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Product selection for liking studies: The sensory informed design

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ABSTRACT

Liking studies are designed to ascertain consumers likes and dislikes on a variety of products. However, it can be undesirable to construct liking studies where each panelist evaluates every target product. In such cases, an incomplete-block design, where each panelist evaluates only a subset of the target products, can be used. These incomplete blocks are often balanced, so that all pairs occur the same number of times. While desirable in many situations, balanced incomplete blocks have the disadvantage that, by their nature, they cannot favor placing dissimilar products next to one another. A novel incomplete-block design is introduced that utilizes the target product's sensory profile to allocate products to each panelist so that they are, in general, as dissimilar as possible while also ensuring position balance. The resulting design is called a sensory informed design (SID). Herein, details on the formulation of SIDs are given. Data arising from these SIDs are analyzed using a simultaneous clustering and imputation approach, and the results are discussed.

1. Introduction

Experimental design is the cornerstone of sensory analysis. The development of Latin square and complete-block designs for sensory and consumer evaluation date back at least as far as Ferris (1957). However, the majority of literary contributions in this area are based on the earlier work of Williams (1949) and the more recent paper by MacFie et al. (1989). Since MacFie et al. (1989), work on developing other types of experimental designs for sensory analysis has flourished. Wakeling and MacFie (1995) extended the results of Williams (1949) to situations where only a subset of treatments can be provided to each experimental unit. Ball (1997) developed incomplete-block designs that are balanced for carry-over effects. Deppe et al. (2001) provided a procedure for constructing nested incomplete-block designs. Kunert and Sailer (2007) discussed the development of generalized Youden designs, where the experimental units are randomized.

In sensory analysis, the experimental units are either consumers or sensory assessors and the treatments are food products. Evaluating consumer preference, i.e., likes and dislikes, is done through a liking study. Formally, liking studies are comprised of p products and n panelists who are asked to rate each product using either a hedonic or line scale. Ofttimes, due to limited resources, time constraints, or to prevent the onset of fatigue, researchers do not ask the panelists to rate the entire set of products. Instead, they present each panelist a subset of k target products.

There are a number of papers discussing the analysis of liking studies that are either complete or incomplete-block designs (see Bastian et al., 2010; Bower and Whitten, 2000; Gilbert et al., 1996; Harker et al., 2008; Lange et al., 2002; Voorpostel et al., 2014, for examples). In a complete-block design, all treatments are applied to every experimental unit the same number of times. Therefore, when the number of target products is too large, a liking study in the form of a complete-block design arises when one subset of k products is assigned to each panelist. An incomplete-block design also utilizes subsets of the target products; however, these subsets change for each panelist. In a balanced incomplete-block design, all products appear the same number of times and all pairs of products appear the same number of times.

Researchers typically desire that one, or each, subset be "representative" of the set of all target products. As such, they usually rely on the recommendation of trained assessors (see Hersleth et al., 2005, for example). However, it is possible that the assessors could be unintentionally subjective and struggle to agree on what qualifies as a truly representative subset. Herein, we say a subset of products is representative of the set of all target products if its elements are as dissimilar as possible, where dissimilarity is determined using the Euclidean distance measure. Formally, using

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their sensory profile, we calculate the Euclidean distance between each target product and argue that the subset of $k > 1$ target products that maximize the Euclidean distance best represents the set of all target products. We form a sensory informed design (SID) by maximizing distance between each target product while also maintaining overall position balance, so that each product occurs the same number of times in each position (or as close to the same number of times as the total number of panelists allows). Of course, we also require that no product is presented to the same panelist more than once.

The remainder of the paper is outlined as follows. In Section 2, we formulate an SID. In Section 3, we review a model-based approach developed for analyzing data with missing values. In Section 4, we apply this model-based approach to two SIDs collected at Compusense Inc., and we conclude with a summary and suggestions for future work (Section 5).

2. The sensory informed design

An SID assumes that consumers have more difficultly discriminating between similar products compared to dissimilar products and requires a sensory profile for the target products. A sensory profile is a $d \times p$ matrix, where d is the number of attributes, constructed by trained assessors who objectively measure each product's attributes using an unstructured line scale at "0" and "100". A score of '0' indicates low intensity and a score of '100' indicates high intensity. Typically, each product will be evaluated multiple times. As such, we use the average attribute scores. Table 1 displays the average scores (i.e., the sensory profile) for the first ten attributes and five products of twelve white breads, denoted $A, \ldots, L$ (cf. Browne et al., 2013). Note that there were 42 attributes in total.

The sensory profile allows us to place each product into a "product space." For an SID, the product space is defined by the Euclidean distance measure. Consider the space constructed by calculating the Euclidean distance between two of the twelve white bread's attributes: color intensity of crust (whole loaf) and color intensity of crumb (Fig. 1). The pair of products with the largest Euclidean distance are considered the most dissimilar, whereas the pair of products with the smallest Euclidean distance are considered the most similar. In Fig. 1, products J and K are the most dissimilar, and products F and I are the most similar.

In an SID, each panelist is given products so that consecutive products are as dissimilar as possible. Fig. 2 illustrates a "greedy" product selection process for one panelist. In this example, four out of twelve white breads are being selected, creating a 12-present-4 design, denoted ${}_{12}P_4$. The first step in constructing an SID is to randomly assign one of the products to a panelist.

Table 1
Mean scores for the first ten attributes and five products resulting from a sensory analysis of a white bread data set.

Attribute	Product				
	A	B	C	D	E
Color Intensity of Crust (Whole Loaf)	57	58	63	48	71
Glossiness of Crust (Whole Loaf)	9	14	15	15	15
Visual Roughness of Crust (Whole Loaf)	9	17	27	15	16
Color Intensity of Crumb	18	28	21	20	21
Cell Uniformity (Crumb)	61	67	71	66	68
Cell Size	20	17	12	14	13
Overall Aroma	30	35	33	31	35
Grain Aroma	8	12	7	8	11
White Flour Aroma	17	16	17	16	16
Yeasty Fermented Aroma	8	12	7	8	11

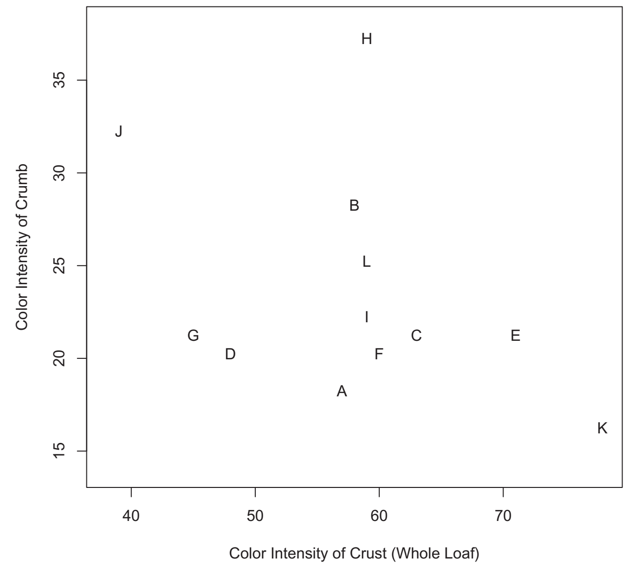

Fig. 1. Color intensity of crumb versus color intensity of crust (whole loaf) for 12 white breads ($A, \ldots, L$).

Panel 1 of Fig. 2 shows that product A is randomly selected as the first product this panelist will evaluate. Product J is then selected because it is the most dissimilar to product A (Panel 2). Now, because there are at least two products selected (A and J), a centroid is calculated. Product K is then selected as it is the most dissimilar from the centroid of products A and J (Panel 3). Finally, product H is selected as it is most dissimilar from the centroid of products A, J and K (Panel 4). Panel 5 gives the shape formed by the selected products, and Panel 6 gives the order that each product will appear to the panelist.

Fig. 2 illustrates a "greedy" selection process that would always be made if the SID was not constructed to adhere to position balance. For example, suppose there are $n = 396$ panelists and we wish to construct a ${}_{12}P_6$ design. To ensure position balance, we require that each product appears $r = 33$ times (where $r = n/p$) in each position, while not letting any panelist rate any one product more than once. Note that, in practice, it will not always be the case that an SID is perfectly balanced. Misuse of the rating apparatus, a non-divisible sample size or neglect on behalf of the panelists are a few of the possible scenarios that could lead to some products being evaluated more than others.

2.1. Formulation

Consider an $n \times k$ matrix where the rows correspond to panelists and the columns represent the order that each product is evaluated (Table 2). From a set of p products, we want to find n subsets of k products such that every subset contains unique elements and, between all subsets, every product appears the same number of times. We allocate products in a column-wise fashion, i.e., we will assign n products to the first position, then we will assign n products to the second position, and so on until all positions are filled.

The construction of an SID is as follows. In the first position, randomly allocate one product to each panelist such that every product appears the same number of times. In the second position, randomly select a panelist such that priority is given to a panelists whose first position contains a product that is very similar to the other products. Assign the randomly selected panelist a second product, j, that belongs to the set of remaining products,