

# Lecture 13

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For more details about the materials covered in this note, see Chapters 6.1, 6.2 and 8.5 of Resnick [1].

## 13.1 Convergence modes

**Definition 13.1.** Let  $\{X_n\}_{n \geq 1}$  be a sequence of random variables defined on a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ , and  $X$  be another random variable defined on the same space.

- (i) We say  $X_n$  converges almost surely to  $X$  if  $\mathbb{P}(\lim_{n \rightarrow \infty} X_n = X) = 1$ , and we write  $X_n \xrightarrow{a.s.} X$ .
- (ii) We say  $X_n$  converges in probability to  $X$  if  $\lim_{n \rightarrow \infty} \mathbb{P}(|X_n - X| > \epsilon) = 0$  for any  $\epsilon > 0$ , and we write  $X_n \xrightarrow{P} X$ .
- (iii) We say  $X_n$  converges in  $L^p$  to  $X$  if  $\lim_{n \rightarrow \infty} E|X_n - X|^p = 0$ , and we write  $X_n \xrightarrow{L^p} X$ .

**Definition 13.2.** Let  $X$  be a random variable with distribution function  $F$ , and  $\{X_n\}_{n \geq 1}$  be a sequence of random variables where  $X_n$  has distribution function  $F_n$ . We say  $X_n$  converges in distribution (or converges weakly) to  $X$  if  $\lim_{n \rightarrow \infty} F_n(x) = F(x)$ , for every  $x \in \mathbb{R}$  at which  $F$  is continuous. We write  $X_n \xrightarrow{D} X$ .

**Remark 13.1.** For convergence in distribution, random variables  $X, X_1, X_2, \dots$  can be defined on different probability spaces.

**Example 13.1.** Let  $Z_1, Z_2, \dots$  be i.i.d. Bernoulli random variables with  $\mathbb{P}(Z_i = 0) = p$  and  $\mathbb{P}(Z_i = 1) = 1 - p$ , where  $p \in (0, 1)$ . Define  $X_n = \max\{Z_1, \dots, Z_n\}$ . Then  $X_n \xrightarrow{a.s.} 1$ . Note that for any  $n < \infty$ ,  $\mathbb{P}(X_n < 1) = p^n > 0$ .

**Example 13.2.** Consider a sequence of random variables  $X_1, X_2, \dots$  such that  $\mathbb{P}(X_n = n) = 1/n$  and  $\mathbb{P}(X_n = 0) = 1 - 1/n$ . Then  $X_n \xrightarrow{P} 0$  since, for any  $\epsilon > 0$ ,  $\mathbb{P}(|X_n| > \epsilon) = 1/n$  and converges to 0. But  $E[X_n] = 1$  for every  $n$ . Hence,  $X_n$  does not converge to 0 in  $L^1$ . Indeed,  $X_n$  does not converge in  $L^p$  for any  $p \geq 1$ .

**Example 13.3** (Continuation of Example 13.2). Recall how we constructed such a sequence of random variables in Example 5.1: consider the probability space  $([0, 1], \mathcal{B}([0, 1]), m)$  where  $m$  denotes the Lebesgue measure and define

$$X_n(\omega) = \begin{cases} n, & \text{if } \omega \in (0, 1/n), \\ 0, & \text{otherwise.} \end{cases}$$

Then for every  $\omega$ , we have  $\lim_{n \rightarrow \infty} X_n(\omega) = 0$ , i.e.  $X_n \xrightarrow{a.s.} 0$ .

**Example 13.4** (Continuation of Example 13.2). However, if we assume  $X_1, X_2, \dots$  are independent, then the sequence  $\{X_n\}$  does not converge almost surely. We do not prove this claim here. Let's consider another construction which does not converge almost surely either. We still consider the probability space  $([0, 1], \mathcal{B}([0, 1]), m)$ . Let's construct  $X_1, X_2, \dots$  as follows:

$$X_1 = \mathbb{1}_{(0,1)}, \quad X_2 = 2\mathbb{1}_{(0,1/2)}, \quad X_3 = 3\mathbb{1}_{(1/2,5/6)}, \quad X_4 = 4(\mathbb{1}_{(5/6,1)} + \mathbb{1}_{(0,1/12)}) \dots$$

See the figure on the next page, which plots  $X_1, X_2, \dots, X_{50}$ . So if  $X_n(\omega)$  converges almost surely to zero, then there must exist some integer  $N < \infty$  such that  $\sum_{n=N}^{\infty} 1/n < 1$ . But this is impossible.

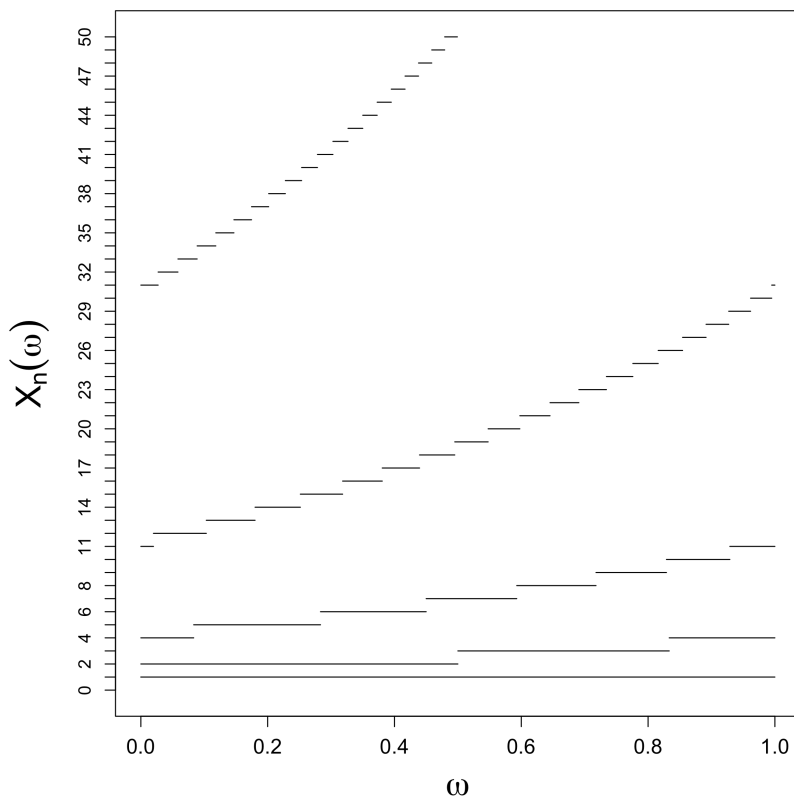
**Example 13.5.** Consider the probability space  $([0, 1], \mathcal{B}([0, 1]), m)$  again. This time let's define a sequence of random variables by

$$\begin{aligned} X_1 &= \mathbb{1}_{(0,1)}, & X_2 &= \mathbb{1}_{(1/2,1)}, \\ X_3 &= \mathbb{1}_{(0,1/3)}, & X_4 &= \mathbb{1}_{(1/3,2/3)}, & X_5 &= \mathbb{1}_{(2/3,1)}, \\ X_6 &= \mathbb{1}_{(0,1/4)}, & X_7 &= \mathbb{1}_{(1/4,1/2)}, & X_8 &= \mathbb{1}_{(1/2,3/4)}, & X_9 &= \mathbb{1}_{(3/4,1)} \dots \end{aligned}$$

We do not plot these functions here, but one can check that  $X_n$  does not converge to 0 almost surely. However, for any  $p \in (0, \infty)$ ,  $E|X_n|^p = \mathbb{P}(X_n = 1) \rightarrow 0$ ; that is,  $X_n \xrightarrow{L^p} 0$ .

**Example 13.6.** Recall the Weak Law of Large Numbers (WLLN). If  $X_1, X_2, \dots$  is an i.i.d. sequence of random variables with  $E(X_i) = \mu$  and  $\text{Var}(X_i) = \sigma^2 < \infty$ . Then  $\bar{X}_n \xrightarrow{P} \mu$ .

**Example 13.7.** Let  $F$  be a distribution function for some continuous random variable. Define  $F_n(x) = F(x + n)$  (check this is a distribution function!) Clearly,  $F_n(x) \rightarrow 1$  for every  $x \in \mathbb{R}$  since  $\lim_{x \rightarrow \infty} F(x) = 1$ . So  $\{F_n\}$  is convergent but the limit is not a distribution function.



**Example 13.8.** Let  $X$  be a Bernoulli random variable with  $P(X = 0) = P(X = 1) = 1/2$  and define a sequence of random variables  $X_1, X_2, \dots$  by letting  $X_n = X$ . Clearly  $X_n \xrightarrow{D} X$  (and it also converges in probability and almost surely.) Now let  $Y = 1 - X$ . Clearly,  $Y$  is another random variable with the same distribution as  $X$  and thus  $X_n \xrightarrow{D} Y$ . However,  $\{X_n\}$  does not converge in probability to  $Y$  since  $|X_n(\omega) - Y(\omega)| = 1$  for any  $n$  and  $\omega$ .

## 13.2 Relations among modes of convergence

**Theorem 13.1.** Let  $\{X_n\}_{n \geq 1}, X$  be defined on the same probability space.

- (i) If  $X_n \xrightarrow{a.s.} X$ , then  $X_n \xrightarrow{P} X$ .
- (ii) If  $X_n \xrightarrow{P} X$ , then  $X_n \xrightarrow{D} X$ .
- (iii) If  $X_n \xrightarrow{L^p} X$  for some  $p > 0$ , then  $X_n \xrightarrow{P} X$ .

(iv) If  $X_n \xrightarrow{L^p} X$  for some  $p > 0$ , then  $X_n \xrightarrow{L^r} X$  for  $0 < r \leq p$ .

*Proof of part (i).* Almost sure convergence means that the event  $\{\lim_{n \rightarrow \infty} X_n = X\}$  has probability 1, which implies that, for any  $\epsilon > 0$ , the event

$$B_\epsilon = \{|X_n - X| > \epsilon \text{ for infinitely many } X_n\}$$

has probability zero. Recall that given a sequence of sets  $\{A_n\}$ , we have that  $\omega \in \limsup_{n \rightarrow \infty} A_n$  if and only if  $\omega$  occurs in infinitely many  $A_n$ . Hence, we can write  $B_\epsilon = \limsup_{n \rightarrow \infty} \{|X_n - X| > \epsilon\}$  and obtain

$$0 = \mathbf{P}(\limsup_{n \rightarrow \infty} \{|X_n - X| > \epsilon\}) = \mathbf{P}\left(\bigcap_{n \geq 1} \bigcup_{k \geq n} \{|X_k - X| > \epsilon\}\right).$$

By the continuity and monotonicity of measures,

$$\begin{aligned} \mathbf{P}\left(\bigcap_{n \geq 1} \bigcup_{k \geq n} \{|X_k - X| > \epsilon\}\right) &= \lim_{n \rightarrow \infty} \mathbf{P}\left(\bigcup_{k \geq n} \{|X_k - X| > \epsilon\}\right) \\ &\geq \limsup_{n \rightarrow \infty} \mathbf{P}(|X_n - X| > \epsilon). \end{aligned}$$

Hence, for any  $\epsilon > 0$ , we have  $\limsup_{n \rightarrow \infty} \mathbf{P}(|X_n - X| > \epsilon) = 0$ . But this means  $X_n \xrightarrow{P} X$ .  $\square$

*Proof of part (ii).* Consider arbitrary  $x \in \mathbb{R}$  and  $\epsilon > 0$ . If  $X_n \leq x$ , then we have either  $|X_n - X| > \epsilon$  or  $X \leq x + \epsilon$ . Hence,

$$\{X_n \leq x\} \subset \{X - x \leq \epsilon\} \cup \{|X_n - X| > \epsilon\}.$$

This implies

$$\begin{aligned} F_n(x) = \mathbf{P}(X_n \leq x) &\leq \mathbf{P}(X - x \leq \epsilon) + \mathbf{P}(|X_n - X| > \epsilon) \\ &= F(x + \epsilon) + \mathbf{P}(|X_n - X| > \epsilon). \end{aligned}$$

Similarly,  $\{X \leq x - \epsilon\} \subset \{X_n \leq x\} \cup \{|X_n - X| > \epsilon\}$  and thus

$$F(x - \epsilon) \leq F_n(x) + \mathbf{P}(|X_n - X| > \epsilon).$$

Letting  $n$  go to infinity and using the assumption that  $X_n \xrightarrow{P} X$ , we obtain

$$F(x - \epsilon) \leq \liminf_{n \rightarrow \infty} F_n(x) \leq \limsup_{n \rightarrow \infty} F_n(x) \leq F(x + \epsilon).$$

If  $F(x)$  is continuous at  $x$ , then  $\lim_{\epsilon \rightarrow 0} F(x - \epsilon) = \lim_{\epsilon \rightarrow 0} F(x + \epsilon) = F(x)$ , which yields

$$F(x) = \lim_{n \rightarrow \infty} F_n(x).$$

Hence,  $X_n \xrightarrow{D} X$ . □

*Proof of part (iii).* By Markov inequality,

$$\mathbf{P}(|X_n - X| \geq \epsilon) = \mathbf{P}(|X_n - X|^p \geq \epsilon^p) \leq \frac{E|X_n - X|^p}{\epsilon^p},$$

which converges to zero for any given  $\epsilon > 0$ . Hence,  $X_n \xrightarrow{P} X$ . □

*Proof of part (iv).* Recall that for  $p \geq r$  and a random variable  $Z$ , we have  $\|Z\|_{L^p} \geq \|Z\|_{L^r}$  (see Example 10.3). Hence,

$$E|X_n - X|^p \geq (E|X_n - X|^r)^{p/r} \geq 0.$$

Since  $E|X_n - X|^p \rightarrow 0$ , we have  $E|X_n - X|^r \rightarrow 0$ . □

## References

- [1] Sidney Resnick. *A Probability Path*. Springer, 2019.
- [2] Jordan M Stoyanov. *Counterexamples in probability*. Courier Corporation, 2013.