LECTURE NOTES #5: Advanced Topics in ANOVA

Reading assignment

- Read MD chs 10, 11, 12, 13, & 14; G chs 12 & 13
  
  When reading the four repeated measures chapters in MD, concentrate on the multivariate approach (Chapters 13 and 14). Read the “traditional univariate approach” (Chapters 11 and 12) for background knowledge so that you can communicate with other people who aren’t familiar with the modern multivariate approach.

Goals for Lecture Notes #5

- Discuss issues surrounding unequal sample sizes in factorial designs
- Introduce random and nested effects
- Introduce repeated measures factors

Major Warning: The statistical content in these lecture notes is not very difficult. However, both SPSS and R will make you pull your hair out. All programs need to make implementing the content in this set of lecture notes easier, but we aren’t there yet. So take my advice from the first day of class—concentrate first on understanding the statistics, then focus on implementing in SPSS and R. This will be the worst part of the entire year in terms of having to cover so much trivial detail about SPSS and R. After this and through April, syntax in both SPSS and R becomes as easy as it was in lecture notes 1, 2 and 3, even though the statistical concepts will become a little more complicated.

1. Factorial designs having cells with unequal sample size

We have been discussing the analysis of variance in terms of a decomposition of sums of squares (e.g., with a two-way design we had \(\text{SST} = \text{SSA} + \text{SSB} + \text{SSAB} + \text{SSE}\)). Such a perfect decomposition applies in general only when every cell has the same number of subjects. When the cells contain an unequal number of subjects, then a decomposition may no longer be unique. The reason is that contrasts will no longer be orthogonal so there is going to be redundancy in some of the sums of squares. The SSE will always be the same, so all approaches under consideration have the same error term. What differs across the approaches for dealing with unequal sample
sizes is how they decompose the main effect terms. The different approaches do not disagree on the interaction term, but they disagree on the main effects.

There are different ways of handling the redundancy due to unequal sample sizes across cells. I will discuss the three most popular methods. We assume that the reason there are unequal sample sizes is because of either random chance or true differences in population sizes. For example, a few subjects failed to show up to the experiment, a few subjects had to be thrown out because they did not take the task seriously and gave what appear to be random responses, etc. This kind of information should be included in the Subjects section of the paper. Researchers should check whether there are particular cells that are losing more subjects than others—that might be informative. If the different cell sizes arose from differential levels of attrition or differential population sizes, then the methods I present are no longer valid. Also, if the researcher intended to have unequal sample sizes, such as in a representative sampling design where some groups are over sampled, then other methods are required that take into account sampling weights. If this applies to you I recommend taking a course on sampling after you complete the 613/614 sequence.

The problem of unequal sample sizes occurs when we want to make claims about main effects, i.e., when we want to collapse cells and look at marginal means. There are different ways to collapse the main effects, and each method can give a different answer. I reiterate, the interaction term and the error term do not involve collapsing because they say something about individual cells, so the various methods will agree on the interaction term and the error term; the methods differ on how they handle the main effects.

The best approach, in my opinion, is what SPSS calls the unique approach; in some versions of SPSS it is called the regression approach. This approach tests the relevant effect having taken into account all other effects. This is the default of the ANOVA and MANOVA commands (in some versions of SPSS, however, ANOVA has a different default). The trick of converting a factorial into a one-way arrangement in order to test contrasts leads to the identical result as the unique approach when there are unequal n. Also, the unique approach tests contrasts in a straightforward way.

A second method, the hierarchical method, only looks at the factor of interest and, when unequal cells are present, confounds all the other effects.

A third method that some people view as a compromise between the unique and the hierarchical approaches. SPSS calls this third approach experimental. The experimental approach enters, in order, all main effects, then all two-way interactions, then all three-ways, etc. This differs from the hierarchical method, which enters every term in the model one at a time rather than in conceptual chunks (main effects, two-way interactions, etc). The unique approach enters everything at once. I'll explain what
“entering terms into a model” and in different order means later. When we cover regression techniques, we will come across a situation where the experimental method makes sense, though for our purposes right now the “experimental method” probably is the least preferred of the three methods.

The following example is taken from Maxwell & Delaney (1990). Consider the starting salaries of a small sample of men and women who either have or don’t have a college degree.

Example illustrating potential misleading effects of unequal sample sizes. The mean for the 12 females is 22.33 and the mean for the 10 males is 22.1, suggesting that females have a slightly higher score. However, if gender comparisons are made within level of college degree category, then the males have a higher score. What is the right main effect for gender? 22.33 for females v. 22.1 for males? 21 for females v. 23.5 for males?

<table>
<thead>
<tr>
<th></th>
<th>College</th>
<th>No College</th>
</tr>
</thead>
<tbody>
<tr>
<td>female</td>
<td>24</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>26</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>20</td>
</tr>
<tr>
<td>female mean</td>
<td>25</td>
<td>17</td>
</tr>
<tr>
<td>male</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>27</td>
<td>24</td>
</tr>
<tr>
<td></td>
<td>27</td>
<td>23</td>
</tr>
<tr>
<td>male mean</td>
<td>27</td>
<td>20</td>
</tr>
</tbody>
</table>

If someone ignored education and simply looked at the 12 women v. the 10 men, the conclusion would be that on average women ($\bar{Y}_w = 22.33$) earn slightly more than men ($\bar{Y}_m = 22.1$). However, if education status is accounted in the analysis (say, by doing the 1,1,-1,-1 contrast in a $2 \times 2$ factorial design), then the opposite conclusion is reached. The mean for the women is 21 (average of college and no college) and the
mean for the men is 23.5\[1\].

These two ways of looking at the data answer different questions. The first asks the question: Are males paid a higher starting salary than females? The second asks the question: Within an education status are males paid a higher starting salary than females? Note that in the second analysis equal weight is given across the four cells. Which method of analysis is right? The answer rests completely on the research question you want to ask. If you want to compare the women in the study to the men completely ignoring college status, then the hierarchical approach may be appropriate. If you want to conditionalize comparisons by educational level, then the regression method is appropriate. SPSS will do both of these analyses. What SPSS calls the hierarchical approach is also referred to as a weighted mean analysis. What SPSS calls the unique approach is also referred to as an unweighted means analysis.

Yet another way of distinguishing the three methods is to look at the contrast weights that are implied by each method. The contrast weights will give us some more intuition about how these methods differ. Recall that the cell sample sizes in this example are NFC=8, NMC=3, NFNC=4, and NMNC=7 (here “NFC” stands for “number of females who went to college”, etc). There were 12 females and 10 males in the study. Here are the contrast weights for the main effect of male v. female implied by the three methods:

<table>
<thead>
<tr>
<th>method</th>
<th>FC</th>
<th>FNC</th>
<th>MC</th>
<th>MNC</th>
</tr>
</thead>
<tbody>
<tr>
<td>unique</td>
<td>1</td>
<td>1</td>
<td>-1</td>
<td>-1</td>
</tr>
<tr>
<td>hierarchical</td>
<td>NFC/NF</td>
<td>NFNC/NF</td>
<td>-NMC/NM</td>
<td>-NMNC/NM</td>
</tr>
<tr>
<td></td>
<td>8/12</td>
<td>4/12</td>
<td>-3/10</td>
<td>-7/10</td>
</tr>
<tr>
<td></td>
<td>.667</td>
<td>.333</td>
<td>-.3</td>
<td>-.7</td>
</tr>
<tr>
<td>experimental</td>
<td>NFC*NMC/NC</td>
<td>NFNC*NMC/NNC</td>
<td>-NFC*NMC/NC</td>
<td>-NFNC*NMC/NNC</td>
</tr>
<tr>
<td></td>
<td>2.18</td>
<td>2.54</td>
<td>-2.18</td>
<td>-2.54</td>
</tr>
</tbody>
</table>

As Maxwell & Delaney note (p. C-14, note 18), the experimental contrast weight is twice the harmonic mean\[2\] of the number of males and females at each level of the college factor. This table highlights that the clearest method is the unique method (the contrast weights are 1s and -1s), unless one wants to have contrast weights depend on group size.

This discussion illustrates another worry researchers should have: are all the relevant variables included in the analysis? It appears that in the example, education level is important and has implications for how we interpret the sex difference, but we probably need to account for type of job. Are these starting salaries for the same type

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1 This discrepancy is related to a more general problem known as “Simpson’s Paradox.”

2 For a definition of the harmonic mean see MD, page C-13, note 14.
of job or are men and women in this sample getting different kinds of jobs. There are probably many other factors that should be considered as well.

Sometimes a researcher intentionally has cells with unequal sample sizes. For example, a researcher might want a sample to represent the ethnicity composition of a population. These situations sometimes arise in field studies and in surveys that are intended to have a representative sample. See Kirk’s advanced ANOVA textbook for a discussion of how to handle designs with this sampling feature.

More detail on the different methods is given in Appendices 2 and 3.

2. Random Effects Model

So far this semester we have been talking about the fixed effects model, which applies when you have specific treatments and want to make inferences only to those treatments. For example, in the sleep deprivation study we selected 12 hrs, 24 hrs, 36 hrs, and 48 hrs. The researcher probably wants to compare only those four conditions.

The random effects model involves the situation where the treatments are sampled from a population, and the researcher wants to make inferences about some population of possible treatments. For example, a memory researcher may want to test recall of high frequency words as opposed to recall of low frequency words. The researcher probably does not care about the particular words chosen. She probably wants to make inferences about the category of high frequency and the category of low frequency words; she doesn’t care about the particular words used in the study.

So, the key to deciding between fixed effects and random effects models is the type of inference you want to make. A classic piece showing the error of using a fixed effects model when one should have done a random effects model is Clark (1973), The language-as-fixed-effect fallacy: A critique of language statistics in psychological research. *Journal of Verbal Learning and Verbal Behavior, 12*, 335-359. A more recent treatment is by Raaijmakers (2003, *Canadian Journal of Experimental Psychology, 57*, 141-151.

Rarely do you see the use of random effects models in psychology. Recently, they have started to show up (again). For example, the Sarason’s dietary fat study that I will present in class.

The key idea in a random effects model is that you not only take into account the random noise (i.e., \( \epsilon \)), but also take into account the sampling “noise” that went into the selection of the levels of a factor. Clark argued that words in a language or memory experiment should be treated as a random effect. [Note that subjects can be
considered a random effect.]

The main difference between how a random effects factor is treated as compared to a fixed effects factor is in the interpretation of the terms in the structural model. In the fixed effects model all terms in the structural model are constants, except for $\epsilon$. In the random effects model some terms other than $\epsilon$ may be given a distribution.

The random effects model adds two assumptions to the usual three ANOVA assumptions (observations are independent, homogeneity of variance, and normally distributed errors):

(a) Treatment effects are normally distributed with a mean of zero and a variance that is estimated from the data.

(b) All treatment effects are independent from each other and the errors.

The source tables for one-way analysis of variance, randomized block designs, and latin square designs are the same for both fixed effects models and random effects models (when all factors are random effects). So, the $p$ values are the same, but the interpretations are slightly different with different implications for a replication. A fixed effects model would be replicated in an identical format (except for subjects who are treated as a random effect). A random effects model for the manipulation(s) would replicate using new levels that were randomly selected. Further, in a random effects model one generalizes the results to the population of interest. You can see how these two different approaches lead to different (underlying, hypothetical) sampling distributions.

In a two-way analysis of variance with both factors treated as random effects the test for the interaction is exactly the same as with the fixed effects model (i.e., $F = \text{MSAB}/\text{MSE}$). However, the main effects are tested differently. The “error term” for the main effect is the mean square term for the interaction. So, for example, the main effect for A would be tested as $F = \text{MSA}/\text{MSAB}$. The reason is that the main effect of A is confounded with the sampling of B (and vice versa). The expected mean square terms are given by:

\[
\begin{align*}
\text{A: } & \sigma^2_\epsilon + n\sigma^2_{\alpha\beta} + nb\sigma^2_\alpha \\
\text{B: } & \sigma^2_\epsilon + n\sigma^2_{\alpha\beta} + na\sigma^2_\beta \\
\text{AB: } & \sigma^2_\epsilon + n\sigma^2_{\alpha\beta} \\
\text{Error: } & \sigma^2_\epsilon
\end{align*}
\]
The calculation of the source table is identical to the fixed effects case except for the last step when the $F$ tests are calculated. Clearly, the correct denominator for the main effects should be the interaction because that cancels the “nuisance” terms. Recall our statement of the $F$ test requiring the “nuisance” terms in the denominator. Ott (1988) presents a nice procedure for finding expected mean terms in general situations. The structural model for the two-way design with both factors being random is

$$Y = \mu + \alpha + \beta + (\alpha\beta) + \epsilon \quad (5-1)$$

I denote random effects with a $\sigma$ subscript to highlight that they are random. The meaning is that each term (e.g., $\alpha$) is a random draw from a random variable that has some variance.

Whenever a new error term is used be sure to use the associated degrees of freedom when comparing the observed $F$ to the critical $F$ from the table. So when testing a main effect in a two-factor ANOVA with both factors treated as random effects, the main effect MS is divided by the MS interaction as shown above, and the “error” degrees of freedom will be the degrees of freedom associated with the interaction term (not the MSE term).

We now consider a two-way factorial where one factor (say, factor A) is treated as fixed and the second factor is treated as a random effect (factor B). The assumptions are as you’d expect by now. The fixed effect part has the usual three assumptions, the random effects part (including the interaction) has the additional assumptions listed above. The expected mean square terms are identical as the ones in the previous paragraph with one exception. The fixed effect A is influenced by the random effect B. However, since A is not assumed to be random there is no “sampling variability” of treatments on A. So, the expected mean square term for factor B does not contain the interaction term.

The complete source table when one factor is a fixed effect and the second factor is a random effect is

- **A (fixed):** $\sigma^2 + n\sigma^2_{\alpha\beta} + \frac{bn\sum_{\alpha} \sigma^2_\alpha}{a-1}$
- **B (random):** $\sigma^2 + n\sigma^2_\beta$
- **AB:** $\sigma^2 + n\sigma^2_{\alpha\beta}$
- **Error:** $\sigma^2$

The main effect for B will use the MSE term in the denominator, whereas the main effect for A will use MSAB in the denominator. Remember the rule that the denominator must have the same terms the numerator has except the particular term being tested.
The structural model for a two-way factorial where only one factor is fixed is

\[ Y = \mu + \alpha + \beta_{0} + (\alpha\beta)_{\sigma} + \epsilon \]  

(5-2)

3. Example of a random effects design

Here are data from an experiment looking at the effectiveness of three different treatments (Maxwell & Delaney, 1990). The three treatments are rational-emotive therapy (RET), client-centered therapy (CCT), and behavior modification (BMOD). The effectiveness scores come from a standardized battery of tests—the greater the score the more “effective” the treatment.

I’m going to deviate from the description given in Maxwell and Delaney. Forty-five subjects were randomly assigned to each of the three treatments (15 subjects per cell). Three therapists were enlisted to conduct the treatments (each therapist administered one of each treatment). Later, we will revise this example (same data) and treat it as though there were nine different therapists.

First, we examine the one-way analysis of variance comparing the three treatments. I’ll omit all the assumption testing (boxplots and such) and only present some of the relevant means. [To save space I list these data in two columns.]
Description of Subpopulations

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Label</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>For Entire Population</td>
<td>42.0000</td>
<td>3.5227</td>
<td>45</td>
<td></td>
<td></td>
</tr>
<tr>
<td>THRPY</td>
<td>1.00</td>
<td>RET</td>
<td>40.0000</td>
<td>3.3166</td>
<td>15</td>
</tr>
<tr>
<td>THRST</td>
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<td></td>
<td>38.0000</td>
<td>2.9155</td>
<td>5</td>
</tr>
<tr>
<td>THRST</td>
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<td>42.0000</td>
<td>2.9155</td>
<td>5</td>
</tr>
<tr>
<td>THRST</td>
<td>3.00</td>
<td></td>
<td>40.0000</td>
<td>3.3912</td>
<td>5</td>
</tr>
<tr>
<td>THRPY</td>
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<td>42.0000</td>
<td>3.1396</td>
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</tr>
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</tr>
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<td>3.0938</td>
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</tr>
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<td>44.0000</td>
<td>3.5355</td>
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</tr>
<tr>
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<td></td>
<td>42.0000</td>
<td>2.3452</td>
<td>5</td>
</tr>
</tbody>
</table>

Total Cases = 45

Here I use the good old fixed effects, one-way ANOVA that ignores therapist to serve as a comparison to the more complicated models that I will present later.

```plaintext
manova score by thrpy(1,3) /design thrpy.
```

Tests of Significance for SCORE using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>426.00</td>
<td>42</td>
<td>10.14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>THRPY</td>
<td>120.00</td>
<td>2</td>
<td>60.00</td>
<td>5.92</td>
<td>.005</td>
</tr>
</tbody>
</table>
```

The conclusion from the omnibus test is that there is a difference between the three treatments as with all omnibus tests. This conclusion is not very helpful. We would need to do contrasts or post hoc tests to learn more. By looking at the means we know...
that \( \text{RET} < \text{CCT} < \text{BMOD} \), but we don’t know whether these individual comparisons between means are statistically significant.

Before we get to random and fixed effects I want to highlight a feature of the MANOVA command in SPSS. It is possible to get a test of significance for the grand mean (the \( \mu \) term in the structural model). This will come in handy when we do repeated measures designs. I thought I’d show this to you now even though it won’t be of much use until we get to repeated measures designs. All that needs to be done is to include the word “constant” in the design line and out comes the test of the grand mean against zero. Note that the error term and the thrpy term are identical to the previous source table.

```spss
manova score by thrpy(1,3)
/design constant thrpy.
```

Tests of Significance for SCORE using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
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<td></td>
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<td>7826.20</td>
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</tr>
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<td>THRPY</td>
<td>120.00</td>
<td>2</td>
<td>60.00</td>
<td>5.92</td>
<td>.005</td>
</tr>
</tbody>
</table>

Explanation: The sum of squares constant is the sum of squares that comes out of doing the grand mean \((1, 1, 1)\) contrast on the three group means for therapy. The three group means are 40, 42, and 44. The value of \( \hat{I} \) is 126. Recall that the formula for SSC is

\[
\hat{I}^2 = \sum \frac{a_i}{n_i}
\]  

(5-3)

The cell sample size \( n_i \) is 15 per group. Plug in the numbers and you should get sum of squares for this contrast equal to 79,380, just as reported in the source table above.

Let’s take into account some of the structure of the design to reduce the error variance (i.e., the within sums of squares). We might be able to get more power by including therapist as a blocking factor. Because there is more than one subject per cell we don’t have a traditional randomized block design. We do have a two-way factorial design. For our purposes the main effect for therapist and the interaction between therapist will both be components of the “blocking” factor. Here are the commands and source table for this two-way analysis of variance.

Here is the factorial ANOVA with both factors treated as fixed.

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3 In the following example I consider the effects of specific factors as being fixed or random. Focus on the meaning the different formulations offer in terms of the research questions being addressed (and the underlying statistical models they imply).
**Lecture Notes #5: Advanced topics in ANOVA**

- **Fixed effects, two-way ANOVA**

```
manova score by thrpy(1,3) thpst(1,3)
/design thrpy thpst thrpy by thpst.
```

Tests of Significance for SCORE using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
</tr>
<tr>
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<td>2</td>
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<td>6.84</td>
<td>.003</td>
</tr>
<tr>
<td>THPST</td>
<td>43.33</td>
<td>2</td>
<td>21.67</td>
<td>2.47</td>
<td>.099</td>
</tr>
<tr>
<td>THRPY BY THPST</td>
<td>66.67</td>
<td>4</td>
<td>16.67</td>
<td>1.90</td>
<td>.132</td>
</tr>
</tbody>
</table>

Again, we’re probably not interested in the differences between therapists or the interaction between therapy and therapist so those two terms will be thought of as “blocking factors.”

Now let’s treat both factors (therapist and therapy) as random effects. The interaction term will be identical to the interaction from the fixed-effects model because you use MSW as the error in both cases. Note the SPSS syntax: I can tell SPSS which error term to use for each term in the structural model.

The syntax defines an alias for the interaction term to be “1”. The syntax requests that the main effect be tested against the error term 1 (i.e., the interaction term) and that the interaction term be tested against the usual MSE (called WITHIN in SPSS jargon). The resulting table contains all the correct F’s and no additional computations are required.

```
manova score by thrpy(1,3) thpst(1,3)
/design thrpy vs 1, thpst vs 1, thrpy by thpst = 1 vs within.
```

Tests of Significance for SCORE using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
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<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
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<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>316.00</td>
<td>36</td>
<td>8.78</td>
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<tr>
<td>Error 1</td>
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<td>4</td>
<td>16.67</td>
<td></td>
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</tbody>
</table>

---

4I don’t mean to imply that therapists and the interaction between therapist and therapy are not important to study. It is just that the way I framed the present study suggests that those two terms should be treated as blocking terms. There are situations where someone would want to study differences between therapists and the interaction between therapist and therapy. But, that is not the question I have posed here.
Note that the therapy main effect is no longer significant. If we believe the model that both therapist and therapy should be treated as random effects, then the correct error term to test the main effect of therapy is the MSAB (mean square for interaction).

Let’s examine the following case. This is the case with Therapy fixed but Therapist random. In this example I defined the error term to be MSW for the therapist/therapy interaction, and the error term for therapy to be the mean square for interaction.

Note that now therapy is not significant, likely due to the loss of degrees of freedom.

The UNIANOVA and GLM commands in SPSS unfortunately do something different with the error terms in a mixed design. By design, SPSS tests both main effects using the interaction term, which is not the convention. First, I present the output of UNIANOVA so you can see the difference in what SPSS does automatically and what you should get by manually specifying the correct error terms, then I present an email from SPSS explaining their take on the problem. If you use the menu system, you will get the wrong answer. Here is a case where you need to use syntax to get SPSS to divide by the right error term.
<table>
<thead>
<tr>
<th>Source</th>
<th>Type III Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>79380.000</td>
<td>1</td>
<td>79380.000</td>
<td>3663.692</td>
<td>.000</td>
</tr>
<tr>
<td>Error</td>
<td>43.333</td>
<td>2</td>
<td>21.667a</td>
<td></td>
<td></td>
</tr>
<tr>
<td>thrpy</td>
<td>120.000</td>
<td>2</td>
<td>60.000</td>
<td>3.600</td>
<td>.128</td>
</tr>
<tr>
<td>Error</td>
<td>66.667</td>
<td>4</td>
<td>16.667b</td>
<td></td>
<td></td>
</tr>
<tr>
<td>thpst</td>
<td>43.333</td>
<td>2</td>
<td>21.667</td>
<td>1.300</td>
<td>.367</td>
</tr>
<tr>
<td>Error</td>
<td>66.667</td>
<td>4</td>
<td>16.667b</td>
<td></td>
<td></td>
</tr>
<tr>
<td>thrpy * thpst</td>
<td>66.667</td>
<td>4</td>
<td>16.667</td>
<td>1.899</td>
<td>.132</td>
</tr>
<tr>
<td>Error</td>
<td>316.000</td>
<td>36</td>
<td>8.778c</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a. MS(thpst)
b. MS(thrp * thpst)
c. MS(Error)

SPSS email

From: nichols@spss.com (David Nichols)
Subject: Expected mean squares and error terms in GLM
Date: 1996/11/05
Message-ID: <55oa9t$1tj@netsrv2.spss.com>#1/1
organization: SPSS, Inc.
newsgroups: comp.soft-sys.stat.spss

I've had a few questions from users about expected mean squares and error terms in GLM. In particular, with a two way design with A fixed and B random, many people are expecting to see the A term tested against A*B and B tested against the within cells term. In the model used by GLM, the interaction term is automatically assumed to be random, expected mean squares are calculated using Hartley's method of synthesis, and the results are not as many people are used to seeing. In this case, both A and B are tested against A*B. Here's some information that people may find useful.

It would appear that there's something of a split among statisticians in how to handle models with random effects. Quoting from page 12 of the SYSTAT DESIGN module documentation (1987):

There are two sets of distributional assumptions used to analyze a two factor mixed model, differing in the way interactions are handled. The first, used by SAS (1985, p. 469-470), can be traced to Mood (1950). Interaction terms are assumed to be a set of i.i.d. normal random variables. The second, used by DESIGN, is due to Anderson and Bancroft (1952). They impose the constraint that the interactions sum to zero over the levels of fixed factor within each level of the random factor.

According to Miller (1986, p. 144): "The matter was more or less resolved by Cornfield and Tukey (1956)." Cornfield and Tukey derive expected mean squares under a finite population model and obtain results in agreement with Anderson and Bancroft.

On the other side, Searle (1971) states: "The model that leads to [Mood's results] is the one customarily used for unbalanced data."
Statisticians have divided themselves along the following lines:

- Mood (1950, p. 344)
- Hartley and Searle (1969)
- Hocking (1985, p. 330)
- Milliken and Johnson (1984)
- Searle (1971, sec. 9.7)
- SAS

- Anderson and Bancroft (1952)
- Cornfield and Tukey (1956)
- Graybill (1961, p. 398)
- Miller (1986, p. 144)
- Scheffe (1959, p. 269)
- Snedecor and Cochran (1967, p. 367)

The references are:


SPSS can be added to the left hand column. We’re assuming i.i.d. normally normally distributed random variables for any interaction terms containing random factors.

In my view the correct column is the right hand column (in reference to the two groups of statisticians that Nichols lists in his email). I don’t know why SPSS decided to go with the arguments made by those in the left hand column. As a heuristics, if Tukey, Scheffe, Cochran, Snedecor, Anderson and Cornfield are in the same camp, then that is the camp one wants to be in.

Summary

We examined four different source tables from four different ways of framing the same study. It will be useful to summarize the four source tables in terms of their respective structural models. Pay careful attention to which terms are random and which terms are fixed.

one-way ANOVA; therapy fixed: \[ Y = \mu + \alpha + \epsilon \]
two-way ANOVA; therapy & therapist fixed: \[ Y = \mu + \alpha + \beta + \alpha\beta + \epsilon \]
two-way ANOVA; therapy & therapist random: \[ Y = \mu + \alpha + \beta + (\alpha\beta) + \epsilon \]
two-way ANOVA; therapy fixed & therapist random: \[ Y = \mu + \alpha + \beta + (\alpha\beta) + \epsilon \]
4. Contrasts and post hoc tests for random effects

If you want to perform contrasts or post hoc tests, you use the same formulae discussed before for ANOVA with one exception. Use the correct error term in place of MSE. That is, whenever a formula (like the Tukey, Scheffe or contrast) calls for an MSE term, be sure to use the correct error term. For example, if I have one fixed and one random factor and I want to perform a contrast over the levels of the fixed factor, then I would substitute the MS interaction term for MSE (similarly for the Tukey and Scheffe). In addition, be sure to use the same degrees of freedom corresponding to the error term you use. So, if I use MS interaction rather than MSE, I would use the degrees of freedom associated with MS interaction rather than the degrees of freedom associated with MSE. This has implications for what critical value you look up in the table for the contrast, Tukey and Scheffe tests.

5. Nesting

Sometimes one factor is nested within another factor (as opposed to being crossed like in the factorial design). An example using the one-way ANOVA will serve to illustrate this concept. Suppose there is one factor with three levels and subjects are assigned to only one treatment. One can think about this design as a randomized-block where subjects are the blocking factor, which is treated as a random-effect.

The structural model for this design is

\[ Y = \mu + \alpha + \pi_{\sigma}/\alpha \quad (5-4) \]

The last term on the right means subjects (\(\pi\)) are nested within the \(\alpha\) term. This term is equivalent to what we called \(\epsilon\). The two are synonymous, but the new notation highlights the idea that subjects are nested and treated as a random effect.

Let me give you another example that is a little more useful (adapted from Maxwell & Delaney). Suppose you want to look at the effects of therapists’ gender. You conduct a study with three male therapists and three female therapists. Each therapist sees four different clients and you have a battery of measures for dependent variables. Here the independent variable of interest is gender. Note that therapist is nested within the levels of gender (obviously, it can’t be crossed) and that client is nested within levels of therapist. Here gender is fixed but therapist is random because presumably we don’t just care about these six therapists but want to generalize to some population of therapists.

For this simple design where there are an equal number of clients per therapist and an equal number of therapist per level of gender, the analysis is simple. To test for a gender difference, compute the mean for each therapist (over the four clients). You will
have six means (three for male therapists and three for female therapists). Perform a
two-sample \( t \) test using gender as a grouping variable on the six score (the six means).
This test automatically treats gender as fixed, and automatically gives you the correct
error term. Note that the question is about gender of therapist, so the error should
be based on the mean of therapists (not on any of the lower levels).

The structural model for the therapist example is

\[
Y = \mu + \alpha + \beta_{\sigma}/\alpha + \pi_{\sigma}/\beta_{\sigma}
\]

where \( \alpha \) is fixed, \( \beta \) is random and nested within \( \alpha \), \( \pi \) is random and nested within \( \beta \),
which is also random. Note that \( \pi_{\sigma}/\beta_{\sigma} \) plays the role of \( \epsilon \), but the former makes it
clear that subjects is a nested factor; it is error but it comes from a specific term of
subjects treated as a random effect nested in another factor that, in this example, is
also a random effect. Maxwell and Delaney give additional cases and a more complete
list of different combinations where the several factors are treated as fixed or random.

Another example…. Suppose you study different instructions given to juries. Juries
would most likely be treated as nested within instruction and treated as a random
effect. But juries are themselves made up of individuals, which are nested within levels
of jury because jurors are randomly selected within a jury.

You should be aware of nesting and note that when nesting is present you may need
to change your level of analysis as I did in the examples above. I didn’t compare
individual clients or individual jurors, but therapists and juries. Again, when all
sample sizes are equal (e.g., in the therapist example there were three therapists
within both levels of gender and four clients across all levels of therapist), then you
can use the mean trick I mentioned above. Otherwise, the complications get a ugly.

A numerical example with a nested factor:

Suppose I treated the ongoing therapy & therapist example as a nested design. Let’s
change the design a little and consider the case where we have nine therapists, such
that three therapists administered one of the three treatments (thus the nine therapists
are nested with in the three therapies). In this design, subjects (\( \pi \)) is a random,
nested effect within therapist (\( \beta \)), therapists is a random, nested effect within therapy,
therapy (\( \alpha \)) is fixed. The structural model is:

\[
Y = \mu + \alpha + \beta_{\sigma}/\alpha + \pi_{\sigma}/\beta_{\sigma}
\]

The SPSS command structure to do this model is (note that each term has a different
error term):
manova score by thrpy(1,3) thpst(1,3) 
/design thrpy vs 1, thpst within thrpy = 1 vs within.

The resulting output is

Tests of Significance for SCORE using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>316.00</td>
<td>36</td>
<td>8.78</td>
<td></td>
<td></td>
</tr>
<tr>
<td>THPST WITHIN THRPY</td>
<td>110.00</td>
<td>6</td>
<td>18.33</td>
<td>2.09</td>
<td>.079</td>
</tr>
<tr>
<td>(ERROR 1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error 1</td>
<td>110.00</td>
<td>6</td>
<td>18.33</td>
<td></td>
<td></td>
</tr>
<tr>
<td>THRPY</td>
<td>120.00</td>
<td>2</td>
<td>60.00</td>
<td>3.27</td>
<td>.109</td>
</tr>
</tbody>
</table>

As I suggested above, when there are an equal number of observations in each cluster, it is possible to perform this identical analysis by first aggregating over subject (i.e., compute the mean for each therapist) and then perform a one-way ANOVA comparing the means of the therapists across therapy.

<table>
<thead>
<tr>
<th>RET</th>
<th>CCT</th>
<th>BMOD</th>
</tr>
</thead>
<tbody>
<tr>
<td>38</td>
<td>41</td>
<td>46</td>
</tr>
<tr>
<td>42</td>
<td>44</td>
<td>44</td>
</tr>
<tr>
<td>40</td>
<td>41</td>
<td>42</td>
</tr>
</tbody>
</table>

Just perform a one-way ANOVA on these numbers. Here is the resulting source table. Note that the degrees of freedom are correct (2 and 6) and the $F$ value is identical to the SPSS run above. However, the sum of squares term “looks” different. The reason the sum of squares term looks different is that the present analysis is tricked into thinking each observation is one subject, but in the previous analysis there were 5 observations per therapist. If you multiply the sum of squares between and sum of squares within by 5 (the cell sample size), you get the same sum of squares as in the previous source table. Note that the $F$ statistics are identical.

<table>
<thead>
<tr>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>between</td>
<td>24</td>
<td>2</td>
<td>12</td>
</tr>
<tr>
<td>within</td>
<td>22</td>
<td>6</td>
<td>3.6667</td>
</tr>
</tbody>
</table>

Again, this “trick” for computing nested ANOVAs works if you have equal sample sizes across groups. If you don’t have equal sample sizes, then it is safer to use the SPSS syntax I gave above for nested factors.
There are other ways of implementing nested designs in SPSS. The UNIANOVA command and MIXED command have the nice feature of automatically figuring out the right error term. So, unlike the MANOVA command where you have to be specific about each error term, both UNIANOVA and MIXED “take out the guess work” (some people could say "take out the intelligent thinking"). Below is the syntax for both commands and some snips of the relevant output appear below.

\textit{UNIANOVA} score by thrpy thpst
\textit{/method=stype(3)}
\textit{/intercept = include}
\textit{/print = descriptive}
\textit{/random = thpst}
\textit{/design = thrpy thpst(thrpy)}.

\textit{MIXED} score by thrpy thpst
\textit{/PRINT=SOLUTION TESTCOV}
\textit{/FIXED=thrpy}
\textit{/METHOD=REML}
\textit{/RANDOM=thpst(thrpy)}.
SPSS output for nested design using UNIANOVA and MIXED.

The UNIANOVA command defines the variable thpst as random and the design line has two terms: thrpy and “thpst nested within thrpy” (note that the higher order term goes inside the parentheses—B(A) means B is nested within A). The MIXED command specifies the same model stating that the variable thrpy is fixed and the nested term “thpst(thrpy)” as random. When the nested factor is treated as random and when the design is balanced (i.e., has an equal number of subjects at each level such as an equal number of patients for each therapist and an equal number of therapist in each therapy), the syntax for MANOVA, MIXED, UNIANOVA, and the trick of computing
group means, all yield the identical test for the highest level (thrpy). Cool.

Unfortunately, things break down when there is an unequal number of observations, such as different number of patients per therapist. These different approaches do not yield the same result. The modern view is to take a special approach to such unequal cases, and this special approach is what is implemented in the MIXED command. So with unbalanced designs best to just stick with MIXED. The GLM and UNIANOVA commands use a “method of moments” approach, which is not well-behaved with unbalanced designs. Fancy programs such as HLM and MIWIN accomplish the same analyses as the SPSS MIXED command but those programs are more specialized and have many more features. Entire courses are taught on programs such as HLM. The term for this approach is “multilevel modeling”, but the basic idea is that one can treat factors as fixed or random, and factors can be crossed or nested. It turns out that repeated measures analyses can be accomplished nicely within this multilevel modeling approach and unequal sample sizes are allowed. This is particularly useful when there is missing data, such as when some subjects miss some of the repeated sessions. Under the multilevel modeling framework all data are analyzed, whereas under the traditional ANOVA repeated measures approach only subjects with complete cases can be analyzed (meaning one must throw away data from those subjects with incomplete data).

6. Repeated Measures

It is a natural transition to move from a discussion of random/fixed effects and nested/crossed factors to the topic of repeated measures ANOVA. The basic idea of a repeated measures design is that rather than have independent groups of subjects randomly assigned to conditions, one collects more than one observation from each participant.

Advantages

(a) each subject serves as his/her own control

(b) fewer subjects are needed

(c) useful for examining change, learning, trends, etc.

(d) minimize error due to individual differences by treating subjects as a blocking factor
Disadvantages

(a) practice effects

(b) differential carry-over effects (e.g., recognition before recall)

(c) demand characteristics

(d) responses across trials need to be highly correlated for within subject designs to have high power

For additional pros and cons regarding within subject designs see Greenwald (1976), *Psychological Bulletin*, 83, 314-20.

7. Paired $t$ Test: simplest repeated measures design

Each subject is measured twice on the same variable. For each subject you compute the difference between the score at time 1 and the score at time 2. Now you have, for each subject, one score—it’s the difference between the two times. Let’s denote the difference for subject $i$ by $D_i$. Perform the usual one sample $t$ test on those difference scores. Thus,

$$t = \frac{\overline{D}}{s_D/\sqrt{n}},$$

where $\overline{D}$ is the mean of the difference scores and $s_D$ denotes the standard deviation of the difference scores. There are $N - 1$ degrees of freedom. This test is performed on difference scores. When testing more complicated repeated-measures designs we will exploit this idea of creating difference scores.
Example of paired t test

<table>
<thead>
<tr>
<th>before</th>
<th>after</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>16</td>
<td>4</td>
</tr>
<tr>
<td>11</td>
<td>9</td>
<td>-2</td>
</tr>
<tr>
<td>12</td>
<td>15</td>
<td>3</td>
</tr>
<tr>
<td>10</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>9</td>
<td>-1</td>
</tr>
<tr>
<td>9</td>
<td>12</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>9</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>10</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>9</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td>-1</td>
</tr>
</tbody>
</table>

\[ \sum D = 17; \overline{D} = 1.7; \sum D^2 = 85 \]

The mean before = 8.5 and the mean after = 10.2. Note that the difference between the two means (10.2 - 8.5) equals the mean of the difference scores 1.7.

The t-test is given by

\[
t = \frac{\overline{D}}{\frac{s_D}{\sqrt{n}}} = 1.7
\]

The critical \( t(9) = 2.26 \), so we fail to reject the null hypothesis.

The CI around the difference is given by

\[
\overline{D} \pm t \frac{s_D}{\sqrt{n}} = 1.7 \pm (2.26) \frac{2.49}{\sqrt{10}} = 1.7 \pm 1.78
\]

The interval is (-0.08, 3.48). It contains 0, so we fail to reject the null hypothesis.

Can you figure out how to construct a CI around the difference? The ingredients are in Equation 5.7. The answer is given in the example below (see box).

We can cast this test in terms of the hypothesis testing template we introduced in
Lecture Notes #1. As stated earlier, the paired t-test is equivalent to taking difference scores of the two times and conducting a one sample t-test on the difference scores.

Hypothesis test template for the paired $t$ test

**Null Hypothesis**
- $H_0$: population mean $D = 0$
- $H_a$: population mean $D \neq 0$ (two-sided test)

**Structural Model and Test Statistic**
The structural model is the same as the randomized blocking variable design treating subjects as a blocking factor that is a random effect. The test statistic operates on the mean $D$ and specifies its sampling distribution. Recall the general definition of a $t$ distribution (lecture notes #1)

$$t \sim \frac{\text{estimate of population parameter}}{\text{estimated st. dev. of the sampling distribution}}$$

For the case of a paired $t$ test we have

$$t_{\text{observed}} = \frac{D}{s_D/\sqrt{n}}$$

**Critical Test Value** The critical $t$ will be two tailed and based on N-1 degrees of freedom.

**Statistical decision** If the observed $t$ computed from the raw data exceeds in absolute value terms the critical value $t_{\text{critical}}$, then we reject the null hypothesis. If the observed $t$ value does not exceed the critical value $t_{\text{critical}}$, then we fail to reject the null hypothesis. In symbols, if $|t_{\text{observed}}| > t_{\text{critical}}$, then reject the null hypothesis, otherwise fail to reject.

The paired-$t$ test is equivalent to doing a (1, -1) contrast on each subject to create a new variable that becomes the variable you analyze. However, contrasts over repeated measures are different than contrasts for between subjects designs. Take the paired-$t$ test as a simple example. The (1, -1) contrast is defined over a subject’s pair of observations (say, time 1 - time 2). The error term is defined on this difference score and not by pooling over cells (hence there is no equality of variance assumption over time).

Recall that the one-way between-subjects ANOVA decomposes SST into treatments (SSB) and error (SSW). The one-way repeated measures ANOVA performs a similar
decomposition, but breaks the SSW into two independent “pieces”: something that has to do with subjects and something that has to do with noise due to particular subject \times treatment combinations. This is exactly the same decomposition we saw in the randomized-block design. The one-way repeated measures is equivalent to the randomized block design where subjects are treated as the blocking factor, which is also treated as random. The repeated-measures design allows one to eliminate the variability due to subjects because subjects is treated as a random effect blocking factor.

8. Structural Model and Expected Mean Square Terms for Repeated Measures ANOVA

The model for a one-way repeated measures ANOVA is

\[ Y = \mu + \alpha_i + \pi + \epsilon \]  

where \( \pi \) refers to the effect of subjects and is treated as a random effect. Instead of writing \( \epsilon \) I could have written \((\alpha \times \pi)_i \) because subjects is a random, crossed (not nested) with \( \alpha \) because each subjects appears in every cell. For comparison, the two-sample t test (where subjects are randomly assigned to groups) subjects is also treated as a random effect but it is treated as a nested factor within the two levels of the experimental factor.

The expected mean square terms for the one-way repeated-measures ANOVA are

**TIME:** \( \sigma^2_\epsilon + \frac{n_T}{T-1} \alpha^2 

**SUBJECT:** \( \sigma^2_\epsilon + T \sigma^2_\pi 

**ERROR:** \( \sigma^2_\epsilon 

Everything generalizes in the obvious way for more complicated designs (i.e., more factors with repeated-measures and also designs that have both repeated-measures and between-subjects factors). But, detailed discussion of these issues will wait till next semester. Turns out that different ways of thinking about the error term lead to different structural models, different source tables, etc. The consensus among methodologists about running repeated measures ANOVA is to do everything in terms of contrasts and bypass the debate of how to handle error terms for the omnibus case.

Now I will build the structural model for a two-way ANOVA where one factor is between-subjects and the other factor is within-subjects. You can think of this design as having two structural models—one for the between-subjects part and one for the within-subjects part. The reason for needing two parts is that the subjects factor is nested with respect to the between factor but the subjects factor is crossed with
respect to the within factor. Thus, we need to treat the two subparts of the design (the between subpart and the within subpart) differently.

Let me remind you of the structural models for the between-subject and within-subject one-way ANOVA. The structural model for the between-subjects one-way ANOVA is

\[ Y = \mu + \alpha + \epsilon \]  \hspace{1cm} (5-9)

I could have written \( \pi\sigma/\alpha \) instead of \( \epsilon \) because subject is nested within \( \alpha \). The source table for this model has two lines (between groups and within groups). Recall that subject is treated as a random effects factor that is nested within treatment.

Next, recall the structural model for the one-way within-subjects ANOVA:

\[ Y = \mu + \beta + \pi\sigma + (\pi \times \beta)\sigma \]  \hspace{1cm} (5-10)

Here \( \beta \) is the fixed time factor (I’m using \( \beta \) instead of \( \alpha \) to avoid confusion in the next paragraph). The source table for this model will have three lines: one for time \( (\beta) \), one for subject \( (\pi\sigma) \), and one for error \( (\pi \times \beta)\sigma \). The error term is the last term: subjects crossed with \( \beta \).

Finally, we combine the two structural models. A mixed ANOVA (both between and within factors) is simply a concatenation of a between ANOVA on one hand with a within ANOVA on the other. Literally sum the two structural models above (Equations 5-9 and 5-10). Be sure not to count the grand mean twice, and also include an interaction between \( \alpha \) (a between subjects factor) and \( \beta \) (a within subjects factor). This results in the following structural model:

\[ Y = \mu + \alpha + \beta + \alpha\beta + \pi\sigma + (\pi \times \beta)\sigma + \epsilon \]  \hspace{1cm} (5-11)

where the \( \epsilon \) comes from the between subjects model. Be sure you can account for all these terms.

Most computer programs print out only five lines in the source table rather than the six that you would expect from the structural model in Equation 5-11. The five lines that are printed are usually organized in this manner:

1. \( \alpha \)
2. \( \epsilon \)
3. \( \beta \)
4. \( \alpha\beta \)
5. \( (\pi \times \beta)\sigma \)
The first line is the between subjects factor and the second line is the error term that is used to test the between subjects factor. That forms the between-subjects portion of the design with its own error term.

The third and fourth lines are the main effect for time and the interaction between the two factors, respectively. The last line is the error term used for both $\beta$ and $\alpha \beta$. I don’t know why most programs omit from the source table the sixth possible term present in the structural model ($\pi_\sigma$). The calculations are correct (that is, the SS corresponding to that term is removed), but it simply is not printed in the source table.

9. An example of a design having one between-subjects factor and one within-subjects factor

I’ll use the MANOVA command. Suppose that you have a $3 \times 3$ design with one factor between and one factor within. That is, three groups with each individual measured three times. The MANOVA syntax is:

```
manova t1 t2 t3 by group(1,3)
/wsfactor time(3)
/contrast(time) = special( 1 1 1
                          1 -1 0
                          1 1 -2)
/contrast(group) = special(1 1 1
                           1 -1 0
                           1 1 -2)
/wsdesign time(1) time(2)
/design group(1) group(2).
```

The two new lines are WSFACOR and WSDESIGN. The WSFACOR call assigns a name (in this example, time) to the three dependent variables. The WSDESIGN subcommand gives the structural model for the within part of the design (note that I defined each contrast separately). The output will be printed in two sections. The first section will have the between part of the design (i.e., group contrast 1 and group contrast 2) tested against the MSE. The second section will have the within part, but that will also be broken up into subparts (one part for each contrast). The reason the within portion is divided into subparts is that each contrast on a within subjects factor uses its own error term (more on this later). So there will be a source table for time(1) with its own error term and also the interaction contrasts between time(1) and each of the two group contrasts. There will also be a source table for time(2), with its own source table, and it will include the interaction contrasts of time(2) with the two group contrasts. The elegance of writing WSDESIGN and DESIGN in the way shown above (i.e., by calling specific contrasts) is that NO omnibus tests are performed and we avoid the ugly mess of nasty additional assumptions. The time(1) SPSS notation
may be confusing—it refers to the first contrast listed under the special command, not to the time 1 variable.

data list free / g t1 t2 t3.
begin data.
1 3 4 5
1 3 2 4
1 4 5 7
2 2 1 6
2 9 8 7
2 8 5 6
3 8 3 2
3 8 7 9
3 7 9 8
end data.

manova t1 t2 t3 by g(1,3)
/wsfactor time(3)
/contrast(time)= special(1 1 1
1 -1 0
1 1 -2)
/contrast(g)=special(1 1 1
1 -1 0
1 1 -2)
/wsdesign time(1) time(2)
/design g(1) g(2).

The resulting three source tables are:

Tests of Significance for T1 using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>74.00</td>
<td>6</td>
<td>12.33</td>
<td></td>
<td></td>
</tr>
<tr>
<td>G(1)</td>
<td>12.50</td>
<td>1</td>
<td>12.50</td>
<td>1.01</td>
<td>.353</td>
</tr>
<tr>
<td>G(2)</td>
<td>20.17</td>
<td>1</td>
<td>20.17</td>
<td>1.64</td>
<td>.248</td>
</tr>
</tbody>
</table>

Tests involving 'TIME(1)' Within-Subject Effect.

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>15.00</td>
<td>6</td>
<td>2.50</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TIME(1)</td>
<td>3.56</td>
<td>1</td>
<td>3.56</td>
<td>1.42</td>
<td>.278</td>
</tr>
<tr>
<td>G(1) BY TIME(1)</td>
<td>3.00</td>
<td>1</td>
<td>3.00</td>
<td>1.20</td>
<td>.315</td>
</tr>
<tr>
<td>G(2) BY TIME(1)</td>
<td>.44</td>
<td>1</td>
<td>.44</td>
<td>.18</td>
<td>.688</td>
</tr>
</tbody>
</table>

Tests involving 'TIME(2)' Within-Subject Effect.

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>23.00</td>
<td>6</td>
<td>3.83</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TIME(2)</td>
<td>2.67</td>
<td>1</td>
<td>2.67</td>
<td>.70</td>
<td>.436</td>
</tr>
<tr>
<td>G(1) BY TIME(2)</td>
<td>1.00</td>
<td>1</td>
<td>1.00</td>
<td>.26</td>
<td>.628</td>
</tr>
<tr>
<td>G(2) BY TIME(2)</td>
<td>5.33</td>
<td>1</td>
<td>5.33</td>
<td>1.39</td>
<td>.283</td>
</tr>
</tbody>
</table>
Notice that NO omnibus tests were printed. Yeah! That is because I did not ask for omnibus tests in the DESIGN and WSDESIGN subcommands. Instead, I asked for specific contrasts. If you want omnibus tests you are going to have to deal with the nasty repeated measures assumptions. Better to avoid omnibus tests altogether, and go directly to contrasts.

SPSS tidbit: you may find it useful to print out the contrasts used by SPSS in the spirit of the /design(solution) subcommand that we used in the between-subjects case. For repeated measures factorial designs you will need to use /design(oneway); for mixed designs with both repeated and between factors, you should use /design(solution oneway).

Here is the GLM syntax:

```
GLM t1 t2 t3 by group
  /wsfactor time 3 special( 1 1 1
  1 1 0
  1 -1 -2)
  /contrast(group) = special(1 1 1
  1 -1 0
  1 1 -2)
  /wsdesign time
  /design group.
```

The key differences in the GLM syntax are that the special contrast is defined directly in the WSFACTOR line, the grouping variable doesn’t need the number of levels specified, and WSDESIGN doesn’t need to separate out each contrast because the output by default is separated by contrasts. The GLM subcommand also has nice features, such as /PLOT=PROFILE(time) to print out means over time, and can be crossed with grouping variables as well. Also, the /PRINT parameters test(mmatrix) subcommand to print out the tests on individual cell means as well as the contrasts actually used by SPSS.

For completeness I show the syntax for conducting the same analysis using the MIXED command in SPSS. This command will become useful when doing more complicated analyses such as hierarchical linear models (HLM). It also has the advantage over MANOVA or GLM that it allows missing data for repeated measures. Whereas MANOVA or GLM drop subjects with missing data from repeated measures analyses, the MIXED command makes use of all the available data and performs the correct test of significance.

Data need to be organized in long format for the MIXED command, that is, each row is one observation so if a subject is measured at three times that subject uses three rows. Here are the reorganized data for the previous example and the MIXED
syntax. The output for the eight contrasts (two main effects for time, two main effects for group, and four interaction contrasts) is identical to that of MANOVA and GLM. I specify “unstructured” (UN) covariances, which means the multivariate version that is less restrictive, but one could specify compound symmetry (CS) to get the more traditional, assumption-laden repeated measures tests. I include columns d1 and d2 for something I may do in class at a later date; for now ignore columns d1 and d2. Note the last two columns: sub codes subject number and time codes which of the three measurements. Sometimes it is useful to sort the data and I provide sorting syntax after the MIXED command for completeness.

data list free /row dv gr d1 d2 sub time.
begin data
1 3 1 1 1 1 1
2 3 1 1 1 2 1
3 4 1 1 1 3 1
4 2 2 1 1 4 1
5 9 2 1 1 5 1
6 8 2 1 1 6 1
7 8 3 1 1 7 1
8 8 3 1 1 8 1
9 7 3 1 1 9 1
10 4 1 -1 1 1 2
11 2 1 -1 1 2 2
12 5 1 -1 1 3 2
13 1 2 -1 1 4 2
14 8 2 -1 1 5 2
15 5 2 -1 1 6 2
16 3 3 -1 1 7 2
17 7 3 -1 1 8 2
18 9 3 -1 1 9 2
19 5 1 0 -2 1 3
20 4 1 0 -2 2 3
21 7 1 0 -2 3 3
22 6 2 0 -2 4 3
23 7 2 0 -2 5 3
24 6 2 0 -2 6 3
25 2 3 0 -2 7 3
26 9 3 0 -2 8 3
27 8 3 0 -2 9 3
end data.
mixed dv by gr time
/fixed = gr time gr*time | SSTYPE(3)
/method=REML
/print = solution
/repeated = time | subject(sub) covtype(un)
/emmeans=tables(gr*time) compare(time)
/test 'main eff 1-gr' time .5 -.5 0 time*gr 1/6 -1/6 0 1/6 -1/6 0 1/6 -1/6 0
/test 'main eff 2-gr' time .5 .5 -1 time*gr 1/6 1/6 -1/3 1/6 1/6 -1/3 1/6 1/6 -1/3
/test 'main eff 1-time' gr .5 -.5 0 time*gr 1/6 1/6 -1/6 -1/6 1/6 -1/6 0 0 0 0
/test 'main eff 2-time' gr .5 .5 -1 time*gr 1/6 1/6 1/6 1/6 1/6 1/6 -1/3 -1/3 -1/3 -1/3
/test 'int1' time*gr 1/2 -1/2 0 -1/2 1/2 0 0 0 0
/test 'int2' time*gr 1/2 1/2 -1 -1/2 -1/2 -1/2 1 0 0 0
/test 'int3' time*gr 1/2 -1/2 0 1/2 -1/2 0 -1 1 0
/test 'int4' time*gr 1 1 -2 1 1 -2 -2 -2 4.
SORT CASES BY sub(A) time(A).
This works at producing the identical output as GLM and MANOVA. I don’t completely understand how the /TEST subcommand works and how the contrast codes are specified. Basically, each /TEST subcommand is a separate contrast. For main effect contrasts, it is necessary to include information about the higher order interaction(s) that include that factor. Interaction contrasts though stand on their own and don’t need lower order contrast information. The order of the interaction contrasts are T1T2T3 repeated for Group1, Group2 and Group3, yielding nine values. Good luck trying to understand the syntax for the contrasts in the /test subcommand; every time I think I have it, I realize I don’t.

10. Assumptions for the paired \( t \) test and repeated measures

A critical assumption is normality (actually, symmetry is the crucial property). If the distribution of the differences is skewed or there are outliers you may consider doing the nonparametric Wilcoxon Signed-Rank test or you could find a suitable transformation on the difference scores. One assumes that subjects are independent from each other (but data from the same subject are allowed to be correlated). Equality of variances between time 1 and time 2 is *not* assumed.

But wait, there’s more! The most critical assumption of a repeated measures ANOVA is lurking not far away. It involves the structure of the variance-covariance matrix as well as the equality of the various variance-covariance matrices for every between-subjects cell. (Sometimes we just call the variance-covariance matrix the “covariance matrix.”) This critical assumption only enters the picture when you perform omnibus tests. This assumption is automatically satisfied when you do contrasts (or more generally, whenever you have a 1 degree of freedom test). This gives another justification for always doing contrasts. How do you examine the assumption on the variance-covariance matrix? Unfortunately, there are no nifty plots to look at. But there are two properties one can examine as indicators of the assumption. One property is called compound symmetry. It is a property that is sufficient for the assumption. The key idea of compound symmetry is equality of the correlation coefficients between all levels of a within-subjects factor. Indeed, compound symmetry uses a pooled error

\[ Q^{-1} A Q = L \]

where \( Q \) is the orthonormal matrix of eigenvectors and \( L \) is the diagonal matrix of eigenvalues. A neat property of \( Q \) orthonormal is that the transpose of \( Q \) equals the inverse of \( Q \). In general, \( Q \) need not be orthonormal but the columns of \( Q \) need to be the eigenvectors. The orthonormalization is useful to get the eigenvalues on the same scale. Using a set of orthogonal \( T - 1 \) contrasts that are “orthonormal” will produce \( T - 1 \) identical eigenvalues.
term, which is the mean of the variance of each variable minus the mean covariance between all possible pairs \((V - C)\).

A more recent development is the less restrictive property of sphericity (necessary and sufficient with respect to the assumption on the variance-covariance matrix). The intuitive idea of sphericity is that the variance of the difference between any two levels of a within-subjects factor is a constant over all possible pairs of levels. That is, the following is assumed to be a constant for all pairs of variables \(i\) and \(j\):

\[
\sigma_i^2 + \sigma_j^2 - 2\sigma_{ij} \tag{5-12}
\]

There are some tests one can do to attach a \(p\) value to the degree of violation. However, as with all tests of significance involving assumptions, the logic does not make sense because with enough subjects you will always reject the assumption and the tests are very, very sensitive to violations from normality.

The reason such assumptions are made is because for an omnibus test one pools cell measures to get one estimate of the error variance. Thus, all time periods need to have the same variance and the same pairwise correlations with all other time periods to make the pooling for the use of omnibus tests interpretable. Again, if you limit your statistical tests to contrasts you automatically satisfy the sphericity assumption. So, ignore the uninformative omnibus tests and you will bypass the need to satisfy the sphericity assumption. Just stick with contrasts.

11. Remedial measures for repeated-measures: What to do when the assumptions are not met.

The first thing to realize is that if you want to test specific contrasts, then you have no problem because the assumption on the off-diagonal of the variance-covariance matrix will automatically be satisfied. This is because there are two covariance terms. Due to the fact that the variance-covariance matrix is always symmetric (the correlation of \(A\) and \(B\) equals the correlation of \(B\) and \(A\)), we know that the two covariances must equal each other. In general, whenever there is a test with one degree of freedom in the numerator, then the variance-covariance matrix for that test is symmetric. To see this think about a simple case such as the \((1, -1)\) contrast. This is taking the difference of two variables. If you have factors with two levels (degrees of freedom for that factor will be 1 in the numerator) or are doing contrasts (contrasts always have one degree of freedom in the numerator), then the critical assumption of repeated measures analysis is satisfied.

Problems arise when you want to examine omnibus tests. For example, a researcher measures the number of hours a subjects spends watching television. The researcher is
interested in age effects and observes the subjects at ages 10, 20, and 30 (a longitudinal design). Our solution, of course, will be to make focused comparisons (contrasts) across the time intervals, e.g., is there a linear trend over time (-1,0,1) or a quadratic trend (1,-2,1) and forget about omnibus tests.

Suppose, however, that you are forced against your will to perform an omnibus test based on three or more time periods. That is, you must perform a test that will only tell you “the time periods differed somewhere” but without knowing where. The assumed structure of the variance-covariance matrix will probably be violated. What do you do? It turns out that transformations will not help you because of the complicated covariance matrix (there are proofs that transformations to “stabilize” a variance-covariance matrix do not exist).

- One strategy is to “play dumb,” ignore the assumption on the variance-covariance matrix, and proceed with the usual repeated-measures omnibus tests. Many people I know use this strategy.
- A second strategy is to find a Welch-like adjustment for the violation of the assumption. There are two techniques that perform such an adjustment. Both of these procedures are in the spirit of Welch’s t-test because they adjust the degrees of freedom. One version was derived by Greenhouse & Geisser (G&G), the other version was derived by Huyndt & Feldt (H&F). Typically, both yield very similar results. Years of study on these two approaches shows that the G&G approach tends to be slightly conservative (i.e., it tends to slightly overcorrect). The H&F approach has a transformation that reduces G&G’s conservative bias. Therefore, most statisticians (except probably Greenhouse and Geisser) tend to favor the H&F approach.

For one-way repeated measures ANOVA, the corrections are based on a measure developed by Box called $\epsilon$, which indexes the discrepancy from the assumption on the covariance matrix. The measure $\epsilon$ ranges between $\frac{1}{T-1}$ and 1, where $T$ is the number of time periods. The lower the $\epsilon$ the worse the assumption fit. If $\epsilon = 1$, then the assumption fits perfectly.

For completeness, here is Box’s definition of $\epsilon$:

$$
\frac{T^2(\overline{\sigma}_{ii} - \overline{\sigma})^2}{(T - 1)(\sum \sum \sigma^2_{ij} - 2T \sum \overline{\sigma}_i + T^2 \overline{\sigma}^2)}
$$

(5-13)

where $\overline{\sigma}_{ii}$ is the average variance, $\overline{\sigma}_{i}$ is the average of all variances and covariances, $\overline{\sigma}_{i}$ is the mean entry in row $i$ of the covariance matrix, and $T$ is the number of times each subject is measured. Note that the Box $\epsilon$ is not the same as the error $\epsilon$ we have been using to denote residuals in the structural model.

There are tests of significance for Box’s $\epsilon$ but they are highly sensitive to violations of normality and one needs to be careful of rejecting very small differences in the presence of large sample size. I don’t recommend using those tests.
There are corrections in the spirit of Welch that use $\epsilon$ to adjust the degrees of freedom. The Greenhouse & Geisser and the Huyndt & Feldt corrections are two examples that adjust degrees of freedom based on $\epsilon$. The Greenhouse and Geisser correction adjusts the degrees of freedom using Box’s $\epsilon$. Rather than use than base the $F$ test on T-1 degrees of freedom for the numerator and (T-1)(N-1) for the denominator, the GG correction multiplies the two degrees of freedom by $\epsilon$. The improvement proposed by HF involves a transformation of Box’s $\epsilon$ to reduce bias.

- Finally, the third strategy is probably the most elegant. Derive a test that does not impute any structure to the variance-covariance matrix. This strategy is called the multivariate analysis of variance. This is the procedure that blesses the SPSS command `MANOVA` with its name. We’ll cover this in more detail next semester.

The multivariate analysis of variance will be covered in more detail next semester. Despite all the hand-waving and fancy mathematics that go along with MANOVA, the intuition is quite simple. The test finds a contrast over time periods (more generally, over dependent variables) that maximizes the $F$ value. Of course, there are appropriate corrections for chance since one can always find a contrast that maximizes an $F$ value. Further, the contrast itself can be interpreted in terms of the weights. In other words, the multivariate analysis of variance hunts down the best set of orthogonal contrasts for a given within subjects factor, and automatically corrects for the “fishing expedition” analogous to Scheffe.

12. More numerical examples and an illustration of a simple way to perform contrasts on designs having repeated measures

(a) One-way repeated measures

Let’s consider a one-way repeated measures design with four levels (say, measurements over four different time periods). Here are some data from twelve subjects:
The omnibus hypothesis that the four measurements yield the identical means is shown below. The SPSS output will be organized as follows: The test for the grand mean is first (labeled CONSTANT), then a test for sphericity, then some measures of epsilon (a measure of the departure from sphericity), then some tests for a multivariate analysis of variance approach that doesn’t make the sphericity assumption, and finally the omnibus test. The title “AVERAGE” just means that the sphericity assumption is made and the error term (MSE) is estimated as the difference between the average of the variances and the average of the covariances. Also, I asked for significance tests for the HF and GG corrections (not all versions of SPSS print these by default).

We will use the MANOVA command. Two new subcommands are **WSDESIGN** and **WSFACTOR**.

```
data list free / id t1 t2 t3 t4.
begin data.
1 92 95 96 98
2 120 121 121 123
3 112 111 111 109
4 95 96 98 99
5 114 112 110 109
6 99 100 99 98
7 124 125 127 126
8 106 107 106 107
9 100 98 95 94
10 108 110 112 115
11 112 115 116 118
12 102 102 101 101
end data.

manova t1 t2 t3 t4
/wsfactor time(4)
/print signif(hf gg)
/wsdesign time.
```
Tests of Significance for T1 using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN+RESIDUAL</td>
<td>4387.23</td>
<td>11</td>
<td>398.84</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CONSTANT</td>
<td>555775.52</td>
<td>1</td>
<td>555775.52</td>
<td>1393.48</td>
<td>.000</td>
</tr>
</tbody>
</table>

Tests involving 'TIME' Within-Subject Effect.

Mauchly's sphericity test, W = .01905
Chi-square approx. = 38.50691 with 5 D. F.
Significance = .000

Greenhouse-Geisser Epsilon = .37577
Huynh-Feldt Epsilon = .38921
Lower-bound Epsilon = .33333

AVERAGED Tests of Significance that follow multivariate tests are equivalent to univariate or split-plot or mixed-model approach to repeated measures. Epsilons may be used to adjust d.f. for the AVERAGED results.

EFFECT .. TIME

Multivariate Tests of Significance (S = 1, M = 1/2, N = 3 1/2)

<table>
<thead>
<tr>
<th>Test Name</th>
<th>Value</th>
<th>Exact F Hypoth. DF</th>
<th>Error DF</th>
<th>Sig. of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pillais</td>
<td>.27586</td>
<td>1.14287</td>
<td>3.00</td>
<td>9.00</td>
</tr>
<tr>
<td>Hotellings</td>
<td>.38096</td>
<td>1.14287</td>
<td>3.00</td>
<td>9.00</td>
</tr>
<tr>
<td>Wilks</td>
<td>.72414</td>
<td>1.14287</td>
<td>3.00</td>
<td>9.00</td>
</tr>
<tr>
<td>Roys</td>
<td>.27586</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: F statistics are exact.

Tests involving 'TIME' Within-Subject Effect.

AVERAGED Tests of Significance for T using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN+RESIDUAL</td>
<td>123.02</td>
<td>33</td>
<td>3.73</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TIME</td>
<td>7.23</td>
<td>3</td>
<td>2.41</td>
<td>.65</td>
<td>.591</td>
</tr>
</tbody>
</table>

The measure $\epsilon$ ranges between $\frac{1}{T-1}$ and 1, where $T$ is the number of time periods. The Box $\epsilon$s for these data are relatively small, suggesting some concern about violating the assumptions. If we want to test the omnibus tests, we can either look at the G-G or H-F tests, or we can dispense with the omnibus tests and just do contrasts as I show next.

Suppose you had some planned contrasts. Then you avoid the above mess and can do the contrasts directly without needing an omnibus test and without making the sphericity assumption. Unfortunately, SPSS still prints out all that junk even though it is not necessary. The GG and HF corrections are not needed for the
contrast tests. Recall that the sphericity assumption is automatically satisfied for contrasts (i.e., any testing having 1 degree of freedom in the numerator).

\[
\text{manova t1 t2 t3 t4} \\
/\text{wsfactor time(4)} \\
/\text{contrast(time) = special( 1 1 1 1} \\
/\text{ 1 -1 -1} \\
/\text{ 1 -1 1 -1} \\
/\text{-1 -1 -1 1)} \\
/\text{print= parameters(estim)} \\
/\text{wsdesign time.}
\]

--- Individual univariate .9500 confidence intervals

\begin{tabular}{lccccc}
  \text{Parameter} & \text{Coeff.} & \text{Std. Err.} & \text{t-Value} & \text{Sig. t} & \text{t Lower -95\% CL} & \text{t Upper} \\
  1 & 215.21 & 5.76 & 37.33 & .00000 & 202.52 & 227.90
\end{tabular}

Tests involving 'TIME' Within-Subject Effect.

Mauchly sphericity test, W = .01905  
Chi-square approx. = 38.50691 with 5 D. F.  
Significance = .000

Greenhouse-Geisser Epsilon = .37577  
Huynh-Feldt Epsilon = .38921  
Lower-bound Epsilon = .33333

AVERAGED Tests of Significance that follow multivariate tests are equivalent to univariate or split-plot or mixed-model approach to repeated measures. Epsilons may be used to adjust d.f. for the AVERAGED results.

EFFECT .. TIME
Multivariate Tests of Significance (S = 1, M = 1/2, N = 3 1/2)

\begin{tabular}{lcccccc}
  \text{Test Name} & \text{Value} & \text{Exact F} & \text{Hypoth. DF} & \text{Error DF} & \text{Sig. of F} \\
  Pillais & .27586 & 1.14287 & 3.00 & 9.00 & .383 \\
  Hotellings & .38096 & 1.14287 & 3.00 & 9.00 & .383 \\
  Wilks & .72414 & 1.14287 & 3.00 & 9.00 & .383 \\
  Roy's & .27586 & & & & \\
\end{tabular}

Note.. F statistics are exact.

Tests involving 'TIME' Within-Subject Effect.

AVERAGED Tests of Significance for T using UNIQUE sums of squares

\begin{tabular}{lcccc}
  \text{Source of Variation} & \text{SS} & \text{DF} & \text{MS} & \text{F Sig of F} \\
  WITHIN CELLS & 123.02 & 33 & 3.73 & \\
  TIME & 7.23 & 3 & 2.41 & .65 & .591 \\
\end{tabular}

Estimates for T2

[STATS FOR 95\% CI OMITTED]

TIME

\begin{tabular}{lccccc}
  \text{Parameter} & \text{Coeff.} & \text{Std. Err.} & \text{t-Value} & \text{Sig. t} \\
  1 & -.5416666667 & .84041 & -.64453 & .53244
\end{tabular}
Estimates for T3
--- Individual univariate .9500 confidence intervals

TIME

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Coeff.</th>
<th>Std. Err.</th>
<th>t-Value</th>
<th>Sig. t</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.5416666667</td>
<td>0.44576</td>
<td>-1.21514</td>
<td>0.24975</td>
</tr>
</tbody>
</table>

Estimates for T4
--- Individual univariate .9500 confidence intervals

TIME

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Coeff.</th>
<th>Std. Err.</th>
<th>t-Value</th>
<th>Sig. t</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.1250000000</td>
<td>0.16428</td>
<td>-0.75089</td>
<td>0.45272</td>
</tr>
</tbody>
</table>

You can also do this with GLM using the following syntax, note the MMATRIX subcommand that displays contrasts separated by semicolons

GLM t1 t2 t3 t4
/WSFACTOR time 4
/MMATRIX "cont1" t1 1 t2 1 t3 -1 t4 -1;
"cont2" t1 1 t2 -1 t3 1 t4 -1;
"cont3" t1 1 t2 -1 t3 -1 t4 1;
/WSDESIGN time.

Oh, a little detail about the MANOVA command. Apparently if a nonorthogonal set of contrasts is given in the contrast=special command, then SPSS decides that you don’t want those contrasts and instead computes something else. Whatever it does, the weird thing is that SPSS gives different results if you reorder the contrasts. Very ugly. If you want to use the MANOVA command with nonorthogonal contrasts in repeated measures designs, then use this version of the syntax instead.

MANOVA t1 t2 t3 t4
/TRANSFORM = special( 1 1 1 1
-1 0 1 0
-1 1 0 0
-1 0 0 1)
/PRI NT TRANSFORM
/ANALYSIS=(T1 T2 T3 T4).

The key difference is that the WSFACTOR subcommand is not given, and instead the /TRANSFORM and the /ANALYSIS subcommand are used. The T1 T2 T3 T4 refers to the four contrasts listed in the special (they do not refer to Time 1 scores, Time 2 scores, etc). T1 refers to the grand mean contrast, T2 the
2nd contrast listed, etc. This MANOVA syntax gives the same result as the GLM command syntax, and like GLM, is not sensitive to the order of specifying the contrasts. Here is the GLM version of the command, which doesn’t mind nonorthogonal contrasts.

```
glm t1 t2 t3 t4
/wsfactor time 4 special( 1 1 1 1
-1 0 1 0
-1 1 0 0
-1 0 0 1).
```

Ugly SPSS stuff.

In my personal data analysis of repeated measures data I avoid all these hassles by doing a convenient shortcut that is very simple. A simple way to generate these tests without using the MANOVA command for the contrast values (or the GLM command) is to create new variables according to the contrast (e.g., the 1 1 -1 -1 contrast would be a new variable that has t1 + t2 - t3 - t4) and then do one sample t tests against zero for those new variables. Note that these contrasts are not the same as the contrasts used in the one-way between-subjects ANOVA, where contrast values applied to cell means consisting of different subjects. In the repeated-measures case the contrast values are used to create a new variable, then simple t-tests can be performed on these new variables.\(^6\)

```
compute cont1 = t1 + t2 - t3 - t4.
compute cont2 = t1 - t2 + t3 - t4.
compute cont3 = t1 - t2 - t3 + t4.
t-test /testval = 0 /variables cont1 cont2 cont3.
```

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number</th>
<th>Standard</th>
<th>Standard</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^6\)There are several ways of performing a one sample t test in SPSS. I illustrate one method in the text, which is fairly straightforward. It involves creating a new variable using the contrast weights and performing a one sample t-test. Another equivalent method is to compute a new variable that has all the positive contrast weights, another variable that has all the negative contrast weights, and compare the two using the paired t test command in SPSS. Here is the command syntax for the first contrast in the example:

```
compute poscont1 = t1 + t2.
compute negcont1 = t3 + t4.
execute.
ttest pairs poscont1 negcont1.
```

Other ways of performing a paired t-test are through the menu system and through this syntax:
```
ttest pairs = poscont1 with negcont1 (paired).
```
These three contrasts are identical to those reported in the previous MANOVA output.

You are free to choose any set of orthogonal contrasts over time. Another natural set of contrasts would be the polynomial contrasts. For four times, this would test the linear, the quadratic and the cubic trends. Intuitively, this corresponds to the trend with no bend (linear), one bend (quadratic) and two bends (cubic); more generally, each term in the polynomial adds another possible bend to the model. With four times, the linear contrast is -3, -1, 1, 3. The point of this contrast is that the weights are equally spaced and equally increasing between time points. The quadratic contrast is 1, -1, -1, 1 (the two outer times have different weights than the two inner points, indicating one bend either U or
inverted U shaped). The cubic is -1, 3, -3, 1; note how this contrast has two switches in sign and weight. Together, the linear, quadratic and cubic trends together can model many different possible trajectories consisting of a weighted combination of these three components. You can test the linear, quadratic and cubic contrasts over time by either computing new scores using the contrast weights and then one sample t tests, or you can use a repeated measures ANOVA program like manova in SPSS.

(b) Two-way repeated measures

The structural model for a factorial design with two repeated measures is ugly (but admittedly, very logical):

\[
Y_{ijk} = \mu + \alpha_j + \beta_k + \pi_i + \alpha\beta_{jk} + \alpha\pi_{ki} + \beta\pi_{ki} + \epsilon_{ijk}
\]  

(5-14)

where \( \alpha \) and \( \beta \) are the two manipulated factors, and \( \pi \) is the factor representing subjects, which is also treated as a random effect.

Consider a simple example of a \( 2 \times 2 \) repeated-measures on both factors design. This could come out of a pre/post test sequence administered in two different settings. Questions one might be interested are things such as “Collapsing over days, is there a difference between the post-tests and the pre-tests?”, “Collapsing over pre/post tests, is there a difference between the first session and the second session?”, “Looking only at the first session, is there a difference between the post-test and the pre-test?”, etc. These questions translate easily into contrasts. For this example, the design is

<table>
<thead>
<tr>
<th></th>
<th>pre-test</th>
<th>post-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>session 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>session 2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

and the contrasts for the above questions are (1 -1 1 -1), (1 1 -1 -1), and (1 -1 0 0), respectively.

Imagine the following data came from the above design (the same data set used to illustrate the one-way repeated-measures). Suppose the researcher wanted to test the main effect for session, the main effect for pre/post, and the interaction (as a specific example of possible orthogonal contrasts that can be tested).
The contrast \((1 \ -1 \ 1 \ -1)\) can be tested by creating a new variable that is the sum of the two pre-tests minus the sum of the two post-tests. This can be done in SPSS with the `COMPUTE` command. The test of significance just uses that new variable and is a one-sample \(t\) test against the null hypothesis that the mean of that new variable (i.e., the contrast value is 0).

```spss
data list free / id s1.pre s1.post s2.pre s2.post.
begin data.
1 92 95 96 98
2 120 121 121 123
3 112 111 111 109
4 95 96 98 99
5 114 112 110 109
6 99 100 99 98
7 124 125 127 126
8 106 107 106 107
9 100 98 95 94
10 108 110 112 115
11 112 115 116 118
12 102 102 101 101
end data.
compute cont1 = s1.pre + s2.pre - s1.post - s2.post.
compute cont2 = s1.pre + s1.post - s2.pre - s2.post.
compute cont3 = s1.pre - s1.post - s2.pre + s2.post.
t-test /testval = 0
/variables cont1 cont2 cont3.
```

```
Variable  Number of Cases  Mean  Standard Deviation  Standard Error
----------- ----------- ---------- --------------- ---------------
CONT1       12          -1.0833  3.088          .892
            12          .0000      .000           .000
TEMP
```
Note that these are the same results we saw in the case of the one-way repeated-measures. The reasons are the identical data set was used as well as the identical set of contrasts.

Identical results are found if one performs a “repeated-measures” analysis of variance. In SPSS this is accomplished with the `MANOVA` command. Note how I defined the factorial repeated measures ANOVA using the `MANOVA` command.

```plaintext
manova s1.pre s1.post s2.pre s2.post
/wsfactor session(2), prepost(2)
/wsdesign session prepost session by prepost.
```

Tests of Significance for T1 using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>4387.23</td>
<td>11</td>
<td>398.84</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CONSTANT</td>
<td>555775.52</td>
<td>1</td>
<td>555775.52</td>
<td>1393.48</td>
<td>.000</td>
</tr>
</tbody>
</table>

Tests involving ‘SESSION’ Within-Subject Effect.
Tests of Significance for T2 using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>93.23</td>
<td>11</td>
<td>8.48</td>
<td>.42</td>
<td>.532</td>
</tr>
<tr>
<td>SESSION</td>
<td>3.52</td>
<td>1</td>
<td>3.52</td>
<td>.42</td>
<td>.532</td>
</tr>
</tbody>
</table>

Tests involving 'PREPOST' Within-Subject Effect.

Tests of Significance for T3 using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>26.23</td>
<td>11</td>
<td>2.38</td>
<td>1.48</td>
<td>.250</td>
</tr>
<tr>
<td>PREPOST</td>
<td>3.52</td>
<td>1</td>
<td>3.52</td>
<td>1.48</td>
<td>.250</td>
</tr>
</tbody>
</table>

Tests involving 'SESSION BY PREPOST' Within-Subject Effect.

Tests of Significance for T4 using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>3.56</td>
<td>11</td>
<td>.32</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SESSION BY PREPOST</td>
<td>.19</td>
<td>1</td>
<td>.19</td>
<td>.58</td>
<td>.463</td>
</tr>
</tbody>
</table>

The three t values correspond to the F values (just square the t’s).

(c) Designs with both between-subjects factors and repeated-measures factors

Now consider a “mixed-design” having one factor that is between-subjects and one factor that is within-subjects. An example comes from Ott (p 807). Suppose the researcher wanted to compare sequence 1 with sequence 2, period 1 with period 2, and test the interaction of sequence and period. One way to accomplish these tests is with the following command. Because all three tests are 1 df tests there are no “global” omnibus tests, and each F corresponds to a specific contrast.
Period

<table>
<thead>
<tr>
<th>Patient</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sequence 1</td>
<td>1</td>
<td>8.6</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>7.5</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>8.3</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>8.4</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>6.4</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>6.9</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>6.5</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>6.0</td>
</tr>
<tr>
<td>Sequence 2</td>
<td>9</td>
<td>7.3</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>7.5</td>
</tr>
<tr>
<td></td>
<td>11</td>
<td>6.4</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>6.8</td>
</tr>
<tr>
<td></td>
<td>13</td>
<td>7.1</td>
</tr>
<tr>
<td></td>
<td>14</td>
<td>8.2</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>7.2</td>
</tr>
<tr>
<td></td>
<td>16</td>
<td>6.7</td>
</tr>
</tbody>
</table>

```
data list free / sequence id period1 period2.
begin data.
end data.

manova period1 period2 by sequence(1,2)
/wsfactor period(2)
/wsdesign period
/design sequence.
```

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>15.86</td>
<td>14</td>
<td>1.13</td>
<td>.46</td>
<td>.507</td>
</tr>
<tr>
<td>SEQUENCE</td>
<td>.53</td>
<td>1</td>
<td>.53</td>
<td>.46</td>
<td>.507</td>
</tr>
</tbody>
</table>

Tests involving 'PERIOD' Within-Subject Effect.

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>.79</td>
<td>14</td>
<td>.06</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PERIOD</td>
<td>.02</td>
<td>1</td>
<td>.02</td>
<td>.27</td>
<td>.611</td>
</tr>
<tr>
<td>SEQUENCE BY PERIOD</td>
<td>1.49</td>
<td>1</td>
<td>1.49</td>
<td>26.30</td>
<td>.000</td>
</tr>
</tbody>
</table>

There is an error term used for the between-subjects factor and a second error term used for any term involving the within-subjects factor (in this case, one of the main effects and the interaction). The sphericity and multivariate analysis of variance output is omitted. SPSS is “smart” enough not to print this information because with tests involving one degree of freedom in the numerator, the issue
of sphericity is irrelevant.

Can this test be done with **COMPUTE** commands followed by one-sample \( t \) tests? I’ll show you a very simple way of performing the mixed design without having to use the MANOVA command in SPSS. But one must perform between-subject ANOVAs on the difference scores and the sum scores, rather than two sample two-sample \( t \) tests. Let me illustrate.

```plaintext
compute persum = period2 + period1.
compute perdiff = period2 - period1.
t-test /testval = 0 /variables perdiff.
```

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of Cases</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>PERDIFF</td>
<td>16</td>
<td>-.0438</td>
<td>.551</td>
<td>.138</td>
</tr>
<tr>
<td></td>
<td>16</td>
<td>.0000</td>
<td>.000</td>
<td>.000</td>
</tr>
</tbody>
</table>

(Difference) Standard Deviation Error | 2-tail | t Degrees of 2-tail
- .0438 | .551 | .138 | . | -.32 | 15 | .755

```plaintext
ttest groups = sequence(1,2) / variables persum perdiff.
```

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of Cases</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>PERSUM</td>
<td>GROUP 1 8</td>
<td>14.1750</td>
<td>1.750</td>
<td>.619</td>
</tr>
<tr>
<td></td>
<td>GROUP 2 8</td>
<td>14.6875</td>
<td>1.212</td>
<td>.429</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>F</th>
<th>2-tail</th>
<th>t</th>
<th>Degrees of 2-tail</th>
<th>t</th>
<th>Degrees of 2-tail</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.08</td>
<td>.354</td>
<td>-.68</td>
<td>14</td>
<td>.507</td>
<td>-.68</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of Cases</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>PERDIFF</td>
<td>GROUP 1 8</td>
<td>-.4750</td>
<td>.377</td>
<td>.133</td>
</tr>
<tr>
<td></td>
<td>GROUP 2 8</td>
<td>.3875</td>
<td>.290</td>
<td>.103</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>F</th>
<th>2-tail</th>
<th>t</th>
<th>Degrees of 2-tail</th>
<th>t</th>
<th>Degrees of 2-tail</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Two of the three contrasts are correct (compared to the previous output from the MANOVA command). What went wrong? Think about the degrees of freedom involved in a one-sample t test—the degrees of freedom are N - 1. Since there are 16 subjects, the TTEST command spits out 15 df’s for the test of persum. But, we know from the previous MANOVA output that the degrees of freedom should be 14. So, in this entire lecture this is the only example where there fails to be a correspondence between the contrast in the MANOVA output and the same contrasts tested through COMPUTE and TTEST.

What is the right way to do this analysis with difference scores? The right way to think about contrasts for mixed designs is in terms of two separate between-subjects analysis of variances. That is, one between-subjects analysis of variance is conducted on the variable persum (the sum over time) and a second between-subjects analysis is conducted on the variable perdiff (the difference over time).

```
manova persum by sequence(1,2)
/design sequence.
```

```
Source of Variation  SS    DF    MS   F   Sig of F
WITHIN CELLS         31.72  14    2.27
SEQUENCE             1.05   1    1.05 .46  .507
```

```
manova perdiff by sequence(1,2)
/design constant sequence.
```

```
Source of Variation  SS    DF    MS   F   Sig of F
WITHIN CELLS         1.58   1    .11
CONSTANT             .03    1    .03 .27  .611
SEQUENCE             2.98   1    2.98 26.30 .000
```

Note that for the first time in this course the CONSTANT term is interpretable. The grand mean for this second between-subjects analysis of variance is testing whether the difference is significantly different than zero. The test for SEQUENCE (on the perdiff variable) is identical to the interaction of SEQUENCE and PERIOD. The test for SEQUENCE in the first between-subjects analysis of variance corresponds to the main effect of SEQUENCE.
13. Multilevel model approach to repeated measures

A different way to represent a within-subject design is to nest time within the subjects factor, where subjects is treated as a random effect factor. The usual structural model for the within-subjects design models each observation as an additive sum of the following terms

\[ X_{ij} = \mu + \alpha_i + \pi_j + \epsilon_{ij} \] (5-15)

where \(\mu\) is the usual grand mean, \(\alpha\) corresponds to the main effect of time (there is one \(\alpha\) each each level of time), \(\pi\) represents the subject factor that is treated as a random effect because subjects are randomly selected from a population (there are as many \(\pi\)s as there are participants), and \(\epsilon\) is the usual error term (there are as many \(\epsilon\) terms as there are number of participants times number of observations over time). Both \(\pi\) and \(\epsilon\) are random variables assumed to follow a normal distribution with mean 0 and variances \(\sigma_{\pi}\) and \(\sigma_{\epsilon}\), respectively. However, in within-subjects designs the variance \(\sigma_{\pi}\) represents a square matrix with as many rows and columns as there are times, with variances in the diagonal and covariances in the off-diagonal. The reason that the \(\sigma_{\epsilon}\) term is not a matrix is because subjects are assumed to be independent from each other (so all the covariances between subjects are 0) and are assumed to have the same error distribution, which is the homogeneity of variance assumption.

There is another way to specify the within-subjects model. The multilevel approach takes the time factor as nested within the subject factor and writes a two-level structural model. The first level models the observed data as a function of a subject effect \(\beta_j\), time and the residual as in

\[ X_{ij} = \beta_j + \alpha_i + \epsilon_{ij} \] (5-16)

There is also a second structural model for the \(\beta_j\), which is written as

\[ \beta_j = \mu + \pi_j \] (5-17)

where \(\pi\) is a random effect parameter assumed to be sampled from a normal distribution with mean 0 and variance matrix \(\sigma_{\pi}\). Note that if one substitutes the linear definition of \(\beta\) (Equation 5-17) into the first level Equation 5-16, one gets the identical structural model for the within-subjects design presented in Equation 5-15. So the multilevel model is not a different model as much as a different approach to handling repeated measures. The advantage of the multilevel approach comes in its generalization to other models, and a common framework for handling many different kinds of designs under one umbrella. For a review of multilevel models see Raudenbush & Bryk’s Hierarchical Linear Models book.

One of the key benefits of the multilevel approach to repeated measures is that it handles missing data in an elegant way. Unlike ANOVA, which discards the entire
subject from the dataset if there is at least one missing time point for that participant, the multilevel model makes use of all available data for each subject.

The SPSS implementation of this approach uses the command MIXED. For example, here is a 2x2 design with repeated measures on both factors. We test the main effects and interactions through contrasts. The data are structured in a slightly different way than usual. Rather than putting all the subject’s data in the same row, each time takes on its own row. So with 4 observations per subject, there will be 4 times the number of subjects rows in the data file.

```
MIXED data BY time
/FIXED = time
/REPEATED = time | SUBJECT(subject) COVTYPE(UN)
/TEST ’main effect 1’ time 1 1 -1 -1
/TEST ’main effect 2’ time 1 -1 1 -1
/TEST ’interaction’ time 1 -1 -1 1.
```

Data structure is important so let me reiterate. This syntax requires that data be entered in a different format. Rather than entering each subject’s data in a single row, every observation is entered in a separate row and new variables are included that code which subject and which time for each observation. So if there are 12 participants and each participant provided four observations, then the data set will have 48=12*4 rows, a column of numbers 1 through 12 to indicate which subject each observation belongs, and a column of numbers 1 through 4 to indicate which time each observation belongs. This is a strange way to implement a repeated measures design for those who are well-versed in the ways of repeated measures where multiple times for the same person are entered in the same row. It is good to get in the habit of sorting the data file by subject as many programs require this sorting and yield inappropriate results if data aren’t sorted.

The subcommand FIXED instructs SPSS to use time as a fixed effect, and the REPEATED subcommand sets up the structure where the time scores are nested within the subject factor. The covariance is assumed to be unstructured. This is the typical assumption that corresponds to the single degree of freedom tests that we presented earlier; there are different types of covariance structures that are possible. We refer the reader to the manual of their statistics package, which in the case of SPSS and most major programs, tend to have good documentation on the different covariance structures for the time factor that are possible within their commands for testing multilevel models. Note: instead of putting COVTYPE(UN) for unstructured covariance matrix, if you enter COVTYPE(CS) that yields the compound symmetry structure on the covariance matrix that we saw earlier.
The MIXED syntax specifies each comparison in separate TEST subcommands. This MIXED syntax produces the same output as the MANOVA and the set of one-sample t-tests we introduced earlier. There are several different ways of implementing this design within the MIXED command that yield the identical results.

14. Simple Effects for Factorial Designs

Sometimes we want to know how factors differ at each level of another factor. For example, suppose one factor is dosage with three levels (high, med, low) and the other factor is sex. We may be interested in how dosage differs for males (essentially a one-way ANOVA on males only) and how dosage differs for females (essentially another one-way on females only). These kinds of focused tests can easily be done with contrasts, though in SPSS the syntax gets tricky if you use MANOVA.

There is another method that many people like to use. It essentially amounts to breaking up omnibus tests into smaller omnibus tests, and breaking those into even smaller omnibus tests, etc., until you are down to single degree of freedom tests. The technique is sometimes called “simple main effects” and “simple interactions”. Well, by now you know exactly my reaction to this procedure. If you eventually want to test contrasts, why not go there in the first place. In any case, I thought it would be good to introduce you to this style of analysis because you may be asked to do this at some point. In some cases, this technique of finding simple main effects ends up being identical to doing contrasts.

Maxwell and Delaney have a good discussion of “simple effects” ideas pages 260-268. I’ll use their example to illustrate these ideas further, as well as show some SPSS syntax. Here are the data they used (part appears in Table 7.5 on page 258, and part appears in Table 7.8 on page 263) and a traditional source table. I’ve also added an extra column of codes to convert the 2x3 factorial into a 6-level one-way ANOVA. Bio has two levels and drug has three levels.

data list free / bio drug dv group.

begin data
  1 1 170 1
  1 1 175 1
  1 1 165 1
  1 1 180 1
  1 1 160 1
  1 2 186 2
  1 2 194 2
  1 2 201 2
  1 2 215 2
  1 2 219 2
  1 3 180 3
  1 3 187 3

end data
Lecture Notes #5: Advanced topics in ANOVA

1 3 199 3
1 3 170 3
1 3 204 3
2 1 173 4
2 1 194 4
2 1 197 4
2 1 190 4
2 2 189 5
2 2 194 5
2 2 217 5
2 2 206 5
2 2 199 5
2 3 202 6
2 3 228 6
2 3 190 6
2 3 206 6
2 3 224 6
1 1 158 1
1 2 209 2
1 3 194 3
2 1 198 4
2 2 195 5
2 3 204 6
end data.

manova dv by bio(1,2) drug(1,3).

Tests of Significance for DV using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>4098.00</td>
<td>30</td>
<td>136.60</td>
<td></td>
<td>.004</td>
</tr>
<tr>
<td>BIO</td>
<td>1296.00</td>
<td>1</td>
<td>1296.00</td>
<td>9.49</td>
<td>.004</td>
</tr>
<tr>
<td>DRUG</td>
<td>4104.00</td>
<td>2</td>
<td>2052.00</td>
<td>15.02</td>
<td>.000</td>
</tr>
<tr>
<td>BIO BY DRUG</td>
<td>1152.00</td>
<td>2</td>
<td>576.00</td>
<td>4.22</td>
<td>.024</td>
</tr>
<tr>
<td>(Model)</td>
<td>6552.00</td>
<td>5</td>
<td>1310.40</td>
<td>9.59</td>
<td>.000</td>
</tr>
<tr>
<td>(Total)</td>
<td>10650.00</td>
<td>35</td>
<td>304.29</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Now, suppose you want to conduct the test between the two biofeedback conditions at EACH level of drug. SPSS can perform this in MANOVA as follows. The variable drug is entered as a main effect. Three main effects “bio within drug(?)” where the question mark is replaced with each level of the drug variable (WITHIN is an SPSS keyword). No interaction is entered. There is a sense in which this simple main effect confounds a main effect and an interaction.

manova dv by bio(1,2) drug(1,3) /design drug, bio within drug(1), bio within drug(2), bio within drug(3).

Tests of Significance for DV using UNIQUE sums of squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN+RESIDUAL</td>
<td>4098.00</td>
<td>30</td>
<td>136.60</td>
<td></td>
<td>.004</td>
</tr>
<tr>
<td>DRUG</td>
<td>4104.00</td>
<td>2</td>
<td>2052.00</td>
<td>15.02</td>
<td>.000</td>
</tr>
<tr>
<td>BIO WITHIN DRUG(1)</td>
<td>1200.00</td>
<td>1</td>
<td>1200.00</td>
<td>8.78</td>
<td>.006</td>
</tr>
<tr>
<td>BIO WITHIN DRUG(2)</td>
<td>48.00</td>
<td>1</td>
<td>48.00</td>
<td>.35</td>
<td>.558</td>
</tr>
<tr>
<td>BIO WITHIN DRUG(3)</td>
<td>1200.00</td>
<td>1</td>
<td>1200.00</td>
<td>8.78</td>
<td>.006</td>
</tr>
</tbody>
</table>
Compare these two source tables. Note that the drug effect is identical in both tables. However, look at the sums of squares for the three bio tests in the second table. Add them up and check that the result is the same as the sum of squares for both the main effect of bio and the interaction term (2448). This confounding of main effect and interaction is another reason why I don’t like this “simple test” approach as a general rule (though I could imagine that in some cases this test could make sense—it all boils down to which contrasts you want to test as I show below). You should double check that this is identical to the test presented in Maxwell and Delaney on page 264 (e.g., the BIO WITHIN DRUG(1) yields an \( F = 8.78 \)). Note that the numbers in parentheses after the word DRUG do not refer to contrast numbers as we have used them in the past (here we have not defined /contrast=special()) but instead refer to the level of the drug factor.

I think it is easier to see what is happening in this “simple effect” test if we do it through a contrast directly. I’ll use ONEWAY for this and recode the six cells of the factorial into a single one-way ANOVA with six levels. Let’s look at the test of bio feedback for the first drug (the BIO WITHIN DRUG(1) above). This is identical to the \((1, 0, 0, -1, 0, 0)\) contrast because we are only comparing two cells and ignoring the rest. Here’s the syntax and the output.

```
oneway do by group(1,6)
  /contrast 1 0 0 -1 0 0 .
```

<table>
<thead>
<tr>
<th>Source</th>
<th>D.F.</th>
<th>Sum of Squares</th>
<th>Mean Squares</th>
<th>F</th>
<th>F Ratio</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between Groups</td>
<td>5</td>
<td>6552.0000</td>
<td>1310.4000</td>
<td>9.59</td>
<td>.0000</td>
<td></td>
</tr>
<tr>
<td>Within Groups</td>
<td>30</td>
<td>4098.0000</td>
<td>136.6000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>35</td>
<td>10650.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Contrast Coefficient Matrix

<table>
<thead>
<tr>
<th>Grp 1</th>
<th>Grp 3</th>
<th>Grp 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grp 2</td>
<td>Grp 4</td>
<td>Grp 6</td>
</tr>
<tr>
<td>Contrast</td>
<td>1</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Pooled Variance Estimate

<table>
<thead>
<tr>
<th>Value</th>
<th>S. Error</th>
<th>T Value</th>
<th>D.F.</th>
<th>T Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contrast</td>
<td>1</td>
<td>-20.0000</td>
<td>6.7478</td>
<td>-2.964</td>
</tr>
</tbody>
</table>
If we square the pooled $t$ we see that it is identical to the $F$ test we reported above ($-2.964^2 = 8.78$). Instead of all that crazy, complicated language about simple main effects you can equivalently conduct this analysis through contrasts, being very clear about which group is being compared to which. Of course, this direct connection between the two approaches occurred because the simple effects approach yielded a single degree of freedom test, which can always be put into a contrast. In general though, simple effects must be followed by simple effects, etc., until you get down to single degree of freedom tests. Another advantage of framing the problem as a one-way is that it gives you the advantage of using the Welch test in cases where the equality of variance assumption is suspect. If your research question requires that you test these two cells independent from the other four, then this is a sensible contrast.

The simple effect approach will do strange things when you have unequal sample sizes because of how it partitions the variance. The answers are much cleaner if you stick to contrasts. With more complicated factorials the “simple effects” approach becomes even uglier. For example, in a factorial with three levels, should one examine the 2-way interaction for each level of the 3rd factor? a factor for each cell in the two-way? test A at each level of B ignoring C? There are many possibilities. The only way to know for sure which is appropriate in your situation is to think about the research question you are asking, convert them into contrasts, and test the contrasts directly.

For completeness, I mention that these “simple effect” tests can also be done on within-subjects factors. For designs with two repeated-measures the syntax for /WSDESIGN is identical to the one shown above for /DESIGN. However, for designs where one factor is between and the other is fixed, SPSS introduces a slight change in syntax—the use of the keyword MWITHIN rather than WITHIN. To test the within factor W at each level of the between factor B use this syntax

```
/WSFACTOR W
/DESIGN MWITHIN B(1), MWITHIN B(2)
```

To test B at each level of W

```
/WSDESIGN MWITHIN W(1), MWITHIN W(2)
/DESIGN B
```
These tests are also identical to performing contrasts directly on the cells being compared.
Appendix 1: Elements of a good results section

An example of a well-written results section appears in Lepper, Ross, and Lau (1986, *JPSP*, 50, 482-491).

A nice feature about this results section is that data, not inferential statistics, are emphasized. These authors state the result first and then provide a *p*-value as a punctuation mark. For example, “Subjects in the success conditions solved significantly more problems (M = 3.04) than did subjects in the failure conditions (M = 1.74), *F*(1, 48) = 28.20, *p* < .0001” (p. 485; note the typo in the article). Here the emphasis is on what was found—subjects in the success condition outperformed subjects in the failure condition.

Contrast this with the more common way results sections are written. Here is a typical sentence, which places emphasis on the inferential test rather than the actual result: “An ANOVA reveals a main effect of the success manipulation, *F*(1, 48) = 28.20, *p* < .0001.” I’ve seen cases where some authors stop there. The reader is left wondering “but was the significant result in the correct direction? What were the differences between the groups? Was it a large or small effect?”

The Lepper, Ross, and Lau results section would have been even better had they shown a figure with the confidence intervals around the means. I calculated the intervals using the MSE calculated by working backwards from the means and *F* value that appeared in the article. I can’t extract the individual standard deviations for each group (the authors should have provided that information), so I computed confidence intervals based on the pooled standard deviation (i.e., $\sqrt{\text{MSE}}$).
This paper also illustrates a relatively new trend to report more information than just the means. We know that means alone can be deceiving. Two groups can have different means because of a couple of outliers in one cell or, more generally, the data violate the assumptions. Lepper, Ross, and Lau (1986) go beyond reporting the means and tell us the pattern of individual subjects. Here is an example:

Only 3 of 26 failure-condition subjects solved as many as three problems (11 subjects solved only the one easy problem, 12 solved it and one other problem, 2 solved three problems, and 1 solved all four problems), whereas only 7 of 26 success-condition subjects solved fewer than three problems (2 subjects solved only the single easy problem and an additional 5 subjects solved only two problems, but 9 solved three problems and 10 solved all four problems). (p. 485)
This sentence could be more succinct, but you get the idea. The authors convey a sense of what happened in the study. Data analysis should go beyond just reporting means and \( p \)-values.

For more details on writing research papers see the APA Publication Manual, in particular the sections “Parts of a Manuscript” and “Writing Style” (pages 7-60 in the 4th Edition). I recommend that you take a look at that manual; it offers sound advice such as report all the relevant descriptive statistics so the reader can reproduce the inferential results you present. If you report means and standard deviations, the reader can reproduce any between-subjects factorial design and followup comparisons such as contrasts, Tukey, Scheffe, or Bonferroni.

While we’re on the topic of writing, I bring up the issue of first sentences. Many people think that one must write science in some special, stuffy supercilious style. Here are the first sentences from classic papers in psychology. It may be that a necessary property for a paper to become a classic is that the reader needs to stay awake long enough to finish the paper.

> My problem is that I have been persecuted by an integer. For seven years this number has followed me around, has intruded in my most private data, and has assaulted me from the pages of our most public journals. (G. Miller, *Psychological Review, 1956, 63, 81-*, famous 7 plus/minus 2 paper)

> Suppose someone shows a three-year old and a six-year old a red toy car covered by a green filter that makes the car look black, hands the car to the children to inspect, puts it behind the filter again, and asks “What color is this car? Is it red or is it black?” (Flavell, 1986, *American Psychologist, 41, 418-*)

> In the central nervous system the visual pathway from retina to striate cortex provides an opportunity to observe and compare single unit responses to several distinct levels. (Hubel & Wiesel, 1959, *J of Physiology, 148, 574-*)

And a good one from a classic economics piece

> Lassie died one night. Millions of viewers, not all of them children, grieved. At least, they shed tears. Except for the youngest, the mourners knew that Lassie didn’t really exist.... Did they enjoy the episode? (Thomas Schelling, The Mind as a Consuming Organ)

> While these are just examples, it is rare that a classic paper begins with the first sentence along the lines of “Smith (1982) found that .... But then Wesson (1984) failed to replicate the major result that .... So the present study attempts to solve this inconsistency.” Blah. Few readers will finish that paper.
Appendix 2: Example of different methods for unequal n

Study looking at salary differences (in thousands) between men and women, and between college educated and non-college educated.

Here we’ll make use of the ANOVA command in SPSS and its built-in facility for performing each of the three methods I discussed in class.

Data:

1 1 24
1 1 26
1 1 25
1 1 24
1 1 27
1 1 24
1 1 27
1 1 23
1 2 15
1 2 17
1 2 20
1 2 16
2 1 25
2 1 29
2 1 27
2 2 19
2 2 18
2 2 21
2 2 20
2 2 21
2 2 22
2 2 19

SPSS Commands

data list free / sex college dollars.

value labels sex 1 ‘female’ 2 ‘male’.
value labels college 1 ‘college’ 2 ‘nocollege’.

begin data.
end data.

anova dollars by sex(1,2) college(1,2).

DOLLARS
by GENDER
COLLEGE

UNIQUE sums of squares
All effects entered simultaneously

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>Sum of Squares</th>
<th>DF</th>
<th>Mean Square</th>
<th>F of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>GENDER</td>
<td>29.371</td>
<td>1</td>
<td>29.371</td>
<td>10.573</td>
</tr>
<tr>
<td>COLLEGE</td>
<td>264.336</td>
<td>1</td>
<td>264.336</td>
<td>95.161</td>
</tr>
</tbody>
</table>
The default method for the ANOVA command is the unique method. This is the method that most directly answers the questions psychologists typically ask (within levels of college education is there a sex difference?). Not all versions of SPSS (in particular the version 6 series, such as on the Mac) have the unique method as the default in ANOVA. To make sure that SPSS is performing the unique method, you can specify it explicitly with this subcommand:

```
anova dollars by sex(1,2) college(1,2)
    /method = unique.
```

A different method is the hierarchical method. This is sometimes useful when one is asking about the differences between marginal means ignoring the other factors. The unique approach answers an analogous question but within each level of the other factors. Compare the main effect for sex in the unique approach (significant) with the main effect for sex in the hierarchical approach (nonsignificant) in the output below.

SPSS will do the hierarchical method if one specifies the /method = hierarchical subcommand. The source table is organized as though each term were entered one at time and all terms before it are still included. Note that for method=hierarchical the order the independent variables are listed in the first line of the ANOVA command makes a difference (order is irrelevant for method=unique). The reason order matters for method=hierarchical is that the hierarchical method identifies one factor as the most important factor, then the second factor, etc., whereas method=unique makes no such designation.

```
anova dollars by sex(1,2) college(1,2)
    /method = hierarchical.
```

---

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>Sum of Squares</th>
<th>DF</th>
<th>Mean Square</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>GENDER</td>
<td>.297</td>
<td>1</td>
<td>.297</td>
<td>.747</td>
</tr>
<tr>
<td>COLLEGE</td>
<td>272.392</td>
<td>1</td>
<td>272.392</td>
<td>.000</td>
</tr>
<tr>
<td>GENDER COLLEGE</td>
<td>1.175</td>
<td>1</td>
<td>1.175</td>
<td>.524</td>
</tr>
<tr>
<td>Explained</td>
<td>273.864</td>
<td>3</td>
<td>91.288</td>
<td>.000</td>
</tr>
<tr>
<td>Residual</td>
<td>50.000</td>
<td>18</td>
<td>2.778</td>
<td></td>
</tr>
</tbody>
</table>
A third method is the experimental method. SPSS will do the experimental method if one specifies the `/method = experimental` subcommand. In older versions of SPSS the experimental method in the ANOVA command was known as the “sequential method” and was the default. To make matters more complicated, the MANOVA command calls the hierarchical method the “sequential” method. Keeping these terms straight is very difficult when different people use different versions of SPSS, and I have a history of confusing these terms in lecture. As long as we all write out the structural models (described in the next Appendix), then we will be okay.

\begin{verbatim}
anova dollars by sex(1,2) college(1,2)
 /method = experimental.

dollars
 by GENDER
 COLLEGE

EXPERIMENTAL sums of squares
Covariates entered FIRST

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>Sum of Squares</th>
<th>DF</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>GENDER</td>
<td>30.462</td>
<td>1</td>
<td>30.462</td>
<td>10.966</td>
<td>.004</td>
</tr>
<tr>
<td>COLLEGE</td>
<td>272.392</td>
<td>1</td>
<td>272.392</td>
<td>98.061</td>
<td>.000</td>
</tr>
<tr>
<td>GENDER COLLEGE</td>
<td>1.175</td>
<td>1</td>
<td>1.175</td>
<td>.423</td>
<td>.524</td>
</tr>
<tr>
<td>Explained</td>
<td>273.864</td>
<td>3</td>
<td>91.288</td>
<td>32.864</td>
<td>.000</td>
</tr>
<tr>
<td>Residual</td>
<td>50.000</td>
<td>18</td>
<td>2.778</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>323.864</td>
<td>21</td>
<td>15.422</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
\end{verbatim}

Note how these three different methods partition the sum of squares for main effects differently (error and interaction are identical). Also, note how the sum of squares doesn’t always add up to sum of squares total, this is due to redundancy. The hierarchical method maintains the property that the two main effects, interaction and error sum of squares add up to sum of squares total, but the hierarchical method may not test the question we are asking. When we want to test contrasts that are not influenced by sample size, then we are forced to give up orthogonality in our design, live with redundancy, and have sum of squares that don’t add up.
Appendix 3: Illustrating the different methods of handling unbalanced designs: One more time

We’ll use the same data looking at salaries using sex and college education. We will perform the different approaches directly with the design subcommand. The reason for showing you this is to highlight how the approaches differ by comparing the different structural models they imply. I’m going to present several runs of MANOVA, each one with a different structural model (but always the same MSE as the error term) so you can see where each of the pieces from the previous appendix come from. You might want to have Table 7.15 (Maxwell & Delaney, page 287-88) available while you work through this appendix; also read the summary section starting on page 286.

Note the use of the /ERROR subcommand. I’m telling the program I want the error term to be the within sums of squares. The first /DESIGN is the unique approach because all terms of the structural model are included simultaneously. That is, the structural model includes $\alpha$, $\beta$, and $\alpha\beta$. The default is to use the within sums of squares as the error so I don’t need to specify it.

The second /DESIGN subcommand is the beginning of the hierarchical approach. The main variable of interested is entered first. Note that the error term is the same error term used in the unique approach. This approach is testing the structural model $Y = \mu + \alpha + \epsilon$ but it is using the MSE term from the full model (all terms, like in the unique approach) rather than the MSE that falls out of the present structural model. So, in computing $F$, the method uses the numerator MS term from one structural model and a denominator MS term from a different structural model.

The third /DESIGN subcommand is step 2 of the hierarchical approach as well as step 1 of the experimental approach: all the main effects are entered simultaneously. Again, the error term is the same error term used in the unique approach. Thus, the structural model is $Y = \mu + \alpha + \beta + \epsilon$. Each of the two terms ($\alpha$ and $\beta$ are tested using the MSE term from the unique method, i.e., the structural model with all terms).

To check your understanding, you should compare the following results with the output in Appendix 2 that used the built in features of ANOVA.

Recall that MANOVA uses the unique approach to unequal sample sizes as the default. Much like the ANOVA command, the MANOVA also has a /METHODS subcommand where you can specify unique, hierarchical, or experimental manually. Below I will specify the models using the design line so you can see directly the structural models of each approach.

```
manova dollars by sex(1,2) college(1,2)
/error within
/design sex college sex by college
/design sex vs within
/design sex vs within college vs within.
```

UNIQUE APPROACH:
Tests of Significance for DOLLARS using UNIQUE sums of squares
Source of Variation  SS  DF   MS   F   Sig of F

WITHIN CELLS  50.00  18  2.78
GENDER         29.37  1  29.37 10.57  .004
COLLEGE        264.34  1  264.34 95.16  .000
GENDER BY COLLEGE  1.17  1  1.17  .42  .524

HIERARCHICAL APPROACH STEP 1:
Tests of Significance for DOLLARS using UNIQUE sums of squares
Source of Variation  SS  DF   MS   F   Sig of F

WITHIN CELLS  50.00  18  2.78
GENDER        30.46  1  30.46 10.97  .004
COLLEGE       272.39  1  272.39 98.06  .000

HIERARCHICAL APPROACH STEP 2 AND EXPERIMENTAL APPROACH STEP 1:
Tests of Significance for DOLLARS using UNIQUE sums of squares
Source of Variation  SS  DF   MS   F   Sig of F

WITHIN CELLS  50.00  18  2.78
GENDER        30.46  1  30.46 10.97  .004
COLLEGE       272.39  1  272.39 98.06  .000

Compare these source tables with the ones presented in the previous Appendix. Such comparisons will help you figure out how these methods differ. The three source tables have the same error term even though they differ in the DESIGN subcommand.

Now, let me show you a more direct way of doing these analyses in the MANOVA command. I'll also ask MANOVA to print out the contrasts it used so that may help you understand what is going on in these different methods. Take a look at the contrasts printed on page 5-4 so you can anticipate what this output should look like.

First, the unique method. Note that the contrasts are as you would expect (e.g., the sex contrast is 1, 1, -1, -1).

```
manova dollars by sex(1,2) college(1,2)
/print design(solution)
/method=unique
/design.
```

Solution Matrix for Between-Subjects Design
1-GENDER  2-COLLEGE
FACTOR PARAMETER
1 1 -1.084  1.084 -1.084  1.084
1 2 -1.084  1.084  1.084 -1.084
2 1 -1.084 -1.084 -1.084 -1.084
2 2 -1.084 -1.084  1.084  1.084

Tests of Significance for DOLLARS using UNIQUE sums of squares
Source of Variation  SS  DF   MS   F   Sig of F

WITHIN CELLS  50.00  18  2.78
GENDER        29.37  1  29.37 10.57  .004
Now, I’ll do the hierarchical method, which in the MANOVA command is called the sequential method. The contrast corresponding to the main effect for Gender is based on sample size, as described in the lecture notes. Note that the GENDER main effect is “hierarchical step 1” and the college effect is “hierarchical step 2”.

```
manova dollars by sex(1,2) college(1,2)
/PRINT design(solution)
/method=sequential
/design.
```

Solution Matrix for Between-Subjects Design
1-GENDER 2-COLLEGE

<table>
<thead>
<tr>
<th>FACTOR</th>
<th>PARAMETER</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 1</td>
<td>1.706</td>
</tr>
<tr>
<td>1 2</td>
<td>.853</td>
</tr>
<tr>
<td>2 1</td>
<td>.640</td>
</tr>
<tr>
<td>2 2</td>
<td>1.492</td>
</tr>
</tbody>
</table>

Tests of Significance for DOLLARS using SEQUENTIAL Sums of Squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>50.00</td>
<td>18</td>
<td>2.78</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GENDER</td>
<td>.30</td>
<td>1</td>
<td>.30</td>
<td>.11</td>
<td>.747</td>
</tr>
<tr>
<td>COLLEGE</td>
<td>272.39</td>
<td>1</td>
<td>272.39</td>
<td>98.06</td>
<td>.000</td>
</tr>
<tr>
<td>GENDER BY COLLEGE</td>
<td>1.17</td>
<td>1</td>
<td>1.17</td>
<td>.42</td>
<td>.524</td>
</tr>
<tr>
<td>(Model)</td>
<td>273.86</td>
<td>3</td>
<td>91.29</td>
<td>32.86</td>
<td>.000</td>
</tr>
<tr>
<td>(Total)</td>
<td>323.86</td>
<td>21</td>
<td>15.42</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Finally, to get the “experimental method” you need to rerun MANOVA reversing the order of the two independent variables. You take the F for the COLLEGE variable from the source table previous to this one with GENDER entered first, and the F test for the GENDER variable from the source table below that contains COLLEGE entered first. That way, you get both F tests as though that variable were entered second. Note how the contrasts weights for the main effects have changed.

```
manova dollars by college(1,2) sex(1,2)
/PRINT design(solution)
/method=sequential
/design.
```

Solution Matrix for Between-Subjects Design
1-COLLEGE 2-GENDER

<table>
<thead>
<tr>
<th>FACTOR</th>
<th>PARAMETER</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 1</td>
<td>1.706</td>
</tr>
<tr>
<td>1 2</td>
<td>.853</td>
</tr>
<tr>
<td>2 1</td>
<td>.640</td>
</tr>
<tr>
<td>2 2</td>
<td>1.492</td>
</tr>
</tbody>
</table>

Tests of Significance for DOLLARS using SEQUENTIAL Sums of Squares

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>SS</th>
<th>DF</th>
<th>MS</th>
<th>F</th>
<th>Sig of F</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN CELLS</td>
<td>50.00</td>
<td>18</td>
<td>2.78</td>
<td></td>
<td></td>
</tr>
<tr>
<td>COLLEGE</td>
<td>242.23</td>
<td>1</td>
<td>242.23</td>
<td>87.20</td>
<td>.000</td>
</tr>
<tr>
<td>GENDER</td>
<td>30.46</td>
<td>1</td>
<td>30.46</td>
<td>10.97</td>
<td>.004</td>
</tr>
<tr>
<td>COLLEGE BY GENDER</td>
<td>1.17</td>
<td>1</td>
<td>1.17</td>
<td>.42</td>
<td>.524</td>
</tr>
<tr>
<td>(Model)</td>
<td>273.86</td>
<td>3</td>
<td>91.29</td>
<td>32.86</td>
<td>.000</td>
</tr>
<tr>
<td>(Total)</td>
<td>323.86</td>
<td>21</td>
<td>15.42</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Take a look at the contrast weights automatically generated by the MANOVA command (don’t let the ugly orthonormalization of the contrast weights throw you off). The formulae for these weights are based on sample size and are given in the lecture notes page 5-4. In the first “sequential” run (sex entered first), sex received the weights corresponding to the hierarchical approach and college received the weights corresponding to the experimental approach. In the second “sequential” run (college entered first), college received the weights corresponding to the hierarchical approach and sex received the weights corresponding to the experimental approach.
Appendix 4: R commands

I may add more information through canvas as we progress through these lecture notes.

Unequal sample sizes

If you want the regression approach in R, then use the `lm()` command. That is, run the ANOVA model as a regression model. For example,

```r
summary(lm(dv ~ factor1*factor2))
```

If you want to use the `aov()` command be careful because a `summary()` on the `aov` output does not produce the regression method. You need to use the `drop1` command to print out the source table corresponding to the regression method as in

```r
out.aov <- aov(dv ~ factor1*factor2)
drop1(out.aov, .~., test="F")
```

As long as I manually define contrasts for each factor, the standard `summary(lm(...))` approach prints out everything I typically need for a paper. Be careful of just relying on R’s default contrast definitions because it uses dummy codes and those do not work correctly with unbalanced designs. If you don’t define your own contrasts you should at least do the following so as to avoid dummy codes.

```r
out.aov <- aov(dv ~ factor1*factor2, contrasts=list(factor1=contr.sum, factor2=contr.sum))
drop1(out.aov, .~., test="F")
```

The reason this works is because the `contr.sum` command gives what are called effect coding. An example for a factor with 5 levels is the following with one level becoming the reference group and each of the four contrasts compare a group to the reference group.

```r
> contr.sum(5)

 1 1 0 0 0
 2 0 1 0 0
 3 0 0 1 0
 4 0 0 0 1
 5 -1 -1 -1 -1
```

In Lecture Notes #8 I will explain the issue with dummy codes in the context of running ANOVA in regression, and why effect coding and contrasts are better. For now, just do this syntax trick in R and you will be ok.
There is also the Anova() command in the car package that can perform two of the three types of approaches to unequal n. First, run your aov() in the usual way but print the source table with the Anova() command instead of the usual anova() command (remember, R is case sensitive) yields the regression method as in

```r
out.aov <- aov(dv ~ factor1*factor2)
Anova(out.aov, type="III")
```

Regression method is also known as type III, the other two are type I (hierarchical) and type II (sequential). But this command assumes you manually defined a set of contrasts on each factor, otherwise use the contrasts=list() argument to lm as mentioned above to avoid the issue with R’s default dummy codes. The Anova() command can also accept a type="II" argument for the experimental method. For the hierarchical method, just do a standard anova() (lower case a) on an aov() or lm() object because that is the default in R.

Random and nested effects

I suggest you compute ANOVAs in the usual way (e.g., aov) and manually compute the correct F tests where you use the appropriate error term.

You can use the lme4 or nlme libraries but they introduce more complication. For example, the author of the lme4 library believes that users should know their appropriate degrees of freedom so models you run in lme4 do not print df and thus no p-values are printed either. Someone else wrote an additional package that adds p-value functionality to the lme4 package, called the LMERConvenienceFunctions library (and a similar package called lmerTest). So as you are learning this material, just compute by hand and as you gain familiarity with the random effect packages like lme4 or nlme, then add the bells and whistles always double checking that you are recreating in syntax what you do by hand.

For random and nested effects, there are same issues when you rely on R’s default dummy code contrasts. Either manually define contrasts on each factor or use the contrasts=list() argument as mentioned above.

Repeated measures

Repeated measures ANOVA is not very well developed in R at this point. Most people end up using a random effect model, such as the lme4 library, since repeated measures models just have a subjects factor that is treated as a random effect as I showed earlier in these lecture notes. This requires putting the repeated measures data in long format as opposed to wide format. Wide format has one row per subject and each time as a separate column; long format has all time data stacked so if there are three time points and 5 subjects long format has 15 (3 times 5) rows. When using long format one also needs to add a variable that codes for time (if three times then a grouping code of 1s, 2s and 3s) and codes for subjects (i.e., subject number). One can specify contrasts on the time time factor, such as 1, 0, -1 and 1, -2, 1 in the case of three times. This format is the preferred format since
it generalizes to more advanced techniques such as multilevel modeling and latent growth
curve models.

If I have all repeated measures factors, I use the short cut presented in the lecture notes
that you can create new variables by weighting the repeated measures with the contrast
weights and running t tests. But if I have a mixed design with both repeated and between
subjects designs, things get a little tricky (e.g., keeping track of degrees of freedom), so I’ll
double check my work with another program.

The car package Anova command can run repeated measures ANOVA with Greenhouse-
Geisser. See the help for the Anova command; the example for multivariate linear model
for repeated-measures data gives an example of a 3 by 5 ANOVA with repeated measures
on both factors. You specify the design and contrasts on the repeated measures factor
through the idesign and icontrast arguments. This requires data in wide format, and uses a
construction of putting all the repeated measures variables on the dependent variable side
by creating a dv matrix.

Baron and Li maintain some R notes for running various statistics. You may find these notes
helpful for various things like computing sphericity, greenhouse-geisser, using the Error() feature
within the aov() command to specify the appropriate error term, etc. They do a
nice job of explaining so I’ll just direct you their notes. It is convenient that they use some
of the same data sets I’ve included in my lecture notes.

http://www.psych.upenn.edu/~baron/rpsych/rpsych.html

You can try a few newer libraries that add functionality such as the ezANOVA() command in
the ez library. I suggest you run through some of the examples in the lecture notes through
some of these newer functions to ensure that you are using them correctly and getting the
same output as the lecture notes to confirm that you using the R syntax correctly.

This is probably the only occasion I’ll say this: for repeated measure ANOVA it is easier to
use SPSS. There isn’t much on the fancy stuff like Box’s $\epsilon$, Greenhouse-Geisser corrections,
etc.

One way repeated measures

For those who insist on using R for repeated measures. I offer a few examples. I’ll illustrate
how one gets different results in different R commands, which is not a good thing. The
major lesson here is know your R commands and test them out on examples where you
know the right answer to make sure you are reproducing those answers in R.

Let’s read in the data I used for the one way repeated measure ANOVA earlier in the lecture
notes (page 5-34). First, I’ll show how to do this by creating three contrast scores and then
following up with one sample t tests. This replicates the one way repeated measures example
in the lecture notes using SPSS. Note that degrees of freedom are 11, which we will compare
with some R output where it is a different value. All is good so far.

> data <- cbind(1:12, c(92,120,112,95,114,99,124,106,100,108,112,102),
+                 c(95,121,111,96,112,100,125,107,98,110,115,102),
+                 c(97,123,113,98,114,102,127,109,100,112,117,105),
+                 c(98,124,114,99,115,103,128,110,101,113,118,106),
+                 c(99,125,115,100,116,104,129,111,102,114,119,107),
+                 c(100,126,116,101,117,105,130,112,103,115,120,108),
+                 c(101,127,117,102,118,106,131,113,104,116,121,109),
+                 c(102,128,118,103,119,107,132,114,105,117,122,110),
+                 c(103,129,119,104,120,108,133,115,106,118,123,111),
+                 c(104,130,120,105,121,109,134,116,107,120,124,112),
+                 c(105,131,121,106,122,110,135,117,108,121,125,113),
+                 c(106,132,122,107,123,111,136,118,109,122,126,114),
+                 c(107,133,123,108,124,112,137,119,110,123,127,115)),
```r
+ c(96,121,111,98,127,106,95,112,116,101),
+ c(98,123,109,99,109,98,126,107,94,115,118,101))

> data

[1,]  1  92  95  96  98
[2,]  2 120 121 121 123
[3,]  3 112 111 111 109
[4,]  4  95  96  98  99
[5,]  5 114 112 110 109
[6,]  6  99 100  99  98
[7,]  7 124 125 127 126
[8,]  8 106 107 106 107
[9,]  9 100  98  95  94
[10,] 10 108 110 112 115
[11,] 11 112 115 116 118
[12,] 12 102 102 101 101

> contrast1 <- data[,2]+data[,3]-data[,4]-data[,5]
> contrast2 <- data[,2]-data[,3]+data[,4]-data[,5]
> contrast3 <- data[,2]-data[,3]-data[,4]+data[,5]
> t.test(contrast1)

    One Sample t-test

  data:  contrast1
  t = -0.64453, df = 11, p-value = 0.5324
  alternative hypothesis: true mean is not equal to 0
  95 percent confidence interval:
    -4.782774  2.616107
  sample estimates:
  mean of x
    -1.083333

> t.test(contrast2)

    One Sample t-test

  data:  contrast2
  t = -1.2151, df = 11, p-value = 0.2498
  alternative hypothesis: true mean is not equal to 0
  95 percent confidence interval:
    -3.0455745  0.8789079
  sample estimates:
```
mean of x
-1.083333

> t.test(contrast3)

One Sample t-test
data: contrast3
t = -0.76089, df = 11, p-value = 0.4627
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
-0.9731653 0.4731653
sample estimates:
mean of x
-0.25

Here is the usual repeated measures omnibus test using the afex package, which requires data in long format. I create three within subject contrasts m1, m2, and int. This is the same omnibus F, degrees of freedom, Greenhouse-Geisser, Box $\epsilon$, etc as in SPSS.

> dv <- c(data[,2],data[,3],data[,4],data[,5])
> sub <- factor(rep(1:12,4))
> #let's select 3 orthogonal contrastas
> m1 <- (rep(c(1,1,-1,-1),each=12))
> m2 <- (rep(c(1,-1,1,-1),each=12))
> int <- (rep(c(1,-1,-1,1),each=12))
> time <- factor(rep(1:4, each=12))
> data.oneway <- cbind(sub, dv,m1,m2,int,time)
> data.oneway

sub  dv  m1  m2  int  time
[1,] 1  92  1  1  1  1
[2,] 2 120  1  1  1  1
[3,] 3 112  1  1  1  1
[4,] 4  95  1  1  1  1
[5,] 5 114  1  1  1  1
[6,] 6  99  1  1  1  1
[7,] 7 124  1  1  1  1
[8,] 8 106  1  1  1  1
[9,] 9 100  1  1  1  1
[10,] 10 108  1  1  1  1
[11,] 11 112  1  1  1  1
[12,] 12 102  1  1  1  1
[13,] 1  95  1  -1 -1  2
Lecture Notes #5: Advanced topics in ANOVA

```
[14,]  2 121  1 -1 -1  2
[15,]  3 111  1 -1 -1  2
[16,]  4  96  1 -1 -1  2
[17,]  5 112  1 -1 -1  2
[18,]  6 100  1 -1 -1  2
[19,]  7 125  1 -1 -1  2
[20,]  8 107  1 -1 -1  2
[21,]  9  98  1 -1 -1  2
[22,] 10 110  1 -1 -1  2
[23,] 11 115  1 -1 -1  2
[24,] 12 102  1 -1 -1  2
[25,]  1  96 -1  1 -1  3
[26,]  2 121 -1  1 -1  3
[27,]  3 111 -1  1 -1  3
[28,]  4  98 -1  1 -1  3
[29,]  5 110 -1  1 -1  3
[30,]  6  99 -1  1 -1  3
[31,]  7 127 -1  1 -1  3
[32,]  8 106 -1  1 -1  3
[33,]  9  95 -1  1 -1  3
[34,] 10 112 -1  1 -1  3
[35,] 11 116 -1  1 -1  3
[36,] 12 101 -1  1 -1  3
[37,]  1  98 -1 -1  1  4
[38,]  2 123 -1 -1  1  4
[39,]  3 109 -1 -1  1  4
[40,]  4  99 -1 -1  1  4
[41,]  5 109 -1 -1  1  4
[42,]  6  98 -1 -1  1  4
[43,]  7 126 -1 -1  1  4
[44,]  8 107 -1 -1  1  4
[45,]  9  94 -1 -1  1  4
[46,] 10 115 -1 -1  1  4
[47,] 11 118 -1 -1  1  4
[48,] 12 101 -1 -1  1  4
```

```r
> library(afex)
> library(car)
> out.aovez <- aov_ez("sub", "dv", data=data.oneway, within=c("time"))
> summary(out.aovez)
```

Univariate Type III Repeated-Measures ANOVA Assuming Sphericity

<table>
<thead>
<tr>
<th></th>
<th>SS num Df</th>
<th>Error SS den Df</th>
<th>F</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>555776</td>
<td>1 4387.2</td>
<td>11 1393.4833</td>
<td>6.154e-13 ***</td>
</tr>
</tbody>
</table>
time 7 3 123.0 33 0.6464 0.5908
---
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Mauchly Tests for Sphericity

<table>
<thead>
<tr>
<th>Test statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>time</td>
<td>0.01905</td>
</tr>
</tbody>
</table>

Greenhouse-Geisser and Huynh-Feldt Corrections for Departure from Sphericity

<table>
<thead>
<tr>
<th>GG eps</th>
<th>Pr(&gt;F[GG])</th>
<th>HF eps</th>
<th>Pr(&gt;F[HF])</th>
</tr>
</thead>
<tbody>
<tr>
<td>time</td>
<td>0.37577</td>
<td>0.4547</td>
<td></td>
</tr>
<tr>
<td>time</td>
<td>0.3892073</td>
<td>0.4594742</td>
<td></td>
</tr>
</tbody>
</table>

Omnibus with compound symmetry checks out. How about the multivariate tests? The afex package doesn’t appear to provide that test. So I switch to lm with a dv that has multiple columns and then use Anova() from the car package to get the multivariate omnibus tests. This replicates the multivariate tests in SPSS. But this is a hassle. Afex wants data in long format, lm wants data in wide format.

> #this command uses wide format data
> #there is no grouping variable so just predictor is just an intercept
> out.lm <- lm(data[,2:5] ~1)
> idata <- data.frame(time=factor(c(1:4)))
> mv.anova <- Anova(out.lm, idata=idata, idesign=~time,
> + type=3)
> summary(mv.anova)

Type III Repeated Measures MANOVA Tests:

------------------------------------------
Term: (Intercept)

Response transformation matrix:

(Intercept)
[1,] 1
[2,] 1
[3,] 1
[4,] 1

Sum of squares and products for the hypothesis:
(Intercept)
(Intercept) 2223102

Multivariate Tests: (Intercept)

<table>
<thead>
<tr>
<th>Df</th>
<th>test stat</th>
<th>approx F</th>
<th>num Df</th>
<th>den Df</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pillai</td>
<td>1</td>
<td>0.99217</td>
<td>1393.483</td>
<td>1</td>
<td>11</td>
</tr>
<tr>
<td>Wilks</td>
<td>1</td>
<td>0.00783</td>
<td>1393.483</td>
<td>1</td>
<td>11</td>
</tr>
<tr>
<td>Hotelling-Lawley</td>
<td>1</td>
<td>126.68030</td>
<td>1393.483</td>
<td>1</td>
<td>11</td>
</tr>
<tr>
<td>Roy</td>
<td>1</td>
<td>126.68030</td>
<td>1393.483</td>
<td>1</td>
<td>11</td>
</tr>
</tbody>
</table>

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

------------------------------------------

Term: time

Response transformation matrix:

time1 time2 time3
[1,] 1 0 0
[2,] 0 1 0
[3,] 0 0 1
[4,] -1 -1 -1

Sum of squares and products for the hypothesis:
time1 time2 time3
time1 14.083333 5.416667 5.416667
time2 5.416667 2.083333 2.083333
time3 5.416667 2.083333 2.083333

Multivariate Tests: time

<table>
<thead>
<tr>
<th>Df</th>
<th>test stat</th>
<th>approx F</th>
<th>num Df</th>
<th>den Df</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pillai</td>
<td>1</td>
<td>0.2758637</td>
<td>1.142866</td>
<td>3</td>
<td>9</td>
</tr>
<tr>
<td>Wilks</td>
<td>1</td>
<td>0.7241363</td>
<td>1.142866</td>
<td>3</td>
<td>9</td>
</tr>
<tr>
<td>Hotelling-Lawley</td>
<td>1</td>
<td>0.3809554</td>
<td>1.142866</td>
<td>3</td>
<td>9</td>
</tr>
<tr>
<td>Roy</td>
<td>1</td>
<td>0.3809554</td>
<td>1.142866</td>
<td>3</td>
<td>9</td>
</tr>
</tbody>
</table>

Univariate Type III Repeated-Measures ANOVA Assuming Sphericity

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<tr>
<th>SS num Df Error SS den Df</th>
<th>F</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept) 555776 1 4387.2</td>
<td>11</td>
<td>1393.4833</td>
</tr>
<tr>
<td>time 7 3 123.0</td>
<td>33</td>
<td>0.6464</td>
</tr>
</tbody>
</table>
---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Mauchly Tests for Sphericity

<table>
<thead>
<tr>
<th>Test statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>time</td>
<td>0.01905 3.6732e-07</td>
</tr>
</tbody>
</table>

Greenhouse-Geisser and Huynh-Feldt Corrections for Departure from Sphericity

GG eps | Pr(>F[GG]) |
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>time</td>
<td>0.37577 0.4547</td>
</tr>
</tbody>
</table>

HF eps | Pr(>F[HF]) |
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>time</td>
<td>0.3892073 0.4594742</td>
</tr>
</tbody>
</table>

Now let's switch to contrasts. We know we get the correct answer with the one sample t test approach using contrast weights to create a new score for each subject. Let's see if we can get R to cooperate.

Here is an attempt with the `aov_ez` command we ran above.

```r
> out.lsmeans <- lsmeans(out.aovez, ~time)
> cont <- list(m1=c(1,1,-1,-1),m2=c(1,-1,1,-1),int=c(1,-1,-1,1))
> contrast(out.lsmeans, cont)
```

<table>
<thead>
<tr>
<th>contrast</th>
<th>estimate</th>
<th>SE</th>
<th>df</th>
<th>t.ratio</th>
<th>p.value</th>
</tr>
</thead>
<tbody>
<tr>
<td>m1</td>
<td>-1.083333</td>
<td>1.114735</td>
<td>33</td>
<td>-0.972</td>
<td>0.3382</td>
</tr>
<tr>
<td>m2</td>
<td>-1.083333</td>
<td>1.114735</td>
<td>33</td>
<td>-0.972</td>
<td>0.3382</td>
</tr>
<tr>
<td>int</td>
<td>-0.250000</td>
<td>1.114735</td>
<td>33</td>
<td>-0.224</td>
<td>0.8239</td>
</tr>
</tbody>
</table>

Unfortunately, the contrast tests are not the same as in SPSS and in the t tests I computed in R. These contrast tests in the afex package use the incorrect error term, which is based on compound symmetry, and incorrect degrees of freedom, even though I'm following suggestions in the manual and on several websites. I didn't have much luck with the Anova command in the car package that supposedly allows for contrasts in repeated measures anova.

Another common approach to test contrasts in repeated measures is as a linear mixed model. It is true that repeated measures can be converted to a linear mixed model as I have said several times. However, it depends on the details whether you get the correct results. I'll just focus on the three contrast tests rather than the omnibus test for this part.
that we need to list the contrasts as predictors. This implementation yields the compound symmetry version of repeated measures that mimics the incorrect p values that came out of the contrasts in the afex package above. I also repeat the example using another function in the nlme package that you'll find references a lot on the web for doing repeated measures anova called gls(). I tried changing the covariance matrix in gls call to a free matrix like in the multivariate approach. This produced p values close to the correct results but not identical.

```r
> library(nlme)
> out.lme <- lme(dv ~ m1+m2+int, random = ~1|sub,
+     data=data.frame(data.oneway), weight=varIdent(form=~1|time),
+     method="REML")
> summary(out.lme)
```

Linear mixed-effects model fit by REML
Data: data.frame(data.oneway)
  AIC   BIC  logLik
253.7848 269.8425 -117.8924

Random effects:
  Formula: ~1 | sub
     (Intercept) Residual
    StdDev: 9.763877 1.669695

Variance function:
  Structure: Different standard deviations per stratum
  Formula: ~1 | time
  Parameter estimates:

Fixed effects: dv ~ m1 + m2 + int
  Value Std.Error DF t-value p-value
(Intercept) 107.60417 2.8311246 33 38.00757 0.0000
m1 -0.27083 0.2661305 33 -1.01767 0.3162
m2 -0.27083 0.2661305 33 -1.01767 0.3162
int -0.06250 0.2661305 33 -0.23485 0.8158

Correlation:
  (Intr) m1 m2
m1 -0.055
m2 -0.018 0.599
int 0.056 -0.189 -0.590

Standardized Within-Group Residuals:

```
> out.gls <- gls(dv ~ m1+m2+int, 
+             data=data.frame(data.oneway), 
+             method="REML") 
> summary(out.gls)

Generalized least squares fit by REML
Model: dv ~ m1 + m2 + int
Data: data.frame(data.oneway)

AIC BIC logLik
354.0678 362.9887 -172.0339

Coefficients:

                     Value Std.Error  t-value p-value
(Intercept)    107.60417  1.461347  73.63355  0.0000
m1             -0.27083  1.461347  -0.18533  0.8538
m2             -0.27083  1.461347  -0.18533  0.8538
int             -0.06250  1.461347  -0.04277  0.9661

Correlation:

       (Intr) m1  m2
m1    0
m2   -0.06250  0
int  -0.06250  0  0

Standardized residuals:

Min             Q1           Med          Q3          Max
-1.481553333   -0.86629716   0.01234628   0.68521842   1.90955763

Residual standard error: 10.12451
Degrees of freedom: 48 total; 44 residual

Both commands give very different results to each other, and both results are different from
the aov_ez command I ran above. Strange. If you do a web search you will see repeated
measures tutorials that present these but hardly any discussion on the vast differences
between them.

Let’s move toward something that works (almost). Recall the key to contrasts in repeated
measures is that we should use the multivariate approach to avoid the compound symme-
try/sphericity assumptions. In order to do that we need to extend the linear mixed model
to have a free covariance matrix rather than a covariance matrix that makes the restrictive
assumptions. The end result is a better error term from the multivariate approach. SPSS
does this automatically in MANOVA and the method of creating scores for each subject
followed by one sample t tests also does this automatically. Here is how to do it in lme and
gls.

```r
> # had to increase iteration number for convergence
> out.lme <- lme(dv ~ m1+m2+int, random = ~1|sub,
+   correlation = corSymm(form = ~1|sub),
+   data=data.frame(data.oneway), weight=varIdent(form=~1|time),
+   method="REML",control=lmeControl(maxIter=100,msMaxIter=200))
> summary(out.lme)
Linear mixed-effects model fit by REML
Data: data.frame(data.oneway)
  AIC     BIC   logLik
234.3039 261.0667 -102.1519
Random effects:
Formula: ~1 | sub
  (Intercept) Residual
  StdDev: 9.210681 3.474544
Correlation Structure: General
  Formula: ~1 | sub
  Parameter estimate(s):
    Correlation:
      1    2    3
    2 0.879
    3 0.745 0.973
    4 0.551 0.870 0.951
Variance function:
  Structure: Different standard deviations per stratum
  Formula: ~1 | time
  Parameter estimates:
     1       2       3       4
  1.0000000 0.9324562 1.3315815 1.4871948
Fixed effects: dv ~ m1 + m2 + int
    Value Std.Error DF  t-value p-value
  (Intercept) 107.60417  2.8825590 33 37.32939 0.0000
   m1  -0.27083  0.4202027 33  -0.64453 0.5237
   m2  -0.27083  0.2228822 33  -1.21514 0.2329
   int  -0.06250  0.0821411 33  -0.76089 0.4521
  Correlation:
    (Intr)  m1    m2
  m1   -0.220
  m2  -0.072  0.905
```
int -0.055 0.216 0.045

Standardized Within-Group Residuals:

<table>
<thead>
<tr>
<th>Min</th>
<th>Q1</th>
<th>Med</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1.5744230</td>
<td>-0.8529488</td>
<td>-0.2596430</td>
<td>0.9401155</td>
<td>1.6252264</td>
</tr>
</tbody>
</table>

Number of Observations: 48
Number of Groups: 12

> #correct specification of the covariance matrix
> out.gls <- gls(dv ~ m1+m2+int,
+   correlation = corSymm(form = ~time|sub),
+   data=data.frame(data.oneway), weight=varIdent(form=~1|time),
+   method="REML")
> summary(out.gls)

Generalized least squares fit by REML
Model: dv ~ m1 + m2 + int
Data: data.frame(data.oneway)
AIC      BIC    logLik
232.3039 257.2825 -102.1519

Correlation Structure: General
Formula: ~time | sub
Parameter estimate(s):
Correlation:
   1     2     3
1 1.0000 0.986 0.954
2 0.986 1.0000 0.964
3 0.954 0.964 1.000
4 0.911 0.964 0.988

Variance function:
Structure: Different standard deviations per stratum
Formula: ~1 | time
Parameter estimates:
   1     2     3     4
1.0000000 0.9918367 1.0470485 1.0728254

Coefficients:

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>Std.Error</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>107.60417</td>
<td>2.8825589</td>
<td>37.32939</td>
<td>0.0000</td>
</tr>
<tr>
<td>m1</td>
<td>-0.27083</td>
<td>0.4202029</td>
<td>-0.64453</td>
<td>0.5226</td>
</tr>
<tr>
<td>m2</td>
<td>-0.27083</td>
<td>0.2228822</td>
<td>-1.21514</td>
<td>0.2308</td>
</tr>
<tr>
<td>int</td>
<td>-0.06250</td>
<td>0.0821411</td>
<td>-0.76089</td>
<td>0.4508</td>
</tr>
</tbody>
</table>

Correlation:
(Intr) m1     m2
m1  -0.220
m2  -0.072  0.905
int -0.055  0.216  0.045

Standardized residuals:

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>Q1</th>
<th>Med</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-1.52373366</td>
<td>-0.84563270</td>
<td>0.00925861</td>
<td>0.66895594</td>
<td>1.87567567</td>
</tr>
</tbody>
</table>

Residual standard error: 9.84424
Degrees of freedom: 48 total; 44 residual

One thing to notice about the lme and gls output is that the t tests for the fixed effects contrasts are correct, but the pvalues are off. This is because the incorrect DFs are used; both tests use df = 33, which is (n-1)(t-1). If we use the right DFs (which should be 11=n-1) we get the correct p-values that match SPSS and the one sample t test method. To illustrate I extract the t values and use df = n - 1 to recompute the pvalues. This corresponds to the correct answers.

```r
> tvals <- summary(out.gls)[[18]][2:4,3]
> tvals

   m1          m2         int
-0.6445299 -1.2151413 -0.7608857

> (1-pt(abs(tvals),11))*2

   m1          m2         int
0.5324424  0.2497504  0.4627246
```

To show you that this is just a degrees of freedom issue, let me take the same t values and reproduce the lme pvalues with 33 degrees of freedom and the gls degrees of freedom with 44 degrees of freedom.

```r
> #reproduce lme pvalues with 33 df
> (1-pt(abs(tvals),33))*2

   m1          m2         int
0.5236873  0.2329349  0.4521283

> #reproduce lme pvalues with 44 df
> (1-pt(abs(tvals),44))*2

   m1          m2         int
0.5236873  0.2329349  0.4521283
```
### I wish using `lme` would be easier so one doesn’t have to adjust p-values manually. The primary advantage of the linear mixed model approach is that it allows for missing data. The traditional repeated measures requires subjects to have data for all times or they are excluded from the analysis. The linear mixed model keeps all available data. It also handles unbalanced designs pretty well and can take advantage of all the generalizations we will add to the mix when we cover regression.

I’ll next use the `lmer` function in the `lme4` package as a different way to implement the linear mixed model. I have to put the data in long format first. I’ll make the contrasts into factors this time to illustrate another complication of using R I will discuss right after examining the output.

```r
> dv <- c(data[,2],data[,3],data[,4],data[,5])
> sub <- factor(rep(1:12,4))
> m1 <- factor(rep(c(1,1,-1,-1),each=12))
> m2 <- factor(rep(c(1,-1,1,-1),each=12))
> int <- factor(rep(c(1,-1,-1,1),each=12))
> #print to see the data matrix
> cbind(sub, dv,m1,m2,int)

```

<table>
<thead>
<tr>
<th>sub</th>
<th>dv</th>
<th>m1</th>
<th>m2</th>
<th>int</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>92</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>120</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>112</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>95</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>114</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>99</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>7</td>
<td>124</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>106</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>9</td>
<td>100</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>10</td>
<td>108</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>11</td>
<td>112</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>12</td>
<td>102</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>13</td>
<td>95</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>121</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>15</td>
<td>111</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>16</td>
<td>96</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>17</td>
<td>112</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>18</td>
<td>100</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>19</td>
<td>125</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>20</td>
<td>107</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>21</td>
<td>98</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

---

I wish using `lme` would be easier so one doesn’t have to adjust p-values manually. The primary advantage of the linear mixed model approach is that it allows for missing data. The traditional repeated measures requires subjects to have data for all times or they are excluded from the analysis. The linear mixed model keeps all available data. It also handles unbalanced designs pretty well and can take advantage of all the generalizations we will add to the mix when we cover regression.

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```r
> dv <- c(data[,2],data[,3],data[,4],data[,5])
> sub <- factor(rep(1:12,4))
> m1 <- factor(rep(c(1,1,-1,-1),each=12))
> m2 <- factor(rep(c(1,-1,1,-1),each=12))
> int <- factor(rep(c(1,-1,-1,1),each=12))
> #print to see the data matrix
> cbind(sub, dv,m1,m2,int)

```
> library(lme4)
> # this will be compound symmetric assumed; lmer doesn't have a way to
> # estimate free covariance matrices (the correlation and weight arguments # in lme)
> out.lmer <- lmer(dv~m1+m2+int+(1|sub),REML=T)
> summary(out.lmer)

Linear mixed model fit by REML ['lmerMod']
Formula: dv ~ m1 + m2 + int + (1 | sub)

REML criterion at convergence: 245.5

Scaled residuals:
     Min     1Q   Median     3Q    Max
-1.72501 -0.55292  0.02703  0.43664  1.94363

Random effects:
Groups   Name     Variance Std.Dev.
sub      (Intercept) 1.094   1.046

[22,]  10  110 2 1 1
[23,]  11  115 2 1 1
[24,]  12  102 2 1 1
[25,]   1  96  1 2 1
[26,]   2  121 1 2 1
[27,]   3  111 1 2 1
[28,]   4  98  1 2 1
[29,]   5  110 1 2 1
[30,]   6  99  1 2 1
[31,]   7  127 1 2 1
[32,]   8  106 1 2 1
[33,]   9  95  1 2 1
[34,]  10  112 1 2 1
[35,]  11  116 1 2 1
[36,]  12  101 1 2 1
[37,]   1  98  1 1 2
[38,]   2  123 1 1 2
[39,]   3  109 1 1 2
[40,]   4  99  1 1 2
[41,]   5  109 1 1 2
[42,]   6  98  1 1 2
[43,]   7  126 1 1 2
[44,]   8  107 1 1 2
[45,]   9  94  1 1 2
[46,]  10  115 1 1 2
[47,]  11  118 1 1 2
[48,]  12  101 1 1 2
sub (Intercept) 98.778 9.939
Residual 3.728 1.931
Number of obs: 48, groups: sub, 12

Fixed effects:

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Std. Error</th>
<th>t value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept) 108.2083</td>
<td>2.9227</td>
<td>37.02</td>
</tr>
<tr>
<td>m11 -0.5417</td>
<td>0.5574</td>
<td>-0.97</td>
</tr>
<tr>
<td>m21 -0.5417</td>
<td>0.5574</td>
<td>-0.97</td>
</tr>
<tr>
<td>int1 -0.1250</td>
<td>0.5574</td>
<td>-0.22</td>
</tr>
</tbody>
</table>

Correlation of Fixed Effects:

<table>
<thead>
<tr>
<th></th>
<th>(Intr)</th>
<th>m11</th>
<th>m21</th>
</tr>
</thead>
<tbody>
<tr>
<td>m11</td>
<td>-0.095</td>
<td></td>
<td></td>
</tr>
<tr>
<td>m21</td>
<td>-0.095</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>int1</td>
<td>-0.095</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

But note there are no pvalues or degrees of freedom listed. That is because the developer of the lme4 package recognizes that it is not easy to write general code to do this correctly across different types of packages. Other people have written additional packages to add onto lme4 (like pbkrtest, lmertest, lmerconveniencefunctions), but these should be used with caution and test them out on data where you know the answer and can compare to other programs that give the correct answer like SPSS manova.

An Aside:

There is an R detail here to point out about the use of factors. Even though three contrasts were defined as factors with values of 1 and -1, when they are printed as numerical values (like after a cbind command) the original numbers are converted to integers starting with 1 as in 1s and 2s in the case of two groups. When factors are used in formulas, their contrast values are used rather than the numerical codes used for the levels. So a weird thing can happen when using R. A factor can have one set of values, a different set of values when it is converted into numerical values, and a third set of values when used in a regression command like lmer. One needs to be careful when interpreting output from a statistics command like a regression. For example,

> #define test as 1s and -1s
> test <- c(1,1,1,-1,-1,-1)
> test

[1]  1  1  1 -1 -1 -1

> #convert to factor, remains as 1s and -1s
> test.factor <- factor(test)
> test.factor

[1] 1 1 1 -1 -1 -1
[1] 1 1 1 -1 -1 -1
Levels: -1 1

> # put into a matrix, test remains 1s and -1s
> # but test.factor is converted to 1s and 2s
> cbind(test, test.factor)

   test test.factor
[1,] 1     2
[2,] 1     2
[3,] 1     2
[4,] -1    1
[5,] -1    1
[6,] -1    1

> # regressions like lm, lmer, glm, etc.,
> # use the contrast codes of factor, which default
> # to dummy codes 1s and 0s; a different set of contrasts than
> # maybe one would expect with 1 and -1
> contrasts(test.factor)

   1
-1 0
1 1

General point: be careful. Don’t just look at the web for an example and use that one. You may be doing a different analysis than the one you think you are doing. An understand linear mixed model if you are going to use it. Don’t just read a blog post that gives an example of a repeated measures anova using linear mixed models and assume it is implemented correctly. You can see how I got very different results one a simple one way repeated measures anova just by tiny changes in the commands, not paying attention to the degrees of freedom I should expect to see to identify when the analysis is going awry, etc.

Two way repeated measure ANOVA

Here is an example with two within subject factors. For simplicity I merely took the one way anova with 4 times and arranged it as a 2x2 repeated measures anova. So there are two factors (m1 and m2) each with two levels. We’ll examine the two main effects and the interaction.

> library(afex)
> summary(aov_ez("sub", "dv", data=data.oneway, within=c("m1","m2")))

Univariate Type III Repeated-Measures ANOVA Assuming Sphericity

<table>
<thead>
<tr>
<th></th>
<th>SS num Df Error SS den Df</th>
<th>F</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
</table>

This yields the correct 3 pvalues per the t tests I did earlier (the one where I manually computed the contrast values for each subject and performed one sample t tests). But this result has 0 sum of squares for the interaction, which can’t be right if the F is .5789. The p values are correct. So something is definitely weird about this output even though it produced the correct pvalues. Note that for a two way ANOVA where each factor has two levels, the \texttt{aov_ez} command produced the correct pvalues, but for the same data represented as a one way ANOVA with four levels it imposed the compound symmetry assumption and yielded incorrect t tests and pvalues. Another weird aspect about repeated measures in R.

\textit{One Between and One Repeated Measures factor}

Finally, an example with one repeated measures and one between subjects. You could just do the contrasts on the sum and difference like I show in the lecture notes (being mindful of the degrees of freedom), but if you want to do this with R packages here is how you would go about it. There are fancier ways of moving data between wide format and long format (see cast and melt commands in the reshape package), here I just do it the bonehead way so you can see clearly what is going on. I illustrate with \texttt{lmer} in the \texttt{lme4} package, replicate with \texttt{mixed} in the \texttt{afex} package, then replicate again with \texttt{lme} from the \texttt{nlme} package, and finally replicate with the \texttt{Anova} function from the \texttt{car} package (interesting way of converting a regular linear model from \texttt{lm} into a mixed design). These are just for illustration; there are other packages that do this too and you may find them easier. I suggest you learn all the options in the program you choose (\texttt{lmer}, etc) and try out several data sets from textbooks you trust until you can recreate the example output. Next semester I will share a very concise function that allows us to test any contrast in any repeated measures, between subjects or mixed designs. It uses some concepts that will be covered in Lecture Notes 10 and 11. It is what I typically use in my own data; it replicates SPSS \texttt{manova} so I’m happy. I do not recommend you just run one program in R you know like \texttt{lme} or \texttt{lmer} and go with that. It is likely that you’ll have an incorrect answer unless you know exactly what you are doing.

Note: this is an easy example because both factors have two levels. You’ll need to double check that this all works in your setting where the repeated measures factor may have more than two levels and the R command you are using may invoke additional assumptions like compound symmetry.

\begin{verbatim}
> data <- cbind(1:16, rep(1:2, each=8),
+ c(8.6,7.5,8.3,8.4,6.4,6.9,6.5,6.7,7.3,7.5,6.4,6.8,7.1,8.2,7.2,6.7),
+ c(8.6,7.5,8.3,8.4,6.4,6.9,6.5,6.7,7.3,7.5,6.4,6.8,7.1,8.2,7.2,6.7)),
\end{verbatim}
+ c(8.7,1.7,4.7,3.6,4.6,8.6,8.6,6.1,5.7,7.9,7.6,6.3,7.5,7.7,8.6,7.8,6.9))
> #data
> longdata <- rbind(data[,4],data[,3])
> longdata <- cbind(longdata,rep(1:2,each=16))
> colnames(longdata) <- c("sub", "sequence", "dv", "period")
> longdata <- data.frame(longdata)
> longdata$sequence <- factor(longdata$sequence)
> longdata$period <- factor(longdata$period)
> longdata$sub <- factor(longdata$sub)
> #some functions like gee require data to be ordered by subject
> #longdata <- longdata[order(longdata$sub),]
> longdata

    sub sequence  dv period
  1    1        1   8.6    1
  2    2        1   7.5    1
  3    3        1   8.3    1
  4    4        1   8.4    1
  5    5        1   6.4    1
  6    6        1   6.9    1
  7    7        1   6.5    1
  8    8        1   6.0    1
  9    9        2   7.3    1
 10   10       2   7.5    1
 11   11       2   6.4    1
 12   12       2   6.8    1
 13   13       2   7.1    1
 14   14       2   8.2    1
 15   15       2   7.2    1
 16   16       2   6.7    1
 17   1        2   8.0    2
 18   2        2   7.1    2
 19   3        2   7.4    2
 20   4        2   7.3    2
 21   5        2   6.4    2
 22   6        2   6.8    2
 23   7        2   6.1    2
 24   8        2   5.7    2
 25   9        2   7.9    2
 26  10        2   7.6    2
 27  11        2   6.3    2
 28  12        2   7.5    2
 29  13        2   7.7    2
 30  14        2   8.6    2
 31  15        2   7.8    2
> library(car)
> # first with lmer; replicates MANOVA output in SPSS, Anova is in the car package
> out1 <- lmer(dv~ period*sequence + (1|sub), REML=T, data=longdata)
> temp <- Anova(out1, type="II", test.statistic="F")
> temp

Analysis of Deviance Table (Type II Wald F tests with Kenward-Roger df)

Response: dv

<table>
<thead>
<tr>
<th>Effect</th>
<th>df</th>
<th>F</th>
<th>Df.res</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>period</td>
<td>1</td>
<td>0.27</td>
<td>1</td>
<td>0.6109803</td>
</tr>
<tr>
<td>sequence</td>
<td>1</td>
<td>0.46</td>
<td>1</td>
<td>0.5070293</td>
</tr>
<tr>
<td>period:sequence</td>
<td>1</td>
<td>26.30</td>
<td>1</td>
<td>0.0001534***</td>
</tr>
</tbody>
</table>

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> # second with the package afex, replicates MANOVA output in SPSS
> library(afex)
> out2 <- mixed(dv~ period*sequence + (1|sub), longdata, method="KR")

Fitting one lmer() model. [DONE]
Calculating p-values. [DONE]

> out2

Mixed Model Anova Table (Type 3 tests, KR-method)

Model: dv ~ period * sequence + (1 | sub)
Data: longdata

<table>
<thead>
<tr>
<th>Effect</th>
<th>df</th>
<th>F</th>
<th>p.value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 period</td>
<td>1</td>
<td>0.27</td>
<td>.61</td>
</tr>
<tr>
<td>2 sequence</td>
<td>1</td>
<td>0.46</td>
<td>.51</td>
</tr>
<tr>
<td>3 period:sequence</td>
<td>1</td>
<td>26.30</td>
<td>.0002</td>
</tr>
</tbody>
</table>

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> # summary(out2)
>
> # third with the package nlme, replicates MANOVA output in SPSS
> library(nlme)
> out3 <- lme(fixed=dv ~ sequence*period, random=~1|sub, data=longdata)
> print(anova(out3))
Lecture Notes #5: Advanced topics in ANOVA

<table>
<thead>
<tr>
<th>numDF</th>
<th>denDF</th>
<th>F-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
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<td>1470.5256</td>
</tr>
<tr>
<td>sequence</td>
<td>1</td>
<td>14</td>
<td>0.4637</td>
</tr>
<tr>
<td>period</td>
<td>1</td>
<td>14</td>
<td>0.2707</td>
</tr>
<tr>
<td>sequence:period</td>
<td>1</td>
<td>14</td>
<td>26.3038</td>
</tr>
</tbody>
</table>

```r
> #fourth approach with car package and lm
data <- data.frame(data)
colnames(data) <- c("sub","sequence","P1","P2")
period.factor <- factor(c("period1","period2"))
idata <- data.frame(period.factor=period.factor)
temp <- lm(cbind(P1,P2) ~sequence, data=data)
out4 <- Anova(temp, idata=idata, idesign=~period.factor, type="II")
summary(out4)
```

Type II Repeated Measures MANOVA Tests:

------------------------------------------
Term: (Intercept)

Response transformation matrix:

(Intercept)

P1 1
P2 1

Sum of squares and products for the hypothesis:

(Intercept) 3332.176

Multivariate Tests: (Intercept)

<table>
<thead>
<tr>
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<th>approx F</th>
<th>numDf</th>
<th>denDf</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>1470.522</td>
<td>1</td>
<td>14</td>
<td>1.3955e-15 ***</td>
</tr>
<tr>
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<td>0.00943</td>
<td>1470.522</td>
<td>1</td>
<td>14</td>
<td>1.3955e-15 ***</td>
</tr>
<tr>
<td>Hotelling-Lawley</td>
<td>1</td>
<td>105.03726</td>
<td>1470.522</td>
<td>1</td>
<td>14</td>
<td>1.3955e-15 ***</td>
</tr>
<tr>
<td>Roy</td>
<td>1</td>
<td>105.03726</td>
<td>1470.522</td>
<td>1</td>
<td>14</td>
<td>1.3955e-15 ***</td>
</tr>
</tbody>
</table>

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

------------------------------------------
Term: sequence

Response transformation matrix:

(Intercept)
Multivariate Tests: sequence

<table>
<thead>
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<th>num Df</th>
<th>den Df</th>
<th>Pr(&gt;F)</th>
</tr>
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<tbody>
<tr>
<td>Pillai</td>
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<td>0.0320563</td>
<td>0.4636511</td>
<td>1</td>
<td>14</td>
</tr>
<tr>
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<td>0.4636511</td>
<td>1</td>
<td>14</td>
</tr>
<tr>
<td>Hotelling-Lawley</td>
<td>1</td>
<td>0.0331179</td>
<td>0.4636511</td>
<td>1</td>
<td>14</td>
</tr>
<tr>
<td>Roy</td>
<td>1</td>
<td>0.0331179</td>
<td>0.4636511</td>
<td>1</td>
<td>14</td>
</tr>
</tbody>
</table>

Term: period.factor

Response transformation matrix:

<table>
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<th>P1</th>
<th>P2</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>1</td>
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</tr>
<tr>
<td>P2</td>
<td>-1</td>
<td></td>
</tr>
</tbody>
</table>

Sum of squares and products for the hypothesis:

| period.factor1 | | | |
|----------------|----------------|
| period.factor1 | 0.030625 | | |

Multivariate Tests: period.factor

<table>
<thead>
<tr>
<th>Df</th>
<th>test.stat</th>
<th>approx F</th>
<th>num Df</th>
<th>den Df</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
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<td>0.0189702</td>
<td>0.2707182</td>
<td>1</td>
<td>14</td>
</tr>
<tr>
<td>Wilks</td>
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<td>0.9810298</td>
<td>0.2707182</td>
<td>1</td>
<td>14</td>
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<tr>
<td>Hotelling-Lawley</td>
<td>1</td>
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<td>0.2707182</td>
<td>1</td>
<td>14</td>
</tr>
<tr>
<td>Roy</td>
<td>1</td>
<td>0.0193370</td>
<td>0.2707182</td>
<td>1</td>
<td>14</td>
</tr>
</tbody>
</table>

Term: sequence:period.factor

Response transformation matrix:

<table>
<thead>
<tr>
<th>period.factor1</th>
<th>P1</th>
<th>P2</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>P2</td>
<td>-1</td>
<td></td>
</tr>
</tbody>
</table>

Sum of squares and products for the hypothesis:

| period.factor1 | | | |
|----------------|----------------|
| period.factor1 | | | |
Multivariate Tests: sequence:period.factor

<table>
<thead>
<tr>
<th></th>
<th>Df</th>
<th>test</th>
<th>stat</th>
<th>approx F</th>
<th>num Df</th>
<th>den Df</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
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<td>1</td>
<td>14</td>
<td>0.00015337 ***</td>
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<tr>
<td>Wilks</td>
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<td>0.3473612</td>
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<td>1</td>
<td>14</td>
<td>0.00015337 ***</td>
<td></td>
</tr>
<tr>
<td>Hotelling-Lawley</td>
<td>1</td>
<td>1.8788477</td>
<td>26.30387</td>
<td>1</td>
<td>14</td>
<td>0.00015337 ***</td>
<td></td>
</tr>
<tr>
<td>Roy</td>
<td>1</td>
<td>1.8788477</td>
<td>26.30387</td>
<td>1</td>
<td>14</td>
<td>0.00015337 ***</td>
<td></td>
</tr>
</tbody>
</table>

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Univariate Type II Repeated-Measures ANOVA Assuming Sphericity

<table>
<thead>
<tr>
<th></th>
<th>SS</th>
<th>num Df</th>
<th>Error</th>
<th>SS</th>
<th>den Df</th>
<th>F</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>1666.09</td>
<td>1</td>
<td>15.8619</td>
<td>14</td>
<td>1470.5216</td>
<td>1.395e-15 **</td>
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</tr>
<tr>
<td>sequence</td>
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<td>1</td>
<td>15.8619</td>
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<td></td>
</tr>
<tr>
<td>period.factor</td>
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<td>1</td>
<td>0.7919</td>
<td>14</td>
<td>0.2707</td>
<td>0.6109803</td>
<td></td>
</tr>
<tr>
<td>sequence:period.factor</td>
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<td>1</td>
<td>0.7919</td>
<td>14</td>
<td>26.3039</td>
<td>0.0001534 ***</td>
<td></td>
</tr>
</tbody>
</table>

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> #fifth approach using the lmerTest package which redefines the lmer function
> #no need to use the Anova() function from the car package; lmerTest
> #redefines the anova function that works on the lmer object
> library(lmerTest)
> out5 <- lmer(dv~ period*sequence + (1|sub),REML=T,data=longdata)
> temp <- anova(out5)
> temp

Analysis of Variance Table of type III with Satterthwaite
approximation for degrees of freedom

<table>
<thead>
<tr>
<th></th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>NumDF</th>
<th>DenDF</th>
<th>F.value</th>
<th>Pr(&gt;F)</th>
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<tbody>
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<td>0.01531</td>
<td>1</td>
<td>14</td>
<td>0.2707</td>
<td>0.6109803</td>
</tr>
<tr>
<td>sequence</td>
<td>0.02623</td>
<td>0.02623</td>
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<td>14</td>
<td>0.4637</td>
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</tr>
<tr>
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<td>1.48781</td>
<td>1</td>
<td>14</td>
<td>26.3039</td>
<td>0.0001534 ***</td>
</tr>
</tbody>
</table>

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> anova(out5, type=2)

Analysis of Variance Table of type II with Satterthwaite
approximation for degrees of freedom

<table>
<thead>
<tr>
<th></th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>NumDF</th>
<th>DenDF</th>
<th>F.value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>period</td>
<td>0.01531</td>
<td>0.01531</td>
<td>1</td>
<td>14</td>
<td>0.2707</td>
<td>0.6109803</td>
</tr>
</tbody>
</table>
What a mess. So many different ways to do this in R, and one needs to be careful because each different approach requires one to be mindful of a particular set of details