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Chapter 21:

MULTIVARIATE DATA-ANALYSIS METHODS IN BIBLIOMETRIC STUDIES OF SCIENCE AND TECHNOLOGY

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Summary

In the past decades quantitative studies in social and behavioral sciences have benefitted both in range and depth from the application of statistical methods, more in particular the multivariate analysis (MVA) methods. These methods are called for when assessing quantitative relations between two or more units of analysis. MVA methods have also become increasingly important analytic aids in large-scale bibliometric (i.e. quantitative, scientific literature-based) studies of science and technology. This paper centres on basic possibilities of this analytic toolkit for this type of studies. An introductory non-mathematical overview is presented for important subclasses of MVA methods suitable for the analysis of multivariate bibliometric data. Section 1 starts with a brief general account of the relevance of bibliometric studies followed by argumentation to justify a structured overview of applicable MVA methods in such studies for those who are unfamiliar with MVA. In Section 2 we continue with a sketch of the role of data-analysis methods in general within this type of studies. Section 3 begins by presenting some data, obtained from scanning articles in bibliometrics-oriented journals, to give an indication on the extent of MVA-usage in bibliometric research articles during the last decade. This introduction is followed by a discussion of some basic properties of multivariate data in general and an outline of a conceptual framework of bibliographic information encompassing all general types of multivariate bibliometric data-arrays. Section 4 is used for classification of general classes of MVA methods based on the

previously discussed inherent properties of MVA and user-imposed constraints on multivariate data. This section is primairily meant as a preliminary to Section 5 in which we present a classification of MVA methods which figure prominently in bibliometric studies. This is followed by synopses of subclasses of MVA methods and the general types of data they can be applied to. In addition, this structured overview is larded with more recent bibliometric applications of this methods. Subsequently, Section 6 contains an illustrative application of two of the discussed MVA methods, as an addition to the basic data as given in Section 3, thus yielding a more detailed insight in the magnitute and trends with respect to the usage of separate MVA methods in bibliometric studies. Finally, in Section 7 we draw some general conclusions and advance our views on the prospects of MVA in bibliometric S&T-studies.

1. Introduction

1.1 The bibliometric approach in science and technology-studies

Products of scientific work has always attracted its share of attention from laymen as well as fellow scientists, but particularly from the funding patrons. In the past decade, in which economic recession and science policy-considerations has led to constant or decreasing budgets, whereas research has become more capital intensive, the urge of funding agencies to assess research performance and identify promising new areas has become urgent. This required routinely evaluating and monitoring the distribution of available funds by both S&T-policy and R&D-management. Accountable decisions on allocation of resources based on expert opinions solely were considered to be possibly not fully adequate. Consequently, the need for readily available analytic tools ('S&T indicators') to assess policy relevant aspects of scientific research and support expert judgement became an important issue. In addition to input indicators based on data with respect to expenditure, number of researchers, equipment etc., data was required for indicators of scientific performance in terms of the output and 'impact' of scientific research. An emphasis has been put on the structure and transfer of information, as embodied by manifest contributions to scientific knowledge, usually in the form of formal printed communications, i.e. research documents such as conference proceedings and publications in professional scientific journals in case of basic science, and patents for technology.

Patents and journal articles are considered to be the major communication-channels for presenting original scientific findings and dissemination of scientific knowledge and their counts serving as an indicator of scientific production. This transfer of knowledge is partly traceable via the so-called 'citation-process', i.e. the flow of information as given in reference lists through which most authors of scientific publications acknowledge certain prior formal and informal communications by the issue of references ('explicit citations'), and in turn they can be cited in future publications. Citation counts are specifically meant to cover the 'impact' of scientific documents on the scientific community. Both the number of scientific publications as well as the number of citations to scientific communications are referred to as bibliometric[1] output-measures of scientific activity. Bibliometric measures (and policy relevant indicators derived thereof) have proved to be a fruitful aid in so-called 'scientometric' assessments[2], capable of providing information on various scientific activities, especially with respect to basic research in the natural and life sciences. Bibliometric assessments of research in the social sciences and humanties and the more applied areas of science such as industrial and technological applications, often suffer from coverage-problems as a result of incomplete or inadequate data on publications or patents, due to factors such as non-journal publishing habits and the decreasing reliance on references as a mode to acknowledge intellectual debts. Inspite of such limitations in range of application as well as the inherent problems with respect to validity and reliability of publication-, citation- and co-citation counts, bibliometric analysis has become a widely used research method for evaluating and monitoring scientific outputs and analyzing (inter)relations between scientific entities, constituting an important assessment aid from both a science-policy and a S&T-studies perspective. The main reason for utilization is found in the fact that bibliometric units of analysis are nevertheless useful objects of study, since they are both (relatively) unobtrusive and offer readily available raw material for a comparative quantitative analysis of scientific activities (cf. Narin and Moll, 1977).

An important incentive in the development toward science-policy aided application of bibliometric data was the - now institutionalized - utilization of bibliometric science-indicators in monitoring national science activities as presented in the biennial U.S. Science Indicators Reports (NSF, 1985). The use of bibliometric measures to assess performance of scientific entities was also stimulated by the emergence of - relatively easily accessible - bibliographic databases with readily available quantifiable (citation)data on scientific publications, in particular the advent of the Science Citation Index (SCI) in the late sixties[3]. The developments in SCI databases in more recent years and the introduction of other computerized documentation services now offer a more complete and in-depth coverage of scientific literature.

1.2 Multivariate analysis of bibliometric data

The developments in bibliometrics during the last two decades has given rise to a trend to utilize bibliometric data for detailed and/or large-scaled assessments of structure and dynamics of (fields of) science. These advances in the application of quantitative methodology is perhaps particularly marked by the increasing sophistication in the use of statistical methods to analyze bibliometric data. This trend is particularly evident when regarding the utilization of the class of multivariate analysis methods (e.g, methods such as Cluster Analysis and Multidimensional Scaling), which are designed for a descriptive or inferential analysis of quantitative data which consists of more than one distinct measurement (hereafter referred to as a variable) on each analysis unit.

In general, a researcher is primarily interested in finding a MVA method which gives an answer to a specific research question. Depending on the nature of the bibliometric analysis the researcher or data-analyst may consider one of the MVA methods for the data analysis. Past experiences, personal preferences and, above all, the direct availbility of standard techniques will generally tend to govern the choice of the method(s) applied. However, an extensive search of the (most) appropriate method is often neglected by researchers; they neither have MVA expertise, time, energy or interest for a thorough comparison of the pros and cons of specific methods, although a better suited MVA method will yield a more accurate or more complete answer to the research question. This is particularly unfortunate, because the effort may well pay off in the application of (newly developed) a more appropriate or additional MVA methods. A thorough investigation of the possibilities might even lead to the conclusion that two or more MVA methods are in fact useful and one may thus profit by applying several related MVA methods yielding 'complementary' or 'convergent' analysis results. A systematic investigation of MVA methods is certainly feasible and can even be relatively simple to perform if one considers the fact that each subclass of MVA methods has its own distinctive features and its own type of data to which it can be applied. The appropriateness of a specific class will primarily be determined by (a) the analysis goal(s) and (b) the type of data one has collected. Both aspects will be discussed in following subsections. In a sense each aspect poses a number of questions to the bibliometric researcher. The answer(s) to subsequent questions will determine the permissible (sub)classe(s) of MVA methods and eventually leads to one or more suitable MVA methods. Such an approach can thus serve as a general guide in finding the most appropriate (subclass of) MVA methods. A taxonomy of MVA methods in the form of such a decision-tree is presented in Section 5.

2. Quantitative analysis of bibliometric data

The general goal of quantitative data-analysis is to provide a discription of data which is sufficiently sparse, that is, characteristics of the data are reduced to a relatively small number of parameters. These derivates of the analysis - as well as, for example, rankings or graphs - must at least describe the underlying structure sufficiently adequate to warrant further practical use. If possible these parameters should lead to, or should be fitted into, a theoretical body or scientific theory. As such (MVA) analysis results can thus contribute in a further development of a bibliometric model of 'science'. Historically, bibliometric data-analysis started by simply counting publications and/or the citations, e.g. determining how many citations have been received by specific scientific entities over a certain period of time (e.g. Cole and Eales, 1917; Lotka, 1926). These now classical studies were in fact first attempts to quantify scientific activity and in fact represent the beginnings of a quantitative model of science. In the decades to follow, numerous additional formalized features were added to this bibliometric model, e.g. the Bradford curve to describe the distribution of publications on a given research topic in scientific journals (Bradford, 1948). Findings from a growing number of studies (cf. Elkana et al., 1978) have shown that bibliometric measures derived from this quantitative model have the potential to serve as relatively objective indicators of scientific activities. Moreover, several applications have in fact given evidence that these indicators are useful tools in evaluating S&T-activities, ranging from university departments (Moed et al., 1985), industrial companies (Koenig, 1983a) to entire nations (Martin and Irvine, 1985).

In the present state of affairs, with an increasing magnitute and complexity of science as both a social and cognitive structure of knowledge, the need for more , and more detailed, information on characteristics of the scientific process, has also placed its demands on the analytic tools used in bibliometric studies. This is reflected in the increasing degree of sophistication of data analyses - both in terms of precision and greater applicability - not only with respect to the number of different scientific entities involved, but also the number of (quantified) facets of these entities. Consequently, a considerable methodological development has taken place in the field of bibliometric analysis to provide the tools needed. This process is marked by the development and application of more sophisticated (semi-)automatic methods to derive useful bibliometric data and statistical methods to analyze it. In general, the scale and complexity of data in present-day bibliometric studies, as well as the necessity to apply MVA methods has given rise to an increased use of computers. As an illustrating example of the developments sketched above, consider the following hallmarks in the history of computational methods to derive journal-citation rankings. Gross and Gross (1927) were pioneers in a citation-based grading of scientific journals. Their rather crude method involved a manual collection and counting of the number of citations given to the journal. Their analysis approach can, in a sense, be described as univariate statistical analysis, because only one variable - the citations - is entered into the analysis. Many years later, Garfield (1972) computes the so-called impact factor (IF) of a journal. This measure is defined as the number of citations given to a journal in a certain year for publications from the previous two years, inversely weighted by the corresponding number of publications in those two years. This simple data-analysis method incorporates both citations and time as variables and can thus be described as bivariate statistical analysis. The necessary data were now automatically retrieved from a computerized bibliographic database. As a further computational refinement, Pinski and Narin (1976) developed the so-called influence weight (IW) for each journal, which can be seen as a multivariate extension of Garfield's IF. The derivation of IW-values involves an iterative computation based on both the cited and citing structure amongst journals. Such a computational method which concerned with the simultaneous analysis more than two variables is generally designated as a multivariate statistical - or multivariate data analysis method. Pinski & Narin's-approach is also exemplary for MVA because it requires a computer in order to analyze the whole of interrelationships between the variables.

3. Multivariate data analysis

3.1 Introduction

The general aim of MVA methods is to provide a parsimonious and simultaneous representation of relations between multiple variables made on each scientific entity within a common set of entities. Such methods are thus an alternative to subjecting data to a series of univariate or bivariate analyses. MVA methods are especially apt to obtain information on the underlying structure, or on specific regularities or patterns, of simultaneous relationships among three or more variables which are (inter)related with each other in varying degrees. The majority of the more sophisticated MVA methods have been developed within the social and behavioral sciences, including the subdisciplines econometrics and biometrics. In recent years MVA methods have seen wider acceptance and use in almost all subject fields of scientific research. The large-scale accessibilty to computers and the wide-spread availability of statistical software packages, such as BMDP (Dixon et al., 1981), SAS (1982) and SPSS (1986), has caused a spur in the application of MVA methods in many scientific disciplines in the 60's and 70's, while leveling-out or stabilizing in the 80's.

Figure 1 gives an indication of this development in bibliometric studies between 1976-1987, as found in research articles published in three prominent journals covering quantitative aspects of studies of science and technology: The Journal of the American Society for Information Science (JASIS), Social Studies of Science (SSS) and Scientometrics (S). As shown, the mean percentage has increased from 6% to 9% during these 12 years; the actual number of MVA applications increased from 15 to 49 (see Table 1 - section 6). However, MVA methods are in fact only 'a tip of the iceberg'; these relatively low usage-percentages are merely a partial indicator of the embracement of data-analysis methods. The actual use of statistics and data-analysis methods, as found in comparable scientific sub-disciplines, is approximately three or fourfold higher[4].

3.2 Analysis goals

Generally, the choice of class of MVA method depends on the type of multivariate research, the major research question(s) and the aim(s) of the analysis. Multivariate bibliometric research will nearly always be of a non-experimental nature, but one can imagine situations in which experimental-research oriented MVA methods, such as multivariate analysis-of-variance (MANOVA), may prove useful in bibliometric data-analysis (a hypothetical MANOVA example is given in subsection 5.2). However, in the sequel we will focus on MVA methods particularly applicable in the analysis of data derived from non-experimental research. If a bibliometric study focuses on the association between (two or more) sets of variables, say between a set of scientific input- and bibliometric output variables, one can speak of the dependence-approach. Three major kinds of research questions summarize the goal(s) of data analysis within the dependence-approach: determining the degree of relationship among separate variables, determining the significance of differences between variables, and prediction of variable-values based on values of other variables. In the interdependence-approach one focuses on the mutual association across all variables with no distinction among the variables. The research question centers on determining a sufficiently sparse discription of the underlying structure of relations among a set of variables. Take for example the case in which one wants to obtain a structural map of a scientific subfield based on journal-journal citation interrelations.

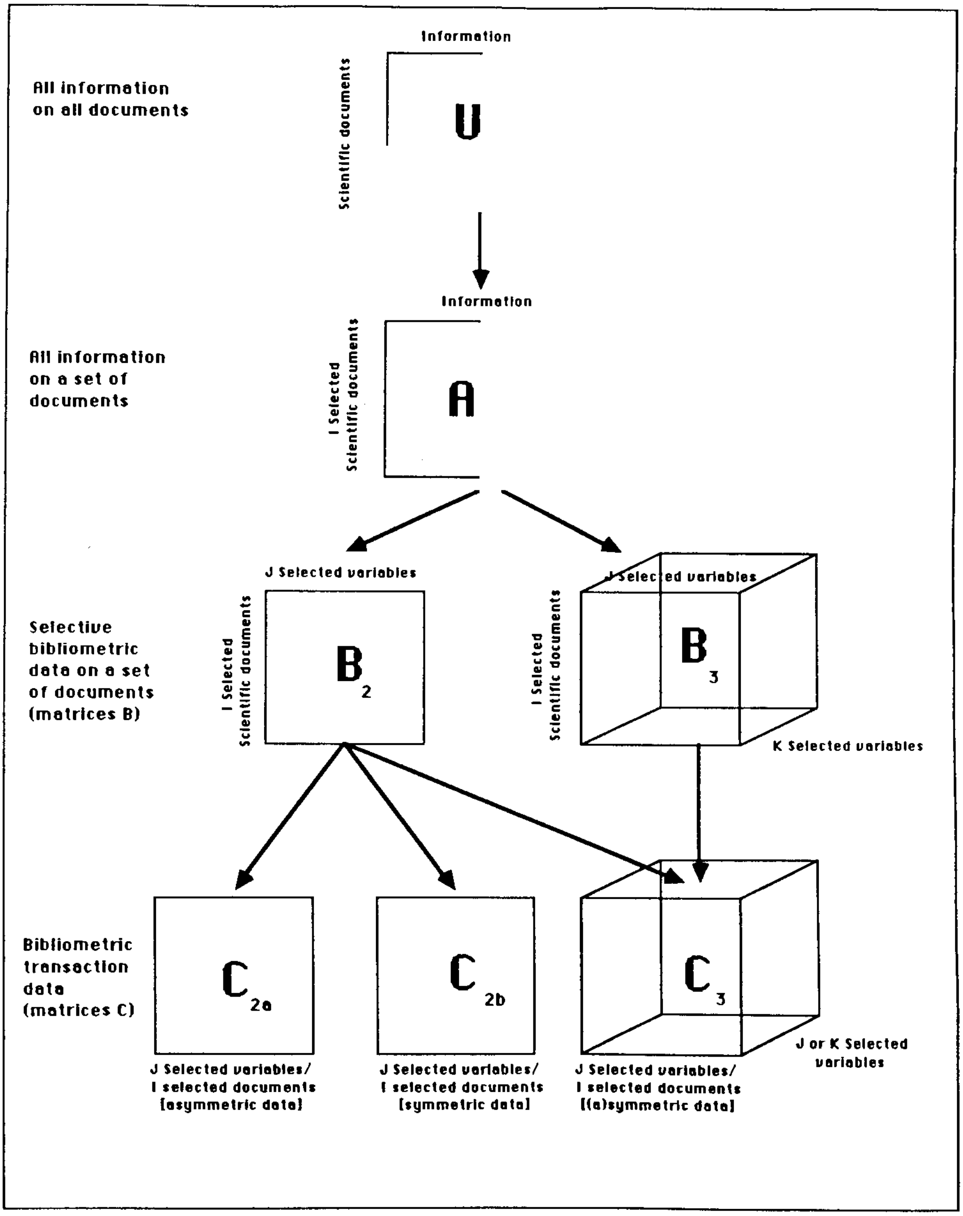

Figure 1. Derivation principal types of bibliometric data matrices.

3.3 Multivariate data

In this subsection we shift our focus from MVA methods to multivariate data. We shall discuss an abstract phenomenological body of information usable in bibliometric research and via formal manipulations develop a structure which encompasses the usual data structures encountered in multivariate bibliometric research. The elementary units of such a structure are, of course, scientific publications (used in its broadest sense). Bibliometric variables gathered on the publications differ with respect to their function in the analysis and their measurement level. We will first give a brief description of the possible types of variables in terms of these two distinctions.

3.3.1 Basic types of variables

The research context and manner in which variables are used dichotomizes variables into two major types:

(I) Independent variables consist of characteristics of research entities or different conditions to which research units are exposed.

(II) Dependent variables are variables with values which are considered to be dependent upon other information (measured by other variables). They are also referred to as output variables. For example, the number of publications of a reseach unit as a dependent variable may be related to, or predicted from, a set of independent variables such as number of researchers, amount of funding, sophistication of equipment, etc.

In addition to these 'external' qualifications of variables there are two important more 'intrinsic' qualifications of variables which concern the manner in which the data values represent the measurements taken on research units. First, variables can be divided as following three classes:

(1) Continuous variables can take on any value within a range of a scale (for example, impactfactor (IF) values - see section 2), i.e. they are measured on a scale that changes values smoothly rather than in steps like in discrete variables.

(2) Discrete variables can take any finite number of values - often referred to as categories - and are thus also known as categorical variables (e.g., $0 \leq$ IF $< 1 = 1$; $1 \leq$ IF $< 2 = 2$; etc.). Such variables can also be converted from continous variables by specifying cut-off values on the continous scale.

(3) Dichotomous or binary variables are simply discrete variables with two categories (e.g., $0 \leq$ IF $< 10 = 1$; $10 \leq$ IF $< \infty = 2$).

A related distinction of variables is based on measurement types, which are generally divided in four general classes (measurement scales). Each scale-type has certain underlying assumptions regarding the relations between the numbers assigned to variables and the permissable mathematical operations on these values without altering the relations within a variable (i.e., transformations of category values). Measurements can be placed in the following four scales :

(a) ratio scaled variables allows a definition of an origin - a zero amount of the variable - and meaningful ratios of scale values. The basic empirical operation is the determination of ratios, thus the only allowed transformation is multiplication with a positive integer.

(b) interval scaled variables have less restictive properties: there is no fixed origin and the basic empirical operation is the equality of differences. This scale thus allows linear transformations of the data.

(c) ordinal scaled variables are simply ordered categorical data, which means that any transformation is allowed as long as the ranking of the values in the variable remain the same. The determination of greater or less is thus the basic empirical operation.

(d) nominal scaled variables are considered as categorical classifications, i.e. the numbers assigned to the units of a variable are only used to place entities in only one category of a variable. Such a variable consists of a set of mutually exclusive and collectively exhaustive classes with no implied order. Thus, the basic empirical operation is the determination of equality.

Continuous or discrete variables with measurements on the ratio or interval measurement scales are generally referred to as metric variables, whereas discrete (categorical) data on the ordinal or nominal scale are considered nonmetric variables. Stevens (1946) is a classic reference for a more detailed discussion of the theory of measurement and the relations among these scales. Bibliometric variables are generally considered to be of type belonging to either a nominal or a ratio measurement scale. However, in nonmetric MVA-methods (see subsection 4.2) it is possible to treat ratio data as interval, or even as ordinal data (i.e., instead of considering 4 authors as the twice the amount of 2 authors one might might apply a less constrained assumption and only consider the order, i.e. 4 authors is more than 2 authors).

3.3.2 A general framework of multivariate bibliometric data

In order to arrive at a suitable ordered structure, we first suppose that we have all available scientific documents and, secondly, all quantitative and qualitative information within and on those documents. This information can be regared as the 'bibliographic universe': U. Obviously, in practice only a subpopulation of documents i (i=1,..,i,.,i',..,I) is considered. The main issue in selecting documents in such an information-retrieval process is that the document set has to be well-defined, in the sense what one can classifiy each document and decide whether it belongs to the wanted document population-A with I documents, or not. To obtain the required subpopulation A one thus needs a selection criterion - a yes/no-decision rule - based on some function-a, operating on the entire document set and leading to A=aU. We must be clear about the concept behind the selection criterion in order to define an unambigious-a. As practical example, consider the following criterion: the document is a member of the desired subpopulation if it originates from a first author with a Dutch affiliation and is published in a 1987-issue of a scientific journal covered by the Science Citation Index.

Additionally, one will also require a selection from the data on the documents in set A. In this second step we define functions b(A) casting both qualitative and quantitative objective properties and relations - which hold for individual documents (the objects of analysis) - from A into a domain B, with the same finite set of variables b_j (j=1,..,j,.,j',..,J) as quantitative independent objects of measurement. Features of documents can thus be classified and coded into numbers, often in the form of categories. The type of function bj depends on the type of data involved and the measurement type imposed on a variable (see subsection 3.3.1). For example, classifications of nominal variables such as type of publication are arbitrarily coded, whereas ratio variables such as the number of pages receive their respective numerical values. In general, all collections of multivariate quantitative data can be visualized in a data matrix, that is an array of elements in which the data are collected in a systematic manner with numerals representing the information. All quantitative information on the publications can thus be collected in a multivariate original data matrix-B. For convenience. This array can be ordered or non-ordered with respect to values in one or more variables, e.g. the type of publications: patents, articles, letters to the editor, etcetera.

In its most simple form, the information is contained in a rectangular data matrix, consisting of J variables as the columns and the I rows representing the documents. Often one does not operate on the individual documents but on aggregates thereof (i.e. the data are selected/grouped on a certain variable). The formal derivation of such a matrix would be to apply a second function to select, say, only the subset of the i (i<I) of the beforementioned Dutch publications which appeared in Dutch-language journals. If the data matrix B has only two so-called modes (rows and columns) we will refer to it as the B2-matrix. A third mode k (k=1,..,k,.,k',..,K) adds the possiblity to introduce an extra variable, such as a time-period descriptor. A

three or more-mode array will be denoted as B3-matrix. This multi-mode framework can be generalized, enabling one to encompass all possible forms of groupings of bibliometric data for any possible type of variable or combinations of variables. Bibliometric information stored in this manner can be organized conceptually in a spatial structure - a 'scientific space' - analoguous to information retrieval systems (cf. Cleveland, 1976). Such a quantitative data structure can be visualized as a multidimensional Euclidean space of finite dimensionality J, in which each variable represents a separate dimension j. Each document is classified for each dimension and is thus located in space as a point so that its coordinates along the various coordinate axes describe different aspects of the publication. Highly similar documents will thus be located in each others vicinity.

In a third step, applying functions c(B) on the quantitative variables in B can be used to create specific derived multivariate data matrices-C, constituting an array in which (inter)connections/(dis)-similarities among documents, on one or more variables, are systematically collected. Functions $g(b_i,b_i')$ can be defined to 'project' specific relations between (aggregates of) publications contained in B onto a 'subspace' C. Alternatively, one can collect data on relations between variables by defining functions that operate on the variables $g(b_j,b_j')$.

It will be clear that the functions b and c can take on many forms and can be applied to any characteristic of the data in matrices A or B, respectively. In fact, the formalism as sketched above can be used to derive any conceivable bibliometric matrix. Data from commonly found bibliometric research settings are now relatively easily embodied in such a bibliometric data matrix. In practice, only a limited number of variables are considered for matrix B of which some have been mentioned in the foregoing. As for C, there are in fact two standard-possibilities to fill this matrix, as far as data analysis is concerned, namely asymmetrically- (i.e., the data structure located under the main diagonal of the matrix is dissimilar to the upper-diagonal part of the matrix) or symmetrically shaped matrices. For notation we will denote the asymmetrical matrices by C2asym and the symmetrical matrices by C2sym. Well-known general types of C2sym-matrices, with information on the structure of the (linear) relations between variables are, for example, Pearson's product-moment correlation matrix and the variance-covariance matrix[5]. Following this formal derivation method, data stemming from more elaborate designs are now also easy to incorporate, such as multi-mode matrices C3, either symmetrically or asymmetrically filled.

4. MVA methods: general classes

4.1 Dependence and independence MVA methods

As mentioned, the focus of the data analysis determines the choice of the MVA method (see subsection 3.2) ; if the bibliometric research centers on the relation between two sets of variables, where each set contains one or more variables as realizations of a dependent variable or criterion variable, the class of MVA methods corresponding to the dependence-approach can be designated as dependence MVA methods. Explanation and prediction of the dependent variable(s) is the principal aim of these methods. This class of methods includes inferential statistics, which is designed to test hypotheses about populations by measuring samples of research units. MVA methods dealing with such questions are also referred to as inferential MVA methods. If one focuses on the mutual association across all variables with no distinction among the variables the so-called interdependence MVA methods are called for. These methods are of a less predictive nature and are generally used either to describe or explore the structure within a set of variables. They have sparseness as the same general objective, i.e., reducing the data to a limited number of the most important features thereby simplifying the interpretation of the whole of characteristics of the data. Hence, one sometimes speaks of descriptive or explorative MVA methods. A third class of MVA methods has common features with both the dependence and interdependence approach. This class of methods is particularly concerned with the study of structural (causal) relations between variables. Henceforth these methods will be referred to as dependence/interdependence MVA methods, or as structural modeling methods.

4.2 Metric and nonmetric MVA methods

Nearly every MVA class can divided into two main subsclasses, depending on assumptions with respect to the formal distribution of the multivariate data. We will start with the group of MVA methods with the most restrictive set of assumptions with respect to the data, the 'classical' or metric MVA methods. There are three major assumptions at the basis of this general type of MVA methods:

(a) The assumption that the variables are multivariate normally distributed is a crucial property in classical MVA. A multivariate normal distribution garantees that each variable has a univariate normal distribution. The multi-normal distribution of variables garantees that the population means of variables and the variance/covariance-matrix encompasses all necessary information on the data for multivariate analysis.

(b) Linearity is the assumption signifying the fact that the regression between values in two sets of variables -each set with one or more variables- is described as a linear function of the values. The corresponding Pearson's product-moment correlation coefficient, which forms the basis for most MVA methods, is sensitive only to the linear component of the relation between two sets of variables. Thus the variables have to be at least measured on an interval (i.e. linear) scale. Nonlinear relationships between varaibles can be examined with bivariate scattergrams and 'linearized' with a data transformation.

(c) Homoscedasticity, or homogeneity of variance, is related to the assumption of normality. If the heteroscedasticity of a variable (i.e., if the residual variance after a regression is not the same in different parts of the value domain), the relationship between two variables is not captured totally by a correlation coefficient. A suitable data transformation can eliminate heteroscedasticity and restore normality.

If these three assumptions apply to the data, the relations between the variables are fully described with Pearson's product-moment correlation matrix. Metric MVA methods thus only use the means, (co)variances and product-moment correlations[5]. These assumptions are essential for the application of inferential statistics, but if the major goal of a metric MVA method is descriptive or explorative, the heteroscedasticity and normality assumption may be relaxed. More serious violations of the assumptions will yield (partly) invalid conclusions from metric MVA methods.

Unfortunately the assumptions underlying metric MVA are often violated in practice, particularly with respect to data gathered in social and behavioral research (bibliometric studies included). The main violators are skewness (i.e. nonnormality) of variable distributions and/or the availability of nonmetric variables only. On a data-theoretical level, the incorporation of only linear relations in such an analysis context is unrealistic and will thus lead to an unwanted simplification of the actual relations between variables. These problems have been recognized in the social and behavioral sciences and have lead to the generalization of the metric MVA methods to the nonlinear or nonmetric MVA methods, thereby leaving standard statistical theory and the associated statistical tests which is founded on the multinormal distribution. In the following, we discuss both metric and nonmetric MVA methods from a perspective based on the nature of quantitative data. More specifically, metric MVA, with analysis 'results' that are invariant under linear transformations of the variables, are called for when the data consists of variables with at least a interval measurement level (the term 'results' has a broad meaning in this case, denoting any aspect of the mathematical basis of the analysis method or its outcome). Conversely, nonmetric MVA is appropriate if the 'results' are to be merely invariant under all one-to-one nonlinear transformations of the variables.

5. MVA methods: an overview of subclasses

5.1 Introduction

After operationalizing specific research question(s), defining the application of either a dependence, interdependence or dependence/interdependence MVA method and, finally, establishing the measurement type of the variables, the stage is set for determining the permissible class(es) of MVA methods. The diagram depicted in Figure 2 shows a decision-tree to choose the appropriate class(es) on the basis of the beforementioned aspects of bibliometric research and the characteristics of the data collected. Note that this taxonomy is only a rough non-exhaustive classification scheme and a necessarily limited representation of the whole of formal relations between these MVA methods. However, it will serve our illustrative purpose well enough.

In the following subsections we proceed by discussing each of these mainstream subclasses of MVA methods, mostly under their generic term as commonly used in the social sciences. Although discussed separately, most of these subclasses are statistically related to one another via the multivariate general linear statistical model of data which is based on linearity and addivity of relations between variables, as discussed in a multitude of textbooks on multivariate statistical theory (e.g., Anderson, 1958; Rao, 1973). Several subclasses in fact consist of a group of highly related methods or modifications of a method (cf. Tenenhaus & Young, 1985). In addition, many hybride MVA methods have been developed within this framework during the past decades. More recently, MVA subclasses have been be brought together in a unifying framework which is based on Euclidean distances (Meulman, 1986). Overviews of MVA methods and linkages between them are given in numerous statistics textbooks. Further information regarding details and mathematical relationships with other MVA methods can be found in references which will accompany the description of each subclass.

Additionally, a variety of more recent examples of bibliometric applications of the MVA methods are given for each MVA subclass.

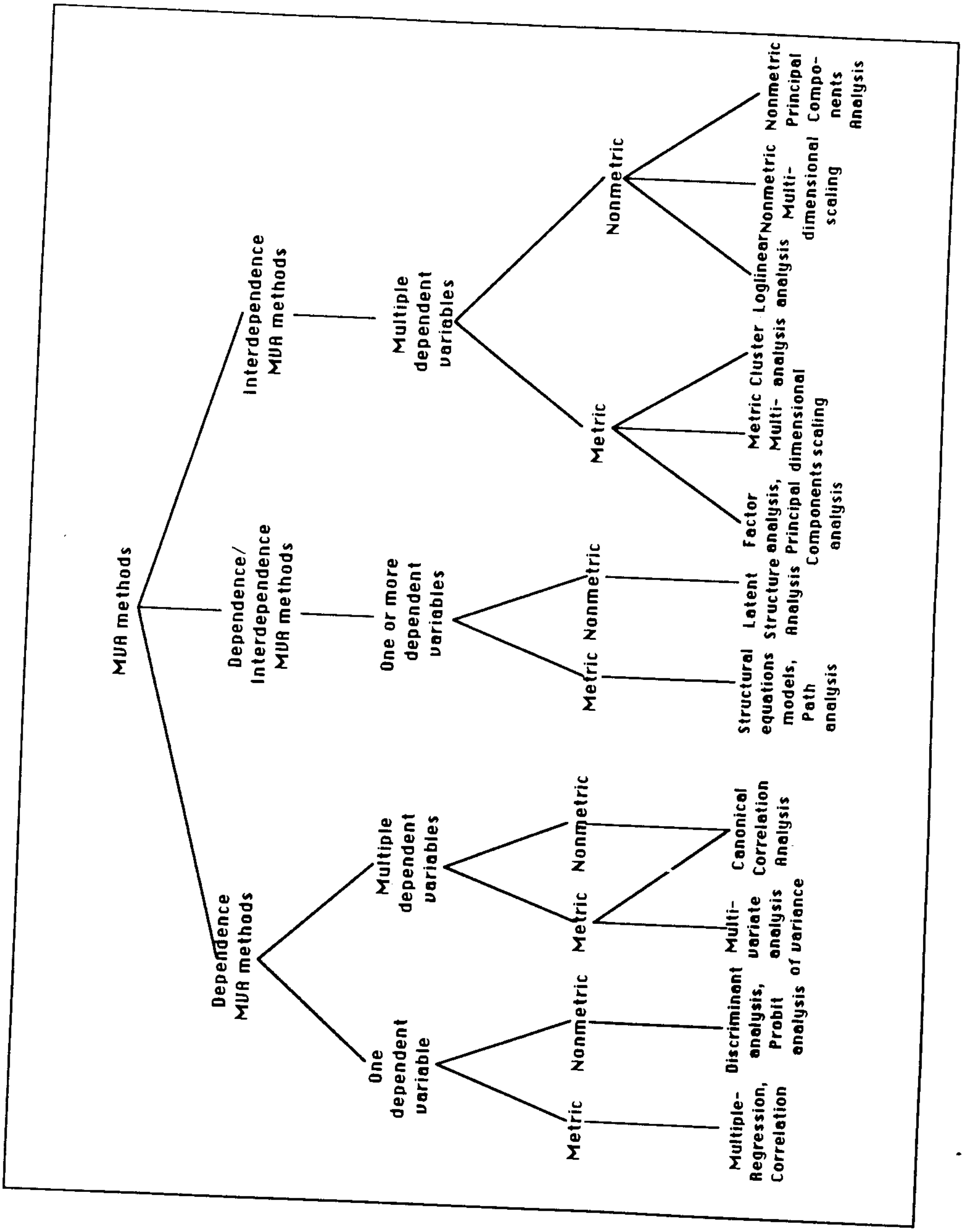

Figure 2. A taxonomy for general classes of MVA methods.

Hypothetical examples are given in those cases in which empirical examples have not been found in our literature study[6] For each MVA subclass the type of allowed datamatrices will be given and denoted in terms of the B and C qualifications as discussed in subsection 3.3.2. Established extensions of MVA methods (i.e., applicable on the multimode B3 and/or C3-matrices) will be mentioned in the respective descriptions of the MVA subclasses. A fairly complete overview of multimode MVA methods can be found in Law et al. (1984).

5.2 Dependence MVA methods

Multiple Regression (MR) is concerned with the study of one dependent variable on multiple (i.e., a set of) dependent variables. The aim is to estimate or predict the mean value of the dependent variable on the basis of the known values of the independent variables. The variables used to predict may or may not themselves be related. MR methods also allow an assessment of the relative contribution of each of the independent variables toward predicting the dependent variable. MR was used by Bennion & Karschamroon (1984) for estimating the usefulness of scientific journals with several bibliometric statistics as independent variables. Koenig (1983) used MR models to find bibliometric indicators of research performance in major pharmaceutical companies. MR is specifically applicable on the basic two-mode bibiometric data-matrix B2, and C2sym in case of a product-moment correlation matrix or covariance matrix (see subsection 3.3.2 for a general description of the B and C types of matrices). For more details on MR the reader is referred to Kerlinger & Pedhazer (1973).
Multiple Correlation (MC) is also a method to assess the degree to which one dependent variable is related to a composite set of other variables, but now based on a linear association, i.e. the product-moment correlations between the variables. MC can thus be seen as a bivariate correlation between the dependent variable and a newly created composite variable, based on the independent variables. It thus provides a measure of relatedness which is often used in combination with MR (see Koenig, 1983b). MC is one of the basic forms of Canonical Analysis (cf. Gittens, 1984), a hybrid MVA class concerned with reducing the structure of product-moment correlations between two or more sets of variables to a more simple form. MC is also specifically applicable on B2 or C2sym.

Discriminant Analysis (DA) has the goal to predict membership in groups (with a categorical dependent variable representing the groups) on the basis of a set of independent variables. The basic problem is to find some function of the values (i.e., a linear combination) which can accurately assign observations into groups. If groups differ significantly on a given set of variables, that set will reliably discriminate among groups. This is the reversed situation compared to MANOVA (see this subsection). In this analysis method one can also assess the relative contributions of the independent variables in predicting group membership. In the case of more than two groups, DA can be used as a special case of canonical correlation analysis (see this subsection). As an hypothetical bibliometric example in which DA could be applied, consider a historical bibliometric analysis within a poorly publicationed scientific discipline which is divided in two theory groups. By performing DA based on the number of citations to prominent members of both groups, scientists with an uncertain position within the discipline can be placed in the most likely group. DA is specifically meant for B2-type matrices. For more details on DA and the kinds of questions addressed by DA the reader is referred to Huberty (1975).

Probit (Logit) Analysis (PA) is used for modeling data in a matrix with a single dependent variable of a binary categorical nature. All independent variables are also categorical. The parameters derived from the model(s) can be used for prediction. The models are based on transformations of the data, in the form of proportions or probabilities. In a bibliometric context, a logit analysis could be used to derive a model for the allocation of research grants by appling it to datamatrix with the dependent variable denoting the award of a grant (category-value: 1) or a refusal (category-value: 0), and the dependent variables containing the marks for various features of the proposition. Logit Analysis, which uses the natural logarithm of the odds ratio, is a also a special case of loglinear analysis (see subsection 5.4). PA can be applied to the B2-type data matrices. For more details of this type of analysis the reader is referred to Finney (1971).

Multivariate Analysis-of-Variance (MANOVA) is designed to investigate differences among two or more levels of an independent variable (groups) in terms of their effect on a set of dependent variables. Thus the primary focus of MANOVA is on testing for significant differences on a set of variables or 'profile' of variables due to changes in one or more (experimentally) controlled variables. Repeated measures are allowed. With more than two groups specific comparisons between groups can be evaluated. Additionally, techniques are available to assess which of the dependent variables are influenced by the indepedent variable. Any number of dependent variables may be used, MANOVA deals with the intercorrelations among them. Hotelling's T^2 is a special case of MANOVA, in which two groups comprise the independent variable. This measure tests the hypothesis that groups differ on a composite set of measures. As a hypothetical example of the use of MANOVA in the field of S&T-studies one can consider the assessment of differences between scientific groups on a number of variables (e.g., scientific awards, mobility) based on a number of bibliometric variables (e.g., number of publications, citations, patents, etc.). MANOVA is applicable on B2 and B3-matrices. More information on MANOVA, as an application of the general linear model, is found in Rao (1973).

Canonical Correlation Analysis (CCA) seeks to determine the linear association between a set of independent variables and a set of dependent variables (Hotelling, 1936). Linear combinations of the variables in the sets are derived, such that Pearson's product-moment correlation between the resulting two composite variables (the canonical variates) is maximal. Redundancy Analysis is a related method concerned with answering the question to what extent the sets of variables contain redundant information (Stewart & Love, 1968). McCain (1986) uses CCA to establish the congruence between maps of a scientific specialty based on co-citations and similarity judgements, by relating the sets of coordinates of the points. CCA is applicable on B2 and C2sym matrices with correlations or covariances. The reader is referred to Gittens (1984) as a more recent textbook on CCA and redundancy analysis. Nonmetric CCA versions are available (e.g., Gifi, 1981).

5.3 Interdependence MVA methods

Factor Analysis (FA) is a well known MVA method when there is some prior hypothesis the underlying structure of the data. FA can be used to assess the structure and the extent to which empirical structure conforms with the hypothetical structure (i.e. the common factor model). Factor analysis focuses on the part of the total variance that a particular variable shares with the other variables constituting the set (the common factor), but allows for individual differences in the variance accounted for by the separate variables. As implied, factor analysis is useful in developing and testing theories on the structure of a set of interdependent variables. FA is found in a multitude and diversity of applications. Nadel (1981) uses FA to assess the underlying structure of citation and co-citation matrices between core articles in a bibliometric study of the changing cognitive organization of a physics specialty. Similar work on changing journal-to-journal citation structures is conducted by Leydesdorff (1986) to measure the effectiveness of science policies. Smart & Elton (1982) use FA to investigate relations between several measures to assess journal significance, while Simonton (1984) applies FA to unravel a underlying structure from a number of scientific-prominence measures. As a last example, Todorov (1985) analyzed the structure of the nations-wide distribution of physics papers. In general, FA is specifically applicable on B2 and C2sym-matrices containing correlations or covariances. More detailed information on FA is found in the classic compendium of Harman (1967).

Principal Components Analysis (PCA) can be regarded as an important variant of FA, but is also often referred to as a MVA method in its own right. The primary goal of PCA is to construct linear combinations of the original observations that account for as much of the (original) total variance as possible. In contrast to FA, no prior underlying structure of data is assumed in PCA. The succesive linear combinations, the principal components, are extracted in such a way that they are uncorrelated with each other and account for successively smaller amounts of the total variance. PCA is thus also valuable in developing a limited number of components usable in futher research. Hustopecky & Vlachy (1978) apply PCA as a method to group several measures of frequency inequality. More details and applications of PCA are given in Jolliffe (1986). Three-mode versions of PCA are available (e.g., Kroonenberg, 1983). Nonmetric PCA generalizations allow for ordinal and nominal data in which the category values of variables with these measurement levels are transformed to maximize their contribution to the principal components (e.g., Gifi, 1981).

Multidimensional Scaling (MDS) methods allow the user to explore and infer the structure underlying preferences- or (dis)similarity data among various objects. The method yields a map of the objects in a low-dimensional Euclidean space, where the position of a particular object in the space reflects its degree of perceived (dis)similarity with the other objects. The (dis)similarity data are assumed to have metric properites, i.e. they are at least interval scaled, thus the similarity (dissimilarity) between two objects decreases (increases) linearly with distance. MDS methods are, for example, used for displaying relations between nations for publishing and citing patterns (Inhaber & Alvo, 1978), the mapping of the cognitive and social structure of scientific specialties by co-citations between core authors or papers (e.g., Small, 1977), the structural representation of journal similarities (Noma, 1982a) or co-nominations of authors (Lenk, 1983). In Noma (1982b) a number of scaling methods are compared to display cited and citing articles in a common space. There are a number of three-mode extensions of MDS (e.g. Carroll & Chang, 1970). MDS is specifically applicable on C2sym and symmetric C3 data-matrices. Carroll & Arabie (1980) is an excellent review article on the-state-of-art in MDS and its multimode generalizations. Shiffman et al.(1981) is recommended for an application-oriented book on MDS. Asymmetrical extensions of MDS-programs have been developed (e.g., Weeks & Bentler, 1982). Multidimensional Unfolding (MDU) and Correspondence Analysis (CA) can also be considered as MDS-methods but they are primiarily meant to operate on asymmetrical matrices. MDU methods aim at finding a low-dimensional Euclidean space in which a continuum of entities and a continuum of objects is presented. The points are arranged in a manner that folding the continuum at any entity-point one obtains the correct order of object-points according to their mutual preference/dominance by that entity, and vice versa (Schöneman, 1970). A three-mode MDU approach is discussed by DeSarbo (1978). MDU is applicable on the bibiometric data-matrices B2 and B3. CA is particularly appropriate for the analysis of contingency (i.e. nonnegative frequency) data. In fact, CA can also be described as a special case of CCA deriving a maximum association between rows and columns of a contingency matrix, and presenting the accordingly rescaled category values for rows and columns in a multidimensional space (Greenacre, 1984). Tijssen et al. (1987) presents an application of CA on a journal cross-citation matrix. CA is also applicable on B2 as well as on C2asym and C2sym-type transaction-matrices. The nonmetric generalization of multidimensional scaling assumes only ordinal data, in which distances are a monotonic function of the (dis)similarity data. Nonmetric MDS is also used to metrize data, i.e. the nonmetric data values are transformed to data with metric properties, by way of an optimal allocation of the variables in a metric space. Applications of nonmetric MDS programs are found in Noma (1982a) and McCain (1986). A nonmetric ADS extension for asymmetric matrices has also been developed (e.g. Okada & Imaizumi, 1987). More information on various nonmetric MDS programs (including nonmetric MDU) is found in Kruskal &Wish (1978).

Cluster Analysis (CLA) a generic term for a data-reduction method, consisting of several types of clustering methods. CLA methods have the common goal to identify a smaller number of groups such that elements in a particular group are, in some sense, more similar to each other than elements belonging to other groups. The construction of homogeneous subgroups is generally based on the (dis)similarity of the profiles of scores on variables. Non-hierarchical CLA methods use centriods as representatives of subgroups. The distance between an element or subgroup to a centroid of another subgroup determines its placement in that subgroup. The iterative process terminates when a stable cluster structure is attained, i.e. all elements remain in their subgroup - the final cluster. Conversely, hierarchical clustering is a special case in which a hierarchical merging of groups of elements in (sub)clusters is performed. This cluster-formation process is often displayed as a tree-like structure (the dendrogram). The diversity within both non-hierarchical and hierarchical CLA methods is largely based on the differences in the computation of the measure of (dis)similarity between clusters. Hartigan (1975) gives a thorough discussion of the different basic types of clustering algorithms. CLA is one of the most commonly used MVA methods in bibliometric S&T studies (see table 1 - section 6), due to its appeal as a tool for 'mapping' interrelations between publishing scientific entities via co-citations (cf. Small & Crane, 1979). As such, a specially developed CLA-method it is often used as a readily available tool directly linked to ISI's bibliographic databases[3] (e.g., Small & Sweeny, 1985). Several CLA methods have been applied to cross-citations between scientific journals, for example aimed at grouping disciplines into subdisciplinary areas (Carpenter & Narin, 1973) or to cluster articles into scientific subfields (Miyamoto & Nakayama, 1983). Block-modelling is a clustering method worth mentioning, because of its bibliometric applications in determining the social structure of groups of scientific authors (e.g., Lenoir, 1979). Three-mode and nonmetric CLA programs are available (e.g., Carroll & Arabie, 1983). CLA is specifically applicable on data matrices of both the B2 and C2-type. An overview of classical CLA method, including comparative approaches, is given in Everitt (1974).

Loglinear Analysis (LLA) is a class of loglinear modeling techniques that enable the user to examine the interrelations between categorical variables constituting matrix of cross classifications. Loglinear models express the cell probabilities of a contingency table in terms of main effects and interactions of the variables in question. LLA is particularly suitable for the analysis of multimode matrices. Noma (1982a) applied LLA to model interjournal-citation relations. LLA is particularly applicable on B2, B3, C2 as well as C3-matrices. For more details concerning LLA the interested reader is referred to Bishop, Fienberg, Holland (1975).

5.4 Dependence/Interdependence (structural modeling) MVA methods

Structural Equations Models (SEM) is a class of models for testing causal hypotheses among a set of variables. The study of the structure of causal patterns starts by constructing a model. The number of dependent and independent variables depends on the causal model specified. Subsequently, the values of the model parameters are estimated from the data. Finally, the fit of the model is tested to the data by comparing the observed interrelations among the variables and the interrelations predicted from the model. The most restrictive class of models are referred to as path analysis, a classic approach imposing assumptions on the model, such as linear and additive relations between variables, unrelated error terms and an interval scaled-dependent (endogeneous) variable. Path analysis is used by Senter (1986) to construct and test a causal model of the productivity of scientists. A modern causal-analysis methodology is found in the LISREL-program (Jöreskog & Sörbom, 1984). LISREL places less restictions on the specified causal models : it allows for unobservable (latent) variables in the model, measurement errors, reciprocal causation and requires that observed (manifest) variables have

underlying multivariate normal distributions.
The latent variables, also referred to as constructs, are implicitely assumed as continuous measured. An elaborate causal model with LISREL was applied by Knorr and Mittermeir (1980), also to determine the structure causal factors underlying the individual publication productivity. Latent Structure Analysis (LSA) is a specific class of causal modeling techniques applicable to investigate causal systems involving both manifest and latent variables of a nonmetric categorical nature (Lazersfeld, 1954). The specific aim of latent structure analysis is to 'account for' the observed interrelations between manifest variables by introducing one or more latent variables. It is obvious that LSA is related to both factor analysis and structural equations models. The interested reader is referred to Jöreskog&Wold (1983) for a discussion of recent developments in LSA and related methods. SEM and LSA are applicable on B2 and C2-type matrices, in the latter case either as a correlation matrix or a covariance matrix.

5.5 Multivariate time series-analysis

Multivariate time-series analysis (TSA) is a subclass which is not shown in Figure 2, because it is basically any type of multi-mode analysis, as long as the third mode represents a time factor. A common analysis approach is to 'cut' the three-mode matrix into two-mode-'slices' and perform an analysis with a MVA-method like MDS for each period ('slice') separately (e.g., Leydesdorff, 1986). However, this will often be a unrealistic MVA approach because an adequate analysis of multivariate time-series data one should incorporate specific serial correlations between successive measurements. In principle, some of the beforementioned three-mode extensions of MVA methods can therefore be applied, more in particular: either a causal-modelling methods in case of sufficient observations and a limited number of points in time, or a suitable modification of the ARIMA time-series model (Cook & Campbell, 1979) in the opposite situation or an explorative three-mode PCA when the beforementioned conditions are not (satisfactorily) fulfilled.

6. MVA methods in bibliometric research '76-'87: a multivariate data analysis

In this illustration of the use of MVA methods we will extend our data on the subject-'MVA in bibliometric research publications' (as given in Figure 1 - subsection 3.1), by first introducing the separate subclasses of MVA methods and, secondly, by adding the three

Table 1 - MVA methods in bibliometric research articles.
Percentages and absolute numbers.

	1976-1979	1980-1983	1984-1987
MR	1.3 (3)	2.7 (10)	2.0 (8)
DA	0.0 (0)	0.8 (3)	0.5 (2)
CCA	0.0 (0)	0.0 (0)	0.3 (1)
FA/PCA	0.9 (2)	2.4 (9)	1.7 (9)
CLA	1.3 (3)	1.6 (6)	3.1 (12)
LLA	0.0 (0)	0.3 (1)	0.3 (1)
MDS	1.7 (4)	1.9 (7)	3.1 (12)
SEM/LSA	1.3 (3)	0.0 (0)	0.7 (3)
TSA	0.0 (0)	0.0 (0)	0.3 (1)

journals into the analysis. Two very suitable explorative MVA methods, which have become in vogue in the social sciences, are applied to the data: correspondence analysis and three-mode PCA (see subsection 5.3). Technical details of the methods and the analysis results are omitted. To obtain a sufficiently filled data matrix, for both descriptive of reasons of brevity and data-analysis purposes, we combined MVA methods which are (highly) related and serve comparable data-analysis purposes (e.g., FA and PCA). Table 1 displays the usage of the separate types of MVA during the past 12 years. As shown, Multiple regression (MR) as an inferential (dependence) MVA method, and Factor Analysis/Principal Components Analysis (FA/PCA) as MR's descriptive (independence) counterparts, dominated in bibliometric research papers in the period 1976-1983. Although both methods were still often used between 1984-1987, the relative number of papers with applications of either MR, FA/PCA or a combination of both, has decreased slightly. These methods lost their leading positions to Cluster Analysis (CLA) and Multidimensional Scaling (MDS), which are both more descriptive-oriented MVA methods. Their gained prominence is particularly due to their (combined) use in constructing co-citation 'maps' of scientific (sub)fields[7].

The structure of the data in Table 1 is analysed by means of Correspondence Analysis. In short, this method computes an optimally two-dimensional approximate of the structure and displays the results graphically as a configuration of points, as shown in Figure 3. Each analysis unit (i.e., each row and column entity) is represented as a point in space. For our illustrative reasons it will suffice to mention that related units are located in each others vicinity. Interpreting such a figure is essentially quite straightforward. For example, it is immediately clear that the labels MDS and CLA are located nearest to the label '84-'87, reflecting the fact that these are the most frequently applied MVA methods this recent period while the extreme positions of CCA and TSA in the same region reflect their exclusive use in recent years.

We now enter the three abovementioned journals into the analysis as a third mode and use the three-mode PCA program TUCKALS3 (Kroonenberg, 1983) to approximate the structure. This method yields, a.o., the component loadings of the analysis units on the components which span the two-dimensional space in which the relations between the three sets of variables are approximated. Similar values for these loadings will indicate a similarity between the analysis units. These values are used to compose Figure 4. The first component (i.e., the horizontal axis), which accounts for most information of the whole of relationships, is largely determined by the fact that multiple regression (MR) is mostly found in research articles in Social Studies of Science (SSS) in the period 1980-1983. The

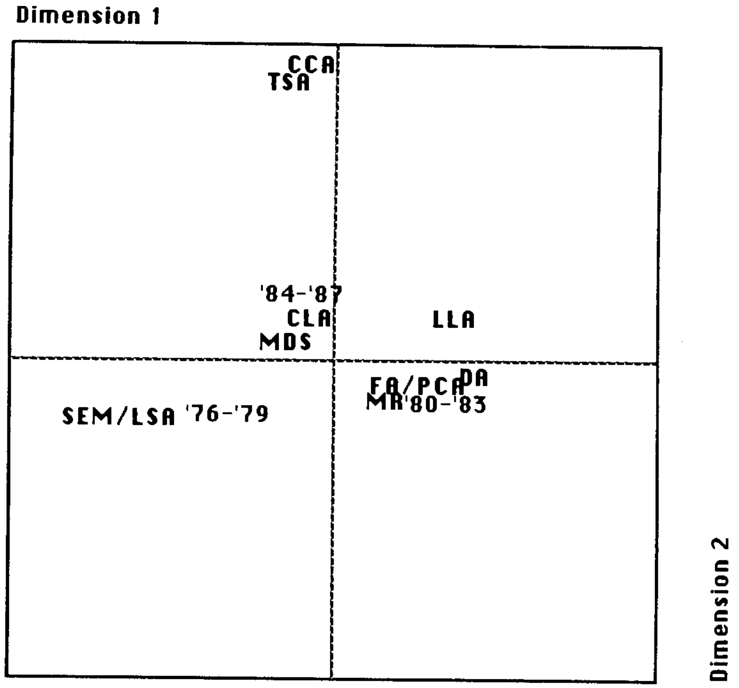

Figure 3. Results of Correspondence Analysis on Table 1. The labels are centered at the location of the analysis units.

second component focuses on the relatively large number of MDS and CLA applications in the periods 1976-1979 and 1984-1987, particularly in The Journal of the American Society for Information Science (JASIS). The journal Scientometrics (S) does not dominate either dimension, reflecting the fact that this journal is 'average' as far as the usage of the beforementioned MVA methods is concerned. Additionally, the loadings of the remaining MVA methods indicate that they are mostly, or exclusively, applied in articles which appeared in Scientometrics.

7. MVA in bibliometrics : a perspective

In recent years, computerized systems containing bibliographic databases have circumvented laborious manual retrieval of bibliometric material, more in particular publications and citations. Although these types of data are sometimes of a questionable quality as far as accurateness and completeness is concerned, the databases have become of major importance in present-day bibliometric studies. They permit one to perform a relatively easy and time-saving large-scale quantitative assessment of scientific activities. This convenience has in fact significantly contributed to the emergence of bibliometrics as an analytic tool in S&T-studies. Simultaneously, new data-analysis methods and their wide-spread availability have created both the possibility and concomitant demand for more sophisticated analyses of the resulting bulk of bibliometric data. The multitude of publications containing applications of MVA methods, as presented in the foregoing sections, is convincing evidence that such data-analysis methods have proved their value and are indeed becoming valuable tools in many large-scale bibliometric studies. MVA methods yielding spatial representations of data structures, such as cluster analysis and multidimensional scaling, have certainly contributed to the viability of bibliometrics particularly due to their assistance in producing 'maps' of science. However, many problems with respect to validity, reliability and applicability of not only MVA methods, but also bibliometric analysis units (in particular citations) as well as bibliometric analysis methodologies (e.g., co-citation analysis) still need to be resolved. Nevertheless, extrapolating from bibliometric-research trends during the last decade which is, a.o., marked by an increasing number of research papers, one can tentatively conclude that bibliometrics has a future as a quantitative research specialty. Futhermore, judging by the amount of useful practical applications for S&T-policy and R&D-management and the (experimental) implementation of bibliometric S&T-indicators, bibliometrics seems on its way to become an established instrument in the assessment of both structural and dynamical features of S&T.

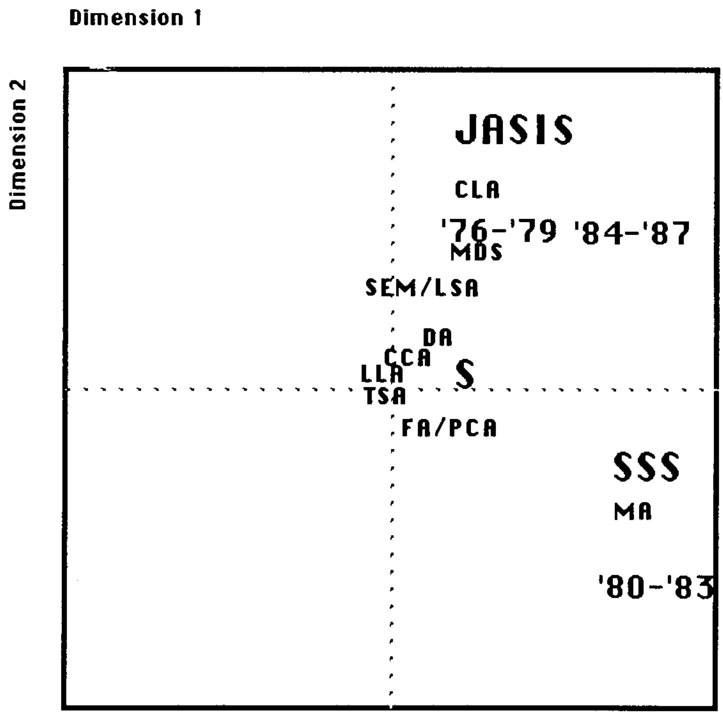

Figure 4. Results of Three-Mode Principal Components Analysis.
The labels are centered at the location of the analysis units.

It is our believe that MVA methods are becoming an indispensable analytic aid in modern large-scale bibliometric studies. It will be clear that the nature and extent of MVA in future bibliometric studies of S&T depends both on developments within bibliometrics and within MVA itself. It is likely that use of MVA methods in the near future will, on one side, be shaped by the increasing quality and computerization of scientific literature data bases and, on the other side, by a demand for more sophisticated studies covering larger 'areas' of science while yielding more detailed information. As far as MVA methods is concerned, the ongoing statistical research on MVA in particular towards nonmetric and multimode generalisations, will eventually lead to applicable new methods or useful options within existing methods. Moreover, the advances in computer hard- and software will bring increasingly larger bibliometric datasets within the realm of MVA. These 'push and pull'-developments will certainly have their effect on data-analysis practice, a.o. bringing about more frequent application of a greater variety of MVA methods. This will hopefully also generate more efforts to obtain the necessary insights in the pros and cons of specific MVA methods in order to modify them into truely suitable tools in the quantitative analysis of bibiometric data.

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Notes

1. The term 'bibliometrics' and its definition is attributed to A. Pritchard (1969). He defined it as "... the application of mathematics and statistical methods to books and other media of communication." Broadus (1987) presents a historical overview of subsequent definitions of 'bibliometrics' and proposes an alternative: "Bibliometrics is the quantitative study of physical published units, or of bibliographic units, or of surrogates of either."

2. The term 'scientometrics' originated as a Russian term for the application of quantitative methods to the history of science (Dobrov & Korennoi, 1969), but is now generally used as a generic

term for a variety of research approaches within the study of science, with a common general idea that quantifiable aspects of science can be utilized to assess characteristics of science. Often 'scientometrics' and 'bibliometrics' are used with the same meaning.

3. The SCI is annually compiled by Garfield's Institute for Scientific Information (ISI), Philadelphia, USA. Later followed by the Social Sciences Citation Index (1973) and the Arts and Humanities Citation Index (1978).

4. The total use of statistics in recent bibliometric research literature is, of course, much higher and probably somewhere between 20% and 40%. Wallace (1985) presents the 1981-figures on use of statistical methods in library and information science: 20% of the articles contain descriptive statistics, while an additional 6% have an application with an inferential statistical method.

5. The Pearson product-moment correlation between two discretely-valued quantitative variables x_1 and x_2, measured on i (i=1,...,N) objects, is defined as $r_{1,2} = cov_{1,2} / (\sqrt{var1} \cdot \sqrt{var2})$, where the variance: $var_1 = \Sigma_i (x_{1i}-M_1)/N$ and the covariance: $cov_{1,2} = \Sigma_i (x_{1i}- M_1) \cdot (x_{2i}-M_2)$, with means $M_1 = \Sigma_i x_{1i}/N$ and $M_2 = \Sigma_i x_{2i}/N$.

6. A reasonably representative literature-search was conducted on the usage of MVA methods. However, as a result of its limited size, additional relevant references to MVA applications in bibliometric studies will therefore perhaps be missing.

7. Co-citation analysis is a method, pioneered by Small (1973), in which a linkage between publications is derived based on the so-called co-citation relations, i.e. two publications are co-cited when they are jointly cited in one or more subsequently published publications. The analysis of pairs of cited publications is used to generate sets of publications based on co-citation patterns, on the assumption that each set indicates a collective cognitive focus. The total of foci forms a collective cognitive representation of the social organization of cognitive knowledge. On a macro-scale, co-citation analysis is of interest as a means for mapping cognitive scientific structures, for scientific specialties, (sub)fields or science as a whole (e.g., Small & Garfield, 1985).

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