

OXFORD

SAS Companion for Experimental Design and Analysis for Psychology

Lynne J. Williams, Mette T. Posamentier,
Betty Edelman & Hervé Abdi



OXFORD UNIVERSITY
PRESS

Oxford University Press is a department of the University of Oxford.
It furthers the University's objective of excellence in research, scholarship
and education by publishing worldwide in

Oxford New York

Auckland Cape Town Dar es Salaam Hong Kong Karachi
Kuala Lumpur Madrid Melbourne Mexico City Nairobi
New Delhi Shanghai Taipei Toronto

With offices in

Argentina Austria Brazil Chile Czech Republic France Greece
Guatemala Hungary Italy Japan Poland Portugal Singapore
South Korea Switzerland Thailand Turkey Ukraine Vietnam

Oxford is a registered trade mark of Oxford University Press
in the UK and certain other countries

Published in the United States
by Oxford University Press, Inc., New York

© Lynne J. Williams, Mette T. Posamentier, Betty Edelman and Hervé Abdi 2009

The moral rights of the authors have been asserted
Database right Oxford University Press (maker)

First published 2009

All rights reserved.

Copies of this publication may be made for educational purposes.

Typeset by
Lynne J. Williams, London, Canada

1 3 5 7 9 10 8 6 4 2

Preface

You have successfully designed your first experiment, run the subjects, and you are faced with a mountain of data. What's next?¹ Does computing an analysis of variance by hand suddenly appear mysteriously attractive? Granted, writing a SAS program and actually getting it to run may appear to be quite an intimidating task for the novice, but fear not! There is no time like the present to overcome your phobias. Welcome to the wonderful world of SAS

The purpose of this book is to introduce you to relatively simple SAS programs. Each of the experimental designs introduced in *Experimental Design and Analysis for Psychology* by Abdi, *et al.* are reprinted herein, followed by their SAS code and listing output. The first chapter covers correlation, followed by regression, multiple regression, and various analysis of variance designs. We urge you to familiarize yourself with the SAS codes and SAS listings, as they in their relative simplicity should alleviate many of your anxieties.

We would like to emphasize that this book is not written as *the* tutorial in the SAS programming language. For that there are several excellent books on the market. Rather, use this manual as your own cook book of basic recipies. As you become more comfortable with SAS, you may want to add some additional flavors to enhance your programs beyond what we have suggested herein.

And, don't forget the semicolons!

¹Panic is *not* the answer!

Contents

Preface i

1 Correlation 1

- 1.1 Example: Word Length and Number of Meanings 1
 - 1.1.1 SAS code 1
 - 1.1.2 SAS listing 3

2 Simple Regression Analysis 5

- 2.1 Example: Memory Set and Reaction Time 5
 - 2.1.1 SAS code 5
 - 2.1.2 SAS listing 7

3 Multiple Regression Analysis: Orthogonal Independent Variables 9

- 3.1 Example: Retroactive Interference 9
 - 3.1.1 SAS code 10
 - 3.1.2 SAS listing 10

4 Multiple Regression Analysis: Non-orthogonal Independent Variables 15

- 4.1 Example: Age, Speech Rate and Memory Span 15
 - 4.1.1 SAS code 15
 - 4.1.2 SAS listing 16

5 ANOVA One Factor Between-Subjects, $S(\mathcal{A})$ 19

- 5.1 Example: Imagery and Memory 19
 - 5.1.1 SAS code 19
 - 5.1.2 SAS listing 20
 - 5.1.3 ANOVA table 21
- 5.2 Example: Romeo and Juliet 21
 - 5.2.1 SAS code 23
 - 5.2.2 SAS listing 23
- 5.3 Example: Face Perception, $S(\mathcal{A})$ with \mathcal{A} random 24
 - 5.3.1 SAS code 24
 - 5.3.2 SAS listing 25

5.3.3	ANOVA table	26
5.4	Example: Images ...	27
5.4.1	SAS code	27
5.4.2	SAS listing	28
5.4.3	ANOVA table	29
6	ANOVA One Factor Between-Subjects: Regression Approach	31
6.1	Example: Imagery and Memory revisited	32
6.1.1	SAS code	32
6.1.2	SAS listing	33
6.2	Example: Restaging Romeo and Juliet	34
6.2.1	SAS code	34
6.2.2	SAS listing	35
7	Planned Orthogonal Comparisons	37
7.1	Context and Memory	37
7.1.1	SAS code	39
7.1.2	SAS listing	40
7.1.3	ANOVA table	44
8	Planned Non-orthogonal Comparisons	45
8.1	Classical approach: Tests for non-orthogonal comparisons	45
8.2	Romeo and Juliet, non-orthogonal contrasts	46
8.2.1	SAS code	47
8.2.2	SAS code	47
8.3	Multiple Regression and Orthogonal Contrasts	49
8.3.1	SAS code	50
8.3.2	SAS listing	51
8.4	Multiple Regression and Non-orthogonal Contrasts	53
8.4.1	SAS code	54
8.4.2	SAS listing	55
9	Post hoc or <i>a-posteriori</i> analyses	59
9.1	Scheffé's test	59
9.1.1	Romeo and Juliet	60
9.1.1.1	SAS code	60
9.1.1.2	SAS listing	61
9.2	Tukey's test	63
9.2.1	The return of Romeo and Juliet	63
9.2.1.1	SAS code	64
9.2.1.2	SAS listing	65
9.3	Newman-Keuls' test	67
9.3.1	Taking off with Loftus...	68
9.3.1.1	SAS code	69

9.3.1.2	SAS listing	69
9.3.2	Guess who?	71
9.3.2.1	SAS code	71
9.3.2.2	SAS listing	72
10	ANOVA Two Factors; $S(\mathcal{A} \times \mathcal{B})$	75
10.1	Cute Cued Recall	75
10.1.1	SAS code	76
10.1.2	SAS listing	77
10.1.3	ANOVA table	78
10.2	Projective Tests and Test Administrators	79
10.2.1	SAS code	79
10.2.2	SAS listing	80
10.2.3	ANOVA table	84
11	ANOVA One Factor Repeated Measures, $S \times \mathcal{A}$	85
11.1	$S \times \mathcal{A}$ design	85
11.1.1	SAS code	85
11.1.2	SAS listing	86
11.2	Drugs and reaction time	87
11.2.1	SAS code	87
11.2.2	SAS listing	88
11.2.3	ANOVA table	90
11.3	Proactive Interference	90
11.3.1	SAS code	90
11.3.2	SAS listing	91
11.3.3	ANOVA table	93
12	Two Factors Repeated Measures, $S \times \mathcal{A} \times \mathcal{B}$	95
12.1	Plungin'	95
12.1.1	SAS code	97
12.1.2	SAS listing	97
12.1.3	ANOVA table	99
13	Factorial Design, Partially Repeated Measures: $S(\mathcal{A}) \times \mathcal{B}$	101
13.1	Bat and Hat...	101
13.1.1	SAS code	102
13.1.2	SAS listing	103
13.1.3	ANOVA table	104
14	Nested Factorial Design: $S \times \mathcal{A}(\mathcal{B})$	107
14.1	Faces in Space	107
14.1.1	SAS code	107
14.1.2	SAS listing	109
14.1.3	F and Quasi- F ratios	110

vi 0.0 CONTENTS

14.1.4 ANOVA table 110

Index 113

1

Correlation

1.1 Example: Word Length and Number of Meanings

If you are in the habit of perusing dictionaries as a way of leisurely passing time, you may have come to the conclusion that longer words apparently have fewer meanings attributed to them. Now, finally, through the miracle of statistics, or more precisely, the Pearson Correlation Coefficient, you need no longer ponder this question.

We decided to run a small experiment. The data come from a sample of 20 words taken randomly from the *Oxford English Dictionary*. Table 1.1 on the following page gives the results of this survey.

A quick look at Table 1.1 on the next page does indeed give the impression that longer words tend to have fewer meanings than shorter words (e.g., compare “by” with “tarantula”.) Correlation, or more specifically the Pearson coefficient of correlation, is a tool used to evaluate the similarity of two sets of measurements (or dependent variables) obtained on the same observations. In this example, the goal of the coefficient of correlation is to express in a *quantitative* way the relationship between length and number of meanings of words.

For a more detailed description, please refer to Chapter 2 on Correlation in the textbook.

1.1.1 SAS code

```
/* CORRELATION
   Word Length & Number of Meanings
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
DATA correl;
TITLE 'CORRELATION: Word Length & Number of Meanings';
INPUT length meanings ;
CARDS;
3 8
6 4
2 10
6 1
```

Word	Length	Number of Meanings
bag	3	8
buckle	6	4
on	2	10
insane	6	1
by	2	11
monastery	9	1
relief	6	4
slope	5	3
scoundrel	9	1
loss	4	6
holiday	7	2
pretentious	11	1
solid	5	9
time	4	3
gut	3	4
tarantula	9	1
generality	10	3
arise	5	3
blot	4	3
infectious	10	2

TABLE 1.1 Length (*i.e.*, number of letters) and number of meanings of a random sample of 20 words taken from the Oxford English Dictionary.

```

2 11
9 1
6 4
5 3
9 1
4 6
7 2
11 1
5 9
4 3
3 4
9 1
10 3
5 3
4 3
10 2
;
PROC MEANS;
PROC PLOT;
    TITLE: 'Word Length & Number of Meanings ';
    PLOT meanings * length = '*';
PROC CORR;

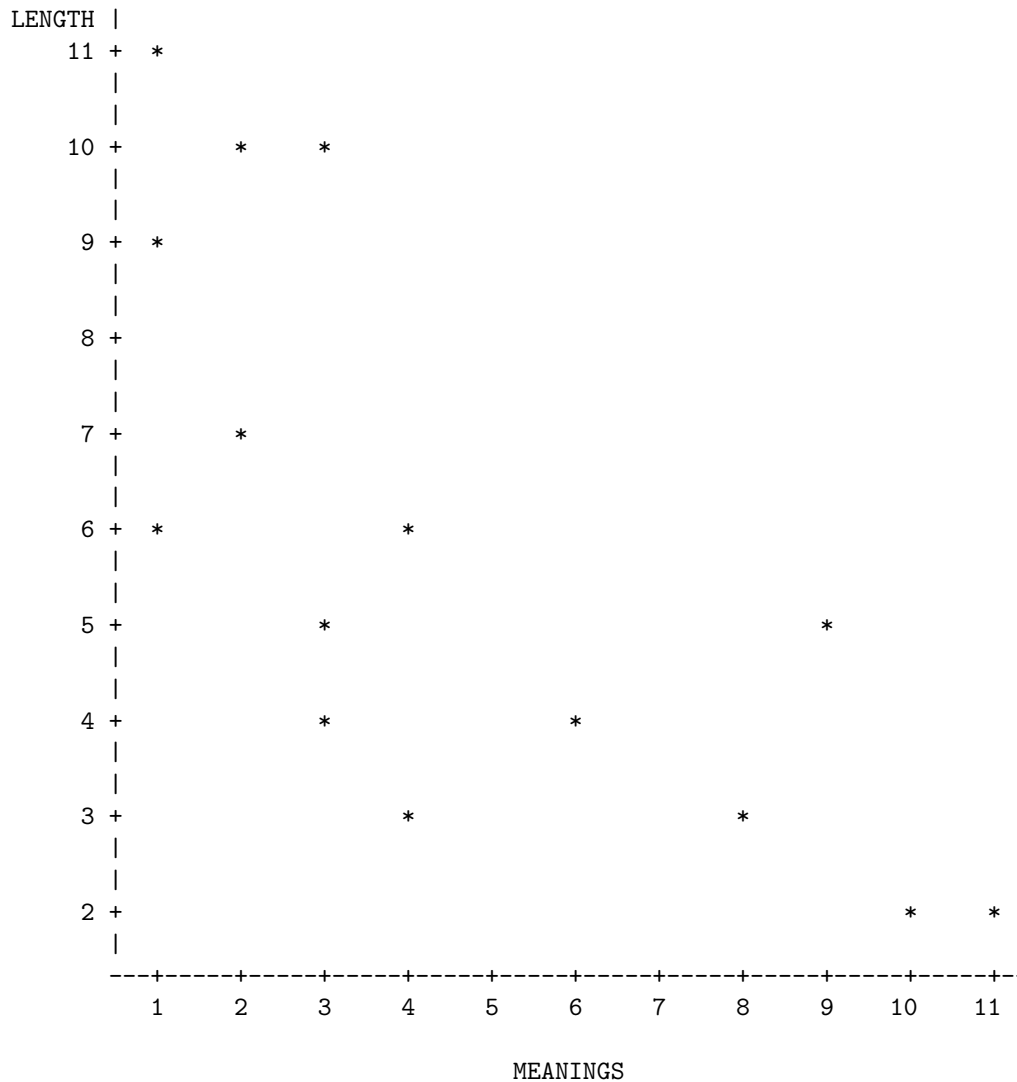
```

```
VAR length meanings;
PROC REG;
  Model length=meanings;
RUN;
```

1.1.2 SAS listing

CORRELATION
Word Length & Number of Meanings

Plot of LENGTH*MEANINGS. Symbol used is '*'.



NOTE: 5 obs hidden.

Word Length & Number of Meanings

Correlation Analysis

4 1.1 Example: Word Length and Number of Meanings

2 'VAR' Variables: LENGTH MEANINGS

Simple Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
LENGTH	20	6.0000	2.8098	120.0000	2.0000	11.0000
MEANINGS	20	4.0000	3.1456	80.0000	1.0000	11.0000

Pearson Correlation Coefficients / Prob > |R| under Ho:
Rho=0 / N = 20

	LENGTH	MEANINGS
LENGTH	1.00000 0.0	-0.73245 0.0002
MEANINGS	-0.73245 0.0002	1.00000 0.0

Word Length & Number of Meanings

Model: MODEL1
Dependent Variable: LENGTH

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	80.47340	80.47340	20.834	0.0002
Error	18	69.52660	3.86259		
C Total	19	150.00000			

Root MSE 1.96535 R-square 0.5365
Dep Mean 6.00000 Adj R-sq 0.5107
C.V. 32.75578

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > T
INTERCEP	1	8.617021	0.72239905	11.928	0.0001
MEANINGS	1	-0.654255	0.14333766	-4.564	0.0002

2

Simple Regression Analysis

2.1 Example: Memory Set and Reaction Time

In an experiment originally designed by Sternberg (1969), subjects were asked to memorize a set of random letters (like *lqwh*) called the *memory set*. The number of letters in the set was called the *memory set size*. The subjects were then presented with a *probe* letter (say *q*). Subjects then gave the answer *Yes* if the probe is present in the memory set and *No* if the probe was not present in the memory set (here the answer should be *Yes*). The time it took the subjects to answer was recorded. The goal of this experiment was to find out if subjects were “scanning” material stored in short term memory.

In this replication, each subject was tested one hundred times with a constant memory set size. For half of the trials, the probe is present, whereas for the other half the probe is absent. Four different set sizes are used: 1, 3, 5, and 7 letters. Twenty (fictitious) subjects are tested (five per condition). For each subject we used the mean reaction time for the correct *Yes* answers as the dependent variable. The research hypothesis was that subjects need to serially scan the letters in the memory set and that they need to compare each letter in turn with the probe. If this is the case, then each letter would add a given time to the reaction time. Hence the slope of the line would correspond to the time needed to process one letter of the memory set. The time needed to produce the answer and encode the probe should be constant for all conditions of the memory set size. Hence it should correspond to the intercept. The results of this experiment are given in Table 2.1 on the following page.

2.1.1 SAS code

```
/* Regression Analysis,  
   Memory Set Size & Reaction Time  
*/  
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;  
DATA example;  
TITLE 'Regression - Sternberg example';
```

6 2.1 Example: Memory Set and Reaction Time

Memory Set Size			
$X = 1$	$X = 3$	$X = 5$	$X = 7$
433	519	598	666
435	511	584	674
434	513	606	683
441	520	605	685
457	537	607	692

TABLE 2.1 Data from a replication of a Sternberg (1969) experiment. Each data point represents the mean reaction time for the Yes answers of a given subject. Subjects are tested in only one condition. Twenty (fictitious) subjects participated in this experiment. For example the mean reaction time of subject one who was tested with a memory set of 1 was 433 ($Y_1 = 433, X_1 = 1.$)

```

INPUT set time;
CARDS;
1 433
1 435
1 434
1 441
1 457
3 519
3 511
3 513
3 520
3 537
5 598
5 584
5 606
5 605
5 607
7 666
7 674
7 683
7 685
7 692
;
PROC MEANS;
PROC REG;
    TITLE 'Regression Line - Set Size vs. Time';
    MODEL time = set;
    PLOT PREDICTED.*set = 'P'
        time*set='*' / OVERLAY;
RUN;

```

2.1.2 SAS listing

Simple Regression - Sternberg example

Variable	N	Mean	Std Dev	Minimum	Maximum
SET	20	4.0000000	2.2941573	1.0000000	7.0000000
TIME	20	560.0000000	92.2239836	433.0000000	692.0000000

Regression Line - Set Size vs. Time

Model: MODEL1

Dependent Variable: TIME

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	160000.00000	160000.00000	1800.000	0.0001
Error	18	1600.00000	88.88889		
C Total	19	161600.00000			

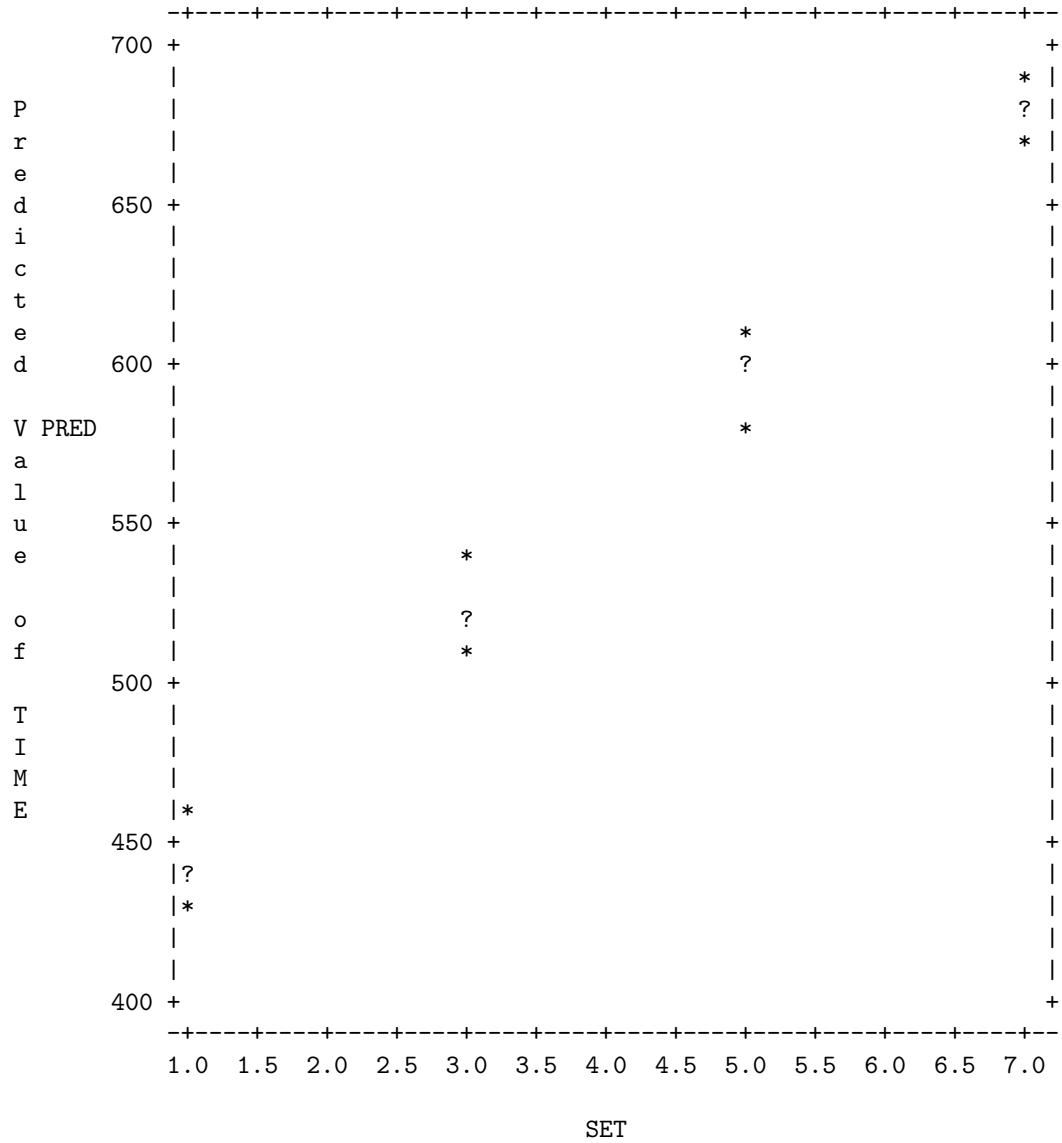
Root MSE	9.42809	R-square	0.9901
Dep Mean	560.00000	Adj R-sq	0.9895
C.V.	1.68359		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > T
INTERCEP	1	400.000000	4.32049380	92.582	0.0001
SET	1	40.000000	0.94280904	42.426	0.0001

Regression Line - Set Size vs. Time

8 2.1 Example: Memory Set and Reaction Time



3

Multiple Regression Analysis: Orthogonal Independent Variables

3.1 Example: Retroactive Interference

To illustrate the use of Multiple Regression Analysis, we present a replication of Slamecka's (1960) experiment on retroactive interference. The term retroactive interference refers to the interfering effect of later learning on recall. The general paradigm used to test the effect of retroactive interference is as follows. Subjects in the experimental group are first presented with a list of words to memorize. After the subjects have memorized this list, they are asked to learn a second list of words. When they have learned the second list, they are asked to recall the first list they learned. The number of words recalled by the experimental subjects is then compared with the number of words recalled by control subjects who learned only the first list of words. Results, in general, show that having to learn a second list impairs the recall of the first list (*i.e.*, experimental subjects recall fewer words than control subjects.)

In Slamecka's experiment subjects had to learn complex sentences. The sentences were presented to the subjects two, four, or eight times (this is the first independent variable.) We will refer to this variable as the *number of learning trials* or X . The subjects were then asked to learn a second series of sentences. This second series was again presented two, four, or eight times (this is the second independent variable.) We will refer to this variable as the *number of interpolated lists* or T . After the second learning session, the subjects were asked to recall the first sentences presented. For each subject, the number of words correctly recalled was recorded (this is the dependent variable.) We will refer to the dependent variable as Y .

In this example, a total of 18 subjects (two in each of the nine experimental conditions), were used. How well do the two independent variables "number of learning trials" and "number of interpolated lists" predict the dependent variable "number of words correctly recalled"? The re-

sults of this hypothetical replication are presented in Table 3.1.

3.1.1 SAS code

```

/* Multiple Regression Analysis - Orthogonal Independent Variables
   Slamecka, "Retroactive Interference"
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
DATA example;
TITLE 'Multiple Regression - Orthogonal Independent Variables';
INPUT X T Y;
LABEL Y='Recall'
      T='Lists'
      X='Trials';
CARDS;
2 2 35
2 4 21
2 8 6
4 2 40
4 4 34
4 8 18
8 2 61
8 4 58
8 8 46
2 2 39
2 4 31
2 8 8
4 2 52
4 4 42
4 8 26
8 2 73
8 4 66
8 8 52
;
PROC REG;
MODEL Y = X T / P SS2 SCORR2;
PROC CORR;
VAR X T Y;
RUN;

```

3.1.2 SAS listing

Multiple Regression - Orthogonal Independent Variables

Model: MODEL1

Dependent Variable: Y Recall

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	5824.00000	2912.00000	112.000	0.0001

Number of learning trials (X)	Number of interpolated lists (T)		
	2	4	8
2	35	21	6
	39	31	8
4	40	34	18
	52	42	26
8	61	58	46
	73	66	52

TABLE 3.1 Results of an hypothetical replication of Slamecka (1960)'s retroactive interference experiment.

Error	15	390.00000	26.00000
C Total	17	6214.00000	

Root MSE	5.09902	R-square	0.9372
Dep Mean	39.33333	Adj R-sq	0.9289
C.V.	12.96361		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > T
INTERCEP	1	30.000000	3.39934634	8.825	0.0001
X	1	6.000000	0.48181206	12.453	0.0001
T	1	-4.000000	0.48181206	-8.302	0.0001

Variable	DF	Type II SS	Squared Semi-partial Corr Type II
INTERCEP	1	2025.000000	.
X	1	4032.000000	0.64885742
T	1	1792.000000	0.28838107

Variable	DF	Variable Label
INTERCEP	1	Intercept
X	1	Trials

X	18	4.666667	2.566756	84.000000
T	18	4.666667	2.566756	84.000000
Y	18	39.333333	19.118823	708.000000

Simple Statistics

Variable	Minimum	Maximum	Label
X	2.000000	8.000000	Trials
T	2.000000	8.000000	Lists
Y	6.000000	73.000000	Recall

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / N = 18

	X	T	Y
X	1.00000	0.00000	0.80552
Trials	0.0	1.0000	0.0001
T	0.00000	1.00000	-0.53701
Lists	1.0000	0.0	0.0216
Y	0.80552	-0.53701	1.00000
Recall	0.0001	0.0216	0.0

4

Multiple Regression Analysis: Non-orthogonal Independent Variables

4.1 Example: Age, Speech Rate and Memory Span

To illustrate an experiment with two quantitative independent variables, we replicated an experiment originally designed by Hulme, Thomson, Muir, and Lawrence (1984, as reported by Baddeley, 1990, p.78 *ff.*). Children aged 4, 7, or 10 years (hence “*age*” is the first independent variable in this experiment, denoted X), were tested in 10 series of immediate serial recall of 15 items. The dependent variable is the total number of words correctly recalled (*i.e.*, in the correct order). In addition to age, the speech rate of each child was obtained by asking the child to read aloud a list of words. Dividing the number of words read by the time needed to read them gave the *speech rate* (expressed in words per second) of the child. Speech rate is the second independent variable in this experiment (we will denote it T).

The research hypothesis states that the age and the speech rate of the children are determinants of their memory performance. Because the independent variable speech rate cannot be *manipulated*, the two independent variables are not orthogonal. In other words, one can expect speech rate to be partly correlated with age (on average, older children tend to speak faster than younger children.) Speech rate should be the major determinant of performance and the effect of age reflects more the confounded effect of speech rate rather than age, per se.

The data obtained from a sample of 6 subjects are given in the Table 4.1 on the next page.

4.1.1 SAS code

```
/* Multiple Regression Analysis  
   Non-Orthogonal Independent Variables  
   "Age/Speech Rate & Memory Span", Hulme, et al.  
*/
```

The Independent Variables		The Dependent Variable
<i>X</i>	<i>T</i>	<i>Y</i>
Age (in years)	Speech Rate (words per second)	Memory Span (number of words recalled)
4	1	14
4	2	23
7	2	30
7	4	50
10	3	39
10	6	67

TABLE 4.1 Data from a (fictitious) replication of an experiment of Hulme *et al.* (1984). The dependent variable is the total number of words recalled in 10 series of immediate recall of items, it is a measure of the *memory span*. The first independent variable is the *age* of the child, the second independent variable is the *speech rate* of the child.

```

OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
DATA example;
TITLE 'Multiple Regression, Non-orthogonal Independent Variables';
INPUT X T Y;
LABEL X='Age'
      T='Speech Rate'
      Y='Memory Span';
CARDS;
4 1 14
4 2 23
7 2 30
7 4 50
10 3 39
10 6 67
;
PROC REG;
  MODEL Y = X T / P SS2 SCORR2;
PROC CORR;
  VAR X T Y;
RUN;

```

4.1.2 SAS listing

Multiple Regression, Non-orthogonal Independent Variables

Model: MODEL1

Dependent Variable: Y Memory Span

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
--------	----	----------------	-------------	---------	--------

```

-----
Model          2   1822.00000   911.00000   110.054   0.0016
Error          3    24.83333    8.27778
C Total        5   1846.83333
-----

```

```

Root MSE      2.87711   R-square     0.9866
Dep Mean     37.16667   Adj R-sq    0.9776
C.V.         7.74111

```

Parameter Estimates

```

-----
Variable  DF      Parameter      Standard      T for H0:
          DF      Estimate        Error        Parameter=0  Prob > |T|
-----
INTERCEP  1      1.666667      3.59753247      0.463        0.6747
X         1      1.000000      0.72496427      1.379        0.2616
T         1      9.500000      1.08744640      8.736        0.0032
-----

```

```

-----
Variable  DF      Type II SS      Squared
          DF      Type II SS      Semi-partial
          DF      Type II SS      Corr Type II
-----
INTERCEP  1      1.776650      .
X         1      15.750000      0.00852811
T         1      631.750000      0.34207202
-----

```

```

-----
Variable  DF      Variable
          DF      Label
-----
INTERCEP  1      Intercept
X         1      Age
-----

```

Multiple Regression, Non-orthogonal Independent Variables

```

-----
Variable  DF      Variable
          DF      Label
-----
T         1      Speech Rate
-----

```

```

-----
Obs      Dep Var      Predict      Residual
          Y          Value
-----
1      14.0000      15.1667      -1.1667
2      23.0000      24.6667      -1.6667
-----

```

3	30.0000	27.6667	2.3333
4	50.0000	46.6667	3.3333
5	39.0000	40.1667	-1.1667
6	67.0000	68.6667	-1.6667

```
-----
Sum of Residuals                0
Sum of Squared Residuals       24.8333
Predicted Resid SS (Press)    108.8657
-----
```

Multiple Regression, Non-orthogonal Independent Variables

Correlation Analysis

3 'VAR' Variables: X T Y

Simple Statistics

```
-----
Variable      N      Mean      Std Dev      Sum
-----
X              6      7.000000    2.683282    42.000000
T              6      3.000000    1.788854    18.000000
Y              6     37.166667   19.218914   223.000000
-----
```

Simple Statistics

```
-----
Variable      Minimum      Maximum      Label
-----
X              4.000000    10.000000    Age
T              1.000000     6.000000    Speech Rate
Y             14.000000    67.000000    Memory Span
-----
```

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / N = 6

```
-----
                X                T                Y
-----
X              1.00000          0.75000          0.80280
Age              0.0            0.0859           0.0545

T              0.75000          1.00000          0.98895
Speech Rate      0.0859           0.0              0.0002

Y              0.80280          0.98895          1.00000
Memory Span      0.0545           0.0002           0.0
-----
```

5

ANOVA **One Factor** **Between-Subjects, $S(A)$**

5.1 Example: Imagery and Memory

Our research hypothesis is that material processed with imagery will be more resistant to forgetting than material processed without imagery. In our experiment, we ask subjects to learn pairs of words (e.g., “beauty-carrots”). Then, after some delay, the subjects are asked to give the second word of the pair (e.g., “carrot”) when prompted with the first word of the pair (e.g., “beauty”). Two groups took part in the experiment: the *experimental* group (in which the subjects learn the word pairs using imagery), and the *control* group (in which the subjects learn without using imagery). The dependent variable is the number of word pairs correctly recalled by each subject. The performance of the subjects is measured by testing their memory for 20 word pairs, 24 hours after learning.

The results of the experiment are listed in the following table:

Experimental group	Control group
1	8
2	8
5	9
6	11
6	14

5.1.1 SAS code

```
/* ANOVA one-factor between subjects, S(A)
   Imagery & Memory
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='-';
DATA imagery;
TITLE 'ANOVA S(A), Imagery & Memory';
INPUT Group$ Score;
CARDS;
```

```

1 1
1 2
1 5
1 6
1 6
2 8
2 8
2 9
2 11
2 14
;
PROC ANOVA;
  CLASS Group;
  MODEL Score = Group;
  MEANS Group;
RUN;

```

5.1.2 SAS listing

ANOVA S(A), Imagery & Memory

Analysis of Variance Procedure
Class Level Information

```

Class      Levels      Values
GROUP          2      1 2

```

Number of observations in data set = 10

Dependent Variable: SCORE

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	90.0000000	90.0000000	15.00	0.0047
Error	8	48.0000000	6.0000000		
Corrected Total	9	138.0000000			

R-Square	C.V.	Root MSE	SCORE Mean
0.652174	34.99271	2.44949	7.00000

Source	DF	Anova SS	Mean Square	F Value	Pr > F
GROUP	1	90.0000000	90.0000000	15.00	0.0047

Level of GROUP	N	Mean	SD
1	5	4.00000000	2.34520788
2	5	10.00000000	2.54950976

5.1.3 ANOVA table

The results from our experiment can be condensed in an *analysis of variance table*.

Source	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>
Between	1	90.00	90.00	15.00
Within <i>S</i>	8	48.00	6.00	
Total	9	138.00		

5.2 Example: Romeo and Juliet

In an experiment on the effect of context on memory, Bransford and Johnson (1972) read the following passage to their subjects:

“If the balloons popped, the sound would not be able to carry since everything would be too far away from the correct floor. A closed window would also prevent the sound from carrying since most buildings tend to be well insulated. Since the whole operation depends on a steady flow of electricity, a break in the middle of the wire would also cause problems. Of course the fellow could shout, but the human voice is not loud enough to carry that far. An additional problem is that a string could break on the instrument. Then there could be no accompaniment to the message. It is clear that the best situation would involve less distance. Then there would be fewer potential problems. With face to face contact, the least number of things could go wrong.”

To show the importance of the context on the memorization of texts, the authors assigned subjects to one of four experimental conditions:

- **1. “No context” condition:** subjects listened to the passage and tried to remember it.

- **2.** “*Appropriate context before*” condition: subjects were provided with an appropriate context in the form of a picture and then listened to the passage.
- **3.** “*Appropriate context after*” condition: subjects first listened to the passage and then were provided with an appropriate context in the form of a picture.
- **4.** “*Partial context*” condition: subjects are provided with a context that does not allow them to make sense of the text at the same time that they listened to the passage.

Strictly speaking this experiment involves one experimental group (group 2: “appropriate context before”), and three control groups (groups 1, 3, and 4). The *raison d’être* of the control groups is to eliminate rival theoretical hypotheses (*i.e.*, rival theories that would give the same experimental predictions as the theory advocated by the authors).

For the (fictitious) replication of this experiment, we have chosen to have 20 subjects assigned randomly to 4 groups. Hence there is $S = 5$ subjects *per* group. The dependent variable is the “number of ideas” recalled (of a maximum of 14). The results are presented below.

	No Context	Context Before	Context After	Partial Context
	3	5	2	5
	3	9	4	4
	2	8	5	3
	4	4	4	5
	3	9	1	4
$Y_{a.}$	15	35	16	21
$M_{a.}$	3	7	3.2	4.2

The figures taken from our SAS listing can be presented in an analysis of variance table:

Source	df	SS	MS	F	$Pr(F)$
\mathcal{A}	3	50.90	10.97	7.22**	.00288
$S(\mathcal{A})$	16	37.60	2.35		
Total	19	88.50			

For more details on this experiment, please consult your textbook.

5.2.1 SAS code

```

/* Analysis of Variance, S(A) design
   One factor, 4 levels
   Bransfords's Romeo and Juliet
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
TITLE 'ANOVA - S(A) - Romeo and Juliet';
DATA example;
  DO group = 1 to 4;
    DO subject = 1 to 5;
      INPUT dv @;
      OUTPUT;
    END;
  END;
CARDS;
3 3 2 4 3
5 9 8 4 9
2 4 5 4 1
5 4 3 5 4
;
PROC ANOVA;
  CLASS group;
  MODEL dv = Group;
PROC MEANS;
  OUTPUT OUT = mgroup MEAN=mean_gr;
PROC PLOT;
  PLOT mean_gr*group;
RUN;

```

5.2.2 SAS listing

ANOVA - S(A) - Romeo and Juliet
Analysis of Variance Procedure

Class Level Information

Class	Levels	Values
GROUP	4	1 2 3 4

Number of observations in data set = 20

ANOVA - S(A) - Romeo and Juliet
Analysis of Variance Procedure

Dependent Variable: DV

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	50.9500000	16.9833333	7.23	0.0028
Error	16	37.6000000	2.3500000		
Corrected Total	19	88.5500000			

R-Square	C.V.	Root MSE	DV Mean
0.575381	35.24071	1.53297	4.35000

Source	DF	Anova SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.002

Variable	N	Mean	Std Dev	Minimum	Maximum
GROUP	20	2.5000000	1.1470787	1.0000000	4.0000000
SUBJECT	20	3.0000000	1.4509525	1.0000000	5.0000000
DV	20	4.3500000	2.1588252	1.0000000	9.0000000

5.3 Example: Face Perception, $S(\mathcal{A})$ with \mathcal{A} random

In a series of experiments on face perception we set out to see whether the degree of attention devoted to each face varies across faces. In order to verify this hypothesis, we assigned 40 undergraduate students to five experimental conditions. For each condition we have a man's face drawn at random from a collection of several thousand faces. We use the subjects' pupil dilation when viewing the face as an index of the attentional interest evoked by the face. The results are presented in Table 5.1 on the facing page (with pupil dilation expressed in arbitrary units).

5.3.1 SAS code

```
/* ANOVA 1 factor, 5 levels;
```

Experimental Groups					
	Group 1	Group 2	Group 3	Group 4	Group 5
	40	53	46	52	52
	44	46	45	50	49
	45	50	48	53	49
	46	45	48	49	45
	39	55	51	47	52
	46	52	45	53	45
	42	50	44	55	52
	42	49	49	49	48
$M_a.$	43	50	47	51	49

TABLE 5.1 Results of a (fictitious) experiment on face perception.

```

Fictitious experiment on face perception
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
TITLE 'ANOVA - 1 Factor - S(A), A random';
DATA anova2;
  DO group = 1 TO 5;
    DO subject = 1 TO 8;
      INPUT dv @;
      OUTPUT;
    END;
  END;
CARDS;
40 44 45 46 39 46 42 42
53 46 50 45 55 52 50 49
46 45 48 48 51 45 44 49
52 50 53 49 47 53 55 49
52 49 49 45 52 45 52 48
;
PROC ANOVA;
  TITLE 'ANOVA - FACE PERCEPTION EXPERIMENT';
  CLASSES group;
  MODEL dv = group;
  MEANS group;
RUN;

```

5.3.2 SAS listing

```

ANOVA - FACE PERCEPTION EXPERIMENT
Analysis of Variance Procedure
Class Level Information

Class      Levels      Values
GROUP      5          1 2 3 4 5

```

Number of observations in data set = 40

Dependent Variable: DV

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	320.000000	80.000000	10.00	0.0001
Error	35	280.000000	8.000000		
Corrected Total	39	600.000000			

R-Square	C.V.	Root MSE	DV Mean
0.533333	5.892557	2.82843	48.0000

Source	DF	Anova SS	Mean Square	F Value	Pr > F
GROUP	4	320.000000	80.000000	10.00	0.0001

Level of GROUP	N	Mean	SD
1	8	43.0000000	2.67261242
2	8	50.0000000	3.38061702
3	8	47.0000000	2.39045722
4	8	51.0000000	2.67261242
5	8	49.0000000	2.92770022

5.3.3 ANOVA table

The results of our fictitious face perception experiment are presented in the following ANOVA Table:

Source	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Pr(F)</i>
\mathcal{A}	4	320.00	80.00	10.00	.000020
$S(\mathcal{A})$	35	280.00	8.00		
Total	39	600.00			

From this table it is clear that the research hypothesis is supported by the experimental results: All faces do not attract the same amount of attention.

5.4 Example: Images ...

In another experiment on mental imagery, we have three groups of 5 students each (psychology majors for a change!) learn a list of 40 concrete nouns and recall them one hour later. The first group learns each word with its definition, and draws the object denoted by the word (the *built image condition*). The second group was treated just like the first, but had simply to *copy* a drawing of the object instead of making it up themselves (the *given image condition*). The third group simply read the words and their definitions (the *control condition*.) Table 5.2 shows the number of words recalled 1 hour later by each subject. The experimental design is $S(A)$, with $S = 5$, $A = 3$, and A as a fixed factor.

	Experimental Condition		
	Built Image	Given Image	Control
	22	13	9
	17	9	7
	24	14	10
	23	18	13
	24	21	16
Σ	110	75	55
$M_{a.}$	22	15	11

TABLE 5.2 Results of the mental imagery experiment.

5.4.1 SAS code

```

/* ANOVA S(A), 3 levels;
   Imagery effects
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='-';
TITLE 'ANOVA 1-factor - S(A)';
DATA example;
  DO group = 1 TO 3;
    DO subject = 1 TO 5;
      INPUT dv @;
      OUTPUT;
    END;
  END;
CARDS;
22 17 24 23 24
13 9 14 18 21
9 7 10 13 16
;

```

```

PROC ANOVA;
  TITLE 'ANOVA - Mental Imagery Experiment';
  CLASSES group;
  MODEL dv = group;
  MEANS group;
RUN;

```

5.4.2 SAS listing

ANOVA - Mental Imagery Experiment

Analysis of Variance Procedure
 Class Level Information

```

Class      Levels      Values
GROUP          3      1 2 3

```

Number of observations in data set = 15

Dependent Variable: DV

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	310.000000	155.000000	10.94	0.0020
Error	12	170.000000	14.166667		
Corrected Total	14	480.000000			

R-Square	C.V.	Root MSE	DV Mean
0.645833	23.52415	3.76386	16.0000

Source	DF	Anova SS	Mean Square	F Value	Pr > F
GROUP	2	310.000000	155.000000	10.94	0.0020

Level of GROUP	N	Mean	SD
1	5	22.0000000	2.91547595
2	5	15.0000000	4.63680925

3 5 11.0000000 3.53553391

5.4.3 ANOVA table

Source	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Pr(F)</i>
\mathcal{A}	2	310.00	155.00	10.33**	.0026
$\mathcal{S}(\mathcal{A})$	12	180.00	15.00		
Total	14	490.00			

We can conclude that instructions had an effect on memorization. Using APA style (*cf.* APA manual, 1994, p. 68), to write our conclusion: “The type of instructions has an effect on memorization, $F(2, 12) = 14.10$, $MS_e = 13.07$, $p < .01$ ”.

6

ANOVA **One Factor** **Between-Subjects: Regression** **Approach**

In order to use regression to analyze data from an analysis of variance design, we use a trick that has a lot of interesting consequences. The main idea is to find a way of replacing the nominal independent variable (*i.e.*, the experimental factor) by a numerical independent variable (remember that the independent variable should be numerical to run a regression). One way of looking at analysis of variance is as a technique predicting subjects' behavior from the experimental group in which they were. The trick is to find a way of coding those groups. Several choices are possible, an easy one is to *represent a given experimental group by its mean for the dependent variable*. Remember from Chapter 4 in the textbook (on regression), that the rationale behind regression analysis implies that the independent variable is under the *control* of the experimenter. Using the group mean seems to go against this requirement, because we need to wait until *after* the experiment to know the values of the independent variable. This is why we call our procedure a *trick*. It works because it is equivalent to more elaborate coding schemes using *multiple* regression analysis. It has the advantage of being simpler both from a conceptual and computational point of view.

In this framework, the general idea is to try to predict the subjects' scores from the mean of the group to which they belong. The rationale is that, if there is an experimental effect, then the mean of a subject's group should predict the subject's score better than the grand mean. In other words, the larger the experimental effect, the better the predictive quality of the group mean. Using the group mean to predict the subjects' performance has an interesting consequence that makes regression and analysis of variance identical: *When we predict the performance of subjects from the mean of their group, the predicted value turns out to be the group mean too!*

6.1 Example: Imagery and Memory revisited

As a first illustration of the relationship between ANOVA and regression we reintroduce the experiment on Imagery and Memory detailed in Chapter 9 of your textbook. Remember that in this experiment two groups of subjects were asked to learn pairs of words (*e.g.*, “beauty-carrot”). Subjects in the first group (control group) were simply asked to learn the pairs of words the best they could. Subjects in the second group (experimental group) were asked to picture each word in a pair and to make an image of the interaction between the two objects. After, some delay, subjects in both groups were asked to give the second word (*e.g.*, “carrot”) when prompted with with the first word in the pair (*e.g.*, “beauty”). For each subject, the number of words correctly recalled was recorded. The purpose of this experiment was to demonstrate an effect of the independent variable (*i.e.*, learning with imagery *versus* learning without imagery) on the dependent variable (*i.e.*, number of words correctly recalled). The results of the scaled-down version of the experiment are presented in Table 6.1.

In order to use the regression approach, we use the respective group means as predictor. See Table 6.2.

6.1.1 SAS code

```
/* Regression Analysis
   Memory and Imagery
*/
OPTIONS PS=66 LS=80 NODATE NONUMBER;
TITLE 'Regression - Imagery & Memory';
```

Control		Experimental	
Subject 1:	1	Subject 1:	8
Subject 2:	2	Subject 2:	8
Subject 3:	5	Subject 3:	9
Subject 4:	6	Subject 4:	11
Subject 5:	6	Subject 5:	14

$$M_{1.} = M_{\text{Control}} = 4 \quad M_{2.} = M_{\text{Experimental}} = 10$$

$$\text{Grand Mean} = M_Y = M_{..} = 7$$

TABLE 6.1 Results of the “Memory and Imagery” experiment.

$X = M_a$. Predictor	4	4	4	4	4	10	10	10	10	10
Y (Value to be predicted)	1	2	5	6	6	8	8	9	11	14

TABLE 6.2 The data from Table 6.1 presented as a regression problem. The predictor X is the value of the mean of the subject’s group.

```

DATA example;
INPUT X Y;
LABEL X='group mean'
      Y='pred value';
CARDS;
4 1
4 2
4 5
4 6
4 6
10 8
10 8
10 9
10 11
10 14
;
PROC REG;
  MODEL Y = X;
RUN;

```

6.1.2 SAS listing

Regression - Imagery & Memory

Model: MODEL1

Dependent Variable: Y pred value

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	90.00000	90.00000	15.000	0.0047
Error	8	48.00000	6.00000		
C Total	9	138.00000			

Root MSE	2.44949	R-square	0.6522
Dep Mean	7.00000	Adj R-sq	0.6087
C.V.	34.99271		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > T
INTERCEP	1	0	1.96638416	0.000	1.0000
X	1	1.000000	0.25819889	3.873	0.0047

Variable

Variable	DF	Label
INTERCEP	1	Intercept
X	1	group mean

6.2 Example: Restaging Romeo and Juliet

This second example is again the “*Romeo and Juliet*” example from a replication of Bransford *et al.*'s (1972) experiment. The rationale and details of the experiment are given in Chapter 9 in the textbook.

To refresh your memory: The general idea when using the regression approach for an analysis of variance problem is to predict subject scores from the mean of the group to which they belong. The rationale for doing so is to consider the group mean as representing the experimental effect, and hence as a predictor of the subjects' behavior. If the independent variable has an effect, the group mean should be a better predictor of the subjects behavior than the grand mean. Formally, we want to predict the score Y_{as} of subject s in condition a from a quantitative variable X that will be equal to the mean of the group a in which the s observation was collected. With an equation, we want to predict the observation by:

$$\hat{Y} = a + bX \quad (6.1)$$

with X being equal to $M_{a.}$. The particular choice of X has several interesting consequences. A first important one, is that the mean of the predictor M_X is also the mean of the dependent variable M_Y . These two means are also equal to the grand mean of the analysis of variance. With an equation:

$$M_{..} = M_X = M_Y . \quad (6.2)$$

Table VI.3 gives the values needed to do the computation using the regression approach.

6.2.1 SAS code

```
/* Regression Analysis Approach - Bransford's Romeo & Juliet
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
DATA Regr;
INPUT group$ mean score;
CARDS;
1 3 3
1 3 3
1 3 2
```

<i>X</i>	3	3	3	3	3	7	7	7	7	7	3.2	3.2	3.2	3.2	3.2	4.2	4.2	4.2	4.2	4.2
<i>Y</i>	3	3	2	4	3	5	9	8	4	9	2	4	5	4	1	5	4	3	5	4

TABLE 6.3 The data from the Romeo and Juliet experiment presented as a regression problem. The predictor *X* is the value of the mean of the subject's group.

```

1 3 4
1 3 3
2 7 5
2 7 9
2 7 8
2 7 4
2 7 9
3 3.2 2
3 3.2 4
3 3.2 5
3 3.2 4
3 3.2 1
4 4.2 5
4 4.2 4
4 4.2 3
4 4.2 5
4 4.2 4
;
PROC ANOVA;
  TITLE 'Romeo & Juliet, ANOVA approach';
  CLASSES group;
  MODEL score = group;
PROC REG;
  TITLE 'Romeo & Juliet, Regression Approach';
  MODEL score = mean;
RUN;
```

6.2.2 SAS listing

Romeo & Juliet, ANOVA approach

Analysis of Variance Procedure
Class Level Information

Class	Levels	Values
-------	--------	--------

GROUP	4	1 2 3 4
-------	---	---------

Number of observations in data set = 20

Dependent Variable: SCORE

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	50.9500000	16.9833333	7.23	0.0028
Error	16	37.6000000	2.3500000		
Corrected Total	19	88.5500000			

R-Square	C.V.	Root MSE	SCORE Mean
0.575381	35.24071	1.53297	4.35000

Source	DF	Anova SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.0028

Romeo & Juliet, Regression Approach

Model: MODEL1

Dependent Variable: SCORE

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	50.95000	50.95000	24.391	0.0001
Error	18	37.60000	2.08889		
C Total	19	88.55000			

Root MSE	1.44530	R-square	0.5754
Dep Mean	4.35000	Adj R-sq	0.5518
C.V.	33.22526		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > T
INTERCEP	1	-1.5099E-14	0.93821333	-0.000	1.0000
MEAN	1	1.000000	0.20248161	4.939	0.0001

7

ANOVA **One factor: Planned Orthogonal Comparisons**

The *planned* comparisons (also called *a priori* comparisons) are selected *before* running the experiment. In general, they correspond to the research hypothesis that is being tested. If the experiment has been designed to confront two or more alternative theories (*e.g.*, with the use of *rival* hypotheses), the comparisons are derived from those theories. When the experiment is actually run, it is possible to see if the results support or eliminate one of the theories. Because these comparisons are planned they are usually *few* in number.

A set of comparisons is composed of orthogonal comparisons if the hypotheses corresponding to each comparison are independent of each other. The maximum number of possible orthogonal comparisons one can perform, is one less than the number of levels of the independent variable (*i.e.*, $A - 1$). $A - 1$ is also the number of degrees of freedom of the sum of squares for A .

All different types of comparisons can be performed following the same procedure:

- *First.* Formalization of the comparison, and expression of the comparison as a set of weights for the means.
- *Second.* Computation of the $F_{\text{comp.}}$ ratio (this is the usual F ratio adapted for the case of testing a comparison).
- *Third.* Evaluation of the probability associated with $F_{\text{comp.}}$.

7.1 Context and Memory

This example is inspired by an experiment by Smith (1979). The main purpose in this experiment was to show that to be in the same context for learning and for test can give a better performance than being in different contexts. More specifically, Smith wants to explore the effect of putting oneself *mentally* in the same context. The experiment is organized as follows. During the learning phase, subjects learn a list made of 80 words in a

room painted with an orange color, decorated with posters, paintings and a decent amount of paraphernalia. A first test of learning is given then, essentially to give subjects the impression that the experiment is over. One day after, subjects are unexpectedly re-tested for their memory. An experimenter will ask them to write down all the words of the list they can remember. The test takes place in 5 different experimental conditions. Fifty subjects (10 *per* group) are randomly assigned to the experimental groups. The formula of the experimental design is $\mathcal{S}(\mathcal{A})$ or $\mathcal{S}_{10}(\mathcal{A}_5)$. The dependent variable measured is the number of words correctly recalled. The five experimental conditions are:

- **1. *Same context.*** Subjects are tested in the same room in which they learned the list.
- **2. *Different context.*** Subjects are tested in a room very different from the one in which they learned the list. The new room is located in a different part of the Campus, is painted grey, and looks very austere.
- **3. *Imaginary context.*** Subjects are tested in the same room as subjects from group 2. In addition, they are told to try to remember the room in which they learned the list. In order to help them, the experimenter asks them several questions about the room and the objects in it.
- **4. *Photographed context.*** Subjects are placed in the same condition as group 3, and, in addition, they are shown photos of the orange room in which they learned the list.
- **5. *Placebo context.*** Subjects are in the same condition as subjects in group 2. In addition, before starting to try to recall the words, they are asked first to perform a warm-up task, namely to try to remember their living room.

Several research hypotheses can be tested with those groups. Let us accept that the experiment was designed to test the following research hypotheses:

- ***Research Hypothesis 1.*** Groups for which the context at test matches the context during learning (*i.e.*, is the same or is simulated by imaging or photography) will perform differently (precisely they are expected to do better) than groups with a different context or than groups with a Placebo context.
- ***Research Hypothesis 2.*** The group with the same context will differ from the group with imaginary or photographed context.
- ***Research Hypothesis 3.*** The imaginary context group differs from the photographed context group

- *Research Hypothesis 4.* The different context group differs from the placebo group.

The following Table gives the set of the four contrasts specified in the SAS program.

Comparison	Gr.1	Gr.2	Gr.3	Gr.4	Gr.5
ψ_1	+2	-3	+2	+2	-3
ψ_2	+2	0	-1	-1	0
ψ_3	0	0	+1	-1	0
ψ_4	0	+1	0	0	-1

The data and results of the replication of Smith’s experiment are given in the two following Tables (Tables 7.1, and 7.2).

	Experimental Context				
	Group 1 Same	Group 2 Different	Group 3 Imagery	Group 4 Photo	Group 5 Placebo
	25	11	14	25	8
	26	21	15	15	20
	17	9	29	23	10
	15	6	10	21	7
	14	7	12	18	15
	17	14	22	24	7
	14	12	14	14	1
	20	4	20	27	17
	11	7	22	12	11
	21	19	12	11	4
$Y_{a.}$	180	110	170	190	100
$M_{a.}$	18	11	17	19	10
$M_{a.} - M_{..}$	3	-4	2	4	-5
$\sum(Y_{as} - M_{a.})^2$	218	284	324	300	314

TABLE 7.1 Results of a replication of an experiment by Smith (1979). The dependent variable is the number of words recalled.

7.1.1 SAS code

```

/* ANOVA one factor, S(A) design with contrasts
   Smith’s experiment on context effects
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='-' ;

```

```

TITLE1 'S(A) design with contrasts';
DATA example;
DO group = 1 TO 5;
  INPUT psy1 psy2 psy3 psy4;
  DO subject = 1 TO 10 ;
    INPUT recall @ ;
    OUTPUT;
  END;
END;
CARDS;
2 2 0 0
25 26 17 15 14 17 14 20 11 21
-3 0 0 1
11 21 9 6 7 14 12 4 7 19
2 -1 1 0
14 15 29 10 12 22 14 20 22 12
2 -1 -1 0
25 15 23 21 18 24 14 27 12 11
-3 0 0 -1
8 20 10 7 15 7 1 17 11 4
;
PROC PRINT;
  TITLE2 'The Data';
PROC GLM ORDER=DATA;
  TITLE2 ' Orthogonal Contrasts with PROC GLM ';
  CLASS group;
  MODEL recall = group ;
  MEANS group;
  CONTRAST 'Psy1. (134) vs (25) ' group 2 -3 2 2 -3;
  CONTRAST 'Psy2. (1) vs (34) ' group 2 0 -1 -1 0;
  CONTRAST 'Psy3. (3) vs (4) ' group 0 0 1 -1 0;
  CONTRAST 'Psy4. (2) vs (5) ' group 0 1 0 0 -1;
PROC REG;
  TITLE2 'Same Analysis with PROC REG, Intercept = M..';
  TITLE3 'F GLM for PSYi = ti**2 for PROC REG ';
  MODEL recall = psy1-psy4;
RUN;

```

7.1.2 SAS listing

S(A) design with contrasts

The Data

OBS	GROUP	PSY1	PSY2	PSY3	PSY4	SUBJECT	RECALL
1	1	2	2	0	0	1	25
2	1	2	2	0	0	2	26
3	1	2	2	0	0	3	17
4	1	2	2	0	0	4	15
5	1	2	2	0	0	5	14
6	1	2	2	0	0	6	17
7	1	2	2	0	0	7	14

8	1	2	2	0	0	8	20
9	1	2	2	0	0	9	11
10	1	2	2	0	0	10	21
11	2	-3	0	0	1	1	11
12	2	-3	0	0	1	2	21
13	2	-3	0	0	1	3	9
14	2	-3	0	0	1	4	6
15	2	-3	0	0	1	5	7
16	2	-3	0	0	1	6	14
17	2	-3	0	0	1	7	12
18	2	-3	0	0	1	8	4
19	2	-3	0	0	1	9	7
20	2	-3	0	0	1	10	19
21	3	2	-1	1	0	1	14
22	3	2	-1	1	0	2	15
23	3	2	-1	1	0	3	29
24	3	2	-1	1	0	4	10
25	3	2	-1	1	0	5	12
26	3	2	-1	1	0	6	22
27	3	2	-1	1	0	7	14
28	3	2	-1	1	0	8	20
29	3	2	-1	1	0	9	22
30	3	2	-1	1	0	10	12
31	4	2	-1	-1	0	1	25
32	4	2	-1	-1	0	2	15
33	4	2	-1	-1	0	3	23
34	4	2	-1	-1	0	4	21
35	4	2	-1	-1	0	5	18
36	4	2	-1	-1	0	6	24
37	4	2	-1	-1	0	7	14
38	4	2	-1	-1	0	8	27
39	4	2	-1	-1	0	9	12
40	4	2	-1	-1	0	10	11
41	5	-3	0	0	-1	1	8
42	5	-3	0	0	-1	2	20
43	5	-3	0	0	-1	3	10
44	5	-3	0	0	-1	4	7
45	5	-3	0	0	-1	5	15
46	5	-3	0	0	-1	6	7
47	5	-3	0	0	-1	7	1
48	5	-3	0	0	-1	8	17
49	5	-3	0	0	-1	9	11
50	5	-3	0	0	-1	10	4

S(A) design with contrasts
 Orthogonal Contrasts with PROC GLM
 General Linear Models Procedure
 Class Level Information

```

-----
Class      Levels  Values
-----
GROUP          5   1 2 3 4 5
-----

```

Number of observations in data set = 50

Dependent Variable: RECALL

```

-----
Source              DF      Sum of Squares      Mean Square  F Value  Pr > F
-----
Model                4      700.000000      175.000000   5.47    0.0011
Error               45     1440.000000      32.000000
Corrected Total     49     2140.000000
-----

```

```

-----
R-Square          C.V.      Root MSE      RECALL Mean
-----
0.327103         37.71236  5.65685      15.0000
-----

```

```

-----
Source              DF      Type I SS      Mean Square  F Value  Pr > F
-----
GROUP              4      700.000000      175.000000   5.47    0.0011
-----

```

```

-----
Source              DF      Type III SS      Mean Square  F Value  Pr > F
-----
GROUP              4      808.000000      202.000000   6.83    0.0002
-----

```

```

-----
Level of          -----RECALL-----
GROUP      N      Mean      SD
-----
1          10      18.000000  4.92160769
2          10      11.000000  5.61743318
3          10      17.000000  6.00000000
4          10      19.000000  5.77350269
5          10      10.000000  5.90668172
-----

```

S(A) design with contrasts
 Orthogonal Contrasts with PROC GLM
 General Linear Models Procedure

Dependent Variable: RECALL

Contrast	DF	Contrast SS	Mean Square	F Value	Pr > F
Psy1. (134) vs (25)	1	675.000000	675.000000	21.09	0.0001
Psy2. (1) vs (34)	1	0.000000	0.000000	0.00	1.0000
Psy3. (3) vs (4)	1	20.000000	20.000000	0.63	0.4333
Psy4. (2) vs (5)	1	5.000000	5.000000	0.16	0.6945

S(A) design with contrasts
 Same Analysis with PROC REG, Intercept = M..
 F GLM for PSYi = ti**2 for PROC REG

Model: MODEL1

Dependent Variable: RECALL

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	4	700.00000	175.00000	5.469	0.0011
Error	45	1440.00000	32.00000		
C Total	49	2140.00000			

Root MSE	5.65685	R-square	0.3271
Dep Mean	15.00000	Adj R-sq	0.2673
C.V.	37.71236		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > T
INTERCEP	1	15.000000	0.8000000	18.750	0.0001
PSY1	1	1.500000	0.32659863	4.593	0.0001
PSY2	1	0	0.73029674	0.000	1.0000
PSY3	1	-1.000000	1.26491106	-0.791	0.4333
PSY4	1	0.500000	1.26491106	0.395	0.6945

7.1.3 ANOVA table

Source	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Pr(F)</i>
\mathcal{A}	4	700.00	175.00	5.469**	.00119
$\mathcal{S}(\mathcal{A})$	45	1,440.00	32.00		
Total	49	2,140.00			

TABLE 7.2 ANOVA Table for a replication of Smith's (1979) experiment.

8

Planned Non-orthogonal Comparisons

Non-orthogonal comparisons are more complex than orthogonal comparisons. The main problem lies in assessing the importance of a given comparison independently of the other comparisons of the set. There are currently two (main) approaches to this problem. The classical approach corrects for multiple statistical tests (*i.e.*, using a Šidàk or Bonferonni correction), but essentially evaluates each contrast as if it were coming from a set of orthogonal contrasts. The multiple regression (or modern) approach evaluates each contrast as a predictor from a set of non-orthogonal predictors and estimates its *specific* contribution to the explanation of the dependent variable.

8.1 Classical approach: Tests for non-orthogonal comparisons

The Šidàk or the Bonferonni, Boole, Dunn inequality are used to find a correction on $\alpha[PC]$ in order to keep $\alpha[PF]$ fixed. The general idea of the procedure is to correct $\alpha[PC]$ in order to obtain the overall $\alpha[PF]$ for the experiment. By deciding that the family is the unit for evaluating Type I error, the inequalities give an approximation for each $\alpha[PC]$. The formula used to evaluate the alpha level for each comparison using the Šidàk inequality is:

$$\alpha[PC] \approx 1 - (1 - \alpha[PF])^{1/C} .$$

This is a conservative approximation, because the following inequality holds:

$$\alpha[PC] \geq 1 - (1 - \alpha[PF])^{1/C} .$$

The formula used to evaluate the alpha level for each comparison using Bonferonni, Boole, Dunn inequality would be:

$$\alpha[PC] \approx \frac{\alpha[PF]}{C} .$$

By using these approximations, the statistical test will be a *conservative* one. That is to say, the real value of $\alpha[PF]$ will always be smaller than the approximation we use. For example, suppose you want to perform four non-orthogonal comparisons, and that you want to limit the risk of making at least one Type I error to an overall value of $\alpha[PF] = .05$. Using the Šidák correction you will consider that any comparison of the family reaches significance if the probability associated with it is smaller than:

$$\alpha[PC] = 1 - (1 - \alpha[PF])^{1/C} = 1 - (1 - .05)^{1/4} = .0127$$

Note, this is a change from the usual .05 and .01.

8.2 Romeo and Juliet, non-orthogonal contrasts

An example will help to review this section. Again, let us return to Bransford's "Romeo and Juliet". The following Table gives the different experimental conditions:

Context Before	Partial Context	Context After	Without Context
----------------	-----------------	---------------	-----------------

Suppose that Bransford had build his experiment to test *a priori* four research hypotheses:

- **1.** The presence of any context has an effect.
- **2.** The context given after the story has an effect.
- **3.** The context given before has a stronger effect than any other condition.
- **4.** The partial context condition differs from the "context before" condition.

These hypotheses can easily be translated into a set of contrasts given in the following Table.

	Context Before	Partial Context	Context After	Without Context
ψ_1	1	1	1	-3
ψ_2	0	0	1	-1
ψ_3	3	-1	-1	-1
ψ_4	1	-1	0	0

If $\alpha[PF]$ is set to the value .05, this will lead to testing each contrast with the $\alpha[PC]$ level:

$$\alpha[PC] = 1 - .95^{1/4} = .0127.$$

If you want to use the critical values method, the Table gives for $\nu_2 = 16$ (this is the number of degrees of freedom of $MS_{S(A)}$), $\alpha[PF] = .05$, and $C = 4$ the value $F_{\text{critical Sidak}} = 7.91$ (This is simply the critical value of the standard Fisher F with 1 and 16 degrees of freedom and with $\alpha = \alpha[PC] = .0127$).

8.2.1 SAS code

```

/* Planned Non-orthogonal Comparisons,
   Bransford's Romeo and Juliet with Sidak correction
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
TITLE 'Planned Non-orthogonal Comparisons';
DATA example;
DO group = 1 to 4;
  DO subject = 1 to 5;
    INPUT score @;
    OUTPUT;
  END;
END;
CARDS;
5 9 8 4 9
5 4 3 5 4
2 4 5 4 1
3 3 2 4 3
;
PROC GLM ORDER=DATA;
  CLASS group;
  MODEL score = group;
  MEANS group / SIDAK;
  CONTRAST ' 1 1 1 -3'
    group 1 1 1 -3;
  CONTRAST ' 0 0 1 -1'
    group 0 0 1 -1;
  CONTRAST '3 -1 -1 -1'
    group 3 -1 -1 -1;
  CONTRAST '1 -1 0 0'
    group 1 -1 0 0;
RUN;

```

8.2.2 SAS listing

```

Planned Non-orthogonal Comparisons
General Linear Models Procedure
Class Level Information

```

```

Class      Levels      Values

```

GROUP 4 1 2 3 4

Number of observations in data set = 20

Dependent Variable: SCORE

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	50.9500000	16.9833333	7.23	0.0028
Error	16	37.6000000	2.3500000		
Corrected Total	19	88.5500000			

R-Square	C.V.	Root MSE	SCORE Mean
0.575381	35.24071	1.53297	4.35000

Source	DF	Type I SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.0028

Source	DF	Type III SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.0028

Planned Non-orthogonal Comparisons
 General Linear Models Procedure
 Sidak T tests for variable: SCORE

NOTE: This test controls the type I experimentwise error rate, but generally has a higher type II error rate than REGWQ.

Alpha= 0.05 df= 16 MSE= 2.35
 Critical Value of T= 3.00
 Minimum Significant Difference= 2.9068

Means with the same letter are not significantly different.

Sidak Grouping		Mean	N	GROUP
	A	7.0000	5	1
	A			
B	A	4.2000	5	2
B				
B		3.2000	5	3
B				
B		3.0000	5	4

Planned Non-orthogonal Comparisons
General Linear Models Procedure

Dependent Variable: SCORE

Contrast	DF	Contrast SS	Mean Square	F Value	Pr > F
1 1 1 -3	1	12.1500000	12.1500000	5.17	0.0371
0 0 1 -1	1	0.1000000	0.1000000	0.04	0.8392
3 -1 -1 -1	1	46.8166667	46.8166667	19.92	0.0004
1 -1 0 0	1	19.6000000	19.6000000	8.34	0.0107

8.3 Multiple Regression and Orthogonal Contrasts

ANOVA and multiple regression are equivalent if we use as many predictors for the multiple regression analysis as the number of degrees of freedom of the independent variable. An obvious choice for the predictors is to use a set of contrasts. Doing so makes contrast analysis a particular case of multiple regression analysis. Regression analysis, in return, helps solving some of the problems associated with the use of non-orthogonal contrasts: It suffices to use multiple regression and semi-partial coefficients of correlation to analyze non-orthogonal contrasts.

In this section, we illustrate the multiple regression analysis approach of the Bransford experiment (*i.e.*, “Romeo and Juliet”). We will first look at a set of orthogonal contrasts and then a set of non-orthogonal contrasts.

A set of data from a replication of this experiment is given in Table 8.1.

In order to analyze these data with a multiple regression approach we can use any arbitrary set of contrasts as long as they satisfy the following

Experimental Condition			
Context before	Partial context	Context after	Without context
5	5	2	3
9	4	4	3
8	3	5	2
4	5	4	4
9	4	1	3

TABLE 8.1 The data from a replication of Bransford's "Romeo and Juliet" experiment. $M_{..} = 4.35$.

constraints:

1. there are as many contrasts as the independent variable has degrees of freedom,
2. the set of contrasts is not multicollinear. That is, no contrast can be obtained by combining the other contrasts¹.

Contrast	Groups			
	1	2	3	4
ψ_1	1	1	-1	-1
ψ_2	1	-1	0	0
ψ_3	0	0	1	-1

TABLE 8.2 An arbitrary set of orthogonal contrasts for analyzing "Romeo and Juliet."

8.3.1 SAS code

```

/* Planned Orthogonal Comparisons,
   Bransford's Romeo and Juliet
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
TITLE 'Planned Orthogonal Comparisons';
DATA example;
  DO group = 1 to 4;
    INPUT psy1 psy2 psy3 @;
  DO subject = 1 to 5;
    INPUT dv @;

```

¹The technical synonym for non-multicollinear is *linearly independent*.

```

        OUTPUT;
      END;
    END;
  CARDS;
  1 1 0 5 9 8 4 9
  1 -1 0 5 4 3 5 4
  -1 0 1 2 4 5 4 1
  -1 0 -1 3 3 2 4 3
  ;
  PROC PRINT
    TITLE2 'The Data';
  PROC GLM ORDER=DATA;
    TITLE2 'Orthogonal Contrasts with PROC GLM';
    CLASS group;
    MODEL dv = group;
    CONTRAST 'Psy1 (1&2) vs (3&4)' group 1 1 -1 -1;
    CONTRAST 'Psy2 (1) vs (2)' group 1 -1 0 0;
    CONTRAST 'Psy3 (3) vs (4)' group 0 0 1 -1;
  PROC REG;
    TITLE2 'Same Analysis with PROC REG, Intercept = M..';
    TITLE3 'F GLM for PSYi = ti**2 for PROC REG';
    MODEL dv = psy1-psy3 / SS1 SCORR1 SS2 SCORR2;
  RUN;

```

8.3.2 SAS listing

ROMEO and JULIET
 Planned Orthogonal Comparisons
 Orthogonal Contrasts with PROC GLM

General Linear Models Procedure
 Class Level Information

Class	Levels	Values
GROUP	4	1 2 3 4

Number of observations in data set = 20

Dependent Variable: DV

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	50.9500000	16.9833333	7.23	0.0028
Error	16	37.6000000	2.3500000		
Corrected Total	19	88.5500000			

R-Square	C.V.	Root MSE	DV Mean
0.575381	35.24071	1.53297	4.35000

Source	DF	Type I SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.0028

Source	DF	Type III SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.0028

Contrast	DF	Contrast SS	Mean Square	F Value	Pr > F
Psy1 (1&2) vs (3&4)	1	31.2500000	31.2500000	13.30	0.0022
Psy2 (1) vs (2)	1	19.6000000	19.6000000	8.34	0.0107
Psy3 (3) vs (4)	1	0.1000000	0.1000000	0.04	0.8392

ROMEO and JULIET
 Planned Orthogonal Comparisons
 Same Analysis with PROC REG, Intercept = M..
 F GLM for PSYi = ti**2 for PROC REG

Model: MODEL1
 Dependent Variable: DV

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	50.95000	16.98333	7.227	0.0028
Error	16	37.60000	2.35000		
C Total	19	88.55000			

Root MSE	1.53297	R-square	0.5754
Dep Mean	4.35000	Adj R-sq	0.4958

C.V. 35.24071

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > T
INTERCEP	1	4.350000	0.34278273	12.690	0.0001
PSY1	1	1.250000	0.34278273	3.647	0.0022
PSY2	1	1.400000	0.48476799	2.888	0.0107
PSY3	1	0.100000	0.48476799	0.206	0.8392

Variable	DF	Type I SS	Type II SS	Squared Semi-partial Corr Type I	Squared Semi-partial Corr Type II
INTERCEP	1	378.450000	378.450000	.	.
PSY1	1	31.250000	31.250000	0.35290796	0.35290796
PSY2	1	19.600000	19.600000	0.22134387	0.22134387
PSY3	1	0.100000	0.100000	0.00112931	0.00112931

8.4 Multiple Regression and Non-orthogonal Contrasts

Most of the time, when experimentalists are concerned with *a priori* non-orthogonal comparisons, each comparison represents a prediction from a given theory. The goal of the experiment is, in general, to decide which one (or which ones) of the theories can explain the data best. In other words, the experiment is designed to eliminate some theories by showing that they cannot predict what the other theory (or theories) can predict. Therefore experimenters are interested in what each theory can *specifically* explain. In other words, when dealing with *a priori* non-orthogonal comparisons what the experimenter wants to evaluate are *semi-partial coefficients of correlation* because they express the *specific* effect of a variable. Within this framework, the multiple regression approach for non-orthogonal predictors fits naturally. The main idea, when analyzing non-orthogonal contrasts is simply to consider each contrast as an independent variable in a non-orthogonal multiple regression analyzing the dependent variable.

Suppose (for the beauty of the argument) that the “Romeo and Juliet” experiment was, in fact, designed to test three theories. Each of these theories is expressed as a contrast.

1. *Bransford's* theory implies that only the subjects from the context before group should be able to integrate the story with their long term knowledge. Therefore this group should do better than all the other groups, which should perform equivalently. This is equivalent to the following contrast:

$$\psi_1 = 3 \times \mu_1 \quad - 1 \times \mu_2 \quad - 1 \times \mu_3 \quad - 1 \times \mu_4$$

2. the *imagery* theory would predict (at least at the time the experiment was designed) that any concrete context presented *during* learning will improve learning. Therefore groups 1 and 2 should do better than the other groups. This is equivalent to the following contrast:

$$\psi_2 = 1 \times \mu_1 \quad 1 \times \mu_2 \quad - 1 \times \mu_3 \quad - 1 \times \mu_4$$

3. The *retrieval cue* theory would predict that the context acts during the retrieval phase (as opposed to Bransford's theory which states that the context acts during the *encoding* phase). Therefore group 1 and 3 should do better than the other groups. This is equivalent to the following contrast:

$$\psi_3 = 1 \times \mu_1 \quad - 1 \times \mu_2 \quad 1 \times \mu_3 \quad - 1 \times \mu_4$$

Contrast	Groups			
	1	2	3	4
ψ_1	3	-1	-1	-1
ψ_2	1	1	-1	-1
ψ_3	1	-1	1	-1

TABLE 8.3 A set of non-orthogonal contrasts for analyzing "Romeo and Juliet." The first contrast corresponds to Bransford's theory. The second contrast corresponds to the imagery theory. The third contrast corresponds to the retrieval cue theory.

8.4.1 SAS code

```

/* Planned Non-orthogonal Comparisons,
   Bransford's Romeo and Juliet
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='-' ;
TITLE 'Planned Non-orthogonal Comparisons';
DATA example;
  DO group = 1 to 4;
    INPUT psy1 psy2 psy3 @;

```

```

DO subject = 1 to 5;
  INPUT dv @;
  OUTPUT;
END;
END;
CARDS;
3  1  1  5  9  8  4  9
-1  1 -1  5  4  3  5  4
-1 -1  1  2  4  5  4  1
-1 -1 -1  3  3  2  4  3
;
PROC PRINT;
  TITLE2 'The Data';
PROC GLM ORDER=DATA;
  TITLE2 'Classical Approach';
  TITLE3 'Non-Orthogonal Constrasts with PROC GLM';
  CLASS group;
  MODEL dv = group;
  MEANS group;
  CONTRAST 'Psy1 (1) vs (2,3,4)'  group 3 -1 -1 -1;
  CONTRAST 'Psy2 (1&2) vs (3&4)'  group 1  1 -1 -1;
  CONTRAST 'Psy3 (1&3) vs (2&4)'  group 1 -1  1 -1;
PROC REG;
  TITLE2 'Same Analysis with PROC REG, Intercept = M..';
  TITLE3 'F GLM for PSYi = ti**2 for PROC REG';
  MODEL dv = psy1-psy3 / SS1 SCORR1 SS2 SCORR2;
RUN;

```

8.4.2 SAS listing

ROMEO and JULIET
Planned Non-orthogonal Comparisons

The Data

OBS	GROUP	PSY1	PSY2	PSY3	SUBJECT	DV
1	1	3	1	1	1	5
2	1	3	1	1	2	9
3	1	3	1	1	3	8
4	1	3	1	1	4	4
5	1	3	1	1	5	9
6	2	-1	1	-1	1	5
7	2	-1	1	-1	2	4
8	2	-1	1	-1	3	3
9	2	-1	1	-1	4	5
10	2	-1	1	-1	5	4
11	3	-1	-1	1	1	2
12	3	-1	-1	1	2	4
13	3	-1	-1	1	3	5
14	3	-1	-1	1	4	4
15	3	-1	-1	1	5	1

16	4	-1	-1	-1	1	3
17	4	-1	-1	-1	2	3
18	4	-1	-1	-1	3	2
19	4	-1	-1	-1	4	4
20	4	-1	-1	-1	5	3

Planned Non-orthogonal Comparisons
Classical Approach
Non-Orthogonal Constrasts with PROC GLM
General Linear Models Procedure
Class Level Information

Class	Levels	Values
GROUP	4	1 2 3 4

Number of observations in data set = 20

Planned Non-orthogonal Comparisons
Classical Approach
Non-Orthogonal Constrasts with PROC GLM
General Linear Models Procedure

Dependent Variable: DV

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	50.9500000	16.9833333	7.23	0.0028
Error	16	37.6000000	2.3500000		
Corrected Total	19	88.5500000			

R-Square	C.V.	Root MSE	DV Mean
0.575381	35.24071	1.53297	4.35000

Source	DF	Type I SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.0028

Source	DF	Type III SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.0028

Level of GROUP	N	Mean	SD
1	5	7.00000000	2.34520788
2	5	4.20000000	0.83666003
3	5	3.20000000	1.64316767
4	5	3.00000000	0.70710678

Planned Non-orthogonal Comparisons
 Classical Approach
 Non-Orthogonal Constrasts with PROC GLM

General Linear Models Procedure

Dependent Variable: DV

Contrast	DF	Contrast SS	Mean Square	F Value	Pr > F
Psy1 (1) vs (2,3,4)	1	46.8166667	46.8166667	19.92	0.0004
Psy2 (1&2) vs (3&4)	1	31.2500000	31.2500000	13.30	0.0022
Psy3 (1&3) vs (2&4)	1	11.2500000	11.2500000	4.79	0.0439

Planned Non-orthogonal Comparisons
 Same Analysis with PROC REG, Intercept = M..
 F GLM for PSYi = ti**2 for PROC REG
 Model: MODEL1
 Dependent Variable: DV

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	50.95000	16.98333	7.227	0.0028
Error	16	37.60000	2.35000		
C Total	19	88.55000			

Root MSE	1.53297	R-square	0.5754
Dep Mean	4.35000	Adj R-sq	0.4958
C.V.	35.24071		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > T
INTERCEP	1	4.350000	0.34278273	12.690	0.0001
PSY1	1	0.650000	0.34278273	1.896	0.0761
PSY2	1	0.600000	0.48476799	1.238	0.2337
PSY3	1	0.100000	0.48476799	0.206	0.8392

Variable	DF	Type I SS	Type II SS	Squared Semi-partial Corr Type I	Squared Semi-partial Corr Type II
INTERCEP	1	378.450000	378.450000	.	.
PSY1	1	46.816667	8.450000	0.52870318	0.09542631
PSY2	1	4.033333	3.600000	0.04554865	0.04065500
PSY3	1	0.100000	0.100000	0.00112931	0.00112931

9

Post hoc or *a-posteriori* analyses

Post hoc analyses are performed after the data have been collected, or in other words, after the fact. When looking at the results, you may find an unexpected pattern. If that pattern of results suggests some interesting hypothesis, then you want to be sure that it is not a fluke. This is the aim of *post hoc* (also called *a posteriori*) comparisons.

The main problem with *post hoc* comparisons involves the size of the family of possible comparisons. The number of possible comparisons, grows very quickly as a function of A (the number of levels of the independent variable), making the use of procedures such as Šidák or Bonferonni, Boole, Dunn inequalities unrealistic.

Two main approaches will be examined:

- Evaluating all the possible contrasts; this is known as *Scheffé's* test.
- The specific problem of pairwise comparisons. Here we will see three different tests: *Tukey*, *Newman-Keuls*, and *Duncan*.

Note that by default, SAS evaluates the contrasts with the α level set at .05. If a lower α is desired, this must be specified by following the post hoc option name with ALPHA=.01. For example, to specify an alpha level of .01 for a Scheffé's test, you would give the following command:

```
MEANS GROUP / SCHEFFE ALPHA=.01.
```

9.1 Scheffé's test

Scheffé's test was devised in order to be able to test all the possible contrasts *a posteriori* while maintaining the overall Type I error for the family at a reasonable level, as well as trying to have a relatively powerful test. Specifically, the Scheffé test is a conservative test. The critical value for the Scheffé test is larger than the critical value for other, more powerful, tests. In every case where the Scheffé test rejects the null hypothesis, more powerful tests also reject the null hypothesis.

9.1.1 Romeo and Juliet

We will use, once again, Bransford *et al.*'s "Romeo and Juliet" experiment. The following Table gives the different experimental conditions:

Context Before	Partial Context	Context After	Without Context
----------------	-----------------	---------------	-----------------

The "error mean square" is $MS_{S(A)} = 2.35$; and $S = 5$. Here are the values of the experimental means (note that the means have been reordered from the largest to the smallest):

	Context Before	Partial Context	Context After	Without Context
$M_a.$	7.00	4.20	3.20	3.00

Suppose now that the experimenters wanted to test the following contrasts *after* having collected the data.

	Context Before	Partial Context	Context After	Without Context
ψ_1	1	1	1	-3
ψ_2	0	0	1	-1
ψ_3	3	-1	-1	-1
ψ_4	1	-1	0	0

The critical value for $\alpha[PF] = .05$ is given by:

$$F_{\text{critical, Scheffé}} = (A - 1)F_{\text{critical, omnibus}} = (4 - 1) \times 3.24 = 9.72$$

with $\nu_1 = A - 1 = 3$ and $\nu_2 = A(S - 1) = 16$.

9.1.1.1 SAS code

```
/* Post Hoc Comparisons - Scheffe' test
   Bransford's Romeo and Juliet
*/

OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
TITLE 'Post Hoc Comparison - Scheffe test';
DATA example;
  DO group = 1 to 4;
    DO subject = 1 to 5;
      INPUT score @;
      OUTPUT;
```

```

        END;
    END;
CARDS;
5 9 8 4 9
5 4 3 5 4
2 4 5 4 1
3 3 2 4 3
;
PROC GLM ORDER=DATA;
    CLASS group;
    MODEL score = group;
    MEANS group / Scheffe;
        CONTRAST ' 1 1 1 -3'
            group 1 1 1 -3;
        CONTRAST ' 0 0 1 -1'
            group 0 0 1 -1;
        CONTRAST '3 -1 -1 -1'
            group 3 -1 -1 -1;
        CONTRAST '1 -1 0 0'
            group 1 -1 0 0;
RUN;

```

9.1.1.2 SAS listing

ROMEO and JULIET
 Post Hoc Comparison - Scheffe test 1

General Linear Models Procedure
 Class Level Information

Class Levels Values
 GROUP 4 1 2 3 4

Number of observations in data set = 20

Dependent Variable: SCORE

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	50.9500000	16.9833333	7.23	0.0028
Error	16	37.6000000	2.3500000		
Corrected Total	19	88.5500000			

R-Square	C.V.	Root MSE	SCORE Mean
0.575381	35.24071	1.53297	4.35000

Source	DF	Type I SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.0028

Source	DF	Type III SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.0028

Post Hoc Comparison - Scheffe test

General Linear Models Procedure

Scheffe's test for variable: SCORE

NOTE: This test controls the type I experimentwise error rate but generally has a higher type II error rate than REGWF for all pairwise comparisons

Alpha= 0.05 df= 16 MSE= 2.35

Critical Value of F= 3.23887

Minimum Significant Difference= 3.0222

Means with the same letter are not significantly different.

Scheffe Grouping	Mean	N	GROUP
A	7.0000	5	1
A			
B A	4.2000	5	2
B			
B	3.2000	5	3
B			
B	3.0000	5	4

Post Hoc Comparison - Scheffe test

General Linear Models Procedure

Dependent Variable: SCORE

Contrast	DF	Contrast SS	Mean Square	F Value	Pr > F
1 1 1 -3	1	12.1500000	12.1500000	5.17	0.0371
0 0 1 -1	1	0.1000000	0.1000000	0.04	0.8392
3 -1 -1 -1	1	46.8166667	46.8166667	19.92	0.0004
1 -1 0 0	1	19.6000000	19.6000000	8.34	0.0107

The results of the Scheffé procedure for the family can be summarized in the following Table:

Comparison	$SS_{\text{comp.}}$	$F_{\text{comp.}}$	Decision	$\Pr(F_{\text{Scheffé}})$
ψ_1	12.15	5.17	<i>ns</i>	.201599
ψ_2	0.10	0.04	<i>ns</i>	$F < 1$
ψ_3	46.82	19.92	reject H_0	.004019
ψ_4	19.60	8.34	<i>ns</i>	.074800

9.2 Tukey's test

The Tukey test uses a distribution derived by Gosset, who is better known under his pen name of Student (yes, like Student-*t*!). Gosset/Student derived a distribution called Student's q or the *Studentized range*, which is the value reported by SAS. The value reported in your textbook is a slightly modified version of his distribution called F -range or F_{range} . F -range is derived from q by the transformation:

$$F_{\text{range}} = \frac{q^2}{2}.$$

9.2.1 The return of Romeo and Juliet

For an example, we will use, once again, Bransford *et al.*'s "Romeo and Juliet." Recall that

$$MS_{S(A)} = 2.35; \quad S = 5$$

and that the experimental results were:

	Context Before	Partial Context	Context After	Without Context
$M_{a.}$	7.00	4.20	3.20	3.00

The pairwise difference between means can be given in a Table:

	$M_{1.}$	$M_{2.}$	$M_{3.}$	$M_{4.}$
$M_{1.}$		2.80	3.80	4.00
$M_{2.}$			1.00	1.20
$M_{3.}$				0.20

The values for $F_{\text{critical, Tukey}}$ given by the table are

$$8.20 \quad \text{for} \quad \alpha[PF] = .05$$

$$13.47 \quad \text{for} \quad \alpha[PF] = .01$$

The results of the computation of the different F ratios for the pairwise comparisons are given in the following Table, the sign * indicates a difference significant at the .05 level, and ** indicates a difference significant at the .01 level.

Note in the SAS output, that the “Critical Value of Studentized Range = 4.046”. Remember the formula to derive the F_{range} from q

$$F_{\text{range}} = \frac{q^2}{2} .$$

For our example,

$$F_{\text{range}} = 8.185 = \frac{4.046^2}{2} .$$

The difference observed between the value reported in the book and that obtained using SAS's value is due to rounding errors.

	$M_{1.}$	$M_{2.}$	$M_{3.}$	$M_{4.}$
$M_{1.}$		8.34*	15.36**	17.02**
$M_{2.}$			1.06	1.53
$M_{3.}$				0.40

Tukey test is clearly a conservative test. Several approaches have been devised in order to have a more sensitive test. The most popular alternative (but not the “safest”) is the Newman-Keuls test.

9.2.1.1 SAS code

```
/* ROMEO and JULIET, Post Hoc Comparisons - Tukey test */

OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='-';
TITLE 'Post Hoc Comparison - Tukey test';
DATA example;
  DO group = 1 to 4;
```

```

      DO subject = 1 to 5;
        INPUT dv @;
        OUTPUT;
      END;
    END;
  CARDS;
  5 9 8 4 9
  5 4 3 5 4
  2 4 5 4 1
  3 3 2 4 3
  ;
PROC GLM ORDER=DATA;
  CLASS group;
  MODEL dv = group;
  MEANS group / TUKEY;
    CONTRAST ' 1 -1 0 0, M1 - M2'
      group 1 -1 0 0;
    CONTRAST ' 1 0 -1 0, M1 - M3'
      group 1 0 -1 0;
    CONTRAST ' 1 0 0 -1, M1 - M4'
      group 1 0 0 -1;
    CONTRAST ' 0 1 -1 0, M2 - M3'
      group 0 1 -1 0;
    CONTRAST ' 0 1 0 -1, M2 - M4'
      group 0 1 0 -1;
    CONTRAST ' 0 0 1 -1, M3 - M4'
      group 0 0 1 -1;
RUN;

```

9.2.1.2 SAS listing

ROMEO and JULIET
 Post Hoc Comparison - Tukey test
 General Linear Models Procedure
 Class Level Information

Class	Levels	Values
-------	--------	--------

GROUP	4	1 2 3 4
-------	---	---------

Number of observations in data set = 20

Post Hoc Comparison - Tukey test

General Linear Models Procedure

Dependent Variable: DV

 Sum of Mean

Source	DF	Squares	Square	F Value	Pr > F
Model	3	50.9500000	16.9833333	7.23	0.0028
Error	16	37.6000000	2.3500000		
Corrected Total	19	88.5500000			

R-Square	C.V.	Root MSE	DV Mean
0.575381	35.24071	1.53297	4.35000

Source	DF	Type I SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.0028

Source	DF	Type III SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.0028

Post Hoc Comparison - Tukey test
General Linear Models Procedure

Tukey's Studentized Range (HSD) Test for variable: DV

NOTE: This test controls the type I experimentwise error rate, but generally has a higher type II error rate than REGWQ.

Alpha= 0.05 df= 16 MSE= 2.35
Critical Value of Studentized Range= 4.046
Minimum Significant Difference= 2.7739

Means with the same letter are not significantly different.

Tukey Grouping	Mean	N	GROUP
A	7.0000	5	1
B	4.2000	5	2
B	3.2000	5	3
B			

B 3.0000 5 4

Post Hoc Comparison - Tukey test
General Linear Models Procedure

Dependent Variable: DV

Contrast	DF	Contrast SS	Mean Square	F Value	Pr > F
1 -1 0 0, M1 - M2	1	19.6000000	19.6000000	8.34	0.0107
1 0 -1 0, M1 - M3	1	36.1000000	36.1000000	15.36	0.0012
1 0 0 -1, M1 - M4	1	40.0000000	40.0000000	17.02	0.0008
0 1 -1 0, M2 - M3	1	2.5000000	2.5000000	1.06	0.3177
0 1 0 -1, M2 - M4	1	3.6000000	3.6000000	1.53	0.2337
0 0 1 -1, M3 - M4	1	0.1000000	0.1000000	0.04	0.8392

9.3 Newman-Keuls' test

Essentially, the Newman-Keuls test consists of a sequential test in which the critical value depends on the range of each pair of means. To make the explanation easier, we will suppose that the means are ordered from the smallest to the largest. Hence M_1 is the smallest mean, and M_A is the largest mean.

The Newman-Keuls test starts like the Tukey test. The largest difference between two means is selected. The range of the difference is A . The null hypothesis is tested for that mean using F_{range} following exactly the same procedure as for the Tukey test. If the null hypothesis cannot be rejected the test stops here, because not rejecting the null hypothesis for the largest difference implies not rejecting the null hypothesis for any other difference.

If the null hypothesis is rejected for the largest difference, then the two differences with a range of $A - 1$ are examined. They will be tested with a critical value of F_{range} selected for a range of $A - 1$. When the null hypothesis cannot be rejected for a given difference, none of the differences included in that difference will be tested. If the null hypothesis can be rejected for a difference, then the procedure is re-iterated for a range of $A - 2$. The procedure is used until all the differences have been tested or declared nonsignificant by implication.

9.3.1 Taking off with Loftus...

In an experiment on eyewitness testimony, Loftus and Palmer (1974) tested the influence of the wording of a question on the answers given by eyewitnesses. They presented a film of a multiple car crash to 20 subjects. After seeing the film, subjects were asked to answer a number of specific questions. Among these questions, one question about the speed of the car was presented with five different versions:

- “HIT”: About how fast were the cars going when they *hit* each other?
- “SMASH”: About how fast were the cars going when they *smashed* into each other?
- “COLLIDE”: About how fast were the cars going when they *collided* with each other?
- “BUMP”: About how fast were the cars going when they *bumped* into each other?
- “CONTACT”: About how fast were the cars going when they *contacted* each other?

The mean speed estimation by subjects for each version is given in the following Table:

	Experimental Group				
	Contact	Hit	Bump	Collide	Smash
	M_1	M_2	M_3	M_4	M_5
M_a	30.00	35.00	38.00	41.00	46.00

$$S = 10; \quad MS_{S(A)} = 80.00$$

The obtained F ratios are given in the following Table.

	Experimental Group				
	Contact	Hit	Bump	Collide	Smash
Contact	—	1.56	4.00	7.56*	16.00**
Hit		—	0.56	2.25	7.56*
Bump			—	0.56	4.00
Collide				—	1.56
Smash					—

9.3.1.1 SAS code

```

/* ANOVA One factor between-subjects
   Post Hoc contrasts, Neuman-Keuls test;
   "Taking off with Loftus ..."
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
TITLE 'ANOVA & Neuman-Keuls test - Taking off with Loftus';
DATA example;
  DO group = 1 TO 5;
    DO subject = 1 TO 10;
      INPUT dv @;
      OUTPUT;
    END;
  END;
CARDS;
21 20 26 46 35 13 41 30 42 26
23 30 34 51 20 38 34 44 41 35
35 35 52 29 54 32 30 42 50 21
44 40 33 45 45 30 46 34 49 44
39 44 51 47 50 45 39 51 39 55
;
PROC GLM ORDER=DATA;
  CLASS group;
  MODEL dv = group;
  MEANS group / SNK;
  CONTRAST ' 1 -1 0 0 0, M1 - M2'
    group 1 -1 0 0 0;
  CONTRAST ' 1 0 -1 0 0, M1 - M3'
    group 1 0 -1 0 0;
  CONTRAST ' 1 0 0 -1 0, M1 - M4'
    group 1 0 0 -1 0;
  CONTRAST ' 1 0 0 0 -1, M1 - M5'
    group 1 0 0 0 -1;
  CONTRAST ' 0 1 -1 0 0, M2 - M3'
    group 0 1 -1 0 0;
  CONTRAST ' 0 1 0 -1 0, M2 - M4'
    group 0 1 0 -1 0;
  CONTRAST ' 0 1 0 0 -1, M2 - M5'
    group 0 1 0 0 -1;
  CONTRAST ' 0 0 1 -1 0, M3 - M4'
    group 0 0 1 -1 0;
  CONTRAST ' 0 0 1 0 -1, M3 - M5'
    group 0 0 1 0 -1;
  CONTRAST ' 0 0 0 1 -1, M4 - M5'
    group 0 0 0 1 -1;
RUN;

```

9.3.1.2 SAS listing

ANOVA & Neuman-Keuls test - Taking off with Loftus

General Linear Models Procedure
Class Level Information

Class Levels Values
 GROUP 5 1 2 3 4 5

Number of observations in data set = 50

Dependent Variable: DV

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	1460.00000	365.00000	4.56	0.0035
Error	45	3600.00000	80.00000		
Corrected Total	49	5060.00000			

R-Square	C.V.	Root MSE	DV Mean
0.288538	23.53756	8.94427	38.0000

Source	DF	Type I SS	Mean Square	F Value	Pr > F
GROUP	4	1460.00000	365.00000	4.56	0.0035

Source	DF	Type III SS	Mean Square	F Value	Pr > F
GROUP	4	1460.00000	365.00000	4.56	0.0035

ANOVA & Neuman-Keuls test - Taking off with Loftus
 General Linear Models Procedure
 Student-Newman-Keuls test for variable: DV

NOTE: This test controls the type I experimentwise error rate under the complete null hypothesis but not under partial null hypotheses.

Alpha= 0.05 df= 45 MSE= 80

Number of Means 2 3 4 5
 Critical Range 8.0565466 9.6944616 10.670799 11.365809

Means with the same letter are not significantly different.

SNK Grouping	Mean	N	GROUP
A	46.000	10	5
A			
B A	41.000	10	4
B A			
B A C	38.000	10	3
B C			
B C	35.000	10	2
C			
C	30.000	10	1

Post Hoc Comparisons - Newman-Keuls test
 General Linear Models Procedure
 Dependent Variable: DV

Contrast	DF	Contrast SS	Mean Square	F Value	Pr > F
1 -1 0 0 0, M1 -	1	125.00000	125.00000	1.56	0.2178
1 0 -1 0 0, M1 -	1	320.00000	320.00000	4.00	0.0516
1 0 0 -1 0, M1 -	1	605.00000	605.00000	7.56	0.0086
1 0 0 0 -1, M1 -	1	1280.00000	1280.00000	16.00	0.0002
0 1 -1 0 0, M2 -	1	45.00000	45.00000	0.56	0.4572
0 1 0 -1 0, M2 -	1	180.00000	180.00000	2.25	0.1406
0 1 0 0 -1, M2 -	1	605.00000	605.00000	7.56	0.0086
0 0 1 -1 0, M3 -	1	45.00000	45.00000	0.56	0.4572
0 0 1 0 -1, M3 -	1	320.00000	320.00000	4.00	0.0516
0 0 0 1 -1, M4 -	1	125.00000	125.00000	1.56	0.2178

9.3.2 Guess who?

Using the data from Bransford's Romeo and Juliet, we ran the *post hoc* contrasts with the Newman-Keuls test.

9.3.2.1 SAS code

```

/* Post Hoc comparison - Newman Keuls
   Bransford's Romeo & Juliet
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
TITLE 'Post Hoc Comparisons - Newman-Keuls';
DATA example;
    DO group = 1 to 4;

```

```

DO subject = 1 to 5;
  INPUT score @;
  OUTPUT;
END;
END;
CARDS;
5 9 8 4 9
5 4 3 5 4
2 4 5 4 1
3 3 2 4 3
;
PROC GLM ORDER=DATA;
  TITLE 'Post Hoc Comparisons - Newman-Keuls test';
  CLASS group;
  MODEL score = group;
  MEANS group / SNK;
  CONTRAST ' 1 -1 0 0, M1 - M2'
    group 1 -1 0 0;
  CONTRAST ' 1 0 -1 0, M1 - M3'
    group 1 0 -1 0;
  CONTRAST ' 1 0 0 -1, M1 - M4'
    group 1 0 0 -1;
  CONTRAST ' 0 1 -1 0, M2 - M3'
    group 0 1 -1 0;
  CONTRAST ' 0 1 0 -1, M2 - M4'
    group 0 1 0 -1;
  CONTRAST ' 0 0 1 -1, M3 - M4'
    group 0 0 1 -1;
RUN;

```

9.3.2.2 SAS listing

Post Hoc Comparisons - Newman-Keuls test

General Linear Models Procedure
Class Level Information

Class	Levels	Values
GROUP	4	1 2 3 4

Number of observations in data set = 20

Dependent Variable: SCORE

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	50.9500000	16.9833333	7.23	0.0028
Error	16	37.6000000	2.3500000		
Corrected Total	19	88.5500000			

R-Square	C.V.	Root MSE	SCORE Mean
0.575381	35.24071	1.53297	4.35000

Source	DF	Type I SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.0028

Source	DF	Type III SS	Mean Square	F Value	Pr > F
GROUP	3	50.9500000	16.9833333	7.23	0.0028

Post Hoc Comparisons - Newman-Keuls test
 General Linear Models Procedure

Student-Newman-Keuls test for variable: SCORE

NOTE: This test controls the type I experimentwise error rate under the complete null hypothesis but not under partial null hypotheses.

Alpha= 0.05 df= 16 MSE= 2.35

Number of Means	2	3	4
Critical Range	2.0553246	2.5017238	2.773862

Means with the same letter are not significantly different.

SNK Grouping	Mean	N	GROUP
A	7.0000	5	1
B	4.2000	5	2
B	3.2000	5	3
B	3.0000	5	4

Post Hoc Comparisons - Newman-Keuls test
 General Linear Models Procedure
 Dependent Variable: SCORE

Contrast	DF	Contrast SS	Mean Square	F Value	Pr > F
1 -1 0 0, M1 - M2	1	19.6000000	19.6000000	8.34	0.0107
1 0 -1 0, M1 - M3	1	36.1000000	36.1000000	15.36	0.0012
1 0 0 -1, M1 - M4	1	40.0000000	40.0000000	17.02	0.0008
0 1 -1 0, M2 - M3	1	2.5000000	2.5000000	1.06	0.3177
0 1 0 -1, M2 - M4	1	3.6000000	3.6000000	1.53	0.2337
0 0 1 -1, M3 - M4	1	0.1000000	0.1000000	0.04	0.8392

10

ANOVA **Two factor design:** $A \times B$ **or** $S(A \times B)$

10.1 Cute Cued Recall

To illustrate the use of a two-factor design, consider a replication of an experiment by Tulving & Pearlstone (1966), in which 60 subjects were asked to learn lists of 12, 24 or 48 words (factor A with 3 levels). These words can be put in pairs by categories (for example, apple and orange can be grouped as “fruits”). Subjects were asked to learn these words, and the category name was shown at the same time as the words were presented. Subjects were told that they did not have to learn the category names. After a very short time, subjects were asked to recall the words. At that time half of the subjects were given the list of the category names, and the other half had to recall the words without the list of categories (factor B with 2 levels). The dependent variable is the number of words recalled by each subject. Note that both factors are fixed. The results obtained in the six experimental conditions used in this experiment are presented in Table 10.1.

Factor B	Factor A					
	a_1 : 12 words		a_2 : 24 words		a_3 : 48 words	
b_1 Free Recall	11	07	13	15	17	16
	09	12	18	13	20	23
	13	11	19	09	22	19
	09	10	13	08	13	20
	08	10	08	14	21	19
b_2 Cued Recall	12	10	13	14	32	30
	12	12	21	13	31	33
	07	10	20	14	27	25
	09	07	15	16	30	25
	09	12	17	07	29	28

TABLE 10.1 Results of a replication of Tulving and Pearlstone’s experiment (1966). The dependent variable is the number of words recalled (see text for explanation).

10.1.1 SAS code

```

/* Analysis of a S(A*B) design using PROC GLM
   Cute Cued Recall; Tulving and Pearlstone
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
TITLE1'Design S(A*B), Cute Cued Recall';
PROC FORMAT;
    VALUE list 1='12 Words' 2='24 Words' 3='48 Words';
    VALUE cue 1='No cue' 2='Cue';
/* Gives names to the levels of A and B for PROC MEANS */
DATA anovab;
group=0;
DO a=1 to 3;
    DO b=1 TO 2;
        group=group+1;
        DO subject=1 TO 10;
            INPUT nbrwords@;
            OUTPUT;
        END;
    END;
END;
LABEL a='List length (12, 24, 48)'
      b='no-cue vs cue at test';
/* Gives names for A and B for PROC MEANS */
FORMAT a list. b cue.;
/* Gives names to the levels of A and B */
CARDS;
11 7 9 12 13 11 9 10 8 10
12 10 12 12 7 10 9 7 9 12
13 15 18 13 19 9 13 8 8 14
13 14 21 13 20 14 15 16 17 7
17 16 20 23 22 19 13 20 21 19
32 30 31 33 27 25 30 25 29 28
;
PROC GLM;
CLASS a b;
/* list and cue are nominal variables */
MODEL nbrwords = a b a*b;
/* describe the model */
MEANS a b a*b ;
/* ask for the means for main effects and for exp. groups */
CONTRAST ' A linear '
        a -1 0 1;
CONTRAST ' A quadratic '
        a 1 -2 1;
CONTRAST ' A 1 vs A2 3 '
        a -2 1 1;
CONTRAST ' A 2 vs 3 '
        a 0 1 -1;
CONTRAST ' AB ??? '
        a*b -2 2 1 -1 1 -1;
RUN;

```

10.1.2 SAS listing

Design S(A*B), Cute Cued Recall
 General Linear Models Procedure
 Class Level Information

Class	Levels	Values
A	3	12 Words 24 Words 48 Words
B	2	Cue No cue

Number of observations in data set = 60

Dependent Variable: NBRWORDS

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	2600.00000	520.00000	57.78	0.0001
Error	54	486.00000	9.00000		
Corrected Total	59	3086.00000			

R-Square	C.V.	Root MSE	NBRWORDS Mean
0.842515	18.75000	3.00000	16.0000

Source	DF	Type I SS	Mean Square	F Value	Pr > F
A	2	2080.00000	1040.00000	115.56	0.0001
B	1	240.00000	240.00000	26.67	0.0001
A*B	2	280.00000	140.00000	15.56	0.0001

Source	DF	Type III SS	Mean Square	F Value	Pr > F
A	2	2080.00000	1040.00000	115.56	0.0001
B	1	240.00000	240.00000	26.67	0.0001
A*B	2	280.00000	140.00000	15.56	0.0001

Level of	-----NBRWORDS-----		
A	N	Mean	SD
12 Words	20	10.0000000	1.86378223

24 Words	20	14.0000000	3.92025778
48 Words	20	24.0000000	5.83997116

Level of B	N	Mean	SD
Cue	30	18.0000000	8.67815331
No cue	30	14.0000000	4.77782233

Level of A	Level of B	N	Mean	SD
12 Words	Cue	10	10.0000000	2.00000000
12 Words	No cue	10	10.0000000	1.82574186
24 Words	Cue	10	15.0000000	3.94405319
24 Words	No cue	10	13.0000000	3.82970843
48 Words	Cue	10	29.0000000	2.74873708
48 Words	No cue	10	19.0000000	2.98142397

Contrast	DF	Contrast SS	Mean Square	F Value	Pr > F
A linear	1	1960.00000	1960.00000	217.78	0.0001
A quadratic	1	120.00000	120.00000	13.33	0.0006
A 1 vs A2 3	1	1080.00000	1080.00000	120.00	0.0001
A 2 vs 3	1	1000.00000	1000.00000	111.11	0.0001
AB ???	1	120.00000	120.00000	13.33	0.0006

10.1.3 ANOVA table

Source	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Pr(F)</i>
<i>A</i>	2	2,080.00	1,040.00	115.56	< .000,001
<i>B</i>	1	240.00	240.00	26.67	.000,007
<i>AB</i>	2	280.00	140.00	15.56	.000,008
<i>S(AB)</i>	54	486.00	9.00		
Total	59	3,086.00			

TABLE 10.2 ANOVA Table for Tulving and Pearlstone's (1966) experiment.

10.2 Projective Tests and Test Administrators

For purposes of illustrating the SAS code for an $\mathcal{A} \times \mathcal{B}$ design with both factors random (Model II), consider the following results from a hypothetical experiment on projective testing. The researchers were interested in the effects of using different test administrators.

Note that only the F values obtained using the random option in the SAS code are valid.

Order (\mathcal{B})	Test Administrators (\mathcal{A})				Means
	1	2	3	4	
I	127	117	111	108	113
	121	109	111	100	
II	117	113	111	100	107
	109	113	101	92	
III	107	108	99	92	99
	101	104	91	90	
IV	98	95	95	87	91
	94	93	89	77	
V	97	96	89	89	90
	89	92	83	85	
Means	106	104	98	92	100

10.2.1 SAS code

```

/* S(AxB) design; A and B random factors
   Effect of Test Administrators
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
TITLE1 'ANOVA 2 factor S(AxB), A and B random';
DATA example;
DO order = 1 to 5;
  DO adm = 1 to 4;
    DO subject = 1 to 2;
      INPUT anxiety@;
      OUTPUT;
    END;
  END;
END;
CARDS;
127 121
117 109
111 111
108 100
117 109
113 113
111 101
100 92

```

```

107 101
108 104
  99  91
  92  90
  98  94
  95  93
  95  89
  87  77
  97  89
  96  92
  89  83
  89  85
;
PROC GLM ORDER=DATA;
  TITLE2 'Using Test Option';
  /* these F values are meaningless! */
  CLASSES order adm;
  MODEL anxiety = order adm order*adm;
  TEST H = order    E = order*adm;
  TEST H = adm      E = order*adm;
PROC GLM ORDER=DATA;
  TITLE2 'Using Random Option';
  /* this option will give you the correct F values */
  CLASSES order adm;
  MODEL anxiety = order adm order*adm;
  RANDOM adm order order*adm / TEST;
RUN;

```

10.2.2 SAS listing

ANOVA 2 factor S(AxB), A and B random
Using Test Option

General Linear Models Procedure
Class Level Information

Class	Levels	Values
ORDER	5	1 2 3 4 5
ADM	4	1 2 3 4

Number of observations in data set = 40

Dependent Variable: ANXIETY

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	19	4640.00000	244.21053	12.21	0.0001
Error	20	400.00000	20.00000		
Corrected Total	39	5040.00000			

R-Square	C.V.	Root MSE	ANXIETY Mean
0.920635	4.472136	4.47214	100.000

Source	DF	Type I SS	Mean Square	F Value	Pr > F
ORDER	4	3200.00000	800.00000	40.00	0.0001
ADM	3	1200.00000	400.00000	20.00	0.0001
ORDER*ADM	12	240.00000	20.00000	1.00	0.4827

Source	DF	Type III SS	Mean Square	F Value	Pr > F
ORDER	4	3200.00000	800.00000	40.00	0.0001
ADM	3	1200.00000	400.00000	20.00	0.0001
ORDER*ADM	12	240.00000	20.00000	1.00	0.4827

Tests of Hypotheses using the Type III MS for ORDER*ADM as an error term

Source	DF	Type III SS	Mean Square	F Value	Pr > F
ORDER	4	3200.00000	800.00000	40.00	0.0001

ANOVA 2 factor S(AxB), A and B random
Using Test Option

General Linear Models Procedure

Dependent Variable: ANXIETY

Tests of Hypotheses using the Type III MS for ORDER*ADM as an error term

Source	DF	Type III SS	Mean Square	F Value	Pr > F
ADM	3	1200.00000	400.00000	20.00	0.0001

ANOVA 2 factor S(AxB), A and B random
Using Random Option

General Linear Models Procedure

Class Level Information

```

-----
Class      Levels      Values
-----
ORDER      5      1 2 3 4 5
ADM        4      1 2 3 4
-----
    
```

Number of observations in data set = 40

Dependent Variable: ANXIETY

```

-----
Source              DF      Sum of Squares      Mean Square      F Value      Pr > F
-----
Model                19      4640.00000      244.21053      12.21      0.0001
Error                20      400.00000      20.00000
Corrected Total      39      5040.00000
-----
    
```

```

-----
R-Square      C.V.      Root MSE      ANXIETY Mean
-----
0.920635      4.472136      4.47214      100.000
-----
    
```

```

-----
Source              DF      Type I SS      Mean Square      F Value      Pr > F
-----
ORDER                4      3200.00000      800.00000      40.00      0.0001
ADM                  3      1200.00000      400.00000      20.00      0.0001
ORDER*ADM            12      240.00000      20.00000      1.00      0.4827
-----
    
```

```

-----
Source              DF      Type III SS      Mean Square      F Value      Pr > F
-----
ORDER                4      3200.00000      800.00000      40.00      0.0001
ADM                  3      1200.00000      400.00000      20.00      0.0001
ORDER*ADM            12      240.00000      20.00000      1.00      0.4827
-----
    
```

ANOVA 2 factor S(AxB), A and B random

Using Random Option

General Linear Models Procedure

```
-----
Source      Type III Expected Mean Square
-----
ORDER      Var(Error) + 2 Var(ORDER*ADM) + 8 Var(ORDER)
ADM        Var(Error) + 2 Var(ORDER*ADM) + 10 Var(ADM)
ORDER*ADM  Var(Error) + 2 Var(ORDER*ADM)
-----
```

Tests of Hypotheses for Random Model Analysis of Variance

Dependent Variable: ANXIETY

Source: ORDER

Error: MS(ORDER*ADM)

```
-----
              Denominator      Denominator
              DF                MS      F Value  Pr > F
-----
DF    Type III MS
-----
    4          800          12          20    40.0000  0.0001
-----
```

Source: ADM

Error: MS(ORDER*ADM)

```
-----
              Denominator      Denominator
              DF                MS      F Value  Pr > F
-----
DF    Type III MS
-----
    3          400          12          20    20.0000  0.0001
-----
```

Source: ORDER*ADM

Error: MS(Error)

```
-----
              Denominator      Denominator
              DF                MS      F Value  Pr > F
-----
DF    Type III MS
-----
   12          20          20          20     1.0000  0.4827
-----
```

10.2.3 ANOVA table

	Source	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	Pr(<i>F</i>)
	\mathcal{A}	3	1,200.00	400.00	20.00**	.00008
	\mathcal{B}	4	3,200.00	800.00	40.00**	.00000
[h]	\mathcal{AB}	12	240.00	20.00	1.00 ns	.48284
	$\mathcal{S}(\mathcal{AB})$	20	400.00	20.00		
	Total	39	5,040.00			

11

ANOVA **One Factor Repeated Measures**, $S \times A$

11.1 $S \times A$ design

For illustrative purposes we designed a hypothetical experiment using a within-subjects design. The independent variable consists of 4 levels and the size of the experimental group is 5 (*i.e.*, 5 subjects participated in the experiment, the results are presented in Table 11.1:

11.1.1 SAS code

```
/* Numerical example of SxA (repeated measures) Design */  
  
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='-';  
TITLE 'ANOVA - Repeated Measures - SxA';  
DATA example;  
INPUT subj$ level$ score;  
CARDS;  
1 1 5  
1 2 4  
1 3 1  
1 4 8  
2 1 7  
2 2 4
```

Subjects	Levels of the independent variable				$M_{.s}$
	a_1	a_2	a_3	a_4	
s_1	5	4	1	8	4.50
s_2	7	4	1	10	5.50
s_3	12	9	8	16	11.25
s_4	4	9	6	9	7.00
s_5	8	9	5	13	8.75
$M_{a.}$	7.20	7.00	4.20	11.20	$M_{..} = 7.40$

TABLE 11.1 A numerical example of an $S \times A$ design.

```

2 3 1
2 4 10
3 1 12
3 2 9
3 3 8
3 4 16
4 1 4
4 2 9
4 3 6
4 4 9
5 1 8
5 2 9
5 3 5
5 4 13
;
PROC ANOVA;
  CLASSES subj level;
  MODEL score = subj level;
  MEANS subj level;
RUN;

```

11.1.2 SAS listing

ANOVA - Repeated Measures - SxA

Analysis of Variance Procedure
Class Level Information

Class	Levels	Values
SUBJ	5	1 2 3 4 5
LEVEL	4	1 2 3 4

Number of observations in data set = 20

Dependent Variable: SCORE

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	239.700000	34.242857	11.71	0.0002
Error	12	35.100000	2.925000		
Corrected Total	19	274.800000			

R-Square	C.V.	Root MSE	SCORE Mean
0.872271	23.11166	1.71026	7.40000

Source	DF	Anova SS	Mean Square	F Value	Pr > F
SUBJ	4	115.300000	28.825000	9.85	0.0009
LEVEL	3	124.400000	41.466667	14.18	0.0003

Level of	-----SCORE-----		
SUBJ	N	Mean	SD
1	4	4.5000000	2.88675135
2	4	5.5000000	3.87298335
3	4	11.2500000	3.59397644
4	4	7.0000000	2.44948974
5	4	8.7500000	3.30403793

Level of	-----SCORE-----		
LEVEL	N	Mean	SD
1	5	7.2000000	3.11448230
2	5	7.0000000	2.73861279
3	5	4.2000000	3.11448230
4	5	11.2000000	3.27108545

11.2 Drugs and reaction time

In a psychopharmacological experiment, we want to test the effect of two types of amphetamine-like drugs on latency performing a motor task. In order to control for any potential sources of variation due to individual reactions to amphetamines, the same six subjects were used in the three conditions of the experiment: Drug A, Drug B, and Placebo. The dependent variable is the reaction time measured in msec. The data from the experiment are presented in Table 11.2 on the following page:

11.2.1 SAS code

```

/* Numerical example of S x A design
   Repeated Measures design
   Drugs & Reaction Time
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
TITLE 'ANOVA - Repeated Measures - S x A';
DATA example;

```

Experimental Conditions				
Subject	Drug A	Placebo	Drug B	Total
s_1	124.00	108.00	104.00	336.00
s_2	105.00	107.00	100.00	312.00
s_3	107.00	90.00	100.00	297.00
s_4	109.00	89.00	93.00	291.00
s_5	94.00	105.00	89.00	288.00
s_6	121.00	71.00	84.00	276.00
Total	660.00	570.00	570.00	1,800.00

TABLE 11.2 Results of a fictitious hypothetical experiment illustrating the computational routine for a $S \times A$ design.

```

DO subject = 1 to 6;
  DO drug = 1 to 3;
    INPUT time @;
    OUTPUT;
  END;
END;
CARDS;
124 108 104
105 107 100
107 90 100
109 89 93
94 105 89
121 71 84
;
PROC SORT;
  BY drug;
PROC MEANS;
  BY drug;
PROC ANOVA;
  CLASSES subject drug;
  MODEL time = subject drug;
RUN;

```

11.2.2 SAS listing

ANOVA - Repeated Measures - S x A

DRUG=1

Variable	N	Mean	Std Dev	Minimum	Maximum
SUBJECT	6	3.5000000	1.8708287	1.0000000	6.0000000
TIME	6	110.0000000	11.0272390	94.0000000	124.0000000

DRUG=2

Variable	N	Mean	Std Dev	Minimum	Maximum
SUBJECT	6	3.5000000	1.8708287	1.0000000	6.0000000
TIME	6	95.0000000	14.4913767	71.0000000	108.0000000

DRUG=3

Variable	N	Mean	Std Dev	Minimum	Maximum
SUBJECT	6	3.5000000	1.8708287	1.0000000	6.0000000
TIME	6	95.0000000	7.6419893	84.0000000	104.0000000

ANOVA - Repeated Measures - S x A

Analysis of Variance Procedure
Class Level Information

Class	Levels	Values
SUBJECT	6	1 2 3 4 5 6
DRUG	3	1 2 3

Number of observations in data set = 18

Dependent Variable: TIME

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	1650.00000	235.71429	1.96	0.1606
Error	10	1200.00000	120.00000		
Corrected Total	17	2850.00000			

R-Square	C.V.	Root MSE	TIME Mean
0.578947	10.95445	10.9545	100.000

Source	DF	Anova SS	Mean Square	F Value	Pr > F
SUBJECT	5	750.000000	150.000000	1.25	0.3561
DRUG	2	900.000000	450.000000	3.75	0.0609

11.2.3 ANOVA table

The final results are presented in the analysis of variance table:

Source	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Pr(F)</i>
<i>A</i>	2	900.00	450.00	3.75	.060
<i>S</i>	5	750.00	150.00		
<i>AS</i>	10	1,200.00	120.00		
Total	17	2,850.00			

TABLE 11.3 ANOVA Table for the Drugs and Reaction Time experiment.

11.3 Proactive Interference

In an experiment on proactive interference, subjects were asked to learn a list of ten pairs of words. Two days later they were asked to recall these words. Once they finished recalling this first list, they were asked to learn a second list of ten pairs of words which they will be asked to recall after a new delay of two days. Recall of the second list was followed by a third list and so on until they learned and recalled six lists. The independent variable is the rank of the list in the learning sequence (first list, second list, ..., sixth list). The dependent variable is the number of words correctly recalled. The authors of this experiment predict that recall performance will decrease as a function of the rank of the lists (this effect is called “proactive interference”). The data are presented in Table 11.4.

11.3.1 SAS code

```

/* S x A design, Repeated Measures
   Proactive Interference
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
TITLE 'ANOVA - SxA';
DATA example;
DO subject = 1 to 8;

```

Subjects	Rank of the list						Total
	1	2	3	4	5	6	
<i>s</i> ₁	17	13	12	12	11	11	76
<i>s</i> ₂	14	18	13	18	11	12	86
<i>s</i> ₃	17	16	13	11	15	14	86
<i>s</i> ₄	18	16	11	10	12	10	77
<i>s</i> ₅	17	12	13	10	11	13	76
<i>s</i> ₆	16	13	13	11	11	11	75
<i>s</i> ₇	14	12	10	10	10	10	66
<i>s</i> ₈	16	17	15	11	13	11	83
Total	129	117	100	93	94	92	625

TABLE 11.4 Results of an experiment on the effects of proactive interference on memory.

```

DO list = 1 to 6;
  INPUT score @;
  OUTPUT;
END;
END;
CARDS;
17 13 12 12 11 11
14 18 13 18 11 12
17 16 13 11 15 14
18 16 11 10 12 10
17 12 13 10 11 13
16 13 13 11 11 11
14 12 10 10 10 10
16 17 15 11 13 11
;
PROC ANOVA;
  CLASS subject list;
  MODEL score = subject list;
  MEANS subject list;
RUN;

```

11.3.2 SAS listing

ANOVA - SxA
 Analysis of Variance Procedure
 Class Level Information

```

-----
Class      Levels          Values
-----
SUBJECT    8      1 2 3 4 5 6 7 8
LIST       6      1 2 3 4 5 6
-----

```

Number of observations in data set = 48

Dependent Variable: SCORE

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	199.333333	16.611111	5.83	0.0001
Error	35	99.645833	2.847024		
Corrected Total	47	298.979167			

R-Square	C.V.	Root MSE	SCORE Mean
0.666713	12.95856	1.68731	13.0208

Source	DF	Anova SS	Mean Square	F Value	Pr > F
SUBJECT	7	52.479167	7.497024	2.63	0.0269
LIST	5	146.854167	29.370833	10.32	0.0001

Level of SUBJECT	N	Mean	SD
1	6	12.666667	2.25092574
2	6	14.333333	3.01109061
3	6	14.333333	2.16024690
4	6	12.833333	3.37144875
5	6	12.666667	2.42212028
6	6	12.500000	1.97484177
7	6	11.000000	1.67332005
8	6	13.833333	2.56255081

Level of LIST	N	Mean	SD
1	8	16.125000	1.45773797
2	8	14.625000	2.38671921
3	8	12.500000	1.51185789
4	8	11.625000	2.66926956
5	8	11.750000	1.58113883
6	8	11.500000	1.41421356

11.3.3 ANOVA table

The results from this experiment are presented in the analysis of variance table.

Source	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>P(F)</i>
<i>A</i>	5	146.85	29.37	10.32**	.000,005
<i>S</i>	7	52.48	7.50		
<i>AS</i>	35	99.65	2.85		
Total	47	21,806.50			

12

Two factors repeated measures, $S \times A \times B$

12.1 Plungin'

What follows is a replication of Godden and Baddeley's (1975) experiment to show the effects of context on memory. Godden and Baddeley's hypothesis was that memory should be better when the conditions at test are more similar to the conditions experienced during learning. To operationalize this idea, Godden and Baddeley decided to use a very particular population: deep-sea divers. The divers were asked to learn a list of 40 unrelated words either on the beach or under about 10 feet of water. The divers were then tested either on the beach or undersea. The divers needed to be tested in both environments in order to make sure that any effect observed could not be attributed to a global effect of one of the environments. The rationale behind using divers was twofold. The first reason was practical: is it worth designing training programs on dry land for divers if they are not able to recall undersea what they have learned? There is strong evidence, incidently, that the problem is real. The second reason was more akin to good principles of experimental design, The difference between contexts undersea and on the beach seems quite important, hence a context effect should be easier to demonstrate in this experiment.

Because it is not very easy to find deep-sea divers (willing in addition to participate in a memory experiment) it was decided to use the small number of divers in all possible conditions of the design. The list of words were randomly created and assigned to each subject. The order of testing was randomized in order to eliminate any possible carry-over effects by confounding them with the experimental error.

The first independent variable is the place of learning. It has 2 levels (on the beach and undersea), and it is denoted A . The second independent variable is the place of testing. It has 2 levels (on the beach and undersea, like A), and it is denoted B . Crossing these 2 independent variables gives 4 experimental conditions:

- 1. Learning on the beach and recalling on the beach.
- 2. Learning on the beach and recalling undersea.

- **3.** Learning undersea and recalling on the beach.
- **4.** Learning undersea and recalling undersea.

Because each subject in this experiment participates in all four experimental conditions, the factor S is crossed with the 2 experimental factors. Hence, the design can be symbolized as a $S \times A \times B$ design. For this (fictitious) replication of Godden and Baddeley's (1975) experiment we have been able to convince $S = 5$ (fictitious) subjects to take part in this experiment (the original experiment had 16 subjects).

The subjects to learn lists made of 40 short words each. Each list has been made by drawing randomly words from a dictionary. Each list is used just once (hence, because we have $S = 5$ subjects and $A \times B = 2 \times 2 = 4$ experimental conditions, we have $5 \times 4 = 20$ lists). The dependent variable is the number of words recalled 10 minutes after learning (in order to have enough time to plunge or to come back to the beach).

The results of the (fictitious) replication are given in Table 12.1. Please take a careful look at it and make sure you understand the way the results are laid out.

Recall that the prediction of the authors was that memory should be better when the context of encoding and testing is the same than when the context of encoding and testing are different. This means that they have a very specific shape of effects (a so-called X -shaped interaction) in

		A Learning Place		\sum $Y_{.1s}$	Means $M_{.1s}$
		a_1 On Land	a_2 Underwater		
b_1 Testing place On Land	s_1	34	14	48	24
	s_2	37	21	58	29
	s_3	27	31	58	29
	s_4	43	27	70	35
	s_5	44	32	76	38
		----- $Y_{11.} = 185$ $M_{11.} = 37$	----- $Y_{21.} = 125$ $M_{21.} = 25$	----- $Y_{.1.} = 310$ $M_{.1.} = 31$	
b_2 Testing place Underwater	s_1	18	22	40	20
	s_2	21	25	46	23
	s_3	25	33	58	29
	s_4	37	33	70	35
	s_5	34	42	76	38
		----- $Y_{12.} = 135$ $M_{12.} = 27$	----- $Y_{22.} = 155$ $M_{22.} = 31$	----- $Y_{.1.} = 290$ $M_{.1.} = 29$	

TABLE 12.1 Result of a (fictitious) replication of Godden and Baddeley's (1975) experiment with deep sea divers (see text for explanation).

mind. As a consequence, they predict that all of the experimental sums of squares should correspond to the sum of squares of interaction.

12.1.1 SAS code

```

/* Two Factors Repeated Measures, S x A x B
   Godden & Baddeley's Plungin' experiment
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
TITLE 'ANOVA - SxAxB';
DATA example;
DO learning = 1 to 2;
  DO testing = 1 to 2;
    DO subject = 1 to 5;
      INPUT memory @;
      OUTPUT;
    END;
  END;
END;
CARDS;
34 37 27 43 44
14 21 31 27 32
18 21 25 37 34
22 25 33 33 42
;
PROC ANOVA;
  CLASSES learning testing subject;
  MODEL memory = learning|testing|subject;
  TEST H = learning E = subject*learning;
  TEST H = testing E = subject*testing;
  TEST H = learning*testing E = subject*learning*testing;
  MEANS learning|testing;
RUN;

```

12.1.2 SAS listing

ANOVA - Two Factors Repeated Measures, SxAxB
Analysis of Variance Procedure

Class Level Information

```

-----
Class      Levels      Values
-----
LEARNING   2      1 2
TESTING    2      1 2
SUBJECT    5      1 2 3 4 5
-----

```

Number of observations in data set = 20

Dependent Variable: MEMORY

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	19	1356.00000	71.36842	.	.
Error	0
Corrected Total	19	1356.00000			

R-Square	C.V.	Root MSE	MEMORY Mean
1.000000	0	0	30.0000

Source	DF	Anova SS	Mean Square	F Value	Pr > F
LEARNING	1	20.000000	20.000000	.	.
TESTING	1	80.000000	80.000000	.	.
LEARNING*TESTING	1	320.000000	320.000000	.	.
SUBJECT	4	680.000000	170.000000	.	.
LEARNING*SUBJECT	4	32.000000	8.000000	.	.
TESTING*SUBJECT	4	160.000000	40.000000	.	.
LEARNI*TESTIN*SUBJEC	4	64.000000	16.000000	.	.

Tests of Hypotheses using the Anova MS for
LEARNING*SUBJECT as an error term

Source	DF	Anova SS	Mean Square	F Value	Pr > F
LEARNING	1	20.0000000	20.0000000	2.50	0.1890

Tests of Hypotheses using the Anova MS for TESTING*SUBJECT as an error term

Source	DF	Anova SS	Mean Square	F Value	Pr > F
TESTING	1	80.0000000	80.0000000	2.00	0.2302

Tests of Hypotheses using the Anova MS for
LEARNI*TESTIN*SUBJEC as an error term

Source	DF	Anova SS	Mean Square	F Value	Pr > F
LEARNING*TESTING	1	320.000000	320.000000	20.00	0.0111

 ANOVA - Two Factors Repeated Measures, SxAxB

Analysis of Variance Procedure

Level of LEARNING	N	Mean	SD
1	10	31.0000000	9.30949336
2	10	29.0000000	7.85988408

Level of TESTING	N	Mean	SD
1	10	32.0000000	8.90692614
2	10	28.0000000	7.90217973

Level of LEARNING	Level of TESTING	N	Mean	SD
1	1	5	37.0000000	6.96419414
1	2	5	25.0000000	7.51664819
2	1	5	27.0000000	8.21583836
2	2	5	31.0000000	7.84219357

12.1.3 ANOVA table

Here are the final results of the Godden and Baddeley's experiment presented in an ANOVA table.

Source	R^2	df	SS	MS	F	$P(F)$
<i>A</i>	0.05900	1	80.00	80.00	2.00	.22973
<i>B</i>	0.01475	1	20.00	20.00	2.50	.18815
<i>S</i>	0.50147	4	680.00	170.00	—	
<i>AB</i>	0.23599	1	320.00	320.00	20.00	.01231
<i>AS</i>	0.11799	4	160.00	40.00	—	
<i>BS</i>	0.02360	4	32.00	8.00	—	
<i>ABS</i>	0.04720	4	64.00	16.00	—	
Total	1.00	19	1,356.00			

13

Factorial Designs: Partially Repeated Measures, $S(\mathcal{A}) \times \mathcal{B}$

13.1 Bat and Hat....

To illustrate a partially repeated measures or split-plot design, our example will be a (fictitious) replication of an experiment by Conrad (1971). The general idea was to explore the hypothesis that young children do not use phonological coding in short term memory. In order to do this, we select 10 children: 5 five year olds and 5 twelve year olds. This constitutes the first independent variable (\mathcal{A} or *age* with 2 levels), which happens also to be what we have called a “tag” or “classificatory” variable. Because a subject is either five years old or twelve years old, the subject factor (S) is nested in the (\mathcal{A}) age factor.

The second independent variable deals with phonological similarity, and we will use the letter \mathcal{B} to symbolize it. But before describing it, we need to delve a bit more into the experiment. Each child was shown 100 pairs of pictures of objects. A pilot study had made sure that children will always use the same name for these pictures (*i.e.*, the cat picture was always called “a cat”, never “a pet” or “an animal”).

After the children had looked at the pictures, the pictures were turned over so that the children could only see their backs. Then the experimenter gives an identical pair of pictures to the children and asks them to position each new picture on top of the old ones (that are hidden by now) such that the new pictures match the hidden ones. For half of the pairs of pictures, the sound of the name of the objects was similar (*i.e.*, hat and cat), whereas for the other half of the pairs, the sound of the names of the objects in a pair was dissimilar (*i.e.*, horse and chair). This manipulation constitutes the second experimental factor \mathcal{B} or “*phonological similarity*.” It has two levels: b_1 phonologically similar and b_2 phonologically dissimilar. The dependent variable will be the number of pairs of pictures correctly positioned by the child.

Conrad reasoned that if the older children use a phonological code to rehearse information, then it would be more difficult for them to re-

member the phonologically similar pairs than the phonologically dissimilar pairs. This should happen because of an interference effect. If the young children do not use a phonological code to rehearse the material they want to learn, then their performance should be unaffected by phonological similarity, and they should perform at the same level for both conditions of phonological similarity. In addition, because of the usual age effect, one can expect the old children to perform on the whole better than the young ones. Could you draw the graph corresponding to the expected pattern of results? Could you express these predictions in terms of the analysis of variance model?

We expect a main effect of age (which is rather trivial), and also (and, this is the *crucial* point) we expect an interaction effect. This interaction will be the really important test of Conrad's theoretical prediction.

The results of this replication are given in Table 13.1.

13.1.1 SAS code

```
/* Partially Repeated Measures, S(A) x B design
   Conrad's Bat and Hat
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='- ' ;
TITLE 'ANOVA - S(A) x B';
DATA example;
DO age = 1 to 2;
```

		B			
		Phonological Similarity			
		b_1 Similar	b_2 Dissimilar	\sum	Means
				$Y_{1..s}$	$M_{1..s}$
a_1 Age: Five Years	s_1	15	13	28	14
	s_2	23	19	42	21
	s_3	12	10	22	11
	s_4	16	16	32	16
	s_5	14	12	26	13
		$Y_{11.} = 80$	$Y_{12.} = 70$	$Y_{1..} = 150$	
		$M_{11.} = 16$	$M_{12.} = 14$	$M_{1..} = 15$	
				$Y_{2..s}$	$M_{2..s}$
a_2 Age: Twelve Years	s_6	39	29	68	34
	s_7	31	15	46	23
	s_8	40	30	70	35
	s_9	32	26	58	29
	s_{10}	38	30	68	34
		$Y_{21.} = 180$	$Y_{22.} = 130$	$Y_{2..} = 310$	
		$M_{21.} = 36$	$M_{22.} = 26$	$M_{2..} = 31$	

TABLE 13.1 Results of a replication of Conrad's (1971) experiment.

```

DO similar = 1 to 2;
  DO subject = 1 to 5;
    INPUT memory @;
    OUTPUT;
  END;
END;
END;
CARDS;
15 23 12 16 14
13 19 10 16 12
39 31 40 32 38
29 15 30 26 30
;
PROC ANOVA;
  CLASSES age similar subject;
  MODEL memory = age subject(age) similar age*similar similar*subject(age);
  MEANS learning|testing;
  TEST H = age          E = subject(age);
  TEST H = age*similar  E = similar*subject(age);
  TEST H = similar      E = similar*subject(age);
RUN;

```

13.1.2 SAS listing

ANOVA - S(A) x B
 Analysis of Variance Procedure

Class Level Information

Class	Levels	Values
AGE	2	1 2
SIMILAR	2	1 2
SUBJECT	5	1 2 3 4 5

Number of observations in data set = 20

Dependent Variable: MEMORY

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	19	1892.00000	99.57895	.	.
Error	0	.	.		
Corrected Total	19	1892.00000			

R-Square	C.V.	Root MSE	MEMORY Mean
1.000000	0	0	23.0000

Source	DF	Anova SS	Mean Square	F Value	Pr > F
AGE	1	1280.00000	1280.00000	.	.
SUBJECT(AGE)	8	320.00000	40.00000	.	.
SIMILAR	1	180.00000	180.00000	.	.
AGE*SIMILAR	1	80.00000	80.00000	.	.
SIMILAR*SUBJECT(AGE)	8	32.00000	4.00000	.	.

Tests of Hypotheses using the Anova MS for SUBJECT(AGE) as an error term

Source	DF	Anova SS	Mean Square	F Value	Pr > F
AGE	1	1280.00000	1280.00000	32.00	0.0005

Tests of Hypotheses using the Anova MS for SIMILAR*SUBJECT(AGE) as an error term

Source	DF	Anova SS	Mean Square	F Value	Pr > F
AGE*SIMILAR	1	80.0000000	80.0000000	20.00	0.0021

Tests of Hypotheses using the Anova MS for SIMILAR*SUBJECT(AGE) as an error term

Source	DF	Anova SS	Mean Square	F Value	Pr > F
SIMILAR	1	180.000000	180.000000	45.00	0.0002

13.1.3 ANOVA table

We can now fill in the ANOVA Table as shown in Table 13.2 on the next page.

As you can see from the results of the analysis of variance, the experimental predictions are supported by the experimental results. The results section of an APA style paper would indicate the following information:

The results were treated as an Age \times Phonological similarity analysis of variance design with Age (5 year olds *versus* 12 year olds) being a between-subject factor and phonological similarity (similar *versus* dissimilar) being a within-subject factor. There was a very clear effect of age, $F(1, 8) = 31.5$, $MS_e = 33.38$, $p < .01$. The expected interaction of age by phonological similarity was also very reliable $F(1, 8) = 35.2$, $MS_e = 2.86$, $p < .01$.

<i>Source</i>	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Pr(F)</i>
<i>between subjects</i>					
<i>A</i>	1	1,280.00	1,280.00	32.00	.00056
<i>S(A)</i>	8	320.00	40.00	-----	
<i>within subjects</i>					
<i>B</i>	1	180.00	180.00	45.00	.00020
<i>AB</i>	1	80.00	80.00	20.00	.00220
<i>BS(A)</i>	8	32.00	4.00	-----	
<hr/>		<hr/>			
Total.....	19	1,892.00			

TABLE 13.2 The analysis of variance Table for a replication of Conrad's (1971) experiment (data from Table 13.1).

01. A main effect of phonological similarity was also detected $F(1, 8) = 52.6$, $MS_e = 2.86$, $p < .01$, but its interpretation as a main effect is delicate because of the strong interaction between phonological similarity and age.

14

Nested Factorial Design:

$$S \times A(B)$$

14.1 Faces in Space

Some faces give the impression of being original or bizarre. Some other faces, by contrast, give the impression of being average or common. We say that original faces are *atypical*; and that common faces are *typical*. In terms of design factors, we say that: Faces vary on the Typicality factor (which has 2 levels: typical *vs.* atypical).

In this example, we are interested by the effect of typicality on reaction time. Presumably, typical faces should be easier to process as faces than atypical faces. In this¹ example, we measured the reaction time of 4 subjects in a face identification task. Ten faces, mixed with ten “distractor faces,” were presented on the screen of a computer. The distractor faces were jumbled faces (*e.g.*, with the nose at the place of the mouth). Five of the ten faces were typical faces, and the other five faces were atypical faces. Subjects were asked to respond as quickly as they can. Only the data recorded from the normal faces (*i.e.*, not jumbled) were kept for further analysis. All the subjects identified correctly the faces as faces. The data (made nice for the circumstances) are given in Table 14.1 on page 111. As usual, make sure that you understand its layout, and try to figure out whether there is some effect of Typicality.

Here, like in most $S \times A(B)$ designs, we are mainly interested in the nesting factor (*i.e.*, B). The nested factor [*i.e.*, $A(B)$] is not, however, without interest. If it is statistically significant, this may indicate that the pattern of effects, which we see in the results, depends upon the *specific* sample of items used in this experiment.

14.1.1 SAS code

```
/* Nested Factorial Design, S x A(B)
   Faces in Space
*/
OPTIONS PS=40 LS=75 NOCENTER NODATE FORMDLIM='-' ;
```

¹Somewhat fictitious, but close to some standard experiments in face recognition.

```
TITLE 'ANOVA - S x A(B)';
DATA example;
INPUT subject typical $ face $ resptime;
CARDS;
1 atyp f1 20
1 atyp f2 22
1 atyp f3 25
1 atyp f4 24
1 atyp f5 19
1 typ f6 37
1 typ f7 37
1 typ f8 43
1 typ f9 48
1 typ f10 45
2 atyp f1 9
2 atyp f2 8
2 atyp f3 21
2 atyp f4 21
2 atyp f5 21
2 typ f6 34
2 typ f7 35
2 typ f8 35
2 typ f9 37
2 typ f10 39
3 atyp f1 18
3 atyp f2 20
3 atyp f3 18
3 atyp f4 21
3 atyp f5 33
3 typ f6 35
3 typ f7 39
3 typ f8 39
3 typ f9 37
3 typ f10 40
4 atyp f1 5
4 atyp f2 14
4 atyp f3 16
4 atyp f4 22
4 atyp f5 23
4 typ f6 38
4 typ f7 49
4 typ f8 51
4 typ f9 50
4 typ f10 52
;
PROC ANOVA;
  CLASSES typical face subject;
  MODEL resptime = subject typical face(typical)
                 typical*subject subject*face(typical);
  TEST H = subject          E = face*subject(typical);
  TEST H = face(typical)   E = face*subject(typical);
  TEST H = typical*subject E = face*subject(typical);
RUN;
```

14.1.2 SAS listing

ANOVA - S x A(B), Nested Factorial Design
 Analysis of Variance Procedure

Class Level Information

```

-----
Class      Levels      Values
-----
TYPICAL    2      atyp typ
FACE       10     f1 f10 f2 f3 f4 f5 f6 f7 f8 f9
SUBJECT    4      1 2 3 4
-----
    
```

Number of observations in data set = 40

Dependent Variable: RESPTIME

```

-----
Source                DF      Sum of Squares      Mean Square      F Value      Pr > F
-----
Model                  39      6280.00000          161.02564        .            .
Error                   0              .                  .              .            .
Corrected Total        39      6280.00000
-----
    
```

```

-----
R-Square      C.V.      Root MSE      RESPTIME Mean
-----
1.000000      0          0             30.0000
-----
    
```

```

-----
Source                DF      Anova SS      Mean Square      F Value      Pr > F
-----
SUBJECT                3       240.00000       80.00000         .            .
TYPICAL                1      4840.00000      4840.00000        .            .
FACE(TYPICAL)         8       480.00000       60.00000         .            .
TYPICAL*SUBJECT       3       360.00000      120.00000        .            .
FACE*SUBJEC(TYPICAL) 24       360.00000       15.00000         .            .
-----
    
```

Tests of Hypotheses using the Anova MS for
 FACE*SUBJEC(TYPICAL) as an error term

```

-----
Source                DF      Anova SS      Mean Square      F Value      Pr > F
-----
SUBJECT                3       240.00000       80.00000         5.33         0.0059
-----
    
```

Tests of Hypotheses using the Anova MS for

FACE*SUBJEC(TYPICAL) as an error term

Source	DF	Anova SS	Mean Square	F Value	Pr > F
FACE(TYPICAL)	8	480.000000	60.000000	4.00	0.0039

Tests of Hypotheses using the Anova MS for
FACE*SUBJEC(TYPICAL) as an error term

Source	DF	Anova SS	Mean Square	F Value	Pr > F
TYPICAL*SUBJECT	3	360.000000	120.000000	8.00	0.0007

14.1.3 F and Quasi- F ratios

Remember the standard procedure? In order to evaluate the reliability of a source of variation, we need to find the expected value of its mean square. Then we assume that the null hypothesis is true, and we try to find another source whose mean square has the same expected value. This mean square is the test mean square. Dividing the first mean square (the effect mean square) by the test mean square gives an F ratio. When there is no test mean square, there is no way to compute an F ratio, especially with SAS. However, as you know, combining several mean squares gives a test mean square called a test “quasi-mean square” or a “test mean square prime.” The ratio of the effect mean square by its “quasi-mean square” give a “quasi- F ratio” (or F'). The expected values of the mean squares for a $S \times A(B)$ design with $A(B)$ random and B fixed are given in Table 14.2 on page 112.

From Table 14.2 on page 112, we find that most sources of variation may be evaluated by computing F ratios using the $AS(B)$ mean square. Unfortunately, the experimental factor of prime interest (*i.e.*, B), cannot be tested this way, but requires the use of a quasi- F' . The test mean square for the main effect of B is obtained as

$$MS'_{\text{test},B} = MS_{A(B)} + MS_{BS} - MS_{AS(B)}. \quad (14.1)$$

The number of degrees of freedom of the mean square of test is approximated by the following formula (Eeek!):

$$\nu'_2 = \frac{(MS_{A(B)} + MS_{BS} - MS_{AS(B)})^2}{\frac{MS_{A(B)}^2}{df_{A(B)}} + \frac{MS_{BS}^2}{df_{BS}} + \frac{MS_{AS(B)}^2}{df_{AS(B)}}}. \quad (14.2)$$

14.1.4 ANOVA table

We can now fill in the ANOVA Table as shown in Table 14.3 on page 112.

Factor \mathcal{B} (Typicality: Atypical vs. Typical)													
b_1 : (Atypical)					b_2 : (Typical)								
$\mathcal{A}_{a(b_1)}$: (Atypical Faces)					$\mathcal{A}_{a(b_2)}$: (Typical Faces)								
a_1	a_2	a_3	a_4	a_5	$M_{1,s}$	a_1	a_2	a_3	a_4	a_5	$M_{2,s}$	$M_{\dots,s}$	
s_1	20	22	25	24	19	22	37	37	43	48	45	42	32
s_2	9	8	21	21	21	16	34	35	35	37	39	36	26
s_3	18	20	18	21	33	22	35	39	39	37	40	38	30
s_4	5	14	16	22	23	16	38	49	51	50	52	48	32
$M_{1,1}, M_{2,1}, M_{3,1}, M_{4,1}, M_{5,1}$					$M_{1,2}, M_{2,2}, M_{3,2}, M_{4,2}, M_{5,2}$								
13 16 20 22 24					36 40 42 43 44								
$M_{1,1} = 19$					$M_{2,2} = 41$								

TABLE 14.1

Data from a fictitious experiment with a $S \times \mathcal{A}(\mathcal{B})$ design. Factor \mathcal{B} is Typicality. Factor $\mathcal{A}(\mathcal{B})$ is Faces (nested in Typicality). There are 4 subjects in this experiment. The dependent variable is measured in centiseconds (in case you wonder: 1 centisecond equals 10 milliseconds); and it is the time taken by a subject to respond that a given face was a face.

Source	Expected Mean Squares	MS_{test}
\mathcal{B}	$\sigma_e^2 + \sigma_{as(b)}^2 + A\sigma_{bs}^2 + S\sigma_{a(b)}^2 + AS\vartheta_b^2$	$MS_{A(B)} + MS_{BS} - MS_{AS(B)}$
\mathcal{S}	$\sigma_e^2 + \sigma_{as(b)}^2 + AB\sigma_s^2$	$MS_{AS(B)}$
$\mathcal{A}(\mathcal{B})$	$\sigma_e^2 + \sigma_{as(b)}^2 + S\sigma_{a(b)}^2$	$MS_{AS(B)}$
\mathcal{BS}	$\sigma_e^2 + \sigma_{as(b)}^2 + A\sigma_{bs}^2$	$MS_{AS(B)}$
$\mathcal{AS}(\mathcal{B})$	$\sigma_e^2 + \sigma_{as(b)}^2$	

TABLE 14.2 The expected mean squares when \mathcal{A} is random and \mathcal{B} is fixed for an $S \times \mathcal{A}(\mathcal{B})$ design.

Source	R^2	df	SS	MS	F	$\text{Pr}(F)$	ν_1	ν_2
Face $\mathcal{A}(\mathcal{B})$	0.08	8	480.00	60.00	4.00	.0040	8	24
Typicality \mathcal{B}	0.77	1	4,840.00	4,840.00	29.33 [†]	.0031 [†]	1	5 [†]
Subject \mathcal{S}	0.04	3	240.00	80.00	5.33	.0060	3	24
Subject by Face $\mathcal{AS}(\mathcal{B})$	0.06	24	360.00	15.00				
Subject by Typicality \mathcal{BS}	0.06	3	360.00	120.00	8.00	.0008	3	24
Total	1.00	39	13,254.00					

[†] This value has been obtained using a Quasi- F approach. See text for explanation.

TABLE 14.3 The ANOVA Table for the data from Table 14.1.

Index

analysis of variance, *see* ANOVA

ANOVA

 Nested factorial design

 ANOVA $\mathcal{S} \times \mathcal{A}(\mathcal{B})$, 107

 One factor

 ANOVA $\mathcal{S}(\mathcal{A})$, 19

 Partially repeated measures

 ANOVA $\mathcal{S}(\mathcal{A}) \times \mathcal{B}$, 101

 Repeated Measures

 ANOVA $\mathcal{S} \times \mathcal{A}$, 85

 Two factor

 ANOVA $\mathcal{S}(\mathcal{A} \times \mathcal{B})$, 75

BADDELEY, 15, 95

Bonferonni inequality, *see* Bonferonni, Boole, Dunn inequality

Bonferonni, Boole, Dunn inequality, 45

BONFERONNI, 45

BONFERONNI, 45

BOOLE, 45

Boole inequality, *see* Bonferonni, Boole, Dunn inequality

BRANSFORD, 21, 34, 46, 49, 53, 60, 63, 71

Comparisons

a posteriori, *see* Post hoc

a priori, *see* Planned

 Planned

 Non-orthogonal, 45

 Orthogonal, 37

 Post hoc, 59

CONRAD, 101

Correlation, 1

Pearson Correlation Coefficient, 1

Duncan test, 59

DUNN, 45

Dunn inequality, *see* Bonferonni, Boole, Dunn inequality

F-ratio, 110

GODDEN, 95

GOSSET, 63

HULME, 15

JOHNSON, 21

LAWRENCE, 15

LOFTUS, 68

Mean square, 110

MUIR, 15

Newman-Keuls test, 59, 67

PALMER, 68

PEARLSTONE, 75

PEARSON, 1

quasi-*F*, 110

quasi-mean square, 110

Regression

 Multiple Regression

 Non-orthogonal, 15

 Orthogonal, 9

 Simple Regression, 5

Retroactive interference, 9

SAS

SAS code, 1, 5, 10, 15, 19, 23,
24, 27, 32, 34, 39, 47, 50, 54

SAS listing, 3, 7, 10, 16, 20, 23,
25, 28, 33, 35, 40, 47, 51, 55

Scheffé test, 59

ŠIDÀK, 45

Šidàk inequality, 45

SLAMECKA, 9

SMITH, 37

STERNBERG, 5

STUDENT, *see* Gosset

THOMSON, 15

Tukey test, 59, 63

TULVING, 75