STAT 510 Homework 7

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1. (a)

$$E(MS_{ou(trt,xu)}) = E\left(\frac{1}{tn(m-1)} \sum_{i=1}^{t} \sum_{j=1}^{n} \sum_{k=1}^{m} (y_{ijk} - \bar{y}_{ij\cdot})^{2}\right)$$

$$= \frac{1}{tn(m-1)} E\left(\sum_{i=1}^{t} \sum_{j=1}^{n} \sum_{k=1}^{m} (\mu + \tau_{i} + u_{ij} + e_{ijk} - \mu - \tau_{i} - u_{ij} - \bar{e}_{ij\cdot})^{2}\right)$$

$$= \frac{1}{tn(m-1)} E\left(\sum_{i=1}^{t} \sum_{j=1}^{n} \sum_{k=1}^{m} (e_{ijk} - \bar{e}_{ij\cdot})^{2}\right)$$

As $e_i jk \sim N(0, \sigma_e^2)$, then

$$E\left(MS_{ou(trt,xu)}\right) = \frac{1}{tn(m-1)} \sum_{i=1}^{r} \sum_{j=1}^{n} (m-1)\sigma_e^2$$
$$= \frac{1}{tn(m-1)} tn(m-1)\sigma_e^2$$
$$= \sigma_e^2$$

(b) Let $A = (I - P_3)$, where $P_3 = \frac{1}{m} I_{tn \times tn} \otimes \mathbf{1} \mathbf{1}_{m \times m}^T$ is a projection matrix. Then $\mathbf{y}^T A \mathbf{y} = \sum_{i=1}^t \sum_{j=1}^n \sum_{k=1}^m (y_{ijk} - \bar{y}_{ij\cdot})^2$. We also have

$$\Sigma = \sigma_u^2 \mathbf{I}_{tn \times tn} \otimes \mathbf{1} \mathbf{1}_{m \times m}^T + \sigma_e^2 \mathbf{I}_{tnm \times tnm} = \sigma_u^2 m \mathbf{P}_3 + \sigma_e^2 \mathbf{I}_{tnm \times tnm}$$

Then

$$A\Sigma = (I - P_3)(\sigma_u^2 m P_3 + \sigma_e^2 I) = \sigma_e^2 (I - P_3) = \sigma_e^2 (I - \frac{1}{m} I_{tn \times tn} \otimes I_{m \times m})$$

$$\Rightarrow \operatorname{tr}(A\Sigma) = tnm\sigma_e^2 (1 - \frac{1}{m}) = \sigma_e^2 tn(m - 1)$$

We know that $E(y) \subset C(P_2) \subset C(P_3)$. Thus $(I - P_3)E(y) = 0 \Rightarrow E(y)^T A E(y) = 0$. Hence,

$$E(\boldsymbol{y}^T\boldsymbol{A}\boldsymbol{y}) = tn(m-1)\sigma_e^2 \Rightarrow E(MS_{ou(trt,xu)}) = \frac{1}{tn(m-1)}tn(m-1)\sigma_e^2 = \sigma_e^2$$

2. (a) $d_j = y_{1j} - y_{2j} = (\mu_1 + u_j + e_{1j}) - (\mu_2 + u_j + e_{2j}) = (\mu_1 - \mu_2) + (e_{1j} - e_{2j})$. We have $e_{ij} \stackrel{iid}{\sim} N(0, \sigma_e^2)$, then $d_j \stackrel{iid}{\sim} N(\mu_1 - \mu_2, 2\sigma_e^2)$.

(b)
$$T = \frac{\bar{d}}{\bar{d}},$$

$$T = \frac{\bar{d}}{\sqrt{\frac{1}{380} \sum_{j=1}^{20} (d_j - \bar{d})^2}}$$
, where $\bar{d} = \frac{1}{20} \sum_{j=1}^{20} d_j$

(c)
$$T \sim t_{19}(\mu_1 - \mu_2)$$

(d)
$$CI = \left[\bar{a} - \bar{b} - t_{38,0.975} \sqrt{\frac{\sum_{j=1}^{20} (a_j - \bar{a})^2 + \sum_{j=1}^{2} (b_j - \bar{b})^2}{380}}, \bar{a} - \bar{b} + t_{38,0.975} \sqrt{\frac{\sum_{j=1}^{20} (a_j - \bar{a})^2 + \sum_{j=1}^{2} (b_j - \bar{b})^2}{380}} \right]$$

(e)
$$\hat{\sigma}_e^2 = \frac{\sum_{j=1}^{20} (d_j - \bar{d})^2}{38}$$

$$\hat{\sigma}_e^2 + \hat{\sigma}_u^2 = \frac{\sum_{j=1}^{20} (a_j - \bar{a})^2 + \sum_{j=1}^{20} (b_j - \bar{b})^2}{38} \Rightarrow \hat{\sigma}_u^2 = \frac{\sum_{j=1}^{20} (a_j - \bar{a})^2 + \sum_{j=1}^{20} (b_j - \bar{b})^2 - \sum_{j=1}^{20} (d_j - \bar{d})^2}{38}$$

(f)

$$X = \begin{bmatrix} 1 & -1 \\ \vdots & \vdots \\ 1 & -1 \\ 1 & 0 \\ \vdots & \vdots \\ 1 & 0 \\ 0 & 1 \\ \vdots & \vdots \\ 0 \end{bmatrix}$$

$$oldsymbol{\Sigma} = egin{bmatrix} 2\sigma_e^2 & & & & & & & & \\ & \ddots & & & & & & & \\ & & \sigma_e^2 & & & & & & \\ & & & \sigma_e^2 + \sigma_u^2 & & & & \\ & & & & \ddots & & \\ & & & & \sigma_e^2 + \sigma_u^2 \end{bmatrix}$$

Then

$$\begin{split} \hat{\mu_1} - \hat{\mu_2} &= \begin{bmatrix} 1 & -1 \end{bmatrix} (\boldsymbol{X}^T \boldsymbol{\Sigma}^{-1} \boldsymbol{X})^- \boldsymbol{X}^T \boldsymbol{\Sigma}^{-1} \boldsymbol{y} \\ &= \frac{1}{\frac{1}{\sigma_e^2 + \sigma_u^2} + \frac{1}{\sigma_e^2}} \left(\frac{1}{\sigma_e^2} \bar{d} + \frac{1}{\sigma_u^2 + \sigma_e^2} (\bar{a} - \bar{b}) \right) \\ &= \frac{1}{\sigma_u^2 + 2\sigma_e^2} \left((\sigma_u^2 + \sigma_e^2) \bar{d} + \sigma_e^2 (\bar{a} - \bar{b}) \right) \end{split}$$

3.

$$egin{aligned} m{X} &= egin{bmatrix} m{1}_{20 imes 1} \otimes m{I}_{2 imes 2} \ m{1}_{20 imes 1} & m{0}_{20 imes 1} \ m{0}_{20 imes 1} & m{1}_{20 imes 1} \end{bmatrix} \ m{Z} &= egin{bmatrix} m{I}_{20 imes 20} \otimes m{1}_{2 imes 1} & m{0}_{40 imes 40} \ m{0}_{40 imes 20} & m{I}_{40 imes 40} \end{bmatrix} \end{aligned}$$

4.

$$\begin{aligned} & \text{BLUE}_{1}(\mu) = \frac{y_{1} + y_{2} + y_{3} + y_{4}}{4} \\ & \text{Var}(\text{BLUE}_{1}(\mu)) = \frac{1}{16} \text{Var}(y_{1} + y_{2} + y_{3} + y_{4}) \\ & = \frac{1}{16} \left(\sum_{i=1}^{4} \text{Var}(y_{i}) + \sum_{i \neq j} \text{Cov}(y_{i}, y_{j}) \right) \\ & = \frac{1}{16} (5 \times 4 + 1 \times 4 \times 3) = 2 \\ & \text{BLUE}_{2}(\mu) = y_{5} \\ & \text{Var}(\text{BLUE}_{2}(\mu)) = \text{Var}(y_{5}) = 4 \end{aligned}$$

We know $BLUE_1(\mu)$ and $BLUE_2(\mu)$ are independent, then

$$BLUE(\mu) = \frac{\frac{1}{2}}{\frac{1}{2} + \frac{1}{4}}BLUE_1(\mu) + \frac{\frac{1}{4}}{\frac{1}{2} + \frac{1}{4}}BLUE_2(\mu) = \frac{2}{3}\frac{y_1 + y_2 + y_3 + y_4}{4} + \frac{1}{3}y_5 = \frac{1}{6}(y_1 + y_2 + y_3 + y_4) + \frac{1}{3}y_5$$