

# Assignment Four

1

- ① (a)  $Y \sim N(a\mu + b, a^2\sigma^2)$   
(b)  $Z \sim N(0, 1)$   
(c)  $Y \sim N(n\mu, n\sigma^2)$   
(d)  $\bar{X} \sim N(\mu, \frac{\sigma^2}{n})$   
(e)  $Z \sim N(0, 1)$   
(f)  $Y \sim N(\sum_{i=1}^n a_i \mu_i, \sum_{i=1}^n a_i^2 \sigma_i^2)$

② (a)  $M_Y(t) = M_{\sum_{i=1}^n X_i}(t) \stackrel{\text{ind}}{=} \prod_{i=1}^n M_{X_i}(t) = \prod_{i=1}^n (1-2t)^{-\nu_i/2}$   
 $= (1-2t)^{-(\sum_{i=1}^n \nu_i)/2}$  MGF of  $\chi^2(\sum_{i=1}^n \nu_i)$

(b)  $Y = \sum_{i=1}^n \left(\frac{X_i - \mu}{\sigma}\right)^2 \sim \chi^2(n)$ , because

- $Z_i = \frac{X_i - \mu}{\sigma} \sim N(0, 1)$
- $Z_i^2 \sim \chi^2(1)$
- $Z_i$  are independent because functions of independent random variables are independent.
- Sum of independent chi-squares is chi-squared, with df = sum of df. This is Q 29.

(c) By independence,  $M_Y(t) = M_{Y_1}(t) M_{Y_2}(t)$   
Because  $Y \neq Y_1$  are chi-squared,

$$(1-2t)^{-(\nu_1+\nu_2)/2} = (1-2t)^{-\nu_1/2} M_{Y_2}(t)$$

$$\Rightarrow \frac{(1-2t)^{-\nu_1/2} (1-2t)^{-\nu_2/2}}{(1-2t)^{-\nu_1/2}} = M_{Y_2}(t) \text{ MGF of } \chi^2(\nu_2)$$

③ (a)  $a_j = 1 - \frac{1}{n}$ ,  $a_i = -\frac{1}{n}$  for  $i \neq j$

(b) 
$$\begin{aligned} \text{Cov}(\bar{X}, X_j - \bar{X}) &= \text{Cov}(\bar{X}, X_j) - \text{Cov}(\bar{X}, \bar{X}) \\ &= \text{Cov}(X_j, \frac{1}{n} \sum_{i=1}^n X_i) - \text{Var}(\bar{X}) \\ &= \frac{1}{n} \sum_{i=1}^n \text{Cov}(X_i, X_j) - \frac{\sigma^2}{n} \\ &= \frac{1}{n} \left[ \text{Cov}(X_j, X_j) + \sum_{i \neq j} \text{Cov}(X_i, X_j) \right] - \frac{\sigma^2}{n} \\ &\stackrel{\text{ind}}{=} \frac{1}{n} \left[ \text{Cov}(X_j, X_j) + 0 \right] - \frac{\sigma^2}{n} \\ &= \frac{1}{n} \text{Var}(X_j) - \frac{\sigma^2}{n} = \frac{1}{n} \sigma^2 - \frac{\sigma^2}{n} = 0 \end{aligned}$$

(Does not depend on normality)

(c)  $\bar{X}$  and  $X_j - \bar{X}$  are both linear combinations of  $X_1, \dots, X_n$ , as in Q3a above. So as in Q1f, they are normally distributed. Since their covariance is zero by Q3b and zero covariance implies independence for the normal,  $\bar{X}$  is independent of  $X_j - \bar{X}$  for  $j=1, \dots, n$ . Finally  $S^2$  is a function of  $(X_1 - \bar{X}), \dots, (X_n - \bar{X})$ , so because functions of independent random variables are independent,  $S^2$  is independent of  $\bar{X}$ .

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This answer is more detailed than you need. Could just say:  $\text{Cov}(\bar{X}, X_j - \bar{X}) = 0$ , and they are normal so they are independent. Functions of independent and  $S^2$  is a function of  $(X_1 - \bar{X}), \dots, (X_n - \bar{X})$ , so it is independent of  $\bar{X}$ .

$$\begin{aligned}
(3d) \quad \sum_{i=1}^n (x_i - \mu)^2 &= \sum_{i=1}^n (x_i - \bar{x} + \bar{x} - \mu)^2 \\
&= \sum_{i=1}^n \left[ (x_i - \bar{x})^2 + 2(x_i - \bar{x})(\bar{x} - \mu) + (\bar{x} - \mu)^2 \right] \\
&= \sum_{i=1}^n (x_i - \bar{x})^2 + 2(\bar{x} - \mu) \sum_{i=1}^n (x_i - \bar{x}) + \sum_{i=1}^n (\bar{x} - \mu)^2 \\
&= \sum_{i=1}^n (x_i - \bar{x})^2 + 2(\bar{x} - \mu) \left( \sum_{i=1}^n x_i - \sum_{i=1}^n \bar{x} \right) + n(\bar{x} - \mu)^2 \\
&= \sum_{i=1}^n (x_i - \bar{x})^2 + 2(\bar{x} - \mu) (\sum x_i - n\bar{x}) + n(\bar{x} - \mu)^2 \\
&= \sum_{i=1}^n (x_i - \bar{x})^2 + 2(\bar{x} - \mu) \left( \sum x_i - n \frac{\sum x_i}{n} \right) + n(\bar{x} - \mu)^2 \\
&= \sum_{i=1}^n (x_i - \bar{x})^2 + n(\bar{x} - \mu)^2
\end{aligned}$$

$$(e) \text{ From (3d), } \sum_{i=1}^n (x_i - \mu)^2 = \sum_{i=1}^n (x_i - \bar{x})^2 + n(\bar{x} - \mu)^2$$

$$\Rightarrow \frac{1}{\sigma^2} \sum_{i=1}^n (x_i - \mu)^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{\sigma^2} + \frac{n(\bar{x} - \mu)^2}{\sigma^2}$$

$$\Rightarrow \sum_{i=1}^n \underbrace{\left( \frac{x_i - \mu}{\sigma} \right)^2}_{Y_1} = \underbrace{\frac{(n-1)S^2}{\sigma^2}}_{Y_1} + \underbrace{\left( \frac{\bar{x} - \mu}{\sigma/\sqrt{n}} \right)^2}_{Y_2}$$

$Y_1 \sim \chi^2(n)$  by (2b),  $Y_2 \sim N(0,1)$  by (1e)

$Y_1$  is a function of  $S^2$ ,  $Y_2$  is a function of  $\bar{x}$ .  $S^2$  and  $\bar{x}$  are independent, so  $Y_1$  &  $Y_2$  are independent.

Then  $Y_1 \sim \chi^2(n-1)$  by (Q2c).

$$(4) (a) Z = \frac{\sqrt{n}(\bar{X} - \mu)}{\sigma}, \quad Y = \frac{(n-1)S^2}{\sigma^2}$$

Independent because Z is a function of  $\bar{X}$  & Y is a function of  $S^2$ , and  $\bar{X}$  &  $S^2$  are independent

$$T = \frac{\frac{\sqrt{n}(\bar{X} - \mu)}{\sigma}}{\sqrt{\frac{(n-1)S^2}{\sigma^2} / (n-1)}} = \frac{\sqrt{n}(\bar{X} - \mu)}{S} \sim t(n-1)$$

$$(b) 1 - \alpha = P(-t_{1-\alpha/2} < T < t_{1-\alpha/2})$$

$$= P(-t_{1-\alpha/2} < \frac{\sqrt{n}(\bar{X} - \mu)}{S} < t_{1-\alpha/2})$$

$$= P(-t_{1-\alpha/2} \frac{S}{\sqrt{n}} < \bar{X} - \mu < t_{1-\alpha/2} \frac{S}{\sqrt{n}})$$

$$= P(-\bar{X} - t_{1-\alpha/2} \frac{S}{\sqrt{n}} < -\mu < -\bar{X} + t_{1-\alpha/2} \frac{S}{\sqrt{n}})$$

$$= P(\bar{X} + t_{1-\alpha/2} \frac{S}{\sqrt{n}} > \mu > \bar{X} - t_{1-\alpha/2} \frac{S}{\sqrt{n}})$$

$$CI \text{ of } (\bar{X} - t_{1-\alpha/2} \frac{S}{\sqrt{n}}, \bar{X} + t_{1-\alpha/2} \frac{S}{\sqrt{n}})$$

$$\text{or } \bar{X} \pm t_{1-\alpha/2} \frac{S}{\sqrt{n}}$$

$$(4c) \quad \bar{x} \pm t_{1-\alpha/2} \frac{s}{\sqrt{n}} = -1.58 \pm 2.262 \frac{\sqrt{1.513}}{\sqrt{10}} = -1.58 \pm 0.88 \\ = (-2.46, -0.70)$$

(d) Yes. The confidence interval is all negative numbers, suggesting that Drug Z worked better.

$$(e) \quad 1-\alpha = P\left(\chi_{\alpha/2}^2 < \frac{(n-1)s^2}{\sigma^2} < \chi_{1-\alpha/2}^2\right)$$

$$= P\left(\frac{1}{\chi_{\alpha/2}^2} > \frac{\sigma^2}{(n-1)s^2} > \frac{1}{\chi_{1-\alpha/2}^2}\right)$$

$$= P\left(\frac{(n-1)s^2}{\chi_{\alpha/2}^2} > \sigma^2 > \frac{(n-1)s^2}{\chi_{1-\alpha/2}^2}\right)$$

$$= P\left(\frac{(n-1)s^2}{\chi_{1-\alpha/2}^2} < \sigma^2 < \frac{(n-1)s^2}{\chi_{\alpha/2}^2}\right)$$

$$(f) \quad \text{With } \nu=9 \text{ df, } \chi_{0.025}^2 = 2.70 + \chi_{0.975}^2 = 19.02$$

So the CI is

$$\left( \frac{(10-1)1.513}{19.02}, \frac{(10-1)1.513}{2.7} \right) = (0.72, 5.04)$$

$$(5) (a) \bar{X} - \bar{Y}$$

$$(b) \bar{X} - \bar{Y} \sim N(\mu_1 - \mu_2, \frac{\sigma^2}{n_1} + \frac{\sigma^2}{n_2})$$

$$(c) Z = \frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{\sqrt{\sigma^2(\frac{1}{n_1} + \frac{1}{n_2})}}$$

$$(d) Y = \frac{(n_1 - 1)S_1^2}{\sigma^2} + \frac{(n_2 - 1)S_2^2}{\sigma^2} \sim \chi^2(n_1 + n_2 - 2)$$

They are independent because  $S_1^2$  is a function of the  $X_i$ ,  $S_2^2$  is a function of the  $Y_i$ , & the  $X_i$  and  $Y_i$  are independent.

$$(e) T = \frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{\sqrt{\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}}} \sqrt{\frac{1}{n_1} + \frac{1}{n_2}} = \frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{\sqrt{\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}}} \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$$

$$(f) = \frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$$

$$(g) df = n_1 + n_2 - 2$$

$$(5b) 1 - \alpha = P\left(-t_{1-\frac{\alpha}{2}} < \frac{\bar{x} - \bar{y} - (\mu_1 - \mu_2)}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} < t_{1-\frac{\alpha}{2}}\right)$$

2 steps

$$\stackrel{\downarrow}{=} P\left(-t_{1-\frac{\alpha}{2}} < \frac{\mu_1 - \mu_2 - (\bar{x} - \bar{y})}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} < t_{1-\frac{\alpha}{2}}\right)$$

$$= P\left(-t_{1-\frac{\alpha}{2}} S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}} < \mu_1 - \mu_2 - (\bar{x} - \bar{y}) < t_{1-\frac{\alpha}{2}} S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}\right)$$

$$= P\left(\bar{x} - \bar{y} - t_{1-\frac{\alpha}{2}} S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}} < \mu_1 - \mu_2 < \bar{x} - \bar{y} + t_{1-\frac{\alpha}{2}} S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}\right)$$

$$(i) s_p = \sqrt{\frac{(9-1)48.2 + (7-1)32.7}{9+7-2}} = 6.45,$$

$$\bar{x} - \bar{y} \pm t_{1-\frac{\alpha}{2}} s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$$

$$= 14.1 - 13.3 \pm 2.145 * 6.45 \sqrt{\frac{1}{9} + \frac{1}{7}}$$

$$= 0.8 \pm 6.97 = (-6.17, 7.77)$$

(j) Nobody. Zero difference is within the confidence interval.

(6) (a)  $[0, \infty)$  Open or closed does not matter

(b) i)  $F_1 = \frac{Y_1/\nu_1}{Y_2/\nu_2}$ ,  $F_2 = \frac{1}{F_1} = \frac{Y_2/\nu_2}{Y_1/\nu_1} \sim F(\nu_2, \nu_1)$

ii)  $P(F_1 \leq x) = P\left(\frac{1}{F_1} \geq \frac{1}{x}\right) = P(F_2 \geq \frac{1}{x})$

(c) 
$$F = \frac{\frac{(n_1-1)S_1^2}{\sigma_1^2} / (n_1-1)}{\frac{(n_2-1)S_2^2}{\sigma_2^2} / (n_2-1)} = \frac{S_1^2}{S_2^2} \cdot \frac{\sigma_2^2}{\sigma_1^2}$$

$$\sim F(n_1-1, n_2-1)$$

Since we want a CI for  $\frac{\sigma_1^2}{\sigma_2^2}$ , a better pivotal

quantity is  $\frac{S_2^2}{S_1^2} \frac{\sigma_1^2}{\sigma_2^2} \sim F(n_2-1, n_1-1)$   
by (b) part i)

(d)  $1-\alpha = P\left(f_{\alpha/2} < \frac{S_2^2}{S_1^2} \frac{\sigma_1^2}{\sigma_2^2} < f_{1-\alpha/2}\right)$

$= P\left(f_{\alpha/2} \frac{S_1^2}{S_2^2} < \frac{\sigma_1^2}{\sigma_2^2} < f_{1-\alpha/2} \frac{S_1^2}{S_2^2}\right)$  with df = 6, 8

(e)  $\left(0.1786 \left(\frac{48.2}{32.7}\right), 4.65 \left(\frac{48.2}{32.7}\right)\right) = (0.26, 6.85)$

(f) No.  $\frac{\sigma_1^2}{\sigma_2^2} = 1$  is in the confidence interval.