

# 1 | Supplement: Convergence of Random Variables

Consider the standard probability space on the unit interval:  $\Omega = [0, 1]$ ,  $\mathcal{F}$  is the Borel  $\sigma$ -algebra, and  $P$  is the Lebesgue measure (the distribution of a  $U(0, 1)$  random variable).

Let  $\{A_n\}_{n=1}^{\infty}$  be a sequence of Borel sets, i.e.,  $A_n \in \mathcal{F}$  for all  $n$ , and let  $\{a_n\}_{n=1}^{\infty}$  be a sequence of real numbers. For each  $n$ , define a random variable  $X_n$  by

$$X_n(\omega) = a_n I_{A_n}(\omega)$$

(recall that  $I_A$  denotes the indicator function of the set  $A$ ). In other words, for each  $\omega \in [0, 1]$  we have

$$X_n(\omega) = \begin{cases} a_n, & \text{if } \omega \in A_n \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

We are interested in various ways the sequence  $\{X_n\}$  may converge or fail to do so. Let's consider the following examples:

1. The sequence  $a_n$  converges to some  $a \in \mathbb{R}$ , and

$$P\left(\bigcup_{n=1}^{\infty} A_n\right) = 1, \quad (2)$$

and for any  $\omega \in \bigcup_n A_n$  there is only a finite number of  $A_n$ 's that do not contain it. In this case,  $X_n \xrightarrow{\text{a.s.}} a$ , regardless of any other details of the sets  $A_n$ .

To see this, consider what happens for each individual  $\omega$ . There are two cases. First,  $\omega$  may not be in any of the  $A_n$ 's. But by (2) the set of all such  $\omega$ 's has probability zero. So we only care about those  $\omega$ 's that are in at least one  $A_n$ . By assumption, any such  $\omega$  is contained in all but finitely many  $A_n$ 's. Therefore, from (1) we see that there is some  $N$  (which may depend on  $\omega$ ) such that

$$X_n(\omega) = a_n, \quad \forall n \geq N.$$

Since  $\{a_n\}$  is a convergent sequence of reals, the subsequence  $\{a_n\}_{n=N}^{\infty}$  converges to the same limit for any  $N$ . Consequently,  $X_n(\omega) \rightarrow a$  for each  $\omega \in \bigcup_n A_n$ . Since the latter event has probability one, we conclude that  $X_n \xrightarrow{\text{a.s.}} a$ , as claimed. Because almost sure convergence implies convergence in probability, we also have  $X_n \xrightarrow{P} a$ .

In the special case that  $a_n \rightarrow 0$ , we will have  $X_n \xrightarrow{\text{a.s.}} 0$  provided (2) holds, without any other conditions on  $\{A_n\}$ .

2. Assume again that the sequence  $\{a_n\}$  converges to some  $a \in \mathbb{R}$ . We are interested in seeing whether  $X_n \xrightarrow{P} a$  as well.

Because  $a_n \rightarrow a$ , for any  $\varepsilon > 0$  there exists some  $N$  (which may depend on  $\varepsilon$ ), such that  $|a_n - a| < \varepsilon$  for all  $n \geq N$ . Consider now an arbitrary  $\omega \in [0, 1]$  and some  $n \geq N$ . If  $\omega \notin A_n$ , then  $X_n(\omega) = 0$  and  $|X_n(\omega) - a| = |a|$ . Unless  $a = 0$ ,  $\omega \notin A_n$  will imply that  $|X_n(\omega) - a| \geq \varepsilon$  for all sufficiently small  $\varepsilon > 0$ . If  $\omega \in A_n$ , then  $|X_n(\omega) - a| = |a_n - a| < \varepsilon$ . Therefore, if  $|X_n - a| \geq \varepsilon$ , then  $\omega \notin A_n$  (to see this, note that if  $\omega \in A_n$ , then it is definitely the case that  $|X_n(\omega) - a| = |a_n - a| < \varepsilon$ ). More precisely,

$$\{\omega \in [0, 1] : |X_n(\omega) - a| \geq \varepsilon\} \subseteq A_n^c, \quad \forall n \geq N.$$

So for all  $n \geq N$  we have

$$P(|X_n - a| \geq \varepsilon) \leq P(A_n^c) = 1 - P(A_n). \quad (3)$$

So if  $P(A_n) \rightarrow 1$ , then  $X_n \xrightarrow{P} a$ . It is not hard to see that  $X_n$  need not converge to  $a$  almost surely, unless we assume something extra about  $\{A_n\}$ . One such instance is as follows. Suppose  $a_n \rightarrow a$ , and the sets  $A_n$  are such that

$$\sum_{n=1}^{\infty} P(A_n^c) < \infty.$$

This together with (3) implies that

$$\begin{aligned} \sum_{n=1}^{\infty} P(|X_n - a| \geq \varepsilon) &= \sum_{n=1}^{N-1} P(|X_n - a| \geq \varepsilon) + \sum_{n=N}^{\infty} P(|X_n - a| \geq \varepsilon) \\ &\leq \sum_{n=1}^{N-1} P(|X_n - a| \geq \varepsilon) + \sum_{n=N}^{\infty} P(A_n^c) \\ &\leq N - 1 + \sum_{n=1}^{\infty} P(A_n^c) \\ &< \infty. \end{aligned}$$

Note that  $N$  will in general depend on  $\varepsilon$ , but this is fine. What we are after is the statement that

$$\sum_{n=1}^{\infty} P(|X_n - a| \geq \varepsilon) < \infty$$

for any  $\epsilon > 0$ , and we don't need the sum to be bounded uniformly for all  $\epsilon$ . By the Borel–Cantelli lemma (Lemma 1.2.2 in the lecture notes),

$$P(|X_n - a| \geq \epsilon \text{ infinitely often}) = 0, \quad \forall \epsilon > 0. \quad (4)$$

We claim that (4) implies that  $X_n \xrightarrow{\text{a.s.}} a$ . Indeed, by definition  $X_n \xrightarrow{\text{a.s.}} X$  if

$$P\left(\left\{\omega : \exists k \in \mathbb{N} \text{ such that } |X_n(\omega) - X(\omega)| \geq \frac{1}{k} \text{ infinitely often}\right\}\right) = 0.$$

(can you see why?). By (4), we conclude that  $X_n \xrightarrow{\text{a.s.}} a$ .

**Reminder:** if  $\{E_n\}$  is a sequence of events, then the event

$$\{E_n \text{ occurs infinitely often}\},$$

also abbreviated as  $\{E_n \text{ i.o.}\}$ , is defined as

$$\{E_n \text{ i.o.}\} = \bigcap_{n=1}^{\infty} \bigcup_{k \geq n} E_k.$$

In other words,  $\{E_n \text{ i.o.}\}$  is the set of all  $\omega \in \Omega$ , such that  $\omega$  belongs to infinitely many  $E_n$ 's.

3. Let us now see whether  $\{X_n\}$  converges in the mean square sense. Again, suppose that  $a_n \rightarrow a$ , where  $a \neq 0$ . Let us see whether  $X_n \xrightarrow{\text{m.s.}} a$  as well. To that end, we have

$$\begin{aligned} \mathbb{E}[|X_n - a|^2] &= \mathbb{E}\left[|a_n I_{A_n} - a|^2\right] \\ &= a_n^2 \mathbb{E}[I_{A_n}] - 2a_n a \mathbb{E}[I_{A_n}] + a^2 \\ &= (a_n^2 - 2a_n a) P(A_n) + a^2 \\ &= (a_n - a)^2 P(A_n) + a^2 (1 - P(A_n)). \end{aligned}$$

Because  $\{a_n\}$  converges to  $a$ , we have

$$\lim_{n \rightarrow \infty} (a_n - a)^2 P(A_n) \leq \lim_{n \rightarrow \infty} (a_n - a)^2 = 0.$$

Since the left-hand side of the above equation is nonnegative, we have

$$\lim_{n \rightarrow \infty} \mathbb{E}[|X_n - a|^2] = a^2 - a^2 \lim_{n \rightarrow \infty} P(A_n).$$

Consequently, if  $P(A_n) \rightarrow 1$ , then  $X_n \xrightarrow{\text{m.s.}} a$ . Because convergence in mean square sense implies convergence in probability,  $X_n \xrightarrow{P} a$  as well. If  $a_n \rightarrow 0$ , then  $X_n \xrightarrow{\text{m.s.}} 0$  as well, regardless of  $\{A_n\}$ , because in that case

$$\mathbb{E}[X_n^2] = a_n^2 P(A_n) \leq a_n^2.$$

The right-hand side converges to zero, so  $\mathbb{E}[X_n^2]$  does too.

Another instance of m.s. convergence to zero is when  $\{a_n\}$  and  $\{A_n\}$  are such that the sequence  $a_n^2 P(A_n)$  converges to zero. (In fact,  $X_n \xrightarrow{\text{m.s.}} 0$  if and only if  $a_n^2 P(A_n) \rightarrow 0$ .) In this case,  $a_n$  need not be convergent. For instance, if  $a_n = n^{\frac{1-\varepsilon}{2}}$  for some  $\varepsilon \in (0, 1)$  and  $P(A_n) \leq n^{-1}$  for all  $n$ , then

$$a_n^2 P(A_n) \leq \frac{n^{1-\varepsilon}}{n} = n^{-\varepsilon} \xrightarrow{n \rightarrow \infty} 0.$$