

# Shortcut for Obtaining SS from DF

trt:  $i = 1, \dots, t$

Obs. units:  $k = 1, \dots, m$

exp. units:  $j = 1, \dots, n$

$y_{ijk}$

$\bar{y}_{...} = \text{overall mean}$

Source

DF

Sum of Squares

represents overall mean  $\bar{y}_{...}$

$(\bar{y}_{i..} - \bar{y}_{...})^2$

$i$

$t - 1$

$\sum_{i=1}^t \sum_{j=1}^n \sum_{k=1}^m (\bar{y}_{i..} - \bar{y}_{...})^2$

$(\bar{y}_{ij.} - \bar{y}_{i..})^2$

$ij$

$t(n - 1)$

$\sum_{i=1}^t \sum_{j=1}^n \sum_{k=1}^m (\bar{y}_{ij.} - \bar{y}_{i..})^2$

$\hat{=}$  Variation of exp. units within each

ou(xu, trt)

$tn(m - 1)$

$\sum_{i=1}^t \sum_{j=1}^n \sum_{k=1}^m (y_{ijk} - \bar{y}_{ij.})^2$

$\hat{=}$  Variation of repeat measurements within each

$(y_{ijk} - \bar{y}_{ij.})^2$

c.total

$tnm - 1$

$\sum_{i=1}^t \sum_{j=1}^n \sum_{k=1}^m (y_{ijk} - \bar{y}_{...})^2$

exp. unit

Source	DF	Sum of Squares	Mean Square
<u>trt</u>	$t - 1$	$nm \sum_{i=1}^t (\bar{y}_{i..} - \bar{y}_{...})^2$	$E( \frac{SS(trt)}{t-1} )$
$xu(trt)$	$tn - t$	$m \sum_{i=1}^t \sum_{j=1}^n (\bar{y}_{ij.} - \bar{y}_{i..})^2$	$\frac{SS}{DF}$
$ou(xu, trt)$	$tnm - tn$	$\sum_{i=1}^t \sum_{j=1}^n \sum_{k=1}^m (y_{ijk} - \bar{y}_{ij.})^2$	
$c.total$	$tnm - 1$	$\sum_{i=1}^t \sum_{j=1}^n \sum_{k=1}^m (y_{ijk} - \bar{y}_{...})^2$	

# Expected Mean Squares

- Based on our linear mixed-effects model ( $y = X\beta + Zu + e$  and associated assumptions), we can find the expected value of each mean square in the ANOVA table.
- Examining these expected values helps us see ways to
  - 1) test hypotheses of interest by computing ratios of mean squares, and  
*test for ht effects or e.g.  $\sigma_u^2 = 0$*
  - 2) estimate variance components by computing linear combinations of mean squares.  
 *$\sigma_u^2$  &  $\sigma_e^2$*

# Expected Mean Squares

- For balanced designs, there are shortcuts (not presented here) for writing down expected mean squares.
- Rather than memorizing shortcuts, I think it is better to know how to derive expected mean squares.
- Before going through one example derivation, we will prove a useful result that you may already be familiar with.

# Expectation of Sample Variance Numerator

Suppose  $\underline{w_1}, \dots, \underline{w_k} \overset{ind}{\sim} (\underline{\mu_w}, \underline{\sigma_w^2})$ . Then

$$\begin{aligned} \underline{k\sigma_w^2} &= \sum_{i=1}^k \sigma_w^2 = \sum_{i=1}^k \underbrace{\mathbb{E}(w_i - \mu_w)^2}_{\sigma_w^2} = \sum_{i=1}^k \mathbb{E}(\underbrace{w_i - \bar{w}.}_{\text{no change}} + \bar{w}. - \mu_w)^2 \\ &= \mathbb{E} \left\{ \sum_{i=1}^k \underbrace{(w_i - \bar{w}. + \bar{w}. - \mu_w)}_{\sigma_w^2}^2 \right\} \quad (a+b)^2 = a^2 + b^2 + 2ab \\ &= \mathbb{E} \left\{ \sum_{i=1}^k [(w_i - \bar{w}.)^2 + (\bar{w}. - \mu_w)^2 + \underbrace{2(\bar{w}. - \mu_w)(w_i - \bar{w}.)}_{\text{constant}}] \right\} \\ &\overset{\text{move sum inside}}{=} \mathbb{E} \left\{ \underbrace{\sum_{i=1}^k (w_i - \bar{w}.)^2}_{\text{move sum inside}} + \sum_{i=1}^k (\bar{w}. - \mu_w)^2 + \underbrace{2(\bar{w}. - \mu_w) \sum_{i=1}^k (w_i - \bar{w}.)}_{=0} \right\} \end{aligned}$$

## Expectation of Sample Variance Numerator (ctd.)

$$\begin{aligned}k\sigma_w^2 &= E \left\{ \sum_{i=1}^k (w_i - \bar{w}.)^2 + \sum_{i=1}^k (\bar{w}. - \mu_w)^2 \right\} \\&= E \left\{ \sum_{i=1}^k (w_i - \bar{w}.)^2 + k(\bar{w}. - \mu_w)^2 \right\} \\&= \underline{E} \left\{ \sum_{i=1}^k (w_i - \bar{w}.)^2 \right\} + \underline{k} E(\bar{w}. - \mu_w)^2 \\&= E \left\{ \sum_{i=1}^k (w_i - \bar{w}.)^2 \right\} + k \text{Var}(\bar{w}.) \\&= E \left\{ \sum_{i=1}^k (w_i - \bar{w}.)^2 \right\} + \cancel{k\sigma_w^2/k} = E \left\{ \sum_{i=1}^k (w_i - \bar{w}.)^2 \right\} + \sigma_w^2\end{aligned}$$

*constant*

$\sigma_w^2/k$

## Expectation of Sample Variance Numerator (ctd.)

We have shown

$$\underbrace{k\sigma_w^2}_{\text{red circle}} = \mathbb{E} \left\{ \sum_{i=1}^k (w_i - \bar{w}.)^2 \right\} + \underbrace{\sigma_w^2}_{\text{red underline}}$$

Therefore,

$$\mathbb{E} \left\{ \sum_{i=1}^k (w_i - \bar{w}.)^2 \right\} = \underbrace{(k-1)\sigma_w^2}_{\text{red circle and red underline}}$$

This is just a special case of the Gauss-Markov model result  $\mathbb{E}(\hat{\sigma}^2) = \sigma^2$ . ( $\mathbf{y} = [w_1, \dots, w_k]^\top$ ,  $\mathbf{X} = \mathbf{1}$ ,  $\boldsymbol{\beta} = [\mu_w]$ ,  $\sigma^2 = \sigma_w^2$ )

## Expected Value of $MS_{trt}$

from slide 9:  $\frac{SS(trt)}{df}$  & then take expectation

$$E(MS_{trt}) = \frac{nm}{t-1} \sum_{i=1}^t E(\bar{y}_{i..} - \bar{y}_{...})^2$$

Write out  $\bar{y}_{i..}$  and  $\bar{y}_{...}$  in terms of our model \*

$$= \frac{nm}{t-1} \sum_{i=1}^t E(\mu + \tau_i + \bar{u}_{i.} + \bar{e}_{i..} - \mu - \bar{\tau}_{.} - \bar{u}_{..} - \bar{e}_{...})^2$$

expand  $( )^2$ ,  
Cross products  
= 0  
bc  $u_{ij}$  &  $e_{ijk}$   
have mean 0

$$= \frac{nm}{t-1} \sum_{i=1}^t E(\tau_i - \bar{\tau}_{.} + \bar{u}_{i.} - \bar{u}_{..} + \bar{e}_{i..} - \bar{e}_{...})^2$$

$$= \frac{nm}{t-1} \sum_{i=1}^t [(\tau_i - \bar{\tau}_{.})^2 + E(\bar{u}_{i.} - \bar{u}_{..})^2 + E(\bar{e}_{i..} - \bar{e}_{...})^2]$$

$$= \frac{nm}{t-1} [\sum_{i=1}^t (\tau_i - \bar{\tau}_{.})^2 + E\{\sum_{i=1}^t (\bar{u}_{i.} - \bar{u}_{..})^2\} + E\{\sum_{i=1}^t (\bar{e}_{i..} - \bar{e}_{...})^2\}]$$

Variable comp.

\*  
 $y_{ijk} = \mu + \tau_i + u_{ij} + e_{ijk}$   
 $\bar{y}_{i..} = \mu + \bar{\tau}_{.} + \bar{u}_{i.} + \bar{e}_{i..}$

$$\bar{y}_{...} = \mu + \bar{\tau}_{.} + \bar{u}_{..} + \bar{e}_{...}$$



So, to simplify  $E(MS_{trt})$  further, note that

$$\underline{\bar{u}_{1.}, \dots, \bar{u}_{t.}} \stackrel{iid}{\sim} \mathcal{N}\left(0, \frac{\sigma_u^2}{n}\right).$$

Thus,

$$E\left\{\sum_{i=1}^t (\bar{u}_{i.} - \bar{u}_{..})^2\right\} = (t-1) \frac{\sigma_u^2}{n}.$$

See slide 14  
for why \*  
(t-1)

Similarly,

$$\bar{e}_{1..}, \dots, \bar{e}_{t..} \stackrel{iid}{\sim} \mathcal{N}\left(0, \frac{\sigma_e^2}{nm}\right)$$

so that

$$E\left\{\sum_{i=1}^t (\bar{e}_{i..} - \bar{e}_{...})^2\right\} = (t-1) \frac{\sigma_e^2}{nm}.$$

use on  
next  
slide

It follows that

$$\begin{aligned}
 E(MS_{trt}) &= \frac{nm}{t-1} \left[ \sum_{i=1}^t (\tau_i - \bar{\tau}.)^2 + E \left\{ \sum_{i=1}^t (\bar{u}_{i.} - \bar{u}_{..})^2 \right\} \right. \\
 &\quad \left. + E \left\{ \sum_{i=1}^t (\bar{e}_{i..} - \bar{e}_{...})^2 \right\} \right] \\
 &= \frac{nm}{t-1} \left[ \sum_{i=1}^t (\tau_i - \bar{\tau}.)^2 + (t-1) \frac{\sigma_u^2}{n} \right. \\
 &\quad \left. + (t-1) \frac{\sigma_e^2}{nm} \right] \\
 &= \frac{nm}{t-1} \sum_{i=1}^t (\tau_i - \bar{\tau}.)^2 + m\sigma_u^2 + \sigma_e^2.
 \end{aligned}$$

Handwritten notes in blue ink:

- $(t-1) \cdot \sigma_u^2 / n$  (above the first term in the second line)
- Arrows pointing from the first term in the second line to the first term in the third line, and from the second term in the second line to the second term in the third line.
- A red oval around the text: # of obs. units within exp. units (below the final equation, with an arrow pointing to the  $m$  in  $m\sigma_u^2$ )

no office hour today: 3/28/25

Similar calculations allow us to add an Expected Mean Squares (EMS) column to our ANOVA table.

Source	<u>EMS</u>
$trt$	$\sigma_e^2 + m\sigma_u^2 + \frac{nm}{t-1} \sum_{i=1}^t (\tau_i - \bar{\tau}.)^2$
<u><math>xu(trt)</math></u>	<u><math>\sigma_e^2 + m\sigma_u^2</math></u>
$ou(xu, trt)$	$\sigma_e^2$

end lecture 24  
Wednesday  
03-26-25