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MULTIPLE LINEAR REGRESSION VIEWPOINTS

A publication of the Special Interest Group
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Single-spaced indented abstract
Introduction (purpose--short review of the literature, etc.)
Method
Results
Discussion (conclusion)
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APPLICATIONS OF SETWISE REGRESSION ANALYSIS

John D. Williams
University of North Dakota

In an earlier issue of Viewpoints, the setwise regression technique was first described (Williams and Lindem, 1971a). A companion publication (Williams and Lindem, 1971b) described the technique together with a description of a computer program to effect the solution. The documentation (Williams and Lindem, 1971c) of the program was also made available. The documentation was requested on a fairly large basis, so that no record has attempted to be made of it's use. Three specific applications of the technique are described in this presentation, however.

First, a description of the process would be useful. Setwise regression analysis is a technique that allows a stepwise solution when the interest is in sets of variables rather than in single variables. Thus, the setwise regression procedure bears a strong resemblance to the stepwise regression procedure. There are, however, advantages to be gained by the use of setwise regression analysis, and a disadvantage of the stepwise procedure is overcome. A disadvantage of the usual stepwise procedure is that it becomes inappropriate when there are more than two categories being binary coded. A simple example can be made with religious affiliation. Four categories might be used: Catholic, Protestant, Jewish and Other. Three binary (1 or 0) predictors can be made with the first three religious affiliations, and the fourth category can be represented as not having membership in the first three categories (i.e., all 0's). If religious affiliation were used in conjunction with other information, the stepwise procedure would not yield a valid indication of the importance of the religious variables. The setwise procedure, on the other hand, would allow a direct approach to such a situation.

The setwise procedure drops one set of variables at a time in a stepwise fashion. There will be as many steps as there are sets. The steps are accomplished by an iterative procedure that allows the R^2 term to be maximized at each step in a backward stepwise procedure. Once a set is discarded, the set is no longer considered at later steps. One set is discarded at each step until there is only one set remaining.

A difficulty with the setwise procedure (and the more familiar stepwise procedure) is that, if typical probability tests are employed, they will over-estimate the significance at any given point. A partial solution to this problem has been offered by Landry and Ehart (1973) who wrote a program to measure the unique contribution in each set at the first stage of an analysis; their program includes a test of significance.

APPLICATIONS

One of the earlier applications of the setwise technique was made by Grooters (1971). Grooters was interested in predicting costs per student credit hour in four state colleges. The input data were means by department for 16 variables, forming nine sets. Four of the sets were single variables, four sets were logical sets and one set was formed among mutually exclusive binary sets similar to the religious set described earlier. Such a situation typically involves a linear dependency within the total set. To remove the dependency, any one of the variables within the set can be excluded, and the analysis can be performed. Using the setwise technique, Grooters was able to isolate a rather intriguing result; student costs are in some measure higher in departments that have a higher incidence of outside of school professional activity (consulting, speaking, local community work, artistic endeavors outside the college setting, etc.). Yet another interesting result was that the average salary paid per member in the department was the first set to drop out. In another study, Sando (1973) used the setwise technique to predict scores on a computer programming test.

To better illustrate the technique, a complete setwise printout in included. The problem considered was predicting the outcome of an election held among the faculty in the Center for Teaching and Learning at the University of North Dakota (Williams, 1973). The specific problem involves 22 predictor variables that have been placed into six sets. The list of variables follows.

LIST OF VARIABLES

Set Number	Variable Number	Variable Name
1	1	Rank: Instructor
1	2	Rank: Assistant Professor
1	3	Rank: Associate Professor
2	4	Building Housed In: Building A
2	5	Building Housed In: Building B
2	6	Building Housed In: Building C
3	7	Previous Program: Indian
3	8	Previous Program: New School
3	9	Previous Program: College of Education
3	10	Previous Program: New School & College of Education combined
3	11	Previous Program: New School & Arts & Sciences combined
4	12	Salary
4	13	Years in Rank
4	14	Years at the University
5	15	Previous Publications: Refereed articles
5	16	Previous Publications: Books
5	17	Previous Publications: Other Articles
5	18	Previous Publications: Reports, speeches
6	19	Present Publications: Refereed articles
6	20	Present Publications: Books
6	21	Present Publications: Other Articles
6	22	Present Publications: Reports, speeches

Variables 23-26 were criteria variables. The focus here is on Variable 24, number of votes for constituency council. Variables 10 and 11 refer to faculty who have previously been simultaneously employed by more than one unit.

Of the sets, three are mutually exclusive binary variables and three are logical sets. For example in set 1, no variable is listed for the rank of professor; this rank is zero-coded. Similarly for sets 2 and 3, a final category of "other" is not included and is zero-coded. On the other hand, sets 4-6 are made of variables that are logically related; the variables in sets 4-6 are essentially

SET	VARIABLES IN SET				
1	1	2	3		
2	4	5	6		
3	7	8	9	10	11
4	12	13	14		
5	15	16	17	18	
6	19	20	21	22	

VARIABLE NO.	MEAN	STANDARD DEVIATION,	CORRELATION X VS Y	REGRESSION COEFFICIENT	STD. ERROR OF REG.COEF.	COMPUTED T VALUE	BETA
1	0.25000	0.43667	-0.C9775	-3.41025	4.89639	-0.69648	-0.42862
2	0.45000	0.50169	-0.03258	-1.99604	4.01139	-0.49759	-0.28823
3	0.21667	0.41545	0.03151	-2.27015	3.76972	-0.60221	-0.27146
4	0.30000	0.46212	-0.11507	-0.54750	3.50644	-0.15614	-0.07282
5	0.46667	0.50310	0.08662	0.62786	3.29772	0.19039	0.09C92
6	0.13333	0.34280	0.14610	0.35750	3.81244	0.09377	0.03527
7	0.13333	0.34280	0.17457	1.41594	4.71332	0.30041	0.13971
8	0.31667	0.46910	-0.11041	-0.02624	4.10286	-0.00640	-0.00354
9	0.31667	0.46910	-0.13121	-0.84069	4.06613	-0.20675	-0.11351
10	0.11667	0.32373	0.27100	1.44919	4.57521	0.31675	0.13503
11	0.05000	0.21978	-0.C9211	-1.69638	4.30350	-0.39419	-0.10731
12	12063.44922	3069.56958	0.28742	0.00017	0.00034	0.50437	C.14983
13	2.50000	2.54117	-0.18142	-0.34032	0.45805	-0.74298	-0.24892
14	3.71667	4.27880	-0.11266	0.06983	0.29865	0.23381	0.C8600
15	0.50000	2.25869	0.22570	0.16043	0.48904	0.32805	0.10430
16	0.25000	0.75C70	0.15759	-0.50707	1.50159	-0.33769	-0.10956
17	2.65000	5.17760	0.12065	-0.19428	0.25640	-0.75775	-0.28953
18	3.78333	7.11191	0.07430	0.01529	0.11295	0.13540	0.03130
19	0.63333	2.C4994	0.28502	0.61272	0.56365	1.08707	0.36152
20	0.06667	0.51640	0.04849	1.12331	1.95482	0.57464	0.16696
21	0.21667	0.82527	0.11044	-1.10404	1.07647	-1.02562	-0.26225
22	C.90000	1.98C41	0.14854	-0.12760	0.36355	-0.35099	-0.07274
DEPENDENT							
24	2.71667	3.47431					

INTERCEPT 3.72447

MULTIPLE CORRELATION 0.52332

STD. ERROR OF ESTIMATE 3.73853

ANALYSIS OF VARIANCE FOR THE REGRESSION

SOURCE OF VARIATION	DEGREES OF FREEDOM	SUM OF SQUARES	MEAN SQUARES	F VALUE
ATTRIBUTABLE TO REGRESSION	22	195.04245	8.86557	0.63431
DEVIATION FROM REGRESSION	37	517.13525	13.97663	
TOTAL	59	712.17749		

FULL MODEL---MULTIPLE CORRELATION=0.52332 R-SQUARED=0.27387 1-R-SQUARED=0.72613

SET OUT	MULT-R	VARIABLES INCLUDED IN REGRESSION
1	0.50905	4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22
2	0.51157	1 2 3 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22
3	0.48533	1 2 3 4 5 6 12 13 14 15 16 17 18 19 20 21 22
4	0.49977	1 2 3 4 5 6 7 8 9 10 11 15 16 17 18 19 20 21 22
5	0.50329	1 2 3 4 5 6 7 8 9 10 11 12 13 14 19 20 21 22
6	0.48053	1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18

SET DROPPED IS 2 MULTIPLE CORRELATION=0.51157 R-SQUARED=0.26170 1-R-SQUARED=0.73830

SET OUT	MULT-R	VARIABLES INCLUDED IN REGRESSION
1	0.49605	7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22
3	0.46846	1 2 3 12 13 14 15 16 17 18 19 20 21 22
4	0.48165	1 2 3 7 8 9 10 11 15 16 17 18 19 20 21 22
5	0.49048	1 2 3 7 8 9 10 11 12 13 14 19 20 21 22
6	0.47093	1 2 3 7 8 9 10 11 12 13 14 15 16 17 18

SET DROPPED IS 1 MULTIPLE CORRELATION=0.49605 R-SQUARED=0.24606 1-R-SQUARED=0.75394

SET OUT	MULT-R	VARIABLES INCLUDED IN REGRESSION
3	0.45072	12 13 14 15 16 17 18 19 20 21 22
4	0.44115	7 8 9 10 11 15 16 17 18 19 20 21 22
5	0.47798	7 8 9 10 11 12 13 14 19 20 21 22
6	0.46543	7 8 9 10 11 12 13 14 15 16 17 18

SET DROPPED IS 5 MULTIPLE CORRELATION=0.47798 R-SQUARED=0.22846 1-R-SQUARED=0.77154

SET OUT	MULT-R	VARIABLES INCLUDED IN REGRESSION
3	0.42755	12 13 14 19 20 21 22
4	0.42688	7 8 9 10 11 19 20 21 22
6	0.44131	7 8 9 10 11 12 13 14

SET DROPPED IS 6 MULTIPLE CORRELATION=0.44131 R-SQUARED=0.19475 1-R-SQUARED=0.80525

SET OUT	MULT-R	VARIABLES INCLUDED IN REGRESSION
3	0.36417	12 13 14
4	0.34974	7 8 9 10 11

SET DROPPED IS 3 MULTIPLE CORRELATION=0.36417 R-SQUARED=0.13262 1-R-SQUARED=0.86738

VARIABLE NO.	MEAN	STANDARD DEVIATION,	CORRELATION X VS Y	REGRESSION COEFFICIENT	STD. ERROR OF REG.COEF.	COMPUTED T VALUE	BETA
12	12063.44922	3069.56958	0.28742	0.00036	0.00015	2.48046	0.31889
13	2.50000	2.54117	-0.18142	-0.30869	0.30403	-1.01532	-0.22578
14	3.71667	4.27880	-0.11266	-0.00005	0.18384	-0.00028	-0.00006
DEPENDENT							
24	2.71667	3.47431					

INTERCEPT -0.86552

MULTIPLE CORRELATION 0.36417

STD. ERROR OF ESTIMATE 3.32127

ANALYSIS OF VARIANCE FOR THE REGRESSION

SOURCE OF VARIATION	DEGREES OF FREEDOM	SUM OF SQUARES	MEAN SQUARES	F VALUE
ATTRIBUTABLE TO REGRESSION	3	94.45111	31.48370	2.85415
DEVIATION FROM REGRESSION	56	617.72656	11.03083	
TOTAL	59	712.17749		

continuous in nature. The print-out follows.

The first portion of the printout, following the listing of the variables in each set, is a full regression solution with all predictor variables included. After the full regression solution, each step in the setwise solution is shown. For example, in the first step, each of the sets are in turn considered for elimination. Because dropping set 2 would allow for the highest R value, set 2 is dropped. This process continues until only one set remains. For this particular problem, set 4, which includes salary (variable 12), years in rank (variable 13) and years at the University (variable 14), is the final remaining set.

A complete listing of the program is available to interested readers.

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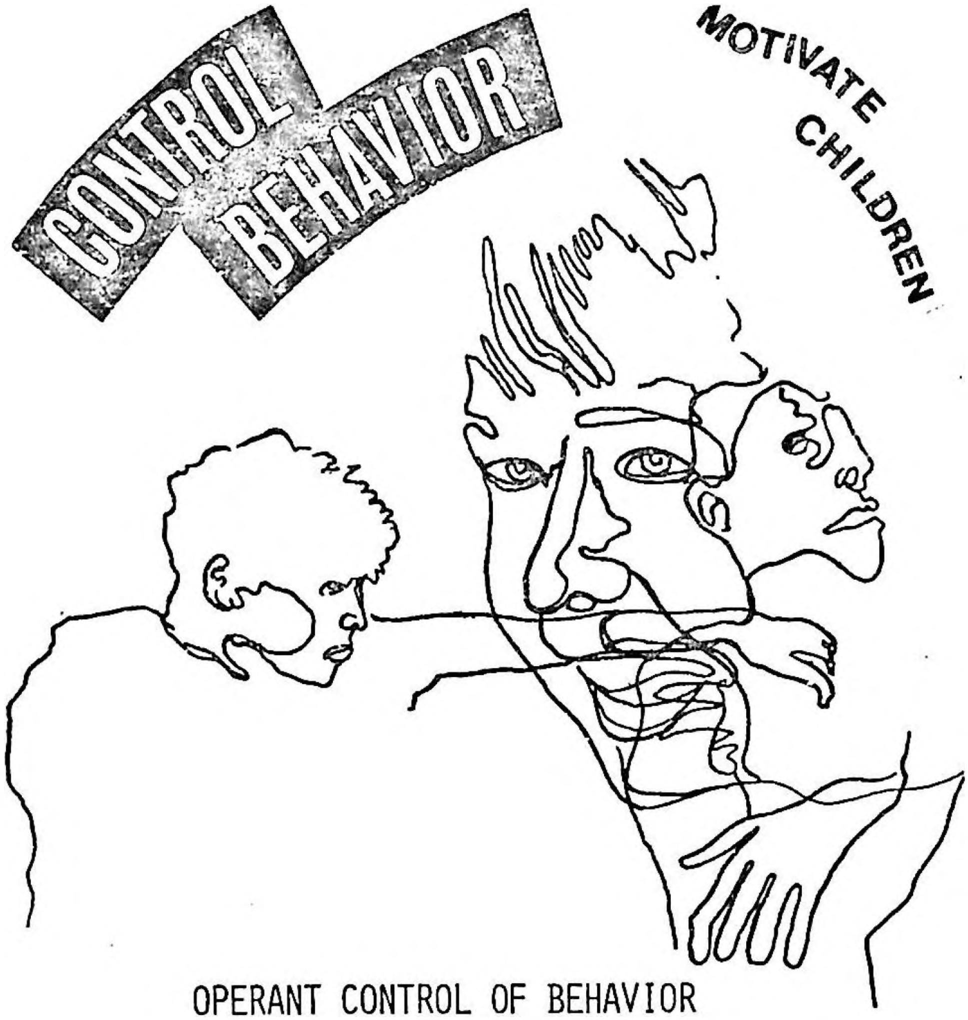

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Utilization of Multiple Regression Analysis in Changing the Verbal Behavior Patterns of Elementary Classroom Teachers Through Self-evaluation

Margaret E. Cummins

ABSTRACT

Multiple regression analysis was used to investigate the effectiveness of a self-evaluation technique in changing the verbal behavior patterns of elementary classroom teachers. Three ratios were employed: the I/D ratio, or ratio of indirect to direct statements by the teacher; the TRR, or teacher response ratio which eliminates questioning and lecturing from the total I/D ratio; and the PIR, or the ratio of pupil talk-response to pupil talk-initiated. The self-evaluation technique for changing the verbal behavior patterns of elementary classroom teachers was not found to be significant for any of the three measures.

INTRODUCTION AND RATIONALE

The control of the pattern of the classroom teacher's verbal interaction with the pupils in her class is just one of the methods the teacher may use to establish a desirable social climate in her classroom which can in turn increase the amount and quality of pupil learning. Ruth Cunningham (1951) called this desirable social climate democratic living which provides an opportunity for making meaningful choices on the basis of discussion and evaluation permitting the skills of self-management and interaction to develop.

Cecil V. Millard (1953) indicated that the quality of group living was a significant factor effecting the quality of education received by children. Millard further suggested that a child who is threatened by teacher mandate, arbitrary assignments, discriminating marking and undesirable grouping, is a candidate for delinquent activity.

Ned A. Flanders (1960) pictures the teacher as the source of influence which supports or initiates the acts or patterns of action in the social process which change the set of social relationships in the social structure.

The purpose of this investigation was to demonstrate that teachers, through a self-evaluation process, could improve the quality of the verbal interaction patterns in their classrooms and thereby improve the climate of the classroom in such a way as to enhance the learning taking place. A self-evaluation treatment instrument was designed which was comprised of a series of guideline questions compatible with the goal of increasing supportive behaviors and flexibility of verbal patterns used by teachers. The self-evaluation treatment was also compatible with Flanders' system of interaction analysis which was selected as the measurement instrument (Amidon and Flanders, 1967). The instrument designed for this study was named "Improvement through Self-evaluation" (ITSE). It was intended that this treatment process would help teachers improve the quality of their verbal interaction patterns through assessment of their own behavior.

METHOD

Sample: The Ss were 29 volunteer elementary classroom teachers from a small city school system. This sample represented over 46% of the available population. The use of volunteers limited the sample population but this procedure was deemed necessary because it was believed that neither participation now change could be mandated and many teachers had personal and professional obligations which precluded participation in projects demanding extra time. It was expected that random assignment of volunteers into the experimental and control groups would partially overcome this bias.

Procedure and Design: The study encompassed a time period of ten weeks. All subjects attended three group meetings. The first meeting included all Ss and procedures common to both conditions were explained. The two subsequent meetings were held with subjects in Condition I and II in separate study groups.

Each S received a cassette tape for recording forty-five minutes of instructional proceedings. These first tapes were collected within a week and were used at the conclusion for pretest evaluation.

Ss in Condition I were presented with a cassette tape to use as a practice tape in self-evaluation. During the self-evaluation period, these Ss were asked to make at least one tape a week. This was to be done at the S's convenience. They were also instructed to prepare a summary of conclusions from the self-evaluation session to be given the E. This summary was to serve as a reliability check that procedures were being followed consistently.

Ss in Condition II engaged in a project developed for their group which was a modification of a study conducted by Edmund Amidon and Ned A. Flanders (in Howes, 1970, Pp. 200-209). Because the project emphasized pupil self-directed group work, it would be less likely to influence the teacher's behavior during interaction taping sessions.

At the end of the ten week period each S received another cassette tape to prepare forty-five minutes of class work involving interaction between teacher and the pupils. Fifteen minutes of the pretest and posttest tapes were scored using Flanders' interaction analysis.

The selection and training of two scorers followed recommendations of Flanders (1965). The reliability between scorers was checked using Flanders' modification of Scott's coefficient for converting tallies into per cent figures. A coefficient of .8 was the minimum accepted. The two scorers tallied verbal responses simultaneously to assure analysis of the same verbal interaction sequence.

At the close of the experimental period, 26 Ss remained. The 104 tally sheets resulting from each scorer's numerical categorization of the pretest and posttest tapes were compiled into matrices. From these matrices three ratios were calculated. The first ratio was the I/D ratio, or ratio of the total indirect to direct teacher statements. The second ratio was the TRR, or teacher response ratio which eliminates the asking of questions and lecturing categories. This ratio minimizes the effect of subject matter on the ratio. The third ratio calculated was the PIR, or pupil initiation ratio. This ratio was proposed by Flanders (1970) to indicate the proportion of pupil talk which was initiated by the pupil as opposed to being a response to a teacher question.

Since it is believed that the ratios are only estimates of the true value, a better estimate of the true value of the ratios computed from the matrices was considered to be the average of the two ratios.

RESULTS

In order to determine if the ratios obtained by the subjects in Condition I who used the ITSE program were significantly different from the ratios of the subjects in Condition II who did not use the treatment program, an analysis of covariance using multiple regression models was used. Six models were used to determine if there was a significant difference between ratios obtained by the two groups when the pretest scores were held constant.

Table 5 presents the statistical models and the resulting data. The format follows that suggested by Newman (1972). Examination of Table 5 reveals that the probability level of .05 set for rejection of the null hypotheses was not obtained for any of the ratios. It must be concluded, therefore, that there was no significant difference between the I/D ratios, the TRR, or the PIR of the two groups of subjects.

From the examination of the weekly summaries prepared by Ss in Condition I, 5 factors in the design appear to require reexamination before replication even though the importance and influence of these factors cannot be determined.

1. All external peer reinforcement had been eliminated. This required suppression of excitement of enthusiasm which might have been generated by the use of ITSE.

2. The design of ITSE did not provide opportunity to practice converting ideas into overt behavior.

3. The weekly written summaries varied greatly. These summaries could possibly have been made more effective

TABLE 5

MODELS, F-RATIOS, AND R^2 FOR PREDICTING POSTTEST SCORES OF SUBJECTS

Models and Explanations	Models	R^2	df	F	P
Hypothesis 1: An analysis of covariance (Pretest score was covaried) to determine if there was significant difference between the I/D ratios of SsGI and SsC-II.					
Model 1 $Y_1 = a_o U + a_1X_1 + a_2X_7 + a_3X_8 + E_1$	Full	.03	1/23	0.23	.64
Model 2 $Y_1 = a_o U + a_1X_1 + E_2$	Restricted	.02			
Hypothesis 2: An analysis of covariance (Pretest score was covaried) to determine if there was significant difference between the TRR of the SsC-I and SsC-II.					
Model 3 $Y_2 = a_oU + a_1X_3 + a_2X_7 + a_3X_8 + E_3$	Full	.16	1/23	3.43	.08
Model 4 $Y_2 = a_oU + a_1X_3 + E_4$	Restricted	.03			

Note. - Table 5 continued on the following page

Table 5 - Continued

Models and Explanations	Models	R^2	df	F	P
Hypothesis 3: An analysis of covariance (Pretest score was covaried) to determine if there was significant difference between the PIR of the SsC-I and SsC-II.					
Model 5. $Y_3 = a_oU + a_1X_5 + a_2X_7 + a_3X_8 + E_5$	Full	.20	1/23	0.96	.34
Model 6 $Y_3 = a_oU + a_1X_5 + E_6$					

if a guide form had been used which would have helped reduce this variability.

4. The use of less than 1000 tallies as suggested by Flanders (1970) may have caused ratios to be spuriously high. However the PIR and TRR as used were designed by Flanders to overcome this instability.

5. The length of time involved in weekly taping and the use of malfunctioning tape recorders caused expressed frustration and irritation to the Ss in Condition I.

CONCLUSIONS

The findings of this study were that the use of ITSE did not significantly change the ratios obtained as measured by the application of Flanders' interaction analysis to audio tapes. The limiting factors presented leave the value of the instrument as an in-service tool still in question. Further research should be undertaken to overcome the weaknesses of this study.

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Incorporating Cost Information into the Selection of Variables in Multiple Regression Analysis

John T. Pohlmann
Southern Illinois University at Carbondale

The problem of finding the best regression equation is considered from the standpoint of predictor costs. Typically, variables are selected for inclusion in prediction equations on the basis of their unique contribution to the prediction of a criterion. A method is presented whereby losses due to lack of predictability and predictor costs are combined in a loss function. The best predictor set is then chosen that simultaneously minimizes losses incurred in measuring the predictors and losses incurred from lack of predictability of a criterion variable.

Incorporating Cost Information into the Selection of Variables in Multiple Regression Analysis

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The typical variable selection problem may be summarized as follows: Given a criterion variable, Y, whose variance you wish to account for by using a potential set of k predictors X_i, i = 1 to k, find a subset of X_i which will do the best job of predicting Y. This task usually reduces to eliminating X_i's that do not uniquely account for a specified minimum amount of variance in Y. Due to the cost factors involved in obtaining measures on the various X_i's, this final set of predictors should be as small as is possible to achieve the desired degree of prediction accuracy.

Traditional Solutions to the Problem

The most widely used method for solving this problem is to try various combinations predictors until each predictor uniquely accounts for a significant proportion of variance in Y at some specified alpha level. Hence the final set of predictors is composed of only those variables that make significant contributors to predicting Y. Various algorithms exist for testing the unique contributions of each X_i. Draper and Smith (1:163) suggest two goals that should guide a researcher in selecting the "best" subset of X_i. First, the final regression equation should be useful for prediction purposes, and secondly, because of the costs involved in obtaining measures on the various X_i's, the equation should contain as few X's as possible. In order to achieve this goal, various stepwise regression procedures may be employed. Each of these procedures specifies an orderly process whereby various combinations of predictors are tried until only the most efficient subset of X_i is left. Efficiency implying that the maximum amount of variance in Y is accounted for with the smallest set of predictors.

Since all stepwise procedures, either directly or indirectly, use only the proportion of variance accounted for in Y as the criterion for including X_i's in the final predictor set, we must assume that an implication is made that each X_i costs the same to measure. This implication follows since none of the standard stepwise regression algorithms incorporate cost information in the selection of predictors.

The position taken in this paper is that Draper and Smith's second goal should be modified as follows:

> Because of the costs involved in obtaining X_i's, the model should contain the least expensive subset of X_i as is possible.

This modification suggests that the goal of selecting the most efficient subset of X_i should be characterized by selecting X's that account for the maximum amount of variance in Y, while simultaneously minimizing the cost of the final subset of X_i.

The Nature of Cost

Each potential predictor can be assigned a cost value on the basis of many factors. Costs are incurred in measuring variables depending upon 1. the actual purchase price of the measuring instruments, 2. the time required to obtain each measure, 3. the difficulty encountered in scoring or ennumerating a subject's performance, or 4. the sophistication, and hence the cost of the staff required to administer the measuring device. In general, time, dollar costs, and complexity all contribute to the cost of measurement. In an applied setting where cost factors are critical, any selection procedure which fails to consider these kinds of factors is not an ideal one.

A Method of Selecting Variables Using Cost Information

In a standard regression equation the solution for the weighting coefficients minimizes the residual variance in the criterion after the predicted scores have been extracted. It may be assumed that some loss is incurred when criterion variance cannot be accounted for, and regression analysis is seen as a means by which these losses may be minimized. Various regression models can be compared with regard to their usefulness in minimizing the criterion residual variance, and hence the losses incurred when the model is used. Another loss is realized when costs are incurred in the measurement of the predictor variables. Consequently, two sources of loss are present, the first being losses incurred by lack of predictability and secondly, losses incurred in gathering predictive information. These two sources of loss should be minimized in the solution for the "best" regression model.

These two sources of loss may be incorporated into a common loss function and the task of model selection may be reduced to finding the model which serves to minimize the common loss. The loss function presented here assumes that the two types of loss are additive. That is, losses due to lack of predictability and predictor measurement may be added in the derivation of the common loss function. This loss function may be characterized as follows:

$$L_I = k_1 \; (c_1 \times \text{cost}_I) + k_2 \; (c_2 \times (1 - R_I^2)) \tag{1}$$

where L = the resulting loss value for the regression equation using predictor subset I.

k_1 and k_2 = constants that will allow differential weighting of cost and validity information.

cost_I = the costs incurred in measuring the predictor subset I.

$(1-R_I^2)$ = the proportion of variance in Y that cannot be accounted for by the regression equation using predictor subset I. R^2 is the squared multiple R.

c_1 and c_2 = weighting coefficients derived so that cost data and validity data can be reduced to a common scale.

The constants k in equation (1) allow the researcher to determine which source of loss will be more important in the derivation of the common loss value. For example, if $k_1 = 1$ and $k_2 = 2$, the researcher is solving for the regression model where losses due to lack of predictability are twice as important as losses stemming from predictor costs.

The term cost_I in equation 1 may be the dollar amount spent in measuring predictor subset I or it may be the time required to obtain the measures. In general, it represents that cost factor the researcher wishes to minimize in selecting the "best" model. The values c_1 and c_2 are weighting coefficients which when multiplied by the cost_I values and the $1 - R_I^2$ values reduce them to a common scale of measurement. For convenience sake, they may be derived in such a way so that the sum of their values will equal 1.0. This may be accomplished by finding the sum of the cost values for all of the predictor subsets, taking the reciprocal, and then by dividing this value into each cost_I. A revised cost value will emerge for each predictor subset, which when summed will equal 1. Algebraically this rule is given as follows:

Let $cost_I$ = the cost of measuring subset I

J = the total number of predictor subsets under consideration

The value of c_1 in equation (1) is then given by

$$c_1 = \left(\sum_{I=1}^{J} cost_I \right)^{-1} \tag{2}$$

This same procedure is used substituting $(1 - R_I^2)$ for $cost_I$ in equation 2 to give c_2.

The discussion that follows shows how the method can be applied to a specific problem. The method proceeds as follows:

<u>Step 1</u>. After the costs have been assigned to each predictor set, those subsets that exceed a maximum tolerable cost are eliminated. <u>Step 2</u>. The cost values are then divided by the sum of the cost values, to give a revised cost value. <u>Step 3</u>. The relative loss incurred for each predictor subset due to its lack of predictability is given by $(1 - R_I^2)$, where R_I^2 is the proportion of variance in Y accounted for by predictor subset I. <u>Step 4</u>. The values $(1 - R_I^2)$ are then divided by the sum of the $(1 - R_I^2)$ values for all predictor sets. <u>Step 5</u>. The values for losses due to predictor cost found in step 1 are added to the values for losses due to lack of predictability found in step 4. The predictor subset with the lowest sum is then chosen as the predictor set.

This final loss structure given in step 5 gives an index for the selection of each predictor subset that weights both cost and validity information. The predictor set with the lowest final combined loss value is, of course, the set chosen.

Sample Problem

Assume that you have cost and validity information on all possible combinations of three predictors for predicting some criterion. Further, assume that you can spend no more than $10.00 per subject in obtaining the required data. The problem is to find the subset of predictors which will do the best job of predicting Y for the least amount of money.

Table 1 shows how the analysis is conducted for the sample problem. Column A contains the cost information for each predictor subset. The predictor set (1, 2, 3) was rejected from further analysis since its dollar cost exceeded the maximum allowable cost. Column B contains the adjusted cost values. The adjustment was obtained by dividing each cost value by the sum of the costs to give a cost value that sums to 1.0. Column C contains the loss information based on the validity of the subset. The value $1 - R^2$ for each predictor subset was chosen as the appropriate indicator of loss due to lack of predictability. Column D contains the adjusted validity loss values. As with the cost data, these adjusted values were obtained by dividing each $1 - R^2$ by the sum of the $1 - R^2$'s for all of the predictor subsets. Column E represents the final composite loss value for each predictor subset. The values in Column E were obtained by adding the respective values for each subset in Columns B and D. The values in Column E represent a loss incurred when each predictor subset is used, equally weighting cost and validity data. Column F shows the respective loss values when validity data is weighted three times as important as losses due to predictor cost. When cost and validity data are equally weighted the predictor set containing variable 3 only is the preferred subset. When validity data is weighted as being three times as important as cost data, the predictor set containing variables 2 and 3 is the preferred set.

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insert Table 1 about here

Discussion

The method for selecting the "best" predictor set in a regression analysis problem presented here insures that cost information will be incorporated into the selection process. This method of approaching the variable selection problem suggests that researchers should try to extract as much predictability out of a set of variables as is possible. Researchers should try to fit various transformations of the original variables, since the cost of transforming the original variables is nil. Higher order polynomial functions should be attempted, along with cross product (interaction) transformations. These transformations are indicated since the cost of obtaining the original measurements is not changed when these complex models are tried. If a researcher is concerned about the possible shrinkage in R^2 that is usually realized when such complex functions are used, he could replace validity data with cross-validated R^2's where original R^2's were used in this sample problem. All of the methodological safeguards that are presently employed in selecting a predictor subset should still be used with this method, but an attempt should be made to simultaneously minimize the costs of predicting criteria.

REFERENCES

1. Draper, N.R.; Smith, H. Applied regression analysis. New York: Wiley, 1966.

Table 1

A Table Depicting Cost and Validity Data, and the Derivation of the Final Loss Function for Selecting the "Best" Predictor Subset

Variables in the Predictor Set	(A) Cost	(B) Revised Cost Value	(C) $1 - R^2$ where R^2 is the proportion of variance in Y Accounted for by the Predictor Set	(D) Revised Loss Value	(E) Combined Loss Value (B + D)	(F) Combined Loss Value on the Basis of Validity Being Three Times as Important as Cost (B + 3D)
1	$ 5	.15	.50	.13	.28	.54
2	4	.12	.55	.14	.26	.54
3	2	.06	.60	.16	.22	.54
1, 2	9	.27	.45	.12	.39	.63
1, 3	7	.21	.40	.10	.31	.51
2, 3	6	.18	.35	.09	.27	.45
1, 2, 3	11	*	--	--	--	--
Ø (null set)	0	.00	1.00	.26	.26	.78
	Sum of Cost = 33 excluding (1,2,3)	Sum = 1.00	Sum = 3.85	Sum = .97		

*Set (1,2,3) was immediately rejected since its costs exceeds the $10.00 maximum.

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The Use of Contrast Coding to Simplifv ANOVA and ANCOVA Procedures in Multiple Linear Regression

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Abstract

Multiple regression (MR) is a powerful and flexible techniques for handling data analysis. The present paper presents a discussion of the use of "contrast coding" in performing analysis of variance and analysis of covariance procedures in MR. Contrast coding provides a method for coding nominal variable in the set of predictor vectors in MR so that such vectors reflect a set of orthogonal comparisons. As a result, one is able to test hypotheses concerning more specific research questions than those usually tested in more traditional MR coding procedures. By adding more components to the general linear model, contrast coding provides a relatively simple and logical basis for extending analysis of variance to its various subclassifications.

Cohen (1968) presented a discussion of contrast coding in multiple linear regression models for use in analysis of variance (ANOVA) and analysis of covariance (ANCOVA). The general theme of Cohen's article was that the main effects and interaction of ANOVA and ANCOVA can be reflected in a linear model through the use of specifically coded predictor vectors. Other writers have referred to these vectors as dummy vectors, nonsense coded vectors, or group membership vectors. In our work with multiple regression, we have found Cohen's system of contrast coding to provide a very logical and relatively simple method for developing regression models to answer more specific questions than the overall main effects and interaction tests generally applied in ANOVA. One purpose of this paper is to present a discussion of the use of contrast coding to reflect orthogonal comparisons.

We have also found that, as Cohen suggests, contrast coding can easily be applied in ANCOVA. Further, we found that for a two-way analysis of covariance, contrast coding leads to a more exact duplication of traditional analysis of covariance than does the standard method of designating group membership predictor vectors. A second purpose of this paper is to present a discussion of the application of contrast coding to ANCOVA.

Analysis of Variance

Consider an experiment in which two treatment conditions are to be compared. In this case, Winer (1962) indicates that each individual score results from a number of sources of variability. According to Winer,

[1] $$X_{ij} = \mu + \tau_j + e_{ij}$$

Where: X_{ij} = an observation on person i under treatment j

μ = grand mean of all potential observations

τ_j = effect of treatment j

e_{ij} = error associated with X_{ij}

In order to answer the question of whether there is a significant difference between Treatments 1 and 2 in a standard regression model (Bottenberg & Ward, 1963; Kelly, Beggs, McNeil, Eichelberger and Lyon, 1969), one would employ the following full model:

[2] Model 1 $$Y = a_0U + a_1X_1 + a_2X_2 + E_1$$

Where: Y = vector of criterion scores

U = unit vector (all elements are 1)

X_1 = 1 if the corresponding criterion score comes from Treatment 1; 0 otherwise

X_2 = 1 if the corresponding criterion score comes from Treatment 2; 0 otherwise

E_1 = error vector

a_0, a_1, a_2 = partial regression weights

It will be noted that Y corresponds to Winer's X_{ij}; a_0 to Winer's μ; a_1 and a_2 to Winer's τ_j and E_j to Winer's e_{ij}. To determine if a significant difference exists between Treatments 1 and 2, Model 1 would be compared to a restricted model (Model 99) which would contain only the unit vector as a predictor vector and an error vector.

[3] Model 99 $Y = a_0U + E$

Using contrast coding to reflect Treatments 1 and 2, the following full model would result:

[4] Model 2 $Y = a_0U + a_1X_1 + E_2$

Where: Y = criterion scores

U = unit vector

X_1 = 1 if criterion from Treatment 1 or -1 if criterion from Treatment 2

E_2 = error vector

a_0, a_1 = partial regression weights

To answer the question as to whether or not Treatments 1 and 2 are different, Model 2 would be compared to Model 99.

The advantage of contrast coding in the above example seems to be in the determination of degrees of freedom. It will be noted that the analysis in this example consists of a simple t-test or an F-test with one degree of freedom in the numerator. In order to perform this analysis, one must set a_1 and a_2 from Model 1 equal to 0. This loss of two vectors results in a loss of only one degree of freedom because there is a linear dependency existing within the set of vectors U, X_1, and X_2 in Model 1. In Model 2, no linear dependencies exist in the predictor variables. As a result, the test for a significant difference between Treatments 1 and 2 is accomplished simply by setting $a_1 = 0$. As a result, the restriction of one regression weight accurately reflects the appropriate number of degrees of freedom for this analysis.

If one were to expand the above two-group example to include four treatment conditions, the advantages of contrast coding in ANOVA become more apparent. If Treatments 3 and 4 are added, the addition of X_3 and X_4 to Model 1 would be required in order to allow for the main effects of Treatments 3 and 4. Model 1 would then be revised to be:

[5] Model 3 $Y = a_0U + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + E_3$

Where: Y, U, X_1, and X_2 are as defined in Model 1

X_3 = 1 if Treatment 3, 0 otherwise

X_4 = 1 if Treatment 4, 0 otherwise

E_3 = error vector

a_0, a_1, a_2, a_3, a_4 = partial regression weights

To test for an overall main effect of treatments, the following restriction would be placed on Model 3:

$a_1 = a_2 = a_3 = a_4 = 0$

It can again be seen that there is one more predictor vector restricted out than degrees of freedom lost. Unless one employs a series of dependent t-tests, the overall treatment main effects appears to be the only question which can be asked and tested in the above regression framework.

Using contrast coding, Model 4 might be used to reflect the various treatment conditions.

[6] Model 4 $Y = a_0U + a_1X_1 + a_2X_2 + a_3X_3 + E_4$

Where: Y = criterion scores

U = unit vector

E_4 = error vector

a_0, a_1, a_2, a_3 = partial regression weights

and where the elements in X_1, X_2, and X_3 reflect the linear, quadratic and cubic trends and are as follows:

If criterion from Treatment	X_1	X_2	X_3
1	-3	1	-1
2	-1	-1	3
3	1	-1	-3
4	3	1	1

The elements presented here are the standard coefficients for orthogonal polynomials. The use of these values would result in X_1, X_2, and X_3 being uncorrelated. As a result, it is possible to partition the variance into its three independent sources.

If one were concerned about asking the overall main effect question, it would be necessary to set $a_1 = a_2 = a_3 = 0$. This test of significance would result in precisely the same outcome as the use of 1 and 0 group membership vectors as presented in Model 3. However, it is possible to ask more specific questions given orthogonal coefficients. One may not only be interested in the overall main effect question. The research hypothesis in a particular research project might be that "the average of Treatment Groups 1 and 4 is different from the average of Treatment Groups 2 and 3" (in other words, the difference follows a quadratic trend). Given Model 4, it would simply require that a_2 be set equal to 0 in order to answer this very specific question.

As indicated above, the values in the vectors are standard coefficients for orthogonal polynomials. It may be that such coefficients do not reflect a particular question of interest. One might want to ask the question as to whether the effect of Treatment 1 equals the average effect of Treatments 2, 3, and 4. Since the standard coefficients for orthogonal polynomials do not reflect this particular question, it would be necessary to establish a different set of coding coefficients. Since the question as to whether Treatment 1 equals the average of Treatments 2, 3 and 4 would require coding coefficients in the predictor vectors to reflect the differential weighting of the Treatments, an appropriate set of coding coefficients might be: Treatment 1 = 3; Treatment 2 = -1; Treatment 3 = -1; Treatment 4 = -1. The values in vectors X_1, X_2, and X_3 of Model 4 might then be as follows:

If criterion from Treatment	X_1	X_2	X_3
1	3	0	0
2	-1	2	0
3	-1	-1	+1
4	-1	-1	-1

In order to answer this question of interest, it would only be necessary to restrict out vector X_1 by setting $a_1 = 0$. X_2 and X_3 are included in the model in order to account for the rest of the overall treatment effect even though such comparisons may not be of interest.

The two examples presented above seem to point to two advantages which accrue from the use of contrast coding in a one-way analysis of variance. First, since the predictor vectors are all independent, the number of predictor variables in a model accurately reflects the degrees of freedom for the analysis. As was pointed out above, this is not the case when standard 1 and 0 group membership vectors are used. Second, the use of contrast coding allows one to ask more specific questions of interest than the overall main effect. The importance of these two factors becomes even more apparent when one considers a two-way analysis of variance.

Consider an experiment in which 2 X 3 factorial design is to be applied and assume that there are two levels of conditions A and three levels of condition B. Winer indicates that the following linear model would account for all sources of variability contributing to an individual score:

[7] $$X_{ijk} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + e_{ijk}$$

Where: X_{ijk} = an observation on person k under treatment i and treatment j

μ = grand mean of all potential observations

α_i = main effect for condition A

β_j = main effect for condition B

$\alpha\beta_{ij}$ = effect of interaction of conditions A and B

e_{ijk} = error associated with X_{ijk}

The various sources of variability in Winer's model can be duplicated in standard multiple regression analysis. However, the need for a test of interaction requires a full model which allows the differences between cell means to vary and a restricted model which would force the differences between cell means to be equal. While this is not a particularly difficult task, it does require some rather lengthy algebraic manipulations of the partial regression weights. Kelly, et.al, (1969) include an excellent presentation of the procedures for performing a two-way analysis of variance in standard regression analysis so we will not attempt to duplicate it here.

Using contrast coding to duplicate the 2 X 3 analysis of variance would require the following full model:

[8] Model 5 $Y = a_0U + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 + E_5$

Where: Y = criterion vector

U = unit vector

X_1 = 1 if subject from A_1 or -1 if from subject A_2

X_2 = -1 if subject from B_1; 0 if subject from B_2 or 1 if subject from B_3

X_3 = 1 if subject from B_1; -2 if subject from B_2 or 1 if subject from B_3

X_4 = X_1 multiplied by X_2

X_5 = X_1 multiplied by X_3

E_5 = error vector

a_0 through a_5 = partial regression weights

It will be noted that the elements of X_2 and X_3 reflect the linear and quadratic trends for the B main effect. In addition, the coefficients in X_4 and X_5 would reflect the linear and quadratic components of the interaction effect. It should also be noted that all five vectors are independent so that the number of predictor vectors accurately reflects the between cells degrees of freedom for this two-way analysis of variance.

The overall main effects and interaction tests can be simply done once Model 5 has been established. In order to test for interaction, one need only set $a_4 = a_5 = 0$ and compare the R^2 of Model 5 to the R^2 of the resulting restricted model. In order to test for a significant A main effect one need only restrict X_1 from Model 5 by setting $a_1 = 0$. To test for the B main effect, X_2 and X_3 must be restricted from Model 5 by setting $a_2 = a_3 = 0$. Each of these tests of significance can be shown to exactly duplicate the results one would obtain through the use of traditional two-way analysis of variance equations.

As was the case with a one-way analysis of variance, the use of contrast coefficients allows one to ask questions of interest other than the overall main effects and interaction. In the example above, suppose one were interested in determining if the interaction contained a significant quadratic trend. This variable of interest is reflected in X_5 of Model 5. In order to test for a significant quadratic interaction trend, one need only set $a_5 = 0$. The linear trend of the interaction could be tested by setting $a_4 = 0$. Further, Model 5 allows one to test for significant linear and quadratic components of the B main effect by setting $a_2 = 0$ and $a_3 = 0$ respectively. The use of contrast coefficients in this linear regression analysis would allow one to examine any one or all of the five independent sources of variance which the between cells degrees of freedom indicate contribute to each individual criterion score. In addition, one could ask other questions of interest by establishing a set of contrast codes which would allow the specific question of interest to be reflected in the predictor vectors.

Analysis of Covariance

The application of the use of contrast coefficients for analysis of covariance is a natural extension of the analysis of variance. The covariate or concomitant variable is entered as a predictor along with the treatment variables in the linear equation. For example, if a covariate were included in Model 4 above the equation would become:

[9] Model 6 $Y = a_0U + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + E_6$

Where: Y = criterion scores

X_1 through X_3 are treatment variables of interest

X_4 = the covariate or concomitant variable

U = unit vector

E_6 = error vector

a_0 through a_4 = partial regression weights

The nature of the equation changes slightly, however, in that the predictor variables (X_1 through X_4 are not all orthogonal to one another. Specifically, there is a real or sample covariance between the covariate (X_4) and each of the variables of interest (X_1 through X_3). When the restriction $a_1 = a_2 = a_3 = 0$ is placed on the equation eliminating the treatment source of variance, the weight associated with the covariate (a_4) will change in value. It can be shown that the variance which is lost by such a restriction is that variance which is associated with the treatment but which is independent of the covariate. In other words, the restriction results in a loss of that variance which is unique to the treatment variables (X_1 through X_3). Such analysis is identical to analysis of covariance as described in such textbooks as Winer (1962), Lindquist (1963) and McNemar (1969). The interpretation made for a significant statistical test for treatment effect obtained by the analysis is that the treatments have an effect on the mean criterion scores over and above that which is accounted for by the covariate. The usual procedure of using group membership vectors in the linear model also duplicates the analysis of covariance for one-way ANCOVA designs. In fact, the only advantages for using contrast coefficients rather than group membership vectors seem to be that (1) contrast coefficients provide a more direct count of independent vectors to obtain degrees of freedom and (2) contrast coefficients allow for tests of more specific questions concerning treatment effects than does the use of group membership vectors.

Winer (1962) indicates that the linear model for a two-factor ANCOVA would be as follows:

[10] $$X_{ijk} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + \gamma_{yk} + e_{ijk}$$

Where: X_{ijk} = an observation on person k under treatment i in condition j given information on the covariate

μ = grand mean of all observations

α_i = effect of the ith treatment

β_j = effect of the jth treatment

$\alpha\beta_{ij}$ = effect due to interaction

γ_{yk} = regression effect on the covariate

e_{ijk} = error associated with X_{ijk}

Suppose, now, that we wish to utilize a model where the α_i effect contains two different conditions and the β_j effect consists of a control group (B_1) and two experimental groups (B_2 and B_3). Then the more traditional regression model for these effects with the covariate and interaction included would be:

[11] Model 7 $$Y = a_0U + a_7A_1B_1 + a_8A_1B_2 + a_9A_1B_3 + a_{10}A_2B_1 + a_{11}A_2B_2 + a_{12}A_2B_3 + a_6X_0 + E_7$$

Where: Y = vector of criterion scores

U = unit vector (All elements are 1)

A_iB_j = 1 if observation is found in both A_i and B_j, 0 otherwise

X_0 = concomitant variable

E_7 = error vector

a_0 and a_6 through a_{12} = partial regression weights

In order to test the interaction effect, one would restrict Model 7 to:

[12] Model 8 $Y = a_0U + a_1A_1 + a_2A_2 + a_3B_1 + a_4B_2 + a_5B_3 + a_6X_0 + E_8$

Where: Y = vector of criterion scores

U = unit vector

A_1 = 1 if criterion from A_1; 0 otherwise

A_2 = 1 if criterion from A_2; 0 otherwise

B_1 = 1 if criterion from B_1; 0 otherwise

B_2 = 1 if criterion from B_2; 0 otherwise

B_3 = 1 if criterion from B_3; 0 otherwise

X_0 = concomitant variable

E_8 = error vector

a_0 through a_6 = partial regression weights

Then the test for interaction ($R_7^2 - R_8^2$) would be a test of whether the proportion of variance unique to interaction is significant.

There is some disagreement among researchers as to procedures for testing main effects following a non-significant test for interaction. Both Ferguson (1971) and Winer (1962) suggest that after finding a non-significant interaction effect, one has the option of treating the interaction sums of squares as error. The sums of squares for interaction could, along with the appropriate degrees of freedom, be pooled with the sums of squares error to form a more stable error estimte. In a paper presented at the 1972 convention of the American Education Research Association, Pohlmann (1972) discussed the limit to which such pooling may aid in guarding against a type II error.

Kelly et.al. (1969) encourage the practice of pooling as discussed in the previous paragraph. Assuming one has chosen to pool, then the A effect could be tested by restricting a_1 and a_2 from Model 8 equal to 0 and the subsequent model becomes:

[13] Model 9 $Y = a_0U + a_3B_1 + a_4B_2 + a_5B_3 + a_6X_0 + E_9$

Where: Y = vector of criterion scores

U = unit vector

E_9 = error vector

B_1, B_2, and B_3 = defined as in Model 8

X_0 = concomitant variable

a_0, a_3, a_4, a_5, a_6 = partial regression weights

$(R_8^2 - R_9^2)$ would seem to be equal to the A main effect whereas $1 - R_8^2$ would consist of a pooled error term which includes the interaction effect. The B main effect would be tested in a manner similar to the test for the A effect.

This, however, does not duplicate the main effect that is found in traditional two factor ANCOVA as described in Winer (1962). In the model:

$$X_{ijk} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + \gamma_{yk} + e_{ijk} \qquad [14]$$

α_i, β_j, $\alpha\beta_{ij}$ are orthogonal to one another and, hence, the presence or absence of any one should not have any effect on the others. However, this is not the case in the presence of the covariate. The covariance patterns between α_i, β_j, and $\alpha\beta_{ij}$, with the covariate γ seem to be of such a nature that the restriction of any of the three effects equal to 0 results in a change (increase or decrease) in the other remaining effects. This would not be the case without the presence of the covariate nor does it affect a one-way ANCOVA. Thus, when the interaction term is pooled with the error in order to test a main effect, the amount of variance associated with that main effect is different from what it would have been without pooling.

The use of contrast coding in a two-factor ANCOVA would provide a method of analysis where one could easily test the main effects without pooling the interaction, thus yielding a duplicate result to the traditional two-factor ANCOVA as discussed by Winer (1962). Furthermore, contrast coefficients allow for tests of more specific questions of interest.

Given the example presented above, where the A effect consists of two conditions and the B effect consists of one control group (B_1) and two experimental groups (B_2 and B_3), the experimenter might be interested in a comparison of the experimental groups of the B condition to the control group (B_1) as the first question of interest. A second question might be if there is a difference between the experimental groups over both A conditions. Then, one may be interested in whether either or both of the B experimental effects are different within the two A conditions.

Note that in all questions, the interest lies in the effect of treatment over and above that of the concomitant variable.

The model appropriate for this ANCOVA would be as follows:

[15] Model 10 $Y = a_0U + a_1A + a_2B_1 + a_3B_2 + a_4AB_1 + a_5AB_2 + a_6X_0 + E_{10}$

Where: Y = criterion vector

U = unit vector

A = 1 if in condition A_1; -1 if condition A_2

B_1 = 2 if in control group; -1 if in either experimental group

B_2 = 0 if in control group; 1 if in experimental group 1 (B_2); -1 if in experimental group 2 (B_3)

AB_1 = (obtained by A x B_1) $A_1B_1 = 2$; $A_1B_2 = -1$; $A_1B_3 = -1$;

$A_2B_1 = -2$; $A_2B_2 = 1$; $A_2B_3 = 1$

AB_2 = (obtained by A x B_2) $A_1B_1 = 0$; $A_1B_2 = 1$; $A_1B_3 = -1$;

$A_2B_1 = 0$; $A_2B_2 = -1$; $A_2B_3 = 1$

X_0 = concomitant variable

E_{10} = error vector

a_0 through a_6 = the regression weight associated with the respective vectors

There are three apparent advantages of contrast coding over the more standard use of group membership vectors. First, the number of parameter estimates are directly reflected by the number of weights (a_0 through a_6) used in the model and, hence, lead to a more direct count of degrees of freedom. Secondly, one can go directly to tests of the questions of interest by restricting the appropriate weight of Model 10. For the four questions of interest specified above this would result in four restricted models by first setting $a_2 = 0$, followed by $a_3 = 0$, $a_4 = 0$, and finally $a_5 = 0$. Each of the resulting restricted models would be compared to Model 10 above. One could still test for an overall interaction effect or for either of the main effects (A or B), by simply restricting all weights for the appropriate vectors equal to 0. The third advantage of contrast coding is that it allows for tests of the main effect without pooling the error term, thus precisely duplicating the two factor ANCOVA as presented in Winer (1962). While such a traditional analysis may not be superior, the authors suspect that the difference in the two analyses would lead to somewhat different conclusions. That is, the traditional ANCOVA and the use of contrast coefficients analyze variance which is independent of all other sources in the model; whereas, the use of standard group membership vectors yields variance components that are in some way common to the interaction.

Summary

The use of contrast coefficients in multiple linear regression models can provide a logical method of analysis for both ANOVA and ANCOVA. Three distinct advantages were indicated in this paper. First, the number of estimated parameters are directly indicated in the model, thus leading to a more natural and direct count for degrees of freedom. Second, contrast coding allows for the testing of specific variables of interest other than the overall main effect and overall interaction effects. Finally, in the case of a two-way ANCOVA, contrast coding does not require pooling interaction with the error term and thus is an exact duplicate of ANCOVA as presented in Winer (1962).

It would seem that the use of contrast coefficients allow for a variety of types of analysis within the general linear model. This would present future researchers with a more integrated concept of data analysis rather than to contribute to fragmentation of the field by discussing regression as separate from ANOVA with all its various subcategories. The use of contrast coefficients encourages researchers to ask specific questions which can be analyzed with F-tests which have only one degree of freedom in the numerator. When there is only one degree of freedom in the numerator, the researcher is in effect dealing with a single source of variability, and as a result, is able to better interpret the meaning of the test of significance. In overall main effects or interaction tests, the numerator generally has more than one degree of freedom in the numerator. The researcher must then attempt to interpret the test of significance realizing that he is analyzing several sources of variability simultaneously.

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VARIATIONS BETWEEN SHRINKAGE ESTIMATION FORMULAS AND THE APPROPRIATNESS OF THEIR INTERPRETATION

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Abstract... This is a discussion paper dealing with the use of shrinkage, different methods for estimating shrinkage, and the accuracy of shrinkage estimates when variables are preselected as in stepwise regression and when variables are not preselected.

Everyone who is familiar with multiple regression is well aware that multiple correlations (R) tend to be biased upward. That is, R tends to be higher in the sample than in the population from which the sample is drawn. It is also true that the R calculated for any sample will tend to shrink when the same regression weights are applied to an equivalent sample that has been randomly drawn from the same population as the first. The shrinkage in both cases is due to the fact that the regression weights are calculated to maximize the prediction of the criterion.

In any sample in which a criterion is being predicted from a set of independent variables, there is a chance of having sampling error. This sampling error is capitalized on when calculating the regression weights, so that the predictive power for any one sample is maximized. For this reason, R tends to be somewhat of an overestimate of the relationship between a set of independent variables and the criterion that exists.

Uhl and Eisenberg (1970) empirically investigated the accuracy of three shrinkage estimation formulas: Wherry's origional formula (1931), McNemar's modification (1962), and Lord's (1950) formula. These formulas are:

$$\hat{R}^2 = 1 - (1 - R^2)\,\frac{N-1}{N-K} \quad \text{(Wherry)}$$

$$\hat{R}^2 = 1 - (1 - R^2)\,\frac{N-1}{N-K-1} \quad \text{(McNemar)}$$

$$\hat{R}^2 = 1 - (1 - R^2)\,\frac{N+K+1}{N-K-1} \quad \text{(Lord)}$$

where:
$\hat{R}$ = the corrected estimate of the multiple correlation
R = the actual calculated multiple correlation
K = the number of independent variables
N = the number of independent observations

Uhl and Esienberg found that even though Whery's and McNemar's formulas are the most commonly used, Lord's formula consistently gave more accurate estimates for the five different N sizes they investigated (N= 50, 100, 150, 250, 325) and for the situations using two through thirteen predictor variables.[1]

Nunnally (1967) states that shrinkage formulas are most appropriate as unbiased estimates of R when the independent variables are not preselected on the bases of their correlation with the criterion. However, when the situation is such that a number of tests are found to be correlated with the dependent variable, and the most highly correlated are then selected as the independent variables for the regression equation, Nunnally suggests that in these cases the shrinkage formula may not reduce the R as much as is needed. He feels the best way to overcome such a problem is to employ as many as 50 subjects for every variable.

Stepwise regression procedures will tend to capitalize

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[1] As the authors of the article pointed out, the empirical study was actually one in which the shrinkage calculated was based on how much an R from one sample would deviate from an R of an equivalent sample.

more on chance variation then does traditional multiple regression procedures. Therefore, even if shrinkage estimates are employed when interpreting stepwise regression results, one should be cautious in interpreting the reliability of any R calculated on a sample, and in generalizing that interpretation to a population or to another sample.

Kelly, et al. (1969) suggests cross validation procedures as estimates of shrinkage instead of using the more mathematical approaches used by Wherry, McNemar, and Lord. The cross validation procedure estimates shrinkage by examining the differences in the R^2s from sample data.

Some of the differences in the shrinkage estimates, using the different procedures may be explainable. For example, Wherry's and McNemar's formulas both attempt to estimate the population R, based on the sample, while Lord's formula attempts to estimate the R from one sample to another sample. This is conceptually similar to the cross validation procedure suggested by Kelly. In deciding which method of estimating shrinkage is to be used, it is important to consider the underlying assumptions of each procedure.

In conclusion, when using regression procedures in which the ratio between subjects and variables is relatively small, the interpretation of R should be made with a great deal of care. When in addition to a small ratio, the variables are preselected, as they are in stepwise regression procedures, the use of shrinkage estimates, while still helpful, may not shrink enough to correct for the capitalization on chance variation. More work is needed in developing and incorporating appropriate shrinkage estimates when one is attempting to generalize beyond the sample data.

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TABLE OF CONTENTS