

Life (in hrs) data for the battery design experiment:

material type	temperature ( $^{\circ}\text{F}$ )					
	15		70		125	
1	130	155	34	40	20	70
	74	180	80	75	82	58
2	150	188	126	122	25	70
	159	126	106	115	58	45
3	138	110	174	120	96	104
	168	160	150	139	82	60

Let  $y_{ijk}$  be the observed response when factor A is at the  $i$ th level ( $i = 1, 2, \dots, I$ ) and factor B is at the  $j$ th level ( $j = 1, 2, \dots, J$ ) for the  $k$ th replicate ( $k = 1, 2, \dots, K$ ).

$$y_{ijk} = \mu_{ij} + \epsilon_{ijk}, i = 1, 2, \dots, I; j = 1, 2, \dots, J; k = 1, 2, \dots, K.$$

Now,  $\hat{\mu}_{ij} = \bar{y}_{ij}$ . under no constraints, and hence

RSS =  $\sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (y_{ijk} - \bar{y}_{ij})^2$  has  $IJ(K - 1)$  d.f.

Reparametrization:  $\mu_{ij} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij}$ , where

$\sum_{i=1}^I \alpha_i = 0$ ,  $\sum_{j=1}^J \beta_j = 0$ ,  $\sum_{i=1}^I (\alpha\beta)_{ij} = 0$  for all  $j$  and  $\sum_{j=1}^J (\alpha\beta)_{ij} = 0$  for all  $i$  are the identifiability conditions.

To investigate the existence of interaction, we should test,

$H_{AB} : (\alpha\beta)_{ij} = 0 (i = 1, 2, \dots, I; j = 1, 2, \dots, J)$  as the restricted model without interaction. Estimation of  $(\alpha\beta)_{ij}$  can also be considered. Now, consider the main effects of factors A and B.

To test for lack of difference in levels of factor A, use,  $H_A : \alpha_i = 0$  for all  $i$ .

To test for lack of difference in levels of factor B, use,  $H_B : \beta_j = 0$  for all  $j$ . If  $H_{AB} : (\alpha\beta)_{ij} = 0$  has been rejected, there is evidence for significant interaction, so main effects cannot be non-existent.

To find estimates, confidence intervals and to conduct tests, we proceed as follows. Since

$\mu_{ij} = \bar{\mu}_{..} + (\bar{\mu}_{i.} - \bar{\mu}_{..}) + (\bar{\mu}_{.j} - \bar{\mu}_{..}) + (\mu_{ij} - \bar{\mu}_{i.} - \bar{\mu}_{.j} + \bar{\mu}_{..}) = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij}$ , we use a similar representation for  $\epsilon_{ijk}$ :

$$\epsilon_{ijk} = \bar{\epsilon}_{...} + (\bar{\epsilon}_{i..} - \bar{\epsilon}_{...}) + (\bar{\epsilon}_{.j.} - \bar{\epsilon}_{...}) + (\bar{\epsilon}_{ij.} - \bar{\epsilon}_{i..} - \bar{\epsilon}_{.j.} + \bar{\epsilon}_{...}) + (\epsilon_{ijk} - \bar{\epsilon}_{ij.}).$$

Therefore, as in one-way classification,

$$\begin{aligned} \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \epsilon_{ijk}^2 &= IJK\bar{\epsilon}_{...}^2 + JK \sum_{i=1}^I (\bar{\epsilon}_{i.} - \bar{\epsilon}_{..})^2 + IK \sum_{j=1}^J (\bar{\epsilon}_{.j} - \bar{\epsilon}_{..})^2 \\ &+ K \sum_{i=1}^I \sum_{j=1}^J (\bar{\epsilon}_{ij.} - \bar{\epsilon}_{i.} - \bar{\epsilon}_{.j} + \bar{\epsilon}_{..})^2 + \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (\epsilon_{ijk} - \bar{\epsilon}_{ij.})^2, \end{aligned}$$

since cross products vanish. Noting that  $\epsilon_{ijk} = y_{ijk} - \mu - \alpha_i - \beta_j - (\alpha\beta)_{ij}$ , with  $\sum_{i=1}^I \alpha_i = 0$ ,  $\sum_{j=1}^J \beta_j = 0$ ,  $\sum_{i=1}^I (\alpha\beta)_{ij} = 0$  for all  $j$  and  $\sum_{j=1}^J (\alpha\beta)_{ij} = 0$  for all  $i$ , we get  $\bar{\epsilon}_{...} = \bar{y}_{...} - \mu$ ,  $\bar{\epsilon}_{i.} = \bar{y}_{i.} - \mu - \alpha_i$ ,  $\bar{\epsilon}_{.j} = \bar{y}_{.j} - \mu - \beta_j$ ,  $\bar{\epsilon}_{ij.} = \bar{y}_{ij.} - \mu - \alpha_i - \beta_j - (\alpha\beta)_{ij}$ . Hence,

$$\begin{aligned} &\sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (y_{ijk} - \mu - \alpha_i - \beta_j - (\alpha\beta)_{ij})^2 \\ &= IJK(\bar{y}_{...} - \mu)^2 + JK \sum_{i=1}^I (\bar{y}_{i.} - \bar{y}_{...} - \alpha_i)^2 + IK \sum_{j=1}^J (\bar{y}_{.j} - \bar{y}_{...} - \beta_j)^2 \\ &+ K \sum_{i=1}^I \sum_{j=1}^J (\bar{y}_{ij.} - \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{...} - (\alpha\beta)_{ij})^2 + \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (y_{ijk} - \bar{y}_{ij.})^2. \end{aligned}$$

Subject to the identifiability conditions, we obtain the least squares estimates:

$\hat{\mu} = \bar{y}_{...}$ ,  $\hat{\alpha}_i = \bar{y}_{i.} - \bar{y}_{...}$ ,  $\hat{\beta}_j = \bar{y}_{.j} - \bar{y}_{...}$  and  $(\hat{\alpha}\hat{\beta})_{ij} = \bar{y}_{ij.} - \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{...}$ . Therefore,  $\text{RSS} = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (y_{ijk} - \bar{y}_{ij.})^2$ , as seen earlier.

Consider  $H_{AB} : (\alpha\beta)_{ij} = 0$  for all  $i, j$ . Due to the identifiability constraints on these parameters, namely,  $0 = \sum_{i=1}^I (\alpha\beta)_{ij} = \sum_{j=1}^J (\alpha\beta)_{ij} = \sum_{i=1}^I \sum_{j=1}^J (\alpha\beta)_{ij}$ , there are  $IJ - I - J + 1 = (I - 1)(J - 1)$  linearly independent equations, so the  $A$  matrix used to express this as a linear hypothesis has rank  $IJ - I - J + 1 = (I - 1)(J - 1)$ . Further, by inspection,

$$\text{RSS}_{H_{AB}} = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (y_{ijk} - \bar{y}_{ij.})^2 + K \sum_{i=1}^I \sum_{j=1}^J (\bar{y}_{ij.} - \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{...})^2,$$

since  $\hat{\mu}$ ,  $\hat{\alpha}_i$  and  $\hat{\beta}_j$  remain as before. Hence

$$\text{RSS}_{H_{AB}} - \text{RSS} = K \sum_{i=1}^I \sum_{j=1}^J (\bar{y}_{ij.} - \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{...})^2 = K \sum_{i=1}^I \sum_{j=1}^J (\hat{\alpha}\hat{\beta})_{ij}^2,$$

which has d.f.  $(I-1)(J-1)$ . To test  $H_{AB}$ , use

$$F_{AB} = \frac{(\text{RSS}_{H_{AB}} - \text{RSS}) / \{(I-1)(J-1)\}}{\text{RSS} / \{IJ(K-1)\}} \sim F_{(I-1)(J-1), IJ(K-1)}$$

under  $H_{AB}$ . Now consider  $H_A : \alpha_i = 0$  for all  $i$ . There are  $I-1$  linearly independent equations here, so the rank of  $A$  matrix is  $I-1$ . Again, by inspection, note that estimates of the remaining parameters,  $\mu$ ,  $\beta_j$  and  $(\alpha\beta)_{ij}$  remain unchanged, so

$$\text{RSS}_{H_A} = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (y_{ijk} - \bar{y}_{ij.})^2 + JK \sum_{i=1}^I (\bar{y}_{i..} - \bar{y}_{...})^2, \text{ so}$$

$$\text{RSS}_{H_A} - \text{RSS} = JK \sum_{i=1}^I (\bar{y}_{i..} - \bar{y}_{...})^2 = JK \sum_{i=1}^I \hat{\alpha}_i^2$$

with d.f.  $I-1$ . Similarly,

$$\text{RSS}_{H_B} = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (y_{ijk} - \bar{y}_{ij.})^2 + IK \sum_{j=1}^J (\bar{y}_{.j.} - \bar{y}_{...})^2, \text{ so}$$

$$\text{RSS}_{H_B} - \text{RSS} = IK \sum_{j=1}^J (\bar{y}_{.j.} - \bar{y}_{...})^2 = IK \sum_{j=1}^J \hat{\beta}_j^2$$

with d.f.  $J-1$ . Therefore, for the respective tests use,

$$F_A = \frac{(\text{RSS}_{H_A} - \text{RSS}) / (I-1)}{\text{RSS} / \{IJ(K-1)\}} \sim F_{I-1, IJ(K-1)}$$

under  $H_A$  and

$$F_B = \frac{(\text{RSS}_{H_B} - \text{RSS}) / (J-1)}{\text{RSS} / \{IJ(K-1)\}} \sim F_{J-1, IJ(K-1)}$$

under  $H_B$ . The decomposition of the total sum of squares along with its d.f. is as follows.

$$\begin{aligned} \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K y_{ijk}^2 &= IJK \bar{y}_{...}^2 + JK \sum_{i=1}^I (\bar{y}_{i..} - \bar{y}_{...})^2 + IK \sum_{j=1}^J (\bar{y}_{.j.} - \bar{y}_{...})^2 \\ &\quad + K \sum_{i=1}^I \sum_{j=1}^J (\bar{y}_{ij.} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{...})^2 + \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (y_{ijk} - \bar{y}_{ij.})^2. \\ IJK &= 1 + (I-1) + (J-1) + (IJ - I - J + 1) + (IJK - IJ). \end{aligned}$$

ANOVA table for 2-factor analysis:

source	d.f	SS	MS	F
A main effects	$I - 1$	$SS_A = JK \sum_{i=1}^I \hat{\alpha}_i^2$	$MS_A =$	$F_A = MS_A / MSE$
B main effects	$J - 1$	$SS_B = IK \sum_{j=1}^J \hat{\beta}_j^2$	$MS_B =$	$F_B = MS_B / MSE$
AB interactions	$(I - 1)(J - 1)$	$SS_{AB} = K \sum \sum (\hat{\alpha}\hat{\beta})_{ij}^2$	$MS_{AB} =$	$F_{AB} = MS_{AB} / MSE$
Error	$IJ(K - 1)$	$RSS = \sum \sum \sum (y_{ijk} - \bar{y}_{ij.})^2$	$MSE = \frac{RSS}{IJ(K-1)}$	
Total (c)	$IJK - 1$	$\sum \sum \sum (y_{ijk} - \bar{y}_{...})^2$		
Mean	1	$IJK \bar{y}_{...}^2$		
Total	$IJK$	$\sum \sum \sum y_{ijk}^2$		

ANOVA for the battery example:

source	d.f	SS	MS	F
plate	2	10684	5342	7.91 (2, 27)
temperature	2	39119	19559	28.97 (2, 27)
interactions	4	9614	2413	3.56 (4, 27)
error	27	18231	675	
total (c)	35	77647		