

# Ch 9. Interval Estimation

## Intro

### Definition

Let  $X_1, \dots, X_n$  have joint pdf/pmf  $f(\mathbf{x} : \theta)$ ,  $\theta \in \Theta$ . Let  $L(\mathbf{X})$  and  $U(\mathbf{X})$  be two statistics such that  $L(\mathbf{X}) \leq U(\mathbf{X})$  with probability 1.

1. The random interval  $I(\mathbf{X}) = [L(\mathbf{X}), U(\mathbf{X})]$  is called an interval estimator for  $\theta$ .
2.  $I(\mathbf{X}) = (-\infty, U(\mathbf{X})]$  is said to be a one-sided upper interval estimator for  $\theta$ .
3.  $I(\mathbf{X}) = [L(\mathbf{X}), \infty)$  is said to be a one-sided lower interval estimator for  $\theta$ .
4. The **coverage probability** of an interval estimator  $I(\mathbf{X})$  is defined as  $P_\theta[\theta \in I(\mathbf{X})]$ .
5. The **confidence coefficient** of  $I(\mathbf{X})$  is defined as  $\inf_{\theta \in \Theta} P_\theta[\theta \in I(\mathbf{X})]$ .

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## Intro

▷ Example:  $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Uniform}(0, \theta)$ . Consider the following three interval estimators of  $\theta$ .

$$I_1(\mathbf{X}) = [aX_{(n)}, bX_{(n)}], \quad 1 \leq a < b$$

$$I_2(\mathbf{X}) = [X_{(n)} + c, \infty)$$

$$I_3(\mathbf{X}) = [X_{(n)} + a, X_{(n)} + b]$$

## Ch 9. Interval Estimation

### Finding Interval Estimator - Inverting test

▷ Example:  $X_1, \dots, X_n \stackrel{iid}{\sim} N(\theta, 1)$

$$H_0 : \theta = \theta_0 \quad \text{vs} \quad H_1 : \theta \neq \theta_0$$

The LRT of size  $\alpha$  is

$$\phi(\mathbf{x}) = \begin{cases} 1, & |\sqrt{n}(\bar{x} - \theta_0)| \geq z_{\alpha/2}, \\ 0, & \text{elsewhere.} \end{cases}$$

$$\implies P_{\theta_0}\{\bar{X} - z_{\alpha/2}/\sqrt{n} \leq \theta_0 \leq \bar{X} + z_{\alpha/2}/\sqrt{n}\} = 1 - \alpha$$

# Ch 9. Interval Estimation

## Finding Interval Estimator - Inverting test

### Theorem

*Let  $X_1, \dots, X_n$  have joint pdf/pmf  $f(\mathbf{x} : \theta)$ ,  $\theta \in \Theta$ . For each  $\theta_0 \in \Theta$ , let  $A(\theta_0)$  denote the acceptance region of a size  $\alpha$  simple test for testing*

$$H_0 : \theta = \theta_0 \quad \text{vs} \quad H_1 : \theta \neq \theta_0$$

*Define a set  $C(\mathbf{x}) = \{\theta_0 \in \Theta : \mathbf{x} \in A(\theta_0)\}$ . Then  $C(\mathbf{X})$  is a **confidence set** with confidence coefficient  $1 - \alpha$ .*

◁ Note:

1.  $C(\mathbf{X})$  is not necessarily an interval.
2. One may need to consider one-sided test for one-sided confidence interval.

## Ch 9. Interval Estimation

### Finding Interval Estimator - Inverting test

▷ Example:  $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$ .  $\mu$  and  $\sigma^2$  are unknown. Find a  $1 - \alpha$  two-sided CI and one-sided lower CI for  $\mu$ .

▷ Example:  $X_1, \dots, X_n \stackrel{iid}{\sim} f(x|\theta) = \theta^2 x e^{-\theta x}, x > 0, \theta > 0$ . Find an approximate (and exact)  $1 - \alpha$  confidence set of  $\theta$ .

# Ch 9. Interval Estimation

## Finding Interval Estimator - Using Pivotal Quantity

### Definition

Let  $X_1, \dots, X_n$  have joint pdf/pmf  $f(\mathbf{x} : \theta)$ ,  $\theta \in \Theta$ . A random variable  $Y = Q(\mathbf{X} : \theta)$  is called a *pivotal quantity (PQ)* if the distribution of  $Y = Q(\mathbf{X} : \theta)$  does not depend on  $\theta$ .

▷ Example:  $X_1, \dots, X_n \stackrel{iid}{\sim} f(x : \theta)$ . Consider the following families of distributions and statistics.

1.  $f(x : \theta) = f_0(x - \theta)$
2.  $f(x : \theta) = \frac{1}{\theta} f_0(x)$
3.  $f(x : \theta) = \frac{1}{\theta_2} f_0[(x - \theta_1)/\theta_2]$

$$\bar{X}_n - \theta, \quad \bar{X}_n/\theta, \quad (\bar{X}_n - \theta_1)/\theta_2$$

## Ch 9. Interval Estimation

### Finding Interval Estimator - Using Pivotal Quantity

▷ Example:  $X_1, \dots, X_n \stackrel{iid}{\sim} \exp(\lambda)$ .

$$T = \sum X_i \sim \text{Gamma}(n, \lambda)$$

( $\text{Gamma}(n, \lambda)$  is a scale family)

Find a  $(1 - \alpha)\%$  confidence interval of  $\lambda$ .

▷ **Example 9.2.15:**  $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Poisson}(\lambda)$ . Find a  $(1 - \alpha)\%$  confidence interval of  $\lambda$ . (Hint: Use **Gamma-Poisson relationship**  $P(U \leq u) = P(V \geq \alpha)$ ,  $U \sim \text{Gamma}(\alpha, \beta)$ ,  $V \sim \text{Poisson}(u/\beta)$ .)

## Ch 9. Interval Estimation

### Finding Interval Estimator - Using Pivotal Quantity

Theorem (See the theorem 2.1.10 for reference)

*Suppose  $T = T(\mathbf{X})$  is a statistic calculated from  $X_1, \dots, X_n$ . Assume  $T$  has a continuous distribution with cdf*

$$F(t : \theta) = P_{\theta}(T \leq t).$$

*Then*

$$Q(T : \theta) = F(T : \theta)$$

*is a PQ.*

◁ Note: In order for  $Q(T : \theta) = F(T : \theta)$  to result in a confidence interval, we want  $F(T : \theta)$  to be monotone in  $\theta$ . A cdf  $F(T : \theta)$  that is increasing or decreasing in  $\theta$  for all  $t$  is said to be stochastically increasing or decreasing.



## Ch 9. Interval Estimation

### Finding Interval Estimator - Using Pivotal Quantity

▷ Example:  $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$ ,  $\sigma^2$  is known. Let  $T(\mathbf{X}) = \bar{X}$ .  
Then

$$Q(T : \mu) = F(T : \mu) = \Phi\left(\frac{T - \mu}{\sigma/\sqrt{n}}\right).$$

▷ Example:  $X_1, \dots, X_n \stackrel{iid}{\sim} f(x : \mu) = e^{-(x-\mu)}$ ,  $x \geq \mu$ . Let  $T(\mathbf{X}) = X_{(1)} = \min_{1 \leq i \leq n} X_i$ . Derive  $(1 - \alpha)100\%$  confidence interval using the cdf of  $T$ .

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## Finding Interval Estimator - Bayesian Interval

### Definition

$[L(\mathbf{x}), U(\mathbf{x})]$  is called a  $(1 - \alpha)100\%$  *credible set* (or *Bayesian interval*) if

$$\begin{aligned} 1 - \alpha &= P[L(\mathbf{x}) < \theta < U(\mathbf{x}) | \mathbf{X} = \mathbf{x}] \\ &= \begin{cases} \sum_{\theta} \pi(\theta | \mathbf{x}) & \text{discrete} \\ \int_{\theta} \pi(\theta | \mathbf{x}) d\theta & \text{continuous} \end{cases} \end{aligned}$$

▷ Example:  $X_1, \dots, X_n \stackrel{iid}{\sim} N(\theta, \sigma^2)$ .  $\theta \sim N(\mu, \tau^2)$ . Find a  $(1 - \alpha)$  credible set.

# Ch 9. Interval Estimation

## Optimal theory for CI

CI: Length of CI vs Coverage probability

### Definition

$f(x)$  is a unimodal pdf if  $f(x)$  is nondecreasing for  $x \leq x^*$  and nonincreasing for  $x \geq x^*$  in which case  $x^*$  is the mode of the distribution.

### Theorem (Theorem 9.3.2. Shortest CI for unimodal pdf.)

*Let  $f(x)$  be a unimodal pdf. If the interval  $[a, b]$  satisfies*

- i.  $\int_a^b f(x)dx = 1 - \alpha$
- ii.  $f(a) = f(b) > 0$
- iii.  $a \leq x^* \leq b$ , when  $x^*$  is a mode of  $f(x)$

*Then no other interval estimator satisfying (i) is shorter than  $[a, b]$ .*

# Ch 9. Interval Estimation

## Optimal theory for CI

▷ Example:  $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$ .  $\sigma^2$  is known.

▷ Example:  $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$ .  $\sigma^2$  is unknown.

# Ch 9. Interval Estimation

## Optimal theory for CI

### Definition (Probability of false coverage)

For  $\theta' \neq \theta$ ,  $P_{\theta}[L(\mathbf{X}) \leq \theta' \leq U(\mathbf{X})]$

For  $\theta' < \theta$ ,  $P_{\theta}[L(\mathbf{X}) \leq \theta']$

For  $\theta' > \theta$ ,  $P_{\theta}[\theta' \leq U(\mathbf{X})]$

### Definition

A  $1 - \alpha$  confidence interval with minimum probability of false coverage is called a *Uniformly Most Accurate (UMA)*  $1 - \alpha$  confidence interval.

## Ch 9. Interval Estimation

### Optimal theory for CI

#### Theorem (UMA CI based on UMP test)

*Let  $X_1, \dots, X_n$  have a joint pdf/pmf  $f(\mathbf{x} : \theta)$ . Suppose that a UMP test of size  $\alpha$  for testing  $H_0 : \theta \leq \theta_0$  vs  $H_1 : \theta > \theta_0$  exists and given as*

$$\phi(\mathbf{x}) = \begin{cases} 1, & \mathbf{x} \notin A^*(\theta_0), \\ 0, & \mathbf{x} \in A^*(\theta_0). \end{cases}$$

*Let  $C^*(\mathbf{X})$  be the confidence interval obtained by inverting the UMP acceptance region. Then, for any other  $1 - \alpha$  confidence region(set, interval),*

$$P_{\theta}[\theta' \in C^*(\mathbf{X})] \leq P_{\theta}[\theta' \in C(\mathbf{X})],$$

*for all  $\theta' < \theta$ . That is, inverting UMP test yields a UMA confidence region(set, interval).*

◁ Note: UMP unbiased test can be inverted to obtain UMA unbiased confidence region(set, interval).

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## Optimal theory for CI

- ◁ Note: UMP unbiased test can be inverted to obtain UMA unbiased confidence region(set, interval).
- ▷ Example:  $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$ .  $\sigma^2$  is known.