

Central Limit Theorem:-

The Central limit theorem is perhaps the most important theorem in all of the statistical inference. It is concerned with the mean of large samples and provides solutions when the shape of the population distribution is unknown or highly skewed.

As the sample size increases the sampling distribution of sample mean approaches to normal distribution with mean as population mean and standard deviation is the population standard deviation by square root of sample size (n).

CLT is used to establish the normality of the results.

∴ In 1733 French Mathematician Abraham de Moivre gave idea of CLT. Later on 1920 George Polya gave it particular name Central limit theorem.

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$$\bar{X} \sim N(\mu, \sigma/\sqrt{n})$$

$$\bar{X} - \mu \sim N(0, \sigma/\sqrt{n})$$

$$\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \sim N(0, 1)$$

CLT and Properties :- Let X_1, X_2, \dots, X_n be a sequence of n independent and identically distributed random variable having finite mean μ and variance σ^2 . Then the CLT states that as sample size increase the distribution of sample statistic of the random variable approaches to normal distribution with mean $\mu_{\bar{X}} = \mu$ and variance $\sigma_{\bar{X}}^2 = \frac{\sigma^2}{n}$. If we define \bar{X} be sample mean or sample average then

$$\bar{X}_n \sim N(\mu, \sigma^2/n)$$

In a similar way

$$Z_n = \frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}}$$

Proof :- we know that moment generating function of normal distribution.

$$M(x)(t) = e^{ut + 1/2 \sigma^2 t^2}$$

In case of standard normal we have

$$M_{Z_n}(t) = e^{t^2/2} \quad Z_n = \frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}}$$

Here $M_{Z_n}(t)$ shows the MGF of

Z_n and we have to show that

$$\text{when } n \rightarrow \infty \quad M_{Z_n}(t) \rightarrow M_{(X)}(t) = e^{t^2/2}$$

By Definition

$$\begin{aligned} M_{Z_n}(t) &= E\left[e^{t(Z_n)}\right] \\ &= E\left[e^{t\left(\frac{\bar{X}-\mu}{\sigma/\sqrt{n}}\right)}\right] \Rightarrow E\left[e^{\frac{t(\bar{X}-\mu)\sqrt{n}}{\sigma}}\right] \end{aligned}$$

$$= E\left[e^{\frac{t(\sum X_i - n\mu)\sqrt{n}}{\sigma}}\right]$$

$$= E\left[e^{\frac{t \cdot \frac{1}{n} \sum (X_i - \mu) \cdot \sqrt{n}}{\sigma}}\right]$$

$$= E\left[\prod_{i=1}^n e^{t \cdot \frac{1}{\sqrt{n}} \left(\frac{X_i - \mu}{\sigma}\right)}\right] \quad \text{--- (A)}$$

Since X_i 's are independent

let $Y_i = \frac{X_i - \mu}{\sigma}$ then $M_{Y_i}(t)$ is the

MGF of X_i and Y_i has same

distribution as X_i . Now (A) becomes

as

$$M_{Z_n}(t) = \prod_{i=1}^n E\left(e^{t \cdot Y_i/\sqrt{n}}\right)$$

$$= \prod_{i=1}^n M_{Y_i}\left(\frac{t}{\sqrt{n}}\right)$$

$$= \left[M_{Y_i}\left(\frac{t}{\sqrt{n}}\right)\right]^n \quad \text{--- (B)}$$

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By using property of MGF when variables are independent and identically distributed then products change into Powers.

Taylor Series for

e^x is

$$e^x = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots$$

$$= \sum_{k=0}^{\infty} \frac{x^k}{k!}$$

This may be written as

$$e^{sx} = \sum_{k=0}^{\infty} \frac{(sx)^k}{k!} = \sum_{k=0}^{\infty} \frac{x^k s^k}{k!}$$

Thus, we have

$$M_X(s) = E(e^{sx}) = \sum_{k=0}^{\infty} E(X^k) \frac{s^k}{k!}$$

OR

$$M_X(t) = E(e^{tx}) = \sum_{k=0}^{\infty} \frac{E(X^k) t^k}{k!}$$

— (C)

From (B) consider $M_{Y_i}(t/\sqrt{n})$ and solve this by using (C) we have

$$M_{Y_i}(t/\sqrt{n}) = \sum_{k=0}^{\infty} \frac{E(Y_i)^k (t/\sqrt{n})^k}{k!}$$

$$= \frac{E(Y_i)^0 (t/\sqrt{n})^0}{0!} + \frac{E(Y_i)^1 (t/\sqrt{n})^1}{1!} + \frac{E(Y_i)^2 (t/\sqrt{n})^2}{2!}$$

+ ...

$$= 1 + \frac{E(X-\mu/\sigma) (t/\sqrt{n})^1}{1!} + \frac{E(X-\mu/\sigma)^2 (t/\sqrt{n})^2}{2!}$$

+ ...

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

+ ...

$$= 1 + \frac{\mu_1}{\sigma} \left(\frac{t}{\sqrt{n}}\right) + \frac{1}{2\sigma^2} \mu_2 \left(\frac{t}{\sqrt{n}}\right)^2 + \dots$$

We know that odd order moments about mean are zero so

$$= 1 + \frac{0}{\sigma} \left(\frac{t}{\sqrt{n}}\right) + \frac{\sigma^2}{2\sigma^2} \left(\frac{t}{\sqrt{n}}\right)^2 + \dots$$

$$= 1 + \frac{t^2}{2n} + \dots$$

$$= 1 + P/n \quad \because P = t^2/2$$

Now equation (B) becomes As

$$M_{Z_n}(t) = (1 + P/n)^n$$

Applying limits on both sides we

have

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$$\begin{aligned}\lim_{n \rightarrow \infty} M_{Z_n}(t) &= \lim_{n \rightarrow \infty} (1 + P/n)^n \\ &= e^P = e^{t^2/2} \\ &= M_X(t)\end{aligned}$$

This indicates that for Z_n has the MGF as the standard normal distribution

$$M_{Z_n}(t) \rightarrow M_X(t) \text{ when } n \rightarrow \infty$$