

# Topic 16

## Interval Estimation

### Building Confidence Intervals

## Outline

### Pivotal Quantities

Constructing Confidence Intervals

### Pivoting Using the Probability Transform

Optimizing the Length of the Confidence Interval

## Pivotal Quantities

A random quantity  $Q(\mathbf{X}, \theta)$  is called a **pivotal quantity** or a **pivot** if

- is a function of  $\mathbf{X}$  and  $\theta$  where  $\theta$  is the only **unknown** parameter.
- The **distribution** of  $Q(\mathbf{X}, \theta)$  does not depend on  $\theta$ .

Examples.

For  $\mathbf{X} = (X_1, \dots, X_n)$ , independent and identically distributed.

- If the  $X_i$  arise from a **location family** with density  $f(x - \theta)$ , then

$$Q(\mathbf{X}, \theta) = \sum_{i=1}^n a_i(X_i - \theta)$$

is a **pivotal quantity**. In particular,  $\bar{X} - \theta$  is a **pivot**.

## Pivotal Quantities

- If the  $X_i$  arise from a **scale family** with density  $\frac{1}{\beta} f\left(\frac{x}{\beta}\right)$ , then

$$Q(\mathbf{X}, \theta) = \frac{\sum_{i=1}^n a_i X_i}{\beta}$$

is a **pivotal quantity**. In particular,  $\sum_{i=1}^n X_i/\beta$  is a **pivot**.

- If the  $X_i$  arise from a **location-scale family** with density  $\frac{1}{\beta} f\left(\frac{x-\theta}{\beta}\right)$

$$Q(\mathbf{X}, \theta) = \frac{\bar{X} - \theta}{S}$$

is a **pivotal quantity**.

**Note.** Even though  $Q(\mathbf{X}, \theta)$  does not depend on  $\theta$ , it is not an **ancillary statistic**. It is not even a **statistic**.

## Constructing Confidence Intervals

To construct a  $\gamma$ -level confidence interval,

- Find  $\ell$  and  $u$  so that

$$P_{\theta}\{\ell \leq Q(\mathbf{x}, \theta) \leq u\} = \gamma.$$

- Define

$$C(\mathbf{x}) = \{\mathbf{x}; \ell \leq Q(\mathbf{X}, \theta) \leq u\}.$$

Then

$$P_{\theta}\{\theta \in C(\mathbf{X})\} = \gamma.$$

If, for each  $\mathbf{x}$ ,  $Q(\mathbf{x}, \theta)$  is **monotone increasing** in  $\theta$ , then let

- $\hat{\theta}_{\ell}(\mathbf{x})$  be the **solution** to  $Q(\mathbf{x}, \theta) = \ell$  and
- $\hat{\theta}_u(\mathbf{x})$  be the **solution** to  $Q(\mathbf{x}, \theta) = u$ .

Then.

$$C(\mathbf{x}) = \{\mathbf{x}; \hat{\theta}_{\ell}(\mathbf{x}) \leq \theta \leq \hat{\theta}_u(\mathbf{x})\}.$$

## Constructing Confidence Intervals

For  $Q(\mathbf{x}, \theta)$  is **monotone decreasing** in  $\theta$ , then **reverse** the roll of  $\hat{\theta}_\ell(\mathbf{x})$  and  $\hat{\theta}_u(\mathbf{x})$ .

**Example.** For  $\mathbf{X} = (X_1, \dots, X_n)$  from a **location family** with **density**  $f(x - \theta)$ , then take  $Q(\mathbf{X}, \theta) = \bar{X} - \theta$  as the **pivot**. Then choose  $\ell$  and  $u$  so that

$$\begin{aligned}\gamma &= P_\theta\{\mathbf{X}; \ell \leq Q(\mathbf{X}, \theta) \leq u\} = P_\theta\{\mathbf{X}; \ell \leq \bar{X} - \theta \leq u\} \\ &= P_\theta\{\mathbf{X}; \ell - \bar{X} \leq -\theta \leq u - \bar{X}\} = P_\theta\{\mathbf{X}; \bar{X} - \ell \geq \theta \geq \bar{X} - u\}\end{aligned}$$

For  $\mathbf{X} = (X_1, \dots, X_n) \sim N(\theta, \sigma_0^2)$ , then take

$$\ell = -\frac{z_{(1-\gamma)/2}\sigma_0}{\sqrt{n}} \quad \text{and} \quad u = \frac{z_{(1-\gamma)/2}\sigma_0}{\sqrt{n}}.$$

## Constructing Confidence Intervals

Example. For  $\mathbf{X} = (X_1, \dots, X_n)$  from a **scale family** with **density**  $\frac{1}{\beta} f\left(\frac{x}{\beta}\right)$ , take  $Q(\mathbf{X}, \beta) = \sum_{i=1}^n x_i / \beta = T(\mathbf{x}) / \beta$  as the **pivot**. Then choose  $\ell$  and  $u$  so that

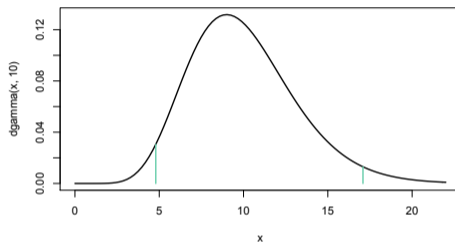
$$\begin{aligned}\gamma &= P_{\beta}\{\mathbf{X}; \ell \leq Q(\mathbf{X}, \beta) \leq u\} \\ &= P_{\beta}\{\mathbf{X}; \ell \leq T(\mathbf{X}) / \beta \leq u\} \\ &= P_{\beta}\{\mathbf{X}; 1/\ell \geq \beta / T(\mathbf{X}) \geq 1/u\} \\ &= P_{\beta}\{\mathbf{X}; T(\mathbf{X}) / \ell \geq \beta \geq T(\mathbf{X}) / u\}\end{aligned}$$

For  $Exp(\beta)$  random variable,  $T(\mathbf{X}) / \beta \sim \Gamma(n, 1)$  is a **pivot**. For an **equal tailed 95%** confidence interval,

## Constructing Confidence Intervals

```
> gamma<-0.95  
> alpha<-(1-gamma)/2  
> qgamma(c(alpha,1-alpha),10)
```

```
[1] 4.795389 17.084803
```



Thus,

$$\begin{aligned} 0.95 &= P_{\beta}\{\mathbf{X}; 4.795 \leq T(\mathbf{X})/\beta \leq 17.085\} \\ &= P_{\beta}\{\mathbf{X}; T(\mathbf{X})/4.795 \geq \beta \geq T(\mathbf{X})/17.085\} \end{aligned}$$



## Constructing Confidence Intervals

Example. For  $\mathbf{X} = (X_1, \dots, X_n) \sim U(0, \theta)$ , take

$$Q(\mathbf{x}, \beta) = \max_i x_i / \theta = T(\mathbf{x}) / \theta$$

as the **pivot**. Then  $M = T(\mathbf{x}) / \theta$  has distribution function  $F_M(t) = t^n$  in the interval  $[0, 1]$ . For an equal tailed  $\gamma$ -confidence interval, set

$$F_M(u) = \frac{1 + \gamma}{2} \quad \text{and} \quad F_M(\ell) = \frac{1 - \gamma}{2}.$$

$$u = \left( \frac{1 + \gamma}{2} \right)^{1/n} \quad \text{and} \quad \ell = \left( \frac{1 - \gamma}{2} \right)^{1/n}.$$

$$\gamma = P_\beta \left\{ \mathbf{X}; T(\mathbf{X}) \left( \frac{1 - \gamma}{2} \right)^{-1/n} \geq \beta \geq T(\mathbf{X}) \left( \frac{1 + \gamma}{2} \right)^{-1/n} \right\}.$$

## Pivoting Using the Probability Transform

**Theorem.** Let  $T$  be a **continuous (test) statistic** with **distribution function**  $F_T(t|\theta)$ ,  $\theta \in \Theta \subset \mathbb{R}$ . Let  $\alpha_1 + \alpha_2 = 1 - \gamma$  be the size of the two tails outside the confidence interval.

For  $F_T(t|\theta)$  a **decreasing function** of  $\theta$ , define  $\hat{\theta}_u(t)$  and  $\hat{\theta}_\ell(t)$  by

$$F_T(t|\hat{\theta}_u(t)) = \alpha_1 \quad \text{and} \quad F_T(t|\hat{\theta}_\ell(t)) = 1 - \alpha_2,$$

respectively. Then, the **random interval**

$$[\hat{\theta}_\ell(T), \hat{\theta}_u(T)]$$

is a  $\gamma$ -level confidence interval.

## Pivoting Using the Probability Transform

**Proof.** Because, for any given value of  $t$ ,  $F_T(t|\theta)$  a decreasing function of  $\theta$ . Thus,

$$1 - \alpha_2 > \alpha_1 \quad \text{implies} \quad \hat{\theta}_\ell(t) < \hat{\theta}_u(t).$$

Moreover,

$$\begin{aligned} F_T(t|\theta) < \alpha_1 &\Leftrightarrow \theta > \hat{\theta}_u(t) \\ F_T(t|\theta) > 1 - \alpha_2 &\Leftrightarrow \theta < \hat{\theta}_\ell(t). \end{aligned}$$

Consequently,

$$\{\theta; \alpha_1 \leq F_T(T|\theta) \leq 1 - \alpha_2\} = \{\theta; \theta_\ell(T) \leq \theta \leq \theta_u(T)\}$$

**Remark.** The proof can be modified to handle the case of  $F_T(t|\theta)$  an increasing function of  $\theta$  and for one-sided confidence intervals.

## Pivoting Using the Probability Transform

Example. For independent  $\mathbf{X} = (X_1, \dots, X_n) \sim U(-\theta, \theta)$ , we will use  $T(\mathbf{X}) = X_{(n)} - X_{(1)}$  to determine the confidence interval. Set

$$U_i = \frac{X_i + \theta}{2\theta}.$$

Then the independent random variables  $\mathbf{U} = (U_1, \dots, U_n) \sim U(0, 1)$ . The

$$T(\mathbf{X}) = X_{(n)} - X_{(1)} = 2\theta((U_{(n)} - \theta) - (U_{(1)} - \theta)) = 2\theta(U_{(n)} - U_{(1)}) = 2\theta D.$$

The distribution

$$F_T(t|\theta) = P_\theta\{T \leq t\} = P_\theta\{2\theta D \leq t\} = P\{D \leq t/(2\theta)\} = F_D(t/(2\theta)),$$

which is a decreasing function of  $\theta$ .

## Pivoting Using the Probability Transform

We have seen that the **distribution** of  $D = U_{(n)} - U_{(1)} \sim \text{Beta}(n - 1, 2)$ .

Let  $Q_D$  be the **quantile function** for  $D$ ,

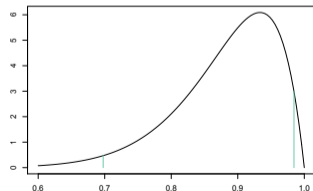
$$\begin{aligned} \left\{ Q_D(\alpha_1) \leq \frac{T(\mathbf{X})}{2\theta} \leq Q_D(1 - \alpha_2) \right\} &= \left\{ \frac{1}{Q_D(\alpha_1)} \geq \frac{2\theta}{T(\mathbf{X})} \geq \frac{1}{Q_D(1 - \alpha_2)} \right\} \\ &= \left\{ \frac{T(\mathbf{X})}{2Q_D(\alpha_1)} \geq \theta \geq \frac{T(\mathbf{X})}{2Q_D(1 - \alpha_2)} \right\} \end{aligned}$$

For  $n = 16$  and  $\gamma = 0.95$ , then the **confidence interval** with **equal probability tails**,

```
> gamma<-0.95; alpha<-(1-gamma)/2
```

```
> qbeta(c(alpha,1-alpha),15,2)
```

```
[1] 0.6976793 0.9844864
```



## Optimizing the Length of the Confidence Interval

As you see the choice of endpoints has the only constraint that the **sum of the tail probabilities** equals  $1 - \gamma$ . One goal is to have the **shortest expected length**. This leads to the following **constrained optimization problem**.

$$\min\{E[\hat{\theta}_u(T) - \hat{\theta}_\ell(T)]; P\{\hat{\theta}_u(T) - \hat{\theta}_\ell(T)\} \geq \gamma\}$$

For the case where the density of  $T$  is **unimodal**, to maximize the probability over an interval of length  $c$ , we differentiate.

$$\frac{d}{da}(F_T(a+c) - F_T(a)) = f_T(a+c) - f_T(a) = 0.$$

If the mode  $t_m$  of the density, then  $a < t_m < a + c$ . Also,

$$f'_T(a) > 0 \quad \text{and} \quad f'_T(a+c) < 0$$

showing that the probability is **maximized**. Notice that if the distribution of  $T$  is symmetric about its mode, then the **equal tailed probabilities** are also the **shortest**.

## Optimizing the Length of the Confidence Interval

Returning to the previous example, we want to find the shortest interval for  $D$  that has probability  $\gamma$ .

```
> gamma<-0.95
> diff<-function(a) qbeta(gamma+a,15,2)-qbeta(a,15,2)
>(astar<-optimize(diff,interval=c(0.001,0.05),maximum=FALSE))
$minimum
[1] 0.04840239
$objective
[1] 0.2621124
> (u<-qbeta(gamma+astar$minimum,15,2))
[1] 0.9962875
> (l<-qbeta(astar$minimum,15,2))
[1] 0.7341751
> dbeta(c(l,u),15,2)
[1] 0.8433389 0.8457852
```

## Optimizing the Length of the Confidence Interval

- Our first confidence interval had equal tails  
 $\alpha_1 = \alpha_2 = 0.025$  and width 0.2868071.
- The density at the left endpoint is lower than on the right.
- This suggests that we can shorten the confidence interval by moving the interval to the right.

