

# Limiting Distribution

Let's consider a sequence of random variables  $X_1, X_2, \dots, X_n, \dots$  defined on a common probability space  $(\Omega, \mathcal{F}, P)$ . We say that a random variable  $X$  is the **limiting distribution** of the sequence  $X_n$  if for every  $\epsilon > 0$ ,

$$\lim_{n \rightarrow \infty} P(|X_n - X| > \epsilon) = 0.$$

This means that as  $n$  increases, the probability that the difference between  $X_n$  and  $X$  is greater than any given  $\epsilon$  approaches zero. In other words, the sequence of random variables  $X_n$  converges in probability to  $X$ .

# ① Limiting Distribution:

$$Y_n \xrightarrow{d} y, \lim_{n \rightarrow \infty} G_n(y) = G(y) \quad \left( \lim_{n \rightarrow \infty} (1 + \frac{c}{n})^{bn} = e^{cb} \right)$$

# ② Convergence in probability:

$$Y_n \xrightarrow{P} y, \lim_{n \rightarrow \infty} P(|Y_n - y| < \varepsilon) = 1$$

**Stochastic convergence:**  $Y_n \xrightarrow{P} c \quad P(Y=c)=1 \rightarrow \lim_{n \rightarrow \infty} P(|Y_n - c| < \varepsilon) = 1$

① The law of large number (for Bernoulli distribution)  $\bar{x}_n \xrightarrow{P} \mu$  with  $E(x_i) = \mu$

$$\text{LLN} \quad \bar{x}_n \xrightarrow{P} \mu$$

$$\text{Var}(x_i) = \sigma^2$$

② Convergence in probability & asymptotic convergence.

If  $\frac{Y_n - m}{\sigma_n} \xrightarrow{d} Z \sim N(0,1)$ , then  $Y_n \xrightarrow{P} m$

③ given  $x_n \xrightarrow{P} c, y_n \xrightarrow{P} d$ , then:

a.  $ax_n + by_n \xrightarrow{P} ac + bd$

b.  $x_n y_n \xrightarrow{P} cd$

c.  $\frac{x_n}{c} \xrightarrow{P} 1$  for  $c \neq 0$

d.  $\sqrt{x_n} \xrightarrow{P} \sqrt{c}$

e.  $\sqrt{x_n} \xrightarrow{P} \sqrt{c}$

④ Slutsky Theorem: Given  $x_n \xrightarrow{P} c, y_n \xrightarrow{d} Y$

a.  $x_n + y_n \xrightarrow{d} c + Y$

b.  $x_n y_n \xrightarrow{d} cY$

c.  $\frac{y_n}{x_n} \xrightarrow{d} \frac{Y}{c}$   $c \neq 0$

# ③ Asymptotic Convergence:

$$\frac{Y_m - m}{\sigma_m} \xrightarrow{d} Z \sim N(0,1) \Rightarrow Y \xrightarrow{\substack{\text{app.} \\ \text{large } n}} N(m, \frac{\sigma^2}{n})$$

(Eg)

① Limiting distribution of central order statistics  $X_{k:n}$ :  $X_{k:n} \xrightarrow{\text{large } n} N(\bar{x}_p, \frac{p(1-p)}{n(p-1)^2})$

② Central Limit Theorem:  $Z_n = \frac{\sum_{i=1}^n X_i - n\mu}{\sigma\sqrt{n}}$  or  $\sqrt{n}(Z_n - \frac{\mu}{\sigma}) \xrightarrow{d} Z \sim N(0,1)$   
 $W_n = \sqrt{n}(\bar{X}_n - \mu) \xrightarrow{d} W \sim N(0, \sigma^2)$

# ④ Function of Sequence RV.

①  $Y_n \xrightarrow{P} c, g(Y_n) \xrightarrow{P} g(c)$

②  $Z \sim N(0,1)$   $\frac{Y_m - m}{\sigma_m} \xrightarrow{d} Z$

③  $Y_n \xrightarrow{d} y, g(Y_n) \xrightarrow{d} g(y)$

$\frac{g(Y_n) - g(y)}{\sigma(g(y))/\sqrt{n}} \xrightarrow{d} Z$

Example helping understand:

① Limiting distribution of central order statistics:

$P[X \leq x_p] = p$ ,  $x_p$  is percentile  $f_X(x_p) \neq 0$

If  $k \rightarrow p$   $X_{k:n}$  is asymptotically normally distributed with asymptotic mean  $x_p$ .  
Variane  $\frac{C^2}{n}$  where  $C^2 = \frac{p(1-p)}{f_X(x_p)^2}$

Example  $F(x) = 1 - e^{-x}$   $k = \frac{n+1}{2}$  (median)

$$F(x_p) = p = 0.5 \quad x_p = -\log(1-p)$$

$$1 - e^{-x_p} = p \quad x_{0.5} = -\log 0.5 = \log 2$$

$$C^2 = \frac{p(1-p)}{(f(x_p))^2} = \frac{0.5(1-0.5)}{(e^{-\log 2})^2} = 1.$$

② Finding limiting distribution:

Let  $Y = nX_{1:n}$

$$\text{Then } G_n(y) = P[Y \leq y] = P[\ln X_{1:n} \leq y] = P[X_{1:n} \leq \frac{y}{n}] = F_{X_{1:n}}\left(\frac{y}{n}\right)$$

③ Transformation method find pdf:

Ex.  $X \sim U(0,1)$   $Y = X^2$

① Define  $Y = g(X)$

$$X = \sqrt{Y}$$

②  $X = g^{-1}(Y)$

$$\left| \frac{dx}{dy} \right| = \frac{1}{2\sqrt{y}}$$

③  $\left| \frac{dx}{dy} \right|$

$$f_Y(y) = \frac{1}{2\sqrt{y}} \quad \text{for } 0 < y < 1$$

④  $f_Y(y) = f_X(x) \left| \frac{dx}{dy} \right| \quad (x = g^{-1}(y))$

④ function of R.V.

(Theorem T.7.6) If  $Y_n \xrightarrow{P} C$ , then for any function  $g(y)$  that is continuous at  $y=c$ .  $g(Y_n) \xrightarrow{P} g(c)$

proof: ①  $g(y)$  is continuous at  $c$ , it follows that for every  $\epsilon > 0$ , a  $\delta > 0$  exists such that  $|y - c| < \delta$  implies

$$|g(y) - g(c)| < \epsilon.$$

because  $P[B] \geq P[A]$  when  $A \subset B$

But because  $Y_n \xrightarrow{P} C$  it follows for every  $\delta > 0$  that

$$\lim_{n \rightarrow \infty} P[|g(Y_n) - g(c)| < \epsilon] \geq \lim_{n \rightarrow \infty} P[|Y_n - c| < \delta] = 1.$$