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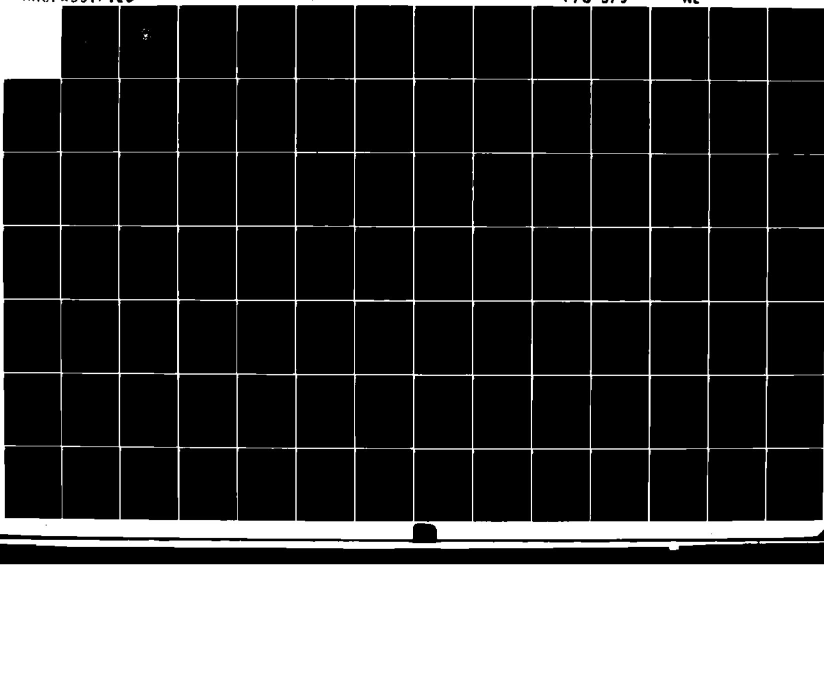

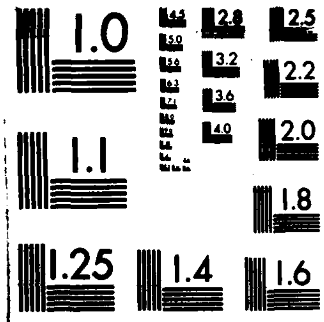

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NAVAL POSTGRADUATE SCHOOL
Monterey, California

THESIS

USING MULTIDIMENSIONAL SCALING
TO DESCRIBE TEACHER PERFORMANCE

by

John F. McCourt

March 1985

Thesis Advisor: R. R. Read

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Back

20. ABSTRACT

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Using Multidimensional Scaling to Describe Teacher Performance

by

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Lieutenant, United States Navy
B.S., United States Naval Academy, 1978

Submitted in partial fulfillment of the requirements for the degree of

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ABSTRACT

The appropriateness of a multidimensional scaling technique (MDS) in attempting to quantify students perceptions of teacher performance is investigated in the following study. Data collected on an interactive computer survey and from Student Opinion Forms (SOF's) are used to determine if satisfactory linear relationships for teacher performance exist. Multiple linear regression and factor analysis attempt to identify what appear to be the most important characteristics in instructor performance according to the perceptions of a control group. Spatial plots are created reflecting these perceptions.

TABLE OF CONTENTS

I. INTRODUCTION

A. PURPOSE

The purpose of this thesis is twofold:

1. To develop methodology that will help discover the important characteristics of instructor performance as perceived by each student group;
2. To develop user friendly software compatible with our IBM 3033 system that facilitates the data collection and processing in support of the foregoing.

The methods designed herein request proximity data or similarity/dissimilarity data on pairwise combinations of professors in the Operations Research department. Also, the respondents are requested to provide ratings on several 'bipolar scales' of suggested instructor characteristics. The methods for discovering the dimensions or relationships that appear to characterize the professors utilize several statistical tools including multidimensional scaling, regression analysis, factor analysis and cluster analysis. The data used in the analysis comes from those students in the Operations Research curriculum graduating in March of 1985.

An interactive computer survey is designed to query the students on their perceptions of the teaching effectiveness of the instructors. Thus, data is input by the students during a twenty minute session on the 3278 terminal. Initially the student links to the software, and when finished, transmits his responses to a central file.

B. SUBJECT

The subject of this thesis deals with quantifying perceptions. Specifically, we would like to obtain an explanation as to why students perceive instructors as being similar or dissimilar and discover the dynamic factors that a particular class uses to discriminate among instructors. The multidimensional scaling technique uses the information from the survey to create a 'multidimensional map' of points. Each point represents the coordinate position of the objects under investigation, in our case, professors. Once this spatial plot is produced, it remains for the researcher to discover those factors that appear to cause the structural relationships.

Multiple regression analysis and factor analysis are two techniques commonly used to describe linear relationships among dependent and independent variables. Each method is given consideration here in attempting to interpret the spatial plot produced by the multidimensional scaling program, KYST [Ref. 1]. Additionally, cluster analysis is used to group the professors into disjoint clusters. This cluster information is presented to the students during exit interviews to help guide the researcher in his attempt to find the underlying relationships.

C. SCOPE

This thesis is presented in four major chapters excluding the introduction. The second chapter describes in detail the background of multidimensional scaling methods. A brief account of regression analysis, factor analysis and cluster analysis is given as well. The third chapter specifies the means by which the data was collected in the interactive survey. Chapter IV emphasizes the analysis of the data. Finally, Chapter V provides a summary of the salient points determined in the study.

D. A BRIEF SUMMARY

A four dimensional interpretation was emphasized in describing the data obtained from the computer survey and the SOF forms. These four factors included, 1) a student-instructor interaction effect; 2) the degree to which a professor was perceived as being organized or prepared for class; 3) a combined effect of grading policy, effort required outside class and pace of the course; and 4) a composite effect combining class size and the degree to which a course relied upon prerequisites. A high correlation appears to exist among those bipolar scales used in the current SOF form. Further investigation hopefully will lead to discovering other factors that will help describe teacher performance. The results obtained in this study are not meant to be predictive but explanatory. The value associated with an instructor for each characteristic may be regarded as his score on that dimension. Thus, rankings of instructors by characteristics are possible.

II. BACKGROUND

A. WHAT IS MULTIDIMENSIONAL SCALING?

Multidimensional scaling involves the problem of depicting n points in multidimensional space such that the interpoint distances correspond in some manner to measured proximity data [Ref. 2: p. 1]. The proximity data can be similarities, dissimilarities, correlation coefficients or any other measure of association as perceived by a set of judges participating in an experiment. Multidimensional scaling techniques attempt to produce the structure or interrelationships among the n objects by assuming a direct correspondence between the measured proximity data, or dissimilarity data δ_{ij} , in our case, and the interpoint distances d_{ij}. Several choices of multidimensional scaling exist, the difference being the assumed relationship between δ_{ij} and d_{ij} . The ultimate product of multidimensional scaling (MDS) will be a spatial map that displays the association between the n objects under investigation. MDS has found considerable application in the social sciences, particularly in the realms of psychology, sociology, economics and education.

A significant point worth pursuing is this idea of correspondence between the proximity data δ_{ij} , and the distance data d_{ij} . A fairly simple method of analyzing a possible relationship would be to observe a scatter plot similar to the one given in Figure 2.1 . The vertical Y axis of the scatter plot contains the measured dissimilarities δ_{ij}, while the horizontal X axis shows the corresponding distances, d_{ij} , computed from the derived set of characteristic vectors.

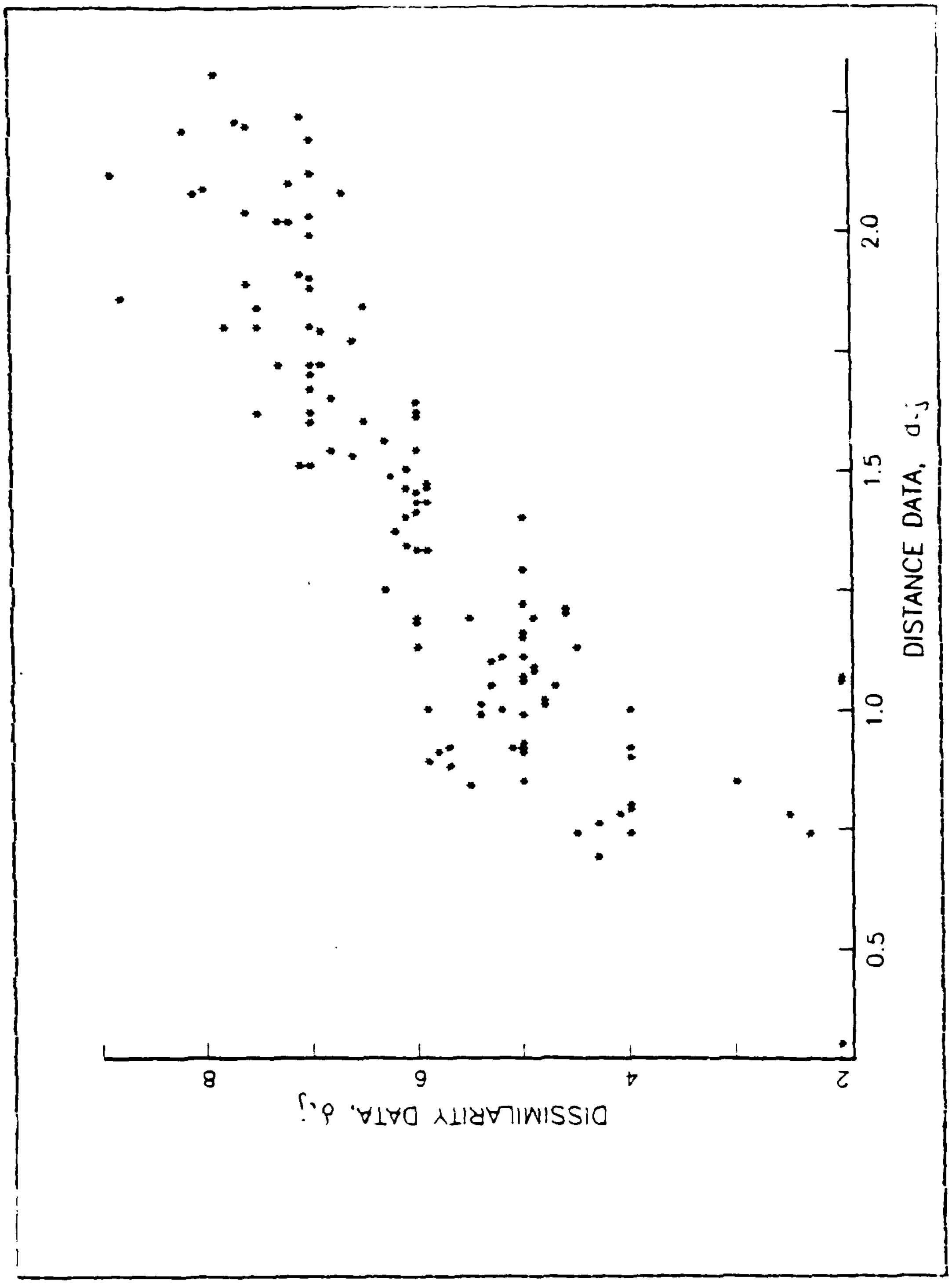


Figure 2.1 Scatter Plot of Distance vs. Dissimilarity Data

about the professors by having the students complete an interactive computer survey at a Naval Postgraduate School computer terminal with display screen. Although the data collection in this manner was not entirely free from its own brand of difficulties, it eliminated the requirement for any paperwork to be handed out or returned. All the results were automatically sent to the researchers computer storage at the completion of the survey. Also, the data was in a ready-to-use state by being contained on computer disk, and hence the need to transcribe results disappeared.

Unfortunately, there are numerous contingencies for which a computer programmer must plan in order to design a computer survey that is simple, thorough, and user-friendly. The interactive computer survey designed for this study served its purpose well. An example of this program, written in fortran, is included in Appendix D.

B. THE COMPUTER SURVEY

Several important requirements that had to be addressed in designing the interactive survey included simplicity, thoroughness and brevity. It was considered important to collect accurate responses and to limit the workload as much as possible. Each judge responded to one hundred-seventy items on the average. Even with this many questions to answer, each student appeared to have completed the survey on the order of twenty minutes. Even still, more work should be done to reduce the amount of information asked of each judge.

The nature of the computer survey progressed as follows. Each judge was required to link to the researchers computer disk, and once accessed, issue a command to run the executive program that drove the survey. Immediately, a panel of the names of the professors in the Operations Research

III. METHODOLOGY

A. LAYING THE FOUNDATION

The first step in this study to understand perceptions was to decide upon a control group of students from whom data would be obtained. In this particular instance, the judges were twenty-three Operations Research students from the section that graduates in March of 1985. The twenty-three students included two foreign nationals, two Marine Corps officers, four women naval officers and fifteen male naval officers all with various educational and career backgrounds.

The information that was to be gleaned from these students was simply this: How do professors in the Operations Research department at the Naval Postgraduate School differ, and in what ways are they similar in teaching styles and methods? There were several methods available to obtain this information. Most simply, a hand written survey with many questions could have been developed and handed to each student to complete and return. The decision was made to handle the data collection via a computer interactive survey in order to minimize the logistics and data manipulation problems associated with a hand written survey. The logistics problem was not a great problem per se, it just meant that a hand written survey had to be distributed and collected with plenty of opportunity for the surveys to become misplaced. From a data manipulation point of view, the data collected from a hand written survey would almost certainly have to be recorded on computer in order to be able to use the results easily and quickly. As a result, the decision was made to attempt to collect the information

[Ref. 6: p. 38]. The three types of problems that result from uncertainties about the covariance matrix and the underlying causal structure are; 1) specific covariance matrices can be created by factor models with the same number of common factors but with different factor loadings; 2) specific covariance matrices can be created by factor models with different number of common factors; 3) certain covariance matrices can be created by factor analytic causal models as well as non-factor analytic causal models [Ref. 6: p. 38].

Two assumptions commonly made in factor analysis are the postulate of factorial causation and the postulate of parsimony. Basically, the postulate of factorial causation requires that the researcher show that the originally observed variables are a linear combination of some causal variables [Ref. 6: p. 43]. The postulate of parsimony allows the researcher to assume a factor model with a smaller number of factors, given that two factor models with different numbers of factors have the same covariance structure [Ref. 6: p. 44].

G. CLUSTER ANALYSIS

A final topic used to assist in this study is cluster analysis. Cluster analysis is a class of techniques that typically place objects into groups or clusters suggested by the data such that objects in a cluster tend to be similar to objects in the same cluster and dissimilar to objects in other clusters [Ref. 7]. The type of cluster analysis followed in this study is disjoint cluster analysis whereby objects may belong to one and only one cluster as opposed to hierarchical cluster analysis where one cluster might be contained within another.

dependent variable. The closer the value of R^2 is to 0, the more likely it is that the model is inappropriate in accounting for the variation in the dependent variable. The reasons for a low value of R^2 are several. For one thing, the relationship under investigation may not be a linear one. If this is the case, linear regression modelling is no longer a satisfactory method to use to describe the relationship. However, given that the relationship is truly a linear relationship, the reason for a low value of R^2 could be the result of specification error. What is meant by this is that the dependent variable for which an explanation is sought, is being explained by an inappropriate set or an insufficient number of independent variables.

The artwork in regression modelling as well as in alternative statistical modelling methods comes from being able to suggest (or divine) the correct explanatory variables. In this particular study, the explanatory variables used came from current student opinion forms and suggestions from previous students in the Operations Research curriculum.

F. FACTOR ANALYSIS

As mentioned before, factor analysis attempts to represent a set of observed variables in terms of a smaller set of hypothetical variables. The hypothetical variables are chosen to account for the covariation among the originally observed variables. The number of common factors present among the observed variables can be estimated from the rank of the adjusted correlation matrix.

Difficulties in factor analysis arise when the factor loadings are not known and have to be estimated from the covariance or correlation matrix. The problem is that given the correlation matrix for the observed variables is known, any one of many causal structures could have produced it

It is not always possible to determine if the local minimum is also the global minimum, but some techniques exist to help verify that this is so. For example, starting the minimization process from several different initial configurations and comparing the final solutions will indicate if the same local minimum is achieved. The final configuration with the best stress value is most likely the global minimum. There is nothing to guarantee that one will always achieve the global minimum, but this is a common problem typical of non-linear optimization problems. In any case, the configuration is only useful if in the end it makes sense and gives insight to the experimenter [Ref. 4: p. 119].

E. MULTIPLE LINEAR REGRESSION

Once the multidimesional scaling algorithm computes the configuration with the lowest stress, the researcher would like to determine the specific dimensions that underlie the data structure. One way to do this is to assume that a linear relationship exists between a dependent variable and several independent variables. Many linear regression models assume that the proportion of explained variation of the dependent variable is the sum of additive effects of statistically significant independent variables [Ref. 5: p. 54]. Other regression models allow for interactive effects between independent variables. The dependent variable is said to be regressed over the independent variables. The result of this regression process is the coefficient of multiple determination, R^2. The value of R^2 indicates the amount of variation in the dependent variable explained by the independent variables. The value of R^2 ranges between 0 and 1. The higher the value of R^2, i.e., the closer it is to 1, the better the model explains or predicts the

D. THE MULTIDIMENSIONAL SCALING ALGORITHM

Since the mathematical technique for determining the optimal configuration, and therefore optimal stress, is somewhat complicated, only a brief description of what is considered necessary will be described here. Suppose that t dimensions are selected to describe a configuration of n points. Then

$$(x_{11}, \ldots x_{1t}, \ldots x_{n1}, \ldots x_{nt})$$

can be used to describe a particular configuration in multidimensional space. For this particular configuration, a specific value of stress exists. The overall objective is to make the stress value as small as possible. This turns out to be a minimization problem of multiple variables and is handled by the method of steepest descent. Specifically, the algorithm begins at an arbitrary configuration and attempts to improve itself by moving in the direction that improves or minimizes the stress value quickest. The direction of movement is known as the negative gradient and can be evaluated from the partial derivarives of the function

$$S=f(x_{11}, x_{12}, \ldots x_{nt})$$

[Ref. 4: p. 118]. For example,

$$(-\partial S/ x_{11}, \ldots, -\partial S/ x_{1t}, \ldots, -\partial S/ x_{nt})$$

is the negative gradient. Once the configuration reaches the point at which it can no longer improve in a particular direction, the new negative gradient is calculated and the process continues. Finally, when a configuration can no longer proceed in any direction with improvement, it has reached a local minimum. Hopefully, the local minimum is also the global minimum, but this is not necessarily true all the time.

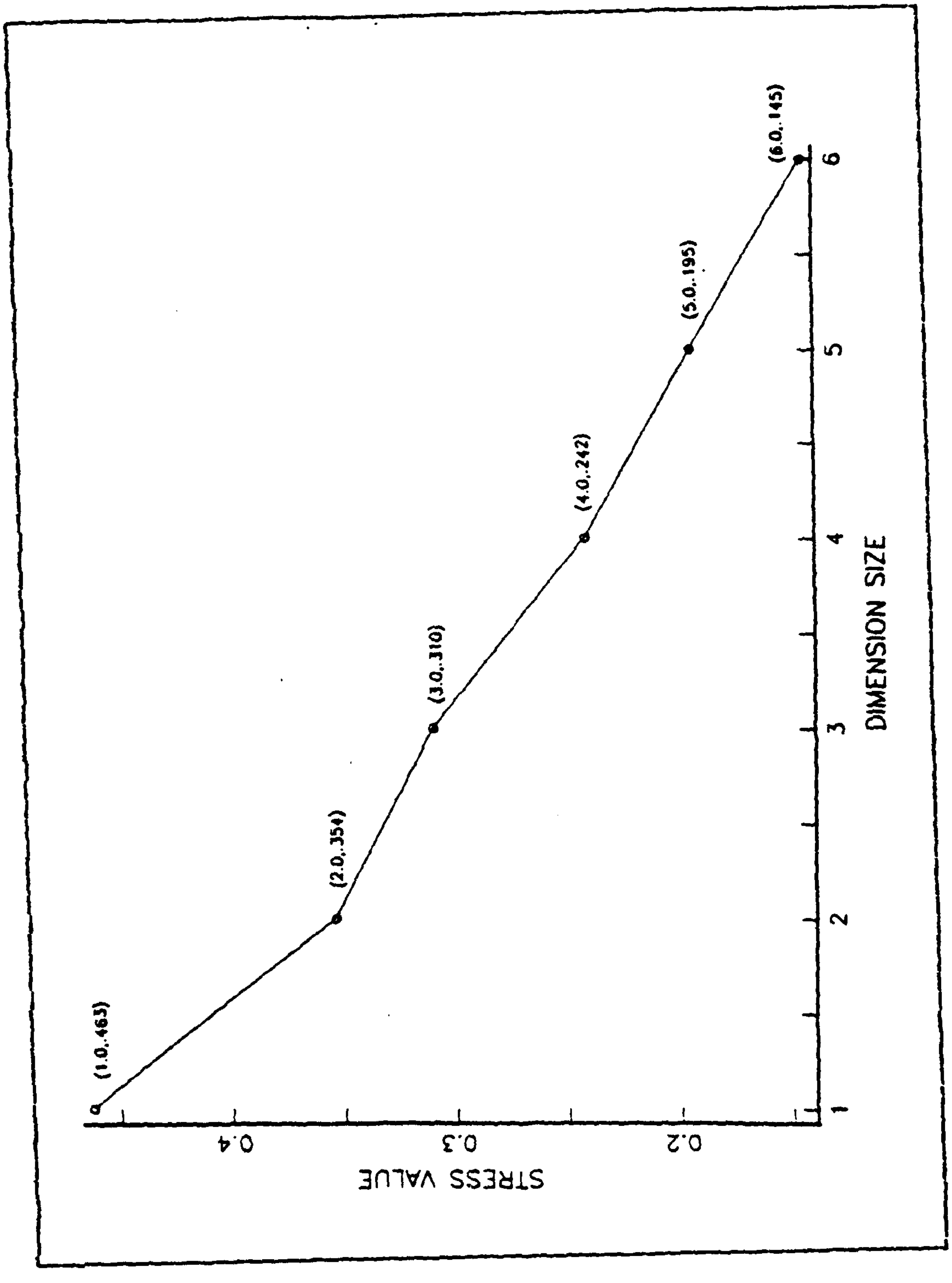


Figure 2.3 Plot of Stress vs. Dimension

are methods, however, which help to indicate why one choice of dimensionality would be more appropriate than others. The most obvious of these is to compare how stress, the goodness-of-fit measure, improves as a function of dimension. One way to do this is to compute the best configuration for several dimensions and create a plot of stress vs. dimension to visually compare the results. It should be pointed out that the more dimensions one uses to explain or interpret the data, the lower the stress becomes. When the number of dimensions, t, exceeds the number of objects minus one, n-1, the stress will always be zero [Ref. 2: p. 16]. What one wants to look for is that dimension above which the stress improves only slightly. If the data is good, a noticeable elbow will show up in the plot to indicate the appropriate dimension. We were not so fortunate in our present study. Figure 2.3 illustrates a stress versus dimension plot.

Probably more than anything else, interpretability should be considered a key criterion to use in selecting the appropriate dimension for analysis. If it is possible to interpret the results of an MDS configuration in two dimensions more readily than in say three dimensions, even though the stress is lower in three dimensions, one should consider employing the two dimensional interpretation. A final criterion suggested by Kruskal [Ref. 2: p. 16], depends upon the accuracy of the data. If an independent estimate exists to corroborate error free or near error free data, then one is allowed to extract more dimensions than one would under more error prone conditions. When all is said and done, the choice of dimensionality rests largely upon the experience of the experimenter.

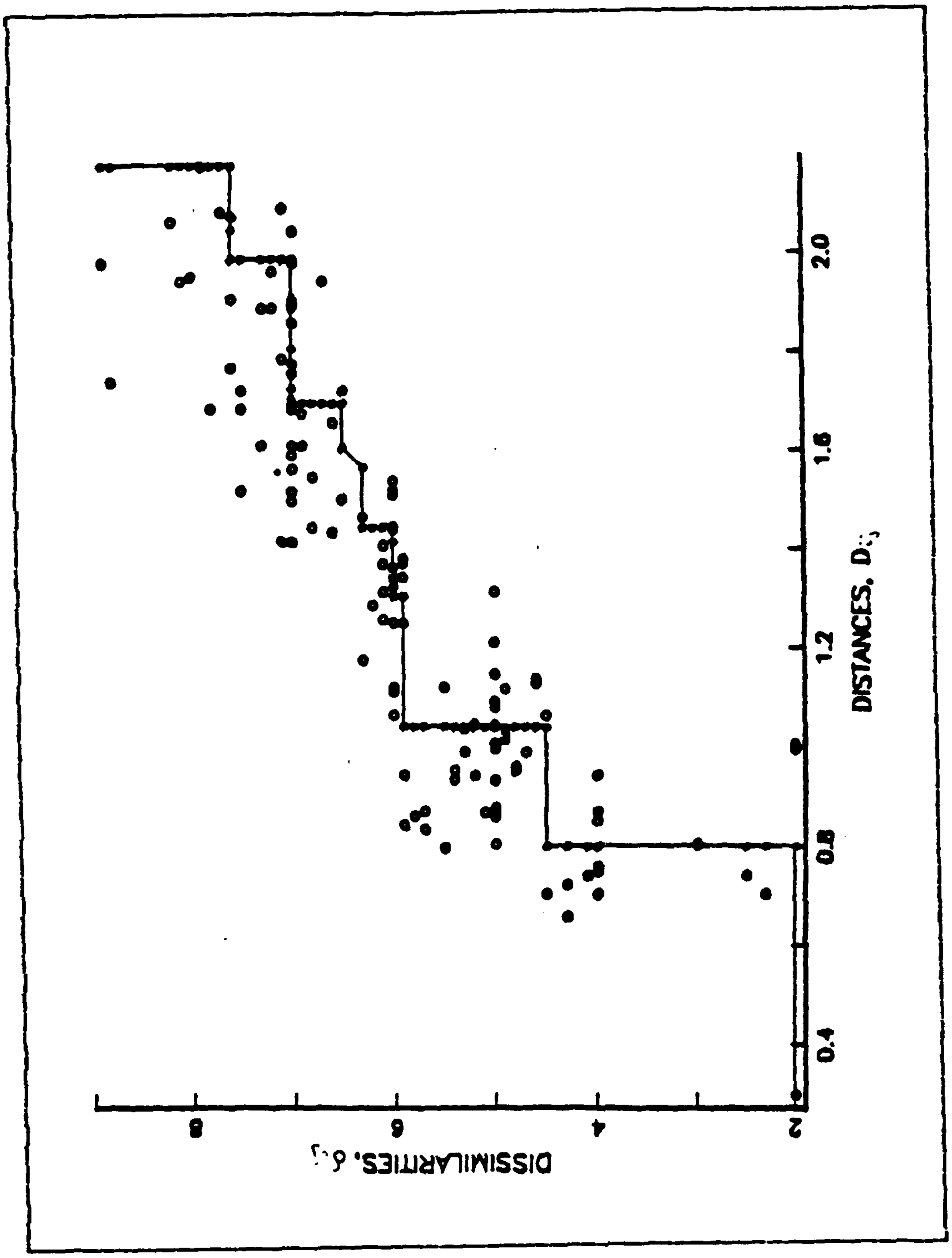


Figure 2.2 The Degree to which the Data do not Satisy the Monotonicity Requirement.

TABLE 1

Table of Stress Values According to Kruskal

STRESS VALUE	GOODNESS OF FIT
.20	POOR
.10	FAIR
.05	GOOD
.025	EXCELLENT
0.0	PERFECT

Figure 2.2 illustrates an example of what we mean by a non-perfect match between the dissimilarity and the distance data. Here, the deviations measured along the horizontal distance axis ,d_{ij} , between the starred coordinates and the circular coordinates, indicate the degree to which this configuration does not meet the monotonicity requirement. The values $\hat{d}_{ij}$ are defined to be those numbers measured from the horizontal X axis that minimize stress subject to the constraint of monotonicity [Ref. 2: pp. 8-9].

C. DIMENSIONAL REQUIREMENTS

The choice of how many dimensions are required to completely specify the output from the multidimensional scaling program is certainly not intuitively obvious. There in greater than three dimensions becomes extremely difficult for anyone trying to discover the meaning of the groupings. The stress, or goodness-of-fit measure, which is described in the next section, is usually expected to reveal the best dimension for analysis.

B. GOODNESS OF FIT:THE STRESS

A performance indicator for each choice of t is needed. The customarily used function is known as the stress. Stress incorporates a fitting technique that measures the degree of nonmonotonicity between the dissimilarities δ_{ij}, and the distances d_{ij}. If a configuration of points existed such that a perfect monotone relationship prevailed between the dissimilarity data and the distance data, then a perfect match would occur and the stress would be zero for that particular dimension size and all dimensions greater. Unfortunately, zero stress rarely if ever occurs naturally in data samples. The best choice then is to determine that configuration of points which minimizes the stress for each choice of dimension, t. The method used to determine stress uses least squares monotonic regression, suitably normalized to produce a non-dimensional value that indicates goodness of fit [Ref. 2: pp. 2-3]. The lower the value of stress, the better the fit. Kruskal [Ref. 2: p. 3], has been able to associate a verbal description with some specific values of stress based upon his experience. These values are indicated in Table 1 . In almost every instance, by increasing the number of dimensions that describe the data, the value of the stress decreases. However, one generally anticipates that the amount of benefit associated with incrementing the dimensionality is marginally insignificant. In other words, a tradeoff exists between keeping the output in a lower dimension to make interpretation easier, if the stress improves only slightly.

In this study the dissimilarity values δ_{ij} and δ_{ji} were assumed to be the same (symmetric matrix), and the values δ_{ii}, were ignored. This results in a partial matrix with upper triangular or lower triangular form not including the main diagonal. The total possible pairwise comparisons are then $n(n-1)/2$.

The actual distance between professors i and j, denoted d_{ij}, is calculated as a euclidian distance in the following manner for t dimensions

$$d_{ij} = \sqrt{(x_{i1} - x_{j1})^2 + \ldots\ldots + (x_{it} - x_{jt})^2} .$$

Like the similarity/dissimilarity matrix, the end result is a matrix of distances such that $d_{ij} = d_{ji}$ and $d_{ii} = 0$. We point out here that although we have specified the euclidean distance as the method by which distances are computed in the computer algorithm, it is possible to substitute non-euclidean distances of the form

$$d\ (x,y) = \left[\sum_{j=1}^{t} | x_j - y_j |^r \right]^{1/r} \text{ for } r \geq 1.$$

In the field of mathematics, these distances are known as Minkowski r-metrics and are true distances in the sense that they satisfy the triangle inequality

$$d_r(x,z) \leq d_r(x,y) + d_r(y,z) .$$

Euclidean distances and Minkowski r-metrics share many properties, however, they do differ when it comes to rotating the solution. When rotations are involved, any rigid rotation leaves euclidean distances unchanged. The only rigid rotations that leave non-euclidean distances unchanged are rotations that transform all permutations of coordinate axes into coordinate axes [Ref. 2: pp. 22-23].

Finally, the number of dimensions used to output the final mapping is not restricted in any way mathematically other than $NT < N(N-1)/2$. However, any visual interpretation judges. Each professor can be thought of as a point in multidimensional space. If it takes t dimensions to accurately describe this multidimensional space, then the coordinate describing professor x would be

$$x_1 = (x_{11}, \ldots x_{1s}, \ldots x_{1t}).$$

For n professors the coordinate system that results looks like

$$x_1 = (x_{11}, \ldots x_{1s}, \ldots x_{1t})$$
$$\cdot$$
$$x_r = (x_{r1}, \ldots x_{rs}, \ldots x_{rt})$$
$$\cdot$$
$$x_n = (x_{n1}, \ldots x_{ns}, \ldots x_{nt}).$$

Thus, the entire space contains a configuration of n points each of t components.

Each judge or student is asked to complete a survey that requires him to provide a value corresponding to how similar or dissimilar he perceives each pairwise combination of professors to be. The scale used in the survey associates the value 1 with the meaning very similar and the value of 9 with the meaning very dissimilar. In order to determine rather than impose the relationships between professors, the characteristics on which the professors are scored are not specified at this time [Ref. 3: p. 9]. The notation for dissimilarity data in this study is δ_{ij}. This value represents the perceived dissimilarity between professor i and professor j. The end result of the data collection is a matrix of dissimilarity values for n stimuli that looks like the following,

$$\begin{bmatrix} \delta_{11} & \cdot & \delta_{1n} \\ & \cdot & \\ \delta_{n1} & \cdot \quad \cdot & \delta_{nn} \end{bmatrix}.$$

It can be seen that an ascending pattern is created between the distances and the dissimilarities. One might even suggest that the relationship is linear, and could be described by an equation of the form a+ bx. Multidimensional scaling methods that use a formula to describe distance as a function of dissimilarities are known as metric MDS. Metric MDS uses the numerical properties of the proximity data to determine distances. Another means by which distances are created from dissimilarity data without using the numerical properties of the dissimilarity data is known as nonmetric MDS. Nonmetric MDS relies totally upon the rank ordering of the dissimilarities to produce the distance data [Ref. 3: p. 22]. One would normally expect small dissimilarities to correspond to small distances and large dissimilarities to correspond to large distances. Although this relationship is rarely a perfect one, the rank orderings of the dissimilarity data is usually enough to create a good fit. Shepard and Kruskal [Ref. 2: p. 2], have done a substantial amcunt of work in nonmetric MDS and this particular method will be followed in this study.

A review of some notation might be appropriate at this point. The n objects about which the investigator is trying to ascertain some fundamental relationship, can really be any set of stimuli. For example, one might be interested in discerning the perceived distances between political candidates with hopes of discovering what issues or dimensions really set them apart from each other in the minds of the judges. Or, one might be interested in discovering the perceived distances between countries in order to explain how some countries might react in some political or economic situations. For this study, the n objects are the professors in the Operations Research department and we are interested in determining what factors cause the professors to be similar or dissimilar in the minds of a fixed set of department would appear, and the judge would be asked to indicate those professors from whom he had taken a course. After selecting his own subset of professors, the judge was asked to rate each pairwise combination of professors in terms of similarity or dissimilarity of teaching style. If the judge had observed n professors, this meant that a judge would have to respond to at least $n(n-1)/2$ prompts for this proximity data. For this study, the sixteen professors are identified by using the letters A thru P. The scale presented to the judge ranged from a value of 1 meaning very similar to a value of 9 meaning very dissimilar. The judges were not limited to integer responses, but real responses were restricted to one decimal place. It was assumed that the proximity scale was an interval scale meaning the distance in similarity or dissimilarity values between say values 2 and 3 was equal to the distance in dissimilarity between values 8 and 9.

Once all the proximity data had been collected, the judges were then asked to score the professors with respect to several bipolar scales. In the case where students had taken a professor for more than one course, the student was instructed to respond to the bipolar scales based on the last course taught by the professor. The scales used in the survey appear in Table 2 and were suggested by previous Operations Research students. The bipolar scales also ranged in value from 1 to 9. Once each judge completed the survey, his or her results were automatically sent to the researchers computer disk for subsequent evaluation.

In addition to the data collected from the computer interactive survey, information gathered from student opinion forms (SOF's) were used to try to interpret characteristics of the different professors. Only those student opinion forms from those classes taught by the professors selected in the interactive survey were considered. The

TABLE 2

Bipolar Scales Used in the Computer Survey

1. CLASS SIZE
2. THEORETICAL VS. APPLIED
3. GRADING POLICY
4. PACE OF COURSE
5. EFFORT REQUIRED OUTSIDE OF CLASS
6. COURSE RELIED UPON PREREQUISITES

bipolar scales used in current SOF forms appear in Table 3 . One problem encountered in the evaluation of these forms dealt with maintaining the purity of the control group. For the most part, the SOF's were completed by the twenty-three students in the control group. However, there were some instances where other students either from other Operations Research sections or from other curriculums were included in the evaluation process. The information collected from the SOF's represented different scales upon which to measure teacher performance. The SOF data was originally converted to an interval scale on a range different from the scales used in the interactive survey. Because linear

TABLE 3

Bipolar Scales Used in the SOF Forms

1. COURSE ORGANIZATION
2. TIME IN CLASS SPENT EFFECTIVELY
3. INSTRUCTOR KNOWS WHEN STUDENTS DONT'T UNDERSTAND MATERIAL
4. DIFFICULT CONCEPTS MADE UNDERSTANDABLE
5. CONFIDENCE IN INSTRUCTORS KNOWLEDGE IN SUBJECT
6. FELT FREE TO ASK QUESTIONS
7. INSTRUCTOR PREPARED FOR CLASS
8. INSTRUCTORS OBJECTIVES MADE CLEAR
9. INSTRUCTOR MADE COURSE WORTHWHILE LEARNING EXPERIENCE
10. INSTRUCTOR STIMULATED INTEREST IN SUBJECT AREA
11. INSTRUCTOR CARED ABOUT STUDENT PROGRESS AND DID HIS SHARE IN HELPING TO LEARN

transformations of the form a+bx are allowed on interval scales, the scale used for the SOF's was changed to match the scale used in the interactive survey. In the case of each set of scales, a separate regression analysis and factor analysis was done. One key parameter we were interested in measuring was the correlation between how the judges evaluated the professors overall performance at different times in the curriculum. SOF data was only available through the end of the summer quarter of 1984 (the end of the judge's sixth quarter). Since the judges completed the computer survey at the beginning of the eigth quarter, only those professors taken through the end of the sixth quarter were evaluated. This meant that a few professors were not included in the final evaluation.

C. OUTPUT FROM MDS

The proximity or dissimilarity data obtained from the interactive survey was used as a direct input to a multidimensional scaling algorithm KYST, partially developed by Kruskal [Ref. 1: p. 1]. The proximity input values for this study appear in Appendix A. The output from the multidimensional scaling program includes visual plots or spatial maps depicting the professors positions in multidimensional space projected down to two dimensions for visual display. Also included as output are coordinates for each professor in multidimensional space. The task that remained was to define the variables that best explained the location of each professor.

One method available for determining what characteristics explain the orientation of the professors from the multidimensional scaling output is multiple linear regression. The median value from each bipolar scale is regressed over the coordinate positions of each professor. From the stress versus dimension curve it was decided to concentrate on a four dimensional interpretation, although three and five dimensional interpretations were considered also. The values of stress, the goodness-of-fit function, turned out to be 0.249 for four dimensions and 0.293 for three dimensions. Neither of these values indicate a very good fit according to Kruskals' own personal experience. This large value of stress was an early indication that this linear model might not be appropriate in explaining teacher performance.

Figure 3.1 shows the resulting regression weights or direction cosines corresponding to each multiple correlation for the four dimensional solution. The direction cosines are regression weights normalized so that their sum of squares equals 1.0 for every scale [Ref. 3: p. 37]. For example, when regression weights of 0.4178, 0.8959, -0.1508, and -0.0026 are given to dimensions 1,2,3 and 4 respectively, the multiple correlation between the resulting coordinate positions and the respective bipolar scale is 0.581.

A bipolar scale will provide a good interpretation of a dimension when its multiple correlation coefficient is high. A value above .90 is desired. The values achieved in this study were low. Values of R^2 close to 0.5 were typical. Also a requirement for good dimensional interpretation is a high regression weight on the dimension it most nearly explains. The results obtained from the bipolar scales used in this study are examined in the next chapter.

D. OUTPUT FROM FACTOR ANALYSIS

Having looked at regression modelling as an approach to interpreting dimensions, factor analysis was also considered a possible means of identifying linear factors that would help describe teacher performance from the data sample. The statistical analysis package, SAS, was used to generate two separate factor analysis outputs. One factor analysis was completed for the bipolar scales associated with the computer survey and another was done on the additional bipolar scales from the SOF forms.

POSITIVE POLES OF RATING SCALES	NORMALIZED REGRESSION COEFFICIENTS (DIRECTION COSINES)				MULTIPLE CORRELATION COEFFICIENT
COMPUTER BIPOLAR SCALES	DIM1	DIM2	DIM3	DIM4	
1. CLASS SIZE	0.3954	0.0190	0.9172	-0.0434	.262
2. THEORETICAL VS. APPLIED	0.2603	-0.8367	-0.4816	-0.0096	.510
3. GRADING POLICY	0.3197	-0.6784	-0.3689	-0.5489	.414
4. PACE OF COURSE	0.2527	-0.5951	-0.4877	-0.5865	.453
5. EFFORT REQUIRED OUTSIDE OF CLASS	0.1391	-0.9142	-0.3253	-0.1975	.376
6. COURSE RELIED-UPON PREREQUISITES	0.0696	-0.3655	-0.5769	-0.7270	.501
SOF BIPOLAR SCALES					
7. COURSE ORGANIZATION	0.5942	0.6474	-0.4223	0.2219	.502
8. TIME IN CLASS SPENT EFFECTIVELY	0.6435	0.6118	-0.0025	0.4597	.493
9. INSTRUCTOR KNOWS WHEN STUDENTS DONT UNDERSTAND MATERIAL	0.9337	0.3301	0.0113	0.1375	.285
10. DIFFICULT CONCEPTS MADE UNDERSTANDABLE	0.8412	0.1880	-0.4612	0.2103	.444
11. CONFIDENCE IN INSTRUCTORS KNOWLEDGE IN SUBJECT	0.2928	0.1832	0.6859	-0.6404	.095
12. FELT FREE TO ASK QUESTIONS	0.9872	-0.0887	0.0466	-0.1238	.405
13. INSTRUCTOR PREPARED FOR CLASS	0.7263	0.5747	-0.3012	0.2265	.447
14. INSTRUCTORS OBJECTIVES MADE CLEAR	0.4178	0.8959	-0.1508	-0.0026	.581
15. INSTRUCTOR MADE COURSE WORTHWHILE LEARNING EXPERIENCE	0.7065	0.4218	-0.4327	-0.3684	.478
16. INSTRUCTOR STIMULATED INTEREST IN SUBJECT AREA	0.6352	0.2174	-0.6073	-0.4245	.298
17. INSTRUCTOR CARED ABOUT STUDENT PROGRESS AND DID HIS SHARE IN HELPING TO LEARN	0.8310	0.2991	-0.4143	-0.2193	.532

Figure 3.1 Regression Weights for the Four Dimensional Solution.

Initially, a correlation matrix was produced from the raw input data. Additionally, the common factors and the factor loadings for each observed variable or bipolar scale was produced. Orthogonal rotations were effected to produce simple structure. A total of two common factors were created from the bipolar scales of the interactive survey, and one common factor was produced from the SOF data. The specifics of the factor analysis output are discussed in the next chapter.

E. OUTPUT FROM CLUSTER ANALYSIS

As a final measure, a disjoint cluster analysis was performed on the MDS data. The clustering routine, Fastclus, was available from the statistical analysis package, SAS. The number of clusters into which the group of instructors were subdivided was specified by the researcher to range from 2 to 6. Membership in a particular cluster was determined based upon the distance from each professors position to the mean value of the cluster. The output from the cluster analysis included identification of the cluster to which each professor belonged.

IV. DATA ANALYSIS

A. INTENT OF THE ANALYSIS

The scope of this chapter will be to analyze the results obtained from the completed interactive survey in the context of multiple linear regression and stepwise regression, factor analysis and cluster analysis. Additionally, information gathered from student opinion forms (SOFs), will be evaluated in so far as what characteristics or bipolar scales appear to have been most important in describing students perceptions of teacher performance.

An issue that requires explanation before the analysis begins concerns a vital assumption made dealing with the scale of the data. Specifically, can an arbitrarily chosen numerical scale with fixed upper and lower bounds enable correct statistical inference from the data sample? In our study, we provided the judges with a numerical scale ranging in value from 1 to 9. The judges were allowed to rate each professor in every category with respect to this scale. In essence we are imposing an interval scale, with equally spaced intervals. Let's consider a judge's response to the question of grading policy. It may be that the judges can rate the different objects, in our case professors, at best on an ordinal scale. The judge may be able to say that professor A is a harder grader than is professor B, but not how much harder. We are assuming that the judges, when responding to these bipolar scales, realize that we are infering an interval scale on their responses. We assume that when they complete the survey, that they realize that each integer value on the scale divides the scale into equal intervals. We assume that a judge will rate each professor knowing that the distance between say a score of 3 and 4 is equal to the distance between a score of 5 and 6. We find ourselves doing this in order to follow the example of Kruskal as closely as possible and because the statistical methods used to evaluate the data require at least an interval scale. Given that we are assuming an interval scale, we feel comfortable in transforming the data with any linear transformation of the form a + bx. The major point being made here is that the researcher should keep in mind the scale of the data when interpreting the significance of the output.

B. WHAT DID WE LEARN FROM MDS?

As mentioned in Chapter II, multidimensional scaling attempts to determine the structural relationships between n objects from a matrix or halfmatrix of proximity data. A major result of the process is the spatial mapping of the n objects, usually projected down to the planes of each pair of dimensions for easy visual interpretation. The final configuration of points represents the best fit of the n objects according to the stress criterion. Table 4 contains the final configurations for all sixteen professors in four dimensions.

In order to determine which dimensionality scheme best suggests the characteristics that set the professors apart from one another, it helps to review the spatial maps created from the data. Appendices B and C contain the spatial plots of the sixteen professors for four and five dimensional solutions. Each pairwise combination of axes is plotted against each other. This spatial orientation can sometimes suggest from mere inspection those characteristics that cause some professors to be more alike than others. However, we do not usually rely upon visual inspection

TABLE 4

Final Configuration for the 16 Professors in 4 Dimensions

PROFESSOR		DIM. 1	DIM. 2	DIM. 3	DIM. 4
1.	A	-0.737	0.249	0.482	0.150
2.	B	1.209	0.069	-0.517	0.172
3.	C	-0.359	-0.207	-0.430	0.094
4.	D	-0.648	-0.382	-0.093	0.666
5.	E	-0.724	-0.569	0.314	-0.113
6.	F	0.639	0.267	0.042	-0.056
7.	G	-0.706	-0.085	-0.154	-0.416
8.	H	0.450	-0.574	0.265	-0.279
9.	I	-0.310	0.642	-0.006	0.434
10.	J	-0.252	0.364	0.312	-0.336
11.	K	1.328	-0.205	0.197	-0.030
12.	L	-0.923	-0.223	-0.311	-0.370
13.	M	0.773	0.391	0.775	-0.113
14.	N	-0.047	-0.254	0.477	0.381
15.	O	-0.159	1.208	-0.611	-0.104
16.	P	0.517	-0.693	-0.743	-0.030

alone. Very often a plot indicating how stress improves as a function of dimension gives the dimensional interpretation. Figure 4.1 is such a plot for the data collected in this study. It can be seen that a one dimensional interpretation yields a very high stress value of 0.463. This would suggest that a one dimensional interpretation alone would be inappropriate. We would like a noticeable elbow to occur in the stress vs. dimension plot, for this normally indicates the most suitable level of interpretation. We observe that this plot does not exhibit the noticeable elbow. Instead, the slope of the curve decreases gradually and we are left to look for other means to help determine dimensionality.

Kruskal and Wish offer an alternate method or rule of thumb in choosing dimensionality [Ref. 3 p. 34]. They suggest that the number of stimulus objects minus one, in our case fifteen, should exceed four times the dimension chosen for interpretation. This would offer a choice of dimension no greater than 3.75. They caveat this statement by saying that this rule has only been found to hold for three dimensions, and that further study is needed to see if it is appropriate for higher dimensions as well. We chose to emphasize a four dimensional interpretation, however a three and five dimensional interpretation were considered also.

C. THE USE OF REGRESSION

Once the choice of dimensionality had been made, the next task was to determine which characteristics represented those dimensions best. To do this, we decided, as do Kruskal and others [Ref. 3: pp. 35-36], to use multiple linear regression as a means of clarifying this issue. Again, we reiterate that a separate regression analysis was conducted for the scales used in the computer survey as well

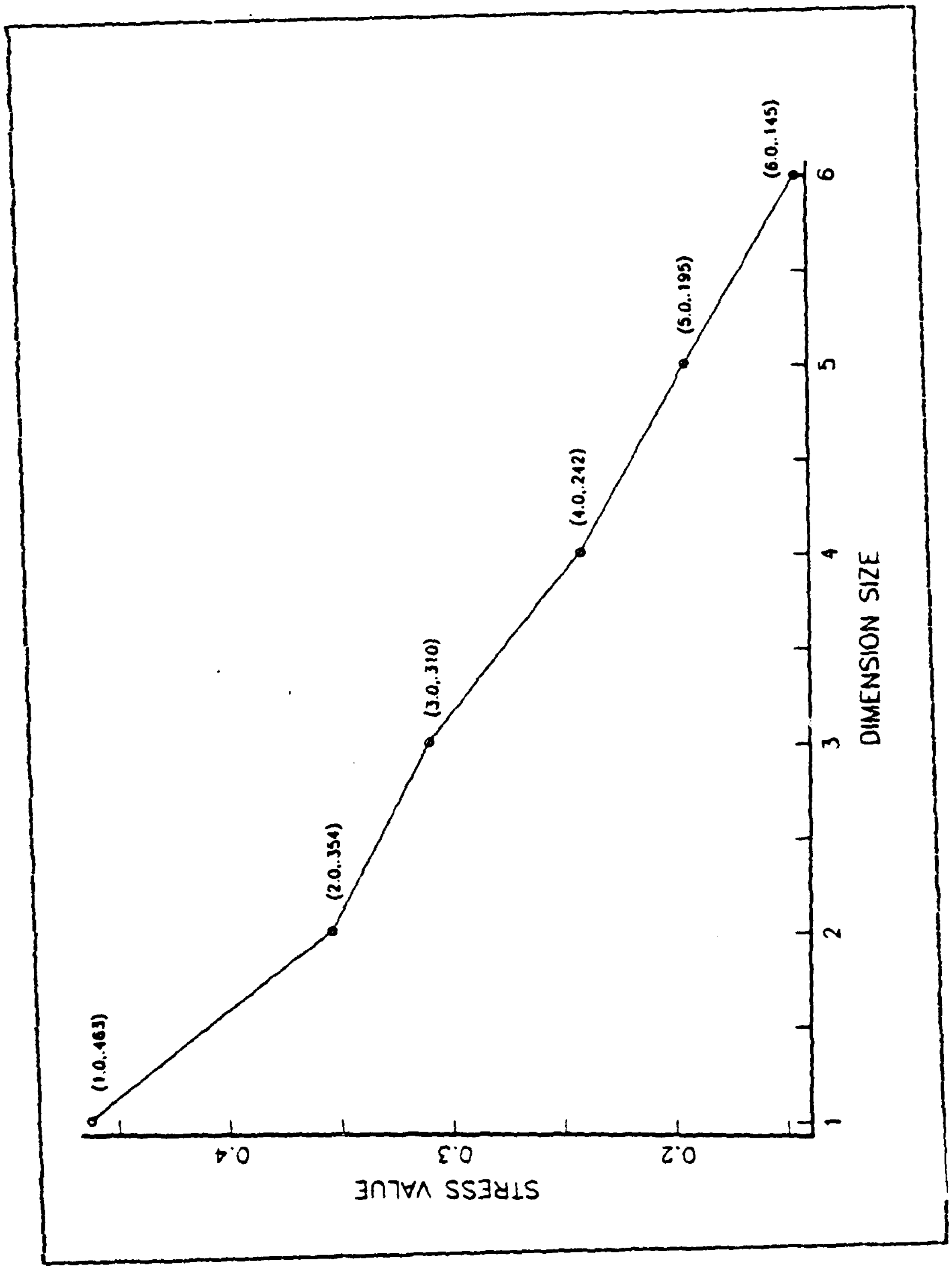


Figure 4.1 Stress vs. Dimension Plot

as the scales obtained from the SOF forms. Specifically, we regressed the median value of each bipolar scale over the coordinates of each professor, and recorded a multiple correlation coefficient. If the value of the multiple correlation coefficient was high, i.e., close to 1, then we felt inclined to believe that this scale was important in distinguishing professors. If the value of the multiple correlation coefficient was low, i.e., close to 0, then that particular scale was not perceived as being important.

Tables 5, 6 and 7 illustrate the two sets of bipolar scales used in the study, the corresponding normalized regression weights or direction cosines, and the multiple correlation coefficients associated with each scale for dimensions 3, 4 and 5. It can be seen that for the most part, the multiple correlation coefficients hover near 0.5 and typically increase as the the dimension increases. Figure 4.2 depicts the changes in the multiple correlation coefficient for each bipolar scale as the dimension for interpretation changes. In the table, bipolar scales 1 thru 6 refer to the scales from the computer survey and bipolar scales 7 thru 17 refer to those scales from the SOF form.

Since none of the scales exhibited truly high correlation coefficients, we chose those that had the highest values and used them to interpret the dimensions in our study. The regression analysis on the computer survey scales suggested that these scales were inappropriate indicators for this set of judges. For the four dimensional analysis, we see that the bipolar scales 'theoretical vs. applied course' and 'course relied upon prerequisites' have the highest correlation coefficients for that group of scales. Specifically, the correlation coefficients are .510 and .501 respectively. The scale 'applied vs. theoretical course' loads heavily on dimension 2 with a normalized regression weight of -0.8367. Thus, it would seem that the

TABLE 5

Regression Weights and Multiple Correlation Coefficients for the Bipolar Scales in 3 Dimensions

POSITIVE POLES OF RATING SCALES	NORMALIZED REGRESSION COEFFICIENTS (DIRECTION COSINES)			MULTIPLE CORRELATION COEFFICIENT
COMPUTER BIPOLAR SCALES	DIM1	DIM2	DIM3	
1. CLASS SIZE	-0.3830	0.0124	0.9237	.245
2. THEORETICAL VS. APPLIED	-0.2557	-0.7464	-0.6144	.557
3. GRADING POLICY	-0.3794	-0.6005	-0.7039	.313
4. PACE OF COURSE	-0.2970	-0.5141	-0.8047	.338
5. EFFORT REQUIRED OUTSIDE OF CLASS	-0.1553	-0.7963	-0.5846	.313
6. COURSE RELIED-UPON PREREQUISITES	-0.0859	-0.3054	-0.9483	.329
SCF BIPOLAR SCALES				
7. COURSE ORGANIZATION	-0.6108	0.7432	-0.2731	.476
8. TIME IN CLASS SPENT EFFECTIVELY	-0.7417	0.6238	0.2464	.428
9. INSTRUCTOR KNOWS WHEN STUDENTS DONT UNDERSTAND MATERIAL	-0.9082	0.4038	0.1098	.285
10. DIFFICULT CONCEPTS MADE UNDERSTANDABLE	-0.8633	0.2921	-0.4115	.442
11. CONFIDENCE IN INSTRUCTORS KNOWLEDGE IN SUBJECT	-0.2878	0.0098	0.9577	.076
12. FELT FREE TO ASK QUESTIONS	-0.9975	-0.0345	0.0614	.394
13. INSTRUCTOR PREPARED FOR CLASS	-0.7567	0.6372	-0.1461	.407
14. INSTRUCTORS OBJECTIVES MADE CLEAR	-0.4244	0.8983	0.1142	.503
15. INSTRUCTOR MADE COURSE WORTHWHILE LEARNING EXPERIENCE	-0.7098	0.5354	-0.3918	.463
16. INSTRUCTOR STIMULATED INTEREST IN SUBJECT AREA	-0.6470	0.3921	-0.6539	.289
17. INSTRUCTOR CARED ABOUT STUDENT PROGRESS AND DID HIS SHARE IN HELPING TO LEARN	-0.3042	0.4645	-0.3707	.527

whom the workload was a concern to the judges. Professors B, H, K, L, and P all have high median factor scores with respect to this common factor. Factor 2 might represent a composite effect between the scales 'class size' and 'course relied upon prerequisites'. Professors B, I and N had high factor scores with respect to this indicator. Factor 3 encompasses a general student-professor interaction effect. Most of the professors had the same spread of factor scores except for professor K. Here the judges exhibited a higher level of controversy for this characteristic.

E. RESULTS OF CLUSTER ANALYSIS

A final means of looking at the groupings of professors focused on a cluster analysis. In this technique, professors who were perceived to be similar to one another were grouped together in the same cluster. Other professors were likewise grouped in other disjoint clusters so that no professor belonged to more than one cluster. The professors were assigned to clusters based upon their interpoint distance from the cluster means. An initial cluster seed is selected and the iterative process continues until the observations become stable, i.e., each observation settles down into a steady state cluster. It remains for the researcher to decide upon the number of clusters that best describe the groupings of professors. One strategy that was employed in determining the appropriate number of clusters resulted from interviews with the students. Tables 13 and 14 display the clusters to which each professor belonged from the four and five dimensional solutions.

TABLE 12

Table of Factor Analysis Results on SOF Data

SOF1=COURSE ORGANIZATION
SOF2=TIME IN CLASS SPENT EFFECTIVELY
SOF3=INSTRUCTOR KNOWS WHEN STUDENTS DONT UNDERSTAND MATERIAL
SOF4=DIFFICULT CONCEPTS MADE UNDERSTANDABLE
SOF5=CONFIDENCE IN INSTRUCTORS KNOWLEDGE IN SUBJECT
SOF6=FELT FREE TO ASK QUESTIONS
SOF7=INSTRUCTOR PREPARED FOR CLASS
SOF8=INSTRUCTORS OBJECTIVES MADE CLEAR
SOF9=INSTRUCTOR MADE COURSE WORTHWHILE LEARNING EXPERIENCE
SOF10=INSTRUCTOR STIMULATED INTEREST IN SUBJECT AREA
SOF11=INSTRUCTOR CARED ABOUT STUDENT PROGRESS AND DID HIS SHARE IN
HELPING TO LEARN

CORRELATION MATRIX

	SOF1	SOF2	SOF3	SOF4	SOF5	SOF6	SOF7	SOF8	SOF9	SOF10	SOF11
SOF1	1.00	0.70	0.60	0.68	0.42	0.49	0.68	0.69	0.69	0.57	0.65
SOF2	0.70	1.00	0.62	0.67	0.43	0.43	0.60	0.59	0.70	0.59	0.60
SOF3	0.60	0.62	1.00	0.72	0.42	0.54	0.58	0.52	0.66	0.57	0.72
SOF4	0.68	0.67	0.72	1.00	0.43	0.55	0.62	0.55	0.70	0.58	0.70
SOF5	0.42	0.43	0.42	0.43	1.00	0.37	0.48	0.35	0.50	0.44	0.46
SOF6	0.49	0.43	0.54	0.55	0.37	1.00	0.57	0.44	0.53	0.46	0.61
SOF7	0.68	0.60	0.58	0.62	0.48	0.57	1.00	0.57	0.63	0.55	0.66
SOF8	0.69	0.59	0.52	0.55	0.35	0.44	0.57	1.00	0.60	0.50	0.58
SOF9	0.69	0.70	0.66	0.70	0.50	0.53	0.63	0.60	1.00	0.74	0.70
SOF10	0.57	0.59	0.57	0.58	0.44	0.46	0.50	0.50	0.74	1.00	0.59
SOF11	0.65	0.60	0.72	0.70	0.46	0.61	0.66	0.58	0.70	0.59	1.00

FACTOR PATTERN

	FACTOR 1
SOF1	0.83906
SOF2	0.80779
SOF3	0.81009
SOF4	0.84420
SOF5	0.59563
SOF6	0.68709
SOF7	0.80055
SOF8	0.74319
SOF9	0.87031
SOF10	0.76053
SOF11	0.84586

EIGENVALUES OF THE CORRELATION MATRIX

TOTAL= 11.00000 AVERAGE= 1.00000

	1	2	3	4
EIGENVALUE	6.79680.72500.57860.5928			
DIFFERENCE	6.0718	0.0464	0.0858	0.1046
PROPORTION	0.6179	0.0659	0.0617	0.0539
CUMULATIVE	0.6179	0.6838	0.7455	0.8438

	5	6	7	9
EIGENVALUE	0.4886	0.3862	0.3430	0.2861
DIFFERENCE	0.1021	0.0432	0.0568	0.0310
PROPORTION	0.0444	0.0351	0.0312	0.0260
CUMULATIVE	0.8438	0.8789	0.9101	0.9361

	9	10	11
EIGENVALUE	0.2552	0.2356	0.2124
DIFFERENCE	0.0196	0.0232	
PROPORTION	0.0232	0.0214	0.0193
CUMULATIVE	0.9593	0.9807	1.0000

TABLE 11

Table of Factor Analysis Results on Survey Data

SCALE 1= CLASS SIZE
SCALE 2= APPLIED VS. THEORETICAL COURSE
SCALE 3= GRADING POLICY
SCALE 4= PACE OF COURSE
SCALE 5= EFFORT REQUIRED OUTSIDE CLASS
SCALE 6= COURSE RELIED UPON PREREQUISITES

CORRELATION MATRIX

	SCALE 1	SCALE 2	SCALE 3	SCALE 4	SCALE 5	SCALE 6
SCALE 1	1.0000	-0.1327	0.1800	0.0647	0.0469	-0.2815
SCALE 2	-0.1327	1.0000	0.3110	0.2671	0.1931	0.2763
SCALE 3	0.1800	0.3110	1.0000	0.5124	0.6104	0.3357
SCALE 4	0.0647	0.2671	0.5124	1.0000	0.5751	0.4928
SCALE 5	0.0469	0.1931	0.6104	0.5751	1.0000	0.5040
SCALE 6	-0.2815	0.2763	0.3357	0.4928	0.5040	1.0000

FACTOR PATTERN

	NO ROTATION		ORTHOGONAL ROTATION	
	FACTOR 1	FACTOR 2	FACTOR 1	FACTOR 2
SCALE 1	-0.02185	0.71926	0.24550	0.36614
SCALE 2	0.46519	-0.30547	0.37584	-0.43299
SCALE 3	0.77483	0.32461	0.83506	0.06612
SCALE 4	0.80453	0.11096	0.80215	-0.12697
SCALE 5	0.82597	0.15145	0.83442	-0.09443
SCALE 6	0.72016	-0.41322	0.56949	-0.60420

EIGENVALUES OF THE CORRELATION MATRIX: TOTAL=6.00000 AVERAGE=1.00000

	1	2	3	4	5	6
EIGENVALUE	2.6844	1.2497	0.8361	0.4983	0.4032	0.3283
DIFFERENCE	1.4347	0.4136	0.3379	0.0952	0.0749	
PROPORTION	0.4474	0.2083	0.1393	0.0831	0.0672	0.0547
CUMULATIVE	0.4474	0.6557	0.7950	0.8781	0.9453	1.0000

separate factor analyses were conducted, one on each set of bipolar scales. Each will be discussed separately.

The factor analysis conducted on the six bipolar scales used in the computer survey yielded the results shown in Table 11 . In addition to the correlation matrix, the unrotated factor loadings and the orthogonally rotated factor loadings appear in the table. Variables with factor loadings that are close numerically suggest a common interaction or measure. It seems as though two common factors are present in the six variables based upon the factor loadings. The first factor explains 44 percent of the variation in the data. This factor seems to combine the affect of 'grading policy', 'effort required outside class', and 'pace of course'. The second factor appears to be a composite effect of 'class size' and 'course relied upon prerequisites'. The scale 'class size' has a high positive factor loading whereas the scale 'course relied upon prerequisites' has a fairly high negative loading. This would seem to make sense since those classes taken early in the curriculum tended to be large and the earlier courses did not usually require a significant amount of prerequisite courses.

The results of the factor analysis on the SOF data yielded the correlation matrix and factor loadings in Table 12 . From this factor analysis, we see that only one common factor accounts for the variance in the data. This is reasonable since most of the bipolar scales from the SOF forms are highly correlated. This factor could describe the student-professor interaction effect discussed earlier.

Figures 4.3, 4.4, 4.5 illustrate boxplots of factor scores for each professor for all three factors. Factor 1 again is an indicator of the combined effect of 'grading policy', 'pace of course', and 'effort required outside class'. It might be condensed into a general workload index with a high factor score indicating those professors for

TABLE 10

Table of Values for R^2 Due to High Multicollinearity

A CHECK FOR MUTICOLLINEARITY AMONG INDEPENDENT VARIABLES RESULTED IN THE FOLLOWING VALUES OF R-SQUARED.

COMPUTER BIPOLAR SCALES

DEPENDENT VARIABLE	RESULTING R-SQUARED
CLASS SIZE	0.526
THEORETICAL VS. APPLIED	0.245
GRADING POLICY	0.951
PACE OF COURSE	0.978
EFFORT REQUIRED OUTSIDE CLASS	0.826
COURSE RELIED UPON PREREQUISITES	0.891

SOF BIPOLAR SCALES

DEPENDENT VARIABLE	RESULTING R-SQUARED
COURSE ORGANIZATION	0.961
TIME IN CLASS SPENT EFFECTIVELY	0.941
INSTRUCTOR KNOWS WHEN STUDENTS DON'T UNDERSTAND MATERIAL	0.905
DIFFICULT CONCEPTS MADE UNDERSTANDABLE	0.947
CONFIDENCE IN INSTRUCTORS KNOWLEDGE IN SUBJECT	0.762
FELT FREE TO ASK QUESTIONS	0.941
INSTRUCTOR PREPARED FOR CLASS	0.963
INSTRUCTORS OBJECTIVES MADE CLEAR	0.848
INSTRUCTOR MADE COURSE WORTHWHILE LEARNING EXPERIENCE	0.986
INSTRUCTOR STIMULATED INTEREST IN SUBJECT AREA	0.930
INSTRUCTOR CARED ABOUT STUDENT PROGRESS AND DID HIS SHARE IN HELPING TO LEARN	0.980

TABLE 9

Output from Stepwise Regression Procedure

RESULTS FROM STEPWISE REGRESSION OF BIPOLAR SCALES FROM INTERACTIVE SURVEY ON INSTRUCTOR OVERALL PERFORMANCE.

ORDER IN WHICH VARIABLE ENTERED THE MODEL	REGRESSION COEFFICIENT	STANDARD ERROR	T-VALUE	% OF VARIATION EXPLAINED
THEORETICAL VS. APPLIED	0.214	0.367	0.584	0.044
GRADING POLICY	-0.517	1.401	-0.368	0.016
EFFORT REQUIRED OUTSIDE CLASS	0.485	0.647	-0.750	0.024
PACE OF COURSE	2.392	3.225	0.742	0.012
COURSE RELIED UPON PRE-REQUISITES	-0.483	0.844	-0.573	0.041
CLASS SIZE	0.028	0.655	0.042	0.001

****

% OF INSTRUCTOR OVERALL PERFORMANCE EXPLAINED BY SCALES 0.138

****

RESULTS FROM STEPWISE REGRESSION OF BIPOLAR SCALES FROM SOF FORMS ON INSTRUCTOR OVERALL PERFORMANCE

ORDER IN WHICH VARIABLE ENTERED THE MODEL	REGRESSION COEFFICIENT	STANDARD ERROR	T-VALUE	% OF VARIATION EXPLAINED
COURSE ORGANIZATION	1.070	0.411	2.605	0.737
INSTRUCTOR KNOWS WHEN STUDENTS UNDERSTAND MATERIAL	1.234	0.224	5.498	0.067
FELT FREE TO ASK QUESTIONS	-1.819	0.339	-5.363	0.036
CONFIDENCE IN INSTRUCTORS KNOWLEDGE IN SUBJECT	2.062	0.440	4.691	0.031
INSTRUCTOR STIMULATED INTEREST IN SUBJECT AREA	-0.415	0.416	-0.996	0.015
TIME IN CLASS SPENT EFFECTIVELY	-1.000	0.350	-2.859	0.031
INSTRUCTOR CARED ABOUT STUDENT PROGRESS AND DID HIS SHARE IN HELPING TO LEARN	1.539	0.629	2.444	0.020
INSTRUCTOR MADE COURSE WORTHWHILE LEARNING EXPERIENCE	-1.795	0.879	-2.041	0.033
INSTRUCTOR PREPARED FOR CLASS	0.679	0.400	1.696	0.004
DIFFICULT CONCEPTS MADE UNDERSTANDABLE	0.575	0.340	1.691	0.011
INSTRUCTORS OBJECTIVES MADE CLEAR	0.107	0.227	0.470	0.001

****

% OF INSTRUCTOR OVERALL PERFORMANCE EXPLAINED BY SOF SCALES 0.986

multicollinearity. Multicollinearity simply means that one or more so called independent variables are highly correlated with another independent variable or is a linear combination of a number of the independent variables. The problem with high multicollinearity is that the estimates for the regression coefficients become unreliable from one sample to the next. Our confidence in our ability to determine the effect of an independent variable withers. To show that high multicollinearity exists, we need to regress each independent variable over all the other independent variables to see if any are a linear combination of the others. Table 10 shows the values of R^2 obtained by regressing each independent variable over the others for both models.

Several options are available when confronted with high multicollinearity as we were in this study. One solution is to increase the sample size. This turned out not to be a useful alternative since our sample size was fixed. Another strategy is to combine several variables that are highly correlated into a single indicator as long as it makes sense. This is possible for several scales on the SOF form which are highly correlated. A third alternative is to discard those variables which are linear combinations of the others and are the cause for the high multicollinearity. After discarding the offending variables, a new regression equation can be created and a check for statistical significance made anew.

D. RESULTS OF FACTOR ANALYSIS

Factor analysis supposes that some common factors smaller in number than the originally observed variables, account for the covariation of the originally observed variables. Factor analysis assumes a linear causal relationship similar to linear regression analysis. For this study, two

TABLE 8

Median Values of Overall Teaching Performance for the Sixteen Professors

THE FOLLOWING SCORES FOR OVERALL PERFORMANCE ARE BASED ON A SCALE OF 1 TO 9 WITH 1 BEING A HIGH SCORE ON OVERALL PERFORMANCE AND 9 BEING A LOW SCORE.

PROFESSOR	SCORE FROM SOF DATA	SCORE FROM COMPUTER SURVEY
A	3	4
B	3	7
C	3	3
D	2	4
E	1	2
F	3	5
G	2	2
H	3	5
I	3	4
J	3	4
K	5	8
L	1	2
M	1	6
N	3	4
O	5	6
P	2	6

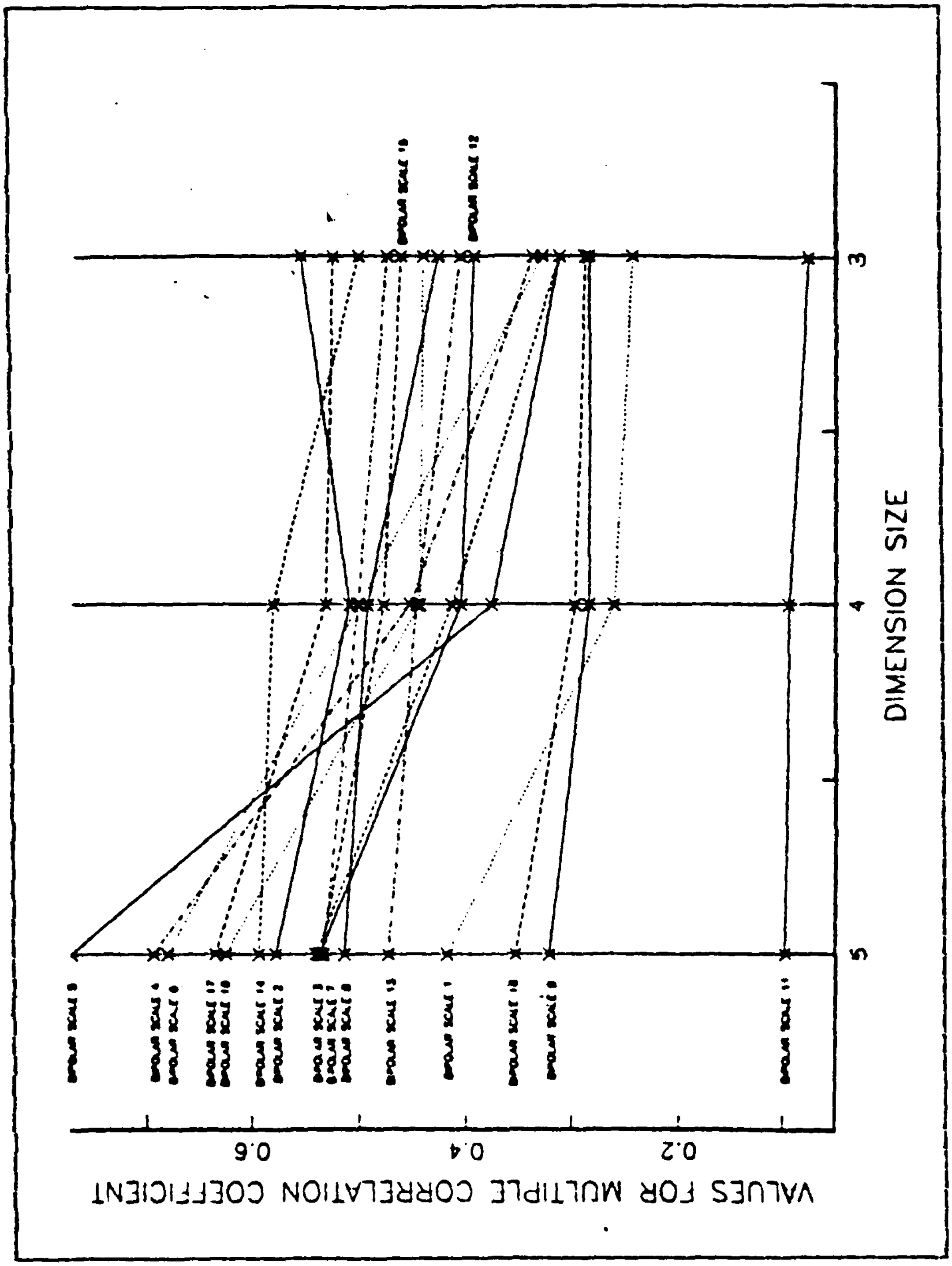


Figure 4.2 Changes in the Value of the Multiple Correlation Coefficient as a Function of Dimension.

Stepwise regression was utilzed in order to determine which scales or independent variables explained the greatest proportion of variance in teacher performance. The APL function STREG, was used to compute the order in which the independent variables were to enter into the regression model. The output from STREG is displayed in Table 9 for both the six scales asked in the computer survey as well as the scales from the SOF forms. The output indicates the order in which the variables entered the model, the coefficients associated with each independent variable, the standard error associated with each coefficient, the corresponding t-value and the proportion of the variation of the dependent variable accounted for by the independent variable. We see that the coefficient of multiple determination, R^2, is low for the six bipolar scales used in the computer survey. In all, these scales account for only 13.8 percent of the variation in the dependent variable, overall instructor performance. However, the stepwise regression performed on the eleven bipolar scales from the SOF forms indicate a coefficient of multiple determination of .986. This set of scales explains more of the variation in the judges responses to overall instructor performance than does the previous set of scales. In particular, 'course organization' appears to have a significant impact on students perception of teacher performance since it accounts for over 73 percent of the variation alone.

One problem that concerned us dealt with the fact that for the SOF data, even with a value of R^2 equal to .986, most of the independent variables were statistically insignificant. Even the scale 'course organization', which accounted for 73 percent of the variation in overall performance , proved to be statistically insignificant at the 0.05 level. A high value of R^2 and statistically insignificant variables usually is symptomatic of high

TABLE 7

Regression Weights and Multiple Correlation Coefficients for the Bipolar Scales in 5 Dimensions

POSITIVE POLES OF RATING SCALES	NORMALIZED REGRESSION COEFFICIENTS (DIRECTION COSINES)					MULTIPLE CORRELATION COEFFICIENT
	DIM1	DIM2	DIM3	DIM4	DIM5	
COMPUTER BIPOLAR SCALES						
1. CLASS SIZE	0.2599	-0.0615	0.5034	-0.4174	-0.6250	.415
2. THEORETICAL VS. APPLIED	0.1920	-0.5889	-0.4225	0.3954	0.5372	.578
3. GRADING POLICY	0.2073	-0.5519	-0.3209	-0.3502	-0.6533	.541
4. PACE OF COURSE	0.1653	-0.4887	-0.4673	-0.0840	-0.7129	.594
5. EFFORT REQUIRED OUTSIDE CLASS	0.0554	-0.5912	-0.3583	-0.4373	-0.5712	.774
6. COURSE RELIED UPON PREREQUISITES	0.0461	-0.3544	-0.6669	0.1185	-0.6429	.680
SUF BIPOLAR SCALES						
7. COURSE ORGANIZATION	0.5923	0.5705	-0.4971	-0.2393	-0.1378	.534
8. TIME IN CLASS SPENT EFFECTIVELY	0.5978	0.5494	-0.2139	-0.3980	0.0893	.514
9. INSTRUCTOR KNOWS WHEN STUDENTS DONT UNDERSTAND MATERIAL	0.8279	0.1494	-0.3035	-0.3379	-0.2931	.321
10. DIFFICULT CONCEPTS MADE UNDERSTANDABLE	0.5850	0.0409	-0.5058	-0.4891	-0.4011	.625
11. CONFIDENCE IN INSTRUCTORS KNOWLEDGE IN SUBJECT	0.3193	0.0471	0.4597	0.3929	-0.7333	.098
12. FELT FREE TO ASK QUESTIONS	0.6480	-0.1608	-0.2297	-0.4110	-0.5765	.537
13. INSTRUCTOR PREPARED FOR CLASS	0.7160	0.4924	-0.4223	-0.2364	-0.1025	.473
14. INSTRUCTORS OBJECTIVES MADE CLEAR	0.4444	0.8517	-0.2445	-0.0279	-0.1285	.594
15. INSTRUCTOR MADE COURSE WORTHWHILE LEARNING EXPERIENCE	0.6543	0.3145	-0.5240	-0.1629	-0.4143	.536
16. INSTRUCTOR STIMULATED INTEREST IN SUBJECT AREASUB-	0.5804	0.1206	-0.6331	0.4832	-0.1123	.353
17. INSTRUCTOR CARED ABOUT STUDENT PROGRESS AND DID HIS SHARE IN HELPING TO LEARN	0.6754	0.1565	-0.4900	-0.1654	-0.5003	.635

felt free to ask questions; 4) instructor made course a worthwhile learning experience and 5) instructor cared about student progress and did his share in helping to learn. Dimension 2 seems to describe information concerning how instructors are perceived as being organized or prepared for their course. The scales with high multiple correlation coefficients that load heavily upon this dimension are 1) course organization; 2) time in class spent effectively and 3) instructors objectives are made clear.

In addition to the bipolar scales used for the interactive survey and the SOF forms, each judge was asked to provide a rating of overall teaching performance for each professor. The median values for each professor were obtained and are tabulated in Table 8 . Although we have kept the analysis of the interactive survey separate from the SOF data, we were interested in the correlation between professor's overall performance judged on two separate occaisions. The first occaision occurred when the judge completed the SOF form for the course taught by the professor. The second occaision was in conjunction with the interactive survey. The correlation between ratings of overall performance for the professors was .58, lower than expected. Suggestions as to why this correlation is low include the effect of time. Judges may be less able to evaluate a particular instructors overall performance as time goes by. Also, students may change their opinions of teachers overall performance after having seen a professor teach a variety of different classes. For example, a student who enjoys applied courses might rate a professor differently after having had him for a Stochastics Models course than he would for say an applied course like Test and Evaluation. In any event, we did expect the correlation on overall performance to be higher than it turned out to be.

TABLE 6

Regression Weights and Multiple Correlation Coefficients for the Bipolar Scales in 4 Dimensions

POSITIVE POLES OF RATING SCALES	NORMALIZED REGRESSION COEFFICIENTS (DIRECTION COSINES)				
COMPUTER BIPOLAR SCALES	DIM1	DIM2	DIM3	DIM4	MULTIPLE CORRELATION COEFFICIENT
1. CLASS SIZE	0.3954	0.0190	0.9172	-0.0434	.262
2. THEORETICAL VS. APPLIED	0.2603	-0.8367	-0.4816	-0.0096	.510
3. GRADING POLICY	0.3197	-0.6784	-0.3689	-0.5489	.414
4. PACE OF COURSE	0.2527	-0.5951	-0.4877	-0.5865	.453
5. EFFORT REQUIRED OUTSIDE OF CLASS	0.1391	-0.9142	-0.3253	-0.1975	.376
6. COURSE RELIED-UPON PREREQUISITES	0.0696	-0.3655	-0.5769	-0.7270	.501
SOF BIPOLAR SCALES					
7. COURSE ORGANIZATION	0.5942	0.6474	-0.4223	0.2219	.502
8. TIME IN CLASS SPENT EFFECTIVELY	0.6435	0.6118	-0.0025	0.4597	.493
9. INSTRUCTOR KNOWS WHEN STUDENTS DONT UNDERSTAND MATERIAL	0.9337	0.3301	0.0113	0.1375	.285
10. DIFFICULT CONCEPTS MADE UNDERSTANDABLE	0.8412	0.1880	-0.4612	0.2103	.444
11. CONFIDENCE IN INSTRUCTORS KNOWLEDGE IN SUBJECT	0.2928	0.1332	0.6859	-0.6404	.095
12. FELT FREE TO ASK QUESTIONS	0.9872	-0.0837	0.0466	-0.1238	.405
13. INSTRUCTOR PREPARED FOR CLASS	0.7263	0.5747	-0.3012	0.2265	.447
14. INSTRUCTORS OBJECTIVES MADE CLEAR	0.4178	0.8959	-0.1508	-0.0026	.581
15. INSTRUCTOR MADE COURSE WORTHWHILE LEARNING EXPERIENCE	0.7065	0.4218	-0.4327	-0.3684	.478
16. INSTRUCTOR STIMULATED INTEREST IN SUBJECT AREA	0.6352	0.2174	-0.6073	-0.4245	.298
17. INSTRUCTOR CARED ABOUT STUDENT PROGRESS AND DID HIS SHARE IN HELPING TO LEARN	0.8310	0.2991	-0.4143	-0.2193	.532

fact that a course was perceived as being theoretical or applied most closely describes the effect of the professors ultimate positioning with respect to dimension 2. Likewise, the scale 'course relied upon prerequisites' loads heavily on dimension 4 with a regression weight of -0.7270. This appears to suggest that dimension 4 is most nearly explained by how the judges perceived how each course relied upon other prerequisite courses. The regression weights have a geometrical interpretation as the cosine of the angle between the dimension upon which it loads, and the associated scale. Unfortunately, the two scales with the next highest multiple correlation coefficients, 'pace of course' and 'grading policy', load heavily upon dimensions 2 and 4 as well. They probably contribute to the explanation of those dimensions also. Not one of the scales with a high multiple correlation coefficient loads heavily upon dimensions 1 or 3. These dimensions are left unexplained and new scales are needed to determine an appropriate explanation.

A similar analysis was conducted for the bipolar scales used in the SOF forms. Here the scales with the highest multiple correlation coefficients were 1) instructors objectives made clear; 2) instructor cared about student progress and did his share in helping to learn; 3) course organization and 4) time in class spent effectively. Again, the same problem occurred here as in the analysis of the previous set of scales. Almost all those scales with the highest multiple correlation coefficients load heavily on only two of the four dimensions, namely dimension 1 and 2. Dimension 1 appears to convey information about how each professor cares or interacts with his students on a personal level. The bipolar scales with high multiple correlation coefficients that load heavily on this dimension are, 1) instructor knows when students don't understand the material; 2) difficult concepts were made understandable; 3)

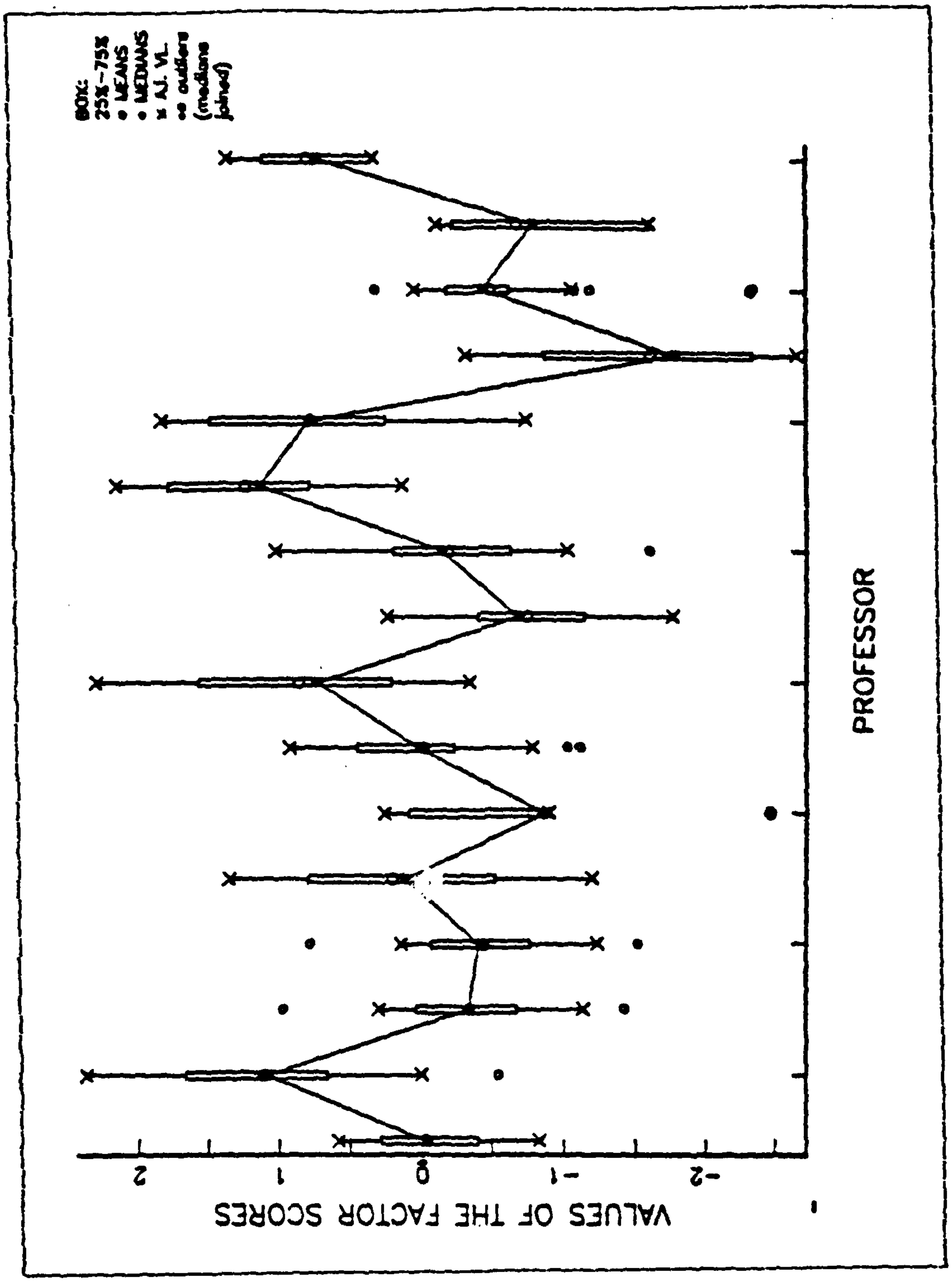


Figure 4.3 Boxplot of Factor Scores for Factor 1

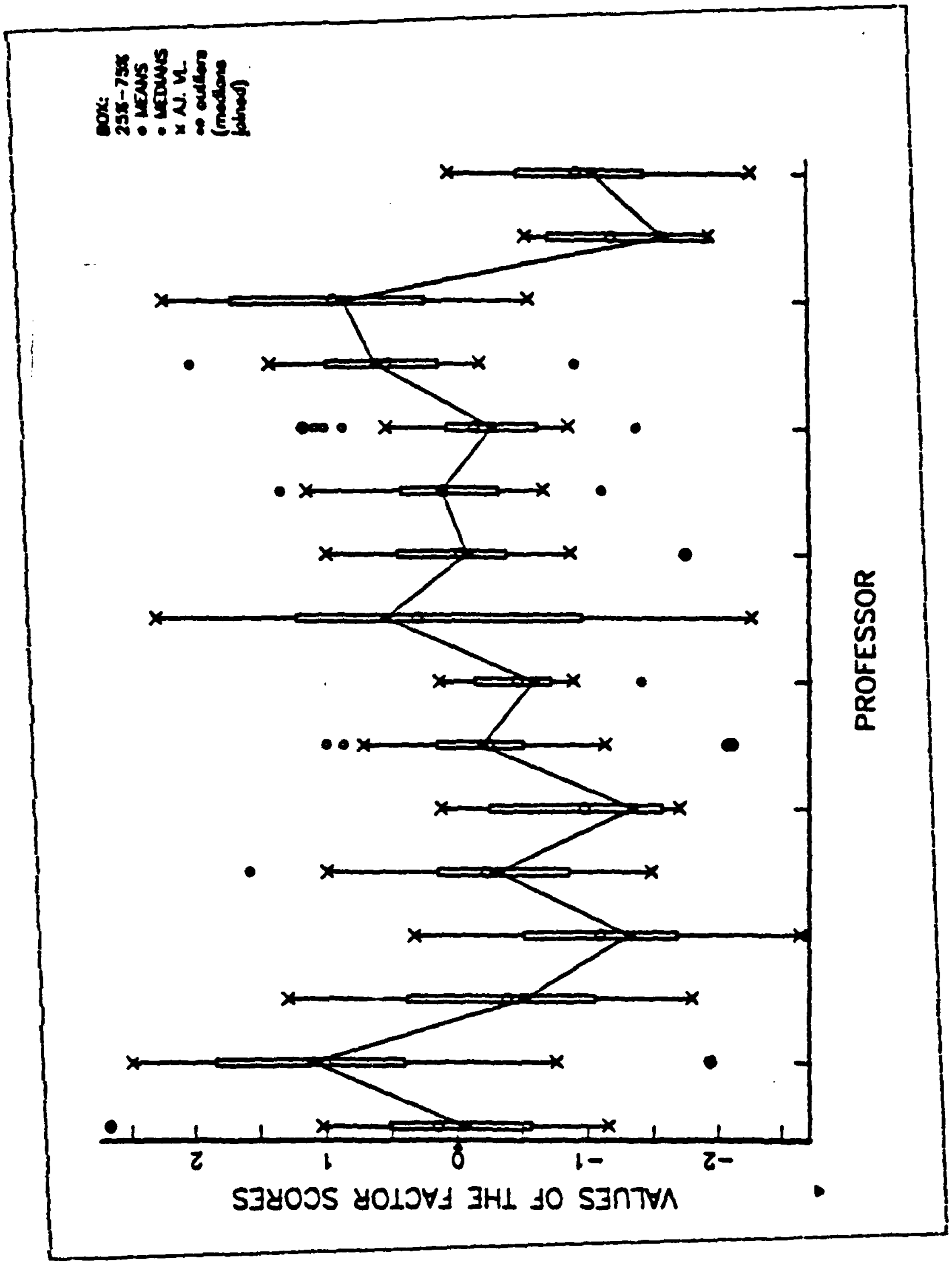


Figure 4.4 Boxplot of Factor Scores for Factor 2

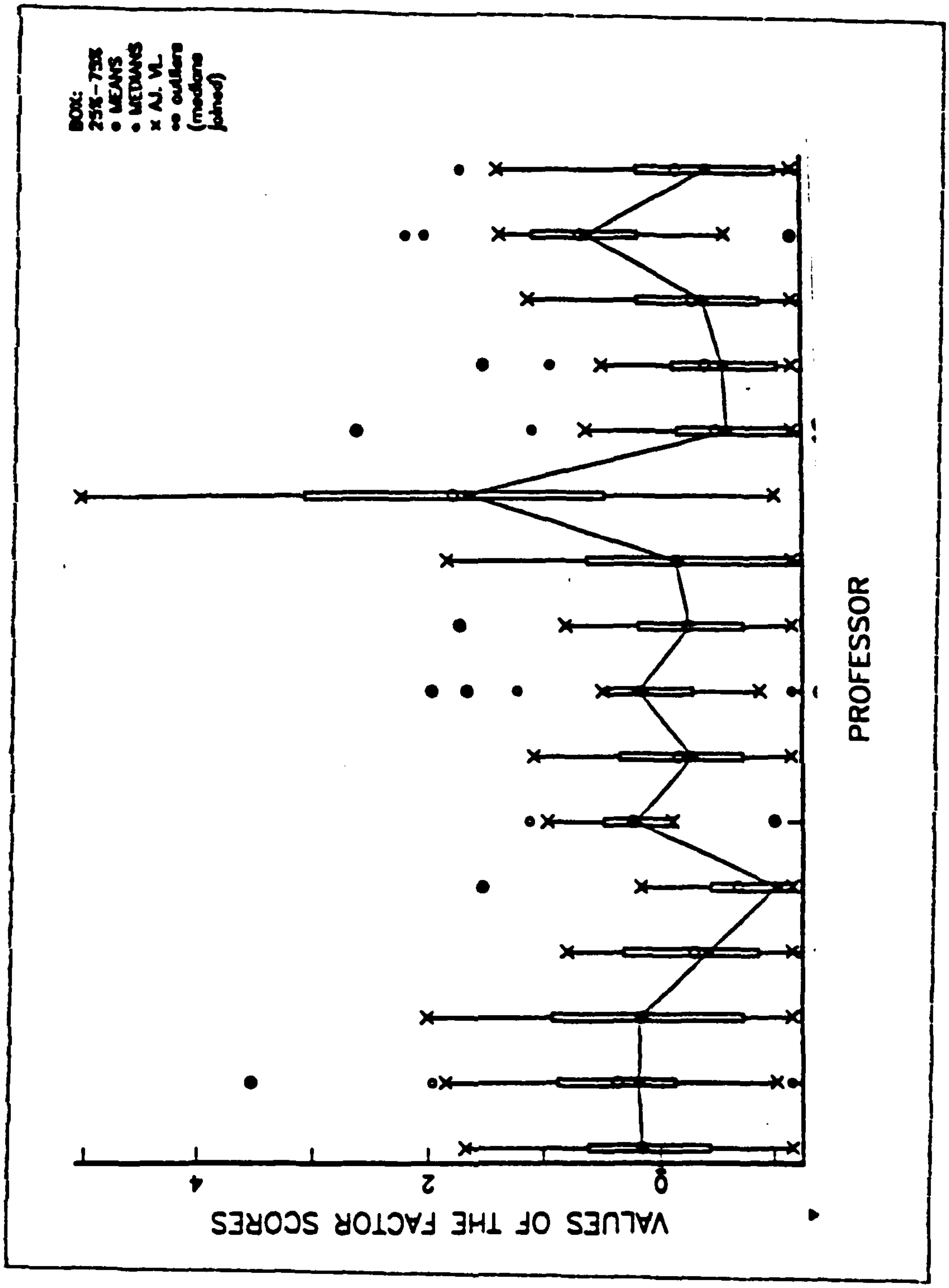


Figure 4.5 Boxplot of Factor Scores for Factor 3

TABLE 13

Table of Clusters for Four Dimensional Solution

GROUPINGS OF PROFESSORS FOR CLUSTER SIZES 2 THRU 6
USING A FOUR DIMENSIONAL SOLUTION

CLUSTER SIZE=2		CLUSTER SIZE=3		CLUSTER SIZE=4		CLUSTER SIZE=5		CLUSTER SIZE=6	
PROF.	CLUS.	PROF.	CLUS.	PROF.	CLUS.	PROF.	CLUS.	PROF.	CLUS
A	1	B	1	A	1	I	1	F	1
C	1	F	1	C	1	O	1	M	1
D	1	H	1	D	1	B	2	B	2
E	1	K	1	E	1	K	2	K	2
G	1	M	1	G	1	F	3	O	3
I	1	A	2	I	1	M	3	H	4
J	1	I	2	J	1	H	4	P	4
L	1	J	2	L	1	P	4	C	5
N	1	O	2	N	1	A	5	D	5
O	1	C	3	B	2	C	5	E	5
B	2	D	3	H	2	D	5	G	5
F	2	E	3	P	2	E	5	L	5
H	2	G	3	F	3	G	5	N	5
K	2	L	3	K	3	J	5	A	6
M	2	N	3	M	3	L	5	I	6
P	2	P	3	O	4	N	5	J	6

TABLE 14

Table of Clusters for Five Dimensional Solution

GROUPINGS OF PROFESSORS FOR CLUSTER SIZES 2 THRU 6
USING A FIVE DIMENSIONAL SOLUTION

CLUSTER SIZE=2		CLUSTER SIZE=3		CLUSTER SIZE=4		CLUSTER SIZE=5		CLUSTER SIZE=6	
PROF.	CLUS.	PROF.	CLUS.	PROF.	CLUS.	PROF.	CLUS.	PROF.	CLUS
A	1	C	1	F	1	I	1	F	1
C	1	D	1	H	1	O	1	M	1
D	1	E	1	K	1	B	2	B	2
E	1	G	1	M	1	K	2	K	2
G	1	L	1	N	1	C	3	C	3
I	1	P	1	B	2	P	3	P	3
J	1	A	2	P	2	F	4	H	4
L	1	I	2	I	3	H	4	A	5
N	1	J	2	O	3	M	4	D	5
B	2	O	2	A	4	A	5	E	5
F	2	B	3	C	4	D	5	G	5
H	2	F	3	D	4	E	5	J	5
K	2	H	3	E	4	G	5	L	5
M	2	K	3	G	4	J	5	N	5
O	2	M	3	J	4	L	5	I	6
P	2	N	3	L	4	N	5	O	6

V. SUMMARY OF RESULTS

A. REVIEW OF THE ESSENTIAL ITEMS

The purpose of this study was to uncover information about students perceptions of teacher performance from data gathered via a computer interactive survey and SOF forms. The control group for the interactive survey was the Operations Research section graduating in March of 1985. The data consisted of proximity information, how similar or dissimilar professors were perceived as being, and rankings on bipolar scales. Bipolar scales were chosen from SOF forms and suggestions from previous Operations Research students. Separate analyses were conducted on both sets of scales. The level of the data was assumed to be interval scale in order to utilize the statistical methods involved in the analysis.

Multidimensional scaling was used as the primary means of evaluating characteristic differences among professors. A monotone relationship among similarity data was the primary constraint used in determining a final spatial mapping of professors coordinate positions in multidimensional space. The goodness-of-fit criterion used to measure the degree to which the data conformed to the monotonicity requirement is known as stress. In essence, a value of stress between .05 and .1 would indicate a very good fit. Unfortunately, the stress value associated with a four dimensional interpretation of our data was .242, indicating a less than good fit. Other methods helped guide the choice of dimensionality.

Aside from visual inspection of the spatial mappings, multiple linear regression analysis was used to determine the most important characteristics that appeared to set the professors apart from one another. This was done by regressing the median values of the bipolar scales over the coordinate positions of each professor in four space, obtained by the MDS program, KYST. The choice of the most important characteristics follows from the bipolar scales with high multiple correlation coefficients. The multiple correlation coefficients associated with all bipolar scales were lower than what was hoped for. The correlation coefficients were typically around .5. For those characteristics deemed important, high regression weights determined exactly which dimension the associated scale most nearly represented. For the bipolar scales used in the interactive survey, the scales 'applied vs theoretical course' and 'course relied upon prerequisites' proved to have the highest correlation coefficients. These scales most nearly explained dimensions 2 and 4. The other two dimensions were more difficult to explain since no scale with a high multiple correlation coefficient loaded heavily on them.

For the set of scales obtained from the SOF forms, a similar result occurred with the scales having high multiple correlation coefficients loading heavily on only two dimensions. The scales with the highest correlation coefficients here were 1) instructors objectives made clear, and 2) instructor cared about student progress and did his share in helping to learn. There seemed to be two indicators coming from the SOF forms. One indicator seemed to focus on instructor organization and preparation. The other indicator involved a student-instructor interaction effect. Basically, how did the judges perceive the instructor as caring about the students progress in the course? This effect seemed to be corroborated in the factor analysis.

In addition to the bipolar scales, students were asked to rate the professors on an overall performance scale.

Multiple and stepwise regression efforts were done using the overall performance evaluations obtained from the SOF forms and at a later date coincident with taking the computer survey. The important information gleaned from the regression analysis suggested that the six bipolar scales used in the computer survey did a poor job in explaining students' perceptions of instuctor overall performance. The coefficient of multiple determination for the regression model was a mere .138. Stepwise regression analysis indicated that the scale 'applied vs. theoretical course' accounted for most of the variation in the dependent variable, overall performance, for its set of scales. Thus, it would seem that whether students perceived a course taught by a professor as being applied or theoretical had a more significant bearing on the overall performance of the professor than the other scales in that set. In any case, none of the scales proved to be statistically significant at the .05 level.

The stepwise regression performed on the SOF data yielded a coefficient of multiple determination, R^2, of .986. This rather high value of R^2 seemed to suggest that the scales used in the SOF forms more nearly explain the variation in overall performance than do the scales used in the computer survey. 'Course organization' accounted for 74 percent of the explained variation. Even with this high value of R^2, most of the coefficients of the independent variables turned out to be statistically insignificant at the .05 level. This indicated that high multicollinearity existed among the scales. A check for multicollinearity proved positive in both sets of scales. Each independent variable was regressed over the other independent variables and high values of R^2 resulted. The multicollinearity problem suggested that a number of the scales, particularly on the SOF forms, be combined into one scale or measure.

In addition to regression analysis, a factor analysis was done on both sets of scales and three separate factors were obtained. Factor 1 was composed of the three scales, 'grading policy', 'effort required outside class' and 'pace of course'. Apparently, the judges found these scales to interact consistently. Factor 2 appeared to describe a composite effect between 'class size' and 'course relied upon prerequisites'. The factor loading was positive on 'class size' and negative on 'course relied upon prerequisites'. One might infer that the larger the class size, the less that course was perceived as requiring prerequisite courses in Operations Research. This appeared to be true since most of the larger classes occurred in the beginning of the curriculum. Factor 3 seemed to describe a student-professor interaction effect. The correlations among the variables in this set were high contributing to high factor loadings on nearly all variables.

A disjoint cluster analysis was conducted on the coordinates generated from the multidimensional scaling algorithm. Each professor was grouped into one and only one cluster. Exit interviews with students suggested that five clusters appeared to be an appropriate number of groups.

B. CONCLUSIONS AND RECCOMENDATIONS

The multidimensional scaling technique seemed to provide a weak explanation of instructor groupings. The reasons for this may be several. First, a linear causal relationship may not be appropriate in describing students' perceptions of instructor performance. Certainly the six bipolar scales used in the interactive survey were not powerful explanatory variables. However, there seem to be one or two strong indicators among the scales used in the SOF forms. Specifically, a student-instructor interaction effect and an instructor organizational and preparation effect appear dominant. What needs to be done in the future is to obtain further scales or characteristics from Operations Research students possibly during exit interviews. Also, one might suggest that another look be given to changing the current SOF form as it stands by combining some of the highly correlated variables and adding characteristics that later prove meaningful. However, it should be noted that what might be considered an important characteristic in describing instructor performance for one student group may prove to be less important for another group.

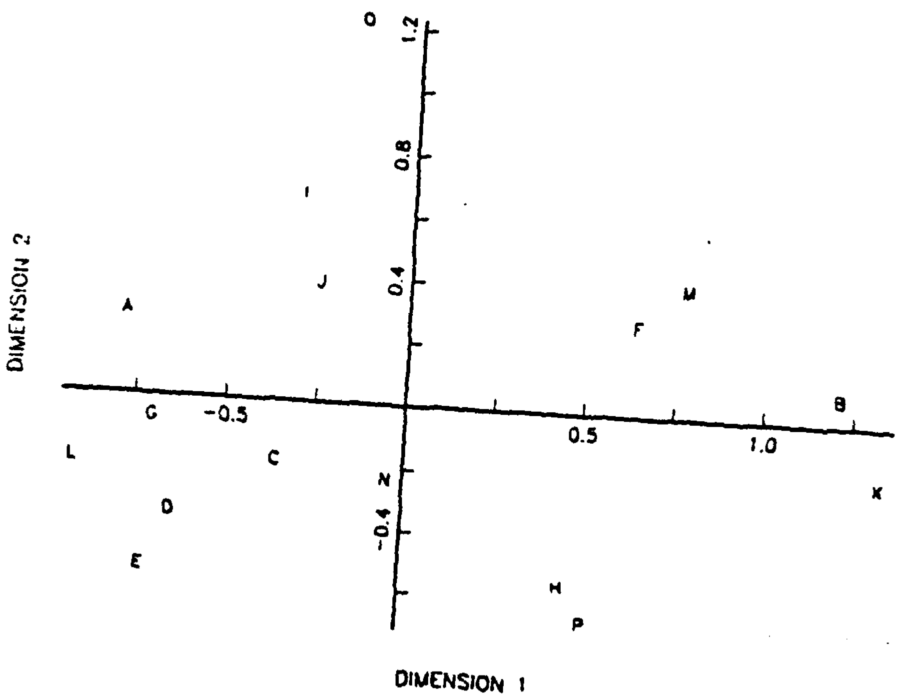
APPENDIX A

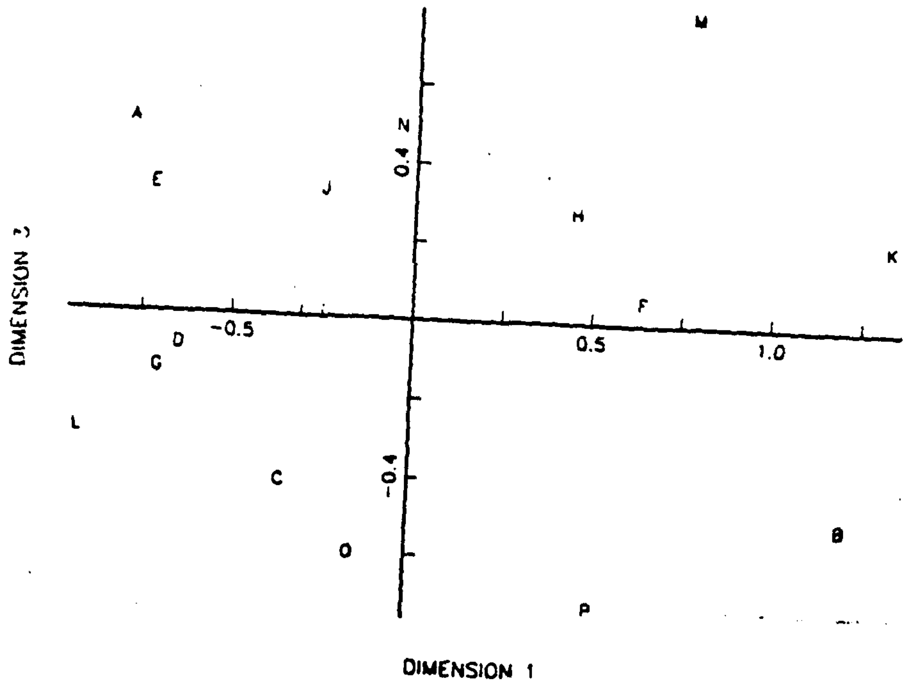
INPUT VALUES FOR MULTIDIMENSIONAL SCALING PROGRAM KYST

```
TORSCA
PRE-ITERATIONS=3
DIMMAX=6,DIMMIN=1
COORDINATES=ROTATE
CARDS
PRINT=DISTANCES
SFORM2
ITERATIONS=50
DIAGONAL=ABSENT
LOWERHALFMATRIX
DATA,REGRESSION=ASCENDING,CUTOFF=-1.0
MAR85 DATA
 16   1   1
(15F4.1)
7.1
5.2 7.0
4.8 7.2 4.0
5.7 7.6 5.0 4.0
7.1 5.0 4.0 6.0 7.5
5.7 7.6 4.3 6.0 2.3 6.0
6.3 6.1 5.5 6.1 4.9 4.0 6.0
5.5 6.9 5.4 5.0 5.9 4.5 4.6 7.0
4.1 6.9 5.0 6.0 4.9 5.4 4.0 6.0 5.1
7.0 4.0 7.5 7.0 8.0 3.0 7.2 5.0 7.1 7.0
5.0 7.7 4.5 5.3 2.5 7.0 2.0 6.6 6.2 4.9 7.9
7.0 6.0 6.0 7.0 6.5 4.3 7.5 5.0 5.9 5.0 5.2 8.9
5.0 6.8 5.9 5.5 5.0 5.0 5.0 5.8 4.7 4.8 6.1 6.1 6.0
6.5 7.0 6.0 7.0 8.1 5.0 7.0 6.7 4.0 5.0 8.2 7.0 8.8 7.0
7.0 2.0 2.0 6.8 6.0 6.3 6.0 5.3 7.8 7.3 5.9 6.0 7.0 5.9 7.3
WEIGHTS
15.
15. 22.
17. 17. 18.
13. 17. 16. 14.
 3.  6.  6.  4.  3.
16. 21. 23. 19. 17.  6.
11. 15. 16. 11. 11.  5. 16.
16. 20. 21. 13. 17.  4. 21. 14.
16. 21. 22. 13. 17.  5. 22. 15. 21.
16. 22. 23. 13. 17.  6. 23. 16. 21. 22.
16. 21. 22. 15. 16.  6. 22. 15. 20. 21. 22.
16. 22. 23. 13. 17.  6. 23. 16. 21. 22. 23. 22.
16. 22. 23. 13. 17.  6. 23. 16. 22. 22. 23. 22. 22.
 2.  4.  4.  3.  3.  1.  4.  3.  4.  4.  4.  4.  4.  5.
 4.  7.  7.  5.  1.  4.  7.  5.  5.  6.  7.  7.  6.  6.  2.
COMPUTE
STOP
```

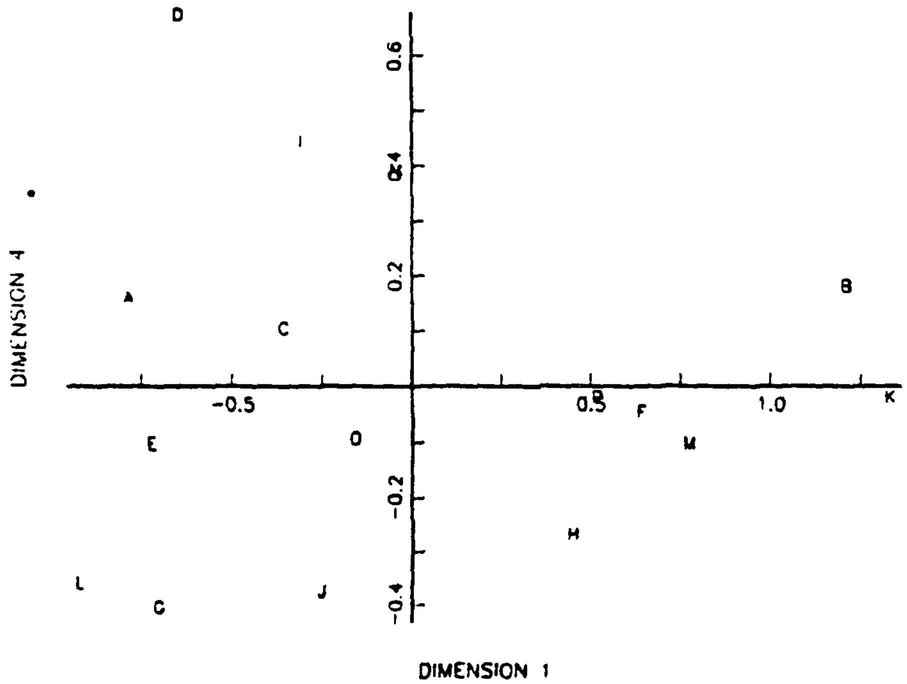
APPENDIX B

FOUR DIMENSIONAL SPATIAL MAPPING OF PROFESSORS POSITIONS





M
A
E
J
H
K
F
D
G
L
C
O
B
P
0.4
-0.4
-0.5
0.5
1.0
DIMENSION 3
DIMENSION 1


D
0.6
I
0.4
DIMENSION 4
A
0.2
B
C
−0.5
0.5
1.0
K
F
E
O
M
−0.2
H
L
J
−0.4
G
DIMENSION 1

APPENDIX D

COMPUTER SOURCE CODE FOR INTERACTIVE COMPUTER SURVEY

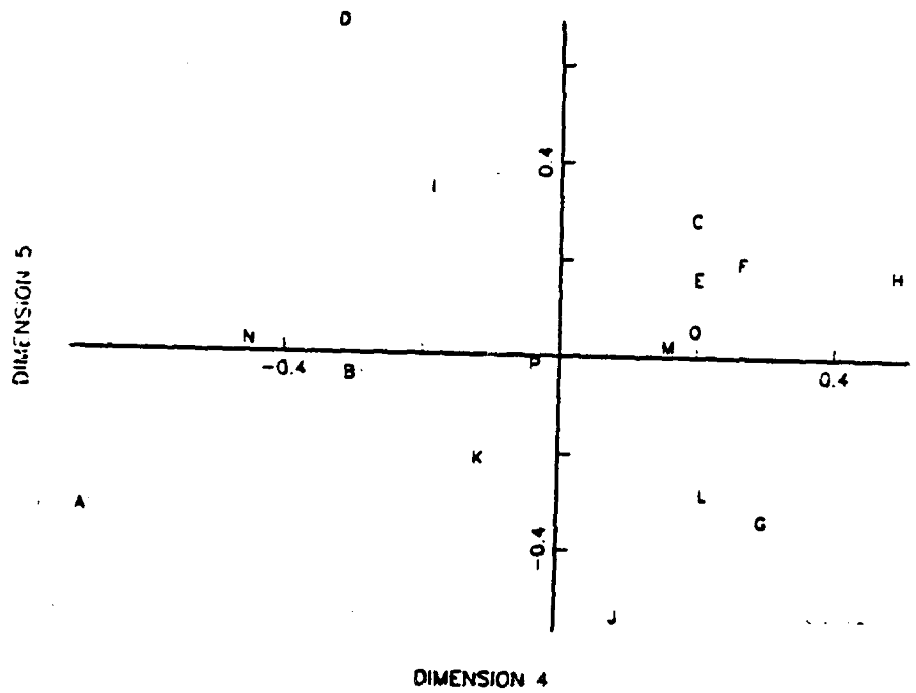
```
C     ***************************************************************
C     *               A LITTLE NOTE ABOUT THE SURVEY                *
C     *                                                             *
C     *      THE FOLLOWING COMPUTER CODE WAS WRITTEN AND IMPLE-     *
C     *      MENTED FOR THE PURPOSE OF OBTAINING PROXIMITY DATA,    *
C     *      I.E. SIMILARITY/DISSIMILARITY DATA ON STUDENT PER-     *
C     *      CEPTION OF TEACHING PERFORMANCE.  STUDENTS ARE ALSO    *
C     *      ASKED TO RATE PROFESSORS ON SEVERAL BIPOLAR SCALES.    *
C     *      THE SURVEY IS COMPOSED PRIMARILY OF FOUR COMPONENTS.   *
C     *      THESE INCLUDE THE CONTROLLING EXECUTIVE PROGRAM MAS,   *
C     *      A PANEL OF PROFESSORS NAMES (SURV1 PANEL) CREATED      *
C     *      ENTIRELY BY THE DISPLAY MANAGEMENT SYSTEM (DMS), A     *
C     *      FILE TO STACK STUDENTS' RESPONSES (SURVMAS DISPLAY)    *
C     *      AND THE ACTUAL FORTRAN PROGRAM, SURV3 FORTRAN.  THE    *
C     *      CHOICE OF FORTRAN AS THE LANGUAGE FOR THE SURVEY WAS   *
C     *      DRIVEN PRIMARILY BY THE PROGRAMMERS' FAMILIARITY WITH  *
      *      THE LANGUAGE AND ITS ABILITY TO SATISFACTORILY HANDLE  *
      *      THE TASK.                                              *
C     ***************************************************************

C     ===============================================================

C                   THE EXECUTIVE PROGRAM MAS

&TRACE ERR
*                   ACCESS DISPLAY MANAGEMENT SYSTEM (DMS) MACHINE
EXEC DMS
*                   CALLS PANEL OF PROFESSORS (SURV1).
*                   DISPLAYS PROFESSOR PANEL.
*                   STACK SELECTED PROFESSORS.
EXEC2 SURVMAS
*                   PLACE SELECTED PROFESSORS IN TEMPORARY CMS FILE
*
XEDIT OR DATA A (NOPROF
*                   START INTERACTIVE QUESTIONING.
*                   OUTPUT RESULTS TO FILE FT02F001
FILEDEF 01 DISK OR DATA A
*                   A MODULE (SURV3 MODULE) WAS CREATED TO ALLEVIATE THE
*                   PROBLEM OF EACH STUDENT NOT HAVING THE NECESSARY
*                   FORTRAN COMPILER.  THE PROGRAM (SURV3 FORTRAN) IS
*                   LOADED AND BEGUN MORE EFFICIENTLY WITH THIS DEVICE.
*
SURV3
ERASE OR DATA
*                   FIND OUT RESPONDENT'S USERID.
*                   WITH THE IPF FUNCTION USERID.
*
USERID
*                   PLACE USERID, DATE, & TIME IN
*                   EXEC2 VARIABLES.
*
&READ VARS &DUMMY &USERID &DUMMY &DATE &TIME &DAY
*
*                   GIVE OUTPUT RESULTS FILENAME OF
*                   THE RESPONDENT AND SEND FILE TO
*                   3177P WITH DISK DUMP.
*                   3177P IS THE PROGRAMMERS' CURRENT ACCOUNT #.
*
RENAME FILE FT02F001 A &USERID PROFS A
*                   EACH FILE IS GIVEN FIXED LOGICAL
                    RECORD LENGTH OF 80 COLUMNS.
COPYFILE &USERID PROFS A (RECFM F LRECL 80
*                ** REMEMBER TO SPOOL PUNCH TO RESEARCHERS USERID #
CP SPOOL PUNCH TO 3177P
*                   FILES ARE SPOOLED AND PUNCHED TO RESEARCHER
DISK DUMP &USERID PROFS
CP SPOOL PUNCH OFF
*                   WHEN SURVEY IS COMPLETED, THE FILE OF RESPONSES
*                   IS ERASED FROM THE RESPONDENTS A DISK
ERASE &USERID PROFS

      ===============================================================
```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I
C
F
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M
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B
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K
A
L
G
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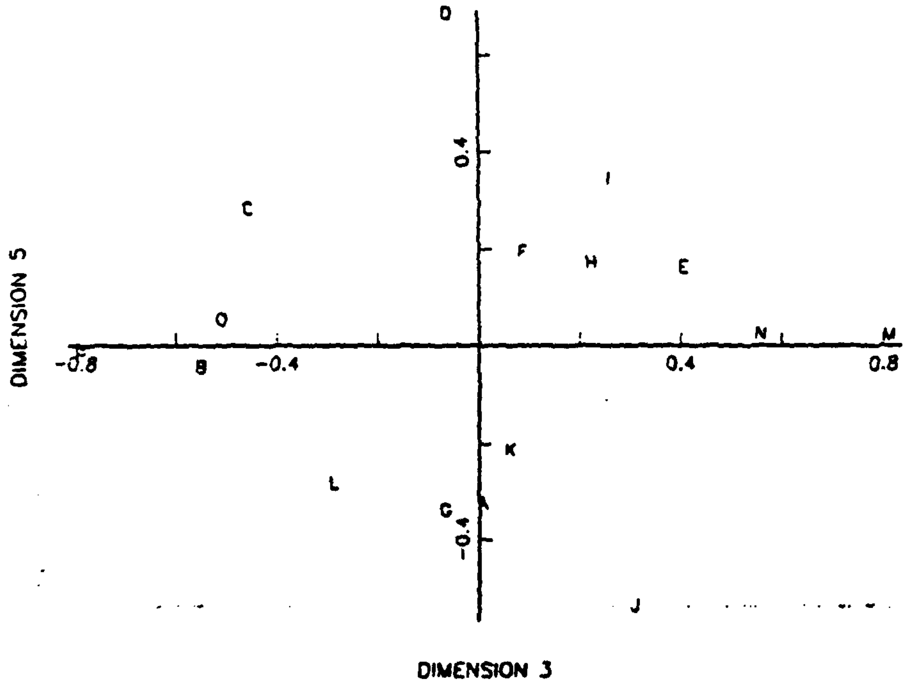
J
DIMENSION 4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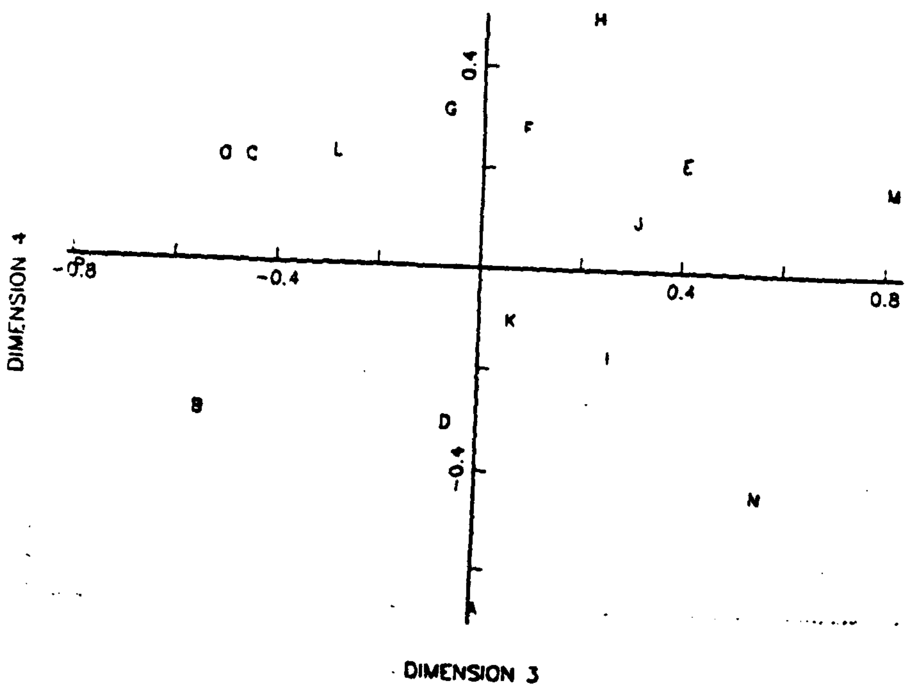

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0.8
H
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O C
L
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M
J
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I
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D
N
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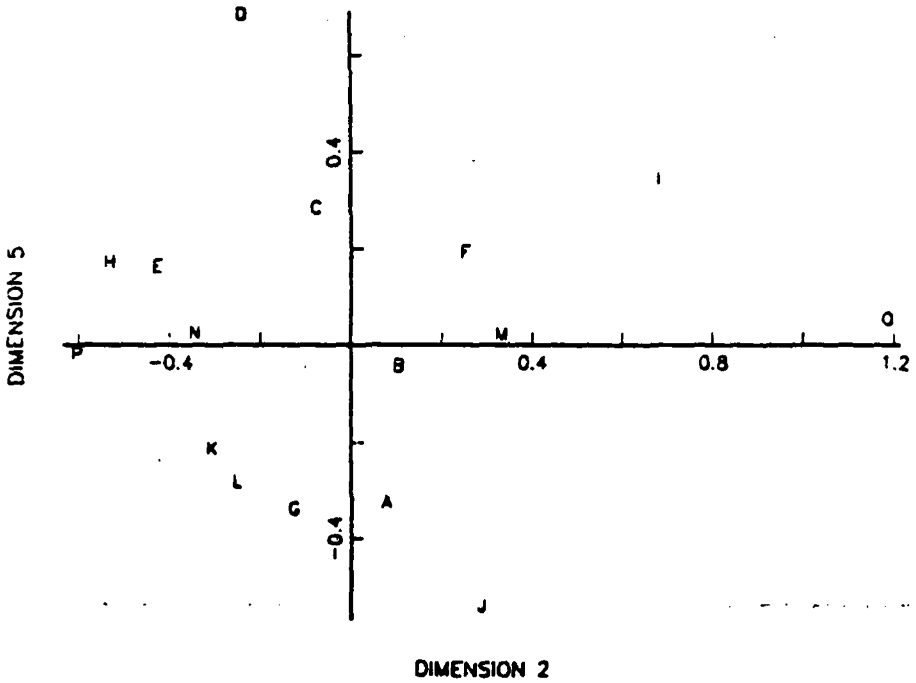
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C
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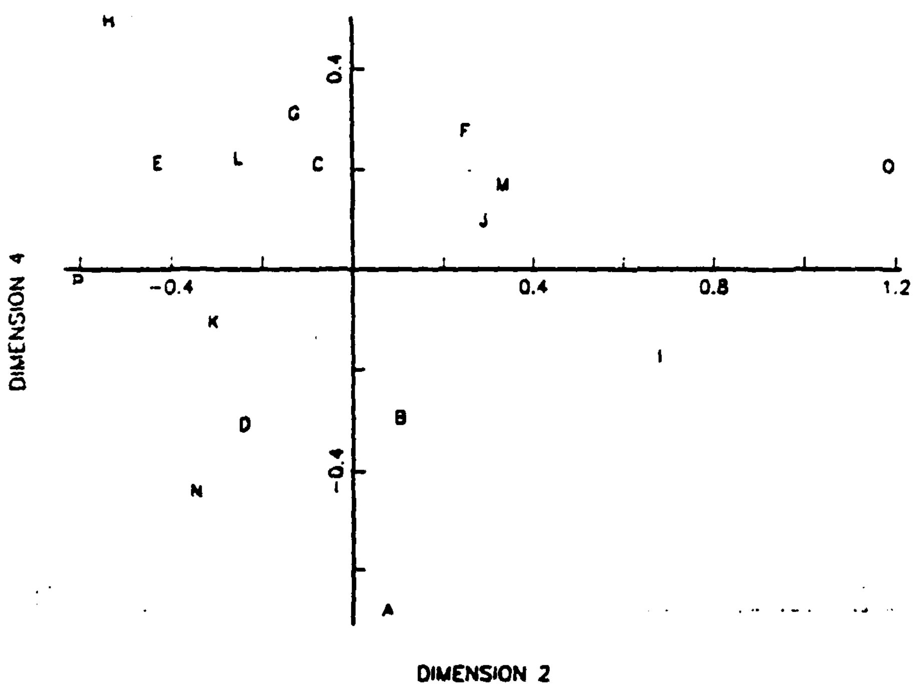
E
N
P
F
I
M
Q
B
K
L
G
A
J



H
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G
F
E
L
C
O
M
J
P
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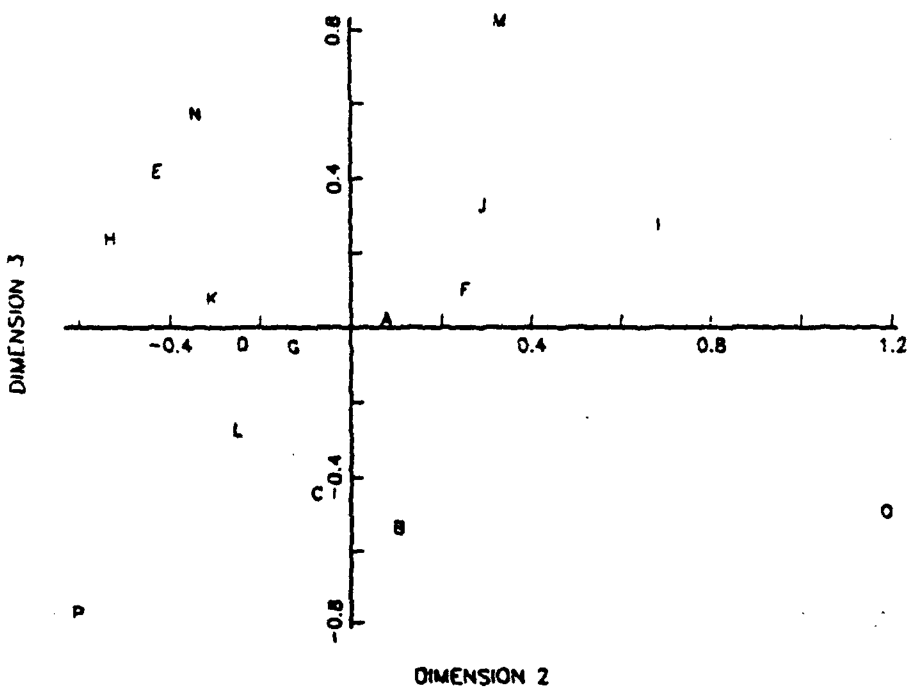
0.4
0.8
1.2
DIMENSION 4
K
I
B
D
-0.4
N
A
DIMENSION 2



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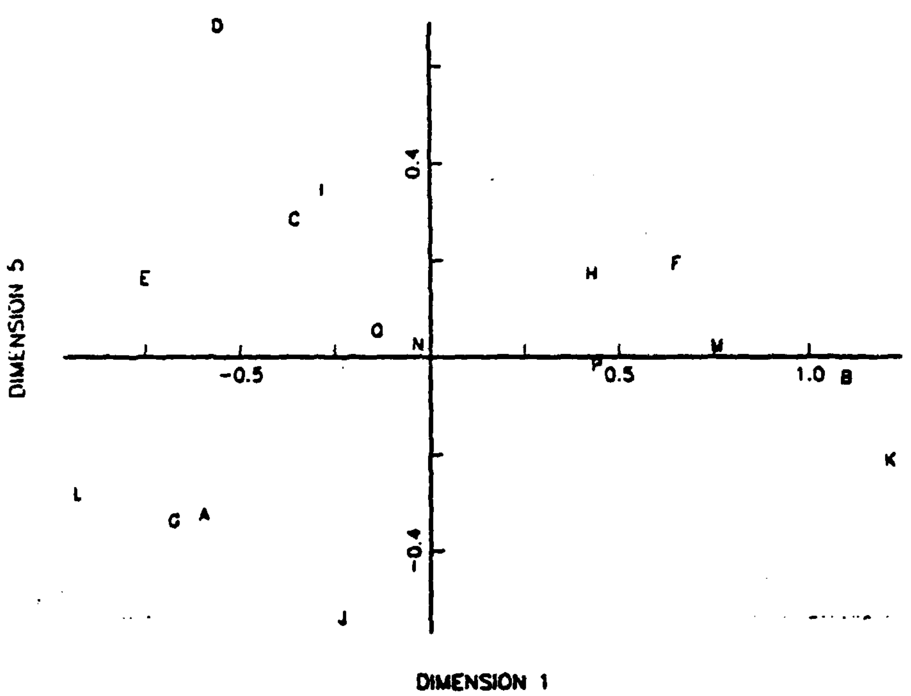
-0.4
-0.8
-0.4
0.4
0.8
1.2
M
N
E
J
I
H
F
K
A
D
G
L
C
B
O
P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B
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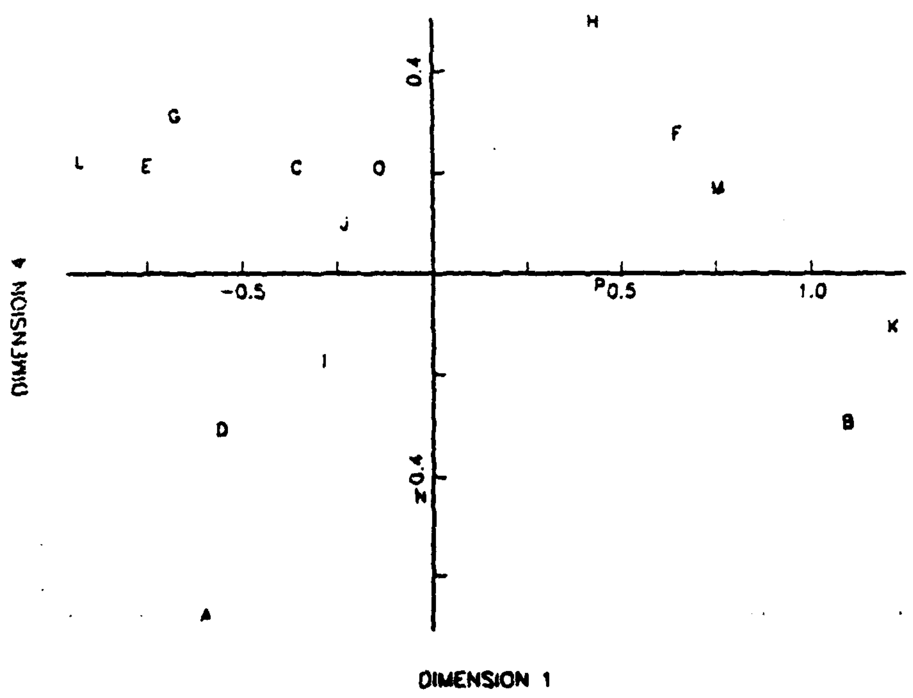
J
DIMENSION 5
DIMENSION 1



H
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G
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L
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C
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M
J
P
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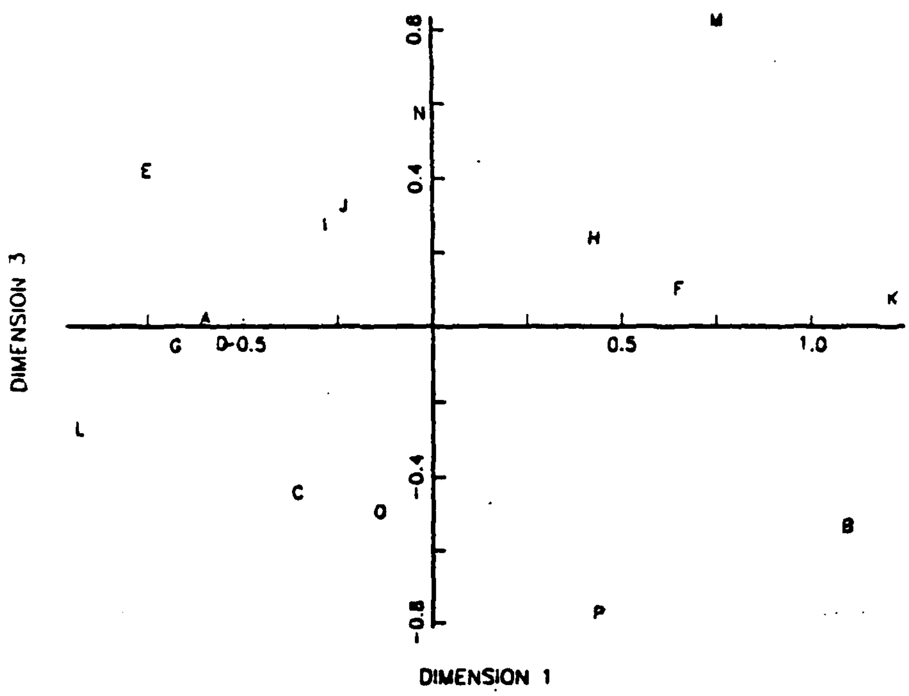
0.5
1.0
K
I
D
B
-0.4
A
DIMENSION 4
DIMENSION 1



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DIMENSION 1
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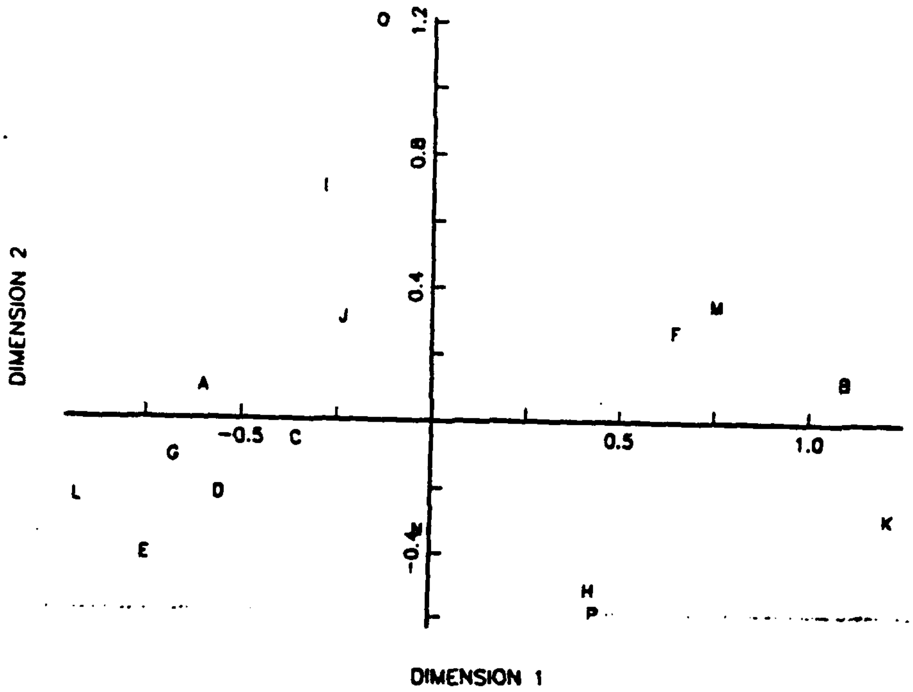
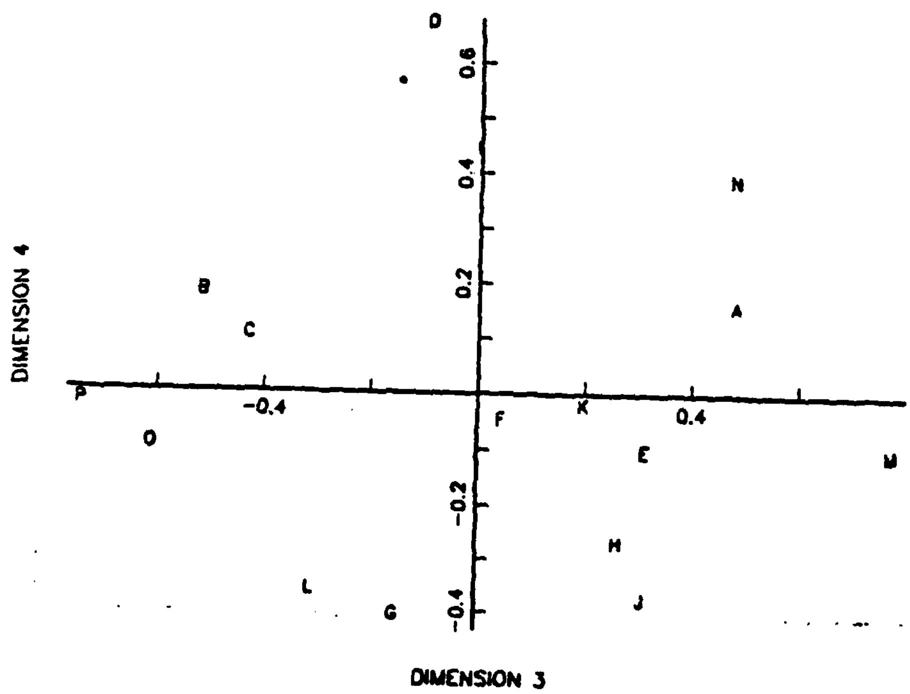
0.4
-0.4
-0.8
-0.5
0.5
1.0
M
N
E
J
I
H
F
K
A
G
D
L
C
O
B
P

APPENDIX C

FIVE DIMENSIONAL SPATIAL MAPPING OF PROFESSORS POSITIONS

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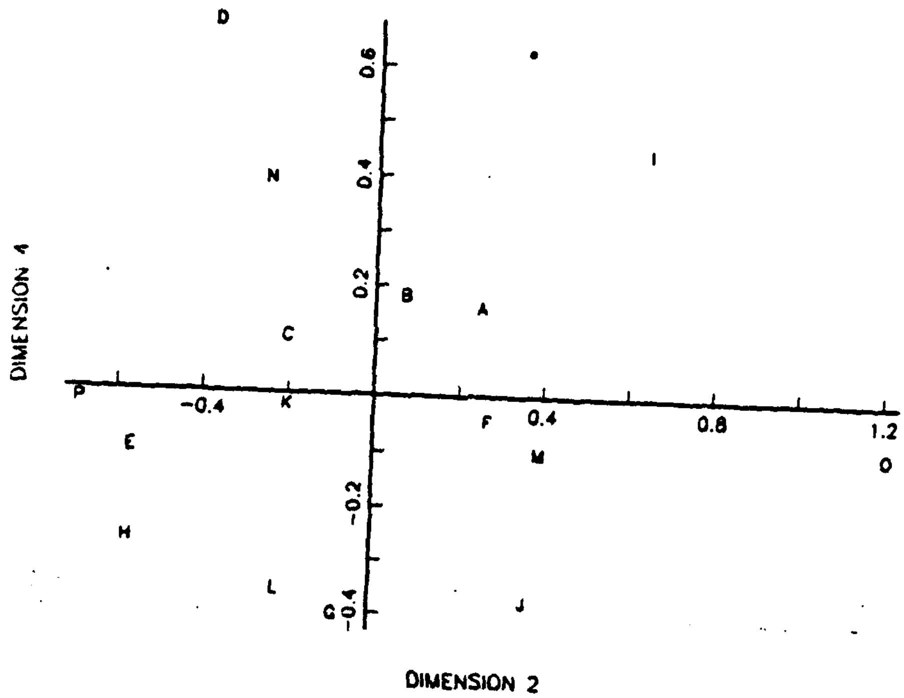
0.4
0.2
-0.2
-0.4
-0.4
0.4
D
N
B
C
A
P
F
K
O
E
M
H
L
G
J



DIMENSION 4
DIMENSION 2
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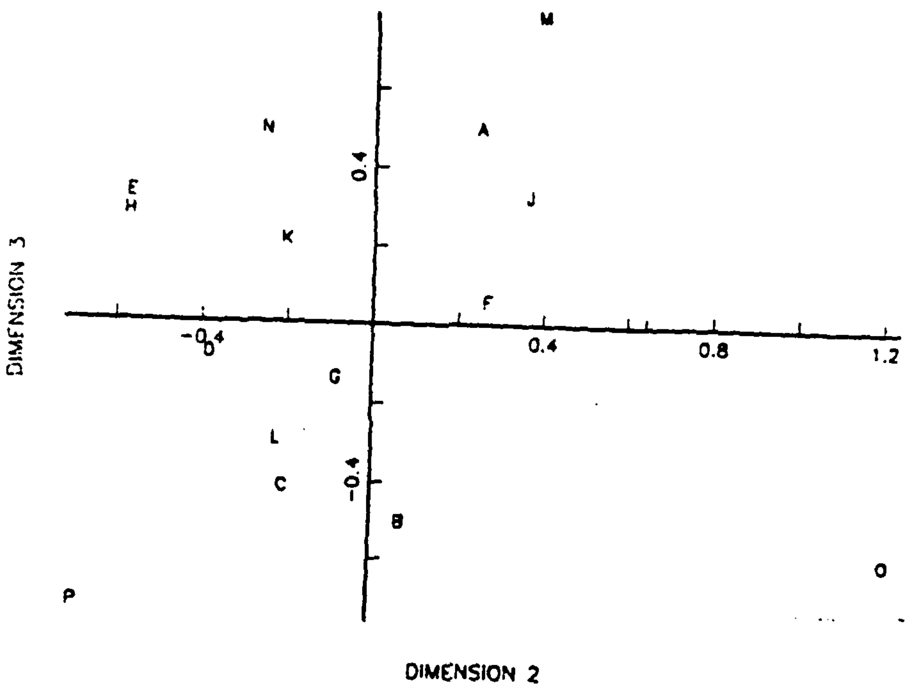
0.4
0.2
-0.2
-0.4
-0.4
0.4
0.8
1.2
D
N
I
B
A
C
P
K
F
E
M
O
H
L
G
J


M
N
A
0.4
E
H
J
K
DIMENSION 3
F
-0.4
D
0.4
0.8
1.2
G
L
C
-0.4
B
O
P
DIMENSION 2

```
C
C          SURV*AS- CALLS THE PANEL OF PROFESSORS (SURV1 PANEL)
C                   AND STACKS THE RESPONSES. THE NUMBER OF PLACE
C                   HOLDERS DEPENDS UPON THE NUMBER OF PROFESSORS
C                   LISTED IN THE PANEL.  IN OUR CASE THERE WERE
C                   39.
C
C
C
USE  PANEL SURV1
&D1  = _
&D2  = _
&D3  = _
&D4  = _
&D5  = _
&D6  = _
&D7  = _
&D8  = _
&D9  = _
&D10  = _
&D11  = _
&D12  = _
&D13  = _
&D14  = _
&D15  = _
&D16  = _
&D17  = _
&D18  = _
&D19  = _
&D20  = _
&D21  = _
&D22  = _
&D23  = _
&D24  = _
&D25  = _
&D26  = _
&D27  = _
&D28  = _
&D29  = _
&D30  = _
&D31  = _
&D32  = _
&D33  = _
&D34  = _
&D35  = _
&D36  = _
&D37  = _
&D38  = _
&D39  = _
DISPLAY
&STACK  I  01&D1
&STACK  I  02&D2
&STACK  I  03&D3
&STACK  I  04&D4
&STACK  I  05&D5
&STACK  I  06&D6
&STACK  I  07&D7
&STACK  I  08&D8
&STACK  I  09&D9
&STACK  I  10&D10
&STACK  I  11&D11
&STACK  I  12&D12
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&STACK  I  16&D16
&STACK  I  17&D17
&STACK  I  18&D18
&STACK  I  19&D19
&STACK  I  20&D20
&STACK  I  21&D21
&STACK  I  22&D22
&STACK  I  23&D23
```

```
&STACK I 24&D24
&STACK I 25&D25
&STACK I 26&D26
&STACK I 27&D27
&STACK I 28&D28
&STACK I 29&D29
&STACK I 30&D30
&STACK I 31&D31
&STACK I 32&D32
&STACK I 33&D33
&STACK I 34&D34
&STACK I 35&D35
&STACK I 36&D36
&STACK I 37&D37
&STACK I 38&D38
&STACK I 39&D39
&STACK FILE
          ================================================================
C
C                         SURV1 PANEL
C
C        THE FOLLOWING PANEL CONTAINS A LIST OF 39 PROFESSORS
C
C
   ¬THE FOLLOWING SURVEY IS DESIGNED TO COLLECT DATA ON STUDENTS'
   ¬PERCEPTIONS OF INSTRUCTOR EFFECTIVENESS.  ENTER THE VALUE 1
   ¬IN THE UNDERSCORED POSITION TO THE LEFT OF EACH PROFESSOR FROM
   ¬WHOM YOU HAVE TAKEN AT LEAST ONE COURSE.

   _@¬ALAN WASHBURN       _@¬ALVIN ANDRUS        _@¬DONALD BARR
   _@¬GERALD BROWN        _@¬JAMES EAGLE         _@¬JAMES ESARY
   _@¬PAUL FISCHBECK      _@¬NEAGLE FORREST      _@¬JACK GAFFORD
   _@¬DONALD GAVER        _@¬JAMES HARTMAN       _@¬THOMAS HOIVIK
   _@¬GILBERT HOWARD      _@¬WAYNE HUGHES        _@¬CHARLES HUTCHINS
   _@¬PATRICIA JACOBS     _@¬HAROLD LARSON       _@¬PETER LEWIS
   _@¬GLENN LINDSAY       _@¬ALAN MCMASTERS      _@¬PAUL MILCH
   _@¬DOUGLAS NEIL        _@¬SAMUEL PARRY        _@¬MARCHMAN PERRY
   _@¬GARY POOCK          _@¬GARY PORTER         _@¬ROBERT READ
   _@¬RUSS RICHARDS       _@¬PAT SANDOCZ         _@¬BRUNO SHUBERT
   _@¬REX SHUDDE          _@¬ARMANDO SOLIS       _@¬MICHAEL SOVEREIGN
   _@¬JOSEPH STEWART      _@¬TIM SULLIVAN        _@¬JAMES TAYLOR
   _@¬KEVIN WOOD          _@¬JAMES YEE           _@¬PETER ZEHNA

   ¬DEPRESS THE ENTER KEY WHEN FINISHED
          ================================================================
C
C                         SURV3 FORTRAN
C
C     VARIABLES DEFINED
C
C     I,J- THESE INTEGER VARIABLES ARE USED AS SIMPLE COUNTERS THROUGHOUT
C          THE PROGRAM
C     N  - REFERS TO THE NUMBER OF PROFESSORS USED ON THE PANEL (SURV1)
C     C  - REFERS TO THE TOTAL NUMBER OF PROFESSORS IN THE SUBSET PERTAIN-
C          ING TO EACH INDIVIDUAL RESPONDENT
C     C1 - EQUATES TO THE VALUE C-1 FOR EACH RESPONDENT.  USED TO HELP
C          LOOP THE RESPONDENT THRU THE PAIRWISE COMPARISONS
C     Z  - INTEGER COUNTER SIMILAR TO I AND J.
C    B(39)- DEFINES  THE RESPONDENTS UNIQUE SUBSET OF PROFESSORS
C    IND,ERRCOM       - VARIABLES USED IN AN ERROR HANDLING SUBROUTINE
C                       ERRSET FOUND IN VS FORTRAN MANUAL.  HELPS TO
C                       MAKE THE SURVEY USER FRIENDLY BY CATCHING IN-
C                       CORRECT RESPONSES, I.E. HITTING THE ENTER KEY
C                       WHEN A NUMERIC WAS REQUESTED.
C    R(39,39)- THE TWO DIMENSIONAL ARRAY OF RESPONSES TO SIMILARITY
C              DATA FOR THE RESPONDENT.  THE REASON IT IS DIMENSIONED
C              AT 39 IS BECAUSE OF THE NUMBER OF PROFESSORS IN THE
C              PANEL
C    BPS(7,39)-SIMILAR TO ABOVE EXCEPT THAT IT STORES THE RESPONSES TO
C              THE BIPOLAR SCALES
```

```
C
C     LIST(39)- A CHARACTER ARRAY OF THE PROFESSORS NAMES
C     A(39)- A CHARACTER ARRAY THAT STORES THE CHARACTER 1 OR A BLANK
C            DEPENDING UPON HOW THE RESPONDENT COMPLETED THE PANEL OF
C            PROFESSORS
C     Y- A CHARACTER VARIABLE THAT CHECKS TO SEE IF THE RESPONDENT ANSWERED
C        CORRECTLY TO CONTINUE ON WITH THE SURVEY
C
      INTEGER I,N,C,J,Z,C1,B(39),INC,ERRCOM
      REAL R(39,39),BPS(7,39)
      CHARACTER*20 LIST(39)
      CHARACTER*4 A(39)
      CHARACTER*1 Y
      COMMON/ERRCOM/INC
      EXTERNAL MYERR
      CALL ERRSET(215,256,-1,1,MYERR,0)
C
C           REMEMBER WE USED 39 PROFESSORS IN OUR PANEL (SURV1)
C
      N=39
C
C           INITIALIZE ARRAYS R AND BPS TO 0.0
C
      DO 5 I=1,N
       DO 6 J=1,N
        R(I,J)=0.0
6      CONTINUE
5     CONTINUE
      DO 8 I=1,7
       DO 9 J=1,N
        BPS(I,J)=0.0
9      CONTINUE
8     CONTINUE
C
C           DEFINE THE CHARACTER ARRAY OF PROFESSORS LIST
C
      LIST(1)='WASHBURN, ALAN R.'
      LIST(2)='ANDRUS, ALVIN F.'
      LIST(3)='BARR, DONALD R.'
      LIST(4)='BROWN, GERALD G.'
      LIST(5)='EAGLE, JAMES N.'
      LIST(6)='ESARY, JAMES D.'
      LIST(7)='FISCHBECK, PAUL S.'
      LIST(8)='FORREST, R. NEAGLE'
      LIST(9)='GAFFORD, JACK'
      LIST(10)='GAVER, DONALD P.'
      LIST(11)='HARTMAN, JAMES K.'
      LIST(12)='HOIVIK, THOMAS H.'
      LIST(13)='HOWARD, GILBERT T.'
      LIST(14)='HUGHES, WAYNE P.'
      LIST(15)='HUTCHINS, CHARLES W.'
      LIST(16)='JACOBS, PATRICIA A.'
      LIST(17)='LARSON, HAROLD J.'
      LIST(18)='LEWIS, PETER A. W.'
      LIST(19)='LINDSAY, GLENN F.'
      LIST(20)='MCMASTERS, ALAN W.'
      LIST(21)='MILCH, PAUL R.'
      LIST(22)='NEIL, DOUGLAS E.'
      LIST(23)='PARRY, SAMUEL H.'
      LIST(24)='PERRY, F. MARCHMAN'
      LIST(25)='POOCK, GARY K.'
      LIST(26)='PORTER, GARY R.'
      LIST(27)='READ, ROBERT R.'
      LIST(28)='RICHARDS, F. RUSSELL'
      LIST(29)='SANDOZ, PATRICK A.'
      LIST(30)='SHUBERT, BRUNO O.'
      LIST(31)='SHUDDE, REX H.'
      LIST(32)='SOLIS, ARMANDO R.'
      LIST(33)='SOVEREIGN, MICHAEL G'
      LIST(34)='STEWART, JOSEPH B.'
      LIST(35)='SULLIVAN, TIMOTHY J.'
      LIST(36)='TAYLOR, JAMES G.'
```

```
      LIST(37)='WOOD, R. KEVIN'
      LIST(38)='YEE, JAMES R.'
      LIST(39)='ZEHNA, PETER W.'
C
C           OBTAIN THE SUBSET OF PROFESSORS SEEN BY EACH RESPONDENT
C
      C=1
      DO 10 I=1,N
       READ(1,20)A(I)
20     FORMAT(2X,A1)
       IF(A(I).EQ.'1') THEN
        B(C)=I
        C=C+1
       ELSE
       END IF
10    CONTINUE
      C=C-1
      C1=C-1
C
C           EXPLAIN THE REQUEST FOR SIMILARITY/DISSIMILARITY DATA
C           FROM THE RESPONDENT
C
48    CALL FRTCMS ('CLRSCRN ')
      WRITE(6,11)
11    FORMAT(1X)
      WRITE(6,12)
12    FORMAT(1X)
      WRITE(6,13)
13    FORMAT(1X)
      WRITE(6,30)
30    FORMAT(1X,'YOU ARE NOW READY TO ENTER IN VALUES FOR SIMILARITY OR
     *DISSIMILARITY FOR')
      WRITE(6,31)
31    FORMAT(1X,'EVERY COMBINATION OF TWO PROFESSORS ACCORDING TO YOUR P
     *ERSONAL LIST.  ONCE')
      WRITE(6,32)
32    FORMAT(1X,'AGAIN, PLEASE ENTER IN A VALUE REFLECTING YOUR PERCEPTI
     *ON OF SIMILARITY OF')
      WRITE(6,33)
33    FORMAT(1X,'TEACHING EFFECTIVENESS USING THE SCALE PROVIDED.  LIMIT
     * RESPONSES TO AT ')
      WRITE(6,34)
34    FORMAT(1X,'MOST ONE DECIMAL POINT.  FOR YOUR CONVENIENCE THE SIMIL
     *ARITY/DISSIMILAR-')
      WRITE(6,35)
35    FORMAT(1X,'ITY SCALE APPEARS BELOW.  FOR EXAMPLE, IF YOU PERCEIVE
     *PROF. BROWN AND')
      WRITE(6,36)
36    FORMAT(1X,'WOOD TO BE VERY SIMILAR IN TEACHING EFFECTIVENESS, YOU
     *MIGHT CHOOSE TO')
      WRITE(6,37)
37    FORMAT(1X,'ASSIGN THAT PAIR A SCORE OF 2.2 TO REFLECT A HIGH DEGRE
     *E OF SIMILARITY.')
      WRITE(6,41)
41    FORMAT(1X)
      WRITE(6,42)
42    FORMAT(T20,'|----+----+----+----+----+----+----+----|')
      WRITE(6,43)
43    FORMAT(T20,'1',T25,'2',T30,'3',T35,'4',T40,'5',T45,'6',T50,'7',T55
     *,'8',T60,'9')
      WRITE(6,44)
44    FORMAT(T20,':',T60,':')
      WRITE(6,45)
45    FORMAT(T18,'VERY',T59,'VERY')
      WRITE(6,46)
46    FORMAT(T17,'SIMILAR',T56,'DISSIMILAR')
      WRITE(6,47)
47    FORMAT(1X)
      WRITE(6,49)
49    FORMAT(1X)
      WRITE(6,53)
53    FORMAT(T10,'TO CONTINUE, DEPRESS THE LETTER R.')
```

```
C
C           THE READER ADVANCES TO DOING PAIRWISE COMPARISONS OF
C           PROFESSORS
C
      READ(5,52) Y
52    FORMAT(A1)
      IF(Y.NE.'R') THEN
       GO TO 48
      ELSE
      END IF
      DO 50 I=1,C1
       Z=I+1
       DO 60 J=Z,C
        CALL PAIR(I,J,F,C,B,LIST)
C
C           THE SUBROUTINE PAIR CONTROLS LOOPING AND ALL PAIRWISE
C           COMPARISONS FOR SIMILARITY DATA
C
60    CONTINUE
50    CONTINUE
65    CALL FRTCMS ('CLRSCRN ')
      WRITE(6,66)
66    FORMAT(1X)
      WRITE(6,67)
67    FORMAT(1X)
      WRITE(6,70)
      WRITE(6,80)
      WRITE(6,90)
      WRITE(6,100)
      WRITE(6,110)
      WRITE(6,120)
      WRITE(6,130)
C
C           THE RESPONDENTS ARE BRIEFED ON THE BIPOLAR SCALES
C
      WRITE(6,140)
70    FORMAT(1X,'WE ARE NOW INTERESTED IN COLLECTING ADDITIONAL INFORMAT
     *ION ON OTHER')
80    FORMAT(1X,'ASPECTS OF YOUR PROFESSORS AND THE COURSES THEY TAUGHT.
     *  THE BIPOLAR')
90    FORMAT(1X,'SCALES USED FOR THIS PART OF THE SURVEY ARE SIMILAR IN
     *DESIGN TO THE')
100   FORMAT(1X,'SIMILARITY/DISSIMILARITY SCALE.  PLEASE LIMIT RESPONSES
     *  TO AT MOST ONE')
110   FORMAT(1X,'DECIMAL PLACE EXCEPT FOR THE FIRST BIPOLAR SCALE WHICH
     *REQUIRES ONE OF')
120   FORMAT(1X,'FOUR INTEGER RESPONSES.  IF YOU HAVE HAD ONE PROFESSOR
     *MORE THAN')
130   FORMAT(1X,'ONCE, YOUR RESPONSE SHOULD REFLECT THE LAST COURSE TAUG
     *HT TO YOU BY')
140   FORMAT(1X,'THAT PROFESSOR.  LET US BEGIN.')
      WRITE(6,150)
150   FORMAT(1X)
      WRITE(6,160)
160   FORMAT(1X,'PLEASE TYPE THE LETTER R TO CONTINUE.')
      READ(5,170) Y
170   FORMAT(A1)
      IF(Y.NE.'R') THEN
       GO TO 65
      ELSE
      END IF
      CALL FRTCMS ('CLRSCRN ')
      DO 180 I=1,C
      WRITE(6,171)
171   FORMAT(1X)
      WRITE(6,172)
172   FORMAT(1X)
      WRITE(6,173)
173   FORMAT(1X,'THIS SCALE DEALS WITH THE TIMEFRAME IN THE CURRICULUM W
     *HEN YOU TOOK THE')
      WRITE(6,174)
174   FORMAT(1X,'COURSE TAUGHT BY THE PROFESSOR LISTED.  FOR THIS SCALE
```

```
     *ENTER ONLY ONE')
      WRITE(6,175)
175   FORMAT(1X,'OF FOUR VALUES (1,2,3 OR 4).')
      WRITE(6,176)
176   FORMAT(1X)
      WRITE(6,177)
177   FORMAT(1X)
      WRITE(6,178)
178   FORMAT(1X)
      WRITE(6,179)
179   FORMAT(1X,T20,'|--------------+--------------+--------------|')
      WRITE(6,181)
181   FORMAT(1X,T20,'1',T35,'2',T50,'3',T65,'4')
      WRITE(6,182)
182   FORMAT(1X,T20,':',T35,':',T50,':',T65,':')
      WRITE(6,183)
183   FORMAT(T12,4(2X,'COURSE TAUGHT'))
      WRITE(6,184)
184   FORMAT(1X,T16,'1ST OR 2ND',T31,'3RD OR 4TH',T46,'5TH OR 6TH',T61,'
     *7TH OR 8TH')
      WRITE(6,185)
185   FORMAT(T9,4(8X,'QUARTER'))
      WRITE(6,186)
186   FORMAT(1X)
      WRITE(6,187)
187   FORMAT(1X)
      WRITE(6,190)LIST(B(I))
190   FORMAT(1X,'ENTER YOUR RESPONSE FOR',1X,A20,2X,'<----')
161   CONTINUE
      IND=0
      READ(5,200,END=162) BPS(1,B(I))
200   FORMAT(F3.2)
      IF(BPS(1,B(I)).GT.4.0) THEN
        GO TO 162
      ELSE
      END IF
      IF(IND.EQ.0) GO TO 163
162     WRITE(6,164)
164     FORMAT(1X,'INCORRECT INPUT, PLEASE ENTER AN INTEGER VALUE',
     *    ' FROM 1 TO 4.')
        REWIND 5
        REWIND 5
        GO TO 161
163   CONTINUE
      CALL FRTCMS ('CLRSCRN ')
180   CONTINUE
      DO 210 I=1,C
      WRITE(6,191)
191   FORMAT(1X)
      WRITE(6,192)
192   FORMAT(1X)
      WRITE(6,193)
193   FORMAT(1X,'THE FOLLOWING SCALE DEALS WITH CLASS SIZE.')
      WRITE(6,194)
194   FORMAT(1X)
      WRITE(6,195)
195   FORMAT(1X)
      WRITE(6,196)
196   FORMAT(T20,'|----+----+----+----+----+----+----+----|')
      WRITE(6,197)
197   FORMAT(T20,'1',T25,'2',T30,'3',T35,'4',T40,'5',T45,'6',T50,'7',T55
     *,'8',T60,'9')
      WRITE(6,198)
198   FORMAT(T25,':',T55,':')
      WRITE(6,199)
199   FORMAT(T21,'VERY SMALL',T51,'VERY LARGE')
      WRITE(6,201)
201   FORMAT(T21,'CLASS SIZE',T51,'CLASS SIZE')
      WRITE(6,202)
202   FORMAT(1X)
      WRITE(6,203)
203   FORMAT(1X)
```

```
      WRITE(6,220)LIST(B(I))
220   FORMAT(1X,'ENTER YOUR RESPONSE FOR',1X,A20,2X,'<----')
231   CONTINUE
      IND=0
      READ(5,230,END=232) BPS(2,B(I))
230   FORMAT(F3.2)
      IF(BPS(2,B(I)).GT.9.0) THEN
       BPS(2,B(I))=BPS(2,B(I))/10.0
      ELSE
      END IF
      IF(IND.EQ.0) GO TO 233
232    WRITE(6,234)
234    FORMAT(1X,'INCORRECT INPUT, PLEASE ENTER AN INTEGER VALUE',
     *  ' FROM 1 TO 9 OR A REAL')
       WRITE(6,238)
238    FORMAT(1X,'VALUE FROM 1.0 TO 9.0.')
       REWIND 5
       REWIND 5
       GO TO 231
233   CONTINUE
      CALL FRTCMS ('CLRSCRN ')
210   CONTINUE
      DO 240 I=1,C
      WRITE(6,211)
211   FORMAT(1X)
      WRITE(6,212)
212   FORMAT(1X)
      WRITE(6,213)
213   FORMAT(1X,'THE FOLLOWING SCALE DEALS WITH WHETHER THE COURSE WAS M
     *ORE THEORETICAL OR')
      WRITE(6,214)
214   FORMAT(1X,'APPLIED IN NATURE.')
      WRITE(6,215)
215   FORMAT(1X)
      WRITE(6,216)
216   FORMAT(1X)
      WRITE(6,217)
217   FORMAT(T20,'|----+----+----+----+----+----+----+----|')
      WRITE(6,218)
218   FORMAT(T20,'1',T25,'2',T30,'3',T35,'4',T40,'5',T45,'6',T50,'7',T55
     *,'8',T60,'9')
      WRITE(6,219)
219   FORMAT(T25,':',T55,':')
      WRITE(6,221)
221   FORMAT(T22,'APPLIED',T50,'THEORETICAL')
      WRITE(6,222)
222   FORMAT(T22,'COURSE',T53,'COURSE')
      WRITE(6,223)
223   FORMAT(1X)
      WRITE(6,224)
224   FORMAT(1X)
      WRITE(6,250)LIST(B(I))
250   FORMAT(1X,'ENTER YOUR RESPONSE FOR',1X,A20,2X,'<----')
251   CONTINUE
      IND=0
      READ(5,260,END=252) BPS(3,B(I))
260   FORMAT(F3.2)
      IF(BPS(3,B(I)).GT.9.0) THEN
       BPS(3,B(I))=BPS(3,B(I))/10.0
      ELSE
      END IF
      IF(IND.EQ.0) GO TO 253
252    WRITE(6,254)
254    FORMAT(1X,'INCORRECT INPUT, PLEASE ENTER AN INTEGER VALUE',
     *  ' FROM 1 TO 9 OR A REAL')
       WRITE(6,258)
258    FORMAT(1X,'VALUE FROM 1.0 TO 9.0.')
       REWIND 5
       REWIND 5
       GO TO 251
253   CONTINUE
      CALL FRTCMS ('CLRSCRN ')
```

```
240    CONTINUE
       DO 270 I=1,C
       WRITE(6,261)
261    FORMAT(1X)
       WRITE(6,262)
262    FORMAT(1X)
       WRITE(6,263)
263    FORMAT(1X,'THIS SCALE REFLECTS HOW DIFFICULT A GRADER YOU PERCEIVE
      *O THE PROFESSOR TO')
       WRITE(6,264)
264    FORMAT(1X,'BE.')
       WRITE(6,265)
265    FORMAT(1X)
       WRITE(6,266)
266    FORMAT(1X)
       WRITE(6,267)
267    FORMAT(T20,'|----+----+----+----+----+----+----+----|')
       WRITE(6,268)
268    FORMAT(T20,'1',T25,'2',T30,'3',T35,'4',T40,'5',T45,'6',T50,'7',T55
      *,'8',T60,'9')
       WRITE(6,269)
269    FORMAT(T25,':',T55,':')
       WRITE(6,271)
271    FORMAT(T23,'EASY',T54,'HARD')
       WRITE(6,272)
272    FORMAT(T22,'GRADER',T53,'GRADER')
       WRITE(6,273)
273    FORMAT(1X)
       WRITE(6,274)
274    FORMAT(1X)
       WRITE(6,280)LIST(E(I))
280    FORMAT(1X,'ENTER YOUR RESPONSE FOR',1X,A20,2X,'<----')
294    CONTINUE
       IND=0
       READ(5,290,END=295) BPS(4,B(I))
290    FORMAT(F3.2)
       IF(BPS(4,B(I)).GT.9.0) THEN
        BPS(4,B(I))=BPS(4,B(I))/10.0
       ELSE
       END IF
       IF(IND.EQ.0) GO TO 296
295     WRITE(6,297)
297     FORMAT(1X,'INCORRECT INPUT, PLEASE ENTER AN INTEGER VALUE',
      *      ' FROM 1 TO 9 OR A REAL')
        WRITE(6,298)
298     FORMAT(1X,'VALUE FROM 1.0 TO 9.0.')
        REWIND 5
        REWIND 5
        GO TO 294
296    CONTINUE
       CALL FRTCMS ('CLRSCRN ')
270    CONTINUE
       DO 300 I=1,C
       WRITE(6,281)
281    FORMAT(1X)
       WRITE(6,282)
282    FORMAT(1X)
       WRITE(6,291)
291    FORMAT(1X,'THIS SCALE MEASURES THE PACE AT WHICH THE CLASS WAS TAU
      *GHT.')
       WRITE(6,292)
292    FORMAT(1X)
       WRITE(6,293)
293    FORMAT(1X)
       WRITE(6,283)
283    FORMAT(T20,'|----+----+----+----+----+----+----+----|')
       WRITE(6,284)
284    FORMAT(T20,'1',T25,'2',T30,'3',T35,'4',T40,'5',T45,'6',T50,'7',T55
      *,'8',T60,'9')
       WRITE(6,285)
285    FORMAT(T25,':',T55,':')
       WRITE(6,286)
```

```
286     FORMAT(T23,'SLOW',T54,'FAST')
        WRITE(6,287)
287     FORMAT(T23,'PACE',T54,'PACE')
        WRITE(6,288)
288     FORMAT(1X)
        WRITE(6,289)
289     FORMAT(1X)
        WRITE(6,310)LIST(B(I))
310     FORMAT(1X,'ENTER YOUR RESPONSE FOR',1X,A20,2X,'<----')
321     CONTINUE
        IND=0
        READ(5,320,END=322) BPS(5,B(I))
320     FORMAT(F3.2)
        IF(BPS(5,B(I)).GT.9.0) THEN
         BPS(5,B(I))=BPS(5,B(I))/10.0
        ELSE
        END IF
        IF(IND.EQ.0) GO TO 323
322      WRITE(6,324)
324      FORMAT(1X,'INCORRECT INPUT, PLEASE ENTER AN INTEGER VALUE',
     *      ' FROM 1 TO 9 OR A REAL')
         WRITE(6,328)
328      FORMAT(1X,'VALUE FROM 1.0 TO 9.0.')
         REWIND 5
         REWIND 5
         GO TO 321
323     CONTINUE
        CALL FRTCMS ('CLRSCRN ')
300     CONTINUE
        DO 330 I=1,C
        WRITE(6,301)
301     FORMAT(1X)
        WRITE(6,302)
302     FORMAT(1X)
        WRITE(6,303)
303     FORMAT(1X,'THE FOLLOWING SCALE MEASURES THE AMOUNT OF EFFORT REQUI
     *RED BY THE STUDENT')
        WRITE(6,315)
315     FORMAT(1X,'OUTSIDE OF CLASS.')
        WRITE(6,304)
304     FORMAT(1X)
        WRITE(6,305)
305     FORMAT(1X)
        WRITE(6,306)
306     FORMAT(T20,'|----+----+----+----+----+----+----+----|')
        WRITE(6,307)
307     FORMAT(T20,'1',T25,'2',T30,'3',T35,'4',T40,'5',T45,'6',T50,'7',T55
     *,'8',T60,'9')
        WRITE(6,308)
308     FORMAT(T25,':',T55,':')
        WRITE(6,309)
309     FORMAT(T19,'LITTLE EFFORT',T50,'MUCH EFFORT')
        WRITE(6,311)
311     FORMAT(T17,'REQUIRED OUTSIDE',T48,'REQUIRED OUTSIDE')
        WRITE(6,316)
316     FORMAT(T23,'CLASS',T53,'CLASS')
        WRITE(6,312)
312     FORMAT(1X)
        WRITE(6,313)
313     FORMAT(1X)
        WRITE(6,340)LIST(B(I))
340     FORMAT(1X,'ENTER YOUR RESPONSE FOR',1X,A20,2X,'<----')
351     CONTINUE
        IND=0
        READ(5,350,END=352) BPS(6,B(I))
350     FORMAT(F3.2)
        IF(BPS(6,B(I)).GT.9.0) THEN
         BPS(6,B(I))=BPS(6,B(I))/10.0
        ELSE
        END IF
        IF(IND.EQ.0) GO TO 353
352      WRITE(6,354)
```

```
354    FORMAT(1X,'INCORRECT INPUT, PLEASE ENTER AN INTEGER VALUE',
     *    ' FROM 1 TO 9 OR A REAL')
       WRITE(6,358)
358    FORMAT(1X,'VALUE FROM 1.0 TO 9.0.')
       REWIND 5
       REWIND 5
       GO TO 351
353   CONTINUE
      CALL FRTCMS ('CLRSCRN ')
330   CONTINUE
      DO 360 I=1,C
      WRITE(6,331)
331   FORMAT(1X)
      WRITE(6,332)
332   FORMAT(1X)
      WRITE(6,333)
333   FORMAT(1X,'THE LAST SCALE ASKS TO WHAT EXTENT THE COURSE RELIED UP
     *ON THE PREREQUISITES.')
      WRITE(6,335)
335   FORMAT(1X)
      WRITE(6,336)
336   FORMAT(1X)
      WRITE(6,337)
337   FORMAT(T20,'|----+----+----+----+----+----+----|')
      WRITE(6,338)
338   FORMAT(T20,'1',T25,'2',T30,'3',T35,'4',T40,'5',T45,'6',T50,'7',T55
     *,'8',T60,'9')
      WRITE(6,339)
339   FORMAT(T25,':',T55,':')
      WRITE(6,341)
341   FORMAT(T19,'COURSE RELIED',T49,'COURSE RELIED')
      WRITE(6,342)
342   FORMAT(T21,'LITTLE ON',T51,'HEAVILY ON')
      WRITE(6,343)
343   FORMAT(T19,'PREREQUISITES',T49,'PREREQUISITES')
      WRITE(6,344)
344   FORMAT(1X)
      WRITE(6,345)
345   FORMAT(1X)
      WRITE(6,370)LIST(B(I))
370   FORMAT(1X,'ENTER YOUR RESPONSE FOR',1X,A20,2X,'<----')
381   CONTINUE
      IND=0
      READ(5,380,END=382) BPS(7,B(I))
380   FORMAT(F3.2)
      IF(BPS(7,B(I)).GT.9.0) THEN
       BPS(7,B(I))=BPS(7,B(I))/10.0
      ELSE
      END IF
      IF(IND.EQ.0) GO TO 383
382    WRITE(6,384)
384    FORMAT(1X,'INCORRECT INPUT, PLEASE ENTER AN INTEGER VALUE',
     *    ' FROM 1 TO 9 OR A REAL')
       WRITE(6,388)
388    FORMAT(1X,'VALUE FROM 1.0 TO 9.0.')
       REWIND 5
       REWIND 5
       GO TO 381
383   CONTINUE
      CALL FRTCMS ('CLRSCRN ')
360   CONTINUE
      CALL FRTCMS ('CLRSCRN ')
      WRITE(6,386)
386   FORMAT(1X)
      WRITE(6,387)
387   FORMAT(1X)
C
C           THE DATA IS COLLECTED AND STORED IN EACH ARRAY
C
      DO 400 I=1,N
       WRITE(2,410)(R(I,J),J=1,N)
410    FORMAT(20F4.1)
```

```
400    CONTINUE
       WRITE(2,415)
415    FORMAT(1X)
       WRITE(2,417)
417    FORMAT(1X)
       DO 420 I=1,7
        WRITE(2,430)(BPS(I,J),J=1,N)
430     FORMAT(20F4.1)
420    CONTINUE
       STOP
       END
C
C              REQUESTS FOR SIMILARITY/DISSIMILARITY SCORES ARE MADE HERE
C
       SUBROUTINE PAIR(I,J,R,C,B,LIST)
       COMMON/ERRCOM/IND
       INTEGER I,C,B(39),J,K,L
       REAL R(39,39)
       CHARACTER*20 LIST(39)
       CALL FRTCMS ('CLRSCRN ')
       WRITE(6,10)
       WRITE(6,11) LIST(B(I))
10     FORMAT(T2,'PLEASE ENTER IN YOUR VALUE FOR SIMILARITY IN TEACHING E
      *FFECTIVENESS COMPARING')
11     FORMAT(1X,A20,1X,'AGAINST THE PROFESSOR INDICATED BY THE ARROW.')
       IF(J.LT.C) THEN
        K=J+1
        WRITE(6,25)LIST(B(J))
25      FORMAT(20X,A20,2X,'<----')
        DO 30 L=K,C
         WRITE(6,35)LIST(B(L))
35       FORMAT(20X,A20)
30      CONTINUE
       ELSE
        K=J
        WRITE(6,40)LIST(B(K))
40      FORMAT(20X,A20,2X,'<----')
       END IF
       WRITE(6,42)
42     FORMAT(T20,'|----+----+----+----+----+----+----+----|')
       WRITE(6,43)
43     FORMAT(T20,'1',T25,'2',T30,'3',T35,'4',T40,'5',T45,'6',T50,'7',T55
      *,'8',T60,'9')
       WRITE(6,44)
44     FORMAT(T20,':',T60,':')
       WRITE(6,55)
55     FORMAT(T18,'VERY',T59,'VERY')
       WRITE(6,46)
46     FORMAT(T17,'SIMILAR',T56,'DISSIMILAR')
50     CONTINUE
       IND=0
       READ(5,45,END=61) R(B(I),B(J))
45     FORMAT(F3.2)
       IF(R(B(I),B(J)).GT.9.0) THEN
        R(B(I),B(J))=R(B(I),B(J))/10.0
       ELSE
       END IF
       IF(IND.EQ.0) GO TO 70
61      WRITE(6,62)
62      FORMAT(1X,'INCORRECT INPUT, PLEASE ENTER AN INTEGER VALUE',
      *     ' FROM 1 TO 9 OR A REAL')
        WRITE(6,63)
63      FORMAT(1X,'VALUE FROM 1.0 TO 9.0.')
        REWIND 5
        REWIND 5
        GO TO 50
70     CONTINUE
       RETURN
       END
C
C              ERROR HANDLING SUBROUTINE USED TO HELP WEED OUT INCORRECT
C              RESPONSES
```

```
C
      SUBROUTINE MYERR(IRETCD,IERR,CHR)
      INTEGER IRETCD,IERR
      CHARACTER*1 CHR
      COMMON/ERRCOM/IND
      IRETCD=0
      IND=1
      RETURN
      END
```

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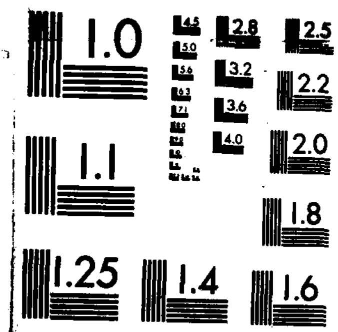

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