

2.1)

✓ a) < EDA on computer >

b) 2 sample t-test

$$\rightarrow y_{jk} \sim N(\mu_j, \sigma^2)$$

$$H_0: \mu_1 = \mu_2 = \mu, \quad \mu_1 = \text{treatment}, \quad \mu_2 = \text{control}$$

$$H_1: \mu_1 \neq \mu_2$$

$$\rightarrow t^* = \frac{\bar{y}_1 - \bar{y}_2 - 0}{\sqrt{\frac{\sigma^2}{n_1} + \frac{\sigma^2}{n_2}}} = \frac{4.86 - 4.7765}{0.8280 \sqrt{\frac{1}{20} + \frac{1}{20}}} = 0.5099$$

poolled
 \Rightarrow assuming equal variance
 $\frac{s_1^2}{s_2^2} \approx 2$
 $s_p^2 = \frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{n_1 + n_2 - 2}$
 $= \frac{(20-1)0.7909^2 + (20-1)0.8625^2}{20+20-2}$
 ≈ 0.8280

$$\rightarrow 95\% \text{ CI} = (\bar{y}_1 - \bar{y}_2) \pm t_{n_1+n_2-2, \alpha/2} \sqrt{\frac{\sigma^2}{n_1} + \frac{\sigma^2}{n_2}}$$

$$= 0.1335 \pm 1.984 (0.2618)$$

$$= [0.396, 0.6634] \in 0 \Rightarrow \text{not significant}$$

$$c) \rightarrow H_0: E(y_{jk}) = \mu \rightarrow y_{jk} \sim N(\mu, \sigma^2)$$

$$H_1: E(y_{jk}) = \mu_j \rightarrow y_{jk} \sim N(\mu_j, \sigma^2)$$

$$\rightarrow \text{MLEs} \rightarrow l_0 = f(\mu | y)$$

$$= \prod_{j=1}^2 \prod_{k=1}^{20} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2}(y_{jk} - \mu)^2}$$

$$\downarrow$$

$$= (\sqrt{2\pi}\sigma^2)^{-40} \exp \left\{ -\frac{1}{2\sigma^2} \sum_{j=1}^2 \sum_{k=1}^{20} (y_{jk} - \mu)^2 \right\}$$

$$l_0 = l_n[l_0]$$

$$\downarrow$$

$$= -\frac{40}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{j=1}^2 \sum_{k=1}^{20} (y_{jk} - \mu)^2$$

$$l'_0 = -\frac{1}{\sigma^2} \sum_{j=1}^2 \sum_{k=1}^{20} (y_{jk} - \mu)$$

$$0 = \dots$$

$$\downarrow = \sum_{j=1}^2 \sum_{k=1}^{20} y_{jk} - 40\mu$$

$\hat{\mu}_{MLE} = \frac{\sum_{j=1}^2 \sum_{k=1}^{20} y_{jk}}{40}$

$$l_1 = f(\mu_1 | y)$$

$$= \prod_{j=1}^2 \prod_{k=1}^{20} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2}(y_{jk} - \mu_1)^2}$$

$$\downarrow$$

$$= (\sqrt{2\pi}\sigma^2)^{-40} \exp \left\{ -\frac{1}{2\sigma^2} \sum_{j=1}^2 \sum_{k=1}^{20} (y_{jk} - \mu_1)^2 \right\}$$

$$l_1 = -\frac{40}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{j=1}^2 \sum_{k=1}^{20} (y_{jk} - \mu_1)^2$$

$$\frac{\partial l}{\partial \mu_1} = -\frac{1}{\sigma^2} \sum_{j=1}^2 \sum_{k=1}^{20} (y_{jk} - \mu_1)$$

$$0 = \dots$$

$$\downarrow = \sum_{j=1}^2 \sum_{k=1}^{20} y_{jk} - 20\mu_1$$

$\hat{\mu}_{MLE} = \frac{\sum_{j=1}^2 \sum_{k=1}^{20} y_{jk}}{20}$

likewise

$\hat{\mu}_{MLE} = \frac{\sum_{j=1}^2 \sum_{k=1}^{20} y_{jk}}{20}$

$$\text{LSEs} \rightarrow s_0 = \sum_{j=1}^2 \sum_{k=1}^{20} (y_{jk} - \mu)^2$$

$$s'_0 = -2 \sum_{j=1}^2 \sum_{k=1}^{20} (y_{jk} - \mu)$$

$$0 = \dots$$

$$= \sum_{j=1}^2 \sum_{k=1}^{20} y_{jk} - 40\mu$$

$\hat{\mu}_{LSE} = \frac{\sum_{j=1}^2 \sum_{k=1}^{20} y_{jk}}{40}$

$$\rightarrow s_1 = \sum_{j=1}^2 \sum_{k=1}^{20} (y_{jk} - \mu_1)^2$$

$$\frac{\partial s_1}{\partial \mu_1} = -2 \sum_{j=1}^2 \sum_{k=1}^{20} (y_{jk} - \mu_1)$$

$$0 = \dots$$

$\hat{\mu}_{LSE} = \frac{\sum_{j=1}^2 \sum_{k=1}^{20} y_{jk}}{20}$

likewise

$\hat{\mu}_{LSE} = \frac{\sum_{j=1}^2 \sum_{k=1}^{20} y_{jk}}{20}$

parameter	estimate
μ	4.79725
μ_1	4.86
μ_2	4.7765

d) using data $\rightarrow \hat{s}'_0 = \dots = 26.232$
 $\hat{s}'_1 = \dots = 26.033$

e) show $\frac{1}{\sigma^2} \hat{s}'_1 = \frac{1}{\sigma^2} \sum_{j=1}^2 \sum_{k=1}^{20} (y_{jk} - \mu_1)^2 - \frac{20}{\sigma^2} \sum_{k=1}^{20} (\bar{y}_j - \mu_1)^2$

? (based on 1.4, which was ?)

show it H_0 is true, $\frac{1}{\sigma^2} \hat{s}'_1 \sim \chi^2_{20}$

$$\rightarrow \frac{1}{\sigma^2} \hat{s}'_1 = \sum_{j=1}^2 \sum_{k=1}^{20} \left(\frac{y_{jk} - \mu_1}{\sigma} \right)^2$$

$$\downarrow \text{ (from ex 1.4 c)}$$

$$= \left[\frac{40-2}{\sigma^2} s^2 + \frac{20}{\sigma^2} \sum_{k=1}^{20} (\bar{y}_j - \mu_1)^2 \right] - \frac{20}{\sigma^2} \sum_{k=1}^{20} (\bar{y}_j - \mu_1)^2$$

$$\sim \chi^2_{20}$$

similarly, if H_0 is true $\rightarrow \frac{1}{\sigma^2} \hat{s}'_0 \sim \chi^2_{20}$

f) not exactly sure how, but... understand result:

$$\frac{\hat{s}'_0 - \hat{s}'_1}{\hat{s}'_1/38} \sim F(1, 38)$$

$$\Rightarrow f = \frac{\chi^2_{1/1}}{\chi^2_{n-2/n-2}} = \frac{SSE_{H_0=0} - SSE_{H_1}}{SSE_{H_1}/df_{H_1}} \sim F(\text{difference in df between reduced \& full models}, \text{df reduced model})$$

reduction in SSE of full model relative to full model

= difference in parameters estimated

$$f^* = \frac{E(SSE_0)}{E(SSE_1)} = \frac{E(SSB/1)}{E(SSE_{k=2})} = \frac{\sigma^2 + \frac{1}{n} \sum_{j=1}^k \mu_j^2}{\sigma^2} = 1 + \frac{\sum \mu_j^2}{n\sigma^2}$$

mean $\mu_j >$ then both μ_j if H_1

g) $\frac{\hat{s}'_0 - \hat{s}'_1}{\hat{s}'_1/38} = 0.2594$

h) $t^2 = F \Rightarrow$ confirmed w/ $0.5099 = 0.2599$

i) < on computer >

2.2

✓

a) $y_{jk} \sim N(\mu_j, \sigma^2)$

unpaired t-test

$$H_0: \mu_1 = \mu_2 = \mu, \quad \mu_1 = \text{before}, \quad \mu_2 = \text{after}$$

$$H_1: \mu_1 \neq \mu_2$$

$$t = \frac{\bar{y}_1 - \bar{y}_2 - 0}{\sqrt{\frac{\sigma^2}{n_1} + \frac{\sigma^2}{n_2}}} = \frac{109.243 - 100.6}{13.006 \sqrt{\frac{1}{20} + \frac{1}{20}}} = 0.6431$$

$$l_0 = s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$$

$$l_0 = \sqrt{\frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{n_1 + n_2 - 2}} = \sqrt{\frac{(20-1)17.5(1.73^2) + (20-1)12.4245^2}{20+20-2}}$$

$$= 13.0064$$

b) paired t-test

$$\rightarrow D_k = y_{1k} - y_{2k} \rightarrow D_k \sim N(\mu_D, \sigma_D^2)$$

$$H_0: \mu_D = 0, \quad \mu_D = \mu_1 - \mu_2$$

$$H_1: \mu_D \neq 0$$

$$\rightarrow t^* = \frac{\bar{D} - 0}{s_D/\sqrt{n_D}} = \frac{2.645 - 0}{4.1167/\sqrt{20}} = 2.873$$

significant

$$t_{crit} = |t_{(14, 0.05)}| = |2t_{(20, 0.025)}| = 2.093$$

n=20

c) different conclusions!

d) $y_{jk} \sim N(\mu_j, \sigma^2)$ in unpaired t-test

$D_k \sim N(\mu_D, \sigma_D^2)$ in paired t-test

2.3

✗

skipping \rightarrow based on previous didn't know

2.4

✓

$$X \begin{matrix} | \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \end{matrix} Y \rightarrow E(Y) = \beta_0 + \beta_1 X + \beta_2 X^2$$

$$\rightarrow g(E(Y)) = e^{E(Y)} = e^{\beta_0 + \beta_1 X + \beta_2 X^2} = \beta_0 + \beta_1 X + \beta_2 X^2$$

$$\rightarrow Y = \begin{bmatrix} 3.15 \\ 4.85 \\ 6.50 \\ 7.20 \\ 8.25 \\ 11.50 \end{bmatrix} \quad \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} \quad X = \begin{bmatrix} 1 & 1.0 & 1.0^2 \\ 1 & 1.2 & 1.2^2 \\ 1 & 1.4 & 1.4^2 \\ 1 & 1.6 & 1.6^2 \\ 1 & 1.8 & 1.8^2 \\ 1 & 2.0 & 2.0^2 \end{bmatrix}$$

2.5

$$E(y_{jk}) = \mu_1 x + \mu_2 x^2 + \mu_3 x^3 \quad y_{jk} \sim N(\mu_{jk}, \sigma^2)$$

$j=1,2$
 $k=1,2,3$

$$E(Y) = X\beta = \begin{bmatrix} \mu_1 & \mu_2 & \mu_3 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \beta = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} \quad Y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \\ y_7 \\ y_8 \\ y_9 \\ y_{10} \end{bmatrix}$$