Consumer Similarity Judgments: A Test of the Contrast Model

Michael D. Johnson
University of Michigan

Abstract

A general model is described that views similarity judgment as a contrasting of product features. The relative influence of common and distinctive features on perceived similarity is considered a function of the context or task environment. A memory probe is used to measure the common and distinctive features consumers associate with various products. The feature measures are then used to estimate the model under three different task environments: similarity, dissimilarity, and subject/referent similarity. The results support the model and the effect of the task environment on judgments of interproduct similarity.

Similarity plays an important role in marketing and in the formulation of marketing strategy. Multidimensional scaling of similarity judgments facilitates product positioning and new product design (Johnson, 1971; Shocker and Srinivasan, 1979). Moreover, attaining a level of perceived similarity or dissimilarity with other products is often the goal of product positioning strategies. Earning a place in the “evoked set" of the consumer may, for example, depend on a product's perceived similarity to other brands. The categorization of consumer products (Day, Shocker & Srivastava, 1979; Gutman, 1980) and objects in general (Rosch, 1975) also depends critically on notions of similarity or substitutability.

It seems important, therefore, to understand the process by which consumers judge similarity. This requires an understanding of both how consumers cognitively represent products and how the information in these representations is used to arrive at a judgment in various contexts. In marketing, similarity relations have been analyzed primarily through the use of spatial representations, such as those produced by multidimensional scaling, discriminant analysis, and factor analysis (Hauser & Koppelman, 1979). Such representations view products as points in a space varying on a small number of continuous dimensions. Although spatial representations have proven very useful, they do not completely explain how consumers cognitively represent or describe products. Consider that many products may be represented using dichotomous features, where products either do or do not contain an attribute, rather than continuous dimensions (Tversky, 1977; Garner, 1978; Johnson, 1981). While, for example, a two-dimensional space may show two beers as having some degree of "lightness" and "sweetness," consumers may simply represent the beers as ''light'' and "sweet.'' Furthermore, the process by which consumers use their cognitive representations to produce similarity judgments has received very little attention in marketing (Johnson, 1981).

This paper describes a psychological model of similarity, referred to as the contrast model (Tversky, 1977), and examines the model's ability to account for consumer judgments of interproduct similarity. More specifically, the goal of this research is to provide a direct test of the model. Previous studies have failed to provide such a test. After describing the model and its advantages, a procedure is outlined for estimating the model. The procedure uses memory probes to measure associated product features. The model is then estimated across three different proximity tasks: similarity, dissimilarity and subject/referent similarity. Finally, the important marketing and marketing research implications of the model are discussed.

THE CONTRAST MODEL

Consumers represent products and judge similarity using a limited number of relevant attributes. Marketers, using spatial representations, often view these attributes as continuous dimensions. Assuming continuous dimensions, however, limits our view of how consumers represent products and judge similarity. The representation of products is often based on very simple, dichotomous dimensions or features, such as whether an ice cream is considered "old fashioned" (Green, Wind & Claycamp, 1975) or a soft-drink is a "cola" (Cooper. 1973). Psychologically, features do seem to be far different from more continuous dimensions. The importance of feature-based representations in psychological theory, originally investigated by Restle (1959), is evidenced by their extensive use in modeling cognitive processes, including semantic judgment (Smith, Shoben & Rips, 1974), preferential choice (Tversky, 1972) and, importantly, proximity judgment (Tversky. 1977; Sbepard & Arabie, 1979).

As an alternative to dimensional approaches, Tversky (1977) has proposed a general model of interobject similarity, called the contrast model.' The model views similarity judgments as the result of contrasting common and distinctive features. Tversky provides considerable support for the model in studies involving people, countries, faces, forms, and figures (Sattath & Tversky, 1977; Tversky & Gati, 1978, 1982; Gati & Tversky, 1982). A major advantage of the contrast model is its ability to explain and predict the influence of context or task environments on proximity judgments. This is particularly important from a managerial perspective. The consumer's environment for comparing products, as in the case of a comparative advertisement, is often a controllable marketing variable. Unfortunately, feature-based approaches to similarity, particularly the contrast model, have received little attention in marketing. It is important, therefore, to look more closely at the contrast model and its ability to describe the way consumers judge similarity.

In his original study, Tversky argues that the assessment of similarity between certain objects is best described as a comparison or "contrast" of features. When faced with a similarity task, people extract and compile from remembered information a limited list of relevant features. Their judgment of similarity is based on a comparison of these features. Formally stated, the similarity between two objects, s(a,b), where a and b are associated with feature sets A and B, respectively, is

$$s(a,b) = \theta f(A \cap B) - \alpha f(A - B) - \beta f(B - A) \quad (1)$$

where $\theta, \alpha, \beta \geqslant 0$

Accordingly, the similarity between two objects is a function of their common features, $(A \cap B)$, features common to a but not to b, (A - B), and features common to b but not a, (B - A). Equation (1) expresses the proximity of a and b as a linear combination, or a contrast, of their common and distinctive features. Overall similarity increases with the measure of common features and decreases with the measure of distinctive features. The parameters θ, α, and β are weights representing the importance of the individual feature sets toward the similarity judgment. The model is not limited to situations where objects are described only by features. As Tversky and Gati argue, "Any nominal variable with more than two levels can always be expressed in terms of binary features by using dummy variables" (1982, p. 126). Importantly, as a psychological model, equation (1) is not restricted to feature-based representations.

The f function in the model measures the salience of features and their contribution to similarity, which is assumed to be monotonic and nonnegative. Both intensive and diagnostic factors affect attribute or feature salience (Tversky 1977). Intensive factors increase the inherent intensity or signal-to-noise ratio of an attribute. Diagnostic attributes are those that distinguish among alternatives in the stimulus set. The diagnosticity of an attribute depends on the objects under study. When judging the similarity among various automobiles, for example, globally common features, such as the fact that all cars have four wheels, are nondiagnostic and unlikely to affect the judgments. If, however, motorcycles are added to the set of stimuli, the number of wheels becomes diagnostic and may affect the judgments. Hence the perceived similarity of a Ford and a Volvo increases when a motorcycle is added to the comparisons.

The contrast model offers advantages that aid in understanding consumer judgments of interproduct similarity. In particular, the model highlights the possible differential importance of the one common and two distinctive feature sets across task environments. The model describes a wide range of proximity relations depending on the weights placed on the three sets of features. The weights themselves depend largely on the context or specific proximity task involved.

One context hypothesis is that the weight of common and distinctive features differs for similarity and dissimilarity judgments. When judging similarity, it seems natural to focus on what alternatives have in common ($\theta > \alpha + \beta$). Alternatively, when judging dissimilarity, we may focus more on what is distinctive to the alternatives ($\alpha + \beta > \theta$). Thus, although similarity and dissimilarity are often assumed to be perfectly negatively correlated, this need not be the case. If a pair of alternatives has both many common and many distinctive features, it may be both more similar in a similarity task and more different in a dissimilarity task than another pair of alternatives, with fewer common and distinctive features. East Germany and West Germany, for example, were judged by Tversky's subjects as being both more similar and more dissimilar than were Ceylon and Nepal. Intuitively, the former pair of countries bas both more common and more distinctive features than the latter. Using consumer products, Johnson (1981) found judgments of similarity and dissimilarity to be poorly correlated for soft-drinks and beer. Coke and Pepsi, for example, were judged as very similar in a similarity context and very dissimilar in a dissimilarity context. In the same study, however, judgments of similarity and dissimilarity among fruits were highly negatively correlated.

That the contrast model emphasizes the effect of common features on proximity is itself an advantage. In the contrast model, the addition of a common feature to a pair of products increases their similarity. Although dimensionally based spatial representations also allow for common features or invariant dimensions, the interpretation of product differences may be more salient. Adding dimensions on which products are invariant does not affect "distance" in a product space. It is important to recognize the effect of common features on judgments when analyzing similarity data. In fact, separate analyses may be required for consumers emphasizing many and few common features (or invariant dimensions), respectively.

Another context hypothesis concerns subject/referent similarity judgments. When consumers are asked to make judgments in a subject/referent format (e.g., "How similar is a to b?" where a is the subject and b is the referent), the focus may be more on the subject. The subject's features are then weighed more heavily than the referent's. The result is that the distinctive features of the subject detract more from similarity than do the distinctive features of the referent. The importance of this hypothesis is that context asymmetries in similarity result (i.e., where the similarity of a to b differs from the similarity of b to a) when alternatives differ in the number of distinctive features (assuming features are equally salient).

Asymmetric judgments have been reported for a wide range of stimuli. Tversky & Gati (1978; see also Tversky, 1977), for example, found subjects' ratings of the similarity of North Korea to Red China to be greater than the similarity of Red

China to North Korea. This result is explained by the greater number of distinctive features associated with Red China. Since the focus is on the subject. Red China's distinctive features detract more from similarity when Red China is the subject rather than the referent in the comparison. Similarly, Johnson (1981) found contextual asymmetries again among brands of soft-drinks and beer, but not among fruits. For example, Shasta Cola was judged more similar to Coke than Coke was to Shasta. This is also explained by assuming that consumers associate more distinctive features with Coke.

An important aspect of the context effects reported above is that they fail to test directly the model's ability to explain how consumers produce judgments of similarity. Assumptions concerning associated features are required for context effects, such as asymmetric judgment, to be consistent with the model's predictions. In a marketing context, a more direct test of the model would be to actually estimate it using consumer products. One problem, however, is that the model is inestimable in its current form. Estimation requires some measure of the common and distinctive features associated with the objects in question along with tolerable assumptions regarding the nature of the functions underlying equation (1). An estimation procedure is proposed below in order to provide a more direct test of the model.

MODEL ESTIMATION

The effect of common and distinctive features on proximity judgments may be estimated by either directly or indirectly controlling associated product features. Using the direct method, Gati & Tversky (1984) assessed the effect of an attribute as a common or distinctive feature by adding the component to either one of two stimuli or to both and comparing the judgments. Using several laboratory stimuli, the model was supported. This direct method is, however, unrealistic when using established consumer products. It is simply unreasonable to presume control over the features consumers associate with Coca-Cola or Budweiser Beer.

An alternative method of estimating the model, involving more indirect control over associated attributes, uses a memory probe to measure the size of the three feature sets (Rosch & Mervis, 1975). Subjects are asked to list the characteristic features or attributes that come to mind for a particular product or object. Data may be elicited either verbally or in writing. Ideally, a verbal listing minimizes any interference with the recall process. A time constraint on the listing should protect the validity of this type of measure (Ericsson & Simon, 1980). The constraint should allow sufficient time to list all immediately salient associations while reducing the chance of spurious elaboration.

Associated features are then coded to estimate the respective feature sets. The features listed for each pair of products by each subject are coded as either common or distinctive. It is possible at this point to obtain weights for individual features and incorporate them into estimates of the feature sets. Either self-reported weights or weights inferred from order of elicitation, for example, may be useful. At this stage of the theoretical research, however, a reasonable assumption can be made that, in conjunction with the memory probe, allows estimation of the model. Simply assume that a measure of the common and distinctive feature sets is obtained by counting the number of features elicited for each pair of products by each subject and averaging across subjects. A linear regression of average proximity judgments against the average number of features in each feature set then provides estimates of the effect of each feature set on the judgments.

This procedure is used here to estimate the model and the effect of common and distinctive features on judgments of interproduct similarity, dissimilarity, and subject/referent similarity. Tversky (1977) reports an estimation of the model using a similar procedure (r = .87), although his results did not involve consumer products. In addition, the estimation here, unlike Tversky's, involves different task environments. Therefore, the estimation also provides a test of the contextual influence of associated features on proximity. The products and judgments used to estimate the model were taken from the Johnson (1981) study involving the three different proximity tasks. A total of 87 subjects were divided among 4 different treatment groups or conditions. One group of subjects judged the similarity among pairs of colas, noncolas, beers, and fruits. A second group judged dissimilarity among the same pairs. A third group judged the subject/referent similarity of a to b among the above pairs along with pairs of desserts and appliances. Finally, a fourth group judged the subject/referent similarity of b to a among the same pairs as group three.

Procedure

After obtaining judgments in each condition, each subject's memory was probed for each of the products used in the study. Subjects were asked to list, in writing, all of the attributes that came to mind when they thought about a given product.

Subjects were instructed to spend no more than 2 minutes on each product and then to move on. A written format was used so that all subjects could be run concurrently through the experiment.

To estimate the model the memory probes for each subject on each product pair were coded for common and distinctive features. To remain simple and objective, attributes were coded as different features if different words were used and coded as common features as long as the same wording was used. It should be noted that although the coding is objective, it may be biased. Consider that one product may be "sweet" while another is "sugary" or one may be "sour" while another is "tart." Associations coded as distinctive may be semantically similar and treated by subjects as common features that increase overall similarity. Given the size of the task and the objective nature of the instructions, one judge coded the 3,463 protocol pairs. As a reliability check, a second judge coded the protocols from the first five subjects. Interjudge reliability, the probability that coding by one judge agrees with the coding of a second judge, was high (.93). Systematic differences were resolved by discussion and incorporated into the coding of the remaining subjects.

After adding up the respective common and distinctive features in each pair protocol, measures of the three feature sets were obtained by averaging across subjects in each condition. The average number of common and distinctive features for subjects in each of the four groups were then regressed against the corresponding proximity judgments. As there were relatively few brands in each product category in the original study (five brands each for colas, noncolas, beer, and fruit; three brands each for desserts and appliances), the data were combined across categories for the analysis. There were a total of 40 average similarities and dissimilarities each (10 possible pairs in each of 4 categories) and 46 average subject/ referent similarities each (all possible within category pairs). The original judgments were obtained using scales ranging from "not at all similar" to "very similar'' for the two types of similarity judgments and from ' 'not at all dissimilar'' to "very dissimilar" for the dissimilarity judgments.

In an attempt to reduce error, a second measure of the products' feature sets was operationalized. Subjects from all 4 task conditions were used to estimate the feature sets for the 40 test pairs that appeared across the 4 conditions (beers, colas, noncoJas, and fruits). The model was estimated a second time for these 40 pairs using the average number of features recalled across all subjects. Although the analysis is no longer strictly based on the subjects producing the judgments, the feature set estimates are based on a much larger sample.

If the contrast model describes bow consumers judge proximity, common features should add to similarity and detract from dissimilarity, whereas distinctive features should detract from similarity and add to dissimilarity. The four sets of judgments provide separate tests of this hypothesis, and the validity of the model, for both of the feature set measures. The influence of the specific task on the weight of common and distinctive features is also tested. The regression weight in a multiple correlation along with the individual correlation of distinctive features should increase when judging dissimilarity relative to judging similarity. Finally, the distinctive features of the subject should receive more weight than the distinctive features of the referent in the subject/referent judgments.

Results

The regression results are shown in Table 1. The columns, from left to right, represent the dependent variable or judgment used in the estimation (i.e., similarity, dissimilarity, or subject/referent similarity), the regression weight of common

TABLE 1
Multiple Regression Results Using Subjects Within Tasks to Estimate Feature Sets

Judgment	Common	Distinctive Left/Subject	Distinctive Right/Referent	r
Similarity	5.00*	−1.27*	−.45	.69*
Disimilarity	−3.41*	.94*	.75*	.77*
Similarity of A to B	4.97*	−.71*	−.81*	.64*
Similarity of B to A	4.07*	−.69*	−1.07*	.76*

Multiple Regression Results Using All Subjects to Estimate Feature Sets

Judgment	Common	Distinctive Left/Subject	Distinctive Right/Referent	r
Similarity	7.03*	−1.28*	−.46	.78*
Disimilarity	−5.51*	1.13*	.54*	.85*
Similarity of A to B	8.07*	−1.34*	−.45*	.81*
Similarity of B to A	7.17*	−1.14*	−.77*	.85*

*Significant, $p < .05$.

features toward the judgment, the regression weight of the distinctive features of the alternative on the left when judging similarity or dissimilarity (i.e., the distinctive features of a when judging “How similar are a and b?'') or the subject in the case of subject/referent judgments (i.e., the distinctive features of a when judging “How similar is a to b?''), the regression weight of the distinctive features of the alternative on the right or the referent (i.e., the distinctive features of b), and the correlation coefficients. The correlation matrix of all the variables is presented in Table 2, with the values in each cell, from top to bottom, representing the correlation between judgments of similarity, dissimilarity, subject/referent similarity of a to b, and subject/referent similarity of b to a, respectively, and the feature set estimates (including total distinctive features) obtained from subjects within each of the respective conditions. Correlation coefficients between these judgments and the feature set estimates based on all possible subjects are presented in parentheses.

The multiple correlations between the three feature sets and the judgments in Table 1 are all reasonably high. Moving from the top half to the bottom half of Table 1, using all

TABLE 2
Correlation Matrix

	Similarity Dissimilarity Simil. (a to b) Simil. (b to a)	Common Features	Distinctive Left/Subject	Distinctive Right/Ref.
Common Features	.433 (.592) − .421 (−.612) .471 (.666) .534 (.665)			
Distinctive Features of Left/Subject	− .472 (−.457) .550 (.545) −.157 (−.414) − .282 (−.472)	.095 (.056) .047 .340 .016		
Distinctive Features of Right/ Referent	− .288 (−.444) .343 (.527) − .350 (−.432) − .342 (−.517)	.076 (− .058) .276 .023 .246	.367 (.766) .319 .301 .303	
Total Distinctive Features	− .463 (−.479) .555 (.571) − .310 (−.449) − .388 (−.525)	.103 (.001) .194 .231 .252	.835 (.945) .827 .820 .794	.818 (.934) .796 .792 .820

possible subjects to estimate the feature sets as opposed to the subset of subjects making the judgments, improves the fit in each case. (The average correlation increases from .71 to .82.) This result suggests that there is more error in measuring the feature sets than there are differences in feature set sizes from group to group. Importantly, the weights on the respective feature sets in Table 1, as well as the individual correlations in Table 2, are in the hypothesized direction in all cases. Common features add to similarity and detract from dissimilarity, whereas distinctive features have the opposite effect. This result supports the effect of both common and distinctive features on each type of judgment as predicted by the contrast model. Considering that several categories are included in each type of judgment, the results are theoretically promising. Explanatory power is high even though judgments were made on the same scale across categories, suggesting that the same or a similar cognitive process is involved when producing the judgments independent of the category.

The weights in the multiple regressions should, naturally, be interpreted with caution. The disproportionately large weights on common features in Tahle 1 may, for example, be due to subjects eliciting, on average, fewer common than distinctive features (.35 versus 4.70). The bias inherent in the coding instructions probably contributes to this result. Recall that attributes may have been coded as different even though they are semantically similar.

The influence of common as opposed to distinctive features across tasks, as revealed in both Tables 1 and 2, supports the hypothesized difference in the similarity and dissimilarity judgments. The relative weight of common features in Table 1 decrease in the Table 1 decreases in the dissimilarity task relative to the three similarity tasks, whereas weights on the distinctive features are roughly compatible. Perhaps more importantly, the independent correlation of total distinctive features to judgments in Table 2 is highest in the dissimilarity task, whereas the correlation to common features is generally highest in the similarity tasks. The interpretability of this result is supported by the minimal correlation between common features and total distinctive features across subjects ($r = .001$).

Finally, the results at the bottom of Table 1 show the distinctive features of the subject receiving more weight than the distinctive features of the referent for subjects making subject/referent judgments. However, the alternative on the left, when making both similarity and dissimilarity judgments, also received more weight than the alternative on the right. This suggests that the weight placed on the subject in a subject/referent judgment may be explained by a simple left to right attention bias. The two distinctive feature sets were, however, overall highly correlated (r = .77), making a comparison of these particular weights problematic.

As predicted by the contrast model, proximity judgments are well predicted by a simple linear combination or contrast of the average number of common and distinctive features associated with the products being judged. Both theoretical and methodological considerations prevent the correlations from being even higher. Incorporating individual differences in feature salience should improve the fit of the model. A memory probe is also an imperfect measure of associated features. Features may be recalled that are very indirectly associated with products yet easy to recall. Finally, even if the probe were considered perfect, the coding of common and distinctive features is not.

The memory probe not only allows for estimation of the model but also helps explain the results of the Johnson (1981) study. In that study, pairs of soft-drinks and beers produced context effects (asymmetries and low correlations between and dissimilarities), whereas pairs of fruits, for example, did not. In hindsight, the categories in which task effects occurred were those with the higher feature set differences. The memory probe results reveal that individual colas, beers, and noncolas differed on average by 1.05, .90, and .89 features recalled, respectively, whereas the corresponding figure for fruits was only .30. It is important from a marketing management perspective to remember that the model predicts task effects only when significant feature set variance exists, again assuming equal feature salience. These results show that a memory probe is one way to determine if such differences exist.

DISCUSSION AND IMPLICATIONS

Much of the beauty of the contrast model lies in its generality. Generality, however, has an obvious trade-off. While offering important insights, the model has basic limitations. First, it is only a structural theory of bow concepts or objects are represented. Although equation (1) highlights the differential importance of features, it does not specifically address the psychological process of judging similarity or how the contrasting of features proceeds (Lopes & Johnson, 1982). A second general limitation is that, whereas contributing factors are discussed, the f function is left unspecified. This is particularly important from a managerial perspective and may limit the model's usefulness. Although diagnostic attributes or features may be surmised from the products of interest, the differential intensity or weighting of individual features may not. Equal intensity cannot always be assumed. Even though one product may have fewer distinctive features than another, its features may be more salient. Even if features are equally salient, the addition of features may not have equivalent effects on overall similarity in the judgmental process. There may be some threshold or minimal feature set size required before judgments are affected. Judgments may also become satiated where, after a number of common (distinctive) features are considered, additional features have no effect. There may, in fact, be a different relationship describing the effect of additions to each of the three feature sets. At this point the nature of the/function is purely speculative. Many interesting questions are unresolved, leaving the model incomplete.

Nevertheless, the ability of the model to account for the various judgments despite the imperfections is interesting. As long as the numerical size of the feature sets can be estimated, much of the variance is accounted for. This result is consistent with the "robust beauty" of unit weighted models in predicting the output of other judgment tasks (Einhom & Hogarth, 1975; Dawes, 1979). That a simple model explains the data quite well, even when judgments across product categories are combined, suggests the use of a relatively simple cognitive process when performing similarity tasks. One such process, proposed by Lopes & Johnson (1982; see also Lopes & Oden, 1980), views subjects as producing similarities by "anchoring" on the similarity value of some salient attribute and adjusting the value, taking into account information from other attributes. These attributes may be either features or dimensions. Anchoring and adjusting (Tversky & Kahneman, 1974) is a simple, serial process that is quite compatible with the contrast model and, in fact, makes it more complete.

Interestingly, anchoring and adjustment leads to judgmental primacy (where an anchor receives relatively more weight toward a judgment than do individual adjustments). Thus the ability of the task environment to affect the weight of the three feature sets may be the result of both feature set relevance and the anchoring process. First, certain features may receive more weight simply because they are more relevant to the judgment, such as common features in a similarity task or distinctive features in a dissimilarity task. Second, these features may receive additional weight because the context leads to an anchoring of attention on the more relevant attributes. In a subject/referent context, for example, the features of the subject may be weighted heavily both because they are more relevant to the judgment and because they receive initial attention. Of course it may be that primacy is simply the result of task relevance and does not operate independently. Future research might explore this question.

Viewing interproduct similarity as contrasting features that vary from task to task has important marketing implications. Traditionally, product positions have been analyzed using primarily dimensional, spatial representations. As noted earlier, unlike the contrast model, spatial representations may not highlight the features that products have in common. Adding common features or invariant dimensions to a spatial analysis has no explicit effect on proximity. As a result, marketers concerned with the limits of competition or product market boundaries (Day, Shocker & Srivastava, 1979; Srivastava, Alpert& Shocker, 1984) may find spatial representations of limited use. Whether or not products or product categories are viable substitutes depends critically on what they are perceived to have in common. By making common features more explicit, the contrast model may prove to be very useful in this regard.

A second limitation of the traditional spatial analysis of markets is that the positioning strategies and new product ideas that follow are typically bounded by the dimensions of the space (Crawford, 1983). Spatial analysis diverts attention away from strategies and product concepts based on either completely new product attributes or attributes new to the category or consideration set. While, for example, a spatial analysis might suggest developing a wine with "fewer calories" or a "lighter taste," it is unlikely to suggest developing a "wine cooler." A strategic advantage of the contrast model is that it is not limited to existing category attributes. The simplicity of the model is one of its main advantages. According to the model, adding common features to a product, via product design or promotion, for example, will facilitate a positioning strategy aimed at getting closer to one or more competitors. Alternatively, adding and highlighting distinctive features is critical when differentiating a product. Importantly, both strategies are consistent with what marketers actually do.

The contrast model's ability to explain and predict the effect of the task environment on perceived proximity also has important product positioning implications. In situations where products differ in number of associated features (as in the case of a new versus an established product), a marketer's control over the task environment can be used to facilitate positioning. If the goal is to position a new brand close to an established brand, the established brand may be used successfully as a referent in product comparisons, such as in a comparative advertisement. Using the established brand as a referent will minimize the effect of the brand's distinctive features on consumer perceptions. Conversely, if the goal is to differentiate a product, an established brand may be used effectively as the subject of the comparison in order to highlight the differences between the products.

From a methodological standpoint, it is important for marketers to recognize whether consumers represent products using features or dimensions when choosing a similarity scaling procedure. First, procedures differ in their implicit representation of stimuli. Although continuous dimensions are readily interpreted using product space procedures, such as multidimensional scaling, features are more directly interpreted using network scaling procedures, such as hierarchical clustering (Johnson, 1967), additive clustering (Arabie. *et al.*, 1981) or additive trees (Sattah & Tversky, 1977). Urban, Johnson & Hauser (1984), for example, use a hierarchical tree procedure to model competitive market structures in which the branches of the trees represent different product features (e.g., foreign versus U.S, automobiles or ground versus instant coffee). Second, scaling procedures fit proximity data better when the stimulus representation is congruent with the representation implicit in the output of the procedure (Pruzansky, Tversky & Carroll, 1982). Implicitly dimensional product space procedures should, therefore, be more appropriate when consumers use dimensions to judge similarity, whereas implicitly feature-based additive tree procedures should be appropriate when consumers use features. Of course, products need not be strictly feature or dimensionally based. As Shepard (1980) points out, even for the same set of stimuli, different methods for analyzing similarity, assuming qualitatively different representations, may bring out different yet equally important aspects of the true underlying psychological representation.

CONCLUSION

Although similarity is recognized as fundamental to marketing and marketing strategy, little attention has been paid to the way similarity judgments are produced. Viewing similarity judgment as a contrast of common and distinctive features appears useful. The results reported here support common and distinctive features as having predictable directional effects on proximity judgments. The results also support the difference in similarity and dissimilarity judgments reported previously. By using the memory probe procedure outlined here, managers can use the contrast model to predict how consumers will judge proximity in various contexts. In many cases it may be useful to view products as being associated with sets of common and distinctive features as well as varying on more continuous dimensions.

REFERENCES

Arabie, P. Carroll, J. D, DeSarbo, W., & Wind, J. (1981). Overlapping clustering: A new method for product positioning. *Journal of Marketing Research*. 18, 310-317.

Cooper, L. G. (1973). A multivariate investigation of preferences. *Multivariate Behavioral Research*, 8, 253-272.

Crawford, C. M. (1983). *New products management*. Homewood, IL: Richard D. Irwin.

Dawes, R. (1979). The robust beauty of improper linear models in decision making. *American Psychologist,* 34, 571-582.

Day, G. S., Shocker, A. D., & Srivastava, R. K. (1979), Customer-oriented approaches to identifying product markets. Journal of Marketing, 43, 4-19.

Einhorn, H. J., & Hogarth, R. M. (1975). Unit weighting schemes for decision making. *Organizational Behavior and Human Performance*, 13, 171-192.

Ericsson, K. A., & Simon. H. A. (1980). Verbal reports as data. *Psychological Review*, 87. 215-251.

Garner, W. (1978). Aspects of a stimulus: Features, dimensions and configurations. In E. Rosch and B. Lloyd (Eds), *Cognition and categorization*. New York. NY: Wiley.

Gati. I., & Tversky, A. (1982). Representations of qualitative and quantitative dimensions. Journal of Experimental Psychology: *Human Perception and Performance*, 8, 325-340.

Gati, I., & Tversky. A. (1984). Weighting common and distinctive features in perceptual and conceptual judgments. *Cognitive Psychology*, 16, 341-370.

Green, P. E. Wind. Y. & Claycamp, H. J. (1975). Brand-feature congruence mapping*. Journal of Marketing Research*, 12. 306-313.

Gutman, J. (1980). A means-end model for facilitating analyses of product matrices based on consumer judgment. In Kent B. Monroe (Ed.), *Advances in consumer research*. Vol. 8, (pp. 116-121). Chicago, IL: Association for Consumer Research.

Hauser, J. R., & Koppelman. F. S. (1979). Alternative perceptual mapping techniques: Relative accuracy and usefulness. *Journal of Marketing Research*, 16, 495-506.

Johnson, M. D. (1981). Context effects in product perception. In Kent B. Monroe (Ed.). *Advances in consumer research.* Vol. 8. (pp. 112-115). Chicago. IL: Association for Consumer Research.

Johnson, R. M. (1971). Market segmentation: A strategic management tool. *Journal of Marketing Research*. 8. 13-18.

Johnson. S. C. (1967). Hierarchical clustering schemes. *Psychometrika*, 32, 241-254.

Lopes, L. L., & Johnson, M. D. (1982). Judging similarity among strings described by hierarchical trees*. Acta Psychologica*, 51. 13-26.

Lopes, L. L., & Oden, G. C. (1980). Comparison of two models of similarity judgments. *Acta Psychotogica*, 45. 161-168.

Pruzansky. S., Tversky, A., & Carroll, J. D. (1982). Spatial versus tree representations of proximity data. *Psychometrika*, 47. 3-24.

Restle, F. A. (1959). A metric and an ordering on sets. *Psychometrika*, 24. 207-220.

Rosch, E. (1975). Cognitive representation of semantic categories. Journal of Experimental Psychology: General, 104, 192-233.

Rosch, E., & Mervis, C. B. (1975). Family resemblances: Studies in the internal structure of categories. *Cognitive Psychology*, 7, 573-603.

Sattath, S., & Tversky, A. (1977). Additive similarity trees. *Psychometrika,* 42, 319-345.

Shepard. R. N. (1980) Multidimensional scaling, tree-fitting, and clustering. *Science*. 210, 390-398.

Shepard. R. N., & Arabie, P. (1979). Additive clustering: Representation of similarities and combinations of discrete overlapping properties. *Psychological Review*. 86, 87-123.

Shocker. A. D., & Srinivasan, V. (1979). Multiattribute approaches for product concept evaluation and generation: A critical review. *Journal of Marketing Research*, 16, 159-180.

Smith, E. E., Shoben. E. J., & Rips, L. J. (1974). Structure and process in semantic memory: A featural model for semantic decisions. *Psychological Review*, 81. 214–241.

Srivastava, R. K., Alpert, M. I., & Shocker, A. D. (1984). A customer-oriented approach for determining market structures. *Journal of Marketing*. 48. 32-45.

Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review*, 79, 281-299.

Tversky, A. (1977). Features of similarity. *Psychological Review*, 84, 327-352.

Tversky, A., & Gati, 1. (1978). Studies of similarity. InE. Rosch and B. Lloyd (Eds.), *Cognition and Categorization*. New York, NY: Wiley.

Tversky. A., & Gati, I. (1982). Similarity, separability, and the triangle inequality. *Psychological Review*, 89. 123-154.

Tversky, A., & Kahneman, D. (1974). Judgments under uncertainty: Heuristics and biases. *Science*. 185, 1124-1131.

Urban, G. L., Johnson, P. L., & Hauser, J. R. (1984). Testing competitive market structures. *Marketing Science,* 3, 83-112.