

Stat 342
Mathematical Statistics
Lecture 18

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Plan:

1. χ^2 distribution (Def & Rel. with Gamma)
2. Student's Theorem (Sampling dist. of \bar{X} & S^2)
3. ~~t & F distribution.~~

χ^2 distribution

Def:

Let $Z \sim N(0, 1)$

$$X = Z^2 \sim \chi^2_{(1)}$$

degree freedom 1

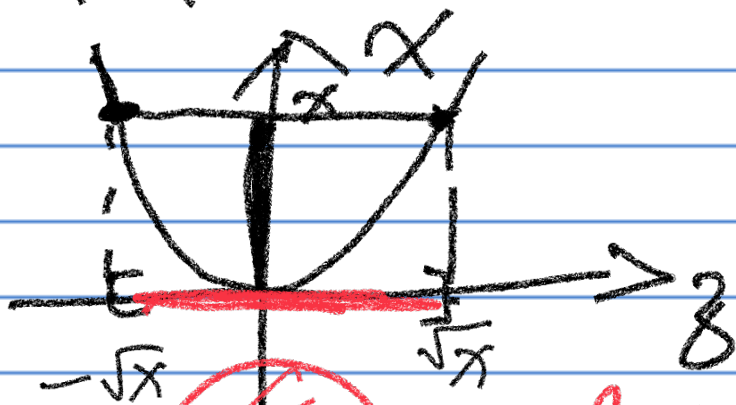
PDF of X :

$$F_X, X \geq 0$$

$$X \leq x$$

$$\Leftrightarrow Z^2 \leq x$$

$$\Leftrightarrow -\sqrt{x} \leq Z \leq \sqrt{x}$$



$\leftarrow f_Z(z)$

$$F_X(x)P(X \leq x) = P(-\sqrt{x} \leq Z \leq \sqrt{x})$$

$$= \int_{-\sqrt{x}}^{\sqrt{x}} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz$$

For $x \geq 0$

$$f_X(x) = F'_X(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x}{2}} \cdot \frac{d\sqrt{x}}{dx}$$

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

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

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

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

(Note: This block contains a circled formula with a red arrow pointing from the first line of the derivation to it, and a large red checkmark below it.)

$$Z^2 \sim \text{Gamma}(\alpha = \frac{1}{2}, \beta = 2)$$

$$\chi^2_1 = \text{Gamma}(\alpha = \frac{1}{2}, \beta = 2)$$

$$E(Z^2) = \alpha \cdot \beta = \frac{1}{2} \cdot 2 = 1$$

$$\stackrel{\text{alt.}}{=} V(Z) = 1$$

$$V(Z^2) = \alpha \cdot \beta^2 = \frac{1}{2} \cdot 2^2 = 2$$

Def of χ^2_n

Let $(z_1, \dots, z_n) \stackrel{\text{IID}}{\sim} N(0,1)$

Let $X = z_1^2 + \dots + z_n^2$ of freedom

We say $X \sim \chi^2_n$, chi square with n degrees

By additivity of Gamma,

$$X \sim \text{Gamma}\left(\frac{1}{2} + \frac{1}{2} + \dots + \frac{1}{2}, 2\right)$$

$$= \text{Gamma}\left(\frac{n}{2}, 2\right)$$

$$f_X(x) \propto e^{-\frac{x}{2}} \cdot x^{\frac{n}{2}-1}$$

$$E(X) = \alpha \cdot \beta = \frac{n}{2} \cdot 2 = n$$

Scaled χ^2_n :

$$Y = \frac{X}{n} = \frac{Z_1^2 + \dots + Z_n^2}{n}$$

$$E(Y) = \frac{E(X)}{n} = \frac{n}{n} = 1$$

$$V(X) = \alpha \cdot \beta^2 = \frac{n}{2} \cdot 2^2 = 2n$$

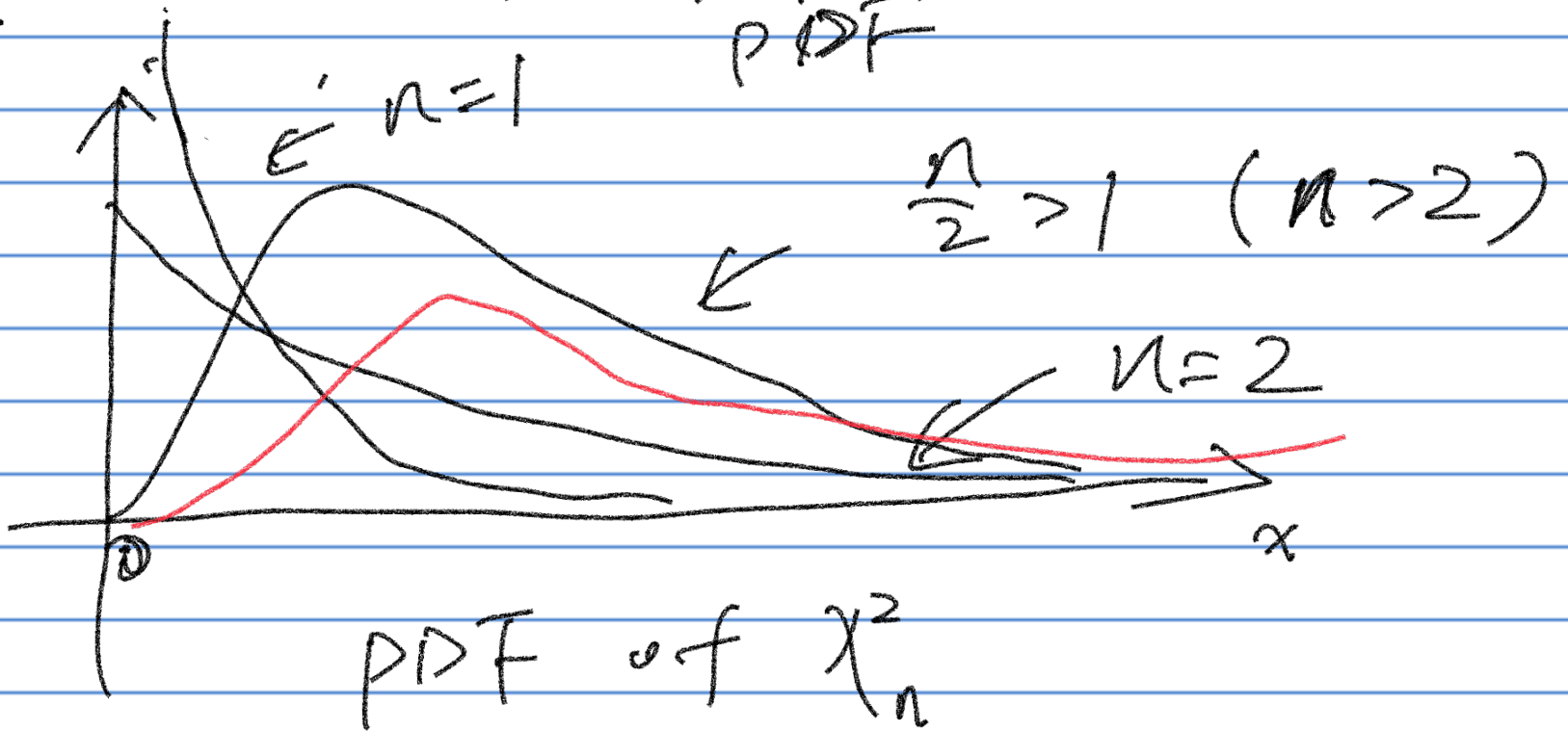
M.G.F. of X

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

Special χ^2_n :

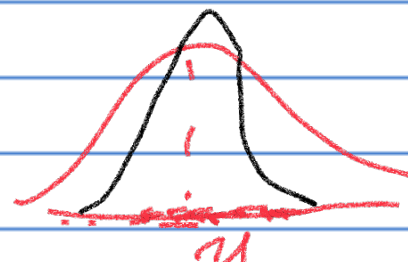
$$\chi^2_2 = \text{Gamma}\left(\frac{2}{2}, \beta=2\right) = \text{exp}(\beta=2)$$

PDF



Student's Theorem

$$X_1, \dots, X_n \stackrel{\text{IID}}{\sim} N(\mu, \sigma^2)$$



$$\bar{X} = \frac{X_1 + \dots + X_n}{n} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

$$V = \sum_{i=1}^n (X_i - \bar{X})^2, \quad S^2 = \frac{V}{n-1} = \frac{SS_{yy}}{n-1}$$

(SS)
1) $\bar{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$ ✓

2) \bar{X} & S^2 indep. ✓

3) $\frac{V}{\sigma^2} \sim \chi^2_{n-1}$ ✓

← Standardization.

another notation for V.

Pf:

$$\text{Let } z_i = \frac{X_i - \mu}{\sigma}, \text{ i.e., } X_i = \mu + \sigma z_i$$

$$z_1, \dots, z_n \stackrel{\text{IID}}{\sim} N(0, 1)$$

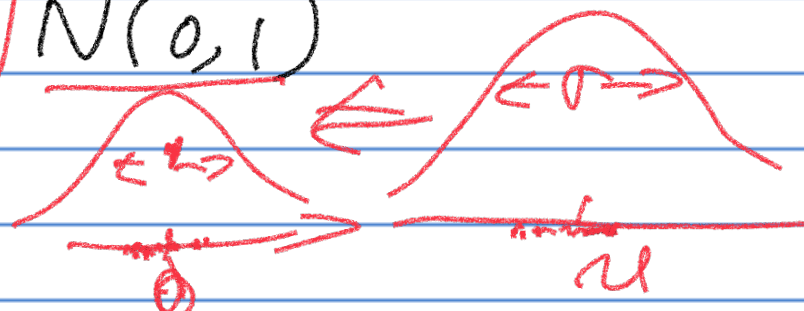
$$\bar{X} = \mu + \sigma \cdot \bar{z}$$

$$E(\bar{z}) = 0, \quad V(\bar{z}) = \frac{1}{n} V(z_i) = \frac{1}{n}$$

$$\bar{z} \sim N(0, \frac{1}{n}) \Rightarrow \sqrt{n} \bar{z} \sim N(0, 1)$$

$$\bar{X} \sim N(\mu, \frac{1}{n} \sigma^2)$$

$$\bar{z} = \frac{\sum z_i}{n}$$



$$X_i = \mu + \sigma z_i$$

$$\begin{aligned}\sum X_i &= \sum (\mu + \sigma z_i) \\ &= \mu \cdot n + \sigma \cdot \sum z_i\end{aligned}$$

$$\frac{\sum X_i}{n} = \mu + \sigma \cdot \bar{z}$$

$$\bar{X} = \mu + \sigma \bar{z}$$

$$V = \sum_{i=1}^n (X_i - \bar{X})^2$$

$$= \sum_{i=1}^n \left[\mu + \sigma z_i - (\mu + \sigma \bar{z}) \right]^2$$

$$= \sigma^2 \sum_{i=1}^n (z_i - \bar{z})^2$$

$$\frac{V}{\sigma^2} = \sum_{i=1}^n (z_i - \bar{z})^2 = V_z$$

$$\bar{z} = \frac{1}{n} \sum_{j=1}^n z_j, \quad \underline{E(\bar{z}) = 0}, \quad \underline{E(z_i - \bar{z}) = 0}$$

$$\underline{\text{Cov}(z_i - \bar{z}, \bar{z})}$$

$$= E((z_i - \bar{z}) \cdot \bar{z})$$

$$= E(z_i \bar{z}) - E(\bar{z}^2)$$

$$= \frac{1}{n} E\left(\sum_{j=1}^n z_i z_j\right) - V(\bar{z})$$

$$= \frac{1}{n} \sum_{j=1}^n E(z_i z_j) - V(\bar{z})$$

$$= \frac{1}{n} \times 1 - \frac{1}{n} = 0$$

$$E(z_j - E(z)) = 0 - 0 = 0$$

$$\text{Cov}(X, Y)$$

$$= E(X \cdot Y)$$

$$- E(X) \cdot E(Y)$$

$$E(z_i^2) = 1$$

$$\text{Cov}(\bar{z}, z_i - \bar{z}) = 0.$$

$$\Rightarrow \bar{z} \perp z_i - \bar{z} \text{ for all } i=1, \dots, n$$

$$\bar{z} \perp \sum_{i=1}^n (z_i - \bar{z})^2 \stackrel{F}{=} V_z$$

$$\bar{x} = \mu + \sigma \bar{z}$$

$$\perp V = \sigma^2 \sum_{i=1}^n (z_i - \bar{z})^2$$

\bar{z} and $z_i - \bar{z}$
are normal.



$$\sum_{i=1}^n z_i^2 = \sum_{i=1}^n \left((z_i - \bar{z}) + \bar{z} \right)^2$$

$$= \sum_{i=1}^n (z_i - \bar{z})^2 + n \cdot \bar{z}^2$$

$$= V_z + G$$

$\sqrt{n} \cdot \bar{z} \sim N(0, 1)$
 $G \sim \chi^2_1$

$$M_{V_z + G}(t) = M_{V_z}(t) \cdot M_G(t)$$

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

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

So $V_z \sim \chi^2_{n-1}$

