

Recall that

Thm (Borel-Cantelli Lemma) Suppose $\sum_{n=1}^{\infty} P(A_n) < \infty$.

Then $P(A_n \text{ i.o.}) = 0$.

As an application of the Borel-Cantelli Lemma, we have the following version of strong law of large numbers.

Thm 2.11. Let X_1, X_2, \dots be i.i.d. with $E X_i = \mu$ and $E X_i^4 < \infty$.

Then $\lim_{n \rightarrow \infty} \frac{X_1 + \dots + X_n}{n} = \mu \text{ a.s.}$

Pf. Replacing X_i by $X_i - \mu$, we may assume that $E X_i = 0$.

Set $S_n = X_1 + \dots + X_n$. We will show that $\lim_{n \rightarrow \infty} \frac{S_n}{n} = 0$ a.s.

Notice that

$$E S_n^4 = E \left(\sum_{1 \leq i, j, k, l \leq n} X_i X_j X_k X_l \right)$$

$$= \sum_{1 \leq i, j, k, l \leq n} E(X_i X_j X_k X_l)$$

Terms in the above sums of the form

$$E(X_i^3 X_j), \quad E(X_i^2 X_j X_k), \quad E(X_i X_j X_k X_l)$$

(if i, j, k, l are distinct)

are all 0. The remaining terms are of the form $E(X_i^2 X_j^2)$ ($i \neq j$) and $E(X_i^4)$.

$$\begin{aligned}
 \text{Hence } E S_n^4 &= \binom{n}{2} \cdot \binom{4}{2} E(X_1^2 X_2^2) + n E(X_1^4) \\
 &= 3n(n-1) E(X_1^2 X_2^2) + n E(X_1^4) \\
 &\leq 3n(n-1) E(X_1^4)^{\frac{1}{2}} E(X_2^4)^{\frac{1}{2}} + n E(X_1^4) \\
 &= (3n^2 - 2n) E X_i^4
 \end{aligned}$$

$$\text{Hence } E S_n^4 \leq C n^2.$$

Let $\varepsilon > 0$. Then by Chebyshhev inequality,

$$P(|S_n| > n\varepsilon) \leq \frac{E S_n^4}{n^4 \varepsilon^4} \leq \frac{C}{n^2 \varepsilon^4}$$

$$\text{So } \sum_{n=1}^{\infty} P(|S_n| > n\varepsilon) < \infty.$$

It follows that $P(|S_n| > n\varepsilon \text{ i.o.}) = 0$. Hence $\lim_{n \rightarrow \infty} \frac{|S_n|}{n} \leq \varepsilon$ a.s.

Since ε is arbitrary, $\frac{S_n}{n} \rightarrow 0$ almost surely. \square

Thm 2.12. (The second Borel-Cantelli lemma).

If the events A_n are independent with $\sum_{n=1}^{\infty} P(A_n) = \infty$, then $P(A_n \text{ i.o.}) = 1$.

Pf. Let $M < N$. By independence and $1-x < e^{-x}$

$$\begin{aligned}
 P\left(\bigcap_{n=M}^N A_n^c\right) &= \prod_{n=M}^N P(A_n) \\
 &\leq \prod_{n=M}^N e^{-P(A_n)} \\
 &= e^{-\sum_{n=M}^N P(A_n)} \rightarrow 0 \quad \text{as } N \rightarrow \infty
 \end{aligned}$$

Hence $P\left(\bigcap_{n=M}^{\infty} A_n^c\right) = 0 \Rightarrow P\left(\bigcup_{n=M}^{\infty} A_n\right) = 1 \Rightarrow P(A_n \text{ i.o.}) = 1.$

■

Cor. 2.13. If X_1, X_2, \dots are i.i.d. with $E|X_i| = \infty$, then

$$P(|X_n| \geq n \text{ i.o.}) = 1,$$

and

$$P\left(\lim_{n \rightarrow \infty} S_n \in (-\infty, \infty)\right) = 0.$$

$$\begin{aligned}
 \text{Pf. } E|X_i| &= \int_0^\infty P(|X_i| > t) dt \\
 &\leq \sum_{n=1}^{\infty} \int_{n-1}^n P(|X_i| > t) dt \\
 &\leq \sum_{n=1}^{\infty} P(|X_i| > n-1) \\
 &= \sum_{n=1}^{\infty} P(|X_{n-1}| > n-1)
 \end{aligned}$$

By the second BC lemma, $P(|X_n| > n \text{ i.o.}) = 1$.

To prove the second claim, observe that

$$\frac{S_n}{n} - \frac{S_{n+1}}{n+1} = \frac{S_n}{n} - \frac{S_n + X_{n+1}}{n+1} = \frac{S_n}{n(n+1)} - \frac{X_{n+1}}{n+1}.$$

Write $C = \left\{ \omega : \lim_{n \rightarrow \infty} \frac{S_n}{n} \in (-\infty, \infty) \right\}$.

On $C \cap \left\{ \omega : |X_n| > n \text{ i.o.} \right\}$, $\frac{S_n}{n(n+1)} \rightarrow 0$ so

$$\left| \frac{S_n}{n} - \frac{S_{n+1}}{n+1} \right| \geq \frac{1}{2} \text{ i.o.}$$

contradicting the fact that $\omega \in C$. Hence $C \cap \left\{ \omega : |X_n| > n \text{ i.o.} \right\} = \emptyset$
which implies $P(C) = 0$. □

Remark: The above result shows that the condition

$E|X_i| < \infty$
in the strong law of large numbers is necessary.

§2.4 Strong law of large numbers.

Thm 2.14. Let X_1, \dots, X_n, \dots be pairwise independent, identically distributed r.v.'s with $E|X_i| < \infty$. Let $\mu = E X_i$. Then

$$\lim_{n \rightarrow \infty} \frac{X_1 + \dots + X_n}{n} = \mu \text{ a.s.}$$

Below we will follow Etemadi's proof.

Lem A Let $Y_k = X_k \mathbf{1}_{(|X_k| \leq k)}$ and

$$T_n = Y_1 + \dots + Y_n.$$

Then it suffices to show that $\frac{T_n}{n} \rightarrow \mu$ a.s.

pf. $\sum_{k=1}^{\infty} P(|X_k| > k)$

$$= \sum_{k=1}^{\infty} P(|X_1| > k) \leq \int_0^{\infty} P(|X_1| > t) dt = E|X_1| < \infty.$$

By the Borel-Cantelli lemma,

$$P(|X_k| > k \text{ i.o.}) = 0.$$

Equivalently,

$$P(X_k \neq Y_k \text{ i.o.}) = 0.$$

This shows that $|S_n(\omega) - T_n(\omega)| \leq R(\omega) < \infty$ a.s. for all n .

Hence $\lim_{n \rightarrow \infty} \frac{T_n}{n} = \mu \text{ a.s.} \Rightarrow \lim_{n \rightarrow \infty} \frac{S_n}{n} = \mu \text{ a.s.} \quad \square$

Lem B. $\sum_{k=1}^{\infty} \frac{\text{Var}(Y_k)}{k^2} < 4 \in |X_1| < \infty.$

Pf. $\text{Var}(Y_k) \leq E(Y_k^2) = \int_0^{\infty} P(|Y_k|^2 > t) dt$
 $= \int_0^{\infty} 2y P(|Y_k| > y) dy \quad \leftarrow (\text{Let } t=y^2)$
 $= \int_0^k 2y P(|Y_k| > y) dy$
 $\leq \int_0^k 2y P(|X_k| > y) dy = \int_0^k 2y P(|X_1| > y) dy.$

Hence

$$\begin{aligned} \sum_{k=1}^{\infty} \frac{\text{Var}(Y_k)}{k^2} &\leq \sum_{k=1}^{\infty} \frac{1}{k^2} \int_0^k 2y P(|X_1| > y) dy \\ &= \sum_{k=1}^{\infty} \frac{1}{k^2} \int_0^{\infty} 2y \cdot \mathbb{1}_{(y < k)} P(|X_1| > y) dy \\ &= \int_0^{\infty} \left(\sum_{k=1}^{\infty} \frac{1}{k^2} \cdot \mathbb{1}_{(y < k)} \right) \cdot 2y P(|X_1| > y) dy \\ &\leq \int_0^{\infty} \left(\sum_{k=1}^{\infty} \frac{2}{k(k+1)} \cdot \mathbb{1}_{(y < k)} \right) \cdot 2y P(|X_1| > y) dy \\ &\leq \int_0^{\infty} \left(\sum_{k=[y]+1}^{\infty} 2 \cdot \left(\frac{1}{k} - \frac{1}{k+1} \right) \right) \cdot (2y) P(|X_1| > y) dy \end{aligned}$$

$$\begin{aligned}
 &\leq \int_0^{\infty} \frac{2}{[y]+1} \cdot 2y \cdot P(|X_1|>y) dy \\
 &\leq 4 \int_0^{\infty} P(|X_1|>y) dy \\
 &= 4 E|X_1|.
 \end{aligned}$$

□

Pf of the strong law of large numbers.

Since both X_n^+ , X_n^- satisfy the assumptions of the theorem and $X_n = X_n^+ - X_n^-$, so we can wlog assume that $X_n \geq 0$.

Now we will first prove the result for a subsequence, and then use monotonicity to control the values in between.

Let $d > 1$ and $k(n) = [d^n]$, where $[x]$ denotes the integral part of x .

For $\varepsilon > 0$, we have

$$\sum_{n=1}^{\infty} P(|T_{k(n)} - E T_{k(n)}| > \varepsilon \cdot k(n))$$

(Chebyshev)

$$\leq \varepsilon^{-2} \cdot \sum_{n=1}^{\infty} \frac{\text{Var}(T_{k(n)})}{k(n)^2}$$

$$= \varepsilon^{-2} \cdot \sum_{n=1}^{\infty} \frac{1}{k(n)^2} \cdot \sum_{m=1}^{k(n)} \text{Var}(Y_m)$$

(in which we use the pairwise independence assumption)

$$= \varepsilon^{-2} \sum_{n=1}^{\infty} \sum_{m=1}^{\infty} \frac{1}{k(n)^2} \cdot \mathbb{1}_{\{m \leq k(n)\}} \text{Var}(Y_m)$$

$$= \varepsilon^{-2} \sum_{m=1}^{\infty} \text{Var}(Y_m) \cdot \sum_{n: k(n) \geq m} \frac{1}{k(n)^2} \cdot (1)$$

Notice that

$$\begin{aligned} \sum_{n: [d^n] \geq m} \frac{1}{[d^n]^2} &\leq \sum_{n: d^n \geq m} 4 \cdot d^{-2n} \\ &= 4 \cdot \sum_{n=\lceil \frac{\log m}{\log d} \rceil} \frac{1}{d^{2n}} \\ &= 4 \cdot d^{-2 \lceil \frac{\log m}{\log d} \rceil} \cdot \frac{1}{1-d^{-2}} \\ &\leq 4 \cdot d^{-2(\lceil \frac{\log m}{\log d} \rceil)} \frac{1}{1-d^{-2}} \\ &= 4 \cdot \frac{1}{m^2} \cdot \frac{1}{1-d^{-2}}. \end{aligned}$$

So by (1),

$$\begin{aligned} \sum_{n=1}^{\infty} P(|T_{k(n)} - E T_{k(n)}| > \varepsilon k(n)) \\ &\leq \varepsilon^{-2} \cdot \sum_{m=1}^{\infty} \frac{\text{Var}(Y_m)}{m^2} \cdot \frac{4}{1-d^{-2}} \\ &< \infty \quad (\text{by Lem B}). \end{aligned}$$

By the Borel-Cantelli lemma,

$$\lim_{n \rightarrow \infty} \frac{|T_{k(n)} - E T_{k(n)}|}{k(n)} \leq \varepsilon \quad \text{a.s.}$$

Since $\Sigma > 0$ is arbitrarily given, we have

$$\lim_{n \rightarrow \infty} \frac{T_{k(n)} - E T_{k(n)}}{k(n)} = 0 \quad (2)$$

However $E Y_k = E(X_k \mathbb{1}_{(X_k \leq k)})$
 $= E(X_1 \cdot \mathbb{1}_{(X_1 \leq k)}) \rightarrow E X_1 = \mu \text{ as } k \rightarrow \infty$
(by the monotone convergence thm).

It follows that $\frac{E T_{k(n)}}{k(n)} \rightarrow \mu \text{ as } n \rightarrow \infty.$

So by (2),

$$\lim_{n \rightarrow \infty} \frac{T_{k(n)}}{k(n)} = \mu.$$

Now for a given $m \in \mathbb{N}$, let n s.t

$$k(n) < m < k(n+1).$$

Then

$$\frac{T_{k(n)}}{k(n+1)} \leq \frac{T_m}{m} \leq \frac{T_{k(n+1)}}{k(n)}$$

Since $\frac{k(n+1)}{k(n)} \rightarrow \alpha$ as $n \rightarrow \infty$, it follows that

$$\frac{\mu}{\alpha} \leq \lim_{m \rightarrow \infty} \frac{T_m}{m} \leq \overline{\lim_{m \rightarrow \infty}} \frac{T_m}{m} \leq \alpha \cdot \mu \text{ almost surely.}$$

But since $\alpha > 1$ is arbitrary, we get

$$\lim_{m \rightarrow \infty} \frac{T_m}{m} = \mu \text{ a.s.}$$

■

The next result shows that SLLN holds whenever $E X_i^+ < \infty$.

Thm d. 15. Let X_1, X_2, \dots be i.i.d. with $E X_i^+ = \infty$ and

$E X_i^- < \infty$. Then

$$\lim_{n \rightarrow \infty} \frac{X_1 + \dots + X_n}{n} = \infty \text{ a.s.}$$

Pf. Let $M > 0$. Set $X_i^M = \min\{X_i, M\}$.

Then X_i^M are i.i.d. with $E|X_i^M| < \infty$.

By the SLLN,

$$\frac{X_1 + \dots + X_n}{n} \geq \frac{X_1^M + \dots + X_n^M}{n} \rightarrow E X_i^M \quad \text{as } n \rightarrow \infty.$$

By the monotone convergence Thm,

Since $(X_i^M)^+ \nearrow X_i^+$, $E(X_i^M)^+ \rightarrow E X_i^+$ as $M \rightarrow \infty$.

But $E(X_i^M)^- = E X_i^-$,

So we have

$$E X_i^M = E(X_i^M)^+ - E(X_i^M)^-$$

$$\rightarrow E X_i^+ - E X_i^- = E X_i \quad \text{as } M \rightarrow \infty.$$

$= \infty$

It follows that

$$\lim_{n \rightarrow \infty} \frac{X_1 + \dots + X_n}{n} = \infty \quad \text{a.s.} \quad \blacksquare$$