

Convergence in distribution

Let X_n :

Theorem: Assume that $\{X_n\}$ is a sequence of r.v.
 Then $\{X_n\}$ converges in distribution to X if and only if
 $E[f(X_n)] \rightarrow E[f(X)]$
 for all bounded, continuous $f: \mathbb{R} \rightarrow \mathbb{R}$.

Notation: $\{X_n\}, \{F_n\}, \{f_n\}$

$X_n \Rightarrow X$
 $F_n \Rightarrow F$
 $f_n \Rightarrow f$ } convergence in distribution.

Levy's Theorem: Let $\{F_n\}$ be a sequence of distribution functions. Then there is a subsequence $\{F_{n_k}\}$ that converges pointwise to a limit function F_∞ . Assume that $\lim_{x \rightarrow -\infty} F_\infty(x) = 0$ and $\lim_{x \rightarrow \infty} F_\infty(x) = 1$. Then F_∞ is a distribution function F and $F_{n_k} \Rightarrow F$.

Proof: Recall the Bolzano-Weierstrass Theorem (MAT 1110):
 Any bounded sequence in \mathbb{R} has a convergent subsequence.

Let x_1, x_2, x_3, \dots be an enumeration of \mathbb{Q} .
 Then by BW, the seq. $\{F_n(x_1)\}$ has a convergent subsequence. Let

F_1^*, F_2^*, \dots
 be the functions occurring in this subsequence. We know $F_1^*(x_1), F_2^*(x_1), \dots$ converge.

Now look at $F_1^*(x_2), F_2^*(x_2), F_3^*(x_2), \dots$. By BW, there is a convergent subsequence, and we let F_1^*, F_2^*, F_3^*

be the functions occurring in this subsequence. Then $\{F_n^*(x_1)\}, \{F_n^*(x_2)\}$ both converge.

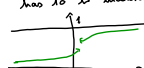
Next look at $\{F_n^*(x_3)\}$. Again there is a convergent subsequence, and if we pick the functions from this subsequence, we get a new subsequence $\{F_n^*\}$. Note $\{F_n^*(x_1)\}, \{F_n^*(x_2)\}, \{F_n^*(x_3)\}$ converge.

Now pick a new subsequence by picking $F_1^*, F_2^*, F_3^*, \dots$

If x_i is a rational number, the sequence $F_1^*(x_i), F_2^*(x_i), F_3^*(x_i), \dots$ must converge.

Define $F_\infty: \mathbb{Q} \rightarrow \mathbb{R}$ by letting $F_\infty(x_i)$ be the limit.

Since F_∞ is the limit of distribution functions it has to be increasing and take values between 0 and 1.



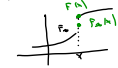
This can only be countably many points $x \in \mathbb{R}$ such that $\lim_{x \rightarrow x^-} F_\infty(x) < \lim_{x \rightarrow x^+} F_\infty(x)$

If x is not of this kind, the sequence $F_1^*(x), F_2^*(x), F_3^*(x), \dots$ has to converge by squeezing.

Repeat the procedure from the beginning of the proof applied to the countably many jump points instead of the values. This will give us a new subsequence that converges even at the jump points. Call this subsequence $\{F_{n_k}\}$. Then $F_{n_k}(x) \rightarrow F_\infty(x)$ for all x .

Assume now that $\lim_{x \rightarrow -\infty} F_\infty(x) = 0$ and $\lim_{x \rightarrow \infty} F_\infty(x) = 1$. F_∞ need not be right continuous, but

$$F(x) = \lim_{y \downarrow x} F_\infty(y)$$

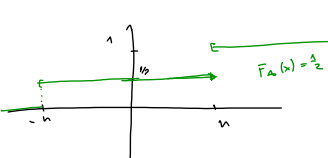


with F is also increasing and we have $\lim_{x \rightarrow -\infty} F(x) = 0$ and $\lim_{x \rightarrow \infty} F(x) = 1$ since these properties hold for F_∞ . Hence F is a distribution function. It still remains to prove that $F_{n_k} \Rightarrow F$.

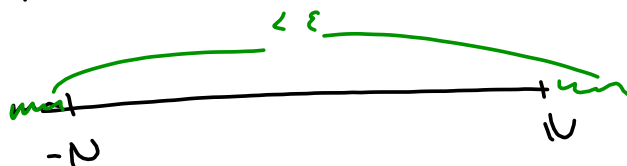
Let x be a cont. point of F . Then $F(x) = F_\infty(x)$ and $F_{n_k}(x) \rightarrow F_\infty(x) = F(x)$. Thus $F_{n_k} \Rightarrow F$.

Example: A situation when we do not get convergence in distribution

$$X_n = \begin{cases} n & \text{with prob } 1/2 \\ -n & \text{with prob } 1/2 \end{cases}$$



Definition: A sequence $\{\mu_n\}$ of distributions is called tight if for every $\varepsilon > 0$, there is a number N such that $\mu_n([-N, N]) > 1 - \varepsilon$.



Corollary: Assume that $\{X_n\}$ is a tight sequence of random variables. Then there is a subsequence $\{X_{n_k}\}$ that converges in distribution.

Proof: Let F_n be the distribution functions. By Helly's Theorem there is a subsequence F_{n_k} converging pointwise to a function F_∞ . The corollary will follow from Helly's Theorem if we can prove that $\lim_{x \rightarrow -\infty} F_\infty(x) = 0$, $\lim_{x \rightarrow \infty} F_\infty(x) = 1$.

Given an $\varepsilon > 0$, there is by tightness an N such that $\mu_n([-N, N]) > 1 - \varepsilon$, and hence $\mu_n([N, \infty)) < \varepsilon$.

Thus $F_n(N) > 1 - \varepsilon$ for all n , and thus $F_\infty(N) > 1 - \varepsilon$.

Hence $\lim_{x \rightarrow \infty} F_\infty(x) = 1$. Same argument for $-\infty$.

Weak convergence

Assume that X is a metric space, and let \mathcal{B} be the Bore σ -algebra on X . Let $\{\mu_n\}$ be a sequence of Bore measures. If μ is another Bore measure, we say that $\{\mu_n\}$ converges weakly to μ if

$$E_{\mu_n}[f] \rightarrow E_{\mu}[f]$$

for all bounded continuous functions

Definition: We say that $\{\mu_n\}$ is tight if for every $\epsilon > 0$, there is a compact set $K_{\epsilon} \subseteq X$ such that $\mu_n(K_{\epsilon}) > 1 - \epsilon$ for all $n \in \mathbb{N}$.

The Helly-Bray Theorem: If $\{\mu_n\}$ is a sequence of prob. measures and is tight, then there is a prob. measure on X such that $\{\mu_n\}$ converges weakly to μ .

Lévy's continuity theorem

Prop: Assume $\mu_n \Rightarrow \mu$. If φ_n and φ are the characteristic functions, then $\varphi_n(t) \rightarrow \varphi(t)$ for all t .

Proof: $\varphi_n(t) = E[e^{itX_n}] = E[\underbrace{\cos(tX_n)}_{\cos(t \cdot X)}] + i E[\underbrace{\sin(tX_n)}_{\sin(t \cdot X)}]$
 cons. and bounded cont. func.
 \downarrow
 $E[\cos(tX)] + i E[\sin(tX)] = E[e^{itX}] = \varphi(t)$

Lemma Assume that μ is a distribution with characteristic function φ . Then for all $A > 0$, then

$$\mu([-2A, 2A]) \geq A \left| \int_{-1/A}^{1/A} \varphi(t) dt \right| - 1 \approx A \cdot \frac{2}{A} - 1 = 2 - 1 = 1$$

Proof: Note for $T > 0$

$$\frac{1}{2T} \int_{-T}^T \varphi(t) dt = \int_{-\infty}^{\infty} \frac{\sin(Tx)}{Tx} d\mu(x)$$

because

$$\begin{aligned} \frac{1}{2T} \int_{-T}^T \varphi(t) dt &= \frac{1}{2T} \int_{-T}^T \left[\int_{-\infty}^{\infty} e^{itx} d\mu(x) \right] dt \\ &= \frac{1}{2T} \int_{-\infty}^{\infty} \left[\int_{-T}^T e^{itx} dt \right] d\mu(x) \\ &= \frac{1}{2T} \int_{-\infty}^{\infty} \left[\frac{e^{itx}}{ix} \right]_{t=-T}^{t=T} d\mu(x) \\ &= \int_{-\infty}^{\infty} \frac{e^{iTx} - e^{-iTx}}{2Tix} d\mu(x) = \int_{-\infty}^{\infty} \frac{\sin Tx}{Tx} d\mu(x) \end{aligned}$$

But then

$$\begin{aligned} \left| \frac{1}{2T} \int_{-T}^T \varphi(t) dt \right| &= \left| \int_{-\infty}^{\infty} \frac{\sin Tx}{Tx} d\mu \right| \\ &= \left| \int_{-2A}^{2A} \frac{\sin Tx}{Tx} d\mu(x) + \int_{-\infty}^{-2A} \frac{\sin Tx}{Tx} d\mu(x) + \int_{2A}^{\infty} \frac{\sin Tx}{Tx} d\mu(x) \right| \\ &\leq \mu([-2A, 2A]) + \frac{1}{2TA} \mu([-2A, -\infty]) + \frac{1}{2TA} \mu([2A, \infty]) \\ &= \mu([-2A, 2A]) + \frac{1}{2TA} (1 - \mu([-2A, 2A])) \end{aligned}$$

Let us choose $T = \frac{1}{A}$:

$$\left| \frac{1}{2} \int_{-1/A}^{1/A} \varphi(t) dt \right| \leq \mu([-2A, 2A]) + \frac{1}{2} (1 - \mu([-2A, 2A]))$$

$$= \frac{1}{2} \mu([-2A, 2A]) + \frac{1}{2}$$

hence

$$\mu([-2A, 2A]) \geq A \left| \int_{-1/A}^{1/A} \varphi(t) dt \right| - 1 \quad \text{Q.E.D.}$$

$$\varphi_n(t) \rightarrow \varphi(t) \implies \mu_n \Rightarrow \mu$$