

Notes on Maxwell & Delaney

PSY710

7 Factorial Designs

In previous chapters we analyzed data from so-called one-way experimental designs, in which subjects were randomly assigned to groups that differed on a single treatment or grouping variable. In this chapter we will analyze data from **factorial experiments**. Factorial experiments contain two or more experimental variables. In a completely crossed factorial experiment, each level of every variable is combined with each level of every other variable. So, if there are two variables with a and b levels, then there will be ab combinations of treatments, which are sometimes called cells. Subjects are then assigned randomly to the various combinations of treatments. Experiments that have equal n per cell are called **balanced** designs. Designs with unequal n are unbalanced. We will start by analyzing data from balanced designs, and then consider unbalanced data near the end of this chapter.

Our analyses will focus on factorial experiments with two experimental factors, A and B . (Higher-order factorial designs are examined in chapter 8.) The design of a factorial experiment that has two variables can be represented as a two-dimensional table, with the rows representing different levels of variable A and the columns representing different levels of variable B . Each cell within the table corresponds to a particular combination of treatments. For example, a_1b_3 , which is the cell in row 1 and column 3, refers to the combination of level 1 of A and level 3 in B . I will often use the terms “cell” or group to refer to a particular combination of treatments. Cell jk refers to the cell in row j and column k .

7.1 Linear Model

The linear model for data collected in a two factor factorial experiment can be expressed as

$$Y_{ijk} = \mu + \alpha_j + \beta_k + (\alpha\beta)_{jk} + \epsilon_{ijk} \quad (1)$$

where Y_{ijk} is the score of individual i in cell jk , μ is a constant, α_j is the effect of treatment a_j , β_k is the effect of b_k , $(\alpha\beta)_{jk}$ is the effect of the *combination* a_jb_k , and ϵ_{ijk} is the error term. Notice that α_j is the effect of a particular level of A without reference to B . In other words, α_j represents the effect of being in row a_j regardless of the level of B . Similarly, β_k represents the effect of being in column b_k regardless of the level of A . As we shall see, the α 's and β 's constitute the **main effects** of A and B , respectively. The effect $(\alpha\beta)_{jk}$, on the other hand, refers to the effect of being in a particular *cell*, and collectively (i.e., across all cells) constitute the **interaction** between A and B , which often is represented as $A \times B$. Interactions are discussed in more detail in section 7.4.1.

The main effects are defined as

$$\alpha_j = \mu_{.j} - \mu_{..} \quad (2)$$

$$\beta_k = \mu_{.k} - \mu_{..} \quad (3)$$

where $\mu_{.j}$ is the marginal mean in row j , $\mu_{.k}$ is the marginal mean in column k , and $\mu_{..}$ is the population grand mean (i.e., the mean of the row and column marginal means). There is one coefficient for each row and column, and the effects are constrained so that they sum to zero:

$$\sum_{j=1}^a \alpha_j = 0 \quad (4)$$

$$\sum_{k=1}^b \beta_k = 0 \quad (5)$$

$$(6)$$

The marginal row and column means are defined as

$$\mu_{.j} = \sum_{k=1}^b \mu_{jk}/b \quad (7)$$

$$\mu_{.k} = \sum_{j=1}^a \mu_{jk}/a \quad (8)$$

which are estimated from our sample as

$$\bar{Y}_{.j} = \sum_{k=1}^b \bar{Y}_{jk}/b \quad (9)$$

$$\bar{Y}_{.k} = \sum_{j=1}^a \bar{Y}_{jk}/a \quad (10)$$

For balanced designs, the formulae for marginal means can be rewritten as

$$\bar{Y}_{.j} = \left(\sum_{k=1}^b \sum_{i=1}^n Y_{ijk} \right) / nb \quad (11)$$

$$\bar{Y}_{.k} = \left(\sum_{j=1}^a \sum_{i=1}^n Y_{ijk} \right) / na \quad (12)$$

Note that the marginal row means are the means calculated from *all* the scores in each row. Similarly, the column marginal means are the means obtained from all of the scores in column. Hence, the row marginal means ignore the column effects, and the column marginal means ignore the row effects.

The interaction terms are defined as

$$(\alpha\beta)_{jk} = \mu_{jk} - (\mu_{..} + \alpha_j + \beta_k) \quad (13)$$

which represents the difference between the cell mean, μ_{jk} , and the sum of the grand mean ($\mu_{..}$) and the row and column main effects. There is one interaction coefficient for each cell. Finally, the interaction terms in each row and each column sum to zero:

$$\sum_{j=1}^a (\alpha\beta)_{jk} = 0 \text{ for each value of } k \quad (14)$$

$$\sum_{k=1}^b (\alpha\beta)_{jk} = 0 \text{ for each value of } j \quad (15)$$

The least squares estimates of the coefficients are

$$\begin{aligned}\alpha_j &= \bar{Y}_{.j} - \bar{Y}_{..} \\ \beta_k &= \bar{Y}_{.k} - \bar{Y}_{..} \\ (\alpha\beta)_{jk} &= \bar{Y}_{jk} - (\bar{Y}_{..} + (\bar{Y}_{.j} - \bar{Y}_{..}) + (\bar{Y}_{.k} - \bar{Y}_{..})) \\ &= \bar{Y}_{jk} - \bar{Y}_{.j} - \bar{Y}_{.k} + \bar{Y}_{..}\end{aligned}$$

The main effects have $(a - 1)$ and $(b - 1)$ degrees of freedom, the interaction has $(a - 1) \times (b - 1)$ degrees of freedom, and the model in Equation 1 has $1 + (a - 1) + (b - 1) + (a - 1)(b - 1)$ parameters.

7.1.1 simple interpretation of linear model

If one cuts through the mathematical notation, the model defined by Equation 1 has a very simple interpretation. In our discussion of the linear model for one-way designs, we noted that the sum of the intercept and group effects constituted a *predicted* score for individual i in group j (i.e., \hat{Y}_{ij}). We can extend this idea to our two-way factorial design:

$$Y_{ijk} = \hat{Y}_{ijk} + \epsilon_{ijk} \quad (16)$$

where \hat{Y}_{ijk} is the predicted score. Equation 16 says that the score of individual i in cell jk is the sum of a predicted score and an error (or residual) term. Now, the predicted score is defined as the sum of the effects in the model:

$$\hat{Y}_{ijk} = \mu + \alpha_j + \beta_k + (\alpha\beta)_{jk}$$

It turns out that the sum of the effects equals the mean of the scores in cell ij . In other words, $\hat{Y}_{ijk} = \bar{Y}_{ij}$. \bar{Y}_{ij} is an estimate of μ_{ij} , so the model can be re-written as

$$Y_{ijk} = \hat{Y}_{ijk} + \epsilon_{ijk} = \mu_{ij} + \epsilon_{ijk}$$

So, Equation 1 is equivalent to saying that the observed score is equal to the sum of the cell mean and an error term, but it describes the cell mean as a sum of three separate effects.

7.2 main effect of A

Generally, the linear model in Equation 1 is used to evaluate three null hypotheses corresponding to the two main effects and the $A \times B$ interaction. The null hypothesis for the main effect of A is

$$\alpha_1 = \alpha_2 = \dots = \alpha_a = 0 \quad (17)$$

which is equivalent to

$$\bar{Y}_{1.} = \bar{Y}_{2.} = \dots = \bar{Y}_{j.} \quad (18)$$

A significant main effect of A means that the row marginal means — i.e., the average of scores within a row and across all levels of B — are not all equal

Your book points out that the sum of squares for factor A , or SS_A , can be obtained by calculating the difference between $SS_{Residual}$ obtained with the restricted model

$$Y_{ijk} = \mu + \beta_k + (\alpha\beta)_{jk} + \epsilon_{ijk} \quad (19)$$

to $SS_{Residual}$ obtained with the full model (i.e. Equation 1). The model in Equation 19 includes the $A \times B$ interaction but not the main effect of A , and therefore violates the **principle of marginality**.¹ One undesirable feature of such models is that SS_A depends crucially on the definition of α . Our definition of an effect is given by Equation 2, but other definitions are possible. For example, we could define effect α_j as the difference between the marginal mean of row j and the marginal row mean of a baseline group (e.g., $j = 1$), giving $\alpha_j = \bar{Y}_j - \bar{Y}_1$. This definition of an effect, which is sometimes called treatment coding, or reference-cell coding (see Appendix B in your textbook), is entirely reasonable. Ideally, we would not want our results to depend on arbitrary definitions of an effect. Unfortunately, in some situations, the SS_A derived from a comparison of Equations 1 and 19 *does* depend on our definition of α . This is one reason why some statisticians argue strongly against the use of models that violate the marginality principle (Venables and Ripley, 2002). In any case, it is important that you realize that comparison of Equations 1 and 19 yields SS_A *only* when α 's are defined as in Equation 2.

Are there other model comparisons that can be used to evaluate the null hypothesis in Equation 17? The answer is, yes. For example we can compare the fits provided by the models

$$Y_{ijk} = \mu + \epsilon_{ijk} \quad (20)$$

$$Y_{ijk} = \mu + \alpha_j + \epsilon_{ijk} \quad (21)$$

Alternatively, we can compare the following two models

$$Y_{ijk} = \mu + \beta_k + \epsilon_{ijk} \quad (22)$$

$$Y_{ijk} = \mu + \alpha_j + \beta_k + \epsilon_{ijk} \quad (23)$$

Notice that both comparisons involve models that differ only in the presence or absence of α coefficients, and so therefore should provide estimates of SS_A . In fact, comparisons of models 1 and 19, 20 and 21, and 22 and 23 yield *identical* values for SS_A **provided that there are equal n per group and we use sum-to-zero coding**.

7.2.1 calculating F

The null hypothesis (Equation 17) is evaluated by comparing SS_A to sum of squared residuals ($SS_{Residuals}$) for the full model (i.e., Eq. 1). It can be shown that

$$SS_A = E_R - E_F = \sum_{j=1}^a \sum_{i=1}^n \alpha_j^2 \quad (24)$$

The sum of squared residuals is

$$SS_{Residuals} = E_F = \sum_{j=1}^a \sum_{k=1}^b \sum_{i=1}^n (Y_{ijk} - \bar{Y}_{jk})^2 \quad (25)$$

Finally, the F test for the main effect of A is

$$F_A = \frac{SS_A / (a - 1)}{SS_{Residuals} / (ab(n - 1))} \quad (26)$$

with numerator and denominator degrees of freedom of $(a - 1)$ and $ab(n - 1)$, respectively.

¹In a quadratic model that contains linear (x) and quadratic (x^2) terms, the linear term is said to be *marginal* to the quadratic term. In the case of factors, a main effect, A , is said to be marginal to interactions that contain it (e.g., $A \times B$, $A \times B \times C$, etc.). According to the principle of marginality, if a model contains a higher-order term (e.g., AB), then it must also contain the terms marginal to it (e.g., A and B).

7.3 main effect of B

The null hypothesis for the main effect of B is

$$\beta_{.1} = \beta_{.2} = \cdots = \beta_{.b} = 0 \quad (27)$$

which is equivalent to

$$\bar{Y}_{.1} = \bar{Y}_{.2} = \cdots = \bar{Y}_{.b} = 0 \quad (28)$$

A significant main effect of B means that the column marginal means — i.e., the average of scores within a column and across all levels of A — are not all equal

The null hypothesis can be evaluated by comparing the sum of squared residuals from the full model (i.e., Equation 1) to the sum of squared residuals for the restricted model

$$Y_{ijk} = \mu + \alpha_j + (\alpha\beta)_{jk} + \epsilon_{ijk} \quad (29)$$

Alternatively, we could compare

$$Y_{ijk} = \mu + \epsilon_{ijk} \quad (30)$$

$$Y_{ijk} = \mu + \beta_k + \epsilon_{ijk} \quad (31)$$

or

$$Y_{ijk} = \mu + \alpha_j + \epsilon_{ijk} \quad (32)$$

$$Y_{ijk} = \mu + \alpha_j + \beta_k + \epsilon_{ijk} \quad (33)$$

All of the comments made about the various comparisons that can be done to calculate SS_A also apply to calculations of SS_B . It can be shown that

$$SS_B = \sum_{k=1}^b \sum_{i=1}^n \beta_k^2 \quad (34)$$

The F test for the main effect of B is

$$F_B = \frac{SS_B/(b-1)}{SS_{Residual}/(ab(n-1))} \quad (35)$$

with numerator and denominator degrees of freedom of $(b-1)$ and $ab(n-1)$, respectively.

7.4 $A \times B$ interaction

The null hypothesis for the AB interaction is

$$(\alpha\beta)_{11} = (\alpha\beta)_{12} = \cdots = (\alpha\beta)_{ab} = 0 \quad (36)$$

A significant $A \times B$ interaction means that the at least one cell mean, \bar{Y}_{jk} , differs from the predicted value of $\mu + \alpha_j + \beta_k$.

The significance of the interaction is evaluated by comparing Equation 1 to

$$Y_{ijk} = \mu + \alpha_j + \beta_k + \epsilon_{ijk} \quad (37)$$

SS_{AB} is given by

$$SS_{AB} = \sum_{j=1}^a \sum_{k=1}^b \sum_{i=1}^n (\alpha\beta)_{jk}^2 \quad (38)$$

The F test for the AB interaction is

$$F_{AB} = \frac{SS_{AB}/((a-1)(b-1))}{SS_{Residual}/(ab(n-1))} \quad (39)$$

with numerator and denominator degrees of freedom of $(a-1)(b-1)$ and $ab(n-1)$, respectively.

7.4.1 interpreting interactions

The linear model in Equation 1 is equivalent to

$$Y_{ijk} = \mu_{ij} + \epsilon_{ijk} \quad (40)$$

where

$$\mu_{ij} = \mu + \alpha_j + \beta_k + (\alpha\beta)_{jk} \quad (41)$$

Notice that Equation 41 implies that the interaction term, $(\alpha\beta)_{jk}$ is the difference between the mean of cell jk and $\mu + \alpha_j + \beta_k$. In other words, **the interaction term is the difference between the cell mean and the predictions of a model that includes only the intercept and main effects.**

An interaction is depicted graphically in Figure 1, which shows the average scores for four groups in a 2x2 factorial experiment. There is a main effect of A : on average, scores are higher in A_2 than A_1 . There is a main effect of B : on average, scores are higher in groups that receive treatment B_1 than in groups that received treatment B_2 . Notice, however, that the difference between B_1 and B_2 is smaller in the two groups that received treatment A_1 than in the two groups that received treatment A_2 :

$$\bar{Y}_{11} - \bar{Y}_{12} < \bar{Y}_{21} - \bar{Y}_{22} \quad (42)$$

This inequality is represented graphically as a deviation from parallelism. A significant interaction means that the two lines representing how scores vary with treatment A — one line for subjects receiving treatment B_1 and another for subjects receiving treatment B_2 — are not parallel.

After looking at Figure 1, you might be tempted to conclude that the $A \times B$ interaction means that the effect of A was significant for subjects receiving treatment B_1 but not for subjects receiving treatment B_2 . Alternatively, you might conclude that the effect of B is significant only in subjects who received treatment A_1 , but not in subjects who received treatment B_2 . **Such conclusions would be premature and (possibly) incorrect.** A significant interaction only means that $\bar{Y}_{11} - \bar{Y}_{12} \neq \bar{Y}_{21} - \bar{Y}_{22}$, or (equivalently) that $\bar{Y}_{12} - \bar{Y}_{22} \neq \bar{Y}_{11} - \bar{Y}_{21}$. Further tests are necessary to determine if, for example, A is or is not significant in subjects who received treatments B_1 or B_2 .

The previous paragraph described a common erroneous interpretation of an interaction. Here I want to describe another common error (Nieuwenhuis et al., 2011). Referring to Figure 1, a significant $A \times B$ interaction means that the effect of B *depends on the level of* A , and/or that the effect of A depends on the level of B . In other words, an interaction indicates that $(B_1 - B_2)$ differs at A_1 and A_2 , or that $(A_1 - A_2)$ differs at B_1 and B_2 (see Equation 42). Now, suppose that we used separate t tests to evaluate the difference between B_1 and B_2 at A_1 and again at A_2 . Further suppose that the t test at A_2 was significant but the test at A_1 was not. Taken together, these tests often are interpreted as showing that there is a significant $A \times B$ interaction, but — and this is the important point — this interpretation is *incorrect* because the two t tests do *not* show that $(B_1 - B_2)$ differs at A_1 and A_2 .

A significant two-way interaction means that the effect of one variable depends on the level of the other. In this situation it often does not make sense to talk about, or further analyze, the main effects of A and B .

7.5 familywise Type I error rates

Testing for main effects of A and B and an $A \times B$ interaction will inflate the *experiment-wise* Type I error rate. Nevertheless, standard practice is to not correct for these multiple tests.

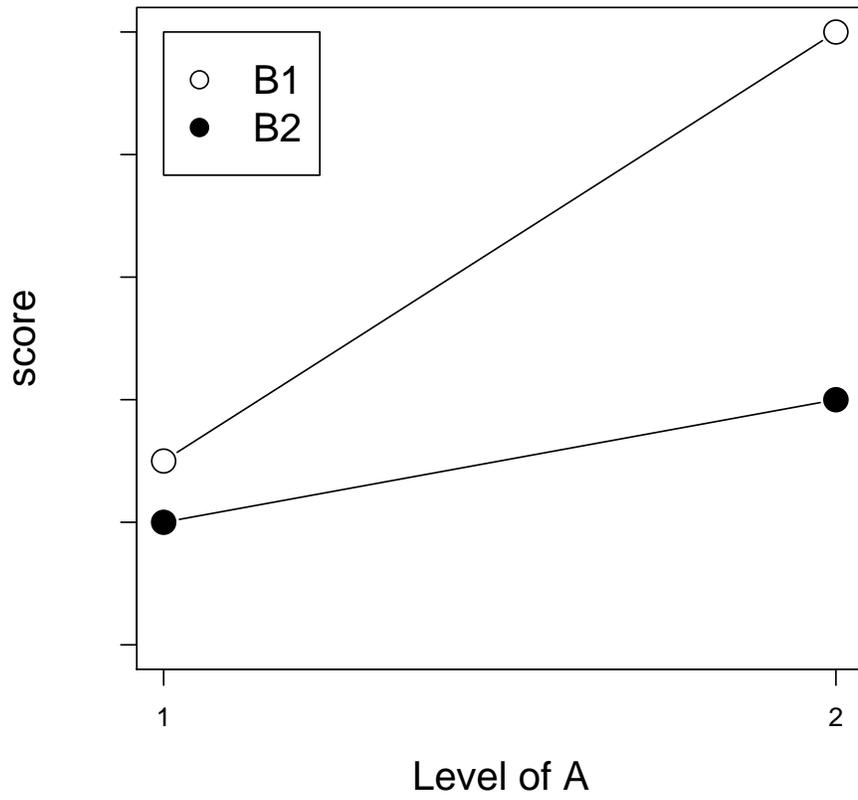


Figure 1: Illustration of an $A \times B$ interaction.

7.6 an example

In this section I will illustrate how to analyze data collected in an experiment that used a balanced factorial design. There are two *factors*, *A* and *B*, and each factor has two levels. The dependent variable is denoted by *y*. Finally, there are 6 scores per cell. Here is how I initialized R and created the fake data:

```
> options(contrasts=c("contr.sum", "contr.poly"))
> a<-rep(c(-1,-1,1,1),each=6)
> b<-rep(c(-1,1,-1,1),each=6)
> ab<-rep(c(-1,1,1,-1),each=6)
> y<-10+2*a+1*b+0.5*ab
> set.seed(123456);
> nz<-rnorm(y)
> y<-y+nz;
> af<-factor(a,labels=c("a1", "a2"),ordered=F)
> bf<-factor(b,labels=c("b1", "b2"),ordered=F)
> myData <- data.frame(y,af,bf)
> names(myData) <- c("y", "A", "B")
```

As was the case for a one-way ANOVA, data from factorial designs can be analyzed with the `lm()` or `aov()` commands. However, the formula that defines the linear model is slightly more complicated than the one used to analyze data collected with one-way designs. In this factorial experiment, the linear model is defined with the the formula $y \sim 1 + A + B + A : B$, where 1 represents the intercept, A and B represent the main effects, and A:B is the A x B interaction. The formula can be interpreted as saying that *y* is modeled as the sum of an intercept term, a main effect of A, a main effect of B, and an A x B interaction. Here, I use the `lm()` and `anova()` commands to do the analysis and print the summary table:

```
> lm.full.model <- lm(y ~ 1 + A + B + A:B, data=myData)
> anova(lm.full.model)
```

The output is listed in the Table 1. In R, the ANOVA table shows *sequential* sums-of-squares. So SS_A is derived from a comparison between models 20 and 21, SS_B comes from a comparison of models 21 and 23, and SS_{AB} comes from a comparison of models 23 and 1.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
A	1	94.25	94.25	84.59	0.0000
B	1	23.21	23.21	20.83	0.0002
A:B	1	4.63	4.63	4.15	0.0550
Residuals	20	22.28	1.11		

Table 1: ANOVA table for full model.

Normally, the `anova` table for the full model is all you need. However, I want to show you that the terms in the full model really do come from a comparison of different reduced models. For example, we can compute SS_A by doing a direct comparison of models 20 and 21:

```
> lm.01 <- lm(y ~ 1, data=myData)
> lm.02.a <- lm(y ~ 1 + A, data=myData)
> anova(lm.01, lm.02.a)
```

Analysis of Variance Table

```
Model 1: y ~ 1
```

```
Model 2: y ~ 1 + A
```

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	23	144.370				
2	22	50.124	1	94.246	41.366	1.801e-06 ***

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

NA Note that the difference between the $SS_{Residual}$ for the two models is the same as SS_A for the full model². Next, we compare models 22 and 23. Again, the change in $SS_{Residual}$ is the same as SS_A from the full model.

```
> lm.02.b <- lm(y ~ 1 + B, data=myData)
> lm.03 <- lm(y ~ 1 + A + B, data=myData)
> anova(lm.02.b, lm.03)
```

Analysis of Variance Table

```
Model 1: y ~ 1 + B
```

```
Model 2: y ~ 1 + A + B
```

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	22	121.16				
2	21	26.91	1	94.246	73.549	2.654e-08 ***

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

NA And, finally, we calculate SS_A using Equation 24:

```
> row.means <- with(myData,tapply(y, A, mean))
> grand.mean <- mean(row.means)
> alphas <- row.means - grand.mean
> row.n <- with(myData,tapply(y, A, length))
> levels(myData$A)
```

```
[1] "a1" "a2"
```

```
> a.levels <- 2
> (SS.a <- sum((alphas^2) * row.n))
```

```
[1] 94.24643
```

All of these methods yield the same value for SS_A . Likewise, the values of SS_B and SS_{AB} can be calculated in several different ways. Trust me.

²Although the comparison yields the same value for SS_A , it does not yield the same F that was obtained in the full analysis. The reason for this difference is that the two analyses use different estimates of the population error variance: the denominators in the F tests differ. In the full analysis, error is estimated after accounting for the (possible) effects of A, B, and the A x B interaction. In the current analysis, error is estimated after accounting for the (possible) effect of A and *ignoring* the (possible) effects of B and the A x B interaction.

7.7 R and marginality

In the previous section, I did not calculate SS_A by comparing models 1 and 19. Let's do so here:

```
> lm.04 <- lm(y ~ 1 + B + A:B, data=myData)
> anova(lm.04, lm.full.model)
```

Analysis of Variance Table

```
Model 1: y ~ 1 + B + A:B
Model 2: y ~ 1 + A + B + A:B
  Res.Df    RSS Df Sum of Sq F Pr(>F)
1      20 22.284
2      20 22.284  0 3.5527e-15
```

Notice that the results do not look like the ones obtained in the previous section. Why not? If you examine the anova table carefully you will see that the residual degrees of freedom equals 20 in both models. This result is surprising because we removed the A main effect in the reduced model, so the residuals degrees of freedom should be greater in that model. The problem here is that R does not look kindly upon models that violate the marginality principle, and so the effects of A have been incorporated surreptitiously into the reduced model. In fact, the command `anova(lm.04)` would show that the degrees of freedom for A and SS_A have been added to the values for the $A:B$ interaction.

```
> anova(lm.04)
```

Analysis of Variance Table

```
Response: y
      Df Sum Sq Mean Sq F value    Pr(>F)
B       1  23.214   23.214   20.835 0.0001883 ***
B:A     2  98.872   49.436   44.370 4.43e-08 ***
Residuals 20 22.284    1.114
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Furthermore, a comparison of the effects for A and the $A \times B$ interaction calculated in the full model

```
> dummy.coef(lm.full.model)
```

```
Full coefficients are
(Intercept):      10.46698
A:
      a1      a2
-1.981649  1.981649
B:
      b1      b2
-0.9834858  0.9834858
A:B:
      a1:b1      a2:b1      a1:b2      a2:b2
-0.4390275  0.4390275  0.4390275 -0.4390275
```

are added together to form the $A \times B$ interaction effects in the reduced model

```
> dummy.coef(lm.04)
```

Full coefficients are

```
(Intercept):      10.46698
B:                b1          b2
                 -0.9834858  0.9834858
B:A:              b1:a1      b2:a1      b1:a2      b2:a2
                 -2.420677  -1.542622  2.420677  1.542622
```

The bottom line is that R intentionally makes it difficult for you to construct and compare models that violate the marginality principle.

7.8 measures of association strength & effect size

We are considering a factorial experiment in which the factors are *fixed* (i.e., all of the factors about which inferences are to be drawn are included in the experiment). In this case, the appropriate (Kirk, 1995) measure of association strength is **partial omega squared** ($\omega_{partial}^2$). $\omega_{partial}^2$ expresses the variance of each treatment effect relative to the sum of the treatment effect variance and error variance. Note that “error” refers to the error calculated from the full model: it is the unexplained variance. Hence, $\omega_{A,partial}^2$ expresses the variance among α 's relative to the sum of the error variance and the α variance, and it *ignores* the variation in the dependent variable that is due to the effects of B or $A \times B$. Here are the definitions of $\omega_{partial}^2$ in terms of the treatment effects:

$$\omega_{A,partial}^2 = \frac{\sum_{j=1}^a (\alpha_j^2/a)}{\sigma_e^2 + \sum_{j=1}^a (\alpha_j^2/a)}$$

$$\omega_{B,partial}^2 = \frac{\sum_{k=1}^b (\beta_k^2/b)}{\sigma_e^2 + \sum_{k=1}^b (\beta_k^2/b)}$$

$$\omega_{AB,partial}^2 = \frac{\sum_{j=1}^a \sum_{k=1}^b [(\alpha\beta)_{jk}^2/(ab)]}{\sigma_e^2 + \sum_{j=1}^a \sum_{k=1}^b [(\alpha\beta)_{jk}^2/(ab)]}$$

Usually it is easier to calculate $\omega_{partial}^2$ using the values listed in the ANOVA table for the full model. Here is how $\omega_{partial}^2$ is defined in terms of $SS_{treatment}$ and $MS_{Residuals}$

$$\omega_{A,partial}^2 = \frac{SS_A - df_A MS_{Residuals}}{SS_A + (N - df_A) MS_{Residuals}}$$

$$\omega_{B,partial}^2 = \frac{SS_B - df_B MS_{Residuals}}{SS_B + (N - df_B) MS_{Residuals}}$$

$$\omega_{AB,partial}^2 = \frac{SS_{AB} - df_{AB} MS_{Residuals}}{SS_{AB} + (N - df_{AB}) MS_{Residuals}}$$

Here is how $\omega_{partial}^2$ is defined in terms of F values:

$$\omega_{A,partial}^2 = \frac{df_A(F_A - 1)}{df_A(F_A - 1) + N}$$

$$\omega_{B,partial}^2 = \frac{df_B(F_B - 1)}{df_B(F_B - 1) + N}$$

$$\omega_{AB,partial}^2 = \frac{df_{AB}(F_{AB} - 1)}{df_{AB}(F_{AB} - 1) + N}$$

If $\omega_{partial}^2 < 0$, then it is set to 0.

For the data shown in Table 1, calculating $\omega_{partial}^2$ from F 's yields

```
> (omega.a <- (1 * (84.59 - 1))/(1 * (84.59 - 1) + 24))
```

```
[1] 0.7769309
```

```
> (omega.b <- (1 * (20.83 - 1))/(1 * (20.83 - 1) + 24))
```

```
[1] 0.4524298
```

```
> (omega.ab <- (1 * (4.15 - 1))/(1 * (4.15 - 1) + 24))
```

```
[1] 0.1160221
```

According to Cohen's 1988 guidelines,

$\omega_{partial}^2 = 0.010$ is a small association

$\omega_{partial}^2 = 0.059$ is a medium association

$\omega_{partial}^2 \geq 0.138$ is a large association

Partial omega squared can be used to calculate Cohen's measure of effect size, f

$$f_{treatment} = \sqrt{\frac{\omega_{partial}^2}{1 - \omega_{partial}^2}}$$

According to Cohen, f 's of 0.1, 0.25, and 0.4 represent small, medium, and large effect sizes, respectively.

7.9 power

Your textbook describes how to calculate statistical power from estimates of the effects in your linear model (see pages 317-319). Here I want to show you how to calculate power using the `pwr` package for R. If you have not yet installed the package on your computer, do so now using the following command:

```
> install.packages("pwr")
```

After installing the package, you must load it into memory with the command `library(pwr)` command. Note that you only need to use this command once per R session. Now we can use `pwr.f2.test` to calculate the power for *any* F test. Suppose we have a two-factor design: factors A and B have three and two levels, respectively. Also, let's assume that the effect sizes for the main effects of A and B are 0.1 (i.e., small) and 0.25 (i.e., medium), respectively. Finally, we assume that we have six subjects per group, and therefore that the degrees of freedom for $MS_{residuals}$ in our ANOVA will be $3 \times 2 \times (6 - 1) = 30$. The following commands calculates the power of the test for a main effect of A when $\alpha = .05$:

```
> library(pwr)
> pwr.f2.test(u=3-1,v=30,f2=(0.1^2),sig.level=.05)
```

Multiple regression power calculation

```
      u = 2
      v = 30
      f2 = 0.01
sig.level = 0.05
power = 0.07319046
```

And here is the power of the test for a main effect of B :

```
> pwr.f2.test(u=2-1,v=30,f2=(0.25^2),sig.level=.05)
```

Multiple regression power calculation

```
      u = 1
      v = 30
      f2 = 0.0625
sig.level = 0.05
power = 0.2777445
```

Note that u and v correspond to the degrees of freedom in the numerator and denominator, respectively, and $f2$ is effect size *squared* (i.e., Cohen's f^2). The results of `pwr.f2.test` indicated that power is quite low for the tests of both main effects. `pwr.f2.test` also can be used to estimate the number of subjects that we would need to attain a power that was at least 0.8:

```
> pwr.f2.test(u=3-1,f2=(0.1^2),sig.level=.05,power=.8)
```

Multiple regression power calculation

```
      u = 2
      v = 963.4709
      f2 = 0.01
sig.level = 0.05
power = 0.8
```

```
> pwr.f2.test(u=2-1,f2=(0.25^2),sig.level=.05,power=.8)
```

Multiple regression power calculation

```

u = 1
v = 125.5312
f2 = 0.0625
sig.level = 0.05
power = 0.8

```

To attain a power of 0.8 for our main effect of A , we would need a 963 degrees of freedom in the denominator of our F test, which means we would need $1 + [963/(3 \times 2)] = 162$ subjects per cell in our 3×2 design. To attain the same power for B , we would need 22 subjects per cell. Of course, we cannot satisfy both of these requirements simultaneously, so we would need approximately 162 subjects per cell to attain a power of *at least* 0.8 for both tests of main effects:

```
> pwr.f2.test(u=3-1,v=(3*2*(162-1)),f2=(0.1^2),sig.level=.05)
```

Multiple regression power calculation

```

u = 2
v = 966
f2 = 0.01
sig.level = 0.05
power = 0.801101

```

```
> pwr.f2.test(u=2-1,v=(3*2*(162-1)),f2=(0.25^2),sig.level=.05)
```

Multiple regression power calculation

```

u = 1
v = 966
f2 = 0.0625
sig.level = 0.05
power = 1

```

Obviously, it would be very difficult, if not impossible, to conduct such a study. Hopefully this example will highlight why you should think about the power of your experiments prior to doing them.

We'll conclude by considering the example described in your textbook (page 319). Consider a 3×4 design (i.e. 3 levels on factor A and 4 levels on factor B). If the effect size for A is $f = 0.25$, how many subjects do we need to attain a power of 0.8? The function `pwr.f2.test` can be used to calculate the degrees of freedom that we need in the denominator of our F test:

```
> pwr.f2.test(u=3-1,f2=(0.25^2),sig.level=.05,power=.8)
```

Multiple regression power calculation

```

u = 2
v = 154.1898
f2 = 0.0625
sig.level = 0.05
power = 0.8

```

The denominator degrees of freedom is given by the formula

$$df_{residuals} = a \times b \times (n - 1)$$

so we would need $n = 14$ subjects per cell to achieve $df_{residuals} = 154$ and a power of 0.8.

```
> pwr.f2.test(u=3-1,v=3*4*(14-1),f2=(0.25^2),sig.level=.05)
```

```
Multiple regression power calculation
```

```
      u = 2
      v = 156
      f2 = 0.0625
sig.level = 0.05
power = 0.8048873
```

7.10 linear contrasts

A significant main effect implies that the marginal means are not all equal, but it does not tell us how the means differ. To get a clearer picture of the differences among means, we often will do one or more linear contrasts. I will use the data from Table 7.5 in your textbook.

```
> names(mw75)
```

```
[1] "drug"      "biofeedback" "score"
```

```
> with(mw75,tapply(score,list(drug,biofeedback),length))
```

```
  no yes
x  5  5
y  5  5
z  5  5
```

```
> with(mw75,tapply(score,list(drug,biofeedback),mean))
```

```
  no yes
x 186 170
y 201 203
z 210 188
```

```
> with(mw75,tapply(score,list(drug,biofeedback),sd))
```

```
      no      yes
x 10.83974  7.905694
y 10.93161 13.910428
z 15.81139 13.838353
```

```
> mw.aov.01<-aov(score~drug*biofeedback,data=mw75)
```

```
> summary(mw.aov.01)
```

```

                Df Sum Sq Mean Sq F value    Pr(>F)
drug            2   3420   1710.0   10.979 0.000411 ***
biofeedback     1   1080   1080.0    6.934 0.014563 *
drug:biofeedback 2    780    390.0    2.504 0.102877
Residuals      24   3738    155.8

```

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The data come from a 3(drug) x 2(biofeedback) factorial experiment. There were five subjects randomly assigned to each of the six experimental conditions. The ANOVA indicates that there were significant main effects of drug, $F(2, 24) = 10.98$, $p = .0004$, and biofeedback, $F(1, 24) = 6.93$, $p = .015$, but that the drug x biofeedback interaction was not significant, $F(2, 24) = 2.50$, $p = .10$. Imagine that I want to compare drugs x and y to each other. If the levels of `drug` are x, y, and z, then I would do a linear contrast with contrast weights $c1 = [-1, 1, 0]$. The following example shows how to perform such a contrast using `aov()`:

```
> levels(mw75$drug)
```

```
[1] "x" "y" "z"
```

```
> c1 <- c(-1,1,0)
```

```
> myC <- cbind(c1)
```

```
> contrasts(mw75$drug) <- myC
```

```
> mw.aov.02<-aov(score~drug*biofeedback,data=mw75)
```

```
> summary(mw.aov.02,split=list(drug=list(1)))
```

```

                Df Sum Sq Mean Sq F value    Pr(>F)
drug            2   3420   1710.0   10.979 0.000411 ***
  drug: C1       1   2880   2880.0   18.491 0.000246 ***
biofeedback     1   1080   1080.0    6.934 0.014563 *
drug:biofeedback 2    780    390.0    2.504 0.102877
  drug:biofeedback: C1 1    405    405.0    2.600 0.119916
Residuals      24   3738    155.8

```

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The contrast was significant, $F(1, 24) = 18.49$, $p = .00025$, so we reject the null hypothesis of no difference between the *marginal means* of drugs x and y. Notice that the output also shows how the value of the linear contrast varies with, or depends upon, the level of `biofeedback`: In other words, the output lists the contrast x biofeedback interaction, which in this case is not significant, $F(1, 24) = 2.6$, $p = .12$.

Next, let's compute the contrast directly from the group means and information in the omnibus ANOVA table:

```
> (drug.means <- with(mw75,tapply(score,drug,mean)) )
```

```

  x  y  z
178 202 199

```

```
> with(mw75,tapply(score,list(drug,biofeedback),length))
```

```

  no yes
x  5   5
y  5   5
z  5   5

> n <- 5
> a <- 2
> MS.resid <- 155.7
> df.resid <- 24
> psi <- sum(c1*drug.means)
> ( SScontrast <- (n*a)*(psi^2)/ (sum(c1^2)) )

[1] 2880

> (F <- SScontrast/MS.resid)

[1] 18.49711

> ( p.value <- 1-pf(F,df1=1,df2=df.resid) )

[1] 0.0002457837

```

Note that the calculation of SS_{contrast} uses $n \times a = 10$, rather than $n = 5$, because we are considering marginal means, not cell means, and there are 10 subjects who receive each drug. Also note that the denominator degrees of freedom for the p-value equals the residuals degrees of freedom.

Finally, let's consider the case where we wanted to compare the different drugs with two orthogonal contrasts:

```

> levels(mw75$drug)

[1] "x" "y" "z"

> c1 <- c(-1,1,0)
> c2 <- c(-1,-1,2)
> myC <- cbind(c1,c2)
> contrasts(mw75$drug) <- myC
> mw.aov.02<-aov(score~drug*biofeedback,data=mw75)
> summary(mw.aov.02,split=list(drug=list(1,2)))

```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
drug	2	3420	1710.0	10.979	0.000411	***
drug: C1	1	2880	2880.0	18.491	0.000246	***
drug: C2	1	540	540.0	3.467	0.074890	.
biofeedback	1	1080	1080.0	6.934	0.014563	*
drug:biofeedback	2	780	390.0	2.504	0.102877	
drug:biofeedback: C1	1	405	405.0	2.600	0.119916	
drug:biofeedback: C2	1	375	375.0	2.408	0.133827	
Residuals	24	3738	155.8			

```

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

We can see that the second contrast, which compares the marginal mean of drug z to the mean of the other two drugs, is not significant (and does not interact with biofeedback).

7.10.1 Tukey HSD

In some situations we want to evaluate all pairwise comparisons among marginal means. In such cases, a Tukey HSD task is appropriate. Using the `which` option in the `TukeyHSD` command allows you to specify which set of marginal means should be tested:

```
> TukeyHSD(mw.aov.02,which="drug")
```

```
Tukey multiple comparisons of means
 95% family-wise confidence level
```

```
Fit: aov(formula = score ~ drug * biofeedback, data = mw75)
```

```
$drug
      diff      lwr      upr      p adj
y-x    24 10.062095 37.93791 0.0006958
z-x    21  7.062095 34.93791 0.0026568
z-y    -3 -16.937905 10.93791 0.8537283
```

```
> TukeyHSD(mw.aov.02,which="biofeedback")
```

```
Tukey multiple comparisons of means
 95% family-wise confidence level
```

```
Fit: aov(formula = score ~ drug * biofeedback, data = mw75)
```

```
$biofeedback
      diff      lwr      upr      p adj
yes-no -12 -21.40528 -2.59472 0.0145635
```

7.11 simple main effects

A significant interaction means that the effect of A *depends* on the level of B or, equivalently, that the effect of B depends on the level of A . Hence, a significant $A \times B$ interaction means that tests of main effects may give a very misleading picture of the effects of A and B . Usually, when the $A \times B$ interaction is significant we should *not* go on to test for main effects. Instead, we should determine if the effect of one variable (e.g., A) is significant within each individual level of the other variable (e.g., B_1, B_2, \dots, B_k). Tests for the significance of one variable within the level of another variable are known as **simple main effects**.

7.11.1 an example

I will give an example of how to compute simple main effects with the data shown in Table 7.11 in your textbook, which is saved as a data file on the CD that came with your textbook. That file does not contain variable names, so R provides default names V1, V2, and V3. I'm going to read the data file, change the variable names to something more useful, and then convert them to factors.

```
> mw11 <- read.table(file = "chapter_7_table_11.dat")
> names(mw11)
```

```
[1] "V1" "V2" "V3"

> names(mw11) <- c("group", "task", "score")
> names(mw11)

[1] "group" "task" "score"

> class(mw11$group)

[1] "integer"

> class(mw11$task)

[1] "integer"

> class(mw11$score)

[1] "integer"
```

The `group` and `task` variables are `integer` variables because the different levels were defined with numbers rather than letters. I want my ANOVA to treat `group` and `task` as `factors`, so I will create two new variables `gf` and `tf`:

```
> mw11$gf <- factor(mw11$group, labels = c("amnesic", "huntingtons", "control"), ordered = FALSE)
> mw11$tf <- factor(mw11$task, labels = c("grammar", "classification", "recognition"), ordered = FALSE)

> names(mw11)

[1] "group" "task" "score" "gf" "tf"

> class(mw11$gf)

[1] "factor"

> class(mw11$tf)

[1] "factor"
```

I use the `lm()` and `anova()` commands to do the analysis and print the summary table. In this factorial experiment, the linear model is defined with the the formula

$$score \sim 1 + gf + tf + gf : tf$$

where `1` represents the intercept, `gf` and `tf` represent the group and task main effects, and `gf:tf` is the group x task interaction. The formula can be interpreted as saying that `score` is modeled as the sum of an intercept term, a group main effect, a task main effect, and a group x task interaction. Here is the ANOVA:

```
> mw11.lm.01 <- lm(score ~ 1+ gf + tf + gf:tf, data = mw11)
> anova(mw11.lm.01)
```

Analysis of Variance Table

Response: score

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
gf	2	5250	2625.00	16.6373	7.64e-06	***
tf	2	5250	2625.00	16.6373	7.64e-06	***
gf:tf	4	5000	1250.00	7.9225	0.0001092	***
Residuals	36	5680	157.78			

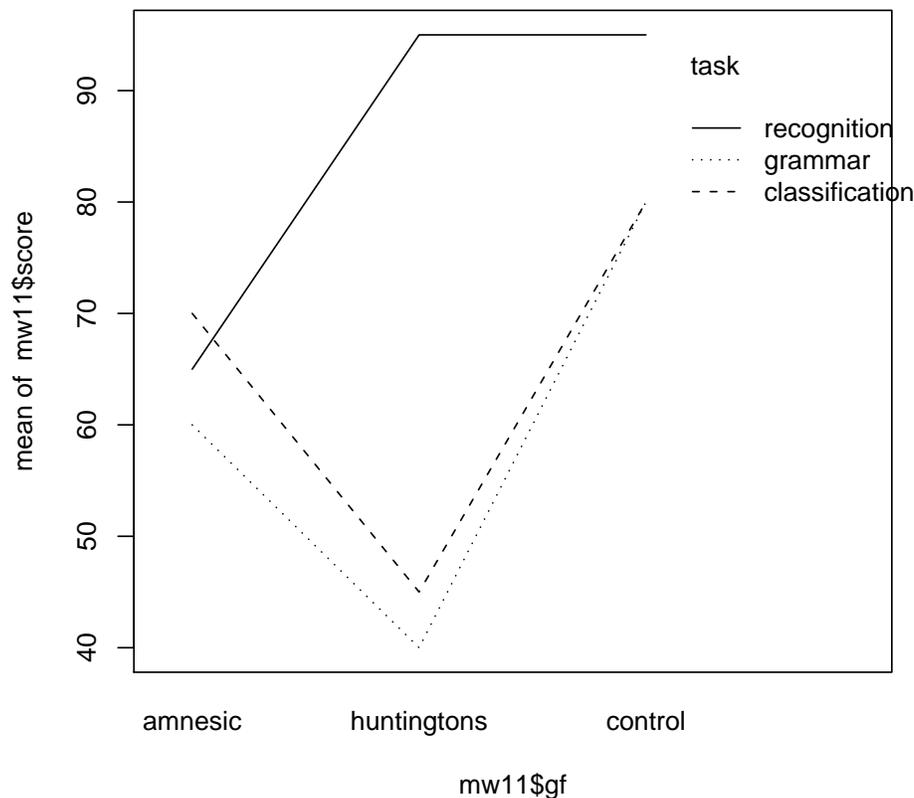
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> *MS.w* <- 157.8> *df.w* <- 36

The interaction between group and task is significant. I save the $MS_{Residuals}$, or MS_{Within} , and the degrees of freedom because we will need them later. The command `interaction.plot` can be used to get a better sense of what the interaction means. The command

```
interaction.plot(x.factor=mw11$gf, trace.factor=mw11$tf, response=mw11$score, trace.label="task")
```

creates the following figure:



It looks as though the effect of task may be significant for the group of Huntington's patients, but not the other groups. I will evaluate this idea by testing the effect of task at each level of group. (N.B.

I am not saying that this test is the most interesting one. I am simply going to use it to illustrate how to calculate simple main effects).

The key part of the analysis is to extract the data from each level of group using R's `subset` command. Here are some examples of how to use the command

```
> subset(mw11, gf == "control")
```

	group	task	score	gf	tf
31	3	1	76	control	grammar
32	3	1	98	control	grammar
33	3	1	71	control	grammar
34	3	1	70	control	grammar
35	3	1	85	control	grammar
36	3	2	92	control	classification
37	3	2	65	control	classification
38	3	2	86	control	classification
39	3	2	67	control	classification
40	3	2	90	control	classification
41	3	3	107	control	recognition
42	3	3	80	control	recognition
43	3	3	101	control	recognition
44	3	3	82	control	recognition
45	3	3	105	control	recognition

```
> subset(mw11, tf == "classification")
```

	group	task	score	gf	tf
6	1	2	72	amnesic	classification
7	1	2	66	amnesic	classification
8	1	2	55	amnesic	classification
9	1	2	82	amnesic	classification
10	1	2	75	amnesic	classification
21	2	2	53	huntingtons	classification
22	2	2	59	huntingtons	classification
23	2	2	33	huntingtons	classification
24	2	2	37	huntingtons	classification
25	2	2	43	huntingtons	classification
36	3	2	92	control	classification
37	3	2	65	control	classification
38	3	2	86	control	classification
39	3	2	67	control	classification
40	3	2	90	control	classification

```
> subset(mw11, tf == "classification" & gf == "control")
```

	group	task	score	gf	tf
36	3	2	92	control	classification
37	3	2	65	control	classification
38	3	2	86	control	classification
39	3	2	67	control	classification
40	3	2	90	control	classification

Next we construct the appropriate linear models and display the anova tables for the effect of task for each group:

```
> lm.task.hunt <- lm(score ~ 1 + tf, data = subset(mw11, gf == "huntingtons"))
> lm.task.amnesic <- lm(score ~ 1 + tf, data = subset(mw11, gf == "amnesic"))
> lm.task.control <- lm(score ~ 1 + tf, data = subset(mw11, gf == "control"))
```

Finally, we print the anova table for each model, extract SS_{task} , and then compute F and p values using MS_{Within} and df_{Within} from our original analysis.

Here is the simple main effect of task for the Huntington's group. Notice how I recalculate F :

```
> anova(lm.task.hunt)
```

Analysis of Variance Table

```
Response: score
          Df Sum Sq Mean Sq F value    Pr(>F)
tf          2   9250   4625.0   29.365 2.385e-05 ***
Residuals 12   1890    157.5
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> (F.task.hunt <- 4625/MS.w)
```

```
[1] 29.30925
```

```
> (p.task.hunt <- 1 - pf(F.task.hunt, df1 = 2, df2 = df.w))
```

```
[1] 2.791744e-08
```

The simple main effect is significant. We could now proceed to do contrasts or pairwise comparisons among the three tasks to see which ones differ. Below, I compute pairwise differences using Tukey's HSD method. Because there are only three groups, however, it might be better to simply do pairwise t -tests and use the Bonferroni adjustment to control Type I error rate (see Table 5.9 in your textbook).

You might think that performing a Tukey HSD test on a simple main effect is done by passing the aov object to TukeyHSD:

```
> aov.task.hunt <- aov(score ~ tf, data = subset(mw11, gf == "huntingtons"))
> TukeyHSD(aov.task.hunt)
```

```
Tukey multiple comparisons of means
 95% family-wise confidence level
```

```
Fit: aov(formula = score ~ tf, data = subset(mw11, gf == "huntingtons"))
```

```
$tf
          diff      lwr      upr      p adj
classification-grammar      5 -16.17551 26.17551 0.8067924
recognition-grammar      55  33.82449 76.17551 0.0000437
recognition-classification  50  28.82449 71.17551 0.0001084
```

However, this test is flawed because it is based on an error term calculated only from a portion of the data rather than all of the data. The following code shows how to calculate F from the means of the three tasks in the `huntingtons` groups:

```
> with(subset(mw11, gf=="huntingtons"), tapply(score, tf, length))

      grammar classification      recognition
      5                5                5

> n <- 5
> b <- 3
> (tf.means.hunt<-with(subset(mw11, gf=="huntingtons"), tapply(score, tf, mean)) )

      grammar classification      recognition
      40                45                95

> pw1<-c(-1,1,0)
> pw2<-c(-1,0,1)
> pw3<-c(0,-1,1)
> psi.pw1 <- sum(tf.means.hunt * pw1)
> psi.pw2 <- sum(tf.means.hunt * pw2)
> psi.pw3 <- sum(tf.means.hunt * pw3)
> SS.pw1 <- n*b*(psi.pw1^2) / sum(pw1^2)
> SS.pw2 <- n*b*(psi.pw2^2) / sum(pw2^2)
> SS.pw3 <- n*b*(psi.pw3^2) / sum(pw3^2)
> MS.w

[1] 157.8

> (F.pw1 <- SS.pw1/MS.w)

[1] 1.188213

> (F.pw2 <- SS.pw2/MS.w)

[1] 143.7738

> (F.pw3 <- SS.pw3/MS.w)

[1] 118.8213
```

Now that we have our F scores, we need to compare them to a critical F calculated using the Tukey HSD formula shown in Table 5.16 in your textbook (page 236). In R, you can calculate this critical F using the `qtukey` command:

```
> alpha.fw <- .05
> df.w

[1] 36

> (F.tukey.critical <- ( qtukey(1-alpha.fw, nmeans=b, df=df.w)^2) / 2 )
```

```
[1] 5.974588
```

Note that $\alpha_{FW} = .05$, that the number of means equals the number of different tasks, and that the degrees of freedom equals the df for the error term that was used to calculate the F 's. Comparing the observed F 's to the critical F indicates that performance in the recognition task differed from performance in the other two tasks, but that performance in the grammar and classification tasks did not differ from each other.

Here is the simple main effect of task for the amnesic group.

```
> anova(lm.task.amnesic)
```

Analysis of Variance Table

Response: score

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
tf	2	250	125	0.7911	0.4756
Residuals	12	1896	158		

```
> (F.task.amnesic <- 125/MS.w)
```

```
[1] 0.792142
```

```
> (p.task.amnesic <- 1 - pf(F.task.amnesic, df1 = 2, df2 = df.w))
```

```
[1] 0.4606085
```

The simple main effect of task among amnesic subjects is not significant.

Here is the simple main effect of task for the control group.

```
> anova(lm.task.control)
```

Analysis of Variance Table

Response: score

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
tf	2	750	375.00	2.3759	0.1351
Residuals	12	1894	157.83		

```
> (F.task.control <- 375/MS.w)
```

```
[1] 2.376426
```

```
> (p.task.control <- 1 - pf(F.task.control, df1 = 2, df2 = df.w))
```

```
[1] 0.1073003
```

The simple main effect of task among control subjects is not significant.

So, our analysis suggests that task has a significant effect on performance among Huntington's patients, but not subjects in the other groups. Moreover, the effect of task appears to reflect the fact that recognition scores are significantly higher than scores on the grammar and classification tasks (in Huntington's patients).

7.11.2 Type I Error Rates

Analyzing the simple main effect of task required us to do three ANOVAs (one for each level of group). Obviously, performing multiple tests of simple main effects will increase the familywise Type I error rate. As your textbook points out, there is some disagreement on the issue of whether you should use the Bonferroni method to control the Type I error rate. One point of view is that you should not do so because you would examine simple main effects only if the omnibus interaction was significant. Another point of view is that the familywise Type I error rate should be kept at the level used in the omnibus ANOVA. In other words, if $\alpha = .05$ was used to evaluate significant interaction and main effects, then you should set $\alpha_{FW} = .05$ when you are analyzing simple main effects. In the example in the preceding section, we would set the per-comparison alpha to $\alpha_{PC} = .05/3 = .0167$.

7.12 Unbalanced Data

So far our analyses of factorial experiments have assumed that the designs are **balanced**: they have equal n in each combination of the experimental factors. There are occasions, however, when our data are **unbalanced**. In the following sections we describe how unbalanced data complicate the analysis of variance, and suggest ways of addressing these complications.

In the following sections, I assume that the full model for a two factor experiment is

$$Y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk} \quad (43)$$

and that

$$\sum_i \alpha_i = \sum_j \beta_j = \sum_i (\alpha\beta)_{ij} = 0 \quad (44)$$

The sum-to-zero constraints in Equation 44 are especially important for interpreting Type III sums of squares (Section 7.12.5).

7.12.1 An example

The following example is taken directly from Chapter 13 in Howell (2002).

An experiment was conducted to study the effect of alcohol on vigilance. Subjects were placed in a driving simulator and told to avoid cars when they emerged suddenly from driveways, and pedestrians who stepped suddenly into the street. Subjects were assigned randomly to two groups: the no-alcohol group drank a non-alcoholic beverage before the driving test, whereas the alcohol group drank an alcoholic beverage. The dependent measure was the number of errors each driver made in one half-hour session. The experiment was conducted in two labs at universities in Michigan and Arizona. The data are presented in Table 2. There are unequal numbers of subjects in each cell of Table 2, so the data are unbalanced. Inspection of the cell means indicates that the results were what you would expect: subjects in the alcohol group made more errors than subjects in the no-alcohol group. Furthermore, the cell means indicate that the pattern of results was, as expected, the same for subjects tested in Michigan and Arizona.

So, what's the problem? Well, if you look at the row means, it appears that subjects from Michigan made more errors than subjects from Arizona: Despite the fact that the cell means in the two rows are exactly the same, the marginal row means differ. Why? Because 10 out of the 15 subjects from Michigan were in the alcohol condition, whereas 11 out of the 16 subjects from Arizona were in the no-alcohol condition. In other words, the effect of **alcohol** is masquerading as an effect of **state**. This mixing up of row and column effects is a general property of unbalanced factorial designs: the row, column, and interaction effects are no longer orthogonal to each other.

Table 2: Data from drinking study.

	no alcohol	alcohol	Row Means
Michigan	13 15 14	18 20 22 19	$\bar{Y}_{1.} = 18$
	16 12	21 23 17 18	
	$\bar{Y}_{11} =$	22 20	
	14	$\bar{Y}_{12} = 20$	
Arizona	13 15 18 14	24 25 17	$\bar{Y}_{2.} = 15.9$
	10 12 16 17	16 18	
	15 10 14	$\bar{Y}_{22} =$	
	$\bar{Y}_{21} = 14$	20	
Column Means	$\bar{Y}_{.1} = 14$	$\bar{Y}_{.2} = 20$	

The fact that the row, column and interaction effects are no longer orthogonal greatly complicates the analysis of variance. To see why, consider the following two linear models:

$$score \sim 1 + alcohol + state + alcohol : state \quad (45)$$

$$score \sim 1 + state + alcohol + state : alcohol \quad (46)$$

The ANOVA tables produced by R for Models 45 and 46 are presented in Table 3. Although the models differ only in the order of terms, the sums of squares assigned by the models to the main effects differ significantly.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
state	1	34.96	34.96	5.13	0.0318
alcohol	1	243.75	243.75	35.77	0.0000
state:alcohol	1	0.00	0.00	0.00	1.0000
Residuals	27	184.00	6.81		

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
alcohol	1	278.71	278.71	40.90	0.0000
state	1	0.00	0.00	0.00	1.0000
alcohol:state	1	0.00	0.00	0.00	1.0000
Residuals	27	184.00	6.81		

Table 3: ANOVA tables for Model 1 (top) and Model 2 (bottom).

7.12.2 Proportional Cell Frequencies

Before I continue to discuss the problems associated with analyzing unbalanced data, I want to describe a case where unbalanced data are *not* hard to analyze. Suppose we had 36 subjects from Michigan, with 24 in the alcohol condition and 12 in the no-alcohol condition. Also, let's suppose that there were 24 subjects from Arizona, with 16 in the alcohol condition and 8 in the no-alcohol condition. In this case, the ratio of subjects in the alcohol and no-alcohol conditions is 2:1 at both

levels of the other variable, **state**. If the proportion of cases in one variable is the same at all levels of the other variables, then the design exhibits **proportionality** and can be analyzed as though the data were balanced. So everything in the following conditions applies to situations where the data are unbalanced and cell sizes are not proportional.

7.12.3 Type I (Sequential) Sums of Squares

R prints so-called Type I, or sequential, sums of squares, which are computed by comparing a series of nested models. The sums of squares in the top of Table 3 are derived by comparing the following four nested models:

- 1.1) $score \sim 1$
- 1.2) $score \sim 1 + state$
- 1.3) $score \sim 1 + state + alcohol$
- 1.4) $score \sim 1 + state + alcohol + state : alcohol$

SS_{state} is derived by comparing models 1.1 and 1.2, $SS_{alcohol}$ is derived by comparing models 1.2 and 1.3, and $SS_{state:alcohol}$ is derived by comparing models 1.3 and 1.4. In the first step of this sequential comparison process, SS_{state} represents *all* of the variation in the dependent variable that is associated with **state**. In the second step, $SS_{alcohol}$ represents the variation in the dependent variable that is associated with **alcohol** *after* removing the variation assigned to **state**. The third step assigns all of the variation in the dependent variable that is associated with the **state** X **alcohol** interaction after removing variation assigned to the two main effects.

The sums of squares in the bottom of Table 3 are derived by comparing the following four nested models:

- 2.1) $score \sim 1$
- 2.2) $score \sim 1 + alcohol$
- 2.3) $score \sim 1 + alcohol + state$
- 2.4) $score \sim 1 + alcohol + state + alcohol : state$

$SS_{alcohol}$ is derived by comparing models 2.1 and 2.2, SS_{state} is derived by comparing models 2.2 and 2.3, and $SS_{alcohol:state}$ is derived by comparing models 2.3 and 2.4. In this case, $SS_{alcohol}$ represents *all* of the variation in the dependent variable that is associated with **alcohol**, but SS_{state} represents the variation that is associated with **state** *after* removing the variation assigned to **alcohol**. The last step is the same as before: $SS_{alcohol:state}$ represents the variation in the dependent variable that is associated with the **state** X **alcohol** interaction after removing the variation that assigned to the two main effects.

In Section 7.12, I noted that the fact that the design is unbalanced means that the main effects of **state** and **alcohol** are not orthogonal. The lack of orthogonality means that some of the variation in the dependent variable that is associated with **state** is also associated with **alcohol**; and some of the variation in the dependent variable that is associated with **alcohol** is also associated with **state**. This state of affairs is often summarized by saying that **state** and **alcohol** account for “overlapping” portions of the variation of the dependent variable. In such cases, the variation assigned to each variable depends on the order in which the assignment takes place. When we compare models 1.2 and 1.1, some variation in the dependent variable is assigned to SS_{state} . However, our example was constructed in such a way that the “effect” of **state** actually was due entirely to the effect of **alcohol**.

So, after comparing models 2.2 and 2.1, and assigning alcohol-associated variation in the dependent variable to $SS_{alcohol}$, there is nothing left to assign to SS_{state} .

One last comment. This discussion should make it clear that each main effect has *two* values for Type I sum of squares: one is calculated by comparing models that ignore the other effects (e.g., comparing models 1.1 and 1.2, or 2.1 and 2.2) and another that is calculated by comparing models that control for the other main effect (e.g., comparing 1.2 and 1.3, or 2.2 and 2.3). *Both* values are Type I sums of squares, so you need to be clear which value you are referring to when you discuss the “Type I sum of squares for factor A”. In your textbook, Type I sums of squares for *A* are calculated while ignoring both the other main effect, *B*, and the $A \times B$ interaction.

7.12.4 Type II Sums of Squares

Type I sums of squares are derived from sequential comparisons of nested models that can result in an asymmetry between the sums of squares for the two main effects. In the top of Table 3, for example, SS_{state} was calculated while ignoring the effects of `alcohol`, whereas $SS_{alcohol}$ was calculated after controlling for the effects of `state`. In the bottom of Table 3, on the other hand $SS_{alcohol}$ was calculated while ignoring the effects of `state`, whereas SS_{state} was calculated after controlling for the effects of `alcohol`. An alternative would be to calculate the sum of squares for each main effect after controlling for the other main effect. For example, we could estimate $SS_{alcohol}$ by comparing the residuals in the following nested models

$$\begin{aligned} score &\sim 1 + state \\ score &\sim 1 + state + alcohol \end{aligned}$$

and estimate SS_{state} by comparing these nested models

$$\begin{aligned} score &\sim 1 + alcohol \\ score &\sim 1 + alcohol + state \end{aligned}$$

These are Type II sums of squares: They are the sum of squares calculated after controlling for the other main effect but ignoring the interaction.

More generally, the Type II sum of squares for an effect is calculated by comparing nested models that lack all interactions that include that effect. For example, suppose an experiment contained factors A, B, and C. The Type II sum of squares for C is obtained by comparing the nested models

$$\begin{aligned} score &\sim 1 + A + B + A : B \\ score &\sim 1 + A + B + A : B + C \end{aligned}$$

Note how the models do not contain any interactions that include C (i.e., A:C, B:C, and A:B:C). According to this definition, the Type I and Type II sum of squares for the State X Alcohol interaction are equivalent.

The second line in each part of Table 3 lists the sum of squares for one main effect after controlling for the other main effect (but ignoring the interaction). These are the Type II sums of squares for `state` and `alcohol`. The Type II sum of squares for the interaction is equivalent to the Type I sum of squares for the interaction, and is listed in the third line of both ANOVA tables.

7.12.5 Type III Sums of Squares

Finally, we consider the sums of squares for an effect that are calculated after accounting for all other effects in the model. SS_{state} is calculated by comparing

$$score \sim 1 + alcohol + alcohol : state$$

$$score \sim 1 + alcohol + alcohol : state + state$$

$SS_{alcohol}$ is calculated by comparing

$$score \sim 1 + state + alcohol : state$$

$$score \sim 1 + state + alcohol : state + alcohol$$

and $SS_{state:alcohol}$ is calculated by comparing

$$score \sim 1 + state + alcohol$$

$$score \sim 1 + state + alcohol + alcohol : state$$

These are Type III sums of squares. They are sums of squares that are obtained by comparing nested models that control for all other effects. One advantage of Type III sums of squares is that they are *not* dependent on the order in which the factors are specified in the linear model.

Note that the Type III sum of squares for the interaction is the same as the Type I and Type II sums of squares. In general, the Type I, II and III sums of squares for the highest-order interaction in the experimental design will be the same. In a 2-factorial design, the Type II sum of squares for each main effect control for the other main effect but ignore the interaction. Type III sum of squares control for the other main effect *and* the interaction. Therefore, Type II and III sums of squares for the main effects will be the same when $SS_{interaction}$ is zero.

7.12.6 principle of marginality

One might think that Type III sums of squares could be computed in R by comparing the two aov models:

```
> aov.full <- aov(y ~ 1 + state + alcohol + state:alcohol, data=myData)
> aov.reduced <- aov(y ~ 1 + state + state:alcohol, data=myData)
> anova(aov.reduced, aov.full)
```

Although this sequence of commands looks correct, it will unfortunately not produce the Type III sums of squares for `alcohol`. The reason for this failure is that the formula in `aov.reduced` violates the **principle of marginality**, which holds that a model that contains an A:B interaction must also contain main effects of A and B. Some (most?) statisticians argue that, in general, such models should not be used. Here is one reason why: Suppose we construct a linear model that relates a dependent variable to a covariate

$$y \sim 1 + \alpha x + \beta x^2$$

and we find that α does not differ significantly from zero. We might be tempted to simplify our model by dropping x :

$$y \sim 1 + \beta x^2$$

This model also violates the principle of marginality because it contains the higher-order term, x^2 , but not the lower-order term x . What's the problem? Well, suppose we change the units of x by adding and/or multiplying it by a constant: $x' = ax + b$. This type of linear transformation of x should not change the results of our statistical analyses, right? Well, if the model obeys the principle of marginality, then a linear transformation of x does not change the results in any significant way: the sum-of-squares associated with x and x^2 remain the same. However, when the model violates the principle of marginality, then a linear transformation of x *does* change the sum-of-squares associated

with x^2 . And we are not just talking about tiny changes: the effects of linearly transforming x can be huge.

Consider another example. We have used the sum-to-zero constraint (Equation 44) when defining the effects in the linear model in Equation 43. It is possible, however, to define effects in other ways. For example, we could designate one condition in our experimental design as the *baseline* in which all of the effects are zero, and the effects for all other conditions would be defined relative to this baseline. Using this definition, it is possible that all of the effects are greater than zero, so the sum-to-zero constraint does not apply. Nevertheless, this definition – which is known as a **treatment** definition of an effect, and actually is the default definition used by R – is perfectly reasonable. The results of our ANOVA should not depend on which definition we use: we should get the same results if we use the sum-to-zero constraint or define the effects relative to a baseline condition. And we do get the same results – the sums of squares assigned to the various factors in our model remain the same, *so long as the model obeys the principle of marginality*. When the model violates the principle of marginality, then the results obtained by an ANOVA will depend on the (seemingly arbitrary) decision of how we define the effects in our model.

All of this is to say that R tries hard to enforce the principle of marginality. Therefore, the code listed at the start of this section, which includes a model that violates the principle of marginality, will not yield the Type III sum of squares for `alcohol`. The reason for the failure is that R surreptitiously introduces the `alcohol` term into the reduced model, and so the difference in $SS_{residual}$ in the two models will be zero. Think of it this way: R is trying to save you from yourself. Nevertheless, Type III sums of squares can be calculated easily in R if you know the secret handshake.

7.12.7 calculating Type III sums of squares in R

The command `drop1(aovModel, . ~ ., test="F")` calculates the change in $SS_{residuals}$ that is caused by removing each term in `aovModel`, one at a time, and evaluates each change with an F test. (The second part of the command, `. ~ .`, tells R that it should drop *all* terms in the model, one at a time.) Notice that this procedure is exactly how Type III sums of squares are computed, so `drop1` calculates Type III sums of squares.

The following code shows how to compute the Type III sum of squares for our example:

```
> howell<-read.csv("howell.csv")
> aov.01<-aov(score~1+state+alcohol+state:alcohol,data= howell)
> drop1(aov.01,.~.,test="F")
```

Single term deletions

Model:

```
score ~ 1 + state + alcohol + state:alcohol
          Df Sum of Sq   RSS   AIC F value    Pr(>F)
<none>                184.00 63.209
state           1      0.00 184.00 61.209   0.000      1
alcohol         1    243.69 427.69 87.357 35.759 2.231e-06 ***
state:alcohol   1      0.00 184.00 61.209   0.000      1
---
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Notice that the results are not dependent on the order of the terms in the model (to within rounding error):

```
> aov.02<-aov(score~1+alcohol+state+state:alcohol,data=howell)
> drop1(aov.02,~,test="F")
```

Single term deletions

Model:

```
score ~ 1 + alcohol + state + state:alcohol
              Df Sum of Sq    RSS    AIC F value    Pr(>F)
<none>                184.00 63.209
alcohol             1    243.69 427.69 87.357  35.759 2.231e-06 ***
state               1         0.00 184.00 61.209   0.000      1
alcohol:state      1         0.00 184.00 61.209   0.000      1
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

7.12.8 linking everything to hypotheses about means

The previous sections described Type I, II, and III sums of squares in terms of comparisons among nested models. Normally, however, we express experimental hypotheses in terms of group means: we want our analyses of main effects, for example, to evaluate null hypotheses of no difference among row and column means. What hypotheses about means are being evaluated when we compute Type I, II, and III sums of squares?

7.12.9 the interaction term

In the case of the A:B interaction, the answer is simple: Type I, II, and III sums of squares are all equal and all test the same hypothesis, namely that every cell mean is simply the sum of the intercept and two main effects:

$$\bar{Y}_{jk} = \mu + \alpha_j + \beta_k \quad (47)$$

or, in other words, that $(\alpha\beta)_{jk} = 0$ for all j and k .

7.12.10 Type I: weighted means

Type I sums of squares evaluate null hypotheses about *weighted* row and column marginal means. A weighted mean takes into account the different n in each group. So, for an $a_{row} \times b_{column}$ design, the weighted row and column marginal means are

$$\bar{Y}_{r.(W)} = \frac{\sum_{k=1}^b n_k \bar{Y}_{rk}}{(n_1 + n_2 \cdots + n_b)} \quad (48)$$

$$\bar{Y}_{.c(W)} = \frac{\sum_{j=1}^a n_j \bar{Y}_{jc}}{(n_1 + n_2 \cdots + n_a)} \quad (49)$$

Type I sums of squares evaluate the null hypotheses that the weighted marginal row and column means are equal:

$$\bar{Y}_{1.(W)} = \bar{Y}_{2.(W)} = \cdots = \bar{Y}_{a.(W)} \quad (50)$$

$$\bar{Y}_{.1(W)} = \bar{Y}_{.2(W)} = \cdots = \bar{Y}_{.b(W)} \quad (51)$$

Are these hypotheses interesting? Usually, no, because differences in weighted means depend on the cell n 's. However, in some cases it is important to incorporate information about cell n into our

analyses (see Howell and McConaughy (1982) for an example), and in those cases testing hypotheses about weighted marginal means is appropriate.

7.12.11 Type II: crazy!

Type II sums of squares can be used to test the following crazy null hypothesis:

$$\sum_{k=1}^b (n_{jk} - (n_{jk}^2/n_{.k})) \mu_{jk} = \sum_{j \neq j'} \Sigma (n_{jk} n_{j'k} / n_{.k}) \mu_{j'k} \quad (52)$$

where $j = 1, 2, 3, \dots, (a - 1)$. Nobody knows what this hypothesis means. So, Type II sums of squares generally do not test anything that you or I can understand. An exception to this general rule is when when $SS_{interaction} \approx 0$. I expand on this point in see Section 7.12.12.

7.12.12 Type III: unweighted means

Type III sums of squares evaluate null hypotheses about unweighted marginal means. In an $a_{row} \times b_{column}$ design, the unweighted mean for row r , $\bar{Y}_{r.(U)}$, is simply the mean of the b cell means in row r , and the unweighted mean for column c , $\bar{Y}_{.c(U)}$, is the mean of the a cell means in column c :

$$\bar{Y}_{r.(U)} = \frac{\sum_{j=1}^b \bar{Y}_{rj}}{b} \quad (53)$$

$$\bar{Y}_{.c(U)} = \frac{\sum_{i=1}^a \bar{Y}_{ic}}{a} \quad (54)$$

Unweighted marginal means do not take into account the differences in n within each cell.

Provided that the effects in the linear model satisfy the sum-to-zero constraint (as in Equation 44), Type III sums of squares can be used to evaluate the null hypotheses that the unweighted marginal row and column means are equal:

$$\bar{Y}_{1.(U)} = \bar{Y}_{2.(U)} = \dots = \bar{Y}_{a.(U)} \quad (55)$$

$$\bar{Y}_{.1(U)} = \bar{Y}_{.2(U)} = \dots = \bar{Y}_{.b(U)} \quad (56)$$

I will say it again: Type III sums of squares can be used to test hypotheses about unweighted marginal means *provided that the effects satisfy the sum-to-zero constraint*³. To illustrate this point, I am going to use `drop1` to calculate $SS_{alcohol}$ when we define an effect relative to a baseline condition:

```
> options(contrasts=c("contr.treatment","contr.poly")) # treatment/baseline definition
> aov.03 <- aov(score~alcohol+state+alcohol:state,data=howell)
> drop1(aov.03,~,test="F")
```

Single term deletions

Model:

	Df	Sum of Sq	RSS	AIC	F value	Pr(>F)
<none>			184.00	63.209		
alcohol	1	123.75	307.75	77.154	18.159	0.000221 ***

³Actually, the requirement is that the contrasts used to define the effects are orthogonal in the row-basis of the model matrix. This means that several definitions of effects can be used to test hypotheses about marginal means using Type III sums of squares, but the only one considered here is the sum-to-zero definition.

```
state          1          0.00 184.00 61.209    0.000 1.000000
alcohol:state  1          0.00 184.00 61.209    0.000 1.000000
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> options(contrasts=c("contr.sum","contr.poly")) # reset
```

Now $SS_{alcohol} = 123.75$, which is considerably less than the value of 184 calculated in Section 7.12.7.

7.12.13 When $SS_{interaction} \approx 0$

Type II and III sums of squares are equal when $SS_{interaction} \approx 0$. In that situation, Type II sums of squares can be used to evaluate null hypotheses about marginal unweighted means. Moreover, in this case Type II sums of squares will provide a more sensitive test of the null hypothesis because the degrees of freedom associated with the interaction effects will be incorporated into $df_{Residuals}$. Therefore, some researchers recommend that you first evaluate the interaction term and if it is not significant – with $p > 0.20$ or $p > 0.25$ – proceed to use Type II sums of squares to evaluate hypotheses about marginal unweighted means. Others recommend against this procedure, arguing instead that the interaction term should remain in the model even if it is not significant, and that you should use Type III tests to evaluate the main effects (Faraway, 2005).

7.12.14 A Numerical Example

To illustrate the ideas described in the previous section, I will analyze the data shown in Table 7.23 (page 339) in your textbook. The data are from an experiment that evaluates the effectiveness of three types of therapy on alleviating depression. The factors are type of **therapy** (cognitive-behavioural, Rogerian, and Assertiveness Training) and severity of **depression** (mild, moderate, and severe)⁴. The dependent variable is the score on the depression scale of the MMPI.

The data are stored in the file `chapter_7_table_23.dat` on the CD that came with your textbook. I copied the file to my working directory and then read it into R with the following command:

```
> mwtable23<-read.table("chapter_7_table_23.dat")
> names(mwtable23)<-c("therapy","depression","mmpi")
> mwtable23$therapy<-factor(mwtable23$therapy,labels=c("cognitive","rogerian","assertive") )
> mwtable23$depression<-factor(mwtable23$depression,labels=c("mild","moderate","severe"))
> class(mwtable23$therapy)

[1] "factor"

> class(mwtable23$depression)

[1] "factor"
```

The next command shows that the data are unbalanced:

```
> with(mwtable23,tapply(mmpi,list(therapy,depression),length) )
```

⁴Subjects are not assigned to severity of depression, so **depression** is a blocking variable, not a true experimental factor. Nevertheless, we will use a fixed-effects model to analyze these data.

	mild	moderate	severe
cognitive	3	5	7
rogerian	5	6	4
assertive	5	4	6

Next, I construct an aov object and then use `drop1` to estimate the Type III sums of squares for the two main effects and interaction:

```
> options(contrasts=c("contr.sum", "contr.poly") ) # use sum-to-zero coding
> mw23.aov.01<-aov(mmpi~therapy+depression+therapy:depression,data=mwtable23)
> drop1(mw23.aov.01, .~, test="F")
```

Single term deletions

Model:

```
mmpi ~ therapy + depression + therapy:depression
              Df Sum of Sq    RSS    AIC F value    Pr(>F)
<none>                1005.4 157.79
therapy              2    204.76 1210.2 162.13  3.6658  0.03556 *
depression           2   1181.11 2186.5 188.75 21.1452 8.447e-07 ***
therapy:depression   4     14.19 1019.6 150.42  0.1270  0.97170
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The first thing to note is that the interaction is not significant, so it makes sense to examine the main effects. The Type III sums of squares for `therapy` and `depression` are 204.76 and 1181.11, respectively. Both are significant, so we reject the null hypotheses that the unweighted marginal means (of mmpi scores) do not vary across types of `therapy` or level of `depression`. (N.B. This second main effect is not interesting.)

In this example, $SS_{therapy:depression}$ was very small and the p value was very large ($p = 0.971$). In other words, if interaction effects do exist then they are likely to be very small. Therefore, we might consider evaluating the main effects using Type II sums of squares. The following commands list two ANOVA tables for models that contain two main effects but no interaction. The second line in each table is the sum of squares for that main effect after controlling for the other main effect while ignoring the interaction (which we think is approximately zero). In other words, those lines contain the Type II sum of squares and, because the interaction is assumed to be zero, test the same null hypotheses as the Type III sums of squares:

```
> mw23.aov.02<-aov(mmpi~therapy+depression,data=mwtable23)
> summary(mw23.aov.02)
```

```
              Df Sum Sq Mean Sq F value    Pr(>F)
therapy        2  101.1    50.6   1.983    0.151
depression     2 1253.2   626.6  24.582 1.09e-07 ***
Residuals    40 1019.6    25.5
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> mw23.aov.03<-aov(mmpi~depression+therapy,data=mwtable23)
> summary(mw23.aov.03)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
depression	2	1115.8	557.9	21.887	3.79e-07	***
therapy	2	238.5	119.2	4.678	0.0149	*
Residuals	40	1019.6	25.5			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The Type II sums of squares for **therapy** and **depression** are 238.48 and 1253.19, respectively. Both are significant, so we reject the null hypothesis of no difference between marginal row means and marginal column means. Again, it is important to remember that this null hypothesis is being evaluated because the interaction is assumed – with good reason, in this case – to be zero. If the interaction was not zero, then Type II sums of squares would be evaluating the crazy null hypothesis listed in Section 7.12.11.

The Type I sums of squares for **therapy** and **depression** – the versions calculated by ignoring all other effects, which are listed in the first lines of the two ANOVA tables – are 101.11 and 1115.82, respectively. These sums of squares can be used to evaluate the null hypotheses that the weighted marginal means do not vary across levels of **depression** or types of **therapy**. The effect of **therapy** is not significant ($F(2, 40) = 1.98$, $p = 0.15$), so we do not reject the null hypothesis of no difference among weighted marginal means. The effect of **depression** is significant (though this finding is not interesting).

7.12.15 Using Anova in the car package

In this section I describe how to use the `Anova()` command (N.B., note the capital A) to compute Type II and III sums of squares. Note that you do not *need* to use `Anova()`; `drop1()`, along with the standard `anova()` or `summary()` commands, are adequate. However, `Anova()` has some features that will be useful for analyzing within-subjects designs, which will be covered in later chapters. Therefore, I thought it might be useful to introduce the command here.

The `Anova()` command is part of the `car` package, which is a suite of commands and data files for R written and maintained by Professor John Fox. You can read about the `car` package at <http://cran.r-project.org/web/packages/car/index.html>. To use `car`, you need to install the software on your computer. From within R, type the following command:

```
> install.packages(pkgs="car")
```

This command installs `car` on your computer; you only have to use it once (plus whenever you periodically update your software). The command `library("car")` loads `car` into memory: you have to use it once per session. You can read about the contents of `car` by typing `?car` at R's command prompt. You can learn more about `Anova` by typing `?Anova` at the command prompt. Again, take note of the capital A in `Anova`.

Finally, we can calculate Type II and III sums of squares. Type III sums of squares only make sense if we are using sum-to-zero coding of our effects. Therefore, I am going to make sure the coding is correct by resetting the coding option.

```
> library("car") # load car (just once per session)
> options(contrasts=c("contr.sum","contr.poly")) # just in case
> Anova(mw23.aov.01,type="II")
```

Anova Table (Type II tests)

Response: mmpi

	Sum Sq	Df	F value	Pr(>F)
therapy	238.48	2	4.2695	0.02168 *
depression	1253.19	2	22.4357	4.711e-07 ***
therapy:depression	14.19	4	0.1270	0.97170
Residuals	1005.42	36		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
> Anova(mw23.aov.01, type="III")
```

Anova Table (Type III tests)

Response: mmpi

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	121174	1	4338.7178	< 2.2e-16 ***
therapy	205	2	3.6658	0.03556 *
depression	1181	2	21.1452	8.447e-07 ***
therapy:depression	14	4	0.1270	0.97170
Residuals	1005	36		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

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