

## 6장. 확률변수의 극한(Limiting Distribution)

### Large sample size properties

Sometimes, the probability distribution for a statistic,  $\bar{X}$ , is hard to describe for small size  $n$ . But we can say something for "large"  $n$ .

### 정의. 확률수렴 ( Convergence in Probability )

A sequence of r.v.  $X_1, X_2, \dots$  converges in probability to a r.v.  $X$  if, for every  $\varepsilon > 0$ ,

$$\lim_{n \rightarrow \infty} P(|X_n - X| \geq \varepsilon) = 0 \text{ or } \lim_{n \rightarrow \infty} P(|X_n - X| < \varepsilon) = 1.$$

Notation:  $X_n \xrightarrow{p} X$

### 6.1 대수의 법칙

#### Thm 6.1 ( Law of large numbers : 대수의 법칙 )

Let  $X_1, X_2, \dots$  be i.i.d random variables with mean  $\mu$  and variance  $\sigma^2 < \infty$ .

Let  $\bar{X}_n = \sum_{i=1}^n X_i/n$  then for every  $\varepsilon > 0$ ,  $\lim_{n \rightarrow \infty} P(|\bar{X}_n - \mu| > \varepsilon) = 0$ .

i.e.,  $\bar{X}_n$  converges in probability to  $\mu$ .

**Proof)** Recall. Chebyshev's inequality (Thm 4.6)

Use Chebyshev's inequality.

$$\text{i.e., } P(|\bar{X}_n - \mu| \geq \varepsilon) = P((\bar{X}_n - \mu)^2 \geq \varepsilon^2) \leq \frac{E(\bar{X}_n - \mu)^2}{\varepsilon^2} = \frac{\text{Var}(\bar{X}_n)}{\varepsilon^2} = \frac{\sigma^2}{n\varepsilon^2} \rightarrow 0$$

as  $n \rightarrow \infty$ .

**Example** ( Consistency of  $S^2$  )

$$E(S^2) = \sigma^2$$

Does  $S^2 \rightarrow \sigma^2$  in probability ??

Same proof works if  $\text{Var}(S^2) \rightarrow 0$ .

## 6.2 분포수렴

### Def 6.1 분포수렴 ( Converges in Distribution )

$X_1, X_2, \dots$  converges in distn to a r.v.  $X$  if  $F_{X_n}(x) \rightarrow F_X(x)$  as  $n \rightarrow \infty$   
at all  $x$  where  $F_X(x)$  is continuous.

(i.e.,  $F_{X_n}(x) = P(X_n \leq x) \rightarrow P(X \leq x) = F_X(x)$  )

**Notation:**  $X_n \xrightarrow{d} X$ , or  $X_n \rightarrow X$  in dist.

### Example

Let  $Y_n \sim \text{Beta}(1 + \frac{1}{n}, 1)$ ,  $Y \sim \text{Beta}(1, 1)$  : i.e., Uniform r.v.

Then,

$$F_{Y_n}(y) = \int_0^y \frac{\Gamma(2 + \frac{1}{n})}{\Gamma(1 + \frac{1}{n})\Gamma(1)} u^{(1 + \frac{1}{n} - 1)} du = \int_0^y (1 + \frac{1}{n}) u^{\frac{1}{n}} du = y^{1 + \frac{1}{n}}$$

$$\Rightarrow F_{Y_n}(y) = \begin{cases} 0, & y \leq 0 \\ y^{1 + \frac{1}{n}}, & 0 < y < 1 \\ 1, & 1 \leq y \end{cases}$$

$$\& F_Y(y) = \begin{cases} 0, & y \leq 0 \\ y, & 0 < y < 1 \\ 1, & 1 \leq y \end{cases}$$

Therefore  $F_{Y_n}(y) \rightarrow F_Y(y)$  at all  $y$  where  $F_Y(y)$  is continuous.

$$\therefore Y_n \xrightarrow{d} Y.$$

**Ex 6.1** Let  $X_1, X_2, \dots, X_n \stackrel{iid}{\sim} U(0, \theta)$ . What is the limiting distribution of  $X_{(n)}$ ?

*Sol.*

$$\begin{aligned} F_{X_{(n)}}(x) &= P(X_{(n)} \leq x) = P(X_1 \leq x, X_2 \leq x, \dots, X_n \leq x) \\ &= \left(\frac{x}{\theta}\right)^n, \quad 0 \leq x \leq \theta. \end{aligned}$$

$$\text{Then, } \lim_{n \rightarrow \infty} F_{X_{(n)}}(x) = \begin{cases} 0 & x < \theta \\ 1 & x \geq \theta \end{cases}$$

$$\text{Let } X = \theta. \text{ Then, } F_X(x) = \begin{cases} 0 & x < \theta \\ 1 & x \geq \theta \end{cases} \quad \text{i.e., } F_{X_{(n)}}(x) \rightarrow F_X(x).$$

$$\therefore X_{(n)} \xrightarrow{d} X, \text{ i.e., } X_{(n)} \xrightarrow{d} \theta. \text{ \& } X_{(n)} \xrightarrow{p} \theta.$$

**Ex 6.2** Let  $X_1, X_2, \dots, X_n \stackrel{iid}{\sim} U(0, \theta)$ .

What is the limiting distribution of  $Y_n = n(\theta - X_{(n)})$ ?

*Sol.*

*Fill out by yourself*

**Thm 6.2 ( Convergence of mgf implies convergence in distribution )**

Let the mgfs of  $X_1, X_2, \dots$  be  $M_1(t), M_2(t), \dots$ , respectively,

and  $M(x)$  be the mgf of  $X$ .

If  $\lim_{n \rightarrow \infty} M_n(t) \rightarrow M(t)$  for all  $t$ , then  $X_n \xrightarrow{d} X$ .

**Ex 6.3**

Let  $X_n \sim \text{Poisson}(\lambda_n)$  and  $\lambda_n \rightarrow \infty$ .

What is the limiting distribution of  $Z_n = \frac{X_n - E(X_n)}{\sqrt{\text{Var}(X_n)}} = \frac{X_n - \lambda_n}{\sqrt{\lambda_n}}$ ?

**Sol.** Use convergence of mgf

$$\begin{aligned}
 M_{Z_n}(t) &= E(e^{tZ_n}) = E\left[e^{t\left(\frac{X_n - \lambda_n}{\sqrt{\lambda_n}}\right)}\right] \\
 &= E\left(e^{-t\sqrt{\lambda_n} + \frac{t}{\sqrt{\lambda_n}}X_n}\right) \\
 &= e^{-t\sqrt{\lambda_n}} E\left(e^{\frac{t}{\sqrt{\lambda_n}}X_n}\right) \\
 &= e^{-t\sqrt{\lambda_n}} M_{X_n}\left(\frac{t}{\sqrt{\lambda_n}}\right) \\
 &= e^{-t\sqrt{\lambda_n}} e^{\lambda_n\left(e^{\frac{t}{\sqrt{\lambda_n}}} - 1\right)} \\
 &= e^{-t\sqrt{\lambda_n} + \lambda_n\left(e^{\frac{t}{\sqrt{\lambda_n}}} - 1\right)} \\
 &= e^{-t\sqrt{\lambda_n} + \lambda_n\left(1 + \frac{t}{\sqrt{\lambda_n}} + \frac{1}{2}\left(\frac{t}{\sqrt{\lambda_n}}\right)^2 + \sum_{k=3}^{\infty} \frac{1}{k!}\left(\frac{t}{\sqrt{\lambda_n}}\right)^k - 1\right)} \\
 &= e^{\frac{t^2}{2} + \sum_{k=3}^{\infty} \frac{1}{k!} \frac{t^k}{\lambda_n^{k/2-1}}} \\
 &\rightarrow e^{\frac{t^2}{2}} \text{ as } n \rightarrow \infty. \therefore \text{mgf of } N(0, 1)
 \end{aligned}$$

$$\therefore Z_n \xrightarrow{d} X, \quad X \sim N(0, 1)$$

**Ex 6.4**

**Read**

### 6.3 중심극한정리 (Central Limit Theorem)

#### Thm 6.3 ( Central Limit Theorem : CLT )

$X_1, X_2, \dots, X_n \stackrel{iid}{\sim} \text{mean } \mu \text{ and variance } \sigma^2, \quad 0 < \sigma^2 < \infty.$

Let  $S_n = \sum_{i=1}^n X_i$ ,  $\bar{X}_n = \sum_{i=1}^n X_i / n$ . Then,

$$Z_n = \frac{S_n - n\mu}{\sqrt{n}\sigma} = \frac{(\bar{X}_n - \mu)}{\sigma/\sqrt{n}} \xrightarrow{d} N(0, 1)$$

That is, for any  $x$ ,  $-\infty < x < \infty$ ,

$$\lim_{n \rightarrow \infty} P\left(\frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} \leq x\right) = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} du = P(Z \leq x)$$

**Proof.**

**Note** : m.g.f. of  $N(\mu, \sigma^2)$  is  $e^{\mu t + \frac{1}{2}\sigma^2 t^2}$ .

**Recall** : If  $M_{Y_n}(t) \rightarrow M_Y(t)$ , then  $Y_n \xrightarrow{d} Y$ .

We will assume m.g.f of  $X_i$  exists and show that

the m.g.f of  $\frac{(\bar{X}_n - \mu)}{\sigma/\sqrt{n}}$  converges to  $e^{t^2/2}$  as  $n \rightarrow \infty$ .

Define  $Y_i = \frac{X_i - \mu}{\sigma}$  and  $M_Y(t)$  denoted m.g.f of  $Y$

$$\Rightarrow Z_n = \frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} = \frac{\sqrt{n} \sum_{i=1}^n (X_i - \mu)}{\sigma n} = \frac{\sum_{i=1}^n Y_i}{\sqrt{n}}$$

Then,  $M_{Z_n}(t) = M_{\frac{1}{\sqrt{n}} \sum_{i=1}^n Y_i}(t) = M_{\sum_{i=1}^n Y_i}\left(\frac{t}{\sqrt{n}}\right) = \left[M_Y\left(\frac{t}{\sqrt{n}}\right)\right]^n.$

Expand  $M_Y\left(\frac{t}{\sqrt{n}}\right)$  in a Taylor's series about "0"

**Note (Taylor's expansion) :**Taylor's expansion of function  $f(x)$  at  $x = a$ 

$$\Rightarrow f(x) = f(a) + \frac{f^{(1)}(a)}{1!}(x-a) + \frac{f^{(2)}(a)}{2!}(x-a)^2 + \dots$$

When  $a = 0$ ,

$$f(x) = f(0) + \frac{f^{(1)}(0)}{1!}(x-0) + \frac{f^{(2)}(0)}{2!}(x-0)^2 + \dots$$

$$M_Y\left(\frac{t}{\sqrt{n}}\right) = \sum_{k=0}^{\infty} M_Y^{(k)}(0) \frac{(t/\sqrt{n})^k}{k!}$$

$$M_Y(0) = E(e^{0Y}) = 1$$

$$M_Y^{(1)}(0) = E(Y) = E\left(\frac{X-\mu}{\sigma}\right) = 0$$

$$M_Y^{(2)}(0) = E(Y^2) = \text{Var}(Y) = \frac{1}{\sigma^2} \text{Var}(X) = \frac{1}{\sigma^2} \sigma^2 = 1$$

$$\Rightarrow M_Y\left(\frac{t}{\sqrt{n}}\right) = 1 + \frac{(t/\sqrt{n})^2}{2} + R_Y(t/\sqrt{n})$$

Note that

$$\lim_{n \rightarrow \infty} \frac{R_Y(t/\sqrt{n})}{(t/\sqrt{n})^2} = 0. \quad \Rightarrow \lim_{n \rightarrow \infty} n R_Y\left(\frac{t}{\sqrt{n}}\right) = 0.$$

$$\begin{aligned} \therefore \lim_{n \rightarrow \infty} (M_Y(t/\sqrt{n}))^n &= \lim_{n \rightarrow \infty} \left[1 + \frac{(t/\sqrt{n})^2}{2} + R_Y\left(\frac{t}{\sqrt{n}}\right)\right]^n \\ &= \lim_{n \rightarrow \infty} \left[1 + \frac{1}{n} \left(\frac{t^2}{2} + n R_Y\left(\frac{t}{\sqrt{n}}\right)\right)\right]^n \\ &= e^{t^2/2} \quad : \text{mgf of } N(0,1) \end{aligned}$$

Here, we use the fact that

$$\lim_{n \rightarrow \infty} a_n = a \text{ 일 때, } \lim_{n \rightarrow \infty} \left(1 + \frac{a_n}{n}\right) = e^a.$$

Meaning of the CLT (Important) :*Read text p.153*

**Example :**  $Y_1, Y_2, \dots, Y_n \stackrel{iid}{\sim} \text{Bernoulli}(p)$  and  $S_n = \sum_{i=1}^n Y_i$

$$\text{i.e., } Y_i = \begin{cases} 1 & \text{with prob. } p \\ 0 & \text{with prob. } 1-p \end{cases}$$

$$\Rightarrow \frac{S_n}{n} = \bar{X}_n, \quad \frac{\bar{X}_n - p}{\sqrt{p(1-p)/n}} \xrightarrow{d} N(0,1)$$

Normal approximation to binomial

$Y \sim \text{Bin}(n, p)$  is approximated by  $N(np, np(1-p))$

Approximation is good if  $n$  is large,  $p$  is not close to "0" or "1".

(  $np \geq 5$  &  $n(1-p) \geq 5$  )

Ref. Continuity correction (연속성 수정)

When we use CLT, a continuity correction is needed for discrete distn.

If  $Y \sim \text{Bin}(n, p)$  &  $n$  is large enough,  $\Phi$  : cdf of  $N(0, 1)$

$$P(Y \leq k) \approx \Phi\left(\frac{k + 0.5 - np}{\sqrt{np(1-p)}}\right)$$

$$P(Y < k) \approx \Phi\left(\frac{k - 0.5 - np}{\sqrt{np(1-p)}}\right)$$

**Ex 6.5 :**  $X \sim \text{Bin}(100, 0.5)$  일 때,  $P(X \geq 60)$  의 근사값?

*Sol.*

$$\begin{aligned} P(X \geq 60) &= 1 - P(X < 60) = 1 - P\left(\frac{X - 0.5 - 50}{\sqrt{25}} \leq \frac{60 - 0.5 - 50}{\sqrt{25}}\right) \\ &= \Phi\left(\frac{60 - 0.5 - 50}{\sqrt{25}}\right) \end{aligned}$$

**Example :**  $X_1, X_2, \dots, X_{25} \stackrel{iid}{\sim} \text{Bin}(5, 0.4)$  일 때,

$$\begin{aligned} P(1 \leq \bar{X} \leq 2.5) &= P\left(\frac{1 - 2}{\sqrt{6/5} / \sqrt{25}} \leq \frac{\bar{X} - 2}{\sqrt{6/5} / \sqrt{25}} \leq \frac{2.5 - 2}{\sqrt{6/5} / \sqrt{25}}\right) \\ &\approx P(-4.56 \leq Z \leq 2.28) = 0.9887 \end{aligned}$$