Multivariate Preference Mapping

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Background: In our Spring 1998 newsletter[1], we discussed a method for the analysis of liking data. The goal of this method was to discover attributes that drive liking. The method, called probabilistic unfolding, displays products and ideals as distributions. Preference data can also be unfolded to provide insights into ideal product characteristics, and can be used to improve products. In fact, preference data are more valuable than liking data to determine the basis for consumer hedonics using unfolding models. Unfortunately, preference experiments are often more expensive to conduct than liking experiments. In this report, an overview of the benefits of multivariate preference unfolding is given using new techniques that specify products and ideals as distributions rather than discrete points. The value of this approach in modeling preference data will be illustrated.

Scenario: In preference tests among category users, your chocolate chip cookie product usually places 3rd or 4th. You would like to diagnose the basis for this preference ordering and improve your product's performance in these tests. In a recent large scale preference test among heavy users of the product category, your current product and a new product prototype were compared with products of three of your major competitors. The results of this test are shown in Table 1.

Table 1. Preference proportions for five products based on 300 consumer preferences per cell.

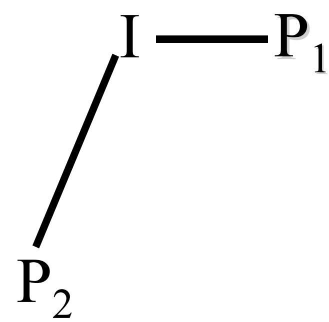
	CP	NP	C1	C2	C3
Current Product (CP)		0.60	0.88	0.80	0.5
New Product (NP)	0.40		0.81	0.77	0.41
Competitor 1 (C1)	0.12	0.19		0.54	0.19
Competitor 2 (C2)	0.20	0.23	0.46		0.21
Competitor 3 (C3)	0.5	0.59	0.81	0.79	

The numbers shown are the preference proportions for the products identified in the first row

Stochastic Transitivity: When A > B and B > C, transitivity implies that A > C. Since A > B, we know that A - C > B - C. If we think of product hedonic values as points on a line such as A, B, and C, then preference proportions might be thought of as monotonically related to differences on this line, i.e. A - B, A - C and B - C. We expect that if A is preferred to B and B is preferred to C, then A should be preferred to C by at least as much as B is preferred to C. This is a form of transitivity known as strong stochastic transitivity. C2 is preferred to C1 by a small margin (54:46). However, C1 beats CP by 8 percentage points more than C2 (88% vs 80%). A similar, though smaller, effect occurs with CP and C3. These two products appear to be equally preferred, but C3 appears to perform better against C1 than CP does. Thus, an assumption of strong stochastic transitivity disagrees with the data in Table 1. Are these results due to experimental error? Variance in the preference proportions will not explain these observations. There is, however, a compelling model of preferential choice that can explain these results. This model does not require strong stochastic transitivity. From this model we will learn what preference results can tell us about how products are located in a perceptual space.

Two Assumptions: Preferential choices are not consistent among a market segment of consumers or even within one consumer. One way of thinking about how preferential choices are generated is to assume that consumers base their choices on information obtained from products tested and on their opinion at that moment about what they ideally prefer. It is assumed that the consumer considers the perceptual variables on which her choice depends and selects the product from the pair that is closest to her imagined ideal product at that time. Figure 1 illustrates how P_1 would be preferred to P_2 because it is closer to an ideal value, I, in a relevant perceptual space.

Figure 1. Ideal and product values in a perceptual space relevant to the preference decision.



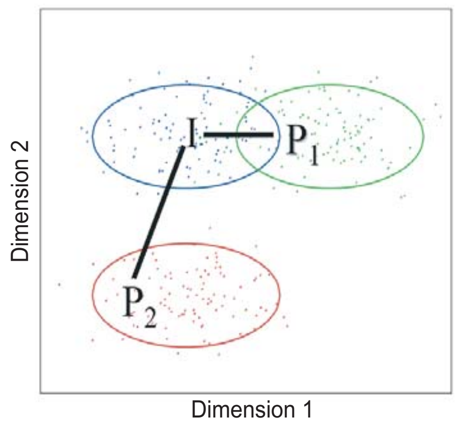
Two assumptions that we will use to explain the preferential choice results of Table 1 are: a) That product and ideal perceptions can be represented as distributions rather than discrete points, and b) a consumer chooses the product that has the least distance to an ideal value on variables that are pertinent to preference. There is a parallel between Thurstonian models for difference tests[2] and the model described here. In each case we have the same assumptions - a distribution assumption about product percepts and an assumption about the decision rule used by consumers to make choices.

Unfolding: Preferential choice proportions are unidimensional variables, but Figure 1 shows how choice decisions may be based on distance comparisons in a multidimensional space. Preferential choice unfolding is a process through which multivariate ideal and product positions are estimated based only on preferential choice proportions. Later we add attribute variables to the unfolded preference map to describe the dimensions of the perceptual space.

Figure 1 shows one subject making a choice at one moment in time, but cannot explain inconsistent choice behavior.

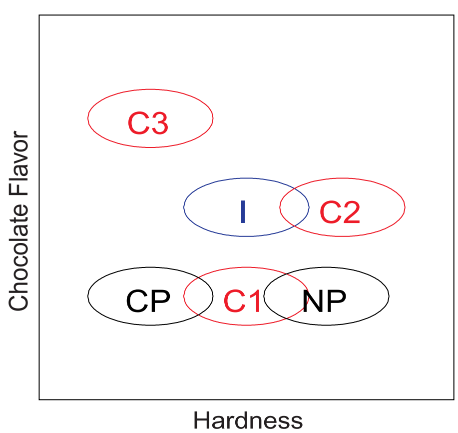
In Figure 2, I, P_1 and P_2 are particular values drawn at one moment from three distributions. The use of distributions for products and ideals not only explains inconsistent choice behavior, but is motivated by the idea that both products and consumer perceptions of products vary.

Figure 2. Distributions of momentary percepts and their 95% confidence limits.



A Multivariate Preference Map: Multivariate unfolding models for preferential choice[3, 4] and preference ratios[5] have been published. These models provide the mathematical basis for estimating the location of products and ideals (their means) as well as the size and shape of the distributions (their variance-covariance matrices). Using the preferential choice model, the map in Figure 3 was estimated as the best fit to the data in Table 1. The method of maximum likelihood was used to obtain these fits. Figure 3 shows that the product and ideal distributions share a common feature - the variance of one of the dimensions is larger than the other and within each dimension the variances are equal.

Figure 3. The preference data of Table 1 unfolded to show the relative positions of products in hardness/chocolate flavor space.



From preference unfolding we determine the location of the product and ideal distributions in a relevant attribute space. Although the unfolding solution displayed in Figure 3 is two dimensional, the technique is not limited to any number of dimensions. Tests can be conducted, in fact, to determine the most parsimonious dimensionality. Once unfolding has been accomplished, we may describe the space by finding the best fitting scales that match product projections onto these scales with product rating means. This type of analysis led to the identification of the hardness and chocolate flavor dimensions shown in Figure 3.

Interpretation of the Preference Scenario: For the ideal product, the variance for hardness is greater than the variance for chocolate flavor. This means that consumers are more sensitive to changes in chocolate flavor than changes in hardness. Although the means of C2 and C1 are equidistant to the ideal mean, C2 is preferred because it is closer to ideal on the most relevant attribute. We can now see why strong stochastic transitivity does not apply to the preference proportions. C1 is preferred to CP by a greater margin than C2 because: a) C1 and CP share the same chocolate flavor mean, but C1 is better positioned on hardness, and b) C2 loses to the current product when hardness ideal values are low - cases on which C1 wins. The new product appears to be a slight improvement over the current product because its hardness is closer to ideal. More attention should be paid to increasing the chocolate flavor of the current product. It is also evident why CP and C3 are equally preferred. They are symmetrically equidistant from the ideal in different directions on chocolate flavor. Finally this new model also explains why C1 is preferred to CP by a larger margin (88% vs. 81%) than C3. CP exhibits the same low chocolate flavor as C1, but is also softer than the ideal. On those occasions when the ideal product is perceived to be high in chocolate flavor, C3 is preferred to C1.

References:

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5. MacKay, D.B., Easley, R.F. and Zinnes, J.L. (1995). A single ideal point model for market structure analysis. *Journal of Marketing Research,* **32**, 433-443.