

STA221

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the analysis

We have new sums of squares decompositions. The details can get brutal - so we'll stay symbolic.

We'll call the factor variables A and B, with I and J levels respectively.

In the additive case we get, assuming a common sample size of n for each combination of factor levels (strongly encouraged in practice!):

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When the experiment is *balanced* (strongly encouraged!) with n in each combination of levels, the error degrees of freedom simplifies to $IJ(n - 1)$.

fire example - no interaction (?!)

##		Df	Sum Sq	Mean Sq	F value	Pr(>F)
##	Bath	1	715.3	715.3	23.954	1.31e-05
##	Launderings	1	202.1	202.1	6.769	0.0125
##	Residuals	45	1343.8	29.9		

sums of squares - a few details

The total sum of squares SS_{Total} is (as always) $(N - 1)$ times the sample variance of the response variable:

$$\sum_{i,j,k} (y_{ijk} - \bar{\bar{y}})^2$$

The treatment sums of squares will be:

$$SS_A = nl \sum_i (\bar{y}_{i..} - \bar{\bar{y}})^2$$

$$SS_B = nJ \sum_j (\bar{y}_{.j.} - \bar{\bar{y}})^2$$

where the dots in the subscript mean “averaged over this index.”

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The key thing to note is that each treatment sum of squares is computed using the average over all levels of the other treatment. . .

. . . which only makes sense when there is no interaction.

error sum of squares

For the sake of completeness:

$$SS_{Error} = \sum_{i,j,k} \left(y_{ijk} - \bar{y}_{ij.} \right)^2$$

Note that $y_{ijk} - \bar{y}_{ij.}$ is also called a “residual”.

model assumptions

Mostly the same as with one treatment factor, with the same verification techniques.

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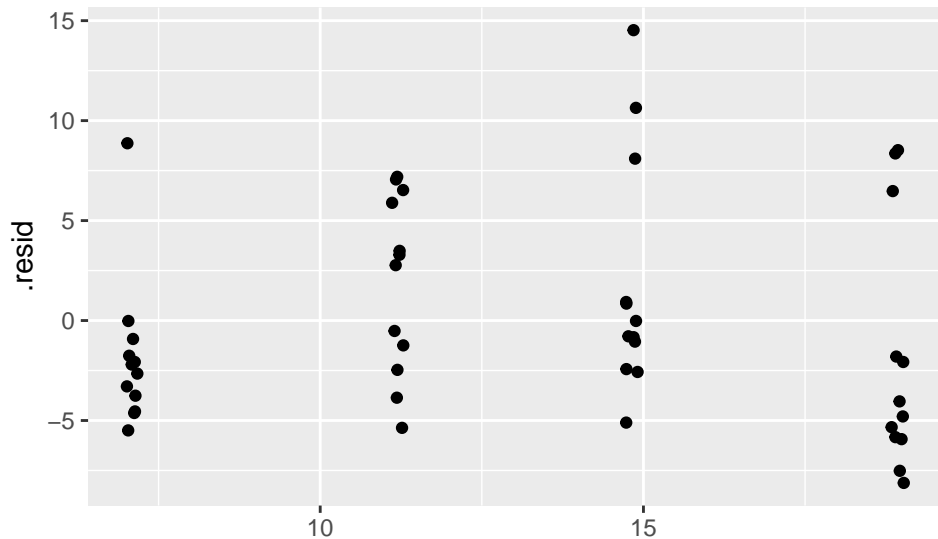
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When $n = 1$, the lack of interaction is also an *assumption*.

fire retardant model assumptions - equal variance

Plot of residuals versus “fitted values” (in this case, just the group averages):

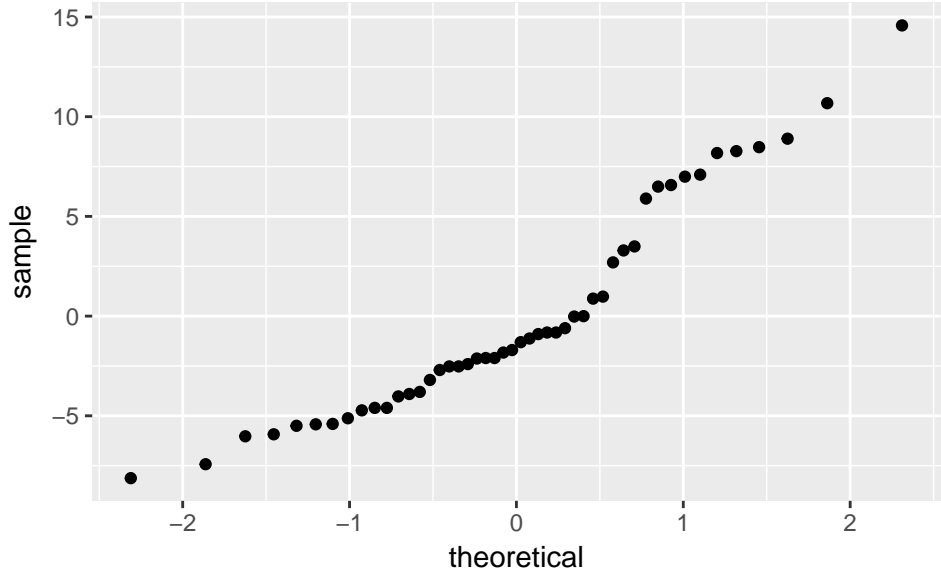


fire retardant model assumptions - equal variance

Since $n = 12$ Levene's test also works:

```
## Levene's Test for Homogeneity of Variance (center = median)
##      Df F value Pr(>F)
## group  3  0.7138  0.549
##      44
```


fire retardant model assumptions - normality



the general model and analysis (with interaction)

This model has the $(\tau\gamma)$ interaction term:

$$y_{ijk} = \mu + \tau_i + \gamma_j + (\tau\gamma)_{ij} + \varepsilon_{ijk} \quad \text{general model}$$

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The sum of squares decomposition is now:

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The interaction sum of squares is:

$$n \sum_{i,j} \left(y_{ijk} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{\bar{y}} \right)^2$$

Small when additive; large when not.

degrees of freedom - balanced case

$$\begin{aligned}SS_{Total} &= SS_A + SS_B + SS_{AB} + SS_{Error} \\(N - 1) &= (I - 1) + (J - 1) + (I - 1)(J - 1) + IJ(n - 1)\end{aligned}$$

Note: $IJ(n - 1) = N - IJ$

We get (in addition):

$$\frac{SS_{AB}/(I - 1)(J - 1)}{SS_{Error}/IJ(n - 1)} \sim F_{(I-1)(J-1), IJ(n-1)}$$

If there is evidence for interaction, do not try to interpret the “main effects”.

flame retardant with interaction

Flame retardant example, with interaction (and without):

##		Df	Sum Sq	Mean Sq	F value	Pr(>F)
##	Bath	1	715.3	715.3	26.726	5.49e-06
##	Launderings	1	202.1	202.1	7.552	0.00866
##	Bath:Launderings	1	166.1	166.1	6.207	0.01657
##	Residuals	44	1177.7	26.8		

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Also, the ANOVA table wouldn't work!

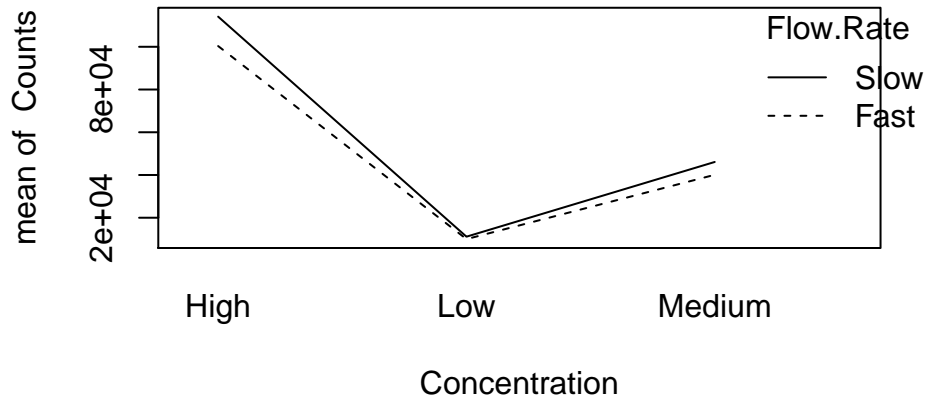
The technique is to use SS_{AB} as the error sum of squares.

another overall example

Chromatography example.

Two factors: flow rate (fast and slow); Concentration (low, med, high)

interaction plot



analysis

##	Df	Sum Sq	Mean Sq	F value	Pr(>F)
## Flow.Rate	1	3.640e+08	3.640e+08	29.645	1.35e-05
## Concentration	2	4.837e+10	2.418e+10	1969.424	< 2e-16
## Flow.Rate:Concentration	2	2.030e+08	1.015e+08	8.267	0.00186
## Residuals	24	2.947e+08	1.228e+07		

assumptions

```
## Levene's Test for Homogeneity of Variance (center = median)
##      Df F value Pr(>F)
## group  5  1.5612 0.2089
##      24
```

assumptions

