

13. The Cochran-Satterthwaite Approximation for Linear Combinations of Mean Squares

Suppose M_1, \dots, M_k are independent mean squares and that

$$\left(\frac{d_i M_i}{E(M_i)} \right) \sim \chi_{d_i}^2 \quad \forall i = 1, \dots, k.$$

It follows that

$$E \left[\frac{d_i M_i}{E(M_i)} \right] = d_i, \quad \text{Var} \left[\frac{d_i M_i}{E(M_i)} \right] = 2d_i, \quad \text{and} \quad M_i \sim \boxed{\frac{E(M_i)}{d_i}} \chi_{d_i}^2$$

for all $i = 1, \dots, k$.

scaled $\chi_{d_i}^2$

Consider the random variable

Chapt 12 : 1.5 hS(χ_k (trt)) -
0.5 hSE

$$\textcircled{M} = a_1 \underline{M_1} + a_2 \underline{M_2} + \cdots + a_k \underline{M_k}, \quad (1)$$

where a_1, a_2, \dots, a_k are known constants in \mathbb{R} .

Note that M is a linear combination of scaled χ^2 random variables.

The Cochran-Satterthwaite approximation works by assuming that M is approximately distributed as a scaled χ^2 , just like each of the variables in the linear combination.

$$\frac{dM}{E(M)} \stackrel{\text{approx.}}{\sim} \chi_d^2 \iff M \stackrel{\text{approx.}}{\sim} \frac{E(M)}{d} \chi_d^2. \quad (2)$$

What choice for d makes the approximation most reasonable?

The Cochran-Satterthwaite formula for the approximate degrees of freedom associated with the linear combination of mean squares defined by M is

$$d = \frac{M^2}{\sum_{i=1}^k a_i^2 M_i^2 / d_i} = \frac{\left(\sum_{i=1}^k a_i M_i \right)^2}{\sum_{i=1}^k a_i^2 M_i^2 / d_i}.$$

Why?

Consider the definition/approximation of M in (1) and (2):

- $M = \underbrace{a_1 M_1 + a_2 M_2 + \cdots + a_k M_k}$ and

(1)

- $\underline{M} \overset{approx.}{\sim} \frac{E(M)}{d} \chi_d^2.$

(2)

- Calculate $\text{Var}(M)$ using M as defined in (1) and also using its approximation given in (2)
- Both variances are functions of d . We equate both variances and solve for d .
- The details are shown on the next two slides.

from (2) on slide 5

$$\begin{aligned}\text{Var}(M) &\approx \left(\frac{\text{E}(M)}{d}\right)^2 \text{Var}(\chi_d^2) \\ &= \left(\frac{\text{E}(M)}{d}\right)^2 \underline{(2d)} \\ &= \frac{2[\text{E}(M)]^2}{d} \\ &\approx \underline{\underline{\frac{2M^2}{d}}}.\end{aligned}$$

slide 2


And

$$\begin{aligned}\underline{\text{Var}(M)} &= \underline{a_1^2 \text{Var}(M_1)} + \cdots + \underline{a_k^2 \text{Var}(M_K)} \\&= a_1^2 \left[\frac{\text{E}(M_1)}{d_1} \right]^2 \underline{2d_1} + \cdots + a_k^2 \left[\frac{\text{E}(M_k)}{d_k} \right]^2 \underline{2d_k} \\&= 2 \sum_{i=1}^k \frac{a_i^2 [\text{E}(M_i)]^2}{d_i} \\&\approx 2 \sum_{i=1}^k a_i^2 M_i^2 / d_i.\end{aligned}$$

Equating these two variance approximations yields

$$\frac{2M^2}{d} = 2 \sum_{i=1}^k a_i^2 M_i^2 / d_i$$

and solving for d yields

$$d = \frac{M^2}{\sum_{i=1}^k a_i^2 M_i^2 / d_i} = \frac{\left(\sum_{i=1}^k a_i M_i\right)^2}{\sum_{i=1}^k a_i^2 M_i^2 / d_i}.$$


Recall the first example from the last slide set.

$$\mathbf{y} = \begin{bmatrix} y_{111} \\ y_{121} \\ y_{211} \\ y_{212} \end{bmatrix}, \quad \mathbf{X} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 0 & 1 \\ 0 & 1 \end{bmatrix}, \quad \mathbf{Z} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}$$

Handwritten annotations: "account for" above \mathbf{X} , "tr 2" with an arrow pointing to the second column of \mathbf{X} . "exp. unit 1" above the first column of \mathbf{Z} with a downward arrow. "exp. unit 3" above the third column of \mathbf{Z} with a checkmark. "exp. unit 2" below the second and third columns of \mathbf{Z} . Blue underlines are present under y_{121} and y_{212} in \mathbf{y} , and under the first column of \mathbf{Z} .

$$\mathbf{X}_1 = \mathbf{1}, \quad \mathbf{X}_2 = \mathbf{X}, \quad \mathbf{X}_3 = \mathbf{Z}$$

$$\mathbf{y}^\top (\mathbf{P}_2 - \mathbf{P}_1) \mathbf{y} + \mathbf{y}^\top (\mathbf{P}_3 - \mathbf{P}_2) \mathbf{y} + \mathbf{y}^\top (\mathbf{I} - \mathbf{P}_3) \mathbf{y} = \mathbf{y}^\top (\mathbf{I} - \mathbf{P}_1) \mathbf{y}$$

Expected Mean Squares

SOURCE	EMS
<i>trt</i>	$\underline{1.5\sigma_u^2 + \sigma_e^2} + (\tau_1 - \tau_2)^2$
<i>xu(trt)</i>	$\sigma_u^2 + \sigma_e^2$
<i>ou(xu, trt)</i>	σ_e^2

$$\begin{aligned} E(1.5MS_{xu(trt)} - 0.5MS_{ou(xu, trt)}) &= 1.5(\sigma_u^2 + \sigma_e^2) - 0.5\sigma_e^2 \\ &= 1.5\sigma_u^2 + \sigma_e^2 \end{aligned}$$

An Approximate F Test

The statistic

$$F = \frac{MS_{trt}}{1.5MS_{xu(trt)} - 0.5MS_{ou(xu, trt)}}$$

is approximately F distributed with 1 numerator degree of freedom and denominator degrees of freedom approximated by the Cochran-Satterthwaite Method:

from SAS, R,

$$d = \frac{(1.5MS_{xu(trt)} - 0.5MS_{ou(xu, trt)})^2}{(1.5)^2 [MS_{xu(trt)}]^2 + (-0.5)^2 [MS_{ou(xu, trt)}]^2}.$$

SAS Code for Example

```
data d;  
    input trt xu y;  
    cards;  
1 1 6.4  
1 2 4.2  
2 1 1.5  
2 1 0.9  
;  
run;
```

SAS Code for Example

Proc Glimmix or Proc Mixed

Random int / Subject = xu

does the same

Methods of Moments

```
proc mixed method=type1;  
  class trt xu;  
  model y=trt / ddfm=satterthwaite;  
  random xu(trt);  
run;
```

tells SAS that xu are nested within treatment

random effects

The Mixed Procedure

Model Information

Data Set	WORK.D
Dependent Variable	y
Covariance Structure	Variance Components
<u>Estimation Method</u>	Type 1
Residual Variance Method	Factor
Fixed Effects SE Method	Model-Based
<u>Degrees of Freedom Method</u>	<u>Satterthwaite</u>

Class Level Information

Class	Levels	Values
trt	2	1 2
xu	2	1 2

Dimensions

Covariance Parameters

Columns in X

Columns in Z

Subjects

Max Obs Per Subject

2

3

3

1

4

σ_u^2 σ_e^2

SAS recognizes the
3 distinct exp.
units

Number of Observations

Number of Observations Read

4

Number of Observations Used

4

Number of Observations Not Used

0

Type 1 Analysis of Variance

End Lecture 27: 04/02/25

Source	DF	Sum of Squares	Mean Square
<u>trt</u>	<u>1</u>	16.810000	16.810000
<u>xu(trt)</u>	<u>1</u>	2.420000	2.420000
<u>Residual</u>	<u>1</u>	0.180000	0.180000

Source	Expected Mean Square	Error Term
trt	$\text{Var}(\text{Residual}) + 1.5$ $\text{Var}(\text{xu}(\text{trt})) + Q(\text{trt})$	$1.5 \text{ MS}(\text{xu}(\text{trt}))$ $- 0.5 \text{ MS}(\text{Residual})$
xu(trt)	$\text{Var}(\text{Residual}) + \text{Var}(\text{xu}(\text{trt}))$	$\text{MS}(\text{Residual})$
Residual	$\text{Var}(\text{Residual})$.