# STSCI 5080 Probability Models and Inference

Lecture 22: Confidence Intervals

November 15, 2018

#### Confidence intervals

#### Definition

Suppose that  $\theta$  is one-dim. and let  $\alpha \in (0,1)$ .

• A data dependent interval  $[A_n, B_n]$ , where  $A_n = A_n(X_1, \dots, X_n)$  and  $B_n = B_n(X_1, \dots, X_n)$ , is a confidence interval (CI) with level  $1 - \alpha$  for  $\theta$  if

$$\underbrace{P_{\theta}(A_n \leq \theta \leq B_n)}_{\text{coverage probability}} \geq 1 - \alpha$$

for any  $\theta \in \Theta$ .

• The interval  $[A_n, B_n]$  is a confidence interval with asymptotic level  $1 - \alpha$  for  $\theta$  if

$$\lim_{n\to\infty} P_{\theta}(A_n \le \theta \le B_n) \ge 1 - \alpha$$

for any  $\theta \in \Theta$ .

#### Rule of thumb

We should construct a CI  $[A_n, B_n]$  in such a way that

$$P_{\theta}(A_n \le \theta \le B_n) = 1 - \alpha \tag{*}$$

for any  $\theta$ , or

$$\lim_{n\to\infty} P_{\theta}(A_n \le \theta \le B_n) = 1 - \alpha$$

for any  $\theta$  if the requirement (\*) is too stringent.

Let

$$X_1,\ldots,X_n \sim N(\mu,\sigma_0^2)$$
 i.i.d.

where  $\mu$  is unknown but  $\sigma_0^2$  is known. The MLE is

$$\widehat{\mu} = \overline{X} \sim N(\mu, \sigma_0^2/n) \quad \text{i.e.} \quad \frac{\sqrt{n}(\widehat{\mu} - \mu)}{\sigma_0} = Z \sim N(0, 1).$$

We note that

$$P_{\mu}\left\{\left|\frac{\sqrt{n}(\widehat{\mu}-\mu)}{\sigma_0}\right| \le z\right\} = P(|Z| \le z) = 2\Phi(z) - 1,$$

where  $\Phi(z)$  is the cdf of N(0,1). In addition, we note that

$$\left| \frac{\sqrt{n}(\widehat{\mu} - \mu)}{\sigma_0} \right| \le z \Leftrightarrow \widehat{\mu} - \frac{z\sigma_0}{\sqrt{n}} \le \mu \le \widehat{\mu} + \frac{z\sigma_0}{\sqrt{n}}.$$

We should choose z in such a way that

$$2\Phi(z) - 1 = 1 - \alpha$$
 i.e.  $z_{\alpha/2} = \Phi^{-1}(1 - \alpha/2)$ .

For example,

$$z_{\alpha/2} \approx \begin{cases} 1.96 & \text{if } \alpha = 0.05 \\ 2.58 & \text{if } \alpha = 0.01 \end{cases}$$

#### Cl for $\mu$ with level $1-\alpha$

A CI for  $\mu$  with level  $1-\alpha$  is given by

$$\left[\widehat{\mu} - \frac{z_{\alpha/2}\sigma_0}{\sqrt{n}}, \widehat{\mu} + \frac{z_{\alpha/2}\sigma_0}{\sqrt{n}}\right].$$

If  $\alpha = 0.05$ , this CI will be

$$\left[\widehat{\mu} - \frac{1.96\sigma_0}{\sqrt{n}}, \widehat{\mu} + \frac{1.96\sigma_0}{\sqrt{n}}\right].$$

#### General case

Suppose that

$$\sqrt{n}(\widehat{\theta} - \theta) \stackrel{d}{\to} N(0, \sigma^2(\theta))$$
 as  $n \to \infty$ 

for some  $\sigma^2(\theta) > 0$  (asymptotic variance). This implies

$$Z_n = \frac{\sqrt{n}(\widehat{\theta} - \theta)}{\sigma(\theta)} \stackrel{d}{\to} Z \sim N(0, 1).$$

So,

$$P_{\theta}(|Z_n| \le z) \approx P(|Z| \le z) = 2\Phi(z) - 1.$$

If we choose  $z = z_{\alpha/2}$ , then

$$P_{\theta}(|Z_n| \leq z_{\alpha/2}) \approx 1 - \alpha.$$

We note that

$$|Z_n| \le z_{\alpha/2} \Leftrightarrow \widehat{\theta} - \frac{z_{\alpha/2}\sigma(\theta)}{\sqrt{n}} \le \theta \le \widehat{\theta} + \frac{z_{\alpha/2}\sigma(\theta)}{\sqrt{n}},$$

which implies that

$$P_{\theta}\left\{\widehat{\theta} - \frac{z_{\alpha/2}\sigma(\theta)}{\sqrt{n}} \le \theta \le \widehat{\theta} + \frac{z_{\alpha/2}\sigma(\theta)}{\sqrt{n}}\right\} \approx 1 - \alpha.$$

We are tempted to use

$$\left[\widehat{\theta} - \frac{z_{\alpha/2}\sigma(\theta)}{\sqrt{n}}, \widehat{\theta} + \frac{z_{\alpha/2}\sigma(\theta)}{\sqrt{n}}\right]$$

as a CI, but

$$\sigma(\theta)$$
 is in general unknown!

# Implication of Slutsky theorem

#### **Theorem**

If 
$$\sqrt{n}(\widehat{\theta} - \theta) \stackrel{d}{\to} N(0, \sigma^2(\theta))$$
 and  $\sigma^2(\theta)$  is continuous in  $\theta$ , then

$$\frac{\sqrt{n}(\widehat{\theta} - \theta)}{\sigma(\widehat{\theta})} \stackrel{d}{\to} N(0, 1).$$

# Implication of Slutsky theorem

#### **Theorem**

If  $\sqrt{n}(\widehat{\theta} - \theta) \xrightarrow{d} N(0, \sigma^2(\theta))$  and  $\sigma^2(\theta)$  is continuous in  $\theta$ , then

$$\frac{\sqrt{n}(\widehat{\theta}-\theta)}{\sigma(\widehat{\theta})} \stackrel{d}{\to} N(0,1).$$

Instead of  $\sigma(\theta)$ , use  $\sigma(\widehat{\theta})$ !

# Recap

#### Cl for $\theta$ with level $1-\alpha$

A CI for  $\theta$  with asymptotic level  $1 - \alpha$  is given by

$$\left[\widehat{\theta} - \frac{z_{\alpha/2}\sigma(\widehat{\theta})}{\sqrt{n}}, \widehat{\theta} + \frac{z_{\alpha/2}\sigma(\widehat{\theta})}{\sqrt{n}}\right].$$

If  $\alpha = 0.05$ , this CI will be

$$\left[\widehat{\theta} - \frac{1.96\sigma(\widehat{\theta})}{\sqrt{n}}, \widehat{\theta} + \frac{1.96\sigma(\widehat{\theta})}{\sqrt{n}}\right].$$

#### Example

Let

$$X_1,\ldots,X_n \sim Po(\lambda)$$
 i.i.d.

for some  $\lambda > 0$ . The MLE is  $\widehat{\lambda} = \overline{X}$ , and by CLT

$$\sqrt{n}(\widehat{\lambda} - \lambda) \stackrel{d}{\to} N(0, \lambda).$$

So a CI for  $\lambda$  with asymptotic level 95% is given by

$$\left[\widehat{\lambda} - \frac{1.96\sqrt{\widehat{\lambda}}}{\sqrt{n}}, \widehat{\lambda} + \frac{1.96\sqrt{\widehat{\lambda}}}{\sqrt{n}}\right].$$

#### Example

Let

$$X \sim Bin(n, p)$$

for some  $0 . The MLE is <math>\widehat{p} = X/n$ , and by CLT

$$\sqrt{n}(\widehat{p}-p) \stackrel{d}{\to} N(0,p(1-p))$$
 as  $n \to \infty$ .

So a CI for p with asymptotic level 95% is given by

$$\left[\widehat{p} - \frac{1.96\sqrt{\widehat{p}(1-\widehat{p})}}{\sqrt{n}}, \widehat{p} + \frac{1.96\sqrt{\widehat{p}(1-\widehat{p})}}{\sqrt{n}}\right].$$

See also Brown, Cai, and DasGupta (2001, Statistical Science) for a discussion on this CI.

# How to determine the sample size?

- Cls can be used to determine the sample size.
- The basic idea is to determine the sample size in such a way that the radius of the CI is less than a desired accuracy.

## Example 22.3 (cont.)

- Suppose that you are interested in the proportion p of the population who supports Party A.
- You draw a sample of n potential voters and X of them support Party A.
- A CI for p with asymptotic level 95% is given by

$$\left[\widehat{p} - \frac{1.96\sqrt{\widehat{p}(1-\widehat{p})}}{\sqrt{n}}, \widehat{p} + \frac{1.96\sqrt{\widehat{p}(1-\widehat{p})}}{\sqrt{n}}\right].$$

 You can determine the sample size n in such a way that the radius of the CI ≤ a desired accuracy. • For example, suppose that we choose n in such a way that the radius of the  $\text{CI} \leq 0.01$ .

The radius is

$$\frac{1.96\sqrt{\widehat{p}(1-\widehat{p})}}{\sqrt{n}} \leq \frac{1.96}{2\sqrt{n}}$$

where we have used the fact that  $\widehat{p}(1-\widehat{p}) \leq 1/4$ .

• So it is enough to take *n* in such a way that

$$\frac{1.96}{2\sqrt{n}} \le 0.01 \Leftrightarrow n \ge 98^2 = 9604.$$

## Variance stabilizing transformation

#### **Definition**

Suppose that  $\sqrt{n}(\widehat{\theta} - \theta) \stackrel{d}{\to} N(0, \sigma^2(\theta))$  and let  $g(\theta)$  be a smooth function in  $\theta$ . The function  $g(\theta)$  is called a variance stabilizing transformation for  $\widehat{\theta}$  if

$$\sqrt{n}\{g(\widehat{\theta}) - g(\theta)\} \stackrel{d}{\to} N(0, 1).$$

Let

$$X_1,\ldots,X_n \sim Po(\lambda)$$
 i.i.d.

for some  $\lambda > 0$ . The MLE is  $\widehat{\lambda} = \overline{X}$ , and by CLT

$$\sqrt{n}(\widehat{\lambda} - \lambda) \xrightarrow{d} N(0, \lambda).$$

Consider the function  $g(\lambda) = 2\sqrt{\lambda}$ . Since  $g'(\lambda) = 1/\sqrt{\lambda}$ , we have

$$\sqrt{n}(2\sqrt{\widehat{\lambda}} - 2\sqrt{\lambda}) \stackrel{d}{\to} N(0, (1/\lambda) \times \lambda) = N(0, 1).$$

So a CI for  $2\sqrt{\lambda}$  with asymptotic level  $1-\alpha$  is given by

$$\left[2\sqrt{\widehat{\lambda}} - \frac{z_{\alpha/2}}{\sqrt{n}}, 2\sqrt{\widehat{\lambda}} + \frac{z_{\alpha/2}}{\sqrt{n}}\right].$$

Now, we note that

$$2\sqrt{\lambda} \in \left[2\sqrt{\widehat{\lambda}} - \frac{z_{\alpha/2}}{\sqrt{n}}, 2\sqrt{\widehat{\lambda}} + \frac{z_{\alpha/2}}{\sqrt{n}}\right] \\ \Leftrightarrow \lambda \in \left[\left(\sqrt{\widehat{\lambda}} - \frac{z_{\alpha/2}}{2\sqrt{n}}\right)^2, \left(\sqrt{\widehat{\lambda}} + \frac{z_{\alpha/2}}{2\sqrt{n}}\right)^2\right].$$

So, the following is also a CI for  $\lambda$  with asymptotic level  $1 - \alpha$ :

$$\left[\left(\sqrt{\widehat{\lambda}} - \frac{z_{\alpha/2}}{2\sqrt{n}}\right)^2, \left(\sqrt{\widehat{\lambda}} + \frac{z_{\alpha/2}}{2\sqrt{n}}\right)^2\right].$$

#### General case

In general, suppose that  $\sqrt{n}(\widehat{\theta} - \theta) \stackrel{d}{\rightarrow} N(0, \sigma^2(\theta))$ . Then

$$\sqrt{n}\{g(\widehat{\theta}) - g(\theta)\} \xrightarrow{d} N(0, \{g'(\theta)\}^2 \sigma^2(\theta))$$

by the delta method. So it is enough to choose  $g(\theta)$  to satisfy

$$\{g'(\theta)\}^2\sigma^2(\theta)=1\quad \text{i.e.}\quad g(\theta)=\underbrace{\int \frac{1}{\sigma(\theta)}d\theta}_{\text{indefinite integral}}.$$

Since this  $g(\theta)$  is increasing in  $\theta$ ,

$$\left[g^{-1}\left(g(\widehat{\theta})-z_{\alpha/2}/\sqrt{n}\right),g^{-1}\left(g(\widehat{\theta})+z_{\alpha/2}/\sqrt{n}\right)\right]$$

will be a CI for  $\theta$  with asymptotic level  $1 - \alpha$ .

Let

$$X_1, \ldots, X_n \sim Ex(\lambda)$$
 i.i.d.

for some  $\lambda > 0$ . The MLE is  $\widehat{\lambda} = 1/\overline{X}$ , and

$$\sqrt{n}(\widehat{\lambda} - \lambda) \stackrel{d}{\to} N(0, \lambda^2).$$

- **①** Find a variance stabilizing transformation for  $\hat{\lambda}$ .
- ② Use the variance stabilizing transformation derived in Part (a) to find a CI for  $\lambda$  with asymptotic level  $1 \alpha$ .

The variance stabilizing transformation is

$$g(\lambda) = \int \frac{1}{\lambda} d\lambda = \log \lambda.$$

2 Since  $g^{-1}(x) = e^x$ ,

$$\left[\exp\left(\log\widehat{\lambda} - z_{\alpha/2}/\sqrt{n}\right), \exp\left(\log\widehat{\lambda} + z_{\alpha/2}/\sqrt{n}\right)\right] \tag{*}$$

is a CI for  $\lambda$  with asymptotic level  $1 - \alpha$ . We note that

$$(*) = \left[\widehat{\lambda}e^{-z_{\alpha/2}/\sqrt{n}}, \widehat{\lambda}e^{z_{\alpha/2}/\sqrt{n}}\right].$$

## Recap

We have discussed two ways to find CIs for MLEs:

lacktriangle The first method is to plug in  $\widehat{ heta}$  for  $\sigma( heta)$  and use

$$\left[\widehat{\theta} - \frac{z_{\alpha/2}\sigma(\widehat{\theta})}{\sqrt{n}}, \widehat{\theta} + \frac{z_{\alpha/2}\sigma(\widehat{\theta})}{\sqrt{n}}\right].$$

 ${\bf 2}$  The second method is to find a variance stabilizing transformation  $g(\theta)$  and use

$$\left[g^{-1}\left(g(\widehat{\theta})-z_{\alpha/2}/\sqrt{n}\right),g^{-1}\left(g(\widehat{\theta})+z_{\alpha/2}/\sqrt{n}\right)\right].$$