

STATISTICS -I

THE CENTRAL LIMIT THEOREM

In probablity theory there is a very elegent theorem called the central limit theorem. A special case of this theorem asserts that if $x1...x_n$ denote the items of a random sample of size from any distribution Having positive variance σ^2 , then the random Variable $\sqrt{n} (x - \mu)/\sigma$ has a limiting normal Distribution with mean 0 and variance 1. the more general form of the theorem is stated but it is proved only in the modifed case.



THEOREMUS

Let x_1 , x_2 x_n denote the items of a random sample from a distribution that has mean μ and positive variance σ^2 then the random variable.

$$y_n = (\sum_{i=1}^{n} x_i - n\mu) / \sigma \sqrt{n} = \sqrt{n(x - \mu)} / \sigma$$

has a limiting normal distribution with mean 0 and variance 1.



We assume the existance of the m.g.f $M(t)=E(e^{tx})$, -h < t < h of the distribution.

However this proof is essentially the same one that would be given if we could use the characteristic function in place of the m.g.f

The function $M(t)=E[e^{t(X-\mu)}]=e^{-\mu t}E[e^{tx}]$ = $e^{-\mu t}$ also exist for -h<t<h .

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since M(t) is the m.g.f for (x-\mu)
       We have m(0)=1,
m'(0)=E(X-\mu) and m''(0)=E[(X-\mu)<sup>2</sup>]=\sigma<sup>2</sup>
By taylor's formula,
        there exists a number ξ between 0 and t such
that
     m(t)=m(0)+m'(0)+(m''(\xi)t^2)/2
                =1+ (m''(\xi)t^2)/2
If \sigma^2 t^2/2 is added and subtracted, then
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 $m(t)=1+\sigma^2t^2/2+[(m''(\xi)-\sigma^2)t^2]/2$.

Next consider M(t;n), where

={ E [exp (t (X- μ)/ σ /n)] }²=[m (t/ σ /n)]²

In equation replace t by $t/\sigma/n$ to obtain $m(t/\sigma/n)=1+t^2/2n+[(m''(\xi)-\sigma^2)t^2]/2n\sigma^2$

Where now ξ is between 0 and $t/\sigma \ln$ with $-h\sigma \ln t \cdot h\sigma \ln$. Accordingly,

$$M(t;n)=\{1+t^2/2n+[(m''(\xi)-\sigma^2)t^2]/2n\sigma^2\}^n$$

Since m"(t) is continuous at t=0 and since $n\rightarrow\infty$, We have

$$\lim_{n\to\infty} [m''(t)-\sigma^2]=0.$$

The limit proposition shows that,

$\lim_{n\to\infty} M(t;n)=e^{t^{2/2}}$

For all real values of t. this proves that the

random variable $Y_n = \sqrt{n(X_n - \mu)/\sigma}$ has a limiting standard normal distribution.

We interpret this theorem as saying that, when n is a large integer, the random variable \overline{X} has an approximate normal distribution with mean μ and variance σ^2/n ; and in applications we use the approximate normal p.d.f As through it were the exact p.d.f of X



ENAMOPLES:

Example:1

let X denote the mean of a random Sample of size 75 from the distribution has the p.d.f

$$f(x)=1,$$
 $0< x<1$
= 0 elsewhere.

Example:2

let $X_1.X_2....X_n$ denote a random Sample from a distribution that is b(1,p).

Here $\mu=p$, $\sigma^2=p(1-p)$, and M(t) exists for all real Values of t. if $Y_n=X_1+X_2+....+X_n$,

Example:3

with the background of example 2, let n=100 and p=1, and suppose that we wish to compute p_r (Y=48,49,50,51,52)

Example:4

let Y_n (Y for simplicity) be b(n,p). Thus Y/n is approximately N(p.p(1-p)/n)]. Statisticians often look for functions of statistics whose variances do not depnd upon the parameter. Here the variance of Y/n depends upon p.Can we find a function, say u(Y,n), whose variance is essentially free of p?

