

11.02

✓ Study of χ^2 Distribution (Chi-square)

$$X \sim N(\mu, \sigma^2) \quad f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}; -\infty < x < \infty$$

$$Z = \frac{X-\mu}{\sigma} \sim N(0, 1) \quad \text{if } \mu=0, \sigma=1$$

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}; -\infty < z < \infty$$

standard normal distribution

Chi-square variate:- The square of a standard normal variate is known as chi-square variate with 1 d.f. thus if $X \sim N(\mu, \sigma^2)$

then $Z = \frac{X-\mu}{\sigma}$ is $N(0, 1)$ and $Z^2 = \left(\frac{X-\mu}{\sigma}\right)^2$ is a chi-square variate with 1 d.f.

In general if x_i , ($i=1, 2, \dots, n$) are n independent normal variate with mean μ_i and variance σ_i^2 , ($i=1, 2, \dots, n$), then $\chi^2 = \sum_{i=1}^n \left(\frac{x_i - \mu_i}{\sigma_i}\right)^2$ is a chi-square variate with n d.f.

② Derivation of the chi square distribution.

Statement:- If x_i ($i=1, 2, \dots, n$) are independent $N(\mu_i, \sigma_i^2)$ variate then the quantity $\chi^2 = \sum_{i=1}^n \left(\frac{x_i - \mu_i}{\sigma_i}\right)^2$ is distributed as

P.D.F. \rightarrow probability density function

χ^2 with m d.f.

Proof: Let, $Z_i = \frac{x_i - \mu_i}{\sigma_i}$, $i=1, 2, \dots, n$.
 Since, $x_i \sim N(\mu_i, \sigma_i^2)$; $Z_i \sim N(0, 1)$

$$M_{x^2}(t) = M \sum_{i=1}^n \left(\frac{x_i - \mu_i}{\sigma_i} \right)^2 (t)$$

$$= M \sum_{i=1}^n Z_i^2 (t)$$

Now
 $M_x(t) = E(e^{tx})$
 $= \int e^{tx} f(x) dx$

Now, $M_{Z_i^2}(t) = E(e^{tZ_i^2})$

$$= \int_{-\infty}^{\infty} e^{tZ_i^2} f(Z_i) dZ_i$$

$$= \int_{-\infty}^{\infty} e^{-tZ_i^2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}Z_i^2} dZ_i$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\left(\frac{1-2t}{2}\right)Z_i^2} dZ_i$$

$\int_0^\infty e^{-ax^2} x^{2n-1} dx$
 $= \frac{a^n}{2} \sqrt{\pi}$
 $\int_0^\infty e^{-ax^2} x^{2n-1} dx = a^n \Gamma(n)$
 $\int_0^\infty e^{-bx^2} x^{2n-1} dx = b^n \Gamma(n)$



Integrating from $-\infty$ to ∞ , we get $\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\left(\frac{1-2t}{2}\right)Z_i^2} dZ_i$
 If we multiply with $\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\left(\frac{1-2t}{2}\right)Z_i^2} dZ_i$, we get $\left(\frac{1-2t}{2}\right) + 1$
 Now, if we multiply with $\left(\frac{1-2t}{2}\right) + 1$, we get t^2 .

$$= \frac{1}{\sqrt{2\pi}} \cdot 2 \cdot \frac{\left(\frac{1-2t}{2}\right)^{-\frac{1}{2}}}{2} \cdot \frac{1}{\sqrt{2}}$$

$$\Gamma(m) = (m-1)!$$

$$= \frac{1}{\sqrt{2\pi}} \cdot \left(\frac{2}{1-2t}\right)^{\frac{1}{2}} \cdot \frac{1}{\sqrt{\pi}}$$

$$\rightarrow \frac{1}{\sqrt{2\pi}} \cdot \frac{\sqrt{2} \sqrt{\pi}}{\left(\frac{2}{1-2t}\right)^{\frac{1}{2}}} \cdot \frac{1}{\sqrt{\pi}}$$

$$\Rightarrow M_{Z_i^2}(t) = (1-2t)^{-\frac{1}{2}}$$

$$\therefore M_x^2(t) = \prod_{i=1}^n M_{Z_i^2}(t)$$

$$= \prod_{i=1}^n (1-2t)^{-\frac{1}{2}}$$

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

Parameter which is the m.g.f of a Gamma variate with parameter $\frac{1}{2}$ and $\frac{n}{2}$.

Since, $f(x) = \frac{x^{n/2} e^{-x/2}}{x^{n-1}}$ is a pdf of a

Gamma variate with parameter λ and n .

$$f(x^2) = \frac{\left(\frac{1}{2}\right)^{n/2}}{\sqrt{\Gamma(n/2)}} e^{-\frac{1}{2}x^2} (x^2)^{\frac{n}{2}-1}$$

$$f(x) = \frac{e^{-\frac{x^2}{2}} (x^2)^{\frac{n}{2}-1}}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})}; \quad 0 \leq x^2 < \infty$$

which is the p.d.f. of x^2 variate
with n d.f.
(Degree of freedom)

$$\begin{aligned} \text{Mean: } E(x^2) &= \int_0^\infty x^2 f(x) dx \\ &= \int_0^\infty x^2 \frac{1}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} e^{-\frac{x^2}{2}} (x^2)^{\frac{n}{2}-1} dx \\ &= \frac{1}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} \int_0^\infty e^{-\frac{x^2}{2}} (x^2)^{\left(\frac{n}{2}-1\right)} dx \\ &= \frac{1}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} \left(\frac{1}{2}\right)^{-\left(\frac{n}{2}+1\right)} \Gamma\left(\frac{n}{2}+1\right) \end{aligned}$$

$\therefore f_{df} = \frac{1}{2^{\frac{n}{2}-\frac{n}{2}-1} \Gamma(\frac{n}{2})} \frac{(\frac{n}{2}) \Gamma(\frac{n}{2})}{(x)}$

degrees of freedom = n \rightarrow [Degrees of freedom]

$$\therefore f(x) = x^{\frac{n}{2}-1} \cdot \frac{\frac{1}{2^n} \left(\frac{1}{2}\right)^{\frac{n}{2}}}{\Gamma(\frac{n}{2})} = \left(\frac{x}{2}\right)^{\frac{n}{2}-1}$$

1.0.8 P.d.f

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

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

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

Ref

$$E(x) = \int x f(x) dx$$

$$E(x^2) = \int x^2 f(x) dx$$

$$M_n(t) = E(e^{tx}) =$$

$$= \int e^{tx} f(x) dx$$

$$\int_0^\infty e^{-ax} x^{m-1} dx = \frac{a^m \Gamma(m)}{2}$$

$$\beta(m, n) = \beta(m, m)$$

$$\Gamma(\frac{1}{2}) = \sqrt{\pi}$$

$$\beta(m, n) = \frac{\Gamma_m \Gamma_n}{\Gamma_{m+n}}$$

$$\Gamma_m = (m-1)! = (m-1) \Gamma(m-1)$$

$$\lambda = \frac{1}{2}, m = \frac{1}{2} = (m-1)(n-2)(n-3) \dots 3.2.1$$

$$f(x) = \frac{x^m e^{-\lambda x}}{n!}$$

$$\text{P.d.f. of gamma variable. } \lambda, n$$

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

chi square distribution and its mean depends on degrees of freedom.

$$\int_0^\infty f(x^n) d x^n = 1$$

$$L.H.S = \int_0^\infty \frac{1}{2^{\frac{m}{2}} \sqrt{\pi} \Gamma(\frac{m}{2})} e^{-\frac{x^2}{2}} (x^2)^{\frac{m}{2}-1} d x^2$$

$$= -\frac{1}{2^{\frac{m}{2}} \sqrt{\pi} \Gamma(\frac{m}{2})} \int_0^\infty e^{-\frac{x^2}{2}} \frac{x^m}{(x^2)^{\frac{m}{2}-1}} d x^2$$

$$= \left[e^{-\frac{x^2}{2}} \right]_0^\infty = 1$$

$$\int_0^\infty e^{-ax} x^{n-1} dx = a^n \Gamma(n)$$

$$x^{\frac{n}{2}}(x) \cdot \frac{1}{\Gamma(\frac{n}{2})} = (x)^{\frac{n}{2}}$$

$$= \frac{\frac{n}{2} \Gamma(\frac{n}{2} + 1)}{2^{\frac{n}{2}} \sqrt{\frac{n}{2}}} \left(\frac{1}{2}\right)^{-\frac{n}{2}} \sqrt{\frac{n}{2}}$$

$$= \frac{1}{2^{\frac{n}{2}} \cdot \frac{n}{2}} = 1.$$

We know that Variance = $E[(x^2)^2] - [E(x^2)]^2$

$$\text{Now, } E[(x^2)^2] = \int_0^\infty (x^2)^2 f(x^2) dx^2$$

$$= \int_0^\infty (x^2)^2 \frac{1}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} e^{-\frac{x^2}{2}} (x^2)^{\frac{n}{2}-1} dx^2$$

$$= \frac{1}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} \int_0^\infty e^{-\frac{x^2}{2}} (x^2)^{\frac{n}{2}+2-1} dx^2$$

$$= \frac{1}{2^{\frac{n}{2}-\frac{n}{2}-2} \Gamma(\frac{n}{2})} \left(\frac{n+2}{2}\right)^{\frac{n}{2}} \left(\frac{1}{2}\right)^{-\frac{n}{2}+2} \frac{1}{\Gamma(\frac{n}{2}+2)}$$

$$= \frac{1}{2^{\frac{n}{2}-\frac{n}{2}-2} \Gamma(\frac{n}{2})} \left(\frac{n+2}{2}\right)^{\frac{n}{2}} \Gamma(\frac{n}{2})$$

$$= \frac{1}{2^{\frac{n}{2}}} \left(\frac{n+2}{2}\right)^{\frac{n}{2}} \frac{1}{2^{\frac{n}{2}}} \left(\frac{n+2}{2}\right)^{\frac{n}{2}}$$

$$\therefore E[(x^2)^2] = n(n+2)$$

$$\begin{aligned}\therefore \text{Var}(x^2) &= E[x^4] - [E(x^2)]^2 \\ &= n(n+2) - m^2 \\ &= 2n\end{aligned}$$

④ Mode of the x^2 distribution:

The mode is that value of x .

M.G.F of x^2 distribution:

$$M_{x^2}(t) = E[e^{tx^2}]$$

$$= \int_0^\infty e^{tx^2} f(x^2) dx^2.$$

$$= \int_0^\infty \left(\frac{1-2t}{2}\right)^{\frac{n}{2}} (x^2)^{\frac{n}{2}-1} dx^2.$$

$$= \frac{1}{\frac{n}{2} \Gamma(\frac{n}{2})} \int_0^\infty \left(\frac{1-2t}{2}\right)^{\frac{n}{2}} t^{-\frac{n}{2}} \Gamma(\frac{n}{2}) dt = a^{-n} \Gamma(n).$$

$$= \frac{1}{\Gamma(\frac{n}{2})} \left(1 - \frac{1}{2t}\right)^{\frac{n}{2}} \left(1 - \frac{1}{2t}\right)^{-\frac{n}{2}} =$$

which is m.g.f. of x^2 distribution.

$$(s+n)m =$$

* First four raw and central moments are as follows:

$$\text{E}(X) = (\delta + \mu) \cdot 10^{-2}$$

$$\mu_1' = \frac{\delta M_{X^2}(t)}{\delta t} \Big|_{t=0}$$

$$= \frac{\delta}{\delta t} (1-2t)^{-\frac{n}{2}} \Big|_{t=0}$$

$$= -\frac{n}{2} (1-2t)^{-\frac{n}{2}-1} (-2) \Big|_{t=0}$$

$$= n(1-2)^{-\left(\frac{n}{2}+1\right)} \Big|_{t=0}$$

$$= n,$$

$$\mu_2' = \frac{\delta^2 M_{X^2}(t)}{\delta t^2} \Big|_{t=0}$$

$$= \frac{\delta}{\delta t} \left(\frac{\delta M_{X^2}(t)}{\delta t} \right) \Big|_{t=0}$$

$$= \frac{\delta}{\delta t} \left[n(1-2t)^{-\left(\frac{n}{2}+1\right)} \right] \Big|_{t=0}$$

$$= -n\left(\frac{n}{2}+1\right)(1-2t)^{-\left(\frac{n}{2}+2\right)}(-2) \Big|_{t=0}$$

$$= -n(n+2)(1-2t)^{-\left(\frac{n}{2}+2\right)} \Big|_{t=2}$$

$$= n(n+2).$$

$$\therefore \mu_2 = \mu'_2 - (\mu'_1)^2$$

$$= n(n+2) - (n)^2$$

$$= 2n$$

μ' - raw moment
 μ - central mom.

$$\text{Now, } \mu'_3 = \frac{\int^3 Mx^2(x)}{\int^3 x^3} \Big|_{t=0}$$

$$= \frac{d}{dt} \left(\frac{\int^2 Mx^2(x)}{\int^2 x^2} \right) \Big|_{t=0}$$

$$= \frac{d}{dt} \left[n(n+2)(1-2t)^{-(\frac{n}{2}+2)} \right] \Big|_{t=0}$$

$$= -n(n+2)(\frac{n}{2}+2)(1-2t)^{-(\frac{n}{2}+3)} \Big|_{t=0}$$

$$= n(n+2)(n+4)(1-2t)^{-(\frac{n}{2}+3)} \Big|_{t=0}$$

$$= n(n+2)(n+4)$$

$$\therefore \nu_3 = \mu'_3 - 3\mu'_2 \mu'_1 + 2(\mu'_1)^3$$

$$= n(n+2)(n+4) - 3n(n+2).n + 2n^3$$

$$= n(n^2+6n+8) - 3(n^3+2n^2) + 2n^3$$

$$= \underline{n^3} + \underline{6n^2} + 8n - \underline{3n^3} + \underline{6n^2} + \underline{2n^3}$$

$$= 8n$$

$$\begin{aligned}
 \text{Now, } \mu_4' &= \frac{\delta^4 M x^2(t)}{\delta t^4} \Big|_{t=0} \\
 &= \frac{\delta}{\delta t} \left(\frac{\delta^3 M x^2(t)}{\delta t^3} \right) \Big|_{t=0} \\
 &= \frac{\delta}{\delta t} \left[n(n+2)(n+4)(1-2t)^{-\frac{n+3}{2}} \right] \Big|_{t=0} \\
 &= -n(n+2)(n+4) \left(\frac{n+6}{2} \right) (1-2t)^{-\frac{n+4}{2}} \Big|_{t=0} \\
 &= n(n+2)(n+4)(n+6) (1-2t)^{\frac{n+4}{2}} \Big|_{t=0} \\
 &= n(n+2)(n+4)(n+6)
 \end{aligned}$$

$$\begin{aligned}
 \mu_4 &= \mu_4' - 4\mu_3'\mu_1' + 6\mu_2'\mu_1' - 3\mu_1'^4 \\
 &= n(n+2)(n+4)(n+6) - 4n(n+2)(n+4)n \\
 &\quad + 6n(n+2)n^2 - 3n^4
 \end{aligned}$$

$$\begin{aligned}
 &= (n(n+2))n^2 - (n+2)(n+4)n^2 \\
 &\quad + (n(n+2))n^2 - (8+16n+12n^2) n^2 \\
 &= 12n^2 + 48n
 \end{aligned}$$

Coefficient of skewness

$$\beta_1 = \frac{\mu_3^2}{\mu_2^3} = \frac{(8n)^2}{(2n)^3} = \frac{64n^2}{8n^3} = \frac{8}{n}$$

$$\therefore \beta_2 = \frac{\mu_4}{\mu_2^2} = \frac{12n^2 + 48n}{(2n)^2} = \frac{12n^2 + 48n}{4n^2} = 3 + \frac{12}{n} \quad 73$$

C.G.F. of χ^2 distribution. (cumulant)

$$\begin{aligned}\phi_{\chi^2}(t) &= \log M_{\chi^2}(t) = \log (1-2t)^{-\frac{n}{2}} \\ &= -\frac{n}{2} \log (1-2t)^{-\frac{n}{2}} \\ &= -\frac{n}{2} \log (1-2t) \\ &= -\frac{n}{2} \left(-2t - \frac{4t^2}{2} - \frac{8t^3}{3} - \frac{16t^4}{4} - \dots \right), \\ &= \frac{n}{2} \left(2t + \frac{4t^2}{2} + \frac{8t^3}{3} + \frac{16t^4}{4} + \dots \right), \\ &= nt + nt^2 + \frac{4}{3}nt^3 + 2nt^4 + \dots\end{aligned}$$

Kappa

$$K_1 = \text{Coefficient of } \frac{t}{1!} = n.$$

$$K_2 = \text{Coef. of } \frac{t^2}{2!} = 2n$$

$$K_3 = \text{Coef. of } \frac{t^3}{3!} = 8n$$

$$K_4 = \text{Coef. of } \frac{t^4}{4!} = 48n$$

$$K_1 = \mu_1' = n$$

$$K_2 = \mu_2' = 2n$$

$$K_3 = \mu_3' = 8n$$

$$K_4 = \mu_4 - 3K_2^2$$

$$\Rightarrow \mu_4 = K_4 + 3K_2^2 \\ \geq 48n + 3(2n)^2 = 48n + 12n$$

(Inferred)

M_{χ^2} if $t \rightarrow \infty$ $\mu = 0$ $\sigma^2 = 1$	Normal $e^{\frac{ht}{2} + \frac{1}{2}\sigma^2 t^2}$ $e^{t/2}$
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7) Limiting form of χ^2 distribution for large degrees of freedom on χ^2 distribution

$$Z = \frac{\chi^2 - \frac{n}{2}}{\sqrt{2n}} \quad M_{Z(t)} = e^{at}$$

$$(1 + \frac{t}{2} + \frac{t^2}{8} + \dots)^{-\frac{n}{2}}$$

$$(1 + \frac{t}{2} + \frac{3t^2}{8} + \dots)^{-\frac{n}{2}}$$

$$\therefore \lim_{n \rightarrow \infty} M_Z(t) = e^{-\frac{t}{2}}$$

$$P = \frac{1}{2} \quad \text{if } t = 0 \quad P = 1$$

$$M_P = \frac{e^t}{2} \quad \text{if } t > 0 \quad P = 0$$

$$M_P = \frac{e^t}{2} \quad \text{if } t < 0 \quad P = 0$$

$$M_P = \frac{1}{2} + \frac{1}{2}e^{-|t|} \quad P = 1$$

Property of χ^2 distribution : If x has χ^2 distribution with n d.f. then

$$\int_0^\infty e^{-\frac{x}{2}} x^{n/2-1} dx = \alpha^{-n}$$

If x has a density function $f(x) = e^{-x}$ for $x > 0$ then $2x$ follows χ^2 distribution with 2 degrees of freedom (d.f.)

(b) The mgf of $2x$ is $M_{2x}(t) = E(e^{2xt})$

$$= \int_0^\infty e^{2xt} f(x) dx.$$

$$= \int_0^\infty e^{2xt} e^{-x} dx.$$

$$= \int_0^\infty e^{-(2t-1)x} dx.$$

$$= \int_0^\infty e^{-(1-2t)x} x^{1-1} dx.$$

$$= (1-2t)^{-1} \Gamma_1.$$

$\therefore M_{2x}(t) = (1-2t)^{-1}$ which is the mgf of χ_2^2 variate.

Hence $2x$ is distributed (or) χ^2 distribution with 2 d.f.

$$f(x) = \frac{e^{-\frac{x}{2}} (x)^{\frac{n}{2}-1}}{2^{\frac{n}{2}} \sqrt{\frac{\pi}{2^n}}} = \frac{e^{-\frac{x}{2}} (x)^{\frac{n}{2}-1}}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})}$$

on both sides $\int_0^\infty e^{-\frac{x}{2}} x^{\frac{n}{2}-1} dx = 2^{\frac{n}{2}} \Gamma(\frac{n}{2})$

for x lies on the interval $(0, \infty)$

If $x \sim N(0, 1)$ then $x^2 \sim \chi^2$ distribution with 1.d.f.

Proof:

Since $x \sim N(0, 1)$, $\therefore f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2}$ for $-\infty < x < \infty$.

Now the m.g.f. of x^2 is $M_{x^2}(t) = E(e^{tx^2})$

$$= \int_{-\infty}^{\infty} e^{tx^2} f(x) dx$$

$$= \int_{-\infty}^{\infty} e^{tx^2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} dx$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-x^2(\frac{1}{2}-t)} dx$$

$$= \frac{1}{\sqrt{2\pi}} \int_0^{\infty} e^{-(\frac{1-2t}{2})x^2} x^{2(\frac{1}{2}-1)} dx$$

$$= \frac{1}{\sqrt{2\pi}} \cdot 2 \cdot \frac{(\frac{1-2t}{2})^{-\frac{1}{2}} \Gamma(\frac{1}{2})}{2}$$

$$\therefore M_{x^2}(t) = \frac{1}{\sqrt{2\pi}} (\frac{1-2t}{2})^{-\frac{1}{2}} \cdot \sqrt{2\pi} \sqrt{\pi}$$

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

which is the m.g.f. of χ^2 variate

Hence x^2 is distributed as χ^2 distribution with 1.d.f.

$$\therefore f(x) \xrightarrow{\text{After simplification}} \frac{e^{-\frac{x^2}{2}} (x)^{\frac{k-1}{2}}}{2^{\frac{k}{2}} \Gamma(\frac{k}{2})} \xrightarrow{\text{After p.m.}} \frac{e^{-\frac{x^2}{2}} (x)^{\frac{k-1}{2}}}{\sqrt{2\pi}} \quad 0 < x < \infty$$

which is (the p.d.f. of x^2 distribution with k d.f.)

~~# Describes the additive property of the chi-square distribution.~~

The sum of independent chi-square variables is also a chi square variate. More precisely, if $x_1^2, x_2^2, \dots, x_k^2$ are ~~independent~~ x_i^2 with n_1, n_2, \dots, n_k d.f. then $x^2 = x_1^2 + x_2^2 + \dots + x_k^2$ follows x^2 distribution with $n = n_1 + n_2 + n_3 + \dots + n_k$ d.f.

Proof: We know that,

$$M_{x^2}(t) = M_{x_1^2} + x_2^2 + \dots + x_k^2(t)$$

$$= M_{x_1^2}(t) M_{x_2^2}(t) \dots M_{x_k^2}(t)$$

$$\therefore (1-2t)^{-\frac{n_1}{2}} (1-2t)^{-\frac{n_2}{2}} \dots (1-2t)^{-\frac{n_k}{2}}$$

$$= \underbrace{(1-2t)^{-\frac{(n_1+n_2+\dots+n_k)}{2}}}_{2}$$

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

Since the m.g.f. of x^2 with m. af. (is x)

$$(1-2t)^{-\frac{n}{2}}$$

so the other r.v. χ^2 with $M_{\chi^2}(t) = (1-2t)^{-\frac{(n+n_1+n_2+\dots+n_k)}{2}}$ of which

is the m.g.f. of a χ^2 variate

with $(n_1+n_2+\dots+n_k)$ d.f. Hence

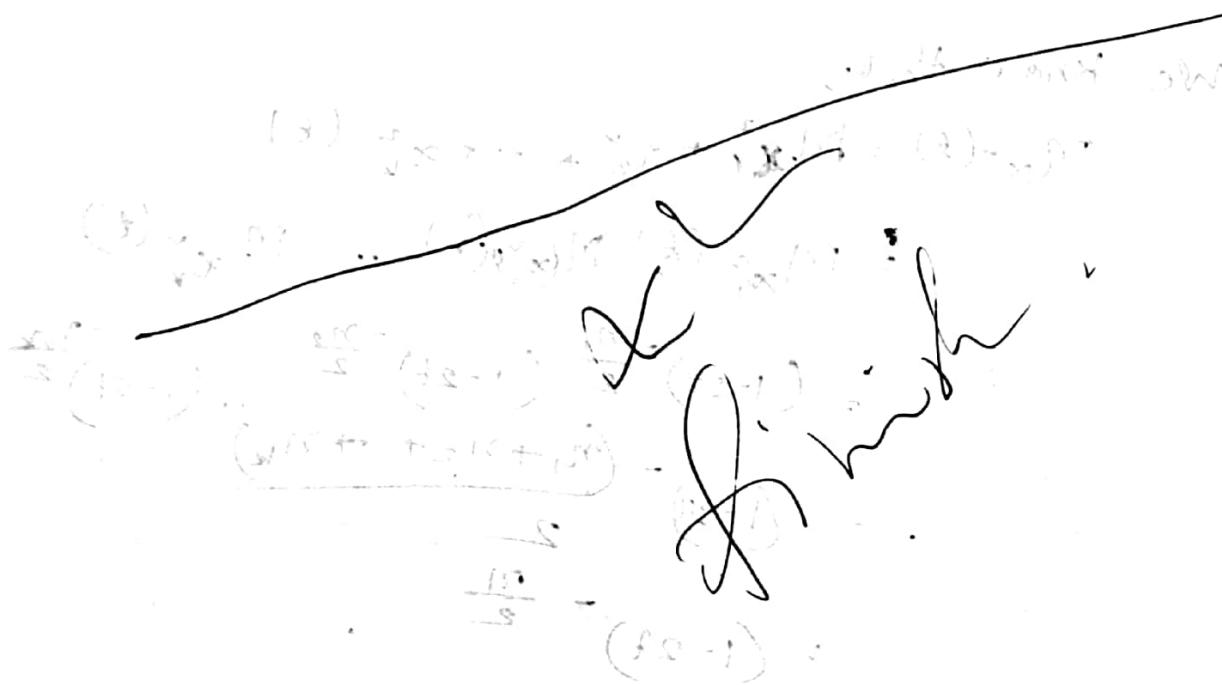
$$\chi^2 = \chi_1^2 + \chi_2^2 + \dots + \chi_k^2$$

χ^2 variate with $n = n_1 + n_2 + \dots + n_k$ d.f.

∴ the mode of χ^2 distribution is $n - k + 1$

[Mode of χ^2 distribution]

Ex. If χ^2 has n d.f. then mode of χ^2 is $n - k + 1$



t-distribution,

$F(x)$ \rightarrow cumulative density function.

$$\frac{d}{dx} F(x) = f(x)$$

$$F(x) = \int_{-\infty}^x f(x) dx$$

$f(x, y) = f(x), f(y)$
Joint d.f. of x & y
Marginal d.f. of x & y

$$\frac{d}{dx_1 dx_2} F(x_1, x_2) = f(x_1, x_2)$$

$$dF(x, x') = f(x, x') dx, dx'$$

$$f(x, x') = f(x) dx, f(x') dx'$$

Derivation of t-distribution \rightarrow to be continued

① Statement:

Let x be normally distributed with mean zero and variance unity.

Let x^2 be distributed as x^2 with n.t. x

and x^2 are independent then the ratio

$\frac{x}{\sqrt{x^2/(n-1)}}$ follows t-distribution with $n-1$ degrees of freedom.

Proof: if the joint p.d.f. of x^2 is given by

$$f(x^2) = \left(\frac{n}{2} \right)^{n/2} x^{n/2-1} e^{-x/2}$$

$$f(x^2) = \left(\frac{n}{2} \right)^{n/2} x^{n/2-1} e^{-x/2}$$

$$f(x^2) = \left(\frac{n}{2} \right)^{n/2} x^{n/2-1} e^{-x/2}$$

$$dF(n, x^*) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^*}{2}} d_n \frac{\frac{n}{2} \Gamma(\frac{n}{2})}{2^{n/2} \Gamma(\frac{n+1}{2})} e^{-\frac{x^*}{2}} (x^*)^{\frac{n}{2}-1}$$

(b) $t < x^*, t > x^*$

$$= \frac{1}{\sqrt{2\pi}} \frac{\frac{n}{2} \Gamma(\frac{n}{2})}{2^{n/2} \Gamma(\frac{n+1}{2})} e^{-\frac{x^*}{2}} t^{\frac{n}{2}-1} (x^*)^{\frac{n}{2}-1} dt$$

$$(x^*, x^*) \left[\begin{array}{l} t - x^* < x < \infty \\ 0 < x^* < \infty \end{array} \right]$$

Now, $t = \frac{x}{\sqrt{x^* n}}$ or, $x = t \sqrt{x^* n} \Rightarrow dx = \sqrt{x^* n} dt$.

The joint p.d.f. of t and x^* is given by

$$dF(t, x^*) = \frac{1}{\sqrt{2\pi}} \frac{\frac{n}{2} \Gamma(\frac{n}{2})}{2^{n/2} \Gamma(\frac{n+1}{2})} e^{-\frac{t^2 x^*}{2n}} e^{-\frac{x^*}{2}} (x^*)^{\frac{n-1}{2}} (x^*)^{\frac{n}{2}-1} dt dx$$

$$dt = \frac{1}{\sqrt{2\pi}} \frac{\frac{n}{2} \Gamma(\frac{n}{2})}{2^{n/2} \Gamma(\frac{n+1}{2})} \sqrt{n} e^{-\frac{x^*(1+\frac{t^2}{n})}{2}} (x^*)^{\frac{n+1}{2}-1} dt dx$$

After simplifying

$$\therefore dF(t) = \left[\frac{1}{\sqrt{2\pi}} \frac{\frac{n}{2} \Gamma(\frac{n}{2})}{2^{n/2} \Gamma(\frac{n+1}{2})} \int_0^\infty e^{-\frac{x^*(1+\frac{t^2}{n})}{2}} (x^*)^{\frac{n+1}{2}-1} dx \right] dt$$

$$= \frac{1}{\sqrt{2\pi}} \frac{\frac{n}{2} \Gamma(\frac{n}{2})}{2^{n/2} \Gamma(\frac{n+1}{2})} \left(\frac{1+\frac{t^2}{n}}{2} \right)^{-\frac{n+1}{2}} \Gamma\left(\frac{n+1}{2}\right) dt$$

$$\begin{aligned}
 &= \frac{\Gamma\left(\frac{n+1}{2}\right) \cdot 2^{\frac{n+1}{2}}}{\sqrt{n} \Gamma\left(\frac{n}{2}\right) \Gamma\left(\frac{1}{2}\right) \left(2^{\frac{n}{2} + \frac{1}{2}}\right) \left(1 + \frac{t^2}{n}\right)^{\frac{n+1}{2}}} \\
 &= \frac{dt}{\sqrt{n} \beta\left(\frac{n}{2}, \frac{1}{2}\right) \left(1 + \frac{t^2}{n}\right)^{\frac{n+1}{2}}}, \quad -\infty < t < \infty
 \end{aligned}$$

which is known as t distribution with d.f. n .

① What is t statistics?

All odd order moments of t distribution are zero.

$$\mu'_{2r+1} = E(t^{2r+1}): \quad r = 0, 1, 2, 3, \dots$$

$$= \int_{-\infty}^{\infty} t^{2r+1} f(t) dt.$$

$$= \int_{-\infty}^{\infty} t^{2r+1} \frac{1}{\sqrt{n} \beta\left(\frac{n}{2}, \frac{1}{2}\right) \left(1 + \frac{t^2}{n}\right)^{\frac{n+1}{2}}} dt,$$

$$= \frac{1}{\sqrt{n} \beta\left(\frac{n}{2}, \frac{1}{2}\right)} \int_{-\infty}^{\infty} \frac{t^{2r+1}}{\left(1 + \frac{t^2}{n}\right)^{\frac{n+1}{2}}} dt$$

$$= \frac{1}{\sqrt{n} \beta\left(\frac{n}{2}, \frac{1}{2}\right)} \int_{-\infty}^{\infty} g(t) dt. \quad \text{where, } g(t) = \frac{t^{2r+1}}{\left(1 + \frac{t^2}{n}\right)^{\frac{n+1}{2}}}; \\ r = 0, 1, 2, 3, \dots$$

$$\text{Now, } g(-t) = \frac{(-t)^{2n+1}}{\left(1 + \frac{(-t)^2}{n}\right)^{\frac{n+1}{2}}} = \frac{-t^{2n+1} \cdot (-1)^{\frac{n+1}{2}}}{\left(1 + \frac{t^2}{n}\right)^{\frac{n+1}{2}}}$$

$$\Rightarrow -g(-t) = \frac{t^{2n+1}}{\left(1 + \frac{t^2}{n}\right)^{\frac{n+1}{2}}}$$

$\therefore g(t) = -g(-t) \therefore g(t)$ is an odd function.

$$\text{So, } \int_{-\infty}^{\infty} g(t) dt = 0.$$

$$\therefore \mu'_{2n+1} = \frac{1}{\sqrt{n} \beta\left(\frac{n}{2}, \frac{1}{2}\right)} (0) = 0; \quad n = 0, 1, 2, \dots$$

\Rightarrow All odd or raw moments of t distribution are zero.

$$\therefore \mu'_{2n+1} = 0 \therefore \mu_{2n+1} = 0, \quad \text{for } n = 0, 1, 2, \dots$$

\Rightarrow All odd order raw and central moments of t distribution are zero.

Even order moments of t distribution.

We know that, $\mu_{2n} = E(t^{2n}) = \int_{-\infty}^{\infty} t^{2n} f(t) dt$.

$$\text{Gamma function} \quad \Gamma(m, n) = \int_0^{\infty} x^{m-1} \frac{x^n}{(1+x)^{m+n}} dx$$

$$= \int_{-\infty}^{\infty} t^{2n} \frac{1}{\sqrt{n} \beta\left(\frac{m}{2}, \frac{1}{2}\right) \left(1 + \frac{t^2}{n}\right)^{\frac{m+1}{2}}} dt.$$

$$= \frac{1}{\sqrt{n} \beta\left(\frac{m}{2}, \frac{1}{2}\right)} \int_{-\infty}^{\infty} \frac{t^{2n}}{\left(1 + \frac{t^2}{n}\right)^{\frac{m+1}{2}}} dt$$

$$= \frac{1}{\sqrt{n} \beta\left(\frac{m}{2}, \frac{1}{2}\right)} \int_{-\infty}^{\infty} g(t)^2 dt \quad \text{where } g(t)^2 = \frac{t^{2n}}{\left(1 + \frac{t^2}{n}\right)^{\frac{m+1}{2}}}$$

$$\text{Now, } g(-t) = \frac{(-t)}{\left(1 + \frac{(-t)^2}{n}\right)^{\frac{m+1}{2}}} = \frac{-t}{\left(1 + \frac{t^2}{n}\right)^{\frac{m+1}{2}}}$$

$$\Rightarrow g(-t) = \frac{t^{2n}}{\left(\frac{t^2}{n}\right)^{\frac{m+1}{2}} \left(1 + \frac{t^2}{n}\right)^{\frac{m+1}{2}}} = (-t)^{2n} \left(\frac{t^2}{n}\right)^{\frac{m+1}{2}}$$

$\therefore g(t) = g(-t) \therefore g(t)$ is even fun.

$$\text{So, } \left(\int_{-\infty}^{\infty} g(t) dt \right)^2 = 2 \int_0^{\infty} g(t)^2 dt$$

$$\mu_{2n} = \frac{2}{\sqrt{n} \beta\left(\frac{m}{2}, \frac{1}{2}\right)} \int_0^{\infty} g(t)^2 dt = \frac{2}{\sqrt{n} \beta\left(\frac{m}{2}, \frac{1}{2}\right)} \cdot \left(\frac{n^m}{2^m (m+1)}\right)^{\frac{1}{2}} = \frac{n^m}{2^m (m+1)^{\frac{1}{2}}}$$

Now putting the value of $g(t)$ in the above equation, we obtain

$$\mu_{2n}' = \frac{1}{\sqrt{n} \beta\left(\frac{n}{2}, \frac{1}{2}\right)} \int_0^\infty \frac{t^{2n}}{\left(1 + \frac{t^r}{n}\right)^{\frac{n+1}{2}}} dt.$$

$$\mu_{2n}' = \frac{n^n}{\sqrt{n} \beta\left(\frac{n}{2}, \frac{1}{2}\right)} \int_0^\infty \frac{\left(\frac{t^r}{n}\right)^n n^n}{\left(1 + \frac{t^r}{n}\right)^{\frac{n+1}{2}}} dt.$$

$$= \frac{n^n}{\sqrt{n} \beta\left(\frac{n}{2}, \frac{1}{2}\right)} \int_0^\infty \frac{\left(\frac{t^r}{n}\right)^n nt^{-1} \frac{rt}{n} dt}{\left(1 + \frac{t^r}{n}\right)^{\frac{n+1}{2}}}$$

$$= \frac{n^{n-\frac{1}{2}}}{\beta\left(\frac{n}{2}, \frac{1}{2}\right)} \int_0^\infty \frac{\left(\frac{t^r}{n}\right)^{(n+1)-1} nt^{-1} d\left(\frac{t^r}{n}\right)}{\left(1 + \frac{t^r}{n}\right)^{\frac{n+1}{2}}} \quad \left| d\left(\frac{t^r}{n}\right) = \frac{rt^r}{n} dt \right.$$

$$\mu_{2n}' = \frac{n^n}{\beta\left(\frac{n}{2}, \frac{1}{2}\right)} \int_0^\infty \frac{\left(\frac{t^r}{n}\right)^{(n+1)-1} \left(\frac{t^r}{n}\right)^{-\frac{1}{2}} dt}{\left(1 + \frac{t^r}{n}\right)^{\frac{n+1}{2}}} d\left(\frac{t^r}{n}\right)$$

$$= \frac{n^n}{\beta\left(\frac{n}{2}, \frac{1}{2}\right)} \int_0^\infty \frac{\left(\frac{t^r}{n}\right)^{(n+\frac{1}{2})-1} dt}{\left(1 + \frac{t^r}{n}\right)^{(n+\frac{1}{2}) + \frac{n+1}{2} - n - \frac{1}{2}}} \left| \begin{array}{l} \beta(m, n) \\ \int_0^\infty x^{m-1} dx \\ \int_0^\infty \frac{x}{(x+1)^{m+n}} dx \end{array} \right.$$

$$= \frac{n^n}{\beta\left(\frac{n}{2}, \frac{1}{2}\right)} \beta\left(n + \frac{1}{2}, \frac{n+1}{2} - n\right). \quad \beta(m, n) = \frac{\Gamma(m)\Gamma(n)}{\Gamma(m+n)}$$

$$= \frac{\Gamma\left(\frac{n+1}{2}\right) n^n}{\Gamma\left(\frac{n}{2}\right)\Gamma\left(\frac{1}{2}\right)} \cdot \frac{\Gamma\left(n+\frac{1}{2}\right)\Gamma\left(\frac{n}{2}-n\right)}{\Gamma\left(\frac{n+1}{2}\right)}$$

After multiplying numerator & denominator by $\Gamma\left(\frac{n+1}{2}\right)$

$$\therefore M_{2n} = \frac{\Gamma\left(\frac{n}{2}-n\right)\Gamma\left(n+\frac{1}{2}\right)n^n}{\Gamma\left(\frac{n}{2}\right)\Gamma\left(\frac{1}{2}\right)} \quad \boxed{n = 1, 2, 3}$$

M_{2n} =

- $n=1$: $\frac{\Gamma(0)\Gamma(1/2)}{\Gamma(1/2)\Gamma(1)} = 1$ (True)
- $n=2$: $\frac{\Gamma(-1)\Gamma(3/2)}{\Gamma(1)\Gamma(1/2)} = -\frac{1}{2}$ (True)
- $n=3$: $\frac{\Gamma(-2)\Gamma(5/2)}{\Gamma(2)\Gamma(1/2)} = \frac{3}{8}$ (True)
- $n=4$: $\frac{\Gamma(-3)\Gamma(7/2)}{\Gamma(3)\Gamma(1/2)} = -\frac{5}{16}$ (True)
- $n=5$: $\frac{\Gamma(-4)\Gamma(9/2)}{\Gamma(4)\Gamma(1/2)} = \frac{35}{128}$ (True)
- $n=6$: $\frac{\Gamma(-5)\Gamma(11/2)}{\Gamma(5)\Gamma(1/2)} = -\frac{315}{512}$ (True)
- $n=7$: $\frac{\Gamma(-6)\Gamma(13/2)}{\Gamma(6)\Gamma(1/2)} = \frac{3465}{4096}$ (True)
- $n=8$: $\frac{\Gamma(-7)\Gamma(15/2)}{\Gamma(7)\Gamma(1/2)} = -\frac{3465}{262144}$ (True)

04.03.18

Student's t distribution

Statement: If x_1, x_2, \dots, x_n is a random sample from normal population with mean μ and variance σ^2 (then $t = \frac{\bar{x} - \mu}{\sigma/\sqrt{n}}$) will be distributed as student's t with $n-1$ d.f, where $\bar{x} = \sum x_i/n$ is the simple mean and $s^2 = \frac{\sum (x_i - \bar{x})^2}{n-1}$ is an unbiased estimate of the population variance or

→ property of t distribution.

- ① State.
- ② odd order mn.
- ③ even - .
- ④ Student's t when $n-1$ is free dist
- ⑤ Skewness, Kurtosis,
- ⑥ Mean, median, variance.

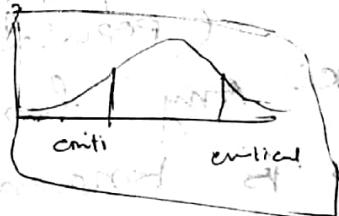
$$F = \frac{\bar{X}_1^2 / n_1}{\bar{X}_2^2 / n_2} = \frac{n_2 \bar{X}_1^2}{n_1 \bar{X}_2^2} \sim F_{n_1, n_2} \text{ for } 0 < F < \infty$$

prefered

III \bar{X}_1^2 / n_1 $\sim \chi^2_{n_1}$ \bar{X}_2^2 / n_2 $\sim \chi^2_{n_2}$ \rightarrow $\chi^2_{n_1} / \chi^2_{n_2} \sim F_{n_1, n_2}$

Null hypothesis H_0 : $\mu_1 = \mu_2$ \rightarrow $\bar{X}_1 = \bar{X}_2$ \rightarrow $\chi^2_{n_1} = \chi^2_{n_2}$ \rightarrow $F = 1$

Alternative hypothesis H_1 : $\mu_1 \neq \mu_2$ \rightarrow $\bar{X}_1 \neq \bar{X}_2$ \rightarrow $\chi^2_{n_1} \neq \chi^2_{n_2}$ \rightarrow $F \neq 1$



Decision Rule: If F is significant ($F > F_{\text{critical}}$) then H_0 is rejected.

Conclusion: A significant difference between the two samples suggests that there is a difference between the two populations.

Significance level: The probability of making a type I error.

Type I error: Rejecting the null hypothesis when it is true.

Type II error: Failing to reject the null hypothesis when it is false.

Power of the test: $1 - \beta$ (probability of correctly rejecting the null hypothesis).

power = $1 - \beta$

Assume H_0 is true: $\mu_1 = \mu_2$ \rightarrow $\bar{X}_1 = \bar{X}_2$ \rightarrow $\chi^2_{n_1} = \chi^2_{n_2}$ \rightarrow $F = 1$

Assume H_1 is true: $\mu_1 \neq \mu_2$ \rightarrow $\bar{X}_1 \neq \bar{X}_2$ \rightarrow $\chi^2_{n_1} \neq \chi^2_{n_2}$ \rightarrow $F \neq 1$

Probability of Type I error: $P(F > F_{\text{critical}} | H_0)$

Probability of Type II error: $P(F \leq F_{\text{critical}} | H_1)$

Power of the test: $1 - \beta$

13.02.18

gupta kevur

#

Parameter: Parameter is an unknown constant which uniquely specify the distribution (Population)

Statistic: Any function of a set of sample values is known as a statistic.

Statistical Hypothesis: A statistical hypothesis is an assertion about the distribution of one or more random variable. From definition it follows that not every hypothesis is a statistical hypothesis. There are two kinds of statistical hypothesis, ① Simple hypothesis. ② Composite hypothesis.

Some definitions

Statistical Hypothesis: A statistical hypothesis is an assertion about the distribution of one or more random variable.

Types of Hypothesis [Null Hypothesis
Alternative]

Null Hypothesis: A statistical hypothesis which is picked up for testing is known as Null hypothesis. It is denoted by H_0 .

Alternative Hypothesis: Any hypothesis other than null hypothesis that we might consider as alternative to null hypothesis is known as Alternative hypothesis. It is denoted by H_1 .

Simple Hypothesis: If the statistical hypothesis completely specifies the distribution then it is called simple hypothesis.

Composite Hypothesis: If the statistical hypothesis does not completely specify the distribution then it is called a composite hypothesis.

~~Test statistic~~: The statistic is used to provide evidence about the null hypothesis is called the ~~test~~ statistic.

~~First kind of Error~~: Rejection of true null hypothesis (H_0) when it is true. It is an incorrect decision or an error. This error is known as first kind of error or Type-I error.

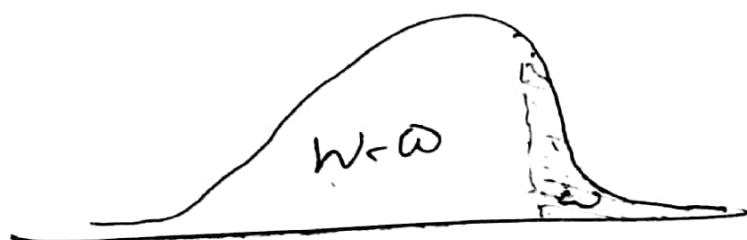
~~Second kind of Error~~: Acceptance of false null hypothesis (H_0) when it is false i.e. H_1 is true. Which is known as second kind of error or Type-II error.

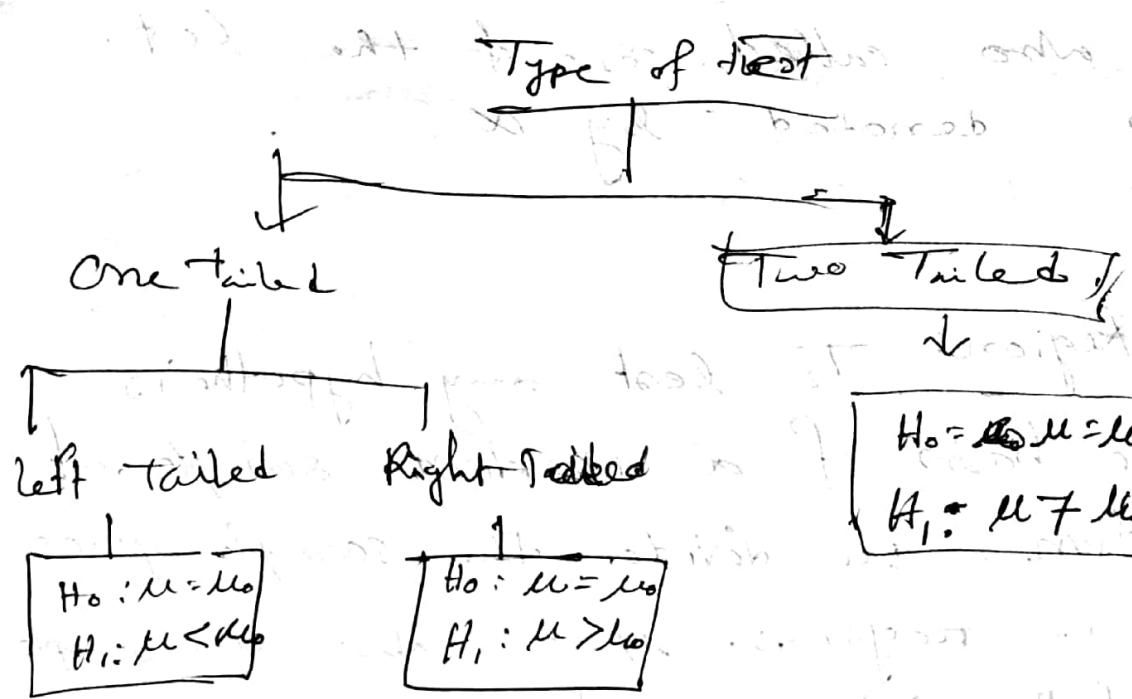
~~Level of significance~~: The probability of null hypothesis (H_0) when it is true is known as the level of significance of the test.

It is also called size of the test.
It is denoted by α .

Critical Region: To test any hypothesis on the basis of a random sample of observations, we divide the sample space into two regions. If the observed sample point falls into one of these regions, say ω then we reject the null hypothesis — this region is called critical region.

Acceptance Region: The region consisting of points belonging to sample space but not to the critical region is called acceptance region. It is denoted by $W - \omega$.





Decision Rule

If $P < 0.05$ then H_0 is rejected at 5% level of significance.

If $P < 0.01$ then H_0 is rejected at 1% level of significance.

Mean Test:

Type of Mean Test	Variance Status	Test statistic
Single Mean Test	with known variance	Z
	with unknown variance	Z or t
Double Mean Test	with known variance	Z
	with unknown variance	t
Several mean test		F

Corrected Term (CT) = $\frac{1}{n} \cdot \sigma^2$

sum of square (SS) = $\sum_{i=1}^k \sum_{j=1}^{n_i} y_{ij} \cdot CT$

Sum of square Between (SSB)

$SS_B = \sum_{i=1}^k \left\{ \frac{T_i^2}{n_i} \right\}$

Sum of square Within (SSW)

Total sum of square = sum of square between + sum of square within

Sum of square between = sum of square between / sum of square within

Sum of square within = sum of square within / sum of square within

Sum of square between = sum of square between / sum of square within

Gupta or kapur

		The null hypothesis is true	
		Type I error (rejecting a true null hypothesis)	Type II error (failing to reject a false null hypothesis)
Decision	We decide to reject null hypothesis	Correct Decision	Correct Decision
	We fail to reject the null hypothesis	Correct Decision	Type II error (failing to reject a false null hypothesis)

B

Power of a Test:

The power of a hypothesis test is the probability ($1 - \beta$) of rejecting a false null hypothesis, which is computed by using a particular significance level α and a particular value of the population parameters that is an alternative to the value assumed true in the null hypothesis. That is the power of the

hypothesis tests in the probability
of supporting an alternative
hypothesis that is true

single mean test (σ known)



$$Z_1 = \frac{\bar{x} - \mu}{\sigma}$$

Normality of \bar{x} based on Z_A

and Z_B under hypothesis H_1

but also Z_A and Z_B are independent

so that $Z_A + Z_B$ is

normal with mean 0 and SD $\sqrt{2}$

also $Z_A + Z_B$ has SD $\sqrt{2}$

standardized Z has SD 1

so $Z_A + Z_B$ has SD 1

9

Rec
337

Dependent variables → Response variable
Independent → Explanatory.
Today

At 5% level of significance
the tabulated value of t are
 ± 1.96 but our calculated
of t is -1.14 which falls
in the acceptance region
so we may accept our
null hypothesis. Hence
our test is insignificant.

2-03.18

$$\begin{pmatrix} dx \\ dy \\ dz \end{pmatrix}$$



\approx calculated

$\mu_1 = \mu_2 = 65.0$ inch

$$(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)$$

$$(\bar{x}_1 - \mu_1) - (\bar{x}_2 - \mu_2)$$

$$s_1^2 = \frac{\sum (x_{1i} - \bar{x}_1)^2}{n_1 - 1}$$

$$s_2^2 = \frac{\sum (x_{2i} - \bar{x}_2)^2}{n_2 - 1}$$

$$s_1^2 (n_1 - 1) = \sum (x_{1i} - \bar{x}_1)^2$$

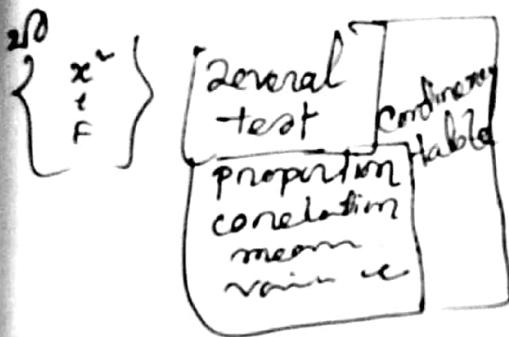
$$s_2^2 (n_2 - 1) = \sum (x_{2i} - \bar{x}_2)^2$$

$$s^2 = \frac{\sum (x_{1i} - \bar{x}_1)^2 + \sum (x_{2i} - \bar{x}_2)^2}{n_1 + n_2 - 2}$$

$$s_1^2 (n_1 - 1) + s_2^2 (n_2 - 1)$$

$$n_1 + n_2 - 2$$

M.L.E. Parameter estimate. Gupta and Kapoor



$$f(x) = \frac{e^{-\frac{x^2}{2}} (x)^{\frac{n}{2}-1}}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} \quad 0 \leq x \leq \infty$$

~~M.G.F~~ M.G.F of x^2 distribution is $M_{x^2}(t) = (1-2t)^{-\frac{n}{2}}$

$$\mu_1' = \frac{d}{dt} (1-2t)^{-\frac{n}{2}} \Big|_{t=0}$$

$\left. \begin{array}{l} \mu_2 = \mu_2 - (\mu_1)^2 \\ \mu_3 = \mu_3 - 3\mu_2 \mu_1 + 2(\mu_1)^3 \end{array} \right\}$
 $\left. \begin{array}{l} \mu_4 = \mu_4 - 4\mu_3 \mu_1 + 6\mu_2 \mu_1 - 3(\mu_1)^4 \end{array} \right\}$

$$m_{x^2}(t) = m_{x_1^2 + x_2^2 + \dots}(t)$$

$$= m_{x_1^2}(t) m_{x_2^2}(t)$$

g.a.f $f(x^2) = \frac{e^{-\frac{x^2}{2}} (x^2)^{\frac{n_2}{2}}}{2^{\frac{n_2}{2}} \sqrt{\frac{n_2}{2}}}$

$$m_x(t) = m_{x_1^2}(t) m_{x_2^2}(t) \dots$$

$$= (1-2t)^{\frac{m_1}{2}} (1-2t)^{-\frac{n_2}{2}}$$

$$= (1-2t)^{-\frac{(m_1+n_2+\dots)}{2}}$$

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

M.G.F. on

$$M_{2n}(t) := E(e^{2nt})$$

$$= \int_0^\infty e^{2nt} f(x) dx.$$

$$= \int_0^\infty e^{-x} (e^{-x})^{2n} f(x) dx = M_2(t) x^{-2n}.$$

$$= \int_0^\infty e^{-(1-2t)x} dx =$$

$$= \int_0^\infty e^{-(1-2t)x} x^{1-2n} dx,$$

$$= (1-2t)^{-2} \Gamma(1-2n).$$

$$m_{2n}(t) = (1-2t)^{-1} \cdot \underbrace{e^{-(1-2t)\frac{n}{2}}}_{\text{job}} \cdot \underbrace{\Gamma(1-2n)}_{=}$$

If x_i : ($i=1 \dots n$) are in line

$N(\mu, \sigma^2)$ then the gen

$$x' = \sum (x_i - \mu) \frac{1}{\sigma} \text{ is } \sim$$

$$\sim N(0, 1).$$

$$\text{Let } Z_i = \frac{x_i - \mu_i}{\sigma_i}, i=1, \dots, n.$$

Since $x_i \sim N(\mu_i, \sigma^2)$;

$$Z_i \sim N(0, 1)$$

$$M_{x^*}(t) = M \sum_{i=1}^n \left(\frac{x_i - \mu_i}{\sigma_i} \right)^* (t)$$

$$= M \sum_{i=1}^n z_i^*(t)$$

$$M_{z_i^*}(t)$$

Now

$$M_{z_i^*}(t) = E(e^{t z_i^*})$$

$$= \int_{-\infty}^{\infty} e^{t z_i^*} f(z_i) dz_i$$

$$= \int_{-\infty}^{\infty} e^{t z_i^*} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} z_i^2} dz_i$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-(\frac{1}{2} - t) z_i^2} dz_i$$

$$\begin{aligned}
 &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\left(\frac{1-2t}{2}\right) z_i^2} (z_i)^{2\cdot\frac{1}{2}-1} dz_i \\
 &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\left(\frac{1-2t}{2}\right) z_i^2} (z_i)^{2\cdot\frac{1}{2}-1} dz_i \\
 &\geq \frac{1}{\sqrt{2\pi}} 2 \sqrt{\left(\frac{1-2t}{2}\right)^{\frac{-1}{2}}} \Gamma\left(\frac{1}{2}\right) \\
 &\geq \frac{1}{\sqrt{2\pi}} \left(\frac{2}{1-2t}\right)^{\frac{1}{2}} \Gamma\left(\frac{1}{2}\right) \\
 &= \frac{1}{\sqrt{2\pi}} \left(\frac{2}{1-2t}\right)^{\frac{1}{2}} \Gamma\left(\frac{1}{2}\right) \\
 &= \boxed{(1-2t)^{-\frac{1}{2}}}.
 \end{aligned}$$

$$\begin{aligned}
 M_{X^n(t)} &= \prod_{i=1}^n M_{Z_i^n}(t) \\
 &= \prod_{i=1}^n M_{Z_i}(t) \\
 &= \prod_{i=1}^n (1-2t)^{\frac{1}{2}}.
 \end{aligned}$$

$$M_{X^n}(t) = (1-2t)^{\frac{n}{2}} \text{ o.r.f.}$$

$$\text{Since } f(n) = \frac{x^n e^{-x^2/2}}{\Gamma n}.$$

$$E(X^n) = \int_0^\infty x^n f(x) dx = \int_0^\infty x^n \frac{x^n e^{-x^2/2}}{\Gamma n} dx = \frac{1}{\Gamma n} \int_0^\infty x^{2n} e^{-x^2/2} dx$$

$$= \frac{1}{\Gamma n} \int_0^\infty x^{2n} e^{-x^2/2} dx = \frac{1}{\Gamma n} \int_0^\infty x^{2n} e^{-x^2/2} dx$$

$$V(X^n) = E(X^n)^2 - [E(X^n)]^2$$

$$\int_0^\infty x^{2n} e^{-x^2/2} dx = \frac{1}{2} \int_0^\infty x^{2n} e^{-x^2/2} dx = \frac{1}{2} \int_0^\infty x^{2n} e^{-x^2/2} dx$$

$$\int_0^\infty x^{2n} e^{-x^2/2} dx = \frac{1}{2} \int_0^\infty x^{2n} e^{-x^2/2} dx = \frac{1}{2} \int_0^\infty x^{2n} e^{-x^2/2} dx$$

$$\int_0^\infty x^{2n} e^{-x^2/2} dx = \frac{1}{2} \int_0^\infty x^{2n} e^{-x^2/2} dx = \frac{1}{2} \int_0^\infty x^{2n} e^{-x^2/2} dx$$

If x_i follow $N(0, 1)$

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

mean. wrt.

α

F Distribution:

Statement: If x_1 and x_2 are independent $\sim N$ variates with d.f. n_1 and n_2 respectively, then

the ratio $F = \frac{\frac{x_1}{n_1}}{\frac{x_2}{n_2}} : \frac{n_2 x_2}{n_1 x_1}$ will possess

F distribution with numerator d.f. n_1 and denominator d.f. n_2 and the distribution

of F will be of the form.

$$d.F(F) = \frac{n_1^{\frac{n_1}{2}} n_2^{\frac{n_2}{2}} F^{\frac{n_1}{2}-1}}{\beta\left(\frac{n_1}{2}, \frac{n_2}{2}\right) (n_F + n_2)^{\frac{n_1+n_2}{2}}}$$

$$\text{d.f. } 0 \leq F < \infty \\ n_1 > 0, n_2 > 0$$

$$\left(\frac{n_1}{2} - 1\right)$$

$$(n_F + n_2)^{\frac{n_1+n_2}{2}}$$

Proof:

Since x_1^{\sim} and x_2^{\sim} are independently distributed x^{\sim} variate with d.f. n_1 and n_2 respectively. Then the joint p.d.f. of x_1^{\sim} and x_2^{\sim} is

$$f(x_1^{\sim}, x_2^{\sim}) = \frac{e^{-\frac{x_1^{\sim}}{2}} (x_1^{\sim})^{\frac{n_1}{2}-1}}{2^{\frac{n_1}{2}} \Gamma(\frac{n_1}{2})} \frac{e^{-\frac{x_2^{\sim}}{2}} (x_2^{\sim})^{\frac{n_2}{2}-1}}{2^{\frac{n_2}{2}} \Gamma(\frac{n_2}{2})}$$

$$= \frac{e^{-\frac{x_1^{\sim}}{2}} e^{-\frac{x_2^{\sim}}{2}} (x_1^{\sim})^{\frac{n_1}{2}-1} (x_2^{\sim})^{\frac{n_2}{2}-1}}{2^{\frac{n_1+n_2}{2}} \Gamma(\frac{n_1}{2}) \Gamma(\frac{n_2}{2})}$$

$$0 < x_1^{\sim} < \infty$$

$$0 < x_2^{\sim} < \infty$$



Now, $F_2 \frac{m_2}{m_1} \frac{\alpha_1^2}{\alpha_2^2}$ and let $\omega = \alpha_2^2$

$\therefore x_1^2 = \frac{m_1}{m_2} x_2^2 F$ and $x_2^2 = \omega$.

$$\Rightarrow x_1^2 = \frac{m_1}{m_2} F \omega$$

$$\text{So } |J| = \begin{vmatrix} \frac{dx_1}{dF} & \frac{dx_2}{dF} \\ \frac{dx_1}{d\omega} & \frac{dx_2}{d\omega} \end{vmatrix} = \begin{vmatrix} \frac{m_1}{m_2} \omega^0 \\ \frac{m_1}{m_2} F \end{vmatrix}$$

$$= \frac{m_1}{m_2} \omega.$$

\therefore The joint pdf of F and ω is

$$f(F, \omega) = \frac{1}{\frac{m_1+m_2}{2} \Gamma(\frac{m_1}{2}) \Gamma(\frac{m_2}{2})} \left(\frac{m_1}{2m_2} F \omega \right)^{\frac{m_1}{2}-1} \left(\frac{\omega}{2} \left(\frac{m_1}{m_2} F \omega \right)^{\frac{m_1}{2}-1} \right)^{\frac{m_2}{2}-1}$$

$$= \frac{1}{\frac{m_1+m_2}{2} \Gamma(\frac{m_1}{2}) \Gamma(\frac{m_2}{2})} \left[-\frac{\omega}{2} \left(1 + \frac{m_1}{m_2} F \right) \right]^{\frac{m_1}{2}-1} \left(\frac{m_1}{m_2} F \right)^{\frac{m_2}{2}-1}$$

$$\left(\frac{\omega}{2} \right)^{\frac{m_2}{2}-1} \left(\frac{m_1}{m_2} \omega \right)^{\frac{m_1}{2}-1}$$

$$= \frac{1}{2^{\frac{n_1+n_2}{2}} \Gamma_{\frac{n_1}{2}} \Gamma_{\frac{n_2}{2}}} e^{-\frac{\omega}{2} \left(1 + \frac{n_1}{n_2} F\right)} \left(\frac{n_1}{n_2}\right)^{\frac{n_1}{2}} (F)^{\frac{n_1}{2}-1}$$

$$\textcircled{w} \quad \frac{n_1+n_2}{2} - 1$$

$$0 < F < \infty$$

$$0 < w < \infty$$

$$\text{Now, } f(F) = \int_w f(F, w)$$

$$= \frac{1}{2^{\frac{n_1+n_2}{2}} \Gamma_{\frac{n_1}{2}} \Gamma_{\frac{n_2}{2}}} \left(\frac{n_1}{n_2}\right)^{\frac{n_1}{2}} (F)^{\frac{n_1}{2}-1}$$

$$\int_0^\alpha e^{-\frac{\omega}{2} \left(1 + \frac{n_1}{n_2} F\right)} \textcircled{w}^{\frac{n_1+n_2}{2}-2} d\omega$$

$$= \frac{1}{2^{\frac{n_1+n_2}{2}} \Gamma_{\frac{n_1}{2}} \Gamma_{\frac{n_2}{2}}} \left(\frac{n_1}{n_2}\right)^{\frac{n_1}{2}} (F)^{\frac{n_1}{2}-1}$$

$$\left\{ \frac{1}{2} \left(1 + \frac{n_1}{n_2} F\right) \right\}_{-\left\{ \frac{n_1+n_2}{2} \right\}}$$

$$\left(\frac{n_1}{n_2}\right)^{\frac{n_1}{2}} (F)^{\frac{n_1}{2}-1}$$

$$\frac{2}{(n_2+n_1 F)}^{\frac{n_1+n_2}{2}}$$

$$= \frac{1}{\frac{n_1+n_2}{2} \Gamma_{\frac{n_1}{2}} \Gamma_{\frac{n_2}{2}}} e^{-\frac{\omega}{2}(1+\frac{n_1}{n_2}F)} \left(\frac{n_1}{n_2} \right)^{\frac{n_1}{2}} (F)^{\frac{n_1}{2}-1}$$

$$\textcircled{1} \quad \frac{n_1+n_2}{2} = 1$$

Now, $f(F) = \int_{-\infty}^{\infty} f(F, \omega) d\omega$

$$= \frac{1}{\frac{n_1+n_2}{2} \Gamma_{\frac{n_1}{2}} \Gamma_{\frac{n_2}{2}}} \left(\frac{n_1}{n_2} \right)^{\frac{n_1}{2}} (F)^{\frac{n_1}{2}-1}$$

$$= \int_0^{\infty} e^{-\frac{\omega}{2}(1+\frac{n_1}{n_2}F)} (\omega)^{\frac{n_1+n_2}{2}-2} d\omega$$

$$= \frac{1}{\frac{n_1+n_2}{2} \Gamma_{\frac{n_1}{2}} \Gamma_{\frac{n_2}{2}}} \left(\frac{n_1}{n_2} \right)^{\frac{n_1}{2}} (F)^{\frac{n_1}{2}-1}$$

$$\left\{ \frac{1}{2} \left(1 + \frac{n_1}{n_2} F \right) \right\}^{-\frac{n_1+n_2}{2}}$$

$$\left(\frac{n_1+n_2}{2} \right)$$

$$\left(\frac{n_1}{n_2} \right)^{\frac{n_1}{2}} (F)^{\frac{n_1}{2}-1}$$

$$= \frac{\frac{2}{\Gamma_{\frac{n_2}{2}} \Gamma_{\frac{n_1}{2}} F}}{\frac{n_1+n_2}{2} \Gamma_{\frac{n_1}{2}} \Gamma_{\frac{n_2}{2}}} \left(\frac{2}{\frac{n_2}{n_1} + \frac{n_1}{n_2} F} \right)^{\frac{n_1+n_2}{2}}$$

$$\frac{F \left(\frac{n_1}{2} + \frac{n_2}{2} \right)}{\Gamma_{\frac{n_1}{2}} \Gamma_{\frac{n_2}{2}}}$$

$$\begin{aligned}
 &= \left(\frac{n_1}{n_2} \right) \frac{m_1}{2} (F)^{\frac{n_1}{2}-1} (2)^{\frac{n_1+n_2}{2}} \cdot \frac{(n_2+n_1F)^{\frac{n_1+n_2}{2}}}{\beta(m, n)} \\
 &\quad \xrightarrow{2 \left(\frac{m_1+n_2}{2} \right) \text{ term}} \frac{(n_2+n_1F)^{\frac{n_1+n_2}{2}}}{\beta(m, n)} \\
 &= \left(\frac{m_1}{n_2} \right)^{\frac{n_1}{2}} (n_2)^{\frac{m_1}{2}} (n_2)^{\frac{n_2}{2}} (F)^{\frac{m_1}{2}-1} \cdot (\times) \\
 &= \frac{\beta(m, n) (n_2+n_1F)^{\frac{n_1+n_2}{2}}}{\beta(m, n) (n_2+n_1F)^{\frac{n_1+n_2}{2}}} \quad 0 \leq F < \infty
 \end{aligned}$$

which is the form
of F distribution with.

$$d.f.f. = \left(\frac{x^b}{b^b} \right)$$

13.05

converge

for numerator

$$\begin{aligned}
 &\int_{0}^{x^b} \frac{x^{m-1}}{\left(\frac{x^b}{b^b} - 1 \right)^{m+n}} dx \\
 &= \left(\frac{x^b}{b^b} \right)^{m+n-1} \cdot \frac{1}{\left(\frac{x^b}{b^b} - 1 \right)^{m+n}} = \left(\frac{x^b}{b^b} \right)^m \cdot \frac{1}{\left(\frac{x^b}{b^b} - 1 \right)^n} \\
 &= \beta(m, n)
 \end{aligned}$$

Property of F distribution:

Establish F distribution from Beta distribution of First kind.

$$f(x) = \frac{1}{\beta(\frac{n_1}{2}, \frac{n_2}{2})} x^{\frac{n_1}{2}-1} (1-x)^{\frac{n_2}{2}-1} \cdot \left(\frac{1}{x}\right)^{\frac{n_2}{2}}$$

let $x = \frac{n_1 F}{n_2 + n_1 F}$

$$\begin{aligned} \therefore \frac{dx}{dF} &= \frac{(n_2 + n_1 F) n_1 - n_1 F (0+n_1)}{(n_2 + n_1 F)^2} \\ &= \frac{n_1 n_2 + n_1^2 F - n_1^2 F}{(n_2 + n_1 F)^2} \end{aligned}$$

$$= \frac{n_1 n_2}{(n_2 + n_1 F)}$$

i.e. $|J| = \left| \frac{dx}{dF} \right| = \frac{n_1 n_2}{(n_2 + n_1 F)^2}$

$$\therefore f(F) = \frac{1}{\beta(\frac{n_1}{2}, \frac{n_2}{2})} \left(\frac{n_1 F}{n_2 + n_1 F} \right)^{\frac{n_1}{2}-1} \left(1 - \frac{n_1 F}{n_2 + n_1 F} \right)^{\frac{n_2}{2}-1}$$

$$= \frac{1}{\beta(\frac{n_1}{2}, \frac{n_2}{2})} \left(\frac{n_1 F}{n_2 + n_1 F} \right)^{\frac{n_1}{2}-1} \left(1 - \frac{n_1 F}{n_2 + n_1 F} \right)^{\frac{n_2}{2}-1} \frac{n_1 n_2}{(n_2 + n_1 F)^2}$$

$$(n_1 n_2)$$

$$\Rightarrow f(F) = \frac{\frac{m_1}{2} \cdot \frac{m_2}{2} \cdot \frac{n_1 + n_2}{2} \cdot F^{\frac{m_1 + m_2}{2} - 1}}{\beta \left(\frac{m_1 + m_2}{2} \right) \left(\frac{m_1 + m_2}{2} \right)^{\frac{m_1 + m_2}{2}}} ; \quad 0 < F < \infty$$

$m_1 > 0$ and $n_1 > 0$

Moments of F distribution

n^{th} moment about origin is given by

$$u'_n = E(F^n)$$

$$= \int_0^\infty F^n \cdot \frac{\frac{m_1}{2} \cdot \frac{m_2}{2} \cdot (F)^{\frac{m_1 + m_2}{2} - 1}}{\beta \left(\frac{m_1 + m_2}{2} \right)} dF$$

$$= \frac{\left(\frac{m_1}{2} \right)^{\frac{m_1}{2}} \left(\frac{m_2}{2} \right)^{\frac{m_2}{2}}}{\beta \left(\frac{m_1 + m_2}{2} \right)} \int_0^\infty \frac{(F)^{\frac{m_1 + 2n}{2} - 1}}{\left(1 + \frac{m_1}{m_2} F \right)^{\frac{m_1 + m_2}{2}}} dF$$

$$= \frac{\left(\frac{m_1}{m_2} \right)^{\frac{m_1}{2}}}{\beta \left(\frac{m_1}{2}, \frac{m_2}{2} \right)} \int_0^\infty \frac{\left(\frac{m_1}{m_2} F \right)^{\frac{m_1 + 2n}{2} - 1}}{\left(1 + \frac{m_1}{m_2} F \right)^{\frac{m_1 + m_2}{2}}} \left(\frac{m_2}{m_1} \right)^{\frac{m_1 + 2n}{2} - 1} \left(\frac{m_2}{m_1} \right) d \left(\frac{m_1}{m_2} F \right)$$

$$= \frac{\left(\frac{m_1}{m_2} \right)^{\frac{m_1}{2}} \left(\frac{m_2}{m_1} \right)^{\frac{m_1 + 2n}{2}}}{\beta \left(\frac{m_1}{2}, \frac{m_2}{2} \right)} \int_0^\infty \frac{\left(\frac{m_1}{m_2} F \right)^{\frac{m_1 + 2n}{2} - 1}}{\left(1 + \frac{m_1}{m_2} F \right)^{\frac{m_1 + m_2}{2}}} \left(\frac{m_2}{m_1} \right)^{\frac{m_1 + 2n}{2} - 1} \left(\frac{m_2}{m_1} \right) d \left(\frac{m_1}{m_2} F \right)$$

mett $\Gamma = \Gamma$ mette

$$= \frac{\left(\frac{m_1}{m_2}\right)^{\frac{m_1}{2}} \left(\frac{m_2}{m}\right)^{\frac{m_2}{2}}}{\beta\left(\frac{m_1}{2}, \frac{m_2}{2}\right)} \int_0^d \frac{\left(\frac{m_1}{m_2} F\right)^{\frac{m_1+2n}{2}}}{\left(1 + \frac{m_1}{m_2} F\right)^{\frac{m_1+2n}{2}} + \left(\frac{m_2-2n}{2}\right)^{\frac{m_1+2n}{2}}} d\left(\frac{m_1}{m_2} F\right) \quad (7)$$

where $0 < m$

$$= \frac{\left(\frac{m_1}{m_2}\right)^{\frac{m_1}{2}} \left(\frac{m}{m}\right)^{\frac{m_2+2n}{2}}}{\beta\left(\frac{m_1}{2}, \frac{m_2+2n}{2}\right)} \quad \text{using beta}$$

$$= \frac{\left(\frac{m_2}{m_1}\right)^n}{\frac{\Gamma\left(\frac{m_1+2n}{2}\right) \Gamma\left(\frac{m_2-2n}{2}\right)}{\Gamma\left(\frac{m_1+m_2}{2}\right)}} \quad (4)$$

$$= \frac{\left(\frac{m_2}{m_1}\right)^n}{\frac{\Gamma\left(\frac{m_1+2n}{2}\right) \Gamma\left(\frac{m_2-2n}{2}\right)}{\Gamma\left(\frac{m_1+m_2}{2}\right)}} \quad (5)$$

$$\left(7 \frac{m_1}{m_2}\right) b \left(\frac{m_2}{m_1}\right)^n = \frac{\left(\frac{m_1}{m_2}\right)^n \Gamma\left(\frac{m_1}{2} + n\right) \Gamma\left(\frac{m_2-2n}{2}\right)}{\Gamma\left(\frac{m_1+m_2}{2}\right) \Gamma\left(\frac{m_1+2n}{2}\right)} \quad n = 1, 2, 3, \dots$$

when $n = 1$ then

$$\begin{aligned} \mu'_1 &= -\frac{n_2}{n_1} \cdot \frac{\sqrt{\frac{n_1}{2} + 1} \sqrt{\left(\frac{n_2}{2} - 1\right)}}{\sqrt{\frac{n_1}{2}} \sqrt{\frac{n_2}{2}}} \\ &= \frac{n_2}{n_1} \cdot \frac{\frac{n_1}{2} \sqrt{\frac{n_1}{2}} \sqrt{\left(\frac{n_2}{2} - 1\right)}}{\sqrt{\frac{n_1}{2}} \left(\frac{n_2}{2} + 1\right) \sqrt{\left(\frac{n_2}{2} - 1\right)}} \\ &= \frac{n_2}{n_2 - 2} = \text{mean where } n_2 > 2. \end{aligned}$$

$$\begin{aligned} \mu'_2 &= \left(\frac{n_2}{n_1}\right)^2 \cdot \frac{\sqrt{\frac{n_1}{2} + 2} \sqrt{\left(\frac{n_2}{2} - 2\right)}}{\sqrt{\frac{n_1}{2}} \sqrt{\frac{n_2}{2}}} \\ &= \left(\frac{n_2}{n_1}\right)^2 \cdot \frac{\left(\frac{n_1}{2} + 1\right) \frac{n_1}{2} \sqrt{\frac{n_1}{2}} \sqrt{\left(\frac{n_2}{2} - 2\right)}}{\sqrt{\frac{n_1}{2}} \left(\frac{n_2}{2} - 1\right) \left(\frac{n_2}{2} - 2\right) \sqrt{\left(\frac{n_2}{2} - 2\right)}} \\ &= \cancel{\left(\frac{n_2}{n_1}\right)} \frac{n_2^2}{n_1^2} \frac{\frac{n_1 + 2}{4}}{\frac{(n_2 - 2)(n_2 - 4)}{2}} \\ &= \frac{n_2^2}{n_1} \frac{(n_1 + 2)}{(n_2 - 2)(n_2 - 4)} ; n_2 > 4. \end{aligned}$$

$$\begin{aligned}
 \mu_2 &= \mu_2' - \frac{\mu_2''}{m} \\
 &= \frac{n_2^2}{m} \frac{(n_1+2)}{(n_2-2)(n_2-4)} - \frac{n_2^2}{(n_2-2)^2} \\
 &= \frac{n_2^2(n_1+2)(n_2-2) - n_1n_2^2(n_2-4)}{n_1(n_2-2)^2(n_2-4)} \\
 &= \frac{n_2^2(n_1n_2 + 2n_2 - 2n_1 - 4) - n_2^2\{n_1(n_2-4)\}}{n_1(n_2-2)^2(n_2-4)} \\
 &= \frac{n_2^2 \left\{ \frac{n_1n_2 + 2n_2 - 2n_1 - 4}{n_1n_2 + 4n_1} \right\}}{n_1(n_2-4)} \\
 &= \frac{n_2^2}{(n_2-2)^2} \cdot \left[\frac{2n_1 + 2n_2 - 4}{n_1(n_2-4)} \right];
 \end{aligned}$$

$$\text{Ansatz: } \frac{2n_1 + 2n_2 - 4}{n_1(n_2-4)} = \frac{2(n_1+n_2-2)}{n_1n_2}.$$

$$\text{LHS: } \frac{2(n_1+n_2-2)}{n_1n_2} = \frac{2(n_1+n_2-2)}{n_1n_2} \quad (\text{Ansatz})$$

$$\text{RHS: } \frac{(n_1+2)(n_2-2)}{(n_1+2)(n_2-2)} = \frac{2(n_1+n_2-2)}{n_1n_2}.$$

$$= \frac{n_2^2}{(n_2-2)^2} \left[\frac{2(n_1+n_2-2)}{n_1(n_2-4)} \right];$$

Establish Beta distribution of first kind from F distribution.

Soln: According to the question, the pdf of F distribution is given by,

$$f(F) = \frac{n_1^{n_1/2} (n_2/2)^{n_2/2}}{\Gamma(n_1/2) \Gamma(n_2/2)} F^{n_1/2 - 1} \beta\left(\frac{n_1}{2}, \frac{n_2}{2}\right) (n_2 + n_1 F)^{\frac{n_1+n_2}{2}} \quad 0 \leq F < \infty$$

$n_1 > 0$ and $n_2 > 0$

$$\text{Let, } X = \frac{n_1 F}{n_2 + n_1 F}$$

$$\text{or, } Xn_2 + n_1 F = n_1 F^{(x-1)} \quad (\text{Eq. 1})$$

$$\text{or, } Xn_2 = n_1 F (1-x)$$

$$\therefore F = \frac{n_2 x}{n_1 (1-x)}$$

$$\therefore \frac{dF}{dx} = \frac{n_2}{n_1} \cdot \frac{(1-x)^{1-x} (0-1)}{(1-x)^2} \beta\left(\frac{n_1}{2}, \frac{n_2}{2}\right)$$

$$= \frac{n_2}{n_1} \cdot \frac{1-x+n}{(1-x)^2}$$

$$= \frac{n_2 (x+1)}{n_1 (1-x)^2}$$

$$\text{i.e., } |J| = \left| \frac{dF}{dx} \right| = \frac{n_2 (x+1)}{n_1 (1-x)^2} \cdot 1 - \frac{n_2}{n_1 x}$$

$$\left(\frac{n_1}{n_2} + \frac{1}{x} \right)$$

$$f(x) = \frac{n_1^{\frac{m_1}{2}} n_2^{\frac{m_2}{2}}}{n_1^{\frac{m_1}{2}} n_2^{\frac{m_2}{2}}} \left(\frac{n_2 x}{n_1(1-x)} \right)^{\frac{m_1+m_2}{2}-1}$$

$$\beta\left(\frac{m_1}{2}, \frac{m_2}{2}\right) \left(n_2 + n_1 \frac{n_2 x}{n_1(1-x)}\right)^{\frac{m_1+m_2}{2}}$$

$$\frac{n_1 n_2^{\frac{m_1+m_2}{2}-1}}{\beta\left(\frac{m_1}{2}, \frac{m_2}{2}\right) \left(n_2 + n_1 \frac{n_2 x}{n_1(1-x)}\right)^{\frac{m_1+m_2}{2}-1}}$$

$$= \frac{n_1 n_2^{\frac{m_1+m_2}{2}-1} \left(\frac{x}{1-x}\right)^{\frac{m_1}{2}-1}}{\beta\left(\frac{m_1}{2}, \frac{m_2}{2}\right) \left(n_2 + n_1 \frac{n_2 x}{n_1(1-x)}\right)^{\frac{m_1+m_2}{2}}}$$

$$= \frac{n_2^{\frac{m_1+m_2}{2}} x^{\frac{n_1}{2}-1}}{\beta\left(\frac{m_1}{2}, \frac{m_2}{2}\right) \left(\frac{n_2(1-x)+n_2 x}{(1-x)}\right)^{\frac{m_1+m_2}{2}}}$$

$$= \frac{n_2^{\frac{m_1+m_2}{2}} x^{\frac{n_1}{2}-1}}{\beta\left(\frac{m_1}{2}, \frac{m_2}{2}\right) \left(\frac{n_2-n_2 x+n_2 x}{(1-x)}\right)^{\frac{m_1+m_2}{2}}}$$

$$= \frac{n_2^{\frac{m_1+m_2}{2}} x^{\frac{n_1}{2}-1}}{\beta\left(\frac{m_1}{2}, \frac{m_2}{2}\right) \left(\frac{n_2}{(1-x)}\right)^{\frac{m_1+m_2}{2}}}$$

$$= \frac{x^{\frac{n_1}{2}-1} (1-x)^{\frac{m_1+m_2}{2}}}{\beta\left(\frac{m_1}{2}, \frac{m_2}{2}\right) \left(\frac{1}{(1-x)^{\frac{m_1}{2}+1}}\right)}$$

$$f(x) = \frac{1}{\beta(\frac{m_1}{2}, \frac{m_2}{2})} x^{\frac{m_1}{2}-1} (1-x)^{\frac{m_2}{2}-1} \quad 0 < x < 1$$

which is the pdf of beta distribution.

(first kind) with parameter $\frac{m_1}{2}$ and $\frac{m_2}{2}$.

Table
12

Table
17

4, 4 6, 6-10, 12, 18; 22, 23, 25, 28, 33, 44,

mean
variance
proportion
correlation
coefficient

$\dots - + - + - \overset{+}{\cancel{-}} + + + + + + + + +$

$N_1 = 11$ after mitomycin being added

$$N_2 = 17 \quad (+).$$

To Barbados with love before ⑪

Aspergillus niger (frigo)

es denkt ab mit uns - hörte Ⓡ

base of the spine has

Miss Atkinson

Chi-square

1. $\chi^2 = \sum (O - E)^2 / E$

(n-1)

Gupta = (n)
Kapur = (n-1)

f. mode, Harmonic mean, reciprocal of arithmetic mean

Arithmetical mean $\frac{1}{n}$ of reciprocals of values

$$E\left(\frac{1}{x}\right) =$$

Properties.

n-th order moment

mean variance

$n \rightarrow \infty$ norm

beta first kind $\leftrightarrow f$

mean, variance

+ + + skewness/kurtosis

$$f \rightarrow \alpha^2$$

① Define point estimation with example.

② What are the methods of point estimation.

③ What are the desirable criteria of a good estimator (4 ta crit)

29.

① unbiased
consistency
efficiency
sufficiency

② what is M.L.E (maximum likelihood est)

③ let x_1, x_2, \dots, x_n be a random sample from a poison distribution with p.d.f given by $f(x|\lambda) = \frac{e^{-\lambda} \lambda^x}{x!}$; $x=0, 1, 2, \dots, \infty$.

Find the maximum likelihood estimator of λ . Show that the estimator is unbiased.

\Rightarrow attribute $\frac{r \times c}{\text{theory}} + \text{math.}$ } mon-param
 non-param
 mean, several, correlation \rightarrow theory.
Keates connection

$$M = 0.43429 \left(1 + \frac{1}{(k-1)} \left\{ \sum \frac{1}{n_i} - \frac{1}{y} \right\} \right)$$