Reprinted from IFPress (2014) 17(3) 3,4

Unfolding

Daniel M. Ennis

Background: Before you unfold a fan, as shown in Figure 1, you can see a compressed set of images stretched out on a line from the center to the periphery. These images may appear as nothing more than ordered blotches. You can imagine what you might see when you unfold the fan, but almost certainly the real image will confound your imagination. Liking and other hedonic measures, expressed as ordered means, are like the blotches on an unopened fan. We will not know what the drivers of liking space looks like and how the items are arranged in it until we unfold the data.

In a previous paper[1], we reviewed some of the more common methods for generating spatial maps of hedonic data and considered the extent to which they are based on a well-defined process. We concluded that the use of a model based on the process that respondents use to generate hedonic data, rather than relying on models that contain no such process considerations, is important to obtaining a meaningful interpretation of hedonic data. In addition, by following a process-based approach, researchers can evolve their thinking about what their data means by testing and improving their models. One of our recommendations was to consider ideal point ideas in hedonic models, particularly those that incorporate uncertainty into the location of items and ideals.

In 1950, Clyde Coombs[2] proposed the idea that for certain types of variables that drive preference or liking, an ideal point may be useful to explain what has been called "single peaked preferences." He reasoned that at lower or higher levels of the liking driver for an item, lower liking ratings may arise because the distance between the item and the ideal is larger. As the liking driver's intensity increases, liking increases to a maximum or satiety point and then decreases, as shown in Figure 2. Although there are variables for which this idea would not apply – fuel efficiency in an automobile, for example – there are many sensory variables that are associated with foods, beverages, personal care, home care, air care and others, for which the response in Figure 2 to increasing intensity is highly applicable.

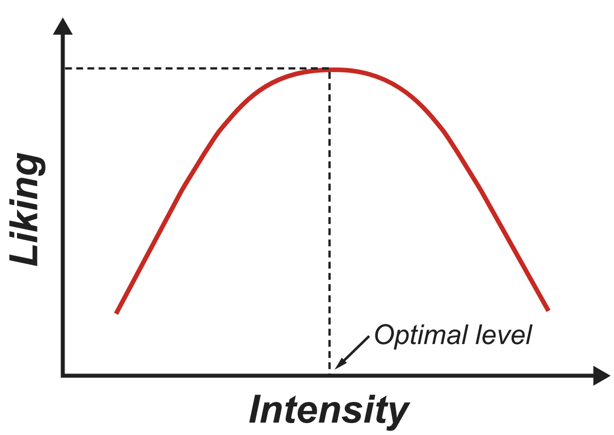


Figure 2. Hypothesized relationship between liking and a sensory attribute, based on distance to an ideal point.

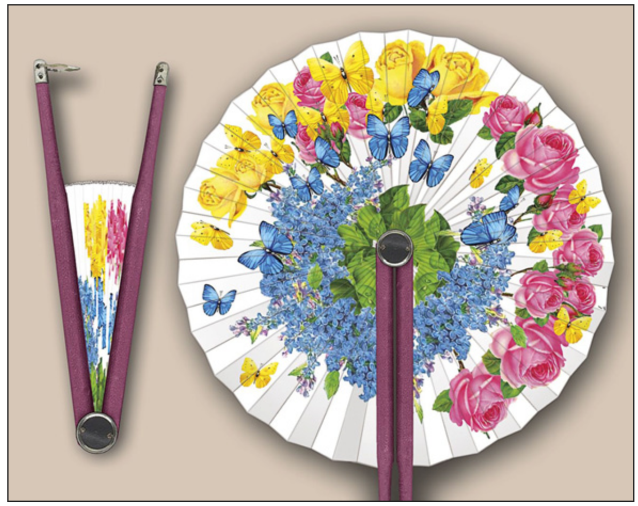


Figure 1. Compressed image of a folded fan offers only a glimpse of the unfolded image.

Scenario: You work as a statistical analyst at a major consumer products company and your consumer insights colleagues regularly engage your services to help them interpret their data. A common request is to map data from consumers who have responded to blind products, brands, or concepts regarding their acceptability. Your attempts to meet your clients' objectives have been mixed. Occasionally, an ideal direction model has been useful when it is clear that the vast majority of consumers respond negatively or positively to increasing levels of the variables that describe the items. But in other cases where you know that there are individual optimal points, such as in the case of sweetness, sourness, flavor strength, hue, or saturation, your analyses have been unsatisfactory and sometimes even uninterpretable. In short, you need to find a better solution for this class of problems.

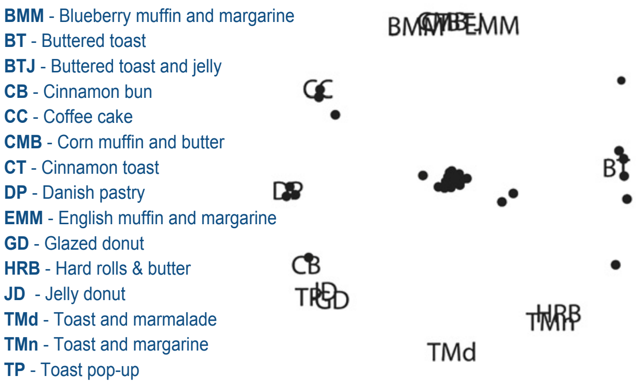
Ideal Point Research and Unfolding: There is often a large gap between the time when a good idea is proposed, and when it becomes practical. Ideal point modeling is such a case. Numerous researchers over the past half century, primarily in the Netherlands and the US, have worked on ways to implement Coombs' concept to find locations for individual ideal points along with locations of items (such as consumer products) in a drivers of liking space. The term "unfolding" has been used to describe the process of producing these spatial representations or maps. Ideally, a solution would reveal meaningful relationships between the ideal points and items – a degenerate solution is one in which the items and ideals cluster together in such a way as to yield an uninterpretable result. Unfortunately, degenerate solutions have routinely occurred[3]. An extreme example of a degenerate solution is shown in Figure 3. In this case, the items form a circle around many of the ideals which are tightly clustered at the center.

If one is willing to accept the concept of an ideal direction rather than an ideal point (so that hedonic responses either only increase or only decrease when an attribute is

Reprinted from IFPress (2014) 17(3) 3,4

changed), there is a well-known solution based on a paper published by Gabriel[4] over 40 years ago. This theory is used in commonly available software packages and Internal Preference Mapping (IPM) is an example of this type of model. Unfortunately, ideal point direction models can give misleading results when satiety occurs. This problem was well illustrated when twenty-seven large consumer category appraisals at Kraft Foods were reanalyzed using both an ideal direction model and an ideal point model[5]. In many cases it was found that optimal values existed on the liking drivers for each particular person, undermining support for the ideal direction concept. This research pointed to the need for ideal point unfolding models but the question remains: If we are to use these models in practice, is there a way to avoid degeneracies?

Figure 3. Degenerate solution for breakfast bread data[9].



Liking and Similarity: Thinking about how consumers generate liking ratings, an important realization is that liking may be thought of as a form of similarity. In this view, a liking rating is a rating of the similarity between an item point and a consumer's ideal point in the drivers of liking space. In particular, liking ratings (and other hedonic ratings) can be converted to estimates of subjective probabilities. Then a similarity model that predicts subjective probabilities from the coordinates of the items and ideals in a drivers of liking space can be fit to the data. However, it is important to consider what type of similarity model to choose to avoid degeneracies.

A Probabilistic Unfolding Model: Unfolding models based on the idea that items and ideals are fixed points (deterministic models) do not have a successful history although progress has been made to improve them recently[6,7]. An alternate approach, however, is to consider that items and ideals can be represented as distributions rather than fixed points because the perception of some items, such as consumer products, varies within products and across individuals. Such thinking gives rise to a family of probabilistic unfolding models. One such model[8], Landscape Segmentation Analysis® (LSA), has been implemented in the *IFPrograms*™ software. In order to test this model, you apply the model to the dataset of Figure 3 on breakfast breads[9], a classic dataset which is often used to test unfolding models, and obtain the results shown in Figure 4. In this case, the items and ideals are intermixed in the solution and the model does not produce a degenerate

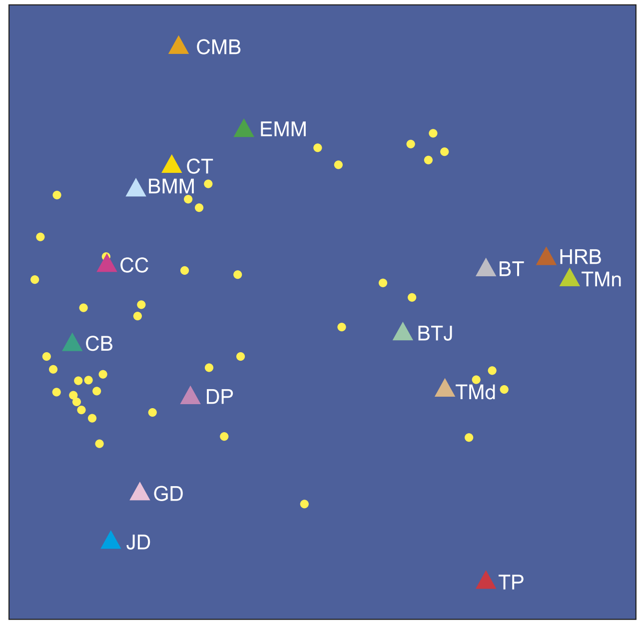


Figure 4. Breakfast bread data unfolded using Landscape Segmentation Analysis (LSA).

solution. Using this model on your own datasets, you find that it provides clear insights without the challenges you previously encountered when using deterministic solutions.

Conclusion: It is useful to unfold hedonic data such as liking to obtain a clear understanding of the relationships between consumers and the items tested. Attempts to do this have often resulted in degenerate solutions, but this problem has been solved using a probabilistic unfolding model. This model provides researchers a reliable way to gain more insight into their hedonic data than was previously possible.

References

1. Ennis, D.M. and Ennis, J.M. (2013). Mapping hedonic data: A process perspective. *Journal of Sensory Studies,* **28**, 324-334.
2. Coombs, C. (1950). Psychological scaling without a unit of measurement. *Psychological Review,* **57**, 145–158.
3. Busing, F. M. T. A. and van Deun, K. (2005). Unfolding degeneracies' history. Degeneracies in multidimensional unfolding (pp. 29-75). Unpublished doctoral dissertation, Catholic University Leuven.
4. Gabriel, K. R. (1971). The biplot graphic display of matrices with application to principal component analysis. *Biometrika,* **58**(3), 453–467.
5. Rousseau, B., Ennis, D., and Rossi, F. (2011). Internal preference mapping and the issue of satiety. *Food Quality and Preference,* **24**(1), 67–74.
6. Busing, F., Groenen, P., and Heiser, W. (2005). Avoiding degeneracy in multidimensional unfolding by penalizing on the coefficient of variation. *Psychometrika,* **70**(1), 71–98.
7. van de Velden, M., Beuckelaer, A. De, Groenen, P. J. F., and Busing, F. M. T. A. (2013). Solving degeneracy and stability in nonmetric unfolding. *Food Quality and Preference,* **27**(1), 85–95.
8. 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.
9. Green, P.E. and Rao, V. (1972). Applied multidimensional scaling. Hinsdale, IL: Dryden Press.