

L23 Linear model: Two-way ANOVA

1. Two-way ANOVA

(1) Populations

In an experiment Factor A with a levels and factor B with b levels produce ab treatments. Response y to treatments form ab populations.

$$y = \mu_{ij} + \epsilon \text{ with } E(\epsilon) = 0, i = 1, \dots, a; j = 1, \dots, b.$$

$$\text{Let } M = \begin{pmatrix} \mu_{11} & \cdots & \mu_{1b} \\ \vdots & \ddots & \vdots \\ \mu_{a1} & \cdots & \mu_{ab} \end{pmatrix} \text{ with } \mu = \text{vec}(M); r_i = \begin{cases} 1 & y \text{ is response under level } i \text{ of A} \\ 0 & \text{otherwise} \end{cases}$$

is indicator for level i of A and $c_j = \begin{cases} 1 & y \text{ is response under level } j \text{ of B} \\ 0 & \text{otherwise} \end{cases}$ is the indicator for level j of B. So in $m = (c_1, \dots, c_b) \otimes (r_1, \dots, r_a)$ the component $r_i c_j$ is the indicator for treatment (i, j) . Then

$$y = (r_1, \dots, r_a) M \begin{pmatrix} c_1 \\ \vdots \\ c_b \end{pmatrix} + \epsilon = [(c_1, \dots, c_b) \otimes (r_1, \dots, r_a)] \text{vec}(M) + \epsilon = m\mu + \epsilon$$

This model gives ab populations.

(2) Samples

$y_1, \dots, y_n$ is a random sample where y_i is observed when $m = m_i$.

$$\text{Let } Y = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} \in R^n, D = \begin{pmatrix} m_1 \\ \vdots \\ m_n \end{pmatrix} \in R^{n \times ab}. \quad \text{Then } Y = D\mu + \epsilon \text{ with } E(\epsilon) = 0 \in R^n.$$

Matrix D matches y_i to its treatment and is called the design matrix.

2. Re-parameterization

(1) Introducing θ

With $\mu_{.j} = \frac{\sum_i \mu_{ij}}{a}$, $\mu_{i.} = \frac{\sum_j \mu_{ij}}{b}$, $\mu_{..} = \frac{\sum_i \sum_j \mu_{ij}}{ab}$, let $\alpha_i = \mu_{i.} - \mu_{..}$, $\beta_j = \mu_{.j} - \mu_{..}$ and $(\alpha\beta)_{ij} = \mu_{ij} - \mu_{..} - \alpha_i - \beta_j$. With $H = ((\alpha\beta)_{ij})_{a \times b}$ and $h = \text{vec}(H)$, introducing

$$\theta = \begin{pmatrix} \mu_{..} \\ \alpha \\ \beta \\ h \end{pmatrix} \in R^{1+a+b+ab} \text{ where } \alpha = \begin{pmatrix} \alpha_1 \\ \vdots \\ \alpha_a \end{pmatrix} \text{ and } \beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_b \end{pmatrix} \in R^b.$$

$$(2) \mu = A\theta \quad \text{with } A = (1_b \otimes 1_a, 1_b \otimes I_a, I_b \otimes 1_a, I_b \otimes I_a) \in R^{ab \times (1+a+b+ab)}$$

Proof Note that $M = (\mu_{ij})_{a \times b} = (\mu_{..} + \alpha_i + \beta_j + (\alpha\beta)_{ij})_{a \times b}$
 $= 1_a \mu_{..} 1_b' + I_a \alpha 1_b' + 1_a \beta' I_b + I_a H I_b.$

$$\text{So } \mu = \text{vec}(M) = (1_b \otimes 1_a) \mu_{..} + (1_b \otimes I_a) \alpha + (I_b \otimes 1_a) \beta + (I_b \otimes I_a) h$$

$$= (1_b \otimes 1_a, 1_b \otimes I_a, I_b \otimes 1_a, I_b \otimes I_a) \begin{pmatrix} \mu_{..} \\ \alpha \\ \beta \\ h \end{pmatrix} = A\theta.$$

$$(3) \text{ Restrictions } G\theta = 0 \quad \text{with } G = \begin{pmatrix} 0 & 1'_a & 0 & 0 \\ 0 & 0 & 1'_b & 0 \\ 0 & 0 & 0 & I_b \otimes 1'_a \\ 0 & 0 & 0 & 1'_b \otimes I_a \end{pmatrix} \in R^{(2+a+b) \times (1+a+b+ab)}$$

Proof In θ , $\sum_i \alpha_i = \sum_i (\mu_{i.} - \mu_{..}) = 0$, i.e., $1'_a \alpha = 0$;

$$\sum_j \beta_j = \sum_j (\mu_{.j} - \mu_{..}) = 0, \text{ i.e., } 1'_b \beta = 0;$$

$$\sum_i (\alpha\beta)_{ij} = \sum_i (\mu_{ij} - \mu_{..} - \alpha_i - \beta_j) = a\mu_{.j} - a\mu_{..} - 0 - a(\mu_{.j} - \mu_{..}) = 0. \text{ Equivalently}$$

$$1'_a H = 0, \text{ i.e., } (I_b \otimes 1'_a)h = 0;$$

$$\sum_j (\alpha\beta)_{ij} = \sum_j (\mu_{ij} - \mu_{..} - \alpha_i - \beta_j) = b\mu_{i.} - b\mu_{..} - b(\mu_{i.} - \mu_{..}) - 0 = 0. \text{ Equivalently}$$

$$H1_b = 0, \text{ i.e., } (1'_b \otimes I_a)h = 0.$$

$$\text{Thus } 0 = \begin{pmatrix} 0 & 1'_a & 0 & 0 \\ 0 & 0 & 1'_b & 0 \\ 0 & 0 & 0 & I_b \otimes 1'_a \\ 0 & 0 & 0 & 1'_b \otimes I_a \end{pmatrix} \begin{pmatrix} \mu_{..} \\ \alpha \\ \beta \\ h \end{pmatrix} = G\theta.$$

3. Model with restrictions

(1) Equivalent models

For populations $y = m\mu + \epsilon \iff y = mA\theta + \epsilon$ under $G\theta = 0$.

For samples $Y = M\mu + \epsilon \iff Y = MA\theta + \epsilon$ under $G\theta = 0$.

(2) Comments

μ has ab free components. θ has $1 + a + b + ab$ components. Each equation reduces the number free parameters by 1. Among $2 + a + b$ equations in $G\theta = 0$, the last is implied by the previous ones. Consequently, in θ there are $(1 + a + b + ab) - (1 + a + b) = ab$ free components.

$$\text{Ex: } \theta = B\mu \text{ with } B = \begin{pmatrix} (1_b \otimes 1_a)^+ \\ [1_b \otimes (I_a - 11^+)]^+ \\ [(I_b - 11^+) \otimes 1_a]^+ \\ [(I_b - 11^+) \otimes (I_a - 11^+)]^+ \end{pmatrix}.$$

$$\text{Proof In } \theta = \begin{pmatrix} \mu_{..} \\ \alpha \\ \beta \\ h \end{pmatrix}, \mu_{..} = \frac{\sum_i \sum_j \mu_{ij}}{ab} = \frac{1'_a M 1_b}{ab} = (1_b^+ \otimes 1_a^+) \mu = (1_b \otimes 1_a)^+ \mu.$$

$$\alpha = M \frac{1_b}{b} - 1_a \frac{1'_a M 1_b}{ab} = (I_a - 11^+) M \frac{1_b}{b} = [1_b^+ \otimes (I_a - 11^+)] \mu = [1_b \otimes (I_a - 11^+)]^+ \mu.$$

$$\beta' = \frac{1'_a M}{a} - \frac{1'_a M 1_b}{ab} 1'_b = 1_a^+ M (I_b - 11^+). \text{ So } \beta = [(I_b - 11^+) \otimes 1_a^+] \mu = [(I_b - 11^+) \otimes 1_a]^+ \mu.$$

$$H = ((\alpha\beta)_{ij})_{a \times b} = (\mu_{ij} - \mu_{..} - \alpha_i - \beta_j)_{a \times b} = M - 1_a \mu_{..} 1'_b - \alpha 1'_b - 1_a \beta'$$

$$= M - 1_a \frac{1'_a M 1_b}{ab} 1'_b - (I_a - 11^+) M \frac{1_b}{b} 1'_b - 1_a 1_a^+ M (I_b - 11^+)$$

$$= M + 1_a 1_a^+ M 1_b 1_b^+ - M 1_b 1_b^+ - 1_a 1_a^+ M = (I_a - 11^+) M (I_b - 11^+)$$

$$\text{So } h = [(I_b - 11^+) \otimes (I_a - 11^+)] \mu = [(I_b - 11^+) \otimes (I_a - 11^+)]^+ \mu.$$

$$\text{Therefore } \theta = \begin{pmatrix} (1_b \otimes 1_a)^+ \\ [1_b \otimes (I_a - 11^+)]^+ \\ [(I_b - 11^+) \otimes 1_a]^+ \\ [(I_b - 11^+) \otimes (I_a - 11^+)]^+ \end{pmatrix} \mu = B\mu.$$