Mapping Hedonic Data: A Process Perspective
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Abstract

Multivariate analyses are commonly used to study differences among items in a multidimensional space and to relate these findings to hedonic assessments of the same items. But there are numerous methods in use and the purpose of this paper is to review these methods from a process standpoint. Specifically, this paper considers the process assumptions behind several of the popular methods for multivariate mapping of hedonic data and argues that experimenters should consider how their data arise so that they can correctly interpret their findings. Among the methods considered in this paper are models based on the hedonic continuum, internal and external preference mapping, and deterministic and probabilistic unfolding of preference and liking.

Practical Applications

Multivariate mapping of hedonic data has led to improved consumer products and a better understanding of consumer liking and choice. In this paper, practitioners will find guidance in their choice of methods through a consideration of the processes that generate their data. Without a process-based perspective, practitioners will not be able to optimally interpret results from the wide variety of available multivariate mapping methods.

Introduction

Improved access to multivariate analysis software has made it relatively easy to conduct multivariate mapping of hedonic data. But correct interpretation of results depends very much on the user's understanding of the models underlying the mapping techniques. Since models reflect the thinking of their inventors, and since we temporarily accept that thinking when we apply mapping techniques, it is valuable to consider what those perspectives might be. Specifically, multivariate mapping methods are designed to uncover a spatial representation of data and there are a virtually unlimited number of possible representations. Since an experimenter generally does not know the underlying spatial structure, there is not always an *a priori* way of knowing how badly distorted the resulting map is relative to the "true" picture. As we show later in this paper, tests of goodness of fit may not be sufficient to avoid this problem. The best strategy is to consider the processes that likely underlie the data generation and to use modeling approaches that are as faithful as possible to those processes. Otherwise, one could obtain confusing or conflicting results with limited applicability and generalization.

In this paper we review the processes behind a number of different methods of modeling hedonic data typically obtained from product testing - the guiding principle of this paper is to consider alternative methods according to the various mechanisms through which the hedonic data may arise. There is no universal or panacea method that applies in all circumstances. Provided that a model's assumptions apply, then that model is appropriate and different models may be required for different applications. We begin by discussing the most straightforward assumption, that of an hedonic continuum. This discussion will lead us to the search for a "drivers of liking" space, which gives rise to a consideration of internal and external preference mapping. We then discuss preferential choice and liking unfolding before concluding.

To help guide the reader through our exposition, Table 1 provides a selection of recent papers in the applied sensory literature that have employed multivariate mapping of hedonic data. These papers are classified according to the mapping techniques they employed. It is worth noting that many of the applications involve Internal and External Preference Mapping and only a few involve Ideal Point Unfolding. It is not the purpose of this paper to discuss each of these applications, but rather to consider the models that underlie them and to consider their process assumptions.

Table 1. Categorization of recent publications in the *Journal of Sensory Studies* and *Food Quality and Preference* utilizing multivariate mapping of hedonic data. (IPM = Internal Preference Mapping, EPM = External Preference Mapping, IPU = Ideal Point Unfolding)

	IPM	EPM	IPU
(Séménou et al., 2007)	✓		
(Gambaro et al., 2007)		✓	
(Meullenet et al., 2007)		✓	
(Meullenet et al., 2008)	✓	✓	
(Alves et al., 2008)	✓		
(Hein et al., 2008)	✓		
(Jaeger et al., 2008)	✓		
(Wajrock et al., 2008)	✓		
(Sveinsdóttir et al., 2009)	✓	✓	
(Resano et al., 2009)	✓		
(Villanueva and Da Silva, 2009)	✓		
(Plaehn, 2009)		✓	
(Tubbs et al., 2010)	✓	✓	
(Varela et al., 2010)	✓		
(Dooley et al., 2010)		✓	
(Worch et al., 2010)		✓	
(Ares et al., 2011)		✓	
(Zhang et al., 2011)		✓	
(Rousseau et al., 2011)			✓
(Paulsen et al., 2012)	✓		
(Symoneaux et al., 2012)	✓		
(Kraggerud et al., 2012)		✓	
(Måge et al., 2012)		✓	
(Menichelli et al., 2012)		✓	
(Nunes et al., 2012)		✓	
(Worch et al., 2012)		✓	
(Jervis et al., 2012)			✓
(van de Velden et al., 2013)			✓
(Worch and Ennis, in press)		✓	✓

The Hedonic or Utility Continuum

When thinking about preference or liking data and how they arise, the simplest idea is that they derive from an hedonic continuum. In the economics literature, this continuum is referred to as *utility*. In this way, liking is treated like a sensory variable such as sweetness or sourness. This approach will not lead to spatial representations of products and consumer ideals, and hence will not support multivariate mapping. However, it

will allow us to quantify the degree of liking and conduct comparative statistical tests on the hedonic scale estimates. Assuming that liking ratings approximate perceived intensities on the underlying hedonic scale, a typical analysis involves an analysis of variance followed by multiple comparison tests to compare liking rating means. Analysis of preferential choice often involves tests using the binomial distribution.

These methods do not actually scale the data on the hedonic continuum, but models have been developed that do. For instance, suppose that in a forced choice preference test one product is preferred to another by 76% to 24%[1]. A Thurstonian probabilistic model[2] for the 2-Alternative Forced Choice method tells us that the scaled difference (d') on the hedonic continuum is 1 in perceptual standard deviation (δ) units as illustrated in Figure 1. This figure is the simplest form of visual representation of the data. If the sample size had been 100, the variance of this estimate would be 0.038, and it would be 0.019 if the sample size was 200. These scale mean and variance estimates can be found using published tables (Bi et al., 1997; Bi, 2006; Ennis et al., 2011) or available software (Ennis, 2003; Christensen, 2011). Similarly, if liking ratings on a category scale for the same products are obtained, one can estimate the value of d' and its variance (Dorfman and Alf, 1969). Rating means or scaling estimates of utility are often modeled as a function of hypothesized explanatory variables using multiple regression (McCullagh and Nelder, 1989; Myers, 1990).

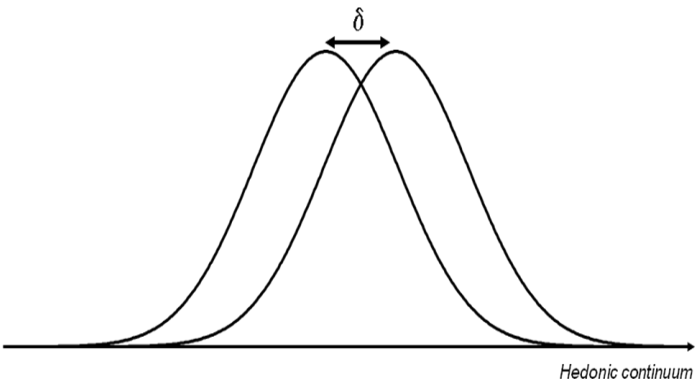

Figure 1. Illustration of the scaled difference between two products on an hedonic continuum based on preferential choice.

In order to predict choice data, such as preferential choice or first choice among multiple alternatives based on utility, a common practice is to use logistic regression (Hosmer and Lemeshow, 2000). This method has become extremely popular in market research, economics and public health where the goal is often to discover explanatory variables that drive a choice outcome. The attractiveness of the logistic model is that it takes a closed form (which means that there are no integrals to evaluate). The difference in utility between two items, u, can be related to preference using the function $e^u/(1+e^u)$ where u is often expressed as a linear function of variables driving utility[3]. It can be seen that if u is large, meaning that the first product has a much larger utility than the second, the preference probability will tend towards 1. If the opposite occurs, it will tend towards zero. When $u = 0$, the probability will be 0.5. As discussed above for liking, the logistic model assumes an hedonic or utility continuum when modeling preference between a pair of items or first choice among a larger set. The popularity of the logistic model seems largely dependent on the ease of computing the model parameters, rather than having a compelling process model account, although it can be derived under an assumption that the utility random variables are double exponentially distributed rather than normally distributed (Train, 2003).

Models based on scaling items on an hedonic or utility continuum do not give a very satisfying account of how hedonic data arise. There are no receptors on the tongue for liking (as there are for sweetness or bitterness) that might help to justify the assumption of a hedonic continuum[4]. Liking or utility are better thought of as arising from a comparison of an immediate experience (such as tasting a product) with a reference or ideal expectation developed from past experience. This idea was provided by Coombs (1950) when he suggested that such comparisons were the reason we see single peak preference functions. As a product moves away from a consumer's ideal reference point in any direction in a drivers of liking space, the consumer's appreciation for that product will decrease. See Figure 2.

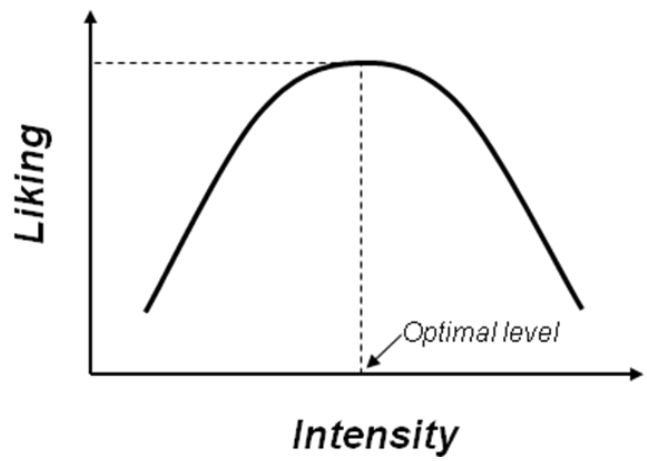

Figure 2. Hypothesized relationship between liking and a sensory attribute, based on distance to an ideal point.

[1] Controlled tests such as these may only have a tenuous connection to real-life experience.

[2] See Lee and O'Mahony (2007) for a recent review of Thurstonian scaling.

[3] A similar approach is used in conjoint analysis (Luce and Tukey, 1964; Green and Rao, 1971; Green and Srinivasan, 1978), which is widely used in sensory science (e.g. Jervis et al. 2012). Since this paper focuses on multivariate mapping, we will not discuss conjoint analysis further – we instead recommend (Orme 2006) for a review.

[4] For example, a molecular model for sweet taste perception would justify a sweetness continuum based on a concentration-dependent function which also depends on receptor and transducer binding constants (Black and Leff, 1983; Ennis, 1991).

This way of thinking allows us to capture satiety effects in a parsimonious manner because the response is primarily driven by distance. If we were required to produce the same single peak preference functions using linear regression, the complexity and number of parameters required would be more extensive and we would need to specify the candidate explanatory variables in advance.

The Drivers of Liking Space

When thinking about differences among products that may drive consumer liking, it is helpful to visualize a space in which each possible product has a location. In this space, each person's ideal product may also be found, so that if we had access to this space, along with the locations of the actual product and individual ideal products, we could predict the appreciation of each person for each of the actual products according to how close or far the ideal products were to the actual products.

In looking into such a space we might also notice that each product and each ideal does not exist as a point, but as a collection of similar points. Some people clearly know what they like - their ideals are tightly clustered together; others are more uncertain – their ideal points form a larger cloud of points. It should be expected that individuals do not have absolute ideal points because they may vary from time to time depending on variables such as mood, time of day, and recent consumption experiences. Some people may even have multiple ideal products that are triggered by the actual product tested (Worch and Ennis, in press), as might be the case with light-colored beers and dark-colored beers. We might also see that products do not have an exactly determined position – they would sit in our space as clusters of varying sizes due to differences in the perception of these products by people at different moments.

Since some people like similar things, collections of individual ideal point clusters may form what we generally describe as market segments. These segments may have simple demographic markers, such as age or gender. They may be more complex and derive from sensory experience, such as people who like sweet products and those who do not. From the size of these collections of ideals or segments, we could assess the potential opportunity for a product with appeal to a particular segment. If, in addition to knowing product and ideal locations, we could also describe this space using reliable information about product characteristics, the result would be a tool of immense value to product developers and marketers. The vision of creating and exploring this "drivers of liking" space has been a stimulus for considerable research and model development over many decades. One attempt at accessing this space has been Internal Preference Mapping, which is the topic of the next section.

Internal Preference Mapping, the Cube, and Satiety

Figure 3 shows a series of products plotted in a cube-like formation - within and around the cube a large number of points are plotted. The products are placed on the vertices of the cube, at its face centers, and in the cube center. The cluster of points represents the ideal points of individuals, and individual liking scores for the products depend on the distance that each point is from each product. See Table 2 for a table of average liking ratings that might arise from such a formation[5].

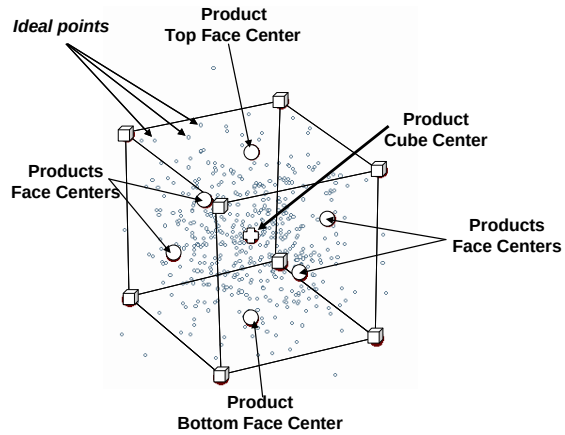

Figure 3. Arrangement of products on the vertices, face centers and center of a cube containing individual ideal points.

Table 2. 9-point rating means for 15 products paced on the vertices, face centers and center of a cube.

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

[5] In this case we assume that liking can be given as $1+8e^{-d}$ where d is the distance from the ideal point to a product. The actual function we choose to relate distance to liking has little bearing on the results we share in this section – similar results will be found for any function that monotonically decreases from 9 to 1 as the distance increases from 0.

In this table, we see that the most highly rated product is the one in the center, which is closest on average to the individual ideals. Next most liked are the face centers and finally the corners. Suppose that we only had access to each individual's liking rating for each product. Would we be able to recover Figure 2?

In practice, we do not know the underlying drivers of liking structure - all we have are liking ratings. Thus we might apply one of the well-known methods for mapping data such as those given in Table 1. One such method is called Internal Preference Mapping (IPM; Chang and Carroll, 1969; Carroll, 1972). In this method we assume that there are vectors representing individuals that point in each case in the direction of an individual's ideal. This method is essentially based on a method called biplotting, originally introduced by Gabriel (1971). Gabriel's interest was in representing the rows and columns of a matrix - the "bi" of biplotting refers to the two-dimensional row and column structure of the data matrix.

In the case of the cube, we know the underlying ideal/product structure in the drivers of liking space and it is instructive to see how IPM recovers that structure. Figure 4 shows the result of applying IPM to the data summarized in Table 2. Based on the liking data, the first three principal components of the vector model are given in Figure 4. In Figure 4 we can see that the method badly distorts the cube and in fact, there is very little resemblance to the cubic structure at all. 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 – these pairings do not exist in the original cubic representation.

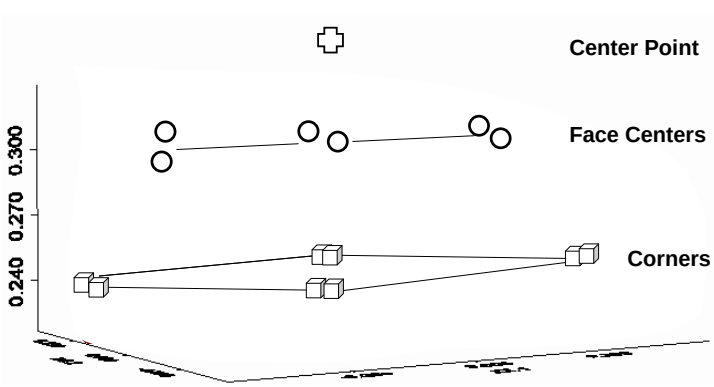

Figure 4. A PCA representation of data summarized in Table 2.

From Figure 4 it is clear that IPM has failed to recover the original cubic spatial representation, even though the model fit is quite good (83% of the variance is explained by the first three principal components.) If we add a fourth dimension, which does not exist in the cubic representation, the model fit increases to 89% - an experimenter may choose that solution and be misled by it. But a reasonable question to ask is: How do we know that a representation like the cube would ever occur? Is it not possible that IPM captures a reality in which people make liking decisions on the basis of ideal directions, and that there are no ideal points? For variables such as fuel efficiency or luxury in automobiles or off-taste in food, IPM may be a perfectly valid and useful model. However, evidence for ideal points, rather than ideal directions, comes from satiety – it is possible to have too much or too little of many sensory attributes (such as sweetness, bitterness, and hardness) with optimum values found at intermediate levels.

Experimental Evidence for Satiety

Rousseau et al. (2011) investigated the effect of satiety on IPM when they reevaluated twenty-seven category appraisals conducted by Kraft Foods. They compared IPM with an individual ideal point model capable of locating individual and product positions. They found strong evidence that IPM extracts an hedonic direction among the first two principal components as anticipated by the theory presented earlier and as illustrated with the cube.

Although IPM is a useful tool when its assumptions apply (Greenhoff and MacFie, 1994), the above results should give pause to any experimenter using IPM. If that experimenter has reason to believe that the products being evaluated exhibit satiety on key attributes, then the IPM solution may be just as misleading to the experimenter as the distorted spatial representation of the cube shown in Figure 4. How is the experimenter to know that the resulting map is untrustworthy if goodness of fit is not to be relied on? We think that the best way to answer that question is to consider the processes that underlie the data creation, what is already known about the product category in question, and theories that can account for the type of processes that the experimenter thinks are at work.

External Preference Mapping and Two Approaches to Product Mapping

We next consider the basis for a commonly used method called External Preference Mapping[6] (EPM; Carroll and Chang, 1970; Carroll, 1972; see also Greenhofff and MacFie, 1994; McEwan, 1996). Table 1 demonstrates that EPM is very popular within sensory - we now consider what assumptions support the model. For this we consider that there are at least two ways of thinking about how products differ. For example, for orange juice, one approach is to consider the sensory variables that drive differences such as pulpiness, sweetness, bitterness, and color. A second way of thinking is to consider only the sensory variables that drive differences in hedonic scores or in preference judgments. These variables could comprise the complete set of sensory variables that describe differences, but could also be a proper subset of those variables.

[6] Once again, the term "Preference" in EPM could easily have been replaced by "liking" or "hedonic".

Due to the availability of analyses based on linear algebra such as Principal Component Analysis (PCA), it is natural to develop mapping techniques based on these models. These techniques quite successfully create maps from sensory profile data that represent sensory differences between products.

Using a map that reflects sensory differences between products on a list of specified attributes, it is possible to estimate locations of individual ideal products using hedonic data. Generally these fitting techniques are based on regression using linear and/or quadratic terms – such techniques form the basis for EPM. A philosophical limitation of this method, however, is that we must assume that the first two or three principal components of the sensory space are drivers of liking, and that the resulting maps are drivers of liking spaces. This may not be true – some variables might not drive liking, and it is also possible that the experimenter did not account for all of the drivers of liking in the original sensory profiling. See (MacKay, 2006) for a thorough criticism of EPM. On the other hand, if an experimenter has a sophisticated understanding of the sensory drivers of liking for the product category, EPM may be appropriate. It should be noted again that each model may have an application depending on whether the process assumptions are justified.

To avoid the dilemma of not knowing the drivers of liking in advance, it would be preferable to derive the drivers of liking space directly from the hedonic data, if possible. Such an approach has the advantage of implicitly using only those variables that have driven the hedonic responses. Once we have created the drivers of liking space, the role of sensory profile data is to explain the dimensions of the drivers of liking space[7].

Unfolding

The term "unfolding" comes from the idea of creating maps based on unidimensional data which can be probabilities, ratings, or ranks - these maps convey information about ideal and product locations. This approach is made possible by realizing that preferential choice can be thought of as a comparison of two proximities to an ideal point, and that liking or other emotional responses can be viewed as measures of similarity between the items tested and an ideal. In a natural setting where actual products are consumed, people may compare their present product experience with an idealized or expected product, the characteristics of which are built up from past experience. The similarity model is built around the idea that the least liked products are furthest from the ideal at a particular moment. Response bias is also included in some models to account for high-raters and low-raters of the same perceived distance or proximity.

Unfolding models have now been applied to many different types of data at both the aggregate level over many subjects and at the individual level. These include liking, preference, satisfaction, purchase interest, applicability (of products and concepts), and complex variables such as refreshing, moisturizing, and freshness (e.g. Ennis et al., 2013). To illustrate the ideas behind the method, we now discuss preferential choice and liking unfolding.

Preferential Choice Unfolding

Unfolding models for preferential choice among pairs of items have been studied extensively in the last sixty years. When Coombs (1950) proposed the idea to compare two items to a reference point so as to produce a preference for one of them, the capability had not yet developed to consider that the items may vary from moment to moment and could be modeled as distributions. He could not, therefore, explain inconsistent choice behavior. This situation changed with the introduction of momentary percepts. This idea was a Thurstonian concept, so we call these models Thurstonian probabilistic models. We assume that, in the drivers of liking space described earlier, the items (products, concepts, individuals, consumer segments) can be represented as multivariate normal distributions on the variables describing this space. In other words, this space does not necessarily contain a complete description of item differences, but only of those that drive preference. The distributions are necessary in order to account for the numerous sources of noise associated with the percepts such as stimulus noise, peri-receptor noise and neural noise (Ennis and Mullen, 1992a; Ennis, 2006).

To model preferential choice data, Zinnes and Griggs (1974) assumed uncorrelated, equal variance, multivariate normal distributions for the items and a common ideal distribution. They assumed that consumer ideals were randomly chosen from this latter distribution. In this model it was assumed that a subject sampled each item independently and compared the resulting percepts with random values from an ideal distribution. An important characteristic of their model was that a separate ideal sampling was assumed for each of the items tested. This is called *independent sampling* of the ideal distribution. By way of contrast, *dependent sampling* would occur if each consumer used the same sample from the ideal distribution to compare with the independently sampled item percepts. Using dependent sampling, DeSoete at al. (1986) developed the "Wandering Ideal Point" model which assumed fixed positions for the item points but distributions for the ideals. Thus, their model is a mixture of deterministic and probabilistic components. Finally, in a series of papers, a generalization of both of these models was achieved in which items and ideals were both treated as general multivariate normal distributions and dependent sampling was assumed (Mullen and Ennis, 1991; Ennis and Mullen, 1992b; Ennis, 1993; Ennis and Johnson, 1994). The key factor leading to these developments was to apply theory on quadratic forms in normal variables to a comparison of distances[8].

[7] Kahneman's (2011) recently described System 1 (fast) and System 2 (slow) mental processes may be related to the generation of hedonic and descriptive responses, respectively.

[8] This general preference model had other applications as well in difference testing (e.g. Ennis and Jesionka, 2011) since the same mathematical model was used to fit data from Torgerson's method of triads. This is because in Torgerson's method a single item is compared to two possibly different items which has the same structure as preferential choice where an ideal is compared to two physical stimuli (Ennis and Mullen, 1992b).

These probabilistic unfolding models explain a number of experimentally observed but counterintuitive results. For example, if A is preferred to B and B is preferred to C, then one might expect that A is preferred to C. But it has sometimes been found experimentally that C is preferred to A - some probabilistic unfolding models can predict this outcome. A less extreme but still counter-intuitive case for preferential choice is given in Table 2. Here there are five products, Current Product (CP), New Product (NP), Competitor 1 (C_1), Competitor 2 (C_2) and Competitor 3 (C_3).

Table 3. Paired preference results which exhibit transitivity violations.

A	B	% Prefer A	% Prefer B
C_3	CP	50	50
C_1	CP	83	17
C_1	C_3	78	22
NP	CP	58	42
NP	C_1	24	76
NP	C_2	23	77
NP	C_3	57	43
C_2	C_1	54	46
C_2	CP	73	27
C_2	C_3	73	27

The probabilities in Table 3 are population values. It can be seen that C_2 is preferred to C_1 (54%:46%). However, C_1 is preferred to CP by a larger margin (83%:17%) than C_2 is preferred to CP (73%: 27%). Figure 5 illustrates why this apparent paradox occurs using a probabilistic unfolding preference model.

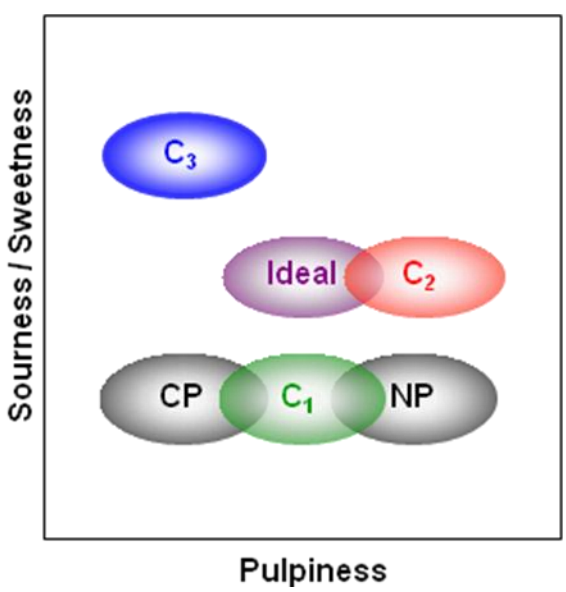

Figure 5. Probabilistic representation of five products and an ideal as multivariate normal distributions which gave rise to the data of Table 3.

Of the two drivers of preference variables, one of them (pulpiness) shows greater relative variance and hence has lower salience than the other (sweetness). C_2 does not differ from the ideal on the most salient dimension and shows greater overlap with the ideal. However, when compared to CP, C_2 cannot compete with CP for ideals that are low on pulpiness as well as C_1 can. The net effect is that C_1 performs better than C_2 when compared to CP, even though C_2 is a more preferred product.

Notwithstanding these theoretically interesting and valuable properties, probabilistic unfolding models for preferential choice have not had large impact in practice for three main reasons. The first reason is the lack of data available to fit these models - data collection for pairwise item comparisons can be extremely expensive. A second reason is their mathematical complexity compared to other models. The third reason is that they do not provide explicit individual ideal point information which is necessary to connect the model results to external demographic and other consumer-relevant data.

Unfolding Other Hedonic Data

We now return to the mapping of hedonic data in general. The history of multidimensional scaling, including unfolding, has been primarily a history of deterministic models in which items and subjects are treated as discrete points as opposed to distributions of momentary percepts. This fact is mainly due to the mathematical complexity of probabilistic models, even though their advantages are well recognized by researchers in the field. There may also be a lack of appreciation for the importance of stimulus variability which cannot be controlled easily in certain modalities, such as the chemical senses (Ennis, 2006) - the deterministic perspective has led to difficulties in part because it is sometimes unrealistic to assume that perceptual variation does not exist. Two glasses of orange juice are demonstrably never identical when people drink them as the physicochemical composition of both the beverages and the oral cavity vary from moment to moment. And even if all this variation were somehow eliminated, there would still be variability in the neural mechanisms (e.g. White et al., 2000). In fact, this neural noise may play a central role in information processing - see (Stein et al., 2005) for a recent review.

Shepard (1962), and later Kruskal (1964), introduced nonmetric multidimensional scaling in the early sixties. Twenty five years later, Shepard still considered the problem as one involving a deterministic account of stimuli when he published on the relationship between similarity and distance, and on the form of the distance metric (Shepard, 1987)[9].

[9] The difficulty that Shepard encountered was that for certain confusable stimuli, he could not explain why the distance metric was Euclidean and the gradient was Gaussian when he had expected them to be city-block/exponential decay. These results were also found by Nosofsky (1986), who also approached the modeling effort deterministically. The issue was resolved by considering a probabilistic account for these confusable stimuli (Ennis, 1988; Nosofsky, 1988; Shepard, 1988).

Busing and van Deun (2005) provided a clear and detailed account of the history of nonmetric unfolding using deterministic models and in particular they discuss attempts made over half a century to resolve the problem of degeneracies. A degenerate solution is an uninterpretable account of the data in which ideals and products are not intermixed when there is an expectation that they should be. A degenerate solution is shown in Figure 6 for an experiment on breakfast items by Green and Rao (1972). Busing and his colleagues have contributed significantly to the development of deterministic unfolding models and have made important progress in solving the degeneracy problem for deterministic models (Busing et al., 2005, 2010; van de Velden et al., 2013).

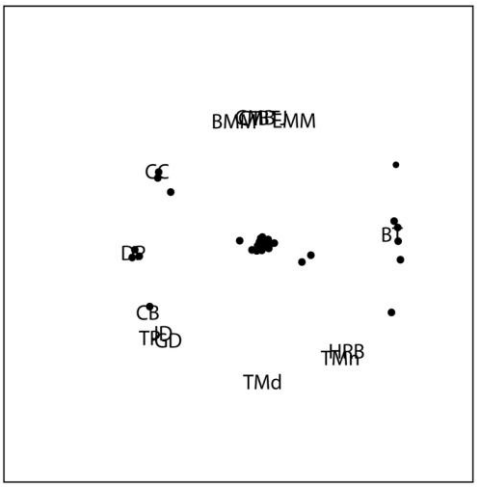

Figure 6. Degenerate solution for breakfast bread rating data (Green and Rao, 1972), reproduced with permission from Busing and van Deun (2005). Breakfast bread plotting codes: **TP** - Toast pop-up; **BTJ** - Buttered toast and jelly; **EMM** - English muffin and margarine; **CMB** - Corn muffin and butter; **BMM** - Blueberry muffin and margarine; **CT** - Cinnamon toast; **HRB** - Hard rolls and butter; **TMd** - Toast and marmalade; **BT** - Buttered toast; **TMn** - Toast and margarine; **CB** - Cinnamon bun; **DP** - Danish pastry; **GD** - Glazed donut; **CC** - Coffee cake; **JD** - Jelly donut.

To apply probabilistic multidimensional scaling to hedonic data, we think of an hedonic rating as reflecting a subjective probability that an actual product is similar to an ideal product, for the particular individual providing the response. This perspective allows us to make use of a multidimensional similarity model (Ennis et al., 1988; Ennis and Johnson, 1993). Unlike the three difficulties listed earlier for preferential choice, hedonic ratings are commonly available in applied settings because they are relatively inexpensive to obtain. The similarity model has a closed form and is easy to compute, thus overcoming the second problem with probabilistic preferential choice models. This model can also be used to obtain individual ideal point and product locations without either preprocessing or additional techniques to avoid degeneracies (Ennis, 2001; Ennis & Rousseau, 2004). This location of individual ideal points represents an advance over unfolding methods that assume either a single ideal point or pre-specified ideal distributions (De Soete et al., 1986; MacKay et al., 1995; MacKay, 2001). These individual ideal points are valuable as they can help to identify latent consumer segments (Ennis & Anderson, 2003). See Figure 7.

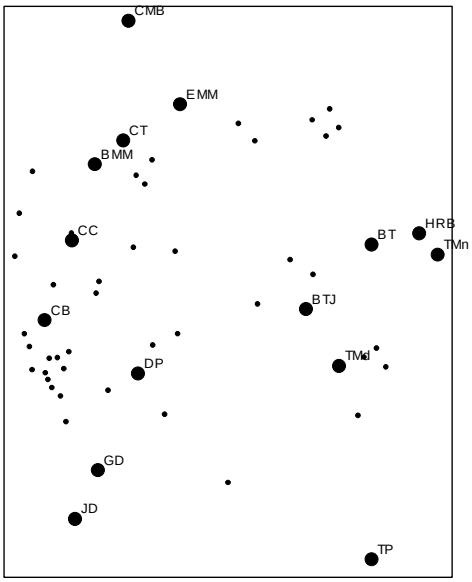

Figure 7. A probabilistic unfolding model solution to the breakfast bread rating data of Green and Rao (1972).

Figure 7 shows a best fitting two-dimensional probabilistic unfolding solution to the same rankings data (Green and Rao, 1972) that were used to create the degenerate solution in Figure 6 - this dataset is often used to test unfolding models (Busing and van Deun, 2005). The solution is not degenerate and is similar to a quasi-metric unfolding solution provided by Kim et al., (1999). This latter model was discussed by Busing and van Deun (2005) and was designed to encourage inter-mixedness of items and subject ideals.

Thus the problem of degeneracies in unfolding has now been solved using both deterministic and probabilistic techniques. The process models underlying these techniques are the most satisfactory of those used in the multivariate mapping of hedonic data as they intrinsically accommodate both satiety and variability (MacKay, 2006). The mathematical challenges these models posed have largely been solved, and future sensory research is likely to include increased use of these methods. For further discussion of probabilistic unfolding, and a comparison of probabilistic unfolding with both external and internal preference mapping, see (Meullenet et al., 2007).

Conclusion

Scientific models are based on certain, usually testable, assumptions. With regard to mapping hedonic data, we encourage researchers to consider the processes by which their data arise. In order to explain an experimental result such as satiety or the numerous counterintuitive results associated with preferences, we recommend that researchers consider the increased use of ideal point models that include parameters to account for perceptual variation. In other situations where satiety does not arise, other methods such as hedonic scaling, IPM, or EPM may be appropriate and easier to use. In concluding we

also note the importance of continued research into data acquisition methods that lead to data with higher ecologic validity.

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