

Lecture 10 : Kolmogorov's Law of Large Numbers

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(These notes are a revision of the work of Vinod Prabhakaran, 2002.)

10.1 Law of the Iterated Logarithm

Let $X_1, X_2, \dots$ be i.i.d. with $\mathbb{E}X_i = 0$, $\mathbb{E}X_i^2 = \sigma^2$, $S_n = X_1 + \dots + X_n$. We know

$$\frac{S_n}{n^{\frac{1}{2}+\varepsilon}} \xrightarrow{a.s.} 0 \text{ as } n \rightarrow \infty.$$

We will show later

$$\frac{S_n}{\sigma n^{\frac{1}{2}}} \xrightarrow{d} N(0, 1) \text{ as } n \rightarrow \infty.$$

For general interest, we state, without proof, the *Law of the Iterated Logarithm*:

$$\limsup_{n \rightarrow \infty} \frac{S_n}{\sigma \sqrt{2n \log(\log n)}} = 1 \text{ a.s.}$$

$$\liminf_{n \rightarrow \infty} \frac{S_n}{\sigma \sqrt{2n \log(\log n)}} = -1 \text{ a.s.}$$

$$\mathbb{P}(S_n > (1 + \varepsilon)\sigma \sqrt{2n \log(\log n)} \text{ i.o.}) = 0$$

$$\mathbb{P}(S_n < -(1 - \varepsilon)\sigma \sqrt{2n \log(\log n)} \text{ i.o.}) = 0$$

10.2 Kolmogorov's Law of Large Numbers

Theorem 10.1 *Let $X_1, X_2, \dots$ be i.i.d. with $\mathbb{E}(|X_i|) < \infty$, $S_n = X_1 + \dots + X_n$. Then $S_n/n \rightarrow \mathbb{E}(X)$ a.s. as $n \rightarrow \infty$.*

Note that the theorem is true with just pairwise independence instead of the full independence assumed here [[1], p.55 (7.1)]. The theorem also has an important generalization to stationary sequences (the *ergodic theorem*, [[1], p.337 (2.1)]).

Proof: *Step 1:* Replace X_i by $\tilde{X}_i = X_i - \mathbb{E}X$ (note $\mathbb{E}X_i = \mathbb{E}X$). Then

$$\frac{\tilde{S}_n}{n} = \frac{S_n}{n} - \mathbb{E}X.$$

So it's enough to consider $\mathbb{E}X = 0$.

Step 2: Now we assume $\mathbb{E}X = 0$. Introduce truncated variables

$$\hat{X}_n := X_n I(|X_n| \leq n).$$

Observe that

$$\mathbb{P}(X_n = \hat{X}_n \text{ ev.}) = 1.$$

(To see this, check

$$\mathbb{P}(X_n \neq \hat{X}_n \text{ i.o.}) = \mathbb{P}(|X_n| > n \text{ i.o.})$$

$$\sum_{n=1}^{\infty} \mathbb{P}(|X_n| > n) = \sum_{n=1}^{\infty} \mathbb{P}(|X| > n) = \mathbb{E} \left(\sum_{n=1}^{\infty} I(|X| > n) \right) < \infty$$

since

$$\sum_{n=1}^{\infty} I(|X| > n) = \sum_{1 \leq n < X} 1 \leq |x| + 1.$$

Compare this to the tail sum formula for a random variable X with values in $0, 1, 2, \dots$

$$\mathbb{E}X = \sum_{n=1}^{\infty} n \mathbb{P}(X = n) = \sum_{n=1}^{\infty} \mathbb{P}(X \geq n).$$

Step 3: Center the truncated variables. Define $\tilde{X}_n := \hat{X}_n - \mathbb{E}(\hat{X}_n)$.

We will show that

$$\left(\frac{S_n}{n} \rightarrow 0 \right) \stackrel{a.s.}{\underset{(a)}}{=} \left(\frac{\hat{S}_n}{n} \rightarrow 0 \right) \stackrel{a.s.}{\underset{(b)}}{=} \left(\frac{\tilde{S}_n}{n} \rightarrow 0 \right),$$

where $\hat{S}_n = \hat{X}_1 + \hat{X}_2 + \dots + \hat{X}_n$ and $\tilde{S}_n = \tilde{X}_1 + \tilde{X}_2 + \dots + \tilde{X}_n$. Then using Kronecker's lemma we will show that $\mathbb{P}(\tilde{S}_n/n \rightarrow 0) = 1$.

(a) comes from the fact that if $\omega \in \left\{ \omega : X_n(\omega) = \hat{X}_n(\omega) \text{ ev.} \right\}$ (which has probability 1), then $S_n(\omega) - \hat{S}_n(\omega)$ is eventually not dependent on n . So

$$\frac{S_n(\omega) - \hat{S}_n(\omega)}{n} \rightarrow 0 \text{ for such } \omega.$$

(b) comes from

$$\frac{\widehat{S}_n}{n} - \frac{\widetilde{S}_n}{n} = \frac{\mathbb{E}\widehat{X}_1 + \mathbb{E}\widehat{X}_2 + \dots + \mathbb{E}\widehat{X}_n}{n} \rightarrow 0 \text{ as } n \rightarrow \infty \quad (\text{By analysis and } \mathbb{E}\widehat{X}_i \rightarrow 0)$$

But

$$\mathbb{E}\widehat{X}_n = \mathbb{E}[X_n I(|X_n| \leq n)] = \mathbb{E}[XI(|X| \leq n)] \rightarrow \mathbb{E}X \text{ as } n \rightarrow \infty.$$

as the integrand is dominated by $|X|$ and note $E(|X|) < \infty$.

Now, we use Kronecker's lemma and the $\mathcal{L}^2$ convergence theorem to show that

$$\sum_{n=1}^{\infty} \frac{\mathbb{E}(\widetilde{X}_n^2)}{n^2} < \infty.$$

$$\begin{aligned} \mathbb{E}(\widetilde{X}_n^2) &= \mathbb{E}\left[\left(\widehat{X}_n - \mathbb{E}(\widehat{X}_n)\right)^2\right] = \mathbb{E}[(X\mathbf{1}(|X| \leq n) - \mathbb{E}(X\mathbf{1}(|X| \leq n)))^2] \\ &\leq \mathbb{E}(X\mathbf{1}(|X| \leq n))^2. \end{aligned}$$

So

$$\begin{aligned} \sum_{n=1}^{\infty} \frac{\mathbb{E}(\widetilde{X}_n^2)}{n^2} &\leq \sum_{n=1}^{\infty} \frac{\mathbb{E}X^2 I(|X| \leq n)}{n^2} = \mathbb{E}\left(X^2 \sum_{n=1}^{\infty} \frac{I(|X| \leq n)}{n^2}\right) \\ &\cong \mathbb{E}\left(\frac{X^2}{|X|}\right) = \mathbb{E}(|X|) < \infty. \end{aligned}$$

This came from

$$\sum_{n=1}^{\infty} \frac{x^2 \mathbf{1}_{(|x| \leq n)}}{n^2} \cong x^2 \sum_{n=1}^{\infty} \frac{1}{n^2} \cong x^2 \frac{1}{|x|} \cong |x|.$$

■

10.3 Convergence in distribution

Definition 10.2 $X_n \xrightarrow{d} X$ if $\mathbb{P}(X_n \leq x) \rightarrow \mathbb{P}(X \leq x)$ for all x at which $x \rightarrow \mathbb{P}(X \leq x)$ is continuous. We call this convergence in distribution or weak convergence.

Note. This is really a notion of convergence of probability measures rather than of convergence of random variables. Now the limit random variable X is only unique in distribution, not unique almost surely. Obviously, if $X \stackrel{d}{=} Y$ and $X_n \xrightarrow{d} X$, then $X_n \xrightarrow{d} Y$.

Theorem 10.3 (Skorokhod) $X_n \xrightarrow{d} X \iff$ there exists a probability with space random variables Y_n with $Y_n \stackrel{d}{=} X_n$, $Y \stackrel{d}{=} X$ and $Y_n \xrightarrow{a.s.} Y$.

Proof: Take a single uniform variable U and use it to create the Y_n and Y . Let

$$F_n(x) = \mathbb{P}(X_n \leq x),$$

$$F(x) = \mathbb{P}(X \leq x),$$

$$Y_n = F_n^{-1}(U),$$

$$Y = F^{-1}(U).$$

Check that

$$F^{-1}(U) = \inf \{x : F(x) > u\}.$$

■

The following proposition is an application of the above.

Proposition 10.4 If $X_n \xrightarrow{d} X$, then for every bounded continuous function $f : R \rightarrow R$

$$\mathbb{E}[f(X_n)] \rightarrow \mathbb{E}[f(X)].$$

Proof: Without loss of generality, $X_n \xrightarrow{a.s.} X$. Then $f(X_n) \rightarrow f(X)$ is bounded, so we can take expectations and use the bounded convergence theorem. ■

References

- [1] Richard Durrett. *Probability: theory and examples, 3rd edition*. Thomson Brooks/Cole, 2005.