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Identifying Latent Segments

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Background: The success of an effort to introduce a new product or to reposition an existing one depends on knowledge of features of products that consumers want. One way of thinking about individual liking and preference differences is to assume that consumers agree that a set of product attributes are important to them, but that they may disagree about their preferred level of these attributes. For instance, although consumers may agree that sweetness in a beverage is an influential attribute, some may prefer a sweet beverage and others may dislike sweetness. In typical market research projects, consumers provide information on many product characteristics. Through expert descriptive and analytical research, other attributes of products can be provided. This information can be used to discover the attributes of products that affect consumer liking.

Individual Reasons for Liking: When consumers make choices or provide liking ratings, we assume that they make these decisions based on attributes of importance to them. If we were able to construct a map of products based on liking information only, descriptive information could be used to describe the space, not to construct it[1,2]. In this report we discuss how results from the analysis of liking ratings can be used to identify individual ideal points. We then show how to determine the location and size of possible market segments.

Scenario: Three of your best selling brands (B1, B2 and B3), two prototypes (P1 and P2) and five competitors' products (C1, C2, C3, C4 and C5) were rated on a 9-point liking scale by a representative, geographically dispersed sample of 500 consumers. Table 1 gives rating frequencies for the 10 products on the 9-point liking scale. You are interested in knowing how consumers cluster with respect to their ideal products. You want to construct this map without using information from the sensory attributes of the products since you want to find the underlying basis for liking. You also want to account for individual liking rating effects because, for instance, it is possible that an 8 for one person may correspond to the same degree of liking as a 7 for another.

Inferences from Table 1: It can be seen from this table that B2, B3, P2 and C5 are the best liked products. C2 and C3 are the least liked products. Although B2 and B3 have similar liking means, B2 obtain many more high ratings (7-9). C5 has a slightly lower mean rating than B2 but receives more 8 and 9 ratings balanced by more 2 and 3 ratings. C1 is interesting because it receives almost the highest number of 9 ratings, but on average did not score highly. These results suggest that B2 and C5 occupy a location close to a cluster of consumers. It could also be the case that the variances of these products often position them close to individual ideals. C1 may be placed in close proximity to a peripheral cluster causing high ratings among that cluster but generally lower ratings from more distant clusters. The detailed structure of Table 1 contains information about the location of ideal point clusters, product positions relative to them and perceptual variances. This information will be unfolded to yield a descriptive product and ideal point map.

Landscape Segmentation Analysis (LSA): In a previous report[2], we discussed a method for identifying individual ideal points using liking ratings based on a similarity model[3,4]. An advantage of this method is that it provides a map of product and individual positions in terms of the variables that drive liking. In addition, this method accounts for individual rating effects. The model is also probabilistic; product and ideal positions are treated as distributions rather than fixed points. It is reasonable to assume that people's perceptions change over time. Following an LSA analysis, we have an account of individual ideal point positions. From this account we would like to deduce how the individuals cluster.

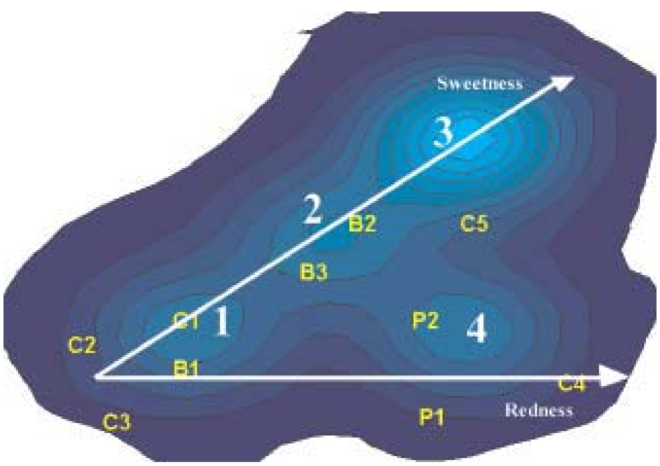
Identifying Latent Segments: Analysis of the individual ideals can be conducted in a number of ways. One way is to form segments using qualitative analysis of contour plots of the density of individual ideal point locations. The density of an ideal point location is a measure of the proximity of other ideal points and is simply proportional to the number of ideal points per unit area. When this measure is high, individual ideals are clustered together; when it is low, individual ideals are well separated and not clustered

Table 1. Liking rating frequencies for 10 products obtained from a representative sample of 500 consumers.

Product	"1"	"2"	"3"	"4"	"5"	"6"	"7"	"8"	"9"	Mean
B1	18	80	92	57	66	50	44	57	36	4.8
B2	0	0	8	17	56	90	136	144	49	6.9
B3	0	0	10	29	67	110	122	119	43	6.7
P1	8	57	103	82	68	76	44	51	11	4.7
P2	0	3	23	41	91	110	82	104	46	6.3
C1	3	38	91	83	65	55	50	67	48	5.3
C2	50	139	86	58	33	30	40	54	10	3.9
C3	109	105	85	52	43	22	45	33	6	3.5
C4	9	64	116	124	62	32	36	45	12	4.4
C5	0	9	22	38	46	63	119	158	45	6.7

together. Qualitative analysis of contour plots is simple and often more useful than quantitative techniques. Quantitative techniques applied to the location of individual ideals include *k*-means cluster analysis and finite mixture models. A drawback to using *k*-means clustering is that there is arbitrariness in deciding on the number of clusters. Finite mixtures, which assume a mixture of distributions (such as multivariate normals) with component weights corresponding to segment size, may also be useful. The theory behind estimating the number of segments is better developed in finite mixtures than in *k*-means clustering, but it is still not completely satisfactory[5]. A finite mixture model applied to the data in Figure 1 shows a fit with four segments, as is evident from visual inspection. These segments are apparent in the contour plot of ideal point densities shown in Figure 1. Sensory vectors are placed on Figure 1 so that product projections onto the vectors agree with the actual scale ratings. These vectors show that the segments differ in desired levels of sweetness and redness. Each individual can be placed in one of the four segments based on their highest likelihood for each of the four distributions. In this example, segments 1, 2 and 3 differ in age (3 youngest, 1 oldest) while segment 4 did not appear to have a well defined demographic identity.

Figure 1: Contour plot of ideal point densities with 10 products and 4 segments (labeled 1-4.) The arrows indicate sensory scale directions.



Relationship to Table 1: Figure 1 provides a compelling account of Table 1. B2 and C5 are indeed closer to a large cluster of consumers (segment 3) which explains their incidence of high ratings. C5 received a notable number of low ratings because of its large distance from segment 1. Although B3 is rated highly because its central location offends no particular segment, it is not as close as B2 and C5 to a major cluster. C1 sits on top of segment 1, but is positioned far from the other clusters. This explains its high and low ratings. The extreme positions of C2 and C3 explain their low ratings.

Optimum Product Placement: Looking at Figure 1 we see that one of your products (B1) is positioned close to two of your competitors and that there are no products in the neighborhood of segment 3. You could remove all of your products from Figure 1 and determine the optimum placement of your product portfolio. There are a number of criteria for defining the optimum placement. One criterion is to maximize the number of first choices for your products. In this case, the product chosen first by an individual is that product which yields the highest predicted liking rating obtained from the similarity model. A second criterion is to maximize the number of top two scores on the liking scale. This less stringent criterion will not take competition into account. The same score results if a product is located in a region that contains many other products or if there are no other products present. This latter criterion is preferable if your marketing and distribution capabilities dominate your competitors so that you essentially operate as if you are alone in the market. A hybrid criterion would be to use the first choice criterion weighted by the strength of your competitors. We will discuss optimum product placement to meet these objectives in a future report.

Conclusion: The ability to locate individual ideals and products to represent a market is valuable as it provides a product development tool to evaluate the current market situation and to develop strategic options for the future. Groups that form latent segments may be identified and the expected performance of new products among these segments, or for the market as a whole, may be identified. The effect of competitors' products in the space may be assessed and the optimal positions for a product portfolio to delight the greatest number of consumers can be determined.

References:

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