The Use of Nonmetric Multidimensional Scaling in Marketing Analysis

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The innovative features of nonmetric multidimensional scaling are discussed in this article. These techniques are now being applied in the study of a variety of marketing problems. Emphasis is on understanding the theoretical and practical differences between these techniques and other scaling devices. An example of use is given and the implications for strategic marketing decisions are discussed.

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WITHIN the past two years marketing analysts have made increasing reference to new methodology, loosely referred to as "scaling."[1] These references are often confusing to the marketing executive for they do not pertain to the scaling procedures such as rating scales, paired comparisons, semantic differentiation, and scalogram analysis, which have been utilized previously in marketing studies. Instead, many analysts are now referring to the set of techniques called nonmetric multidimensional scaling which seems to be admirably suited to the analysis of several problem areas in marketing.

The purposes of this paper are: (1) to explain, in a nontechnical fashion, the theory and procedures underlying nonmetric multidimensional scaling; (2) to present an example of its use; and (3) to speculate on further marketing applications.

The Problem of Measurement

Measurement involves the assignment of numbers to objects or properties of objects according to a set of rules. The rules by which numbers are assigned during measurement define the properties of the scales which are a result of measurement.[2] For example, road mileages represent a *ratio* scale, so-called because the ratios of distances among cities have meaning. A natural origin—zero point—exists from which all distances can be measured. In many instances of measurement, however, a natural zero does not exist yet the size of the distance between *pairs* of objects has meaning. These are called *interval* scales. A very obvious example is the measurement of temperature in which different arbitrary zero points are established according to the rules of the measurement process one is using. Thus, regardless of the temperature scale being used, it is correct to say that the temperature difference from 20° to 40° is twice that of 20° to 30°, but it is not correct to say that 40° is twice as warm as 20°.

Ratio and interval scales are both *metric* scales because they contain information about equality relationships (that is, *how much*

[1] Yoram Wind, "Mathematical Analysis of Perception and Preference for Industrial Marketing," in Keith Cox and Ben M. Enis, eds., *A New Measure of Responsibility for Marketing* (Chicago, Ill.: American Marketing Association, June, 1968), pp. 284-294; James R. Taylor, "The Meaning and Structure of Data as Related to Scaling Models," in Robert L. King, ed., *Marketing and the New Science of Planning* (Chicago, Ill.: American Marketing Association, August, 1968), pp. 309-315.

[2] Warren S. Torgerson, *Theory and Methods of Scaling* (New York: John Wiley and Sons, Inc., 1958), Chapter 1.

larger or smaller) among the objects being measured. Explicit distance functions are defined by the rules of measurement. It is possible, however, to generate scales by rules of measurement in which inter-object relationships are described simply by inequality or *nonmetric* relationships (that is, *which one* is larger or smaller), as will be shown. The rules of the measurement process which produce nonmetric scales are (1) objects can be ordered, and (2) (sometimes) intervals among objects can be ordered.

Relevance to the Marketing Situation

People cannot ordinarily provide accurate and reliable data about equality relationships among objects such as competing brands, or about brand characteristics. Psychological evidence of this is overwhelming.[3] Yet because of the ease of manipulating metric data, and because of the lack of nonmetric analytical procedures, marketing analysts have invariably assumed the existence of a metric scale. For example, analysts using a t test of significance applied to different rating scale scores frequently assume an interval (metric) scale where it is not appropriate.

At this point, it is entirely proper to ask, "So what? What harm is being done? And, do you have a better method?"

The lack of recognition that different assumptions can be made about data may account for some of the disappointing results which have been reported in attempts to predict market behavior. By assuming interval data when neither data nor theory supports it, the marketing analyst, in interpreting (for example) the results of consumer product evaluations, is quite liable to postulate that unnecessarily strong relationships exist between the evaluations and subsequent consumer behavior. When a relationship is not verified by empirical evidence, the validity of the relationship is questioned, when the error may lie instead in the *strength* of the postulated relationship.

Metric Results from Nonmetric Inputs

The techniques of nonmetric multidimensional scaling require only nonmetric (ordinal) input measures, yet metric (ratio scale) results are ordinarily obtained. This result, metrically invariant output from only ordinal input, stems from the reduction in the number of constraints needed to represent a k dimensional nonmetric solution in a metric space of less than k dimensions. This can be demonstrated intuitively.

All order relationships among n objects can be depicted in a space of n-1 dimensions.[4] As an example, the distance between any two objects can be represented by a straight line which is a unidimensional space. Similarly the distance relationships among any three objects can be completely described by a triangle which requires only a two-dimensional space to represent the three order relationships. As the number of objects (n) becomes large, the number of order relationships (that is, nonmetric constraints) required grows approximately with the *square* of n (actually $[n(n-1)/2]$). *However, the number of metric constraints required for complete specification of n points grows only linearly with n.* Thus, 45 *ordinal* relationships $[10(10-1)/2=45]$ are required to show completely the structure among ten objects. If one were to plot these same ten objects in a two-dimensional space, only 20 coordinates ($n \cdot k$ or $10 \cdot 2$) would be needed. The net result is that with large n a metric solution involving a space of considerably fewer dimensions may be contained within the set of $[n(n-1)/2]$ relationships. In Shepard's words, ". . . the metric information was contained in the original numbers all along—only in such a dilute form that we did not recognize it. But when this same information is squeezed into a smaller set of numbers, it finally becomes concentrated enough to be recognized for what it is."[5]

The Roadmap Problem—An Illustrative Example

A useful way of evaluating any new analytical procedure is to relate it to a problem with a known solution. In this case the problem to be considered was the placement of key cities on a map of the United States.[6]

In terms of nonmetric multidimensional scaling,

[3] Same reference as footnote 2, Chapters 4-10. Also Roger N. Shepard, "Metric Structures in Ordinal Data," *Journal of Mathematical Psychology*, Vol. 3 (July, 1966), pp. 287-315, at pp. 310-312; and Frank Restle, *Psychology of Judgment and Choice* (New York: John Wiley and Sons, Inc., 1961).

[4] J. F. Bennett and W. L. Hays, "Multidimensional Unfolding: Determining the Dimensionality of Ranked Preference Data, *Psychometrika*, Vol. 25 (December, 1960), pp. 27-43.

[5] Roger N. Shepard, "Analysis of Proximities as a Technique for the Study of Information Processing in Man," *Human Factors* (February, 1963), pp. 33-48, at p. 35.

[6] Marshall G. Greenberg, "A Variety of Approaches to Nonmetric Multidimensional Scaling," Paper presented at the 16th International Meeting of the Institute of Management Sciences, New York (March, 1969).

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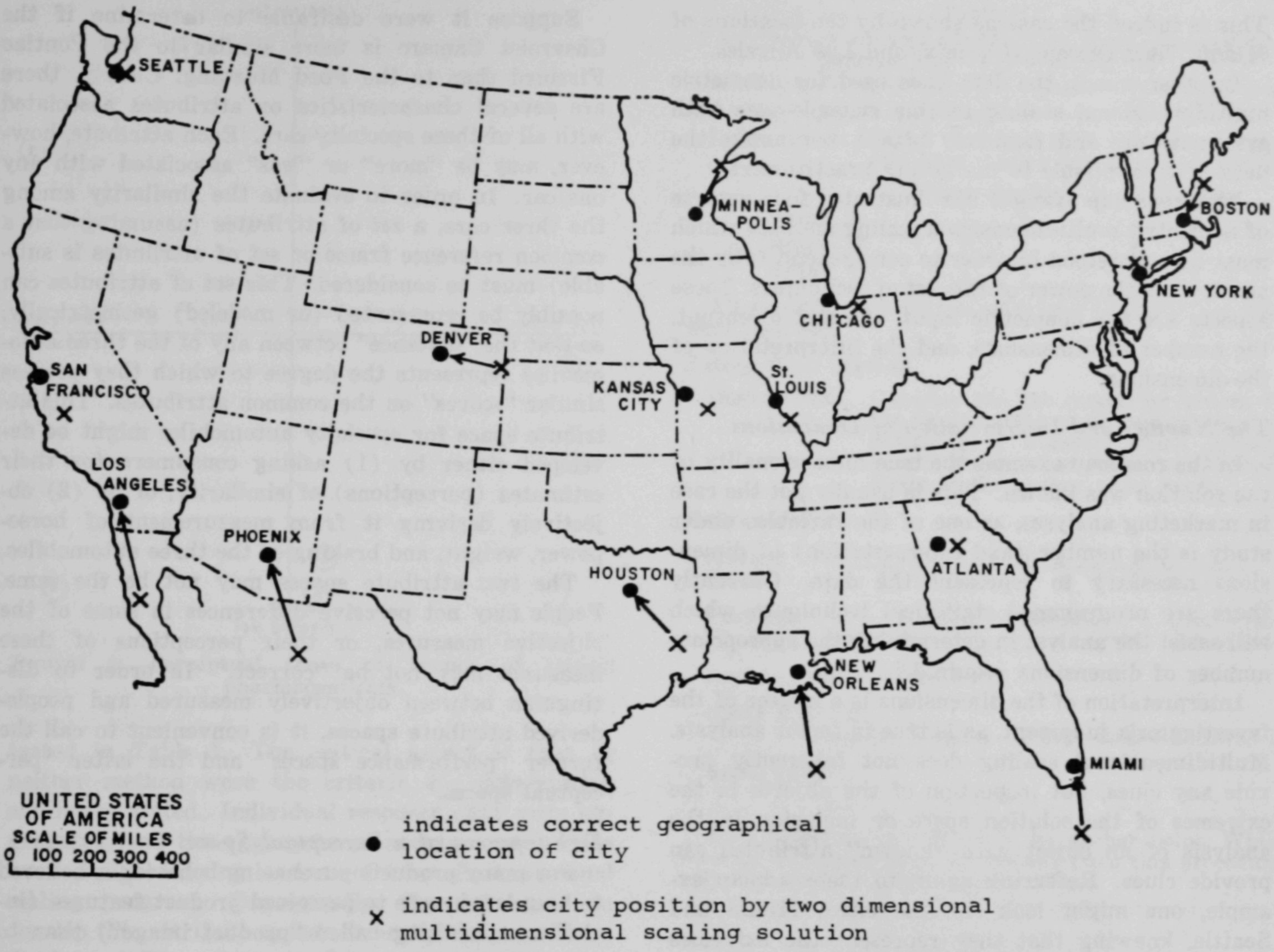

FIGURE 1. Comparison of actual geographic locations of fifteen cities with the locations defined by the two-dimensional multidimensional scaling solution.

the minimum data necessary to "solve" this problem are the rank orders of the inter-city distances. An atlas of the United States was used in calculating inter-city road mileages among all pairs of 15 cities. There are, therefore, 105 inter-city distances $[n(n-1)/2]$. Conversion of actual inter-city distances into rank order data was achieved by assigning the number "1" to the shortest road distance, that is, Boston-New York; the number "2" to the next shortest distance, that is, Kansas City-St. Louis; and so on, until all 105 inter-city distances were assigned a number. Ties were given equal numbers. This data base of rank orders was then utilized as input to a nonmetric multidimensional scaling program.

Clearly, the solution to the problem of city placement is known. What is required is a two-dimensional figure, with the axes labeled north-south and east-west. The nonmetric multidimensional scaling result should indicate clearly a two-dimensional solution and should place the cities in their correct geographic location on a United States map.

In Figure 1 the two-dimensional result obtained from a nonmetric multidimensional scaling program[7] is compared to the actual geographic locations of the cities. The correct geographic locations are identified by a dot (•) and the scaling solution by an "x." The fit between the scaling positions and actual geographic locations is quite good, although errors of approximately 200 miles are evident in the South and West. However, a substantial part of the error can be explained.

The differences are due primarily to imperfect data. Road distances often are *not* the shortest straight line distances between any pair of cities, but reflect natural detours such as mountain ranges and lakes, and the intricacy of the road network in any section of the country. The imperfections in the mileage data base affected some of the rank order placements. Thus, cities which are more inaccessible due to terrain and/or to being in more sparsely settled sections of the country are more likely to be "out of place" on the nonmetric scaling solution.

[7] The actual program used was TORSCA. See F. W. Young and W. S. Torgerson, "TORSCA, A Fortran IV Program for Shepard-Kruskal Multidimensional Scaling Analysis," *Behavioral Science*, Vol. 12 (July, 1967), pp. 498-9.

This is indeed the case as shown by the locations of Miami, New Orleans, Phoenix, and Los Angeles.

In other words, the data base used for nonmetric multidimensional scaling in this example was both systematically and randomly biased, not unlike the data often available to marketing practitioners.

This roadmap example has illustrated four aspects of nonmetric multidimensional scaling methods which must be understood in order to comprehend fully the novelty and the power of this set of techniques. These aspects are the nonmetric input, the metric output, the number of dimensions, and the interpretation of the dimensions.

The Number and Interpretation of Dimensions

In the roadmap example the true dimensionality of the solution was known. This is usually not the case in marketing analyses, as one of the variables under study *is* the number (and interpretation) of dimensions necessary to represent the data. Currently there are programmed statistical techniques which will assist the analyst in determining the appropriate number of dimensions required.[8]

Interpretation of the dimensions is a matter of the investigator's judgment, as is true in factor analysis. Multidimensional scaling does not inherently provide any clues, but inspection of the objects in the extremes of the solution space or inclusion in the analysis of an object with "known" attributes can provide clues. Referring again to the roadmap example, one might look for the cities Miami and Seattle, knowing that they represent the extremes of Southeast and Northwest.

In summary, the techniques described in this paper utilize only order relationships among data, but can often provide metric information about distance relationships. Moreover, a *multi*dimensional solution may result even though the input measures were merely unidimensional (that is, the rank orders of the inter-object relationships).

Applications of Nonmetric Multidimensional Scaling to Marketing Problems

Marketing analyses often involve two distinct types of data bases. In one case the data such as sales, profits, or the presence or absence of a particular product feature are objectively determined. In the second case the data are defined by the perceptual processes of individuals. Examples of this type of data are perceptions, attitudes, and preferences. In many cases analysis of the same problem utilizing the two types of data can yield disparate results. A hypothetical problem will make this clear.

Suppose it were desirable to determine if the Chevrolet Camaro is more similar to the Pontiac Firebird than to the Ford Mustang. Clearly, there are several characteristics or attributes associated with all of these specialty cars. Each attribute, however, may be "more" or "less" associated with any one car. In order to evaluate the similarity among the three cars, a *set* of attributes (assuming that a common reference frame or set of attributes is suitable) must be considered. This set of attributes can possibly be represented (or modeled) geometrically, so that the "distance" between any of the three automobiles represents the degree to which they possess similar "scores" on the common attributes. This attribute space for specialty automobiles might be developed either by (1) asking consumers for their estimates (perceptions) of similarity, or by (2) objectively deriving it from measurement of horsepower, weight, and braking of the three automobiles.

The two attribute spaces may not be the same. People may not perceive differences in some of the objective measures, or their perceptions of these measures may not be "correct." In order to distinguish between objectively measured and people-derived attribute spaces, it is convenient to call the former "performance spaces" and the latter "perceptual spaces."

Development of a Perceptual Space

For many products purchasing behavior is believed to be related more to perceived product features (including something called "product image") than to actual performance characteristics. This might be true perhaps in explaining consumer purchasing patterns with respect to frequently purchased grocery items such as detergent, coffee, and beer. Similarly, it has been suggested that perceptions, rather than objective analysis of laboratory reports, can "explain" physician selection of competing brands of ethical pharmaceuticals.

In a recently completed pilot study, physician perceptions of, and preferences for, brands of drugs within two classes of ethical pharmaceuticals were analyzed.[9] Figure 2 illustrates a typical perceptual space derived in this study. A composite space of only two dimensions based on a statistical goodness of fit measure and on interpretability appeared to be necessary to portray accurately inter-brand relationships.

To develop this perceptual space data were collected from a sample of general medical practitioners who were simply asked to render overall similarity judgments for all product pairs. Two methods of data collection were utilized successfully—triadic combinations and rating scales. These procedures are illus-

[8] Same reference as footnote 7. Also Joseph B. Kruskal, "Multidimensional Scaling by Optimizing Goodness of Fit to a Nonmetric Hypothesis," *Psychometrika.* Vol. 29 (March, 1964), pp. 1-27, and "Nonmetric Multidimensional Scaling: A Numerical Method," *Psychometrika*, Vol. 29 (June, 1964), pp. 115-29.

[9] Lester A. Neidell, *Physician Perception and Evaluation of Selected Ethical Drugs: An Application of Nonmetric Multidimensional Scaling to Pharmaceutical Marketing,* unpublished doctoral dissertation, University of Pennsylvania, 1969.

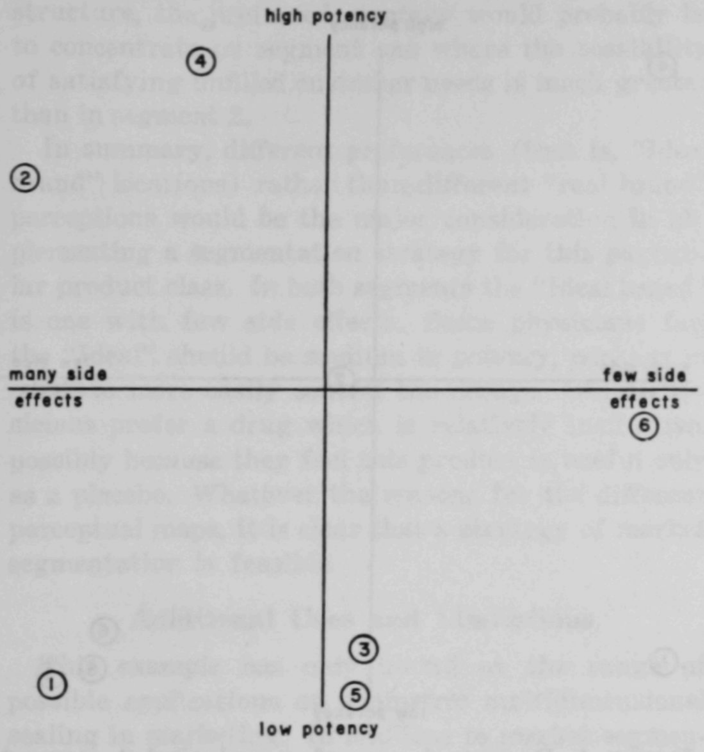

FIGURE 2. Perceptual space of brands of ethical pharmaceuticals.

trated in Table 1. The critical aspect is that in neither method were the criteria for determining similarity stated. Individual response data were aggregated, and the aggregate or average perceptions were analyzed using a nonmetric multidimensional scaling program. Conceptually, the data used to develop this attribute space are vastly different from those used in performance space studies. However, after the similarity measures used for input are derived, the computational procedure is identical.

Figure 2 contains five "real" brands (Brands 1-5) which were identified during data collection, and one hypothetical brand (Brand 6) which was labeled the hypothetical "Ideal brand" during data collection. The concept of the "Ideal brand" is a simple one; it merely states that the closer a real brand is to the "Ideal brand," the more preferred is the real brand.[10] By definition, the "Ideal brand" is the most preferred brand.

This use of the "Ideal brand" concept introduces another aspect of nonmetric multidimensional scaling. *Preferences and/or preference distributions can be super-imposed on, or jointly derived with, most attribute spaces, for both performance and perceptual data.*[11]

The usefulness of this feature can be demonstrated by analyzing Figure 2. Suppose that this sample of physicians was actually a representative national

TABLE 1
ILLUSTRATION OF THE METHODS OF DATA COLLECTION USED IN THE PHYSICIAN STUDY

Method of Triadic Combinations

Instructions: Select the *two* most similar and the two *least* similar brands in each triple.

	Most Similar	*Least Similar*
Brand A	( )	( )
Brand B	( )	( )
Brand C	( )	( )

All possible combinations of triples [(6!/3!3!) = 20] were included.

Rating Scale Method

Instructions: Compare the five remaining brands to the brand acting as an anchor point by assigning a number which reflects your assessment of their overall similarity to the anchor point brand.

Reference Scale

Anchor Point 0 1 2 3 4 5 6 7 8 9 10

Perfectly Similar ← Similar Dissimilar → Completely Dissimilar

Anchor Point: Brand 5

Other Brands:

Brand 3	Brand 4	Ideal	Brand 2	Brand 1
___	___	___	___	___

Scale Value:

Each brand in turn acted as an anchor point. While interval measures might be derived from this procedure only the ordinal results were utilized.

sample, and further, that the two dimensions were equally important to the sample. Since by definition the "Ideal brand" would be most preferred, this suggests that Brands 3 and 5 would have the largest market shares of the five brands. If a drug manufacturer were to introduce a new brand in this product class, he would attempt to place it close to the "Ideal brand."

Labeling of the axes of this perceptual space was achieved by analyzing other data collected during the study and by relying on the advice of knowledgeable people in the pharmaceutical industry. The two dimensions were identified as "potency" and "side effects." Thus, Brands 2 and 4 were perceived to be highly potent, but also to induce (undesirable) side effects. Brands 1, 3, and 5 were perceived to be considerably weaker than the other two brands, but despite this, Brand 1 still had associated with it undesirable side effects.

Market Segmentation Analysis

In terms of marketing strategy, the position of the "Ideal brand" (Brand 6) suggests that a more "ideal" brand might be introduced. This implies, however, that a single "Ideal brand" exists which will be the "most preferred" brand for all respondents. Alternatively, *different* "Ideal brands" might exist. For example, suppose that the similarities

10 Clyde H. Coombs, *A Theory of Data* (New York: John Wiley and Sons, Inc., 1964), p. 141.

11 See Paul E. Green, Frank J. Carmone, and Patrick J. Robinson, *Analysis of Marketing Behavior Using Nonmetric Scaling and Related Techniques* (Cambridge, Massachusetts: Marketing Science Institute, March, 1968).

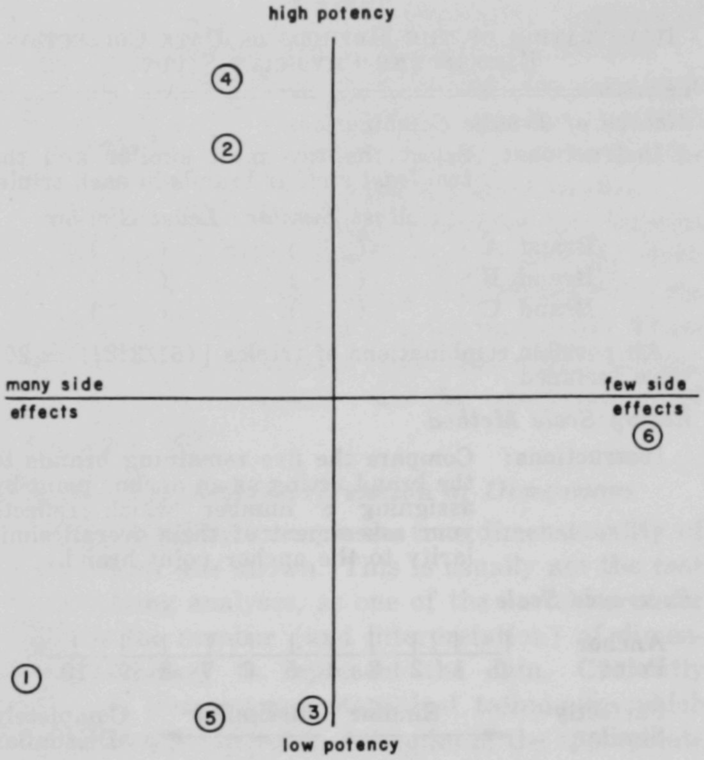

FIGURE 3. Perceptual map of first market segment.

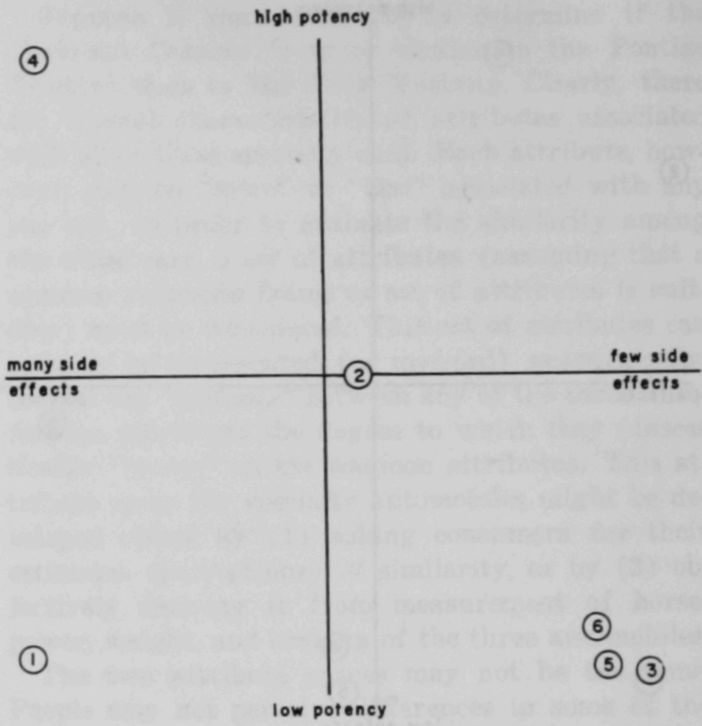

FIGURE 4. Perceptual map of second market segment.

data were collected from two distinct sets of physicians, one group of which placed the "Ideal brand" near Brands 2 and 4, while the other perceived their "Ideal brand" to be similar to Brands 3 and 5. If this were true, then the single "average Ideal" would be one that satisfies neither of these groups very well.

To further complicate marketing strategy decisions, the perceptual spaces of the *real brands* may not be similar. For example, on the average Brands 2 and 4 were perceived as similar; however, there may be a subset of respondents who did not believe this to be true. For this particular product class the possibility that different perceptual maps existed was supported by clinical evidence. According to this evidence, the interbrand relationships of Brands 1, 3, 4, and 5 were accurately portrayed, but the positioning of Brand 2 was inaccurate. Brand 2 should have been midway between Brand 4 and Brands 3 and 5 in both potency and side effects. Was it possible that some of the respondent physicians did in fact perceive the relationships of Brand 2 to the other four brands "correctly"?

In summary, average perceptual maps may be a statistical artifact. In order to decide among alternative strategies it is necessary to assess the scatter or variability of perceptions.

A procedure called cluster analysis was utilized to determine if the aggregate perceptual maps did in fact disguise the existence of different perceptual maps. The objective of cluster analysis is to delineate any natural groupings that exist in a set of data.[12] No clearly defined rules exist, however, to determine an "optimum" number of clusters to extract from any given data bank. In this particular product class, analysis of the volume of potential segments suggested that a maximum of two market segments could be profitably developed. Accordingly, only two clusters of respondents were developed. Similarities judgments were aggregated within each cluster, and again nonmetric multidimensional scaling was applied. The results are shown in Figures 3 and 4.

Figures 2 (aggregate analysis) and 3 (first market segment) are quite similar with respect to interbrand relationships. However, in Figure 4 (which represents a second market segment) Brand 2 was perceived as being medium in potency and side effects, as suggested by the clinical evidence. The "Ideal brand" for this subset of respondents also "moved"; it was very similar to Brands 3 and 5.

In both market segments, Brands 3 and 5 were closest to the "Ideal," suggesting that a single "optimum" brand choice might resemble either of these two brands. Such a choice, however, would leave a company very vulnerable to competition in segment one, since there is room for a brand to be "more ideal" in terms of the needs of these physicians. This choice would also face extremely stiff competition in segment two where it would be difficult to move a new brand into a position closer to the "Ideal" than either Brands 3 or 5. Thus, if this were a completely virgin market and if the brand placements were hypothetical entities, a brand resembling 3 and 5 might be considered optimum. Given the existing market

[12] See R. R. Sokal and P. H. A. Sneath, *Principles of Numerical Taxonomy* (San Francisco: Freeman and Company, 1963); Stephen C. Johnson, "Hierarchical Clustering Schemes," *Psychometrika*, Vol. 32 (March, 1965), pp. 241-254; and Paul E. Green, Ronald Frank, and Patrick Robinson, "Cluster Analysis in Test Market Selection," *Management Science*, Vol. 13 (April, 1967), pp. B387-B400.

structure, the preferred strategy would probably be to concentrate on segment one where the possibility of satisfying unfilled customer needs is much greater than in segment 2.

In summary, different preferences (that is, "Ideal brand" locations) rather than different "real brand" perceptions would be the major consideration in implementing a segmentation strategy for this particular product class. In both segments the "Ideal brand" is one with few side effects. Some physicians feel the "Ideal" should be medium in potency, perhaps in order to more easily control the dosage. Other physicians prefer a drug which is relatively ineffective, possibly because they feel this product is useful only as a placebo. Whatever the reasons for the different perceptual maps, it is clear that a strategy of market segmentation is feasible.

Additional Uses and Limitations

This example has only hinted at the range of possible applications of nonmetric multidimensional scaling in marketing. In addition to market segmentation analysis and new product studies, the techniques of nonmetric multidimensional scaling might be applied to the study of product life cycle, vendor and advertising evaluation, test marketing, salesmen and store image studies, and brand switching research.[13]

This is not to say that there are no limitations or problems to this methodology. There are. First of all there is a practical problem—data availability. This is particularly true in developing *perceptual spaces*, because the data must often be specially collected. Therefore, these analyses can be expensive, as anyone involved in empirical research can testify.

Second, there are computational problems. How unique are the attribute spaces given noisy and/or missing data? How reliable, statistically, are the solutions? It is clear that additional empirical and analytical work is needed in this area.

Third, there are theoretical questions. One of these concerns distance measurement. In the results discussed above, the ordinary Euclidean distance measure was utilized. There are other distance measures, which if utilized, might change drastically some of the interpretations earlier suggested.[14] One distance measure suggested in psychological literature is the "city-block" measure, in which distance between any two objects is *not* the shortest straight line distance, but is instead a function of the absolute distance traveled in terms of corners or right angles.

This limited discussion of the possible pitfalls of these new techniques is intended to indicate that, as with *any* set of analytical procedures, there are unresolved issues. Nonmetric multidimensional scaling offers the possibility of new insights into analysis of market behavior. It cannot, however, be used indiscriminately.

Summary

This paper has tried to introduce the reader to a set of new analytical procedures—nonmetric multidimensional scaling. An acquaintance with the specialized language of this technique is necessary to fully comprehend its possibilities. The central idea is that a multidimensional *attribute space* can be developed from a unidimensional data bank in which distances represent the degree of similarity among objects. Potential applications cover many facets of marketing. An example developed a *perceptual space* for competing ethical pharmaceuticals. Also in this example, the concept of a joint space, incorporating both perceptual and preference data, was introduced. In the example, the interpretation of the analyses, and their potential effects on marketing strategies, were stressed. The article concluded with a short discussion of some of the difficulties which might be encountered when utilizing these techniques.

[13] Paul E. Green and Frank J. Carmone, "The Performance Structure of the Computer Market: A Multivariate Approach," *Economic and Business Bulletin*, Vol. 21 (Fall, 1969), pp. 1-11, and same reference as footnote 11, Chapter 1.

[14] Roger N. Shepard, "Attention and the Metric Structure of the Stimulus," *Journal of Mathematical Psychology*, Vol. 1 (February, 1964), pp. 54-87.