# Research Design - - Topic 11

MRC Analysis and Single Factor Designs © 2010 R.C. Gardner, Ph.D.

1. General Overview of MRC and GLM

2. Example of a single factor design from Kirk (and Topic 3) Effect Coding Dummy Coding

3. Running SPSS Regression (Linear) using Effect coding

4. Running SPSS Regression (Linear) using Dummy coding

5. Assumptions

#### **Applications and Implications**

It is often said that multiple correlation can be used to identify good predictors. This is not the case. Multiple correlation does not identify predictors of a criterion. It identifies variables that add to prediction. There is a difference. Note that:

The Pearson product moment correlation between a variable and the criterion can be considered a measure of prediction. The correlation coefficient is the regression coefficient in standard score form.

The regression coefficient in multiple regression is a measure of the extent to which a variable adds to the prediction of a criterion, given the other variables in the equation. It is not a correlation coefficient.

#### General Linear Model Approach Using MRC

The Model: Analysis of variance can be seen as an instance of the general linear model.

Thus, Cohen & Cohen (1983, p. 4) state "Technically, AV/ACV and conventional multiple regression analysis are special cases of the "general linear model" in mathematical statistics. It thus follows that any data analyzable by AV/ACV may be analyzed by MRC, while the reverse is not the case".

In a more recent edition of the book, Cohen, Cohen, West & Aiken (2003, p. 4) state" The description of MRC in this book includes extensions of conventional MRC analysis to the point where it is essentially equivalent to the general linear model. It thus follows that any data analyzable by ANOVA/ANCOVA may be analyzed by MRC, whereas the reverse is not the case".

### **MRC** Analysis

Cohen (1968) noted that, if group membership is defined in terms of a series of arbitrary variables (A), analysis of variance can be viewed as a special case of multiple regression. Thus, one can write a regression equation as:

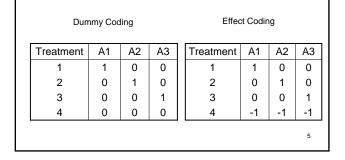
$$X_i = b_o + b_1 A_1 + b_2 A_2 + \ldots + \varepsilon_i$$

where the number of arbitrary variables is one less than the number of treatment levels. The predicted value for each individual is the mean of the treatment condition for that individual and the A variables are codes defining the treatment levels.

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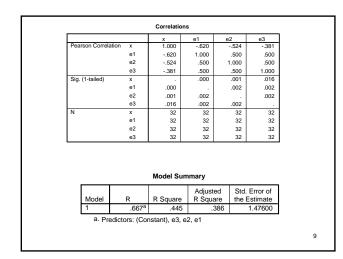
**Types of Coding**: There are many types of coding. Each yield the same multiple correlation but the regression coefficients differ. We will consider two types, **Dummy Coding** and **Effect Coding**. Following are two examples involving 4 treatment levels of a factor.

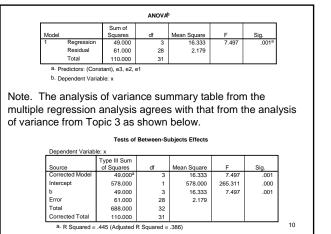


Examp	ole from Ki	rk (1995,	p.230) u	ised in To	pic 3
	A <sub>1</sub>	A <sub>2</sub>	A <sub>3</sub>	A <sub>4</sub>	
	4	4	5	3	
	6	5	6	5	
	3	4	5	6	
	3	3	4	5	
	1	2	3	6	
	3	3	4	7	
	2	4	3	8	
	2	3	4	10	
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Means	3.00	3.50	4.25	6.25	4.25
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2	1.00	6.00	1.00	.00	.00	1.00	.00	.00			- 11
3	1.00	3.00	1.00	.00	.00	1.00	.00	.00			- 11
4	1.00	3.00	1.00	.00	.00	1.00	.00	.00			-8
5		1	-				-				- 11
6	2.00	4.00	.00	1.00	.00	.00	1.00	.00			- 11
7	2.00	5.00	.00	1.00	.00	.00	1.00	.00			- 21
8	2.00	4.00	.00	1.00	.00	.00	1.00	.00			
9	2.00	3.00	.00	1.00	.00	.00	1.00	.00			- 1
10							-				- 11
11	3.00	5.00	.00	.00	1.00	.00	.00	1.00			- 11
12	3.00	6.00	.00	.00	1.00	.00	.00	1.00			-11
13	3.00	5.00	.00	.00	1.00	.00	.00	1.00			-11
14	3.00	4.00	.00	.00	1.00	.00	.00	1.00			-11
15	4.00	3.00	.00	.00	.00	-1.00	-1.00	-1.00			-11
16	4.00	5.00	.00	.00	.00	-1.00	-1.00	-1.00			-11
1/	4.00	5.00	.00	.00	.00	-1.00	-1.00	-1.00			-11
19	4.00	5.00	.00	.00	.00	-1.00	-1.00	-1.00			- 11
20	4.00	5.00	.00	.00	.00	-1.00	-1.00	-1.00			-11

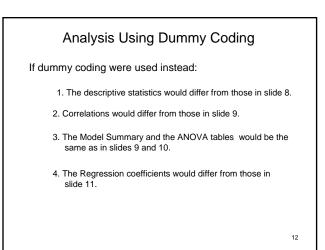
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		Descri	otive Statistics						
	Mean Std. Deviation N								
	х	4.2500	1.88372	32					
	e1	.0000	.71842	32					
	e2	.0000	.71842	32					
	e3 .0000 .71842 32 8								





-	The me	eaning of with		gression t Coding	coeffic	ients
			Coefficie	nts <sup>a</sup>		
		Unstand Coeff	dardized icients	Standardized Coefficients		
	odel	В	Std. Error	Beta	t	Sig.
1.0	000 (Const	,	.26092		16.28838	.00000
	e1	-1.25000	.45193	47673	-2.76591	.00994
	e2	75000	.45193	28604	-1.65955	.10817
	e3	.00000	.45193	.00000	.00000	1.00000
$b_o = \overline{0}$	a. Dependent $\overline{G} = 4.25$ $\overline{X}_1 - \overline{G} =$		= -1.25			
$b_2 = \bar{2}$	$\overline{X}_2 - \overline{G} =$	= 3.50 – 4.2	5 =75	i		

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	with	Dumn	ny Coding	J		
		Coefficie	nts <sup>a</sup>			
	Unstand Coeffi		Standardized Coefficients			
Model	B	Std. Error	Beta	t	Sig.	
1 (Constant)	6.250	.522	Dota	11.977	.000	
d1	-3.250	.738	759	-4.404	.000	
d2	-2.750	.738	642	-3.726	.001	
d3	-2.000	.738	467	-2.710	.011	
a. Dependent Varia	ible: x					
$b_o = \overline{X}_4 =$						
$b_1 = \overline{X}_1 - \overline{X}_2$	4 = 3.00	-6.25 =	-3.25			
$b_2 = \overline{X}_2 - \overline{X}_2$	$\overline{K}_4 = 3.5$	50-6.25	5 = -2.75			
$b_3 = \overline{X}_3 - \overline{X}_3$	$\overline{X}_4 = 4$	.25-6.2	25 = -2.00			1

Relation Between the Experimental Design and GLM Models							
The two m	The two models are:						
$X_{ai} =$	$X_{ai} = \mu + \alpha_a + \varepsilon_{ai} \qquad X_i = b_0 + b_1 A_1 + \dots + \varepsilon_i$						
Therefo	ore $\mu + \alpha_a =$	$b_0 + b_1 A_1 + \dots$					
	Dummy Coding	Effect Coding					
For a = 1	$\mu + \alpha_1 = b_0 + b_1$	$\mu + \alpha_1 = b_0 + b_1$					
For a = 2	$\mu + \alpha_2 = b_0 + b_2$	$\mu + \alpha_2 = b_0 + b_2$					
For a = 3 For a = 4	$\mu + \alpha_3 = b_0 + b_3$ $\mu + \alpha_4 = b_0$	$\mu + \alpha_3 = b_0 + b_3$ $\mu + \alpha_4 = b_0 - b_1 - b_2 - b_3  {}_{14}$					

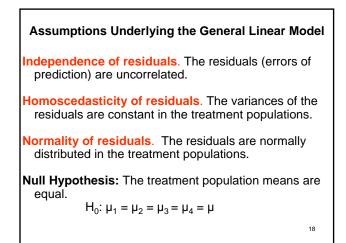
Understanding Regression Coefficients: Dummy Co	ding
Given $\mu + lpha_4 = b_0$	
Therefore $b_0=\mu+lpha_4=\mu+\mu_4-\mu=\mu_4$	
Given $\mu + \alpha_1 = b_0 + b_1$	
Therefore $b_1=\mu+lpha_1-b_0=\mu_1-\mu_4$	
Given $\mu + \alpha_2 = b_0 + b_2$	
Therefore $b_2 = \mu + \alpha_2 - b_0 = \mu_2 - \mu_4$	
Given $\mu + \alpha_3 = b_0 + b_3$	
Therefore $b_{_3}=\mu+\alpha_{_3}-b_{_0}=\mu_{_3}-\mu_{_4}$	15

Understanding Regression Coefficients: Effect Coding Given the four equations  $\begin{array}{c} \mu + \alpha_1 = b_0 + b_1 \quad \therefore b_0 + b_1 = \mu_1 \\ \mu + \alpha_2 = b_0 + b_2 \quad \therefore b_0 + b_2 = \mu_2 \\ \mu + \alpha_3 = b_0 + b_3 \quad \therefore b_0 + b_3 = \mu_3 \end{array}$   $\mu + \alpha_4 = b_0 - b_1 - b_2 - b_3 \quad \therefore b_0 - b_1 - b_2 - b_3 = \mu_4$ Summing yields  $4b_0 = \mu_1 + \mu_2 + \mu_3 + \mu_4 = 4\mu$ Therefore  $\begin{array}{c} b_0 = \mu \\ And \\ b_1 = \mu_1 - \mu \\ b_2 = \mu_2 - \mu \\ b_3 = \mu_3 - \mu \end{array}$ <sub>16</sub>

# **Major Observations**

- 1. Either type of coding yields a multiple correlation of .667, and the test of significance produces an F(3,28) = 7.497.
- 2. The results are identical to those obtained using an analysis of variance program.
- 3. The meaning of the regression coefficients differs for every type of coding.

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## References

- Cohen, J. (1968). Multiple regression as a general data-analytic system. *Psychological Bulletin*, 70,426-443.
- Cohen, J. & Cohen, P. (1983). *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences (Second Edition).* Hillsdale, NJ: Lawrence Erlbaum.
- Cohen, J., Cohen, P., West, S.G., & Aiken, L.S. (2003). *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences (Third Edition)*. Hillsdale, NJ: Lawrence Erlbaum.

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