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INTERACTIVE MATRIX DISPLAYS AND MANAGEMENT INFORMATION REPORTING: A FEASIBILITY ASSESSMENT

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Abstract

This thesis opens up a line of investigation in graphic methods for the display of numerical management information. A specific class of graphic representations, called Matrix Displays, is defined as the direct mapping of data tables into two-dimensional graphic matrices. Each data item is represented by variations in the sizes of dots or bars, or in the density of grey shadings.

A three-step research methodology is chosen to assess the feasibility of Matrix Displays for management information reporting: (1) Findings in other fields relevant to the thesis of feasibility are identified, (2) a theory of the usefulness of Matrix Displays and a corresponding model are then proposed, and finally (3) the practical utility of the Matrix Display model is assessed in a real-life managerial environment.

First, it is found that two different fields of research provide strong evidence that Matrix Displays are technically feasible. Experimental results on human visual performance demonstrate that Matrix Displays can aid perceptual tasks such as discrimination and pattern recognition. Multidimensional analytic research suggests that simple statistical structures (such as clusterings and linear or circular orderings) show up as density gradients around the main diagonal of a

similarity matrix where similarity coefficients are mapped into shades of grey. Both lines of evidence lead to a theoretical contribution on the proper distance metric for defining spatial relationships in Matrix Displays. Then, a general-purpose model of data analysis with Matrix Displays is designed into an interactive computer program called MATBORD (for Matrix Display Boards). This program incorporates three levels of matrix data analysis, namely, raw, profile, and similarity data displays. Rules for reorganizing any Matrix Display by permutation and/or grouping operations are suggested. Furthermore, a variety of scaling, binning, and enhancement procedures for improving the graphic transfer of information to the user are provided.

Finally, the practical utility of Matrix Displays is assessed in a real-life managerial environment. In a case study of implementation, MATBORD is used to prepare two quarterly reports enabling a manager at the Department of Labor Regional Office in San Francisco to evaluate the performance of twelve subordinate entities. Later, the managerial feasibility of Matrix Displays is investigated in a session where the above manager and his staff are invited to interact directly with MATBORD in a laboratory environment. As a result, it is found that Matrix Displays are both technically feasible and management feasible, in the sense that managers accept this mode of representation. However, the direct use of a Matrix Display of similarity data by a manager seems to require a fair amount of learning and practice. This suggests that the systematic implementation of Matrix Displays in a management environment may necessitate the intermediary function of an information analyst.

DEDICATION

To Corinne

Ce sont les travaux de l'homme qui sont grands:
Celui qui met le lait dans les vases de bois,
Celui qui cueille les épis de blé piquants et droits,
Celui qui garde les vaches prés des aulnes frais,
Celui qui fait saigner les bouleaux des forêts,
Celui qui tord, prés des ruisseaux vifs, les osiers,
Celui qui raccommode les vieux souliers
prés d'un foyer obscur, d'un vieux chat galeux,
d'un merle qui dort, et des enfants heureux;
Celui qui tisse et fait un bruit retombant,
lorsqu'à minuit les grillons chantent aigrement;
Celui qui fait le pain, celui qui fait le vin,
Celui qui sème l'ail et les choux au jardin,
Celui qui recueille les oeufs tiédes.

F. Jammes

De l'Angelus de l'Aube à l'Angelus du Soir, 1897

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I had the extraordinary chance to meet highly spirited friends, Gerry Duguay, Jean-Pierre Protzen, Mike Cawdrey, and the cheerful group in Churchman's seminar, in particular Art Stamps, who designed the graphic frame of the dedication page. I benefited from the affectionate support of Peter and Joyce Gaffney, Sister Judith Guevara, and those people who kept writing from France: Marcel Bourgeois, who fostered my enthusiasm, Jacques Balmary, who gave me roots and earth, Hamid Kitous, who opened to me his berberian soul, and Father Lin whose spirit protected this work.

Finally, I thank Ardie Rutan and Judy Paukert for preparing the

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PREFACE

It seems worthwhile to provide some historical background on how I came to choose this thesis topic.

My interest for graphic displays was initiated while I was a student of Professor Bertin, head of the Laboratoire de Cartographie at the Ecole des Hautes Etudes, Paris. Dr. Bertin gave me a basic background in graphic display theory and encouraged me to observe empirically the role of graphic displays for management. Under his direction, I ran a field study on the formatting of management reports in a large oil company in France.

Later, Drs. Churchman and Crossman helped me to pursue this interest by guiding me in a pilot study of the use of graphic displays in managerial documents. A case study of an airline maintenance information system (United Airlines Company) and of stockmarket analysis reports (American Express Company; Davis, Skaggs & Company) confirmed the results obtained in France. The study led to the definite conclusion that two basic classes of graphic representations had some usefulness for management, namely, time-series and Matrix Displays.

The choice to focus on Matrix Displays was a difficult decision, guided by a belief and by some circumstances.

The belief was that, because two-dimensional data tables have a prevailing role in numerical management reporting, their direct representation as Matrix Displays might become a general mode of representation. The circumstances were determined by my involvement in a conjoint research project of the Lawrence Berkeley Laboratory and the U.S. Manpower Administration, where it appeared that Matrix Displays would be of more immediate utility than any other form of graphic representations.

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INTRODUCTION

This thesis presents and analyzes ways of improving the transfer of information between the management data-base and the manager through Matrix Displays, a specific class of graphic representations.

Background

The notion that graphic representations can help the human user interpret statistical data can be traced back to Playfair (1805) and, more recently, Brinton (1914). Until recently, however, the rational aspects of graphic displays were underestimated, because of an emphasis on the aesthetic side of graphics and the overpowering significance attributed to numbers. Over the last quarter century, several converging attempts have been made to bring graphics to a rational definition; that is, to define formal rules for the process of mapping statistical data into graphic variables.

(1) Researches of <u>cognitive processes</u> show that perception and cognition are definitely related. For instance, Shepard, Hovland, and Jenkins (1961) used a graphic display to support tasks of categorization by human subjects. More generally, experimental results place graphic on a par with verbal language as a mode of representation (Atwood, 1971). Consequently, the idea that human cognition has a dimensional spatial character is explored in relation to human problem solving (Newell and Simon, 1972).

(2) <u>Statistics</u> is another field where the rational side of graphics has been recognized. For instance, Wilk and Gnanadesikan (1968)

systematize the use of probability plots in order to discover the properties of parameter distributions. Anderson (1960) proposed using graphic variables such as the orientation and length of bars to convey the multidimensionality of a data set. Chernoff (1973) suggests using the various features of a face (for example, position of nose, shape of mouth, etc.) to convey multidimensional variations. More generally, the notion of a "non-metric" approach to multidimensional scaling (Shepard, 1964a, 1964b) has resulted in a trend of research which emphasizes graphic considerations (Shepard, 1974).

(3) Finally, geography exemplifies an applied field where the consideration of graphic problems--such as mapping a three-dimensional earth onto a two-dimensional map--has been a tradition at least since Mercator. Recently, a French cartographer, Jacques Bertin, has proposed a set of rational rules for the construction and manipulation of graphic displays (1967, 1969, 1970). Since I have had an opportunity to meet and study with Professor Bertin, this thesis owes much of its *furia francese* to Bertin's ideas.

Problem

In this thesis, I adopt a management science viewpoint and address the question of how graphic displays can help the manager interpret an available data-base.

Although there exist many ways and modes of graphic representation, and each might have different implications for management, we shall restrict our attention to the specific case of Matrix Displays. Matrix Displays are displays organized in a matrix-like fashion, with lines (rows) and columns such as those found in management data tables.

For instance, the comparison of the performance of *n* managerial entities on a set of *p* management criteria can be visually realized on a *n* X *p* Matrix Display with *n* profiles of *p* vertical bars. Because Matrix Displays directly map tabular data into graphical representations, it has been proposed that they can be of general use in management information situations where data tables are used extensively (Bertin, 1969; Kitous, 1972). Moreover, the lack of management science research on Matrix Displays suggests that the research payoff would be higher with Matrix Displays than with other well-studied graphic formation such as time-series.

Consequently, I shall address the research question of how Matrix Displays can help the manager inquire into his data-base.

Method

The method that I shall use is exploratory rather than confirmatory, because the field of graphic display research--and particularly Matrix Display research--is still largely undeveloped.

The research methodology is called "feasibility assessment" by analogy with technological assessment studies which aim at evaluating the impact of new technologies on a complex of social variables (Weisbecker, 1974). In the context of management science, this feasibility assessment approach obeys three requirements.

(a) To identify findings in various fields which support the thesis of the feasibility of Matrix Displays.

- An exploration of the research literature had led to the recognition that two dramatically different fields of scientific inquiry contain findings relevant to Matrix Displays. These two fields are Experimental Psychology (human visual performance) and Data Analysis (multidimensional scaling).

(b) To translate the findings so that their relevance can be clearly seen and to structure the rèlevant information into a theory of Matrix Displays.

- One essential aspect of my contribution is to show that the observations and results generated by two different lines of inquiry converge to a suprising extent toward a theory of Matrix Displays. Accordingly, I formulate some hypotheses on how those results can be integrated into such a theory, and I propose a set of quantitative measures and guidelines for the use of Matrix Displays.

(c) To assess the feasibility of Matrix Displays in a managerial environment.

- The idea here is to obtain some cues as to how a managerial audience would receive and use Matrix Displays for daily decision-making. I propose to focus on the specific situation of management information reporting, and I provide an implementation study involving the participation of managers at the United States Department of Labor.

The means which I have used to achieve this methodology are several-fold. Intellectually, I have contrasted in a dialectical manner the human subject ("HUS") of experimental psychology and the multidimensional data analyst ("MDA") of statistics, so as to reach a synthetical viewpoint. Practically, I have designed an interactive model on the basis of the above theoretical contribution, and I have written the corresponding computer program to permit interactive Matrix Display usage. Empirically, I have assessed the utility of Matrix Displays by way of an interactive session where managers themselves prepared a management report including matrix displays and numerical tables. This session was actually the result of a long preparatory process, and it gave an opportunity to managers and academic faculty to confront their views on the utility of graphics.

Results

The major contribution of this thesis is to show that Interactive

Matrix Displays are feasible aids to management information reporting:

(1) On the one hand, I demonstrate the technical feasibility of Matrix Displays. A three-step process of data analysis transforms a Raw data matrix into a Profile (normalized) matrix, which is itself used for computing a matrix of Similarity coefficients. The Similarity matrix has a fundamental role as a basis for sophisticated multidimensional analysis.

(2) On the other hand, I assess the managerial feasibility of Matrix Displays. The main result here is that managers accept the Raw and Profile matrices as a support to management information inquiries. However, the notion of Similarity and its corresponding Matrix Display seem much more difficult to understand and, therefore, to accept. Consequently, a suggestion is made that an "information analyst" be the interface management person between the manager and the interactive process of data analysis with Matrix Displays.

The plan of the thesis reflects this two-fold approach: Chapters II, III, and IV present a technical contribution to a theory of Matrix Displays; chapter VI deals with the managerial feasibility of Matrix Displays for information reporting. Chapter V has the difficult role of translating the theory into a feasible model, applicable to the managerial reality. Finally--or rather: to start with--the first chapter is a general introduction to the issues we shall deal with in this thesis, and particularly to the relation between Matrix Displays and management.

CHAPTER I

FROM MANAGEMENT INFORMATION SYSTEMS TO MATRIX DISPLAYS

The aim of this chapter is to provide a description of the general area, as well as the purpose and method of this research. In the sections below, I shall attempt to present sequentially:

(1) The general area of our inquiry; that is, management information systems from the viewpoint of the relations between the individual manager and his data-base;

(2) The restriction of our research to the "mode of presentation" variable, and more specifically the use of graphic displays by managers;

(3) The general traits of a methodology for a synthetic assessment of the utility of graphics for management (graphic displays as models);

(4) The choice of a specific type of graphic representation called "Matrix Display" as being the essential vehicle of our assessment study.

I.1 Management Information Systems and the Manager

One general problem of a management information system (MIS) is the problem of interfacing managers and management data so that information be perceived. There are many different ways to realize this interface, from the building of categorical codes, such as in Accounting, to the use of qualitative verbal reports, where intuition plays a larger role than numerical precision. There are also many possible ways to observe the information search in the organization setting, depending on whether group phenomena or individual behavior is the relevant issue.

The present thesis focuses primarily on the information search of the individual manager who seeks to extract some meaningful information out of a data-base. Here the notion of a data-base implies (1) that the data are available in numerical form and (2) the information systems are computer-based.

With this specification in mind, the following definition covers most of the ground that we shall explore in this chapter:

> An information system consists of a person of a certain psychological type who faces a problem within some organizational context for which he needs evidence to arrive at a solution, where the evidence is made available through some mode of presentation (after Mason and Mitroff, 1973).

This definition decomposes the interfacing relation between the manager and the data into its most noticeable elements. However, these elements are not always independent. For instance, the mode of representation influences the formulation of the problem which, in turn, determines how evidence is gathered in a given organizational context. Similarly, the psychological type of the manager might influence the choice of a mode of representation. The above definition thus provides a somewhat artificial, but nevertheless useful, framework for discussing information systems.

Putting aside the question of the mode of representation, which I shall address in some depth later, the remaining issues can be classified under two headings:

(1) How the manager's biases and models influence an information query

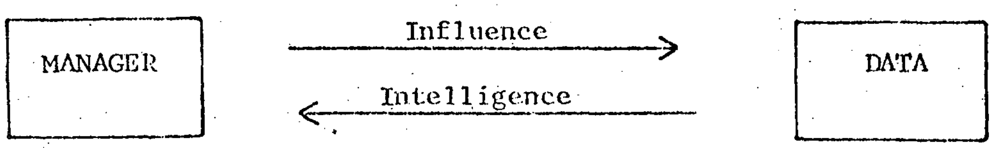
(2) How the MIS itself can be made "intelligent" by incorporating rules of inference

In order to integrate these two different approaches to the MIS problem, we need to examine a third approach:

(3) An interactive paradigm for information transfer

I.1.1 Aspects of Managerial Influence

There are two alternative (and complementary) ways to look at the relations between the manager and the data-base: On the one hand, it is possible to consider that the manager uses his own mental models and a priori intuitions to filter and select some relevant information out of the data universe. This approach, which consists in going from the manager to the data, might be called the "influence" approach, since the manager is supposed to know beforehand what to look for in the data. On the other hand, it is possible to consider the inverse relation of going from the data-base to the manager to design analytic methods which filter and prepare the data in such a way that they are directly usable by the manager. This second approach I call the "intelligence" approach, since it amounts to developing intelligent methods for the recovery of data structures. The diagram below shows how the two suggested approaches complement:



The available MIS research literature divides equally between those two approaches.

Researches on the influence aspects have emphasized the discovery of factors which explain how managers' mental models and/or attitudes influence their search for information. We shall here focus on three such factors:

a. Cognitive Style

The notion of cognitive style has received wide success in studies of the implementation of management science proposals, where it was observed that the difference in the "thinking styles" of managers and researchers could account for some of their misunderstandings. In particular, it was observed that managers tend to use heuristic reasoning where common sense, intuition, and feelings about future developments have more part than formal models. For instance, an experimental study by Huysmans (1970) showed that "heuristic" (manager-like) subjects who received information in an analytic form (equations, numerical data, etc.) advocate a lower degree of use of the information than "analytic" (scientist-like) subjects. Barbichon and Ackerman (1970) obtain the same result in a French environment and differentiate the "empirical" (management) type from the "mathematical" (scientific) type. Mason and Mitroff (1973) use the expression "psychological type" to convey a more complex typology where they distinguish modes of cognition from modes of evaluation of cognition. The alternate modes of cognition are sensation and intuition; the alternate modes for evaluation are thinking and feeling. Each of the four types obtained by combining these binary criteria has a different concept of information. For a manager who is a sensation type, information will be "raw data" or "hard facts," while an intuition type will look for "stories" and "sketches of future possibilities." On the other hand, the thinking type will emphasize the formal, abstract characteristics of the data, while the feeling type will look for "stories that have a strong moral component."

b. Organizational Factors

The organizational context in which the manager is placed introduces various biases, distortions, and transformations in the way he perceives data:

-His task induces him to take a biased view at data. For instance, Cyert and March (1963) observed that cost analysts tend to overestimate costs and sales managers to underestimate sales. Dearborn and Simon (1958) show that, more generally, each executive perceives the aspects of the situation that relates specifically to the activities and goals of his department.

-His hierarchical position may make him perceive what he wants to hear. "If the recipient is a Superior, there will be a tendency to make the information consistent with the transmitter's perception of what the recipient wants to hear (Ference, 1970)." More generally, a process of uncertainty absorption takes place in the organization so that the inferences, instead of the data themselves, are communicated.

-His experience with the data over time enables him to select important figures, recognize errors, and adapt to "noise" effects (Cyert and March, 1963). There is, however, a risk of missing the important information when it comes, since it takes some time to recognize large incongruities in the data (Bruner and Postman, 1969).

c. Motivational Factors

The individual motivation and beliefs of the manager also play a considerable role in his perception of the data. For instance, Hammer and Ringel (1965) show that the lack of confidence of a manager in the data set cause him to delay action or even to refuse to act. Earlier, Tajfel (1957) had shown that differences in the a priori value attributed to the data influence the perception of their objective importance. More generally, a nonmotivated user won't make use of the data, while a motivated manager may unduly emphasize certain aspects in the data. Mulhern (1972) presents an actual situation where managers preferred to create data which fitted their view rather than to use available data which they did not understand.

I.1.2 Aspects of MIS Intelligence

The above section has shown that, according to one school of research, the manager is inevitably led to look at the data with his own cognitive style and with the biases which his task, position, and beliefs impose on him. Another school of research, oriented more toward statistical than behavioral considerations, focuses on the other end of the MIS problem; that is, data processing aspects. The general idea is to entrust the computer system with tasks of statistical inference so that the manager is given a digest of the data rather than the raw data themselves.

This approach has resulted in proposals for making the MIS become intelligent and, consequently, has resulted in scales for judging the intelligence of observed management information systems. Two such scales are presented below:

Table 1.1

Zannetos (1968)	Montgomery (1971)
1. Store modules of raw data	1. Pre-process raw data (Clean, Edit)
2. Classify data (perceive differences)	2. Create, organize, eliminate files
3. Extract differences	3. Maintain and update files
4. Store simple cause/effect relationships	4. Retrieve information
5. Manipulate cause/effect relationships	5. Perform logical operations on data
6. Infer probabilistically and challenge models	6. Apply statistical transformations
7. Derive functional relations from experience	7. Generate digest reports
8. Appreciate own inferential behavior	

Although Zannetos' model is somewhat more idealistic than Montgomery's, they both illustrate the same point; namely, that actual systems rarely go beyond steps 3 or 4, while suitable systems should have capacities starting at step 5 and up. Consequently, the researchers advocating the intelligence approach, recommend that computer systems be refined and sophisticated enough to provide a level of "intelligence" (inferential power).

Some researchers have gone even further by proposing that moral issues be added to the factual and statistical aspects of the manager's information query. Kunz and Rittel (1970) propose that four different types of issues be distinguished:

(1) Factual issues: Is x the case?
(2) Moral issues: Shall x become the case?
(3) Explanatory issues: Is x the reason for y?
(4) Instrumental issues: Is x an appropriate means for accomplishing y?

Types (1) and (3) above are included in Zannetos' and Montgomery's frameworks. On the other hand, Types (2) and (4) include moral and teleological issues which are also part of the management process. The extent to which computer systems can replace management in this respect is still not very clear at this point. We leave it here as an open question--our own observation being that present computers have no "moral" capacity.

Very little evidence is available on the utility of systems which present a modicum of "intelligence"; that is, some data digesting. One interesting experiment was with an interactive system in a production-inventory situation (Chervany and Dickson, 1974), where data was presented either in raw form, or condensed by means of summary statistics. The results of the experience support the general contention that the condensation of the data improves the managerial performance. It was also shown that the performance of managers using the summary data was more predictable than that of managers using the raw data. But one unexpected and undesirable side effect was that the users of the summary data had less confidence in their decisions.

I.1.3 An Interactive Paradigm for Information

The above result--that managers using summary statistics achieved a better performance, but had less confidence in their decisions than managers using raw data,--shows that the "intelligence" of a MIS may adversely "influence" its users. A sophisticated system may have informational benefits but behavioral costs in the sense that its users do not "trust" it in various ways. Reciprocally, a system which produces masses of raw data is beneficial cost-wise (the cost per datum is very low), but results in information overload on the user side. There needs to be a balance between the level of sophistication of a system and the level of satisfaction of its users.

At the elementary level of the relation between the manager and the data-base, it is proposed that information results from the interaction of the manager's mental models with the data evidence: It is the manipulation of event (data) to observer (manager) that allows him to discover meaning (Johnson, 1969). According to this view, the information search is described as an interactive process between the manager and his data so as to reach a line of evidence which satisfies the manager's query. This description is general enough to account for a whole set of possible empirical situations of information search. Is it possible to describe the interactive relationship between the manager and the data into more specific terms?

The notion of a trade-off between the costs and the benefits of information provides one interesting specification of the interaction paradigm. According to the cost:benefit model (Marschak, 1968, 1974), the interaction between the manager and his data is dictated by the economic objective of maximizing the utility of information. The utility is defined as a function of two criteria, benefit (gross payoff) and cost, increasing in the former and decreasing in the latter. The costs of a system are easily computed as the costs of the information services to the manager. On the other hand, it is more difficult to determine the economic benefits of a system. Marschak proposed than an economic evaluation of the benefits is possible, where "benefit" is defined as: The expected desirability of the outcomes of managerial actions decided on the basis of the information produced by the system.

This cost:benefit formulation has been tested in experiments where subjects are placed in a situation of information-purchase (Irwin and Smith, 1957; Lanzetta and Kanareff, 1962; Edwards, 1965; Hershman and Levine, 1970). The experimental results show that:

(1) The general strategy of information purchase obeys the rule "purchase another datum if it is subjectively worth more than it costs."

(2) Subjects' strategies satisfy the above qualitative rule rather than optimize its utility-maximization formulation. Depending on the circumstances, subjects purchase less information (Lanzetta and Kanareff) or more information (Hershman and Levine) than the maximization of utility would indicate.

This general result points to the value of the cost:benefit approach more as qualitative paradigm than a uniquely quantifiable model.

When the cost:benefit model is used to evaluate a given MIS, it may be particularly difficult to estimate the system's benefits in the same terms as its costs (for example, in dollars). Most of the benefits of an information system relate to some behavioral change, over a period of time, in a variety of ways, as opposed to the economic, immediate, specific nature of costs. Consequently, it has been advocated that the benefits of a given system be estimated in qualitative rather than quantitative terms. For instance, Swanson (1974) measures the management benefits of an actual system through an attitudinal (qualitative) variable called "managerial appreciation." More generally, it is proposed that the benefits of a system be evaluated in reference to the qualitative appreciation of its users.

The emphasis on the users' appreciation is fairly new in management science, where the natural tendency for scientists is to measure a system's benefits in accordance to their own technical viewpoint (Churchman, 1972b). Consequently, it requires some effort on the scientist's part to accept that users may have a say in the appreciation of system's benefits. According to King and Cleland (1975), it may even require the scientist to change radically his value system, and to adopt the belief that

> a technically-optimum system which goes unused is inferior to a system which is technically inferior, but perceived to be useful by the organization's managers.

The present thesis is an effort to reconciliate the two sides of MIS design--technical optimality and practical utility. Accordingly, it will include developments and results concerning the technical feasibility as well as the managerial feasibility of graphic displays.

I.2 Management and Graphics

I.2.1 Graphic Displays in Management

It is a well-observed fact of management life that graphic displays are used in a variety of situations and trades. For instance, in a field study realized in France (Kitous, 1972), graphic displays were found to be practically used in the building industry (Gantt type charts), in the oil industry (inventory control charts), and in public administration (scatter plots and maps to display statistical data). These findings were confirmed by a subsequent empirical study made in the United States; business documents collected on-site show a definite tendency for managers to use graphic displays as an aid to decision-making (Internal reports were collected at the United Airlines Company, Davis Skaggs Company, and the United States Department of Labor in San Francisco). There even exist specific business periodicals exclusively devoted to the publication of graphic charts, such as the "3-Trends" series in the stockmarket business.

The variety of graphic formats used in management situations seems overwhelming. However, it is possible to differentiate between two basically different modes of graphic representation:

(1) Certain representations, such as those used in advertising, present pictorial information: people, familiar films, or photos. The basic characteristic of these is to be aesthetically pleasing.

(2) Another branch of graphics has developed formal displays based upon geometric and/or symbolic rules, where learning has a certain role to play. By opposition with the immediate, intuitive status of pictorial representations, these representations have a rational or constructed status.

At the macrolevel of a general theory of graphic displays, there are undoubtedly relations between these two basic graphic formats. For the purpose of this thesis, however, only the second type of graphic representations will be considered, thus excluding purely aesthetic considerations out of the boundaries of the present research.

According to a theoretical framework proposed by Bertin (1967), the area of rational, or constructed, graphics can be divided into three types: plots, graphs, and maps. In each case, two- or three-dimensional representations are possible. Since most management applications are two-dimensional, and since two-dimensionality carries the essential implications of any such graphic representation, we shall limit our attention to two-dimensional displays.

(a) Plots

A plot is any graphic representation such that the two dimensions of the plane are explicitly used. Each dimension represents a variable, or some explicit set of differentiable variations such as categories. The table shown below presents different types and instances of "plots," with some corresponding management applications:

Table 1.2

Types	Instances	Applications
Continuous plane (Cartesian)	Time-series	Economic Forecasting Control Systems
	Scatter-Plots	Market Analysis
Discrete plane	Matrix Displays (e.g., Bar Profiles)	Performance Comparisons

The concept which is essential to the plotting of data is the notion of two-dimensional position; that is, it is possible to determine a 2-D "address" for each available data item. Depending on how the plane is used, it is said to be used in a continuous or discrete manner. We shall later examine the specific case of matrix displays in more detail.

(b) Graphs

A graph is a set of points, called nodes, such that at least some pairs of nodes are connected by branches, called edges. A whole set of mathematical methods, placed under the name "graph theory" have been specifically devised to solve graph problems (Berge, 1958, 1968; Ore, 1963). The most important definitions, with respect to management applications are:

(1) A graph is said to be connected when there exists a path between any two of its nodes.

(2) A circuit in a graph is a path which is closed on itself.

(3) A tree is a connected graph that has no circuits.

The table shown below summarizes some of the graphic aspects of graphs.

Table 1.3

Types	Instances	Applications
Graph	Networks of relations	Group behavior in organizations
Connected graph	PERT diagram and Gantt chart	Production scheduling, activity networks
Trees	Hierarchical representations	Organization Chart

The use of graphs has found a large application in the managerial world, which may be accounted for by the relative simplicity of their design (Citrenbaum, 1972).

(c) Maps

A map is a constructed representation of spatial relations in the human physical world. Maps are the most ancient graphic representations to have been rationally constructed for human usage. They present some fascinating problems of projection (projecting three dimensions into two) and "mapping" (producing maps at various resolution levels). Maps are currently used in almost all managerial activities involving spatial decisionmaking such as transportation, urban planning, warehouse locations, etc.

I.2.2 Interactive Graphics and Management

The recent availability of low-cost computer graphics terminals has triggered the process of implementation of graphic aids in managerial environments. The rationale behind the use of such terminals is that:

(1) They insure repeatability and precision in the design of graphic displays; the displays are drawn by the computer according to formal, repetitive rules (Sutherland, 1963).

(2) They permit obtaining several different displays (multiple pictures) of the same data-base, which is an improvement over the "one-pass" procedure where one display only is produced (Welsch, 1974b).

(3) The power of the computer is coupled with the generality of the graphic formats, thus enabling heuristic search methods to be applied to problems which cannot be solved by the usual optimization methods (Newell, 1969; Garman, 1970).

The most important reasons why interactive computer graphics have recently reached a large management audience is their low cost. The following table summarizes some price data (in 1975-1976) for interactive graphic terminals, including computer interfaces:

Table 1.4

Brand	Device	Model	Purpose	Price($)	Lease ($/month)
Digivue	Plasma Display	512-60	All	$6,000	-
Imlac	Refresh Tube	PDS-ID	All	9,970	-
Princeton	Storage Tube	801	All	8,150	-
Tektronix	Storage Tube	4010	All	4,000	150-350
		4051	All	6,995	280-450
Quotron	Alpha-screen	800	Stockmarket	-	200-300
MCM	Alpha-printer	MCP	APL-keyboard	5,500	-

As can be seen by comparing the upper part of the table (graphic terminals) with its lower part (alphanumeric terminals), the price range for graphic terminals ($4,000-$10,000) is only slightly superior to the price range for alphanumeric terminals. Moreover, it is expected that the price of graphic terminals will still decrease in the years ahead, due to the development of improved technologies (Society for Information Display, Proceedings Los Angeles, 1975). On the basis of the prices above, it is possible to estimate the display cost of an elementary plot produced interactively at about $1.00, under the assumptions that the terminal is used 5 hours per day to produce an average of 15 plots each hour. Even with a threefold increase (to include the computer-processing cost), this cost remains fairly low compared to the cost of a human-made plot.

Management science research in interactive computer graphics has developed on the lines of Sutherland's computer program called Sketchpad (1963). The general idea is to use graphic displays as means for communicating the results of analytical procedures applied to typical problems. Sketchpad itself enables the user to measure the mechanical tensions and forces which a graphic representation implies (for example, draw a bridge and measure the implied forces). Typical management science applications include:

(1) Garman's Mags (1970) which uses Gantt charts as an interface to the solution of simple and complex job-shop scheduling problems.

(2) Welsch's Troll (1974a) where scatter plots and tree representations are interfaced to statistical methods.

(3) Scriabin and Vergin's Layout (1975) which uses graphic layouts as a means to convey spatial constraints in plant layout problems.

I.2.3 Management and Graphics: A Research Problem

The aforementioned evidence concerning the relations between management and graphics can be summarized into two propositions:

P1: Graphic displays are widely used in practical management situations.

P2: It is possible to design interactive systems where the interface between the user (manager) and the data analytic procedures is made up of graphic displays.

These propositions are useful descriptions of what is practically done and what can potentially be done. But they do not explain whether specific graphic representations would be useful, and if so why. Only one study in management science seems to have thoroughly considered the issues associated with the usage of graphic displays (Scott Morton, 1971). Having observed how real-life managers reacted to the introduction of an interactive graphic system in their direct environment, Scott Morton in his research (Ph.D. thesis) reaches the conclusion that graphic displays had a strong positive effect since they related precisely to the cognitive needs of the managers involved in the planning process. Time-series plots improved the coordination between the production and marketing policies of the firm, and furthermore in the planning of the production itself graphs introduced organizational changes. This evidence drives us directly to the present dissertation which will focus on a specific class of graphic displays.

I.3 A Management Science Approach to Graphic Displays

In this section, we develop the view that graphic displays are models having definite cognitive implications for decision making. Consequently, it seems possible to apply a management science approach to an explanation of the relations between management tasks and graphic displays. A methodology is proposed for assessing the feasibility of graphic displays in a managerial environment.

I.3.1 The Cognitive Implications of Graphic Displays

The common belief which has hindered the development of rational graphic research is the idea that graphic displays are essentially the "cosmetics" of management life. This belief is itself related to the notion that graphic displays are used to make things "look pretty," and that they must come at the very end of the data analytic process. Too much attention to the aesthetical side of graphics has led to neglect of its rational side and to belief that graphics have no "thinking" implications.

Happily enough, this common credence has not prevented a number of statisticians, economists, and geographers from examining the thinking side of graphics--that is, graphic displays as an aid to human cognition. The results obtained to date are summarized below in a sixfold categorization expressed in qualitative terms. This categorization provides explanatory guidelines as to why graphic displays might be useful interfaces in the manager/data relationship.

(1) Graphic Displays convey relations of proximity between objects.

This is the most evident, yet least understood property of graphic displays. The perception of relations of proximity between objects enables the user to recognize groups of neighboring objects. Consequently, it may be the basis for the determination of clusters, with all its implications for categorization purposes (Zahn, 1971).

(2) Graphic Displays permit us to recognize relations of similarity.

Although distant in space, two objects might be similar (for example, have the same color). Graphic Displays permit us to recognize such similarities and, more generally, to compare the features of perceived objects. This is the basis for inferential activities based on comparison: For instance, two time-series might be compared according to their trends, cycles, and turning points (Burns and Mitchell, 1946; Box and Jenkins, 1970).

(3) Graphic Displays lead to inferences based upon simple geometric structures.

Scatter plots are interpreted in terms of "clouds" of <u>points</u>, regression procedures in terms of a regression <u>line</u>, and independence between variables in terms of <u>orthogonality</u> (right angularity). The appearance of geometric structures in the display has strong implications for the associated cognitive process (cf. the development of specific procedures for recognizing normality in analysis of variance, Wilk and Gnanadesikan, 1968).

(4) Graphic Displays reduce the amount of detail in the data.

The degree of detail available in a map can be varied simply by changing the mapping scale which relates the "map space" (in inches) to the "physical space" (in miles). Similarly, graphic displays, in general, offer an opportunity for mapping numerical items into graphic variations which have less resolution. This reductive process may be detrimental to absolute precision, but it often results in a better perception of the relative importance of events (global trends and patterns) (Bertin, 1967).

(5) Graphic Displays can be manipulated for better interpretation.

Geometric transformations such as rotation, translation, and (under certain assumptions) scaling by a positive constant can be applied to cartesian displays. This permits giving a substantive interpretation to spatial configurations (it is of much use in Factor Analysis). Other than cartesian plots, there are display types that also have their own manipulative rules: For instance, when a graph is known to be "planar," it can be rearranged so that no two edges intersect, thus facilitating the perception of implied relations (Ore, 1963).

(6) Graphic Displays require some implicit geometric knowledge.

Cross-cultural studies of visual perception (Segall, Campbell, and Herskovits, 1966) have shown that other cultures than ours do not perceive displays the same way. It is suggested that most 2-D graphic representations require some implicit knowledge of geometric notions and conventions. Most such knowledge is of a high school level.

It results from the above sixfold argument that graphic displays have a certain generality for data analytic purposes. Welsch (1974a, 1974b) and Tukey (1971, 1975) propose that they be the essential means for exploratory data analysis. Quenouille (1952) goes further and proposes that graphic displays be used for statistical testing purposes. It is sufficient, at this point, to observe that graphic displays have been recognized as a rational means for aiding intellectual inference. This may explain why they have found such popularity in management circles.

I.3.2 Graphic Displays as Models

Up to this point, we have argued as if all forms of graphic display had the same value and/or implications. It is suggested now that there are major types of graphic representation and that each type has its own assumptions and implications in much the same way as management science models do. One subtle and interesting way to uncover the fundamental assumptions of a given mode of display is to consider the distance axioms on which it rests.

In any type of graphic representation, there exists a metric; that is, a scale that assigns to every pair of points a and b a distance value d(a,b). The following conditions are usually regarded to be reasonable axioms of distance (after Beals, Krantz, and Tversky, 1968):

<u>Equation 1.1</u> Positivity: $d(a,a) = 0$ and $d(a,b) \geqslant 0$ if $a \neq b$
The distance between a point and itself is zero. The distance between any two points is positive.

<u>Equation 1.2</u> Symmetry: $d(a,b) = d(b,a)$

<u>Equation 1.3</u> Triangle inequality: $d(a,b) + d(b,c) \geqslant d(a,c)$
Given any three points is graphic space, the sum of the distances from the first to the second and from the second to the third is not less than the distance from the first to the third.

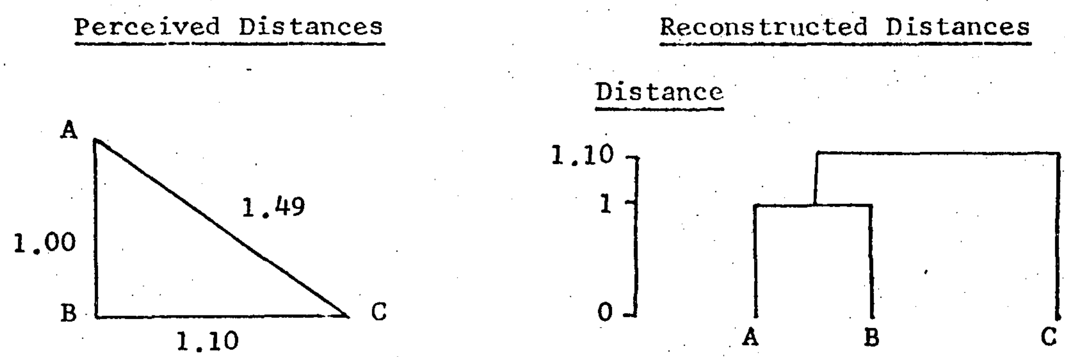
Most graphic modes of representation satisfy these three conditions, plus a fourth one, more specific and more constrained than the above. For instance, distances in the Cartesian plane obey Equations 1.1, 1.2, and 1.3, plus the Euclidean axiom:

<u>Equation 1.4</u> $d(a,b) = \left[(x_a - x_b)^2 + (y_a - y_b)^2\right]^{\frac{1}{2}}$
where x and y are the x and y-axis coordinates.

Quite in the same manner, most graphic representations satisfy a "fourth axiom."

When graphic displays are used in management circumstances, attention is almost never paid to the "fourth axiom," which is made implicitly by the chosen mode of graphic representation (consequently, one may "force" some data set into a representation which does not quite correspond to it). For instance, it has been recently proposed to use hierarchical tree representations to indicate clusters of attitudes in marketing analysis (Green and Wind, 1975). Nowhere in this marketing proposal are the distance implications of hierarchical trees clearly assessed. Suppose, for instance, that the perceived distances between three brands A, B, and C are as follows (left):

Figure 1.1



The three objects A, B, and C presented on the left hand side diagram can be hierarchically clustered (tree on the right) by the following operations:

(1) Start by clustering A and B which have the shortest distance.

(2) Then join C to the object-cluster (A,B) at the minimum distance of C with (A,B): that is, at d(B,C) = 1.10.

Clearly the hierarchical tree on the right (Figure 1.1) does not convey the original distance relations within the data, because d(A,C) = 1.10 instead of 1.49. This results from the very process of building a hierarchical tree. It has been shown indeed that distance relations in a hierarchical tree obey the following condition:

Equation 1.5 $d(A,C) \leqslant \text{MAXIMUM}\left[d(A,B),\ d(B,C)\right]$

This axiom called the "ultrametric inequality" (Johnson, 1967) is a necessary and sufficient condition for a hierarchical tree representation to hold. It is more constrained than the "triangle inequality" mentioned above (Equation 1.3) since clearly:

Equation 1.6 $\text{MAXIMUM}\left[d(A,B),\ d(B,C)\right] \leqslant d(A,B) + d(B,C)$

Consequently, we might say that the "ultrametric inequality" is the "fourth axiom" specification for hierarchical tree graphics.

In summary, the choice of a graphic mode of representation--such as hierarchical trees, cartesian plots, etc.,--involves using a particular topological model. It is proposed that the topological assumptions corresponding to a given graphic model must be elicited before such model is extensively used. This is particularly important in a management science context.

I.3.3 A Methodology of Feasibility Assessment

Before we propose a methodology for dealing with the graphic display issue, let us summarize the thread of our argumentation to this point:

(1) We choose to focus on the relation between the individual manager and his data-base.

(2) Graphic display seems to be a widely used manager/data interface, with a large variety of possible formats.

(3) Interactive computer graphic systems illustrate the paradigm of an interactive search for information through graphics.

(4) Besides the observation that graphics and analytical methods complement well, there is not much management science evidence on the relations between graphics and management.

(5) A line of research in statistics suggests that graphic displays are an efficient support to cognitive tasks.

(6) Another line of research (topology) shows that graphic displays are spatial models with strong metric implications. This suggests to explore the available research results in the visual perception of graphic displays.

The purpose of our research is to put together a useful structure for management graphics as suggested in (4) above.

In view of this purpose, and the lack of graphic knowledge within management science, it is necessary to propose a methodology which combines safety and risk. On the advice of C. W. Churchman, a methodology of feasibility assessment has been chosen, with the following features:

(a) Among the variety of graphic displays in (2), select one graphic type and formulate the thesis that it is feasible to use in this particular type of display as a support to management tasks.

(b) Identify findings relevant to the thesis of the feasibility of the above type of display. In particular, qualify the tentative lines (5) and (6) above for this specific type of display.

(c) Structure the findings into some guidelines for a theory of the selected display type, and eventually provide a quantitative formulation to those guidelines.

(d) Translate the above findings and the theoretical formulation into management science terms so that their relevance is clearly seen.

(e) Develop a model of the utilization of the selected type of graphic representation within specific tasks of management. This model might receive an interactive formulation as suggested in (3).

(f) Implement the above model on a case-study basis, with the participation of one or a few managers. Record and analyze their reactions to the proposed graphic displays (as suggested in I.1.3).

The safety factors in the above methodology are (a), (b), and (f); the risk factors are (c), (d), and (e). The methodology should at least confirm or deny the feasibility of the proposed graphics and gather some empirical evidence in a specific managerial environment. The best result which it could provide is a theoretical framework having an explanatory value as to why the selected graphic mode is useful for management tasks. Thus, the concept of "feasibility assessment," as it is used here, involves much more than merely the consideration of the physical realization of graphics. It includes their justification on the basis of scientific evidence available across disciplines, their theorization by a work of synthesis, and the observation of the process by which some managers come to incorporate and/or reject graphics into their management process.

The plan of this thesis reflects its methodology (points (a) to (f) above):

(a) In the next section (I.4), we select a certain type of graphic representations called "Matrix Displays."

(b) Evidence supporting the thesis of the feasibility of Matrix Displays is given in chapters II (Experimental Psychology) and III (Data Analysis).

(c) A contribution to a theory of Matrix Displays is provided in chapter IV (quantification procedures are proposed).

(d) and (e) Chapter V defines a model of Matrix Display usage for management tasks; an interactive computer graphics program (MATBORD) is designed on the basis of this model.

(f) Finally, chapter VI describes the implementation of Matrix Displays in a Manpower Administration context.

I.4 Matrix Displays and Management: An Opening

The first step recommended in the above methodology is the selection of a type of graphic representation for in-depth study. This choice could be somewhat arbitrary; in our case, it has been guided by empirical considerations, which we shall try to enunciate now.

I.4.1 Some Results of an Empirical Study

In 1971-72, I had an opportunity to carry out a field study aimed at determining the empirical formats which managers use in order to display their own data. On the advice of J. Bertin, I formulated the exploratory hypothesis that these formats would indicate how the manager individually relates to his data. I interviewed a sample of 17 medium- to upper-line managers in France; three United States managers were latter added to the study. I required each manager to designate the informational document which he thinks most important for his own managerial needs, and to describe how this specific document is used in relation to daily decisions. Moreover, I collected a copy of the document for later analysis.

The results of this study are relevant to our inquiry into graphic displays (Kitous, 1972). Of the 20 managers I interviewed, 6 were found to use graphic documents as an individualized aid to decision making; the other 14 used numerical data tables. I also found that managers using graphics displays were careful to keep the numerical sources of the data available, either by superimposing numbers on the plots, or by keeping a data table along with the graphic display. The amount of data "contained" within a graphic display was found to be approximately equal to the amount of data made available through numerical tables: In both cases, I found an average number of 100 to 150 data items per page. All the personalized reports were found to be short (2 to 3 pages maximum).

Among the six graphic displays which were collected, four were "time-series" type and two were "Matrix Display" types. By "Matrix Displays" I mean displays organized in a matrix-like fashion, with graphic variations located at the intersection of rows and columns. For instance, I collected a weekly matrix profile used by a marketing manager to compare the sales of several food products over a variety of distribution channels (supermarkets, co-op stores, etc.). The difference between time-series and Matrix Displays is several-fold, including:

(1) Difference in concept: Time-series emphasize the time orientation of all events, while Matrix Displays show effects in space (space of products X space of distribution channels).

(2) Difference in display: Time series are based upon a cartesian, continuous representation, while Matrix Displays use a representation with discrete, categorical row and column entries.

(3) Difference in preparation and updating: Time-series are relatively easy to prepare and update on commercial graph paper. Matrix Displays require either much work, or the availability of specific office material such as magnetic boards, card holders, color pastes, etc. (One French interviewee had such a material. In the United States, "Executive Planning Inc." produces equivalent materials.)

I.4.2 Research on Matrix Displays

According to the results of the above research, two different possible graphic displays might be selected for a management science inquiry: time-series plots or Matrix Displays. After some in-depth thinking, I chose to focus on the case of Matrix Displays, which is, indeed, a managerial decision.

> In making the decision as to what problem he should work on, the operations researcher is in effect making a managerial judgment that working on some particular problem is a better use of resources than any other alternative use (Churchman, 1972a, p. 9).

The rational part of this choice can be expressed as:

(1) The belief that Matrix Displays are potentially of general usage in management, because they fit the tabular format of numerical data (Bertin, 1968).

(2) The observation that there has been very little reflection on the significance of Matrix Displays for management. It seems that the research payoff would be higher here than on time-series displays, which have already benefited from statistical research (from Burns and Mitchell (1946) to Box and Jenkins (1970)).

(3) The empirical finding that Matrix Displays are difficult to prepare and update through ordinary paper-and-pencil means suggests that interactive computer graphics could find here an interesting application. The "cost gap" which seems to prevent Matrix Displays from receiving a larger audience could be bridged by interactive display procedures.

I.4.3 Definition and Example of Matrix Display

Definition. A Matrix Display is the two-dimensional graphic representation of a data table such that:

(1) The rows and columns of the table are represented as rows and columns on the Matrix Display.

(2) Each data item of the table is mapped into a graphic variation in the Matrix Display.

(3) Homogeneous data items are represented by homogeneous graphic variations. (It is recommended to use data tables containing homogeneous data; that is, data expressed in the same units.)

Illustration. I chose a published case of use of Matrix Displays, so that the reader may refer to it. Furthermore this example provides a Matrix Display of size 20 X 8 (20 rows by 8 columns) which is typically in the medium-high portion of the range of matrix sizes which we expect to meet. The field study which I mentioned earlier revealed that most data tables are within the range 5 X 5 to 20 X 20 (25 to 400 data items).

In an article comparing the development of countries in tropical Africa, Mabogunje (1973) uses United Nations data to show the differential development of six African countries and two developed countries (Japan and the United States). Three Matrix Displays are used to present Industrial Employment, Value Added, and Fixed Capital Formation in 20 industries. I consider here the Industrial Employment variable, but similar results are obtained with the other two variables. Table 1.5 (placed at the end of this chapter) represents the percent distribution of people employed in the 20 industries for each country. For instance, Malawi has 6.8 percent of its industrial employment in the Textile industry, 29.6 percent in Food products, etc. Each such data item is represented by a circle of size proportional to the corresponding figure. This provides a Matrix Display (Figure 1.1) where variations in the size of dots is used to convey variations in proportions. Mabogunje's comments relate to the large imbalance in the distribution of African working population, as opposed to the balanced distribution of Japan or the United States.

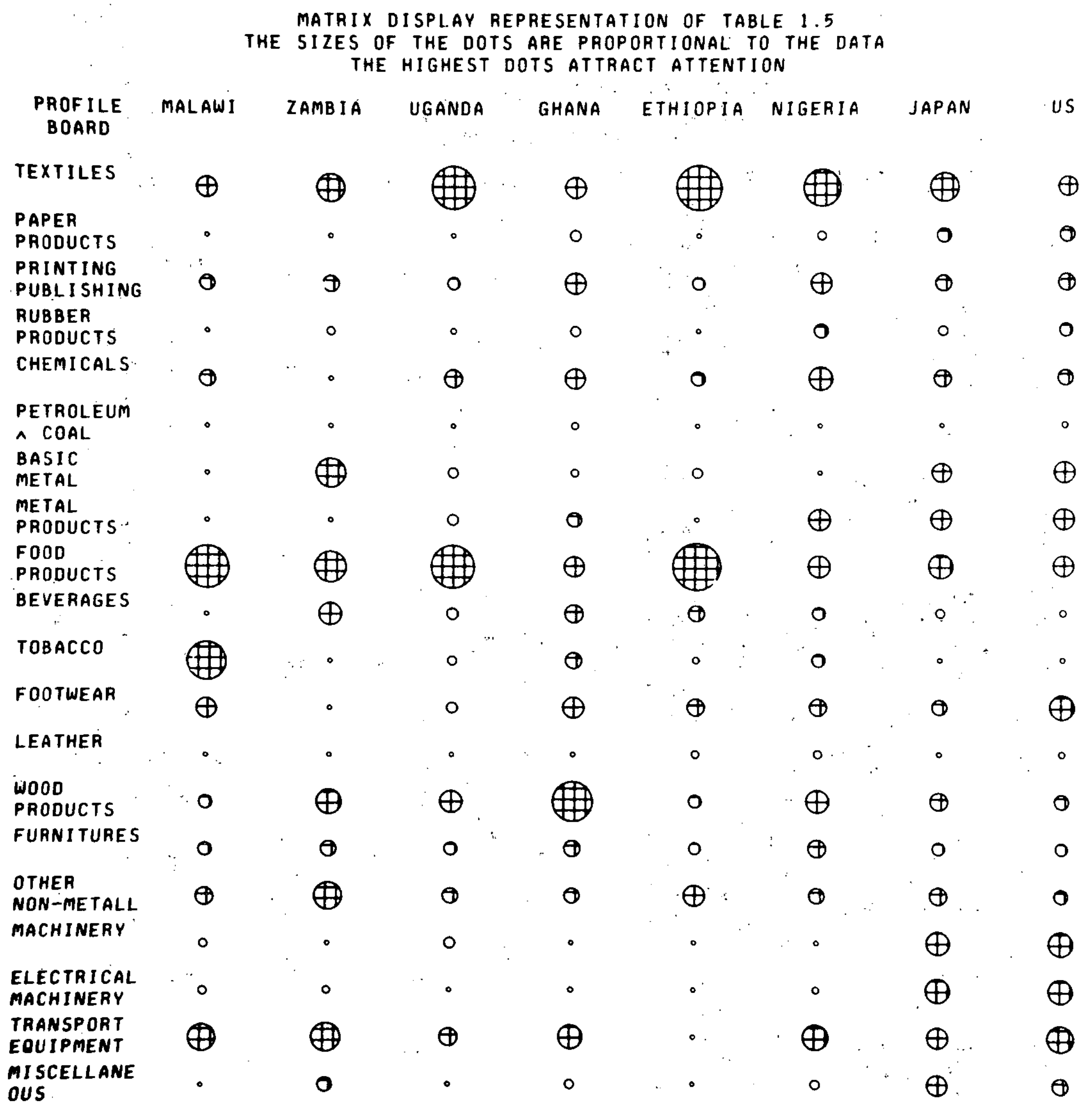
Figures 1.2 and 1.3 presents two alternatives to the use of dot sizes. Figure 1.2 uses vertical bar profiles, and Figure 1.3 uses shades of grey represented by the density of grid lines to display the same basic information. The most interpretable display seems to be obtained with bar profiles. This should not be a surprising result since it has long been known in statistics (Gini, 1939) that graphic profiles adequately convey the concept of distribution. The value-shaded Matrix Display (1.3) is not as readily interpretable, and the comparison of grey densities is difficult except for contiguous cells. This suggests that perceptual effects may affect the recognition of data within Matrix Displays, and leads to the idea that some results in experimental psychology would clarify the issues related to the use of Matrix Displays.

THE DISTRIBUTION OF INDUSTRIAL EMPLOYMENT IN AFRICA
COMPARED TO JAPAN AND U.S.A
(AFTER MABOGUNJE,1973)

PROFILE BOARD	MALAWI	ZAMBIA	UGANDA	GHANA	ETHIOPIA	NIGERIA	JAPAN	US
TEXTILES	.068	.123	.294	.071	.319	.216	.129	.059
PAPER PRODUCTS	0.	0.	.001	.019	.003	.013	.033	.036
PRINTING PUBLISHING	.036	.043	.025	.072	.025	.069	.041	.046
RUBBER PRODUCTS	0.	.011	.006	.017	.002	.032	.015	.028
CHEMICALS	.041	0.	.053	.068	.032	.089	.047	.039
PETROLEUM ^ COAL	0.	0.	0.	.009	0.	.001	.004	.007
BASIC METAL	0.	.140	.017	.010	.017	.002	.059	.074
METAL PRODUCTS	0.	0.	.020	.035	0.	.076	.067	.073
FOOD PRODUCTS	.296	.158	.303	.067	.367	.078	.096	.072
BEVERAGES	0.	.083	.023	.055	.042	.027	.014	.008
TOBACCO	.242	0.	.014	.044	.008	.029	.004	.005
FOOTWEAR	.066	0.	.020	.074	.050	.049	.037	.100
LEATHER	0.	0.	0.	.004	.010	.012	.005	.007
WOOD PRODUCTS	.029	.101	.081	.261	.028	.085	.052	.036
FURNITURES	.029	.039	.028	.043	.023	.052	.026	.026
OTHER NON-METALL	.051	.124	.038	.037	.072	.039	.050	.034
MACHINERY	.012	0.	.020	0.	0.	.004	.086	.096
ELECTRICAL MACHINERY	.012	.010	.003	.005	0.	.008	.095	.096
TRANSPORT EQUIPMENT	.117	.133	.053	.093	0.	.105	.072	.114
MISCELLANE OUS	0.	.033	.001	.014	0.	.015	.068	.043

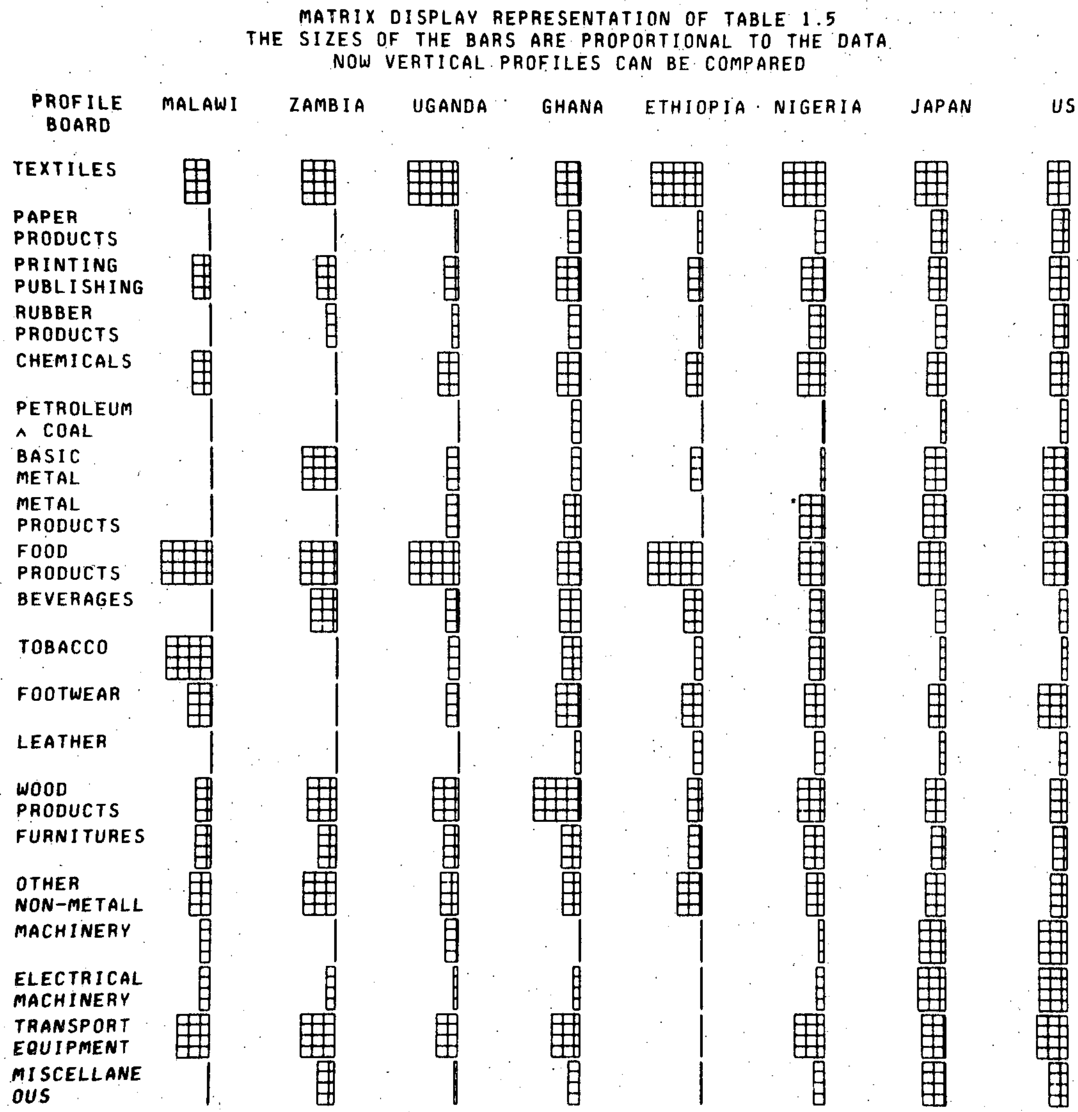
XBL 767-8645

Table 1.5



XBL 767-8644

Figure 1.1



XBL 767-8643

Figure 1.2

MATRIX DISPLAY REPRESENTATION OF TABLE 1.5
THE SHADES ARE PROPORTIONAL TO THE DATA
DARKEST SHADES CORRESPOND TO HIGHEST DATA VALUES

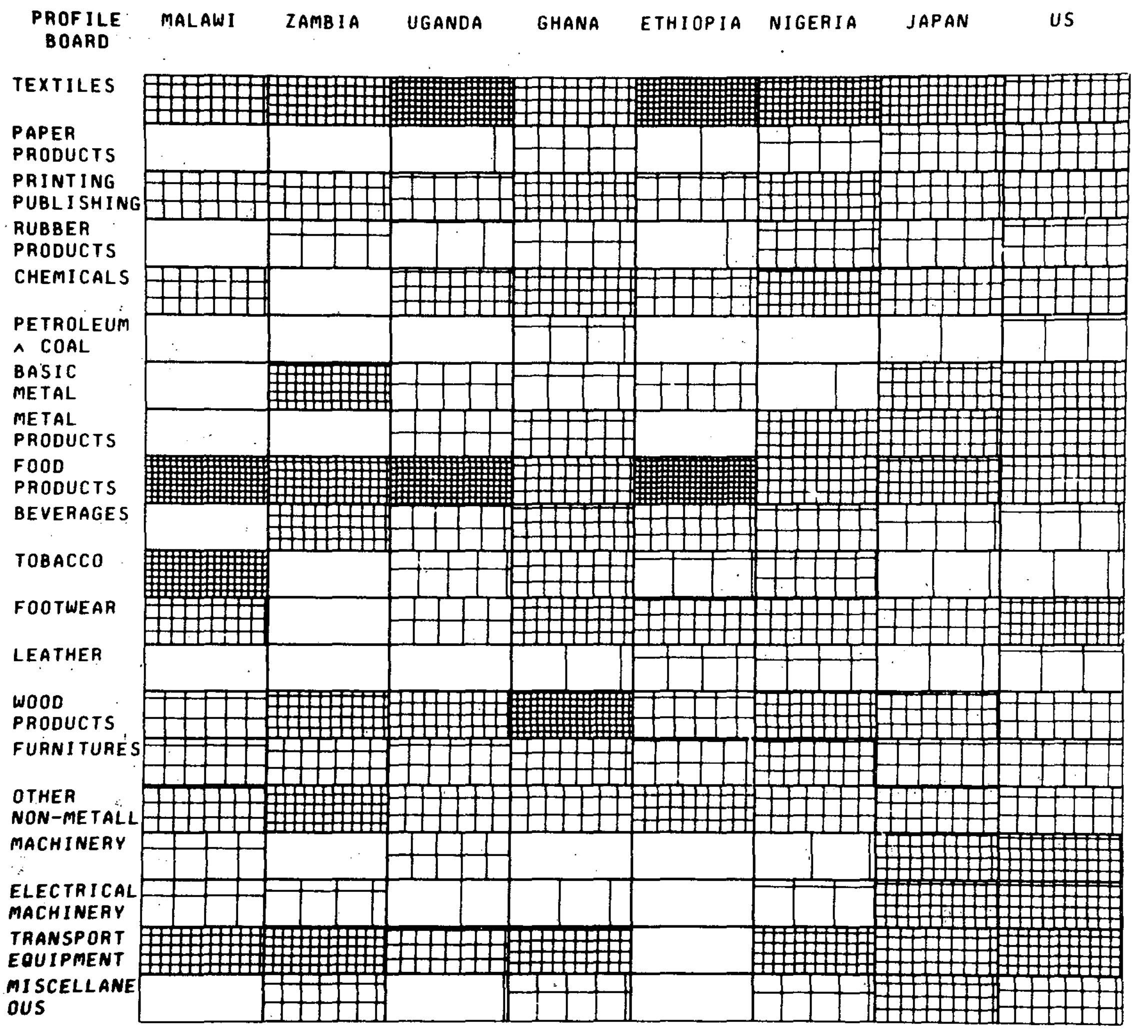


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Figure 1.3

CHAPTER II

MATRIX DISPLAYS AND HUMAN VISUAL PERFORMANCE

The objective of the present chapter is to provide an answer to the question:

> To what extent do experiments on human perception support the feasibility thesis?

Given the multiple implications of this question, I shall try to review and to organize the available evidence so that the strong points, as well as the weaknesses, of research results clearly appear. All over this section, I shall make use of the acronym HUS to stand for "the human subject," in relation to experimental data. The acronym provides a convenient fiction for the purpose of paying attention in a systematic manner to the way HUS reacts to Matrix Displays.

Practically, when I say that HUS is faced with a Matrix Display, I mean that HUS tries to extract information from a matrix which is filled with visual items of varying size and/or form and/or shade, etc. This practical situation has never been studied as such in experimental psychology, because of its inherent complexity. There is, however, a large number of research works which touch on various aspects of this situation, and which can be assembled together so as to provide a quite complete coverage of the HUS perception of Matrix Displays.

This chapter is divided into four sections which organize the topic so that the coverage of the issues goes from the simplest situation (only one dot in the Matrix Display) to the most complex situations (the matrix is fully filled with graphic items). Although the research evidence, which we shall mention, is mostly experimental, I shall at times make use of some empirical results or observations gathered in more general circumstances. Given the intent of this thesis to be a contribution to an assessment of Matrix Displays, we shall adopt an attitude of critique, inference, and synthesis, rather than the usual descriptive tone of a review.

I focus here on the perceptual aspects of the relation between HUS and Matrix Displays. This will lead me to refer extensively to tasks of perceptual judgment which have been defined in experimental psychology. Two types of tasks will be referred to during this chapter.

(1) Tasks of categorical (or absolute) judgment, where HUS attempts to place a given stimulus into its proper category. This includes tasks such as finding its proper name (Paired-Associate tasks), or such as calling its size or reproducing its position on an absolute scale (Discrimination tasks).

(2) Tasks of comparative (or relative) judgment, where HUS compares a given stimulus to a given standard. This approach is used for the development of psychophysical scales (paired comparison and other methods). Another instance of use is when HUS is asked to compare two visible dot patterns in two different matrices.

II.1 The Discrimination of One Dot in a Matrix Display

The simplest perceptual problem on which we possess some experimental evidence is one where the user is asked to discriminate the position of one dot in an otherwise empty Matrix Display. By "discrimination" is meant here the capacity of HUS to recognize the position of a dot along the discrete x and y coordinates of a matrix. The experimental procedure rests upon absolute judgment tasks such as:

(1) One matrix containing one dot is presented at a time.

(2) HUS responds by reproducing or calling the dot's position within the matrix.

The measure of the performance which is used is called "Information Transmission" and it reflects the amount of discrimination which HUS shows.

The measurement of Information Transmission is based on Shannon's theory of communication (1949). The fundamental idea is that an event is more informative, the more unexpected it is: Since it is possible to measure "expectedness" by way of a probability measure, it is possible to evaluate information as a function of the event's probability. When we consider a set of events instead of only one event, the same reasoning holds and a measure of "unexpectedness" or uncertainty can be computed on the event set. Shannon proposed the following measure of uncertainty:

$$I = \sum_{i=1}^{n} (p_i \times \log_2(1/p_i)) \qquad \text{Eq. 2.1}$$

This equation provides an additive measure of information, since $I_1 + I_2 = I_{1,2}$ according to $\log p_1 + \log p_2 = \log(p_1 \times p_2)$. The use of a logarithmic function of base 2 relates to the definition of the basic unit as a "bit"; that is, it represents an amount of uncertainty equivalent to that of a binary digit (0/1 digit or yes/no answer). A further characteristic of this measure of information is that it is sensitive to both the number of event set and to the relative probability of occurrence of these events themselves.

The latter is very useful in perceptual experiments, since it enables the experimenter to compare the uncertainty of the stimulus set (which he defines) with the uncertainty of the response set (which HUS's answers provide). From this comparison, it becomes possible to compute an Information Transmission (I.T.) figure which indicates by how much HUS "recognizes" or "incorporates" information (Garner and Hake, 1951). Suppose, for instance, an absolute judgment experiment where HUS is asked to discriminate the left vs. right position of a dot within a linear field of two positions. Suppose further that HUS is presented 100 random instances (50 left-sided, 50 right-sided), and that the distribution of his responses with respect to the stimulus set show the following pattern:

Table 2.1

Table of Results (Fictitious Experiment)

	Stimulus		
Responses	Left	Right	Sum
Left	48	5	53
Right	2	45	47
Sum	50	50	100

If information was perfectly transmitted by HUS, we would find that any "left" stimulus receives a "left" response, and any "right" stimulus is perceived on the right half of the field. This is not the case here since 2 "left" stimuli received "right" responses, and 5 "right" stimuli received "left" responses.

Hence we need a measure of information which recognizes the extent to which HUS responses correspond to the experimenter's stimuli. Shannon's measure has been shown to be suitable, since Information Transmission can be written (Garner, 1962, p. 56):

I.T. = Total Possible Uncertainty - Actual Remaining Uncertainty

In the case shown above, the Total Possible Uncertainty is equal to the sum of the marginal uncertainties of the stimuli and the responses:

(1) For the stimuli (bottom marginal row of table) the uncertainty is 1 bit since "left" and "right" are equi-probable.

(2) For the responses (right and marginal column to table), the uncertainty is computed on the basis of Equation 2.1, which gives a .997 bit uncertainty.

(3) The actual remaining certainty is the joint uncertainty of the stimuli and responses as shown inside the table, which is computed to be 1.356 bits.

As a result, the information transmitted (I.T.) is estimated here to be:

$$IT = 1. + .997 - 1.356 = .641 \text{ bits}$$

In this (fictitious) case, the experimenter would say that HUS is able to pick up .641 bits out of the 1 bit stimulus information.

Besides the Information Transmission measure, other experimental measures have proven to be of much usefulness: Two such measures are the measure of the reaction time which it takes HUS to respond to a stimulus, and the measure of the rate of errors in his responses. In fact, Reaction Time (RT) and Error Rate (ER) measures are of more general applicability than the I.T. measure, and they adapt more easily to complex experimental designs. In the following II.3 section, I shall show that perceptual phenomena of a qualitative nature, such as the recognition of patterns, are more easily captured by reaction time and error rate measures than by the Information Transmission measure. When the latter is used, the experimenter may have some difficulties understanding the meaning of the results, as shown below by the discussion of the notion of "redundancy."

II.1.1 Assimilation of Information Regarding the Position of a Dot

The problem that I shall address here is how well does HUS discriminate the position of a dot located as a 2-dimensional area.

Before we consider two-dimensional problems, let us observe what happens in the one-dimensional case where HUS must judge the position of a pointer on a line. Hake and Garner (1951) ran an experiment on this issue; by varying the number of pointer positions from 5 to 50 (that is, from 2.32 to 5.64 bits), they were able to observe the human capacity to make absolute judgments in one dimension. The main result which they obtained is that the human capacity is limited to an information transmission level of about 3.3 bits, which is approximately equivalent to an ability to discriminate ten positions in an absolute judgment fashion. This results has been interpreted as an indication that there is some form of a "channel capacity" limit in perceptual discrimination and that it is possible to describe perceptual discrimination ability for a given problem with a single number (Garner, 1962, p. 69). In fact, the capacity obtained in the case of judgments of positions of a pointer on a line is relatively greater than those obtained for other visual variables such as hue, size, or brightness (respectively 3.1, 2.84, and 2.34 bits according to Eriksen and Hake, 1955). According to Fitts and Posner (1967, p. 49), this might be due to some "anchoring" effect since, in judging the position of a pointer along a line, HUS can use the ends of the line as convenient references of "anchors."

The main result, however, remains that the capacity of HUS to discriminate positions in absolute manner along a one-dimensional axis is severely limited by some form of "channel capacity" effect. Does the same phenomenon occur in two-dimensional situations?

In a particularly interesting experiment, Klemmer and Frick (1953) have studied the question of how much information HUS "takes in" about the position of a black dot in a white square. The exposure time of the display was .03 seconds. The subject looked at a 40 X 40 inches projection screen, and he was provided with answer sheets representing an empty square with grid lines. (This had the effect of providing Matrix Display type answer sheets to HUS.) The size of the square matrix was varied from 3 X 3 to 20 X 20, hence generating amounts of information from 3.2 to 8.6 bits. The main result is that Information Transmission increased only up to about 4.5 bits (approximately 24 positions) where it became constant, thus indicating again a "channel capacity limit" type of phenomenon. Since the channel capacity for judgments of positions in a single dimension is 3.3 bits, we get the result that information transmission is greater with two dimensions than with one, but at a cost in information transmission. (See p. 44 for the effects of using a variable number of dots.) In other words, if the effects of the two dimensions simply added to each other we would get 6.6 bits instead of the actual 4.5 bits. This result fits well the general observation that an increase in the dimensionality of the stimulus increases total information transmissions, but decreases the average information transmissions per dimension (Garner, 1962, p. 120).

II.1.2 <u>Adding "Third-dimension" Variations to a Dot in Two Dimensions</u>

In a review study of experimental research at the University of Louvain, Fauville (1963) proposes the following framework of research:

> A dot which can occupy one of the ten divisions of a line is the simplest scheme for a 1-dimensional perception. If it can occupy a cell in a matrix, then we have a 2-dimensional perception. If now, instead of a dot, we choose to represent a geometrical form with different modalities, then we have a 3-dimensional perception. And so with colors, orientations, grey shadings . . . .

Since we already presented experimental results regarding the first two steps of this research program, there remains only the last one to be considered, namely, the effect of presenting a visual item which can itself be chosen among a collection of items (instead of being a simple dot).

This direction was explored by Fauville (1963) who used 4 X 4 Matrix Displays where the position of an item chosen among four possible items was to be discriminated by HUS. Given that the total amount of information which is presented in that situation is 6 bits, Fauville found that variations of shape, orientation, and color respectively convey 5.7, 5.6, and 5.3 bits of information. One implication of this finding is that different graphic variables might impair different "losses" in the information transmitted. Another implication is that compounding dimensions (two spatial plus one purely visual) increases the total information transmission to HUS, at the cost of a decrease in the average performance per dimension. Here the average discrimination performance is comprised between 1.77 and 1.90 bits, to be compared with Klemmer and Frick's result of 1.99 bits, per dimension for a 4 X 4 matrix (1953) and with Hake and Garner's observation that the information transmission is quasi perfect for the discrimination of five positions on a line (1951).

This result is particularly interesting since it shows that an artificial "third dimension" variation can increase the information transmission capacity of a 2-dimensional matrix.

II.1.3 <u>Effect of the Length of Exposure Time on Spatial Discrimination</u>

I mentioned earlier that Klemmer and Frick's experiment was done with a stimulus duration of .03 seconds. More generally, all the experiments of this type are run under conditions of limited time exposure (almost always less than a second), so as to capture the effect of perceptual limitations. In the practical conditions of use of Matrix Displays, however, HUS has the choice of remaining exposed to the graphic stimulus for long periods of time. For instance, a manager who looks at a display for a minute is looking at it 2,000 times longer than a subject in Klemmer and Frick's experiment. Hence, the question: Has time exposure significant effect on the discrimination of the position of a dot in a Matrix Display?

In their experiment on multidimensional stimulus identification, Egeth and Pachella (1969) focus on the very question of the effect of stimulus duration on discrimination. Using a tachistoscope, a 15 X 15 matrix and an absolute judgment task, they vary the presentation times from .1 second to 10 seconds and measure the information transmission in both conditions where HUS is asked to judge only 1 dimension (unidimensional situations) and where he is asked to judge on 2 dimensions (bidimensional situation). The results which they obtain are as follows:

Table 2.2

Task	Information Presented (in bits)	Information Transmitted (in bits) Exposure Time .1	2.0	10.0 (seconds)
Unidimensional	3.91	2.74	3.39	3.49
Bidimensional	7.81	4.94	5.85	6.79

This table clearly shows that the exposure time has a significant effect ($p < .001$) on the discrimination of the position of a dot both in one dimension and in two dimensions. It is particularly interesting to observe that, at a cost in time, HUS can recover the information about the position of a dot so that almost all the information is transmitted. Hence, the proposition that we should pay attention to the time factor in situations of practical use of Matrix Displays is justified.

II.2 Multiple Dot Discrimination in a Matrix Display

Up to now I offered comments on the experimental evidence regarding the human capacity to discriminate the position of one dot in an otherwise empty matrix. Let us now turn our attention to the more complex situation where HUS is presented a set of dots and asked to discriminate their respective positions. Is a set of dots perceived as the simple juxtaposition of several dots, or does some form of global, "pattern-like" perception take place?

II.2.1 Multiple Dots and the Dimensionality of the Matrix Stimulus

As we said earlier, a matrix stimulus is basically two-dimensional. It has been observed, however, than when increasing the number of dots to be presented on a single matrix, the overall capacity of HUS to "absorb" information itself increases. For instance, Klemmer and Frick (1953) using a 3 X 3 matrix increased the number of dots to be presented from 1 to 4 and observed that HUS was able to follow up that increase. In a further inquiry into this phenomena, they varied the number of dots from 1 to 2 in a single experiment, and similarly from 1 to 3 and from 1 to 4. Again, HUS clearly showed his capacity to follow up the increase in the information presented as appears in the following table (Table 2.3) of Klemmer and Frick's results. Fauville (1963) confirmed these results by experimenting with 2 dots in a 10 X 10 matrix.

What is clearly shown here is that there is very little loss of information in the multiple-dot matrices. Increasing the number of dots

Table 2.3

Discrimination of (1 to 4) Dots in a 3 X 3 Matrix

	Fixed number of dots				Varied number of dots		
	Number of Dots				Number of dots		
	1	2	3	4	1-2	1-3	1-4
Information presented (bits)	3.2	5.2	6.4	7.0	5.5	7.0	8.0
Information transmitted (bits)	3.2	5.1	6.1	6.6	5.4	6.9	7.8
Average I.T./dimension	1.6	1.7	1.5	1.3	1.8	1.7	1.5

increases the information absorption capacity of HUS from 4.5 bits maximum in the 1-dot case (see subsection III.1.1) to 6.6 bits for 4 dots, and up to 7.8 bits for the 1-to-4 dots experimental situation. Since a comparable increase in Information Transmission could be obtained only by compounding visual dimensions of variation (such as color, brightness, etc.), this procedure of presenting more than one dot at a time has been interpreted to be a method of increasing the dimensionality of the Matrix Display (Garner, 1962, p. 119). In other words, by multiplying the number of dots, the dimensionality of the matrix space is increased to more than its basic two dimensions. If each dot amounts to a dimension, then a matrix showing four dots is six-dimensional. As a matter of fact, this interpretation suits the general principle that an increase in the dimensionality of the stimulus increases total information transmission but decreases average information transmission per dimension (see bottom row of Table 2.3).

According to Garner (1970, p. 353), the relative "efficiency" of the addition of dots on a Matrix Display might be due to the fact that the two dimensions which serve as the matrix axes (vertical and horizontal) are perceptually independent. A confirmation of this notion has been given by Egeth and Pachella (1969) who showed that the horizontal and vertical dimensions of a Matrix Display do not interfere in the discrimination of a dot. There seems, however, to be also a limit in the number of dots which can be used to increase the Matrix Display dimensionality: According to an experiment by French (1954a), the optimal information transmission would be attained with seven dots in an 8 X 14 matrix and would decrease beyond that number. This suggests an absolute limit of about 35 bits in the information transfer about matrix patterns. This limit would be a valid indication of how many different patterns a human can discriminate out of the same data set (about 3.6 X 10^{10} patterns).

II.2.2 Effects of Noise on the Perception of Multiple Dot Patterns

When several dots are permitted at once a Matrix Display, it becomes meaningful to inquire about the effects of noise on the perception of the data. By "noise," I mean any distortion and/or interference which modify the physical stimulus itself. At a very elementary level it is remarkable that, in order for two dots to be discriminated (i.e., perceived separately), they must subtend an arc of at least 1 minute at the HUS's eyes (Van Cott and Kinkade, 1972). This standard is valid for normal subjects (i.e., HUS with 20/20 vision) and for targets perceived under normal conditions of background luminance; it corresponds to the capacity of the human eye to perceive at most a .17 millimeter grap separating two dots from a distance of 60 centimeters. If two dots are shown closer than that, there is a good chance that they will be perceived as one dot only, hence demonstrating some "noise" effect.

If we put aside the issue of visual acuity, there are two ways by which noise may affect the visual perception of a Matrix Display:

(1) The display might show noisy dots along with the true signal dots (i.e., there are extra "noise" dots).

(2) The display might show the relevant number of dots, but these might be dis-placed (i.e., there is some noise in the positioning of the dots).

Experimental evidence is available on both aspects, as we shall see now.

French (1954b) required HUS to find in a pattern of noise each of a series of multiple dot patterns. Since both the target pattern and the noisy pattern appeared on the screen, the task was to recognize within a 5 seconds exposure time whether or not the target pattern was present within the noisy pattern. French varied independently the number of target dots (from 2 to 9) and the number of noise dots (from 1 to 8). The experimental results are as follows (figures estimated from French's data plot):

Table 2.4

Number of Dots	Percent Errors in Recognition Task								
	1	2	3	4	5	6	7	8	9
Increase Noise dots	22	26	30	30	33	35	34	39	-
Increase Target dots	-	40	33	30	31	28	26	24	24

From this table it appears that increasing the complexity (i.e., number of dots) of the target pattern improves progressively the recognition performance. On the other hand, increasing the visual noise produces a progressive decrement in recognition of the target. According to French, the recognition performance decreased when the signal-to-noise ratio became inferior to 3:1, which indicates that HUS tolerates a certain amount of noise but that his performance is severely affected by noise when it gets beyond the proposed signal-to-noise ratio.

In a series of experiments aimed at the study of spatial noise, Posner and Keele (1968) used dot patterns varying in distortion from an original prototype pattern. All patterns had the same number of dots (9 dots), but the positions of the dot were distributed by way of simple rules of distortions. For instance, the 1-bit distortion rule was that any dot in a given prototype pattern was to be randomly moved either up or down in the first adjacent matrix cell. Several levels of distortions were so defined, and HUS had to learn to associate four different distortions of each prototype (without knowing the prototype itself) with a single key press (Paired-Associate learning). Then the experimental task was for HUS to recognize a series of patterns some of which had been learned before, some of which were new patterns at the same levels of distortion, and finally some of which were the actual un-distorted prototype patterns. One fundamental hypothesis that Posner wanted to test was whether HUS could learn the reference prototype through the sole presentation of its distorted instances. The main result of Posner's experiments was that in fact HUS actually recognizes the unknown prototype pattern about as well as the learned distorted patterns. In other words, HUS is able to abstract a faithful representation of the prototype dot pattern through distorted instances of it: Hence, HUS is able to perceive a "central tendency" through noise in spatial positions. Of course, this is true as long as the level of distortion of the dot patterns is not too high. Posner suggests that up to an individual deviation of each dot by two steps in any direction in the adjacent cells, the actual prototype pattern is still recognized. Since there are 24 alternative possible deviations, this amounts to saying that a prototype can be recognized so long as its displacement does not exceed 4.58 bits per dot.

In summary, then HUS is able to perceive dot patterns amidst noise dots and/or in spite of spatial dis-placement. This is true, however, only up to a certain point where recognition collapses as noise increases.

II.2.3 Matrix Displays as "Gestalts"

Besides noise effects, effects of a more "qualitative" nature might affect the perception of dot patterns in Matrix Displays. For instance, it was observed by French (1954a) in a paired-associate experiment that, for patterns varying in number of dots from 1 to 12, the easiest patterns for any number of dots were characterized either by an approximation to symmetry or by some degree of "good continuation" or "stringing out" of points. Further evidence on this point was given by Sekuler and Abrams (1968) who had HUS judge the identity of two 4 X 4 matrices presented side by side. Their conclusion then was that HUS was "processing matrices as gestalts, comparing the whole of a matrix with the whole of the other." Similarly, Fauville (1963) interpreted the slight difference between information presented and information transmitted in multiple dot matrices (see Table 2.3 above) as the indication that Matrix Displays might be somewhat perceived as "wholes."

Let us now go deeper into an analysis of this issue.

II.3 Gestalt Effects in Matrix Display Patterns

The main result which we have reached thus far is that, if an assemblage of dots is presented, they are not perceived each singly nor as a chaotic total mass, but rather in some sort of a structured way.

The perception of a structure depends partially on the objective features of the constellation of points, and we are now trying to find out which of these objective features play a major role in HUS's perception. For this purpose it seems suitable to examine the relation between Gestalt concepts (Wertheimer, 1925) and notions derived from Information Theory (Shannon and Weaver, 1949). In what follows we shall particularly examine the relation between the concept of "Goodness of figure" (Gestalt) and the notion of "Redundancy" (Information Theory).

The concept of a good figure is based upon the observation that the set of dots follows some uniform pattern: Dots might be linearly aligned, or they may be positioned in a symmetric fashion, or the total figure may show some form of "balance" (Woodworth and Schlosberg, 1954, p. 625). In information theory, a message is said to be redundant if there are more symbols than the minimum necessary to transmit a particular amount of information; redundancy is useful because it provides a way to enhance certain aspects of the message and, therefore, to overcome perturbation and distortions brought on by noise. Because Gestalt psychologists have emphasized that symmetrical figures, say, are more readily perceived than asymmetrical figures, and because a property such as symmetry can be described in terms of redundancy, there has been some speculation that information measures could adequately convey the meaning of such qualitative expressions as "goodness of figure." In this section, we shall address the issue of how Gestalt concepts of a qualitative nature related to information theoretic measures. As a consequence, we shall consider:

(1) A variety of performance measures (reaction time, error rate, etc.) instead of the "Information Transmission" only.

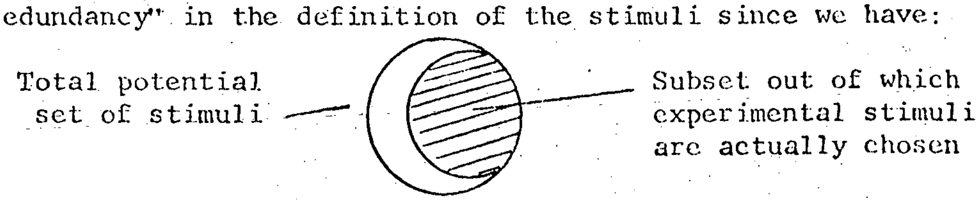
(2) A variety of tasks (paired-association, sorting, delayed reproduction) instead of just straightforward discrimination (for example, immediate reproduction).

(3) A variety of authors having attacked the problem of goodness of matrix patterns in a variety of ways. Here I shall basically contrast the approaches of Attneave (1955), Fitts and Posner (1956), and Checkosky and Whitlock (1973).

II.3.1 . <u>A Study of Redundancy in Visual Pattern Recognition</u>

This subsection is devoted to the critique of a series of experiments on the effect of redundancy on visual pattern recognition (Fitts and Posner, 1956; Anderson and Leonard, 1958). I shall expose in sequence the problem, the experimental approach, the results obtained, and my interpretation of the results' meaning.

(1) <u>The Problem</u>. According to Information Theory, any event which is a member of a large set of events is assigned a probability of occurrence and the total uncertainty (or informativeness) of the set depends upon the relative probabilities of the various events (see Equation 2.1). When applied in the context of psychological experimentation, the information measure is used to compute the uncertainty of the set of potential stimuli; that is, Matrix Displays, which can be generated through application of a simple combinatorial rule. Now suppose that the experimenter wants to restrict his attention to a subset of the potential total set of stimuli only, then this very restriction creates some "redundancy" in the definition of the stimuli since we have:



The information theoretic measure of redundancy (R) is defined in accordance with the above diagram; that is:

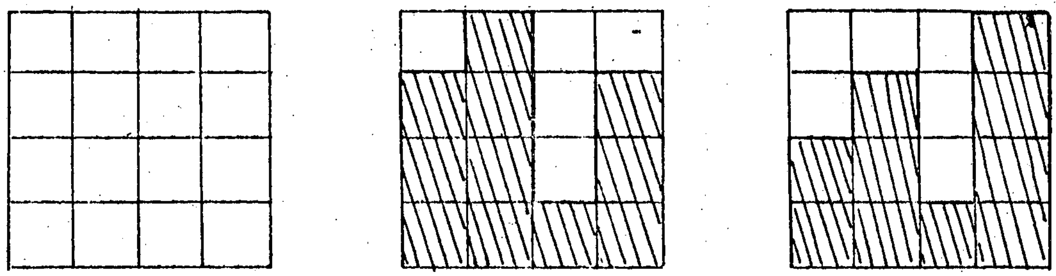
$$R = 1 - \frac{\text{Actual Uncertainty of Subset}}{\text{Potential Uncertainty of Entire Set}} \quad \text{Eq. 2.2}$$

The research question which can be raised is whether HUS is sensitive to redundancy in the above sense; that is:

> Is HUS's response to a particular pattern a fraction of the redundancy associated with the subset of patterns of which it is a member?
>
> And, more specifically, does redundancy facilitate the recognition of patterns by HUS?

(2) A Procedure. Fitts and Posner (1956) devised an experimental procedure for dealing with these research questions. Starting with a square matrix of given size, they generate a solid vertical bar within each column of the matrix, the height of the bar being determined by same sampling procedure. For instance, given a 4 X 4 matrix, it is possible to generate 4^4 different bar profiles since we have four possible heights for each of the four possible bar columns within the matrix. Alternately, we might say that the process of generating bar patterns randomly within a square matrix creates 2 bits X 4 = 8 bits of information. Now suppose that, instead of using a random sampling rule, we use a rule of sampling without replacement. In other words, once the height of the first column has been chosen, the height of the second column can take only three values, etc., up to the fourth column so that there cannot be two bars of equal height within a profile. Fitts and Posner call this procedure "constrained," as opposed to the "random" initial procedures; the following figure represents the effect of the two sampling rules (Figure 2.1). Here the constrained profiles are characterized by the property that no two columns may have the same height, which in turn restricts the set of all possible such figures to

Figure 2.1



4 X 4 Matrix Random Profile "Constrained" Profile

be a subset considerably smaller than the set of all possible random figures. In other words, constrained figures are "redundant" in an information theoretic sense, and this redundancy can be compared on the basis of Equation 2.2 (in the 4 X 4 situation which we illustrate: $R = 1 - (\log (4\ )/8 \text{ bits}) = 42.75$ percent).

(3) <u>Results</u>. Fitts and Posner (1956) have investigated the effect of this form of redundancy on pattern recognition by presenting HUS alternately with "random" and "constrained" stimuli, built on a 8 X 8 matrix. HUS was presented with each stimulus for 2 seconds and then he had to sort out in systematic manner 6 patterns identical to the stimulus and interspersed among 42 other foreign patterns. Mean recognition time was the performance criterion, and the patterns could be presented in single fashion (one profile only), or doubled (two identical profiles), or mirrored (the profile is reproduced by symmetry). The results are as follows:

Table 2.5

Mean Recognition Time (seconds)

Type of Profile	Single	Double	Mirrored	Mean
Random	1.79	1.87	1.76	1.81
Constrained	2.50	2.67	2.49	2.55

Clearly, the random patterns are discriminated more rapidly than the constrained patterns in all cases. This indicates that the effect of "redundancy" was detrimental to HUS's performance; in other words, the fact that the constrained figures were picked out of a restricted subset of potential stimuli did not improve, but rather slowed down the recognition performance. Hence, the seemingly "strange" result that set of stimuli with largest variability (random set) gave a better performance than a set of stimuli with lower variability (constrained set). This result was further verified by Anderson and Leonard (1958) with a similar classification task, and with a different situation of paired-associate learning.

(4) Comments. The fact that redundancy was detrimental rather than beneficial to profile pattern recognition in Fitts and Posner's experiment (1956) is not totally counter-intuitive. Suppose, for instance, that we introduce here the qualitative (Gestalt) notion of "goodness" of figure: Clearly, the constrained figures are not "good figures" because, due to the sampling restriction that no two columns have the same height, these figures always show irregular assymetric patterns. On the other hand, the random figures have almost always some chance of containing several doublets of bars of equal height; hence, facilitating the fixation of the gaze and the structuration of the perception (anchoring effects). This suggests that the computation of an amount of redundancy according to an information theoretic formula tells only one side of the pattern recognition process, and that it is equally important to consider the more specific visual characteristics of patterns in order to hypothesize whether the form of redundancy will be beneficial or detrimental to pattern recognition.

II.3.2 Information and Goodness of a Matrix Pattern

The question of the form of redundancy is of more qualitative nature than the question of the amount of redundancy. Instead of considering the statistical properties of samples of figures, it requires that we pay attention to the individual characteristics of figures in terms of their "goodness." This in turn brings in the question of how to harmonize the quantitative notion of redundancy, or information, with the qualitative notion of goodness of figure so as to get a better understanding what happens when HUS is faced with a Matrix Display.

An interesting attack of this issue has been illustrated by a series of experiments in which Attneave (1955) compared the perception of random vs. symmetric matrix dot patterns.

(1) The Problem. Symmetry is one of the most important qualities which might characterize the goodness of a figure. Attneave's investigation concerns the relations between symmetry and information, where the information content of a matrix pattern is evaluated in an information theoretic sense. The specific question which Attneave addresses is:

> Are symmetric patterns better perceived than random ones because they contain less information, or does their superiority persist even when information is held constant?

(2) A Procedure. The general idea is to compare how two matrices of equal size are perceived, given that one shows a random pattern of dots, while the other shows a symmetric pattern. The specific procedure which is used is as follows:

(1) First generate a random pattern in a 4 X 3 matrix so that the occurrence of a dot in any cell is determined independently with a probability .5 by means of a table of random numbers. This defines a 12-bits dot pattern.

(2) Then duplicate this 4 X 3 base pattern by symmetry in a 4 X 5 matrix, and duplicate the 4 X 5 matrix itself by symmetry in a 7 X 5 matrix. Hence, from one 4 X 3 base pattern, two symmetric patterns of same information content (12 bits) are defined in 4 X 5 and 7 X 5.

(3) Alternatively generate 4 X 5 and 7 X 5 random patterns by using the same rule as for the generation of the base 4 X 3 pattern. Here the information contents of the matrices generated are respectively 20 and 35 bits. This procedure then provides two groups of 4 X 5 and 7 X 5 matrices; one group is characterized by symmetric patterns, the other by random patterns.

(3) Results. The differences in HUS performance on random vs. symmetric patterns was assessed for a variety of tasks including immediate reproduction of the patterns, identification of the patterns by names, and delayed recall of pattern names. (The two latter tasks are typically paired-associate tasks.) Attneave obtained the following results, where the index of errors is computed as the ratio of the percent error rate over the corresponding error rate with the reference 4 X 3 base pattern.

Table 2.6

Error Ratio
(Data inferred from Attneave's plots)

Task	Symmetric Patterns 4 x 5	Symmetric Patterns 7 x 5	Random Patterns 4 x 5	Random Patterns 7 x 5
Immediate Reproduction	2.25	3.75	2.75	4.63
Delayed Recall	1.50	1.63	2.00	2.38
Identification	1.06	1.09	1.40	1.57

(4) Comments. These results indicate that symmetric patterns are consistently recognized better than random patterns in matrices of equivalent size. But since all error rates are greater than 1, they also indicate that HUS always made more mistakes with a symmetric pattern than with its corresponding source pattern in the 4 X 3 matrix. In other words, given the same amount of information (12 bits), a symmetric

pattern of larger dimension (4 X 5 and 7 X 5 matrices) is not recognized better than a random pattern of smaller dimensions (4 X 3 matrix). Here we find that the redundancy introduced by symmetry doesn't improve HUS performance over a smaller reference pattern of same information content.

It is remarkable, however, that among the selected three tasks, Identification gave the smallest rate of errors. Since this task was the closest to being a pure pattern recognition task, we might infer that HUS developed some form of an "organizing" process which the information measure does not convey. Attneave himself observes that HUS tended to remember where dots were located with respect to each other, rather than whether individual cells were dotted. This amounts to saying that the computation of matrix information as the sum of individual cells information misses one important aspect of human perception: namely, the fact that pattern recognition is related to global features of the patterns.

II.3.3 The Goodness of Matrix Patterns

On the basis of the two preceding sections, we may now perceive an apparent incompatibility between an information theoretic approach and Gestalt concepts:

(1) On the one hand, information theory enables us to deal with the statistical properties of matrix patterns (sample selection, matrix size, etc.)

(2) On the other hand, Gestalt theory emphasizes the geometrical properties of individual patterns such as symmetry, good continuation, and other forms of regularity.

Is it possible to reconcile both approaches so as to understand better the factors which influence the human perception of matrix patterns?

(1) The Problem. According to an information theoretic viewpoint,

a critical factor in the perception of a single stimulus is the size of its subset relative to the size of the total set. One critical aspect of the application of information theory to display problems is then the choice of which criteria to use in order to define subsets of stimuli. It seems that the Gestalt criteria would find here a perfect ground for application, since they suggest that certain display features have a more important role than others.

Suppose, for instance, that we pick up symmetry as being an important feature in the perception of matrix patterns, then the question which we need address is: How does the criteria of symmetry affect the definition of subsets of matrix patterns in the universe of all possible patterns?

(2) A Procedure. Let us first observe that, in order to determine the universe of all patterns that can be obtained on a square matrice each cell of which can take any of two values (filled or unfilled), we need only know two parameters, namely,

(1) The size of the matrix (m X m)

(2) The number of filled positions (p)

If we know these two parameters, we can generate all possible patterns in a systematic manner.

One such systematic manner can be defined by way of two geometric operations:

(1) R, which operates a pattern rotation through 90^{o}

(2) S, which operates a reflection in the middle vertical line, i.e., the y axis

According to Prokhovnik (1959), we can define the universe of all possible patterns on the basis of a smaller number of configurations, or equivalence classes.

(1) Symmetric configurations are those invariant under any combination of rotation R and reflexion S, i.e., the group $[R,S]$ of order 8.

(2) Semi-symmetric configurations are those invariant under the subgroups of $[R,S]$ of order 4, i.e., $[R^2, SR]$.

(3) Anti-symmetric configurations are those invariant under the subgroups of order 2, i.e., $[R^2 , S , SR^2 , \text{and } SR^3]$.

(4) Finally, asymmetric configurations are those which are invariant under I (identity operator) only.

In other words, we may generate at least one pattern for any given configuration through use of the S,R, and I operators: In fact, we know that we can respectively generate 8, 4, 2, and 1 patterns in asymmetric, anti-symmetric, semi-symmetric, and symmetric configurations.

This approach provides a vehicle for reconciling information measures and Gestalt concepts. Since each configuration can be considered to form an equivalence class, and since it is possible to know the size of that class (i.e., the number of patterns it contains), we have a means of measuring the relative informativeness of each pattern. At the same time, we are able to assess the geometric goodness of the patterns in terms of the symmetry they show, since each pattern belongs to an equivalence class which is qualified in terms of symmetry.

(3) Some experimental results. According to what I said above, "good" patterns should be those which are generated from configurations possessing some amount of symmetry (i.e., symmetric, semi-symmetric, or anti-symmetric configurations), while "bad" patterns belong to asymmetric equivalence classes. This distinction was actually used by Checkosky and Whitlock (1973) in an experiment where the recognition performance of HUS using asymmetric patterns was compared with that of HUS using

anti-symmetric patterns.

The experimental stimuli were 3 X 3 matrices containing 5 dot-patterns, members of equivalence sets of size 4 (good patterns) and 8 (bad patterns). HUS was asked to learn a set of 2 or 3 patterns which were consistently either good or bad patterns. Later HUS was presented with a series of patterns one at a time, and he was asked to respond "yes" if the test pattern matched any of the learned patterns and "no" otherwise.

In order to assess the performance of HUS, Checkosky and Whitlock (1973) recorded both the recognition time and the percent errors made on "good" and "bad" patterns.

Table 2.7

Type of Answer	Recognition Time (ms)		Percent Error	
	Good Pattern	Bad Pattern	Good Pattern	Bad Pattern
no	629	688	2.88	3.50
yes	600	690	7.00	12.60

On the basis of this table it appears quite clearly that "good" patterns are recognized faster and more accurately than "bad" patterns. This indicates that HUS is able to take advantage of the fact that good patterns are selected out of subsets having certain characteristics of symmetry. Another interesting result is that, when the patterns previously learned had to be identified (the "yes" situation), HUS did much better with good than with bad patterns (the increase in errors is less than the corresponding increase for "bad" patterns, and the mean recognition time even decreased). This indicates that the identification task takes advantage of a global feature such as symmetry, which confirms the result of Sekuler and Abrams (1969).

(4) Comments. The experiment of Checkosky and Whitlock (1973) demonstrates that the Gestalt concept of "goodness" can be approached in a quantitative manner. The choice of matrix patterns on the basis of their symmetry set membership is directly related to the information theoretic notion of redundancy. In other words this experiment provides us with a case where the goodness of a figure is properly assessed by way of quantitative measures: Here the Gestalt concept of symmetry is directly related to the information theoretic notion of redundancy.

This has important implications for a theory of Matrix Displays since it provides some evidence that the user of a Matrix Display is able to take advantage of Gestalt effects. It reinforces the view (Fauville, 1963) according to which HUS can perceive matrix patterns in a global fashion. It also confirms Attneave's intuition (1955) that the user of a Matrix Display is somewhat more able to perceive the relations between the displayed elements (dots) than the precise location of the elements themselves. In fact, it seems that Gestalt effects enable HUS to go beyond the limits of his absolute channel capacity in much the same way as "chunks" of letters increase his capacity to absorb verbal information (Miller, 1956).

II.4 From Experimental to Practical Matrices

Up to this point, we have focused on those experimental results which present a direct interest for the thesis that Matrix Displays are feasible aids to perceptual tasks. In particular, it is possible to summarize those results into a set of six propositions:

(1) The capacity of HUS to discriminate the absolute position of a dot in an empty matrix is limited to about 4.5 bits

(24 positions or cells in the matrix).

(2) Multiple dot displays improve HUS performance up to another absolute limit of about 35 bits, or about 3.6×10^{10} patterns (as estimated from French's experiment (1954a) with 7 dots in a 112-cells matrix).

(3) Besides the two-dimensional position of a dot, HUS is able to take advantage of any additional "third dimension" variation such as variations in the size, color, value shading, etc., of the dots. This permits to increase, if needed, HUS's information transmission capacity almost proportionately to the information presented, at the cost of multiplying the visual variables.

(4) Gestalt effect (such as symmetry, goodness of form, good continuations, etc.) have a considerable role in matrix pattern perception, as shown by time and error data. Apparently, HUS is able to recognize and take advantage of any such regularity present in the matrix data. It is difficult, but possible, to connect the quantitative measurement of information to the qualitative characteristics of Gestalt regularity.

(5) HUS can tolerate a moderately high amount of noise in the matrix patterns--both in the positions of dots and in the organization of patterns as wholes. An estimate of the signal-to-noise ratio down to which HUS can recover the proper picture is a 3:1 ratio. Below this level, HUS performance is dramatically impaired.

(6) HUS's performance improves as the observation time increases. Since it requires about 10 seconds for HUS to pick up the absolute position of a dot in a medium-sized matrix (for example, 15 X 15), we expect that the information pickup on larger and/or fully-filled matrices will require order of minutes.

The above experimental results provide solid guidelines as to the value of Matrix Displays for visual recognition procedures. However, it is remarkable that these results, which we assembled here for the purpose of supporting our thesis, have been obtained under limited experimental conditions such as:

(a) Use of sparse matrices (rarely filled at more than 50 percent)

(b) With essentially binary stimuli (each cell is either filled or empty)

(c) Showing mainly categorical data

As a result, the practical situation--which we expect to meet--of a management user faced with a nearly full, multiple valued, and possible non-categorical data matrix, seems to be far outside the experimental circumstances.

Hence, there is a need for us to explore the ways in which the empirical situation of matrix usage can be connected to the important results found in experimental settings. In the subsections which follow, we examine the three above points (a, b, and c) so as to show that the available experimental evidence is applicable to empirical situations as well. Again, I shall use experimental results concerning HUS's performance in perceptual situations.

II.4.1 Full Multilevel Matrices

When a matrix is filled with graphic symbols taking multiple values, the possibility to discriminate between "filled" and "empty" positions seems to be lost, because all matrix positions are filled. This, however, does not mean that the matrix can no longer be used for discrimination purposes: In fact, the contrary phenomenon occurs, that a filled matrix is still more advantageous to discrimination tasks than a nearly empty matrix. Only the complexity of the problem increases by (at least) a factor of two.

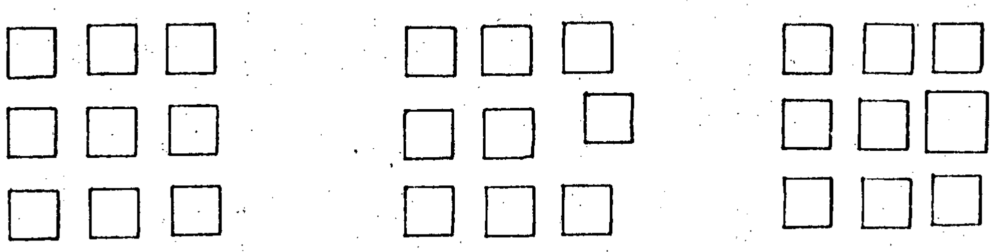
This X 2 factor has a rationale behind it: Given a fully filled matrix, there are two ways in which discrimination between cells may occur. On the one hand, HUS may discriminate differences in the overall arrangement of cells, i.e., differences (or irregularities) in positions. On the other hand, HUS may discriminate differences in the overall similarity between the visual characteristics of the cells. These two possible approaches correspond to two elementary comparative tasks, which have been enunciated long ago by Gestalt theorists (Wertheimer, 1925; Woodworth and Schlosberg, 1954, p. 625) as:

(1) The comparative judgment of the proximity of items

(2) The comparative judgment of the similarity of items

For instance, consider the following display matrices:

Figure 2.2



(1) (2) (3)

The first matrix shows a homogeneous, fully filled field with cells having the same size and regularly positioned with respect to each other. The second matrix shows the same basic items, with a slight modification in the position of one cell at the second row, third column. This modification disrupts the perception of the whole matrix, since the reader's attention is immediately attracted by the irregularity in the arrangement. It illustrates the role of proximity in the recognition of fully filled matrices. Finally, the last matrix, (3), shows the effects of using one item distinctly differing in size from the other items.

The fundamental idea which is illustrated here is that a full matrix offers at least as much opportunity for discrimination tasks as a nearly empty matrix. HUS is able to make use of both spatial clues (relations of proximity between items) and visual clues (relations of similarity between items) in discrimination activities. The fact that a matrix is filled does not modify the basic problem of discrimination; rather it gives it more complexity, in the sense that elementary variations have now to be judged against background of other items. Very few experiments have been run with matrices in "filled" conditions. I would like to mention the one by Williams (1969) who used "cluttered fields" approximating the filled matrix situation, in order to evaluate the effectiveness of color vs. size vs. shapes variations for discrimination. Another is the series of experiments in children's cognitive development realized by Piaget and Inhelder (1967). Both approaches confirm that it is possible to extend to filled, multilevel matrices the results obtained on simpler, nearly empty matrices.

II.4.2 Psychophysical Considerations

I mentioned above that a matrix which is filled offers an opportunity for similarity comparisons between graphic items. This raises the question of how the distribution of values of the graphic items influences HUS performance.

Although no direct evidence is available on this point, we possess some elements which come from the field known as "psychophysics." If we consider that HUS compares elementary items two at a time, this perceptual situation is somewhat equivalent to the comparative judgment of a stimulus with a standard, leading to such answers as: "same," "bigger," or "smaller." The concept of psychophysics is to relate the psychological sensation (that is, the human judgment) to the underlying physical characteristics of the stimuli. The fundamental result is the observation that, as expected, psychological sensation is related to physical variation. As early as 1860, Fechner had formulated a logarithmic law according to which, when two stimuli increase proportionately in size, their difference (or "just noticeable difference") is perceived as increasing logarithmically (i.e., less than proportionately). Bertin (1967) shows that this law holds for variations of sizes of dots.

However, recent research has definitely shown that the logarithmic formulation of the psychophysical law is not universal. Psychophysical transformations other than the logarithmic function have been found to hold, depending on the exact graphic variation used (e.g., size, shape, density of shades, etc.) and depending on the user's recognition tasks. For instance, Bertin (1967) proposes that a logistic function (S-shaped) is appropriate for variations in value density. Jenks and Knos (1961) define several possible transformations including the inverse logarithmic function (i.e., the exponential). These results can be applied to the case of Matrix Displays: They suggest that a variety of psychophysical transformations be available to the user, which would apply them depending on the specific circumstances and needs.

II.4.3 Non-Categorical Data and Graphic Variables

Most experimental evidence on the perception of Matrix Displays has been gathered in circumstances where categorical data only was used. Since management application may require the consideration of other data types, it is important to observe how a variety of data types may affect matrix perception. The figure below (Figure 2.3) shows the three basic data types which a management table may contain. The distinction made here between categorical, ordinal, and cardinal data corresponds to the

Figure 2.3

0	1	1	0
0	0	1	0
1	0	1	0
1	1	1	0

Categorical data

2	4	1	3
12	8	5	9
11	6	10	16
7	13	14	15

Ordinal data

.23	.56	.22	.36
.86	.40	.16	.47
.72	.52	.44	.37
.36	.60	.75	.12

Cardinal data

distinction of measurement theory between nominal, ordinal, and quantitative measurement (Ackoff, 1962). In the above figure, the categorical data are binary items such as those classically used in perceptual experiments: Graphically, they show up us 2-states cells (either empty or filled). More generally, categorical data show up as n-states cells where the n-states are conveyed by means of any graphic variation (such as size, value shading, shape, color, orientation, texture, etc.).

When ordinal or cardinal data must be graphically represented, an interesting problem of mapping occurs, namely,

> Can ordinal and cardinal variations be conveyed by any kind of graphic variable?

Bertin's research (1967) proves that not any graphic variable can convey ordinal or cardinal variations. In fact, it shows that very few graphic variables can convey variations other than categorical: Namely,

(1) Variations of texture, shading, and size can convey relations of order between items (ordinal data)

(2) Only variations of size can convey quantitative relations between data items (cardinal data)

The result is of considerable importance for the practical usage of Matrix Displays, since it indicates a fundamental limitation in the capacity of "third dimension" variables (i.e., variables other than the plane's 2-D) to convey fully metric, quantitative data variations. This limitation is not critical to the use of Matrix Displays, to the extent that it is always possible to combine graphic variables so as to represent as much quantitative variation as needed. One of its effects, however, may be to reduce the metricity, or quantitative precision, of the data which HUS absorbs display-wise.

In sum, this chapter based on experimental evidence, has shown that:

(1) Matrix Displays can support perceptual tasks such as discrimination and pattern recognition.

(2) HUS's information absorption capacity is limited by various perceptual characteristics. But HUS is able to reduce the information overload by taking advantage of any structural feature such as redundancy, symmetry, etc., present in the display.

(3) There is a difference in degree, not in kind, between the experimental use of Matrix Displays and their practical usage. Experimental results apply to the practical situation of a management user as well.

As a consequence, we definitely conclude that Matrix Displays are feasible aids to human visual perception.

CHAPTER III

MATRIX DISPLAYS AND MULTIDIMENSIONAL DATA ANALYSIS

The aim of this chapter is to assess the utility of Matrix Display for supporting Data Analysis, and more specifically, the analysis of multidimensional data sets. As opposed to the previous chapter, where we dealt with tasks of immediate perception, we are now concerned with tasks of cognitive inference based upon the recognition of statistical structures within the data. The structures which have been recognized of much usefulness in multidimensional analysis are those related to ordering and/or clustering tasks. We shall hereafter evaluate the capabilities and limits of Matrix Displays as a mode of representation and discovery for such structures.

As in the preceding chapter, I shall make use of a specific acronym to designate in a homogeneous and permanent fashion the user of Matrix Displays which we consider in this chapter. This character, called MDA--for "Multidimensional Data Analyst"--, will be the actor of our inquiry into the ability of Matrix Displays for multidimensional analysis. As we shall see, MDA proceeds to an analysis by focusing on a specific type of data matrix, called the similarity matrix. The primary research question that we shall face will then be:

> To what extent does research in multidimensional scaling support the thesis of the feasibility of Matrix Displays?

There is very little research material available to answer this question. Only the works of Guttman (1954, 1955a, 1955b, 1966) offer a direct attack on the issues involved with the discovery of structural patterns in a similarity matrix. There are, however, a lot of scattered pieces of evidence that the Matrix Display of similarity data has some payoff for multidimensional analysis. In the sections which follow I shall then attempt to combine and integrate the available evidence in the best manner, so as to show that the Matrix Display of similarity data is a feasible aid to MDA. I shall, in particular, demonstrate that three typical analytic tasks (one-dimensional ordering, two-dimensional ordering, and cluster analysis) can be accomplished by way of Matrix Displays.

III.1 Multidimensional Analysis and Matrix Displays

III.1.1 Principles of Multidimensional Analysis

A multidimensional data set typically consists of an n X p matrix with n object entries and p attribute entries, with each object scored on each attribute. To the extent that the scores are normalized, it is possible to describe the data matrix as a set of n profiles over p attributes. The basic aim of multidimensional analysis is to reduce the complexity of the n X p data set to a set of lower complexity, n X q such that q is very small compared to either n or p.

The general principle which has been used to solve this problem is based on the observation that the statistical reduction of an n X p universe into an n X q universe (where $q \ll n,p$) amounts to an equivalent reduction in the space of representation: If each of the p attributes was represented as a dimension in space, each of the n objects could be plotted on this p-dimensional space; the problem of multidimensional analysis is to reduce the dimensionality of the space from p to q without losing the spatial configuration of the _n_ objects in the process. The principle which is then used to guide the analysis is that it is acceptable to represent _p_-dimensional data in a space of dimensionality much lower than _p_, if and only if the relations of spatial proximity between the _n_ objects keep reflecting the relation of similarity between these objects.

The concept which is central to multidimensional analysis is that of similarity: If two objects have exactly the same profile over the _p_ attributes, they are said to be fully similar; conversely, objects with exactly opposed profiles are said to be fully dissimilar. There exists a whole variety of ways to compare numerical estimates of similarity, called similarity coefficients: Depending on the type of data at hand, the objectives of the analysis, and the degree of precision which is required, MDA may use various measures, from "association coefficients" for non-metric data to "resemblance coefficients" for fully metric data (Sneath and Sokal, 1973). One typical, widespread example of similarity coefficient is Pearson's product-moment correlation coefficient (see Equation 5.1) with properties (for any two objects I and J in the set):

(1) Correlation (I,I) = maximum = +1

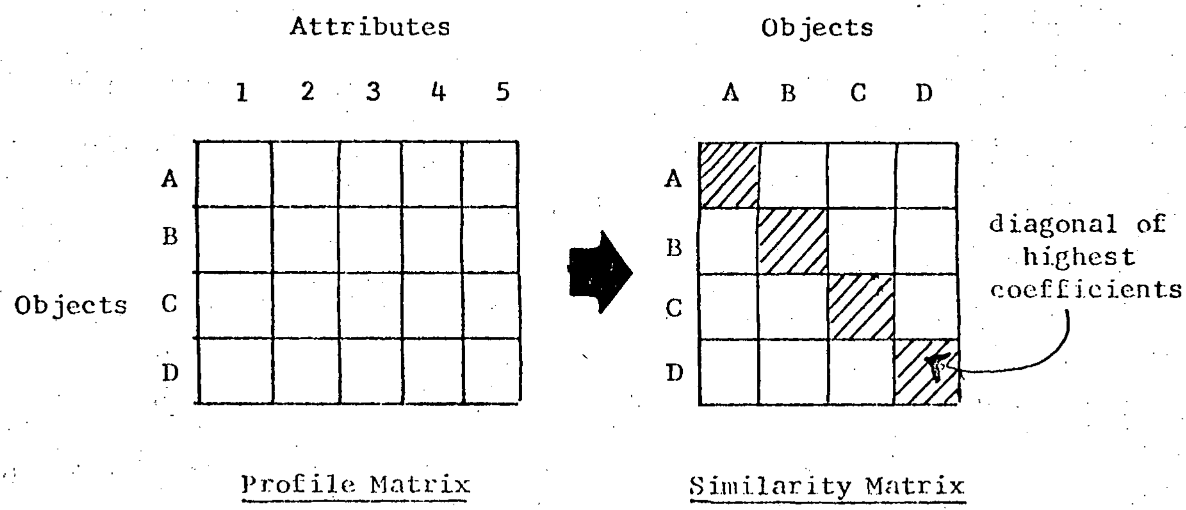
(2) Correlation (I,J) = correlation (J,I)

(3) Correlation (I,J) belongs to interval $[-1, +1]$

In general, similarity coefficients verify property 1 (the similarity of an object with itself is maximum) and property 2 (the similarity between two objects is independent of their order). But property 3 is a specific feature of the Pearson product-moment correlation coefficient and related measures.

In any case, as a result of similarity computations, MDA gets an n X n similarity matrix which is symmetric around its main diagonal (property 2 above). Hence, the first step in multidimensional analysis can be illustrated as the process of going from the n X p data matrix to an n X n similarity matrix:

Figure 3.1



Once the n X n similarity matrix is obtained, the problem of multidimensional analysis is to find a representation of the n objects in a space of dimensionality q (with q $\ll$ n,p) such that the relation of proximity in space typically correspond to relations of similarity between objects: The more similar two objects, the closer they should be in q-space.

III.1.2 Methodology of Multidimensional Analysis

Originally, the methodology of multidimensional analysis has developed upon the notion that it is possible to approximate the n x n similarity matrix by one of lower rank (Eckart and Young, 1936). This has led to Factor Analysis and related methods, where MDA looks for the space of lowest dimensionality which is compatible with a stringent criterion of statistical validity. One such criterion, of general utility, is the percent variance in the $\underline{n}$ X $\underline{n}$ similarity matrix accounted for by the recomputed $\underline{q}$ X $\underline{q}$ factor matrix. For instance, a 95 percent level variance accounted for is generally regarded as a sufficient guarantee that the $\underline{q}$-dimensional representation faithfully reproduces the $\underline{n}$ X $\underline{n}$ similarity matrix.

The procedure which is used in the above approach is to set *a priori* a certain wanted level of validity, and then to search for the lowest dimensionality compatible with it, i.e.,

> Given the $\underline{n}$ X $\underline{n}$ similarity matrix, find the space of lowest dimensionality $\underline{q}$ which is compatible with a fixed criterion level $\bar{C}$.

As a result of formulating a criterion level $\bar{C}$ of high statistical significance, it has generally been observed that the "lowest" dimensionality $\underline{q}$ which results is relatively high (a minimum of 5 to 7 dimensions). This high dimensionality in turn affects the interpretability of the analysis, since MDA cannot easily interpret configurations in a 6 or 7-dimensional space. As a consequence, an alternative approach has emerged, where the problem is "reversed," i.e.,

> Given the $\underline{n}$ X $\underline{n}$ similarity matrix, fix the dimensionality of the space to $\underline{q}$, and find the configuration which, within that space, gives the best fit to a statistical criterion $\bar{C}$.

This formulation is at the origin of the Multidimensional Scaling methods (Torgerson, 1958; Shepard, 1962a, 1962b; Kruskal, 1964a, 1964b). According to these methods, MDA seeks primarily to obtain readily interpretable configurations--hence, configurations in a space of low dimensionality. For instance, Shepard (1974) recommends that one- and two-dimensional spaces would provide for suitable representations of similarity data. In accordance with this view, the statistical criterion to be used for judging the adequacy of a representation is less stringent than a criterion of absolute validity such as the variance criterion. For instance, non-metric measures of goodness-of-fit, based only on the correspondence between ranks in the orderings of similarity coefficients and proximities have been specifically devised (Kruskal, 1964a, 1964b). In summary, the use of scaling methods permits representations which are generally less accurate but more interpretable than traditional factor analytic methods.

The methodological debate which MDA must face when deciding upon which multidimensional method to use is then whether to choose accuracy at a cost in interpretability, or interpretability at a cost in accuracy. This debate resembles very closely what Tukey (1971, 1975) calls the debate between "exploratory" data analysis vs. "confirmatory" data analysis: On the one hand, an exploratory approach aims at finding low-dimensional, readily interpretable configurations; on the other hand, a confirmatory approach seeks primarily to obtain a high level of statistical significance. As we shall see now, the use of a matrix representation of similarity data changes the nature of this debate, because it lends itself to both an exploratory and a confirmatory approach.

III.1.3 Multidimensional Analysis with Matrix Displays

In the classical formulation of multidimensional analysis which we gave in III.1.1, MDA attempts to reduce a $\underline{p}$-dimensional space, obtained by interpreting each attribute as a dimension in space, to a space of lower dimensionality, $\underline{q}$. The goodness-of-fit of the configurations in

$\underline{q}$ dimensions to the original $\underline{p}$-dimensional data is measured through reference to the p-space in which similarity coefficients have been computed for each couple of objects (I, J). This methodology then involves a comparison of the relations of proximity between the objects in two different spaces: the Euclidean $\underline{q}$-dimensional space of representation and the statistical space of similarity coefficients.

When multidimensional analysis is based upon Matrix Displays, it is proposed that the similarity matrix itself be the display space (Czekanowski, 1932; Guttman, 1955a; Shepard, 1974). As a consequence, the previous methodology of comparing relations of proximity in space to relations of similarity in data becomes more involved. The general idea is to compare the structural features of the configurations which appear on the similarity matrix with "ideal pattern gradients." These ideal pattern gradients correspond to the geometrical templates which Degerman (1972) proposes to be the fundamental simple structures which MDA must seek to discover:

> The <u>Dimension</u> structure, which reflects the notion of a line in space where neighborhood relations and rank-ordering can be figured
>
> The <u>Circular</u> structure, which conveys the notion of an ordered structure closed on itself in a circular fashion (like a ring; Knuth, 1968)
>
> The <u>Discrete class</u>, or Cluster structure, which permits the representation of the concept of mutually exclusive, independent, and nominal classes

These ideal simple structures pervade the whole field of multidimensional analysis because they are the tools which permit the organization of cognition and the setting up of the appropriate inferences when MDA is faced with a given set of data. They have, however, greater importance for the method of using Matrix Displays because it has been shown--in a more or less direct fashion--that to each of these ideal templates, there corresponds specific patterns on the similarity matrix (Guttman, 1954; Dunn, 1975). As a consequence, the problem of multidimensional analysis becomes one of:

(1) Reorganizing the row and column entries of the matrix so that it shows a pattern which approximates one (or a combination) of the ideal template(s)

(2) Evaluating the goodness-of-fit of the actual configurations to the postulated corresponding template(s)

This in turn implies that the nature of the methodological issue of validity vs. interpretability, which appeared above as conflicting requirements, is changed. I shall observe here that the more valid a matrix configuration--in the sense that it fits a pattern--the greater its interpretability. This observation will itself be at the root of the quantitative assessment of Matrix Displays that I shall deliver in chapter IV.

In the present chapter I shall focus on the available research evidence which is scarce and needs to be reinterpreted to apply to the Matrix Display issue. The following sections, each of which focus on one of the three simple structures of Degerman (1972), provide a translation and a reorganization of the available evidence so that it supports the thesis of the feasibility of Matrix Displays for multidimensional analysis.

III.2 Matrix Displays and One-Dimensional Order Analysis

III.2.1 Principle of One-Dimensional Ordering

A one-dimensional ordering is a perfect ordering along a dimension, i.e., an ordering such that, given <u>n</u> objects, they are perfectly ranked at equally-spaced intervals from first to last along a certain continuum. This continuum, or dimension, represents the criterion of ranking. In the case which we are concerned with now, this criterion must be discovered by analysis: The n objects are known through their similarity relations, and the problem is to arrange them in rank-order so their distance relations along the rank-ordering inversely correspond to their relations of similarity. This is a direct application of the principle of proximity-similarity which I presented earlier as a general principle in multidimensional analysis (p.71). In essence, the principle of proximity-similarity states that the relative positions of objects in space should be directly related to their relative similarities--the closer two objects, the more similar they be. This principle has a key role all over multidimensional analysis because the spatial representation of objects is so central to the interpretation process (Torgerson, 1958; Coombs, 1964; Shephard, 1966; Benzecri, 1973).

When applied to the situation of rank-ordering, the principle of proximity-similarity needs some more specification because the relation of order has been strictly defined in an axiomatic manner by way of:

(1) The axiom of transitivity:
$I \leq J$ and $J \leq K \Rightarrow I \leq K$, when I, J, and K are objects and $<$ indicates precedence and $=$ indicates coincidence

(2) The axiom of anti-symmetry:
$I < J$ and $J < I \Rightarrow I = J$

(3) The axiom of connectedness:
For any $I \neq J$, either $I < J$ or $J < I$

When all these axioms hold on a given object-set, this set is said to possess a complete ordering. When axiom 3 does not hold, the ordering is said to be only partial (Debreu, 1959). The interest of the notion of ordering more generally lies in its implications for cognitive inference: Because order is the most elementary measure of the relations between objects in a set (Ackoff, 1962), its finding permits multiple cognitive operations to take place. In the context of management, the rank-ordering of managerial entities on the basis of their performance provide the manager with (at least) a framework for control and for instrumental activity (Miller, 1969).

In the Matrix Display formulation of the problem of finding a one-dimensional ordering, the similarity matrix plays an essential role both as a "container" of the n X n similarity data, and as a mode of representation by itself. Considering the mode of representation, it has been suggested that the numerical values of the elementary similarity coefficients be visually "translated" by way of shades of grey with black meaning maximum similarity and white meaning minimum similarity (Bertin, 1967; Dunn, 1975; Lohrding, 1975). This convention will be adopted hereafter, where the cells of the similarity matrix will be cross-hatched according to a shading scheme. For instance, with correlation coefficients belonging to the interval (0,1) the darkest shade will be assigned to the value 1 and the lightest shade to the value 0, all intermediary values being represented with corresponding intermediary shades.

The interest of using this visual equivalent of the similarity matrix stems from the fact that, in the case where the object entries of the matrix can be perfectly rank-ordered, this shows up as a specific gradient over the matrix. This gradient has been put into evidence by Guttman (1954, 1955a, 1955b, 1966), who calls it the "simplex" pattern since it indicates a simple linear order among the object entries. The simplex is characterized by the fact that the largest coefficients are next to the main diagonal and taper off as one goes to the upper right and lower left corners of the matrix. In other words, the further away two objects are in the matrix entries, the smaller their similarity coefficients. Guttman (1954) proposes a functional formulation of this relation as:

$$\text{Similarity }(I,K) = \text{Similarity }(I,J) \times \text{Similarity }(J,K) \quad \text{where } I < J < K \qquad \text{Eq. 3.1}$$

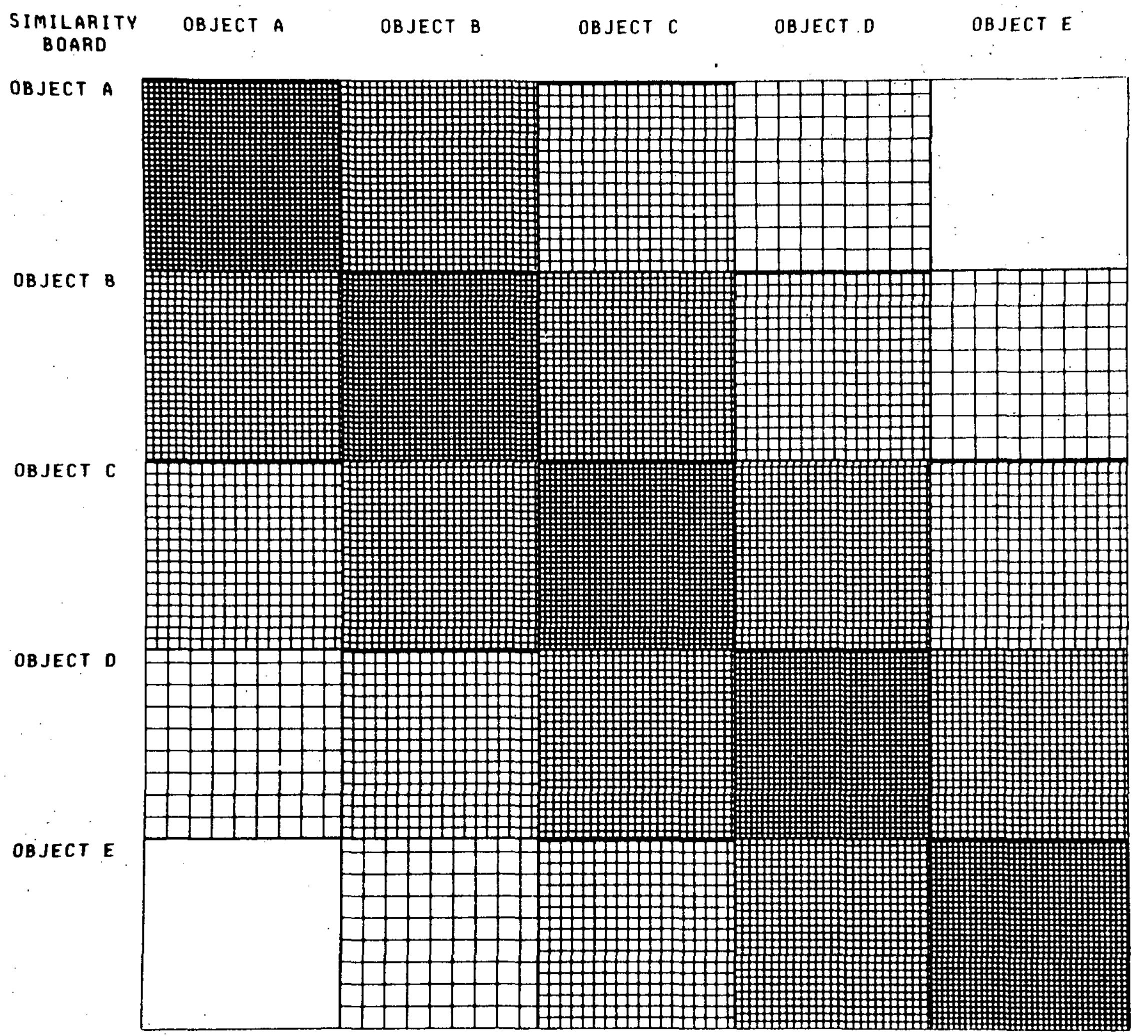
Suppose, for instance, that five managerial entries (A,B,C,D,E) are perfectly rankable along a dimension indicating their quality of performance. Then their matrix of similarity will show up this property by displaying a perfect simplex pattern (see Figure 3.2).

In summary then, the discovery of a one-dimensional ordering between objects amounts to the finding of a simplex pattern in the matrix of their similarity coefficients.

III.2.2 Method for the Discovery of a Simplex Pattern

In general, the order in which MDA finds the objects (i.e., the rows and columns of the matrix) at the outset of the analysis is purely random. The analytic problem becomes then one of recovering a simplex pattern on the basis of a similarity matrix which shows a random ordering of objects. This might itself be a difficult process: For instance, a slight perturbation of the ordering shown in Figure 3.2 (permuting the objects C and E) results in a completely different display (Figure 3.3). The process of analysis is, in fact, to go from representations like Figure 3.3 to representations like Figure 3.2. In other words, MDA must find the specific permutations simultaneously along the row and column entries such that, except for random fluctuations, the entries decrease monotonically with distance from the principal diagonal (Shepard, 1974). The row and column entries need to be rearranged

AN EXAMPLE OF PERFECT SIMPLEX PATTERN
(AFTER GUTTMAN, 1954)



XBL 767-8641

Figure 3.2

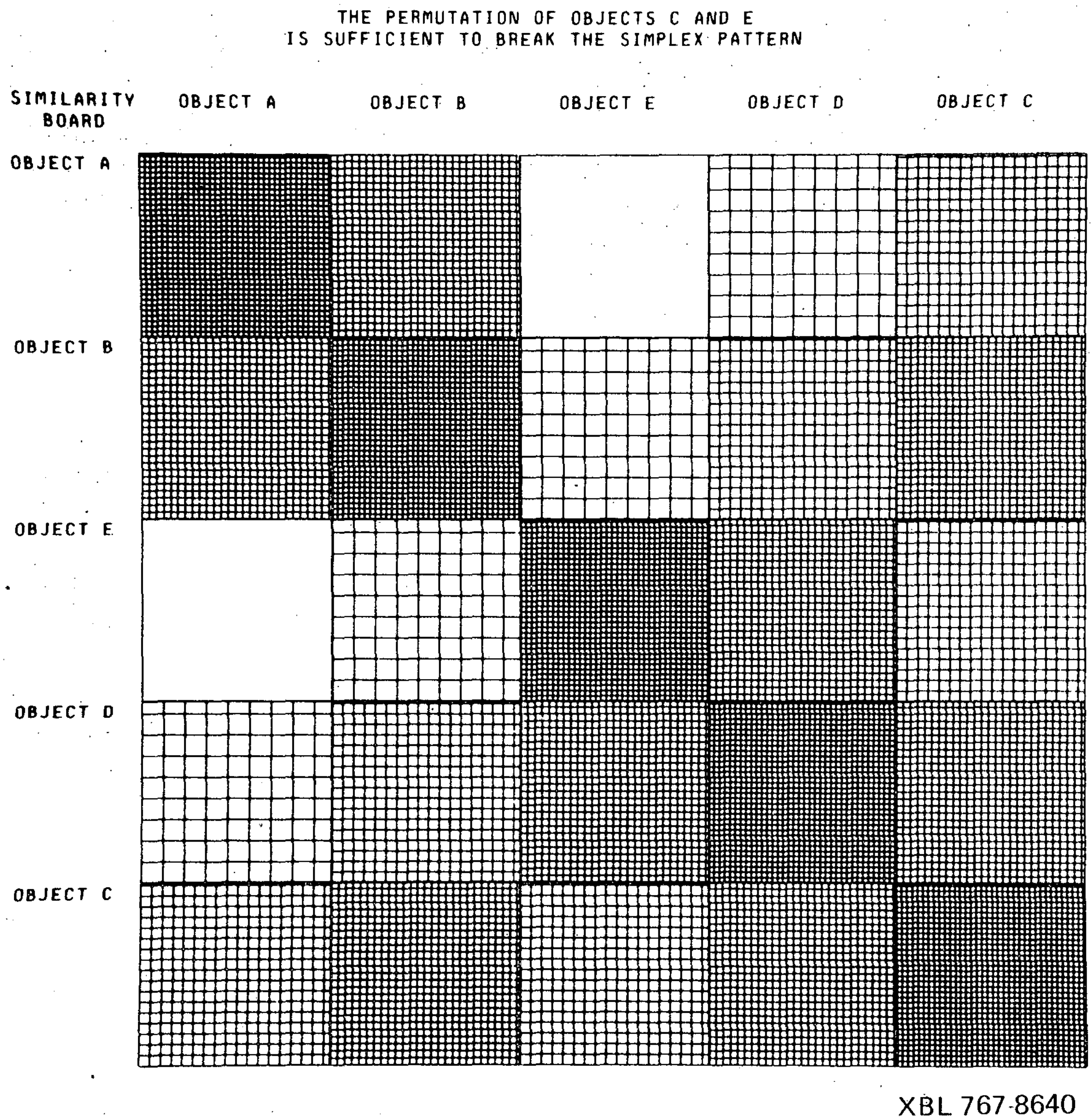

THE PERMUTATION OF OBJECTS C AND E
IS SUFFICIENT TO BREAK THE SIMPLEX PATTERN
SIMILARITY BOARD
OBJECT A
OBJECT B
OBJECT E
OBJECT D
OBJECT C
XBL 767-8640

Figure 3.3

simultaneously in order for the matrix symmetry to be kept.

The principle of proximity-resemblance applies to this problem of matrix reorganization in the following manner:

(1) On the one hand, it is possible to determine distance relations between objects on the basis of their positions along the rank-order.

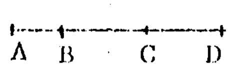
(2) On the other hand, the similarity data provides estimates of the resemblance between pairs of objects.

The analytic problem is then to find that one-dimensional ordering which maximizes the correspondence between the inter-object proximities and the inter-object similarities.

That a rank-ordering of objects implies distance relations between them can be seen in the following example. Suppose that four objects A, B, C, and D are ranked in that order, then a set of order relations between the inter-object distances also holds:

Figure 3.4

<u>Complete Ordering</u> (objects)



<u>Partial Ordering</u> (distances)

$AB = BC = CD < AC = BD < AD$

The most noticeable result is that, to the complete ordering of the four objects (A,B,C,D), there corresponds only a partial ordering of their six inter-object distances. Equivalenty, we might say that a rank-order of objects implies a series of ties in their distances (for n objects, there are n - 1 ties in the lowest distance value, etc., . . ., up to 2 ties only for the second highest distance value--in all: $(n - 1) X (n - 2)/2$ ties). The analytic problem is then to assess, at any point during the process of rearranging the matrix rows and columns, the extent to which the implied relations of distances effectively fit the similarity data themselves.

This problem is formally equivalent to a problem which is known as the "optimal linear ordering" or the "electrical layout problem" in operations research (Adolphson and Hu, 1973; Goldstein and Lesk, 1975):

> Given a set of n electrical components (i.e., objects) and their n X (n - 1)/2 levels of wire interconnections, assign the n components to n successive, regularly spaced positions in line so as to minimize the overall length of connecting wire which is used.

Since the notion of "interconnecting wire" is strictly equivalent to the notion of similarity, the problem of finding an optimal linear ordering is identical to the problem of rearranging the rows and columns of the similarity matrix so as to approximate a simplex pattern. The criterion which has been proposed for optimal linear ordering thus applies as well to the discovery of a simplex. This criterion has been specified as:

$$\text{Minimize} \sum_{I=1}^{n-1} \sum_{J=I+1}^{n} D(I,J) \times S(I,J) \qquad \text{Eq. 3.2}$$

where D(I,J) is the distance between I and J along the rank-order (chain distance), and S(I,J) is their coefficient of similarity. The summation is done only on one-half of the similarity matrix, because the matrix is symmetric around its main diagonal. An intuitive interpretation of the above criterion can be given by observing that it amounts to putting furthest apart objects having the least similarity, and, reciprocally, putting closest together objects which have the most similarity.

Given the above criterion, the process of searching for a simplex can possibly be done visually by MDA. Until recently, however, this eventuality could not be reasonably proposed, due to the cost of manipulating similarity displays only by way of paper and pencil (Sneath and Sokal, 1973). The present availability of low-cost interactive graphic terminals permits one to envision a state-of-the-art where the burden of constructing the display would be left to the computer, freeing MDA for more creative work (Lohrding, 1975). In the case of the search for a simplex, this "more creative" work would eventually consist in the permutation of rows and columns so that the configuration approximates the general features of a simplex pattern.

This process, however, might be a tedious one, since there are $n!/2$ possible different permutations of n objects, and since the visual load imposed on MDA may exceed his recognition abilities. (I shall develop this theme in chapter IV.) Consequently, it is proposed that numerical methods be used to help MDA in his search for a simplex pattern. Because of the very high number of possible permutations, the numerical methods proposed in data analytic situations equivalent to that of the search for a simplex, are local search procedures:

> Starting with an initial arrangement (usually chosen at random), one searches a small set of modifications of it for an improved arrangement. We call this a local search procedure. The iteration consists of applying the local search algorithm until no improvement can be made (Goldstein and Lesk, 1975, p. 15).

Among the variety of available local search techniques, two seem to be particularly suited to the search of a simplex pattern in a similarity matrix:

(1) Permutation algorithms, which test for all the possible permutations of a small number m of contiguous objects in the present rank-ordering, and shift the m-window along the n-ordering until no further improvement is made

(2) Insertion algorithms, which select one or several objects and insert them in every position, searching for an improved

arrangement

The computational cost is of the order of n X (m!) for permutation algorithms and of the order of n^2 for insertion algorithms. It is possible to combine both types of procedures with more elaborate search schemes such as branch-and-bound techniques (Lawler and Wood, 1966; Nilsson, 1971).

In summary, I have shown in the two previous sections that it is possible for MDA to use a method of one-dimensional analysis based upon a Matrix Display of similarity data. The thrust of my argumentation has been as follows:

(1) A one-dimensional ordering of the objects shows up as a specific pattern in the similarity matrix: the simpler.

(2) The search for a simplex pattern necessitates multiple permutations and rearrangements of the matrix entries.

(3) The process of permutation can be helped by a formal criterion of optimization which estimates the correspondence between the known relations of similarity and the observed proximities between the objects.

(4) Finally, it is possible to envision an interactive process whereby MDA uses both visual methods and numerical local search algorithms to rearrange the matrix entries.

III.2.3 Unsolved Problems in Simplex Analysis

As we said earlier, the research literature which is available to infer the feasibility of Matrix Displays is scarce and incomplete. I would like here to point out several of the areas in which more research results are needed in order for the Matrix Display of similarity data to become a tool for analysis. I shall later in this thesis (chapter IV) provide a set of original results which partially answer the problems mentioned below.

Problem 1: What kind of distance metric should be used to

> account for the computations of inter-object distances on the similarity matrix?

I have shown that it is possible to help the process of reorganizing matrix entries by way of a numerical criterion (Equation 3.2) which incorporates a distance measure. This distance measure, however, cannot possibly be the usual Euclidean distance, because the matrix space does not correspond to the Euclidean model: It offers discrete, equally spaced variations, instead of the continuous interval-scale variation of a Euclidean space. Hence, the need for a reflection on the nature of the metric which underlies a Matrix Display.

> Problem 2. How can MDA assess the extent to which an actual configuration fits the perfect simplex pattern?

Even when the entries of the similarity matrix are rearranged in the best manner (i.e., so that the partial ordering of the inter-object distances inversely correspond to the complete ordering of the similarity coefficients), nothing guarantees that the data themselves do conform to a perfect simplex pattern. In all practical situations, MDA must expect the observed objects to be rankable only to a limited extent; by way of consequence, the actual pattern which the similarity matrix shows must be expected to approximate the perfect simplex only. Since the inferences of MDA are essentially based upon the use of the rank-order model as a cognitive template, there is a need for validation procedures: The degree of validity of MDA's inferences clearly depends upon the degree of validity of the empirical pattern observed, as compared to the perfect simplex. Hence, the need for some research into procedures specifically suited to the validation of matrix patterns.

> Problem 3. Can simplex analysis be helped by graphical methods of mapping the similarity data into a smaller number of shade variations?

I said earlier that the matrix representation of similarity data is based upon the idea that it is possible to map the data into corresponding variations of shading. The nature of this correspondence and its optimal format have never been clearly studied (to my knowledge). Since several graphical reduction procedures might be used in order to map the similarity data into a fewer number of graphic items, it is important that a comparative and combined assessment of these several methods be done. Given the experimental evidence that I gathered in chapter II, and the nature of MDA's requirements, I shall propose in chapter IV an original treatment of this problem.

III.3 Matrix Displays and Two-Dimensional Order Analysis

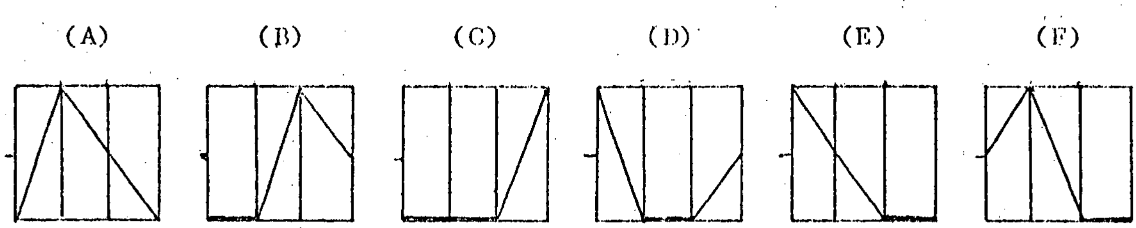
The methodology of finding a two-dimensional ordering in a similarity matrix is similar to that used for one-dimensional ordering. There are, however, a number of specificities which make two-dimensional ordering a more complex problem than one-dimensional ordering.

III.3.1 The Problem: Definition of the Circumplex Pattern

When the available similarity data is such that it cannot fit properly a one-dimensional (simplex) hypothesis, it is necessary to refer to a two-dimensional hypothesis and to observe the ordering of the n objects in two, rather than one, dimensions. Intuitively, a perfect two-dimensional ordering would be such that its projections on the two dimensions would show two completely independent orderings, so as to provide MDA with maximum information. This conjecture has been proven mathematically to hold true by Guttman (1954), who proposes that the ideal model of a two-dimensional ordering is a circle--which indeed has the property that its points can be orthogonally projected in two dimensions. Guttman then proposes to call "circumplex" (circular order of complexity) the ideal model of a circular ordering as it appears on the similarity matrix. In the discussion which follows, the circumplex will play a role analogous to that which the simplex had above.

The notion of a circumplex corresponds to Degerman's "circular structure" in two dimensions (see above, p. 74 and Degerman, 1972). The value of the circumplex for cognitive inference lies in its illustrating the notion of an ordering which is defined only up to a circular permutation. This type of ordering has no beginning nor end (the objects are not ranked from "higest" to "lowest") but rather all the objects have equal rank: The only law which holds is a law of neighboring, like in the positions of individuals round a table. Shepard and Carroll (1966) propose an example of circular ordering which is akin to a management situation. Suppose a series of three-attribute performance profiles, such that each profile resembles its neighbors and the last profile resembles the first one:

Figure 3.4



This series of profiles possess the interesting property that each successive profile is deduced from the preceding one by a simple transformation, and the two extreme profiles (F) and (A) are similar. Typically, this series can be said to "fold back" on itself and consequently the order (A,B,C,D,E,F) is circular.

As the simplex, the circumplex can be defined as a formal order pattern on the similarity matrix (Guttman, 1954). It is indicated by a gradient such that the largest coefficients are along the main diagonal, taper off about halfway from the main diagonal, and increase again toward the extreme corners of the matrix. This exactly corresponds to the mathematical notion of a "circulant" (Reed, in Guttman, 1955a). Figure 3.5 presents a perfect circumplex obtained according to an additive definition given by Guttman (1956, p. 326). This circumplex is shown on the symmetric matrix as a diagonal ordering, with the added feature that it folds back on itself (the extremes A and F are similar). The same circumplex can equivalently be shown as a two-dimensional circular ordering by arranging the row and column entries of the matrix so that the ordering (A,B,C,D,E,F) is obtained within the matrix itself. Figure 3.6 shows that the row ordering (A,B,F,C,E,D) and the column ordering (F,E,A,D,B,C) corresponds to the internal circular ordering (A,B,C,D,E,F).

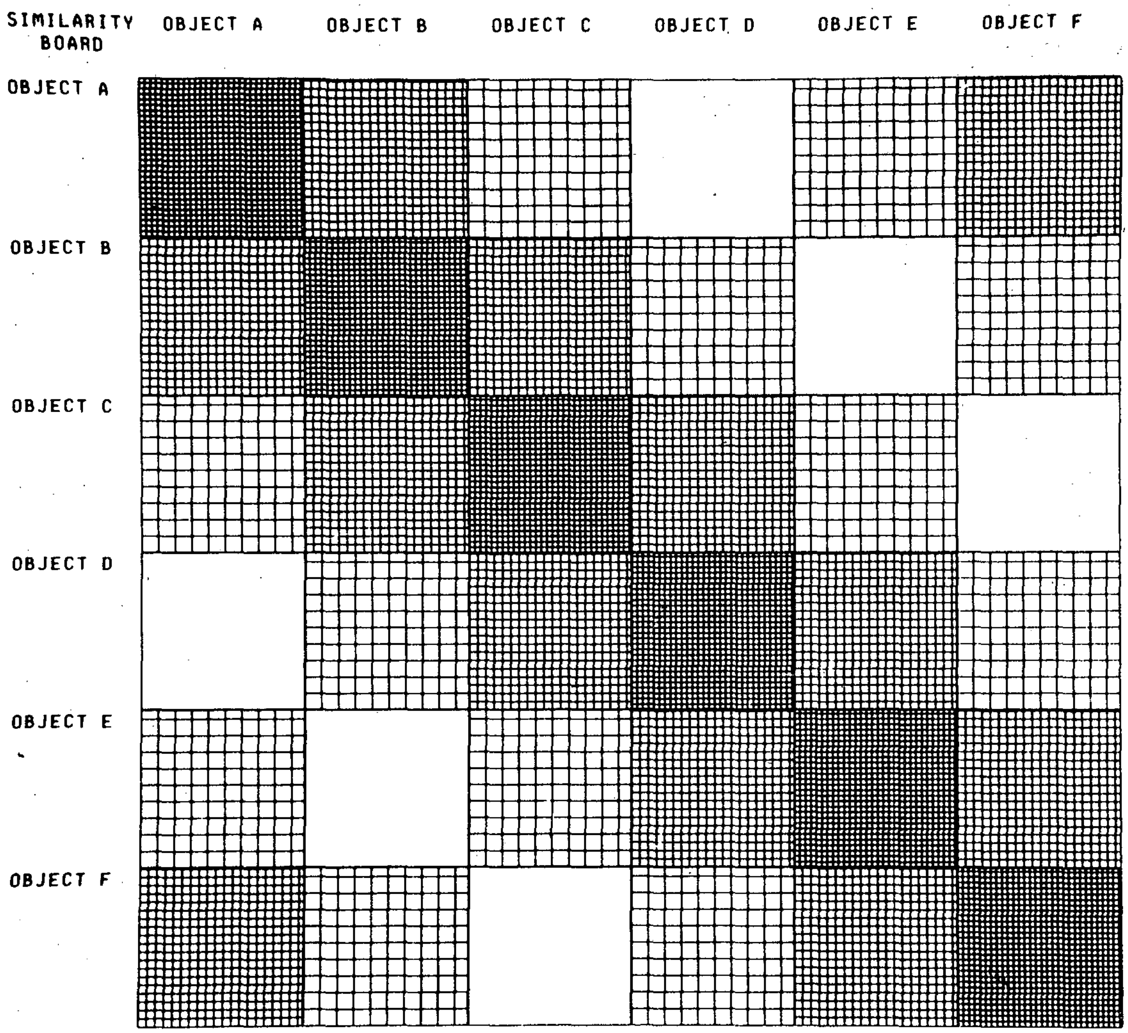
In summary, it is proposed here that the search for a two-dimensional ordering on the Matrix Display of similarity data be oriented toward the discovery of a circumplex pattern. This pattern is defined as a specific gradient in the symmetric similarity matrix, obtained when both the row and the column entries show the same ordering. It can also be shown as an approximate circle in two dimensions by rearranging the matrix entries orthogonally to each other.

III.3.2 Method for the Discovery of a Circumplex Pattern

According to the above subsection, the two-dimensional matrix ordering problem can be formulated:

> Given the n X n symmetric similarity matrix, rearrange simultaneously its rows and columns so as to approximate a circumplex

AN EXAMPLE OF PERFECT CIRCUMPLEX PATTERN
(AFTER GUTTMAN, 1954)



XBL 767-8639

Figure 3.5

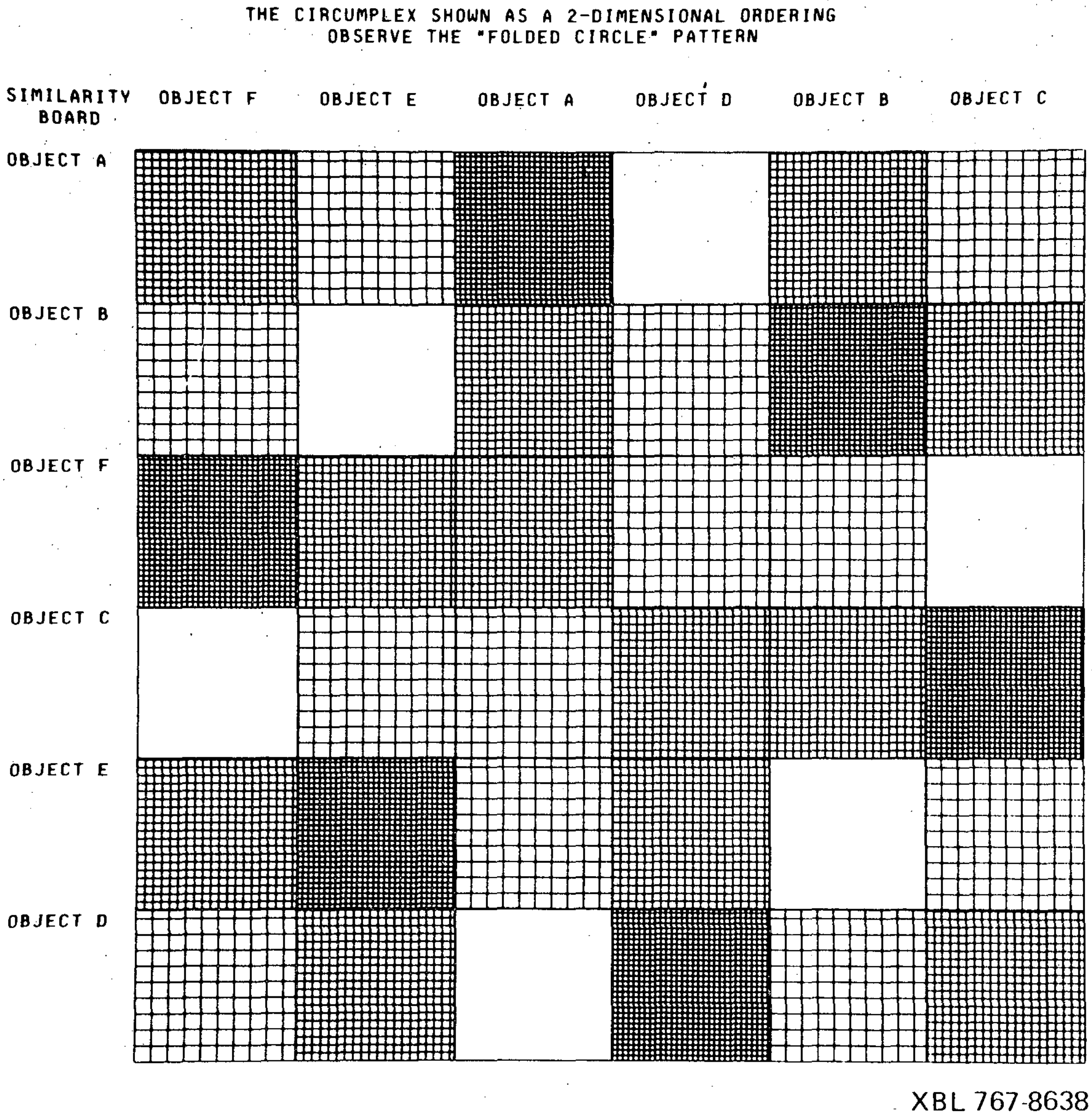

THE CIRCUMPLEX SHOWN AS A 2-DIMENSIONAL ORDERING
OBSERVE THE "FOLDED CIRCLE" PATTERN
SIMILARITY BOARD
OBJECT F
OBJECT E
OBJECT A
OBJECT D
OBJECT B
OBJECT C
OBJECT A
OBJECT B
OBJECT F
OBJECT C
OBJECT E
OBJECT D
XBL 767-8638

Figure 3.6

pattern in the best manner.

Not much direct research evidence is available to solve this problem. It is possible, however to decompose it into subproblems so that previous methodological research applies to it. One such decomposition, which I propose to adopt, is:

(1) Find an optimal circular ordering of the n objects.

(2) Among the possible n cyclic permutations of this ordering, choose the one which shows the best circumplex pattern on the similarity matrix.

(3) If a two-dimensional representation is needed, rearrange the ordering of one matrix entry orthogonally to the other.

The most complex of these three subproblems is (1), which is formally equivalent to the "traveling salesman problem" in Operations Research (Bellmore and Nemhauser, 1968; Lin, 1965):

> Given the set of distances between n cities, a salesman is required to visit each of the n given cities once and only once, starting from any city and returning to it after having visited the (n - 1) others. What tour* should he choose in order to minimize the total distance traveled?

The problem of circular ordering is equivalent to the traveling salesman problem to the extent that the $n(n - 1)/2$ similarity coefficients can be interpreted as indicators of proximity (i.e., inverse of distances). Consequently, the criterion becomes one of maximizing the total similarity among objects along the tour. Mathematically, the problem can be formulated:

> Given $S = S(I,J)$ the set of the $n(n - 1)/2$ similarity coefficients and $t = (i_1, i_2, \ldots, i_n, i_1)$ any tour and
>
> $t' = \left[(i_1, i_2), (i_2, i_3), \ldots, (i_{n-1}, i_n), (i_n, i_1)\right]$ the ordered pair representation of t.

---

*A tour: A path passing once and only once through each city and closed on itself.

$$:\text{Maximize} \sum_{(I,J)\in t'} S(I,J) \qquad \text{Eq. 3.3}$$

This criterion insures that the optimal tour t is such that the sum of the similarities between neighboring objects is maximum.

Recently, a computational procedure has been proposed for solving the problem in a general fashion (Held and Karp, 1971). Since its cost is pretty high, and since it does not fit the purpose of the present work which emphasizes interactive data analysis techniques, I shall rely here upon more classical approaches to the traveling salesman problem--that is, heuristic, local search procedures. One such method, called the "ℓ-opt" method, is of special interest for my purpose.

The ℓ-opt method (Lin, 1965) has been suggested on the basis of graph-theoretic considerations, namely, the theorem that, in general, an optimal tour does not intersect itself (Barachet, 1957). Clearly, then, a tour which intersect itself can be improved by replacing (at least) the two arcs which intersect with the corresponding non-intersecting arcs. A tour is said to be 2-optimal if it is impossible to obtain a better tour by replacing any two of its arcs by another set of two arcs. More generally, Lin (1965) proposes that a tour be said to be ℓ-optimal ("ℓ-opt") if it is impossible to obtain a tour with higher similarity by replacing any ℓ of its arc by another set of ℓ arcs. Lin further develops a set of theorems according to which all the possible tours can be partitioned into 1-opt, 2-opt, . . ., n-opt subsets, where the n-opt subset actually contains the overall optimum tour.

The interest of these graph-theoretic considerations is that they permit one to devise a tour-to-tour improvement algorithm with a high benefit-cost ratio. The procedure is to start with a random tour and systematically try to find the corresponding 3-opt tour by replacing any three arcs of the tour by three other ones. When three arcs are broken, the resulting strings of objects are permuted in all possible manners, searching for a better arrangement (the objects within each string retain their relative order). Once an improvement is found, the resulting tour is treated as an initial tour and the process is iterated (Lin, 1965; Goldstein and Lesk, 1975). The benefit-cost advantage of this procedure stems from the fact that it has a nontrivial probability of achieving the best optimal tour, at a cost which is proportional only to n^3 (as compared to the $(n - 1) /2$ cost of searching systematically through all the possible tours).

In the context of the search for a circumplex pattern, it is possible to envision a man-machine iterative procedure where MDA selects an initial tour and then runs the 3-opt algorithm to find a better 3-opt tour. MDA then visually checks the correspondence between the resulting pattern and a circumplex. He may then decide to modify it by a manual permutation and to run the 3-opt algorithm again; or, he may decide to stop at this point, having decided that the resulting pattern is among the best which could be reached with the available similarity data. In light of this process, problem (2) and problem (3) receive the following solutions (see p. 87 for statement of problems (2) and (3)):

(2) The n cyclic permutations of the chosen 3-opt tour are tried out, and the one which provides the best approximation to a circumplex pattern on the symmetric matrix is selected.

(3) It is possible to use a simple rule to find the ordering which is orthogonal to a given ordering. For instance, a simple orthogonal ordering rule might be based upon the observation that the objects with median position in one ordering should be placed at the extremes of the other ordering, and reciprocally (Coombs, 1964).

III.3.3 Unsolved Problems in Circumplex Analysis

The main areas of incomplete knowledge regarding circumplex analysis are essentially similar to those which I mentioned in reference to simplex analysis (III.2.3). They take, however, a slightly different form, to the extent that the circumplex is a specific pattern, with its own features and requirements. The three questions which I mentioned earlier take the following form for a circumplex:

(1) Considering the qualitative formulation of the circumplex on the symmetric similarity matrix:

> Is it possible to find a quantitative distance metric that would account for the formation of such a circular ordering pattern?

Clearly, the concept of a circle requires a continuous, euclidean formulation, and the Matrix Display does not have such formulation. Hence, again, the question of the postulates of the distance metric corresponding to a Matrix Display.

(2) Considering the one-dimensional, symmetric matrix, which is used in the analytic process of recognizing a circumplex,

> What statistical criterion of goodness-of-fit could MDA use in order to assess the fit between a given configuration and the ideal circumplex pattern?

This is the problem of validation, and it is not possible to conceive a data analytic approach without providing some guidelines on this point.

(3) When the similarity matrix is directly used as a basis for display, there are some implications as to,

> How the Matrix Display representation relates to the matrix analysis process.

In particular, the mapping rules which are used in the process of translating numerical coefficients into shades of grey seem to have an important bearing on the recognition of circumplex patterns by MDA.

III.4 Matrix Displays and Cluster Analysis

I now turn to an assessment of the utility of Matrix Displays for conveying the notion of discrete, mutually exclusive, and exhaustive classes of objects on the similarity matrix. This corresponds to the third "simple structure" which Degerman (1972) calls the "discrete class," or cluster structure.

There has been very little research (actually, none, except for a proposal by Dunn, 1975) on how the Matrix Display representation of the similarity matrix can help MDA discover clustering structures. Consequently, this section cannot be built as the two preceding ones, on the consideration of previously defined ideal templates--such as the simplex and the circumplex--which are proposed to guide the analytic process. Rather I shall attempt here first to present the problem and methodological issues involved with clustering, and then to show how a matrix representation relates to these considerations. The conclusion which I shall reach is that it is feasible to use Matrix Displays to detect the presence of clusters on the similarity matrix: Clusters actually show up as square groupings of homogeneous shade placed symmetrically around the main diagonal.

III.4.1 The Problem of Clustering

I call "problem of clustering" the problem of grouping a set of n objects into a smaller number of homogeneous, exhaustive, and mutually exclusive clusters. The cognitive advantages to be gained from the construction of discrete clusters of objects or events are that:

(1) It reduces the mental load (e.g., memory) required to describe and to remember the set of objects (Miller, 1956; Shepard et al., 1961).

(2) It provides a framework for instrumental activity, such as

when a manager defines a management policy for each cluster of entities (Cormack, 1971).

(3) It permits the establishment of category systems (Bruner, Goodnow, and Austin, 1956).

These three features make cluster analysis one of the most important aspects of multidimensional analysis, as is shown by the current upsurge of interest in clustering methodology (Sneath and Sokal, 1973).

The mathematical formulation of the clustering problem needs to refer to the notion of a partition:

Given a finite set N of n objects a partition P of N is a collection of m subsets $[c_1, \ldots, c_m]$ such that, for i, j = 1, 2, . . ., m:

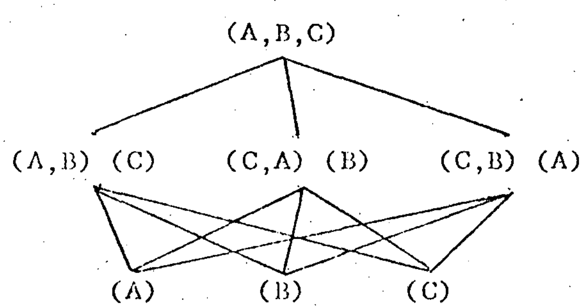
(1) $c_i \neq 0$ i.e., no class is empty

(2) $i \neq j \Rightarrow c_i \cap c_j = \emptyset$ i.e., all classes are disjoint

(3) $\bigcup_{1}^{m} c_i = N$ i.e., the union of all classes is N

It is possible to generate in a systematic fashion all the possible partitions of a set N into m classes, with m varying from 1 to n (Bell's generating function, Berge, 1968, p. 37). All the possible partitions can be represented as the nodes of a lattice. For instance, a set of n = 3 objects (A,B,C) generates the lattice:

Figure 3.7



1-class partition (P-lumper)

2-classes partition

3-classes partition (P-splitter)

The highest node in the lattice represents the lumper partition where all the n objects are packed into one class (m = 1), while the lowest node is the splitter partition, with each object forming a single class (m = n). All other partitions are intermediary between the extremes.

The interest of drawing this lattice stems from the fact that Cluster Analysis is a methodology for searching the best partition P^* in the lattice. The n objects are visually given as points in space, and the problem is to find that partition P^* of the n points such that the m classes of the partition effectively represent clusters of neighboring points. Since the position P-splitter obviously represents an optimal partition in each case (because each point is its own neighbor), this specification needs something more:

(1) Either the number of classes m is fixed to $\bar{m}$, and P^* is the optimal partition at the $\bar{m}$ level of the lattice (horizontal search)

(2) Or the number of classes m is let free to vary from 1 to n, and MDA looks for a set of hierarchically nested positions (vertical search).

Practically, the second formulation has been found to be more convenient and much more economical than the first one. Although it does not guarantee the attainment of the absolutely optimum partition for a given number of classes m, it generally leads to reasonably homogeneous clusters of objects close in space.

III.4.2 Cluster Analysis with the Minimum Spanning Tree

Principle. The above approach (2) can be easily implemented through the "minimum spanning tree" concept. Suppose n points are given in space, forming a network, possibly multidimensional. Then a tree spanning these points is any set of straight line segments, joining pairs of points (Gower and Ross, 1969), such that:

(a) No closed loops occur.

(b) Each point is visited by at least one line.

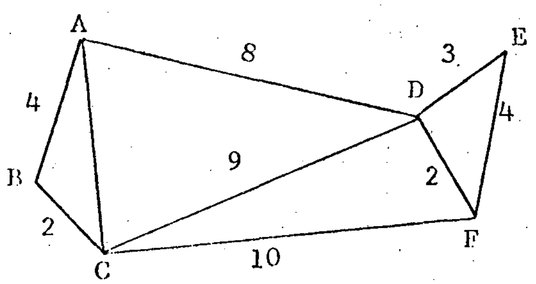
(c) The tree is connected.

If we call "length of the tree" the sum of the lengths of its segments (sum of distances), then the minimum spanning tree has

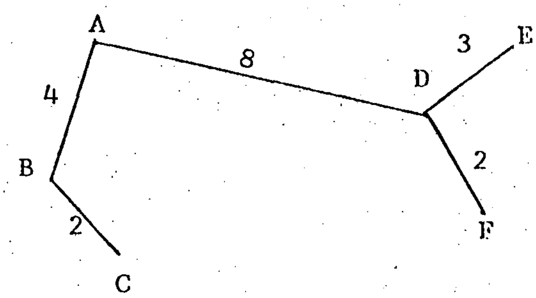
(d) The minimum possible length.

For instance, to the network shown on the left below there corresponds the minimum spanning tree shown on the right:

Figure 3.8



Network in Space



Minimum Spanning Tree

The minimum spanning tree of a set of points can be used as a basis for clustering because it has the following properties (Zahn demonstrates them as theorems, 1971):

(1) For any partition of the points into two disjointed classes, the minimum spanning tree gives the edge of minimum length between the two classes.

(2) Any of the minimum spanning tree edges is a minimum link for a binary partition.

(3) If there are real clusters in space, the minimum spanning tree does not break them.

These properties can be illustrated on the above example:

(1) For the partition [(A,B,C) (D,E,F)] the edge AD has minimum length (as compared to CD or CF).

(2) Any edge of the minimum spanning tree, such as AB, is the edge of minimum length between the classes of a two-class partition (here (A,D,E,F) and (B,C)).

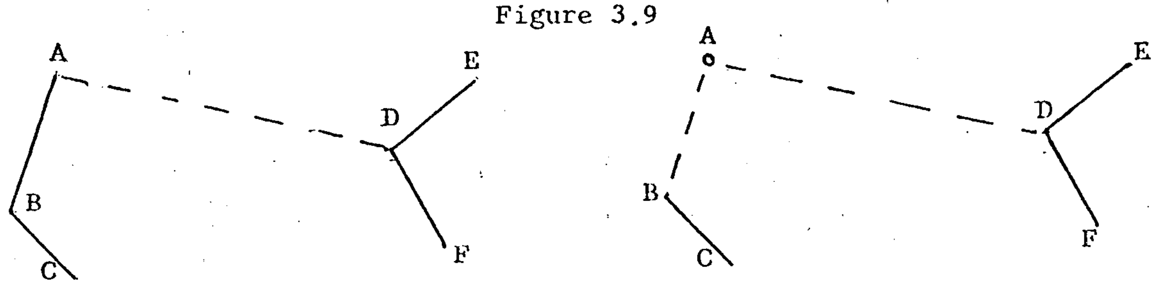
(3) The minimum spanning tree, by passing through each point so that the total distance is minimized, respects the relations of proximity inherent in the data.

The above theorems insure that, in principle, the minimum spanning tree spans the objects in such a way that (at least) approximately compact clusters are obtained.

Method. The most economic algorithm for computing the minimum spanning tree of a set of points has been independently formulated by Prim (1957) and Dijkstra (1959). Gower and Ross (1969) provides an example of implementation of this algorithm, which requires the order of n^2 computations.

Once the minimum spanning tree is found, the problem of defining m clusters becomes the problem of deleting (m - 1) edges from the tree so that the resulting connected subtrees correspond to the m most compact clusters. Zahn (1971) proposes a rule for deletion: A tree edge IJ whose length is significantly larger than the average of nearby edge lengths on both sides I and J should be deleted. For instance, the following diagram shows solutions for m = 2 and m = 3 (m is the desired number of classes in the partition):

Figure 3.9



2 classes clustering
(A,B,C) (D,E,F)

3 classes clustering
(A) (B,C) (D,E,F)

As can be seen, the clusters which are obtained through this method are hierarchically nested within each other, since each lower level clustering (going down the partition lattice) results from a disaggregation of the partition at the previous level. (Here (A,B,C) has been broken into (A) and (B,C).)

As I said earlier, the use of the minimum spanning tree method does not guarantee MDA that the partition P which is reached for any number of classes m is the optimal P^* at this level of partition. There is, however, good evidence that the minimum spanning tree provides a high benefit-cost ratio, since:

(1) Its results are in close conformity to the spatial relations of proximity between objects.

(2) It is insensitive to small amounts of noise widely and randomly spread over the observed space.

(3) It is economical computation-wise.

Limits of the minimum spanning tree approach. Johnson (1967) provides an interpretation of the meaning of the clusters obtained through the minimum spanning tree approach, in terms of the properties of the distance metric associated to those clusters. If we call "a chain" from object I to object J, any sequence of objects $(x_1, x_2, \ldots, x_p)$ which permit going from $I(=x_1)$ to $J(=x_p)$, and if the size of a chain is its largest link distance:

$$\text{size of chain } (I,J) = \underset{k = 1,2,\ldots,p}{\text{maximum}} \left[D(x_k, x_{k+1})\right]$$

then the minimum spanning tree provides, for each couple of objects I and J, the minimal chain size of all possible chains from I to J:

$$D'(I,J) = \underset{\text{all possible chains}}{\text{minimum}} \left[\text{size of chain } (I,J)\right] \qquad \text{Eq. 3.4}$$

Johnson (1967) shows that the distance metric D' satisfies a specific distance axiom (the ultrametric inequality) which is more constrained than the usual triangle inequality axiom (see chapter I, p. 25).

As a consequence, the clusters which are obtained through application of the minimum spanning tree approach are, in general, approximations to the actual clusters present in the data. Specifically, it has been shown that the minimum spanning tree approach tends to result in long, chain-like, and occasionally straggly clusters (Benzecri, 1973; Sneath and Sokal, 1973).

III.4.3 Applicability of a Matrix Representation to Cluster Analysis

As we shall see now, there exists some few but definite research evidence that the matrix representation of similarity data might help MDA in the process of cluster analysis.

Principle. As with order analysis, the basic data set which is available to MDA is the similarity matrix, where each similarity coefficient (I,J) represents an estimate of the resemblance between the two objects I and J. It is proposed that this similarity matrix be represented, as before, by way of shades of grey proportional to the values of the similarity coefficients (the higher the similarity, the darker the shade).

The fundamental principle to be used to guide the analysis here is the very principle which was used for order analysis, namely:

> Reorganize the matrix entries so that the relations of proximity between objects correspond to their relations of similarity.

This principle, when applied to the specific problem of cluster analysis, leads, however, to a different process of pattern recognition than the approximation of simplex or circumplex patterns.

The recognition of clusters on a Matrix Display. When a real clustering is present in a set of objects, it shows up on the similarity matrix under a "canonical form."

> In this canonical form the entries of the matrix decrease monotonically away from the main diagonal up or down along any column, and right or left along any row (Dunn, 1975, p. 333).

In other words, the clusters show up as square blocks of homogeneous shading, located symmetrically with respect to the main diagonal. Moreover, when some of the clusters present a hierarchical structure, this manifests itself in the matrix "as a nested progression of sharply delineated diagonal blocks converging downward into the black end of the scale (Dunn, ibid)." For instance, Figure 3.11 shows the cluster structure obtained by reorganizing the similarity matrix of Figure 3.10. An interpretation of this Matrix Display (3.11) can be given as follows:

(1) Two clusters are totally dissimilar: (2,6,1,8,7,4) and (5,9,3).

(2) Within the first cluster it is possible to discriminate two subclusters (2,6,1) and (8,7,4).

(3) Again, it is possible to decompose (2,6,1) into (2,6) and (1).

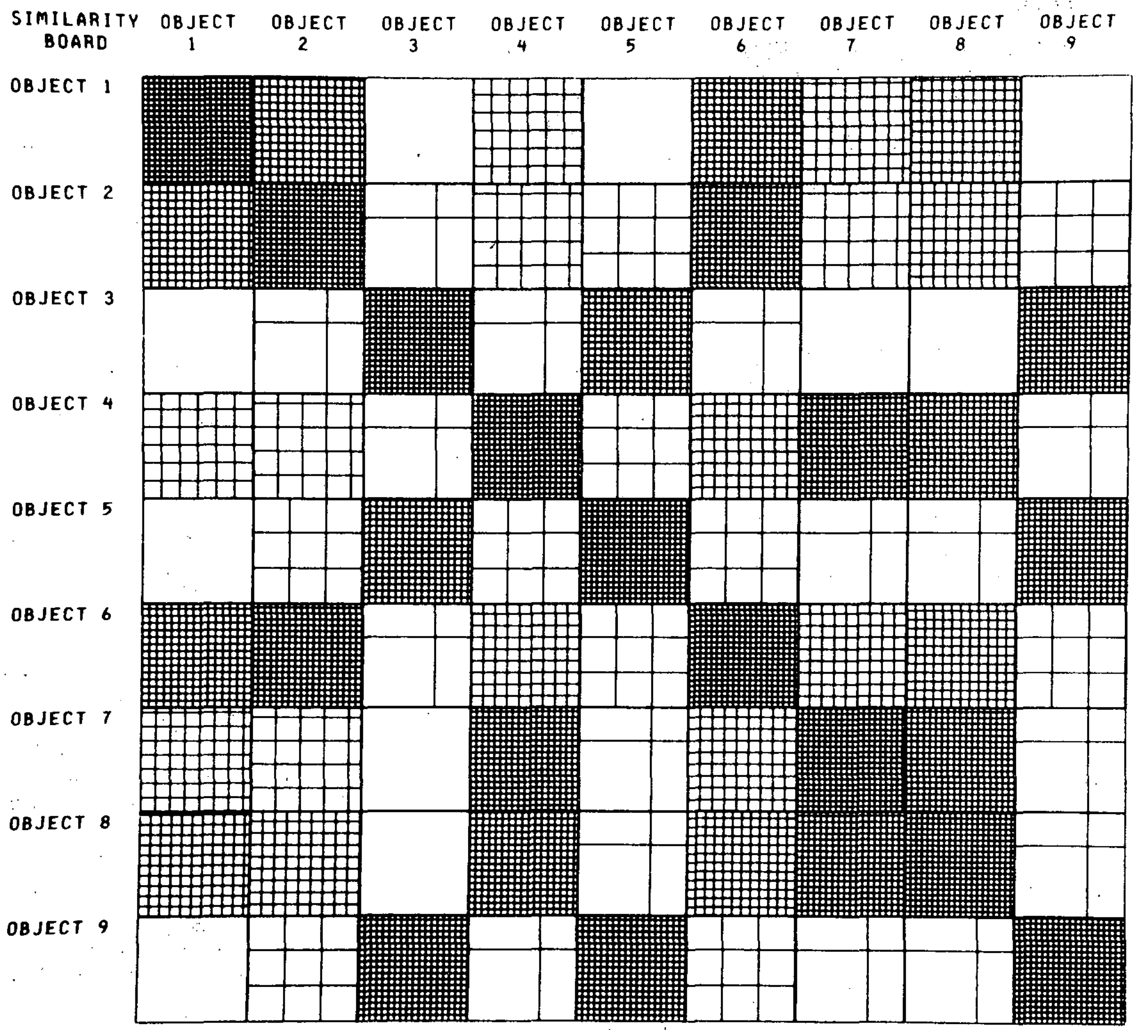
In consequence, it is observed that the Matrix Display conveys two different aspects of the clustering:

(1) A partition-aspect, since it is possible to choose a given level of positioning, m, and determine the relevant m classes. For instance, m = 3 gives (2,6,1) (8,7,4) and (5,9,3) in the above example.

(2) A hierarchical nesting aspect, since it is possible to recognize the following nesting relations on the above matrix (see Figure 3.12, p. 99).

Dunn (1975) further shows that the canonical cluster form of the similarity matrix is related to the minimum spanning tree algorithm. This algorithm can be used by MDA as an aid in the reorganization of the row and column entries of the matrix so that clusters show up.

EXAMPLE OF A SHADED SIMILARITY MATRIX
(AFTER DUNN, 1975)



XBL 767-8637

Figure 3.10

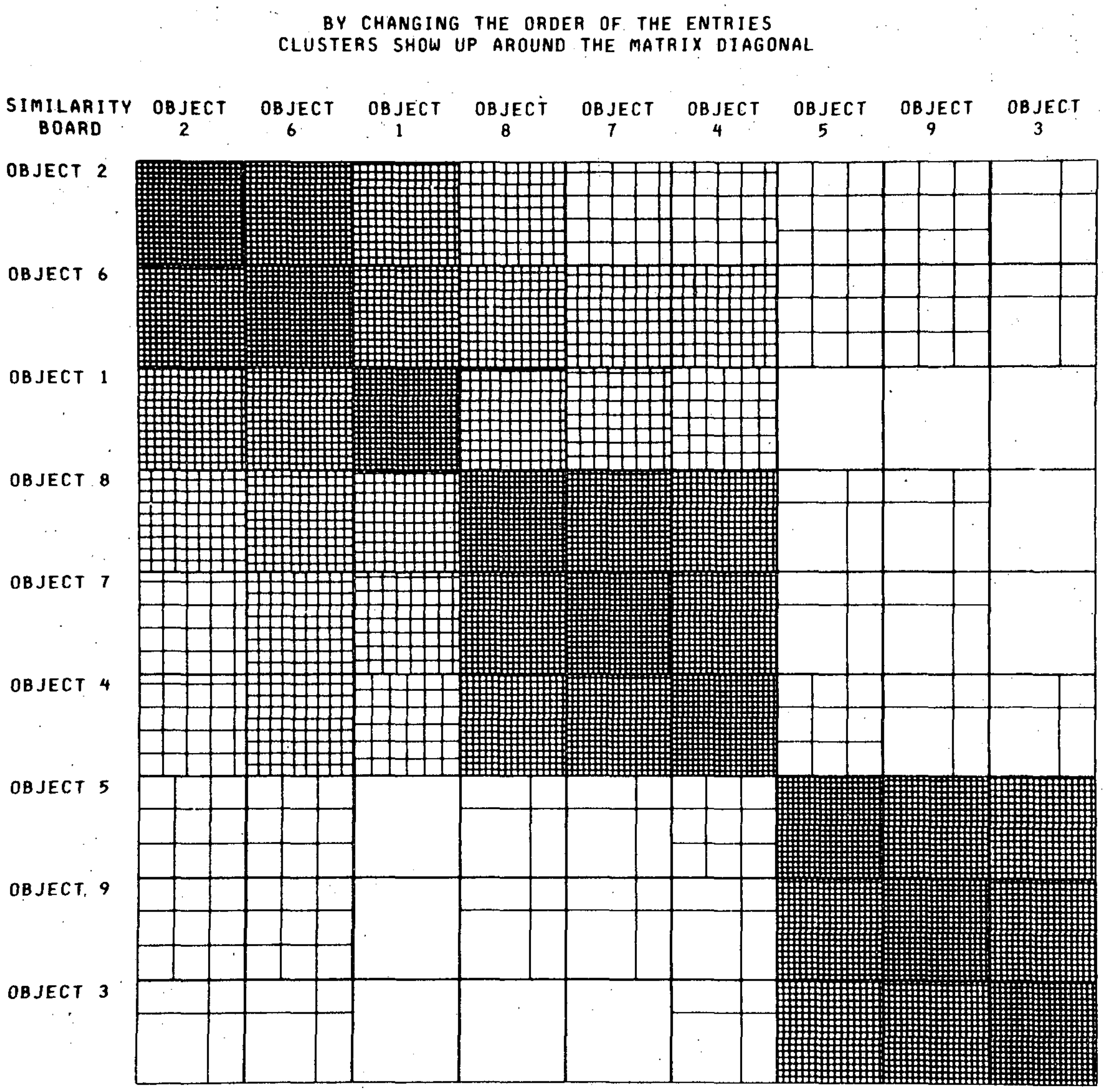


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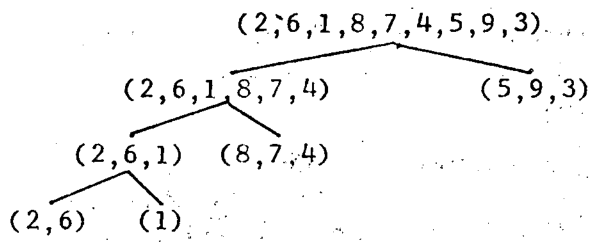
Figure 3.11

Figure 3.12



Rather than "minimum" spanning tree, one should say here "maximum" spanning tree, since the criterion to be used is the maximization of the similarities along the tree (as opposed to the minimization of distances). The reason why I devoted the previous section to spanning tree optimization procedures is then because of the implicit correspondence between the canonical form of clusters in a similarity matrix and the maximum spanning tree procedure.

Some questions. As before in the cases of one- and two-dimensional analysis, there are a number of issues unexplored and where some additional work would be needed. Among these I selected the following three questions, which directly relate to those mentioned earlier in III.2.3 and III.3.3.

(1) The distance metric and its implications:
Is there a rationale why clusters should appear as square blocks along the main diagonal of the matrix?

(2) The validity-check question:
Is it possible to validate the results of a matrix clustering process by the recourse to some statistical criterion of validity?

(3) The graphic mapping question:
Can MDA's search for clusters be helped by graphic transformations which would help cluster detection?

The following chapter proposes some elements of answer to these questions, as an original contribution to the theory of Matrix Displays.

In summary, the present chapter has shown:

(1) That three simple structures, of value for multidimensional analysis, have visual equivalents in similarity matrix patterns,

(2) That the process of analysis with the similarity matrix consists in permuting and rearranging in various ways the rows and columns so that specific gradients show up, and

(3) That heuristic, local search optimization methods can reasonably help the process of rearranging matrix entries.

As a consequence, it appears that Matrix Displays are feasible aids for the discovery of simple statistical structures. In particular, it seems possible to envision interactive procedures by which the user could benefit from the coupling of display techniques and analytic methods so as to determine such simple structures.

CHAPTER IV

A QUANTITATIVE APPROACH TO MATRIX DISPLAYS

The aim of this chapter is to show that the two lines of evidence generated thus far, namely,

(1) The evidence concerning the human visual performance with Matrix Displays (chapter II) and

(2) The evidence pertaining to the utility of Matrix Displays for multidimensional data analysis (chapter III),

mutually reinforce and point to an integrated, quantitative approach to Matrix Displays.

The proposed quantitative approach is a contribution to a theory of Matrix Displays, since it requires that the available experimental and empirical results be integrated at a higher level of abstraction. Simultaneously, the proposed approach is a contribution to the practice of Matrix Displays since the qualitative material of previous chapters is translated into formal guidelines and measures for practical usage. This dual emphasis on theory and practice is not to be seen as something unexpected: It comes directly from the very purpose of the present work to assess and to justify the feasibility of Matrix Displays.

The primary forms of this quantitative approach will be limited to three issues which seem to be central to an assessment of Matrix Displays:

(1) The problem of measuring distances between matrix positions

(2) The related problem of assessing the goodness-of-fit between actual configurations and ideal templates

(3) The question of reducing the graphic information so that the information transfer to the user is maximized

These three issues were mentioned earlier in chapter III as research problems: I have found that it is possible to solve them (at least in an approximate manner) by relating together perceptual evidence and analytic findings. As a result, this chapter demonstrates that Matrix Displays are an effective interface between perception and analysis.

One of the achievements of this chapter is to point to specific areas where future research would have important payoffs. Another, more essential, achievement is to provide a variety of quantitative procedures which will be used as formal rules in the design of a model of Matrix Display usage (chapter V).

IV.1 A Distance Metric for Matrix Displays

IV.1.1 Formulation of Two Plausible Distance Models

The goal of the matrix analysis of similarity data is to describe the set of the observed objects in terms of a spatial configuration on the matrix itself. Since this spatial configuration implies relations of distance between objects, the problem of representation is to arrange the objects in such a way that their relations of distances inversely correspond to their similarities. Once a distance measure is defined, it becomes possible to improve the process of rearranging the matrix rows and columns so that better fit to the underlying similarity data is obtained. For instance, it becomes possible to use an optimization criterion such as Equation 3.2.

The definition of a distance model (or a class of models) for matrix displays involves both perceptual and statistical considerations.

The axioms of a distance model must obviously correspond to the way HUS perceives distance relations in the Matrix Display. Simultaneously, the same axioms must be able to account for those patterns in the similarity data which are deemed to be significant by MDA. The essential quality of a distance model is thus to be an interface between perceptual and statistical factors, and, consequently, to possess explanatory power as to why Matrix Displays are useful aids.

The usual, Euclidean definition of the distance between two points I and J of coordinates (x_I, y_I) and (x_J, y_J) in a two-dimensional space is:

$$D(I,J) = \left[(x_I - x_J)^2 + (y_I - y_J)^2\right]^{\frac{1}{2}} \qquad \text{Eq. 4.1}$$

This definition assumes that the two-dimensional space is continuous everywhere, so that the segment IJ is made up of an infinite number of intermediary points (Thomas, 1969). Pythagoras' theorem, which states that the square of the hypotenuse in a right-angled triangle is equal to the sum of the squares of the two other sides, is a direct consequence of the above axiom. Another consequence is that the shortest distance between two points is a straight line.

This axiom has been found, however, to possess quite important limitations on the following grounds.

(1) From a mathematical viewpoint, it is only one among the general class of distance metrics called the power metric (or Mikowski metric) characterized by:

$$D(I,J) = \left[|x_I - x_J|^r + |y_I - y_J|^r\right]^{1/r} \qquad \text{Eq. 4.2}$$

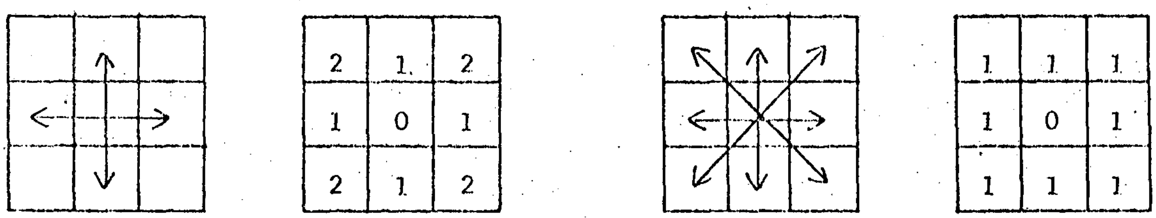
The Euclidean metric (Equation 4.1) corresponds to the special case of r = 2, but other metrics can just as well be constructed with other values of r. (As we shall see below, r = 1 and r = ∞ also provide useful metrics.)

(2) From a perceptual viewpoint, it has been shown experimentally

> that the distance models used by HUS have more variety than the simple Euclidean model would account for (Attneave, 1950; Shepard, 1964; Hyman and Well, 1967): Hence, the recognition that there corresponds different distance metrics to different perceptual situations.

<u>Two Models</u>. The Matrix Display mode of representation offers a case where the Euclidean axiom no longer applies. By its very nature, a Matrix Display shows a fixed number of discrete elementary cells corresponding to discrete, countable row and column entries. As a consequence of its inherent discreteness, a Matrix Display does not fit the notion of a space continuous everywhere, as is implied by Equation 4.1. Rather, a Matrix Display is an essentially discontinuous space, where distance measures increase by sudden steps at the crossing of between-cells boundaries. From this viewpoint, there seems to be two possible models of the relations of distance between an elementary cell and its adjacent neighbors.

Figure 4.1



(a) Orthogonal Model (b) Adjacency Model

The orthogonal model assumes that, from a given cell, the only possible displacements are either horizontal or vertical. As a consequence, the distance relations between a cell and its neighbors are those indicated in the right hand side of Figure 4.1(a): The cells located on a diagonal from the center cell are at D = 2 because two elementary displacements (one horizontal, one vertical) are necessary to reach them.

The orthogonal model has received a mathematical formulation as the additive "city-block" metric. This metric is formulated by way of Equation 4.2, with r = 1:

$$D(I,J) = |x_I - x_J| + |y_I - y_J| \qquad \text{Eq. 4.3}$$

According to the original idea of Attneave (1950) the city-block situation is typically that of an American city where no diagonal displacement is possible across a given block, so that the only way to join two opposite corners is to walk both sides of the block.

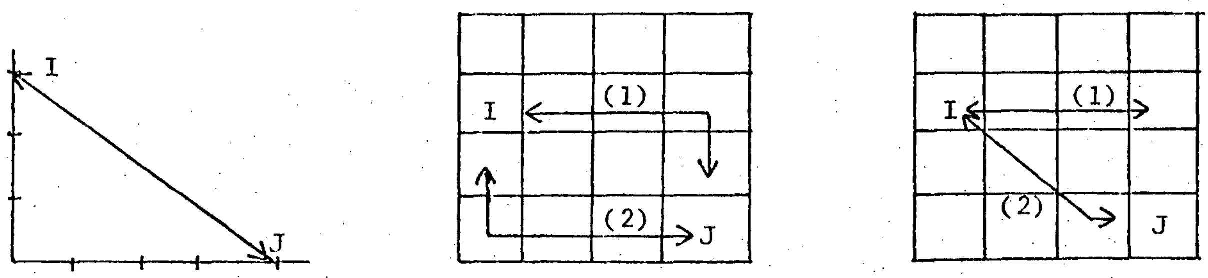
The adjacency model, on the other hand, allows for diagonal displacements across blocks, so that the eight cells adjacent to a given matrix cell are equally distant from it, at D = 1. The mathematical formulation of this model is formally equivalent to the limit case obtained with $r = \infty$ in Equation 4.2, and I call it the "Supremum block metric" by analogy with the "Supremum metric" in the Euclidean case:

$$D(I,J) = \text{MAXIMUM}\left[\, |x_I - x_J|,\ |y_I - y_J| \,\right] \qquad \text{Eq. 4.4}$$

For any two given cells I and J, the above equation provides the minimum number of adjacent matrix cells which it is necessary to cross in order to go from I to J. The maximum of the two absolute differences in coordinates thus provides in any case the minimum path between any two matrix cells.

Interpretation of the Two Models. The contrast between the classical Euclidean model and the two models which I propose for the measurement of matrix distances can be illustrated by considering the elementary distance between two points I and J in space (Figure 4.2). The basic difference between the Euclidean model and the other two models is that the latter proceed by a simple process of counting blocks. Accordingly, I call them the "block models."

Figure 4.2



Euclidean (D = 25 = 5)

Orthogonal (City block) (D = 5)

Adjacency (Supremum block) (D = 3)

The block models may not be the only possible models for distances on a Matrix Display. However, they are the most plausible models because they rest upon two most relevant assumptions:

(1) A Matrix Display is an essentially discrete mode of representation.

(2) The neighborhood of a matrix cell is defined as a subset of those cells which are adjacent to it.

One interesting feature of block models is that they provide several equivalent paths between any two given points (in the above display two equivalent paths (1) and (2) are proposed between I and J). Another feature is that the block models result in integer distance values, and consequently they tend to provide ties in the distance measures (Shepard, 1974).

The perceptual implications of the two models are slightly different, since the adjacency model permits diagonal moves. This model is intuitively more appealing than the orthogonal (city-block) model, because we expect HUS to be able to perceive distances in a diagonal fashion. To my knowledge it is the first time that such a model is proposed at the juncture of perception and statistical analysis.

IV.1.2 The Metric Description of the Simplex and Circumplex Patterns

In chapter III, I described qualitatively two patterns which, when present in the similarity matrix, indicate order relations between the observed objects. I would like now to assess the extent to which the above distance models are compatible with these specific patterns.

The Simplex. I described earlier the simplex as a pattern such that the largest similarity coefficients are next to the main diagonal and taper off as one goes to the upper right and lower left corners of the matrix. Guttman (1955b) observes that, although this pattern can be obtained by a variety of formation rules on the similarity data, only one necessary and sufficient condition is actually required to hold, namely:

$$D(I,K) = D(I,J) + D(J,K) \qquad (I \leq J \leq K) \qquad \text{Eq. 4.5}$$

where I, J, and K are three objects in that order along the matrix entries

I show now that this condition is verified by both distance models which I defined above, i.e.,

- The orthogonal (additive city-block) metric
- The adjacent (supremum block) metric

Suppose we are given a symmetric similarity matrix, with row and column entries A, B, C, D, E, F, such that each object is located on the main diagonal, at the intersection of the row and the column bearing its label:

Figure 4.3

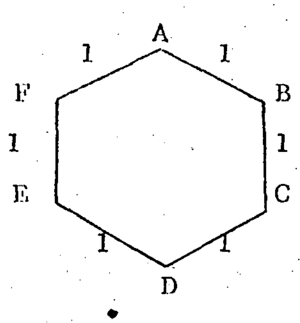
	A	B	C	D	E	F
A	A	1	2	3	4	5
B		B	1	2	3	4
C			C	1	2	3
D				D	1	2
E					E	1
F						F

Then it is possible to compute the distances between each couple of objects and to write it down within the corresponding cell. It turns out that (1) the orthogonal and the adjacency models provide the same distance measure and (2) those distances form a simplex pattern (the lowest distances are next to the diagonal, and they increase as one goes to the upper right and lower left corners of the matrix).

In general, Equation 4.5 holds for both the orthogonal and the adjacent distance models on the symmetric matrix.

<u>The Circumplex</u>. The circumplex has been defined earlier as the indication of a perfect circular ordering between the observed objects. A qualitative description of the circumplex pattern in the symmetric similarity matrix was given as a gradient such that the largest coefficients are along the main diagonal, taper off about halfway from the main diagonal, and increase again toward the extreme corners of the matrix. The following diagram accounts for this description:

Figure 4.4



	A	B	C	D	E	F
A	A	1	2	3	2	1
B		B	1	2	3	2
C			C	1	2	3
D				D	1	2
E					E	1
F						F

The regular cyclic graph on the left has as many vertices as there are objects, and each edge has the same length (D = 1). The matrix on the right shows the between-objects distances computed along the cyclic graph. The corresponding matrix pattern corresponds to the ideal template of a perfect circumplex.

It is possible, as Guttman suggests (1954), to characterize the circumplex by a one-dimensional distance function such as:

$$D(I,J) = \begin{cases} |x_I - x_J| & \text{for } 0 \leqslant |I - J| < N/2 \\ N - |x_I - x_J| & \text{for } |I - J| \leqslant N/2 \end{cases}$$

where N is the number of observed objects

However, this distance model is not convincing because:

(1) It lacks generality (it characterizes the perfect circumplex only.

(2) It has no perceptual justification (clearly, the extreme right corner can not be perceived as being close to the main diagonal).

It is interesting here to contrast this hypothetical model with the block models: Both block models have generality (they are deduced from the general power metric of Equation 4.2) and can be interpreted in relation to spatial perception.

The displays below show the objects A, B, C, D, E, and F forming a circular pattern on the similarity matrix. Notice that, in order to get that circular pattern, I have arranged the row and column entries of the matrix in independent fashion. The data correspond to distance computations carried out in accordance with Equations 4.4 and 4.5.

Figure 4.5

	F	E	A	D	B	C
A	4	5	A	6	3	6
B	5	6	3	5	B	3
F	F	3	4	6	5	6
C	6	5	6	4	3	C
E	3	E	5	3	6	5
D	6	3	6	D	5	4

Orthogonal Model

	F	E	A	D	B	C
A	2	4	A	5	2	3
B	4	3	2	4	B	2
F	F	2	2	3	4	5
C	5	4	3	2	2	C
E	2	E	4	2	3	4
D	3	2	5	D	4	2

Adjacency Model

If we now rearrange the matrix entries so that the matrix is symmetric around its main diagonal, we get the patterns:

Figure 4.6

	A	B	C	D	E	F
A	A	3	6	6	5	4
B		B	3	5	6	5
C			C	4	5	6
D				D	3	6
E					E	3
F						F

Orthogonal Model

	A	B	C	D	E	F
A	A	2	3	5	4	2
B		B	2	4	3	4
C			C	2	4	5
D				D	2	3
E					E	2
F						F

Adjacency Model

	A	B	C	D	E	F
A	A	2	4	5	4	2
B		B	2	4	5	4
C			C	2	4	5
D				D	2	4
E					E	2
F						F

Modified Adjacency Model

The two matrices on the left show the patterns obtained with the orthogonal and the adjacency models. These patterns approximate the circumplex shown in Figure 4.4, but they do not provide a perfect fit since the increment/decrement process from the main diagonal to the extreme corners is not entirely regular.

In an attempt to explain why the above models do not reproduce the perfect circumplex, I have found that a slight modification of the adjacency model leads to the needed pattern:

$$D(I,J) = \underset{\substack{\text{over} \\ \text{all } N-1 \text{ cyclic} \\ \text{permutations}}}{\text{MAXIMUM}} \left[\text{MAX}\left(|x_I - x_J|, |y_I - y_J| \right) \right] \qquad \text{Eq. 4.6}$$

By applying the (N - 1) possible cyclic permutations of the N objects, and by choosing for each couple of objects the maximum among the (N - 1) corresponding distance values, the ideal circumplex is reached (as shown in Figure 4.6, right). The rationale behind this modified adjacency metric is that, because of the impossibility of obtaining a perfect circle on a Matrix Display, some irregularities are introduced in the matrix representation of a circular order. For instance, although the objects

B and E are diametrically opposed in Figure 4.5, their adjacency distance takes value 3, while the adjacency distance for another diametrically opposed couple such as (A,D) takes value 5. By a cyclic permutation of the objects so that A, B, C, etc., are moved one step to the former positions of B, C, D, etc., it is observed that (B,E) takes now the former value of (C,F) and (A,D) takes the former value of (B,E). By applying all possible permutations and selecting the largest distance value, the perfect circumplex pattern is thus recovered.

Implications. In sum, the above study implies that:

(1) The qualitative features of the simplex and the circumplex can be quantified by the supremum block metric, or versions of it.

(2) It is expected that a generalized version of the supremum block metric will account for distance relations in Matrix Displays in general circumstances.

(3) The definition of a generalized supremum block metric may provide a crucial interface between visual perception and data analysis, as presented in chapters II and III.

IV.1.3 A Hypothetical Distance Metric for Matrix Displays

A generalized version of the supremum block, or adjacency metric is proposed here as a hypothetical distance metric for Matrix Displays:

$$D(I,J) = \Phi\left[\mathrm{MAX}(\ x_I - x_J\ ,\ \ y_I - y_J\ )\right] \qquad \text{Eq. 4.7}$$

where Φ is a monotonically increasing function ($\Phi = 1$ in Equation 4.4 and $\Phi =$ MAX in Equation 4.6)

Because of (1) the necessarily limited ambition of this dissertation, (2) its orientation toward feasibility assessment and applied issues, and (3) the almost total lack of previous inquiries into the above metric model, I shall not embark on the major research study which its confirmation would require. I shall, however, provide some directions of research which I think would be fruitful in this respect.

Direction 1: Topological exploration. Taking the cells of the similarity matrix as points in the two-dimensional space defined by its rows and columns, characterize the general class of patterns which the hypothesized metric would produce.

Direction 2: Perceptual experimentation. Determine the extent to which HUS perceives distance relations within a Matrix Display in accordance with the hypothesized model. Inquire into the effects of matrix size, type of graphic item (shade, texture, etc.) and discriminability of the cell entries on the perception of distance.

Direction 3: Relations of the supremum block metric to other metrics. Examine the relations between the generalized supremum block and other metrics. In particular, consider those matrix patterns which might be accounted for by different metric assumptions.

IV.2 Matrix Patterns and Statistics: A Connection

The aim of this section is to show that the traditional, hypothesis-testing approach of statistics is complementary with the visual, matrix approach proposed in this thesis. Through reference to the distance measure elaborated in IV.1, it is possible to design statistical procedures for checking the goodness-of-fit of empirical patterns to ideal matrix patterns such as the simplex and the circumplex. One such procedure, based upon the ordinal characteristics of similarity data and matrix distances, is proposed below. Methodological remarks on the connection between matrix patterns and statistical testing follow this proposal.

IV.2.1 The Ordinal Character of Similarity Displays

The matrix analysis of n X n similarity data obeys the general principle of multidimensional analysis, that the n objects be arranged in space so that their distances inversely correspond to their similarities:

> It is postulated that the distance between any two points in the space is a function of the degree of similarity between the two stimuli. If the two stimuli are identical, the distance between their corresponding points in the space is zero. As the degree of dissimilarity increases, the distance between the corresponding points increase (Torgerson, 1958, p. 250).

The application of this principle raises the question of how to measure the statistical fit between the similarity data and the inter-object distances implied by the matrix configuration.

It is proposed here that the goodness-of-fit between the similarity data and the distances on the configuration be measured by comparing order relations on the similarities with inverse order relations on the distances. The rationale for this proposal is twofold:

(a) It can be argued that the similarity coefficients contain valuable rank-order information, but not more (i.e., only their own rank-order matters), because:

   (1) It is possible to recover almost full metric configurations on the basis of rank-order information (Shepard, 1966).

   (2) The similarity data might be imprecise and the consideration of their quantitative value might be misleading (Crossman, personal communication, 1975).

   (3) When similarity data are presented graphically, the matrix user picks up order relations much better than quantitative relations (e.g., the result illustrated in II.4 that shades of grey convey relations of order better than anything else).

(b) The measurement of distances between objects on the similarity matrix obeys a rank-ordering rule. For instance, the adjacency block model (Figure 4.4) provides:

   (1) Distances taking integer values

   (2) Within the interval (0, n - 1) for a n X n matrix

(3) With numerous ties

The requirement that order relations on matrix distances convey exactly inverse order relations on similarity data can be expressed as:

$$D(I,J) \leq D(K,L) \Longleftrightarrow S(I,J) \geq S(K,L) \qquad \text{Eq. 4.8}$$

where (I,J) and (K,L) are any two couples of different objects

The sole consideration of relations of order (instead of more complex quantitative relationships) has the effect of reducing the complexity of the representation problem. Since rank-orders are not affected by any monotonic transformation (of the type $X = f(x)$ where f is monotonically increasing), it is possible to apply any such transformation to either the similarity data or the distance measures. Moreover, the equals sign on both sides of Equation 4.8 indicates that a further reduction operates when ties in distances correspond to un-tied similarities and vice-versa.

IV.2.2 A Goodness-of-Fit Index for Matrix Patterns

Kruskal (1964a, 1964b) proposed earlier a goodness-of-fit measure for configurations in Euclidean space. I build on this idea and propose here an analogous measure for configurations in the matrix space. This measure permits quantifying the necessary and sufficient conditions of Equation 4.8 in the following manner:

Suppose R(I,J) indicates the rank of the distance D(I,J) between the objects I and J in the similarity matrix (distances are ranked from lowest to highest).

And suppose that $\hat{R}(I,J)$ is the rank of the similarity coefficient S(I,J) within the rank-order of similarities (from highest to lowest).

Then it is possible to measure the goodness-of-fit G between matrix distances and similarity data by:

$$G = 1 - \sum_{1}^{m} \left[R(I,J) - \hat{R}(I,J)\right]^2 \Big/ \sum_{1}^{m} \left[R(I,J) - \bar{R}(I,J)\right]^2 \qquad \text{Eq. 4.9}$$

where (1) m is the number of needed comparisons, i.e., $m = n \times (n - 1)/2$ in the symmetric matrix $m = n \times n$ in the non-symmetric matrix (2) $\bar{R}(I,J)$ is the inverse rank-order of distances

The quadratic expression on the right-hand side is the equivalent to what Kruskal (1964a, 1964b) calls the "stress-measure." Its denominator represents the worst possible situation, i.e., when the rank-order of the similarities is exactly the reverse of the rank-order of the distances. Thus the stress measure is expressed as a percent figure of Actual deviation over Potential maximum deviation. Consequently, G, the goodness-of-fit index, is expressed as the complement of the "stress" to 100 percent.

The goodness-of-fit measure G permits comparing several configurations and choosing the one having the highest G value. It can then be used as an optimization criterion guiding the search for the best configuration corresponding to an empirical similarity set. In this sense, it is a substitute for a criterion such as Equation 3.2.

IV.2.3 Testing Pattern Hypotheses in the Similarity Matrix

When the distance relations implied by a given configuration conform to an ideal matrix pattern, the measure G is a measure of confidence to the hypothesis that the actual configuration fits the perfect pattern. Unfortunately, there does not exist any study on the empirical sampling distribution of G under usual statistical assumptions (such as normality, etc.). Consequently, the index G does not provide a quantitative means to assess the validity of pattern hypotheses, although it might qualitatively indicate the direction of validity. (Kruskal (1964a, 1964b) suggests that a G greater than 95 percent indicates an "excellent" fit.)

In summary, it is possible to relate together statistical testing procedures and the visual approach advocated in this thesis. The exact modalities of this connection are still largely conjectural, but I suggest that goodness-of-fit measures based upon the ordinal characteristics of similarity data be used. This justifies the claim made earlier in chapter III, that analytic procedures and Matrix Displays can be harmonized so that the user gets <u>both</u> readily interpretable configurations in two dimensions and statistical estimates of goodness of fit to patterns.

IV.3 Mapping Data into Matrix Displays

I suggested above a process of data analysis based upon the attainment of specific patterns in the Matrix Display, through permutations of the rows and columns. The "attainment" of matrix patterns, however, is largely dependent on another factor, which is their perceptual recognition by the matrix user. In parallel with the process of rearraning the two-dimensional matrix space, I need then consider the process of mapping the numerical data into graphic variations. This process, which adds a "third dimension"* to the display, should ultimately result in an improvement of the user's performance in the recognition of significant configurations.

IV.3.1 Guidelines for the Matrix Mapping Process

The experimental evidence gathered in chapter II provides a set of observations on how HUS perceives matrix configurations. These ob-

*This "third dimension" variation is visual, not spatial (see III.1.2).

servations make it possible to propose qualitative guidelines for helping the process of matrix pattern recognition.

<u>Guideline 1.</u> Reduce the data complexity to a point where it becomes readily perceivable by the user.

This guideline is supported by the experimental evidence concerning the absolute limitations of HUS in relation to:

(1) Recognition performance (channel capacity effects)

(2) Dramatic effects of visual noise above a certain level

(3) Trade-off between observation time and information pick-up (see chapter II, p. 41 for more details)

<u>Guideline 2.</u> Map data variations into graphic variations so that the perceived relations between visual items fit best the actual relations between numerical data.

This guideline results from the set of experimental observations which I mentioned in II.4, namely:

(1) There is a limitation in the capacity of visual variables to convey fully metric data variations.

(2) In order for perceived relations to match actual data relations, scaling transformations must be applied to the initial data (psychophysical functions).

(3) Which psychophysical transformation to use depends upon the type of graphic item used and the user's needs.

As a consequence, it is suggested that several psychophysical transformations be available for matrix mapping purposes.

<u>Guideline 3.</u> Determine the magnitudes of graphic items so that their distribution optimizes the discrimination performance.

This guideline reflects the emphasis of experimental psychology on the information theoretic notion of "equal probability": Each stimulus should provide as much discrimination as possible, in as independent a form as possible from the others (Garner, 1962). Applications of this notion include the distribution of visual items into classes of equal size, the definition of equal-interval scales, and non-metric procedures based upon the ordinal characteristics of the data.

IV.3.2 Rules for the Matrix Mapping Process

The above guidelines indicate qualitative directions for improving the information transfer to the Matrix Display user. In order to become useful in a practical display context, those guidelines need to be quantified as formal rules of mapping. Three such sets of rules are proposed hereafter as "binning," "enhancement," and "scaling" procedures. These will later find an application in the design of MATBORD, an interactive system using Matrix Display interfaces.

Binning. One way to reduce the number of discriminably different graphic items is to map m different data values into ℓ different graphic bins, with $\ell \ll m$. The effect of this reductive process is to present the user with only ℓ steps of visual variation, instead of the original m steps. Consequently, tasks of discrimination, comparison, grouping, etc., are made easier.

Enhancement rules. The general rule of psychophysical research is that, given a continuum of physical stimuli σ varying in intensity, the corresponding variations in psychophysical sensation x are such that:

$$x = g(\sigma)$$

where g is a monotonically increasing function of σ. This result can be used to formalize the inverse process of choosing the values of the stimuli so that a certain set of sensations are obtained. In the Matrix Display case, one needs to get differential sensations which match differences in the data themselves, so that:

$$\sigma = g^{-1}(x) = f(x)$$

where x = matrix data and $f = g^{-1}$

The general formulation which I propose to use incorporates the notion that, in order to apply the above equation, one needs to know the range of the data. The inverse psychophysical transformation is then written:

$$\sigma_x = k_0 + k_1 \times [f(x) - f(x_{min})] / [f(x_{max}) - f(x_{min})] \quad \text{Eq. 4.10}$$

where x_{min} and x_{max} are the minimum and the maximum data values
x is any data value
k_0 and k_1 are auxiliary constants

Since f represents the specific inverse psychophysical transformation which is used in a given situation, the above equation includes a variety of psychophysical rules. In relation to the arguments presented in II.4.2, I propose that f be chosen among the following three different functions:

(1) The exponential-base 10 function (Fechner, 1860)

(2) The square-root function (Jenks and Knos, 1961)

(3) The logistic function (Bertin, 1967)

The basic effect of these functions is to enhance one portion or another of the distribution of data values:

(1) Fechner's rule enhances the values located toward the high end of the distribution.

(2) The square-root rule has the inverse effect of enhancing values in the low range.

(3) The logistic rule is a composite of the above two rules which results in an enhancement of the medium range of the distribution.

These numerical functions have been known for some time to apply to the psychophysical problem. What is relatively new here is their application to the inverse problem of designing graphic scales so that they convey the differential relations of data values. The fact that three alternative rules are proposed gives some flexibility to the enhancement process, thus fitting the requirement that different rules apply to different perceptual tasks and to different graphic items.

Scaling. The scaling problem arises from the necessity to map numerical data into visual variations of magnitudes. Two types of scaling procedure might be used, depending on the measurement characteristics which are attributed to the data.

(1) When the data have ordinal characteristics, they can be scaled simply by rank-ordering them. A rank-order corresponds to the assumption that the data items are rankable at regularly-spaced intervals along a continuum. This is the least stringent of measurement requirements; it results in the general method of sorting items according to their size.

(2) When the data have cardinal (truly quantitative) characteristics, the scaling process involves range comparisons, of the type (all variables are supposed positive):

$$\sigma_x = [x - x_0] / [x_{max} - x_{min}] \qquad \text{Eq. 4.11}$$

where σ_x is the value of the graphic stimulus
x_{max}
x_{max} and x_{min} are the extreme values of the distribution
x is an observed data value
x_0 is a reference value

When $x_0 = 0$, the scaling is done with respect to null origin, i.e., it is absolute; with $x_0 = x_{min}$, the scaling is relative to the minimum value in the observed distribution.

The effect of both ordinal and cardinal scaling is to map the numerical variations of the data on a (0, 1) interval. Ordinal scaling has several advantages in connection with visual tasks since it distributes data at equally-spaced intervals along the (0, 1) continuum. This is particularly suited for global pattern recognition, since it permits one to discriminate better successive steps of variation. In IV.2.1, it was proposed to use an ordinal rule with similarity matrix, since the thrust of matrix analysis was the recognition of specific patterns. However, other perceptual tasks may require a detailed account of the quantitative relations between data items. Cardinal scaling is then used to map the data items into proportional graphic items.

IV.3.3 A Measure of Information Reduction in the Mapping Process

The process of mapping a set of data into graphic variations is a process of information reduction since the combined operation of binning, enhancement, and scaling procedures tend to diminish the variety of the original data. At most, information is conserved when data scaling is proportional, no binning is applied, and enhancement is not used.

On the other hand, the use of any of the above mapping rules, such as (1) binning the m data items into a smaller number of bins ℓ, (2) scaling cardinal data by way of an ordinal scale, and (3) enhancing certain portions of the data distribution, results is some information reduction.

In certain circumstances of Matrix Display usage, it might be important to obtain an estimate of the reduction operated. Since the mapping process establishes a relation between any data item and its graphic equivalent (measured on the (0, 1) interval), an estimate of the global reduction operated is given by the product-moment correlation between the m data items and their corresponding graphic values. This correlation coefficient provides a measure of the "fidelity" (F) of the graphic representation to the initial data base. It is computed as:

$$F = \frac{\sum_i \sum_j (\sigma_x - \bar{\sigma})\ (x - \bar{x})}{\left[\sum_i \sum_j (\sigma_x - \bar{\sigma})^2\right]^{\frac{1}{2}} \left[\sum_i \sum_j (x - \bar{x})^2\right]^{\frac{1}{2}}} \qquad \text{Eq. 4.12}$$

where $\bar{x}$: mean value of data set
$\bar{\sigma}$: mean value of stimulus set
x, σ_x: data value and corresponding stimulus value for cell (i, j)
i, j: indices of matrix rows and columns

The higher the value of F, the closer does the graphic mapping fit the original data variations.

IV.4 Integrating Perception and Analysis

IV.4.1 Dialectics of Information Reduction and Information Creation

The two lines of reasoning which I have pursued up to this point are as follows:

(1) On the one hand, I have argued that, since the human visual capacities are limited, it is necessary to establish mapping procedures which reduce the data complexity to a level perceptually acceptable by the matrix user.

(2) On the other hand, I have shown that, through procedures for permuting rows and columns, the matrix user may recover global patterns from which he infers statistical structures.

These two lines of thinking contain a seeming paradox, since it is argued that information should be reduced (1), while at the same time proposing that information should be created through inferential judgments (2).

Posner (1964) suggests that this paradox reveals a fundamental characteristic of the cognitive performance of human beings, namely, the ability to combine information reductive and information creative tasks so as to obtain the best knowledge out of a complex situation. Attneave (1963) expresses this notion in compact form:

> The situation is somewhat like that of an executive who considers a mountain of data . . . in order to arrive at a one-bit decision (p. 634).

The point here is that the process of reducing much data to a few inferences leading to a decision is a creative process at least as much as it is a reductive process. The process of informational search can thus be described as a process encompassing both information reductive and information creative steps.

IV.4.2 An Example of Use of Matrix Displays

This section provides an example of informational search with Matrix Displays combining information reduction and information creation steps. I used a table of economic data (The Economist, January 5, 1974) representing the levels of three indicators (Industrial Production, Unemployment, and Many Supply) for nine O.E.C.D. countries, from which I computed the correlations between the countries' profiles. Table 4.1 at the end of this chapter shows the resulting correlation data. This table is mapped into a Matrix Display (Figure 4.7) by representing each correlation coefficient by a shade proportional to its size. The highest values (such as the correlation of Germany with itself, +1.00) are represented by a heaving shading; the lowest values (such as the correlation between Germany and the U.S.A, -1.00) are mapped into a blank cell.

The above Matrix Display presents the full information in visual form, but the resulting picture is quite fuzzy. Applying the mapping and manipulative transformation proposed above, permits the reorganization of this picture so that it leads to clear-cut inferences. For instance, the following transformations lead to the Matrix Display presented in Figure 4.8:

(1) Using an ordinal scale (such as suggested in section IV.2)

(2) Binning the correlation data into three bins (section IV.3)

(3) Manipulating the entries so as to approximate a simplex pattern (section III.2)

This picture represents an information reduction step, since it does not convey the full information contained in the quantitative data of Table 4.1. An estimate of this reduction is provided by the measure F (Equation 4.12) which takes the value .93 in this particular case. This value indicates that the graphic variations in the Matrix Display correlate at .93 with the exact data values in Table 4.1. The matrix mapping thus results in a loss of precision with respect to the initial data values.

Another feature of Figure 4.8 is the spatial reorganization of its entries. To the original ordering--Germany, France, Britain, Italy, Holland, Belgium, Ireland, U.S.A., and Japan--a new ordering has been substituted: Holland, Germany, France, Belgium, Ireland, Italy, U.S.A., Britain, and Japan. This spatial reorganization results in an approximated diagonal (simplex) pattern, which indicates that the countries' profiles can be rank-ordered from Holland to Japan. The measure of goodness-of-fit to a simplex hypothesis (Equation 4.9) provides a value of G = 82 percent which indicates a fairly acceptable fit. Moreover, the picture reveals the existence of two major clusters: Holland to France and Ireland to Japan. Belgium seems to stand in-between those two clusters which indicates that its profile combines the characteristics of both clusters.

Figure 4.8 represents a graphic reduction of the available information. It is possible to recover the full information of the initial data-base (Table 4.1) by reversing the mapping to the original mapping of Figure 4.7. When this is done, Figure 4.9 is obtained. Clearly, the approximate character of the simplex pattern is still more visible here.

In sum, the Matrix Display analysis of similarity data offers an opportunity for combining information reduction and information creation so that inferences can be drawn from patterns. Which degree of reduction to operate depends upon the user's aims in mapping the data into graphic variations. Information creation results basically from the reorganization of the matrix entries so that significant patterns show up.

IV.4.3 Conclusion

Having gathered in chapters II and III the perceptual and analytic evidence supporting Matrix Displays, I have in chapter IV demonstrated their technical feasibility. To help their design, I proposed formal guidelines and quantitative measures, and, to favorize the dialectics of informational search, I claimed an interactive use. In a brief example I finally showed how perceptual and analytic factors integrate in practical circumstances.

My task is now to evaluate the utility of Matrix Displays in a managerial context. I will call this third stage the managerial feasibility of Matrix Displays.

MATRIX OF CORRELATION BETWEEN COUNTRIES'PROFILES
THE DARKER THE SHADE THE HIGHER THE CORRELATION

SIMILARITY BOARD	GERMANY	FRANCE	BRITAIN	ITALY	HOLLAND	BELGIUM	IRELAND	USA	JAPAN
GERMANY	1.00	.93	-.85	-.97	.98	-.38	-.92	-1.00	-.76
FRANCE	.93	1.00	-.90	-.95	.97	-.40	-.86	-.96	-.68
BRITAIN	-.85	-.90	1.00	.78	-.93	-.05	.61	.85	.91
ITALY	-.97	-.95	.78	1.00	-.95	.56	.97	.99	.61
HOLLAND	.98	.97	-.93	-.95	1.00	-.29	-.86	-.99	-.81
BELGIUM	-.38	-.40	-.05	.56	-.29	1.00	.71	.43	-.31
IRELAND	-.92	-.86	.61	.97	-.86	.71	1.00	.93	.45
USA	-1.00	-.96	.85	.99	-.99	.43	.93	1.00	.73
JAPAN	-.76	-.68	.91	.61	-.81	-.31	.45	.73	1.00

XBL 767-8634

Table 4.1

0 0 0 0 4 6 0 0 4 1 7

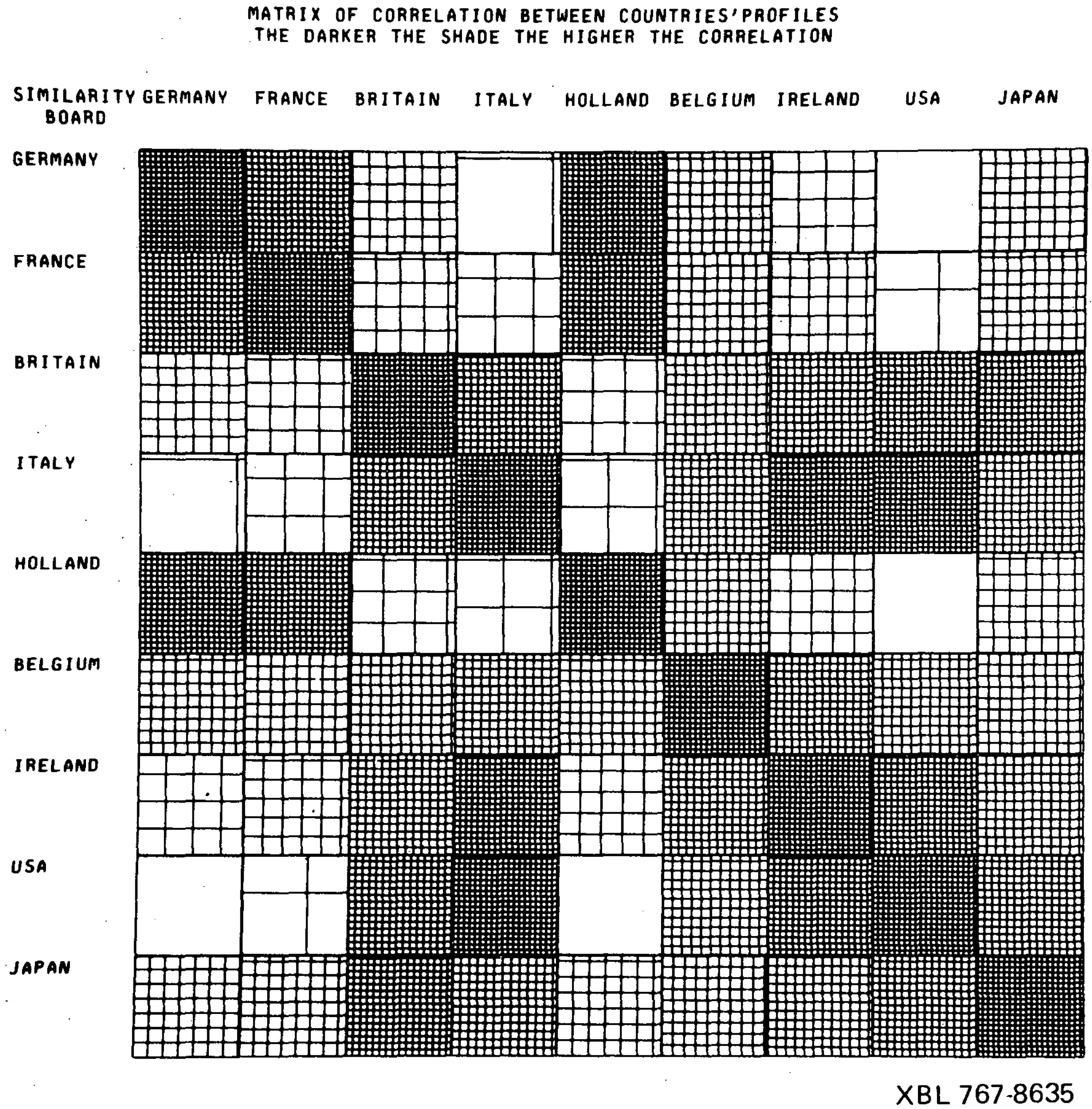
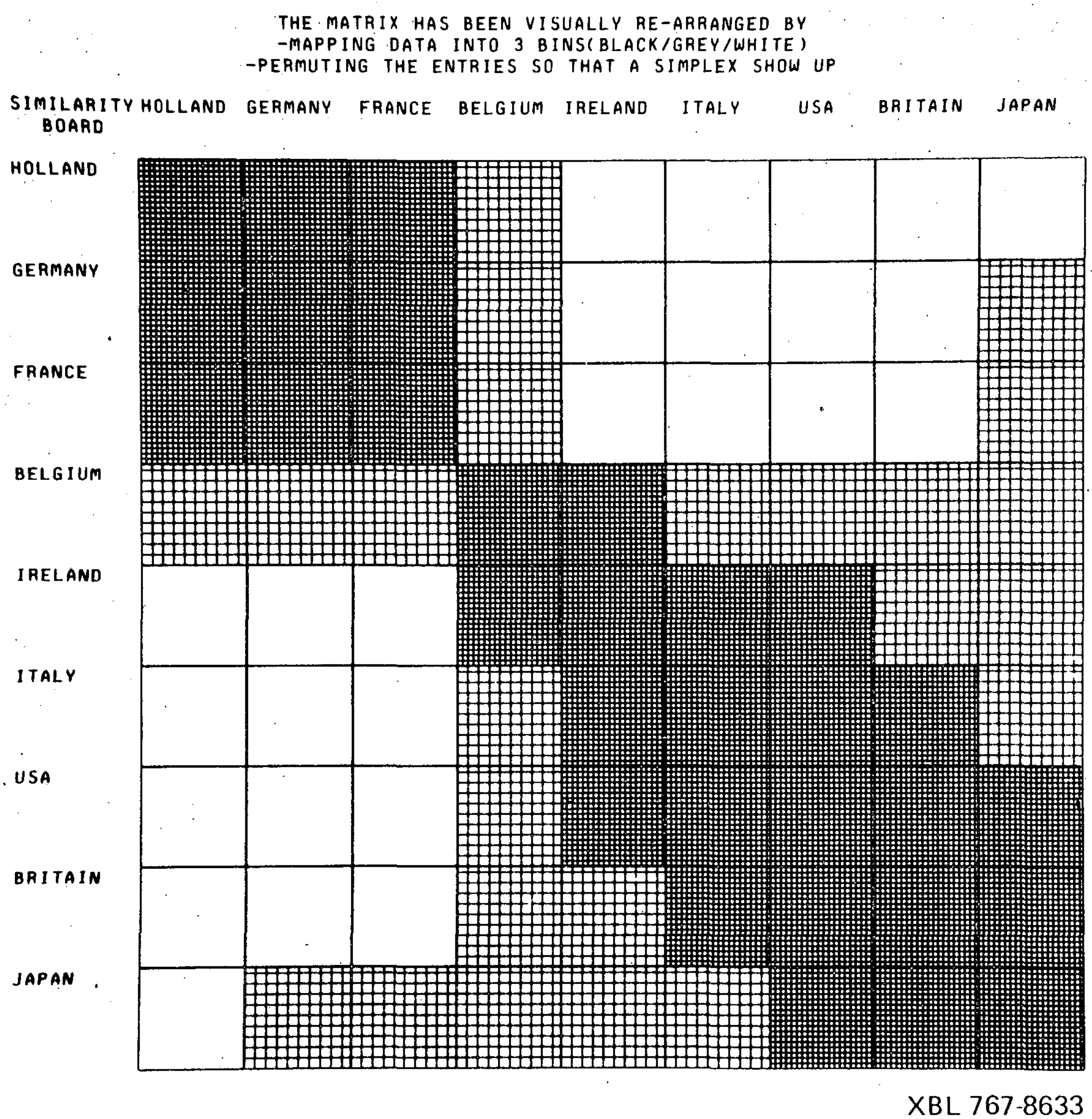


Figure 4.7



THE MATRIX HAS BEEN VISUALLY RE-ARRANGED BY
-MAPPING DATA INTO 3 BINS(BLACK/GREY/WHITE)
-PERMUTING THE ENTRIES SO THAT A SIMPLEX SHOW UP
SIMILARITY BOARD
HOLLAND
GERMANY
FRANCE
BELGIUM
IRELAND
ITALY
USA
BRITAIN
JAPAN
XBL 767-8633

Figure 4.8

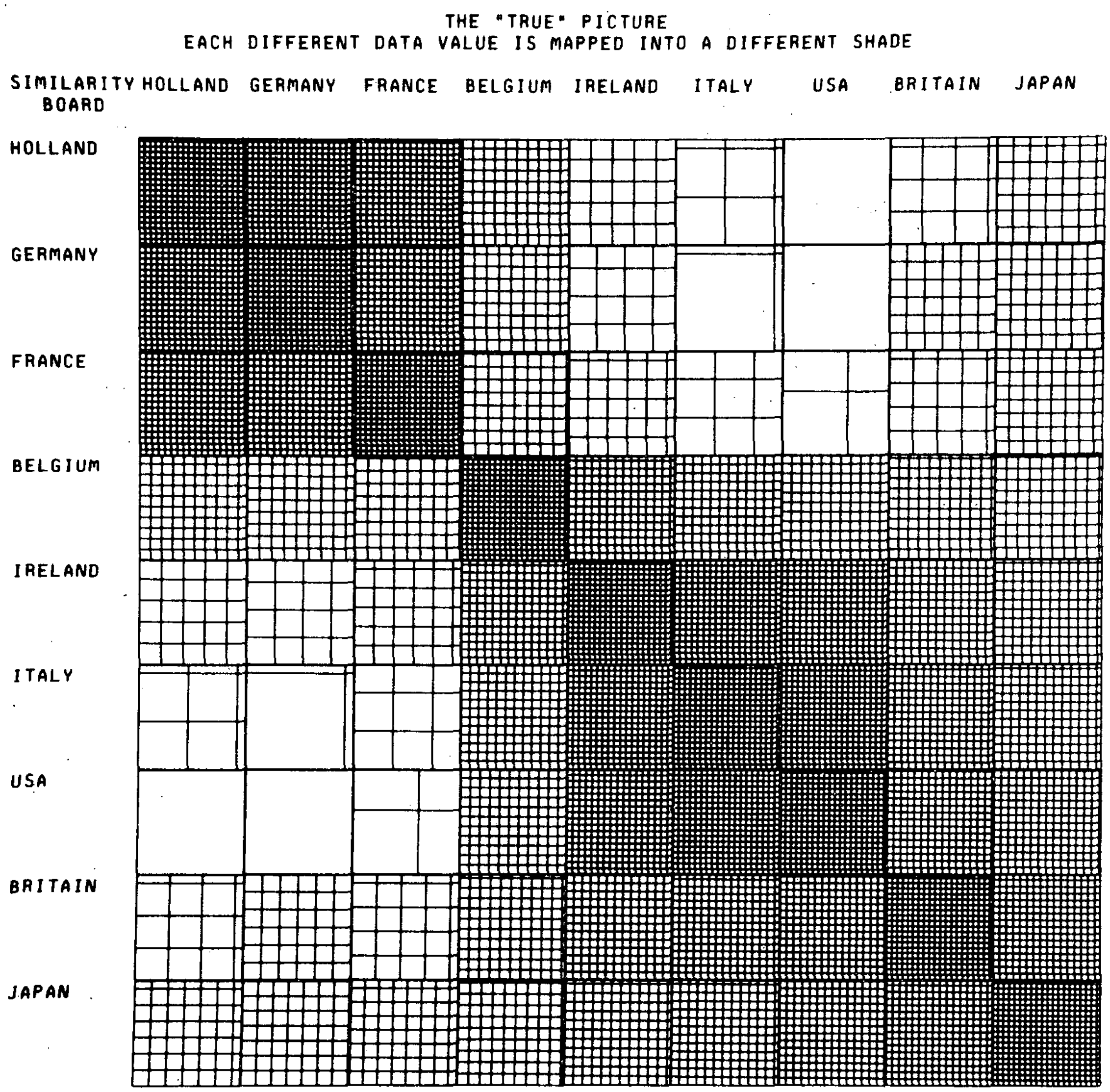


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Figure 4.9

CHAPTER V

MATRIX DISPLAYS AND MANAGEMENT REPORTING: DESIGN OF A GENERAL-PURPOSE MATRIX DISPLAY PROCESSOR

This chapter applies the findings of chapters II, III, and IV to Matrix Displays as an aid to management. This application represents an original contribution to management science.

In this process I shall:

(1) Concentrate on some specific tasks of management--case preparation, report writing, and documentation of decision-making

(2) Select those results which are specifically relevant to the above tasks, and try to match Matrix Displays to the practical needs of managers

(3) Consider the behavioral reactions and attitudes of a few managers in a realistic management context, the regional office of the U.S. Manpower Administration in San Francisco presented in chapter VI

The resulting Matrix Display model integrates graphic, analytic, and manipulative operations in an interactive fashion. This model is used to design an interactive computer graphics program entirely based upon Matrix Display interfaces ("Matrix Display boards," hence the name of the program: MATBORD). This program demonstrates that it is feasible to produce interactive Matrix Display aids to management. The next chapter uses MATBORD to evaluate the attitudes of management people toward Matrix Displays.

V.1 Matrix Displays and Management Information Reporting

In the previous chapters, I showed how Matrix Displays relate to human perception and cognition. This enabled me to propose a set of quantitative rules and measures as a "tool kit" for the analysis and design of Matrix Displays. Now I will apply this "tool kit" to the world of management, by focusing the attention on a typical managerial activity where Matrix Displays can be hypothesized to be useful aids--management information reporting.

V.1.1 Management Information Reporting

The preparation of management reports belongs to what March and Simon (1958) call the "uncertainty absorption" process in decision-making. The successive editing steps that transform "raw" data tables into the limited number of inferences and/or conclusions presented in a management report is an example of uncertainty absorption. The recipient manager uses the report to reduce his information load and to help him make up his mind about which course of action to adopt.

Information reporting may be described as a three-step process:

(1) Selection of a "bounded domain of information content" (Miller, 1969). In an organization, each manager is given a certain limited domain of inquiry. Each such domain has a place in the hierarchical (superior/subordinate) structure of the organization and in its horizontal department structure. Management reports intended for a specific manager must reflect his responsibility domain (Miller, 1969).

(2) Analysis of the selected field of inquiry. Once a certain informational domain has been selected, the available data is analyzed. In this process of analysis, the manager usually focuses on a restricted set of information categories (Ball and Hall, 1970).

(3) Reporting the results of the analysis. The recipient manager receives a report which generally contains both the data used and the conclusions reached by the subordinate manager. He may accept or refuse the line of evidence which the report suggests, based upon his confidence in his subordinate's judgment, his knowledge of the data, and his own judgment. If he refuses to accept the report, a new process of report generation might be initiated, until the evidence converges

sufficiently well to make a decision (Crossman, personal communication, 1975).

Matrix Displays might be a useful aid to the process of management reporting, since a given Matrix Display obviously:

(1) Represents the selection of a specific set of data (the data table corresponding to the matrix)

(2) Supports a process of analysis based on both semantic cues (by using the labels of the rows and columns as category names) and analytical procedures (as seen in chapters III and IV)

(3) Permits the results to assume both graphic and numerical formats, since a data table corresponds to each Matrix Display

V.1.2 A Three-Step Process for Matrix Data Analysis

Chapters III and IV showed that Matrix Displays can help the data analyst recognize statistical structure in a set of similarity data. This useful result, however, is not directly applicable to the case of management reporting, since the data-bases used in management environments are rarely, if ever, made up of similarity data. In order for the concept of similarity to find an application in management, it must be related to the "rank-and-file" of management data, i.e., "raw" data-bases.

If we consider only the case of non-time-series data (as suggested in chapter I), the general format of a management table is that of an object set X attribute set data matrix (Benzecri, 1973). For instance, an $\underline{n}$ X $\underline{p}$ data matrix is a table with $\underline{n}$ managerial entities scored on $\underline{p}$ managerial attributes. The scores might be in money terms (expenses), and/or people counts (census/survey), and/or quantities of materials (inventories), etc. The managerial entities might be overlapping (one entity partially including another) or some might be missing.

Similarly, the attributes might be redundant with each other, and double-counting and missing data may occur in various ways.

In contrast with this situation, the "ideal data table" for statistical analysis (Cattel, 1966; Benzecri, 1973) is characterized by:

(1) Homogeneity. The data items are expressed in the same units all over the n X p table.

(2) Exhaustivity. The objects represent different, non-overlapping entities, and their union forms a relevant managerial universe. Similarly, the attributes represent different, non-overlapping characteristics, and their union forms a relevant universe of characterization of the sets of objects at hand.

For instance, a table representing the age distribution in 6 age groups of the French population in the 21 census regions would be an empirical illustration of the above conditions, since the 21 regions represents the exhaustive set of entities which make up the administrative definition of France and the 6 age groups exhausts all the possibilities of age, with no ambiguity (supposing the birthdate of every French citizen is known).

The actual data tables of management can approach the "ideal data table" model by a two-way process:

(1) Use statistical techniques to achieve homogeneity. For instance, scaling procedures combine the four operations of arithmetic so as to homogenize the gross size and/or the variability of each row and/or column of the matrix table (Sneath and Sokal, 1973).

(2) Use pertinence and reflection as a means for selecting properly exhaustive data sets. Williams and Lance (1965) use the concept of "profitability" to describe the criterion of pertinence applied to the choice of a data universe.

Clearly, there is a mix of empirical judgment and technical criteria in the choice of a suitably homogeneous and exhaustive table of raw data. As Benzecri puts it:

> The part played by arbitrariness in the definition of the data universe is relatively important. However, the end results of the study can be reasonably secure if the manager takes care of respecting the basic regularities required in the use of statistics (Benzecri, 1973, p. 23).

Besides the requirements of (approximate) homogeneity and exhaustivity, there are some requirements concerning the number of observations corresponding to the data table and the statistical confidence which might be placed in those observations. Consequently, coupling of Matrix Display methods to management data requires that the data be approximately "clean." This might limit the use of Matrix Displays where the data are very heterogeneous, overlapping, redundant, missing, grossly inexact, and/or too few in number.

Once the available data is rendered clean by choice and/or filtering procedures, it provides an acceptable raw data-base for analysis purposes. A problem at this point might be that the objects or the attributes have very different "sizes." For instance, in the above example of the distribution of the French population in 6 age groups across 21 regions, the Paris area may show a total of 15 million people, while the "Massif Central" area (mountainous zone) may show only 1 million people. Since the manager may be interested in comparing population profiles rather than absolute population figures, there is a need for normalizing population across regions. One possibility is to take the ratio of the population in each age group to the total population for each region. Other normalization procedures include standardization and ranging (Sneath and Sokal, 1973). The result in each case is a profile data table, where profiles are comparable across rows (objects) and/or across columns (attributes). The concept which emerges here is the distinction between raw data and profile data, where the raw table emphasizes size effects and the profile table emphasizes shape effects.

Once profile data are available, it becomes possible to compute statistical measures of similarity between the observed profiles (see Figure 3.1 in chapter III). This is the third step in the analytical process. The results of this step are basically the Cluster and Order structures which I studied in detail in chapters III and IV. The patterns which are found on the similarity matrix can be interpreted on the corresponding profile matrix. Obviously, if clusters of homogeneous objects show up in the similarity matrix, they should be readily interpretable by looking at the corresponding objects' profiles in the profile matrix. For instance, if three French regions cluster together on the similarity matrix corresponding to the age distribution problem, their profiles on the corresponding profile matrix should be fairly similar.

In sum, it is possible to connect the analytical methods of chapters III and IV to the practical case of management data tables, through a three-step process inspired by statistical considerations:

Figure 5.1

RAW DATA MATRIX	⇨	PROFILE DATA MATRIX	⇨	SIMILARITY DATA MATRIX

The profile matrix stage plays the part of a buffer stage between the raw data collected in the given management environment and the similarity data which can be used for sophisticated data analysis.

V.1.3 Management Reporting with Matrix Displays

In section V.1.1, I described the process of management reporting as a process comprising the three stages of (1) Data Selection, (2) Analysis, and (3) Reporting. Using the above distinction between Raw, Profile, and Similarity Matrices, it is possible to show that Matrix Displays can support management information reporting. The subsections below provide a method for constructing management reports with Matrix Displays.

Data selection is made through the choice of a certain raw data universe--a set of objects scored on a number of attributes. Given that (a) this universe might be non-homogeneous, (b) the user might want to restrict his attention to a subset of the data, and (c) the user might want to "clump" data categories together, the data selection stage encompasses operations of calibration such as:

(1) Apply statistical scaling to render the raw data homogeneous

(2) Select only certain rows and columns within the data universe, and form the raw matrix of the corresponding subset

(3) Aggregate objects and/or attribute categories to reduce the number of matrix entries to be observed

The process of matrix analysis and inference is based upon a generalization of:

(1) Ordering tasks including simple rank-ordering of a row or column according to the sizes of its data entries

(2) Clustering tasks including simple grouping operations on the rows and/or columns of the Matrix Display

Simple ordering and clustering tasks can be accomplished directly on the raw or profile matrices. When a more complex analysis is needed, the multidimensional approach advocated in chapter III can be applied to similarity matrices. Because the matrix entries are labelled (objects and attributes have names), it is possible for the Matrix Display user to rank the entries and to form clusters based upon the conceptual relations between those names. For instance, managerial entities might be ranked in alphabetical order, or according to any other criterion external to the data themselves. In this case, the user is said to use a concept-oriented (rather than data-oriented) approach.

Besides ordering and clustering tasks, there might be a need for quite specific tasks of analysis in a given managerial context. In the Manpower Administration field study (chapter VI), it was suggested to me that one valuable "picture" would be obtained if it were possible to "sort out" all data items with size greater than a given level. A third type of task was then considered:

(3) Sorting tasks including operations of sorting data elements greater or lower than a given level

These tasks were called "flagging" by the interviewed managers, who described their needs for a capability to "flag" those managerial entities exceeding in either direction a certain suitable level of performance.

The final stage of reporting is realized by communicating the results of the analysis to the recipient manager. These results are communicated in graphic form, by showing patterns in raw, profile, and/or similarity data, which are used as a basis for managerial inference. Since the use of graphic displays may severely limit the ability of the manager to judge the precision of the numbers, it seems absolutely necessary that the report also include the data tables corresponding to the displays. Also, verbal comments may be added to the displays and data, so as to help the recipient's interpretation.

V.2 An Interactive Model and Its Methodological Implications

In the first chapter of this thesis (I.1.3), I offered the view that management information results from an interactive process between the manager and his data-base. Obviously, this interactive formulation has direct implications for the design of an interactive computer graphics system for the preparation of management reports. In the present section I examine the methodological aspects involved in modeling management reporting as an interactive Matrix Display process.

V.2.1 Management Information and Problem-solving Behavior

One possible way to describe "externally" the managerial quest for information is to adopt the view that the manager is an "information-processing" system. This system at any point in time has a certain "knowledge state," and it seeks to attain another improved knowledge state through specific operations. This formalization is relatively neutral, or "descriptive," to the extent that neither the nature of the knowledge states nor the type of the possible operators are specified. Hence, it includes affective, emotional factors as well as cognitive, intellectual aspects of the manager's informational search.

In this thesis, I have chosen to focus on the cognitive and intellectual aspects of the managerial search for information (see chapter I). Consequently, I define the concepts of "knowledge state" and "operator" as formal representations and functional operations. This choice in turn implies focusing on the "problem-solving" aspects of the information query. According to Newell and Simon (1972, p. 826), human problem-solving behavior involves four basic decisions:

(1) At a knowledge state, to select an operator to be applied

(2) At a new knowledge state, to determine whether problem-solving shall continue from this stage or not

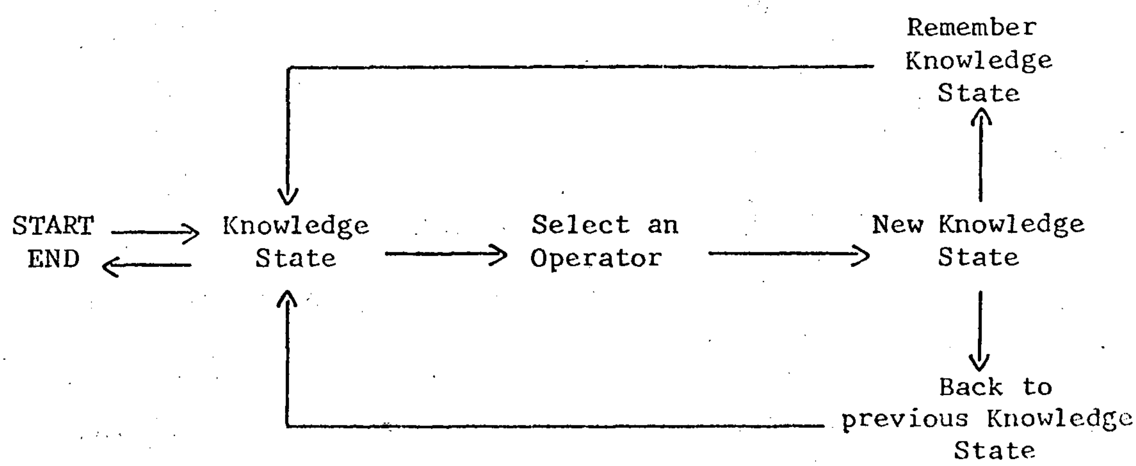
(3) At any knowledge state, to determine whether this knowledge

state should be remembered

(4) At the decision to abandon a knowledge state, to select another knowledge state as the back up state

I find it convenient to represent the above decisions as an integrated model of information search behavior:

Figure 5.2



According to this model, then, information search amounts to finding within the large space of possible knowledge states, the knowledge state(s) which solve the informational problem of the manager.

The experimental studies by Newell and Simon (1972) suggest that the problem-solving process possesses invariant features across a variety of situations and tasks. Four such features, which have strong implications for the definition of an interactive model of Matrix Display usage, are listed below:

(a) The set of operators used by problem-solvers is small.

(b) The number of alternative knowledge states to which the problem-solver wishes to return is very small (one or two at most).

(c) Moves from a knowledge state to another are merely incremental.

(d) The nature of the task determines the way the problem-solver structures his query.

V.2.2 An Interactive Model of Matrix Display Usage

The above results definitely imply the interactive character of problem-solving, since the problem-solver proceeds incrementally through trial-and-error search paths. With chess and crypt-arithmetic problems such as those studied by Newell and Simon (1972), the game board and the paper-and-pencil media easily support interactive problem-solving. With Matrix Displays, however, it is not possible to imagine an interactive search process unless a quite sophisticated medium of information display is used: For instance, an interactive computer graphic terminal.

In this section, Newell and Simon's concept of knowledge state is translated to mean Matrix Display representation. Thus we consider that the information search behavior of the manager can be described as a process of trial-and-error between alternative matrix representations, until suitable representations are found. The set of such representations contitutes itself a management report.

The operators which permit modification of the structure of a Matrix Display (point (a) above) are very few in number. Basically, there are two possible matrix operations:

(1) Permutation, which permits interchanging the positions of any two matrix rows I and K (or any two columns J and L)

(2) Mapping, which determines how a given datum at location (I,J) in the data table is mapped into a graphic item at location (I,J) in the Matrix Display

If we now consider the process of returning to previous knowledge (point (b) above), it appears that matrix representations allow the user-manager to return to "previous" displays, in the following sense: Given a situation where the user is facing a similarity matrix, he can return to the corresponding profile and raw matrices at any time he wishes. The process of returning from a level of analysis to a lower level is essential to the interpretation of analytical results. For instance, the absolute rank-ordering which is implied by the discovery of a simplex pattern in the similarity matrix (III.2) must be interpreted back on the profile and raw matrices. Hence the Raw/Profile/Similarity scheme presented in Figure 5.1 can be interpreted backward as well as forward.

Point (c) above suggests that the "moves" from a knowledge state to another are merely incremental. I interpret this finding to mean that human problem-solving proceeds by small, incremental steps rather than by large "jumps" in reasoning. But it is not very clear what small vs. large moves means in relation to the interactive use of Matrix Displays. Intuitively, it seems that the notion of the size of a move depends upon the type of task which one wants to execute (point (d) above): Simple tasks require elementary moves, while complex tasks require sophisticated moves.

In the Matrix Display case, there exists a continuum of possible design choices, from a purely visual matrix system to an entirely automatic system. In the visual approach, the user is given a very small number of elementary, general-purpose operators such as "permute," "compare," or "map data into shades," which he uses as tools to help his visual recognition capability. In the automatic approach, the user has available a set of data-crunching procedures which determine in autonomous fashion such results as the optimal linear ordering of the rows and/or columns of the matrix, the optimal partition of the rows and/or columns in a given number of classes, etc.; which level of sophistication to choose in the system's design depends upon the client which the Matrix Displays are intended to serve.

V.2.3 The Choice of a Client and a Method of Inquiry

In his considerations on the "Design of Inquiring Systems," Churchman (1971) recommends that attention be given to the question:

Who should the inquiring system serve?

The answer to this question may look self-evident, since it seems at first sight that any system serves some user. Unfortunately, the practice of management information systems shows that such systems often fail to serve any sound management purpose (Dearden, 1972) -- hence the legitimacy of Churchman's observation that one should reflect upon whom the system is intended to serve. For instance, the evidence accumulated in chapters II, III, and IV of this thesis could be used to serve any one of the following clients:

(1) The data-formatting specialist (drawer, graphic designer, etc.)

(2) The professional statistician interested in the multidimensional analysis of correlation matrices

(3) Middle-line management in terms of its information reporting needs

The choice which I have made to focus on type 3 corresponds to the management science emphasis of this thesis (chapter I).

Once the client type is chosen, the problem of scientific inquiry becomes one of observing how the client reacts to the proposal; in management science terms, the inquirer needs to observe how the manager accepts and/or rejects the proposed interactive system. This requirement is very strong and yet very difficult to satisfy, as shown by the variety of methodological approaches which researchers have used.

On the one hand, there is a tendency to limit the system design and to "calibrate" its clients so that a fully experimental procedure be used. For instance, Chervany and Dickson (1974) use college students as a proxy for "managers." On the other hand, there is a strong requirement to use "real-world" experienced managers (Willworth, 1972). Most studies are based upon a compromise approach: For instance, Garman (1970) involves housewives in a study of interactive job-shop scheduling behavior, and Swanson (1974) directly records managerial reactions to a real-life retrieval system.

In this thesis, I advocate a compromise approach, based upon the following principles:

(1) Design a limited, prototype interactive system.

> This corresponds to Garman's idea of a "demonstration system" (1970), Johnson and Baker's "breadboard system" (1974), and Gerrity's (1970) "functional stage" model. It is also advocated by Segal (1970).

(2) Associate real-life managers to the design of the prototype.

> This corresponds to the claim made by Segal (1970), Gerrity (1970), and Johnson and Baker (1974) that a "descriptive" model of actual management needs be incorporated along with the "normative" model corresponding to scientific evidence (i.e., ponder the results in chapter IV by the empirical judgments collected in section VI.1).

(3) Observe the reactions of actual management users to the system.

> This requires choosing a suitable management context, with controls on the following elements: cognitive style of the users (preferably, they should not be "opposed" to graphic displays), pertinence of the data sets for interactive inquiry (management should be confident in the data themselves), relevance of the interactive operators to the basic tasks which the observed managers need accomplish.

V.3 MATBORD: An Interactive Matrix Display Processor

In accordance with the above methodology (point (1)), a prototype system for interactive Matrix Display usage has been designed by the author. This system is a computer graphics processor, representing nine man-months of effort and is written in Fortran. It uses about 60 K of central memory. A detailed user's manual is provided in Appendix A.

This processor is called "MATBORD," which is an acronym for Matrix Display Board. Each matrix representation is considered to be a board which, exactly like a game board, supports the cognitive operations associated with the analytic process. In this application program, I consider input tables of size up to 30 X 30 (900 data items), with

(1) Homogeneous data (data expressed in identical units)

(2) No row or column nestings (all rows and columns are separate)

These two conditions insure that the requirements of homogeneity and exhaustivity are formally met.

V.3.1 The Analytic Process with MATBORD

In accordance with Figure 5.1, MATBORD is structured along a three-step analytic process which enables the user to go from raw to profile to similarity data. At each step, the corresponding data is displayed as a matrix board--i.e., graphic variations are used to convey data variations. The profile board has a central part in this analytic process, not only because it is the necessary intermediary step between the raw board and the similarity board, but also because it is the most important analytic notion used in MATBORD.

The notion of data profiles pervades the various fields of applied statistics, from "economic profiles" to "psychological profiles." This notion carries two types of implication, namely, (a) different objects are scored over the same attributes and (b) the scores are "normalized" so that any extraneous effect such as the effects of the size of the individual objects is partialed out. In the context of MATBORD, the concept of profile refers essentially to the (b) process by which raw scores are normalized.

Since MATBORD is restricted to homogeneous sets of data, there are two metric operations which can be used the normalize the data:

(1) Either the data are normalized by Difference, i.e., taking their difference to a "mean" value,

(2) Or they are normalized by Proportion, i.e., taking their ratio to the value of a certain "sum."

(3) A third alternative is to combine Difference and Proportion which gives the ratio of a "difference to mean" to a "sum." I call this operation Normalization (after Sneath and Sokal, 1973).

The concepts of "sum," "mean," and "difference to mean" have specific statistical definitions. For instance, a raw table showing population counts X_{ij} for county i in age class j can be normalized by proportion, i.e.,

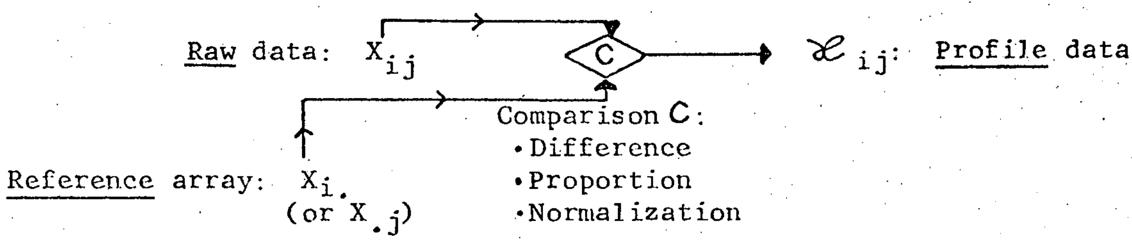
(1) Compute for each county its total population $X_{i.}$

(2) Take the proportion $X_{ij}/X_{i.}$ for each (i,j)

The result of this operation is a profile table showing the percent distribution of the population in each county between age classes.

Conceptually, the definition of sums ("totals") and mean values ("averages") corresponds to the addition of a supplementary array of values to the initial raw table. For instance, in a table where rows represent counties and columns represent age classes, the computation of total populations per county adds another column array to the previous columns. Reciprocally, the computation of total populations per age class would add another row to the table. The process of defining data profiles is based upon the comparison of raw data values with such row and/or column reference arrays.

Figure 5.3



In the context of managerial applications, reference arrays can be defined directly as ideal reference targets. For instance, with Actual over Plan performance data, a possible reference target is the 100 percent performance level. To account for such situations, MATBORD allows the direct definition of reference arrays by the user. In other words, reference arrays can be defined either directly by the user, or statistically by the computation of sums or averages.

Once the profile data are obtained, it is possible to display them in much the same way as the raw data themselves are represented, i.e., in a Matrix Display fashion. It becomes then possible to refine the analysis a step further and to use an automatic procedure for computing measures of similarity between profiles. Several such procedures are conceptually available (Sneath and Sokal, 1973; Benzecri, 1973). I have chosen to use Pearson's product-moment correlation coefficient, since it seems to be of most general value:

$$r_{ik} = \frac{\sum_j \mathcal{X}_{ij} \times \mathcal{X}_{kj}}{\left[\sum_j \mathcal{X}^2_{ij} \times \sum_j \mathcal{X}^2_{kj}\right]^{\frac{1}{2}}} \qquad \text{Eq. 5.1}$$

where $\mathcal{X}_{ij}$ and $\mathcal{X}_{kj}$ are the profile scores of the objects i and k on the attribute j

The coefficient r_{ik} is interpreted as indicating the degree of similarity between the profiles of the objects i and k. Since the roles of objects and attributes is interchangeable on the matrix, the correlation r_{jl} between the profiles of the attributes j and l can be computed as well. Starting with a n X p profile matrix, this procedure results in obtaining n X n similarity matrix (for the objects) or a p X p similarity matrix (for the attributes).

In sum, MATBORD offers a set of four commands for the user to direct the analytic process with Matrix Displays:

(1) The RAW command orders displaying the original raw data set as a Matrix Display.

(2) The REFERENCE command orders specifying the kind of reference array (row or column) to be used for profile computations.

(3) The PROFILE command proceeds from the application of the difference or proportion operator to the raw data with respect to the reference array.

(4) The profile board itself can be used to compute SIMILARITY coefficients, which are displayed as a n X n or p X p matrix board, depending on whether the similarity between objects or between attributes is considered.

V.3.2 Levels of Sophistication in MATBORD

I mentioned earlier than an interactive system such as MATBORD might take various forms depending on which user it intends to serve. Since MATBORD is basically intended to help management poeple prepare reports for management usage, not any level of sophistication might be acceptable. The choice of which sophistication level to "build-in" requires a delicate balance between the necessity of respecting the thought processes of managers (not overwhelming them with unneeded statistical operations) and the objsective of producing non-trivial results.

In light of the objectives of this thesis MATBORD could possibly include three levels of sophistication corresponding to an increasingly sophisticated data analysis:

Level A: Edition and manipulation of raw, profile, and similarity data, with an interactive graphical analysis based on the visual recognition of data patterns

Level B: Addition of semi-intelligent operators for accomplishing simple tasks such as ranking and sorting data by size, "clumping" raw data together (Miller, 1969), and operating various graphic transformations

Level C: Provide sophisticated heuristics for the discovery of multidimensional structures such as clusters, and approximations to the simplex and circumplex patterns on the similarity matrix (chapters III and IV)

The empirical field study which I did in parallel with the design of MATBORD (section VI.1) led me to develop Levels A and B in priority to Level C.

The version of MATBORD which was actually implemented includes basically Level A and Level B procedures. Level C procedures are proposed in the section devoted to potential extensions to MATBORD below. For additional details, the reader is referred to Appendix A.

Level A procedures:

(1) Analysis operators

These operators operate elementary manipulation of the display boards such as:
(a) Permutation of two designated rows (or columns)
(b) Grouping of rows (or columns) into a set of groups (blank lines permit to separate groups visually)
(c) Sequencing rows (or columns) in a user-directed manner

(2) Graphic Mapping

Several types of plotting items are made available to the user--variations in the size of circles, variations in the size of vertical or horizontal bars, variations in the density of shades. In the default situation, MATBORD shows the raw data matrix by variations in the size of circles, the profile matrix by horizontal or vertical bars (depending on which way the profiles go), and the similarity matrix as shades of grey. This design choice reflects the belief that the cognitive operations associated with raw data involve primarily the comparison of sizes, while profile data would require the comparison of multi-attribute profiles. Representing the similarity data by density shades helps the recognition of patterns.

(3) Calibration operators

Several single operators enable the management user to select subsets within the data. These operators include "masking" unneeded rows or columns and "restoring" them at will. Also a specific command is provided for the purpose of changing an outlier (excessively large or small data value) to a more reasonable value. The rationale for this command is that, say, an excessively large value disrupts the perception of a whole display (all other items appear very small compared to it).

Level B procedures

(1) Analysis operators

Two operators corresponding to the tasks of ranking a designated row (or column) and sorting a whole display on the basis of a numerical criterion are made available. The latter corresponds to the needs of a manager who wants to "flag" at a glance all those entities which over and/or under perform a certain target level. Also an operator is provided for testing the goodness of fit G of a similarity matrix pattern to a simplex hypothesis (Equation 4.9).

(2) Graphic mapping

Here the three mapping operators suggested in section IV.3 are made available to the user. That is the user can Bin, Scale, and Enhance the data at will. Rules for scaling include the use of a proportional, an absolute, or a ranking (ordinal) scale. Enhancement transformations include enhancing low, high, or medium range values through square-root, exponential, and logistic functions. A fidelity measure F (Equation 4.12) is provided for estimating the graphic reduction involved in the mapping process.

(3) Calibration

The user has available a command for "clumping" several rows (or columns) into one aggregated row (or column). The aggregation scheme includes averaging or summing the corresponding data values.

The total set of commands represented by the above procedures includes 22 commands. The distinction between Level A and Level B procedures is transparent to the user, who needs only know the distinction between Analysis, Graphic Mapping, and Calibration procedures.

V.3.3 Potential Extensions

An area where MATBORD could be potentially extended is Multidimensional Analysis. The evidence of chapters III and IV suggests that automatic procedures could be used to reorganize the matrix entries, such as:

(1) Determine a simplex pattern indicating a linear rank-ordering (Equation 3.2 and associated heuristics)

(2) Determine a circumplex pattern indicating a circular rank-ordering (Equation 3.3 and associated heuristics)

(3) Determine a clustering pattern with a given number of classes (Equation 3.4 and maximum spanning tree computations)

Such procedures can be potentially added to MATBORD, for the purpose of refining the analysis of the similarity data (Level C above).

Another potential area where the analytic process could be refined is the definition of procedures for attributing differential weights to the row and column entries of the matrix. For instance, it may be the case that the management user gives more weight to some attributes than to others. An interactive procedure for the definition of "profiles of weights" would have much interest in management applications such as budget planning.

On the graphic mapping side, an automatic procedure for "tuning" the picture so that it provides best discriminability would be a possible development.

Finally, the calibration process could be extended so that situations of heterogeneous data (data expressed in different units), missing data, and nested entries could be handled.

V.4 The Preparation of a Management Report

This section is intended to provide an overview of the research questions associated with the managerial feasibility of Matrix Displays. First, I provide an example of preparation of a management report with MATBORD (V.4.1 and V.4.2); then I formulate some basic research issues relating to the practical use of Matrix Displays for "real-life" management report preparation (V.4.3).

V.4.1 Selection of a Data Set

I showed earlier that the first step in the preparation of a management report is the selection of a relevant data universe.

In the example which follows, I present an analysis of the management data table shown in Table 5.1 (see end of this chapter). This table represents the distribution of unemployed people, registered in Federal aid programs over twelve California counties, between wage categories. The data were obtained on the basis of quarterly reports called "Quarterly Summary of Client Characteristics." A facsimile of such report is shown in Figure 5.4: I selected the data presented as lines

Figure 5.4
Facsimile of "Quarterly Summary of Client Characteristics"

U.S. DEPARTMENT OF LABOR • Manpower Administration QUARTERLY SUMMARY OF CLIENT CHARACTERISTICS	2. GRANT NUMBER
1. PRIME SPONSOR'S NAME AND ADDRESS	3. QUARTER COVERED (Mo., Day, Year) a. From b. To 4. REGION CODE 5. STATE CODE

CHARACTERISTICS A		LINE NO. B	TOTAL CLIENTS C	TERMINATIONS Total D	TERMINATIONS Entered Employment E
TOTAL		01			
SEX	Male	02			
	Female	03			
AGE	18 and Under	04			
	19 - 21	05			
	22 - 44	06			
	45 - 54	07			
	55 - 64	08			
	65 and Over	09			
EDUCATION	8 and Under	10			
	9 - 11	11			
	HS Graduate or Equivalent	12			
	Post-High School	13			
FAMILY INCOME	AFDC	14			
	Public Assistance, Other	15			
	Economically Disadvantaged	16			
ETHNIC GROUP	White	17			
	Black	18			
	Oriental or Asian	19			
	American Indian	20			
	Alaskan Native	21			
	Other	22			
SPANISH AMERICAN		23			
LIMITED ENGLISH SPEAKING ABILITY		24			
MIGRANT OR SEASONAL FARM FAMILY MEMBER		25			
VETERAN	Special Vietnam Era	26			
	Other	27			
HANDICAPPED		28			
FULL-TIME STUDENT		29			
OFFENDER		30			
LABOR FORCE STATUS	Employed	31			
	Underemployed	32			
	Unemployed	33			
	Not in Labor Force	34			
RECEIVING UNEMPLOYMENT INSURANCE		35			

WAGES F		Line No. G	BEFORE PARTICIPATION H	UPON ENTERING EMPLOYMENT I
HOURLY WAGE	Less than $1.00	36		
	$1.00 - 1.99	37		
	$2.00 - 2.99	38		
	$3.00 - 3.99	39		
	$4.00 - 4.99	40		
	$5.00 - 5.99	41		
	$6.00 or More	42		
AVERAGE WAGE		43		

6. SIGNATURE AND TITLE	7. DATE SIGNED	8. TELEPHONE NO.

36 to 42, column H of this report. This data corresponds to the tallying of registered unemployed people according to their former wages before becoming unemployed. Twelve such reports, each corresponding to a different California county, were collected for the same quarterly period.

I argued earlier (V.1.2) that the "ideal data table" for statistical analysis should have the properties of homogeneity and exhaustivity. The raw data Table 5.1 practically satistifes those conditions since:

(1) All data values are being expressed in "counts of people"; thus they provide homogeneous data.

(2) The table columns provide an exhaustive set of seven wage categories, from "under 1.00 dollar" to "over 6.00 dollars." (Any wage belongs to one and only one category.)

(3) The table rows can be considered to provide an exhaustive set of twelve geographical areas. No county overlaps any other, and the union of all counties provides a greater geographical area. In fact, those counties are geographically contiguous, and they form the "California Central Valley."

This table represents quite an ideal data universe for matrix analysis. However, a detailed examination of this universe reveals some undesirable features, namely, the presence of matrix cells with no observations ("zero cells"). Practically all zeros are concentrated at column 7 (wages over 6 dollars) and at row 7 (Merced). This offers an opportunity for using the calibration commands available in MATBORD, namely, "Block" (for agglomerating data entries) and "Mask" (for suppressing an unwanted entry):

(1) It is possible to agglomerate columns 6 and 7 to form an aggregate category including the former "5/5.99 dollars" and "Over 6 dollars" categories. This new aggregate can be labelled as the "Over 5 dollars" category.

(2) It is possible to suppress the row which is labelled "Merced," since it appears to be an unreliable data array (it is quite unexpected to find all the unemployed population within the

same wage category: The conclusion is that there may be an error in the data collection process).

Consequently, the calibrated data can be pictured as the Matrix Display shown in Figure 5.5.

V.4.2 An Example of Matrix Analysis Process

I described earlier the process of Matrix Analysis as a three-stage process whereby Raw data are transformed into Profile data, which are themselves the basis for Similarity analytic procedures. The following Figures 5.5 to 5.9 provide an instance where this three-step process is used for management information reporting. The end-result is a picture which provides some indication as to the proper ordering and clustering of the observed set of California counties into groups showing approximately similar wage profiles.

(1) The first analytical step is to transform the available raw data matrix into a profile matrix. As we saw earlier, this requires the definition of a reference array and an operation for normalizing the data values. Here the reference array is obtained by computing the sum of the data values for each row (i.e., the total population served in each county); the proper operation is then to compute proportions to the total for each county, hence providing wage profiles. The effects of profile computations are properly seen if one compares Figure 5.6 (Profile Matrix) to Figure 5.5 (Raw Matrix). Clearly, the raw matrix shows essentially size effects, since the perception is attracted by the biggest programs such as Fresno, Sacramento, or Stockton. On the other hand, the profile matrix provides a normalized account where each county has basically the same size; the programs now differ in "shape" only, i.e., in the relative distribution of their participants

between wage categories.

(2) The analysis could easily stop at this point. However, it seems possible to make a better use of the Matrix Display of Figure 5.6 by rearranging the row entries (i.e., the counties) so that those with similar profiles are put close to each other. For instance, Butte and Santa Barbara, which are physically distant in the matrix row entry, have quite similar profiles, and the user would benefit from seeing them close to each other. This process of rearranging the entries of the profile matrix is quite difficult to accomplish on the basis of visual comparisons only. It is possible to help it by computing coefficients of similarity between profiles, which provides a next step in the analysis. The resulting similarity matrix is shown in Figure 5.7. The values of the similarity coefficients have been put into three grey-shade "bins," in order to ease perception (reduction of information). Clearly, Imperial and Modesto stand out since they do not resemble closely any other county.

(3) The Similarity matrix is reorganized so that Imperial and Modesto end up in the most extreme positions, and all other counties are arranged so that an approximate simplex pattern (diagonal) shows up (Figure 5.8). This pattern is approximate to the extent that most counties are similar (as indicated by the large shaded square from San Luis Obispo to Butte). Also, Fresno appears to be an "average" county in the sense that it resembles the two major clusters (San Luis Obispo to Inland and Kern to Butte). The profile matrix which corresponds to this similarity plot is presented in Figure 5.9; it shows both an ordering of the counties from Imperial to Modesto and a clustering into two major groups. Visually one might observe the general northwest/southeast

gradient which indicates that the wage distribution progresses from lower to higher wages as one goes down the row ordering from Imperial to Modesto. In particular, Imperial which has a large fraction of its population in wage categories below $1.99 and Modesto which shows a wage pattern above $3.00 are most opposed.

The end-result of the process is a picture which indicates major groupings of California counties according to their wage distribution. Clearly, this picture may help management tasks such as determining the "poorest" and "richest" counties, allocating funds differentially to counties of various profiles of wages, etc. This shows that the process of Matrix Analysis defined above can be used for management information reporting purposes.

V.4.3 Some Research Issues

The above example shows that Matrix Displays can be used as a presentation medium for numerical management information. But it does not tell how managerial clients may react to Matrix Displays, how they may adapt to their use, etc. It seems that one most essential aspect of a managerial feasibility study is the real-life testing of such displays.

Given the chosen client (middle-line management), a study of Matrix Displays in a real-life situation should provide some empirical cues on the following issues:

(1) To what extent is the concept of Matrix Display (i.e., the graphic format itself) understood and accepted?

(2) Do managerial clients understand the suggested three-step process of analysis (Raw, Profile, and Similarity)? Do they need to? To what extent?

(3) What level of sophistication in display operation (see the

above section V.3.2) do managers understand? What sophistication do they need in order to obtain the desired "end-product" pictures?

(4) Should the whole process of analysis be done by and/or communicated to the manager? If not, who should prepare the Matrix Displays, and how should one choose among the resulting displays?

(5) Should the manager be associated in the interactive production of Matrix Displays? Should he be asked to sit in front of a display console?

(6) Should the management report with Matrix Displays also include the corresponding numerical data? Should each display be accompanied by its corresponding data table? Or are the pictures sufficient because they "tell enough"?

The following chapter presents a case-study of Matrix Display implementation using the MATBORD prototype. This case-study provides some empirical material useful to answer the above six issues in a tentative manner.

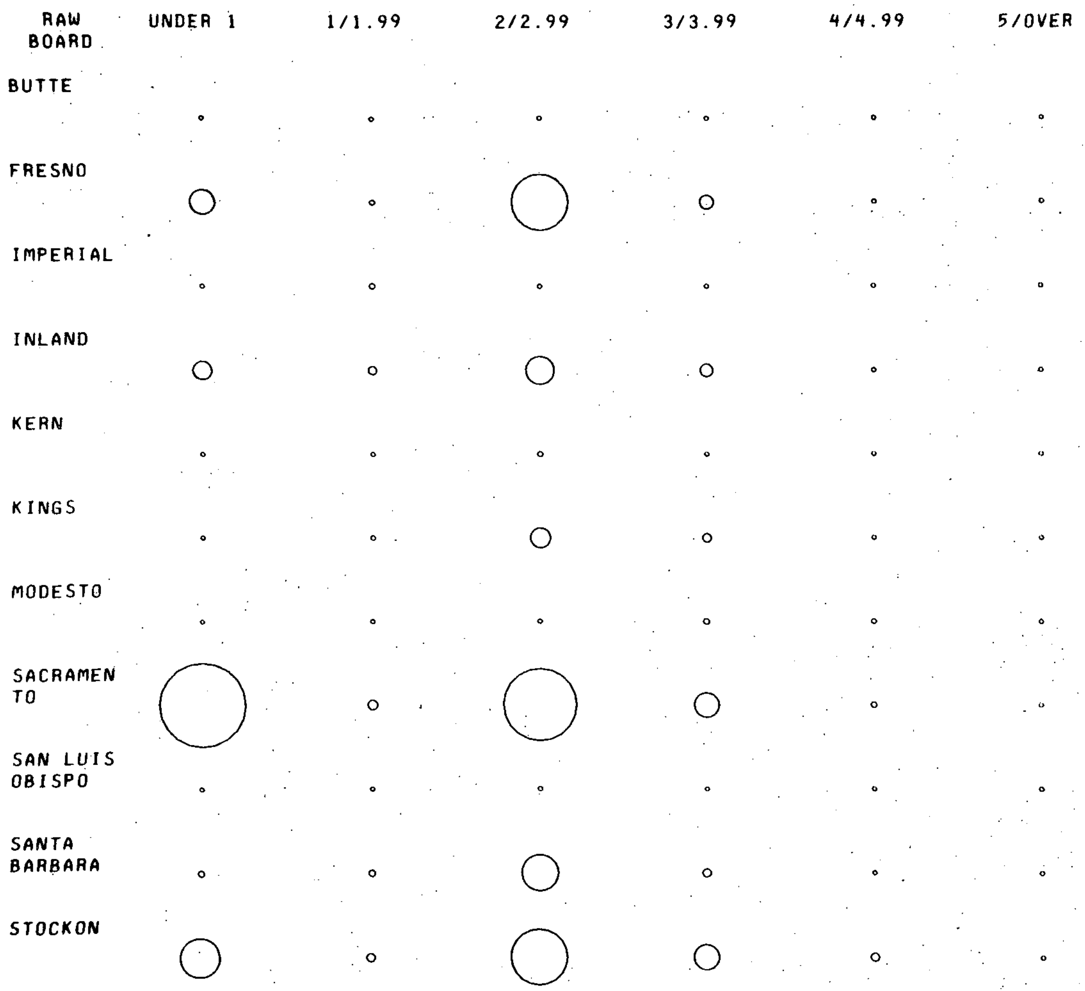
DISTRIBUTION OF THE REGISTERED POPULATION
INTO WAGE CATEGORIES(HOURLY WAGES IN DOLLARS)
FOR 12 CALIFORNIAN COUNTIES

RAW BOARD	UNDER 1	1/1.99	2/2.99	3/3.99	4/4.99	5/5.99	OVER 6
BUTTE	0	2	27	14	6	1	0
FRESNO	233	48	533	132	35	10	5
IMPERIAL	10	53	14	2	0	0	0
INLAND	175	78	269	121	27	14	6
KERN	16	5	50	3	1	0	1
KINGS	38	46	190	83	17	10	3
MERCED	39	0	0	0	0	0	0
MODESTO	0	14	4	56	48	24	6
SACRAMENTO	804	92	691	235	54	7	1
SAN LUIS OBISPO	13	2	12	4	2	0	0
SANTA BARBARA	59	62	346	78	24	8	6
STOCKON	371	79	530	239	79	26	1

XBL 767-8631

Table 5.1

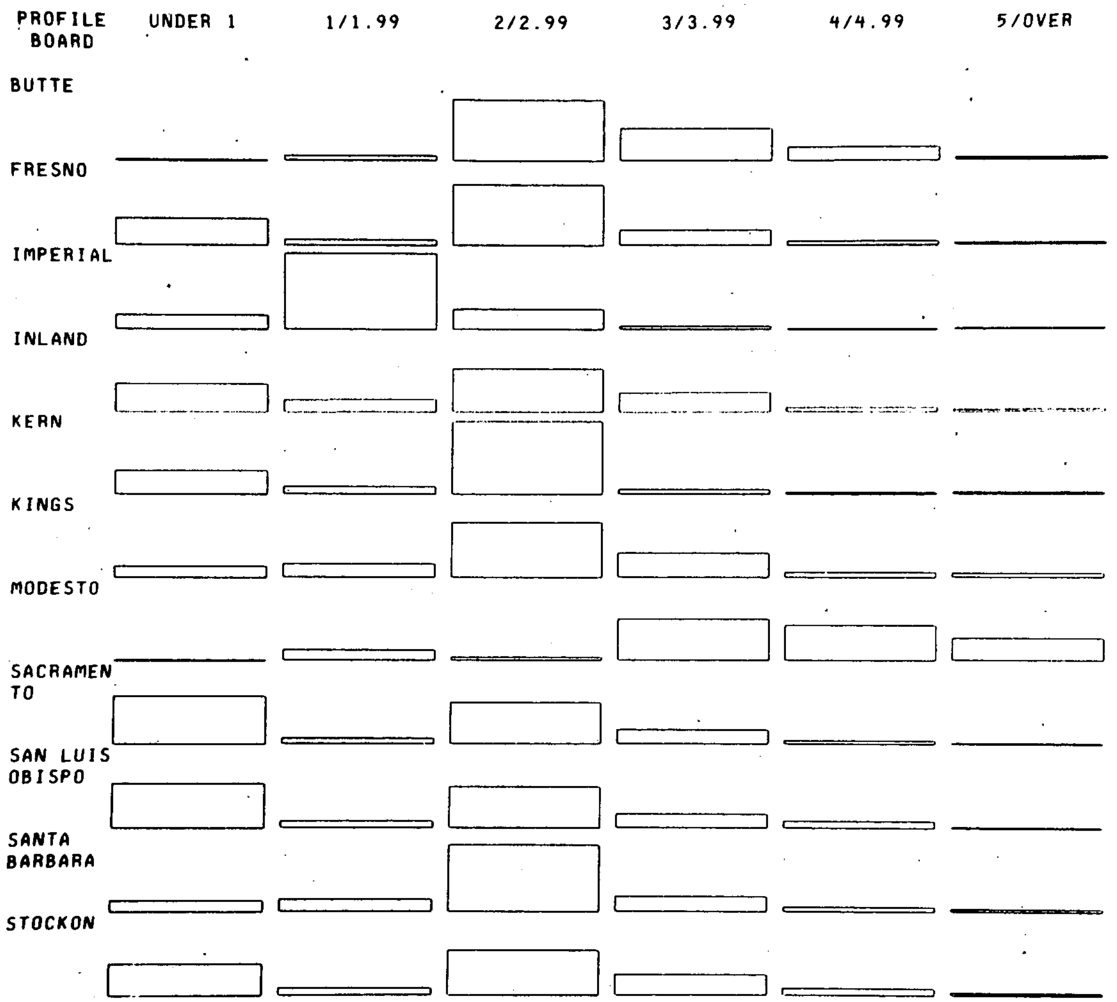
MATRIX AFTER CALIBRATION OPERATIONS
-MERCED HAS BEEN MASKED FOR "IMPRECISE INFORMATION"
-THE WAGE CATEGORIES 5/5.99 AND 6/OVER HAVE BEEN
AGGLOMERATED INTO ONE CATEGORY(5/OVER)



XBL 767-8630

Figure 5.5

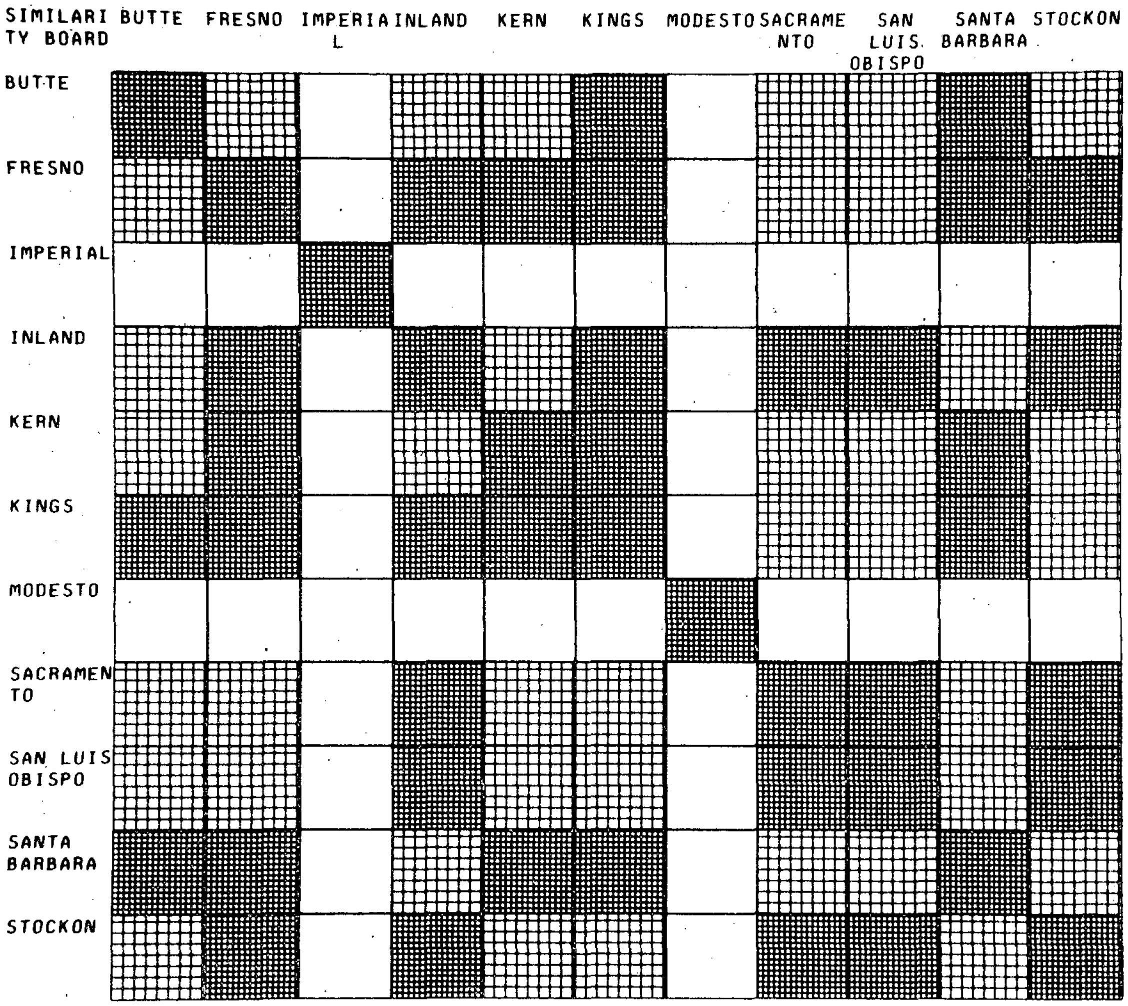
PROFILES OF WAGES
FOR EACH OF THE COUNTIES
(POPULATION REGISTERED IN UNEMPLOYMENT PROGRAMS)



XBL 767-8629

Figure 5.6

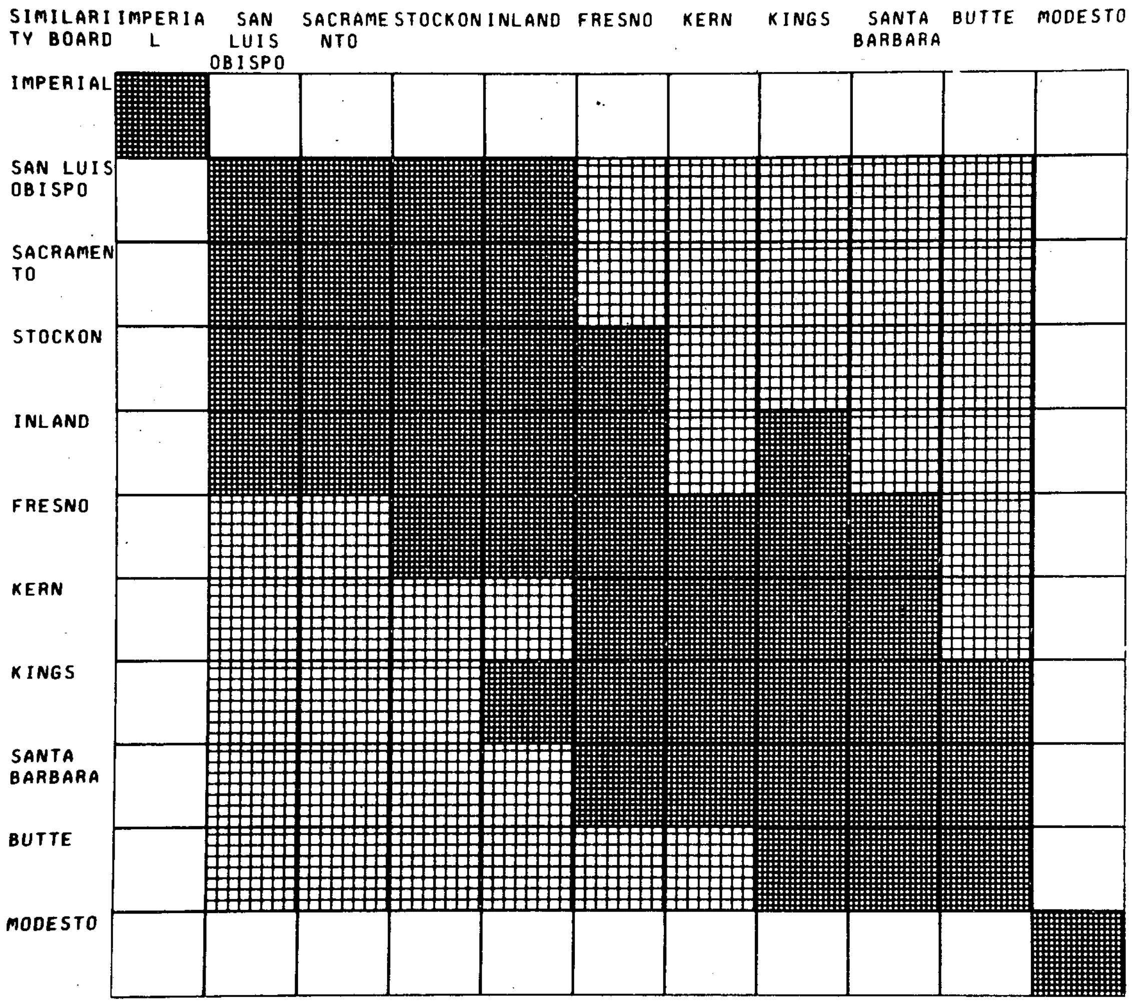
SIMILARITIES BETWEEN THE PROFILES OF WAGES
SHOWN IN THE ABOVE PICTURE
THE DARKER THE SHADE, THE HIGHER THE SIMILARITY
(TO EASE PERCEPTION, BINNING HAS BEEN APPLIED)



XBL 767-8646

Figure 5.7

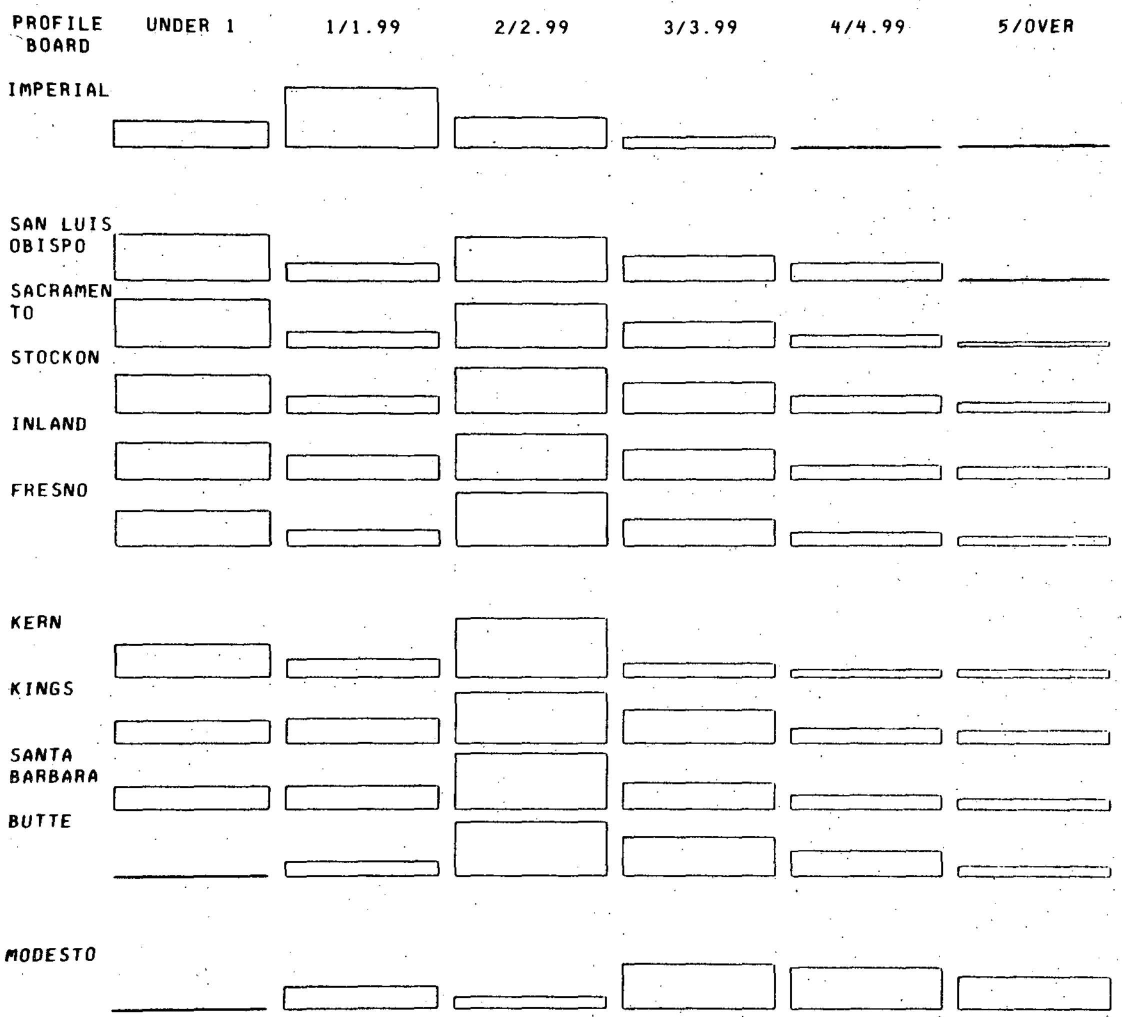
THE SIMILARITY MATRIX AFTER MANIPULATION
IMPERIAL AND MODESTO ARE PUSHED TO THE EXTREMES
ALL OTHER COUNTIES ARE RANKED IN A SIMPLEX PATTERN



XBL 767-8647

Figure 5.8

THIS IS THE RESULTING PROFILE MATRIX
OBSERVE THE GENERAL NORTHWEST/SOUTHEAST GRADIENT
IT INDICATES A RANKING FROM LOWEST WAGES(IMPERIAL)
TO HIGHEST WAGES(MODESTO)



XBL 767-8648

Figure 5.9

CHAPTER VI

INTERACTIVE MATRIX DISPLAYS AND MANAGERS: A FEASIBILITY APPROACH

In this chapter some empirical observations concerning the feasibility of Matrix Displays in an actual management environment will lead me to the conclusion that Matrix Displays are "acceptable" modes of representation for management. This result, however, must be interpreted with caution since (a) I studied only one case of Matrix Display implementation in a managerial environment and (b) a variety of managerial reactions were observed, including difficulties to understand the notion of a similarity matrix. But, on the whole, there is a definite tendency for the observed management people to accept and to use the proposed displays for information purposes.

Given the emphasis on feasibility assessment, the opportunity to have actual management people involved in the study was provided by a project on Management Information Systems at the U.S. Manpower Administration Regional Office in San Francisco. This project had graphic and data analytic implications which offered the possibility of trying out the capabilities of Matrix Displays for Management Information Reporting in a limited environment. A three-step process including

(1) A field study by interviewing several managers,

(2) The preparation of management reports for a specific manager, and

(3) An interactive session at the terminal with the active

participation of the above manager and his staff brought out a large amount of qualitative material. I also gathered a reasonable amount of quantitative evidence through tracing the interactive session (time and cost data) and the measurement of managerial attitudes on attitude-scales questionnaires.

VI.1 The C.E.T.A. Management Information System

In this section I describe the general features of the managerial context in which Matrix Displays were later introduced. Although I intend to focus on management information issues, I will provide a view on the organization structure which supports the management information system and then describe the general methodology which I used to intervene within this management environment.

VI.1.1 C.E.T.A. Management at the U.S. Manpower Administration

In December 1973, the Congress of the United States passed the Comprehensive Employment and Training Act (C.E.T.A) under Public Law 93-203. As stated in the Law, the purposes of C.E.T.A. are:

(1) To provide job training and employment opportunities for economically disadvantaged, unemployed or under-employed persons

(2) To assure that training and other services lead to maximum employment opportunities, and

(3) To enhance self-sufficiency by establishing a flexible and decentralized system of Federal, State, and Local programs.

Under C.E.T.A., the State and Local governments are considered as Prime Sponsors of manpower programs, and they are given authority and responsibility for program planning and operation. The Federal government assists each individual Prime Sponsor in meeting its responsibilities; the Regional Offices of the Manpower Administration (Department of

Labor) represent the Federal Government at the state and local levels.

The Organization of the Regional Offices. The Comprehensive Employment and Training Act decentralizes operational decisions, such as training unemployed persons so that they have a better chance on the labor market, at the level of Prime Sponsors (i.e., urban and suburban communities). However, to the extent that the Secretary of Labor determines a nationwide labor policy, there is a need to integrate various local decisions into a broader framework which fits the federal policy. The ten Regional Offices of the U.S. Manpower Administration are the intermediary management authority which monitors the integration of Prime Sponsors' policies within the federal policy.

Regional Offices have a twofold responsibility in the implementation of C.E.T.A..

(1) They designate the Prime Sponsors, review and approve their operating plans, allocate the funds, and assess plan implementation.

(2) They provide technical assistance to Prime Sponsors through a pool of specialists in program planning, management information systems, financial reporting, etc.

In actual practice of C.E.T.A., these two roles of monitoring and assisting Prime Sponsors are thoroughly intertwined. The organization chart of the Regional Offices shows a balance between line and staff roles. On the "line" side, the Head of the Regional Office, who is delegated from the Secretary of Labor the authority on a given regional area, delegates this authority, in turn, to the managers of subregional areas. On the "staff" side, the Regional Office has a number of technical specialists with whom it can assist Prime Sponsors. Moreover, nationwide programs, such as the Equal Employment Opportunity Program, have a specific staff management at the Regional Office.

For instance, the Region XI Office in San Francisco, where I set up a field study (see section VI.2 below), has the organization chart shown in Figure 6.1. This chart shows that line management is defined on a geographical basis. The region is divided into two areas, these areas divided into subareas, so that each middle-line manager has a number of Prime Sponsors to monitor. The middle-line management (for example, "C.Z.B.") is itself assisted by a certain amount of staff (for example, "B.C.").

The Grant's Cycle. The overall scheme according to which a C.E.T.A. grant is applied for, approved, implemented, and evaluated is a cycle which links together the middle-line management at the Regional Office and the local Prime Sponsors. The Federal Representatives (such as "A.P." in Figure 6.1) carry on the roles of liaison officers between the Regional Office and the Prime Sponsors. Each Prime Sponsor is monitored at the Regional Office by a Federal Representative, who has the ability to set up meetings and on-site visits at the Prime Sponsor's.

The following diagram depicts the grant's cycle as a four-step process (U.S. Department of Labor, 1974a, No. 5):

Figure 6.2

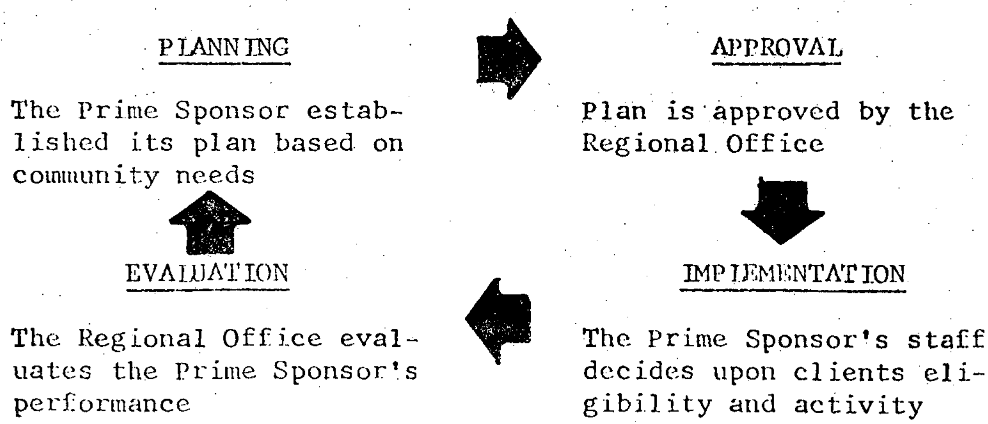
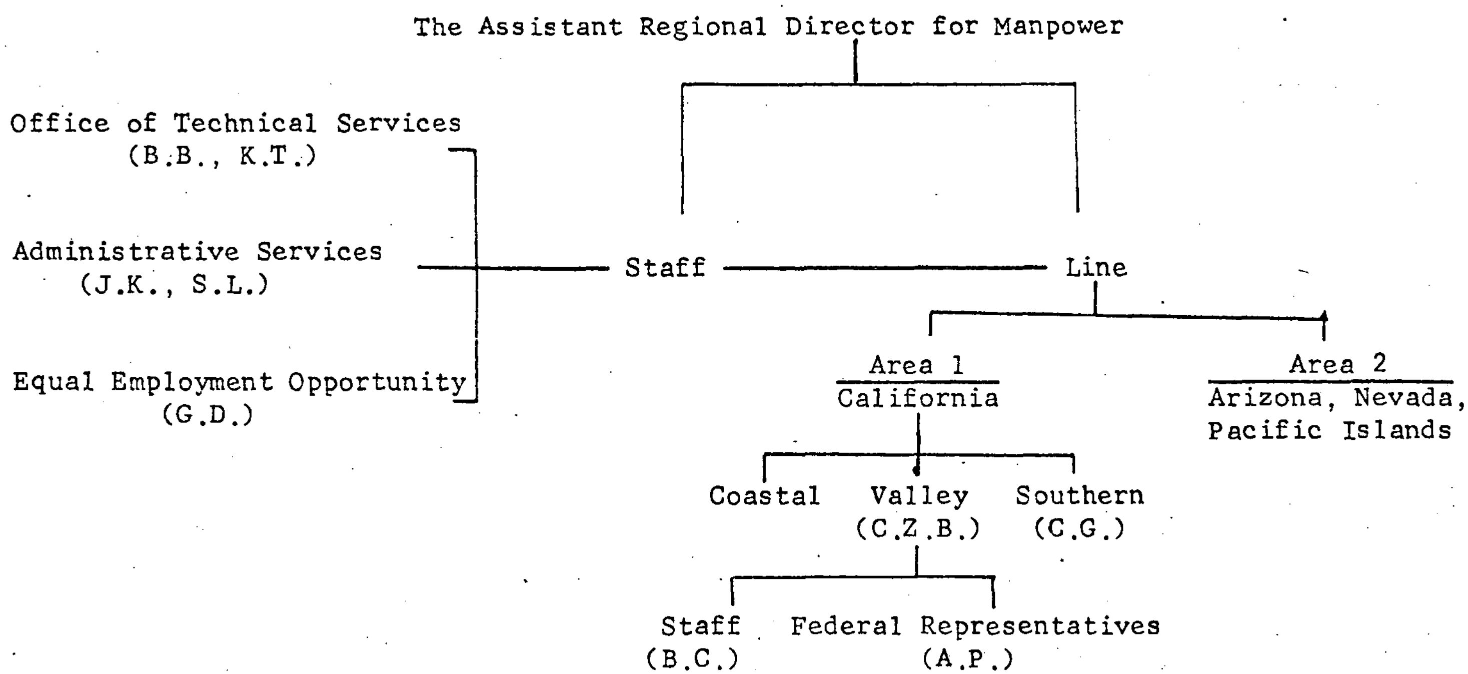


Figure 6.1



NOTE: Initials in parentheses refer to the persons who participated in my study.

This cycle runs on a quarterly basis:

(1) The plan is proposed annually by the Prime Sponsor on the basis of demographic and labor market data for the area, with a plan breakdown by quarter. During the course of the year (July 1 to June 30), the Prime Sponsor may ask for modifications to the plan (on a quarterly basis).

(2) The Regional Office reviews the plan and its modifications. The correspondence between the plan and the general C.E.T.A. objectives, as well as the local needs in the area, is appreciated and the costwise feasibility of the plan assessed before approval is given.

(3) The Prime Sponsor implements the plan and decides upon clients' eligibility and activity patterns (counseling, training, placements). During the plan's implementation, the Federal Representative mandated by the Regional Office is available for on-site visits and performance reviews.

(4) Through the Federal Representative's on-site visits, as well as through federally required information reports, the Regional Office's manager continuously monitors the Prime Sponsor's performance. Periodic review meetings are held on a quarterly basis, and trouble-shooting procedures may be triggered through alarm indicators.

Focusing on Middle-line Management. On the basis of the above discussion, it appears that middle-line managers have at the Regional Office a key role as an interface between the federal policy and the Prime Sponsors' decisions. The role of middle-line managers can be characterized by three features, namely,

(a) That the manager is not directly involved in local labor market operations (since this is the Prime Sponsor's responsibility)

(b) That rather his management responsibility consists in monitoring the performance of autonomous Prime Sponsors

(c) That each manager has to deal with several Prime Sponsors at once (from five to fifteen depending on their size)

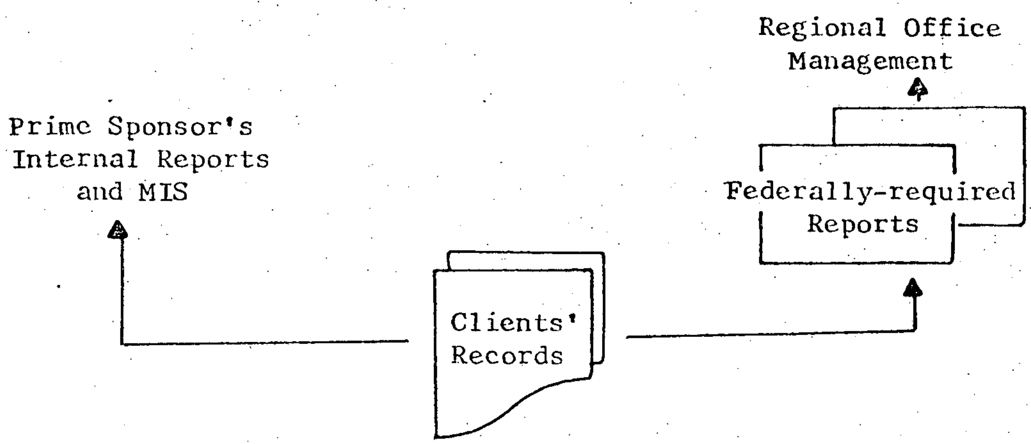
It appears that the manager's function is much different from the Federal Representative's, since he deals with a set of Prime Sponsors (instead of just one) which he monitors from a distance (instead of relying upon on-site visits).

Consequently, middle-line managers of C.E.T.A. programs at the Regional Office are necessarily dependent upon information as a management medium. There exists a variety of information sources which a C.E.T.A. manager can use, including the direct information from his subordinates (Federal Representatives) or from the public (letters of complaint, rumors), and the numerical information provided by formal management reports. Given the objective of this thesis, I now focus on this last type of information.

VI.1.2 The C.E.T.A. Management Information System

The basic information for C.E.T.A. management is generated at the Prime Sponsor's level where C.E.T.A. clients are recognized eligible, then enrolled into programs (training, placements), and finally terminated (they find a job or drop out of the program). Consequently, the Prime Sponsor's MIS must serve both the internal information needs of the Prime Sponsor and the federal needs in C.E.T.A. information. The basic source of information are the clients' records, hence the resulting information system depicted in Figure 6.3. I am concerned here basically with the information reports communicated to the Regional Office, i.e., the "federally-required" reports.

Figure 6.3



These reports are required by federal law. Since C.E.T.A. intended to standardize the administrative procedures, these reports are both simple and complete. They are simple because they are obtained from the direct tally of clients' records and are complete thanks to a massive compacting of data into one-page documents. There are four such one-page documents, three of which have a direct interest for management purposes (I exclude the Cash Transactions document).

(1) The Project Operating Plan (P.O.P.) is prepared annually, and it plays the role of a contractual agreement between the Prime Sponsor and the Manpower Administration.

(2) The Quarterly Summary of Clients' Characteristics (Q.S.C.C.) provides a general profile of the population being served,, along socio-economic characteristics.

(3) The Quarterly Progress Report (Q.P.R.) recapitulates Plan vs. Actual performance on the same itemized entries shown by the P.O.P. As the Q.S.C.C., the Q.P.R. is due 30 days after the end of each quarter.

A facsimile of the Q.S.C.C. was shown in the previous chapter (Figure 5.4), The next page shows a facsimile of the Q.P.R. (Figure 6.4).

The Quarterly Progress Report is the most important source of data available to middle-line managers at the Regional Office. It permits determining several performance indicators, such as the ratio

Figure 6.4
Facsimile of the Quarterly Progress Report

a. GRANTEE'S NAME AND ADDRESS	U.S. DEPARTMENT OF LABOR Manpower Administration **CETA QUARTERLY PROGRESS REPORT**	b. GRANT NUMBER
	c. REPORT PERIOD *(Month, Day, Year)* From: To:	d. TYPE OF PROGRAM ☐ 1-Title I ☐ 2-Title II ☐ 3-Other *Specify* ....

I. ENROLLMENT AND TERMINATION SUMMARY

ENROLLMENT AND TERMINATION CATEGORIES	PLAN	ACTUAL	% OF PLAN
A. Individuals served, program year to date *(Sum of A.1 and A.2)*			
1. Individuals entering this program year			
2. Individuals carried over from previous year			
B. Individuals terminated, program year to date *(Sum of B.1 thru B.3)*			
1. Total entering employment			
a. Direct Placements, no CETA training or employment			
b. Indirect Placements, following CETA training or employment			
c. Self Placement			
2. Other Positive Terminations			
3. Non-Positive Terminations			
C. Individuals Enrolled, end of quarter *(A minus B)*			

D. ANTICIPATED DURATION OF JOB PLACEMENTS

If entries are made in I.B.1.a *(Direct Placements)* or I.B.1b *(Indirect Placements)*, enter the anticipated duration of the job in which the individual is placed.

PROGRAM YEAR TO DATE	Direct *(I.B.1a)*	Indirect *(I.B.1b)*
1 thru 3 days		
4 thru 150 days		
More than 150 days		

II. ENROLLMENT IN PROGRAM ACTIVITIES

PROGRAM ACTIVITY	(a) Number of individuals served in each program activity; program year to date			(b) Enrollment in each program activity at the end of the quarter; individuals concurrently enrolled in more than one activity may be counted in each activity in which he or she is enrolled.		
	PLAN	ACTUAL	% OF PLAN	PLAN	ACTUAL	% OF PLAN
A. Classroon Training *(Prime Sponsor)*						
B. Classroom Training *(Voc. Ed.)*						
C. On-The-Job Training						
D. Public Service Employment						
E. Work Experience						
F. Other Activities						

III. SUMMARY FINANCIAL ACTIVITIES *($ in Thousands)*

A. Total CETA funds available for expenditure *(Sum of A.1 plus A.2)*		
1. Funds carried in from previous program year or other contracts or grants		
2. Funds received, program year to date		
B. Accrued expenditures, program year to date *(Sum of B.1 thru B.6)*		
1. Administration		
2. Allowances		
3. Wages		
4. Fringe Benefits		
5. Training		
6. Services		

IV. CUMULATIVE FINANCIAL ACTIVITY—PROGRAM YEAR TO DATE *($ in Thousands)*

	PLAN	ACTUAL	% OF PLAN
A. Prime Sponsor Obligations			
B. Accrued expenditures by Program Activity of the Prime Sponsor *(See III.B); (Sum of B.1 through B.6)*			
1. Classroom Training, Prime Sponsor			
2. On-The-Job Training			
3. Public Service Employment			
a. Wages			
b. Fringe Benefits			
c. Other			
4. Work Experience			
5. Services to Clients			
6. Other Activities			
C. Accrued expend. for Voc. Ed. in Special Grants to Governor			
D. Accrued expenditures, non-Federal funds			
E. Accrued expenditures of other Federal funds not in Prime Sponsor's Grant			
F. Total accrued expenditures *(Sum of B, C, D, and E)*			

V. SIGNIFICANT SEGMENTS

Indicate the number of individuals in each segment groups served during the program year to date

SIGNIFICANT SEGMENTS	PLAN	ACTUAL	% OF PLAN	SIGNIFICANT SEGMENTS	PLAN	ACTUAL	% OF PLAN
A.				F.			
B.				G.			
C.				H.			
D.				I.			
E.				J.			

VI. OTHER ACTIVITIES *(Reference II.6; IV.B.6)*

On a separate sheet indicate achievements in any other activity or special programs. Achievement should be contrasted to objectives in either a quantitative or narrative presentation. *(Optional)*

VII. INDIRECT EXPENSE

A. TYPE OF RATE	B. INDIRECT RATE	C. BASE	D. TOTAL AMOUNT
☐ 1-Provisional ☐ 2-Predetermined ☐ 3-Final ☐ 4-Fixed			$

VIII. CERTIFICATION: I CERTIFY that to the best of my knowledge and belief this report is correct and complete and that all outlays and unpaid obligations are for the purposes set forth in the grant award document.

A. NAME AND TITLE OF AUTHORIZED OFFICIAL	B. SIGNATURE	C. DATE SIGNED

of Placements over total Enrollments, the average costs, etc. The Regional Office Handbook (U.S. Department of Labor, 1974b) suggests that it can be used for a trouble-shooting procedure based on a 15 percent rule: Deviations of Actual performance to Planned performance exceeding plus or minus 15 percent should be recognized as indicating potential problem areas.

VI.1.3 Opportunity and Method for an Intervention

The opportunity for a direct intervention within the above context came from the Regional Management Information System project (R.M.I.S.) initiated by the Region IX Manpower Administration and the Lawrence Berkeley Laboratory at the University of California:

> Recognizing that the Manpower Administration's present information retrieval system is not designed for flexible large-scale manipulation, the overall aim of the project is to develop the computer tools--interactive data retrieval systems, computer graphics, report generation systems, and computer mapping--which will enable managers, at all levels within the organization, to access data easily in a form which they readily understand (U.S. Department of Labor, 1975).

Among the research topics suggested within this overall framework, the design of graphic aids called for my attention.

In particular, it appeared to me that the above set of one-page data documents, such as the Quarterly Progress Report, could not be easily used as a support to decision-making since:

(1) From a human factors viewpoint, the format seemed to be too compact to facilitate cognitive tasks.

(2) In order to compare the performance of several Prime Sponsors, the manager would have to manipulate several pages at a time, which is not easy.

(3) No real data analysis effort was involved in the preparation of these documents (except for the computation of Actual/Plan percentages).

In sum, the one-page documents appeared to be justified as a data-base containing the most relevant data middle-line managers could use, but not as formats for direct managerial usage.

At this point, I hypothesized that Matrix Displays would provide a relevant display format for management reports. This hypothesis was formulated on the basis of:

(1) The observation that C.E.T.A. data is multidimensional in kind, i.e., it results from the consideration of a set of Prime Sponsors along a set of performance criteria.

(2) The position of middle-line managers in the organization chart as intermediary linkages between a set of Prime Sponsors and the federal policy. This implies that middle-line managers have to accomplish a number of comparison tasks such as to compare the performance of several Prime Sponsors, to form groups having the same profile of performance, etc.

(3) A circumstantial reason was that, due to the relative recency of the C.E.T.A. Act, it was felt that the managerial context would offer more opportunity for change and improvement than a long-time routinized environment.

In the path of Scott Morton (1971), I chose a depth-type research methodology rather than a breadth-type. I developed close relations with a few management persons and went with them all the way to the actual implementation of Matrix Displays in their own management environment. I thus decided on three major steps:

(1) Exploration of the information needs of managers by a field study (April-August 1975)

(2) Preparation of management reports for a specific group of management users (September 1975-January 1976)

(3) Interactive session where the above management users participated in the on-line preparation of a management report for their own use (February 1976)

Steps 1 and 2 are presented in the next section. Step 3 led to such a wealth of results that it is presented in two different sections: One section (VI.3) focuses on the Matrix Display aspect, and the other (VI.4) deals with the more general issues of the relations between management and interactive information systems.

VI.2 C.E.T.A. Management and Matrix Display Reporting

VI.2.1 A Field Study of Informational Needs

In the field study I tried to determine areas where present C.E.T.A. information documents (such as the Quarterly Progress Report) failed to satisfy the needs of managers, and where Matrix Displays could possibly help management information reporting.

I interviewed a few C.E.T.A. management people on the basis of an open-ended questionnaire. At the beginning of each interview, I presented myself as a specialist in graphic display, working on formatting procedures for C.E.T.A. data. The eleven questions of the questionnaire served as guidelines during the interview, but the managers were free to express their own feelings and suggestions about the information reporting procedures. The questionnaire was organized so as to have each manager highlight the actual vs. potential use of C.E.T.A. data. Attention was paid to the cognitive aspects of the manager's tasks and to the format of the C.E.T.A. documents. Finally, the manager was asked to express his attitude with respect to graphic displays, so as to control for the "cognitive style" factor.

In these interviews, each lasting from one to two hours, four managers participated: Two area managers (C.G. and C.Z.B.), the manager of the Equal Employment Opportunity Program (G.D.), and the manager of the Operational Planning and Control System and his assistant (J.K. and S.L.). (The management positions of these persons are indicated on

Figure 6.1). These interviews were tape-recorded, which provided a total of six hours of verbal protocols. The list below shows each question, with its answer in summary form.

Q.1: What is, in your opinion, the purpose of C.E.T.A. documents?

The purpose of C.E.T.A. documents is clearly perceived as a data-base for management usage and, particularly, for the monitoring of Prime Sponsors' performance against plan.

Q.2: How do you read these documents?

Managers seem to read only a very small number of critical variables out of the large universe which is presented. For instance, only three or four items are read on the Quarterly Progress Report, namely, the enrollments, the actual placements vs. plan, and the actual expenditures vs. plan.

Q.3: Do you pay attention to individual figures, sums, others?

Managers all cite the rule that "plus or minus 15 percent deviations to plan" should be looked for.

Q.4: Does the data formatting suit your needs?

As a general rule, the interviewed managers heavily criticize the format of the C.E.T.A. documents on the basis that:

(a) It contains too much data.
"There is so much data that it is almost impossible to use . . . Nothing makes it easy to identify problems . . . ."

(b) The format is inappropriate.
"They designed machine-input forms, not forms that can be used for data analysis as they stand."

(c) The management tasks are impaired.
"What they have in fact said by setting the report this way is that lots of comparisons are inappropriate . . . . Anybody who wants to use the data has to use separate forms."

Q.5: Do you mentally analyze the data? If yes, how?

The managers appear to actively participate in the process of making the data meaningful (estimating percentages, or totals, and circling the most important figures on the document itself).

Q.6: Could you please give an example where the C.E.T.A. forms are used as (1) a trouble-shooting device, (2) a tool for ranking C.E.T.A. Prime Sponsors, and (3) a device for forming groups of Prime Sponsors showing a similar performance profile?

Managers reacted very readily to this question by providing examples and suggestions. But they see the three above tasks more as potential than as actual usage of the forms: "If we could 'flag' those Prime Sponsors which exceed 15 percent deviation to plan. . . ." "If there were ranking tables that showed how Prime Sponsors rank in Intake, and in Placements, that would be most useful . . . ." "It could be interesting to divide the Prime Sponsors into two groups: Those who are substantially accomplishing and those who are off . . . ."

Q.7: Could you develop a short description of a typical decision-making situation where to use C.E.T.A. documents?

An actual example where a manager tried to rank Prime Sponsors is provided by an interviewee as follows: "We did a rough exercise last Spring when we had to make judgments about the Prime Sponsors, trying to assess significant under-performers and over-performers. We tried to rank them on the basis of both enrollments and expenditures . . . ."

Q.8: Do you create information documents for your own use?

The relative newness of C.E.T.A. does not seem to have permitted managers to create their own documents. However, they mention that they currently do scratch computations when needed, plus some work of juxtaposing on the same sheet data from different sources.

Q.9: How much confidence do you have in C.E.T.A. data?

Managers place reasonable confidence in C.E.T.A. data, although they recognize that their confidence may vary with Prime Sponsors. ("But that's a fact of life. We have to accept it.")

Q.10: Do you think that your information could be improved?

Managers offer several suggestions for improving the information transfer, namely,

(a) To improve the consistency between different forms (Quarterly Progress Report and Quarterly Summary of Clients' Characteristics)

(b) To determine suitable performance criteria ("We do not have any fixed guidelines as to what a problem is . . . . What is a good unit cost? . . . We have to develop performance standards . . . .")

(c) To develop simple data analytic procedures ("If only a quick way to compare performance to plan across Prime Sponsors were available . . . .")

Q.11: How do you feel about graphic displays as a formatting mode?

Most managers had favorable reactions to the idea of using graphic displays.
"You see, just reading a list of figures like this (the Quarterly Progress Report) leaves me cold. Why have all those statistics when a display can tell you all?" "For instance, it takes time to make sense out of the relation '75 to 25 to 2,' while a graphic display could tell you all like that . . . ."

VI.2.2 Observations on the Management Information Reporting Process

The field study confirmed the hypothesis that C.E.T.A. data forms, such as the Quarterly Progress Report, were not considered convenient summaries for management information purposes. Also, it showed that managers were quite ready to use graphic displays under the assumption that they could help them absorb more of the available information. Finally, the field study helped determine which operators managers need apply to raw data in order to give it some meaning, i.e., comparisons, rankings, and groupings, thus confirming that Matrix Displays could be useful.

In addition, in examining the interview protocols, I discovered how difficult it was for the managers I interviewed to separate the problem of information into several factors such as the data factor ("content") and the formatting factor ("form"). The basic criterion which managers seem to use in order to judge the "goodness" of their information is a global appreciation of its usefulness. The following comment, recorded during an interview, illustrates this atttitude:

> Presentation of material just because it looks interesting is not a valid enough reason for presenting it . . . . What I need to know is: Once you've manipulated the data, what comes out? Is it any useful for my purposes as a manager?

Typically, it appears that in order to be a "good" piece of information the data must have all of the following qualities:

(1) Being useful (i.e., the data universe is relevant)

(2) Being accessible (i.e., the information is easy to "pick up")

(3) Being suitable (i.e., suited to the tasks which the manager wants to accomplish)

VI.2.3 Preparing Management Reports with Matrix Displays

On the basis of the above observations, I determined that an "optimal" procedure for the assessment of Matrix Displays as an aid to management reporting was to empirically prepare a management report for a specific user, or group of users. This choice would enable controlling

(1) The relevant data universe,

and it would then permit observing fundamental management needs with respect to

(2) The display format and

(3) The suitable operators to help the information "pick-up".

I chose to focus on a manager-client with an immediate need for an improvement in his information reporting system and with no favorable bias toward the research. This client, C.Z.B. in Figure 6.1, is in charge of the monitoring of twelve C.E.T.A. programs in the area called the "California Valley." His initial attitude was one of "impatience" toward the "computer people":

> I'm becoming very impatient with the computer capability developing two years down the pipe . . . . I'm not interested in developing a

system that will be beneficial only to you folks; I am interested in a system that is going to be beneficial to us . . . . (C.Z.B.).

Developing a test example of a management report for his own use appealed to C.Z.B. as a way to bring closer together the two worlds of management and "computers." We agreed that the test example would be defined in relation to the information needs of C.Z.B. and his staff (A.P. and B.C.) and that the application would have an experimental character. Furthermore, we agreed on having an experimental session directly at the interactive graphics terminal where C.Z.B. and his staff would be invited.

Preparing management reports on test examples considerably influenced the design of MATBORD. Initially (June 1975), MATBORD was made up of two boards only, the Raw board and the Similarity board. Finally (February 1976), it incorporated the intermediary Profile board, plus a number of operators of great usefulness for C.E.T.A. management.

The collaborative agreement with C.Z.B. and his staff led me to prepare two reports. The first report (September 9, 1975) was essentially graphical, and it enabled me to observe the spontaneous behavior of managers in relation to Matrix Displays. These reactions, which I recorded, can be arrayed into six results:

(1) There is an absolute need for managers to get the data along with the display plots. ("Give me the data on that.")

(2) The similarity matrix is too difficult a concept to absorb without being prepared for it. ("I don't understand it.")

(3) The raw board is actively used by managers for size comparisons. ("Which are biggest?")

(4) Simple statistical notions such as averages and percentages have a key role in managerial information pick-up. ("We should have the Valley average down here"; "We need a total.")

(5) Information should be prepared to a number of simple tasks, such as "flagging those which deviate more than 15 percent to plan," "designating those which are below average," etc.

(6) Managers learn a lot from displays. (For instance, A.P. discovered visually that the C.E.T.A. program in Sacramento had more participants than the one in Inland--he thought the reverse was true.)

The second report (December 12, 1975) incorporated the improvements suggested by the above results. Between the first and the second report I modified considerably the initial design of MATBORD and incorporated a number of operators such as "Reference" (which permits one to compute averages, sums, etc.), "Sort" (which permits one to extract deviant entities), and "Outlier" (which permits one to eliminate and/or replace an outlying data value). Clearly, the contact with the managerial reality influenced much my system's design. As a result, the second management report was very well received by C.Z.B. and his staff. This report was prepared on the basis of a data set showing the Actual/Plan performance of the twelve Valley Prime Sponsors over three C.E.T.A. programs (Title 1, Title 2, and Title 6). For each Title, the performance on both Enrollments and Expenditures was available, hence providing a 12 X 6 data matrix. This matrix was processed graphically in two different ways:

(1) As a whole it led to the display of:

(a) A Raw board (Figure 6.5)
(b) A Profile board computed by difference of the "ideal" 100 percent performance to Plan (Figure 6.6)
(c) The same as above, but "flagging" only those deviations which exceed + or - 15 percent to 100 percent performance (Figure 6.7)
(d) An alternative Profile board computed by difference of the average level of performance for each Title (Figure 6.8)

(2) By focusing on the Title 1 program only, I obtained:

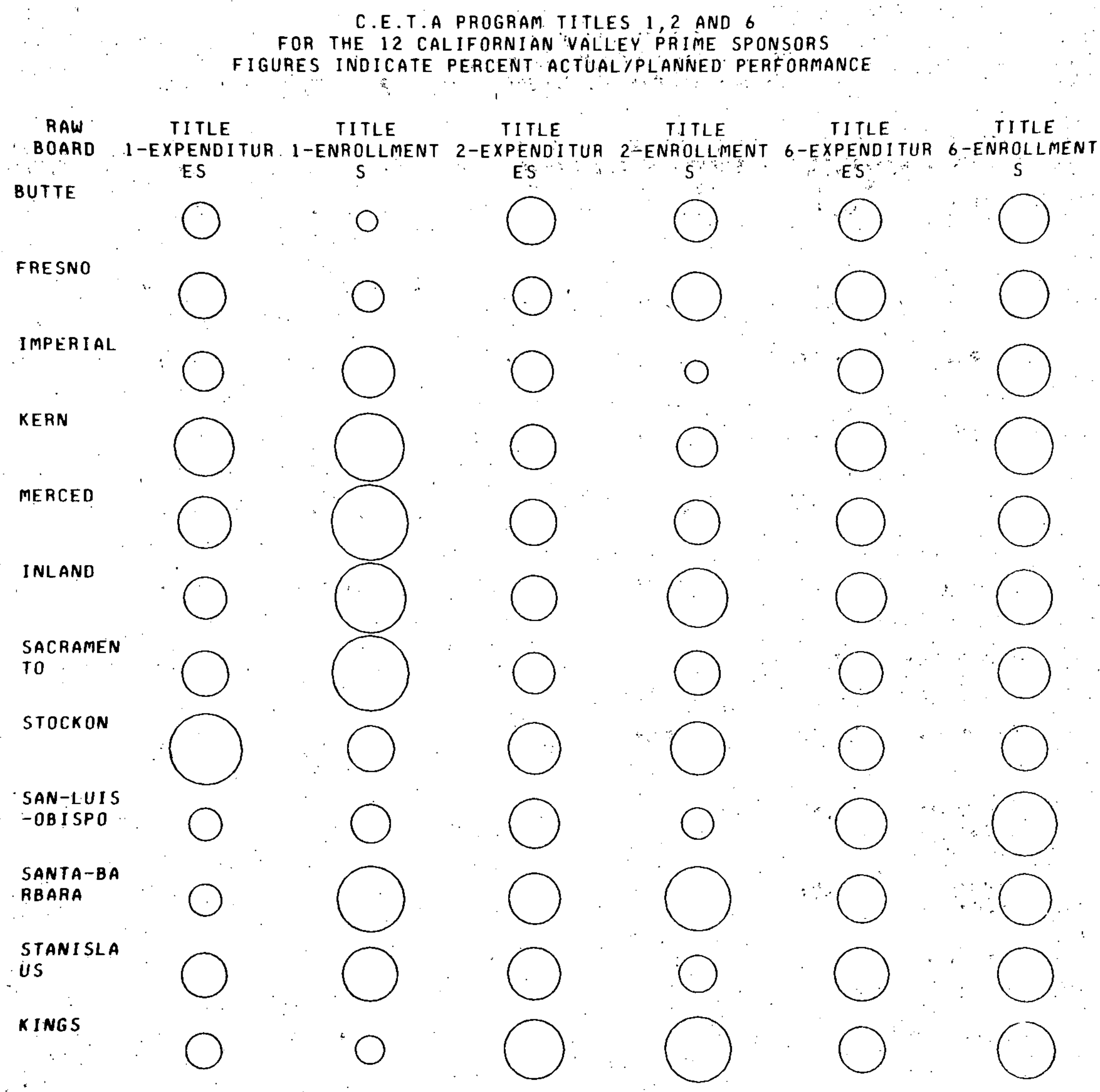


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Figure 6.5

C.E.T.A PROGRAM TITLES 1,2 AND 6
FOR THE 12 CALIFORNIAN VALLEY PRIME SPONSORS
FIGURES INDICATE PERCENT ACTUAL/PLANNED PERFORMANCE

RAW BOARD	TITLE 1-EXPENDITURES	TITLE 1-ENROLLMENTS	TITLE 2-EXPENDITURES	TITLE 2-ENROLLMENTS	TITLE 6-EXPENDITURES	TITLE 6-ENROLLMENTS
BUTTE	.69	.39	.91	.80	.80	.93
FRESNO	.87	.59	.73	.92	.94	.91
IMPERIAL	.75	.98	.79	.43	.84	.99
KERN	1.11	1.30	.86	.76	.94	1.09
MERCED	.99	1.44	.88	.85	.91	.96
INLAND	.80	1.33	.86	1.13	.95	1.04
SACRAMENTO	.87	1.44	.79	.85	.82	.98
STOCKON	1.36	.88	.99	1.02	.85	.86
SAN-LUIS-OBISPO	.62	.74	.95	.60	.97	1.22
SANTA-BARBARA	.61	1.26	.98	1.23	.92	.98
STANISLAUS	.85	1.03	1.00	.71	1.03	1.04
KINGS	.67	.54	1.13	1.24	.87	1.08

XBL 767-8650

Data Table For Figure 6.5

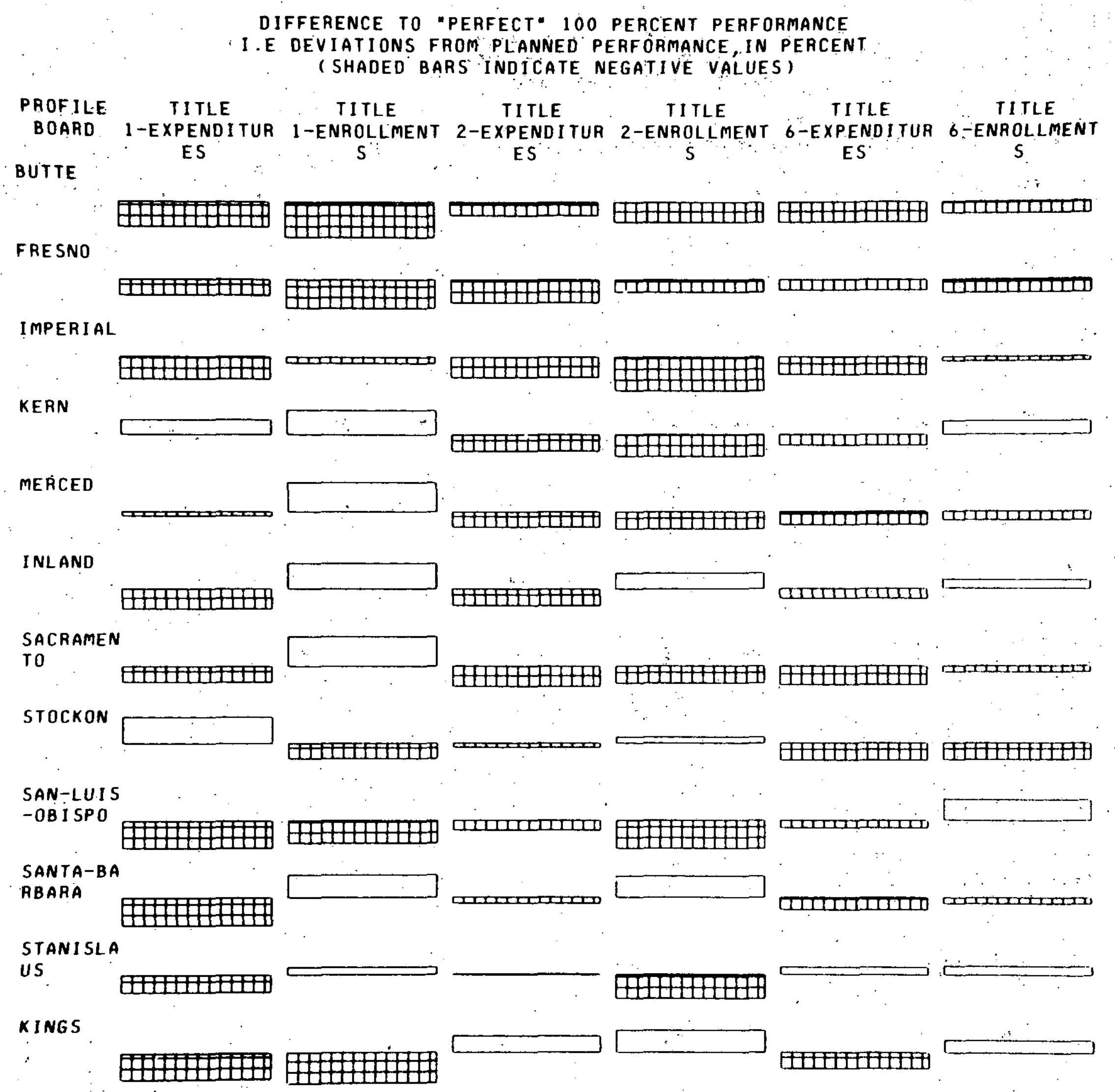

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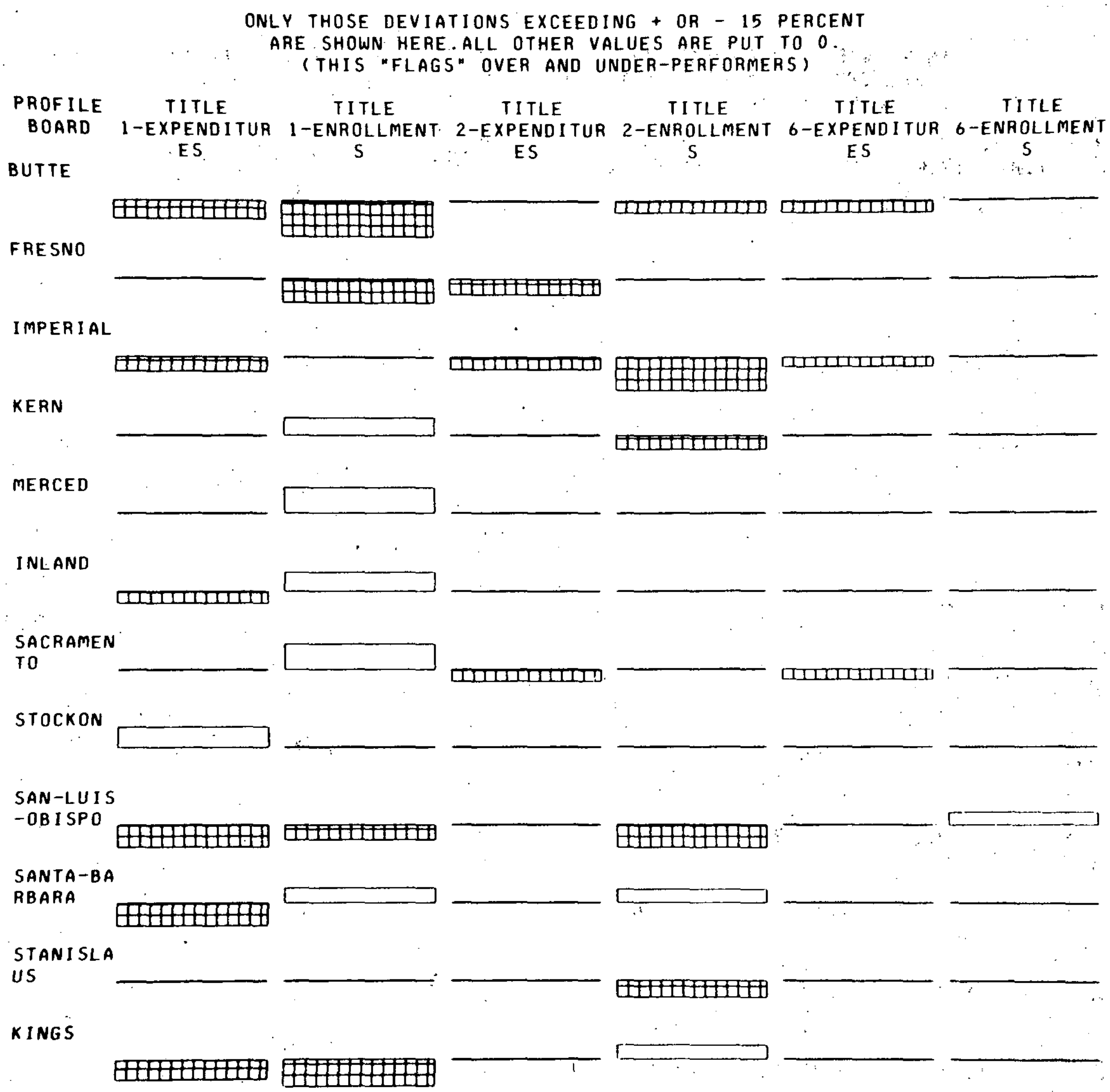
Figure 6.6

DIFFERENCE TO "PERFECT" 100 PERCENT PERFORMANCE
I.E DEVIATIONS FROM PLANNED PERFORMANCE, IN PERCENT
(SHADED BARS INDICATE NEGATIVE VALUES)

PROFILE BOARD	TITLE 1-EXPENDITURES	TITLE 1-ENROLLMENTS	TITLE 2-EXPENDITURES	TITLE 2-ENROLLMENTS	TITLE 6-EXPENDITURES	TITLE 6-ENROLLMENTS
BUTTE	-.31	-.61	-.09	-.20	-.20	-.07
FRESNO	-.13	-.41	-.27	-.08	-.06	-.09
IMPERIAL	-.25	-.02	-.21	-.57	-.16	-.01
KERN	.11	.30	-.14	-.24	-.06	.09
MERCED	-.01	.44	-.12	-.15	-.09	-.04
INLAND	-.20	.33	-.14	.13	-.05	.04
SACRAMENTO	-.13	.44	-.21	-.15	-.18	-.02
STOCKON	.36	-.12	-.01	.02	-.15	-.14
SAN-LUIS-OBISPO	-.38	-.26	-.05	-.40	-.03	.22
SANTA-BARBARA	-.39	.26	-.02	.23	-.08	-.02
STANISLAUS	-.15	.03	0.	-.29	.03	.04
KINGS	-.33	-.46	.13	.24	-.13	.08

XBL 767-8652

Data Table for Figure 6.6



XBL 767-8653

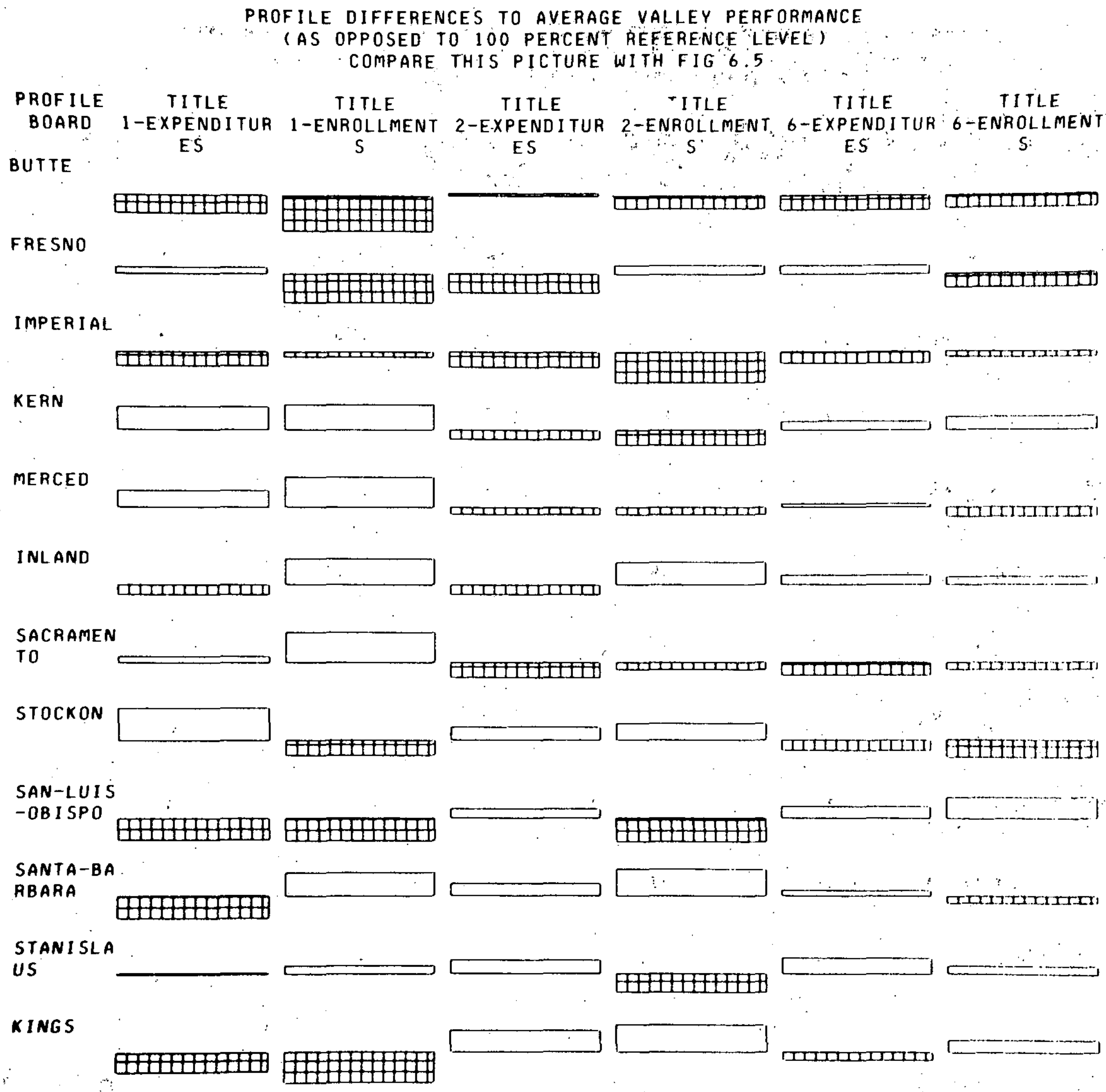
Figure 6.7

ONLY THOSE DEVIATIONS EXCEEDING + OR - 15 PERCENT
ARE SHOWN HERE.ALL OTHER VALUES ARE PUT TO 0.
(THIS "FLAGS" OVER AND UNDER-PERFORMERS)

PROFILE BOARD	TITLE 1-EXPENDITURES	TITLE 1-ENROLLMENTS	TITLE 2-EXPENDITURES	TITLE 2-ENROLLMENTS	TITLE 6-EXPENDITURES	TITLE 6-ENROLLMENTS
BUTTE	-.31	-.61	0.	-.20	-.20	0.
FRESNO	0.	-.41	-.27	0.	0.	0.
IMPERIAL	-.25	0.	-.21	-.57	-.16	0.
KERN	0.	.30	0.	-.24	0.	0.
MERCED	0.	.44	0.	0.	0.	0.
INLAND	-.20	.33	0.	0.	0.	0.
SACRAMENTO	0.	.44	-.21	0.	-.18	0.
STOCKON	.36	0.	0.	0.	0.	0.
SAN-LUIS-OBISPO	-.38	-.26	0.	-.40	0.	.22
SANTA-BARBARA	-.39	.26	0.	.23	0.	0.
STANISLAUS	0.	0.	0.	-.29	0.	0.
KINGS	-.33	-.46	0.	.24	0.	0.

XBL 767-8654

Data Table for Figure 6.7



XBL 767-8655

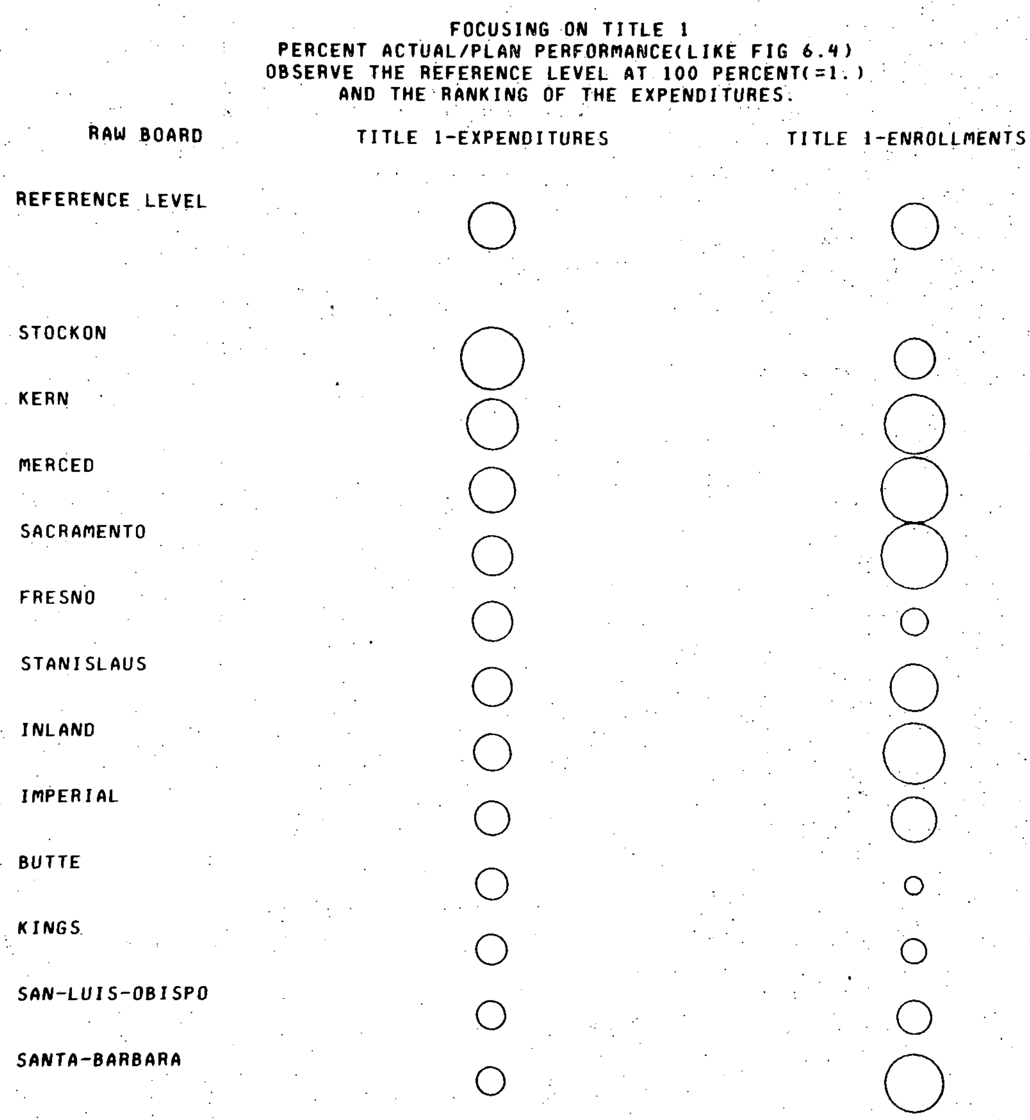
Figure 6.8

PROFILE DIFFERENCES TO AVERAGE VALLEY PERFORMANCE
(AS OPPOSED TO 100 PERCENT REFERENCE LEVEL)
COMPARE THIS PICTURE WITH FIG 6.5

PROFILE BOARD	TITLE 1-EXPENDITURES	TITLE 1-ENROLLMENTS	TITLE 2-EXPENDITURES	TITLE 2-ENROLLMENTS	TITLE 6-EXPENDITURES	TITLE 6-ENROLLMENTS
BUTTE	-.16	-.60	.00	-.08	-.10	-.08
FRESNO	.02	-.40	-.18	.04	.04	-.10
IMPERIAL	-.10	-.01	-.12	-.45	-.06	-.02
KERN	.26	.31	-.05	-.12	.04	.08
MERCED	.14	.45	-.03	-.03	.01	-.05
INLAND	-.05	.34	-.05	.25	.05	.03
SACRAMENTO	.02	.45	-.12	-.03	-.08	-.03
STOCKON	.51	-.11	.08	.14	-.05	-.15
SAN-LUIS-OBISPO	-.23	-.25	.04	-.28	.07	.21
SANTA-BARBARA	-.24	.27	.07	.35	.02	-.03
STANISLAUS	.00	.04	.09	-.17	.13	.03
KINGS	-.18	-.45	.22	.36	-.03	.07

XBL 767-8656

Data Table for Figure 6.8



XBL 767-8657

Figure 6.9

FOCUSING ON TITLE 1
PERCENT ACTUAL/PLAN PERFORMANCE(LIKE FIG 6.4)
OBSERVE THE REFERENCE LEVEL AT 100 PERCENT(=1.)
AND THE RANKING OF THE EXPENDITURES.

RAW BOARD	TITLE 1-EXPENDITURES	TITLE 1-ENROLLMENTS
REFERENCE LEVEL	1.00	1.00
STOCKON	1.36	.88
KERN	1.11	1.30
MERCED	.99	1.44
SACRAMENTO	.87	1.44
FRESNO	.87	.59
STANISLAUS	.85	1.03
INLAND	.80	1.33
IMPERIAL	.75	.98
BUTTE	.69	.39
KINGS	.67	.54
SAN-LUIS-OBISPO	.62	.74
SANTA-BARBARA	.61	1.26

XBL 767-8658

Data Table for Figure 6.9

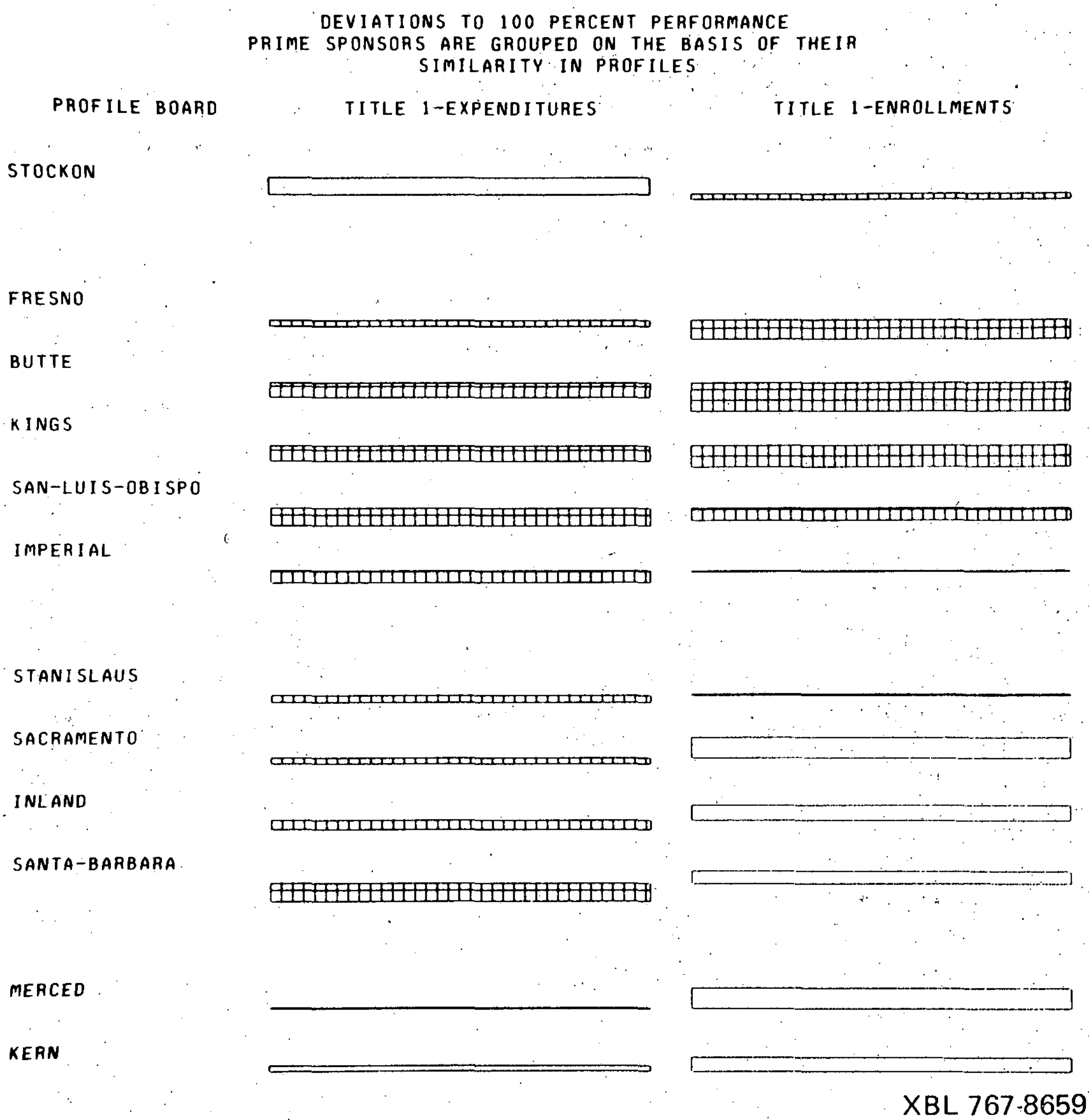

DEVIATIONS TO 100 PERCENT PERFORMANCE
PRIME SPONSORS ARE GROUPED ON THE BASIS OF THEIR
SIMILARITY IN PROFILES
PROFILE BOARD
TITLE 1-EXPENDITURES
TITLE 1-ENROLLMENTS
STOCKON
FRESNO
BUTTE
KINGS
SAN-LUIS-OBISPO
IMPERIAL
STANISLAUS
SACRAMENTO
INLAND
SANTA-BARBARA
MERCED
KERN
XBL 767-8659

Figure 6.10

DEVIATIONS TO 100 PERCENT PERFORMANCE
PRIME SPONSORS ARE GROUPED ON THE BASIS OF THEIR
SIMILARITY IN PROFILES

PROFILE BOARD	TITLE 1-EXPENDITURES	TITLE 1-ENROLLMENTS
STOCKON	.36	-.12
FRESNO	-.13	-.41
BUTTE	-.31	-.61
KINGS	-.33	-.46
SAN-LUIS-OBISPO	-.38	-.26
IMPERIAL	-.25	-.02
STANISLAUS	-.15	.03
SACRAMENTO	-.13	.44
INLAND	-.20	.33
SANTA-BARBARA	-.39	.26
MERCED	-.01	.44
KERN	.11	.30

XBL 767-8660

Data Table for Figure 6.10

(a) A ranked plot of the Raw data, with the reference level at 100 percent performance (Figure 6.9)
(b) A plot of Profile data, arranged by groups of homogeneous performance (Figure 6.10)

This presentation was very well received by the managerial "clients," but from a research viewpoint it lacked one of the most important aspects of MATBORD, namely, the use of a similarity board and its associated concepts.

VI.3 An Interactive Session with Managerial Participation

The above test examples of management reports using Matrix Displays gave me an opportunity to study the spontaneous reactions of management people to the use of Matrix Displays. I felt, however, that, in relation to the design of MATBORD, there was a research need for observing the reactions of managers to the interactive system itself. In particular, I hoped that a direct interactive session at the terminal would bring:

(1) An opportunity for the complete tracing of an interactive session, providing an amount of material on the frequency of use of commands in MATBORD and on the think times associated with those commands

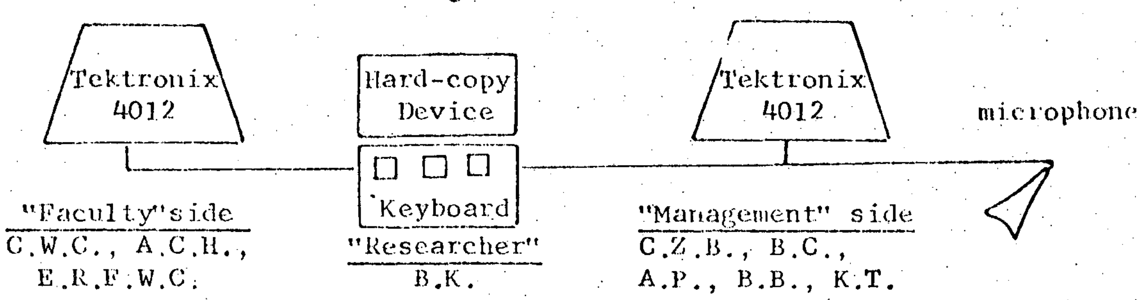
(2) Some behavioral evidence as to how the managers adapt (or do not adapt) to the several levels of data analysis provided by the system

(3) Some elements of reflection as to the potential problems and benefits associated with the implementation of Matrix Displays in a managerial context

Given the exploratory character of this work and its emphasis on the participation of "real-life" managers, I designed an original method for the organization of the interactive session. The difficulty of assuming two distinct roles, as the designer and proponent of a system and as the scientific inquirer looking at how managers behave with respect to the system was solved on the suggestion of C. W. Churchman to invite the three faculty members of this thesis committee to observe the interaction. They would represent the "scientific inquiry" viewpoint, thus freeing the researcher for an active participation in the interactive session.

The participants in the interactive session included besides C.Z.B. and his staff (B.C. and A.P.), two other staff members of the Region IX Office of the Manpower Administration, namely, B.B. and K.T. (see Figure 6.1). At this time, B.B. was the liaison agent between the Manpower Administration and the Lawrence Berkeley Laboratory so that he was perfectly aware of the development of MATBORD. (K.T. was his aide.) The interactive session was set-up in such a way that each "audience" (faculty and management) had its own graphic screen. The two screens were synchronous so that the commands, keyed-in by the author, resulted in the same sequence of pictures. The layout of the room was as follows:

Figure 6.11



The interactive session itself was integrated within a larger semi-experimental framework including:

(1) The presentation of MATBORD through a 25 minute videotape, showing the general capabilities of the system on a "dummy" data set (after an idea by A. C. Hoggatt)

(2) The interactive session itself. During the session, the

sequence of commands (time and cost) were traced by the computer, and a microphone recorded the verbal reactions of the management participants. After the session, the managers were asked to fill out an evaluation questionnaire of the "attitude scale" type.

(3) A round-table discussion with the active participation of both management and faculty about the merits and limitations of MATBORD. This discussion was also tape-recorded.

In the following subsections, I focus on the results brought out by the interactive session itself (2). The protocols of the round-table discussion (3) are such a rich material that I devote most of section VI.4 to their interpretation.

VI.3.1 General Features of the Interactive Session

I directed the interactive session along a plan of analysis strictly analogous to the one followed in the test run (Figures 6.5 to 6.10). However, given the interactive character of the session and its intent, I had the difficult task to follow the suggestions of the audience and still to show most of the system's capabilities. Faculty members helped me understand the suggestion of the management participants, and thus they determined the "turning points" of the interaction.

The interaction was 73 minutes 5 seconds long, and its total cost, including the computer cost ($14) and the terminal cost ($6), was about $20. The statistics of use of commands are given in Table 6.1. A number of observations result from this table:

(1) The most frequently used commands ($N \geqslant 6$) include display mode commands (Profile, Raw), graphic formatting commands (in particular, the capability to Plot the digits themselves), and simple analytic commands (Sequence and Group) which both depend upon user specifications.

(2) The commands which are most costly ($0.40) are those relating to the use of a similarity board, i.e., Similarity, Bin, and Switch. (The latter was used exclusively in relation to the similarity board.) The commands involving the re-

organization of the whole data structure (Sequence, Rank, Restore, Raw) are second in cost at about $0.25. Finally, commands which involve simple arithmetic and/or plotting procedures are pretty cheap (around $0.15). This corresponds to what should be expected.

(3) The overall average think time is slightly inferior to a minute (56 seconds). Of course, this figure has only an indicative value, since it includes a variety of factors (perception/cognition/inference). However, it provides an order of magnitude of the time which it takes a human user to "react to" a given Matrix Display board. It is interesting to note that the longest average times are associated with those operators which rearrange the picture either analytically (by permuting rows or columns in a significant order) or graphically.

(4) Another command of particular value seems to be the command which permits obtaining the numerical data table corresponding to any Matrix Display ("Plot Digits"). Given its low cost ($0.11) and its high think time value (up to 2 minutes 50 seconds maximum think time), this command seems to have a quite high informational value. This confirms the result reached in the field study that Matrix Displays need be complemented by the corresponding data tables.

(5) The above table shows that the Profile command was very popular. This is confirmed by a study of the total length of time spent in Profile mode. Given that at any point in the analytic process the display is either in Raw or Profile or Similarity mode, it is clear that the total length of time in any mode includes a variety of elementary operations (i.e., commands such as Rank, Sequence, Group, etc.). Table 6.2 shows a study of the length of time spent in the three modes during the major phases of analysis. The system was in Profile mode 60 percent of the time, which confirms the claim that the computation of data profiles is central to the Matrix Display analytic process.

(6) Table 6.2 data also provides for the interesting observation that each analytical phase (I, II, and III) lasted approximately the same amount of time (i.e., 20 minutes to 26 minutes). This suggests that the average size of an informational inquiry might be limited by cognitive factors such as the need to preserve continuity in thought processes (Miller, 1968). It might be the case that the interactive use of Matrix Displays proceeds by "chunks of inquiry" approximately 20 minutes long (or equivalently 20 commands long).

Table 6.1

Commands	Number of calls (N)	Average cost (in $)	Average Think-Time (T)	Average Think-Time (T)
Profile	8	$0.16	49 sec	1 min 29 sec
Sequence	8	0.23	57 sec	2 min 11 sec
Plot (Digits)	6	0.11	59 sec	2 min 50 sec
Plot (Graphics)	6	0.16	25 sec	52 sec
Group	6	0.17	1 min 20 sec	2 min 48 sec
Raw	6	0.21	37 sec	1 min 41 sec
Enhance	5	0.13	2 min 55 sec	10 min 8 sec
Rank	4	0.23	2 min 6 sec	5 min 6 sec
Restore	4	0.28	39 sec	1 min 2 sec
Switch	4	0.39	37 sec	50 sec
Window	3	0.13	11 sec	21 sec
Similarity	2	0.43	15 sec	30 sec
Bin	2	0.44	1 min 19 sec	3 min 17 sec
Reference	1	0.14	-	53 sec
Compact	1	0.11	-	15 sec
Sort	1	0.15	-	8 sec
Utility Commands	13	0.02	10 sec	50 sec
Total	79	0.18	56 sec	10 min 8 sec

NOTE: The highest figures are underlined.

Table 6.2

Modes	Phases I	Phases II	Phases III	Total
Raw	6 min 31 sec	3 min 23 sec	3 min 28 sec	13 min 22 sec
Profile	12 min 22 sec	17 min 27 sec	15 min	44 min 49 sec
Similarity	6 min 23 sec	-	8 min 31 sec	14 min 54 sec
Total	25 min 16 sec	20 min 50 sec	26 min 59 sec	73 min 5 sec

VI.3.2 The Verbal Protocol of Managerial Reactions

Given the emphasis of this work on feasibility issues, I complemented the time-and-cost data by two qualitative assessments of Matrix Displays. The presence of management people at the terminal was an opportunity to study verbal reactions and attitudes in relation to the displays which were presented. This qualitative data was collected in two different ways, namely, (1) the recording of the participants' verbal comments and (2) attitude scale questionnaires where the managerial participants rated the system.

This section describes the results obtained under (1). The complete protocol of verbal reactions to the system in shown in Appendix B. An attentive study of this protocol shows that C.Z.B. was the leading character during the interactive session. It is possible to observe the evolution of C.Z.B.'s satisfaction or dissatisfaction as the interaction goes on. For purposes of clarification the interactive session can be divided into three phases:

(1) During the first phase, the C.E.T.A. data set is analyzed as a whole, and C.Z.B. is satisfied up to a point where I suggest to go on into the similarity mode. Figure 6.12 shows the evolution of C.Z.B.'s satisfaction (+) and dissatisfaction (-) during this phase. Clearly, the manager's satisfaction decreases as soon as the similarity board is on the screen (numbers refer to the interventions in the protocol, Appendix B).

(2) During the second phase, it was decided to break the data set into three meaningful subsets and to analyze each independently. As shown by the Figure 6.13, C.Z.B.'s satisfaction grew in the process, after some difficulty "getting started." C.Z.B.'s satisfaction culminates in comment no. 50, "Gee. That tells something." It then decreases with the recognition that the interactive process is longer than it should be in the sense that "what a manager wants to know is the end-product (no. 54)."

(3) Finally, the third phase (Figure 6.14) is again an analysis of the whole data set whereby I attempted to establish a

C.Z.B.'s Satisfaction During the Interaction

(Numbers refer to the interventions in Appendix B.)

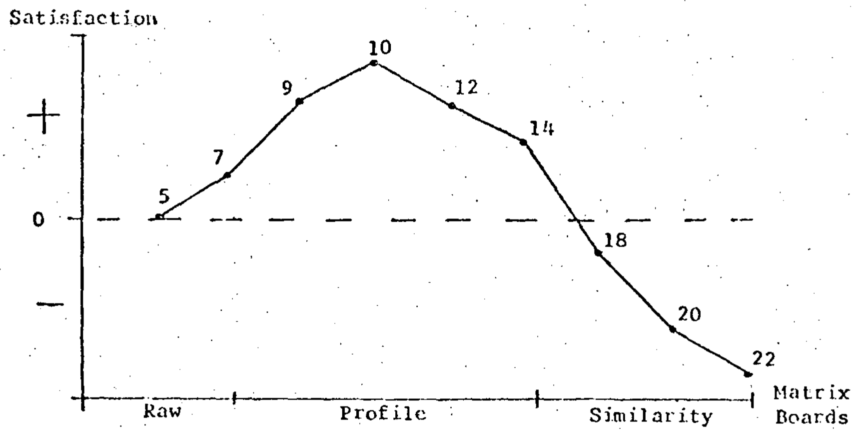


Figure 6.12
(First phase of interaction)

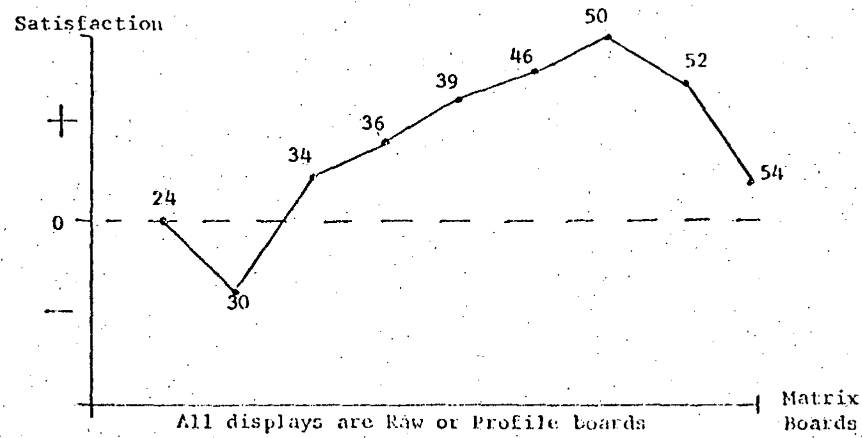


Figure 6.13
(Second phase of interaction)

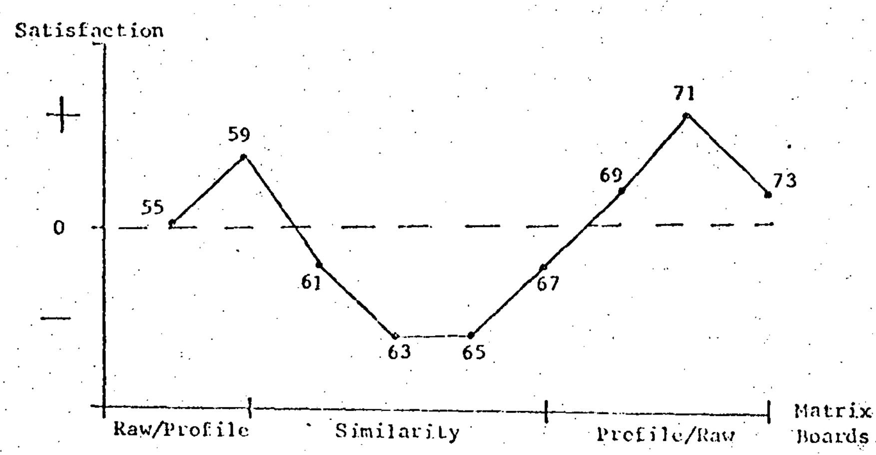


Figure 6.14
(Third phase of interaction)

clustering of the Prime Sponsors based upon a similarity plot. C.Z.B.'s reactions then were moderately negative and started becoming positive again when the system was back into Profile mode.

The main result which the above plots illustrate is the relative difficulty for C.Z.B. to accept the Similarity board, as opposed to the Profile or Raw boards. It clearly appears that the Similarity display, with all its analytical implications, was "difficult to swallow" for the following (verbalized) reasons:

(1) A manager does not have time to spend in a detailed analytical process. He needs "quick scans ((34), (54), (61))."

(2) The similarity board is not easy to understand: "Just visually it is not easy to see what it means ((20), (22))."

(3) The connection between the concepts of "clustering" and "similarity" is not perceived. For C.Z.B., a relevant clustering is a clustering which shows up on the Profile matrix ((12), (18)).

An attentive study of C.Z.B.'s reactions further reveals his difficulty in coping with the concept of multidimensionality. For him the criterion of clustering must be simple--such as "cluster together those which are 90 percent of Plan, those which are 70 to 90 percent of Plan, etc. ((26))."--or else the concept of clustering is lost. At one point, C.Z.B. receives an explanation from B.C. ((42), (44)) which illuminates for him the concept of dependence between two different factors. But reasoning on more than two factors at a time seems very difficult, if not impossible to him.

On the other hand, the process by which reference arrays are defined so as to permit profile computations is perfectly understood ((7), (32), (46), (37)). Even the general process of deepening progressively the analysis up to a point where "the evidence holds together in the best manner" seems to be clearly understood, at least by the end of the interactive session (67). The spontaneous tasks which the manager and his staff execute by pointing at the screen fit well the hypotheses that size and profile comparisons are central to management information pick-up ((9), (10), and (38) to (52)). Another observation is that the level of need in analytical sophistication differs among the management participants themselves: For instance, A.P. (27) expresses a very low level of comprehension over the whole session (much lower than C.Z.B. himself), while B.C. is quite active in the process. He recommends courses of action (29), comments on the relation between variables ((38), (42), (44)), integrates size effects within a profile analysis (51), and finally proposes to improve the interactive program itself by incorporating weighing procedures (73).

In summary, the verbal protocols of the interactive session suggests that:

(1) The general concept of Matrix Displays and the process of analysis have been perceived correctly. This supports the thesis of the feasibility of Interactive Matrix Displays.

(2) The Raw and Profile boards are accepted and recognized as display aids. However, the Similarity board does not seem to be an acceptable format for direct managerial usage.

(3) Its usefulness is recognized at a technical, analytic level. "Analytic types," such as B.C., seem to be interested in a similarity board approach.

VI.3.3 Management Attitudes

Immediately after the interactive session ended, the participants were asked to fill out a questionnaire covering most of the system's capabilities. The fifteen questions asked for a rating of each feature on a 5-interval attitude scale, from "very useful" (score, +2) to "not useful at all" (score, -2). The questions related to:

(1) The process of matrix analysis, i.e., attitudes with respect to the Raw, Profile, and Similarity boards, as well as the understanding of the notion of "Reference" arrays

(2) The use of analytic operators such as Ranking, Grouping, "Flagging" deviant entities, and clustering procedures based upon a more sophisticated statistical analysis of the similarity matrix

(3) The graphic aspects, including the process of mapping numbers into graphic items and the display features themselves

(4) The possibility of calibrating the raw data by data selection procedures (Masking) and by aggregation procedures ("Clumping")

Each of the interaction participants (C.Z.B., B.C., A.P., B.B., and K.T.) filled out a questionnaire, thus providing five answer sheets. To these I added two more questionnaires filled out by two staff members of the Regional Office, who happened to participate in an exactly similar session two days later (February 11, 1976). These staff people, J.K. and S.L. in Figure 6.1, are in charge of Data Analysis at the Regional Office. By pooling the complete attitude data together I get the 15 X 7 raw data matrix shown in Table 6.3. Each elementary score may take an integer value between -2 (lowest score) and +2 (highest score). The left-hand side column and the upper row of the table show average scores over users and over system's capabilities. Missing values (absence of answers) have been replaced by the average score of the respondent himself. For instance, B.C. who did not answer the question on Profile is given the score .92 on that question, i.e., his own average score over all other questions he answered.

The row and column entries of Table 6.3 are ranked according to the corresponding averages. On the user's side, it is quite remarkable that the highest average scores (average scores greater than +1) are given by primarily staff people (S.L., K.T., and B.B.), while the lowest average score (lower than .5) is given by the person having a purely "line" responsibility (A.P.); and C.Z.B. stands somewhere between these extremes. On the system's capabilities side, it is quite remarkable that the two attitudinal questions relating to "help in learning" and to "answer own management needs" receive the highest average judgment score (+1.43) and the lowest average judgment score (+.43).

Between these two extreme attitudes, there appears to be a better appreciation of the system's compact analytic operators (ranking, grouping, flagging), and calibration procedures (data selection, aggregating) than of its mapping (mapping, display) and statistical analysis features (similarity, clustering). This indicates that the managerial users are more able to appreciate and use an end-product picture than to understand the analytic process itself. A typical example in this respect is the Profile command, which stands high in the user's appreciation (average judgment, +1.20), while its necessary preparatory step, the Reference command, stands quite low (average judgment, +.57). In other words, managerial users tend to appreciate more the end-result than the process of analysis itself.

A graphic representation of Table 6.3 is shown in Figure 6.15. Clearly, the overall appreciation of the system is largely positive. There are very few negative judgments (indicated by dark spots), and all such are principally located in A.P.'s judgments. This raw data matrix can be used to compute differential profiles, by taking the difference between each user's judgments and the average judgment column. This results in Figure 6.16, where furthermore C.Z.B.'s judgments have been rank-ordered from highest to lowest difference to average. Observe that C.Z.B.'s judgments are above the average judgment for those aspects of the system which can be understood in a non-technical manner: grouping, ranking, clustering, and "help learning," "answer own needs," and "help management tasks" kinds of appreciation. It is also interesting to note that C.Z.B. seems to have appreciate the general process of defining reference arrays for the purpose of running a statistical analysis. On the other hand, the more technical aspects such as the mapping process, the definition of a Similarity board, and even the Profile board receive less appreciation than average. Overall C.Z.B.'s profile is very well balanced between above average ("positive") and below average ("negative") judgments.

When the same display is organized on the basis of A.P.'s judgments (Figure 6.17), an interesting picture emerges whereby A.P. seems to be pretty unique in his attitude to the system. His general profile show more negative than positive judgments, with positive judgments concentrated mainly on the display features of the system. Practically all the analytic capabilities are seen negatively including calibration procedures, low-level analytic features, and the general process of defining Profile and Similarity boards. The only exception is the definition of References which indicates that A.P. is favorably disposed to the display of Raw data only. All other users' profiles are largely different from A.P.'s, particularly in that they show mainly positive deviations to average. For instance, S.L.'s profile is almost the reverse of A.P.'s, showing a clear satisfaction with analytic (rather than graphic) features. K.T. and B.B. show positive judgments of both analytic and graphic display features. B.C. and C.Z.B. have "balanced profiles" with a mix of positive and negative judgments. Only does J.K. show a largely negative profile, but in a quite different manner from

Table 6.3

RAW BOARD	AVE.JUD GMENT	S.L	K.T	B.B	B.C	C.Z.B	J.K	A.P
AVERAGE SCORE	.92	1.27	1.27	1.21	.92	.87	.58	.29
HELP LEARNING	1.43	1.00	1.00	2.00	2.00	2.00	0.	2.00
RANKING	1.43	2.00	1.00	2.00	1.00	2.00	2.00	0.
GROUPING	1.33	2.00	2.00	2.00	1.00	2.00	.58	-1.00
PROFILE	1.20	2.00	1.00	1.00	.92	1.00	1.00	.29
DATA SELECTION	1.14	2.00	0.	2.00	1.00	1.00	1.00	1.00
AGGREGATING	1.00	1.27	2.00	2.00	1.00	1.00	1.00	-1.00
FLAGGING	1.00	2.00	1.00	1.21	.92	0.	0.	2.00
MANAGEMENT TASKS	.83	1.00	1.00	1.00	1.00	1.00	.58	0.
MAPPING	.83	2.00	2.00	0.	1.00	-1.00	.58	1.00
SIMILARITY	.71	1.00	2.00	1.00	1.00	0.	1.00	-1.00
CLUSTERING	.71	1.00	2.00	0.	1.00	1.00	1.00	-1.00
STATISTICAL ANALYSIS	.71	1.00	1.00	0.	2.00	1.00	0.	0.
DISPLAY	.71	0.	1.00	1.00	1.00	0.	0.	2.00
REFERENCES	.57	0.	1.00	2.00	-1.00	1.00	0.	1.00
OWN NEEDS	.43	1.00	1.00	1.00	0.	1.00	0.	-1.00

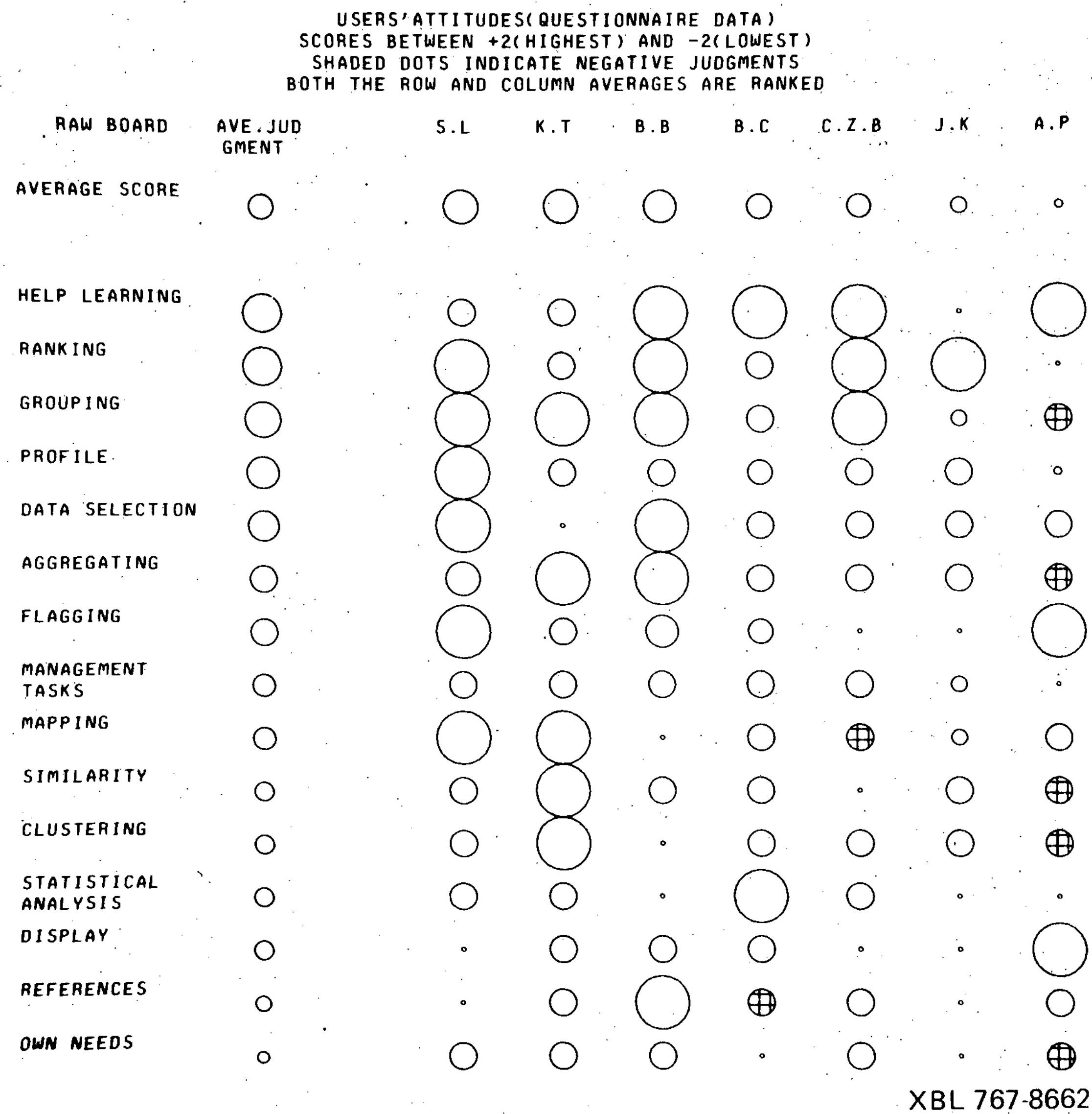

USERS'ATTITUDES(QUESTIONNAIRE DATA)
SCORES BETWEEN +2(HIGHEST) AND -2(LOWEST)
SHADED DOTS INDICATE NEGATIVE JUDGMENTS
BOTH THE ROW AND COLUMN AVERAGES ARE RANKED
RAW BOARD
AVE.JUD GMENT
S.L
K.T
B.B
B.C
C.Z.B
J.K
A.P
AVERAGE SCORE
HELP LEARNING
RANKING
GROUPING
PROFILE
DATA SELECTION
AGGREGATING
FLAGGING
MANAGEMENT TASKS
MAPPING
SIMILARITY
CLUSTERING
STATISTICAL ANALYSIS
DISPLAY
REFERENCES
OWN NEEDS
XBL 767-8662

Figure 6.15

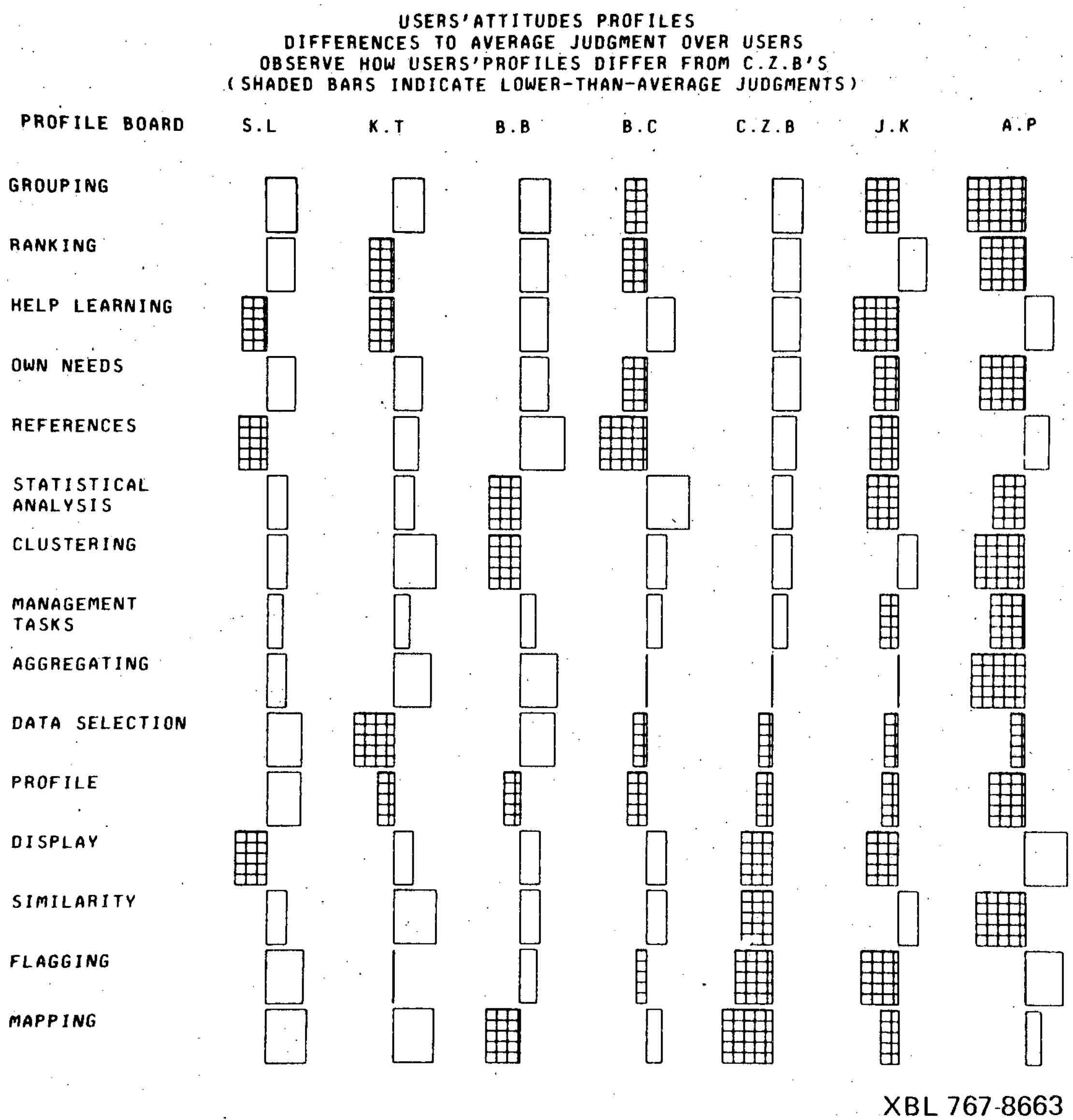
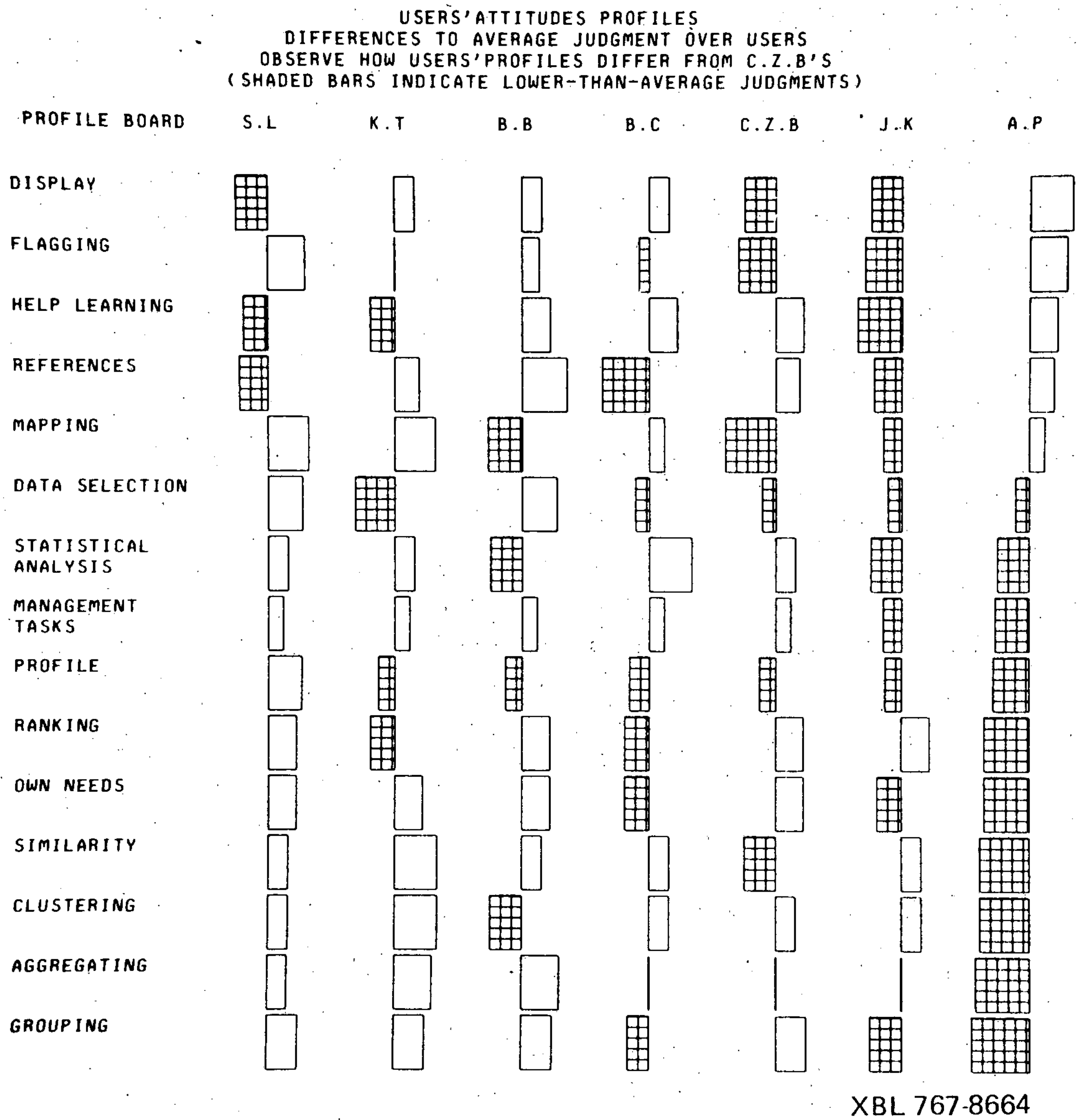

USERS'ATTITUDES PROFILES
DIFFERENCES TO AVERAGE JUDGMENT OVER USERS
OBSERVE HOW USERS'PROFILES DIFFER FROM C.Z.B'S
(SHADED BARS INDICATE LOWER-THAN-AVERAGE JUDGMENTS)
PROFILE BOARD
S.L
K.T
B.B
B.C
C.Z.B
J.K
A.P
GROUPING
RANKING
HELP LEARNING
OWN NEEDS
REFERENCES
STATISTICAL ANALYSIS
CLUSTERING
MANAGEMENT TASKS
AGGREGATING
DATA SELECTION
PROFILE
DISPLAY
SIMILARITY
FLAGGING
MAPPING
XBL 767-8663

Figure 6.16



USERS'ATTITUDES PROFILES
DIFFERENCES TO AVERAGE JUDGMENT OVER USERS
OBSERVE HOW USERS'PROFILES DIFFER FROM C.Z.B'S
(SHADED BARS INDICATE LOWER-THAN-AVERAGE JUDGMENTS)
PROFILE BOARD
S.L
K.T
B.B
B.C
C.Z.B
J.K
A.P
DISPLAY
FLAGGING
HELP LEARNING
REFERENCES
MAPPING
DATA SELECTION
STATISTICAL ANALYSIS
MANAGEMENT TASKS
PROFILE
RANKING
OWN NEEDS
SIMILARITY
CLUSTERING
AGGREGATING
GROUPING
XBL 767-8664

Figure 6.17

A.P.'s: J.K.'s only above average scores relate to the sophisticated analysis part, including the Ranking, the Similarity, and the Clustering commands.

In sum, the results of the attitude questionnaire show:

(1) A general positive attitude toward Matrix Displays and the interactive MATBORD system.

(2) Large variations in the understanding and appreciation of the analytic process. Some users seem to be content with the Raw data board only (A.P.); others are satisfied at the Similarity level and up (J.K.). However, most users seem to be more at ease with the intermediary Profile stage.

(3) In general, the users appreciate a certain amount of sophistication in the commands (level B sophistication in V.3.2), so long as their effects remain understandable. There seems to be a difficulty in the appreciation of technical notions, particularly for the middle-line management level (C.Z.B., B.C., and A.P.). To a certain extent, staff people look quite ready to deal with technical notions (B.B., K.T., and S.L.).

VI.4 MIS and Interactive Matrix Displays: A Future?

The above results seem to indicate that the managerial feasibility of Matrix Displays is not as straightforward a matter as their technical feasibility. On the one hand, it seems that the use of Raw and Profile displays for management information purposes is clearly appreciated by the observed managerial people. On the other hand, it appears that the notion of Similarity and its corresponding procedures and displays is difficult for management users to understand and therefore to appreciate. Consequently, there seems to be a gap between the technical feasibility and the managerial feasibility of Matrix Displays, to the extent that the use of such displays for analytic purposes may be partially rejected.

An interesting source of reflection on those matters is provided by the round-table discussion between management and faculty participants which followed the interaction. The protocol of this discussion is presented in Appendix C and commented upon below. (Numbers in parentheses refer to the interventions recorded in that protocol.)

VI.4.1 A Manager and His Informational Needs

The comments of C.Z.B. during the round-table discussion are an invaluable source of reflection on the informational needs of <u>a</u> manager. Hopefully, however, this reflection might help highlight a class of needs which is proper to a larger number of management people.

For purposes of clarification, I group under six major headings the informational needs which C.Z.B. emphasized over the discussion.

(1) Need for immediate information.

> "How can we get information quickly? How do we retrieve quickly? I am looking for immediate response time." (2)
>
> "Why wait five years after the termination of a project to analyze it. Why not analyze what's going on during the operational phase, and, hopefully we can come up with an analysis?" (9)

(2) Need for specifically prepared information.

> "The information is in the computer, but we, as managers, need to ask specifically certain questions to get it out." (2)
>
> "How do I sell this concept: Give me the things to read out which I want to see quickly?" (36)

(3) Need for getting clear lines of evidence.

> "Forty-seven Prime Sponsors are a lot. If a picture tells me 'those are the factors,' then it clarifies my thoughts." (42)
>
> "In a nutshell, if it is a ten-step process, how can I get four sheets of paper; what will give me that information?" (2)

(4) Need for a homogeneous information system.

"If you focus down on what is a management information system, there may be 100 different opinions as to what is an information system. As a Fed-rep, each one will know what's going on within their project. But as a manager, I will not know nor will my boss know, and as you go right up the line to Washington, they will not know." (9)

"The system should be able to break down from national to regional, to the valley, to particular Prime Sponsor." (13)

"I think I am looking for some standardization." (42)

(5) Need for communicating information to others (acting on them).

". . . so that I can get a handle on Prime Sponsors' performance and alert the Fed-reps if there appears to be a problem." (2)

". . . trying to visualize and understand how this could be presented to other people (say, if I'm making a presentation to the Prime Sponsors)." (2)

(6) Need for a synthetic comprehension of system's capabilities.

"I don't really care about the best approach, so long as I can understand and use it . . . ." (42)

"I'm looking for a kind of "end-of-the-tunnel" information . . . basically, I'm thinking what goes into the tunnel and what goes out of the tunnel and what kind of a quick analysis I need in-between. . . . while we are going thru the tunnel, the computer will be doing certain action, but then on the end, the manager will have this kind of information." (2)

Also the manager expressed his satisfaction on certain, limited aspects of Matrix Displays:

(7) A global appraisal of Matrix Displays.

"Graphically, I can see much more quickly . . . ." (2)

"I found it helpful to me as we come to clustering those that are off 15 percent one way or another . . . . I think it's starting to zero-in on a particular kind of problem that would be quite helpful to me." (11)

"I'm convinced . . . that this test run alerted me to certain problems. . . . Graphics will assist me in referring out those Prime Sponsors that may have potential problems. I think that the system has possibilities." (19)

Although this was a form of a recognition of the utility of Matrix Displays, the prevailing feeling was that of a gap between the needs (1) through (6) and the proposed system (7).

VI.4.2 Suggestions for a Gap-Bridging Person

Two of the participants in the round-table discussion had a leading role in suggesting ways in which the system could answer managerial needs. A.C.H., on the academic side, and B.B., on the management side, converged together trying to conciliate the two seemingly conflicting requirements:

(1) Get clear informational statements for the manager (A.C.H., 32).

(2) Get analytic justifications of such statements (A.C.H., 22).

The method which they suggest to use is based upon the idea that there should be an intermediary link between the computer and the manager. They propose that this link, "the analyst," is the direct client of the Matrix Display process and that he himself works for the manager.

> Somebody is going to have to analyze this: it's not likely to be in top management; it's not likely to be in the Fed-reps. It is likely to be an analyst somewhere and he is going to be interested in the Similarity board (B.B., 12).

> Having watched several projects, the desire is to get the manager in touch with the computer; but actually I don't see it happening. Rather I see the computer getting in touch with the analyst getting in touch with the manager (B.B., 35).

> Maybe you should shift this (system) a little bit and work more closely to the analyst and get clear statements about what the data says. The whole thing must be tuned . . . (A.C.H., 32).

Furthermore, the discussion also provides a basis for defining a few characteristics of the analyst's job, namely:

(1) The capacity to adapt to his audience from "Fed-reps" to top management.

"There is a key to each level and by going through all the levels, each one is going to want to see a different thing (B.B., 12)."

"Hopefully, we could tell the same thing to different people in different ways (B.B., 41)."

(2) The capacity to justify the pictures obtained in relation to the data themselves.

"As soon as this thing is producing answers that you, managers, believe, you are going to have a problem to convince your assistants to pay attention (A.C.H., 22)."

(3) The capacity to advise management on the basis of the analytical results.

"It seems to me that you should be able to tell (a manager who fails), 'how do I change my operations so that I come up on those measures you tell me you are going to evaluate' (A.C.H., 26)."

"You can look at those similarities between those which perform well and look at the way their programs are operating, and say, 'Here are the similarities among the operations of people who are performing well. Maybe you could do the same, or better' (B.B., 27)."

One managerial participant in the interactive session, B.C., offered reactions which suggest that he might have an information analyst's profile. His perception of the process of Matrix Display analysis (4,6), his distinction between longitudinal time-series system and the multidimensional character of MATBORD (8), and his appreciation of graphic displays as an aid to "lay persons" (21) offer some evidence that his understanding of Matrix Displays was higher than average.

In sum, the round-table discussion led to the suggestion that there needs to be an intermediary person between managerial users and MATBORD. This analyst should be capable of using all the analytic resources of the system (such as the Similarity board), so as to discover suitable statistical structures in the data; he should essentially communicate end-product pictures, so that the manager is informed in as economical a way as possible; and finally he should be able to adapt to a variety of information clients within the organization, from middle-line to top management.

VI.4.3 Some Conclusions

In section V.4.3, I enunciated a few research issues which the managerial feasibility aspect elicited. The empirical case study of implementation which I realized in a management environment permits formulating some exploratory results on those issues:

(1) The concept of Matrix Display (i.e., the graphic format of a matrix representation) is understood and well accepted by management people. (There was no questioning at all of the graphic format.)

(2) The three-step analytical process is accepted differentially by management people: The Raw and Profile boards are fairly well accepted (only one user over seven did object to the Profile board); the Profile concept is highly appreciated, and fairly used in terms of "think times." On the other hand, only one user over seven clearly indicated his support of the Similarity concept. All the other users' reactions range from mild acceptance to complete rejection of the similarity matrix. The manager who had a central role in the implementation process (C.Z.B.) showed a psychological "blockage" toward the direct use of this analytic notion.

(3) It appears that management people accept a fairly high level of sophistication in the system's commands, so long as they understand the end-result pictures. It seems that the use of a Similarity board would have been better understood if automatic manipulation routines ("level C" sophistication in V.3.2) had been made available, thus accelerating the process of similarity analysis.

(4) One definite result is that the manager does not need to get all the pictures generated during the process of matrix analysis. Rather he needs a selection of a very few pictures ("I need three pictures" was C.Z.B.'s claim) preferably prepared beforehand by an information analyst.

(5) The question was raised of how would an intermediary analyst decide upon which pictures to select for managerial usage. A suggestion was made that the manager sit in front of the graphic screen and be presented very quickly a set of pictures among which to choose. Another suggestion was to let the analyst choose the relevant pictures according to his knowledge of the manager's needs.

(6) It seems that the pictures should always be presented along with the corresponding data, and the list of operations made to arrive at the specific displays. There was a claim made that the manager must be able to explain how any picture is arrived at and to justify it in front of adversary opinions. Moreover, it was suggested that Matrix Displays be used for education purposes (improving management by showing "profiles of good performance").

About six months after the above session took place, two-thirds of the interactive Matrix Display system (MATBORD) was incorporated within a larger graphic system for management information reporting (CHART, Benson, 1976). Practically, the <u>Raw</u> and <u>Profile</u> modes and all the graphic mapping and simple analytical commands were chosen to belong to this larger system. This represents quite a major appreciation of the feasibility of interactive Matrix Displays for management information reporting. It confirms the results of the case study at the U.S. Manpower Administration.

It is characteristic, however, that the Similarity board, which represents the major technical step in matrix data analysis, has not yet been selected to belong to the larger graphic system mentioned above. It is a conclusion of this thesis that the concept of Similarity and its implications

(1) Have much value in a technical sense (i.e., <u>are technically and theoretically feasible</u>)

(2) Are not directly acceptable by a manager (i.e., <u>are not feasible as a direct aid to management</u>)

Consequently, there seems to be a definite need for an intermediary analytic level between the manager, the data, and the concept of Similarity. It is proposed in this thesis that a "management information analyst" function is necessary in the organization chart of those organizations which plan to use interactive Matrix Displays.

In summary, this thesis has shown ways in which Matrix Displays can be made useful to management. In particular, it has clearly assessed the costs and rewards associated with the use of Matrix Displays. In the long run, it is expected that the benefits will largely balance the learning efforts required from managers to use Matrix Displays.

APPENDIX A

MATBORD

An Interactive Graphics Program
for Management Information Analysis
using Matrix Display Techniques

Bernard Kitous

March 20, 1976

Welcome to the interactive Matrix-board.

The general principle of MATBORD is to represent numerical data tables into a graphic display format, so that data analysis can be done in a visual fashion. The displays are called MATRIX DISPLAY BOARDS, since they can be manipulated row-wise and column-wise as matrix boards would be. The system of graphic representation includes circles, bars and shades.

MATBORD can be used as an aid to decision-making. Specifically, as a user of the system, you can accomplish management tasks such as:

- FLAG (sort out) deviant entities, according to the size of their deviations.
- RANK entities from lowest to highest.
- GROUP entities into homogeneous clusters.
- AGGREGATE similar entities into one macro-entity.

Since all these tasks are accomplished graphically, you get a direct perception of their results, and you can monitor the interaction according to where the pay-off seems best.

The matrix boards themselves can be used in three different modes, which correspond to three different steps in data analysis:

-RAW: If you want to consider the raw numerical table that you selected, then you stay into RAW mode.
-PROFILE: If you need to look at data profiles determined in reference to a certain criterion, you go into PROFILE mode.
-SIMILARITY: finally you might want to go further into the analysis and ask for a presentation of the similarities between data profiles, in which case you go into SIMILARITY mode.

This three-staged sequence can be used to find multidimensional structure in the data, such as when grouping entities which have similar profiles across a whole set of attributes.

In summary, MATBORD tights up graphic techniques and data analysis principles so that typical management tasks are facilitated.

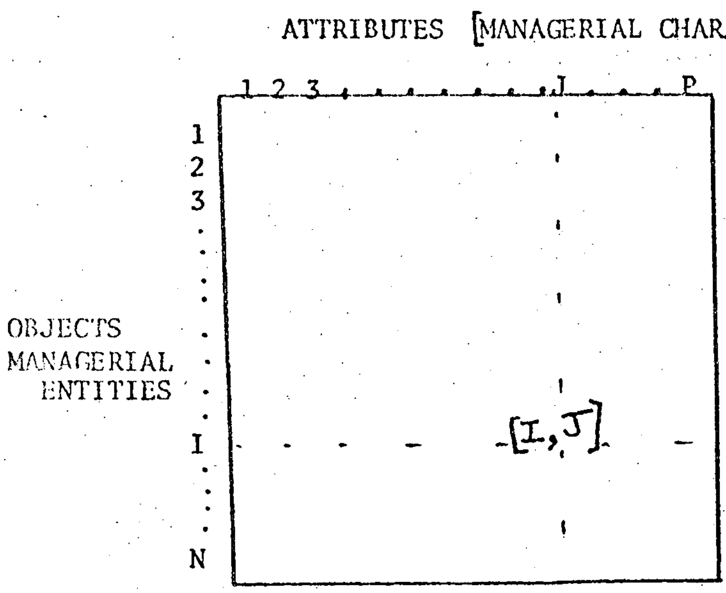
I - DESIGN OF MATBORD

1.1. Matrix Display Boards

A MATRIX DISPLAY BOARD is the direct translation of a numerical data tables into a graphic display so that:

- to each NUMBER, or data item, there corresponds a GRAPHIC item (e.g., a bar of varying length)
- the general outlook of the display is that of a 2-dimensional table, or MATRIX, with ROW and COLUMN entries.
- the matrix inself can be manipulated as a game BOARD during the interaction.

Typically, a numerical table of management data shows the performances of a set of N managerial entities, or OBJECTS, over a set of P managerial characteristics, or ATTRIBUTES. In general, the convention is to represent objects as rows, and attributes as columns:



The Matrix cell [I,J] shows the performance of entity I on characteristic J.

In MATBORD, there are general rules for the manipulation of both entries: rows or columns can be switched, rank-ordered, or grouped in use-directed fashion. Similarly, the computer may help in the re-organization of rows and/or columns on the basis of formal features in the data. Finally the mapping of the numerical data items into graphic items is done according to specific rules of sealing, which might be modified by the user.

1.2 Steps in Data Analysis

When a manager looks at a RAW matrix table showing performance data, he may choose to compare managerial entities according to the absolute size of their performance. In this situation, entities with low performance are contrasted with entities of high performance: for instance, it is meaningful to rank-order the managerial entities from lowest to highest performances. Since the primary factor of interest lies with size variations in the RAW data itself, data analysis is then done through a direct consideration of the RAW table.

MATBORD provides for a second step in the analysis when the RAW data is not homogeneous, or when the user wants to compare overall shapes rather than size variations. Suppose, for instance, that a housewife wants to compare several supermarkets on the basis of a price sample of food items. Since food prices might be as diverse as \$.25 for 1 LB-Oranges and \$2.65 for 5 LBS-Sugar, there is a need for comparing the relative deviations to the average price for each product rather than comparing absolute prices.. In turn, this provides the housewife with supermarkets' PROFILES, where a "good" supermarket shows a PROFILE of prices lower-than-average. Another instance where a

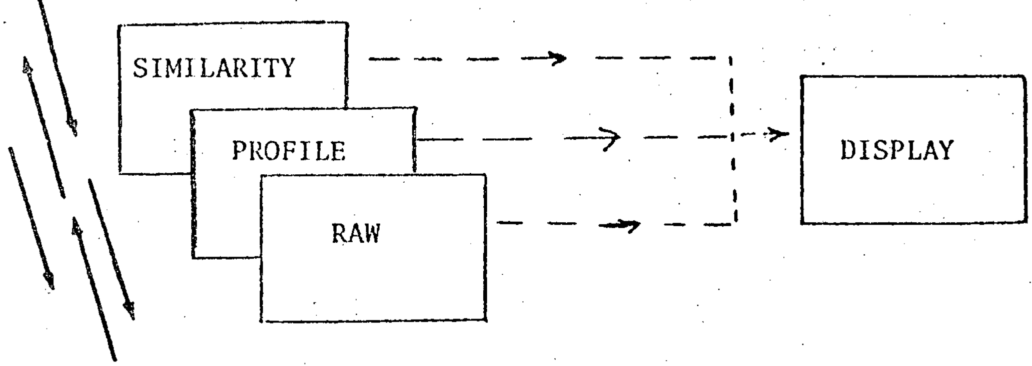
PROFILE board is useful is when the user needs to transform absolute counts (e.g., Census counts) into proportions. More generally, the process of obtaining a PROFILE board from a RAW table is useful in a variety of inquiries supported by MATBORD.

Finally, when the user wants to compare objects' PROFILES in a systematic fashion, MATBORD enables him to observe between objects SIMILARITIES. For instance, correlation coefficients provide a symmetric matrix where each cell indicates the SIMILARITY between the object-row and the object-column. This matrix board can be manipulated visually, and its entries rearranged so that significant patterns, such as clusters around the main diagonal, show up. In turn, these patterns indicate a multidimensional structure in the set of objects, which can be interpreted back on the PROFILE and the RAW boards.

In summary, MATBORD offers the user three modes of inquiry through the definition of RAW, PROFILE and SIMILARITY boards.

1.3 Data Structure

The data structure in MATBORD is as follows:



1. The Data Analysis sequence enables the user to call three kinds of analytic boards: the RAW, PROFILE and SIMILARITY modes. However,

these boards cannot be called in random order, and the following rules must be respected:

- Always start the analysis by a look at the RAW board.
- Call SIMILARITY only when PROFILE has been defined.

There is no sense in computing similarities between profiles if the profiles themselves have not been defined. On the other hand, we may call back RAW directly from the SIMILARITY board. (See arrows indicating permissible moves on the left-hand side of diagram).

2. Once an analytic board has been defined, it must be plotted in graphic form. For this purpose, a set of mapping routines (indicated by arrows (2) on diagram) has been written, which includes such transformation as:

   - SCALING in data items into a 0 - 1 range of graphic variations. The available rules include ABSOLUTE, RELATIVE and RANKING scales.
   - BINNING, or the mapping of a whole set of data items into a reduced number of graphic bins.
   - ENHANCING, which permits the use of enhancement rules for improving the perception of the low, the medium or the high numbers in the data distribution.

Besides those routines, the user may choose three kinds of graphic representations: circles, bars, or shades.

1.4 Commands for Basic Modes

* RAW:

This command shows the RAW data as circles of varying sizes. RAW is used as the first call of any interaction, since it immediately follows the selection of a data TABLE. Once an interaction is on its way, RAW may be called at any point with the effect of showing the data set which is currently the basis of the analysis. Since it is expected that the RAW data set will be re-defined along the interactive inquiry (see 2.1 calibration), this command enables the user to know the current data-base.

The call is simply made by typing-in:

- RAW

* PROFILE:

As a second step in the analysis, the user may need consider PROFILES either in the Row or the Column direction. In order to compute PROFILES, the system compares the RAW data arrays to pre-set criterion arrays. These arrays are defined through a call to REFERENCE or to THRESHOLD (see p.199). Hence the condition for calling PROFILE is that a REFERENCE criterion be previously defined. Once this done, the user needs specify a rule for comparing the data arrays to the criterion. This comparison may involve taking differences, or proportions, or normalized differences (i.e. difference/corresponding reference value).

Hence the following calls which plots PROFILE bars:

```
-PROFILE    [ROWS]      [DIFFERENCE]
            [COLUMNS]   [PROPORTION]
                        [NORMALIZE]
```

* SIMILARITY:

It is possible to compute the SIMILARITY between two profiles taken at a time, by way of a general indicator of resemblance such as Pearson's Product-Moment Correlation coefficient:

[sum of profiles' products] /Square Root [sum of products of profiles' squares]

By considering all couples of PROFILES in a systematic fashion, MATBORD generates a shaded SIMILARITY matrix on the selected PROFILE entry.

The call to SIMILARITY is then:

- SIMILARITY [ROWS]
[COLUMNS]

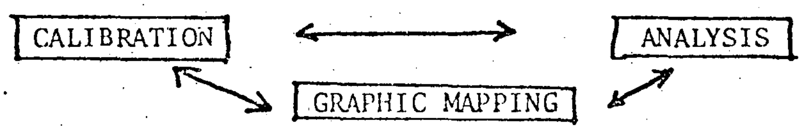
II - COMMANDS IN MATBORD

MATBORD offers its user three types of commands for directing the interactive data analysis:

- CALIBRATION commands enable the user
  . to replace outlying data values (OUTLIER)
  . to select subsets of data and to recover subsets having been masked (WINDOW, MASK and RESTORE)
  . to aggregate row or column entries on the RAW board (BLOCK, COMPACT)
- ANALYSIS commands enable the user
  . to go progressively into more sophisticated analysis as seen above (RAW, PROFILE, SIMILARITY)
  . to normalize the data for profile computations (REFERENCE, THRESHOLD)
  . to apply operators for permutation and order analysis (PERMUTE, SEQUENCE, RANK, DIAGONAL)
  . to apply a simple grouping operator (GROUP)
  . to apply an operator for sorting purposes (SORT)
- GRAPHIC MAPPING commands enable the user
  . to plot the data in various graphic ways (PLOT)
  . to monitor graphic operations (SCALE, BIN, ENHANCE)
  . to obtain an estimate of the fidelity of the graphic mapping (FIDELITY)

Besides these three kinds of commands, MATBORD includes a number of utility commands for input (TABLE), formatting (LABEL, TITLE, (HARDCOPY), redefinition of raw data-base (DECLARE, BACKUP) and stopping (STOP).

Any interactive process in MATBORD can be represented as a circular process of going from one command type to another:



Let us now provide a detailed account of each command.

2.1. Commands for Calibrations

*OUTLIER [ROW] <N1> [COLUMN] <N2> <XVALUE>
[COLUMN] [ROW]

This command enables the user to replace a designated outlier at coordinates (N1, N2) by a value <XVALUE>.

*WINDOW [ROW] <N1> <N2>
[COLUMN]

Using this command amounts to selecting on the row or column entries a data subset starting at <N1> and ending at <N2>. It results in masking all other rows or columns.

*MASK [ROW] <LIST OF NUMBERS>
[COLUMN]

This command results in masking the rows or columns identified in the list of numbers.

*RESTORE [ROWS] <N>
[COLUMNS]

The user might restore <N> previously masked rows or columns by a call to this routine. The scheme is of a LIFO type, i.e.: last element in/first element out, and the default for <N> is 1.

*BLOCK [ROWS] <LIST OF NUMBERS> [SUM]
[COLUMNS] [AVERAGE]

This command enables the user to agregate a set of rows or columns on the RAW board. The set, designated by LIST OF NUMBERS is BLOCKED into one new row or column, while its component elements are MASKED out of user's sight. Rules for BLOCKING include SUMMING and AVERAGING.

```
*COMPACT          [ROWS   ]   [SUM     ]
                  [COLUMNS]   [AVERAGE]
```

This command automatically BLOCKS the current groups into aggregates. For instance a RAW matrix with three groups of rows will be reduced to a three-row matrix.

2.2. Commands for Analysis

```
*REFERENCE        [ROW   ]    [AVERAGE]
                  [COLUMN]    [SUM    ]
                              [INSERT ]
                              [NUMBER ]        <N>
                              [MASK   ]
                              [RESTORE]
```

This command allows the user to specify the criterion array to be used for the definition of a PROFILE board. This REFERENCE array might be:

- computed, by summing or averaging over rows or columns.
- directly inserted as a label plus an array of values.
- designated by permuting to the row (or column) numbered N.
- finally it might be masked or restored as any other row or column array.

```
*THRESHOLD        [ROW   ]   <X VALUE>
                  [COLUMN]
```

When the use wants to define a uniform reference value (i.e. the REFERENCE is the same across all columns or rows) he calls THRESHOLD and fixes the value <XVALUE> .

*PERMUTE [ROWS] <N1> <N2>
[COLUMNS]

This command enables the user to permute two rows or columns at a time. It affects the whole data structure at once so that all boards "know" that the switching has occured. When applied on the SIMILARITY board, both entries are switched at once so as to keep the matrix symmetry.

*SEQUENCE [ROWS] <LIST OF NUMBERS> [FORWARD]
[COLUMNS] [BACKWARD]

Rows or columns can be rank-ordered in user-directed fashion. The user only needs specify a list of numbers corresponding to the order into which he would like the current rows or columns to be re-ordered. Hence if the list starts with the number 10, it means that the user wants the current element number 10 to become the first element (element number 1) in the new ordering. Furthermore the user can specify if he wants this ordering to be interpreted FORWARD (First element in ordering is first on board) or BACKWARD (first element is put last). The default option is FORWARD. As for the SWITCH command, all boards are affected at once.

*RANK [ROW] <N> [HIGH]
[COLUMN] [LOW]

This command ranks the array of values of the designated row or column from highest to lowest (HIGH option) or from lowest to highest (LOW option). The default is HIGH. Also RANK affects the boards in much the same way as SEQUENCE does.

*DIAGONAL

This command is used only in SIMILARITY mode. It provides a test for evaluating the badness-of-fit of the current diagonal pattern to a perfect diagonal pattern. This test is based on a stress measure which is analogous to KRUSKAL'S non-metric stress. (In Psychometrika, 1964, 29, 1-27 and 115-129). It indicates the extent to which the rank-order of the matrix entries is far from fitting a perfect rank-order.

*<u>GROUP</u> [ROWS] <LIST OF NUMBERS>
[COLUMNS]

This command groups the rows or columns of the boards on the basis of a list of numbers entered by the user. These numbers represent the cardinals (or sizes) of the groups to be formed in sequential order. For instance a list which reads 2 5 3 means that there should be formed three groups, the first group comprising two, the second group five and the third group three elements. When the sum of the numbers in the list do not equal the total number of elements, the remaining elements are considered to form a group by themselves.

*<u>SORT</u> [UNDER] <XVALUE> [ABSOLUTE]
[OVER] [RELATIVE]

This command, which can be used only in PROFILE mode, sorts out data values lower than (or alternatively greater than) a specified value <XVALUE>. When the user wants to SORT un-signed values, the ABSOLUTE option is used. When only signed values (positive or negative) must be sorted, the RELATIVE option is used. Default is ABSOLUTE.

2.3 Graphic Mapping Commands

*PLOT [CIRCLE]
[HORIZONTAL]
[VERTICAL]
[SHADES]
[DIGITS]

This command is used to change the definition of the graphic representation, since by convention MATBORD represents:

- RAW data as CIRCLES
- PROFILE data as either VERTICAL (Row profile) or HORIZONTAL (Column profile) bars.
- SIMILARITY data as SAHDES.

The user may re-set the graphic variable to be either one of those four possibilities. Moreover he can ask to see DIGITS (i.e. numerical data) rather than graphic items.

*SCALE [ABSOLUTE]
[RELATIVE]
[RANKING]

In order to map data values into graphic items, we need apply a SCALING transformation which re-set the values into the display range 0/1. The rules which might be used for scaling are:

- ABSOLUTE scaling where the maximum absolute data value is mapped into the display value 1, and all other absolute values are mapped accordingly
- RELATIVE scaling where the distribution of the data values from Minimum value to Maximum value (RANGE) is mapped into the 0/1 display interval.
- RANK-ORDER scaling where the data values are rank ordered from lowest to highest (i.e. from first to last) and mapped into the 0/1 interval in proportion to their ranks. This results in regularly spaced numbers.

MATBORD uses the following default values: the RAW, PROFILE and SIMILARITY boards are respectively scaled RELATIVE, ABSOLUTE and

RANKING. By calling SCALE, the user can change these conventions.

*BIN <N>

A data table which contains V data values and no ties (no two values are identical) is properly represented as a matrix display containing V graphic items differing, say, in size or shape. Under certain circumstances, however, the user may need to reduce the variety of the display so as to improve his perception of specific patterns or trends. This can be done by putting the V values into <N> different BINS, so that each BIN contains the same number of values, and its own value is determined by averaging those values. Binning can be applied to any of the three boards: RAW, PROFILE or SIMILARITY. It is particularly useful with the SIMILARITY board, since it permits to extract clusters on the basis of black or white shading. (The number N is made equal to 2).

*ENHANCE [LOW]
[HIGH]
[MEDIUM]
[ORDINARY]

The use of MATBORD might be faced with the problem of improving his discrimination of certain portions of the data distribution. For instance, he may want to improve the discrimination of values in the LOW range, or the HIGH range or the MEDIUM range of the distribution. the ENHANCE command permits

- to ENHANCE the LOW range through a square-root transformation.
- to ENHANCE the HIGH range through an exponential transformation.
- to ENHANCE the MEDIUM range through a logistic transformation.

The ORDINARY option permits to go back to a no-enhancement situation.

*FIDELITY

In MATBORD, each data table is mapped into a graphic representation. Since the various mapping transformations (SCALE, BIN, ENHANCE) may have the effect of reducing the original data variety, there is a need for measuring the FIDELITY of the correspondence between the data and the display. This FIDELITY measure is provided by computing the correlation between the data matrix and the display matrix.

2.4 Utility Commands

*TABLE DATA

This command inputs a data table with two modalities: (same input command as in CHART; see CHART write-up).

- the user may directly type-in a new TABLE by using the following input format: first, type-in the M column labels (one per line), then a blank line, and then in turn each row label followed by its corresponding M data values.
- or, by selecting the DATA option, the user may read-in a data table previously stored in the input file with the same format as above.

*LABEL [ROWS] <LENGTH>
[COLUMNS]

When the user wants to modify the length of either row or column labels, he may do so by specifying a LABEL's length. Default length is N=10 characters.

*TITLE [TOP] [LIST OF TITLE LINE NUMBERS]
[BOTTOM]
[LEFT]
[RIGHT]
[<NULL>]

Enters and Positions selected title lines (see CHART write-up).

*HARDCOPY

This command provides a hardcopy of the correct picture, plus the corresponding data table on the pre-set HARDCOPY device.

*DECLARE [RAW]
[SIMILARITY]

1. It might happen at times that a PROFILE board looks like a sound data table to start again the analysis from. In that case the PROFILE board is declared RAW board.
2. In other situations it might be suitable to look over the PROFILE board as if it were a SIMILARITY board. In that case the program checks the board's symmetry (equal number of rows and columns) before making the move.

*BACKUP

When the DECLARE statement is used (case 1.), the former RAW board is stored away. This former board can always be called back if needed again. In fact, at any point during an interaction, the user is allowed to call the BACKUP board.

*STOP

This command STOPS the execution of the program. Contrarily to all previous instructions where three letters suffice to the interaction, this must be typed-in as a four-letter word.

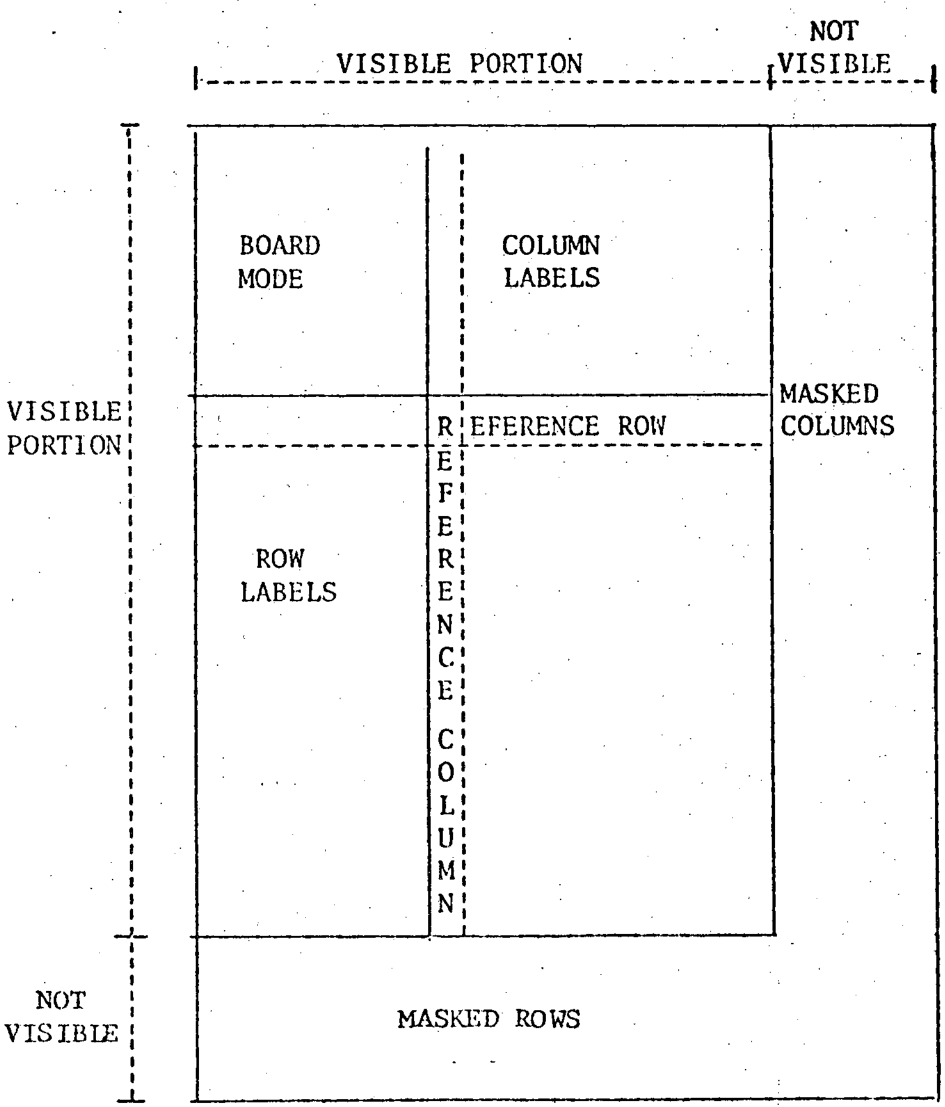
III - USING MATBORD

3.1 Display Organization

In MATBORD, all the boards are organized according to the same format. This format allows for three types of information:

- the labelling of the component elements on board entries.
- the definition of arrays of values along either the row or column entry.
- the masking of unneeded arrays.

Hence each board comprises a visible portion and an invisible one, according to the following diagram:



When considering only the visible portion of the board which the user sees, the following features apply:

- the board mode (RAW, PROFILE or SIMILARITY) is always indicated in the upper left corner.
- when a REFERENCE row or column is created, it is always placed first in the list of rows or columns.
- finally the user can modify the LABEL sizes by calling the LABEL routine.

3.2 How to use MATBORD commands

Not all commands can be used in any board mode. The following table indicates under which mode(s) each command can be used.

MODE	RAW	PROFILE	SIMILARITY
COMMAND			
- CALIBRATION			
.OUTLIER	x		
.WINDOW	x		
.MASK	x		
.RESTORE	x		
.BLOCK	x		
.COMPACT	x		
- ANALYSIS			
.REFERENCE	x		
.THRESHOLD	x		
.PERMUTE	x	x	x
.SEQUENCE	x	x	x
.RANK	x	x	x
.DIAGONAL			x
.GROUP	x	x	x
.SORT		x	
- GRAPHIC MAPPING			
.PLOT	x	x	x
.SCALE	x	x	x
.BIN	x	x	x
.ENHANCE	x	x	x
.FIDELITY	x	x	x
- UTILITY			
.TABLE	x	x	x
.LABEL	x	x	x
.TITLE	x	x	x
.HARDCOPY	x	x	x
.DECLARE		x	
.BACKUP	x	x	x
.STOP	x	x	x

3.3 Program Operation

- CONTROL CARDS

In order to use MATBORD, you need prepare the following deck:

1. DISPOSE (FILE = MF, M = ME)
2. LIBCOPY (GRAPHIC, LGO, SWLGO, SCLGO, XXLGO)
3. LIBGEN (F = LGO, P = ULIB)
4. LINKSET (P = ULIB, EO)
5. LIBCOPY (GPL, PROGRAM, MATBOAR)

On card nº 2, XXLGO = TXLGO if using the Tektronix 4012

XXLGO = GTLGO if using the GT-40

XXLGO = TZLGO for Tektronix or GT-40

XXLGO = TTLGO for Terminal output.

- DATA SETS

Data tables can be entered directly at the terminal or they can be stored in advance. In this case, the following control card should be added:

6. LIBCOPY (YOURSTORE, DATA, UTABLE)

when several tables are stored at once, an EOR card should separate them.

- USE OF COMMANDS

You need type in only the first three letters of each command, since only the first three letters are parsed (except for STOP where you must type-in all four letters).

- PLEASE

If you find anything wrong in this program, immediately notify the author.

3.4 Examples of use

If you load the following control card:

6. LIBCOPY (GPL, DATA, UTEST)

you will find a series of three tables illustrating the main concepts of MATBORD.

- First TABLE DATA: Housewife's commodity basket.

The data shows the prices of 9 house items in 4 shopping centers. The problem is to determine where to buy commodities. Start with the following commands.

RAW

REFERENCE ROW AVERAGE

PROFILE ROW NORMALIZE

...etc.

- Second TABLE DATA: Management performance data

The data shows the percent performance in ACTUAL/PLANNED expenditures for 12 management entities over a set of 3 programs. Find the best performer? the best group of performers? the group of over-spenders?

Start with the following:

RAW

REFERENCE ROW AVERAGE

PROFILE ROW DIFFERENCE

SIMILARITY ROW.

...etc.

- Third TABLE DATA: Population profiles.

The data shows how the population of twelve districts distribute into characteristics such as: SEX, AGE, EDUCATION, ETHNIC GROUP.

The problem is to compute population profiles so as to cluster together district of similar profiles.

Start with:

RAW

REFERENCE COLUMN NUMBER 1 (contains population totals)

PROFILE COLUMN PROPORTION

SIMILARITY ROW

...etc.

APPENDIX B

Protocol of the Interactive Session at the Terminal (excerpts)

February 9, 1976

10:42:45 am to 11:55:50 am

Management Participants (U.S. Department of Labor)	Faculty Observers	Experimenter
- C.Z.B (Manager)	- C.W.C (Business Admin.)	- B.K (Bernard)
- B.C (Bill, aide)	- A.C.H (Business Admin.)	
- A.P (Al, aide)	- E.R.F.W.C (Industrial Engineering & Psychology)	
- B.B (Bruce, representant U.S. DOL at Lawrence Berkeley Lab.)		
- K.T (Kevin, aide of Bruce)		

B.K (1) This is the first data set you gave me. It shows a comparison Actual over Planned performance for the 12 Valley Prime Sponsors, under Title One, Title Two and Title Six programs. For each program we have two data arrays: Enrollments and Expenditures. What we are showing here is a Percent figure.

C.W.C (2) Percentages with respect to Plan ?

C.Z.B (3) Right, Actual over Plan. It is broken down on a quarter basis. The Prime Sponsors respond quarterly against their plan, so that we're looking at enrollments, we're also looking at dollars... So we are trying to measure the actual against the planned, what they said they were going to do and how well they performed against the plan... This is the second quarter period - September thru December.

(Part I of the Interaction)

B.K (4) So we have percentages. For instance, Butte is performing 98% of its plan on Title One (Enrollments), and 237% of its plan on Title Two (Enrollments) etc... Now we can show this, visually as a matrix display, with each figure being represented by a circle of proportional size.

C.Z.B (5) I'm particularly interested in that first plot that you had on percentages of that plan, so we should have a hard copy of that. That one we need.

B.K (6) Now what I would suggest is to do what we did with the test run, and compute the average performance for each Title program, in enrollments and expenditures.

C.Z.B (7) Why don't we rather take the absolute reference level at 100% so that we compare them to 100% success on plan?

B.K (8) O.K. So I'm going to compute the difference between those data and a 100% performance, which gives the Profile board.

C.Z.B (9) Look at Kern, here, under-expenditures in Title Two! and this one here...

C.Z.B (10) Look at this 2.28 here for Merced. I would be very curious to know how Merced got 228% more enrollments with spending only .16% more.

B.K (11) What we did in the test run was to select those which were under or over a certain percent, we might do this now if you wish.

C.Z.B (12) Why don't we cluster them? Is that what you're talking about? Let's cluster them and see how it comes out as far as the... scan here, you know, can we put them in clusters?

B.K (13) Alright... We might start by ranking the first column, Title One enrollments and see what happens.

C.Z.B (14) I realize we are doing three things on this one. You have Title One, Title Two and Title Six, each of which has different administrative costs. So you have three titles that we're comparing at the same time...

B.K (15) We are trying to compare the profiles of Prime Sponsors so as to cluster together those which resemble.

C.W.C (16) So it might be that Kings could very well be put with Stockton? ...and it might be that Fresno has a tougher job?

B.K (17) Now what we can do on the basis of that is to compute an index of similarity between the profiles of Prime Sponsors, and this I do now... Each of those cells is shaded so that the greatest similarities are most shaded and the lowest less shaded. Using a graphic trick, I can bin the data into a lower number of shades, say, 2 shades - black or white - and now you can see better the contrast between cells.

(The screen shows a similarity plot)

C.Z.B (18) Excuse me... The previous step, as far as a manager, was better... This one is kind of superfluous to me. It makes more sense to me to see it clustered in the other board. This is a two-step process that is not necessary for me to know.

B.K (19) After this manipulation, we go back to the profiles to cluster them there, but I need to do this first, because visually it is easy to find clusters on the similarity data...

C.Z.B (20) O.K. But just visually it is not easy to see what this means. You have to go from Imperial here to Imperial over here. I need it clustered so that I can understand what I'm seeing. It's like my Kenn... See, I can't tell by this whether I'm looking at Title 1, whether I'm looking at Title 2 or whether I'm looking at Title 6... This would probably be a technical job, if you have to go thru those steps for the computer to understand.

C.W.C (21) What you're saying C.Z, is that it is not useful?

C.Z.B. (22) What I'm saying is that since we had the other percentages by title, it would seem logical to me that we do the grouping by Title... This, I think, distracts me. It gets me into another mode, that I don't really know what I'm looking at. If I can see the percentages + or - with reference to 100% performance, why not then take them and cluster them by Title?

B.K (23) O.K. Let's stop doing that and let's go to the Profile board.

(Part II of the Interaction)

C.Z.B (24) O.K. Now this is the one we ran previously. Can we array these? Could we go from the ranking to the clustering... Now can we cluster those Prime Sponsors by performances of Actual versus Planned in each program Title, in that kind of a mode where you have dark spots.

B.K (25) You can cluster them visually, in other words, you can say that Kings resembles San Luis and resembles Merced, and on the other hand, Santa Barbara resembles Kern and Stockton...

C.Z.B (26) O.K. On Kings now, is that block there 95% of plan, or is it 85% of plan, or what is it of plan? You see, I don't know, we have to look at the other sheets. Maybe you can cluster those 90% of Plan in one cluster, 70 - 90% in another cluster...

A.P (27) I don't know what we are going to get out of it...

A.C.H (28) Now you have three groups here, corresponding to program Titles. What about doing each program Title individually, without mixing those different effects?

B.C (29) Yes, that would seem of more value. We want an analysis of Title 1, slash, an analysis of Title 2, slash, and finally one with Title 6.

C.Z.B (30) As a manager, I do not need to see ten steps when only three would be appropriate. Now, maybe the computer has to have those ten steps to get people three. I think that's what I'm responding to.

B.K (31) O.K. Now we mask all other elements, and we select only the data for Title 1 and we go into Profile mode by taking the difference to the 100% reference level given by the "threshold". Now we see that Kings and Merced, for instance, have similar profiles. They are high on enrollments, and low (below 100%) on expenditures. Now San Luis Obispo and Santa Barbara also have similar profiles, high on enrollments and above 100% on expenditures. We can then cluster them visually...

C.Z.B (32) You see, this is meaningful, reference enrollments and expenditures. I'm quickly looking for: if they are in expenditures and low in enrollments I'd wonder about their administrative costs in No. 1, because on Title 1, it should be less than 10% of total costs. It appears as though, just on administrative costs, that they are certainly below with high enrollments or operation costs. So that is just a quick scan for me to see how does it stack up with expenditures. Does that seem to make sense to you, Bill or Al?

B.C (33) Yes... If we could figure out in what particular subcomponent under enrollment, and under or over expenditures, we'll run that as well.

C.Z.B (34) O.K. That comes later. It has to be plugged-in. But now it looks O.K. That looks O.K. It will give me a quick scan for Title 1. Could we have a hardcopy of that? Question: why should Stockton be up there and not San Luis Obispo?

B.K (35) Stockton is up there because here it is negative on expenditures (it's below 100%), while San Luis Obispo is positive there (over 100%). So that you get basically three groups (1) high in enrollments/low in expenditures, (2) pretty high on enrollments, higher than 100% on expenditures, (3) a third group which is rather under-enrolling and under-expended...

C.Z.B (36) So Imperial is slightly over-enrolled and substantially under expended. Let's print that one two... Now can we run the same thing for Title 2 and 6: let's have a readout on the percentages and then come with this kind of clustering...

B.K (37) This is the picture for Title 2.

B.C (38) Hold that right there. There seems to be no similarity in the performance in Title 1 as far as over expenditure and over enrollments.

C.Z.B (39) Look. O.K. Merced has over-enrollments, and Sacramento has over enrollments. Now that over enrollment has continued in Sacramento since last summer. They have been saving money though they did not believe us! Look at Kings, Merced and Sacramento... I think it would be helpful if we could have this read out and then come back to the other profile for quick comparison. Let's now concentrate on this one and the one we had just before. I think what I'm looking for is the minimum number of sheets that will highlight on what's going on with the prime sponsors.

B.K (40) We might form groups at this point, say three groups.

C.Z.B (41) Now that breaks it out so that I can quickly see. A question: on an analysis of performance, these would be low performance here, the bottom three?

B.C (42) Not necessarily. It would depend on what you base your performance on. Those bottom three appear to be fore-planned in that they over enrolled and under expended. It should be a direct relationship from expenditures to enrollments.

C.Z.B (43) That's right. So, Bill, they might be holding administrative costs deliberately low.

B.C (44) Whereas the top four - that's logical - are over enrolled and slightly over expended.

A.P (45) The next five are under enrolled and under expended.

C.Z.B (46) The comment is that if we can quickly get a visual analysis (say for instance, at the bottom three there, we determined a low performance) we also have something else to plug into that, which is a team approach that will go in and focus in on those 3 prime sponsors. What we are looking at right now are enrollments and expenditures. The next step is to look at the characteristics whether they are serving ethnic, female, or low income groups. It appears that by looking at these thus far, on a 100% performance basis, they are running fairly close to plan. Can you have the percentage read out and give me a print out on the clusters? Give ± 15% deviations or more...

B.K (47) Now we go into Title 6.

C.Z.B (48) Imperial is high enrollments, low expenditures... Fresno is high enrollments, low expenditures...

B.K (49) What we might do is rank them on the basis of the enrollments from highest to lowest, which is a simple thing to do...

C.Z.B (50) Gee! that tells something. Look at Fresno, Al: High enrollments, low expenditures. It is curious, very curious... San Luis Obispo, low expenditures...

B.C. (51) That's such a small program. Look at Merced, or Kings, well it's a small one too. But look at Santa Barbara, over enrollment, under expenditures...

C.Z.B (52) The one that is really outstanding is Imperial, right. High enrollments, but expenditures are fairly close to plan... Maybe what we need to give you is specific 1,2,3,4 Charts that would be helpful, although you may have to go through the process of, say 10 steps as an example.

B.K (53) I think we agree but it's good too that you see how this works.

C.Z.B (54) Yes, I think it's good to know how it works, but how many managers will have that much time? If it's going to be used as an easier decision-making process, you would not have to know the ten steps, but basically what you want to know is the end-product.

(Part III of the Interaction)

C.Z.B (55) So this is a comparison now of enrollments and expenditures for all three titles, right?

B.K (56) Yes that's right. We can now sort all those values which are over 15% deviation to plan. The system sorts out all the values greater than ± 15% deviation, and replaces all the other ones with zeros so that we just see the ones standing out.

C.Z.B (57) That's not a bad profile then... But then, again, after this one, I think if you could show the high performance, the medium, the low... you want to do that? There was one that was considerably over. I forget which one now...

A.P (58) Yes, Merced.

C.Z.B (59) Can these now be clustered in reference to ± 15%? O.K. Let's see that chart. Are all three Titles like this on one chart?

B.K (60) In order to cluster them we have to do the analytic process of computing similarity coefficients, because the profiles now are much longer than before.

(The screen shows a similarity plot.)

C.Z.B (61) Euh... What I'm getting at is that there is probably a process that you have to go through in order to arrive at a certain thing. I'm not being critical, but in a way, being critical, there has to be shortcuts. As a manager, each time we want to arrive at something, we should not have to go through the 10 step process. I get the feeling that you are locked into doing those things but I'm asking, as a Manager, how can we take that base ± 15% of actual versus plan, and go into the next step of clustering? Showing the major problems or the minor problems, and who are average. Is that possible?

B.K (62) That's possible to obtain the result you wish, but I have to go through this lengthy process. There are two ways you can shorten that: either you have someone who does it for you, or you have an automatic device which does it for you. I do not have the automatic device, so someone needs to be here.

C.Z.B (63) Because as a manager now, I have the feeling that to have a manager sit down for an hour and go through the process and say "Look, man, I'll see you next week" - if you can walk say "Look, this is what is involved in it and these are 10 steps, but however I can give you 3 steps", O.K. then I'll listen to you.

C.W.C (64) So all that you're saying is that there is no great problem, except he does not know what pictures to present you...

C.Z.B (65) See what I keep trying to do is bring the theory back in operations and have a marriage someplace in-between. Bruce, maybe I'm not asking the right question?

B.B (66) No, I think it is pretty clear. First he needs to know which of the ten things you need to know. Then you've got to have some understanding of what he's done to get that. And then, after you both know those things, the rest can be pretty well automated so that sometimes when you sit down at the scope, you'll get just the three pictures you want and you'll have some understanding of how you got the pictures. So that when someone jumps up and says "how did you cluster me with so-and-so", you can answer "you look alike in this and this".

C.Z.B (67) I think what we are going to do is -- first we want to know by Prime Sponsors, their performance against the 100% performance to plan. After we do that we would like to know by clustering mode, who has similar problems and what does the similarity mean. As far as enrollment and expenditures, tell us whether they are high or low, you know, by a quick graphic run.

B.B (68) Then what I hear you saying is that when you see the profile charts, you get it better than with those similarity plots. However an analyst can look at the similarity displays and get a lot more information out of them?

C.Z.B (69) I can understand when he clusters them. But this kind of similarity thing takes me a little aboard... Because what I'd like to do is to take these simple plots (it really is not that thorough an analysis) and then go back to the prime sponsors, check it out on the spot, and then your total analysis really would occur with corrective action at that level.

B.K (70) O.K., now we get 3 clusters, and we can go back in Profile mode to interpret what they mean.

C.Z.B (71) Now, look at that!

B.C (72) It would be interesting if we could weight that against the total grant, even if it is a very small grant. So that we know whether it is significant in actual dollars?

C.Z.B (73) O.K. Maybe at this point, we could suggest that we break for lunch.

APPENDIX C

Excerpts of the Round-table Discussion after the Interactive Session

February 9, 1976
12:30 pm to 14:00 pm

Management Participants (U.S. Department of Labor)	Faculty (U.C.)	Experimenter
- C.Z.B (Manager)	- C.W.C (Business Admin)	- B.K (Bernard)
- B.C (Bill, aide)	- A.C.H (Business Admin)	
- A.P (Al, aide)	- E.R.F.W.C (Industrial Engineering & Psychology)	
- B.B (Bruce, representing U.S. DOL at Lawrence Berkeley Lab.)		
- K.T (Kevin, aide of Bruce)		

B.K. (1) Maybe we could start the discussion first by looking at the tasks that this graphics system does, like selecting a certain data set, eliminating the outlayers and alerting on deviations of plus or minus 50% to plan, and things like that. How do those tasks suit your needs?

C.Z.B (2) I'm looking at it, I think, from two standpoints. I would like for my staff to inject their comments, but thinking more as a manager as to what information would be useful to me to get a feel or the trend of all prime sponsors. It can be a kind of alert system for my Fedreps and also back to the prime sponsor. Secondly, from what I've heard this morning trying to visualize or understand how this could be presented to other people, say, if I'm making a presentation to the prime sponsor.

As a manager, I think I'm looking for a kind of the end of the tunnel kind of information. What goes in, you know, if we are going on BART to the City, certainly my ears may feel a change in pressure as I go through, but basically I'm thinking what goes into the tunnel and what goes out of the tunnel and what kind of a quick analysis do I need in between. So, in relating to running information, the quarterly information, maybe we should have a kind of a clear indication as to what the process was all about. I'm thinking as a presenter now, not only presenting this to my staff but presenting this to CETA type sponsor. "Gentlemen, you are going to be receiving this kind of information regarding planned versus actual or actual versus planned on Titles I, II, and VI and also on characteristics of your significant segments whether they are female, whether they are ethnic origin, or low income or what. And, thirdly, then, we'll be trying to array for your costs regarding vocational education classes, classroom training, how do these relate to placement - the cost?, how do these relate to administrative costs?"

Now there are various steps in between that graphic picture, but there are other steps that may be taken and then I think I would elaborate upon those steps - realizing, and I think it would clarify, that the computer can only respond so quickly, so, as we go thru that tunnel, this is what we are going to put in. While we are going thru the tunnel, the computer will be doing certain action, but then on the end, the manager will have this kind of information. So many people went into the tunnel at this end, and so many came across at this cost, and so on and so forth - if that's an example.

I think I could have turned off at that point. It was interesting you know as to how you rate them, but I found my mind wondering as to what is he telling the computer, what is the computer trying to tell us, are we really focusing in on what information does a manager need to make some decisions. I think we were coming to that point, but I felt we were running out of time, and then I felt we were trying to hurry the computer by trying to arrive at some quick analysis as to what we wanted to see. So, I think the information is in the computer, but I think we, as managers, need to ask specifically certain questions to get it out of the computer. It seems to me that you have given a lot of thought - there is a lot more planning and thought and programming that goes into the system rather than just a quick output and I appreciate that.

But, again, as a manager, I'm wondering how can we get information quickly? How do we retrieve information quickly? So what I'm looking for is an immediate response time, with analysis built in, so that I can get a handle on prime sponsor performance or alert the Fedreps if this appears to be a problem. "There appears to be a trend between or among twelve prime sponsors. This may not necessarily be significant, but I'd like for you, as a Fedrep, to check into what a prime sponsor would say: How about this particular factor? Why are administrative costs much higher than your enrollments? How do you have high enrollments and low administrative costs? Do you really have sufficient staff to have an adequate information system or is your reporting such that you do not have a handle on your financial system?" I think these are the kinds of questions I'm asking and to me, graphically, I can see that much more quickly, although the Fedreps will be doing this individually.

It is difficult for me as a Manager, to look at 12 prime sponsors. At this point we do not have standards as far as evaluation, so it is my thesis that we must measure against something. We must measure performance against that plan whether that plan is good, bad, or indifferent. Because the Congress will be asking us, "how have you assessed your prime sponsors? Assessed against what?" I guess, in a nutshell, what I'm looking for, if it is a ten-steps process, is how can I get four sheets of paper that will give me that summary information.

B.C (3) Apparently the capability is within the computer to skip several of the processes as a matter of analysis. This is something that would address one of C.Z's concerns to achieve only that one piece of paper or these four pieces of paper.

B.C (4) I think another problem is that we really haven't specifically delineated what we are - for several reasons. In the first place, I don't think we fully understand the capabilities that you can provide. I, personally, have a much clearer understanding now than I had four hours ago.

A.P (5) I agree with Bill, but I don't think we really know what we want to get out of this. I think Bernard has given us quite a bit of information, and I think its more for you. As a Fedrep, I can do a lot more with a QPR than I can with any of this. I'm only responsible for Sacramento; OK? I can look at the QPR and I can see if they are above or below and how much.

B.C (6) I think we have the raw data we need. I think it is put in a format that firstly C.Z can manage, and make some sort of assignments to the individual Fedrep responsible for Butte and Santa Barbara or whatever. I'm saying that Butte and Santa Barbara appear to have some of the problems which you presented us. Over enrollments and under expenditures. So I think that the raw data is there. I think it is a matter of manipulating that data into a format that we can manage and I think that format is something we can't clearly define yet.

C.Z.B (7) Well, possibly this is more of a system for management. We are looking at performance on a broad scale and then asking the Fedrep to do some analysis and also some onsite verification. I think it has a second step possibility. Realize that this is quarter information. I hope that if it has merit, that it would go to a monthly basis. The third step, we could do some comparison, for instance we could do monthly comparisons as far as performance. That should give you a continuum, on a month-to-month basis hopefully, or a quarterly basis if we can't go to the monthly, as to what Sacramento prime sponsor or Santa Barbara prime sponsor are doing. That should tie in definitely with the program summary that is in the plan they are supposed to do, tie in with the financial information in the plan, and so on and so forth. It could be used, possibly as a tracking system we could go back and ask the computer to prepare quarterly and monthly programs.

B.C (8) Then, you are talking about a longitudinal sort of tracking system? But these are two separate problems. A longitudinal problem, and the problem of taking the current data and only looking at that current data. I think, what you are saying is absolutely right, it is terribly desirable - the longitudinal kind of tracking system.

C.Z.B (9) Say, at the current time, we have 47 different prime sponsors in the region; we have 47 different Fedreps plus backup Fedreps. You may have 94 to 100 different ways of operating. Now, if you focus down on what is an information system - a management information system - there may be 100 different opinions as to what is an information system. So, you know there is many things built into this as a manager. How do we get a handle as to performance against plan, how do we alert the Fedrep and the prime sponsors to "Look! There may be potential problems in this area, maybe we need to correct and modify in a timely fashion." We need to have, I think, some timely retrievable information for comparison if we need it. Why wait five years after the termination of a project to analyze it? Why not analyze what's going on during the operational phase and hopefully we can come up with some analysis. Now, as an individual Fedrep, each one will know what's going on within their project. But as a manager, I will not know nor does my boss know what he will know and as you go right up the line to Washington, they will not know. And if they come back from Washington and say, "Look, I want an analysis of whatever factors in Region 9 of prime sponsors" we would be going in 100 different directions, I think.

B.K (10) Can you kind of evaluate how the system could have that job of looking across prime sponsors and across their characteristics? That's one question which I have.

C.Z.B (11) Let me respond to it while you ask. I found it helpful to me, although we would have to look at each prime sponsor for verification, as we come to clustering those that are off 15% one way or another. At least, their performance against plan. That suggests to me that they are having certain kinds of problems particularly as we look at them. I think the system is starting to zero in on a particular kind of problem. I think this is quite helpful to me.

B.B (12) C.Z was suggesting that we have 47 prime sponsors that we are interested in what they are altogether. Now, we had only one dataset and it was a very simple dataset. We have the capability to study several kinds of performance at once. Maybe, placements as percentage of people of intake, placements as a cost, placements, etc., that we could analyze over several factors all at one time to give a much more comprehensive view. For instance, if we take in the cream-of-the-crop, then we turn out cheap placements, but if we take people that are really hard to get jobs and turn placements, that's something else. We have the capability in this tool to begin to explore that kind of thing which is very, very difficult to do visually. That's why we tend to only talk about placements or tend to talk about placements per cost. This system, first, is getting a sophisticated view of the real performance, and permits to begin to compare performance to other criteria like, you know, how are they shuffling people through the programs. Maybe it turns out that the people who take in really hard-core disadvantaged people and turn out placements are running them into on-the-job training rather than basic education or vice-versa. We can begin, in a sophisticated way, to explore the kinds of similarities that there are among the people of the programs who are achieving well.

Now, taking the regional viewpoint, you would want to do that amongst all the prime sponsors. Then, take C.Z's viewpoint, you would want to take it among his prime sponsors. Then take Al's viewpoint here, you would want to say, "Well, you Sacramento prime sponsor is following the pattern of the good, the so-so, the lousy!" So there is a key to every level and each level is going to have to analyze this and it's not likely to be a top management, it's not likely to be in the Fedreps; it is likely to be an analyst somewhere and he is going to be interested in an analysis of stuff in a similarity board, in the kinds of analysis he can perform. Then, he is going to want to set up a series of output, one to go to H., our top boss, which shows up the whole region; one to go to C.Z who will show his area; and one to A.P to show how he stacks up compared to the rest of them. So, I see those multiple levels of service.

C.Z.B (13) Bruce, on your comment here, you know, one of the other phases we need to run, even if it is at Sacramanto or even if it is at the Fresno level, we may want to know why they are putting more people at OJT (On the Job Training) or classroom training in reference to placements... We can start comparing, I think, the administrative costs relative to those factors and also placement out here. So the system should be able to break down from national to regional, to the valley, to particular prime sponsors.

B.B (14) We are going to need somewhere an analyst to start thinking about the things you are talking about. Setting it up so that when you sit down before the screen, it pops up - OK - "it turns out that all these people that are 100% of plan just changed their plan".

C.Z.B (15) If you start looking at program performance, there should be some relation to their own plan and it has to be in a timely fashion. Hopefully, this kind of system or some kind of system will alert us that there needs to be a change in policy.

B.C (16) Then, are you saying that the present thrust of the emphasis should be on planned versus actual?

C.Z.B (17) I think that is a very elementary step, but I'm not sophisticated, you know, at this point to receive the whole picture. The only thing I know that we can measure against is the plan, "what is their actual performance against what do they plan to accomplish".

C.W.C (18) The display thing assumes that you have got the picture and we now have to worry about the management of Bernard's thesis (we three are managers of this thesis). The basic thesis behind Bernard's work is that somehow or other, graphics or some form of display is beyond the numbers and tell you more than you would get by just looking at the numbers in an array. That's, I think, for us the basic question.

C.Z.B (19) I'm convinced from the test run that we did last September that this test run alerted me to certain problems within my specific area. I'm convinced, at least in my own mind as a manager, that graphics will assist me in referring out those prime sponsors that may have potential problems. I have set that aside, but I think the system has possibilities. Now, I'm trying to see what substance we get out.

C.W.C (20) That's what Bernard is doing, trying to see whether there is something in these graphics that say something to you. A couple of us here were brought up as statisticians and it was said to us "Here is some data to massage, and massage it the way you want"... Bernard's point is that you would not be able to get it across to people that way, by an analysis of the numbers alone. It seems to me to be more inclination to look at that chart in graphic mode than to look at numbers.

B.C (21) It is certainly more understandable to the lay person, and that's what we are dealing with. If we are dealing with an analyst, it may or may not be the case. But we are dealing generally with lay people.

A.C.H (22) Let me push the question further down like... there is a moral problem which I see emerging. You have got a manager at some point. He falls down here, he falls down there, he is cheating on this, so you get him. And you present him with all of this and he says: "Why should I believe this?" Well, in statistics you find some form of a proof in numbers. Now, C.Z, you are showing impatience with that, because you say "Give me the answers". Well, that's fine until you get in front of that guy in Fresno who says "I do not believe you!" Then you have to be able to come back on and say, "This is because... " and you go through the process of somehow convincing him that he should pay attention to his work.

I am involved in a thing like this with the post office where the mail carriers are given a sample of mail, and the forecast then comes after that and the managers are up in arms "That sample is drawn at a peculiar time at peculiar days and so on... " I find a similar debate in here: as soon as this thing is producing answers that you, managers, believe, you are going to have a problem to convince your assistance to pay attention - and you'll get that problem too, and it's related to this question of whether you want only answers or whether you want answers with analysis.

C.Z.B (23) I have a comment on that, something that in our business would be meaningful to me, would be to take this QPR (Quarterly Progress Report), and bring it along with the pictures and say "Look, we have run your data through the computer, and this is how you deviate from plan".

A.C.H (24) So do you feel that his right performance is the important thing?

C.Z.B (25) Well, I probably take the position that we plugged in his own data, so that he should understand. Say "Look, from this information, we got these pictures". I am questioning the time, whether that person would take the time to try to understand the displays. The manager in Fresno might turn you to their MIS person who will probably understand this, the ten steps. But the manager himself may not have that much time. For instance, Al talks to a manager and says "This has been the analysis, this is what comes out, this is how it clusters".

A.C.H (26) If I follow that all the way, then he really does not have to believe it; what he has to believe is that if you are going to evaluate him on how he comes out on those things, so if you tell him "O.K., you fell down on these three measures and I am not going to do what you want me to do until you bring those up" then he will pay attention to it. But when it seems to me that you should be able to tell him how should he change his operations so that he comes up on those measures you tell him you are going to evaluate.

B.B (27) I think you can tell him because you can look at those similarities between those which perform well and look at the way their programs are operating, and say "Here are the similarities among the operations of people who are performing well, maybe you could do the same, or better". Then you begin to help the manager run the program better.

A.C.H (28) We did this in the Savings and Loans industry some time ago, and we published for the Commission of Regulations a list of performance ratios and then we generated a two-page table which showed the performance ratios grouped by size categories and characteristics. This went to the commissioner and he would say to some manager: "Wait a minute... on ratio 13 you are about the next to lowest in your group size. Till you improve your ratio 13, I do not see what reason you have to ask for a grant". It worked...

B.B (29) There are two levels there. One is that, some way or another, ratio 13 has to get up and then there is the question of what is involved with ratio 13. Maybe we could have two people talking, one is a manager and the other is the analyst.

A.C.H (30) This is what we actually did, and it works, but it requires an enormous amount of organizational backup, a level that requires some sophistication of the system. You reverse those things and say "this is what is alleviated with success", they tell you what success is and you tease out of the grass how to get that.

B.C (31) Well, you are talking about the Savings and Loans example, which is certainly a very large universe, much larger than what we are talking about. I do not know if we need as much as 13 ratios.

A.C.H (32) You do not need thirteen ratios, three only maybe. But it would be nice if you could be able to characterize your various agents in such a way that they find themselves being compared with meaningful others. In Bernard's system it helps to find which the meaningful others are... I am wondering if the focus of this thing, which is focusing on the manager alone should not be also to focus on the analyst; you, C.Z, do not want to sit here in front for two hours and get a piece of paper, but the analyst does not mind. Maybe you should shift this a little bit and work more closely to the analyst and get clear statements about what the data says. The whole thing must be tuned.

E.R.F.W.C (33) But if the manager knows what he does want, he can interact directly and then he can find answers more effectively than going through the analyst, who is actually interpreting his manager.

K.T (34) But it may well be that a simplified routine, makes the job of the manager much easier. This is what C.Z is looking for. Then we could have another set of routines that perhaps Fedreps are interested in. And then for the researcher or the analyst who perhaps is looking at the regional performance, (and how the region fits in the nation as a whole) he might be interested in still more detailed routines.

This a powerful tool when the decisions are made for the coming year - where to fit the money, where to fit the people. If you can go back to a prime sponsor, or another prime sponsor can say "Aha, this is a profile of success, limited, or failure", then a set of graphs coming from that profile routine would give an answer. As Bruce pointed out, there are levels of use. I know C.Z is impatient and would like to get step C right away, but we have to go from A1, A2 and B1, B2, etc.

B.B (35) The concept of getting the manager involved is very good because you get right away what the manager actually says, and the analyst should be in a procedure to hear what the manager says. Perhaps it is for the analyst to then sit down and to work it out, so that the manager can see what he wants to see in the fewest number of steps. And then C.Z sits down the screen and you flash him what he wants to see, and then along the line he says "Yes, but how about ...?" And the analyst, Bernard in this case, can go through and flash you whatever is necessary to get the answers to his new questions. So you get an interaction between a tool, the analyst, and the manager which has a high payoff. Some pre-programmed things flash off right away, and then there is the ability to make some additional inquiries and get answers right away.

Having watched several different projects, the desire is to get the manager in touch with the computer; but actually I don't see it happening; rather I see the computer getting in touch with the analyst getting in touch with the manager. Computers are becoming analyst tools, for analysts to do sophisticated things quite rapidly and to make this exchange between the analyst and the manager very rapid. But the ability of the manager first to understand what is going on (and maybe he is not interested), and second to learn how to type "Profile" or "Raw" board is more than the manager is ever going to be able to do.

I am not saying that it is this, or that it is a question of getting simpler graphics... you need somebody there who knows all the many possibilities and it will take a manager a long time to learn. I don't see these tools falling into the manager's hands except at a very high summary level, with a program where you write the word "Script" and you get whatever is written on the script. It's a very high summary level, where the manager sees what is there. But if he wants anything different, he goes on to the script and asks the analyst "Eh, how do I get this and that"... And that's where I see the level of computer-managerial interaction.

C.Z.B (36) Unfortunately to do this or something else, we are going to need a lot of time; granted that all those other various steps are needed, how do we manage to get the time to know the system? Whatever system, there are some basic concerns which I think the manager should have - I am addressing it at my level.

I see, Bernard, you know what you are doing, and I know that the capability is there to make problems pop up. But what I am looking at as a manager is "how do I sell this concept: give me the things to read out which I want to see quickly".

C.W.C (37) Isn't it that manager-to-manager conversation has been amplified by the graphics? Or could it be? Say, how the Fresno manager compares to the other one over here, Sacramento... My God, that's a serious improvement, isn't it?

C.Z.B (38) O.K., but let me clarify - I am not only looking down to managers that are running the programs. I am looking at our own internal management in this department.

C.W.C (39) But, on request, you can say "Look, I have spotted where the troubles are just at a glance right here".

E.R.F.W.C (40) You see, you can pick up particular displays that attract you and that you find useful. The analyst, like Bernard, would generate a stack of these, and you will just sample those you want.

B.B (41) Hopefully we could tell the same thing to different people in different ways.

C.Z.B (42) I think I am looking for some standardization. I don't really care about the best approach, so long as I can understand and use it. Forty-seven prime sponsors are a lot. If a picture tells me "those are the factors", then it clarifies my thoughts.

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