

special case ③ of Gamma (α, β): $\alpha = \frac{1}{2}, \beta = 2$ — χ_n^2 dist

Recall: the MGF of Gamma(α, β) is $M(t) = (1 - \beta t)^{-\alpha}$.

so the MGF of χ_n^2 is $M(t) = (1 - 2t)^{-\frac{n}{2}}$

so the MGF of χ_1^2 is $M(t) = (1 - 2t)^{-\frac{1}{2}}$

Theorem 2: Let $Z_1, \dots, Z_n \stackrel{iid}{\sim} N(0, 1)$, then $\sum_{i=1}^n Z_i^2 \sim \chi_n^2$.

Pf: Based on Theorem 1, $Z_i^2 \sim \chi_1^2$, so the MGF of Z_i^2 is

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

Because Z_1^2, \dots, Z_n^2 are independent

$$M_{\sum_{i=1}^n Z_i^2}(t) = M_{Z_1^2}(t) \cdots M_{Z_n^2}(t) = \prod_{i=1}^n M_{Z_i^2}(t)$$

$$= (1 - 2t)^{-\frac{1}{2} \cdot n} = (1 - 2t)^{-\frac{n}{2}} = \text{MGF of } \chi_n^2$$

so $\sum_{i=1}^n Z_i^2 \sim \chi_n^2 = \text{Gamma}(\frac{n}{2}, 2)$

Corollary: Let $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$. then $\sum_{i=1}^n \left(\frac{X_i - \mu}{\sigma}\right)^2 \sim \chi_n^2$.

Pf: Since $X_i \sim N(\mu, \sigma^2)$, so $\frac{X_i - \mu}{\sigma} \sim N(0, 1)$. Then apply Thm 2.

Theorem 3: Let $X \sim \chi_m^2$, $Y \sim \chi_n^2$, and X & Y are independent. then $X + Y \sim \chi_{m+n}^2$

Pf: The MGF of X is $M_X(t) = (1 - 2t)^{-\frac{m}{2}}$

\dots Y is $M_Y(t) = (1 - 2t)^{-\frac{n}{2}}$

Because X & Y are independent, the MGF of $X + Y$ is

$$M_{X+Y}(t) = M_X(t) \cdot M_Y(t) = (1 - 2t)^{-\frac{m}{2}} \cdot (1 - 2t)^{-\frac{n}{2}} = (1 - 2t)^{-\frac{m+n}{2}}$$

$$= \text{MGF of } \chi_{m+n}^2$$

So $X + Y \sim \chi_{m+n}^2$.

Recall: $X \sim N(\mu_1, \sigma_1^2)$, $Y \sim N(\mu_2, \sigma_2^2)$, and X, Y are independent.

then $X + Y \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$

$X - Y \sim N(\mu_1 - \mu_2, \sigma_1^2 + \sigma_2^2)$

$aX + bY \sim N(a\mu_1 + b\mu_2, a^2\sigma_1^2 + b^2\sigma_2^2)$

prove them by MGF

important properties of normal r.v.s.

Theorem 1: Let $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$. Define $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$

Show that \bar{X}_n and $X_i - \bar{X}_n$ are independent.

Pf: To show that the joint MGF of $(\bar{X}_n, X_i - \bar{X}_n)$ can be factorized into the MGF of \bar{X}_n and the MGF of $X_i - \bar{X}_n$.

Recall that $M_{(X,Y)}(s,t) = M_X(s) \cdot M_Y(t) \Leftrightarrow X \& Y$ are indep.

Based on the definition of joint MGF,

$$M_{(\bar{X}_n, X_i - \bar{X}_n)}(s,t) = E[e^{s\bar{X}_n + t(X_i - \bar{X}_n)}]$$

$$\begin{aligned} \text{Note that } s\bar{X}_n + t(X_i - \bar{X}_n) &= (s-t)\bar{X}_n + tX_i = (s-t) \frac{1}{n} \sum_{i=1}^n X_i + tX_i \\ &= \left(\frac{s-t}{n} + t\right) X_i + \frac{s-t}{n} \sum_{j \neq i} X_j \end{aligned}$$

$$\text{So } M_{(\bar{X}_n, X_i - \bar{X}_n)}(s,t) = E\left[e^{\left(\frac{s-t}{n} + t\right) X_i + \frac{s-t}{n} \sum_{j \neq i} X_j}\right]$$

$$\stackrel{X_1, \dots, X_n \text{ iid}}{=} E\left[e^{\left(\frac{s-t}{n} + t\right) X_i} \cdot \prod_{j \neq i} e^{\frac{s-t}{n} X_j}\right]$$

$$= E\left[e^{\left(\frac{s-t}{n} + t\right) X_i}\right] \cdot \prod_{j \neq i} E\left[e^{\frac{s-t}{n} X_j}\right]$$

$$= M_{X_i}\left(\frac{s-t}{n} + t\right) \cdot \prod_{j \neq i} M_{X_j}\left(\frac{s-t}{n}\right)$$

Recall that $X_i \sim N(\mu, \sigma^2)$, the MGF is $M_{X_i}(t) = e^{\mu t + \frac{\sigma^2 t^2}{2}}$

$$\text{So } M_{(\bar{X}_n, X_i - \bar{X}_n)}(s,t) = e^{\mu\left(\frac{s-t}{n} + t\right) + \frac{\sigma^2}{2}\left(\frac{s-t}{n} + t\right)^2} \cdot \prod_{j \neq i} e^{\mu\left(\frac{s-t}{n}\right) + \frac{\sigma^2}{2}\left(\frac{s-t}{n}\right)^2}$$

same term multiplied by $(n-1)$ times

$$= \left(e^{\mu\left(\frac{s-t}{n}\right) + \frac{\sigma^2}{2}\left(\frac{s-t}{n}\right)^2} \right)^{n-1}$$

$$\stackrel{\text{}}{=} e^{\mu\left(\frac{s-t}{n} + t\right) + \frac{\sigma^2}{2}\left(\frac{s-t}{n} + t\right)^2 + \mu\left(\frac{s-t}{n}\right) \cdot (n-1) + \frac{\sigma^2}{2}\left(\frac{s-t}{n}\right)^2 \cdot (n-1)}$$

$$\text{Want } M_{(\bar{X}_n, X_i - \bar{X}_n)}(s,t) = M_{\bar{X}_n}(s) \cdot M_{X_i - \bar{X}_n}(t) \quad (\#)$$

$$M_{\bar{X}_n}(s) = e^{\mu s + \frac{\sigma^2 s^2}{n \cdot 2}}$$

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

~~X_i~~ Note that X_i and \bar{X}_n are NOT independent

But we can derive the dist of $X_i - \bar{X}_n$:

$$\rightarrow X_i - \bar{X}_n = X_i - \frac{1}{n} \sum_{i=1}^n X_i = (1 - \frac{1}{n}) X_i - \frac{1}{n} \sum_{j \neq i} X_j \sim N(0, \frac{n-1}{n} \sigma^2)$$

$$\left\{ \begin{array}{l} E[X_i - \bar{X}_n] = E[X_i] - E[\bar{X}_n] = \mu - \mu = 0 \\ \text{var}[X_i - \bar{X}_n] = \text{var}[(1 - \frac{1}{n}) X_i - \frac{1}{n} \sum_{j \neq i} X_j] \stackrel{\text{ind}}{=} (1 - \frac{1}{n})^2 \text{var}[X_i] + (\frac{1}{n})^2 \sum_{j \neq i} \text{var}[X_j] \\ = (1 - \frac{1}{n})^2 \sigma^2 + (\frac{1}{n})^2 (n-1) \sigma^2 \\ = \left(\frac{(n-1)^2}{n^2} + \frac{n-1}{n^2} \right) \sigma^2 \\ = \frac{n^2 - 2n + 1 + n - 1}{n^2} \sigma^2 = \frac{n^2 - n}{n^2} \sigma^2 \\ = \frac{n-1}{n} \sigma^2 \end{array} \right.$$

$$\text{So } M_{X_i - \bar{X}_n}(t) = e^{-\frac{(n-1)\sigma^2 t^2}{n \cdot 2}}$$

We are left to show that (*) is equivalent to

$$\mu \left(\frac{s-t}{n} + t \right) + \frac{\sigma^2}{2} \left(\frac{s-t}{n} + t \right)^2 + \mu \left(\frac{s-t}{n} \right) (n-1) + \frac{\sigma^2}{2} \left(\frac{s-t}{n} \right)^2 (n-1)$$

$$\stackrel{?}{=} \mu s + \frac{\sigma^2 s^2}{2n} + \frac{(n-1)\sigma^2 t^2}{2n}$$