

Chi-Square Distribution

15.1 * Z is called standard normal variate.

Define χ^2 distribution
2M
The square of a standard normal variate Z is called Chi-Square Distribution with degree of freedom 1.

If X is normally distributed over mean μ & variance σ^2 , then $X \sim N(\mu, \sigma^2)$

$$Z = \frac{X - \mu}{\sigma}$$

Squaring on both sides, we get

$$Z^2 = \left(\frac{X - \mu}{\sigma} \right)^2 \Rightarrow \text{Chi-square variate with 1 d.f.}$$

If X can be generalised to n independent normal variates with mean μ_i & variance σ_i^2

(i) x_i , $i = 1, 2, \dots, n$, then

$$\chi^2 = \sum_{i=1}^n \left(\frac{x_i - \mu_i}{\sigma_i} \right)^2 \text{ is a chi-square variate of } n \text{ d.f.}$$

15.2 Derivation of p.d.f. of χ^2 -distribution:

(First method only enough)

* Deriving pdf of χ^2 -distribution using Moment Generating Function

If X_i , ($i = 1, 2, \dots, n$) are independent $N(\mu, \sigma^2)$, then we have to derive the distribution of

$$\chi^2 = \sum_{i=1}^n \left(\frac{x_i - \mu_i}{\sigma_i} \right)^2 \quad (i = 1, 2, \dots, n)$$

Let $u_i = \frac{x_i - \mu_i}{\sigma_i} \sim N(0, 1)$. Then

$$\chi^2 = \sum_{i=1}^n u_i^2$$

Since x_i are independent, then u_i is also independent.

u_i 's are independent & identically distributed random variable over $(0, 1)$.

∴ Moment Generating Function is given by

$$M_{\chi^2}(t) = M_{\sum u_i^2}(t) \quad \text{(summation of } n \text{ terms)}$$

(multiplying) \leftarrow $= \prod_{i=1}^n M_{u_i^2}(t) = [M_{u_i^2}(t)]^n \rightarrow \textcircled{1}$

[Since \prod is called capital 'pi'. It denotes product operator.]

We know that

$$M_x(t) = E(e^{xt}) = \int_{-\infty}^{\infty} e^{tx} f(x) dx \quad \text{[Refer pg: 9.8 Normal Distribution]}$$

$$M_{u_i^2}(t) = E[\exp(u_i^2 t)]$$

$$= \int_{-\infty}^{\infty} \exp(u_i^2 t) f(x_i) dx_i$$

$$\left[\because f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \right] \quad \text{(Refer page: 9.5)}$$

$$M_{u_i^2}(t) = \int_{-\infty}^{\infty} \exp(tu_i^2) \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x_i-\mu)^2}{2\sigma^2}} dx_i$$

substitute $u_i = \frac{x_i - \mu}{\sigma}$ in the above equation.

Differentiating it, we get

$$du_i = \frac{1}{\sigma} dx_i \Rightarrow \boxed{dx_i = \sigma du_i}$$

$$M_{u_i}(t) = \int_{-\infty}^{\infty} \exp(tu_i^2) \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{(x_i - \mu)^2}{2\sigma^2}\right\} dx_i$$

$$= \int_{-\infty}^{\infty} \exp(tu_i^2) \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{x_i - \mu}{\sigma}\right)^2\right] dx_i$$

$$= \int_{-\infty}^{\infty} \exp(tu_i^2) \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{u_i^2}{2}\right) \sigma du_i$$

$$M_{u_i}(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \exp(tu_i^2) \exp\left(-\frac{u_i^2}{2}\right) du_i$$

(Adding the powers
& taking LCM)

$$\left[\begin{aligned} e^{tu_i^2} \times e^{-\frac{u_i^2}{2}} &= e^{tu_i^2 + \left(-\frac{u_i^2}{2}\right)} \\ &= e^{-u_i^2 \left(\frac{1-2t}{2}\right)} \end{aligned} \right]$$

$$M_{u_i}(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \exp\left\{-\left(\frac{1-2t}{2}\right)u_i^2\right\} du_i \quad \text{--- (i)}$$

We know that by gamma function,

$$\int_{-\infty}^{\infty} e^{-a^2 x^2} dx = \frac{\sqrt{\pi}}{a}, \text{ where } a^2 \text{ is coefficient of } x^2 \text{ in the exponential term}$$

Here in equation (i) $a = \left(\frac{1-2t}{2}\right)^{1/2}$; $x^2 = u_i^2$

$$\begin{aligned} M_{u_i^2}(t) &= \frac{1}{\sqrt{2\pi}} \left[\frac{\sqrt{\pi}}{\left(\frac{1-2t}{2}\right)^{1/2}} \right] \\ &= \frac{1}{\sqrt{2}} \times \frac{\sqrt{\pi}}{\left(\frac{1-2t}{2}\right)^{1/2}} \\ &= \frac{1}{\sqrt{2}} \times \frac{\sqrt{2}}{\sqrt{1-2t}} \quad (\text{Taking reciprocal}) \end{aligned}$$

$$M_{u_i^2}(t) = \frac{1}{\sqrt{1-2t}} = (1-2t)^{-1/2} \rightarrow (2)$$

Sub (2) in (1)

$$M_{x^2}(t) = \left[M_{u_i^2}(t) \right]^n = \left[(1-2t)^{-1/2} \right]^n = (1-2t)^{-n/2}$$

$$\therefore M_{x^2}(t) = (1-2t)^{-n/2}$$

This is the M.G.F. of a gamma variate with parameters $\frac{1}{2}$ & $\frac{n}{2}$

By uniqueness theorem of M.G.F's

$$\chi^2 = \sum_{i=1}^n \left(\frac{X_i - \mu_i}{\sigma_i} \right)^2 \text{ is a gamma variate}$$

Differentiating,

$$\therefore dP(\chi^2) = \frac{\left(\frac{1}{2}\right)^{n/2}}{\Gamma(n/2)} \left[\exp\left(-\frac{1}{2}\chi^2\right) \right] (\chi^2)^{\left(\frac{n}{2}-1\right)} d\chi^2$$

$$dP(\chi^2) = \frac{(1)^{n/2}}{\left(\frac{1}{2}\right)^{n/2} \Gamma(n/2)} \exp\left(-\frac{\chi^2}{2}\right) (\chi^2)^{\left(\frac{n}{2}-1\right)} d\chi^2$$

This is the required pdf of Chi-square distribution with n degrees of freedom.