

Weak convergence of distribution functions



Let $\xi_1, \xi_2, \dots, \xi_n$ be independent and identically distributed random variables with $\mathbb{E}[\xi_1] = 0$ and $\mathbb{E}[\xi_1^2] = 1$. Let

$$W_n = \frac{1}{\sqrt{n}} \sum_{i=1}^n \xi_i,$$

and let F_n be its distribution function. Then, by the central limit theorem,

$$F_n(x) \rightarrow \Phi(x) \quad \text{for every } x \in \mathbb{R}.$$

We want to give a sufficient and necessary condition for weak convergence.



Definition 1 (Weak convergence)

Let $\{F_n\}$ be a sequence of distribution functions, and we say $\{F_n\}$ is weakly convergent if there exists a non-decreasing function F satisfying that

$$\lim_{n \rightarrow \infty} F_n(x) = F(x) \quad \text{for every continuity point } x \in \mathbb{R},$$

denoted by

$$F_n \xrightarrow{w} F.$$



Remark

If $F_n \xrightarrow{w} F$, and let $X_n \sim F_n$ and $X \sim F$, then

$$X_n \xrightarrow{d} X.$$

- X_n and X may not be defined on the same probability space. [Example here.]
- However, we can construct X_n 's and X on the same probability space, such that $X_n \sim F_n$, $X \sim F$, and

$$X_n \xrightarrow{a.s.} X.$$



Example 2

Let X_1, X_2, \dots be a sequence of random variables whose distribution functions are

$$F_n(x) = \begin{cases} 1 - (1 - \frac{1}{n})^{nx} & x > 0 \\ 0 & \text{otherwise.} \end{cases}$$

Show that $X_n \xrightarrow{d} \text{Exponential}(1)$.



Theorem 3

If $F_n \xrightarrow{w} F$, then there exist random variables $\{X_n\}$ and X defined on the same probability space $(\Omega, \mathcal{F}, \mathbb{P})$ such that $X_n \sim F_n$ for every $n \geq 1$ and $X \sim F$ satisfying that

$$X_n \xrightarrow{a.s.} X.$$

Proof.

Recall the inverse functions of F_n and F are defined as

$$F_n^{-1}(t) = \inf\{x \in \mathbb{R} : F_n(x) \geq t\}, \quad F^{-1}(t) = \inf\{x \in \mathbb{R} : F(x) \geq t\}.$$

If $t \in (0, 1)$ is a continuity point of F^{-1} , then

$$\lim_{n \rightarrow \infty} F_n^{-1}(t) = F^{-1}(t). \quad (\text{to be proved in the next page}).$$

Based on this result, consider the probability space $((0, 1), \mathcal{B}(0, 1), \mathbb{P})$, where \mathbb{P} is the Lebesgue measure. For any $t \in (0, 1)$, define

$$X_n(t) = F_n^{-1}(t), \quad X(t) = F^{-1}(t).$$

Then, (why?)

$$\mathbb{P}(\{t \in (0, 1) : \lim_n X_n(t) \neq X(t)\}) = \mathbb{P}\{t \text{ is a dis-continuity point of } F^{-1}\} = 0.$$

Therefore, $X_n \xrightarrow{a.s.} X$.

Proof.

Let $t \in (0, 1)$ be a continuity point of F^{-1} . Since F has at most countably many discontinuities, we can find a continuity point x of F such that for any $\varepsilon > 0$,

$$F^{-1}(t) - \varepsilon < x < F^{-1}(t).$$

By the definition of F^{-1} ,

$$x < F^{-1}(t) \implies F(x) < t,$$

and by the weak convergence of F_n ,

$$\lim_{n \rightarrow \infty} F_n(x) = F(x),$$

we have there exists $N \geq 1$ such that as long as $n \geq N$,

$$|F_n(x) - F(x)| < \frac{1}{2}(t - F(x)), \implies F_n(x) < t.$$

Therefore,

$$x \leq F_n^{-1}(t) \implies F^{-1}(t) - \varepsilon < x \leq F_n^{-1}(t).$$

By the definition of \liminf , we have shown that for any $\varepsilon > 0$, there exists $N \geq 1$ such that for any $n \geq N$,

$$F^{-1}(t) < F_n^{-1}(t) + \varepsilon,$$

which means that

$$F^{-1}(t) \leq \liminf_{n \rightarrow \infty} F_n^{-1}(t).$$

Similarly,

$$\limsup_{n \rightarrow \infty} F_n^{-1}(t) \leq F^{-1}(t).$$



Part 2: Continuous functions $g(X_n)$



Theorem 4

If $X_n \xrightarrow{a.s.} X$, and let g be a continuous function, then

$$g(X_n) \xrightarrow{a.s.} g(X).$$

Proof.

By definition, let

$$D = \{\omega : \lim_{n \rightarrow \infty} X_n(\omega) \neq X(\omega)\},$$

then $\mathbb{P}(D) = 0$. Because g is continuous, then

$$\{\omega : \lim_{n \rightarrow \infty} X_n(\omega) = X(\omega)\} \subset \{\omega : \lim_{n \rightarrow \infty} g(X_n(\omega)) = g(X(\omega))\},$$

and thus

$$\mathbb{P}\{\omega : g(X_n(\omega)) \neq g(X(\omega))\} \leq \mathbb{P}(D) = 0.$$





Theorem 5

If $X_n \xrightarrow{\text{a.s.}} X$, then for any bounded and continuous function g , then

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

Proof.

We assume that $|g(x)| \leq M$ for some $M > 0$. As $g(X_n) \xrightarrow{a.s.} g(X)$, then for any $\varepsilon > 0$,

$$\mathbb{P}(|g(X_n) - g(X)| > \varepsilon) \rightarrow 0 \quad \text{as } n \rightarrow \infty.$$

Therefore,

$$\begin{aligned} |\mathbb{E}[g(X_n)] - \mathbb{E}[g(X)]| &\leq \mathbb{E}|g(X_n) - g(X)| \\ &= \mathbb{E}|g(X_n) - g(X)| \mathbf{1}_{|g(X_n) - g(X)| > \varepsilon} + \mathbb{E}|g(X_n) - g(X)| \mathbf{1}_{|g(X_n) - g(X)| \leq \varepsilon} \\ &\leq 2M \mathbb{P}(|g(X_n) - g(X)| > \varepsilon) + \varepsilon. \end{aligned}$$

Taking $n \rightarrow \infty$, and $\varepsilon \rightarrow 0$, we have the right hand side goes to 0. ■



Theorem 6

Let $\{F_n\}$ be a sequence of distribution functions and let F be a distribution function. Let $\{X_n\}$ be a sequence of random variables satisfying that $X_n \sim F_n$ and let X be such that $X \sim F$. The following conditions are equivalent:

- (i) $F_n \xrightarrow{w} F$.
- (ii) $X_n \xrightarrow{d} X$.
- (iii) For any bounded and continuous function g , then

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

Proof.

Conditions (i) and (ii) are equivalent by definition. We only prove that (i) and (iii) are equivalent.

(i) \implies (iii). As $F_n \xrightarrow{w} F$, by the Skorokhod's representation theorem (see Theorem 3), then there exists a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ on which we can define $\{\tilde{X}_n\}$ and \tilde{X} such that

$$\tilde{X}_n \stackrel{d}{=} X_n, \quad \tilde{X} \stackrel{d}{=} X$$

and

$$\tilde{X}_n \xrightarrow{a.s.} \tilde{X}.$$

Therefore,

$$\mathbb{E}[g(X_n)] = \mathbb{E}[g(\tilde{X}_n)] \rightarrow \mathbb{E}[g(\tilde{X})] = \mathbb{E}[g(X)], \quad \text{as } n \rightarrow \infty. \quad \blacksquare$$

Proof.

Proof of (iii) \implies (i). For any continuity point x of F , let $g_{x,\varepsilon}$ be defined as

$$g_{x,\varepsilon}(w) = \begin{cases} 1 & w \leq x \\ 0 & w > x + \varepsilon, \\ \text{linear} & x < w \leq x + \varepsilon. \end{cases}$$

We can see that $g_{x,\varepsilon}$ is continuous and bounded. If (iii) is true, then

$$\limsup_{n \rightarrow \infty} \mathbb{P}(X_n \leq x) \leq \limsup_{n \rightarrow \infty} \mathbb{E}[g_{x,\varepsilon}(X_n)] = \mathbb{E}[g_{x,\varepsilon}(X)] \leq \mathbb{P}(X \leq x + \varepsilon).$$

Letting $\varepsilon \rightarrow 0$ gives

$$\limsup_{n \rightarrow \infty} \mathbb{P}(X_n \leq x) \leq \mathbb{P}(X \leq x).$$

Observe that

$$\liminf_{n \rightarrow \infty} \mathbb{P}(X_n \leq x) \geq \liminf_{n \rightarrow \infty} \mathbb{E}[g_{x-\varepsilon, \varepsilon}(X_n)] = \mathbb{E}[g_{x-\varepsilon, \varepsilon}(X)] \geq \mathbb{P}(X \leq x - \varepsilon).$$

Letting $\varepsilon \rightarrow 0$ gives

$$\liminf_{n \rightarrow \infty} \mathbb{P}(X_n \leq x) \geq \mathbb{P}(X < x).$$

If x is a continuity point of F , then $\mathbb{P}(X < x) = \mathbb{P}(X \leq x)$, which implies that

$$\mathbb{P}(X \leq x) \leq \liminf_{n \rightarrow \infty} \mathbb{P}(X_n \leq x) \leq \limsup_{n \rightarrow \infty} \mathbb{P}(X_n \leq x) \leq \mathbb{P}(X \leq x),$$

and this proves the result. ■



Definition 7

We say F_n convergence weakly to F if

$$\int_{-\infty}^{\infty} g(x) dF_n(x) \rightarrow \int_{-\infty}^{\infty} g(x) dF(x) \quad \text{as } n \rightarrow \infty$$

for all bounded and continuous function g . Or, let $X_n \sim F_n$ and $X \sim F$, F_n converges weakly to F if

$$\mathbb{E}[g(X_n)] \rightarrow \mathbb{E}[g(X)] \quad \text{as } n \rightarrow \infty.$$



Theorem 8

Consider the sequence X_1, X_2, \dots and the random variable X . Assume that X_n 's and X are supported on $\mathbb{N}_0 = \{0, 1, 2, \dots\}$, and their pmf are p_n 's and p , respectively. Then, $X_n \xrightarrow{d} X$ if and only if

$$\lim_{n \rightarrow \infty} p_n(k) = p(k) \quad \text{for all } k \in \mathbb{N}_0.$$

Proof.

Since X is integer-valued, its CDF, $F_X(x)$, is continuous at all $x \in \mathbb{R} - \{0, 1, 2, \dots\}$. If $X_n \xrightarrow{d} X$, then

$$\lim_{n \rightarrow \infty} F_{X_n}(x) = F_X(x), \quad \text{for all } x \in \mathbb{R} - \{0, 1, 2, \dots\}.$$

Thus, for $k = 0, 1, 2, \dots$, we have

$$\begin{aligned} \lim_{n \rightarrow \infty} p_n(k) &= \lim_{n \rightarrow \infty} \left[F_{X_n} \left(k + \frac{1}{2} \right) - F_{X_n} \left(k - \frac{1}{2} \right) \right] && (X_n \text{ 's are integer-valued}) \\ &= \lim_{n \rightarrow \infty} F_{X_n} \left(k + \frac{1}{2} \right) - \lim_{n \rightarrow \infty} F_{X_n} \left(k - \frac{1}{2} \right) \\ &= F_X \left(k + \frac{1}{2} \right) - F_X \left(k - \frac{1}{2} \right) && (\text{since } X_n \xrightarrow{d} X) \\ &= p(k) && (\text{since } X \text{ is integer-valued}). \end{aligned}$$

To prove the converse, assume that we know

$$\lim_{n \rightarrow \infty} p_n(k) = p(k), \quad \text{for } k = 0, 1, 2, \dots .$$

Then, for all $x \in \mathbb{R}$, we have

$$\begin{aligned} \lim_{n \rightarrow \infty} F_{X_n}(x) &= \lim_{n \rightarrow \infty} P(X_n \leq x) \\ &= \lim_{n \rightarrow \infty} \sum_{k=0}^{\lfloor x \rfloor} p_n(k), \end{aligned}$$

where $\lfloor x \rfloor$ shows the largest integer less than or equal to x .

Since for any fixed x , the set $\{0, 1, \dots, \lfloor x \rfloor\}$ is a finite set, we can change the order of the limit and the sum, so we obtain

$$\begin{aligned}\lim_{n \rightarrow \infty} F_{X_n}(x) &= \sum_{k=0}^{\lfloor x \rfloor} \lim_{n \rightarrow \infty} p_n(k) \\ &= \sum_{k=0}^{\lfloor x \rfloor} p(k) \quad (\text{by assumption}) \\ &= P(X \leq x) = F_X(x). \quad \blacksquare\end{aligned}$$



Example 9

Let X_1, X_2, X_3, \dots be a sequence of random variable such that

$$X_n \sim \text{Binomial} \left(n, \frac{\lambda}{n} \right), \quad \text{for } n \in \mathbb{N}, n > \lambda,$$

where $\lambda > 0$ is a constant. Show that X_n converges in distribution to $\text{Poisson}(\lambda)$.

Solution.

By Theorem 8, it suffices to show that

$$\lim_{n \rightarrow \infty} p_n(k) = P_X(k), \quad \text{for all } k = 0, 1, 2, \dots$$

We have

$$\begin{aligned} \lim_{n \rightarrow \infty} p_n(k) &= \lim_{n \rightarrow \infty} \binom{n}{k} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k} \\ &= \lambda^k \lim_{n \rightarrow \infty} \frac{n!}{k!(n-k)!} \left(\frac{1}{n^k}\right) \left(1 - \frac{\lambda}{n}\right)^{n-k} \\ &= \frac{\lambda^k}{k!} \cdot \lim_{n \rightarrow \infty} \left(\left[\frac{n(n-1)(n-2) \dots (n-k+1)}{n^k} \right] \left[\left(1 - \frac{\lambda}{n}\right)^n \right] \left[\left(1 - \frac{\lambda}{n}\right)^{-k} \right] \right). \end{aligned}$$

Note that for a fixed k , we have

$$\lim_{n \rightarrow \infty} \frac{n(n-1)(n-2) \dots (n-k+1)}{n^k} = 1,$$

$$\lim_{n \rightarrow \infty} \left(1 - \frac{\lambda}{n}\right)^{-k} = 1,$$

$$\lim_{n \rightarrow \infty} \left(1 - \frac{\lambda}{n}\right)^n = e^{-\lambda}.$$

Thus, we conclude

$$\lim_{n \rightarrow \infty} p_n(k) = \frac{e^{-\lambda} \lambda^k}{k!}$$





Theorem 10

Let h be a continuous function. If $X_n \xrightarrow{d} X$, then $h(X_n) \xrightarrow{d} h(X)$.



Proof.

To show that $h(X_n) \xrightarrow{d} h(X)$, it suffices to show that for any bounded and continuous function g ,

$$\mathbb{E}[g(h(X_n))] \rightarrow \mathbb{E}[g(h(X))] \quad \text{as } n \rightarrow \infty,$$

but this is true because $g \circ h$ is also a bounded and continuous function. ■

A further condition to show weak convergence



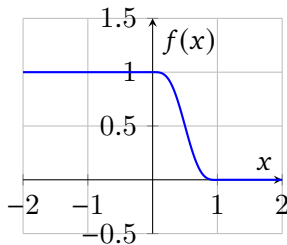
Theorem 11

Let g be a bounded function having three bounded and continuous derivatives, that is,

g, g', g'', g''' are bounded and continuous.

If $\mathbb{E}[g(X_n)] \rightarrow \mathbb{E}[g(X)]$, then $X_n \xrightarrow{d} X$.

A smooth function with bounded h'''



$$h(x) = \begin{cases} 1 & \text{if } x \leq 0, \\ 0 & \text{if } x > 1, \\ 1 - 140\left(\frac{1}{4}x^4 - \frac{3}{5}x^5 + \frac{1}{2}x^6 - \frac{1}{7}x^7\right) & \text{if } 0 < x \leq 1. \end{cases}$$



Theorem 12 (Weak convergence implies convergence of ch.f.)

If $\{F_n\}$ weakly converges to F , then

$$\varphi_n(t) \rightarrow \varphi(t) \quad \text{pointwise.}$$

Here,

$$\varphi_n(t) = \int_{-\infty}^{\infty} e^{itx} dF_n(x), \quad \varphi(t) = \int_{-\infty}^{\infty} e^{itx} dF(x).$$

In other words, if $X_n \sim F_n$ and $X \sim F$, then

$$\varphi_n(t) = \mathbb{E}[e^{itX_n}], \quad \varphi(t) = \mathbb{E}[e^{itX}].$$



Proof.

Note that the function $g(x) = e^{itx} = \cos(tx) + i \sin(tx)$, and both $\cos(tx)$ and $\sin(tx)$ are bounded and continuous for all $x \in \mathbb{R}$ and for all $t \in \mathbb{R}$. Therefore, for any $t \in \mathbb{R}$, by Theorem 6, we have

$$\varphi_n(t) \rightarrow \varphi(t).$$





Theorem 13

If a sequence of characteristic functions $\{\varphi_n(t)\}$ converges to $\varphi(t)$, and if $\varphi(t)$ is continuous at $t = 0$. Then, the corresponding distribution functions $\{F_n\}$ converges weakly to F , where $\varphi(t)$ is the characteristic function F .



Proof.

The proof is omitted. You can find a proof from Theorem 5.2.5 in Xianping Li's book.
At this level, you can just believe that this theorem is true. ■



Theorem 14

If $X_n \xrightarrow{d} X$ and $Y_n \xrightarrow{d} c$, then

$$X_n + Y_n \xrightarrow{d} X + c, \quad X_n Y_n \xrightarrow{d} cX.$$

Remark

This theorem is not true for general $Y_n \xrightarrow{d} Y$.