

# Stat 709: Mathematical Statistics

## Lecture 28

Jun Shao

Department of Statistics  
University of Wisconsin  
Madison, WI 53706, USA

## Lecture 28: Asymptotic inference

Statistical inference based on asymptotic criteria and approximations is called *asymptotic statistical inference* or simply *asymptotic inference*. We have previously considered asymptotic estimation. We now focus on asymptotic hypothesis tests and confidence sets.

### Definition 2.13

Let  $X = (X_1, \dots, X_n)$  be a sample from  $P \in \mathcal{P}$  and  $T_n(X)$  be a test for  $H_0 : P \in \mathcal{P}_0$  versus  $H_1 : P \in \mathcal{P}_1$ .

- (i) If  $\limsup_n \alpha_{T_n}(P) \leq \alpha$  for any  $P \in \mathcal{P}_0$ , then  $\alpha$  is an *asymptotic significance level* of  $T_n$ .
- (ii) If  $\lim_{n \rightarrow \infty} \sup_{P \in \mathcal{P}_0} \alpha_{T_n}(P)$  exists, it is called the *limiting size* of  $T_n$ .
- (iii)  $T_n$  is *consistent* iff the type II error probability converges to 0.
- (iv)  $T_n$  is *Chernoff-consistent* iff  $T_n$  is consistent and the type I error probability converges to 0.  
 $T_n$  is *strongly Chernoff-consistent* iff  $T_n$  is consistent and the limiting size of  $T_n$  is 0.

## Lecture 28: Asymptotic inference

Statistical inference based on asymptotic criteria and approximations is called *asymptotic statistical inference* or simply *asymptotic inference*.

We have previously considered asymptotic estimation.

We now focus on asymptotic hypothesis tests and confidence sets.

### Definition 2.13

Let  $X = (X_1, \dots, X_n)$  be a sample from  $P \in \mathcal{P}$  and  $T_n(X)$  be a test for  $H_0 : P \in \mathcal{P}_0$  versus  $H_1 : P \in \mathcal{P}_1$ .

- (i) If  $\limsup_n \alpha_{T_n}(P) \leq \alpha$  for any  $P \in \mathcal{P}_0$ , then  $\alpha$  is an *asymptotic significance level* of  $T_n$ .
- (ii) If  $\lim_{n \rightarrow \infty} \sup_{P \in \mathcal{P}_0} \alpha_{T_n}(P)$  exists, it is called the *limiting size* of  $T_n$ .
- (iii)  $T_n$  is *consistent* iff the type II error probability converges to 0.
- (iv)  $T_n$  is *Chernoff-consistent* iff  $T_n$  is consistent *and* the type I error probability converges to 0.  
 $T_n$  is *strongly Chernoff-consistent* iff  $T_n$  is consistent and the limiting size of  $T_n$  is 0.

## Remarks

- Obviously if  $T_n$  has size (or significance level)  $\alpha$  for all  $n$ , then its limiting size (or asymptotic significance level) is  $\alpha$ .
- If the limiting size of  $T_n$  is  $\alpha \in (0, 1)$ , then for any  $\varepsilon > 0$ ,  $T_n$  has size  $\alpha + \varepsilon$  for all  $n \geq n_0$ , where  $n_0$  is independent of  $P$ .  
Hence  $T_n$  has level of significance  $\alpha + \varepsilon$  for any  $n \geq n_0$ .
- However, if  $\mathcal{P}_0$  is not a parametric family, it is likely that the limiting size of  $T_n$  is 1 (see, e.g., Example 2.37).
- This is the reason why we consider the weaker requirement in Definition 2.13(i).
- If  $T_n$  has asymptotic significance level  $\alpha$ , then for any  $\varepsilon > 0$ ,  $\alpha_{T_n}(P) < \alpha + \varepsilon$  for all  $n \geq n_0(P)$  but  $n_0(P)$  depends on  $P \in \mathcal{P}_0$ ; and there is no guarantee that  $T_n$  has significance level  $\alpha + \varepsilon$  for any  $n$ .
- The consistency in Definition 2.13(iii) only requires that the type II error probability converge to 0.
- We may define uniform consistency to be  $\lim_{n \rightarrow \infty} \sup_{P \in \mathcal{P}_1} [1 - \alpha_{T_n}(P)] = 0$ , but it is not true in most problems.

## Remarks

- If  $\alpha \in (0, 1)$  is a pre-assigned level of significance for the problem, then a consistent test  $T_n$  having asymptotic significance level  $\alpha$  is called *asymptotically correct*, and a consistent test having limiting size  $\alpha$  is called *strongly asymptotically correct*.
- The Chernoff-consistency (or strong Chernoff-consistency) in Definition 2.13(iv) requires that both types of error probabilities converge to 0.
- Mathematically, Chernoff-consistency is better than asymptotic correctness.  
After all, both types of error probabilities should decrease to 0 if sampling can be continued indefinitely.
- However, if  $\alpha$  is chosen to be small enough so that error probabilities smaller than  $\alpha$  can be practically treated as 0, then the asymptotic correctness (or strongly asymptotic correctness) is enough, and is probably preferred, since requiring an unnecessarily small type I error probability usually results in an unnecessary increase in the type II error probability.

## Example 2.37

Consider the testing problem

$$H_0 : \mu \leq \mu_0 \quad \text{versus} \quad H_1 : \mu > \mu_0$$

based on i.i.d.  $X_1, \dots, X_n$  with  $EX_1 = \mu \in \mathcal{R}$ .

If each  $X_j$  has the  $N(\mu, \sigma^2)$  distribution with a known  $\sigma^2$ , then the test  $T_{c_\alpha} = I_{(c_\alpha, \infty)}(\bar{X})$  with  $c_\alpha = \sigma z_{1-\alpha} / \sqrt{n} + \mu_0$  and  $\alpha \in (0, 1)$  has size  $\alpha$  (and, therefore, limiting size  $\alpha$ ).

For any  $\mu > \mu_0$ ,

$$1 - \alpha_{T_{c_\alpha}}(\mu) = \Phi\left(z_{1-\alpha} + \frac{\sqrt{n}(\mu_0 - \mu)}{\sigma}\right) \rightarrow 0 \quad (1)$$

as  $n \rightarrow \infty$ .

This shows that  $T_{c_\alpha}$  is consistent and, hence, is strongly asymptotically correct.

The convergence in (1) is not uniform in  $\mu > \mu_0$ , but is uniform in  $\mu > \mu_1$  for any fixed  $\mu_1 > \mu_0$ .

## Example 2.37

Consider the testing problem

$$H_0 : \mu \leq \mu_0 \quad \text{versus} \quad H_1 : \mu > \mu_0$$

based on i.i.d.  $X_1, \dots, X_n$  with  $EX_1 = \mu \in \mathcal{R}$ .

If each  $X_j$  has the  $N(\mu, \sigma^2)$  distribution with a known  $\sigma^2$ , then the test  $T_{c_\alpha} = I_{(c_\alpha, \infty)}(\bar{X})$  with  $c_\alpha = \sigma z_{1-\alpha} / \sqrt{n} + \mu_0$  and  $\alpha \in (0, 1)$  has size  $\alpha$  (and, therefore, limiting size  $\alpha$ ).

For any  $\mu > \mu_0$ ,

$$1 - \alpha_{T_{c_\alpha}}(\mu) = \Phi\left(z_{1-\alpha} + \frac{\sqrt{n}(\mu_0 - \mu)}{\sigma}\right) \rightarrow 0 \quad (1)$$

as  $n \rightarrow \infty$ .

This shows that  $T_{c_\alpha}$  is consistent and, hence, is strongly asymptotically correct.

The convergence in (1) is not uniform in  $\mu > \mu_0$ , but is uniform in  $\mu > \mu_1$  for any fixed  $\mu_1 > \mu_0$ .

## Example 2.37 (continued)

Since the size of  $T_{c\alpha}$  is  $\alpha$  for all  $n$ ,  $T_{c\alpha}$  is not Chernoff-consistent. A strongly Chernoff-consistent test can be obtained as follows.

Let

$$\alpha_n = 1 - \Phi(\sqrt{n}a_n), \quad (2)$$

where  $a_n$ 's are positive numbers satisfying  $a_n \rightarrow 0$  and  $\sqrt{n}a_n \rightarrow \infty$ .

Let  $T_n$  be  $T_{c\alpha}$  with  $\alpha = \alpha_n$  for each  $n$ .

Then,  $T_n$  has size  $\alpha_n$ .

Since  $\alpha_n \rightarrow 0$ , The limiting size of  $T_n$  is 0.

On the other hand, (1) still holds with  $\alpha$  replaced by  $\alpha_n$ .

This follows from the fact that

$$z_{1-\alpha_n} + \frac{\sqrt{n}(\mu_0 - \mu)}{\sigma} = \sqrt{n} \left( a_n + \frac{\mu_0 - \mu}{\sigma} \right) \rightarrow -\infty$$

for any  $\mu > \mu_0$ .

Hence  $T_n$  is strongly Chernoff-consistent.

However, if  $\alpha_n < \alpha$ , then, from the left-hand side of (1),

$1 - \alpha_{T_{c\alpha}}(\mu) < 1 - \alpha_{T_n}(\mu)$  for any  $\mu > \mu_0$ .

## Example 2.37 (continued)

Consider now the situation where the population  $P$  is not in a parametric family.

We still assume that  $\sigma^2 = \text{Var}(X_i)$  is known.

Using the CLT, we can show that for  $\mu > \mu_0$ ,

$$\lim_{n \rightarrow \infty} [1 - \alpha_{T_{c\alpha}}(\mu)] = \lim_{n \rightarrow \infty} \Phi \left( z_{1-\alpha} + \frac{\sqrt{n}(\mu_0 - \mu)}{\sigma} \right) = 0,$$

i.e.,  $T_{c\alpha}$  is still consistent.

For  $\mu \leq \mu_0$ ,

$$\lim_{n \rightarrow \infty} \alpha_{T_{c\alpha}}(\mu) = 1 - \lim_{n \rightarrow \infty} \Phi \left( z_{1-\alpha} + \frac{\sqrt{n}(\mu_0 - \mu)}{\sigma} \right),$$

which equals  $\alpha$  if  $\mu = \mu_0$  and 0 if  $\mu < \mu_0$ .

Thus, the asymptotic significance level of  $T_{c\alpha}$  is  $\alpha$ .

Combining these two results, we know that  $T_{c\alpha}$  is asymptotically correct.

## Example 2.37 (continued)

However, if  $\mathcal{P}$  contains all possible populations on  $\mathcal{R}$  with finite second moments, then one can show that the limiting size of  $T_{c\alpha}$  is 1 (exercise).

For  $\alpha_n$  defined by (2), we can show that  $T_n = T_{c\alpha}$  with  $\alpha = \alpha_n$  is Chernoff-consistent (exercise).

But  $T_n$  is not strongly Chernoff-consistent if  $\mathcal{P}$  contains all possible populations on  $\mathcal{R}$  with finite second moments.

## Example

Let  $(X_1, \dots, X_n)$  be a random sample from the exponential distribution  $E(0, \theta)$ , where  $\theta \in (0, \infty)$ .

Consider the hypotheses  $H_0 : \theta \leq \theta_0$  versus  $H_1 : \theta > \theta_0$ , where  $\theta_0 > 0$  is a fixed constant.

Let  $T_c = I_{(c, \infty)}(\bar{X})$ , where  $\bar{X}$  is the sample mean.

$\bar{X}/\theta$  has the gamma distribution with shape parameter  $n$  and scale parameter  $\theta/n$ .

## Example 2.37 (continued)

However, if  $\mathcal{P}$  contains all possible populations on  $\mathcal{R}$  with finite second moments, then one can show that the limiting size of  $T_{c_\alpha}$  is 1 (exercise).

For  $\alpha_n$  defined by (2), we can show that  $T_n = T_{c_{\alpha_n}}$  with  $\alpha = \alpha_n$  is Chernoff-consistent (exercise).

But  $T_n$  is not strongly Chernoff-consistent if  $\mathcal{P}$  contains all possible populations on  $\mathcal{R}$  with finite second moments.

## Example

Let  $(X_1, \dots, X_n)$  be a random sample from the exponential distribution  $E(0, \theta)$ , where  $\theta \in (0, \infty)$ .

Consider the hypotheses  $H_0 : \theta \leq \theta_0$  versus  $H_1 : \theta > \theta_0$ , where  $\theta_0 > 0$  is a fixed constant.

Let  $T_c = I_{(c, \infty)}(\bar{X})$ , where  $\bar{X}$  is the sample mean.

$\bar{X}/\theta$  has the gamma distribution with shape parameter  $n$  and scale parameter  $\theta/n$ .

## Example (continued)

Let  $G_{n,\theta}$  denote the cumulative distribution function of this distribution and  $c_{n,\alpha}$  be the constant satisfying  $G_{n,\theta_0}(c_{n,\alpha}) = 1 - \alpha$ .

Then,

$$\sup_{\theta \leq \theta_0} P(T_{c_{n,\alpha}} = 1) = \sup_{\theta \leq \theta_0} [1 - G_{n,\theta}(c_{n,\alpha})] = 1 - G_{n,\theta_0}(c_{n,\alpha}) = \alpha,$$

i.e., the size of  $T_{c_{n,\alpha}}$  is  $\alpha$ .

Since the power of  $T_{c_{n,\alpha}}$  is  $P(T_{c_{n,\alpha}} = 1) = P(\bar{X} > c_{n,\alpha})$  for  $\theta > \theta_0$  and, by the law of large numbers,  $\bar{X} \rightarrow_p \theta$ , the consistency of  $T_{c_{n,\alpha}}$  follows if we can show that  $\lim_n c_{n,\alpha} = \theta_0$ .

By the central limit theorem,  $\sqrt{n}(\bar{X} - \theta) \rightarrow_d N(0, \theta^2)$ .

Hence,  $\sqrt{n}(\frac{\bar{X}}{\theta} - 1) \rightarrow_d N(0, 1)$ .

By Pólya's theorem (Proposition 1.16),

$$\lim_n \sup_t \left| P\left(\sqrt{n}\left(\frac{\bar{X}}{\theta} - 1\right) \leq t\right) - \Phi(t) \right| = 0,$$

where  $\Phi$  is the cumulative distribution function of the standard normal distribution.

## Example (continued)

When  $\theta = \theta_0$ ,

$$\alpha = P(\bar{X} \geq c_{n,\alpha}) = P\left(\sqrt{n}\left(\frac{\bar{X}}{\theta_0} - 1\right) \geq \sqrt{n}\left(\frac{c_{n,\alpha}}{\theta_0} - 1\right)\right).$$

Hence

$$\lim_n \Phi\left(\sqrt{n}\left(\frac{c_{n,\alpha}}{\theta_0} - 1\right)\right) = 1 - \alpha,$$

which implies  $\lim_n \sqrt{n}\left(\frac{c_{n,\alpha}}{\theta_0} - 1\right) = \Phi^{-1}(1 - \alpha)$  and, thus,  $\lim_n c_{n,\alpha} = \theta_0$ .

Let  $\{a_n\}$  be a sequence of positive numbers such that  $\lim_n a_n = 0$  and  $\lim_n \sqrt{n}a_n = \infty$ .

Let  $\alpha_n = 1 - \Phi(\sqrt{n}a_n)$  and  $b_n = c_{n,\alpha_n}$ .

From the previous derivation, the size of  $T_{b_n}$  is  $\alpha_n$ , which converges to 0 as  $n \rightarrow \infty$  since  $\lim_n \sqrt{n}a_n = \infty$ .

Using the previous argument, we can show that

$$\lim_n \left| 1 - \alpha_n - \Phi\left(\sqrt{n}\left(\frac{c_{n,\alpha_n}}{\theta_0} - 1\right)\right) \right| = 0,$$

## Example 2.37 (continued)

which implies that

$$\lim_n \frac{\sqrt{n}}{\Phi^{-1}(1 - \alpha_n)} \left( \frac{c_{n,\alpha_n}}{\theta_0} - 1 \right) = 1.$$

Since  $1 - \alpha_n = \Phi(\sqrt{n}a_n)$ , this implies that  $\lim_n c_{n,\alpha_n} = \theta_0$ .

Since  $b_n = c_{n,\alpha_n}$ , the test  $T_{b_n}$  is Chernoff-consistent.

## Definition 2.14

Let  $X = (X_1, \dots, X_n)$  be a sample from  $P \in \mathcal{P}$ ,  $\vartheta$  be a  $k$ -vector of parameters related to  $P$ , and  $C(X)$  be a confidence set for  $\vartheta$ .

- (i) If  $\liminf_n P(\vartheta \in C(X)) \geq 1 - \alpha$  for any  $P \in \mathcal{P}$ , then  $1 - \alpha$  is an *asymptotic significance level* of  $C(X)$ .
- (ii) If  $\lim_{n \rightarrow \infty} \inf_{P \in \mathcal{P}} P(\vartheta \in C(X))$  exists, then it is called the *limiting confidence coefficient* of  $C(X)$ .

## Example 2.37 (continued)

which implies that

$$\lim_n \frac{\sqrt{n}}{\Phi^{-1}(1 - \alpha_n)} \left( \frac{c_{n, \alpha_n}}{\theta_0} - 1 \right) = 1.$$

Since  $1 - \alpha_n = \Phi(\sqrt{n}a_n)$ , this implies that  $\lim_n c_{n, \alpha_n} = \theta_0$ .

Since  $b_n = c_{n, \alpha_n}$ , the test  $T_{b_n}$  is Chernoff-consistent.

## Definition 2.14

Let  $X = (X_1, \dots, X_n)$  be a sample from  $P \in \mathcal{P}$ ,  $\vartheta$  be a  $k$ -vector of parameters related to  $P$ , and  $C(X)$  be a confidence set for  $\vartheta$ .

- (i) If  $\liminf_n P(\vartheta \in C(X)) \geq 1 - \alpha$  for any  $P \in \mathcal{P}$ , then  $1 - \alpha$  is an *asymptotic significance level* of  $C(X)$ .
- (ii) If  $\lim_{n \rightarrow \infty} \inf_{P \in \mathcal{P}} P(\vartheta \in C(X))$  exists, then it is called the *limiting confidence coefficient* of  $C(X)$ .

## Remarks

- Note that the asymptotic significance level and limiting confidence coefficient of a confidence set are very similar to the asymptotic significance level and limiting size of a test, respectively.
- Some conclusions are also similar.
- For example, in a parametric problem one can often find a confidence set having limiting confidence coefficient  $1 - \alpha \in (0, 1)$ , which implies that for any  $\varepsilon > 0$ , the confidence coefficient of  $C(X)$  is  $1 - \alpha - \varepsilon$  for all  $n \geq n_0$ , where  $n_0$  is independent of  $P$ .
- In a nonparametric problem the limiting confidence coefficient of  $C(X)$  might be 0, whereas  $C(X)$  may have asymptotic significance level  $1 - \alpha \in (0, 1)$ , but for any fixed  $n$ , the confidence coefficient of  $C(X)$  might be 0.