ABSTRACT

One of the most common research designs in the analysis of empirical data is the repeated measures ANOVA. Yet despite the frequency with which this type of design is encountered, SAS offers no "automatic" procedure for analyzing such data. Consequently, the purpose of the present paper is to show that repeated measures designs are indeed capable of being analyzed by SAS. With a few relatively simple assignment statements, a user can obtain not only an "overall" repeated measures ANOVA, but can also test specified contrasts from among the repeated measures.

In terms of the overall analysis, the paper details how the user can (1) employ the OUTPUT statement to appropriately modify the data array for entry into PROC ANOVA or PROC GLM; (2) utilize an artificial classification variable (SUBJECTS) as a nested variable to create the error term for all completely crossed factors; and (3) use the residual error term to test the repeated measures main effects and interactions.

The paper goes on to discuss a method for further decomposing the design into single df contrasts. It discusses not only how to construct such contrasts but also how to normalize them so as to obtain numerically correct sums-of-squares. In addition, it explains how the NOINT option in GLM should be employed to test these contrasts. Data from two recent empirical studies are employed to illustrate these analyses.

INTRODUCTION

This paper addresses the topic of analyzing experimental designs in which each experimental unit (e.g., subject) is observed and measured at each of several different levels of an experimental factor (trials, time periods, etc.). Designs such as these are commonly referred to as "repeated measures" (R-M) designs. As Winer (1971) suggests, designs which incorporate repeated measures are frequently employed in the social sciences, for they offer the experimenter increased control over individual differences among the experimental units. This results in a concomitant increase in the precision with which the statistical parameters can be estimated. A second, and somewhat more dubious advantage of their use is economy of subjects—"by having each subject serve as his own control (and hence increasing the precision of parameter estimation), the experimenter attempts to work with a smaller sample size" (Winer, 1971, p. 517).

Given that the researcher is faced with the analysis of a R-M design, it becomes immediately apparent that SAS offers no "automatic" procedure for analyzing such a design. By "automatic," I simply mean that no SAS procedure exists whereby an unmodified data set can be directly submitted, and an appropriate analysis can be directly obtained. Despite this fact, it is the purpose of this paper to suggest that SAS is indeed capable of correctly analyzing R-M designs. With a few relatively simple assignment statements, a user can obtain not only an "overall" repeated measures ANOVA, but can also test specified contrasts from among the repeated measures. The remainder of this paper, therefore, details these procedures and offers examples of their application to empirically derived data.

Before beginning this discussion, however, one additional introductory note is in order. Whenever several, repeated measures are obtained on a single experimental unit, these measurements cannot be assumed to be statistically independent. As a result, special assumptions about the nature of their dependence and/or special analytic techniques are required. Although these assumptions and techniques are discussed briefly in later sections, it is assumed for the purpose of this paper that the covariance matrices of the R-M designs to be analyzed exhibit "compound symmetry" (Winer, 1971, pp. 522-524). In actual practice, of course, such assumptions should be empirically verified (see Greenhouse & Geisser, 1959; Box, 1953).

PERFORMING R-M ANALYSES

For the purpose of illustration, the following discussion assumes a 3 x 2 x 3 mixed model design. Factors A and B (with 3 and 2 levels, respectively) are assumed to be completely randomized or "between-groups" factors—each experimental unit is measured at only one level of each factor. Factor C possesses three levels, which correspond to experimental "Trials." Since each subject is measured on each of the three Trials, factor C is the R-M factor.
Analytic Options and the Implementation of SAS

A researcher who is faced with the type of design outlined above has three different, but certainly not mutually exclusive, analytic options within the SAS system. The first of these, which basically foregoes the mixed-model ANOVA in favor of a completely randomized MANOVA, has been advocated by Finn (1969, 1974), Bock (1963), and others. These authors maintain that the assumption of compound symmetry is seldom met in practice. As a result, performing a univariate, R-M ANOVA in these instances will produce inaccurate results. Their proposed alternative is to treat the levels of the R-M factor as multiple dependent measures and submit them to a multivariate analysis of variance. Since MANOVA makes no assumption of compound symmetry (see Graybill, 1976), this approach offers clear-cut advantages in some situations. Nevertheless, its implementation into SAS is a straightforward application of the GLM procedure and hence it requires no additional discussion in terms of the primary purpose of this paper.

The remaining two approaches, however, are not so straightforward in terms of SAS procedures. The underpinnings of these two approaches has been discussed in detail by Poor (1973), and he labels them the "traditional" and the "alternative" approaches. Perhaps a more heuristic labelling would be the "overall" and "contrast" approaches. As Poor (1973) suggests, and as shall be seen in subsequent examples, these options are equivalent in their numerical output, but different in terms of (1) their implementation into SAS, and (2) the purposes to which they might be put by a researcher.

The Traditional or Overall Approach

Perhaps the most heuristic way to describe the overall approach is to suggest that it attempts to incorporate all sources of variation for a factor into a single scalar quantity or sums-of-squares (SS), and to perform a single test of significance on the overall "main effect" of the factor. If more than one factor is included in the design, interaction effects must also be tested. (Table 2 presents an example of the typical output produced by this approach.)

Many times, this approach is viewed as preliminary to a more detailed decomposition of the various SS; i.e., an initial determination of whether any significant variation has occurred in the design. In fact, if the researcher's hypotheses do not predict specific, a priori differences between levels of a factor, this preliminary, overall analysis is requisite (Scheffe, 1959).

In order to analyze such a design, several writers (Poor, 1973; Winer, 1971) have suggested creating an additional, dummy-like, between-groups factor—namely, Subjects. Although the Subjects factor has "n" levels, each level appears in one and only one level (cell) of the other between groups factors. Consequently, Subjects can be treated as a random factor which is nested within the cells of the other between-groups factors. These factors (and their interaction) can then be tested by employing the main effect of Subjects-nested-within-groups as the error term. The remaining repeated measures factors and their interactions can be tested by the residual error term.

Implementation

To perform this overall or traditional analysis in SAS, two important considerations must be kept in mind. First, since each subject is treated as a unique level of the Subjects factor, each subject must be given a distinct and ideally continuous numerical designation (i.e., 1 through n). This allows the ANOVA or GLM procedure to treat Subjects as a classification (independent) variable.

The second consideration concerns the way in which the data are arrayed. It would seem a normal practice to include all of the data for a subject on a single computer card. To perform the overall analysis, however, each observation (for the present example, each Trial!) must be arrayed as if on an individual card. Obviously, this could be achieved by actually punching a separate card for each observation, but this method precludes using the same data set to perform the "contrast" analysis discussed in subsequent sections. As an alternative, the OUTPUT statement can be used to create the appropriate data array. The sample deck set-up in Table 1 illustrates both the use of the OUTPUT statement and the appropriate control cards to perform the overall, R-M ANOVA.

Table 1. SAS control cards needed to perform the overall, R-M analysis

DATA KIDS;
INPUT SUBJECT METHOD REIN SESSION1 SESSION2 SESSION3;
C=1; SCORE=SESSION1; OUTPUT;
C=2; SCORE=SESSION2; OUTPUT;
C=3; SCORE=SESSION3; OUTPUT;
CARDS;
.
.
PROC GLM;
*THE ANOVA PROCEDURE COULD ALSO BE USED;
CLASS SUBJECT REIN METHOD C;
MODEL SCORE = REIN METHOD REIN*METHOD SUBJECT
(REIN*METHOD) C REIN*C METHOD*C REIN*METHOD*C;
TEST R=REIN METHOD REIN*METHOD E=SUBJECT
(REIN*METHOD);
The procedure discussed above was applied to data collected in a recent study by Courtright and Courtright (1977), which investigated different methods of teaching grammatical rules to language disordered children. The first experimental factor consisted of three different teaching approaches and was labelled "Method." The second factor represented the presence or absence of a reinforcement variable and was labelled "Rein." Finally, factor "C" consisted of the three clinical sessions across which the children were observed and measured. Table 2 recreates the most salient aspects of the SAS output.

Table 2. Partial SAS output for overall, R-M analysis

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>Type I SS</th>
<th>F Value</th>
<th>Pr F</th>
</tr>
</thead>
<tbody>
<tr>
<td>REIN</td>
<td>1</td>
<td>0.75000000</td>
<td>0.06</td>
<td>0.8153</td>
</tr>
<tr>
<td>METHOD</td>
<td>2</td>
<td>406.12982963</td>
<td>14.97</td>
<td>0.0001</td>
</tr>
<tr>
<td>REIN*METHOD</td>
<td>2</td>
<td>18.30000000</td>
<td>0.68</td>
<td>0.5122</td>
</tr>
<tr>
<td>SUBJECT</td>
<td>30</td>
<td>1300.27777778</td>
<td>3.18</td>
<td>0.0001</td>
</tr>
<tr>
<td>REIN^C</td>
<td>2</td>
<td>7.38688889</td>
<td>0.27</td>
<td>0.7635</td>
</tr>
<tr>
<td>METHOD^C</td>
<td>4</td>
<td>12.81481281</td>
<td>0.24</td>
<td>0.9175</td>
</tr>
<tr>
<td>REIN*METHOD^C</td>
<td>4</td>
<td>21.44444444</td>
<td>0.39</td>
<td>0.8127</td>
</tr>
</tbody>
</table>

These data were taken from Courtright and Courtright (1977). The final step in implementing the contrast approach involves creating a variable to use in testing the contrasts. Because we have created contrasts, the primary statistical hypothesis is that the grand mean of each contrast is zero. From a general linear model approach (Graybill, 1976), this entails testing that the intercept of the model is significantly different from zero. To perform this test, a user must (1) set a constant equal to one for each subject, (2) include this constant as the first term on the right hand side of the model, and (3) employ the NOTEST option so that the automatic intercept is suppressed and the constant becomes (and is tested as) the intercept of the model. Table 3 presents the necessary control cards for performing the contrast analysis.

Table 3 presents the SAS output obtained from this analysis. It can be seen that three summary tables are produced—one for the between-groups factors and one for each of the two contrasts. It should be noted that for the two tables in which MU is included, the inclusion of the between-groups factors does not produce tests on their main effects and interaction. Rather, since MU is artificially included and tested, these additional tests represent the extent to which the contrast being tested by MU interacts with the between-groups factors. To illustrate this, one need simply combine the SS for the two summary tables which test MU, and (assuming the...
contrasts have been normalized) they will equal the SS for the R-M factors which were obtained from the overall analysis.

Table 3. SAS control cards needed to perform the contrast, R-M analysis

```
DATA KIDS;
INPUT SUBJECT METHOD REIN SESSION1 SESSION2 SESSION3;
TOTAL=(SESSION1 + SESSION2 + SESSION3)/SQRT(3);
LINEAR=(SESSION1 - SESSION3)/SQRT(2);
QUAD=(SESSION1 + SESSION3 - 2*SESSION2)/SQRT(6);
* EACH CONTRAST IS DIVIDED BY THE SQUARE ROOT OF THE SUM OF THE SQUARED ORTHOGONAL POLYNOMIAL COEFFICIENTS. THIS SUCCEEDS IN NORMALIZING THE CONTRASTS;
MU=1;
*THIS IS THE CONSTANT TERM NEEDED TO TEST THE CONTRASTS;
CARDS;
.PROC GLM;
CLASSES A B;
MODEL TOTAL = A B A*B;
*THIS MODEL TESTS THE COMPLETELY RANDOMIZED FACTORS OF THE DESIGN;
PROC GLM;
CLASSES A B;
MODEL LINEAR = A B A*B; NOINT;
```

Extensions and Qualifications

Returning to the discussion of the overall analysis, this approach can obviously be extended to designs which include additional R-M factors. For example, suppose that within each of the three Sessions, each subject was measured twice---e.g., Baseline/Experimental Treatment/Generalization design. Such a design would require that two R-M factors be analyzed and tested (see Courtright and Courtright, 1976 for an example). This extension, however, requires only that the number of OUTPUT statements be increased to include all combinations of the two R-M factors. Also, since this type of design would require a separate error term for each R-M factor, the Subjects factor must be nested within several additional combinations of factors and extra TEST statements must be included.

Again, however, these procedures are a straightforward extension of the basic overall analysis.

Table 4. Partial SAS output for contrast, R-M analysis

```
Source df  Type I SS  F Value Pr F
```

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>Type I SS</th>
<th>F Value</th>
<th>Pr F</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEPENDENT VARIABLE: TOTAL</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>REIN</td>
<td>1</td>
<td>0.75000000</td>
<td>0.02</td>
<td>0.8962</td>
</tr>
<tr>
<td>METHOD</td>
<td>2</td>
<td>408.12982963</td>
<td>4.71</td>
<td>0.0167</td>
</tr>
<tr>
<td>REIN*METHOD</td>
<td>2</td>
<td>18.50000000</td>
<td>0.21</td>
<td>0.8090</td>
</tr>
<tr>
<td>DEPENDENT VARIABLE: LINEAR</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MU</td>
<td>1</td>
<td>1568.00000000</td>
<td>91.90</td>
<td>0.0001</td>
</tr>
<tr>
<td>REIN</td>
<td>1</td>
<td>1.38688889</td>
<td>0.08</td>
<td>0.7774</td>
</tr>
<tr>
<td>METHOD</td>
<td>2</td>
<td>8.58333333</td>
<td>0.25</td>
<td>0.7792</td>
</tr>
<tr>
<td>REIN*METHOD</td>
<td>2</td>
<td>1.19444444</td>
<td>0.04</td>
<td>0.9656</td>
</tr>
<tr>
<td>DEPENDENT VARIABLE: QUAD</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MU</td>
<td>1</td>
<td>66.46296296</td>
<td>6.32</td>
<td>0.0175</td>
</tr>
<tr>
<td>REIN</td>
<td>1</td>
<td>6.00000000</td>
<td>0.59</td>
<td>0.4491</td>
</tr>
<tr>
<td>METHOD</td>
<td>2</td>
<td>4.23148148</td>
<td>0.21</td>
<td>0.8159</td>
</tr>
<tr>
<td>REIN*METHOD</td>
<td>2</td>
<td>20.25000000</td>
<td>0.99</td>
<td>0.3825</td>
</tr>
</tbody>
</table>

*These data were taken from Courtright and Courtright (1977).

A minor qualification is in order. As the number of R-M factors increases, the core requirements for SAS also increase. Perhaps more importantly, as the sample size increases (thus requiring more levels of the Subjects factor), core requirements increase dramatically. As a result, one may find that even moderately large designs require more core than can be supplied. The solution, of course, is to employ the contrast approach and then combine the SS from the several summary tables by hand. The results are equivalent, but since each MODEL statement in the contrast approach analyzes only a piece of the design, core requirements are considerably decreased.

One final extension concerns the construction of contrasts among the levels of the between-groups factors. Since this approach is discussed by Service (1972, p. 30), only a brief account will be included here. In the present example, the Method factor has three levels and thus can be decomposed into two contrasts. A linear contrast would result from including an Assignent statement such as:

```
LINEAR = (METHOD=1) - (METHOD=3);
```

And a quadratic contrast would result from including:

```
QUAD = (METHOD=1) + (METHOD=3) - 2*(METHOD=2);
```

It should be noted that since these are contrasts within the design matrix, no normaliza-
CONCLUSION

The purpose of this paper has been to indicate how SAS can be employed to analyze R-M ANOVA designs. Although a brief discussion of extensions was included, space does not allow a full treatment of this topic. A good rule of thumb, however, is that if a design can be analyzed by hand, it can be analyzed by SAS. Implementation into SAS, therefore, is a matter of conceiving of the design model in terms of its matrix algebra equivalent and implementing that matrix equivalent into SAS. Given the flexibility of SAS in general and the GLM procedure in particular, it seems safe to conclude that there are few designs which cannot be analyzed by SAS.

REFERENCES


