Analytic Approaches to Accounting for Individual Ideal Points

Daniel M. Ennis

Background: When Goldilocks made her food and mattress choices, she exhibited a common preference for items of moderate intensity. Instead of the hottest or coldest, softest or hardest, she chose the intermediate points. Even in the case of her furniture choice where she chose the smallest chair, one could easily construct a sufficiently small chair that she would reject. Although there are attributes, such as luxury, fuel efficiency or off-taste, for which it might seem that there is no upper or lower bound on the desired level of the attribute, this is not generally the case. For many consumer products, sensory drivers of consumer liking have non-extreme optimum points for many consumers. Of course, there are people who crave higher and higher intensity and others who retreat to the lowest level of sensory stimulation, but in many cases they sit on the banks of the main flow of consumer choice.

In our previous technical reports on Landscape Segmentation Analysis® (LSA) it was shown how product positions and individual ideal densities could be determined in a space of attributes that drive liking for the products tested[1]. We have shown how this method, based on a model of similarity[2,3], has many applications in studying motivations for product consumption[4,5], product-concept (name) fits[6], market segmentation based on liking[7], product and portfolio optimization[8], and product performance/image tradeoffs[9]. In this report it will be shown how two different analysis approaches to handling individual ideal points lead to very different conclusions and the implications of this result in modeling consumer behavior will be discussed.

Scenario: Your company produces and markets non prescription health care products. One of your products is a well-known stomach medicine, a liquid antacid, and there is interest in optimizing the level of certain features of the product. These features are sweetener level, color (saturation), and flavor level. Thinking of these features as points on a cube, you design products corresponding to the corners (vertices), face centers, and the center of the cube as shown in Figure 1. These fifteen products are evaluated, over several sessions, in a randomized order by five hundred consumers of this type of product. Consumers are instructed to taste each product and then expectorate and rinse thoroughly with distilled water after each evaluation. Ratings on a 9-point liking scale for each product are obtained. The mean liking ratings for the fifteen products are shown in Table 1. It can be seen that the highest liking mean is obtained for the product at the cube's center and that the face center products are liked more than the products at the corners. Within these groups, liking rating means are similar among the products.

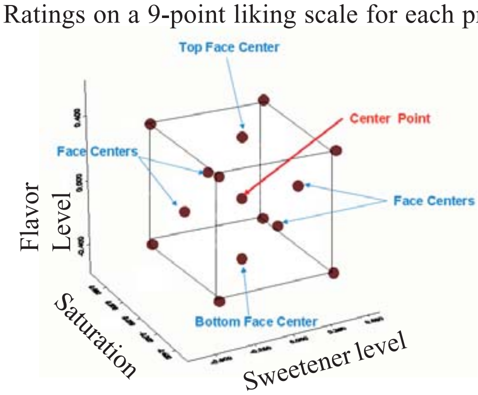

Figure 1. Physical characteristics used in the design (e.g., sweetener content.)

Product position	Liking Mean
1 (Corner)	5.48
2 (Corner)	5.52
3 (Corner)	5.45
4 (Corner)	5.47
5 (Corner)	5.39
6 (Corner)	5.41
7 (Corner)	5.29
8 (Corner)	5.32
9 (Center)	8.01
10 (Face)	7.03
11 (Face)	7.07
12 (Face)	7.08
13 (Face)	7.01
14 (Face)	6.96
15 (Face)	6.95

Table 1. Mean liking ratings for the 15 products.

Unknown to you, these results occur because individuals differ in the levels of the attributes that they like, but their ideal points form a single large cluster concentrated at the center of a cube as shown in Figure 2. This cube is different from the design cube of Figure 1 since it corresponds to the perceived levels of the design variables, not the variables themselves. For instance, in Figure 1 one of the variables is sweetener level, but the corresponding variable in Figure 2 is sweetness. This one-to-one correspondence does not always occur as the sensory space is a mental representation of the physical space. As already discussed, most of these consumers, like Goldilocks,

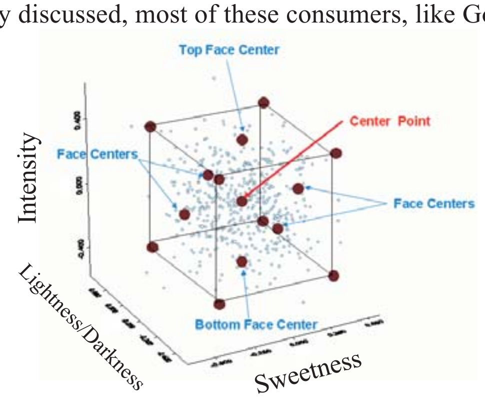

Figure 2. The actual underlying perception of the products (unknown to the experimenter) in a space with individual ideals.

like products with intermediate levels of the product features. There is a minority who like low levels of all attributes and and some who like the highest level of all attributes but most consumers do not fit this profile. You conduct two different analyses that are commonly used to interpret liking ratings. One is a display of the first three principal components of the individual liking ratings in which each consumer is represented as a vector pointing in the direction of the individual consumer's ideal. The second is a 3-dimensional LSA analysis in which each consumer's ideal point is estimated along with commonly perceived product positions.

Vector and Individual Ideal Points: One could think of a liking rating as arising from a projection of a product point in a space of the sensory attributes that drive liking onto a vector representing an individual. The position of the product on the vector, relative to other products similarly projected, provides an indication of the relative degree of liking for that product. The direction indicted by the vector representing an individual is the ideal direction, but the location of the ideal point is unknown. This type of model is well suited to account for attributes, such as luxury or off-taste, for which the consumer's ideal will fall outside any conceivable region of the sensory space into which products are placed. In the case of attributes, such as sweetness or flavor level, for which the consumer will reject products with too much or too little of the attribute, this is not a good way of accounting for liking data as will be seen presently. A model that provides individual points inside or outside the space representing consumer ideals would be preferable in this case.

Based on the liking data, the first three principal components of the vector model are given in Figure 3. Because the model only has ideal directions to work with, the most highly liked product, the one in the center of the cube, is forced out of the cube and forms the highest point on what appears to be a liking dimension with the lower rated products at the vertices suppressed into the base. Note also that the model pushes the vertex products and face center products together in pairs, which do not exist in the original cube representation.

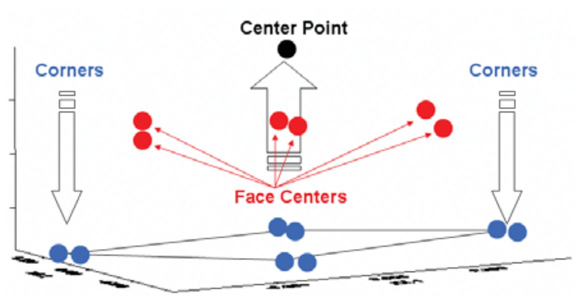

Figure 3. PCA's interpretation of the cube.

Analyses of the Liking Data Using LSA: A 3-dimensional LSA analysis of the liking data is shown as Figure 4. This analysis is entirely based on the liking ratings and was obtained from IFPrograms without any reference to Figures 1 and 2. It can be seen that this analysis recovers the cube structure and places the products at the corners, at the face centers and in the middle of the cube. The individual ideals occur as a large cluster placed within the cube. According to this analysis, consumers respond to three sensory variables, presumably associated with the three variables used in the design, sweetener level, saturation and flavor level. It is clear why the products at the corners and face centers received similar liking mean ratings. Although different products appeal to different consumers, they are placed about equidistant from the individuals as a group. If there had been segmentation of this consumer cluster, it would have shown up as differences in liking means for the products at the vertices and face centers of the cube.

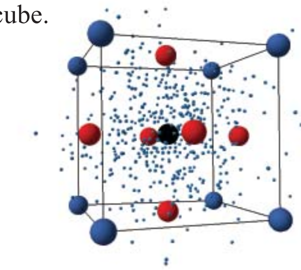

Figure 4. 3D LSA from liking data.

Understanding Product Maps: Ease of access to multivariate analysis software makes it relatively easy to conduct analyses, such as those used in this report. Interpretation of the results of those analyses depends very much on the user's understanding of the assumptions made in constructing the models. If the correct answer to the analysis reported is a cube with sensory dimensions dependent on the three design variables, this structure would not emerge from the vector model analysis and very misleading guidance on product design would occur. Generally, one does not know the underlying structure, so there is no way to know how badly distorted the resulting map is. Tests of goodness of fit may not be sufficient to avoid this problem. The best strategy is to think about the most likely structure underlying the data generating process and use modeling approaches that are as faithful as possible to that theory. Otherwise, one is very likely to end up with confusing, sometimes conflicting, results that have limited applicability and generalization.

References (available at www.ifpress.com):

1. Ennis, D.M. (2001). Drivers of Liking® for multiple segments. *IFPress*, **4**(1), 2-3.
2. Ennis, D. M., Palen, J. and Mullen, K. (1988). A multidimensional stochastic theory of similarity. *Journal of Mathematical Psychology*, **32(4)**, 449-465.
3. Ennis, D. M. and Johnson, N. L. (1993). Thurstone-Shepard similarity models as special cases of moment generating functions. *Journal of Mathematical Psychology*, **37(1)**, 104-110.
4. Ennis, D.M. and Rousseau, B. (2002). Motivations for product consumption. *IFPress*, **5**(3), 2-3.
5. Ennis, D.M., and Rousseau, B. (2004). Motivations for product consumption: Application of a probabilistic model to adolescent smoking. *Journal of Sensory Studies,* ***19*****(2)**, 107-117.
6. Rousseau, B. and Ennis, D.M. (2004). Product-concept fits. *IFPress*, **7**(3), 2-3.
7. Ennis,D.M. and Anderson, L. (2003). Identifying latent segments. *IFPress*, **6**(1), 2-3.
8. Ennis, D.M. (2003). Designing new product portfolios. *IFPress*, **7**(1), 2-3.
9. Ennis, D.M. (2005). Measuring product performance/image tradeoffs. *IFPress*, **8**(1), 2-3.