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TECHNIQUES FOR PERCEPTUAL MAPPING

I. INTRODUCTION

As a firm tries to manage its brand's equity, it leverages how the brand is perceived relative to the competition. Correcting perceptions of weakness or taking advantage of perceived strengths can both strengthen the brand's position in the marketplace.

Frequently, brand research is centered on a hierarchy of effects model as shown below. Although slightly different models have been proposed in different industries, they follow the same general pattern.

A potential buyer becomes aware of a product, and then becomes interested in the product. Then the buyer considers purchasing the product. The potential buyer becomes an actual buyer with the purchase of the product. He or she then evaluates the purchase and whether or not to buy the product again.

In many industries, there is a clear relationship among brand awareness, consideration and purchase, and therefore, market share. However, we also know not all brands are equal, and some are more successful converting awareness into consideration and some at converting consideration into trial.

If consumers are aware of our brand but don't consider it, or if they consider it but don't purchase it, we could investigate how the brand is perceived through corporate image research.

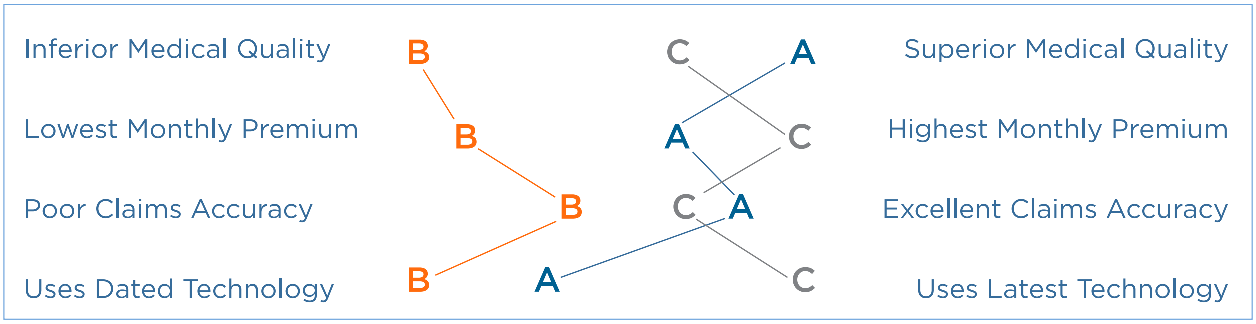
One form of corporate image research shows comparisons among brands on specific product features or attributes. Graphs that show the market's perceptions of brands or companies are called perceptual maps. Many different techniques have been developed to produce maps reflecting consumers' perceptions. The more sophisticated maps show relationships among brands, among attributes, and among brands and attributes.

Here, it appears that Brand A is better than competitors at being considered, but rarely purchased. Brand D, however, is less likely to be considered but among those considerers is much more likely to be purchased. These graphs would suggest that Brand D has a poor image but a strong product.

Conversely, Brand A's image would appear to be better than its product, given the proportion of people who consider but don't purchase. Both companies could diagnose their perceptual aberrations through corporate image research.

HEIRARCHY OF EFFECTS

Awareness ▶ Interest ▶ Consideration ▶ Trial ▶ Evaluation ▶ Repeat



The results from corporate image research can take many forms. For instance, consider the above:

This shows direct comparisons between products on specific product features or descriptions (attributes). Researchers call graphs that show the market's perceptions of companies such as this one perceptual maps. This example represents a simple perceptual map, but during the past 50 years researchers have developed several techniques to produce maps reflecting buyers' perceptions. The more sophisticated maps show relationships between brands, between attributes, and between attributes and brands. Compared to the simple map above (which just shows the relationship between brands on one attribute at a time), the sophisticated maps provide a great deal of information. The rest of this document will discuss only techniques that holistically combine multiple brands and product attributes onto one map.

There are two major classes of perceptual mapping algorithms. The two classes are generally referred to as compositional and decompositional methods. Decompositional techniques have many names but they typically fall under an umbrella term of multi-dimensional scaling (or MDS).

Decompositional methods were extremely popular in the 1950s and 1960s. Since that time, though, they have fallen out of favor as more advanced methods have become available. Decompositional methods are still fervently used by some.

Decompositional methods begin with data that represent similarities between brands. The data can be collected through direct similarity questioning, techniques such as repertory grid, or by other measures of association, such as correlations. Decompositional methods deal primarily with brand-to-brand relationships. The brand- to- brand relationships are mapped without regard to why two brands might be similar, which occasionally creates problems in interpretation.

Unlike decompositional methods which begin with brand level similarities, compositional methods begin with measurements of brands on attributes[1]. There are three primary types of compositional methods: factor analysis, discriminant analysis, and correspondence analysis. Normally, the measurements used are interval scaled ratings[2]. Using a compositional approach, brand-to-brand relationships are shown as in decompositional techniques, but unlike decompositional methods, the attributes creating that similarity are directly observed rather than inferred. In discriminant analysis and correspondence analysis the attributes are also included in the resulting map.

[1] Therefore, one requirement of all compositional methods is that the researcher develop an exhaustive list of attributes before conducting any data collection. For product categories that are not well understood, this might be difficult. If the researcher is unable to develop such a list accurately, decompositional methods might be the only alternative.

[2] Ratings are normally required, although correspondence analysis uses contingency data (cross-tabulated) data. Correspondence analysis is unique in not requiring metric data, while techniques like discriminant analysis have been found to be robust with respect to violations of the requirement of interval data.

Decompositional and compositional methods will be discussed below in detail. First, a history of the development of the techniques will be reviewed. Following the historical perspective, the strengths and weaknesses of each method will be discussed.

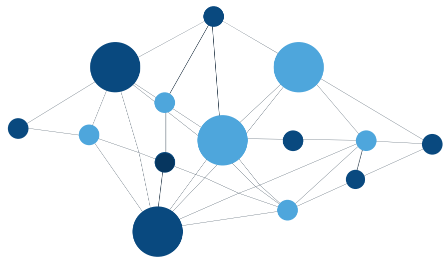
II. BACKGROUND AND HISTORY

References of using factor analysis as a perceptual technique date back to the 1930s[3], but the first wave of perceptual research would likely be associated with multidimensional scaling. In the early 1960s, researchers sought an approach using ordinal (non-ratings) input data to produce output with metric qualities. This approach (known as multidimensional scaling or MDS) was largely developed by Bell Labs, especially by Shepard and Kruskal. While elegant theoretically, the data requirements and frequent problems with interpretation created headaches for many researchers.

Coincidentally, factor analysis once again became vogue as a replacement to MDS. Factor analysis is compositional in nature (alleviating the interpretation problems) and can use standard ratings data as input (eliminating the problems encountered collecting similarities data). Meyers and Tauber attempt an explanation of its appeal in the 1970s. "One of the most obvious alternatives [to MDS] was factor analysis, a technique that was both widely understood and easily applied by most investigators.... Moreover, the output format was for all practical purposes indistinguishable."

At about the same time, the application of another common multivariate method was gaining support. Discriminant analysis was used to determine differences between brands. This method was presented in the literature and popularized by Johnson.

In the 1980s, researchers were introduced to yet another mapping method called Correspondence Analysis, sometimes referred to as Dual Scaling. The method of CA has actually been around since the 1950s, but had been used almost exclusively by academic researchers in South Africa and



France before the middle 1980s. The technique is compositional in nature, but unlike the two compositional methods above (factor and discriminant), correspondence analysis does not require ratings data. Instead, correspondence analysis uses aggregate level counts.

III. MAPPING TECHNIQUES

Decompositional Multidimensional Scaling (MDS)

MDS is really a broad name for a wide variety of algorithms. At the heart of all of the methods, though, is a desire to produce a map in a low dimensional space (normally two dimensions) that shows similarities between products. Some of the more common names of MDS algorithms include ALSCAL, INDSCAL, MDPREF, MDSCAL, ASCAL, KYST, and PREFMAP. For the purposes of this exposition, the differences between these models are not important.

The data input requirements for MDS are generally not stringent. Most techniques use aggregate data, while methods exist to utilize individual data. The data are referred to as similarities data, but the popular computer programs are capable of handling a number of types of input, such as correlations or distances.

There are several ways to collect brand similarity data. The most straightforward is to ask respondents directly to rate how similar two brands are on a scale, where a "1" indicates two brands are identical, and a "9"

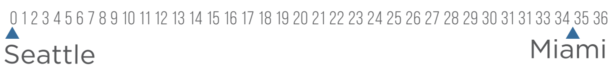
[3] For early examples, see Eckart and Young, Burt, Hotelling. Good summaries of factor analysis (or principal components analysis) are provided in Dunteman or Horst.

indicates that two brands differ widely. Many respondents find this level of abstraction difficult to deal with, though. Repertory grid is a particularly useful technique for developing similarities. In repertory grid, respondents are presented with three products and asked to indicate which is most unique (or alternatively which two are most alike)[4].

	Seattle	Miami	Kansas City	Los Angeles	New York
Seattle					
Miami	3454	—			
Kansas City	1994	1516	—		
Los Angeles	1190	2817	1728	—	
New York	2975	1350	1220	2913	—

The following simplified example of MDS will provide an understanding of the basic processes involved behind an MDS analysis. Let's look at highway distances between five U. S. cities: Seattle, Miami, Kansas City, Los Angeles, and New York. The table below shows the mileage between each pair of cities.

Notice that only half of the matrix is



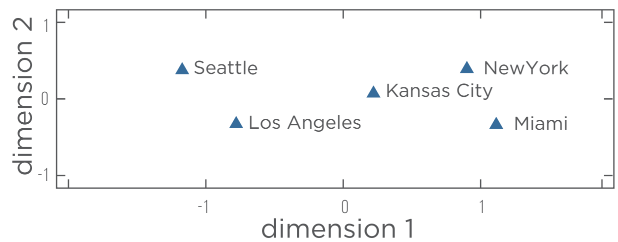
necessary in that the distance between Seattle and Miami is the same as the distance between Miami and Seattle.

The goal of MDS is to take these 10 pairwise distances and place them on one map. Let's begin by looking first at the Seattle-Miami distance, 3454. We can arbitrarily place these two cities on the following continuum:

Note that the distance between Seattle and Miami is roughly 34.5, corresponding to the 3454 mile distance.

We see that Kansas City can be neatly added to the same uni-dimensional plot and maintain the distance metric as outlined above. Seattle and Miami are still 34.5 units away, Kansas City and Seattle are now 20 units away from each other (corresponding to the actual distance of 1994 miles) and Kansas City and Miami are 14.5 units away from each other (corresponding to the actual distance of 1516 miles).

However, this simple approach falls apart if we try to add Los Angeles. LA is 1190 miles from Seattle, which would suggest a position near 12 on the scale above. LA is also 2817 miles from Miami, which would suggest a position near 7 on the scale above. We could split the difference and position LA at approximately 10 on the map. Then we have a new problem. Kansas City and LA should be 17 units apart, based on the actual distance of 1728, but by placing LA at 10, they would only be 10 units apart. LA does not fit as neatly on



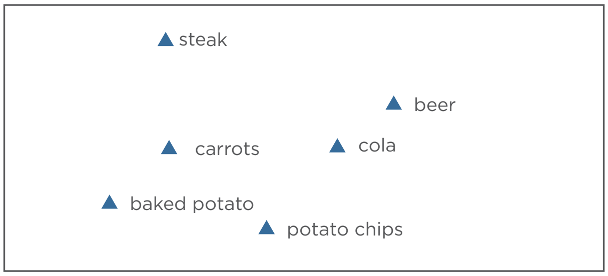
the map (or in this dimension) as the first three cities did. Anyone familiar with US geography could explain why. Seattle, Kansas City, and Miami lie in more or less a straight line. It is exactly that line that is represented by the continuum above. Los Angeles is not on that line. To accurately plot Los Angeles, a second dimension would be required. By using the matrix above with an MDS algorithm, we can produce the following plot.

While a cartographer might be somewhat displeased with this result, the researcher that would otherwise be faced with presenting the raw distance measurements in the table above would be very excited.

[4]The repertory grid is introduced in many marketing research and social research textbooks. For more information on repertory grid, see Fransella and Bannister.

This pleasing result is the real benefit of mapping techniques. This approach (MDS) was very popular for much of the 1960s and 1970s.

Note that MDS requires only half of a data input matrix in which similarities or differences are expressed between all pairs of elements. The rows are the same as columns. In this example, the rows and columns are cities, but for traditional perceptual mapping they would be brands. Once the brands are positioned on the map, it is up to the researcher to



interpret the axes or dimensions. The dimensions in this example are easily interpreted. Dimension 1 (horizontal) is East-West, and Dimension 2 (vertical) is North-South. When the elements are brands, the interpretability of the dimensions isn't always that clear. In fact, one of the largest pitfalls of MDS is the possibility of developing a map that cannot be interpreted (or finding one that cannot adequately fit in a two dimensional space).

For instance, consider the following hypothetical MDS plot. Interpreting this map could prove very tricky. Looking left to right, the left side of the map could be meal-like and the right could be snack-like. Alternatively, the left side could be solid food, and the right could be drinks or the left could be natural and the right processed. For this very reason decompositional methods have become less popular over the last couple of decades.

Compositional Methods
Factor Analysis (FA)

Factor Analysis produces maps that look like MDS plots as it produces maps which position brands relative to other brands. Unlike MDS, though, factor analysis maps are composed. That is, they are "made up" based on ratings of brands on several attributes, rather than just overall similarities between brands.

While decompositional methods might ask respondents to indicate how similar two brands are, compositional methods would ask respondents to rate each brand on several attributes[5]. For example, a respondent might be asked to rate brands on the following set of attributes:

- Medical Quality
- Technological Innovativeness
- Claims/Billing Accuracy
- Lowest Premium
- Value for the Price
- Strong Presence in the Community

Additionally, respondents might be asked to indicate how important each attribute is. Factor analysis is then used to reduce the number of dimensions under investigation.

Factor analysis is a data reduction technique that summarizes and combines attributes based on the correlations of those attributes[6]. The results of factor analysis are new variables (factors) that are made up of linear combinations of the original variables. Factor analysis was used in primarily two ways to construct maps. Some researchers would factor analyze the attribute importances and then, using those functions, create factor scores for each product studied. Other researchers would factor analyze the actual ratings of all products and then create factor

[5] Compositional methods don't necessarily require ratings, although they are the most common. Correspondence Analysis, for example, only requires contingency tables, which can be constructed based on simple associations.

[6] Although the term Factor Analysis is used throughout, two approaches are common: (1) Factor Analysis, and (2) Principal Components Analysis. The two approaches are similar in that they produce components or factors that explain the largest amount of the variance. In practice, Principal Components analysis is probably a more practical technique, though the term factor analysis is more common. The differences are beyond the scope of this overview on perceptual mapping, but the interested reader is referred to Gorsuch (1983), Stewart (1981), or Dunteman (1989).

scores for each product. The results of either map have been empirically shown to be similar, although they won't always[7].

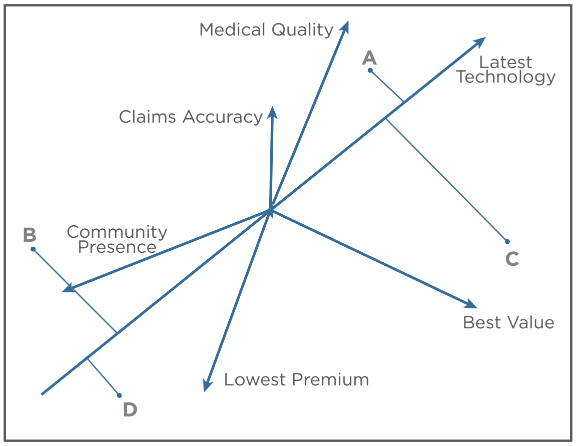
Technically, the problem with this approach is that factor analysis seeks to combine variables (create factors) that explain the greatest amount of the total variance. There are two types of variance: within brand variance and between brand variance. The between brand variance represents the true perceptual differences between one brand and another. The within brand variance is a function of the amount of agreement by respondents about a particular brand. For instance, if respondents' perceptions agree about a particular brand, the within brand variance will be small. However, if there is great disagreement about the perceptions of a particular brand, the within brand variance will be high. The issue becomes that these two sources of variation are combined by factor analysis, that is, they are confounded[8]. Thus, the differences in product ratings are ignored until after the factor equations are derived and are incorporated only to produce each brand's factor scores[9].

Early studies showed that the factor analysis approach was superior to other compositional methods such as discriminant analysis (Hauser and Koppleman, Simmie). Limitations with those studies were discovered and the evidence now suggests that factor analysis is not theoretically or empirically superior (Moore, Huber and Holbrook). Today, factor analysis is rarely used.

Discriminant Analysis (DA)

Another compositional approach which enjoys more acceptance today among many researchers is discriminant analysis based perceptual mapping. Like factor analysis, discriminant analysis uses ratings data of brands on attributes. Also like FA, DA seeks to explain (maximize) variance of the ratings. Unlike FA which uses the total variance (within brand and between brand variance), DA maximizes the ratio of between brand to within brand variance. Put another way, only the actual differences between brands drives the solution in DA, while lack of agreement about brands' ratings (within brand variation) also drives FA. So one benefit of discriminant analysis is that the technique discriminates between brands.

Another benefit of discriminant analysis is that it includes the attributes in the map. Unlike the MDS and FA techniques which only position brands relative to other brands, discriminant analysis shows brands and attributes. The brands are positioned in the space as points (as they are in the two techniques above), and the attributes are represented as vectors emanating from the origin of the map. This is sometimes called a point and vector solution. Therefore, DA illustrates the relationship between attributes (their correlation to other attributes), how much each brand is seen as embodying each attribute, and how similar competing brands are perceived to be. The figure below shows an example point and vector perceptual map from discriminant analysis.



[7] *See Pilon.*

[8] *Researchers say that factor analysis is an interdependence technique because dependent and independent variables are not specified. In the context of the discussion above about confounded variances, factor analysis will describe the relationship in the data (both types of error), while other techniques (e.g., discriminant analysis) will look for differences between brands.*

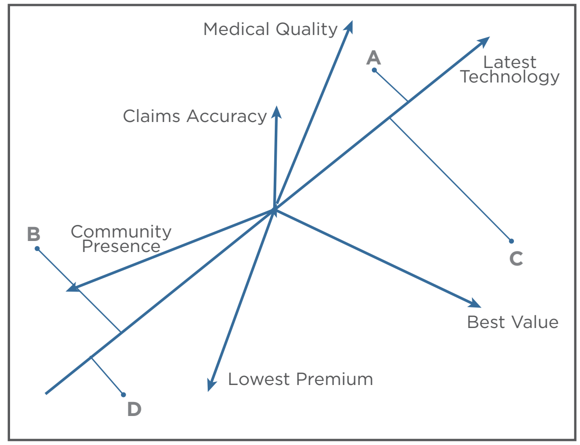
[9] *It is not entirely true to say they are ignored, in that they are included in the total variance to be explained, but since the two variance measures are confounded, the brand to brand difference (the between brand variance) is only partially driving the solution, if at all.*

The relationship between attributes is determined by how nearly parallel the attributes are to each other. Vectors that head in opposite directions are perceived by respondents as opposites, such as Medical Quality and Lowest Premium. It is not perceived that a brand can do well on both. Vectors that are at right angles are seen as independent. In this map, Best Value and Medical Quality are seen as independent by respondents. Vectors that head in basically the same direction are positively correlated, as are Medical Quality and Latest Technology, meaning they are seen as embodying the same feature or quality by the respondent.

The relationship between brands is determined by their proximity. The nearer the brands in the map, the more they are perceived to be similar. For example, Brands A and E are perceived similarly. Brands A and D have very different images.

The relationship between brands and attributes is a function of the position of a brand in the direction of the vector. The interpretation of brand associations are not based upon a brand's proximity to the vector, but its directional relationship along the vector. To interpret these brand associations (compare brands on an attribute), simply draw a line perpendicular to the attribute that intersects the brand point. Doing this for all the brands provides an accurate rank order of respondents' perception of all brands on that attribute. The following map illustrates how to interpret the brands' position on Latest Technology.

This map shows that Brand A has the strongest image as providing the Latest Technology. That interpretation is made because the perpendicular line from the Latest Technology vector that intersects Brand A, is furthest in the direction of Latest Technology. Brand C is the next strongest brand on Latest Technology, even though it is the brand furthest away from the vector. The distance from the vector is not meaningful, only the position relative to the direction of the vector.

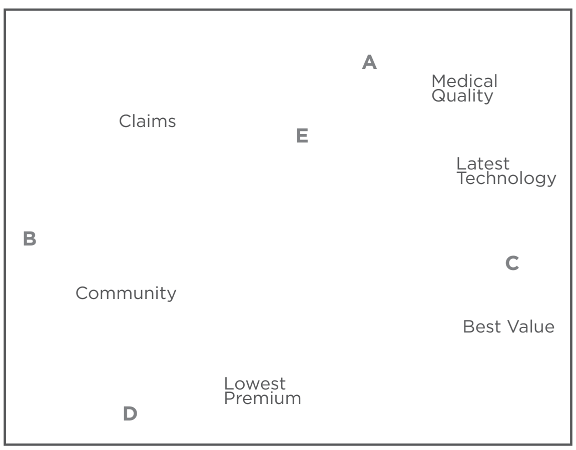


Correspondence Analysis (CA)

Correspondence Analysis (dual scaling) is a third compositional approach. Unlike the other compositional approaches discussed, CA doesn't require ratings data for each brand on each attribute. In fact, the data input to CA are simple associations, or joint occurrences with brands and attributes. The data can be most easily collected by asking respondents to name brands that they associate with each of several attributes. The simplicity of this data collection makes CA a powerful technique when perceptual data are a "nice-to-have" part of a research survey.

Like DA, both attributes and brands appear on the map. However, both elements appear as points. CA is an interdependence technique, like FA, so it is not seeking to explain the largest portion of differences between brands. Rather, CA works on a principle much like a chi-square test of significance. In the chi-square analogy, CA will calculate an expected cell size (based on marginal frequencies) and compare that expected cell size to the observed cell size (the actual data). The closer the observed cell size (the joint occurrence) is to the expected cell frequency, the closer that element of the map is to the center of the map. Analogously, the more different the observed and expected cell sizes, the closer to the perimeter of the map the element will be positioned. CA works by scaling a single row relative to all columns, and a single column relative to all rows. That is, both rows and columns are treated equally, but one row is scaled independently of all other rows and one column is scaled independently of all other columns.

The interpretation of CA is like DA in some respects, but not as similar as one would hope. The closer brands are to each other, the more similar they are perceived to be, and the closer attributes are to each other, the more similar they are perceived to be. Brands that are near the origin are perceived to be rather undifferentiated while brands that are near the perimeter of the map are perceived to be more unique. An example correspondence analysis map is shown below.



However, the similarities end there. In Correspondence Analysis the relationships between brands and attributes are not represented through proximities in the map. That is, just because a particular brand is plotted closer to a particular attribute than another brand, it is not necessarily true that the closer brand is seen as having "more" of that attribute. All that can be inferred from a map produced using correspondence analysis is that all brands that are close to an attribute have "some" association with that attribute, but no determination can be made as to which brand has "more" of that attribute[10]. Interpretation of CA is not based upon a distance. The location of an attribute is the centroid of coordinates of brands that have positive residuals (observed – expected) with that attribute. This centroid principle is probably the most widely misunderstood component of CA, the most misused interpretation of CA, and the largest weakness of the technique.

IV. DESIGNING AND EXECUTING A CORPORATE IMAGE STUDY

Several mapping techniques have been discussed, the ways in which the techniques differ have been highlighted, and potential limitations of each have been provided. The first key to conducting corporate image research is selecting the right approach or technique for projects.

The right approach depends on the project scope and objectives, but in general, discriminant analysis based perceptual mapping is the preferred technique if understanding corporate or brand image is a primary research objective. If, however, the focus of the research is not primarily image related, then correspondence analysis could be appropriate. If collecting the ratings data required for discriminant analysis would be too difficult or consume too much time in the survey, association data could be collected more easily, and used in correspondence analysis.

The second key is understanding the components of image. If the dimensions are not understood or not understood well, the team should take the time to conduct qualitative research to ensure that the full range of dimensions is covered. Also, it is best not to assume that one dimension is measured because a related attribute is included in the study. Frequently, this will prevent shifts in the perceptual space from being noticed. In addition, the exact wording of the attributes should be pre-tested extensively.

[10] The interested reader is referred to Carroll, Green and Schaffer.

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