

Stat 5206
4-22-24

(1)

Rule for df:

df = product of ($\# \text{levels} - 1$)
for each lone subscript terms
($\# \text{levels}$) for each dual
subscript

In our last example,

$$df_{AB} = (a-1)(b-1)$$

$$df_e = abc(a-1)$$

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Rule for find SS terms.

Start by symbolically multiplying the df

$$AB: \quad df = (a-1)(b-1) = ab - a - b + 1$$

for each term in the expansion, put a dot
for each missing index, square the term, divide
by the # levels of each missing index, + sum over
all present indices.

$$SS_{AB} = \sum_i \sum_j \frac{y_{ij\ldots}^2}{cn} - \sum_i \frac{y_{i\ldots}^2}{bcn} - \sum_j \frac{y_{\cdot j\ldots}^2}{acn} + \frac{y_{\ldots\ldots}^2}{aben}$$

Satterthwaite's Approximate F test

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Construct 2 new MS terms

$$MS' = MS_1 + \dots + MS_u \quad \text{no terms in common}$$

$$MS'' = MS_v + \dots + MS_w$$

so that $E(MS') - E(MS'') = \text{Constant} + \text{true Variance Component}$

for yesterday's example

the desired

$$\text{try } MS = MS_A + MS_{AC}$$

$$MS' = MS_{A\bar{B}} + MS_{AC}$$

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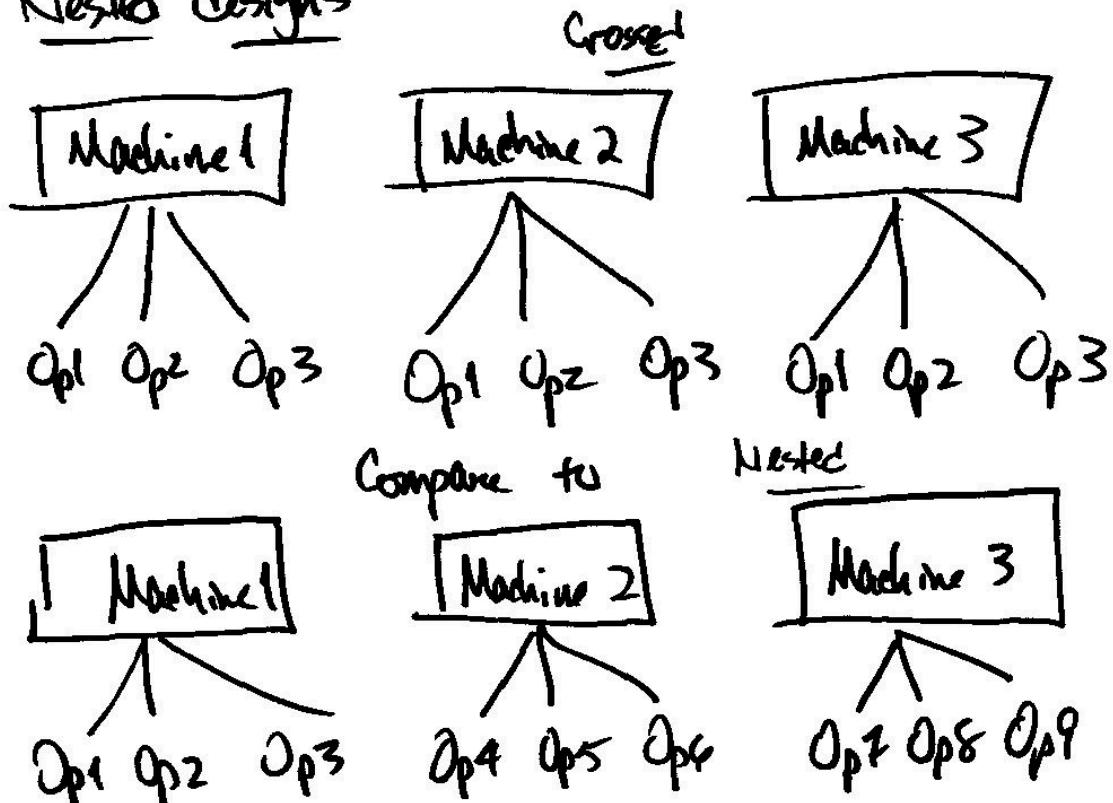
Satterthwaite proved that $\frac{MS'}{MS''}$ has

an approximate F distribution with p, q df,

$$\text{where } p = \frac{(MS')^2}{\frac{MS_1^2}{df_1} + \dots + \frac{MS_u^2}{df_u}}, q = \frac{(MS'')^2}{\frac{MS_v^2}{df_v} + \dots + \frac{MS_w^2}{df_w}}$$

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Nested designs



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Model for a nested design:

$$y_{ijk} = \mu + \gamma_i + \beta_{j(i)} + \epsilon_{(i)k}$$

↑ ↑
 machine operator, nested
 within machine

Parameter estimates, assuming both effects are fixed

Assume $\sum_{i=1}^a \gamma_i = 0$ and $\sum_{j=1}^b \beta_{j(i)} = 0 \quad \forall i$

$$SSE = \sum_i \sum_j \sum_k [y_{ijk} - (\mu + \gamma_i + \beta_{j(i)})]^2$$

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$$\frac{\partial SSE}{\partial \mu} = \sum_{i,j,k} [y_{ijk} - (\mu + \tau_i + \beta_{j(i)})] (-1) \stackrel{\text{set}}{=} 0$$

$$y_{...} - N\mu - 0 - 0 = 0$$

$$\therefore \hat{\mu} = \frac{y_{...}}{N} = \bar{y}_{...}$$

$$\frac{\partial SSE}{\partial \tau_i} = \sum_j \sum_k [y_{ijk} - (\mu + \tau_i + \beta_{j(i)})] (-1) \stackrel{\text{set}}{=} 0$$

$$y_{i..} - b_n \mu - b_n \tau_i - 0 = 0$$

$$\hat{\tau}_i = \frac{y_{i..} - b_n \bar{y}_{...}}{b_n} = \bar{y}_{i..} - \bar{y}_{...}$$

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$$\frac{\partial SSE}{\partial \beta_{j(i)}} = \sum_k [y_{ijk} - (\mu + \tau_i + \beta_{j(i)})] (-1) \stackrel{\text{set}}{=} 0$$

$$y_{ij.} - n\mu - n\tau_i - n\beta_{j(i)} = 0$$

$$\hat{\beta}_{j(i)} = \frac{y_{ij.} - n\bar{y}_{...} - n(\bar{y}_{i..} - \bar{y}_{...})}{n}$$

$$= \bar{y}_{ij.} - \bar{y}_{...} - \bar{y}_{i..} + \bar{y}_{...}$$

$$= \bar{y}_{ij.} - \bar{y}_{i..}$$

Compare to the crossed model:

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$$\hat{\mu} = \bar{y}_{...}, \quad \hat{\gamma}_i = \bar{y}_{i..} - \bar{y}_{...}$$

$$\hat{\beta}_j = \bar{y}_{.j.} - \bar{y}_{...}, \quad \hat{\gamma}\beta_{ij} = \bar{y}_{ij.} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{...}$$

$SS \nmid df$, using rule from Tuesday's class

$$df_A = a-1 \quad \gamma_i$$

$$df_{B(A)} = (b-1)a = ab - a \quad \beta_j(\varepsilon)$$

Compare to crossed: $df_A = a-1, df_B = b-1,$
 $df_{AB} = (a-1)(b-1)$

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$$SS_A = \sum_i \frac{y_{i..}^2}{bn} - \frac{\bar{y}^2}{N}$$

$$SS_{B(A)} = \sum_i \sum_j \frac{y_{ij.}^2}{n} - \sum_i \frac{y_{i..}^2}{bn}$$

Example: A: machine fixed a levels

B: operator random nested within machine
 b operators - "

n replicates

	a F_i	b R_j	n R_k	EMS
τ_i	0	b	n	$b n \frac{\sum \tau_i^2}{a-1} + n \sigma_p^2 + \sigma^2$
$B_{j(A)}$	1	1	n	$n \sigma_p^2 + \sigma^2$
ϵ_{ijk}	1	1	1	σ^2

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$$F \text{ tests for } A: \frac{MS_A}{MS_{B(A)}}$$

$$B(A): \frac{MS_{B(A)}}{MS_e}$$

Example: y measures hardness of material

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2 different alloy formulations

3 different heats for each alloy

2 ingots of each alloy

2 replications

A: alloy $a=2$ fixed

B: heat $b=3$ fixed nested within A

C: ingt $c=2$ random nested with both A & B

$$n = 2$$

	a F i	b F j	c R k	n R l	EMS
γ_i	0	3	2	2	$12 \sum y_i^2 + 2\sigma_y^2 + \sigma^2$
$\beta_j(i)$	1	0	2	2	$4 \frac{\sum \beta_{j(i)}^2}{4} + 2\sigma_y^2 + \sigma^2$
$\gamma_{k(ij)}$	1	1	1	2	$2\sigma_y^2 + \sigma^2$
$\epsilon_{(ijk)l}$	1	1	1	1	σ^2

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$$\begin{array}{ll|l}
 A: \frac{MS_A}{MS_{C(AB)}} & df = 1, 6 & C(AB): \frac{MS_{C(AB)}}{MS_\epsilon} \\
 B(A): \frac{MS_{B(A)}}{MS_{C(AB)}} & df = 4, 6 & df = 6, 12
 \end{array}$$

Source	df	
A	1	$a-1$
B(A)	4	$(b-1)a$
C(AB)	6	$(c-1)ab$
ERF	12	$(n-1)abc$
TOT	23	$N-1$

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