

# 13: INTRO TO THE BOOTSTRAP

Stat250 S25

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## 1 Roadmap

Observe  $X_1, \dots, X_n \sim F(\theta)$  with  $\theta$  unknown. Estimate  $\hat{\theta} = g(X_i)$ .

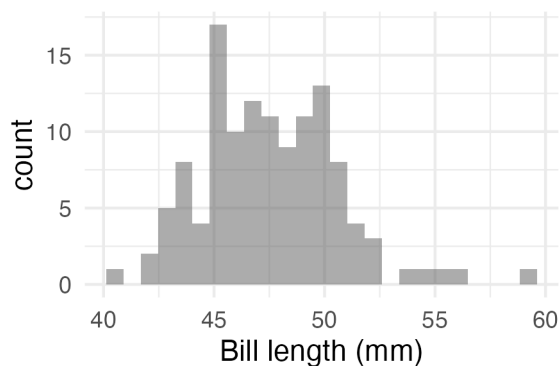
Do we expect  $\hat{\theta}$  to be **exactly equal** to  $\theta$ ?

What are **plausible values** for  $\theta$  given an observed  $\hat{\theta}$ ?

We want to develop an interval estimate of a population parameter:

1. *Exact method*: Find the sampling distribution in closed form (Ch 4). REquires knowledge of the distribution of the data
2. **Bootstrap Method**: Use the sample to approximate the population and simulate a sampling distribution (Ch5)
3. *Asymptotic method*: Use large-sample theory to approximate the sampling distribution (e.g., appeal to the CLT; Ch7)

## 2 Example: gentoo penguin bill length



min	40.90
Q1	45.30
median	47.30
Q3	49.55
max	59.60
mean	47.50
sd	3.08
n	123.00
missing	1.00

### 2.1 The one-sample bootstrap algorithm

Given a sample of size  $n$  from a population,

1. Draw a resample of size  $n$ , **with replacement**, from the sample.
2. Compute the statistic of interest.
3. Repeat this resampling process (steps 1-2) many times, say 10,000.
4. Construct the bootstrap distribution of the statistic.

### 3 How does the bootstrap work?



	Mean	SD	Bias
Population	1	0.5	
Sample			
Sampling distribution			
Bootstrap distribution			

### 4 Why does the bootstrap work?

First, recall the definition of the CDF:

$$F_x(x_0) = P(X \leq x_0)$$

In other words,  $F_x$  is the probability of the event  $\{X \leq x_0\}$ . If we observe a sample of  $X_1, \dots, X_n \sim F_x$ , a natural estimator for this probability is the observed proportion of observations where  $\{X_i \leq x_0\}$ .

$$\hat{F}_n = \frac{\sum \mathbb{I}(X_i \leq x_0)}{n}$$

so \_\_\_\_\_ is an estimator for \_\_\_\_\_

Each bootstrap sample is drawn from  $\hat{F}$ :

$$X_1^{*(1)}, X_2^{*(1)}, \dots, X_n^{*(1)} \sim \hat{F}_n$$

As  $n$  increases,  $\hat{F}_n$  gets closer to true  $F$



It turns out that  $\hat{F}_n$  is an \_\_\_\_\_ and \_\_\_\_\_ estimator for  $F$ !

- When  $n$  is large,  $\hat{F}_n$  is very close to  $F$
- So any statistic that is based on  $\hat{F}_n$  is very similar to the same statistic based on  $F$
- Re-sampling from our original sample results in a sampling distribution that is very similar to the theoretical sampling distribution
- This is true even if we don't know what the theoretical sampling distribution is!

## 5 R Implementation

```
y <- gentoo$bill_length_mm # original sample
n <- nrow(gentoo)          # sample size
N <- 10^4                  # desired no. resamples
boot_means <- numeric(N)   # a place to store the bootstrap stats

# Resampling from the sample
for (i in 1:N) {
  x <- sample(y, size = n, replace = TRUE)
  boot_means[i] <- mean(x, na.rm = TRUE) # you can choose other statistics
}

# Calculate a 95% percentile interval
quantile(boot_means, probs = c(0.025, 0.975))
```

```
2.5%    97.5%
46.97258 48.06372
```