

Convergence in distribution

Def: $X_n \rightarrow X$ in distribution $F_n(x) \rightarrow F(x)$ at all points x where F is continuous.

Assume that F is continuous at a, b . Then

$$P[a < X_n \leq b] = F_n(b) - F_n(a) \rightarrow F(b) - F(a) = P[a < X \leq b]$$

Hence $\lim_{n \rightarrow \infty} P[a < X_n \leq b] = P[a < X \leq b]$

Theorem: $\{X_n\}$ converges to X in distribution if and only if

$$(*) \quad \lim_{n \rightarrow \infty} E[f(X_n)] = E[f(X)]$$

for all bounded, continuous function $f: \mathbb{R} \rightarrow \mathbb{R}$.

Proof: Assume that $X_n \rightarrow X$ in distribution. We are first going to prove (*) for continuous function with compact support, i.e. there is a number $k \in \mathbb{R}$ such that $f(x) = 0$ when $|x| \geq k$.

Given $\epsilon > 0$, there is a $\delta > 0$ such that whenever $|u-v| < \delta$, then $|f(u)-f(v)| < \epsilon$ (we could find an compact intervals are uniformly continuous). Hence we can partition $[-k, k]$ into subintervals $(a_{i-1}, a_i]$, \dots , $(a_{n-1}, a_n]$ with lengths less than δ such that a_0, a_1, \dots, a_n are continuity points for F (the dist. function of X).

Let $\varphi(x) = \sum_{i=1}^n f(a_i) \mathbb{1}_{(a_{i-1}, a_i]}$

Note that $|\varphi(x) - f(x)| < \epsilon$. Note that

$$\begin{aligned} |E[f(X_n)] - E[f(X)]| &= |E[f(X_n) - \varphi(X_n)] + E[\varphi(X_n) - \varphi(X)] + E[\varphi(X) - f(X)]| \\ &\leq E[|f(X_n) - \varphi(X_n)|] + |E[\varphi(X_n) - \varphi(X)]| + E[|\varphi(X) - f(X)|] \\ &\leq 2\epsilon + |E[\sum_{i=1}^n f(a_i) \mathbb{1}_{(a_{i-1}, a_i]}(X_n) - \sum_{i=1}^n f(a_i) \mathbb{1}_{(a_{i-1}, a_i]}(X)]| \\ &\leq 2\epsilon + \sum_{i=1}^n f(a_i) [P[a_{i-1} < X_n \leq a_i] - P[a_{i-1} < X \leq a_i]] \end{aligned}$$

Letting n go to infinity, we see that $|E[f(X_n)] - E[f(X)]|$ gets less than ϵ , and as $\epsilon > 0$ is arbitrary, we must have $E[f(X_n)] \rightarrow E[f(X)]$.

It now need look at a function f which is bounded, continuous, but not compact support.

Given $\epsilon > 0$, choose k such that and define \hat{f} as shown.

$$\begin{aligned} |E[f(X_n)] - E[f(X)]| &= E[f(X_n) - \hat{f}(X_n)] + E[\hat{f}(X_n) - \hat{f}(X)] + E[\hat{f}(X) - f(X)] \\ &\leq 2M P[X_n < -k] + 2M P[X_n > k] + E[\hat{f}(X_n) - \hat{f}(X)] + 2M P[X < -k] + 2M P[X > k] \\ &\leq 8M\epsilon + E[\hat{f}(X_n) - \hat{f}(X)] \rightarrow 0. \end{aligned}$$

Hence for large n , $E[f(X_n) - f(X)] \leq 8M\epsilon$. Since $\epsilon > 0$ is arbitrary, this means $\lim E[f(X_n)] = E[f(X)]$.

Remember now that

$$(x) \lim_{n \rightarrow \infty} E[f(X_n)] = E[f(X)] \text{ for all bounded, cont. } f.$$

Remember that a is a continuity point for F . Now to prove that $\lim_{n \rightarrow \infty} F_n(a) = F(a)$

$$\text{Note that } F_n(a) = P[X_n \leq a] = E[\mathbb{1}_{(-\infty, a]}(X_n)]$$

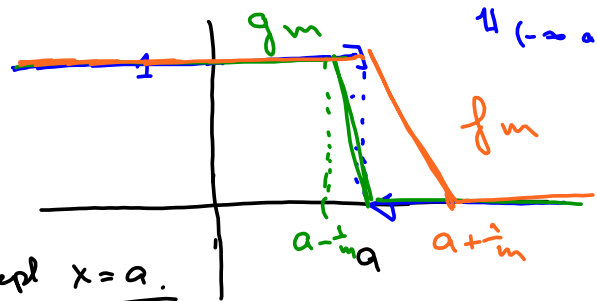
$$F(a) = P[X \leq a] = E[\mathbb{1}_{(-\infty, a]}(X)]$$

Approx:

$$g_m(x) \leq \mathbb{1}_{(-\infty, a]}(x) \leq f_m(x)$$

$$g_m(x) \rightarrow \mathbb{1}_{(-\infty, a]}(x) \text{ for all } x \text{ except } x=a.$$

$$f_m(x) \rightarrow \mathbb{1}_{(-\infty, a]}(x) \text{ for all } x.$$



$$\liminf E[g_m(X_n)] \leq \liminf_{n \rightarrow \infty} E[\mathbb{1}_{(-\infty, a]}(X_n)] \leq \limsup_n E[\mathbb{1}_{(-\infty, a]}(X_n)]$$

$$\leq \limsup_n E[f_m(X_n)]$$

$$\begin{matrix} \text{(x) } \parallel \\ E[g_m(X)] \\ \dots \dots \dots \parallel \\ \downarrow m \rightarrow \infty \\ E[\mathbb{1}_{(-\infty, a]}(X)] \end{matrix} \xrightarrow{\text{DCT}} \begin{matrix} \parallel \\ \mathbb{1}_{(-\infty, a]}(X) \text{ a.s.} \\ \dots \dots \dots \parallel \\ \downarrow m \rightarrow \infty \\ E[\mathbb{1}_{(-\infty, a]}(X)] \end{matrix}$$

Hence

$$E[\mathbb{1}_{(-\infty, a]}(X)] \leq \liminf E[\mathbb{1}_{(-\infty, a]}(X_n)]$$

$$\leq \limsup E[\mathbb{1}_{(-\infty, a]}(X_n)] \leq E[\mathbb{1}_{(-\infty, a]}(X)]$$

Hence $\lim E[\mathbb{1}_{(-\infty, a]}(X_n)] = E[\mathbb{1}_{(-\infty, a]}(X)]$

which is what we had to prove!

Trivial Exam 1, 2019, Prob 4

a) $\{x_n\}$ sequence of numbers

$$S_n = \frac{x_1 + x_2 + \dots + x_n}{\sqrt{n}}$$

$$S_n^k = \frac{x_k + x_{k+1} + \dots + x_n}{\sqrt{n}}$$

Show that: $\limsup_{n \rightarrow \infty} S_n = \limsup_{n \rightarrow \infty} S_n^k$

$$|S_n - S_n^k| = \left| \frac{x_1 + x_2 + \dots + x_{k-1}}{\sqrt{n}} \right| \leq \left(\frac{(k-1)M}{\sqrt{n}} \right) \quad \text{when } \epsilon$$

$M = \max\{|x_1|, |x_2|, \dots, |x_{k-1}|\}$

Given $\epsilon > 0$, I can always find $m \in \mathbb{N}$ such that

$$|S_n - S_n^k| \leq \epsilon \quad \text{when } n \geq m.$$

$$\left| \sup_{n \geq m} S_n - \sup_{n \geq m} S_n^k \right| \leq \epsilon.$$

Then

$$\left| \limsup_{n \rightarrow \infty} S_n - \limsup_{n \rightarrow \infty} S_n^k \right| \leq \epsilon$$

$$\left| \limsup S_n - \limsup S_n^k \right| < \epsilon$$

Since $\epsilon > 0$ is arbitrary, we must have

$$\limsup S_n = \limsup S_n^k$$

b) Assume now that $\{X_n\}$ is a sequence of independent random variables and put

$$S_n = \frac{X_1 + X_2 + \dots + X_n}{\sqrt{n}}$$

Show that for any Borel set B , the set

$$A = \{\omega : \limsup S_n \in B\}$$

$$\text{is a tail event, i.e. } A \in \mathcal{F}_\infty^* = \bigcap_{n \in \mathbb{N}} \mathcal{F}_n^*$$

$$\text{where } \mathcal{F}_n^* = \sigma(X_{n+1}, X_{n+2}, \dots)$$

$$A = \{\omega : \limsup S_n \in B\} = \{\omega : \limsup S_n^k \in B\} \in \mathcal{F}_{k-1}^*$$

$$\text{where } S_n^k = \frac{X_k + X_{k+1} + \dots + X_n}{\sqrt{n}}$$

Since this works for any k , we must have $A \in \mathcal{F}_\infty^*$

510 If $X_n \rightarrow 0$ a.e., then $\frac{X_1 + X_2 + \dots + X_n}{n} \rightarrow 0$ a.e.

Show that there are independent sequences $\{X_n\}$

s.t. $X_n \rightarrow 0$ in prob., but $\frac{X_1 + \dots + X_n}{n}$ does not go to 0 in prob.

First part: It is known that if $x_n \rightarrow a$, then

$$\frac{x_1 + x_2 + \dots + x_n}{n} \rightarrow a$$

Cesaro convergence.

Second part: Assume that $\{X_n\}$ are independent r.v. with

$$X_n = \begin{cases} 2^n & \text{with prob } \frac{1}{n} \\ 0 & \text{with prob } 1 - \frac{1}{n} \end{cases} \quad \left. \begin{array}{l} \sum P(B_n) = \sum \frac{1}{n} = \infty \\ \text{B.C. with prob } 1, \text{ then with} \\ \text{infinitely many successes.} \end{array} \right\}$$

Claim $X_n \rightarrow 0$ in prob. (from the definition)

$$\frac{X_1 + \dots + X_n}{n} \not\rightarrow 0 \text{ in prob.}$$

If ω is in the set of prob 1 when there are infinitely many successes, $\frac{X_1 + \dots + X_{n-1} + 2^n}{n} \geq \frac{2^n}{n} > 1$ we will have infinitely many occurrences of this kind

No convergence in prob.

5.11 X_1, \dots, X_n independent, $E[X_i] = 0$, $E[X_i^2] < \infty$.

$$S_k = X_1 + \dots + X_k$$

$$\Lambda = \left\{ \omega : \max_{k \leq n} |S_k| \geq \varepsilon \right\}$$

$$\Lambda = \Lambda_1 \cup \Lambda_2 \cup \dots \cup \Lambda_n \quad \text{disjoint}$$

$$\Lambda_k = \left\{ \omega : |S_k| \geq \varepsilon \text{ and } |S_i| < \varepsilon \text{ for all } i \leq k-1 \right\}$$

Show that $\int_{\Lambda_k} S_n^2 dP \geq \int_{\Lambda_k} S_k^2 dP$

$$\begin{aligned} \int_{\Lambda_k} S_n^2 dP &= \int_{\Lambda_k} (S_k + (S_n - S_k))^2 dP \\ &= \int_{\Lambda_k} S_k^2 dP + \int_{\Lambda_k} 2S_k(S_n - S_k) dP + \int_{\Lambda_k} (S_n - S_k)^2 dP \\ &= \int_{\Lambda_k} S_k^2 dP + \int_{\Lambda_k} (S_n - S_k)^2 dP \geq \int_{\Lambda_k} S_k^2 dP \end{aligned}$$

$$P\left[\max_{k \leq n} |S_k| \geq \varepsilon\right] \leq \frac{1}{\varepsilon^2} E[S_n^2] \quad \text{Kochuncuvenur ineq.}$$

$$E[S_n^2] \geq \int_{\Lambda} S_n^2 dP = \sum_{k=1}^n \int_{\Lambda_k} S_n^2 dP \geq \sum_{k=1}^n \int_{\Lambda_k} \varepsilon^2 dP$$

$$\geq \sum_{k=1}^n \varepsilon^2 P(\Lambda_k) = \varepsilon^2 P(\Lambda)$$

$$= \varepsilon^2 P\left[\max_{k \leq n} |S_k| \geq \varepsilon\right]$$