

Chapter Seven

Central Limit Theorem

In this chapter, we shall give some important properties of the theory of large samples in statistical inference.

7-1 Chebyshev's Inequality

The Chebyshev's inequality is a useful theoretical tool as well as it helps us to find upper and lower bounds for certain probability when only the mean and variance of the probability distribution are known.

Def. 1

If x is a r.v. with a finite mean μ and variance σ^2 , then for any $k > 0$, we have,

$$P\{|x - \mu| \geq k\} \leq \frac{\sigma^2}{k^2} \iff P\{|x - \mu| \geq k\sigma\} \leq \frac{1}{k^2}$$

$$\text{or } P\{|x - \mu| < k\} \geq 1 - \frac{\sigma^2}{k^2} \iff P\{|x - \mu| < k\sigma\} \geq 1 - \frac{1}{k^2}$$

ex. 1: Suppose that x is a random variable with mean $\mu = 20$ and variance $\sigma^2 = 16$. Find the probability that x will lie between 15 and 25?

sol.

$$\begin{aligned} p(15 < x < 25) &= p(15 - 20 < x - \mu < 25 - 20) \\ &= p(-5 < x - \mu < 5) \\ &= p(|x - \mu| < 5) \end{aligned}$$

we have, $p(|x - \mu| < k) \geq 1 - \frac{\sigma^2}{k^2}$

$$\therefore p(|x - \mu| < 5) \geq 1 - \frac{16}{25}$$

$$\implies p(|x - \mu| < 5) \geq \frac{9}{25}$$

ex. 2: If it is known that x has a mean of 25 and a variance of 16, then find $p(17 < x < 33)$?

$$\begin{aligned} \text{sol. } p(17 < x < 33) &= p(17 - 25 < x - \mu < 33 - 25) \\ &= p(-8 < x - \mu < 8) = p(|x - \mu| < 8) \end{aligned}$$

We have, $p(|x - \mu| < k) \geq 1 - \frac{\sigma^2}{k^2}$

$$\implies p(17 < x < 33) = p(|x - \mu| < 8) \geq 1 - \frac{16}{64}$$

7.2 The Weak Law of Large Numbers:

This theorem deals with the fact that under some conditions the average of a sequence of random variables converges to the expected average.

Theorem:

Let X_1, X_2, \dots, X_n be a random sample of size n drawn from a population with a finite mean μ .
Let \bar{X}_n be the sample mean of the random sample.
Then for any $\epsilon > 0$,

$$P\{|\bar{X}_n - \mu| > \epsilon\} \rightarrow 0 \text{ as } n \rightarrow \infty$$

7.3 Central Limit Theorem:

Suppose X_1, X_2, \dots, X_n be a random sample of size n drawn from a population with a finite mean μ and a finite variance σ^2 . Let \bar{X}_n be the sample mean of the random sample.
Consider the normalized random variable:

$$Z_n = \frac{\bar{X}_n - E(\bar{X}_n)}{\sqrt{\text{var}(\bar{X}_n)}}$$

Let the distribution function of Z_n is $F_n(x) = P(Z_n \leq x)$.
Then, $\lim_{n \rightarrow \infty} F_n(x) = \Phi(x)$

توزيع: ex 3 : let x be the number of successes in 5000 Bernoulli trials with probability of success of 0.7 on a given trial

Use the central limit theorem to estimate:

- عندما حجم العينة يكبر هذا الشكل توزيع البيانات توزيع طبيعي
1. $P(X < 4950)$
 2. $P(3920 < X < 4240)$

sol.

$$P(a < X < b) = P\left(\frac{a - \mu}{\sigma} < \frac{X - \mu}{\sigma} < \frac{b - \mu}{\sigma}\right)$$

$$P(X < a) = P\left(\frac{X - \mu}{\sigma} < \frac{a - \mu}{\sigma}\right)$$

$$\mu = np \Rightarrow \mu = 5000(0.7) = 3500$$

$$\sigma^2 = npq = (5000)(0.7)(0.3) = 1050$$

$$\sigma = \sqrt{1050} = 32.40$$

$$\boxed{1.} \quad P(X < 4950) = P\left(\frac{X - \mu}{\sigma} < \frac{4950 - 3500}{32.40}\right) =$$

$$= P(Z < \quad)$$

$$= \Phi(\quad) =$$

$$\boxed{2.} \quad P(3920 < X < 4240) = P\left(\frac{3920 - 3500}{32.40} < \frac{X - \mu}{\sigma} < \frac{4240 - 3500}{32.40}\right)$$

$$= P(\quad < Z < \quad)$$

$$= \Phi(\quad) - \Phi(\quad)$$

5

$$-X - \mu$$

2.06
 ex 2
 x. 4: ^{easy} let $\bar{X}_n = \bar{X}_{15}$ denote the mean of a random
 of size 15 from the distribution whose p.d.f is:

$$f(x) = \frac{3}{2} x^2 \quad -1 < x < 1, \text{ zero otherwise}, \text{ And } \mu = 0, \sigma^2 = \frac{3}{5}$$

Use the central limit theorem to compute:
 $P(0.03 \leq \bar{X} \leq 0.15)$?

$$\text{sol. } P(0.03 \leq \bar{X} \leq 0.15) = P\left(\frac{0.03 - E(\bar{X}_n)}{\sqrt{\text{var}(\bar{X}_n)}} \leq \frac{\bar{X} - E(\bar{X}_n)}{\sqrt{\text{var}(\bar{X}_n)}} \leq \frac{0.15 - E(\bar{X}_n)}{\sqrt{\text{var}(\bar{X}_n)}}\right)$$

$$E(\bar{X}_n) = E(\bar{X}_5) = \mu = 0$$

$$\text{var}(\bar{X}_n) = \text{var}(\bar{X}_{15}) = \frac{\sigma^2}{n} = \frac{\sigma^2}{15} = \frac{3/5}{15} = \frac{3}{75}$$

$$\therefore P(0.03 \leq \bar{X} \leq 0.15) = P\left(\frac{0.03 - 0}{\sqrt{\frac{3}{75}}} \leq Z \leq \frac{0.15 - 0}{\sqrt{\frac{3}{75}}}\right)$$

$$= P(0.15 \leq Z \leq 0.75)$$

$$= \Phi(0.75) - \Phi(0.15)$$

$$= 0.2138$$

ex. 5 If 10 fair dice are rolled, find the approximate probability that the sum obtained is between 30 and 40.
 Hint: Use the central limit theorem. let $\mu = 3.5$, $\sigma^2 = \frac{35}{12}$

Sol. $p(30 \leq \sum_{i=1}^{10} x_i \leq 40) = ?$ let $S = \sum_{i=1}^{10} x_i$.

$$p(30 \leq S \leq 40) = p\left(\frac{30 - \mu_S}{\sigma_S} \leq \frac{S - \mu_S}{\sigma_S} \leq \frac{40 - \mu_S}{\sigma_S}\right)$$

$$\begin{aligned} \mu_S = E(S) &= E\left(\sum_{i=1}^{10} x_i\right) = \sum_{i=1}^{10} E(x_i) \\ &= \sum_{i=1}^{10} 3.5 = (10)(3.5) = 35 \end{aligned}$$

$$\begin{aligned} \sigma_S^2 = \text{var}(S) &= \text{var}\left(\sum_{i=1}^{10} x_i\right) \\ &= \sum_{i=1}^{10} \text{var}(x_i) = \sum_{i=1}^{10} \frac{35}{12} = (10) \frac{35}{12} = \frac{350}{12} \end{aligned}$$

$$\therefore p(30 \leq S \leq 40) = p\left(\frac{30 - 35}{\sqrt{\frac{350}{12}}} \leq Z \leq \frac{40 - 35}{\sqrt{\frac{350}{12}}}\right)$$

$$= p(-0.9257 \leq Z \leq 0.9257)$$

$$= \Phi(0.9257) - \Phi(-0.9257)$$

$$= 0.65$$

Ex. 7: Suppose 3% of the items made by a factory are defective. A sample of 100 items is drawn at random. What is the probability that it will contain exactly 2 defective items? Using:

a. Binomial distribution?

b. Poisson distribution?

Sol. $n=100$, $p=\frac{3}{100}$, $q=1-p=\frac{97}{100}$

a.
$$P(X) = \left\{ \binom{n}{x} p^x q^{n-x} \quad x=0,1,2,\dots,n \right\}$$

$$P(X) = \left\{ \binom{100}{x} (0.03)^x (0.97)^{100-x} \quad x=0,1,2,\dots,100 \right\}$$

$$\Rightarrow P(X=2) = \binom{100}{2} (0.03)^2 (0.97)^{100-2} = 0.2251$$

b.
$$P(X) = \left\{ \frac{e^{-\lambda} \lambda^x}{x!} \quad x=0,1,2,\dots \right\}$$

$$\lambda = np = 100(0.03) = 3$$

$$P(X) = \left\{ \frac{e^{-3} 3^x}{x!} \quad x=0,1,2,\dots \right\}$$

$$\Rightarrow P(X=2) = \frac{e^{-3} 3^2}{2!} = 0.2240$$

The difference is 0.0011

7.5 The Hypergeometric Approximation to the Binomial distribution:

Theorem: Suppose that x is a hypergeometric random variable with parameters n, N, D - let $p = \frac{D}{N}$, if D and $N-D$ are large, n and x are small compared with D and $N-D$, then the p.m.f of x given by:

$$p(x) = \begin{cases} \binom{n}{x} p^x q^{n-x} & x=0, 1, \dots, n \\ 0 & \text{o.w.} \end{cases} \quad p = \frac{D}{N}$$

Ex. 8

let x be random variable such that $x \sim \text{Hyp}(20, 200, 1000)$
If $x=20$, find $p(x=20)$? Use binomial dist.?

Sol. $p = \frac{D}{N} = \frac{200}{1000} = 0.2 \implies q = 0.8$

$$p(x) = \begin{cases} \binom{20}{x} (0.2)^x (0.8)^{20-x} & x=0, 1, \dots, 20 \\ 0 & \text{o.w.} \end{cases}$$

$$p(x=20) = \binom{20}{10} (0.2)^{10} (0.8)^{20-10} = 0.0020$$

problems

1. If x is a random variable such that $E(x) = 7$ and $E(x)^2 = 13$. Use Chebyshev's inequality to determine a lower bound for the probability $P(-2 < x < 8)$?
2. If x is a random variable with mean 33 and variance 16, use Chebyshev's inequality to determine a lower bound for $P(23 < x < 43)$?
3. Suppose that x is a random variable with mean and variance both equal to 20. What can be said about $P(0 \leq x \leq 40)$?
4. Let x_1, x_2, \dots, x_{20} be independent Poisson random variables with mean 1. Use the central limit theorem to approximate $P(\sum_{i=1}^{20} x_i > 15)$?
5. Let \bar{x}_{36} be the mean of a random sample of size 36 from an exponential distribution with mean 3. Approximate $P(2.5 < \bar{x}_{36} < 4)$?
6. Let \bar{x}_{12} be the mean of a random sample of size 12 from a uniform distribution on the interval $(0, 1)$. Approximate $P(\frac{1}{2} \leq \bar{x}_{12} \leq \frac{2}{3})$?

[7.] Approximate $p(39.5 \leq \bar{x}_{32} \leq 41.25)$, where \bar{x}_{32} is the mean of a random sample of size 32 from a distribution with mean $\mu = 40$ and variance $\sigma^2 = 8$.

[8.] let $Y_{15} = x_1 + x_2 + \dots + x_{15}$ be the sum of a random sample of size 15 from the distribution whose p.d.f is,

$$f(x) = \begin{cases} \frac{3}{2} x^2 & -1 \leq x \leq 1 \\ 0 & \text{o.w} \end{cases}$$

Approximate $p(-0.3 \leq Y_{15} \leq 1.5)$?

Central limit theorem

For \bar{X} we have.

$$E\bar{X} = \mu, \quad V(\bar{X}) = \frac{\sigma^2}{n}$$

2.35

Thus as n increasing the variance of \bar{X} decrease.

The dist. of \bar{X} clearly depend on n .

so we are dealing with sequence of dist.

—
To denote this we will place the subscript n on the random sample of size n , we write (\bar{X}_n) in the case of the
• mean of a random sample
of size n .

By using the chebyshev's inequality consider $\epsilon > 0$

$$P\{|\bar{X}_n - \mu| > \epsilon\}$$

the random sample of size n , we write (\bar{X}_n) is the
mean of a random sample
of size n .

By using the chebyshev's inequality consider $\epsilon > 0$

$$P\{|\bar{X}_n - \mu| \geq \epsilon\}$$
$$= P\left\{|\bar{X}_n - \mu| \geq \left(\frac{\epsilon \sqrt{n}}{\sigma}\right) \left(\frac{\sigma}{\sqrt{n}}\right)\right\}$$

But the standard deviation of \bar{X} is $\frac{\sigma}{\sqrt{n}}$

Hence using chebyshev's inequality with $K = \frac{\epsilon \sqrt{n}}{\sigma}$

^{we have}
~~where~~

$$P\{|\bar{X}_n - \mu| \geq \epsilon\} \leq \frac{\sigma^2}{\epsilon^2 \sqrt{n}}$$

Since the prob. is non negative it follows that.

$$\lim_{n \rightarrow \infty} P\{|\bar{X}_n - \mu| \geq \epsilon\} \leq \lim_{n \rightarrow \infty} \frac{\sigma^2}{\epsilon^2 \sqrt{n}} = 0$$

this implies that.

Hence using Chebyshev's inequality with $K = \frac{\epsilon \sqrt{n}}{\sigma}$

we have
where

$$P\{|\bar{X}_n - \mu| \geq \epsilon\} \leq \frac{\sigma^2}{\epsilon^2 \sqrt{n}}$$

Since the prob. is non negative it follows that.

$$\lim_{n \rightarrow \infty} P\{|\bar{X}_n - \mu| \geq \epsilon\} \leq \lim_{n \rightarrow \infty} \frac{\sigma^2}{\epsilon^2 \sqrt{n}} = 0$$

this implies that.

$$\lim_{n \rightarrow \infty} P\{|\bar{X}_n - \mu| \geq \epsilon\} = 0$$

or equivalently

$$\lim_{n \rightarrow \infty} P\{|\bar{X}_n - \mu| < \epsilon\} = 1$$

38

الحد
المحصلي

The preceding discussion shows that the prob. associated with the dist. of \bar{X}_n becomes concentrated in an arbitrary small interval about μ as n increases. This is one of the forms of the law of large numbers.

P.154

Example let x_1, x_2, \dots, x_n denote a v. s. from a dist. $b(1, p)$, $0 < p < 1$
this we know that.

$$Y_n = x_1 + x_2 + \dots + x_n.$$

from the preceding results, with ~~assumption~~

show that.

$$\lim p\left[\left|\frac{Y_n}{n} - p\right|\right] < \epsilon$$

Theorem

Central limit theorem

Let \bar{X}_n be the mean of ar. s. X_1, \dots, X_n of size n from a dist. with a finite mean μ and a finite positive variance σ^2 , then the dist. of

$$W_n = \frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} = \frac{\sum_{i=1}^n X_i - n\mu}{\sqrt{n} \sigma}$$

is $N(0,1)$ in the limit as $n \rightarrow \infty$

2.45-
2.45-
2.45-

The Central limit theorem

or Convergence to Normal dist (Lindeberg's theorem)

let X_1, X_2, \dots be indep. r.v.'s with each X_k having finite mean m_k and finite variance σ_k^2

let $S_n = \sum_{k=1}^n X_k$, $k=1, 2, 3, \dots$

then

$$E(S_n) = \sum_{k=1}^n m_k$$

$$\text{Var}(S_n) = \sum_{k=1}^n \sigma_k^2$$

$$[X_1, \dots, X_n] \dots [X_1, \dots, X_n]$$

...
...
...

$$S_n = \sum_{k=1}^n X_k, n=1, 2, \dots$$

...
...
...

$X \sim \text{Bernoulli}(p)$

$$E X = p$$

$$\text{Var}(X) = p(1-p)$$

$$X \sim N(m=p, \sigma^2=p(1-p))$$

تقريب التوزيع المركزي

let

$$T_n = C_n^{-1} (S_n - E(S_n))$$

standardization

F_k be the dist. fun. of X_k

if for $\epsilon > 0$

$$\frac{1}{C_n^2} \sum_{k=1}^n \int_{\{x_i : |x - m_k| \geq \epsilon C_n\}} (x - m_k)^2 dF_k(x) \rightarrow 0 \text{ as } n \rightarrow \infty$$

$$\{x_i : |x - m_k| \geq \epsilon C_n\}$$

Chebyshev's

Then it converges in dist. to normal variable X^*

i.e. $N(0, 1)$

المؤثرات Implications of Lindeberg's theorem

ex A

لواظف هنا
البديل

① the Uniformly bounded case

Assume $|X_k| \leq M \forall k$ and $C_n \rightarrow \infty$

$$\text{then } \int_{\{x: |x - m_k| \geq \epsilon\}} (x - m_k)^2 dF_k(x) = E(X_k - m_k)^2 \mathbb{I}_{\{|X_k - m_k| \geq \epsilon\}}$$

$$\{x: |x - m_k| \geq \epsilon\}$$

لواظف هنا البديل

by Chebyshev's

C_n^2 توافق sum البديل توافق

$$\therefore \frac{1}{C_n^2} \sum_{k=1}^n \int_{\{x: |x - m_k| \leq C_n\}} (x - m_k)^2 dF_k(x)$$

$$\leq (2M)^2 \underbrace{P\{|X - m_k| \geq \epsilon\}}_{\substack{\text{by Chebyshev's } C_n^2 \\ \uparrow \\ \frac{1}{C_n^2} \sum_{k=1}^n \sigma_k^2}}$$

$$\frac{1}{C_n^2} \sum_{k=1}^n \int_{\{x: |x - m_k| \leq C_n\}} (x - m_k)^2 dF_k(x) \leq \frac{2M^2 \cdot \sigma_k^2}{\epsilon^2 C_n^2} \rightarrow 0$$

as $C_n \rightarrow \infty$
بديل

The identical dist. case

Assume that the X_k are i.i.d, with finite mean μ and finite variance $\sigma^2 > 0$

if F is the dist. of the X_k , then

$$\frac{1}{C_n} \sum_{k=1}^n \int_{\{x: |x - \mu_k| > \epsilon_n\}} (x - \mu_k)^2 dF_k(x)$$

$$= \frac{1}{n\sigma^2} \sum_{k=1}^n \int_{\{x: |x - \mu_k| > \epsilon_n\}} (x - \mu_k)^2 dF(x)$$

$$= \frac{1}{\sigma^2} \int_{\{x: |x - \mu| > \epsilon_n\}} (x - \mu)^2 dF(x) \longrightarrow 0$$

since σ^2 is finite $\{x: |x - \mu| > \epsilon_n\} \downarrow \emptyset$

as $n \rightarrow \infty$

\emptyset sign set $\rightarrow 0$

The Bernoulli case

let S_n be the number of successes in n Bernoulli trials with prob. of successes p on a given trial we may write

$$S_n = X_1 + X_2 + \dots + X_n$$

where the X_k are indep. and.

$$P\{X_k = 1\} = p$$

$$P\{X_k = 0\} = 1 - p = q$$

we may take X_k as the ^{indicator} indicator of a success on trial k .

Thus Cor 2 applies with.

$$m = E(X_k) = p$$

$$\sigma^2 = E(X_k^2) - (E X_k)^2 = npq.$$

$$E(S_n) = nm = np$$

$$\sigma_n^2 = n\sigma^2 = npq$$

Thus $T_n = \frac{S_n - np}{(npq)^{1/2}}$ and $T_n \xrightarrow{d} x^*$ ^{by CLT}

That is $P\{T_n \leq x\} \rightarrow F^*(x), \forall x$ where

$$F^*(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{1}{2}t^2} dt \quad \text{standard normal}$$

Liapounov's Condition

Assume that.

$$\frac{1}{C_n^{2+\delta}} \sum_{k=1}^n E[|X_k - m_k|^{2+\delta}] \rightarrow 0$$

for some $\delta > 0$

$$\begin{aligned} E[|X_k - m_k|^{2+\delta}] &= \int_{-\infty}^{\infty} |x - m_k|^{2+\delta} d f_k(x) \\ &\geq \int_{\{x: |x - m_k| \geq \epsilon_n\}} |x - m_k|^{\delta} |x - m_k|^2 d f_k(x) \\ &\geq \epsilon_n^{\delta} \int_{\{x: |x - m_k| \geq \epsilon_n\}} (x - m_k)^2 d f_k(x) \end{aligned}$$

$$\begin{aligned} \text{then } \frac{1}{C_n^{2+\delta}} \sum_{k=1}^n \int_{\{x: |x - m_k| \geq \epsilon_n\}} (x - m_k)^2 d f_k(x) \\ \leq \frac{1}{C_n^{2+\delta}} \sum_{k=1}^n \frac{E[|X_k - m_k|^{2+\delta}]}{\epsilon_n^{\delta} C_n^{\delta}} \quad \leftarrow \text{منه } \frac{1}{C_n^{2+\delta}} \\ = \sum_{k=1}^n \frac{E[|X_k - m_k|^{2+\delta}]}{\epsilon_n^{\delta} C_n^{2+\delta}} \rightarrow 0 \quad \leftarrow \text{منه } \frac{1}{C_n^{2+\delta}} \end{aligned}$$

Martingals

المشوار
متر

(CP4 a)

Def. let (Ω, \mathcal{F}, P) be a prob. space $\{X_1, X_2, \dots\}$
a sequence of integrable r.v.'s on (Ω, \mathcal{F}, P)
and $\mathcal{F}_1 \subset \mathcal{F}_2 \subset \dots$ an increasing sequence
of sub σ -field on \mathcal{F} .

X_n is assumed \mathcal{F}_n measurable that is

$$\text{i.e. } X_n: (\Omega, \mathcal{F}_n) \rightarrow (\mathbb{R}, \mathcal{B}(\mathbb{R}))$$

The sequence $\{X_n\}$ is said to be martingale
relative to \mathcal{F}_n iff:

For all $n = 1, 2, \dots$

① $E(X_{n+1} / \mathcal{F}_n) = X_n$ a.e (almost everywhere)

② a sub-martingals iff

$$E(X_{n+1} / \mathcal{F}_n) \geq X_n \text{ a.e. and.}$$

③ a super martingals iff:

$$E(X_{n+1} / \mathcal{F}_n) \leq X_n \text{ , a.e.}$$

$\mathcal{F}_{n+1} \ni \text{also } X_{n+1} \text{ is } \mathcal{F}_{n+1} \text{ measurable}$

Comments

(a) if $\{X_n, \mathcal{F}_n\}$ is a martingale then

$$E(X_{n+k} / \mathcal{F}_n) = X_n \quad n, k = 1, 2, 3, \dots$$

$$\begin{aligned} \text{i.e. } E(X_{n+2} / \mathcal{F}_n) &= E[E(X_{n+2} / \mathcal{F}_{n+1}) / \mathcal{F}_n] \\ &= E(X_{n+1} / \mathcal{F}_n) \\ &= X_n \end{aligned}$$

(b) if $\{X_n, \mathcal{F}_n\}$ is a martingale, then

$$E(X_{n+1} / X_1, \dots, X_n) = X_n \quad n = 1, 2, \dots$$

(c) if $\{X_n, \mathcal{F}_n\}$ is a martingale iff:

$$\int_A X_n dP = \int_A X_{n+1} dP \quad \forall A \in \mathcal{F}_n, n = 1, 2, \dots$$

Let Y_1, Y_2, \dots be independent r.v.s with zero mean and set $X_n = \sum_{k=1}^n Y_k$

$\mathcal{F}_n = \mathcal{F}(Y_1, \dots, Y_n)$ then $\{X_n, \mathcal{F}_n\}$ is a martingale

Sol

$$\begin{aligned} E(X_{n+1} / \mathcal{F}_n) &= E(X_n + Y_{n+1} / Y_1, Y_2, \dots, Y_n) \\ &= X_n + E(Y_{n+1} / Y_1, Y_2, \dots, Y_n) \end{aligned}$$

Since X_n is \mathcal{F}_n -measurable

$$\begin{aligned} \Rightarrow &= X_n + E(Y_{n+1}) \text{ By independency} \\ &= X_n + 0 \\ &= X_n \end{aligned}$$

$$(1-x-x^2) \frac{1}{1-x} = 1-x$$

ex let y_1, y_2, \dots be indep. r.v.'s with

$$E(y_j) = a_j \neq 0$$

$$\text{and set } X_n = \prod_{j=1}^n \left(\frac{y_j}{a_j} \right),$$

$F_n = f(y_1, \dots, y_n)$ then $\{X_n, F_n\}$ is a martingale

sol

$$E(X_{n+1} / F_n) = E\left[\frac{X_n y_{n+1}}{a_{n+1}} \mid y_1, y_2, \dots, y_n\right]$$

$$= X_n E\left(\frac{y_{n+1}}{a_{n+1}}\right)$$

$$= X_n \left(\frac{a_{n+1}}{a_{n+1}}\right)$$

$$= X_n$$

Central limit theorem

P261-262

Consider a sequence of independent and identically dist. random variables. $\{X_n\}$ with mean $E(X_n) = \mu$ and $\text{Var}\{X_n\} = \sigma^2$

let

$$S_n = \sum_{i=1}^n X_i, \quad \bar{X}_n = \frac{S_n}{n}$$

Then

$$E(\bar{X}_n) = E\left(\frac{X_1 + \dots + X_n}{n}\right) = \frac{n\mu}{n} = \boxed{\mu}$$

and

$$\text{Var}(\bar{X}_n) = \text{Var}\left(\frac{X_1 + \dots + X_n}{n}\right) = \frac{n\sigma^2}{n^2} = \boxed{\frac{\sigma^2}{n}}$$

it is clear that $\text{Var}(\bar{X}_n) \rightarrow 0$ as $n \rightarrow \infty$

This means that the density fun. of \bar{X}_n is concentrated around the mean μ for large n . We shall see later that as $n \rightarrow \infty$ the dist. fun. of \bar{X}_n tends to the normal dist. under certain conditions. This property is one of the forms of the central limit theorem which is.

Theorem

Let x_1, x_2, \dots be a sequence of i.i.d. r.v.'s each with mean μ and variance σ^2 . Then the dist. of $Z_n = \frac{S_n - E(S_n)}{\sqrt{\text{var}(S_n)}}$ tends to the standard normal as $n \rightarrow \infty$, that is

$$P\{Z_n \leq z\} = \Phi(z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt \quad \text{as } n \rightarrow \infty$$

proof: the theorem of Convergence in dist.

that is,

The
Theorem

let $\phi_n(t)$ be the characteristic fun. of x_n . if $x_n \xrightarrow{d} x$ then $\phi_n(t) \rightarrow \phi(t)$, where $\phi(t)$ is the c.d.f. of x .
if $\phi_n(t) \rightarrow \phi(t)$ and the limit fun. is continuous at $t=0$, then
 $x_n \xrightarrow{d} x$

نموذج

it is sufficient to show that $\phi_{Z_n}(t) \rightarrow \phi(t)$ as $n \rightarrow \infty$
where $\phi_{Z_n}(t)$ and $\phi(t)$ are the c.d.f. of Z_n and Z (standard normal dist.), respectively. we have.

$$E(S_n) = n E(X_i) = n \mu$$

$$\text{and } \text{Var}(S_n) = n \text{Var}(X_i) = n \sigma^2$$

also we have.

$$\begin{aligned} \phi_{S_n}(t) &= \phi_{X_1 + \dots + X_n}(t) = \prod_{i=1}^n \phi_{X_i}(t) \\ &= [\phi_X(t)]^n \end{aligned}$$

because X_i are i.i.d. r.v.'s

Therefore.

$$Z_n = \frac{S_n - n\mu}{\sqrt{n} \sigma}$$

Therefore

$$\begin{aligned} \phi_{Z_n}(t) &= e^{\frac{-itn\mu}{\sqrt{n}\sigma}} \cdot \phi_{S_n}\left(\frac{1}{\sqrt{n}\sigma}\right)^n \\ &= e^{\frac{-it\sqrt{n}\mu}{\sigma}} [\phi_X\left(\frac{1}{\sqrt{n}\sigma}\right)]^n \end{aligned}$$

By the Taylor series expansion of $\phi_X(t)$

we get.

$$\phi_X(t) = 1 + itE(X) - \frac{t^2}{2!} E(X^2) + o(t^2)$$

Therefore

$$\phi_X\left(\frac{1}{\sqrt{n}\sigma}\right) = 1 + \frac{it}{\sqrt{n}\sigma} E(X) - \frac{t^2}{2n\sigma^2} E(X^2) + o\left(\frac{t^2}{n\sigma^2}\right)$$

and

Page
P243

$$E(S_n) = n E(X_i) = n \mu$$

$$\text{and } \text{Var}(S_n) = n \text{Var}(X_i) = n \sigma^2$$

also we have.

$$\phi_{S_n}(t) = \phi_{X_1 + \dots + X_n}(t) = \prod_{i=1}^n \phi_{X_i}(t)$$

$$= [\phi_X(t)]^n$$

because X_i are i.i.d. r.v.'s

Therefore.

$$Z_n = \frac{S_n - n\mu}{\sqrt{n} \sigma}$$

Therefore

$$\begin{aligned} \phi_{Z_n}(t) &= e^{-itn\mu/\sqrt{n}\sigma} \cdot \phi_{S_n}\left(\frac{t}{\sqrt{n}\sigma}\right)^n \\ &= e^{-\frac{it\sqrt{n}\mu}{\sigma}} \left[\phi_X\left(\frac{t}{\sqrt{n}\sigma}\right)\right]^n \end{aligned}$$

By the Taylor series expansion of $\phi_X(t)$

we get.

$$\phi_X(t) = 1 + it E(X) - \frac{t^2}{2!} E(X^2) + o(t^2)$$

Therefore

$$\phi_X\left(\frac{t}{\sqrt{n}\sigma}\right) = 1 + \frac{it}{\sqrt{n}\sigma} E(X) - \frac{t^2}{2n\sigma^2} E(X^2) + o\left(\frac{t^2}{n\sigma^2}\right)$$

and

$$\begin{aligned}\phi_{Z_n}(t) &= e^{\frac{-it\sqrt{n}\mu}{\sigma}} \cdot \left[1 + \frac{itE(x)}{\sqrt{n}\sigma} - \frac{t^2}{2n\sigma^2} E(x^2) + o\left(\frac{t^2}{n\sigma^2}\right) \right]^n \\ &= e^{\frac{-it\sqrt{n}\mu}{\sigma}} \left[1 + \frac{it\mu}{\sqrt{n}\sigma} - \frac{t^2}{2n\sigma^2} (\sigma^2 + \mu^2) + o\left(\frac{t^2}{n\sigma^2}\right) \right]^n\end{aligned}$$

where $EX = \mu$, $V(x) = \sigma^2 = EX^2 - (EX)^2$
 $\sigma^2 = EX^2 - \mu^2$

$$\Rightarrow = e^{\frac{-it\sqrt{n}\mu}{\sigma}} \left[1 + \frac{it\mu}{\sqrt{n}\sigma} - \frac{t^2}{2n} + o\left(\frac{t^2}{n\sigma^2}\right) \right]^n$$

but we have.

$$\begin{aligned}& \lim_{n \rightarrow \infty} \left[1 + \frac{\frac{it\mu\sqrt{n}}{\sigma} - \frac{t^2}{2}}{n} + o\left(\frac{t^2}{n\sigma^2}\right) \right]^n \\ & \rightarrow e^{\frac{it\mu\sqrt{n}}{\sigma} - \frac{t^2}{2}} \quad \text{as } n \rightarrow \infty\end{aligned}$$

therefore.

$$\begin{aligned}\lim_{n \rightarrow \infty} \phi_{Z_n}(t) &= e^{\frac{-it\sqrt{n}\mu}{\sigma}} \cdot e^{\frac{it\mu\sqrt{n}}{\sigma} - \frac{t^2}{2}} \\ &= e^{-\frac{t^2}{2}}\end{aligned}$$

$$= \phi_Z(t)$$

where $\phi_Z(t) = e^{-\frac{t^2}{2}}$ is the c.d.f. of the standard normal dist.

therefor the dist. of Z_n approaches the standard normal distribution. 5/3