

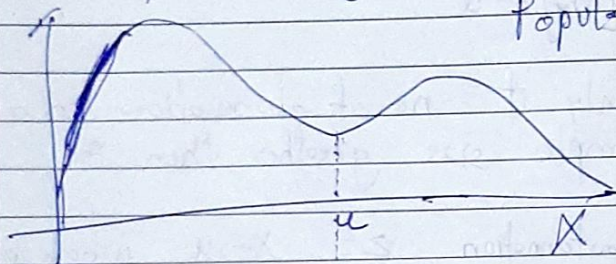
Sampling distribⁿ:-

- Theoretical distribⁿ

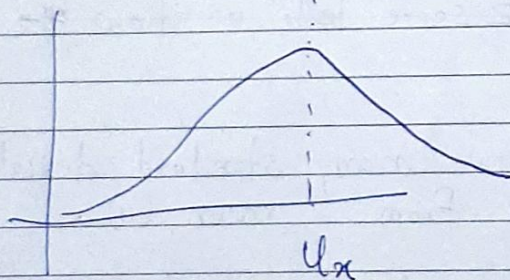
The distribⁿ of a statistic like - mean, etc where

we take 1 sample calculate mean & then take another sample calculate mean & when we do this repeatedly we get a distribⁿ for the mean statistic. Central Limit Theorem says that if we have enough samples no matter which statistic we compute we get a Normal distribution.

Populatⁿ distribⁿ



Sampling Distribⁿ



Populatⁿ distribⁿ is unknown we will never know mean or std of Populatⁿ distribⁿ

Sampling distribⁿ is a theoretical distribⁿ. If we take many samples from populatⁿ distribⁿ calculate the static we will get the sampling Distribⁿ which is a Normal distribⁿ.

CLT even tells us the mean & std of the sampling distribⁿ.

Parameter	Populat ⁿ Distrib ⁿ	1 Sample drawn from populat ⁿ	Sampling Distrib ⁿ
Mean	μ	\bar{X}	$\mu_{\bar{X}} \& E(\bar{X}) = \mu$
std	σ	s	$\sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}}$

n : sample size

Because we are taking samples calculating their means & plotting the mean of ~~Target populatⁿ & Sampling di~~
~~for~~ Populatⁿ & Sampling distribⁿ will be same
So $E[\bar{X}] = \mu$

CLT holds only if no of observations in a sample i.e sample size greater than 30.

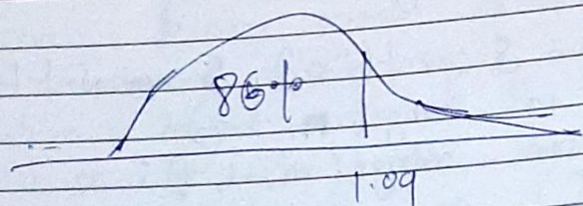
There is a transformation $Z = \frac{\bar{X} - \mu}{\sigma}$ which produces

$Z \sim N(0,1)$ Z score tells us how ~~the~~ far the datapoint x

Z score tells us how many standard deviations is the datapoint x from mean (μ).

Z table or standard Normal table is a table which gives what percentage of ~~p~~ values below a z score.

Suppose a z score = 1.09 & ~~has~~ is our input & z table gives 0.862 i.e 86% of values fall below these value



Standardizing formula for sampling distribⁿ

$$Z = \frac{\bar{X} - \mu_x}{\frac{\sigma_x}{\sqrt{n}}} = \frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}}$$

\bar{X} = ~~the~~ Sample pt of Sampling
Distribⁿ is a statistic like mean

* CI for populatⁿ standard deviatⁿ or Large Sample size

$$Z = \left(\frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}} \right) \sqrt{n} = \frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}}$$

we know \bar{X} , ~~μ~~ , σ because ~~either~~
pop std is given.
we don't know μ ($\mu = \mu_x$)

$$\mu = \bar{X}$$

$$CI = \bar{X} - Z\left(\frac{\sigma}{\sqrt{n}}\right) \leq \mu \leq \bar{X} + Z\left(\frac{\sigma}{\sqrt{n}}\right)$$

we have to decide level of confidence.
 α is the probability that CI will not contain the True populatⁿ Mean. $(1 - \alpha)$ is confidence level

Std :

Div :

Roll No :

Sub :

School / College :

Suppose our CI is very wide & has very high confidence level. But there is of no use bcoz it hardly qualifies as meaningful. The best CI is narrow with high confidence level. There is a Tradeoff b/w confidence level & width of CI. As $Z_{\alpha} \uparrow$ the width of CI \uparrow & Z_{α} increases bcoz the level of confidence is increasing. The role of sample size n is that as $n \uparrow$ the std will \downarrow & the CI will get narrower.



Large Sample size

Date : _____

Given

Now we want to make inference
abt populatⁿ mean (μ).

We take a sample.

Sample Mean = \bar{X}

Sample std = s

we choose confidence level = 0.95, so

$Z_{0.95} = 1.96$

~~&~~ Large Sample size $n = 200$

→

To With above given we know that Central Limit Theorem
is true & the Sampling distributⁿ is a Normal &
our sample mean comes from the sampling distributⁿ.

No we create a band around our sample mean
so the true populatⁿ mean falls in this band 95%
of time.

$$\left(\bar{X} - \frac{1.96 \times s}{\sqrt{n}}, \bar{X} + \frac{1.96 \times s}{\sqrt{n}} \right)$$

we just say that populatⁿ std is known infact
we never know any parameter of populatⁿ but
bcoz the sample size is large enough the Central Limit
Theorem is true & we can use sample std dev as a
point estimate for populatⁿ std.