Statistical Inference and Multivariate Analysis (MA324)

Lecture SLIDES
Lecture 24

Interval Estimation



Indian Institute of Technology Guwahati

Jan-May 2023



Two-sample Problems

Example 1: Let $X_1, X_2, \ldots, X_n \overset{i.i.d.}{\sim} N(\mu_1, \sigma^2)$ and

 $Y_1,\,Y_2,\,\ldots,\,Y_m\stackrel{i.i.d.}{\sim}N(\mu_2,\,\sigma^2).$ Also, assume that X_i 's and Y_j 's are independent. Here, $\mu_1,\,\mu_2$, and σ are assumed to be unknown and we are interested to construct a $100(1-\alpha)\%$ CI for $\mu_1-\mu_2$. Let us first try to construct a pivot based on minimal sufficient statistic $(\overline{X},\,\overline{Y},S^2)$, where the pooled sample variance S^2 is defined by

$$S^{2} = \frac{1}{n+m-2} \left[\sum_{i=1}^{n} (X_{i} - \overline{X})^{2} + \sum_{i=1}^{m} (Y_{i} - \overline{Y})^{2} \right].$$

Now, notice that

$$\overline{X} - \overline{Y} \sim N\left(\mu_1 - \mu_2, \, \sigma^2\left(\frac{1}{n} + \frac{1}{m}\right)\right) \implies T = \frac{\left(\overline{X} - \overline{Y}\right) - (\mu_1 - \mu_2)}{\sigma\sqrt{\frac{1}{n} + \frac{1}{m}}} \sim N(0, \, 1)$$

Of course, T is a pivot, but we cannot use it to construct the required confidence interval due to the presence of unknown σ in T.



Example 2: Let $X_1, X_2, \ldots, X_n \overset{i.i.d.}{\sim} N(\mu_1, \sigma_1^2)$ and

 $Y_1,\,Y_2,\,\ldots,\,Y_m\stackrel{i.i.d.}{\sim}N(\mu_2,\,\sigma_2^2).$ Also, assume that X_i 's and Y_j 's are independent. Here, $\mu_1,\,\mu_2,\,\sigma_1,$ and σ_2 are assumed to be unknown and we are interested to construct a $100(1-\alpha)\%$ CI for $\frac{\sigma_2^2}{\sigma_1^2}.$ In this case minimal sufficient statistic is $(\overline{X},\,\overline{Y},\,S_1^2,\,S_2^2),$ where S_1^2 and S_2^2 are sample variances based on the samples X_i 's and Y_j 's, respectively. In this case,

$$T = \frac{\sigma_2^2 S_1^2}{\sigma_1^2 S_2^2} = \frac{\frac{(n-1)S_1^2}{(n-1)\sigma_1^2}}{\frac{(m-1)S_2^2}{(m-1)\sigma_2^2}} \sim F_{n-1, m-1}.$$

Thus,

$$P\left(F_{n-1, m-1, 1-\frac{\alpha}{2}} \le \frac{\sigma_2^2 S_1^2}{\sigma_1^2 S_2^2} \le F_{n-1, m-1, \frac{\alpha}{2}}\right) = 1 - \alpha$$

so that a $100(1-\alpha)\%$ CI for $\frac{\sigma_2^2}{\sigma_1^2}$ is

$$C(\boldsymbol{X}) = \left[\frac{S_2^2}{S_1^2} F_{n-1, m-1, 1-\frac{\alpha}{2}}, \frac{S_2^2}{S_1^2} F_{n-1, m-1, \frac{\alpha}{2}} \right].$$

Asymptotic CI

- In many cases it is very difficult to find pivot for a small sample. For example, it is difficult to find a pivot to construct CI for successes probability of a Bernoulli distribution.
- However, we may able to find CI quite easily if the sample size is sufficiently large. This CI is called asymptotic confidence interval.
- For this purpose, convergence in distribution (mainly CLT or large sample distribution of MLE) and convergence in probability (consistent estimator) are handy tools.

Distribution Free Population Mean

Let X_1, X_2, \ldots be i.i.d. random variables with mean μ and finite variance σ^2 . Then, using CLT

$$\frac{\sqrt{n}\left(\overline{X}_n - \mu\right)}{\sigma} \xrightarrow{\mathcal{L}} Z \sim N(0, 1).$$

Thus, if we have a RS with large sample size n, we can approximate the distribution of $\frac{\sqrt{n}(\overline{X}_n - \mu)}{\sigma}$ using a standard normal distribution. Hence,

$$P\left(-z_{\alpha/2} \le \frac{\sqrt{n}\left(\bar{X}_n - \mu\right)}{\sigma} \le z_{\alpha/2}\right) \approx 1 - \alpha.$$

If σ is **known** and n is sufficiently large, we can use the last statement to find an asymptotic CI for μ and it is given by

$$\left[\bar{X}_n - \frac{\sigma}{\sqrt{n}} z_{\alpha/2}, \, \bar{X}_n + \frac{\sigma}{\sqrt{n}} z_{\alpha/2}\right].$$

If σ is **unknown**, we can proceed as follows. Using WLLN, we have $\frac{S_n}{\sigma} \xrightarrow{P} 1$, and hence,

$$\frac{\sqrt{n}\left(\bar{X}_n - \mu\right)}{S_n} \xrightarrow{\mathcal{L}} Z \sim N(0, 1).$$

Hence, $P\left(-z_{\alpha/2} \leq \frac{\sqrt{n}\left(\bar{X}_n - \mu\right)}{S_n} \leq z_{\alpha/2}\right) \approx 1 - \alpha$. An asymptotic CI for μ is given by

$$\left[\bar{X}_n - \frac{S_n}{\sqrt{n}} z_{\alpha/2}, \, \bar{X}_n + \frac{S_n}{\sqrt{n}} z_{\alpha/2}\right].$$

Note that this **method can be used for any distribution** of X_1, X_2, \ldots, X_n , as long as the **conditions of CLT hold true**. Therefore, it is called **distribution free**.

Using MLE

Let $\widehat{\theta}_n$ be a **consistent estimator** of θ and $\sqrt{n}\left(\widehat{\theta}_n-\theta\right) \xrightarrow{\mathcal{L}} N(0,\,b^2(\theta))$, where $b(\theta)>0$ for all $\theta\in\Theta$. Assume that $b(\cdot)$ is a **continuous function**. Then, $\frac{b(\widehat{\theta}_n)}{b(\theta)} \xrightarrow{P} 1$, and hence, $\frac{\sqrt{n}\left(\widehat{\theta}_n-\theta\right)}{b(\widehat{\theta}_n)} \xrightarrow{\mathcal{L}} N(0,\,1)$.

A $100(1-\alpha)\%$ asymptotic CI for θ is given by

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

Under some regularity conditions, we may use MLE of θ in place of $\widehat{\theta}_n$.

◆□▶ ◆圖▶ ◆臺▶ ◆臺▶ · 臺 · 釣९♡

Example 3: Let $X_1,\,X_2,\,\dots,\,X_n \overset{i.i.d.}{\sim} Bernaoulli(p)$, where $p \in (0,\,1)$. We are interested to construct asymptotic CI for p. We know that $\widehat{p}_n = \overline{X}_n \overset{P}{\longrightarrow} p$ and $\frac{\sqrt{n}(\overline{X}_n - p)}{\sqrt{p(1-p)}} \overset{\mathcal{L}}{\longrightarrow} N(0,\,1)$. Here, $b(p) = \sqrt{p(1-p)}$, which is a continuous function in $p \in (0,\,1)$. Hence, $\frac{\sqrt{n}(\overline{X}_n - p)}{\sqrt{\overline{X}_n(1-\overline{X}_n)}} \overset{\mathcal{L}}{\longrightarrow} N(0,\,1)$. A $100(1-\alpha)\%$ asymptotic CI for p is

$$\left[\overline{X}_n - \sqrt{\frac{\overline{X}_n(1-\overline{X}_n)}{n}}z_{\alpha/2}, \, \overline{X}_n + \sqrt{\frac{\overline{X}_n(1-\overline{X}_n)}{n}}z_{\alpha/2}\right].$$