

The Bootstrap

Probability and Statistics for Data Science

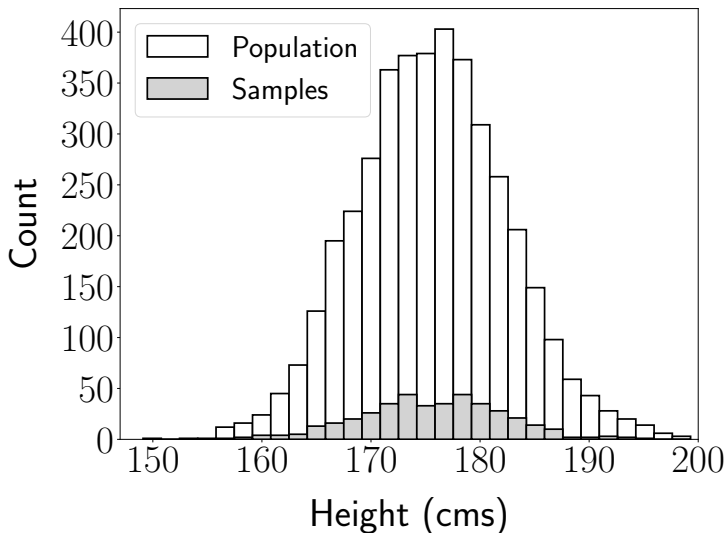
Carlos Fernandez-Granda



These slides are based on the book [Probability and Statistics for Data Science](#) by Carlos Fernandez-Granda, available for purchase [here](#). A free preprint, videos, code, slides and solutions to exercises are available at <https://www.ps4ds.net>

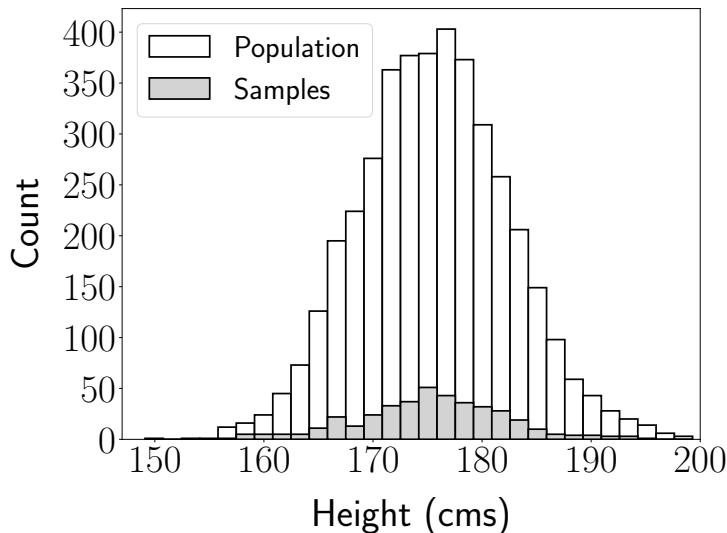
Random sampling

Sample mean = 175.5 ($\mu_{\text{pop}} = 175.6$)



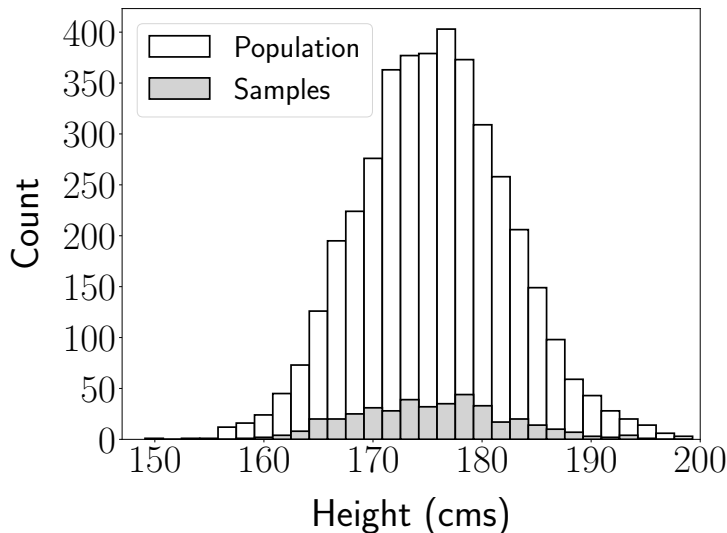
400 random samples

Sample mean = 175.2 ($\mu_{\text{pop}} = 175.6$)



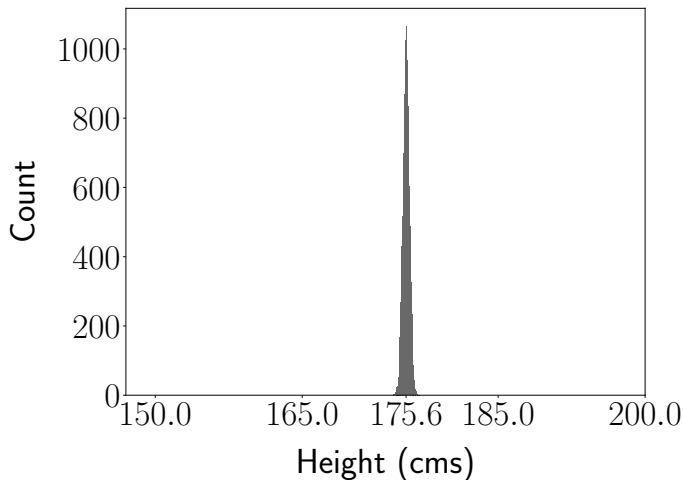
400 random samples

Sample mean = 176.1 ($\mu_{\text{pop}} = 175.6$)



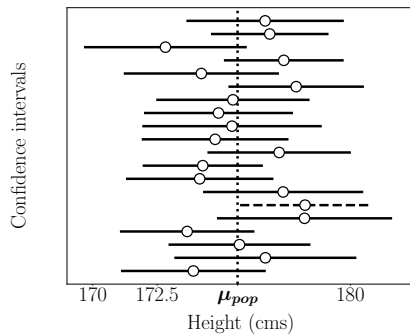
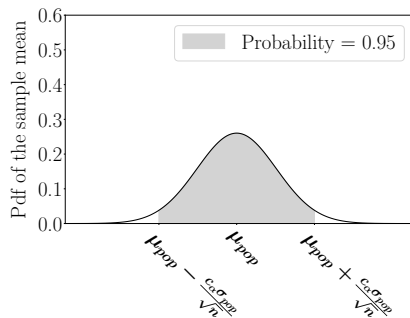
Sample means of 10,000 subsets of size 400

Goal: Quantify uncertainty from available data



Confidence interval

Main idea: Report a **range** of values that contain parameter with high probability (e.g. 95%)



Standard error

We need to estimate standard error

For sample mean

$$\text{se} [\tilde{m}] = \frac{\sigma_{\text{pop}}}{\sqrt{n}}$$

We use sample standard deviation to estimate σ_{pop}

What if we don't know the formula?

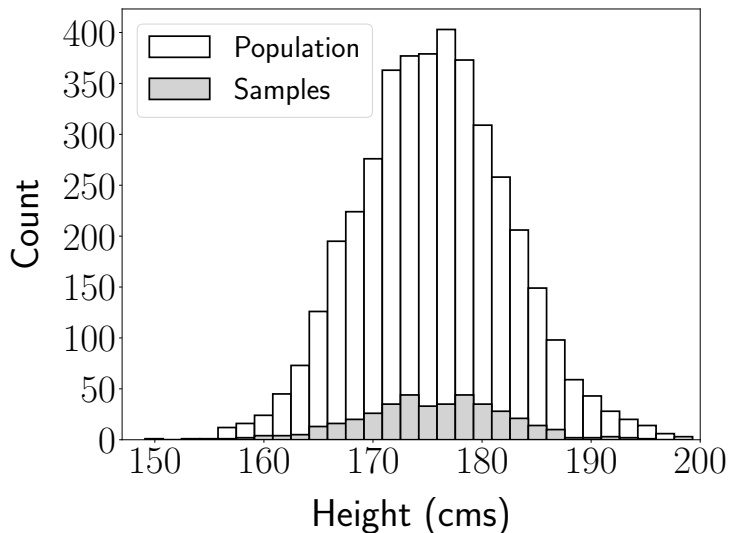
Challenge

How to estimate standard error computationally?

If we can sample more data, this is easy

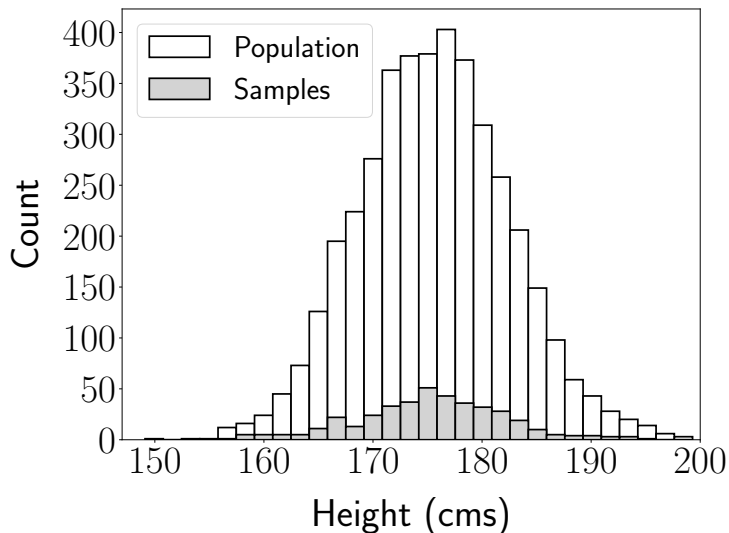
We sample n data points

Sample mean: 175.5



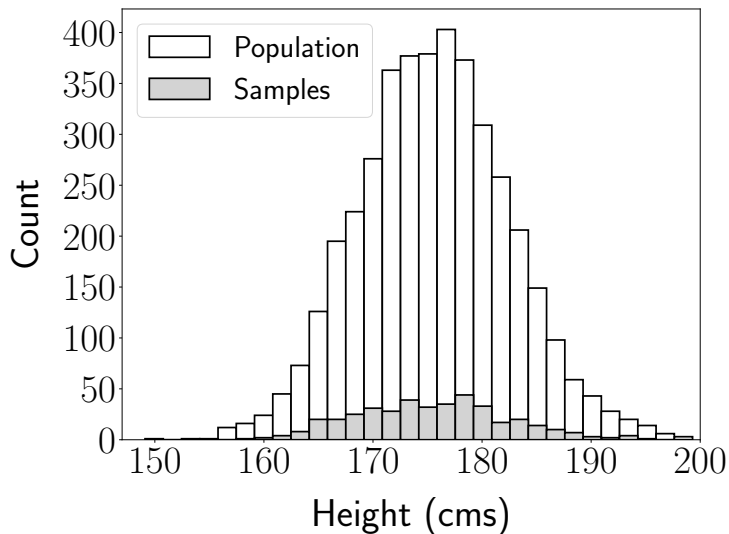
and n more

Sample mean: 175.2



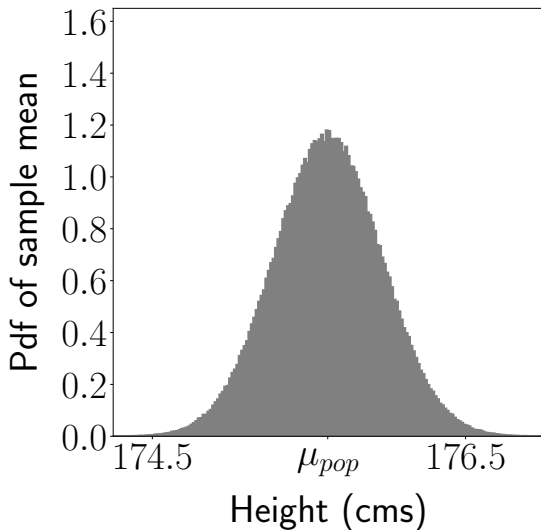
and n more

Sample mean: 176.1



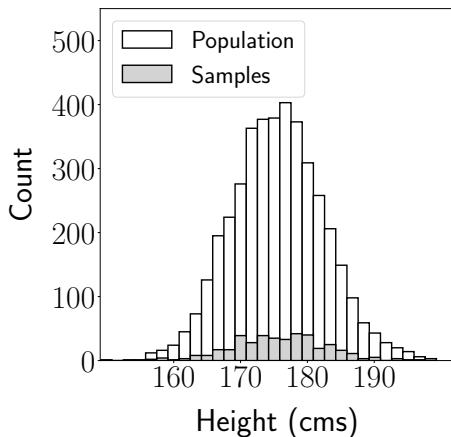
Distribution of sample means

Standard error = standard deviation = 0.343



Problem

We only have n data points



Idea: Sample from the n data as if *they were the population*

The bootstrap

Samples: x_1, \dots, x_n

Bootstrap indices: $\tilde{k}_1, \tilde{k}_2, \dots, \tilde{k}_n$

Sampled independently and uniformly with replacement

$$P\left(\tilde{k}_j = i\right) = \frac{1}{n} \quad 1 \leq i, j \leq n$$

Bootstrap samples: $\tilde{b}_1, \dots, \tilde{b}_n$

$$\tilde{b}_j = x_{\tilde{k}_j} \quad 1 \leq j \leq n$$

The bootstrap



Bootstrap standard error

Samples: x_1, \dots, x_n

Estimator: $h(x_1, \dots, x_n)$

Bootstrap samples: $\tilde{b}_1, \tilde{b}_2, \dots, \tilde{b}_n$

The bootstrap standard error of h is

$$\text{se}_{\text{bs}} = \sqrt{\text{Var} \left[h(\tilde{b}_1, \tilde{b}_2, \dots, \tilde{b}_n) \right]}$$

Monte Carlo approximation

(1) Generate K batches, $b_j^{[k]}$, $1 \leq j \leq n$, $1 \leq k \leq K$

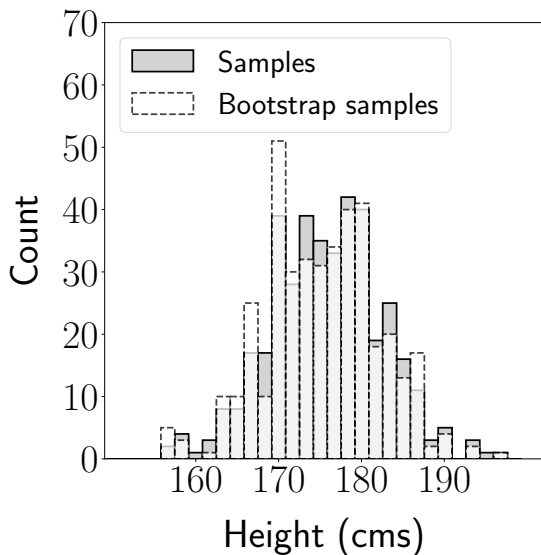
(2) Compute parameter estimates

$$W := \{w_1, w_2, \dots, w_K\}, \quad w_k := h(b_1^{[k]}, b_2^{[k]}, \dots, b_n^{[k]})$$

(3) Bootstrap standard error: [Sample standard deviation of \$W\$](#)

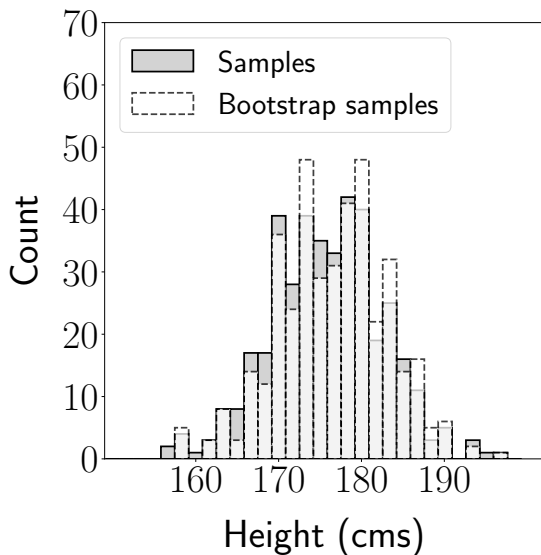
Bootstrap samples

Bootstrap sample mean: 175.3



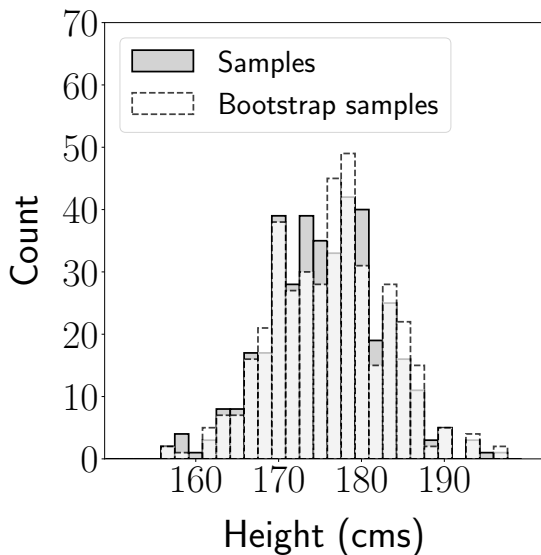
Bootstrap samples

Bootstrap sample mean: 176.6



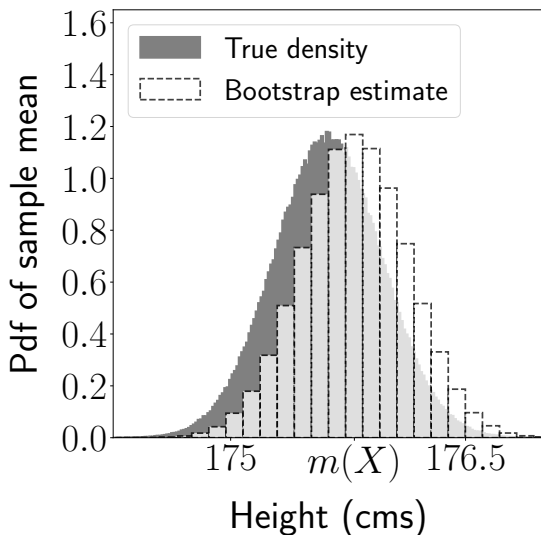
Bootstrap samples

Bootstrap sample mean: 176.2



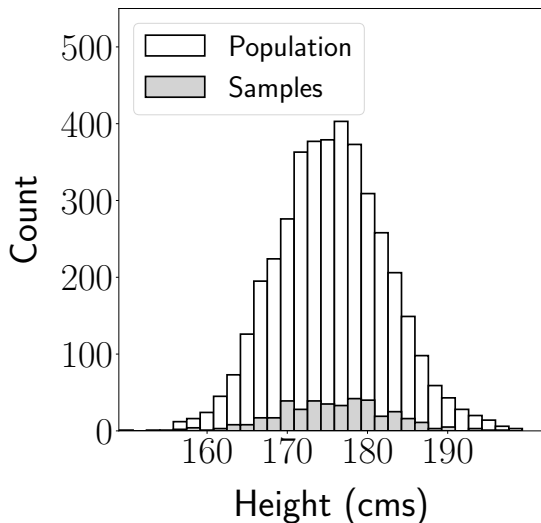
Distribution of bootstrap samples

Bootstrap standard error: 0.339 (True standard error: 0.343)



Traditional standard-error estimate

$$\sqrt{\frac{v(X)}{n}} = 0.340 \text{ (Bootstrap estimate: 0.339)}$$



Bootstrap standard error of the sample mean

Samples $X := \{x_1, \dots, x_n\}$ are the "population"

$$\tilde{m}_{\text{bs}} := \frac{1}{n} \sum_{k=1}^n \tilde{b}_k$$

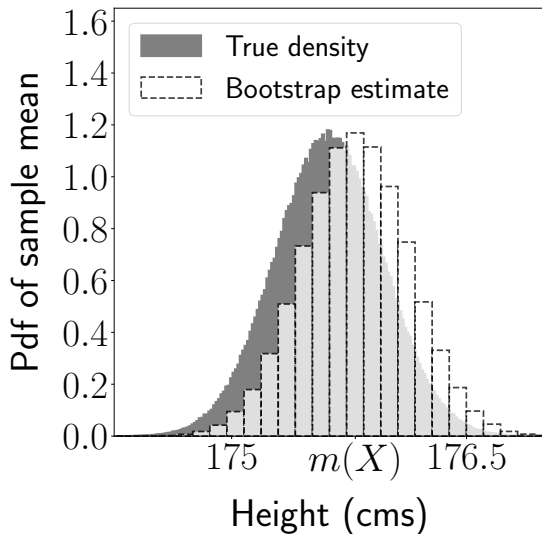
$E[\tilde{m}_{\text{bs}}] = \text{"Population" mean}$

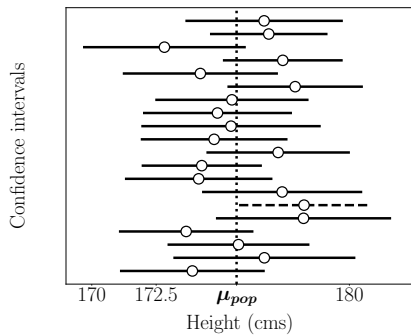
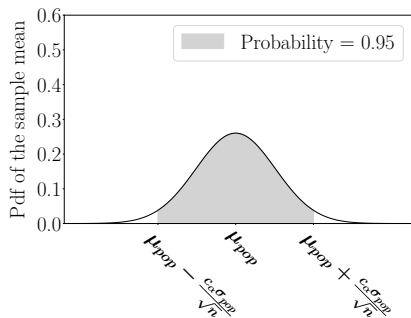
$$= \frac{1}{n} \sum_{j=1}^n x_j = m(X)$$

$$\begin{aligned} \text{se}_{\text{bs}}^2 = \text{Var}[\tilde{m}_{\text{bs}}] &= \frac{\text{"Population" variance}}{n} \\ &= \frac{\frac{1}{n} \sum_{j=1}^n (x_j - m(X))^2}{n} \\ &= \frac{n-1}{n^2} v(X) \end{aligned}$$

Distribution of bootstrap samples

Bootstrap standard error: 0.339 ($\sqrt{\frac{v(X)}{n}} = 0.340$)





Confidence interval for a Gaussian

Let \tilde{a} be Gaussian with mean μ and variance σ^2

$$\tilde{\mathcal{I}}_{1-\alpha} := [\tilde{a} - c_\alpha \sigma, \tilde{a} + c_\alpha \sigma] \quad c_\alpha := F_{\tilde{z}}^{-1} \left(1 - \frac{\alpha}{2} \right)$$

$$\tilde{\mathcal{I}}_{0.95} := [\tilde{a} - 1.96\sigma, \tilde{a} + 1.96\sigma]$$

Bootstrap Gaussian confidence interval

Samples: $X := \{x_1, \dots, x_n\}$

Estimator: $h(X)$

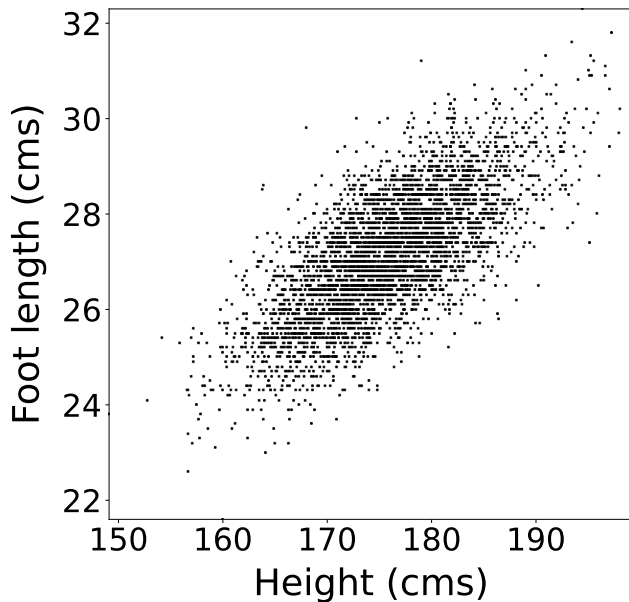
Bootstrap standard error: se_{bs}

$1-\alpha$ bootstrap Gaussian confidence interval

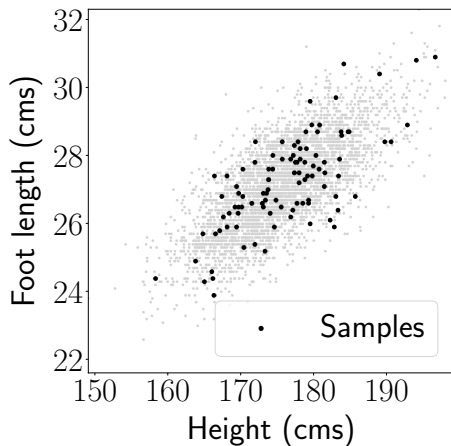
$$\mathcal{I}_{1-\alpha}^{BSG} := [h(X) - c_\alpha se_{bs}, h(X) + c_\alpha se_{bs}] \quad c_\alpha := F_Z^{-1} \left(1 - \frac{\alpha}{2} \right)$$

$$\tilde{\mathcal{I}}_{0.95} := [h(X) - 1.96 se_{bs}, h(X) + 1.96 se_{bs}]$$

Population correlation coefficient: 0.718



100 samples

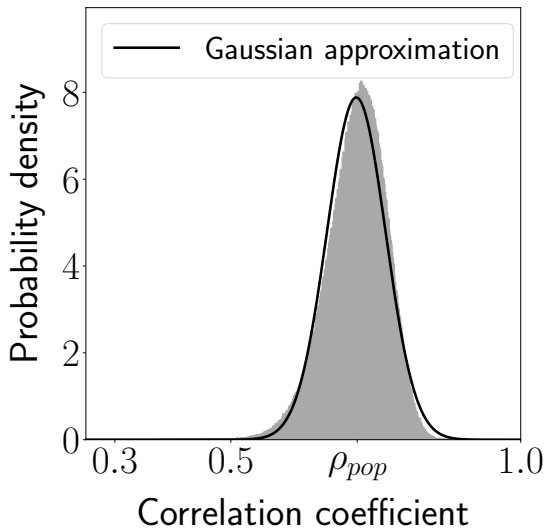


Sample correlation coefficient: $\rho_{\text{sample}} = 0.727$

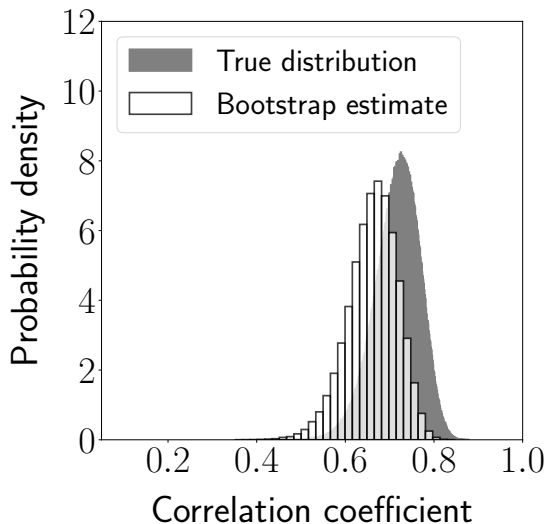
Confidence interval?

Distribution of sample correlation coefficient

True standard error: 0.051



Bootstrap standard error $se_{bs} = 0.056$



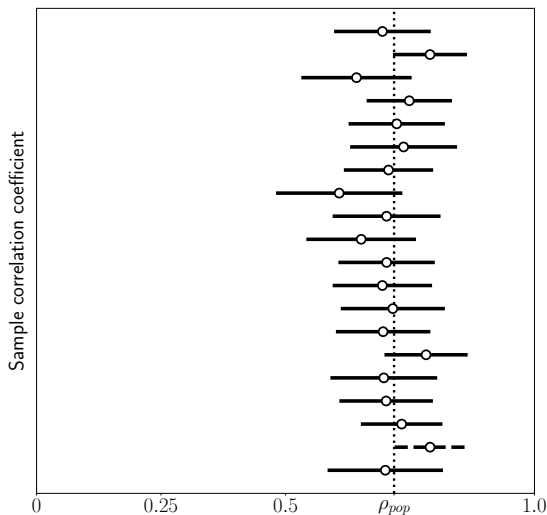
Bootstrap Gaussian confidence interval

$$\mathcal{I}_{1-\alpha}^{\text{BSG}} := [\rho_{\text{sample}} - c_{\alpha} \text{se}_{\text{bs}}, \rho_{\text{sample}} + c_{\alpha} \text{se}_{\text{bs}}]$$

$$\begin{aligned}\mathcal{I}_{0.95}^{\text{BSG}} &:= [\rho_{\text{sample}} - 1.96 \text{se}_{\text{bs}}, \rho_{\text{sample}} + 1.96 \text{se}_{\text{bs}}] \\ &= [0.617, 0.837]\end{aligned}$$

Bootstrap Gaussian confidence intervals

Coverage: 93.7% (out of 10^4)



What have we learned

Definition of the bootstrap

Bootstrap standard error

Bootstrap Gaussian confidence interval