

← prepare the table

1. put 0 if at least one row index matches column index and Fixed

2. put 1 if - - - - -

- - - - - and Random

in the remaining put # of levels.

2. get E(MS)

• Delete columns with index and rows without index

• multiply Fixed $\rightarrow Q(\tau) = \frac{\sum \tau_i^2}{a-1}$

+ Random $\rightarrow \sigma_B^2$

+ σ^2

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$$E(MS_{\tau}) = bnQ(\tau) + n\sigma_r^2 + \sigma^2 = bn \frac{\sum \tau_i^2}{a-1} + n\sigma_r^2 + \sigma^2$$

$$E(MS_{\beta}) = an\sigma_{\beta}^2 + 0 \cdot n\sigma_r^2 + \sigma^2 = an\sigma_{\beta}^2 + \sigma^2$$

$$E(MS_y) = n\sigma_r^2 + \sigma^2$$

$$E(MSE) = \sigma^2$$

Example: 2-factor fixed model

$$y_{ijk} = \mu + \tau_i + \beta_j + (\tau\beta)_{ij} + \varepsilon_{ijk}, \quad \begin{matrix} i=1, \dots, a \\ j=1, \dots, b \\ k=1, \dots, n \end{matrix}$$

Factor	F	F	R
	a	b	n
	i	j	k
τ_i	0	b	n
β_j	a	0	n
$(\tau\beta)_{ij}$	0	0	n

$$E(MS_{\tau}) = bnQ(\tau) + \sigma^2$$

$$E(MS_{\beta}) = anQ(\beta) + \sigma^2$$

$$E(MS_{\tau\beta}) = nQ(\tau\beta) + \sigma^2$$

$$Q(\tau) = \frac{\sum \tau_i^2}{a-1}$$

$$Q(\beta) = \frac{\sum \beta_j^2}{b-1}$$

$$Q(\tau\beta) = \frac{\sum \sum (\tau\beta)_{ij}^2}{(a-1)(b-1)}$$

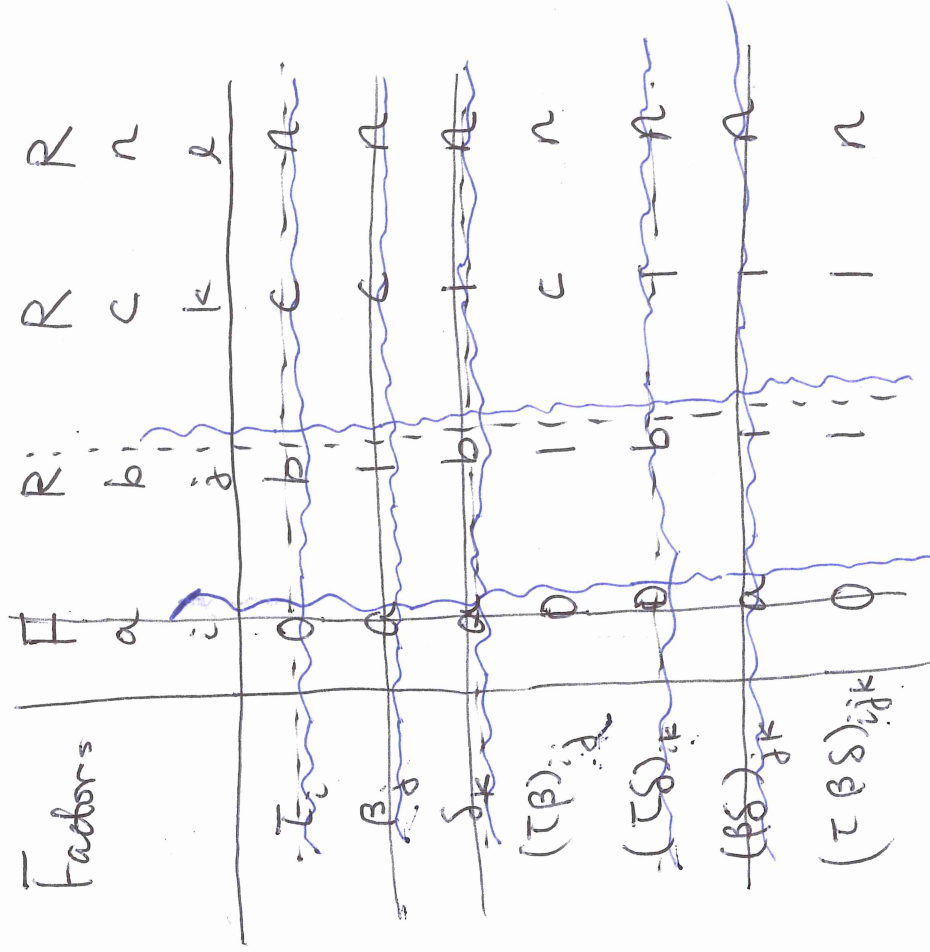
Example 3-way ANOVA

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$$y_{ijkl} = \mu + \tau_i + \beta_j + \delta_k + (\tau\beta)_{ij} + (\tau\delta)_{ik} + (\beta\delta)_{jk} + (\tau\beta\delta)_{ijk} + \varepsilon_{ijkl}$$

$i=1, \dots, a$
 $j=1, \dots, b$
 $k=1, \dots, c$
 $l=1, \dots, n$

fixed random



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$$\begin{aligned}
 E(MS_{\tau}) &= \sigma^2 + bc n Q(\tau) + cn \sigma_{\tau\beta}^2 + bn \sigma_{\tau\gamma}^2 + n \sigma_{\tau\beta\gamma}^2 \\
 \rightarrow E(MS_{\beta}) &= \sigma^2 + ac n \sigma_{\beta}^2 + an \sigma_{\beta\gamma}^2 \\
 E(MS_{\gamma}) &= \sigma^2 + ab n \sigma_{\gamma}^2 + an \sigma_{\beta\gamma}^2 \\
 \rightsquigarrow E(MS_{\tau\beta}) &= \sigma^2 + cn \sigma_{\tau\beta}^2 + n \sigma_{\tau\beta\gamma}^2 \\
 E(MS_{\tau\gamma}) &= \sigma^2 + bn \sigma_{\tau\gamma}^2 + n \sigma_{\tau\beta\gamma}^2 \\
 \rightarrow E(MS_{\beta\gamma}) &= \sigma^2 + an \sigma_{\beta\gamma}^2 \\
 \rightsquigarrow E(MS_{\tau\beta\gamma}) &= \sigma^2 + n \sigma_{\tau\beta\gamma}^2
 \end{aligned}$$

$$E(MSE) = \sigma^2$$

Eg: $H_0: \sigma_{\beta}^2 = 0$, $H_A: \sigma_{\beta}^2 > 0$

$$\frac{MS_{\beta}}{MS_{\beta\gamma}} \sim F_{(b-1), (b-1)(c-1)}$$

$H_0: \sigma_{\tau\beta}^2 = 0$, $H_A: \sigma_{\tau\beta}^2 > 0$

$$\frac{MS_{\tau\beta}}{MS_{\tau\beta\gamma}} \sim F_{(a-1)(b-1), (a-1)(b-1)(c-1)}$$

$$H_0: \tau_1 = \tau_2 = \dots = \tau_a = 0, \quad H_A: H_0 \text{ not holds}$$

$$\text{bca } Q(\tau) + E(MS_{\tau\beta}) + E(MS_{\tau\delta}) = E(MS_{\tau} + MS_{\tau\beta\delta}).$$

$$F = \frac{MS_{\tau} + MS_{\tau\beta\delta}}{MS_{\tau\beta} + MS_{\tau\delta}}$$

~ approximate F test

$F_{p,q}$

$$p = \frac{(MS_{\tau} + MS_{\tau\beta\delta})^2}{\frac{MS_{\tau}^2}{df_{\tau}} + \frac{MS_{\tau\beta\delta}^2}{df(\tau\beta\delta)}}$$

$$q = \frac{(MS_{\tau\beta} + MS_{\tau\delta})^2}{\frac{MS_{\tau\beta}^2}{df(\tau\beta)} + \frac{MS_{\tau\delta}^2}{df(\tau\delta)}}$$

In general, approx df. of $Q = \sum c_i MS_i$ is

$$Q^2 = \frac{\sum (c_i MS_i)^2}{df_i}$$

Satterthwaith procedure

Test: $H_0: \sigma_\beta^2 = 0$ $H_A: \sigma_\beta^2 > 0$

1. Method, approximate F-test (balanced, nearly balanced)
2. Method, LRT (Likelihood ratio test)

(Normal dist. assumption)

$$\lambda = \frac{\max_{\theta \in H_0} L(\theta)}{\max_{\theta \in H} L(\theta)}$$

$$-2 \log \lambda \sim \chi^2_{(1)}$$

Parameter estimation.

likelihood-based Methods

estimates cannot be written in closed form

Numerical solution (consistent, asymptotic property)

R: `nlme` (package `nlme`)

`lmer` (package `lme4`)

Restricted ML: maximize L under the constraints $\sigma^2 \geq 0$, $\sigma_\mu^2 \geq 0$

- Mixed Model (ANOVA II)

Two-way mixed model (Restricted)

One fixed, one random, the interaction is considered to be random.

$$Y_{ijk} = \mu + \underset{\downarrow}{\alpha_i} + \underset{\downarrow}{\beta_j} + (\alpha\beta)_{ij} + \underset{\downarrow}{\varepsilon_{ijk}} \quad r$$

$$\sum \alpha_i = 0$$

$$\beta_j \sim N(0, \sigma_\beta^2)$$

$$(\alpha\beta)_{ij} \sim N\left(0, \frac{a-1}{a} \sigma_\alpha^2\right) \text{ subject to } \sum_i (\alpha\beta)_{ij} = 0 \text{ for each } j$$

$$\text{Cov}(\alpha\beta_{ij}, \alpha\beta_{ij'}) = -\frac{\sigma_\alpha^2}{a}$$

Chapter 21. Randomized Block Designs

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In any experiment, variability arising from ~~nuisance~~ nuisance factor
↓
can affect the results. not interested

nuisance factor: { known not controlled (Randomization)
known and controllable (blocking design)

Idea: grouping of experimental units into homogeneous groups (Blocks)

— If all units are homogeneous — need only 1 Block
exp units are assigned to trts at random.

Completely Randomized Design

— If more than 1 groups required: within each block
units are more homogeneous than between blocks

Some blocked design

• Randomized complete block design (RCBD)

For "a" trts — "b" blocks with "a" exp units each. Any trt assigned to the same number of exp units with any block.

trt	b				t _i	b		
	1	2	3	4		1	2	3
A	A	B	A	B		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
B	B	C	C	A		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
C	C	A	B	C		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Incomplete block design.

Assumption: No interaction between the components of trt structure and the components of design structure, and among the comp of design structure.

Randomized Block Designed.

Each trt is included once in each Block.

$$y_{dij} = \mu + \rho_i + \tau_j + \varepsilon_{ij}$$

If τ_j, p_i interact (Restricted version)

\downarrow random
• n replications in each cell. $\sum_{j=1}^a (\tau p)_{ij} = 0$

$$E(MS(\tau)) = \sigma^2 + n n_b Q(\tau) + n \sigma_{\tau p}^2$$

$$E(MS(p)) = \sigma^2 + a n \sigma_p^2$$

$$E(MS(\tau p)) = \sigma^2 + n \sigma_{\tau p}^2$$

$$E(MSE) = \sigma^2$$

• If unrestricted version.

$$E(MS(p)) = \sigma^2 + a n \sigma_p^2 + n \sigma_{\tau p}^2$$

• Efficiency of blocking

$$E = \frac{\sigma_r^2}{\sigma_b^2}$$

σ_r^2 = variance in a completely random design.

σ_b^2 = variance in a block design

$$\begin{aligned}
 \hat{\sigma}_b^2 &= MSBL.TR \\
 \hat{\sigma}_r^2 &= \frac{SSBL + SSBL.TR}{df} \\
 &= \frac{(n_b - 1) MSBL + (n_b - 1)(a - 1) MSBL.TR}{(n_b - 1)a}
 \end{aligned}$$

In text book an unbiased est of σ_r^2 is

$$\frac{(n_b - 1) MSBL + n_b(a - 1) MSBL.TR}{n_b a - 1}$$

$$\begin{aligned}
 \hat{E} &= \frac{\hat{\sigma}_r^2}{\hat{\sigma}_b^2} = \frac{(n_b - 1) MSBL + (n_b - 1)(a - 1) MSBL.TR}{(n_b - 1)a MSBL.TR} \\
 &= \frac{1}{a} \frac{MSBL}{MSBL.TR} + 1 - \frac{1}{a}
 \end{aligned}$$

$$\hat{E} > 1 \Leftrightarrow \frac{MSBL}{MSBL.TR} > 1$$