

$$\begin{aligned} 1a) \text{Var}(y_i) &= \text{Var}(1x_i | \varepsilon_i) \\ &= 1x_i^2 \text{Var}(\varepsilon_i) \\ &= x_i^2 \sigma^2 \end{aligned}$$

$$\begin{aligned} \text{Cov}(1x_i | y_i, 1x_j | y_j) &= 1x_i | 1x_j | \text{Cov}(y_i, y_j) \\ &= 1x_i | 1x_j | 0 \\ &= 0 \end{aligned}$$

Thus,  $\text{Var}(y) = \sigma^2 \text{diag}(x_1^2, \dots, x_n^2)$ , i.e.,

$$\text{Var}(y) = \sigma^2 \begin{bmatrix} x_1^2 & 0 & \dots & 0 \\ 0 & x_2^2 & & \\ \vdots & & \ddots & \\ 0 & \dots & 0 & x_n^2 \end{bmatrix}$$

1b)  $\text{Var}(y) = \sigma^2 V$ , where

$$V = \text{diag}(x_1^2, x_2^2, \dots, x_n^2).$$

Because  $x_1, x_2, \dots, x_n$  are known,

$V$  is known. Thus, this is a special case of the Aitken model.

The design matrix is

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \equiv \underline{x} \quad \text{and the parameter vector} \\ \text{is } \underline{\beta} = [\beta] \quad (p=1).$$

The BLUE is

$$\begin{aligned} (X'V^{-1}X)^{-1}X'V^{-1}y &= (\underline{x}'V^{-1}\underline{x})^{-1}\underline{x}'V^{-1}y \\ &= \frac{\sum_{i=1}^n x_i y_i / x_i^2}{\sum_{i=1}^n x_i^2 / x_i^2} = \frac{1}{n} \sum_{i=1}^n \frac{y_i}{x_i}. \end{aligned}$$

2a) This is a split-plot experiment.  
 The whole-plot experimental units are pots. The split-plot experimental units are seedlings.

b) seedlings

<u>Source</u>	<u>DF</u>
Watering level	$3-1=2$
pot(wat. lev.)	$(10-1)(3)=27$
injection	$2-1=1$
Wat. lev. x injection	$(3-1)(2-1)=2$
error	87
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C. total	$120-1=119$

Note that "error" is a combination of  
 injection x pot(wat. lev.)  $(2-1)(27)=27$

and

seedling (injection, pot, wat. lev.)  $= (2-1)(60)=60$ .

3a) Let  $\varepsilon \sim N(0, 1)$  and independent of  $w_1$ .

Then  $w_2$  has the same distribution as  $w_1 + \varepsilon$ .

$$\Rightarrow \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \stackrel{d}{=} \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} w_1 \\ \varepsilon \end{bmatrix}$$

$$\sim N\left(\begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \mathbf{I} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}\right)$$

$$\stackrel{d}{=} N\left(\underline{0}, \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix}\right) \equiv N\left(\begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}\right)$$

$$b) E(w_1 | w_2) = \mu_1 + \Sigma_{12} \Sigma_{22}^{-1} (w_2 - \mu_2)$$

$$= 0 + (1) \left(\frac{1}{2}\right) (1.7 - 0)$$

$$= 0.85$$

$$\begin{aligned} 4a) \quad Y_{1j} - Y_{2j} &= \mu_1 + u_j + e_{1j} - (\mu_2 + u_j + e_{2j}) \\ &= \mu_1 - \mu_2 + e_{1j} - e_{2j} \end{aligned}$$

$$\begin{aligned} E(Y_{1j} - Y_{2j}) &= \mu_1 - \mu_2 + E(e_{1j}) - E(e_{2j}) \\ &= \mu_1 - \mu_2 \end{aligned}$$

$$\begin{aligned} \text{Var}(Y_{1j} - Y_{2j}) &= \text{Var}(e_{1j} - e_{2j}) = \text{Var}(e_{1j}) + \text{Var}(e_{2j}) \\ &= 2\sigma_e^2. \end{aligned}$$

Thus,  $d_1, \dots, d_{20} \stackrel{\text{iid}}{\sim} N(\mu_1 - \mu_2, 2\sigma_e^2)$ .

(We have normality because linear combinations of normals are normal. We have independence because all  $e_{ij}$ 's are independent.)

4 b) We should conduct a paired-data t-test. If you forgot the expression for the test statistic that you should have learned in a first statistics course, it is fortunately easy to derive using what we have learned this semester.

Take

$$y = \underline{d}, \quad X = \underline{1}, \quad \beta = \mu_1 - \mu_2, \quad \sigma^2 = 2\sigma_e^2$$

$$\hat{\beta} = (X'X)^{-1}X'y = (\underline{1}'\underline{1})^{-1}\underline{1}'y = \bar{y} = \bar{d}.$$

$$\text{Var}(\hat{\beta}) = \sigma^2(X'X)^{-1} = 2\sigma_e^2/n = \sigma_e^2/10$$

$$\begin{aligned} \hat{\sigma}^2 &= \frac{\widehat{\sum e^2}}{2\sigma_e^2} = \frac{(y - X\hat{\beta})'(y - X\hat{\beta})}{n - \text{rank}(X)} \\ &= \frac{\sum_{i=1}^{20} (d_i - \bar{d})^2}{19} \end{aligned}$$

Thus, to test  $H_0: \mu_1 = \mu_2 \Leftrightarrow H_0: \mu_1 - \mu_2 = 0$ ,

We use 
$$t = \frac{\bar{d}_\cdot}{\sqrt{\hat{\sigma}^2/n}} = \frac{\bar{d}_\cdot}{\sqrt{\frac{\sum_{i=1}^{20} (d_i - \bar{d}_\cdot)^2}{19} / 20}}$$

4c) Noncentral  $t$  with d.f. = 19  
and noncentrality parameter

$$\frac{\mu_1 - \mu_2}{\sqrt{\sigma^2/20}} = \frac{\mu_1 - \mu_2}{\sqrt{20\sigma^2/20}} = \frac{\mu_1 - \mu_2}{\sqrt{\sigma^2/10}}$$

This is true because

$$t = \frac{\bar{d}_\cdot - (\mu_1 - \mu_2)}{\sqrt{\sigma^2/20}} + \frac{\mu_1 - \mu_2}{\sqrt{\sigma^2/20}}$$


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$$\frac{\bar{d}_\cdot - (\mu_1 - \mu_2)}{\sqrt{\sigma^2/20}} \sim N(0,1)$$

independent of

$$\frac{\hat{\sigma}^2}{\sigma^2} \sim \chi^2_{19/19}$$

4d) This is the classic case of two independent normal samples,

If you forgot the formulas, they are easy to derive. Take

$$\underline{y} = \begin{bmatrix} a \\ \tilde{a} \\ b \\ \tilde{b} \end{bmatrix}, \quad X = \begin{bmatrix} \tilde{1}_{20 \times 1} & \tilde{0}_{20 \times 1} \\ \tilde{0}_{20 \times 1} & \tilde{1}_{20 \times 1} \end{bmatrix}, \quad \underline{\beta} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}$$

$$\sigma^2 = \text{Var}(u_j + e_{ij}) = \sigma_u^2 + \sigma_e^2.$$

$$\hat{\underline{\beta}} = (X'X)^{-1} X' \underline{y} = \begin{bmatrix} 20 & 0 \\ 0 & 20 \end{bmatrix}^{-1} \begin{bmatrix} a. \\ b. \end{bmatrix} = \begin{bmatrix} \bar{a}. \\ \bar{b}. \end{bmatrix}$$

$$\underline{c}' \hat{\underline{\beta}} = [1, -1] \begin{bmatrix} \bar{a}. \\ \bar{b}. \end{bmatrix} = \bar{a}. - \bar{b}.$$

$$\begin{aligned} \text{Var}(\underline{c}' \hat{\underline{\beta}}) &= \underline{c}' \sigma^2 (X'X)^{-1} \underline{c} = \sigma^2 [1, -1] \begin{bmatrix} 1/20 & 0 \\ 0 & 1/20 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} \\ &= \sigma^2 / 10 \end{aligned}$$

$$\hat{\sigma}^2 = \frac{(y - X\hat{\beta})'(y - X\hat{\beta})}{n - \text{rank}(X)}$$

$$= \frac{\sum_{i=1}^{20} (a_i - \bar{a}_i)^2 + \sum_{i=1}^{20} (b_i - \bar{b}_i)^2}{38}$$

Thus, the formula for the interval is

$$\bar{a}_i - \bar{b}_i \pm t_{38}^{(.975)} \sqrt{\frac{\sum_{i=1}^{20} (a_i - \bar{a}_i)^2 + \sum_{i=1}^{20} (b_i - \bar{b}_i)^2}{(38)(10)}}$$

4e) From previous parts we have

$$E\left(\frac{\sum_{i=1}^{20} (d_i - \bar{d})^2}{19}\right) = 2\sigma_e^2$$

and

$$E\left(\frac{\sum_{i=1}^{20} (a_i - \bar{a})^2 + \sum_{i=1}^{20} (b_i - \bar{b})^2}{38}\right) = \sigma_u^2 + \sigma_e^2.$$

$$\text{Thus, } \hat{\sigma}_e^2 = \frac{1}{2} \frac{\sum_{i=1}^{20} (d_i - \bar{d})^2}{19}$$

$$\text{and } \hat{\sigma}_u^2 = \frac{\sum_{i=1}^{20} (a_i - \bar{a})^2 + \sum_{i=1}^{20} (b_i - \bar{b})^2}{38}$$

$$- \frac{1}{2} \frac{\sum_{i=1}^{20} (d_i - \bar{d})^2}{19}$$

4f) You could set the problem up as

$$Y = \begin{bmatrix} d. \\ \bar{a}. \\ \bar{b}. \end{bmatrix}, \quad X = \begin{bmatrix} 1 & -1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad \beta = \begin{bmatrix} M_1 \\ M_2 \end{bmatrix}$$

$$\Sigma \sim N \left( \begin{matrix} 0 \\ 0 \end{matrix}, \underbrace{\begin{bmatrix} \sigma_e^2/10 & 0 & 0 \\ 0 & \frac{\sigma_u^2 + \sigma_e^2}{20} & 0 \\ 0 & 0 & \frac{\sigma_u^2 + \sigma_e^2}{20} \end{bmatrix}}_{\Sigma} \right)$$

You could then compute

$$(X' \Sigma^{-1} X)^{-1} X' \Sigma^{-1} Y$$

Alternatively, we know that

$\bar{d}_i$  and  $\bar{a}_i - \bar{b}_i$  are independent

estimators of  $M_1 - M_2$ . The BLUP

will be of the form

$$\alpha \bar{d}_i + (1-\alpha) (\bar{a}_i - \bar{b}_i)$$

with weights inversely proportional

to the variances of  $\bar{d}_i$  and  $\bar{a}_i - \bar{b}_i$ .

$$\text{Var}(\bar{d}_i) = \frac{2\sigma_e^2}{20} = \sigma_e^2/10$$

$$\text{Var}(\bar{a}_i - \bar{b}_i) = \frac{\sigma_u^2 + \sigma_e^2}{10}$$

Thus,

$$\begin{aligned} \lambda &= \frac{10/\sigma_e^2}{\frac{10/\sigma_e^2}{\sigma_e^2} + \frac{10}{\sigma_u^2 + \sigma_e^2}} = \frac{10(\sigma_u^2 + \sigma_e^2)}{10(\sigma_u^2 + \sigma_e^2) + 10\sigma_e^2} \\ &= \frac{\sigma_u^2 + \sigma_e^2}{\sigma_u^2 + 2\sigma_e^2} \end{aligned}$$

The BLUP is, therefore,

$$\frac{\sigma_u^2 + \sigma_e^2}{\sigma_u^2 + 2\sigma_e^2} \bar{d} + \frac{\sigma_e^2}{\sigma_u^2 + 2\sigma_e^2} (\bar{a}_i - \bar{b}_i)$$

Point values were as follows:

1a) 6	2a) 6	3a) 8	4a) 7	4d) 8
1b) 9	2b) 4	3b) 9	4b) 8	4e) 8
	2c) 9		4c) 8	4f) 10