A new approach to product set selection and segmentation in preference mapping

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ABSTRACT

A common problem in food product development is to identify the consumers’ drivers of liking and to understand in what way they relate to the acceptance data. Usually, one will also be interested in identifying segments of consumers. The main objective of this study was to investigate the use of fuzzy clustering within the area of preference mapping when different consumer groups test different sets of products. A case study on low-fat cheese was used to explore and illustrate the proposed approach. Two groups of 57 and 58 consumers, respectively, participated in the consumer test. Based on sensory profiling, different cheese products evenly distributed in the sensory space were selected for each group. Each consumer rated their acceptance based on a blind tasting of six cheeses. One of the segments was identified to have a linear preference pattern, while the other two had non-linear patterns.

1. Introduction

A common problem in product development is to identify the drivers of liking in the actual market (Gambaro, Ares, Gimenez, & Pahor, 2007; Green & Srinivasan, 1978; Gustafsson, Herrmann, & Huber, 2003; McEwen, 1996). In most cases, one will also be interested in identifying the segments of consumers with similar preference patterns, and a number of techniques have been put forward for this purpose, based on various types of cluster analysis (Wedel & Kamakura, 1998; Wedel & Steenkamp, 1989, 1991). These methods can be used in both a preference mapping context and in a conjoint analysis context (Næs, Kubberød, & Sivertsen, 2001), although in this paper the focus will be on preference mapping applications.

Preference mapping is based on relating sensory profile data to individual consumer preference data using statistical regression methods such as principal component regression (PCR) and partial least squares regression (PLSR) and then presenting the results graphically in maps (Schlich & McEwan, 1992). A major problem when using these methods, in particular for non-linear ideal points models (McEwen, 1996), is the trade-off that has to be made between the statistical need for as many tested products as possible and the practical limitation related to how many products a consumer can actually test. Many products give precise model estimates, but too many products may produce consumer fatigue which makes the experimental setup more tedious. Analyzing all consumers in the same model may be a possible solution, but this would mean that one only focuses on the average liking, which is generally not recommended. In many cases, segmentation is therefore the most natural approach, representing a type of compromise between individual modelling and a joint approach, while at the same time providing information about possible group patterns in the data sets.

In this paper, we will consider an approach to segmentation within preference mapping based on both a new way of selecting products to consumers, and in the use of fuzzy cluster analysis (FCM) by using regression distance to analyse the data. This new way of selecting products allows for the selection of different products for different consumers and also to represent the product space of sensory interest as evenly as possible. In our case study, we consider two groups of consumers testing two different sets of products. The fuzzy clustering method, with the use of the residual distance, allows for analyzing this type of data, since only the residual between the preference value and the model for the preference value is used in the clustering. For references to this approach, in both theoretical aspects and applications within consumer science, we refer to Berget, Mevik, and Næs (2008), Næs and Isaksson (1991) and Wedel and Steenkamp (1989, 1991). Using fuzzy clustering also has other advantages related to membership values, flexibility and good convergence properties as will be discussed below. This method has previously been used for conjoint studies, but as far as we know not for preference mapping. A case study on low-fat cheese will be used to explore and
illustrate the proposed approach. The primary purpose of this case study was to gain an improved understanding of the Norwegian consumers’ preference for low-fat cheese, and to identify possible consumer segments.

2. Selection of products for different consumer groups

In this paper, it is assumed that an initial set of products that represents all products of interest are available (Helgesen, Solheim, & Næs, 1997). In this case, this group of products represents the entire market of the cheese type studied. It will also be assumed that the sensory data is available for this initial group of products. In order to provide as much information as possible from each consumer and to avoid consumer segments based on only one part of the sensory region, each consumer is given products that cover the entire principal component analysis (PCA) score plot (based on sensory analysis) as evenly as possible (usually in two dimensions). This product selection criterion is important for several reasons (Næs & Isaksson, 1991), and should be used regardless of whether the data is meant for linear or ideal point preference mapping. First of all, covering the entire area, even for products close to the border, is important for getting the best possible precision from the estimates. Secondly, the even spread of the products ensures that all parts of the region are represented, thereby providing good opportunities for checking model quality. A third argument that was put forward in Zemroch (1986), and Næs and Isaksson (1991), is that this type of product selection is robust in the sense that it will produce reasonable models, even in cases where the model assumptions are not totally correct. For example, even if the true relation is slightly non-linear, the predicted values from the model are reasonably good even if a linear model is fitted. When different products are tested by different consumers, one should make sure that each set of products covers the sensory regions as evenly as possible. This means, for instance, that one should avoid products from one group of products that are too close to each other.

There are different ways of conducting product selection using these criteria, based on either a simple visual selection directly from the PCA score plot or based on strategies using some type of statistical cluster analysis. If the first two or three components represent most of the sensory variability (which is usually the case), the PCA selection is just as good as the one that is assisted by statistical clustering. PCA selection also provides the possibility for freely choosing products that satisfy other requirements, than just an even spread. In this case study, the PCA approach was used because products of special interest had to be part of the study.

If a more “formal” procedure is wanted, one can follow the procedure proposed by Næs and Isaksson (1991). This procedure is based on first performing a cluster analysis for all the products (sensory attributes). The clustering is stopped when the number of clusters is identical to the number of products that can be presented to each consumer, such as six in this case. One product is then selected from each cluster for each consumer. For related work, we refer to Riviere, Monrozier, Rogeaux, Pages, and Saporta (2006).

3. Segmentation and model fitting methods

In most case studies of this type, the sensory variables are strongly collinear (Martens & Næs, 1989), and one needs to use regression methods that can handle this type of problem. One possible way of solving the problem is to compress the data by using PCA prior to regression or cluster analysis (Martens & Næs, 1989; McEwen, 1996). For regular linear preference mapping, both PCR and PLS can be used, but for ideal point mapping the most natural approach is based on polynomial PCR.

3.1. The ideal point model

The ideal point model to be used for each of the consumers here will be the second degree polynomial based on two principal components, i.e.

\[ y = b_0 + b_{11} x_1 + b_{22} x_2 + b_{12} x_1 x_2 + b_{13} x_1^2 + b_{23} x_2^2 + e \]  

where the \( y \) is the preference value, \( b_0 \) is the intercept, the \( b_i \)'s are the regression coefficients, the \( r_i \)'s are the two first principal components of the sensory data, and \( e \) is the random error. As can be noted, the standard linear preference mapping PCR model is a special case obtained by setting the last three regression coefficients equal to zero. In each of the clusters found later in this paper, we will use analysis of variance in order to test for the importance of the square terms and interaction term in model (1). Note that although model (1) handles non-linear relations between the principal components and \( y \), it essentially a linear model which can be handled by using regular linear regression analysis.

In order to reduce the number of parameters in the model, different simplifications have been proposed (McEwen, 1996). One is based on deleting the interaction term (elliptic model) and the other is based on setting the coefficients for the quadratic terms equal to the same value (circular model). These modifications may be useful when model (1) is used for the fitting of individual acceptance data, but when used in clustering as is done here, this type of reduction has little effect on the ratio between the number of observations and the number of parameters. As will be seen below, the general structure of model (1) was important for capturing the full structure of the segments in the case study.

3.2. The proposed method based on fuzzy clustering (FCM)

The FCM approach, based on residual distance to be used here, is essentially the same method as the approach used in Wedel and Steenkamp (1989), Wedel and Steenkamp (1991), Næs and Isaksson (1991), and Næs et al. (2001), but the context is different. Other related approaches are latent class mixture models based on residuals and the more sophisticated approach which incorporates random individual regression coefficients for each consumer within each segment (Gustafsson et al., 2003).

The FCM is general in nature, and can be used for a large number of distances that measure the distance between objects and segments. The general criterion used and which is to be minimized is the following:

\[ J = \sum_{j=1}^{C} \sum_{i=1}^{N} u_{ij}^m d_{ij}^2, \quad m \geq 1 \]  

where the \( d_i \)'s are the distance between objects \( i \) and segments \( j \), and the \( u_{ij} \)'s are the corresponding membership values. The \( C \) and \( N \) are the number of segments and the number of observations, respectively. The \( u_{ij} \)'s can be interpreted as the degree of membership for each individual to each of the segments, and can be very useful for the investigation of the degree of clustering in the data. The \( m \) is the fuzzifier parameter to be determined by the user. The most common value to use for \( m \) is 2 (Berget et al., 2008; Bezdec, 1981; Zahid, Limouri, & Essaid, 1999), but in the present paper another value is chosen based on a study of the properties of the solution found. Since fuzzy clustering has better convergence properties than K-means clustering (Rousseeuw, 1995), which essentially corresponds to \( m \) equal to 1 in model (2), only values larger than 1 were tested. The general algorithm for solving this is simple and based on iteration between two independent steps, one optimizing \( u \) and the other optimizing \( b \).
The FCM method is important for many purposes and with many different types of distances, but in the present paper the focus will be on the residual distance between objects and segments (Wedel & Steenkamp, 1989, 1991). The residual distance is obtained by comparing the true acceptance value with the fitted value from a regression equation in the principal components (and their squares) of the sensory data. The idea is that segments of consumers who have a similar acceptance pattern will have the same relation between \(x\) and \(y\). The general criterion in model (2) can then be presented as

\[
J = \sum_{j=1}^{C} \sum_{i=1}^{N} (y_{ij} - x b_{ij})^2
\]

where the \(b\)’s are the regression coefficients for the different segments. In our special case of ideal point modelling, the vector \(x\) is the vector defined by \(1, t_1, t_2, t_1^2, t_2^2, t_1 t_2\) and \(b\) is the vector of the corresponding regression coefficients (see model (1)). We refer to the papers by Wedel and Steenkamp (1989), Wedel and Steenkamp (1991), and Naes and Isaksson (1991) for further information about the properties and optimization of the FCM method.

After convergence, the algorithm provides a suggested splitting of objects into subgroups, indicated by the membership values (the \(t\)’s) and also regression coefficients \(b\) within each group. This means that the method provides information about both the degree of membership to the different clusters and to the regression coefficients that define how the principal components of the sensory data influence the liking in the different segments. For segmentation purposes, the different consumers are placed in the cluster for which they have the largest membership value. The regression coefficients can be used directly as the models for the segment. For instance, these can be represented by contour plots as will be shown in the case study. If so desired, the stationary points of the models (max., min. or saddle point) can be obtained by using the standard optimization procedure. The stationary point can be plotted within the sensory map, together with the contours.

As can be noted, the residual distance is only dependent on the difference between the measured value and the function of the principal components. Therefore, it is essentially independent of the values of the \(t\)’s. If two consumers have the same pattern, this will be visible in the residuals without requiring that the two consumers have the same scores values, i.e. it is not necessary that they test the same products. Also note that this approach does not require that the same number of products be used for each consumer. These aspects are essential here, since the selection of products to be discussed is based on giving different products to different consumers. Note that standard regular cluster analysis requires that the vectors are comparable, which is not the case if the products are different, and can therefore not be used here. For more discussion of this advantage, see Naes and Isaksson (1991), Wedel and Steenkamp (1989), and Wedel and Steenkamp (1991).

### 4. The case study

The focus of the case study was to characterize the Norwegian low-fat cheese market, and to detect possible sensory properties that are important drivers of liking or disliking for different consumer groups.

The study consisted of two parts: a descriptive sensory analysis of 17 semi-hard, low-fat cheese products that were considered to be representative for the market of interest, and a consumer test with 12 of the cheeses, in which each consumer tasted only six. The original 17 low-fat cheeses (from 5% to 17% fat content) were either experimentally produced or commercially available in Finland, Sweden or Norway (see Table 1). This relatively large variation in fat content (from 5% to 17%) is within the normal range for low-fat cheese sold on the Scandinavia market. All material used for each cheese product came from the same production batch, and was therefore treated as homogeneous in the statistical analysis.

The product selection procedure described in Section 2 was used to select two sets of products, each of the sets containing six products each, which was considered a manageable number for each of the consumers. The overall group of consumers was randomly split in two, with one group testing one of the product sets (consumer group 1), and the second group testing the other product sets (consumer group 2). Each consumer was asked about his or her acceptance of the six products tested. This resulted in two data sets being analyzed by the FCM, namely one data table containing the sensory attribute values for all 12 products, and one data set containing preference values for the same 12 products. The FCM method matches the two by pairing each measured acceptance value with the corresponding principal components of the sensory properties of the actual product.

#### 4.1. Descriptive sensory analysis

A trained panel of 11 assessors performed sensory profiling according to “Generic Descriptive Analysis” as described by Lawless and Heymann (1999). The assessors were tested, selected and trained according to ISO standards (ISO, 1993), and the sensory laboratory used followed the ISO standards (ISO, 1988). The assessors agreed upon 30 attributes describing the variation of the cheese variants (the significant sensory attributes can be seen in Fig. 1). All attributes were evaluated on an unstructured line scale with labelled endpoints going from no intensity (value 1.0) at the left side to high intensity (value 9.0) at the right side. In a pre-test session, the assessors were trained in the use of the scale by testing products that were considered to be extreme for the selected attributes which are typical for the low-fat cheeses tested (products 1 and 6). The cheese products were served at a temperature of 17 °C in pieces of 50 g each. The assessors evaluated the products at an individual pace using a computerized system for the direct recording of data (CSA Compusense v 5.24, Canada). Two replicates were performed by each assessor for each cheese product. All products and replicates were served in a randomized way.

The descriptive sensory data was analyzed using both univariate (Statistix v 8.1, Analytical Software, US) and multivariate data

<table>
<thead>
<tr>
<th>Product no.</th>
<th>Fat content (%)</th>
<th>Country of origin</th>
<th>Product set no.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>16</td>
<td>Norway</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>16</td>
<td>Norway</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>13</td>
<td>Norway</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>16</td>
<td>Norway</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>10</td>
<td>Norway</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>17</td>
<td>Sweden</td>
<td>2</td>
</tr>
<tr>
<td>7</td>
<td>15</td>
<td>Finland</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>5</td>
<td>Sweden</td>
<td>2</td>
</tr>
<tr>
<td>9</td>
<td>17</td>
<td>Finland</td>
<td>2</td>
</tr>
<tr>
<td>10</td>
<td>17</td>
<td>Finland</td>
<td>2</td>
</tr>
<tr>
<td>11</td>
<td>17</td>
<td>Sweden</td>
<td>1</td>
</tr>
<tr>
<td>12</td>
<td>5</td>
<td>Sweden</td>
<td>1</td>
</tr>
<tr>
<td>13</td>
<td>10</td>
<td>Sweden</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>10</td>
<td>Sweden</td>
<td>1</td>
</tr>
<tr>
<td>15</td>
<td>17</td>
<td>Sweden</td>
<td>1</td>
</tr>
<tr>
<td>16</td>
<td>10</td>
<td>Sweden</td>
<td>1</td>
</tr>
<tr>
<td>17</td>
<td>17</td>
<td>Sweden</td>
<td>1</td>
</tr>
</tbody>
</table>
analysis (The Unscrambler v 9.2, Camo AS, Norway). Analyses of variance (ANOVA, mixed model with interactions and with assessor effect and interactions considered to be random) were performed in order to identify the sensory attributes that were differentiated between products. Based on a Tukey HSD All-Pairwise Comparisons test, all sensory attributes were found to be significant except nutty odour, nutty flavour, sun odour, sun flavour and metallic flavour. These five non-significant sensory attributes were not included in the further data analyses.

4.2. Selection of products for consumer study

The primary choice criterion for the selection of products was intended to cover the entire experimental region as evenly as possible. It was decided that six products were the highest number of products that could be presented to each of the consumers in a single session. Two product sets were created, but other possibilities also exist. The most extreme possibility is to let all the consumers test a different set which satisfies the above criteria, but this is much more difficult to handle from a logistical point of view. The company behind the study wanted specific products (products 1, 2, 3, and 5) to be part of the study, and in addition, both sets of products had to generally have all fat levels represented. The different product sets were tested by two different groups of consumers. Consumers were randomly selected to one of the two groups. Having relatively large consumer groups makes it likely that consumers from both groups will be represented within each of the clusters, thus ensuring that each cluster represents the whole region in a dense way.

For the purpose of selecting 12 cheese products for the consumer test, a PCA of the average response over replicates and assessors (significant attributes, p < 0.05) was performed (mean centred data, no standardization) (Mardia, Kent, & Bibby, 1980). Full cross-validation (Martens & Næs, 1989) was used for validation of the components.

4.3. Consumer testing

The test included 115 consumers who met the following criteria: consumers of hard or semi-hard cheese, 25–50 years of age, residing in the eastern part of Norway and interested in health issues.

The test consisted of a hedonic evaluation of products without additional information given, i.e. the consumers were told that they were participating in a cheese test, not that it was low-fat cheese. The hedonic evaluations rated the degree of liking on a modified version of the nine point hedonic scale by Per Yam and Pilgrim (1957). The modified scale was anchored with “Dislike Extremely” and “Like Extremely” and with a neutral centre point of “Neither Like nor Dislike”. The cheese products were served in an order which used a balanced design (Earthy, MacFie, & Hedderley, 1997; MacFie, Bratchell, Greenhoff, & Vallis, 1989). When they finished, each of the consumers received a gift card.

4.4. Statistical methods used

A PCA was performed on the sensory data for the purpose of products set selection and also for the purpose of providing input data for the regression. In addition, a PCA was used on the consumer data in order to obtain information about the dimensionality of the consumer acceptance.
In this paper, main attention is given to the use of fuzzy clustering by the use of the residual distance. The model used in the regression is the model (1) shown above. For each product and consumer combination, the actual principal components values were paired with the true acceptance value for that combination. The fuzzifier \( m \) was determined in order to minimize the average residual values within each cluster. To a large extent, the selection of the number of segments is a subjective matter, since one can seldom expect to find well separated segments. In this paper, focus was given to three clusters, but the 3 segments’ solution was also compared to the 2 and 4 segments' solutions for validation purposes. The convergence of the procedure was tested, based on using a different starting point and comparing the solutions. The calculations were done using self made software in SAS-IML (SAS v 9.1.3, SAS Institute Inc., US).

The structure of each cluster was investigated using contour plots (MATLAB v 7.7, The MathWorks, Inc., US). For each segment obtained, an analysis of variance was used to investigate the significance of the various terms in the quadratic polynomial model. See Table 2 for an example of such an analysis of variance. The residuals drops strongly from two to three clusters, the drop from 2 to 3 being notable. The results are presented in Table 2. An overall assessment of the different results indicated that \( m = 1.1 \) gives the results with the best fit, but the values of \( m = 1.2 \) and \( m = 1.3 \) gave results which were very similar. For the purpose of the rest of this paper, we used the value \( m = 1.1 \) for all the calculations.

As illustrated in Fig. 2, the best value of the average absolute residuals drops strongly from two to three clusters, the drop from

5.3. Segmentation

In the following, we will give the primary attention to two principal components in the model. The main reason for this is that an initial PCA (internal preference mapping) of the two consumer groups indicated that the preference space was mainly two-dimensional, as the validated explained variance did not increase beyond two components.

5.3.1. Choice of the fuzzifier \( m \)

The first aspect tested was the choice of the fuzzifying parameter \( m \). This was done by calculating the average absolute residual for all observations in the data set. Several values of \( m \) between 1.1 and 2.2 were tested. The value of \( m = 2.0 \) is often used (Berget et al., 2008; Bezdec, 1981; Zahid et al., 1999), but there is evidence for sometimes choosing otherwise. The results are presented in Table 2. An overall assessment of the different results indicated that \( m = 1.1 \) gives the results with the best fit, but the values of \( m = 1.2 \) and \( m = 1.3 \) gave results which were very similar. For the purpose of the rest of this paper, we used the value \( m = 1.1 \) for all the calculations.

As illustrated in Fig. 2, the best value of the average absolute residuals drops strongly from two to three clusters, the drop from

### Table 2

<table>
<thead>
<tr>
<th>( m )</th>
<th>2 Segments ( (C_2) )</th>
<th>3 Segments ( (C_3) )</th>
<th>4 Segments ( (C_4) )</th>
<th>5 Segments ( (C_5) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>1.481</td>
<td>1.356</td>
<td>1.286</td>
<td>1.236</td>
</tr>
<tr>
<td>1.2</td>
<td>1.481</td>
<td>1.359</td>
<td>1.288</td>
<td>1.232</td>
</tr>
<tr>
<td>1.3</td>
<td>1.483</td>
<td>1.363</td>
<td>1.288</td>
<td>1.231</td>
</tr>
<tr>
<td>1.4</td>
<td>1.487</td>
<td>1.368</td>
<td>1.287</td>
<td>1.235</td>
</tr>
<tr>
<td>1.6</td>
<td>1.488</td>
<td>1.373</td>
<td>1.305</td>
<td>1.246</td>
</tr>
<tr>
<td>1.8</td>
<td>1.488</td>
<td>1.363</td>
<td>1.290</td>
<td>1.253</td>
</tr>
<tr>
<td>2.0</td>
<td>1.488</td>
<td>1.379</td>
<td>1.372</td>
<td>1.354</td>
</tr>
<tr>
<td>2.2</td>
<td>1.485</td>
<td>1.447</td>
<td>1.405</td>
<td>1.372</td>
</tr>
</tbody>
</table>

5.2. Product selection for the consumer test

The product selection for the consumer study was mainly based on the spread of the products in the first and second dimension (see Fig. 1), but as mentioned, other criteria also had to be fulfilled (see Section 4.2). In Fig. 1, the cheese products selected for each of the two consumer groups are shown. The six cheese products selected for consumer group 1 were as follows: 2 (16% fat content), 7 (15% fat content), 12 (5% fat content), 13 (10% fat content), 15 (17% fat content), 16 (10% fat content), while consumer group 2 tasted the following cheese products: 1 (16% fat content), 3 (13% fat content), 5 (10% fat content), 6 (17% fat content), 8 (5% fat content), 9 (17% fat content). As can be seen, each group received products from the entire low-fat range (from 5% to 17% fat content). In addition, the sensory region was well covered by both product sets.
three to four becomes smaller, and the drop from four to five is smaller still. We therefore decided to concentrate on the solution with three segments. As can be seen from Table 3, the number of consumers is quite evenly spread among the three clusters, which means that there is enough information within each cluster to support model (1). In order to gain some insight into the dependence of the conclusions of this choice, some attention was also given to the solutions with two and four clusters.

The stability of the FCM algorithm (for fuzzifier \( m = 1.1 \) and for \( C = 2, C = 3 \) and \( C = 4 \) clusters) was studied by using different starting values (i.e. membership values \( u_{ij} \)). Many of the solutions gave identical results to those presented, but a few gave somewhat different results. The user is encouraged to test out different starting points and select a solution that represents the smallest criterion value. The algorithm converged after a limited number of iterations, typically less than 50.

The solutions presented are those which correspond to the lowest value of the average absolute residuals (i.e. the best results). In situations where different solutions were obtained, they were compared using contour plots, with much of the same tendency found for these solutions as for the one presented (more below).

Some of the consumers changed segments, but the general structure of the clusters was similar.

Looking at the number of individuals from the two consumer groups within each cluster, we found that for the two cluster \((C_2 = 1, n_1 = 19, n_2 = 28; C_2 = 2, n_1 = 32, n_2 = 36)\) and the three cluster \((C_3 = 1, n_1 = 27, n_2 = 11; C_3 = 2, n_1 = 11, n_2 = 19; C_3 = 3, n_1 = 21, n_2 = 17)\) solutions, the individuals from each group were relatively evenly distributed within the clusters. However, especially for the second cluster in the four cluster solution \((C_4 = 1, n_1 = 20, n_2 = 17; C_4 = 2, n_1 = 6, n_2 = 19; C_4 = 3, n_1 = 18, n_2 = 12; C_4 = 4, n_1 = 15, n_2 = 8)\), this was not the case.

### 5.3.2. Results for 2PC's and 3 segments

The analyses of variance for the solution are given in Table 3. For the first segment \((C_3 = 1, n = 47)\), both the linear and the quadratic terms are significant, while the effect of the cross-product is not. For the next segment \((C_2 = n = 30)\), both principal components and the cross-product are significant. For the last segment \((C_3 = 3, n = 38)\), only the first principal component is clearly significant (with the cross-product only slightly significant at the 5% level), indicating a model which is close to linear with the path of steeped ascent/descent in the direction of the first component. The \(R^2\)’s for the three segments are 0.18, 0.24 and 0.41, respectively. Table 3 shows the number of individuals from each consumer group that make up each cluster, and as can be seen, these numbers of consumers are quite comparable for all three clusters. Significant quadratic regression was seen for two \((C_3 = 1 \text{ and } 2)\) of the three clusters, which indicates that more than half of the consumers are members of clusters with a non-linear relation between the principal components and the acceptance values.

The contour plots from each of the three clusters in the two component situation are visualized from Figs. 3–5. The average score of the consumer clusters is shown, and as can be seen, they fit the models well. The figures show that one of the clusters is rather linear, while the other two are non-linear.

**Fig. 3** shows that the first cluster \((C_1 = n = 47)\) has a global preference maxima, in which product 1 (16% fat content), product 2 (16% fat content) and roughly product 7 (15% fat content) are all located. These three cheese products can be described as relatively fatty, soft and pale with some cream odour, cream flavour, acidic odour and acidic flavour. On average, the liking scores for the first product set ranged from 5.1 to 7.4 (2.3), and the scores for the other product set ranged from 5.9 to 7.7 (1.8). This may indicate that the consumers in this cluster generally liked all the low-fat cheese products. This is interesting since the consumers were only told that they were about to taste cheese, but not low-fat cheese. The difference in the average scoring between the two sets is very similar. It seems that this cluster \((C_1 = 1)\) represents consumers who are quite satisfied with three of these particular low-fat cheeses, and in total they give quite high average scores of liking.

**Fig. 4** shows that for the second cluster \((C_2 = n = 30)\), the preferences can be described by a saddle point, with the highest preferences going in two different sensory directions, thus showing the need for using a model which can handle non-linear relations. A closer look at the raw data for this particular cluster \((C_2 = 2)\) confirms that in general, the preferences of these consumers indeed go in opposite directions. One of the directions is represented by product 6 (17% fat content) which can be described as a product having a fermented sour flavour, a bitter taste and a sticky texture. The other direction can be represented by product 16 (10% fat content), which has a sweet taste and a grainy, rubbery and hard texture. The consumers in the cluster \((C_2 = 2)\) seem to have a more complex preference pattern, perhaps due to more experiences with numerous types of cheese. On average, the liking scores for the first product set ranged from 3.7 to 7.1 (3.4), and the scores for the second product set ranged from 4.7 to 7.6 (2.9). Note that for this cluster, the difference in the average scores between the two product sets is also quite similar.

**Fig. 5** shows a nearly linear preference for the third cluster \((C_3 = n = 38)\) going towards a fatty, soft, pale cheese with cream odour, cream flavour, acidic odour and acidic flavour, without reaching its preference maxima. This cluster \((C_3 = 3)\) seems to consist of consumers who prefer cheeses with attributes similar to those often found in full-fat cheeses. Looking closer at the average scoring, one notices that the range in the average score is as large

<table>
<thead>
<tr>
<th>Segment</th>
<th>Number of individuals from each consumer group</th>
<th>Regression</th>
<th>DF</th>
<th>SS (Type I)</th>
<th>R²</th>
<th>F</th>
<th>P</th>
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<tr>
<td>C₁ = 1 (n = 47)</td>
<td>n₁ = 27</td>
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<td>2.72</td>
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<td>n₂ = 20</td>
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<td>32.55</td>
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<td>C₃ = 3 (n = 38)</td>
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</table>
as 4.9 for the first product set (average score range from 2.4 to 7.3), and 4.3 for the other product set (average score range from 2.1 to 6.4). Again, the difference in the average liking scoring between the two product sets is quite small. A result like this could have occurred if the cluster consisted of individuals who used the extremes of the hedonic scale, but this was not the case here. The third cluster therefore seems to consist of consumers who are very particular in their cheese preference.

In the following, we will also consider briefly the solutions with 2 and 4 segments. The main reason for this is to see how dependent the conclusions above are on the choice of segments.

5.3.3. Results for 2PC’s 2 segments

The analyses of variance for the two cluster solution gave $R^2$'s equal to 0.33 and 0.03. The latter is a very small value, which indicates that this is not a good cluster structure. As an example of how
the membership values look, they are presented in Fig. 6 for the two cluster solution. As can be seen, many values are close to 0 and 1 which is a result of the small $m$ value ($m = 1.1$), which is known to give a rather crisp clustering. The $u$-values closer to 0.5 represent those consumers with a weak membership to the two clusters. How to use the membership values will not be pursued further (see Bezdec (1981) for more information).

Contour plots of the two cluster models showed that one cluster was very linear, while the other cluster had a clear saddle point preference structure. Comparing the results from the two cluster and three cluster solution, it seems that the most linear cluster in the two cluster situation consists mainly of individuals from the linear cluster in the three cluster situation (Fig. 5), (72% $C_3 = 3$, 19% $C_3 = 1$ and 9% $C_3 = 2$). The other cluster, which has a clear saddle point preference structure in the two cluster situation, is largely a merge of clusters one and two in the three cluster situation (Figs. 3 and 4) (56% $C_3 = 1$, 38% $C_3 = 2$ and 6% $C_3 = 3$). In other words, it seems that going from two to three clusters splits the cluster with a very small $R^2$ into two clusters with a much clearer structure.

5.3.4. Results for 2PC’s 4 segments

In this case, the $R^2$ for the four models are 0.19, 0.30, 0.51 and 0.37, indicating a reasonable fit within each cluster. Contour plots of the four cluster models showed that one cluster was very similar to the cluster in Fig. 3 ($C_4 = 1$ consisted of 79% $C_3 = 1$), while other clusters were very similar to the general structure in Fig. 4 ($C_4 = 2$ consisted of 83% $C_3 = 2$). The last two clusters were quite linear, one with a preference going from the right to the left ($C_4 = 3$ consisted of 79% $C_3 = 3$) and one going from the top to the bottom of the plot ($C_4 = 4$ consisted of 21% $C_3 = 1$, 17% $C_3 = 2$ and 21% $C_3 = 3$). As seen, the additional cluster (going from three to four clusters) is made of individuals from all the clusters in the three segment solution. This means that the preference pattern of the linear cluster in the three cluster solution is sort of a compromise between the two linear clusters in the four cluster solution. It is interesting to note that the structure with a cluster having preferences at opposite sides of the plot is maintained when going from three to four clusters.

6. Conclusion

This study tested a new approach to product set selection and segmentation in preference mapping. The selection method allowed for different products to be tested by different consumers. It was shown that fuzzy clustering with the use of residual distance can be a useful tool for the segmentation of consumers in preference mapping. In particular, this method was tested for ideal point

![Fig. 5. Contour plot for the third segment from the two component three segment situation ($C_3 = 3$, size $n = 38$). Cheese presented to consumer group 1 is marked with a square and cheese presented to consumer group 2 is marked with a circle. The average scores from the 38 consumers are shown.](image1)

![Fig. 6. Plot of $u_1$-values for the two component two cluster solution ($m = 1.1$). The plot for $u_2$ is opposite since the sum of $u_1$ and $u_2$ is 1. The consumers here are sorted according to $u$ value.](image2)
models. The method also proved useful in keeping the number of served products low (reducing the cost of the study and minimizing the risk of fatigue, adaptation and satiety), while still being able to model the preferences of different consumer segments. The case study focused on two principal components. The method can, however, also be used in situations with more principal components in the model. Since residuals are used as criterion in the fuzzy clustering, the procedure easily handles the different sets of products served to the different consumer groups. Three different preference patterns for low-fat cheese were characterized in the case study. The method proved stable with respect to the cluster solutions found, and no convergence problems were detected.

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References