A Process Perspective to Understand Hedonics

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Background: People have always formulated explanations for what they observe. These observations can be classified as superstition, pseudoscience, alchemy, and non-process and process models falling under the general classification of engineering and science. Non-process models are based on heuristics or ease of use; process models are based on theoretical processes which underlie the observables such as germ theory as opposed to "the humors," which was the basis for bloodletting. Sometimes ideas last for centuries, but can be washed away in a tide of change in a few years. Changes that occurred after Pasteur conducted his sterilization experiments gave birth to the science of microbiology. Process models are constructed using interpretable parameters and have the greatest chance of providing a basis for new thinking and new discoveries. This technical report, by examining models used to represent hedonic observations, will recommend practitioners base their conclusions on process-based models.

Scenario: You work for a major food company and routinely conduct category appraisals to study variables that drive consumer liking and to compare your product performance with that of your competitors[1]. One of the datasets you analyzed involved an evaluation of twenty-six processed cheeses in a hot presentation by two hundred and twelve consumers. The consumers rated the items on a liking scale as well as a number of descriptive attributes. In this technical report, attention will be directed to understanding the liking data using unfolding models[2].

Non-Process Models: When thinking about preference or liking data and how they arise, a simple idea is to consider a hedonic continuum. In the economics literature, this continuum is referred to as *utility*. It seems reasonable, from a process perspective, to use this idea when thinking about a sensory variable, such as sweetness or sourness, since these sensations arise from binding processes at the periphery. However, there are no known receptors on the tongue for liking or preference, so this process would not apply. To predict choice data, such as preferential choice or first choice among multiple alternatives, a common practice is to use logistic regression[3]. This method is extremely popular in market research, economics, and public health and the basis for its attractiveness is that it takes a closed form (which means that there are no integrals to evaluate.) The logistic model assumes a hedonic or utility continuum when modeling preference between a pair of items or first choice among a larger set and this assumption is its Achilles' heel. The popularity of the logistic model occurs mainly because of the ease of computing the model parameters. An often cited justification for the logistic model is that if the percepts that comprise the hedonic continuum are double exponentially distributed then differences will follow a logistic distribution. But even if we accept the idea of a hedonic continuum arising from peripheral and central events, averaging over millions of active neurons should lead to a normality assumption about the distribution of the percepts. There appears to be no process-based justification for the use of the logistic model, notwithstanding its ease of use. There are at least two problems with the model. One is that the choice probability is affected by irrelevant alternatives. A well-known example is the prediction that a way to overcome city congestion through public transport is to introduce a myriad of different colored busses because the introduction of each additional bus will reduce the choice to drive. A second problem is that the model cannot handle latent multivariate variables that drive hedonics or utility. To study drivers of liking, for instance, the model links the hedonic continuum to a linear combination of pre-specified variables. Very often, however, these variables are unknown.

Another non-process method used to study hedonic responses is External Preference Mapping (EPM)[4,5]. EPM reduces ratings data on product or concept variables to a space of low dimensionality and then fits points in this space based on liking data. Generally these fitting techniques are based on regression using linear and/or quadratic terms. A limitation of this method is that it is assumed that the first two or three principal components of the derived space are drivers of liking, and that the resulting maps are drivers of liking spaces. This is the same problem inherent in the use of logistic regression to evaluate hedonic drivers since it is also possible that the experimenter did not account for the drivers of liking in the original variable profiling.

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 based on a process that produces them. Once we have created the drivers of liking space, the role of additional variable data is to explain the dimensions of the drivers of liking space. Methods that do this type of modeling are called unfolding methods.

Process Models: If there are no receptors on the tongue or on the olfactory epithelium for liking and preference, how then do liking and preference data arise? One process account is to consider that each subject uses previous experience to establish a perceptual space of variables that drive a hedonic reaction and that there is an ideal point located in this space for each subject. Figure 1 illustrates this idea through an ideal point on the sweetness intensity continuum. When an item is presented to the subject, it enters the space and its distance to the ideal determines the hedonic reaction. Preference is determined by the item closest to the ideal. Each item and each ideal may also possess perceptual variance to account for the idea that perceptual intensities may

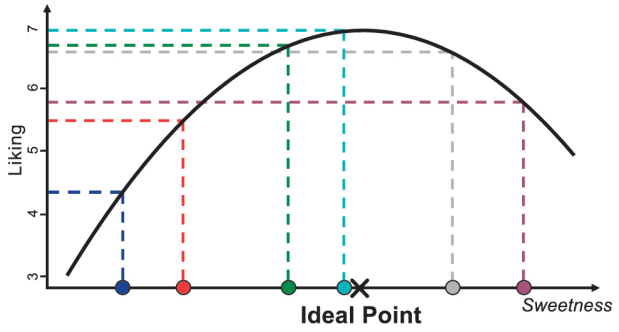

Figure 1. Coombs' process model explains how liking data arise based on the concept of an ideal point. Liking increases with sweetness to a satiety point and then decreases.

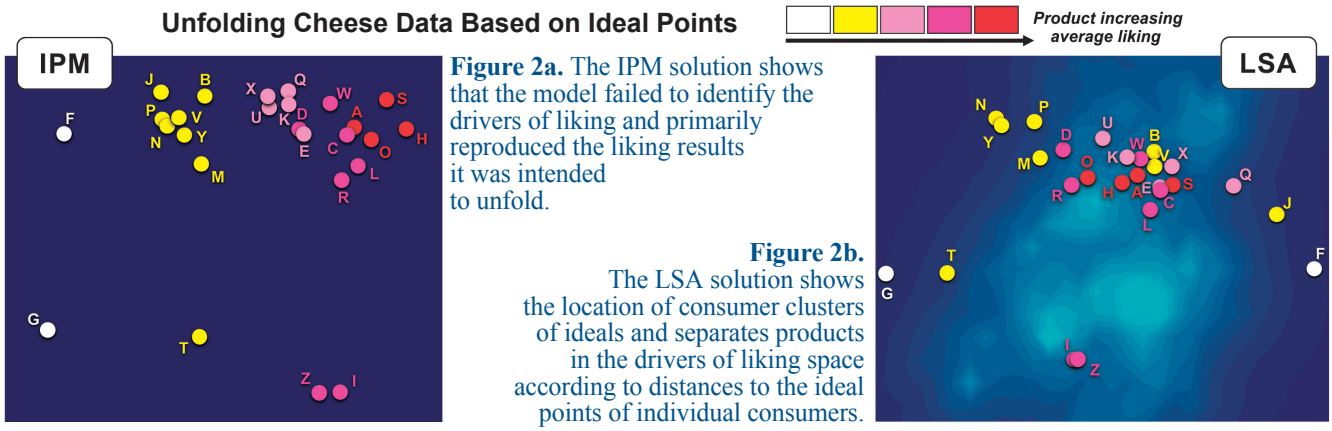

Figure 2a. The IPM solution shows that the model failed to identify the drivers of liking and primarily reproduced the liking results it was intended to unfold.

Figure 2b. The LSA solution shows the location of consumer clusters of ideals and separates products in the drivers of liking space according to distances to the ideal points of individual consumers.

vary for the same subject and the same item. This description derives from and extends ideas originally proposed by Coombs and Thurstone and is the basis for Landscape Segmentation Analysis® (LSA). Since some people like similar things, collections of individual ideal point clusters may form what we generally call *market segments*. These segments may have simple demographic markers, such as age or gender. Or they may be more complex and derive from sensory experience, such as people who like sweet products and those who do not.

Internal Preference Mapping[6,7] (IPM) is a method that assumes that there are vectors representing individuals that point in each case in the direction of an individual's ideal. The location of the ideal is unknown, only its direction, and this is a severe limitation for many items that exhibit a satiety point where too little or too much is undesirable. Most food and beverage products would fit into this category. For variables such as fuel efficiency or luxury in automobiles or off-taste in food, IPM may be a useful process 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. Rousseau *et al*.[8] (2012) 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 a hedonic direction among the first two principal components as anticipated by the theory underlying the method. Although IPM is a useful tool when its assumptions apply, the results reported by Rousseau *et al*. should be of concern 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 will be misleading.

Modeling the Category Appraisal: Figures 2a and 2b compare your results from fitting IPM and an individual ideal point unfolding model, Landscape Segmentation Analysis. Products are color-coded with the least liked products in white and the most liked products in red. In a case such as this where satiety has occurred, the figures clearly show that IPM does not actually unfold the data. This is evidenced by the fact that there is a strong hedonic direction existing in the drivers of liking space. The IPM does little more than provide a grouping of the products according to the degree to which they are liked. This was already known by comparing mean liking scores. Figure 2a shows the most liked products in red, the next most liked in magenta, followed by pink, yellow, and then white. In the LSA space where the ideal point densities are visible (Figure 2b), products J and N are apparently both disliked but for different reasons as they occupy locations on opposite ends of the east-west direction. LSA also separates product B from the other products that share similar lower liking ratings (shown in yellow). The most liked products occupy the center of the map, closest to the greatest concentration of consumers.

Conclusion: A problem with "the humors" as a model for disease is that its components were never subjected to rigorous testing. Scientific models are based on certain testable assumptions. With regard to mapping hedonic data, we encourage researchers to consider the processes by which their data arise and ask themselves whether the parameters of their models are interpretable or are simply arbitrary. In order to explain an experimental result such as satiety, we recommend that researchers consider the use of individual ideal point models that also include parameters to account for perceptual variation.

References

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