

[6.2] Let a_n be so big that $P(|X_n| > a_n) \leq \frac{1}{n^2}$, and let $c_n = na_n$.

Then, by the Borel-Cantelli lemma, almost surely $|X_n| \leq a_n$ for all but finitely many n , so $\left| \frac{X_n}{c_n} \right| \leq \frac{1}{n}$ for all but finitely many n -s.

This implies $P\left(\frac{X_n}{c_n} \rightarrow 0\right) = 1$. □

[6.4] For convergence in probability or almost surely, X_n has to be at least convergent weakly, which implies that p_n has to be convergent, so $p_n \rightarrow p$ for some $p \in [0, 1]$, and $X \sim B(p)$. Now if $p \notin \{0, 1\}$, then a sequence of independent X_n has no chance to converge to X in probability, since $P(|X_n - X_{n+1}| = 1) \not\rightarrow 0$. So we need $p_n \rightarrow 0$ or $p_n \rightarrow 1$ and, respectively, $X_n \rightarrow 0$ or $X_n \rightarrow 1$.

⊕ Let's see $X_n \rightarrow 0$ first.

a.) $X_n \rightarrow 0$ in probability ~~iff~~ $\Leftrightarrow P(|X_n| > \varepsilon) \rightarrow 0$ for every ε ,

but for $\varepsilon < 1$ $\{|X_n| > \varepsilon\} = \{X_n = 1\}$, so

$$X_n \rightarrow 0 \text{ in prob.} \Leftrightarrow P(X_n = 1) \rightarrow 0 \Leftrightarrow p_n \rightarrow 0.$$

b.) $X_n \rightarrow 0$ almost surely $\stackrel{X_n \in \{0,1\}}{\Leftrightarrow} X_n = 0$ for all but finitely many n .

$\stackrel{B-C}{\Leftrightarrow}$
independence

$$\sum_n P(X_n \neq 0) < \infty \Leftrightarrow \sum_n p_n < \infty.$$

Ⓛ Similarly for $X_n \rightarrow 1$:

a.) $X_n \rightarrow 1$ in prob. $\Leftrightarrow P(X_n \neq 1) \rightarrow 0 \Leftrightarrow 1 - p_n \rightarrow 0 \Leftrightarrow p_n \rightarrow 1$

b.) $X_n \rightarrow 1$ a.s. $\stackrel{B-C}{\Leftrightarrow} \sum_n P(X_n \neq 1) < \infty \Leftrightarrow \sum_n (1 - p_n) < \infty$.

6.8

a.) We need to see that for $\forall \varepsilon > 0$, if n is big enough then $\mathbb{P}(|Y_n - Y| > \varepsilon) < \varepsilon$. Since $Y_n = f(X_n)$ and $Y = f(X)$, when $f: \mathbb{R} \rightarrow \mathbb{R}$ is continuous, $|Y_n - Y|$ can only be big when $|X_n - X|$ is also big.

More precisely: if f was uniformly continuous, so that for $\forall \delta > 0 \exists \delta' > 0$ s.t. if $|x - x_0| < \delta'$, then $|f(x) - f(x_0)| < \delta$, then, with this δ' ,

$$\mathbb{P}(|Y_n - Y| > \delta) \leq \mathbb{P}(|X_n - X| > \delta') < \varepsilon \text{ for } n \text{ big enough,}$$

because $X_n \rightarrow X$ in probability.

Unfortunately, a continuous $f: \mathbb{R} \rightarrow \mathbb{R}$ is in general not uniformly continuous. To treat this problem, for any given $\varepsilon > 0$, choose K so big that $\mathbb{P}(|X| > K) < \frac{\varepsilon}{2}$. Now the interval

$I := [-K-1; K+1]$ is compact, so our continuous f is surely

uniformly continuous on I , so $\exists \delta' > 0$ s.t. $|x - x_0| < \delta'$ implies

$|f(x) - f(x_0)| < \delta$ for every $x, x_0 \in I$. Now [we can assume $\delta' < 1$]

if $|f(X_n) - f(X)| > \delta$, then either $|X_n - X| > \delta'$, or $|X| > K$,

which means that

$$\mathbb{P}(|Y_n - Y| > \delta) \leq \mathbb{P}(|X_n - X| > \delta') + \mathbb{P}(|X| > K) \leq \frac{\varepsilon}{2} + \frac{\varepsilon}{2} = \varepsilon \text{ if}$$

n is big enough. \square

[6.8] b.) ~~$P(X_n \leq M) = 1$, then $E X_n = \int_{-\infty}^{\infty} f(x) dx$~~

$E X_n = \int_{-\infty}^{\infty} f(x) dx$ and $E X = \int_{-\infty}^{\infty} f(x) dx$ where $f: \mathbb{R} \rightarrow \mathbb{R}$ is given by $f(x) = x$.

If this f was bounded, then $X_n \xrightarrow{\text{weakly}} X$ would imply

$E f(X_n) \rightarrow E f(X)$. f is not bounded, but if the X_n

are r.s. bounded by M , then so is X , and

f can be "replaced" by some bounded continuous f_M ,

for which $f = f_M$ on $[-M, M]$. E.g. ~~$f_M(x) = \min(|x|, M)$~~

$$f_M(x) := \begin{cases} -M, & \text{if } x < -M \\ x, & \text{if } -M \leq x \leq M \\ M, & \text{if } x > M \end{cases} \quad \text{will do.}$$

So $E f_M(X_n) = E X_n$ and $E f_M(X) = E X$,

and $X_n \xrightarrow{\text{weakly}} X$ implies $E f_M(X_n) \rightarrow E f_M(X)$ \square

c.) Let $P(X_n = n) = \frac{1}{n}$ and $P(X_n = 0) = 1 - \frac{1}{n}$. Then $X_n \xrightarrow{\text{prob.}} 0$, but

$E X_n = 1$ for every n .

[6.10] Let X_1, X_2, \dots be i.i.d. $\sim \text{Uni}[0, 1]$. Then

$$L_n := \int_0^1 \int_0^1 \dots \int_0^1 \frac{x_1^2 + \dots + x_n^2}{x_1 + \dots + x_n} dx_1 dx_2 \dots dx_n = E \frac{X_1^2 + \dots + X_n^2}{X_1 + \dots + X_n} = E \frac{\frac{X_1^2 + \dots + X_n^2}{n}}{\frac{X_1 + \dots + X_n}{n}}$$

Now the L.L.N. says that $\frac{X_1 + \dots + X_n}{n} \rightarrow E X = \frac{1}{2}$ and $\frac{X_1^2 + \dots + X_n^2}{n} \rightarrow E X^2 = \frac{1}{3}$,

so $\frac{X_1^2 + \dots + X_n^2}{X_1 + \dots + X_n} \rightarrow \frac{1/3}{1/2} = \frac{2}{3}$ almost surely, thus also in probability.

Since $0 \leq X_i^2 \leq X_i \leq 1$, $\frac{X_1^2 + \dots + X_n^2}{X_1 + \dots + X_n} \in (0, 1)$, and HW 6.8 implies

then $L_n \rightarrow E \frac{2}{3} = \frac{2}{3}$. \square