# **MODULE 7**

## LIMITING DISTRIBUTIONS

# **LECTURE 41**

# **Topics**

## 7.3 SOME PRESERVATION RESULTS

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In this section, we will discuss the algebraic operations under which convergence in probability and/or convergence in distribution is preserved.

#### Theorem 3.1

Let  $\{X_n\}_{n\geq 1}$  and  $\{Y_n\}_{n\geq 1}$  be sequences of random variables and let X be another random variable.

- (i) Let  $g: \mathbb{R} \to \mathbb{R}$  be continuous at  $c \in \mathbb{R}$  and let  $X_n \xrightarrow{p} c$ , as  $n \to \infty$ . Then  $g(X_n) \xrightarrow{p} g(c)$ , as  $n \to \infty$ .
- (ii) Let  $h: \mathbb{R}^2 \to \mathbb{R}$  be continuous at  $(c_1, c_2) \in \mathbb{R}^2$  and let  $X_n \stackrel{p}{\to} c_1, Y_n \stackrel{p}{\to} c_2$ , as  $n \to \infty$ .
- (iii) Let  $g: \mathbb{R} \to \mathbb{R}$  be continuous on a support  $S_X$  of X and let  $X_n \overset{d}{\to} X$ , as  $n \to \infty$ . Then  $g(X_n) \overset{d}{\to} g(X)$ , as  $n \to \infty$ .
- (iv) Let  $h: \mathbb{R}^2 \to \mathbb{R}$  be continuous at all points in  $D = \{(x, b): x \in S_X\}$ , where b is a fixed real constant and  $S_X$  is a support of X. If  $X_n \xrightarrow{d} X$  and  $Y_n \xrightarrow{p} b$ , as  $n \to \infty$ , then  $h(X_n, Y_n) \xrightarrow{d} h(X, b)$ , as  $n \to \infty$ .

**Proof.** We shall not attempt to prove assertions (iii) and (iv) here as their proofs are slightly involved.

(i) Fix  $\varepsilon > 0$ . Since  $g: \mathbb{R} \to \mathbb{R}$  is continuous at  $c \in \mathbb{R}$ , there exists a  $\delta \equiv \delta(\varepsilon, c)$  such that

$$|x - c| < \delta \Rightarrow |g(x) - g(c)| < \varepsilon$$

or equivalently

$$|g(x) - g(c)| \ge \varepsilon \Rightarrow |x - c| \ge \delta$$
.

Therefore,

$$0 \le P(\{|g(X_n) - g(c)| \ge \varepsilon\}) \le P(\{|X_n - c| \ge \delta\}) \xrightarrow{n \to \infty} 0 \qquad \text{(since } X_n \xrightarrow{p} c)$$

$$\Rightarrow \lim_{n \to \infty} P(\{|g(X_n) - g(c)| \ge \varepsilon\}) = 0$$

$$\Rightarrow g(X_n) \stackrel{p}{\to} g(c), \quad \text{as } n \to \infty.$$

(ii) Fix  $\varepsilon > 0$ . Since  $h: \mathbb{R}^2 \to \mathbb{R}$  is continuous at  $(c_1, c_2) \in \mathbb{R}^2$ , there exists a  $\delta = \delta(\varepsilon, c_1, c_2)$  such that

$$|x - c_1| < \delta$$
 and  $|y - c_2| < \delta \Rightarrow |h(x, y) - h(c_1, c_2)| < \varepsilon$ ,

or equivalently

$$|h(x,y) - h(c_1,c_2)| \ge \varepsilon \Rightarrow |x - c_1| \ge \delta \text{ or } |y - c_2| \ge \delta.$$

Therefore,

$$P(\{|h(X_n, Y_n) - h(c_1, c_2)| \ge \varepsilon\}) \le P(\{|X_n - c_1| \ge \delta\} \cup \{|Y_n - c_2| \ge \delta\})$$

$$\le P(\{|X_n - c_1| \ge \delta\} + P\{|Y_n - c_2| \ge \delta\}) \text{ (using Boole's inequality)}$$

$$\xrightarrow{n \to \infty} 0 + 0 = 0 \left(\operatorname{since} X_n \xrightarrow{p} c_1 \text{ and } Y_n \xrightarrow{p} c_2\right)$$

$$\Rightarrow \lim_{n \to \infty} P\left(\{|h(X_n, Y_n) - h(c_1, c_2)| \ge \varepsilon\}\right) = 0$$

$$\Rightarrow h(X_n, Y_n) \xrightarrow{p} h(c_1, c_2), \text{ as } n \to \infty. \blacksquare$$

Throughout, we shall use the following convention. If, for a real constant c, we write  $X_n \xrightarrow{d} c$ , as  $n \to \infty$ , then it would mean that  $X_n$  converges in distribution, as  $n \to \infty$ , to a random variable degenerate at c (i.e.,  $X_n \xrightarrow{p} c$ , as  $n \to \infty$ ). Similarly, for a random variable X,  $0 \times X$  will be treated as a random variable degenerate at 0.

Now we provide the following useful lemma whose proof, being straight forward, is left as an exercise.

## Lemma 3.1

- (i) Let X and Y be random variables and let c be a real constant. If  $P({Y = c}) = 1$  then  $X + Y \stackrel{d}{=} X + c$  and  $XY \stackrel{d}{=} cX$ , where  $0 \times X$  is treated as a random variable degenerate at 0.
- (ii) Let  $\{X_n\}_{n\geq 1}$  and  $\{Y_n\}_{n\geq 1}$  be sequences of real numbers such that  $X_n \stackrel{d}{=} Y_n$ , n=1,2,... If, for some real constant  $c,X_n \stackrel{p}{\to} c$ , as  $n\to\infty$ , then  $Y_n \stackrel{p}{\to} c$ , as  $n\to\infty$ .
- (iii) Let  $\{X_n\}_{n\geq 1}$  and  $\{Y_n\}_{n\geq 1}$  be sequences of real numbers such that  $X_n \stackrel{d}{=} Y_n, n = 1, 2, ...$  If, for some random variable X,  $X_n \stackrel{d}{\to} X$ , as  $n \to \infty$ , then  $Y_n \stackrel{d}{\to} X$ , as  $n \to \infty$ .
- (iv) Let  $\{a_n\}_{n\geq 1}$  be sequence of real numbers such that  $\lim_{n\to\infty}a_n=a\in\mathbb{R}$  and  $\operatorname{let}\{X_n\}_{n\geq 1}$  be a sequence of random variables such that  $X_n$  is degenerate at  $a_n, n=1,2,...$ . Then  $X_n\stackrel{p}{\to}a$ , as  $n\to\infty$ .

### Theorem 3.2

Let  $\{X_n\}_{n\geq 1}$  and  $\{Y_n\}_{n\geq 1}$  be sequences of random variables and let  $\{a_n\}_{n\geq 1}$  and  $\{b_n\}_{n\geq 1}$  be sequences of real numbers such that  $\lim_{n\to\infty} a_n = a$  and  $\lim_{n\to\infty} b_n = b$ .

- (i) Suppose that, for some real constants  $c_1$  and  $c_2$ ,  $X_n \xrightarrow{p} c_1$  and  $Y_n \xrightarrow{p} c_2$ , as  $n \to \infty$ . Then, as  $n \to \infty$ ,  $X_n + Y_n \xrightarrow{p} c_1 + c_2$ ,  $X_n - Y_n \xrightarrow{p} c_1 - c_2$  and  $X_n Y_n \xrightarrow{p} c_1 c_2$ . Moreover, if  $c_2 \neq 0$ , then  $\frac{X_n}{Y_n} \xrightarrow{p} \frac{c_1}{c_2}$ , as  $n \to \infty$ .
- (ii) Suppose that, for a real constant c and a random variable  $X, X_n \xrightarrow{d} X$  and  $Y_n \xrightarrow{p} c$ , as  $n \to \infty$ . Then, as  $n \to \infty$ ,  $X_n + Y_n \xrightarrow{d} X + c$ ,  $X_n Y_n \xrightarrow{d} X c$  and  $X_n Y_n \xrightarrow{d} c X$ . Moreover, if  $c \ne 0$ , then  $\frac{X_n}{Y_n} \xrightarrow{d} \frac{X}{c}$ , as  $n \to \infty$ .
- (iii) Suppose that, for a real constant c,  $X_n \stackrel{p}{\to} c$ , as  $n \to \infty$ . Then  $a_n X_n + b_n \stackrel{p}{\to} ac + b$ , as  $n \to \infty$ .
- (iv) Suppose that, for a random variable X,  $X_n \xrightarrow{d} X$ , as  $n \to \infty$ . Then  $a_n X_n + b_n \xrightarrow{d} a X + b$ , as  $n \to \infty$ .

**Proof.** (i) and (ii) follow from Theorem 3.1 (ii) and (iv) as  $h_1(x, y) = x + y$ ,  $h_2(x, y) = x - y$  and  $h_3(x, y) = xy$  are continuous functions on  $\mathbb{R}^2$ , and  $h_4(x, y) = \frac{x}{y}$  is continuous on  $D = \{(s, t) \in \mathbb{R}^2 : t \neq 0\}$ .

(iii) Let  $Y_n$  be a random variable that is degenerate at  $a_n$  and let  $Z_n$  be a random variable that is degenerate at  $b_n$ , n = 1, 2, ... Then  $Y_n \stackrel{p}{\to} a$  and  $Z_n \stackrel{p}{\to} b$ , as  $n \to \infty$ 

(Lemma 3.1 (iv)). Now using (i) we get  $X_nY_n + Z_n \xrightarrow{p} ac + b$ , as  $n \to \infty$ . Since  $a_nX_n + b_n \stackrel{d}{=} X_nY_n + Z_n$ , n = 1,2,..., (Lemma 3.1 (i)), the assertion follows on using Lemma 3.1 (ii).

(iv) Let  $Y_n$  and  $Z_n$  be as defined in (iii). Then  $Y_n \stackrel{p}{\to} a$  and  $Z_n \stackrel{p}{\to} b$ , as  $n \to \infty$ . Using (ii) we get  $X_n Y_n + Z_n \stackrel{d}{\to} aX + b$ , as  $n \to \infty$ . Since  $a_n X_n + b_n \stackrel{d}{=} X_n Y_n + Z_n$ , n = 1, 2, ..., the assertion follows on using Lemma 3.1(iii).

#### Remark 3.1

The CLT asserts that if  $X_1, X_2, ...$  are i.i.d. random variables with mean  $\mu$  and finite variance  $\sigma^2 > 0$ , then

$$Z_n \stackrel{\text{def}}{=} \frac{\sqrt{n}(\overline{X}_n - \mu)}{\sigma} \stackrel{d}{\to} Z \sim N(0,1), \text{ as } n \to \infty,$$

where  $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$ . Since  $\frac{\sigma}{\sqrt{n}} \to 0$ , as  $n \to \infty$ , using Theorem 3.2 (iv) we get

$$\bar{X}_n - \mu = \frac{\sigma}{\sqrt{n}} Z_n \stackrel{d}{\to} 0 \times Z$$
, as  $n \to \infty$ .

Note that  $0 \times Z$  is a random variable degenerate at 0. Thus it follows that

$$ar{X}_n - \mu \stackrel{d}{ o} 0, \quad \text{as } n o \infty$$
  
 $\Leftrightarrow ar{X}_n - \mu \stackrel{p}{ o} 0, \quad \text{as } n o \infty$   
 $\Leftrightarrow ar{X}_n \stackrel{p}{ o} \mu, \quad \text{as } n o \infty.$ 

The above discussion suggests that, under the finiteness of second moment (or variance), the CLT is a stronger result than the WLLN.

#### Example 3.1

Let  $\{X_n\}_{n\geq 1}$  and  $\{Y_n\}_{n\geq 1}$  be sequences of random variables.

- (i) If  $X_n \stackrel{p}{\to} \ln 4$  and  $Y_n \stackrel{p}{\to} 2$ , as  $n \to \infty$ , show that  $X_n + \ln Y_n \stackrel{p}{\to} \ln 8$  and  $e^{X_n} \ln Y_n \stackrel{p}{\to} \ln 16$ , as  $n \to \infty$ ;
- (ii) If  $X_n \stackrel{d}{\to} Z \sim N(0,1)$ , as  $n \to \infty$ , show that  $X_n^2 \stackrel{d}{\to} Q_1 \sim \chi_1^2$  (the chi-square distribution with one degree of freedom), as  $n \to \infty$ .
- (iii) If  $X_n \stackrel{d}{\to} Z \sim N(0,1)$ , and  $Y_n \stackrel{p}{\to} 3$ , as  $n \to \infty$ , show that  $X_n Y_n \stackrel{d}{\to} V \sim N(0,9)$  and  $2X_n + 3Y_n \stackrel{d}{\to} Q_2 \sim N(9,4)$ , as  $n \to \infty$ .

(iv) For a given  $\theta > 0$ , if  $X_1, X_2, ...$  are i.i.d.  $U(0, \theta)$  random variables and  $X_{n:n} = \max\{X_1, ..., X_n\}$ , n = 1, 2, ..., show that  $e^{X_{n:n}} \stackrel{p}{\to} e^{\theta}$ ,  $X_{n:n}^2 + X_{n:n} + 1 \stackrel{p}{\to} \theta^2 + \theta + 1$  and  $e^{-\frac{n(\theta - X_{n:n})}{\theta}} \stackrel{d}{\to} U \sim U(0, 1)$ , as  $n \to \infty$ .

## Solution.

- (i) Since  $h_1(x) = \ln x$ ,  $x \in (0, \infty)$  is a continuous function, using Theorem 3.1 (i) it follows that  $\ln Y_n \stackrel{p}{\to} \ln 2$ , as  $n \to \infty$ . Now on using Theorem 3.2 (i) we get  $X_n + \ln Y_n \stackrel{p}{\to} \ln 4 + \ln 2 = \ln 8$ , as  $n \to \infty$ . Also, since  $h_2(x) = e^x$ ,  $x \in \mathbb{R}$ , is a continuous function on  $\mathbb{R}$ , on using Theorem 3.1 (i), we get  $e^{X_n} \stackrel{p}{\to} e^{\ln 4} = 4$ , as  $n \to \infty$ . Now on using Theorem 3.2(i) it follows that  $e^{X_n} \ln Y_n \stackrel{p}{\to} 4 \ln 2 = \ln 16$ , as  $n \to \infty$ .
- (ii) Since  $h_3(x) = x^2, x \in \mathbb{R}$ , is a continuous function on  $\mathbb{R}$ , using Theorem 3.1 (iii) we get  $X_n^2 \stackrel{d}{\to} Z^2$ , as  $n \to \infty$ . Let  $Q_1 = Z^2$ . Since  $Z \sim N(0,1)$ , we have  $Q_1 \sim \chi_1^2$  (Theorem 4.1 (ii), Module 5). Consequently  $X_n^2 \stackrel{d}{\to} Q_1 \sim \chi_1^2$ , as  $n \to \infty$ .
- (iii) Using Theorem 3.2 (ii) we get  $X_nY_n \stackrel{d}{\to} 3Z$ , as  $n \to \infty$ . Let V = 3Z. Since  $Z \sim N(0,1)$  we have  $V = 3Z \sim N(0,9)$  (Theorem 4.2 (ii) Module 5) and, therefore,  $X_nY_n \stackrel{d}{\to} V \sim N(0,9)$ , as  $n \to \infty$ . Using theorem 3.2 (iii) and (iv) we get  $2X_n \stackrel{d}{\to} 2Z$  and  $3Y_n \stackrel{p}{\to} 9$ , as  $n \to \infty$ . Now using Theorem 3.2 (ii) we also conclude that  $2X_n + 3Y_n \stackrel{d}{\to} 2Z + 9$ , as  $n \to \infty$ . Let  $Q_2 = 2Z + 9$ . Since  $Z \sim N(0,1)$ , we have  $Q_2 \sim N(9,4)$  (Theorem 4.2 (ii), Module 5).
- (iv) From Example 1.4 we have  $X_{n:n} \stackrel{p}{\to} \theta$ , as  $n \to \infty$ , and  $Y_n = n(\theta X_{n:n})$   $\stackrel{d}{\to} Y \sim \operatorname{Exp}(\theta)$ , as  $n \to \infty$ . Since  $h_4(x) = e^x$ ,  $x \in \mathbb{R}$ ,  $h_5(x) = x^2 + x + 1$ ,  $x \in \mathbb{R}$ , and  $h_6(x) = e^{\frac{x}{\theta}}$ ,  $x \in \mathbb{R}$ , are continuous functions on  $\mathbb{R}$ , using Theorem 3.1 (i) and (ii), we get  $e^{X_{n:n}} \stackrel{p}{\to} e^{\theta}$ ,  $X_{n:n}^2 + X_{n:n} + 1 \stackrel{p}{\to} \theta^2 + \theta + 1$  and  $e^{-\frac{Y_n}{\theta}} \stackrel{d}{\to} e^{-\frac{Y}{\theta}}$ , as  $n \to \infty$ . Let  $U = e^{\frac{Y}{\theta}}$ . Since  $Y \sim \operatorname{Exp}(\theta)$ , it is easy to verify that  $U \sim U(0,1)$ . Consequently,  $e^{-\frac{n(\theta X_{n:n})}{\theta}} = e^{-\frac{Y_n}{\theta}} \stackrel{d}{\to} U \sim U(0,1)$ , as  $n \to \infty$ .