$(X_{1}^{*(1)}, \dots, X_{n}^{*(1)}) \rightarrow \hat{\theta}_{n}^{*(1)}$$

$$\dots \dots \dots \dots$$

$$(X_{1}^{*(b)}, \dots, X_{n}^{*(b)}) \rightarrow \hat{\theta}_{n}^{*(b)}$$

$$\dots \dots \dots \dots$$

$$(X_{1}^{*(B)}, \dots, X_{n}^{*(B)}) \rightarrow \hat{\theta}_{n}^{*(B)}$$

to get $(\hat{\theta}_n^{*(1)}, \hat{\theta}_n^{*(2)}, \dots, \hat{\theta}_n^{*(B)})$, the bootstrap sampling distribution of $\hat{\theta}$.

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Bootstrap variance estimation

$$\widehat{V}_{\text{boot}} = \frac{1}{B} \sum_{b=1}^{b=B} \left(\hat{\theta}^{*(b)} - \frac{1}{B} \sum_{b=1}^{b=B} \hat{\theta}^{*(b)} \right)^2$$

• What are the bootstrap estimates of Bias, Standard error and MSE?

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Validity of the bootstrap

We are using two approximations:

$$\begin{array}{ll} \mathsf{Law}\; (\widehat{\theta} - \theta) & \approx & \mathsf{bootstrap}\; \mathsf{law}(\widehat{\theta}^* - \widehat{\theta}) \\ & \approx & \mathsf{bootstrap}\; \mathsf{sampling}\; \mathsf{law}\; (\widehat{\theta}^{*1} - \widehat{\theta}, \widehat{\theta}^{*2} - \widehat{\theta}, \dots, \widehat{\theta}^{*B} - \widehat{\theta}) \end{array}$$

- The first approximation is from the bootstrap approximation of the population's law by the empirical distribution: it becomes small as *n* becomes large
- The second approximation is due to Monte Carlo error and can be made small by choosing B large (B=200 or B=1000)

Basic bootstrap intervals

The law of $\widehat{\theta}-\theta$ is approximated by the law of $\widehat{\theta}^*-\widehat{\theta}.$

bootstrap quantiles: let $b^*_{\alpha/2}$ and $b^*_{1-\alpha/2}$ be the quantiles of the sampling bootstrap law

$$(\widehat{\theta}^{*1} - \widehat{\theta}, \widehat{\theta}^{*2} - \widehat{\theta}, \dots, \widehat{\theta}^{*B} - \widehat{\theta})$$

i.e. the fraction of bootstrap estimates that satisfy $b_{\alpha/2}^* \leq \widehat{\theta}^{*b} - \widehat{\theta} \leq b_{1-\alpha/2}^*$ is $1-\alpha$.

 $\hookrightarrow \mathit{IC}(\theta) = \left[\widehat{\theta} - b_{1-\alpha/2}^*; \ \widehat{\theta} - b_{\alpha/2}^*\right] \text{ is a confidence interval for } \theta. \text{ Its approximate confidence level is } 1-\alpha.$

Why?

Bootstrap-t intervals

If a standard error for $\widehat{\theta}$ is available, let $\widehat{s} = \widehat{s}(X_1, \ldots, X_n)$ be the estimate of the s.e. of $\widehat{\theta}$ (from the Fisher information for example), then we compute the *t-statistic*

$$t = \frac{\widehat{\theta} - \theta}{\widehat{s}}$$

Then the bth bootstrap t-statistic is

$$t^{*b} = \frac{\widehat{\theta}^{*b} - \widehat{\theta}}{\widehat{s}^{*b}}$$

where $\widehat{s}^{*b} = \widehat{s}(X_1^{*(b)}, \dots, X_n^{*(b)})$.

Let $qt_{\alpha/2}^*$ and $qt_{1-\alpha/2}^*$ be the $\alpha/2$ lower and upper quantiles of the sampling distribution of these bootstrap t-statistics, then the confidence interval for θ is

$$[\widehat{\theta} - qt_{1-\alpha/2}^*\widehat{s}, \ \widehat{\theta} - qt_{\alpha/2}^*\widehat{s}]$$