The exploratory role three-mode principal component analysis can play in analyzing multivariate longitudinal organizational data is outlined by an exposition of the technique itself, and by its application to organizational data from Dutch hospitals. Relationships with some other techniques for such data are indicated.

Three-Mode Principal Component Analysis of Multivariate Longitudinal Organizational Data

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Social change has always loomed large as one of the main foci of interest for sociology. Nevertheless, over and over again sociologists (e.g., Dahrendorf, 1958) have complained that (far) too little attention has been and is paid in the discipline to the dynamics of social life. One reason that at least sociologists with a bent for quantitative research often tend to shy away from studying the past might be the relative scarcity of sufficiently comparable data at various points in time.

One could expect organizations on average to be better provided with data concerning their histories than other social systems. After all, bureaucratic forms of human association are characterized among other things by the practice of recording in writing

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the most important acts, decisions, and rules that guide their functioning. Indeed organizations have more or less accessible archives that form potentially rich sources of data to those who want to investigate their creation, growth, and development over time.

Does this imply that the sociology of organizations forms at least an exception to the rule that sociology is short of historical analysis of a quantitative nature? Alas, this is not the case. In a recent survey of developments of organizations over time, Child and Kieser (1981: 28) ascertain that "most organizational research has not been directed at the process of development over time; it has been cross-sectional."

Kimberly (1976b: 580) found in a review of research into organizational size and structure that a mere 3 out of 76 studies actually used longitudinal data. In a more recent review Miller and Friesen (1981) cite a few more longitudinal studies on primarily business organizations. They, too, note a real dearth of studies *on* organizations, in contrast to longitudinal studies *in* organizations (see Kimberley, 1976a, for this distinction). Miller and Friesen classify longitudinal studies in five types, based on the number of organizations and variables employed and on the use of a qualitative or quantitative approach. Within Type 5 (multivariate, quantitative studies of many organizations), to which our example belongs, they only mention seven studies, all of which appeared after 1973.

There are many general problems inherent in longitudinal organizational research (see, e.g., Meyer, 1979: 42-65; Kimberley, 1976a; Ivancevitch and Matteson, 1978; Miller and Friesen, 1981)

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of getting the data in a form suitable for analysis (see Lammers, 1974, for the difficulties with the data of our example). The number of methods for analysis of reasonably sized multivariate longitudinal data sets is not overly large, and in this article we want to discuss the utility of a descriptive method that might make longitudinal study of organizations more feasible and/or attractive to organizational sociologists. In particular, we will discuss three-mode principal component analysis (Tucker, 1963, 1966; Kroonenberg and De Leeuw, 1980; Kroonenberg, 1983a) as a possible technique for analyzing organizational data in an exploratory fashion. It will be argued that such an exploratory analysis for large-scale multivariate data sets can be extremely useful as a preliminary step for further causal modeling (see "Other Approaches"). Furthermore, we will demonstrate, with the aid of data pertaining to Dutch hospitals, that it can be a method to deal with the kind of multivariate longitudinal data often available on organizations. As far as we have been able to trace, the only other study dealing with longitudinal data on hospitals is Denton (1982).

After a short, mainly conceptual introduction into three-mode principal component analysis, we will discuss the data and the research questions involved. The three-mode analysis of the data will be presented in reasonable detail to allow an impression of the capability of technique. We will also discuss other approaches to the analysis of multivariate longitudinal data and their relationships with three-mode principal component analysis. And, finally, we will discuss the relative merits of three-mode principal component analysis for longitudinal organizational data.

THREE-MODE PRINCIPAL COMPONENT ANALYSIS

Both in sociology and elsewhere it often happens that one has information available on several variables from a number of persons, objects, or organizations, and one is interested in knowing whether the measurements could be described by a smaller number of linear combinations of the original variables. In this article we will refer to such linear combinations as "components," and we will assume that a few of these components will adequately approximate the systematic part of the data. In order to be able to refer to the components in practical applications, the components will be labeled descriptively, without implying that the components necessarily represent (underlying) theoretical constructs.

As an example one could imagine that the scores on several organizational variables are largely determined by linear combinations of such components as task differentiation within an organization and the overall size of the organization. These components can be determined from the original measurements by standard principal component analysis.

Suppose in the same example that the researcher has measurements available at various points in time. The data can now be classified by three different kinds of quantities or *modes* of the data: organizations, variables, and points in time. Again, the investigator is interested in the components that explain the larger part of the variation in the variables, but now for all points in time simultaneously. Moreover, it is of interest to know whether the organizations are mere replications of each other or can be seen as linear combinations of "typical" organizations or what has been called "genotype organizations" (Lammers, 1974). In the example to be discussed, one may think of a hospital to consist of a linear combination of a hospital with a large degree of specialization and a general hospital that is all things to all people. A similar question may arise with respect to the development of the measurements over time, that is, whether the longitudinal changes can be described as a combination of say a constant, linear, and quadratic trend.

One way to approach such questions is to analyze the question for each mode separately. For instance, the structure in the variables can be investigated after averaging over the points in time, or by analyzing the (organizations × points in time)-by-variables matrix disregarding the dependency in the data. A more satisfactory way to analyze the data, which can be arranged in a three-dimensional block of organizations by variables by points in time, is to search for the linear combinations of all three modes simultaneously. This would entail finding principal components for each of the three modes (organizations, variables, and points in time) and determining how these components are related.

In the example to be analyzed, one could try to answer questions such as, "Does the structure of the variables, as expressed by task differentiation and size, show different trends for different genotype hospitals?" By performing separate analyses on each of the modes such questions are not immediately answerable, but they can be explicitly answered by three-mode principal component analysis, as the model includes specific parameters for such questions about the interactions of components. These interaction parameters can be collected in a three-mode matrix, which is commonly called the "core matrix."

From a technical point of view, three-mode principal component analysis is a generalization of the singular value decomposition of two-mode data, say I organizations by J variables (for a technical discussion of singular value decomposition, see, e.g., Good, 1969). In essence, the decomposition is a simultaneous principal component analysis of both organizations and variables, in which the interactions between the M components of the organizations and the P components of the variables are represented by the core matrix G (see Figure 1). For two-mode data the core matrix is square (P = M) and diagonal with diagonal elements g_{mm} (m = 1..M) under the assumption that the component matrices are orthonormal for both variables (B) and organizations (A). Each g_{mm} is equal to the square root of the eigenvalue associated with the m^{th} component of the variables and the m^{th} components of the organizations.

Figure 2 shows the decomposition of a three-mode matrix according to the three-mode principal component model. Comparison between Figure 1 and Figure 2 shows the analogy between the singular value decomposition and three-mode principal component analysis. Instead of two component matrices A and B, there are now three such matrices, A, B, and C. And just as the data matrix does, the core matrix with singular values has three modes, and it again contains the interactions between the compo-

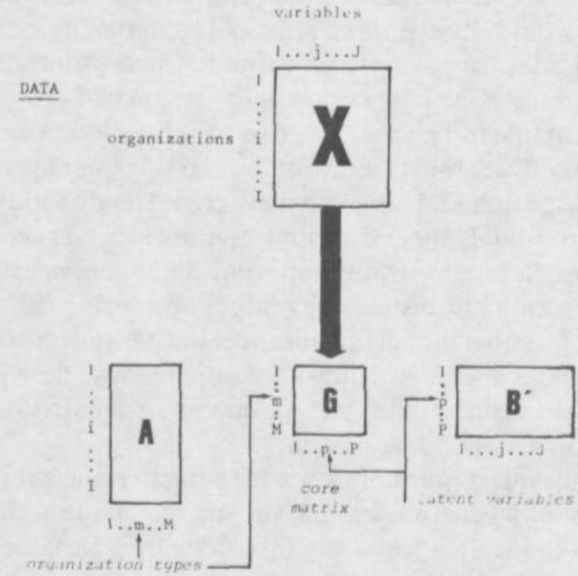


Figure 1: Singular Value Decomposition

nents; but these interactions are far more complex than in the two-mode case, as any component of a mode can interact with any component of another mode. In order to match the simplicity of the two-mode case, all modes should have the same number of components, and the core matrix G with elements g_{mpq} should only have nonzero elements on the body diagonal, that is, $g_{mpq} = 0$, unless $m = p = q$ (see Harshman and Berenbaum, 1981, for a model with such characteristics).

A more formal description of the three-mode principal component model may be made as follows. If we write the elements of the data matrix X of organizations by variables by points in time as x_{ijk} ($i = 1..I$; $j = ..J$; $k = 1 .. K$), then the model has the following form

$$x_{ijk} = \sum_{m=1}^{M} \sum_{p=1}^{P} \sum_{q=1}^{Q} a_{im} b_{jp} c_{kq} g_{mpq} + \delta_{ijk} \qquad [1]$$

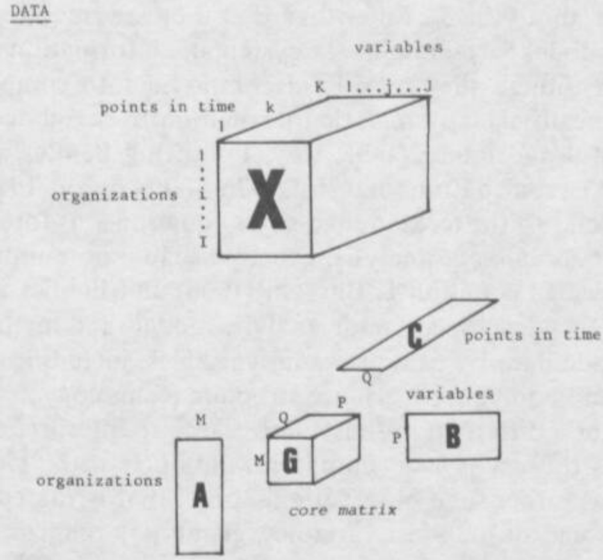


Figure 2: Three-Mode Principal Component Analysis

which may be written in matrix notation using the Kronecker product

$$X = AG(B' \otimes C') + \Delta \qquad [2]$$

As discussed above $A = (a_{im})$, $B = (b_{jp})$, and $C = (c_{kq})$ are component matrices of organizations, variables, and points in time, respectively. They are what psychologists refer to as "loadings," and the matrices may be taken as columnwise orthonormal without loss of generality. $G = (g_{mpq})$ is the core matrix with the interactions between the components. Finally $\Delta = (\delta_{ijk})$ is the matrix with residuals or errors of approximation.

In common factor analysis the standard assumption about the error terms is that they are unique for each variable and independent of each other such that their covariance matrix is diagonal and contains the unique variances. However, in ordinary principal component analysis there is no specific provision for the concept of uniqueness. Similarly in equation 1 no assumptions are made about the δ_{ijk} other than that they are small, implying that the model part contains the systematic information and the δ_{ijk}, even though they may be decomposed into components, contain insufficient systematic information to be modeled in a meaningful and interpretable way. Following Bentler and Lee (1978: 343; see also Frane and Hill, 1976: 400; Kruskal, 1978: 322), we will refer to the technique to solve equation 1 as three-mode *principal component* analysis, exactly because no uniquenesses are defined in equation 1. Bloxom (1968) and Bentler and Lee (1978, 1979) developed factor-analytic models and methods for three-mode data by using random variables, including uniquenesses, and applying covariance structure technology.

A slightly different, but instructive, way to interpret the core matrix is to view it as a (miniature) data box with "idealized" quantities rather than observational ones, that is, "latent" variables instead of manifest variables, genotype organizations instead of real organizations, and time trends instead of time itself. A value g_{mpq} in the core matrix is then the score of an organization of type m on a latent variable p for a particular trend q. In this way the core matrix can be seen to embody the basic relationships that exist in the data.

In his first exposition of three-mode factor analysis, Tucker (1963) also discusses analyzing longitudinal data, but used artificial data. In that article he suggests two supplementary ways to assist in analyzing the outcomes from a three-mode analysis by increasing detail at the cost of parsimony of description. In particular, equation 1 may be first written as Tucker's equation 10:

$$x_{ijk} = \sum_{m=1}^{M} \sum_{p=1}^{P} a_{im} b_{jp} n_{mpk} + \delta_{ijk} \qquad [3]$$

with

$$n_{mpk} = \sum_{q=1}^{Q} c_{kq} g_{mpq} \qquad [4]$$

and thus

$$X_k = AN_k B' + \Delta_k \qquad [5]$$

in which X_k is the (I × J) matrix of observations at time k; the N_k are the "core matrices for occasions." The n_{mpq} can be interpreted as the measure for the relationship between the m^{th} component of mode A, and the p^{th} component of mode B.

The development can even be taken further by rewriting equation 3 as Tucker's equation 14:

$$x_{ijk} = \sum_{p=1}^{P} b_{jp} s_{ipk} + \delta_{ijk} \quad [6]$$

with

$$s_{ipk} = \sum_{m=1}^{M} a_{im} n_{mpk} \quad [7]$$

An s_{ipk} can be thought of as the component score of individual i at occasion k on component p of mode B. In our example we are not explicitly interested in component scores of the hospitals but rather in the component scores of the variables at each occasion for each type of hospital or hospital component—in other words, how the scores on the variables change over time for different types of hospitals. This means we will look at

$$t_{mjk} = \sum_{p} b_{jp} n_{mpk} \quad [8]$$

Implicit in this presentation is that the relationships between observed hospitals and their components is constant over time, and that all changes are assigned to changes in the component scores of the variables. Even though in standard two-mode analyses, component scores always refer to the observational units, in three-mode analysis this is not necessarily true as three different kinds of component scores may be defined, of which equations 7 and 8 are two of the three possibilities. Which type will be most useful depends on the main focus of an analysis.

It can be shown that with the Kroonenberg-De Leeuw methods for estimating the parameters in equations 1 and 3, it is possible to separate the total sum of squares of the data, SS(Total), into two additive parts,

$$SS(Total) = SS(Fit) + SS(Residual) \quad [9]$$

or

$$\sum_i \sum_j \sum_k x_{ijk}^2 = \sum_i \sum_j \sum_k \hat{x}_{ijk}^2 + \sum_i \sum_j \sum_k \delta_{ijk}^2 \quad [10]$$

where the $\hat{x}_{ijk}$ are the fitted data using model 1 or 3. Furthermore, it can be shown that for each element e (= hospital, variable, or occasion) of a mode

$$SS(Total_e) = SS(Fit_e) + SS(Res_e) \quad [11]$$

This partitioning is extremely useful in assessing how well an element fits compared to other elements of the same mode. In other words, both very influential elements (outliers) and ill-fitting elements may be identified. One way to investigate this, especially when there are many elements in a mode, is by plotting per mode the $SS(Fit_e)$ against the $SS(Res_e)$; (see below, Figure 6). When there are not too many elements in a mode inspecting the relative fit,

$$RSS(Fit_e) = SS(Fit_e)/SS(Total_e) \quad [12]$$

is often sufficient.

Psychologists such as Wohlwill (1973: 273-283) and Bentler (1973: 161-162) mention briefly that three-mode component and factor analyses have some potential for treating multivariate longitudinal data, but both authors indicate that very little experience with these techniques is available, and find the real potentialities therefore difficult to assess.

In our view the promise of three-mode principal component analysis and its analogues in the covariance structure approach (see below) lies in the simultaneous treatment of serial and variable dependence (see also Lohmöller, 1978). Serial dependence can be assessed from component analysis of the time mode (here: years - C), variable dependence from the component analysis of the variable mode (B), and their interaction from the core matrix. By analyzing variables over subjects and occasions with standard principal component analysis (e.g., Vavra, 1972; Visser, 1985: 63, 172), or by treating variables at each occasion as separate variables, and analyzing these with standard component analysis (e.g., Visser, 1985: 64, 151ff., 172), the variable and serial dependence, and their interactions, become confounded or are ignored.

Relatively nontechnical descriptions of three-mode principal component analysis can be found in Levin (1965), Tucker (1965), and Kroonenberg (1983a: Ch. 2). More technical details can be found in the papers by Tucker (1963, 1966), Lohmöller (1979), Kroonenberg and De Leeuw (1980), and the book by Kroonenberg (1983a). To our knowledge no specific descriptions have been given in sociological journals or readers.

The analyses presented here were performed using the programs TUCKALS3 and TUCKALS2 developed by Kroonenberg using the alternating least squares (ALS) algorithms described by Kroonenberg and De Leeuw (1980) and Kroonenberg (1983a), in which the the technical aspects of the algorithms are dealt with. Detailed investigations into the quality and formal properties of ALS-estimators have not yet been undertaken (see Kroonenberg, 1983a: 66-67, for an outline of this problem).

Three-mode principal component analysis has thus far mainly been developed and applied by psychologists, and has seldom been used in organizational research. Studies known to us, which have used the technique in the form described by Tucker, and which refer in some way to organizations, are the following: Frederiksen et al. (1972) in their analysis of behavior of managers in various situations, Algera (1980) and Zenisek (1980) in job satisfaction studies, and Cornelius et al. (1979) in a job classification study for the U.S. Coast Guard. All these studies investigate phenomena *in* organizations, but no studies using three-mode principal component analysis or factor analysis are known to us that deal with research *on* organizations.

In this article the emphasis is almost exculsively on the use of three-mode analysis in longitudinal research. The technique has, however, far wider applicability than in just this field, but its application in sociology is rare. Data structures such as (dis)similarity data, profile data, growth curves, replicated correlation or covariance matrices, interactions in contingency tables, and interactions originating from three-way analysis of variance have been successfully treated with three-mode principal component analysis (see Kroonenberg, 1983b, for an almost complete bibliography, which also includes the above-mentioned studies).

DATA AND RESEARCH QUESTIONS

In order to gain some insight into the growth and development of large organizations, Lammers (1974) collected data on 22 organizational characteristics of 188 hospitals in the Netherlands from the Annual Reports of 1956-1966. Virutally all hospitals in the Netherlands were included in this study with the exception of University hospitals, which differ in many respects from other hospitals in the Netherlands; also excluded are clinics that only treat one or a few related diseases, for example, eye hospitals. In total, 40 hospitals were not included in this study. Lammers (1974) gives an extensive rationale for the selection of the variables in this study. Unfortunately, that part has never been formally published and is only available in Dutch. As the data are mainly used here for illustration, we will only give a very short description of them without treating the selection process in detail.

When one defines organizations as social units that seek to fulfill explicitly defined goals by division of labor and by coordinating their activities, it seems that in a study investigating the growth and development of organizations one should at least include variables such as those dealing with task differentiation (T), functional specialization (F), coordination (C), and those related to the overall size of the organization (S). In Table 1 the specific variables are given with their categorizations (for further details on data preparation, see Appendix), mnemonics, and their a priori classification into the categories mentioned above.

The main purpose of the investigation was to describe the growth and development of the hospitals as a group. It was, of course, of particular interest which variables were most important in this respect. Univariate information is contained in Lammers (1974), and here we will only look at multivariate aspects of the data. In particular, we want to answer the following questions:

(1) What is the overall organizational structure of hospitals, and is this structure the same for all hospitals?
(2) Which trends can be discerned with respect to the structural organization of the hospitals?
(3) Do different kinds of hospitals exhibit different structural trends?

RESULTS FROM THREE-MODE COMPONENT ANALYSIS

To answer these questions we will first have to decide upon the "most appropriate" analysis for these data. After this has been determined, we will look at the component loadings for the three modes, followed by an examination of the core matrix. In the discussion we will answer the three questions explicitly.

Choice of solution. Before going into a substantive discussion of the analysis and results, some preliminary issues have to be dealt with. First, in preliminary analyses (see Kroonenberg, 1983a: ch. 11 for details) using all available 22 variables (see Table 1), a number of them did not fit well into the overall structure defined by the other variables—the ratios Rushing's (1967) index (RUSH), ratio of qualified nurses (QUAN), ratio of nurses inside/outside the wards (WARD)—and the variables with small ranges—economic director (ECON), openness (OPEN), and research capacity (RESC). It turned out that the fit of these variables, as measured by equation 12, is none too good: RSS(Fit) was .26, .09, 12, .08, .05, and .45, respectively, indicating that they do not fit the model as determined by the other variables. From the original data it can be seen that the ratios are more variable and probably less reliable than most other variables, which might explain their bad fit. The other three variables probably suffer from their restricted ranges (2, 3, and 3 response categories, respectively), the more so because their distributions are skewed

TABLE 1
Variables, Categorizations, and Types

nr	mne-monic	variable	categories	varia-ble type
1	TRAI	*training capacity*	number of training facilities	T
2	RESC	*research capacity*	1: no research or experiments 2: radio-active isotope research *or* animal experiments 3: radio-active isotope research *and* animal research	T
3	ECON	*economic director*	present or absent	C
4	FACI	*facility index*	number of facilities such as laboratories and libraries	S
5	WARD	*ratio qualified nurses inside/outside wards*	1:0.00-0.99 5:4.00-4.99 8:7.00-7.99 2:1.00-1.99 6:5.00-5.99 9:8.00-8.99 3:2.00-2.99 7:6.00-6.99 10:none outside wards 4:3.00-3.99	C
6	QUAN	*ratio qualified nurses/total number of nurses*	1:0.01-0.30 3:0.41-0.50 5:0.61-0.70 2:0.31-0.40 4:0.51-0.60 6: > 0.70	C
7	FUNC	*number of functions*	1: 1-10 3:16-20 5:26-30 7: > 35 2:11-20 4:21-25 6:31-35	F
8	STAF	*total staff*	1: 1- 50 6:251-300 11:501-550 2: 51-100 7:301-350 12:551-650 3:101-150 8:351-400 13:651-750 4:151-200 9:401-450 14: 750 5:201-250 10:451-500	S
9	RUSH	*Rushing index*	spread of work: $\text{RUSH} = 1 - \frac{\Sigma x^2 \;/\; (\Sigma x)^2}{1 - (1/N)}$ (x = number of people having a function, N = number of functions) 1:.00<R<.80 4:.84≤R<.86 6:.88≤R<.90 2:.80≤R<.82 5:.86≤R<.88 7:≥ .90	F
10	EXEC	*executive (managerial and supervising) staff*	1: 1- 5 4:16-20 7:31-35 2: 6-10 5:21-25 8:36-40 3:11-15 6:26-30 9:>40	C
11	NMPR	*non-medical professionals*	number of pharmacists, psychologists, etc.	F
12	CLER	*clerical staff*	1: 0 3: 6- 10 5: 16- 20 7:> 30 2: 1- 5 4: 11- 15 6: 21- 30	C
13	PARA	*paramedical staff*	1: 0 5: 16- 20 9: 41- 50 2: 1- 5 6: 21- 25 10: 51- 60 3: 6-10 7: 26- 30 11:>60 4: 11-15 8: 31- 40	F
14	NMED	*other non-medical staff*	1: 1-10 4: 51- 70 7:111-150 2: 11-30 5: 71- 90 8:>150 3: 31-50 6: 91-110	F
15	NURS	*total number of nurses*	1: 1-25 4: 76-100 7:151-175 10:>300 2: 26-50 5:101-125 8:176-200 3: 51-75 6:126-150 9:201-300	S
16	BEDS	*total number of beds*	1: 1-50 4:151-200 7:301-400 2: 51-100 5:201-250 8:401-600 3:101-150 6:251-300 9:>600	S
17	PATI	*total number of patients*	1: 1-1000 5:4001-5000 8:7001-8000 2:1001-2000 6:5001-6000 9:8001-9000 3:2001-3000 7:6001-7000 10:> 9000 4:3001-4000	S
18	OPEN	*openness*	closed/partly closed/open to consulting physicians from non-affiliated specialists	C

TABLE 1 Continued

nr	mne-monic	variable	categories	variable type
19	MCSP	*main clinical specialisms*	number of specialisms	T
20	MPSP	*main polyclin. specialisms*	number of specialisms	T
21	CSUB	*clinical subspecialisms*	number of specialisms	T
22	PSUB	*polyclin. subspecialisms*	number of specialisms	T

NOTE: T = task differentiation; F = functional specialization; C = coordination; S = size.

as well. As a referee remarked, these discrete variables do not satisfy the assumptions of the model (see, also, the Appendix). On the basis of these observations it was decided to eliminate the above six variables from the analyses to follow.

The second issue is the proper choice of the number of components. Due to the simultaneous estimation of all parameters in the three-mode model, only the user-specified numbers of components for each mode are available from a single analysis, whereas in (two-mode) principal component analysis, usually the contributions of all components are available. This prohibits the use of criteria such as Cattell's scree test. The situation is even more complicated because solutions with different numbers of components are not nested; that is, allowing for an extra component in one mode does not only affect the other components in that mode but also the components in the other modes. When the data are well-structured, this lack of nesting is not always noticeable, or problematic, but it makes developing simple guidelines for choosing an adequate number of components rather difficult. The most reasonable strategy, therefore, seems to be to compare the results from several analyses, and decide on this basis how many components to retain. In Table 2 the *variations* or sums of squares accounted for by the components in several solutions are given. The lack of nesting can be seen clearly, illustrating the problem of the "proper" number of components. On the basis of Table 2 a 3 ×

TABLE 2
Variable Space

Nr	Variable	Mne-monic	Type	Components 1	Components 2
8	Total staff	STAF	S	29	-13
15	Total number of nurses	NURS	S	29	-10
14	Other non-medical staff	NMED	F	29	- 7
16	Total number of beds	BEDS	S	29	- 6
17	Total number of patients	PATI	S	28	- 3
12	Clerical staff	CLER	C	28	- 4
13	Paramedical staff	PARA	F	28	- 8
1	Training capacity	TRAI	T	26	5
7	Number of functions	FUNC	F	26	8
10	Executive staff	EXEC	C	25	3
4	Facility index	FACI	S	25	- 1
21	Clinical subspecialisms	CSUB	T	23	2
22	Polyclin. subspecialisms	PSUB	T	22	18
11	Non-medical professionals	NMPR	F	22	-20
19	Main clinical specialisms	MCSP	T	11	62
20	Main polyclin. specialisms	MPSP	T	5	69
	Percentage explained variation			68	8

NOTE: Decimal points omitted for components (29 = .29). Nr is number of variable in Table 1. Variable types: S = size; F = functional specialization; C = coordination; T = task differentiation.

2 × 2-solution—that is, 3 components for hospitals, 2 for variables, and 2 for points in time—seems to be a reasonable choice.

Variables (Mode B). The first two principal components of the variables (Table 3) account for 68% and 8% of the total variation

TABLE 3
Comparison of Various Solutions

Type of Solution	Relative Fit: Overall	Mode A 1	Mode A 2	Mode A 3	Mode A 4	Mode B 1	Mode B 2	Mode B 3	Mode C 1	Mode C 2	Mode C 3
22 Variables											
2x2x2	.56	.49	.06	-	-	.50	.06	-	.55	.004	-
3x3x3	.61	.49	.06	.05	-	.50	.06	.05	.61	.005	.0001
16 Variables											
2x2x2	.71	.67	.07	-	-	.68	.07	-	.71	.005	-
3x2x2	.76	.64	.07	.05	-	.68	.08	-	.71	.05	-
3x3x2	.76	.64	.07	.05	-	.68	.08	.007	.71	.06	-
4x2x2	.76	.64	.07	.05	.006	.68	.08	-	.71	.06	-

NOTE: An M × P × Q solution: M components mode A; P components mode B; Q components mode C. Relative fit = SS(Fit)/SS(Total).

as measured by the sum of squares of the data points. The first component reflects that overall size of the organization is the overriding characteristic for the variables. The component size is, in fact, indicated by variables from all a priori classes, such as number of beds (BEDS-S), total staff (STAF-S), clerical staff (CLER-C), other nonmedical staff (NMED-F), and training facilities (TRAI-T). Variables strongly deviating from this pattern are main clinical specialisms (MCSP-T) and main polyclinical specialisms (MPSP-T). Together they dominate the second principal component, indicating that independent of size, hospitals may have more or less main specialisms, and therefore this component will be referred to as "range of (medical) specialisms."

It is noteworthy that we have only been able to recover partially the a priori classification of the variables (see Table 1). The variables indicative of the overall size of the organization align nicely with the first component. The task differentiation variables MPSP and MCSP define the second axis, but CSUB, PSUB, and TRAI, which are in the same group, side mainly with size. The coordination variables and the functional specialization variables seem to indicate primarily size again. Thus the a priori distinction between classes of variables received only limited support from the data.

Time (Mode C). Note first of all that the first trend or time component explains 71% of the total variation, whereas the second trend explains some 5% (see Table 4). The first component is much larger because it reflects strongly the overall scoring level of the hospitals. It indicates, therefore, something like the overall average size of the hospitals taken together at the same time point. Such an overall level factor tends to dominate deviations from this level. After all, most organizations like hospitals do not vary widely in size as a group. On the other hand, it is exactly the differences between years that are the subject of our inquiry. The nice ordinal arrangement of the years (information that is not explicitly used in the analysis) suggests that in the data, systematic relationships exist with time.

As alluded to above, the first trend can best be described as "level," which is very stable; that is, the overall structural organization remains the same except for a slight increase in the first years (say 1956-1959). The second trend, "gain," shows a very steady increase, which may be superimposed on the overall level. One may expect such components are these from longitudinal data showing a simplex-like structure in the time mode, be it that the relative importance of the components depends on the relative sizes of the values in such matrices. The strong first component indicates that level is far more important than change, and that there will only be a small drop-off in the corner of the simplex-like structure. The correlation matrix of the time mode (not shown) indicates this very clearly, as do the correlation matrices of the separate variables.

Hospitals (Mode A). To represent the hospitals adequately, we needed three components, accounting for 64%, 7%, and 5% of the total variation, respectively. (Coordinates of the hosptials are too voluminous to display in a table, but may be obtained from the first author.) To interpret the hospital space, it must be remem-

TABLE 4
Components of Time Mode

Year	Components 1	Components 2
1956	.27	-.50
1957	.29	-.39
1958	.29	-.30
1959	.30	-.22
1960	.31	-.08
1961	.31	.00
1962	.31	.11
1963	.31	.17
1964	.31	.28
1965	.31	.37
1966	.31	.45
% explained variation	71	5

bered that the hospitals are the observational units. One cannot properly speak, therefore, of dependencies between hospitals. The hospital components are based on "profile similarities." Hospitals with similar scores on variables, thus with similar profiles, have similar loadings on the components. The explanation of the structure in the hospital space thus has to be made via the variables.

The labeling of components of observational units (here: hospitals) requires some extra care. It seems logical to describe the components in terms of the variable characteristics, and this is what is commonly done in standard principal component analysis. With that technique it is a natural way to proceed because the variable and hospital components have a one-to-one relationship. As mentioned above, in three-mode component analysis this relationship is no longer one-to-one, and it is therefore desirable to designate the hospital components more or less independently of the variable components. In some cases external information on the observational units may be used to label the axes. Lacking such information the hospitals can be best described by defining "idealized hospitals" (Tucker and Messick, 1963; Cliff, 1968), "genotype hospitals" (Lammers, 1974), or "hospital Gestalts or archetypes" (Miller, 1981; Miller and Friesen, 1980). All real hospitals are then taken to be linearly weighted combinations of such (geno)types. To describe such types, however, we need to know how the three types came about; this information is contained in the core matrix, to which we turn next.

Interactions between components—core matrix (G). To investigate the different hospital types and to assess possible structural changes with respect to the variables, it is necessary to take a detailed look at the core matrix G. For the present discussion we chose to present the three-mode core matrix as three (2 × 2) matrices, one for each hospital component (Table 5). The g_{mpq} represent the combinations of the m^{th} component of mode A (hospitals), the p^{th} component of mode B (variables), and the q^{th} component of mode C (time). Furthermore, g^2_{mpq}/ SS(Total) is the proportion explained variation by the combination of components; for example, the combination of the first components of all modes, g_{111}, explains $145^2 / 33088 = .63$ of the total variation in the data (which was rescaled without loss of generality by the program to $188 \times 16 \times 11 = 33088$). In the following paragraphs we will discuss each core plane corresponding to a hospital type in turn.

TABLE 5
Core Matrix

	Hospital Type					
	General		Specialized		Growth	
	Size	Range	Size	Range	Size	Range
Raw Core Matrix						
Level	145	-1	-0	-49	-0	-7
Gain	1	-7	-9	4	38	5
% Explained Variation						
Level	63.5	.0	.0	7.1	.0	.1
Gain	.0	.1	.2	.0	4.4	.1
Designation of elements						
Level	g_{111}	g_{121}	g_{211}	g_{221}	g_{311}	g_{321}
Gain	g_{112}	g_{122}	g_{212}	g_{222}	g_{312}	g_{322}

NOTE: Size = overall size of the organization; Range = range of specialisms.

The first type of hospitals is characterized by a high interaction of the size and level components (g_{111} = 145), indicating that hospitals with a (large) positive loading on the first hospital component have a large overall stable size, and hospitals with (large) negative loadings have a small, overall stable size. One might, furthermore, infer that the range-of-specialisms variables decrease slightly for the positively loading hospitals, and increase slightly for the negatively loading hospitals, and increase slightly for the negatively loading hospitals. However, the core element in question, g_{122} (= −7), is small, and its proportion of the total variation is a mere 0.1%. We will refer to the first type of hospitals as "general hospitals," indicating that they have the most commonly occurring profiles.

The second type of hospitals is characterized by their narrow range (or lack) of main specialisms (g_{221} = −49). The minus sign indicates that hospitals with high loadings on the second hospital component have relatively low scores on the main specialism variables. The other combinations of components (g_{212} = –9 and g_{222} = 4) indicate a decrease in size and an increase in range of specialisms for high-loading hospitals, but the proportions explaining variation (.002 and .000) are again very small. We will refer to the high-loading hospitals as "restricted hospitals" or "specialized hospitals."

The third type of hospitals is characterized by a high interaction between the size variables and the gain component (g_{312} = 38). It should be noted that no hospital loads negatively on the third hospital component, and thus no hospital decreases markedly in the size variables. The higher the loading, the larger the growth in size of the hospital. The other core elements (g_{321} = –7 and g_{322} = 5) suggest that the higher loading hospitals have a somewhat narrow range of specialisms, which increases somewhat over time, but again the effect explains a negligible amount of variation.

The core matrix as discussed above gives a very compact description of the major patterns in the data. As suggested by Tucker (1963; see above), one might also wish to be less compact and introduce more detail in the description. A first step would be to use the "core matrices for occasions," that is, the N_k of equation 5, and examine how each of the combinations of a component of mode A (hospitals) and a component of mode B (variables) evolves over time. Typically this can be done most instructively by plotting for each pair (m, p) the n_{mpk} against time (k = 1..K). The curves displayed in Figure 3 can be computed via equation 4, or one may directly estimate A, B, and the N_k from equation 3, as was done here using the first author's program TUCKALS2. In figure 3 all six combinations of components of mode A and B are plotted, but it is clear that only three combinations are really important. Comparison with Table 5 shows that these trends correspond to the three largest elements of the three-mode core matrix, as they should do. The interpretations given above for the various elements of the three-mode core matrix can be seen to agree with the core matrices for occasions, be it that the changes over time can now be studied in more detail.

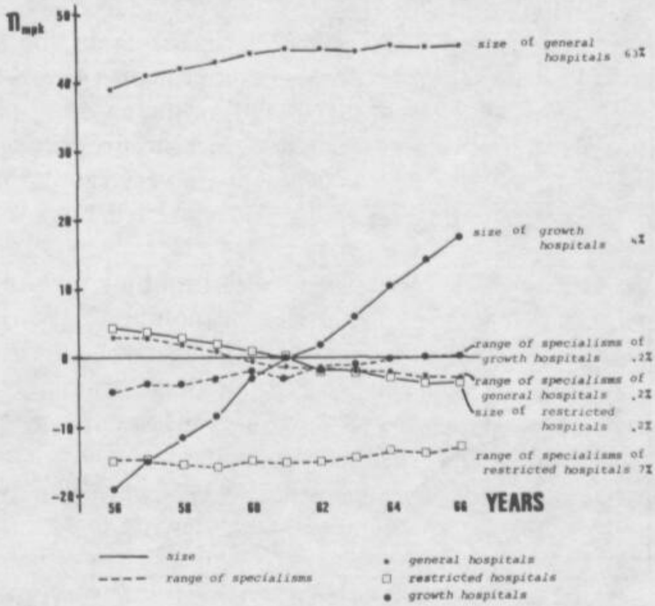
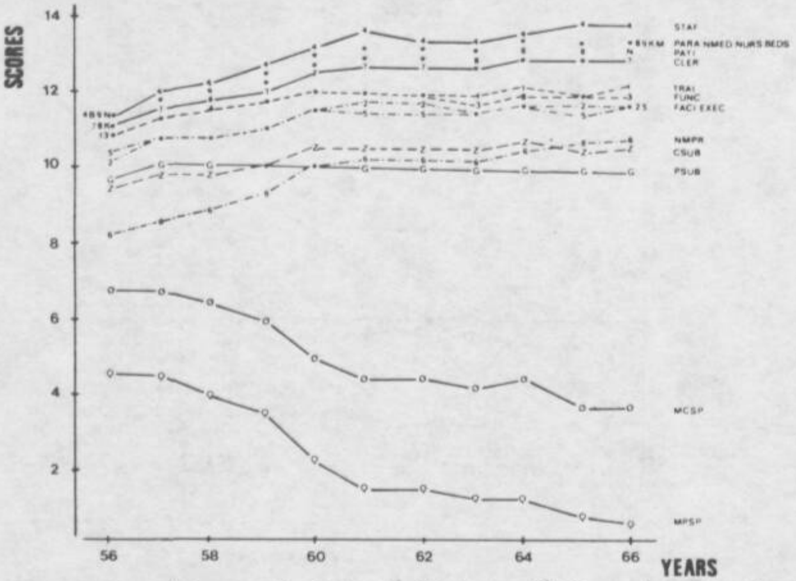


Figure 3: Trends for Hospital Types (based on core matrices for occasions)

It is especially the combination of one component of a particular mode with more than one component of another mode that is the strength of the three-mode approach. Here the component size is both combined with the general hospitals and with the growth hospitals, allowing for a separation of different patterns in the changes over time for different types of hospitals in the same variables.

As a following step we may introduce yet more detail by computing the trends of each variable separately for each type of hospital according to equation 8. In Figure 4 we show on the same scale for each type of hospital the changes in the variables over time. The trends in the variables are "smoothed" by applying the three-mode analysis compared to a direct plotting of the trends from the raw data. Moreover, we only need three plots instead of 188, that is, one for each hospital type, and the plots give more detail than the plots of the average scores on the variables. In

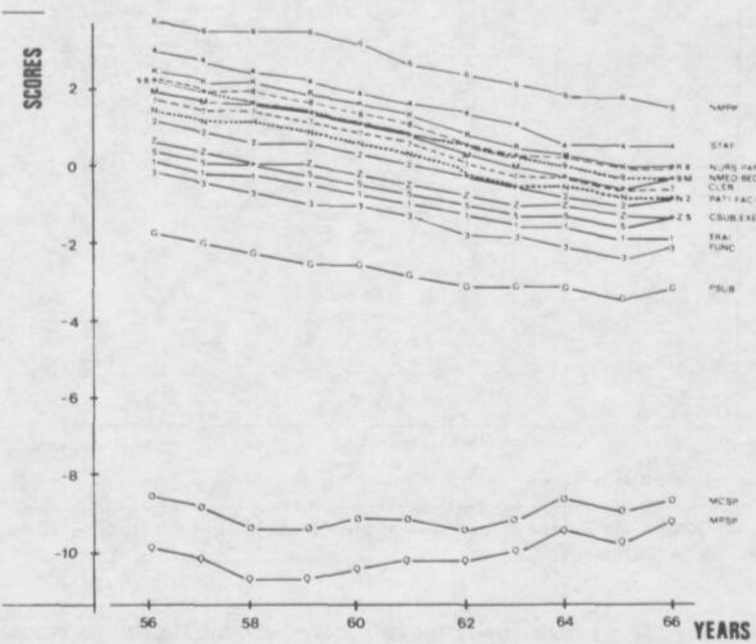


NOTE: TRAI—training capacity; FACI—facility index; FUNC—number of functions; STAF—total staff; EXEC—executive staff; NMPR—nonmedical professionals; CLER—clerical staff; PARA—paramedical staff; NMED—other nonmedical staff; NURS—total number of nurses; BEDS—total number of beds; PATI—total number of patients; MCSP—main clinical specialisms; MPSP—main polyclinical specialisms; CSUB—clinical subspecialisms; PSUB—polyclinical subspecialisms.

Figure 4a: Component Scores of Variables at Each Point in Time per Hospital Type: General Hospitals

looking at these plots it should be remembered that the component scores are still deviation scores.

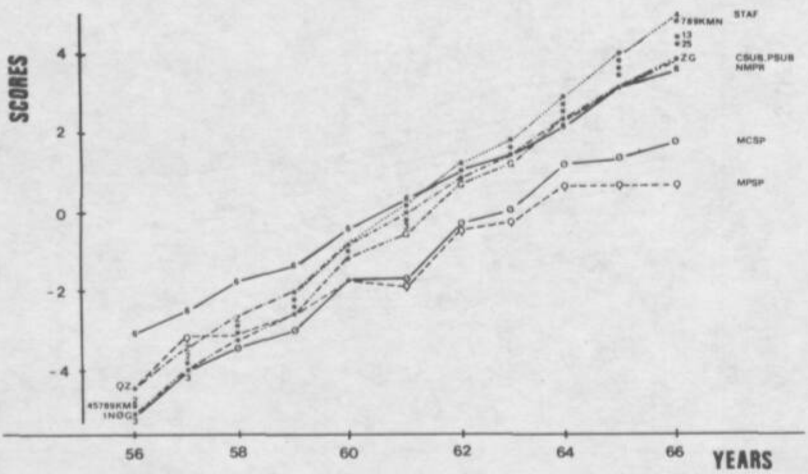
After looking at Figure 3 the major patterns are by now familiar: stability in the size variables for the general hospitals with a slight increase in the first years (see Table 4). Closer inspection, however, shows that the subspecializations do not follow this general trend in exactly the same manner; they tend to be more stable than the other size variables. The very small elements of the three-mode core matrix show up in these plots more explicitly than one would have expected from their small explained variation. For instance, g_{122} (= −7) indicated that the range of specialisms tended to become narrower, and in Figure 4A this is directly



See note to Figure 4a.

Figure 4b: Component Scores of Variables at Each Point in Time per Hospital Type: Restricted (or specialized) Hospitals

reflécted in the decline of the two main specialism variables. Similar statements and comparisons may be made for the behavior of the variables with respect to the other types of hospitals. Two remarks may be made with respect to the increasing detail of description by using equations 4 and 8. If a core matrix is very complex and difficult to interpret, one could go to more detailed levels of the analysis to understand what is happening. Likewise when no clear grouping of elements in a mode can be found to label the axes, one might forego this level of abstraction by dropping the component description, and go back to the original elements themselves, that is, to the variables, observational units, or occasions, while maintaining the smoothing effect of the three-mode analysis.



See note to Figure 4a.

Figure 4c: Component Scores of Variables at Each Point in Time per Hospital Type: Growth Hospitals

Joint plots and sums-of-squares plots. To investigate the relationships between the hospitals and the variables in yet another way, one may construct plots that simultaneously show hospitals and variables for each of the time trends. Such joint plots are constructed by adjusting the component loadings of the hospitals, and those of the scales via rotation and stretching of these components so that they may be meaningfully projected in the same space. The information on how the rotation and stretching should be performed for each time trend is contained in the core plane corresponding to the time trend; for example, $G_q = (g_{mpq} | m = 1,.., M; p = 1,..., P)$ is used to construct the joint plot for the q^{th} time trend (for further details see Kroonenberg, 1983a: 164ff). For the interpretation of these plots it is generally convenient to represent the elements of one mode (e.g., hospitals) by points, and those of the other mode (e.g., variables) as vectors through the origin. Hospitals with large projections on the positive side of a vector (variable) have high scores on that variable, hospitals with small projections near the origin have average scores (given the center-

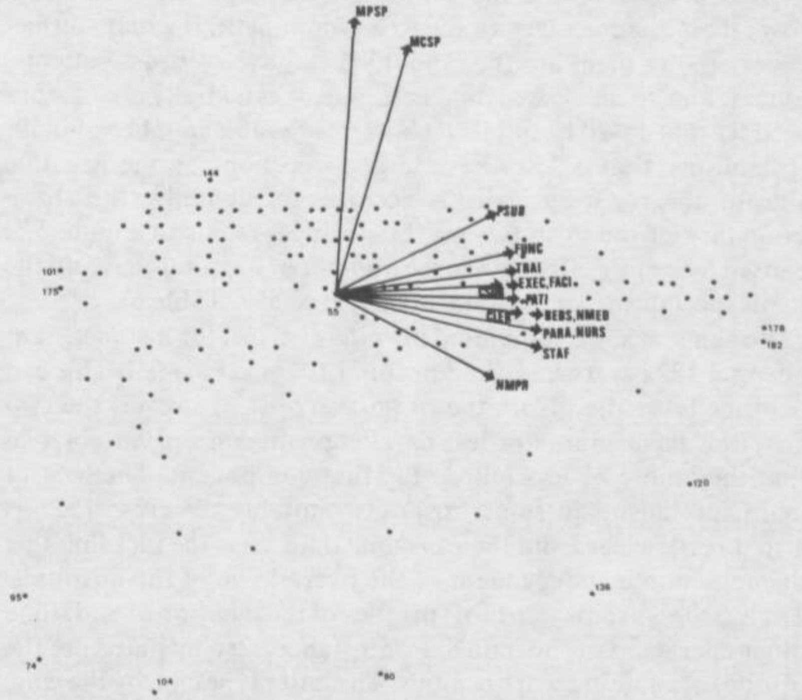


Figure 5: Joint Plot for Hospitals and Variables (based on first-time component-level)

ing used), and hospitals with large projections on the negative side of the vector have low scores on the variable.

In Figure 5 the joint plot of the variables and the hospitals are shown for the first time trend. Note that G_q is here a (3×2) matrix, and thus has rank two. This implies that the joint plot is two-dimensional and that the relative sizes of the elements in G_q determine how the three-dimensional hospital space is projected into the common space of variables and hospitals. Looking at G_1, it is clear that the axes are a rather faithful image of both the first two hospital and the two variable components, as g_{311} and g_{321} are rather small compared to g_{111} and g_{221}. Note by the way that Table 5 shows the (2×2) G_m, and that we slice the core matrix here into (3×2) G_q.

Most hospitals have more or less parallel profiles as follows from their alignments with the first component; the main differences among them are the amount they have of beds, patients, nurses, and so on. The second component essentially arises from the fact that 15-20 hospitals lack a considerable number of main specialisms, that is, they have large projections on the negative side of the main specialisms vectors. Incidentally, the sharp boundary of the hospitals on the positive Y-axis in Figure 5 is caused by ceiling effects: A large number of hospitals have all the main specialisms a hospital can have (see also Table 6).

Looking at some individual hospitals we see, for instance, that hospital 182 is very large and hospital 101 is very small. This can be directly verified from the original scores. However, the two hospitals have a more or less parallel profile on the variables so that they more or less fall on the first component. The lack of main specialisms in some hospitals—notably, 74, 104, 135—is also directly clear from their original data, as is the fact that this phenomenon is independent of the overall size of the hospitals. Table 6 shows some (parts of) profiles of the mentioned and some other characteristic hospitals. For instance, also included are the profiles of some growth hospitals. The latter type can, by the way, also be shown in a joint plot using the core plane G_q ($q = 2$) corresponding to the second time component. For the sake of brevity, it is not included here, but may be obtained from the first author.

To acquire further information on peculiarities of specific hospitals in comparison with the majority, it is particularly useful to inspect the degree to which the data of each hospital is accounted for by the model. This can be done via a so-called "sums-of-squares plot" (Figure 6), which allows comparisons between the fitted variation and the residual variation of each hospital (see equations 11 and 12). As an example, consider hospital 106, which has a reasonably large total sum of squares, but some 43% of this is not fitted by the model, which had an overall relative fitted sum of squares of 76%. Going back to the original data, it turns out that this hospital acquired in 1964 a (new) polyclinic as its number of polyclinical main specialisms went in that year from

TABLE 6
Characteristics of Selected Hospitals

	Hospital Type			Component			Variables*			
Nr.	Size	Range	Growth	1	2	3	BEDS	STAF	MCSP	MPSP
101	SMALL			-.12	-.02	.04	1	1	6	9
55	AVERAGE			-.03	-.05	.03	3	3	8	8
182	LARGE			.18	.04	.02	9	14	8	8
74	small	NARROW		-.13	.26	.10	1	1	3	2
104	average	NARROW		-.08	.28	.06	3	3	3	1
135	largish	NARROW		.08	.30	.08	8	11	3	3
142	average	WIDE		-.06	-.08	.06	3	3	8	9
5	average	wide	NONE	-.07	.08	-.00	3 3	2 7	8 8	7 7
28	smallish	average	FAST	-.09	.05	.13	1 3	1 3	1 8	5 9
115	average	average	FAST	-.01	.02	.19	3 6	5 13	8 8	9 9
60	large	wide	FAST	.09	-.03	.15	5 8	2 2	8 8	9 9

*Average over 11 years, or values in 1956 and 1966 maxima of variables: BEDS = 9; STAF = 14; MCSP = 8; MPSP = 9. Size = overall size of the organization; Range = range of specialisms.

0 to 7, and its polyclinical subspecialisms from 0 to 5; they stayed at this level in the next two years. Similarly, another very ill-fitting hospital, 105 (relative fit = .16), seems to have too few beds with respect to its total personnel in comparison with other hospitals. On the other side of the plot we find well-fitting hospitals such as 176 (relative fit = .93) and 182 (relative fit = .94).

OTHER APPROACHES

So far we have concentrated exclusively on three-mode principal component analysis as a means to analyze multivariate longitudinal organizational data. However, for a proper assessment of the technique in longitudinal analyses in general, it should be

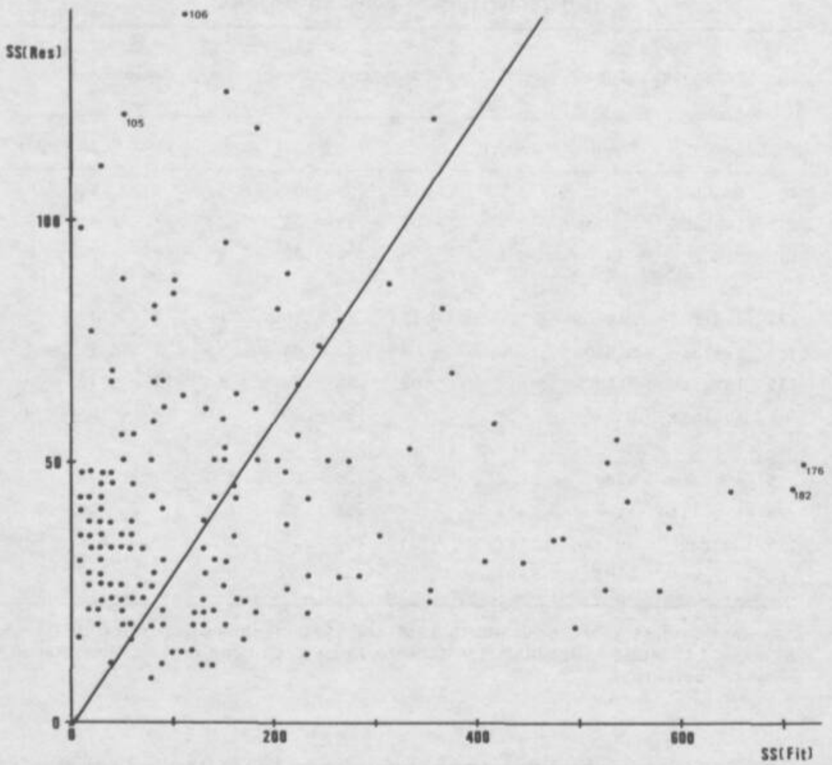


Figure 6: Sums of Squares Plot for Hospitals (line represents average relative fit)

placed in the context of other ways of dealing with multivariate longitudinal data.

The main interest with designs with many variables, many observational units, and rather few points in time focuses on analyzing correlational or covariance structures at each occasion, between occasions, or for all occasions simultaneously.

A distinction should be made between the "individual differences" techniques, such as three-mode principal component analysis, and the "statistical" approach using the theory of covariance structures by condensing over one mode (here: hospitals) and treating it stochastically. In fact, in situations with sufficient knowledge of substantive theory, given enough observational units and no indication of grave structural differences among them, the covariance structure approach (e.g., employed by Meyer, 1972) seems the ideal way to proceed. Theoretical papers dealing with longitudinal analyses via this approach are Jöreskog (1978, 1979), Jöreskog and Sörbom (1977), Bentler (1978, 1980), Lohmöller and Wold (1980), and Swaminathan (1984). When structural modeling breaks down, such as in the present example in which a 176 by 176 covariance matrix would have to be analyzed, more exploratory methods such as three-mode principal component analysis, and similar methods such as PARAFAC (Harshman and Berenbaum, 1981), can be extremely useful.

Traditionally, lacking the prerequisites for employing structural modeling, one had to make do with less powerful methods, such as common factor analysis and principal component analysis. Bentler (1973) and Visser (1985) discuss various proposals in this field. Compared to these techniques, three-mode principal component analysis has much to offer. In the first place, it is possible to derive one joint component space of the variables for the eleven years. There is no need to perform separate component analyses for each of the eleven years and compare the resulting spaces via matching techniques. Second, to derive the variable components, it is not necessary to condense the data over one mode, in this case hospitals; thus it is not necessary to assume a priori that hospitals are replications and that their scores are the result of repeated sampling from the same multivariate distributions. By keeping the three-mode data matrix as it is, differences among hospitals can be meaningfully analyzed along with the structure in the variables. Perhaps the greatest power of the present method is the summarization of a large amount of data by a very small number of parameters. In fact, one might say that the twelve numbers of the core matrix in Table 5 represent the most compact expression of what the data have to tell.

On the negative side it should be noted that a serious failing of most factor and principal component methods is that they do not include the most salient aspect of the research design—namely, time. The sequential nature of the data is only used to interpret the results and is not an essential part of the analysis.

Miller and Friesen (1981: 1021) cite as one of the problems of "Type 5" studies, which deal quantitatively with multivariate data of many organizations, that "there is rarely an attempt to build integrated dynamic models of the organizations being studied." Clearly the present technique is hardly suitable for model building and testing, although—at least in principle—it could be extended to incorporate restrictions on the configurations of various modes. On the other hand an exploratory analysis such as the present one can pave the way toward model building by assisting a judicious selection of variables, organizations, and years.

One of the dangers, for instance, with model building using only a few variables is the threat of specification error; that is, other factors that intervene between dependent and independent variables might be present. By first using a large-scale exploratory analysis, important variables can be assessed in their relationship with other possibly relevant variables. Using results from the exploratory study, the entire set of variables may be reduced and become more amenable for modeling with linear structural equations, a three-mode path analysis (Lohmöller and Wold, 1980), or via general linear models including both dependent and independent variables.

Similarly, three-mode analysis may be used to show whether there is structural continuity and (ir)regular change. Considering the stability in the present example, it is not necessary to include all the years in a further analysis, but a limited selection will suffice. At the same time, via the hospital components and the sums-of-squares plot we have found out which hospitals we would like to include or exclude from further analyses. Especially badly fitting hospitals might be excluded because they could confuse the main issues by introducing large error variances.

DISCUSSION

The substantive results will be summarized by answering the three research questions posed above. First, the majority of the organizational variables have large positive correlations, which are assumed to have arisen from their dependence upon the overall size of the organizations. Excluded from this pattern are the numbers of clinical and polyclinical main specialisms, which vary independently from the sizes of the hospitals. This structure is valid for all hospitals in as far as the model provides an adequate fit to their data. The majority of the hospitals are primarily characterized by their scores on the size variables whereas some 15 to 20 hospitals stand out due to their lack of main specialisms. With respect to the developments over time, one may say that the general trend is that large hospitals stay large compared to the small ones and vice versa. Furthermore, the hospitals lacking a number of main specialisms do not tend to catch up with the other hospitals. Superimposed on this general picture of stability is a small but not negligible growth component that is manifest more in some hospitals than in others, and the growth tends to concentrate more in the size variables than in the main specialisms.

Formulated in this way, the results may seem rather crude, revealing only very large-scale patterns. This is indeed true, but it has to be remembered that a large amount of data had to be summarized; this leads nearly automatically to large-scale conclusions. Moreover, intermediate levels of summarization can be derived on the basis of the three-mode results via the core matrices for occasions, and the component scores. In addition, the analysis provided a large number of indications of where to look for interesting details about individual hospitals and separate variables. Finally, it should be remembered that the variables are not the only ones that an organizational sociologist would like to select to get a grip on the dynamics of change in hospitals. Official data in the pubic domain that are comparable over hospitals do, however, not often consist of all the interesting variables in this respect. Miller and Friesen (1980) used a far larger and possibly more relevant data base in their investigation into a large sample of organizations. This is probably what would be needed for a more in-depth and theoretically richer study into hospitals as well.

APPENDIX

PRELIMINARIES TO THE THREE-MODE ANALYSIS

The 22 variables that were the starting point for this study form a rather mixed set; for example, economic director (ECON) is a dichotomy, openness (OPEN) is a trichotomy, WARD, QUAL, and RUSH are ratios, and the majority are counted variables. As three-mode principal component analysis in its present form is in principle designed for metric data, it is not directly advisable to include such variables in a single analysis, especially not the discrete ones. In the present case it was attempted to keep all variables in the analysis because of their substantive interest, but, as we have seen, neither the discrete variables nor the ratios fitted very well in the structure defined by the other variables. In fact, they might even have obscured some interesting trends.

Some of the variables were categorized into roughly ten intervals with increasing length for the last few categories. This had the effect of removing some of the skewness from a number of counted variables (a log-transformation could have served the same purpose), facilitating visual inspection of the trends in the data, preparing the data for other analyses requiring a limited number of data values, and allowing for easy missing data substitutions. The categorization, details of which are given in Table 1, will, of course, obscure small differences, but this should not be important in the three-mode analysis. An unfavorable effect of the categorization with larger ranges for the higher categories is that the growth component for some variables may be underestimated. On the other hand, it was felt that the marginal utility of a unit is decreasing when increasing number of units are available.

The TUCKALS programs used do not allow for missing data; therefore, values had to be substituted for the 29 missing data (Weesie and Van Houwelingen, 1983, have developed another algorithm and program to allow for missing data). Using the time series of a variable for an individual hospital, the missing values were interpolated by eye and rounded to the nearest integer. The categorizations made such interpolations very simple; for the raw data specific, say regression, procedures should have been employed.

To investigate the linearity of the bivariate relations among the variables, the data were analyzed using a multivariate nonlinear procedure, HOMALS-homogeneity analysis (Gifi, 1981) for each year separately, and for all years together. The main result of these analyses was that the assumption of linearity in the bivariate relationships of the categorized variables was generally tenable, and it was, therefore, assumed that no gross misrepresentations would occur when the categorized variables were used in the three-mode principal component analysis as reported in this article.

A final operation that is necessary is to remove unwanted effects of differences in means of the variables, and of differences in scale. Such preprocessing is almost always necessary before a three-mode analysis is attempted (see Kruskal, 1984; Kroonenberg, 1983a: ch. 6; Harshman and Lundy, 1984). Here variables were standardized over the 11 × 188 years-hospital combinations; that is, each variable was transformed to have zero mean and unit standard deviation. It should be noted that the purpose and procedure of the present standardization is somewhat different from the procedure in regression analysis. In regression analysis, sometimes standardization is performed per occasion (a procedure much criticized by, for example, Blalock, 1967), whereas here standardization was performed over all points in time together, thus maintaining differences in mean and scale per variable between occasions. The sole purpose of the procedure was to avoid differences in mean and scale—which cannot be meaningfully compared between variables—from being removed. Components influenced by such differences cannot be meaningfully interpreted.

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