

## Lemma

If  $U \sim \text{Uniform}[0, 1]$

then  $F^{-1}(U)$  is a random variable with c.d.f.  $F$

proof

$$P(F^{-1}(U) \leq y) \stackrel{!}{=} P(U \leq F(y))$$

because  $F$  is monotone increasing.

Now  $0 \leq F(y) \leq 1$  because  $F$  is a c.d.f.

We know  $P(U \leq x) = x$  for  $0 \leq x \leq 1$ ,

$$\text{so } P(F^{-1}(U) \leq y) = F(y). \quad \blacksquare$$

## Example

$X \sim \text{Exp}(\lambda)$ , then  $F(x) = 1 - e^{-\lambda x}$

$$\text{Set } y = 1 - e^{-\lambda x}$$

$$\Rightarrow e^{-\lambda x} = 1 - y$$

$$\Rightarrow x = -\frac{1}{\lambda} \log(1 - y)$$

$$\Rightarrow F^{-1}(y) = -\frac{1}{\lambda} \log(1 - y)$$

$$F^{-1}(U) = -\frac{1}{\lambda} \ln(1 - U) \sim \text{Exp}(\lambda)$$

## For Loops in R

For loops are a way of repeating the same operation over and over again.

The structure of a for loop is

for ( $\langle \text{variable} \rangle$  in  $\langle \text{vector} \rangle$  {do command})

$\langle \text{vector} \rangle$  is a set of values for which we want the command repeated.

$\langle \text{variable} \rangle$  takes values in  $\langle \text{vector} \rangle$ .

## Bootstrapping

Suppose we want to make inferences about  $\phi(\theta_1, \dots, \theta_p)$  from observed data.

We have been assuming that the  $Y_i$ 's are taken from some distribution and using the data  $y_1, \dots, y_n$  to estimate the  $\theta_1, \dots, \theta_p$ .

An alternative method is called bootstrapping or the bootstrap method.

In this method, we form an empirical sampling distribution of  $\phi$  from the  $Y_i$ 's. We sample from the  $Y_i$ 's over and over again with replacement. This is called resampling. For each resample, we estimate  $\phi$  again.

The procedure we follow given  $y_1, \dots, y_n$  is

(1) The empirical distribution is

$$F_n^n(y) = \frac{1}{n} \left| \left\{ 1 \leq i \leq n : y_i \leq y \right\} \right|$$

(A) Draw a sample of size  $n$  from  $F_n^n(y)$ . This is equivalent to sampling from  $y_1, \dots, y_n$  with replacement.

(B) From this bootstrap sample form an estimate  $\phi^*$  of  $\phi$  in the same way we formed  $\hat{\phi}$  from  $y_1, \dots, y_n$

Repeat (A) and (B)  $B$  times obtaining

$B$  estimates  $\phi_1^*, \dots, \phi_B^*$  of  $\phi$ .

Now we can  
1. estimate the mean of  $\hat{\phi}$

$$\text{by } \frac{1}{B} \sum_{i=1}^B \phi_i^*$$

2. estimate the median of  $\hat{\phi}$

by the 0.5 empirical quantile of the  $\phi_i^*$ .

### Parametric Bootstrap

We assume the  $X_i$ 's come from a

distribution with parameter  $\theta$ .

We estimate  $\theta$  by method of moments or maximum likelihood to obtain  $\hat{\theta}$ .

Now we generate samples from the distribution with parameter  $\theta$  and proceed as before

### Example

Suppose  $Y_i \sim \text{Exponential}(\theta)$

Our sample is  $0.61, 6.47, \dots, 0.75$

$$\bar{y} = \frac{1}{0.3530}$$

$$\hat{\lambda} = \frac{1}{\bar{y}} = 0.3530$$

We now use Exponential (0.3530) to generate new samples, and proceed as before.