by Richard M. Johnson

Market Segmentation: A Strategic Management Tool

Perceptual mapping remains an invaluable new product development resource.

Like motivation research in the late 1950s, market segmentation is receiving much attention in research circles. Although this term evokes the idea of cutting up a market into little pieces, the real role of such research is more basic and potentially more valuable.

For purposes of this discussion, market segmentation analysis refers to examination of the structure of a market as perceived by consumers, preferably using a geometric spatial model, and to forecasting the intensity of demand for a potential product positioned anywhere in the space.

The purpose of such a study, as seen by a marketing manager, might be:

- To learn how the brands or products in a class are perceived with respect to strengths, weaknesses, similarities, etc.

- To learn about consumers' desires and how these are satisfied or unsatisfied by the current market.

- To integrate these findings strategically, determining the greatest opportunities for new brands or products and how a product or its image should be modified to produce the greatest sales gain.

From the position of a marketing research technician, each of these three goals translates into a separate technical problem:

- To construct a product space, a geometric representation of consumers' perceptions of products or brands in a category.

- To obtain a density distribution by positioning consumers' ideal points in the same space.

- To construct a model that predicts preferences of groups of consumers toward new or modified products.

Solutions to the first two problems can be illustrated with actual data, although currently solutions for the third problem are more tentative.

Construct Product Space

A spatial representation or map of a product category provides the foundation on which other aspects of the solution are built. Many equally useful techniques are available for constructing product spaces that require different assumptions and possess different properties.

Following is a list of useful properties of product spaces that may be used to evaluate alternative techniques:

- Metric: distances between products in space should relate to perceived similarity between them.

- Identification: directions in the space should correspond to identified product attributes.

- Uniqueness/reliability: similar procedures applied to similar data should yield similar answers.

- Robustness/foolproofness: procedures should work every time. It should not be necessary to switch techniques or make basic changes to cope with each new set of data.

- Freedom from improper assumptions: other things being equal, a procedure that requires fewer assumptions is preferred.

EXECUTIVE BRIEFING

*In each issue of **Marketing Management** we reprint an important article from a past issue of one of our sister publications. This article, by Sawtooth Software, Inc. founder and chairman, Richard M. Johnson, first appeared in the **Journal of Marketing Research** in February 1971. When asked how the article has "aged" over the years, Johnson said: "Perceptual mapping remains to this day a superb way of describing important aspects of markets graphically, illuminating differences between desires and perceptions of different market segments, and helping managers develop insights about their markets."*

One basic distinction has to do with the kinds of data to be analyzed. Three kinds of data are frequently used: similarity/dissimilarity data, preference data, and attribute data.

Similarity/Dissimilarity Data. Here a respondent is not concerned in any obvious way with dimensions or attributes that describe the products judged. He makes global judgments of relative similarity among products, with the theoretical advantage that there is no burden on the researcher to determine in advance the important attributes or dimensions within a product category.

Examples of such data might be: (1) to present triples of products and ask which two are most or least similar, (2) to present pairs of products and ask which pair is most similar, or (3) to rank order *k*-1 products in terms of similarity with the *k*th.

Preference Data. Preference data can be used to construct a product space, given assumptions relating preference to distances. For instance, a frequent assumption is that an individual has ideal points in the same space, and that product preference is related in some systematic way to distances from his ideal points to his perception of products' locations.

As with similarity/dissimilarity data, preference data place no burden on the researcher to determine salient product attributes in advance. Examples of preference data that might lead to a product space are: (1) paired comparison data, (2) rank orders of preference, or (3) generalized overall ratings (as on a 1 to 9 scale.)

Attribute Data. If the researcher knows in advance important product attributes by which consumers discriminate among products, or with which they form preferences, then he may ask respondents to describe products on scales relating to each attribute. For instance, they may use rating scales describing brands of beer with respect to price vs. quality, heaviness vs. lightness, or smoothness vs. bitterness.

Procedures. In addition to these three kinds of data, procedures can be metric or nonmetric. Metric procedures make assumptions about the properties of data, as when in computing a mean one assumes that the differences between ratings of values one and two is the same as that between two and three, etc.

Nonmetric procedures make fewer assumptions about the nature of the data; these are usually techniques in which the only operations on data are comparisons such as "greater than" or "less than." Nonmetric procedures are typically used with data from rank order or paired comparison methods.

Another issue is whether or not a single product space will adequately represent all respondents' perceptions. At the extreme, each respondent might require a unique product space to account for aspects of his perceptions. However, one of the main reasons for product spaces' utility is that they summarize a large amount of information in unusually tangible and compact form.

Allowing a totally different product space for each respondent would certainly destroy much of the illustrative value of the result. A compromise would be to recognize that respondents might fall naturally into a relatively small number of subgroups with different product perceptions. In this case, a separate product space could be constructed for each subgroup.

Frequently a single product space is assumed to be adequate to account for important aspects of all respondents' perceptions. Differences in preference are then taken into account by considering each respondent's ideal product to have a unique location in the common product space, and by recognizing that different respondents may weigh dimensions uniquely.

Techniques that have received a great deal of use in constructing product spaces include nonmetric multidimensional scaling, factor analysis, and multiple discriminant analysis.

Factor analysis has been available for this purpose for many years, and multidimensional scaling was discussed as early as 1938. Nonmetric multidimensional scaling, a comparatively recent development, has achieved great popularity because of the invention of ingenious computing methods requiring only the most minimal assumptions regarding the nature of the data. Discriminant analysis requires assumptions about the metric properties of data, but it appears to be particularly robust and foolproof in application.

Examples of Product Spaces

Imagine settling on a number of attributes which together account for all of the important ways in which products in a set are seen to differ from each other. Suppose that each product has been rated on each attribute by several people, although each person has not necessarily described more than one product.

Given such data, multiple discriminant analysis is a powerful technique for constructing a spatial model of the product category.

First it finds the weighted combination of attributes that discriminates most among products, maximizing an *F*-ratio of between-product to within-product variance. Then, second and subsequent weighted combinations are found that discriminate maximally among products, within the constraint that they all be unrelated to one another.

Having determined as many discriminating dimensions as possible, average scores can be used to plot products on each dimension. Distances between pairs of products in this space reflect the amount of discrimination between them.

Exhibit 1 shows such a space for the Chicago beer market as perceived by members of Market Facts' Consumer Mail Panels in a pilot study conducted in September 1968. Approximately 500 male beer drinkers described eight brands of beer on each of 35 attributes.

The data indicated that a third sizable dimension also existed, but the two dimensions pictured here account for approximately 90% of discrimination among images of these eight products.

The location of each brand is indicated on these two major dimensions. The horizontal dimension contrasts premium quality on the right with popular price on the left. The vertical dimension reflects relative lightness. In addition, the mean rating of each product on each of the attributes is shown by relative position on each attribute vector.

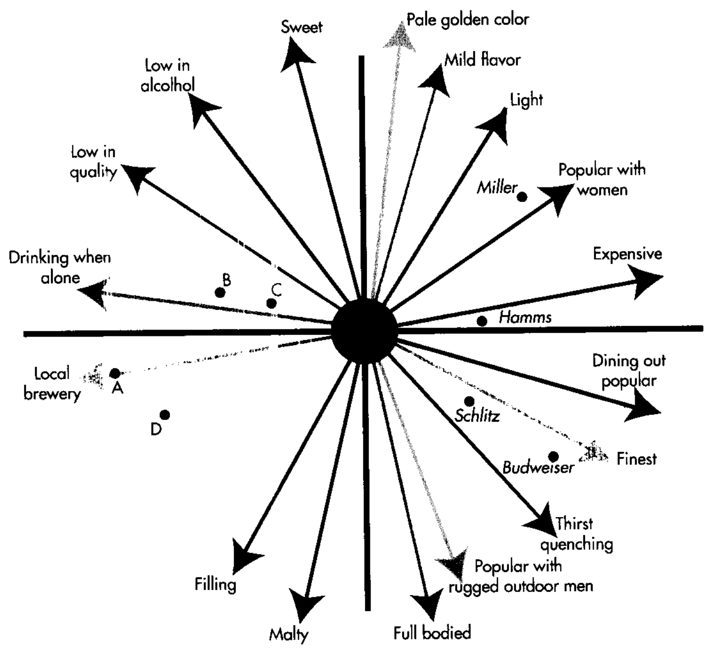
For instance, Miller is perceived as being most popular with women, followed by Budweiser, Schlitz, Hamms, and four unnamed, popularly priced beers.

As a second example, the same technique was applied to political data. During the weeks immediately preceding the 1968 presidential election, a questionnaire was sent to 1,000 Consumer Mail Panels households. Respondents were asked to agree or disagree with each of 35 political statements on a four-point scale. Topics were Vietnam, law and order, welfare, and other issues felt to be germane to current politics.

Respondents also described two preselected political figures, according to their perceptions of each figure's stand on

EXHIBIT 1

The Chicago beer market



- Given customary assumptions of multivariate normality, there is a test of significance for distance (dissimilarity) between any two products.

- Unlike nonmetric procedures, distances estimated among a collection of products do not depend upon whether or not additional products are included in the analysis. Any of the brands of beer or political figures could have been deleted from the examples and the remaining object locations would have had the same relationships to one another and to the attribute vectors.

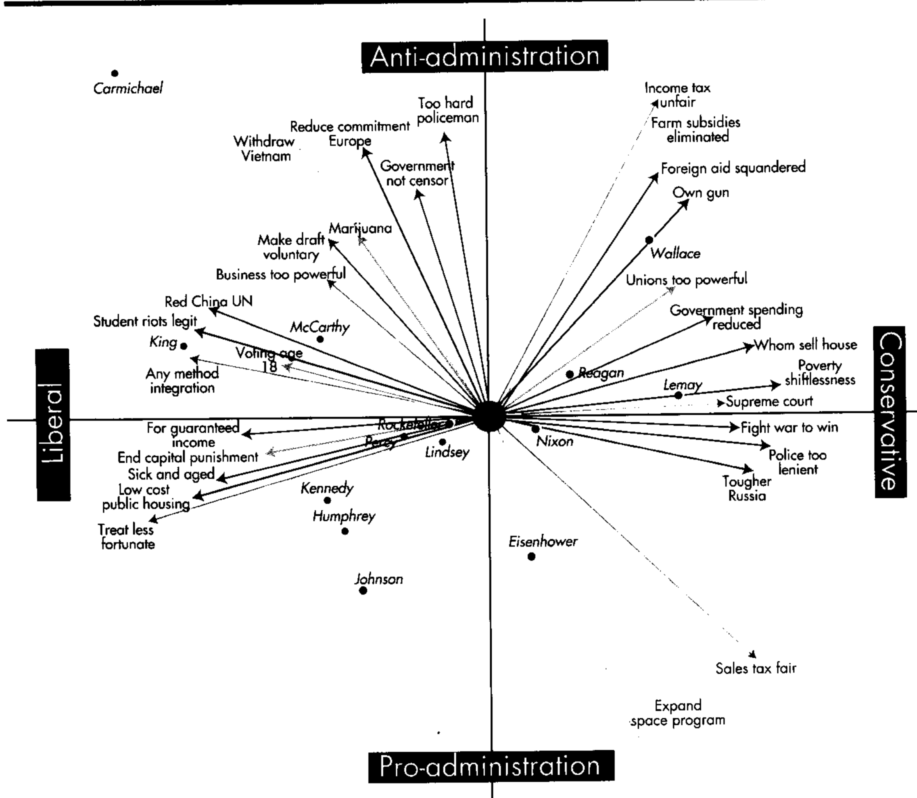
- The technique is reliable and well known, and solutions are unique because the technique cannot be misled by any local optimum.

Distribution of Ideal Points

After constructing a product space, the next concern is estimating consumer demand for a product located at any particular point. The demand function over such a space is desired and can be approximated by one of several general approaches.

EXHIBIT 2

The political space, 1968



each issue. Discriminant analysis indicated two major dimensions accounting for 85% of the discrimination among 14 political figures.

The liberal vs. conservative dimension is apparent in the data, as shown in Exhibit 2. The remaining dimension apparently reflects perceived favorability of attitude toward government involvement in domestic and international matters.

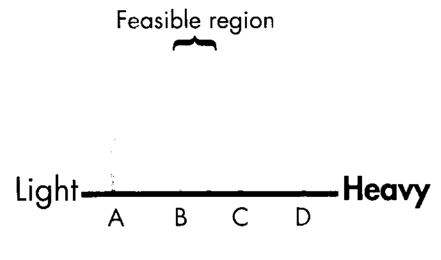
As in the beer space, it is only necessary to erect perpendiculars to each vector to observe each political figure's relative position on each of the 35 issues.

Multiple discriminant analysis is a major competitor of nonmetric multidimensional scaling in constructing product spaces. The principal assumptions the former requires are that: (1) perceptions be homogeneous across respondents, (2) attribute data be scaled at the interval level (equal intervals on rating scales), (3) attributes be linearly related to one another, and (4) amount of disagreement (error covariance matrix) be the same for each product.

Only the first of these assumptions is required by most nonmetric methods, and some even relax that assumption. However, the space provided by multiple discriminant analysis has the following useful properties:

EXHIBIT 3

A one-dimensional product space



The first is to locate each person's ideal point in the region of the space implied by his rank-ordered preference. His ideal point would be closest to the product he likes best, second closest to the product he likes second best, etc.

There are several procedures that show promise using this approach, although difficulties remain in practical execution. This approach has trouble dealing with individuals who behave in a manner contrary to the basic assumptions of the model, as when one chooses products first on the far left side of the space, second on the far right side, and third in the center.

Most individuals giving rank orders of preference do display such nonmonotonicity to some extent, understandably producing problems for the application of these techniques.

The second approach involves deducing the number of ideal points at each region in space by using data on whether a product has too much or too little of each attribute. This procedure has not yet been fully explored, but at present seems to be appropriate to the multidimensional case only when strong assumptions about the shape of the ideal point distribution are given.

The third approach is to have each person describe his ideal product, with the same attributes and rating scales as for existing products. If multiple discriminant analysis has been used to obtain a product space, each person's ideal product can then be inserted in the same space.

There are considerable differences between an ideal point location inferred from a rank order of preference and one obtained directly from an attribute rating.

To clarify matters, consider a single dimension, heaviness vs. lightness in beer. If a previous mapping has shown that Brands A, B, C, and D are equally spaced on this one dimension, and if a respondent ranks his preferences as B, C, A, and D, then his ideal must lie closer to B than to A or C, and closer to C than A.

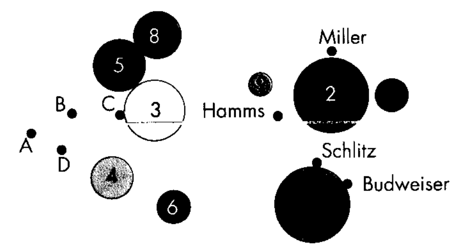
This narrows the feasible region for his ideal point down to the area indicated in Exhibit 3. Had he stated a preference for A, with D second, there would be no logically corresponding position for his ideal point in the space.

However, suppose these products have already been given the following scale positions on a heavy/light dimension: A = 1, B = 2, C = 3, and D = 4. If a respondent unambiguously specifies his ideal on this scale at 2.25, his ideal can be put directly on the scale, with no complexities. Of course, it does not follow necessarily that his stated rank order of preference will be predictable from the location of his ideal point.

There is no logical reason why individuals must be clustered into market segments. Mathematically, one can cope with the case where hundreds or thousands of individual ideal points are each

EXHIBIT 4

A strategic management tool

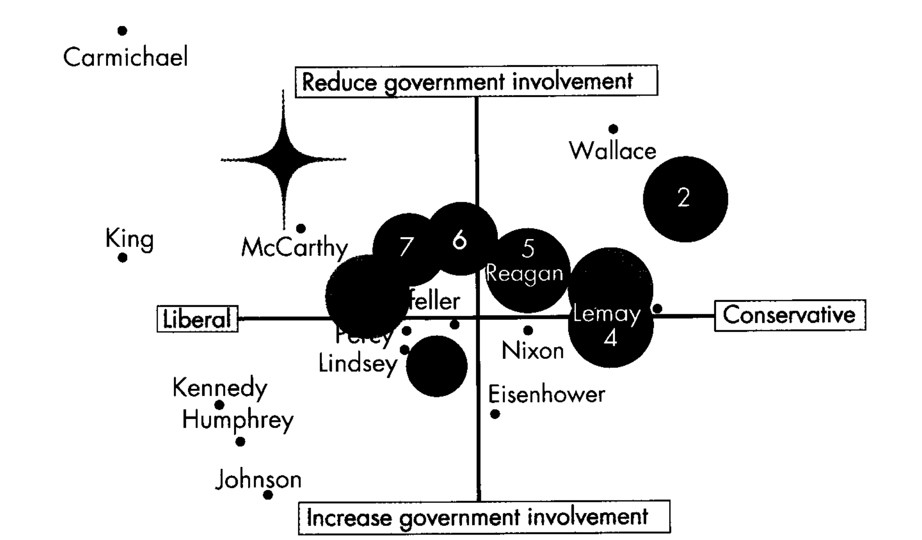


located in the space. However, it is much easier to approximate such distributions by clustering respondents into groups. Cluster analysis has been used with the present data to put individuals into a few groups with relatively similar product desires (beer) or points of view (politics).

Exhibit 4 shows an approximation to the density distribution of consumers'

EXHIBIT 5

Voter segment positions relative to political figures



Percent of Total Voters

Cluster 1 - 18%	Cluster 6 - 11%
Cluster 2 - 14%	Cluster 7 - 10%
Cluster 3 - 14%	Cluster 8 - 8%
Cluster 4 - 13%	Cluster S - college
Cluster 5 - 12%	Students, est. 5%

ideal points in the Chicago beer market, a "poor man's contour map."

Ideal points tended somewhat to group themselves (circles) into clusters. It is not implied that all ideal points lie within the circles, since they are really distributed to some extent throughout the entire space. Circle sizes indicated the relative sizes of clusters, and the center of each is located at the center of its circle.

A representation such as this contains much potentially useful marketing information. For instance, if people can be assumed to prefer products closer to their ideal points, there may be a ready market for a new brand on the lower or "heavy" side of the space, approximately neutral in price/quality.

Likewise, there may be opportunities for new brands in the upper middle region, decidedly light and neutral in price/quality. Perhaps popularly priced Brand A will have marketing problems, since this brand is closest to no cluster.

Exhibit 5 shows a similar representation for the political space, where circles represent concentrations of voters' points. These are not ideal points, but rather personally held positions on political issues.

Clusters on the left side of the space intended to vote mostly for Humphrey and those on the right for Nixon in the 1968 election. Throughout the space, the percentage voting Republican increases generally from left to right.

It may be surprising that the center of the ideal points lies considerably to the right of that of the political figures. One possible explanation is that this study dealt solely with positions on issues, so matters of style or personality did not enter the definition of the space.

It is entirely possible that members of clusters one and eight, the most liberal, found Nixon's position on issues approximately as attractive as Humphrey's, but they voted for Humphrey on the basis of preference for style, personality, or political party.

Likewise, members of cluster two might have voted strongly for Wallace, given his position, but he received only 14% of this cluster's vote. He may have been rejected on the basis of other qualities.

A small experiment was undertaken to test the validity of this model. Responses from a class of sociology students in a Western state university showed them to be more liberal and more for decreasing government involvement internationally than any of the eight voter clusters. Their position is close to McCarthy's, indicated by an "S."

Strategic Integration

Having determined the position of products in a space and seen where consumer ideal points are located, how can such findings be integrated to determine appropriate product strategy?

A product's market share should be increased by repositioning: (1) closer to ideal points of sizable segments of the market, (2) farther from other products with which it must compete, and (3) on dimensions weighted heavily in consumers' preferences.

Even these broad guidelines provide some basis for marketing strategy. For instance, in Exhibit 4, Brand A is clearly farthest from all clusters and should be repositioned.

In Exhibit 5, Humphrey, Kennedy, and Johnson could have increased their acceptance with this respondent sample by moving upwards and to the right, modifying their perceived position. Presumably, endorsement of any issue in the upper right quadrant or a negative position on any issue in the lower left quadrant of Exhibit 2 would have helped move Humphrey closer to the concentration of voters' ideal points.

Although the broad outlines of marketing strategy are suggested by spaces such as these, it would be desirable to make more precise quantitative forecasts of the effect of modifying a product's position.

Unfortunately, the problem of constructing a model to explain product choice behavior based on locations of ideal points and products in a multidimensional space has not yet been completely solved, although some useful approaches are currently available.

As the first step, it is useful to concentrate on the behavior of clusters of respondents rather than that of individuals, especially if clusters are truly homogeneous. Data predicting behavior of groups are much smoother and results for a few groups are far more communicable to marketing management than findings stated in terms of large numbers of individual respondents.

If preference data are available for a collection of products, one can analyze the extent to which respondents' preferences are related to distances in the space.

Using regression analysis, one can estimate a set of importance weights for each cluster or, if desired, for each respondent, to be applied to the dimensions of the product space.

Weights would be chosen providing the best explanation of cluster or individual respondent preferences in terms of weighted distances between ideal points and each product's perceived location.

If clusters rather than individuals are used, it may be desirable first to calculate preference scale values or utilities for each cluster. Importance weights can then be obtained using multiple regression to predict these values from distances.

If explanations of product preference can be made for existing products, which depend only on locations in space, then the same approach should permit predictions of preference levels for new or modified products to be positioned at specific locations in the space.

Models of choice behavior clearly deserve more attention. While the problem of constructing the product space has received much attention, we are denied the full potential of these powerful solutions unless we are able to quantify relationships between distances in such a space and consumer choice behavior.

Summary

Market segmentation studies can produce results that indicate desirable marketing action. Techniques presently available can: (1) construct a product space, (2) discover the shape of the distribution of consumers' ideal points throughout such a space, and (3) identify likely opportunities for new or modified products.

In the past, marketing research has often been restricted to tactical questions such as package design or pricing levels. However, with the advent of new techniques, marketing research can contribute directly to the development of strategic alternatives to current product marketing plans.

There remains a need for improved technology, particularly in the development of models for explaining and predicting preferential choice behavior. The general problem has great practical significance and provides a wealth of opportunity for development of new techniques and models. MM