Consumer segmentation in multi-attribute product evaluation

by means of non-negatively constrained CLV3W

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Abstract

In consumer studies, segmentation has been widely applied to identify consumer subsets on the basis of their preference for a set of products. From the last decade onwards, a more comprehensive evaluation of product performance has led to take into account various information such as consumer emotion assessment or hedonic measures on several aspects, like taste, visual and flavor. This multi-attribute evaluation of products naturally yields a three-way (products by consumers by attributes) data structure. In order to identify segments of consumers on the basis of such three-way data, the Three-Way Cluster analysis around Latent Variables (*CLV3W*) approach (Wilderjans & Cariou, 2016) is considered. This method groups the consumers into clusters and estimates for each cluster an associated latent product variable and attribute weights, along with a set of consumer loadings, which may be used for the purpose of cluster-specific product characterization. As consumers who rate the products along the attributes in an opposite way (i.e., raters' disagreement) should not be in the same cluster, in this paper, we propose to add a non-negativity constraint on the consumer loadings and to integrate this constraint within the versatile *CLV3W* approach. This non-negatively constrained criterion implies that the latent variable for each cluster is determined such that consumers within each cluster are as much related - in terms of a positive covariance - as possible with this latent product component. This approach is applied to a consumer emotion ratings dataset related to coffee aromas.

Keywords: *consumer segmentation; three-way structure; clustering of variables; CLV; CLV3W; Clusterwise Parafac; latent variables; acceptance patterns; non-negativity.*

1 Introduction

A common way to evaluate the performance of products consists of capturing consumer preferences in terms of their overall liking ratings for a given set of products. As consumers differ in products' liking, consumer segmentation, which is a key procedure to exhibit consumer subsets who rate products similarly, is often used to better understand the diversity of preferences across consumers (Onwezen et al., 2012; Vigneau, Qannari, Punter, & Knoops, 2001). In a second step, the obtained consumer segments can be used to study the relationships between acceptability and sensory data by means of an external preference mapping at an aggregated level rather than at the level of individuals (Carbonell, Izquierdo, & Carbonell, 2007; Cariou, Verdun, & Qannari, 2014; Santa Cruz, Martínez, & Hough, 2002; Vigneau & Qannari, 2002). In addition, these consumer subsets can further be characterized in terms of consumer features, like demographics (Helgesen, Solheim, & Næs, 1997; Sveinsdóttir et al., 2009).

To identify consumer segments, a number of cluster analysis techniques have been proposed and widely applied (Næs, Brockhoff, & Tomic, 2010). In the context of preference data, often crisp clustering methods, such as k-means or (Ward's) hierarchical clustering (and cutting the obtained dendrogram at a certain number of clusters), are applied to mean-centered data (McEwan, 1996; Qannari, Vigneau, Luscan, Lefebvre, & Vey, 1997). These techniques provide non-overlapping clusters in which each consumer is assigned to a single group only. Alternatively, some authors advocated the use of fuzzy cluster analysis techniques (Berget, Mevik, & Næs, 2008; Johansen, Hersleth, & Næs, 2010; Westad, Hersleth, & Lea, 2004) as these methods enjoy nice properties such as fuzzy membership and flexibility. In the same vein, a latent class approach (De Soete & Winsberg, 1993) based on mixture distributions and fuzzy class memberships has been proposed for consumer segmentation (Onwezen et al., 2012; Séménou, Courcoux, Cardinal, Nicod, & Ouisse, 2007).

As in preference data, rows mostly refer to products and columns to consumers, some authors have proposed a clustering of variables approach to perform consumer segmentation. In the statistics community, a well-known clustering of variables algorithm is the Varclus SAS/STAT procedure (Sarle, 1990). Alternatively, Vigneau and Qannari (2003) proposed a Clustering around Latent Variables (CLV) approach and applied it in sensory analysis (Vigneau & Qannari, 2002; Vigneau et al., 2001).

Traditionally, consumer segmentation was performed based on one attribute, like overall product liking, only (i.e., based on two-way product by consumer data). Nevertheless, in some situations, consumers may rate the same set of products according to different attributes, resulting in three-way product by consumer by attribute data (Nunes, Pinheiro, & Bastos, 2011). For example, Santa Cruz et al. (2002) reported a study in which consumers were asked to rate the different samples according to both overall and detailed acceptance (e.g., appearance, manual texture and flavor). Further, in order to perform "measuring beyond liking", Meiselman (2013) stressed the potential use within consumer studies of various kinds of measures for product evaluation, like satisfaction, perceived benefits, perceived quality and perceived wellness. Finally, more recently, a growing interest is observed in measuring consumer emotions associated with products (Cardello & Jaeger, 2016; King, Meiselman, & Carr, 2010).

To perform consumer segmentation based on three-way data, several approaches have been proposed:

- Consumers are clustered (Fig. 1) based on the data of a single attribute (e.g., a general acceptance measure), and, in a second step, the obtained clusters are characterized on the basis of the other attributes (Onwezen et al., 2012; Santa Cruz et al., 2002). A disadvantage of this method is that the resulting partition only depends on the chosen attribute in the first step of the procedure.

- A cluster analysis is performed on the data for each attribute separately, and the various consumer partitions are compared to each other. For example, using emotion associations for two meal types, Piqueras-Fiszman and Jaeger (2016) found a strong similarity between the consumer partitions for both meal types. In the same vein, Gordon and Vichi (1998) and Vichi (1999) proposed a consensus approach in which an optimal partition is sought among a set of dendrograms or partitions. The main weakness of this procedure is that all detailed information on products and attributes gets lost when determining the consensus, which may result in the grouping of consumers who disagree in the product evaluation for some of the attributes.
- Clustering consumers based on the unfolded, according to the attribute mode, three-way array (Fig. 1). Problematic with this approach is that, as is true for the two approaches discussed above, the three-way structure in the data is ignored, which may obfuscate information relevant for the clustering of consumers.

Insert Figure 1 here

Recently, Wilderjans and Cariou (2016) developed the *CLV3W* approach[1] and applied it in the context of a conventional sensory procedure. This resulted in a clustering of the sensory attributes, a sensory latent variable and product scores per cluster, together with a weighting scheme indicating the agreement of each assessor with the panel. Note that *CLV3W* groups sensory descriptors together according to their covariance, either positive or negative, with the latent component of each cluster. In a consumer evaluation context, however, in which

[1] It should be noted that the *CLV3W* model in which variables (e.g., attributes) are clustered is identical to a *ParaFac with Optimally Clustered Variables* (*PFOCV*) model (Krijnen, 1993).

consumers are clustered instead of attributes, it does not makes sense to group together consumers that have negatively correlated multi-attribute product evaluations (i.e., consumers with a reversed product ordering). Indeed, consumer clusters need to consist of consumers that have similar product evaluation patterns. The goal of this paper therefore pertains to tailoring *CLV3W* towards a consumer segmentation context. To this end, the *CLV3W* approach is extended by imposing an additional non-negativity constraint on the vector of consumer loadings. As such, a clustering of the consumers into a small number of mutually exclusive groups is obtained, simultaneously, with (non-negative) consumer loadings, a latent product variable and associated attribute weights for each cluster. Note that a single latent variable is derived for each consumer cluster as determining a one-component model is more suited to identify consumer acceptance patterns that are characteristic for each cluster than a multidimensional model. The main advantage of *CLV3W* over other proposed methods for consumer segmentation based on three-way data is that this method fully takes the three-way structure of the data into account when clustering the consumers.

The rest of the paper is organized as follows. In section 2, we give an outline of the *CLV3W* method, herewith explaining how the additional non-negativity constraint complies with the consumer segmentation requirements. In section 3, *CLV3W* is illustrated with a case study involving consumer emotions measured on a set of coffee aromas. Finally, some concluding remarks are presented.

2 *CLV3W-NN*: Constrained *CLV3W* for three-way consumer segmentation

2.1 Structure of the data

Suppose that the ratings of I products with respect to K attributes were recorded for J consumers, resulting in an $I \times J \times K$ data array $\underline{\boldsymbol{X}}$ (Fig. 1). Each lateral slice j $(j = 1, \ldots, J)$ of

$\underline{\boldsymbol{X}}$ (Kiers, 2000), which is a matrix $\boldsymbol{X}_j$ $(I \times K)$, pertains to the data of a single consumer. Without loss of generality, we assume that all $\boldsymbol{X}_j$ $(j = 1, \ldots, J)$ are column-wise centered to remove the consumer effect for all the attributes.

2.2 The *CLV3W* method with non-negativity constraint (*CLV3W-NN*)

Starting from a three-way data matrix $\underline{\boldsymbol{X}}$, in a *CLV3W* (Wilderjans & Cariou, 2016)[2] analysis, the J consumers are allocated to Q non-overlapping clusters G_q $(q = 1, \ldots, Q)$ in such a way that the sum of squared covariances between $\boldsymbol{t}_q$, a latent product variable for the cluster G_q to which consumer *j* belongs, and a weighted average of the attribute scores of each consumer *j* $(j = 1, \ldots, J)$ is maximized:

$$g = \sum_{j=1}^{J} \sum_{q=1}^{Q} p_{jq} cov^2(\boldsymbol{X}_j \boldsymbol{w}_q, \boldsymbol{t}_q), \tag{1}$$

with $\boldsymbol{w}_q$ being the cluster-specific attribute weights that are constant for all assessors belonging to G_q, and p_{jq} denoting whether consumer *j* is allocated $(p_{jq} = 1)$ or not $(p_{jq} = 0)$ to cluster G_q. Maximizing the *CLV3W* criterion is equivalent to minimizing the least squares loss function associated with a *Clusterwise Parafac* model (Wilderjans & Ceulemans, 2013) with Q clusters and one component in each cluster (Wilderjans & Cariou, 2016):

$$f = \sum_{j=1}^{J} \sum_{q=1}^{Q} p_{jq} \left\| \boldsymbol{X}_j - \alpha_{jq} \left(\boldsymbol{t}_q \boldsymbol{w}'_q \right) \right\|_F^2, \tag{2}$$

with all symbols as defined above and α_{jq} denoting the loading of consumer j for cluster G_q; note that $\alpha_{jq} = 0$ when consumer j does not belong to cluster G_q. Note further that this *CLV3W*

[2] Note that in Wilderjans & Cariou (2016), *CLV3W* is used in a conventional sensory context in which the main goal is to cluster attributes.

model is (almost) identical to a Q-cluster *ParaFac with Optimally Clustered Variables* – (*PFOCV*) model (Krijnen, 1993).

To ensure consumers who rate the products along the attributes in a similar way being in the same cluster and consumers who disagree in the product evaluation along the attributes to be in different clusters, a non-negativity constraint is imposed on the consumer loadings α_{jq}. This constraint implies that for each consumer belonging to a particular cluster, the weighted average of his/her attribute scores is positively related to the latent product variable associated to the cluster in question: $cov(\boldsymbol{X}_q \boldsymbol{w}_q, \boldsymbol{t}_q) \geq 0$. The model with the latter constraint incorporated will be denoted by the acronym *CLV3W-NN*, with *NN* referring to the non-negativity constraint.

2.3 Algorithm

To fit a Q-cluster *CLV3W-NN* model to a three-way data set at hand, first, an initial partition of the consumers into Q clusters is obtained by means of one of the following three procedures: (1) a random or (2) a rational initialization procedure or (3) a procedure based on a priori knowledge of the researcher/user. In a random initialization procedure, the J consumers are randomly allocated to Q clusters, with each consumer having an equal probability of being assigned to each cluster. A rational initialization procedure may consist of running an Agglomerative Hierarchical Clustering (AHC) analysis based on criterion f in (2) using Ward's aggregation criterion (for more information on this procedure, see Wilderjans & Cariou, 2016). The obtained Q-cluster solution can be used as a rational start for the *CLV3W-NN* algorithm. Finally, it is also possible to adopt a user-provided consumer partition as initial partition. Such a user-provided partition may be derived from the results of earlier analysis or may be constructed based on expectations regarding the partition (i.e., which consumers do and which ones do certainly not belong together in a cluster).

Iterative steps of the algorithm. After obtaining an initial consumer partition, the *CLV3W-NN* algorithm continues by iterating two updating steps until convergence. In the first step, each consumer is re-assigned to his/her best fitting cluster based on his/her data and the current value of the cluster-specific parameters $\boldsymbol{t}_q$ and $\boldsymbol{w}_q$. To this end, for each cluster G_q $(q = 1, \ldots, Q)$, the optimal non-negative α_{jq} given $\boldsymbol{t}_q$ and $\boldsymbol{w}_q$ is computed by means of a non-negativity constrained linear regression (Bro & De Jong, 1997; Lawson & Hanson, 1974; Smilde, Bro, & Geladi, 2004), and consumer j is re-allocated to the cluster G_q for which $f_{jq} = \left\|\boldsymbol{X}_j - \alpha_{jq}\left(\boldsymbol{t}_q \boldsymbol{w}'_q\right)\right\|_F^2$ reaches its minimal value. In a second step, the cluster-specific parameters $\boldsymbol{t}_q$, α_{jq} and $\boldsymbol{w}_q$ are re-estimated given the partition updated in the previous step. This latter step can be performed by fitting a one-component *Parafac* model (Carroll & Chang, 1970; Harshman, 1970; Hitchcock, 1927) with non-negativity constraint on the consumer loadings[3] to each three-way array $\underline{\boldsymbol{X}}^{(q)}$ $(q = 1, \ldots, Q)$, with $\underline{\boldsymbol{X}}^{(q)}$ being an array that is obtained by only taking the data slices $\boldsymbol{X}_j$ of $\underline{\boldsymbol{X}}$ associated to consumers j that belong to cluster G_q (for more information and a comparison of algorithms for *Parafac* with and without non-negativity constraint, see Bro & De Jong, 1997; Faber, Bro, & Hopke, 2003; Tomasi & Bro, 2006); for Matlab and R based software to fit *Parafac* models with and without non-negativity constraint, see the N-way MATLAB toolbox (Andersson & Bro, 2000) and the R packages Three-way (Giordani, Kiers, & Del Ferraro, 2014) and multiway (Helwig, 2016). After execution of the second step, a check is performed to control whether or not there are empty clusters. When this is the case, the consumer who shows the weakest association with his/her cluster in terms of function value $\left\|\boldsymbol{X}_j - \alpha_{jq}\left(\boldsymbol{t}_q \boldsymbol{w}'_q\right)\right\|_F^2$ is re-allocated to (one of) the empty cluster(s); this procedure is continued until there are no empty clusters any more. The algorithm is considered

[3] It should be noted that imposing a non-negativity constraint solves the degeneracy problem, which may occur when applying the original Parafac model (see Harshman, 1970; Mitchell & Burdick, 1994; Smilde et al., 2004; Krijnen, Dijkstra, & Stegeman, 2008; Kroonenberg, 2008; Stegeman, 2006, 2007; De Silva & Lim, 2008).

converged when (1) updating the consumer cluster memberships leads to the same consumer partition, and, as a consequence, to an identical value on the loss function or (2) the improvement in the loss function value is negligible (i.e., smaller than some pre-defined tolerance value, like $.0000001$).

Multi-start procedure. Because the presented *CLV3W-NN* algorithm depends on the initial partition that has been used, the algorithm may yield a solution that is not optimal; note that this feature is common to many clustering algorithms, like, for example, the very popular Lloyd (1982) algorithm for K-means (Steinley, 2003, 2006a, 2006b). An often used way to overcome this limitation of the *CLV3W-NN* algorithm consists of using a multi-start procedure in which the algorithm is run multiple times, each time with a different initialization of the consumer partition, and the solution with the optimal loss function value encountered across all runs of the multi-start procedure is taken as the final solution. With respect to the initial consumer partition, in order to lower the risk of the algorithm retaining a suboptimal solution, we advise to use a multi-start procedure with 50 random starts, the rational *AHC* start, and, when available, one or more user-provided initializations.

Software. Functions to perform a *CLV3W-NN* analysis have been implemented in Matlab (version 2014b) and in R (version 3.2.0) and are available upon request from the authors. Moreover, R code to perform a *CLV3W-NN* analysis will soon be added to the *R* package *ClustVarLV* (Vigneau, Chen, & Qannari, 2015).

2.4 Model selection: Determining the number of clusters Q

An often used procedure to estimate the optimal number of clusters Q consists of, first, applying *CLV3W-NN* analyses with increasing numbers of clusters (e.g., one, two, three, etc.), and, next, identifying the solution that optimally balances model fit and model complexity. To this end, one may resort to (a generalized version of) the scree test of Cattell (1966), in which, for the solutions under consideration, the loss function value (2), which functions as a (mis)fit measure, is plotted against the number of clusters (i.e., model complexity). The solution corresponding to the sharpest elbow in the plot is considered the optimal solution. Instead of eyeballing for the sharpest elbow, one may use the *CHull* method (Ceulemans & Kiers, 2006; Wilderjans, Ceulemans, & Meers, 2013), which allows user to identify the optimal solution in a more automated way. Besides relying on the model selection strategies described above, one should always also consider the interpretability and stability of the solution when deciding about the optimal number of clusters.

3 Case Study: coffee aromas emotions dataset

3.1 Coffee dataset

To illustrate the use of *CLV3W-NN*, we consider a case study pertaining to consumer emotions associations for a variety of coffee aromas.

List of terms relevant to describe aroma-induced feelings. Fifteen affective terms (see Table 1) were selected, including eight factors exhibited by Chrea et al. (2009), like happiness, disgust, soothing, energizing and sensory, and the two orthogonal bipolar dimensions of pleasant-unpleasant and arousing-sleepy (Russell & Pratt, 1980). Following recommendations of Thomson and Crocker (2013), mainly positive emotions were selected as “the majority of people seem to exist in a generally positive state of mind”.

Insert Table 1 here

Stimuli. Stimuli were samples of aromas used for training olfactory memory. Twelve samples from the coffee aroma set “Le nez du café” (Jean Lenoir Edition, 2012) were chosen to reflect different aspects of the coffee aromas (see Table 2). They represented a spectrum from pleasant to unpleasant aromas, including several aroma families, like fruity odors and floral notes.

Insert Table 2 here

Participants. Eighty-four persons (66 females and 18 males) from ONIRIS took part in this study. 77 of them were undergraduate students, they were younger than 25 years old, while the others belonged to the personal staff of ONIRIS and were older than 25. No participant received any training.

Scale. The participants were asked to complete each rating (i.e., rating the odor of 12 aromas on 15 emotion terms) on a 5-point rating scale. Such a scale was advocated by several authors within the scope of data exploration (Weijters, Cabooter, & Schillewaert, 2010).

Experimental procedure. The experiment took place in a well ventilated room that allowed for hosting four participants at a time. Each participant received a sheet with information regarding the experiment and instructions on how to answer the emotion questionnaire. Data were collected using the Sphinx Plus^2-V5 software (Le Sphinx Développement, SARL, Chavanod, France). Aromas were presented with pills that were labelled with a random three-digit code. The presentation order of the pills was defined using a mutually orthogonal Latin squares design (MacFie, Bratchell, Greenhoff, & Vallis, 1989). The order of the attributes was randomized across all combinations of participants and products. On average, participants needed 15 minutes to complete the questionnaire.

3.2 Pre-processing and analyzing the data

Before analyzing, in order to deal with some known variations among the consumers, each matrix is column-wise centered to remove the consumers' main (or shift) effect for each attribute. Further, to control for consumers using different ranges of the scoring scales, isotropic scaling factors were applied, yielding an equal total variance for each data block $\boldsymbol{X}_j$ (Kunert & Qannari, 1999).

Next, we analyzed the pre-processed data with *CLV3W-NN* with one up to ten clusters. We adopted a multi-start procedure consisting of one rational starting partition (i.e., the partition obtained with the Agglomerative Hierarchical Clustering procedure) and 50 random initial partitions and retained the solution that yielded the lowest loss function value f in (2).

3.3 Results and discussion

Determining the number of clusters. The evolution of the loss criterion (2) against the number of clusters is depicted in Figure 2; in this figure, for each number of clusters, the loss values obtained from 50 random initial partitions and the rational Agglomerative Hierarchical Clustering procedure are summarized by means of a boxplot. From this figure, it appears that the solution with two clusters should be retained as it shows the sharpest elbow. The two-cluster solution captures 23% of the total variance of the three-way data.

Insert Figure 2 here

Results. For the retained *CLV3W-NN* solution with two clusters, the obtained clustering of the consumers along with the consumer loadings is presented in Figure 3, whereas the product scores (resp. attribute weights) for each cluster are depicted in Figure 4 (resp. Figure 5). Note that in Figures 3, 4 and 5, the two axes D1 and D2 correspond to the two clusters (i.e., the consumer loadings, product scores and attribute weights for the first and second cluster are displayed on D1 and D2, respectively).

Insert Figure 3 here

Inspecting the retained solution, it appears that the two clusters are equally sized as both contain 42 consumers each. For each consumer, a loading is estimated that reflects the level of agreement of the consumer with the cluster he/she belongs to. Looking at the consumer loadings (Figure 3), one can identify the most prototypical consumers for each cluster as those consumers with the highest loadings. Note that there is one consumer that has a zero value, indicating that this consumer is clearly in disagreement with the rest of the panel and therefore can be considered as rather uninformative. It is worth noting that this zero loading also appears in the "sparse LV" strategy adopted in *CLV* (Vigneau, Qannari, Navez, & Cottet, 2016)

Insert Figure 4 here

When inspecting the product scores (see Figure 4), one can see strong similarities between the two cluster-specific latent variables, enabling the identification of sets of coffee aroma products that are rated similarly on the attributes across raters. A first set of products, consisting of Basmati rice, Cedar, Earth, and Medicinal, has a negative score for both latent variables. Secondly, Apricot, Flower coffee and Lemon aromas are encountered with positive scores on the two latent variables. Three products stress the opposition between the two consumer clusters in the evaluation of the aromas. These products correspond to Hazelnut, Honey and Vanilla, which are three aromas that yield negative emotions, with regard to the first consumer subset, and positive emotions for the second consumer cluster. Finally, Coriander seeds and Hay are encountered with scores around zero for both clusters.

Insert Figure 5 here

In Figure 5, attributes are presented in (more or less) ascending order according to their component weight for each cluster. Looking at this order, one can associate it with the bipolar dimension of pleasant-unpleasant in which disgusted, irritated and unpleasant (i.e., having negative weights) are opposed to amused, happy and well (i.e., positive weights). Note that several attributes have a relatively small weighting value, like unique and surprised. Regarding surprised, this could be explained by the fact that surprised may be more associated with an arousing-sleepy latent dimension than with the pleasant-unpleasant one. With respect to unique, it may be the case that consumers have difficulties with scoring the aromas according to this emotion. Amazingly, the distribution of the weights is basically the same across the two clusters. This finding is not caused by a specific property of *CLV3W-NN* as this method does not impose any constraint on the cluster-specific vector of weights. This similarity in weight distributions may be a consequence of the consumers having the same overall perceptions of the emotion attributes. However, consumers differ in the associations between these emotions (or some of them) and the different aromas (see Figure 4). In particular, the set of aromas consisting of Hazelnut, Honey and Vanilla, evokes totally different emotions between both consumer groups.

In a nutshell, *CLV3W-NN* reveals the following findings from the coffee aromas dataset:

- the 15 emotion terms are perceived in a similar way by the consumers in terms of the main bipolar unpleasant-pleasant dimension.
- Basmati rice, Cedar, Earth and Medicinal are mainly associated with negative emotions, like disgusted, irritated and unpleasant, whereas Apricot, Flower coffee and Lemon elicit positive emotions, like amused, happy and well.
- Two groups of consumers can be identified based on their opposing evaluation of the aromas of Hazelnut, Honey and Vanilla: a first group associates these aromas with negative emotions, whereas a second group has positive emotions toward these aromas.

4 Conclusion

To perform consumer segmentation on the basis of a three-way product by consumer by attribute data array, we proposed the *CLV3W-NN* approach which aims at identifying simultaneously subsets of consumers - with positively correlated multi-attribute product scores - and a latent product component associated to each group as in *CLV3W* (Wilderjans & Cariou, 2016). Compared to the latter method, *CLV3W-NN* operates with the same optimization criterion but imposes a non-negativity constraint on the consumer vector of loadings. This constraint ensures consumers who rate the products along the attributes in a similar way being grouped into the same cluster and consumers who disagree regarding the product evaluations across the attributes to be in different clusters. *CLV3W-NN* provides at the same time (1) clusters of consumers, (2) a latent product component capturing the product evaluation patterns associated to each consumer group, (3) a system of weights indicating the importance of each attribute for each cluster of consumers, and (4) a vector of consumer loadings reflecting their level of agreement - in terms of covariance - with the latent component of their group. This latter aspect makes it possible to identify at the same time prototypical consumers having a high level of agreement with their group and non-informative consumers disagreeing from the rest of the panel.

Compared to a classical approach consisting of performing a cluster analysis on each attribute slice of the three-way array, *CLV3W-NN* offers an overall output that is easier to interpret and which does not require additional consensus methods to aggregate the various obtained partitions (one per attribute slice). *CLV3W-NN* provides a crisp partition of consumers which is easy to tune and to interpret by the sensory practitioner. We have shown how this approach could be applied within the context of consumer emotions associations. In particular, *CLV3W-NN* identified the products leading to the main difference between consumer subsets.

We have also pointed out that the systems of weights associated to each group were close to each other. This aspect may indicate that the panel of consumers has the same overall perceptions regarding the attributes but differs on the evaluation of the products. Further research is needed to investigate a consumer segmentation approach that assumes the set of attributes being equally weighted by the whole panel of consumers. Indeed, this latter aspect may be a key finding for the sensory practitioner. It may, as well, make the results easier to compare by means of product patterns defined on the same attribute-weighted component. In parallel, more work is needed to adapt our approach to more complex data structures such as the L-shaped data structure combined to a three-way array.

References

Andersson, C. A., & Bro, R. (2000). The N-way toolbox for MATLAB. *Chemometrics and Intelligent Laboratory Systems, 52*(1), 1-4.

Berget, I., Mevik, B.-H., & Næs, T. (2008). New modifications and applications of fuzzy -means methodology. *Computational Statistics & Data Analysis, 52*(5), 2403-2418.

Bro, R., & De Jong, S. (1997). A fast non-negativity-constrained least squares algorithm. *Journal of Chemometrics, 11*(5), 393-401.

Carbonell, L., Izquierdo, L., & Carbonell, I. (2007). Sensory analysis of Spanish mandarin juices. Selection of attributes and panel performance. *Food Quality and Preference, 18*(2), 329-341.

Cardello, A. V., & Jaeger, S. R. (2016). Measurement of consumer product emotions using questionnaires. *Emotion Measurement*, 165.

Cariou, V., Verdun, S., & Qannari, E. M. (2014). Quadratic PLS regression applied to external preference mapping. *Food Quality and Preference, 32, Part A*, 28-34.

Carroll, J. D., & Chang, J.-J. (1970). Analysis of individual differences in multidimensional scaling via an N-way generalization of "Eckart-Young" decomposition. *Psychometrika, 35*(3), 283-319.

Cattell, R. B. (1966). The scree test for the number of factors. *Multivariate behavioral research, 1*(2), 245-276.

Ceulemans, E., & Kiers, H. A. L. (2006). Selecting among three-mode principal component models of different types and complexities: A numerical convex hull based method. *British Journal of Mathematical and Statistical Psychology, 59*(1), 133-150.

Chrea, C., Grandjean, D., Delplanque, S., Cayeux, I., Le Calvé, B., Aymard, L., et al. (2009). Mapping the semantic space for the subjective experience of emotional responses to odors. *Chemical Senses, 34*(1), 49-62.

De Soete, G., & Winsberg, S. (1993). A latent class vector model for preference ratings. *Journal of classification, 10*(2), 195-218.

Faber, N. K. M., Bro, R., & Hopke, P. K. (2003). Recent developments in CANDECOMP/PARAFAC algorithms: a critical review. *Chemometrics and Intelligent Laboratory Systems, 65*(1), 119-137.

Giordani, P., Kiers, H. A., & Del Ferraro, M. A. (2014). Three-way component analysis using the R package ThreeWay. *Journal of Statistical Software, 57*(7), 1-23.

Gordon, A., & Vichi, M. (1998). Partitions of partitions. *Journal of classification, 15*(2), 265-285.

Harshman R. A. (1970). Foundations of the PARAFAC procedure: models and conditions for an explanatory multi-modal factor analysis. *UCLA Working Papers in Phonetics, 16*, 1–84.

Helgesen, H., Solheim, R., & Næs, T. (1997). Consumer preference mapping of dry fermented lamb sausages. *Food Quality and Preference, 8*(2), 97-109.

Helwig, N. E. (2016). Component models for multi-way data. R package version 1.0-2. http://CRAN.R-project.org/package=multiway.

Hitchcock, F. L. (1927). The expression of a tensor or a polyadic as a sum of products. *Journal of Mathematics and Physics, 6*(1), 164-189.

Johansen, S. B., Hersleth, M., & Næs, T. (2010). A new approach to product set selection and segmentation in preference mapping. *Food Quality and Preference, 21*(2), 188-196.

Kiers, H. A. L. (2000). Towards a standardized notation and terminology in multiway analysis. *Journal of Chemometrics, 14*(3), 105-122.

King, S. C., Meiselman, H. L., & Carr, B. T. (2010). Measuring emotions associated with foods in consumer testing. *Food Quality and Preference, 21*(8), 1114-1116.

Krijnen, W. P. (1993). *The analysis of three-way arrays by constrained PARAFAC methods*. Leiden, The Netherlands: DSWO Press.

Kunert, J., & Qannari, E. M. (1999). A simple alternative to generalized procrustes analysis: application to sensory profiling data. *Journal of Sensory Studies, 14*(2), 197-208.

Lawson, C. L., & Hanson, R. J. (1974). Linear least squares with linear inequality constraints. *Chap, 23*, 158-173.

Lawson, C. L., & Hanson, R. J. (1995). *Solving least squares problems*: SIAM.

Lloyd, S. (1982). Least squares quantization in PCM. *IEEE transactions on information theory, 28*(2), 129-137.

MacFie, H. J., Bratchell, N., Greenhoff, K., & Vallis, L. V. (1989). Designs to balance the effect of order of presentation and first-order carry-over effects in hall tests. *Journal of Sensory Studies, 4*(2), 129-148.

McEwan, J. A. (1996). Preference mapping for product optimization. In T. Næs & E. Risvik (Eds.), *Multivariate analysis of data in sensory science* (pp.71-102). Amsterdam: Elsevier Science.

Meiselman, H. L. (2013). The future in sensory/consumer research: ………....evolving to a better science. *Food Quality and Preference, 27*(2), 208-214.

Næs, T., Brockhoff, P. B., & Tomic, O. (2010). Quality control of sensory profile data. In: *Statistics for Sensory and Consumer Science*: (pp.11-38). Chichester (UK): John Wiley & Sons, Ltd.

Nunes, C. A., Pinheiro, A. C. M., & Bastos, S. C. (2011). Evaluating consumer acceptance tests by three-way internal preference mapping obtained by parallel factor analysis (PARAFAC). *Journal of Sensory Studies, 26*(2), 167-174.

Onwezen, M. C., Reinders, M. J., van der Lans, I. A., Sijtsema, S. J., Jasiulewicz, A., Dolors Guardia, M., et al. (2012). A cross-national consumer segmentation based on food benefits: The link with consumption situations and food perceptions. *Food Quality and Preference, 24*(2), 276-286.

Piqueras-Fiszman, B., & Jaeger, S. R. (2016). Consumer segmentation as a means to investigate emotional associations to meals. *Appetite, 105*, 249-258.

Qannari, E., Vigneau, E., Luscan, P., Lefebvre, A., & Vey, F. (1997). Clustering of variables, application in consumer and sensory studies. *Food Quality and Preference, 8*(5), 423-428.

Russell, J. A., & Pratt, G. (1980). A description of the affective quality attributed to environments. *Journal of Personality and Social Psychology, 38*(2), 311.

Santa Cruz, M. J., Martínez, M. C., & Hough, G. (2002). Descriptive analysis, consumer clusters and preference mapping of commercial mayonnaise in Argentina. *Journal of Sensory Studies, 17*(4), 309-325.

Sarle, W. (1990). The VARCLUS procedure. *SAS/STAT User's Guide*.

Séménou, M., Courcoux, P., Cardinal, M., Nicod, H., & Ouisse, A. (2007). Preference study using a latent class approach. Analysis of European preferences for smoked salmon. *Food Quality and Preference, 18*, 720-728.

Smilde, A., Bro, R., & Geladi, P. (2004). Visualization. *Multi-Way Analysis with Applications in the Chemical Sciences*, 175-220.

Steinley, D. (2003). Local optima in K-means clustering: what you don't know may hurt you. *Psychological Methods, 8*(3), 294.

Steinley, D. (2006a). K-means clustering: a half-century synthesis. *British Journal of Mathematical and Statistical Psychology, 59*(1), 1-34.

Steinley, D. (2006b). Profiling local optima in K-means clustering: Developing a diagnostic technique. *Psychological Methods, 11*(2), 178.

Sveinsdóttir, K., Martinsdóttir, E., Green-Petersen, D., Hyldig, G., Schelvis, R., & Delahunty, C. (2009). Sensory characteristics of different cod products related to consumer preferences and attitudes. *Food Quality and Preference, 20*(2), 120-132.

Thomson, D. M. H., & Crocker, C. (2013). A data-driven classification of feelings. *Food Quality and Preference, 27*(2), 137-152.

Tomasi, G., & Bro, R. (2006). A comparison of algorithms for fitting the PARAFAC model. *Computational Statistics & Data Analysis, 50*(7), 1700-1734.

Vichi, M. (1999). One-mode classification of a three-way data matrix. *Journal of Classification, 16*(1), 27-44.

Vigneau, E., Chen, M., & Qannari, E. M. (2015). ClustVarLV: an R package for the clustering of variables around latent variables. *The R Journal, 7*(2), 134-148.

Vigneau, E., & Qannari, E. M. (2002). Segmentation of consumers taking account of external data. A clustering of variables approach. *Food Quality and Preference, 13*(7-8), 515-521.

Vigneau, E., & Qannari, E. M. (2003). Clustering of variables around latent components. *Communications in Statistics - Simulation and Computation, 32*(4), 1131-1150.

Vigneau, E., Qannari, E. M., Navez, B., & Cottet, V. (2016). Segmentation of consumers in preference studies while setting aside atypical or irrelevant consumers. *Food Quality and Preference, 47, Part A*, 54-63.

Vigneau, E., Qannari, E. M., Punter, P. H., & Knoops, S. (2001). Segmentation of a panel of consumers using clustering of variables around latent directions of preference. *Food Quality and Preference, 12*(5-7), 359-363.

Weijters, B., Cabooter, E., & Schillewaert, N. (2010). The effect of rating scale format on response styles: The number of response categories and response category labels. *International Journal of Research in Marketing, 27*(3), 236-247.

Westad, F., Hersleth, M., & Lea, P. (2004). Strategies for consumer segmentation with applications on preference data. *Food Quality and Preference, 15*(7–8), 681-687.

Wilderjans, T. F., & Cariou, V. (2016). CLV3W: A clustering around latent variables approach to detect panel disagreement in three-way conventional sensory profiling data. *Food Quality and Preference, 47, Part A*, 45-53.

Wilderjans, T. F., & Ceulemans, E. (2013). Clusterwise Parafac to identify heterogeneity in three-way data. *Chemometrics and Intelligent Laboratory Systems, 129*, 87-97. doi:10.1016/j.chemolab.2013.09.010

Wilderjans, T. F., Ceulemans, E., & Meers, K. (2013). CHull: A generic convex-hull-based model selection method. *Behavior Research Methods, 45*(1), 1-15.

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Table 1. Overview of the 15 emotional attributes of the coffee aromas data.

Positive	**Negative**
Energetic	Angry
Calm	Unpleasant
Relaxed	Irritated
Nostalgic	Disgusted
Happy	Disappointed
Free	
Excited	
Well-being	
Amused	
Unique	

Table 2. Overview of the 12 aromas and the category they belong to of the coffee aromas data.

Category	**Aroma**
Earthy	Earth
Dry vegetation	Hay
Woody	Cedar
Spicy	Vanilla, Coriander seeds
Floral	Flower coffee
Fruity	Apricot, Lemon
Animal	Honey
Roasted	Basmati rice, Hazelnut
Chemical	Medicinal

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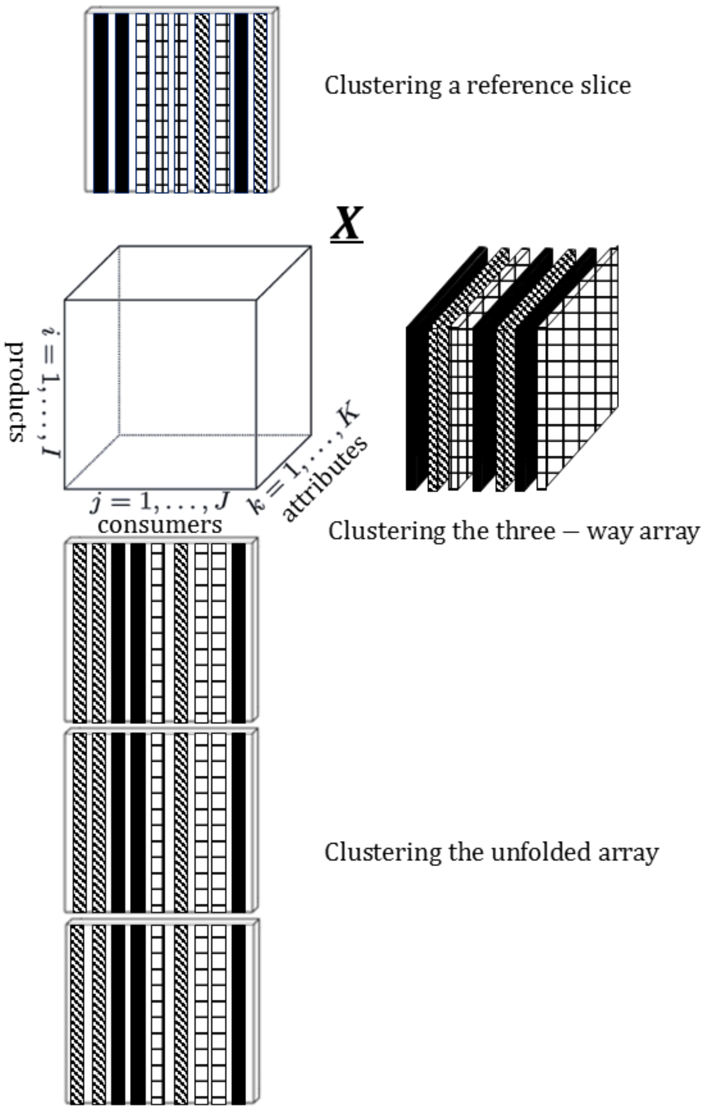


Figure 1. Clustering schemes in the context of a three-way data structure: (1) clustering on a reference slice, (2) clustering on the unfolded array and (3) clustering the three-way array.

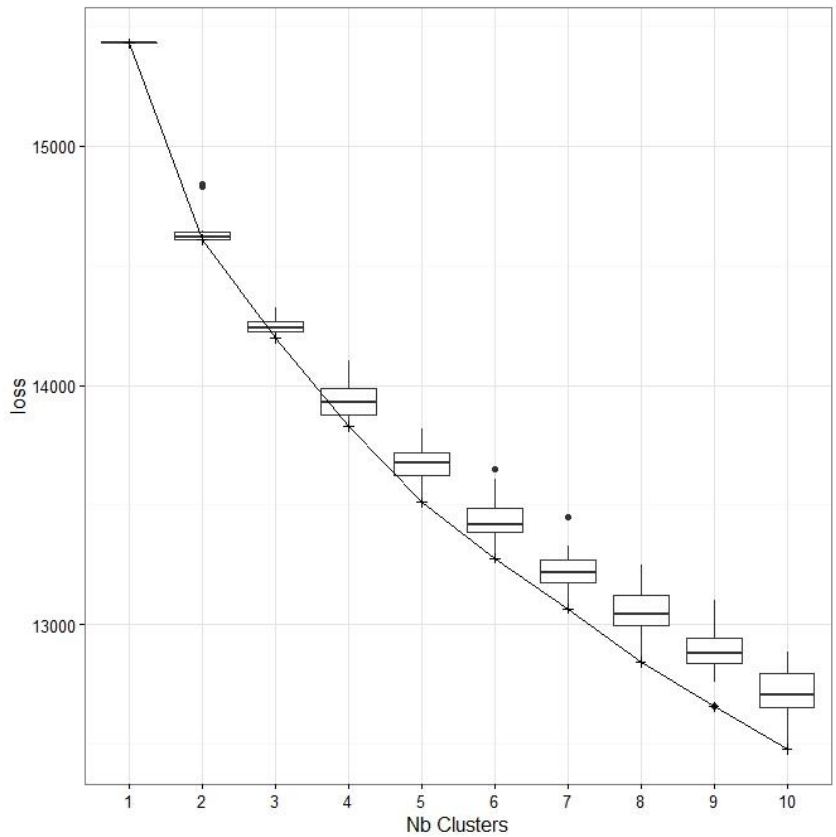
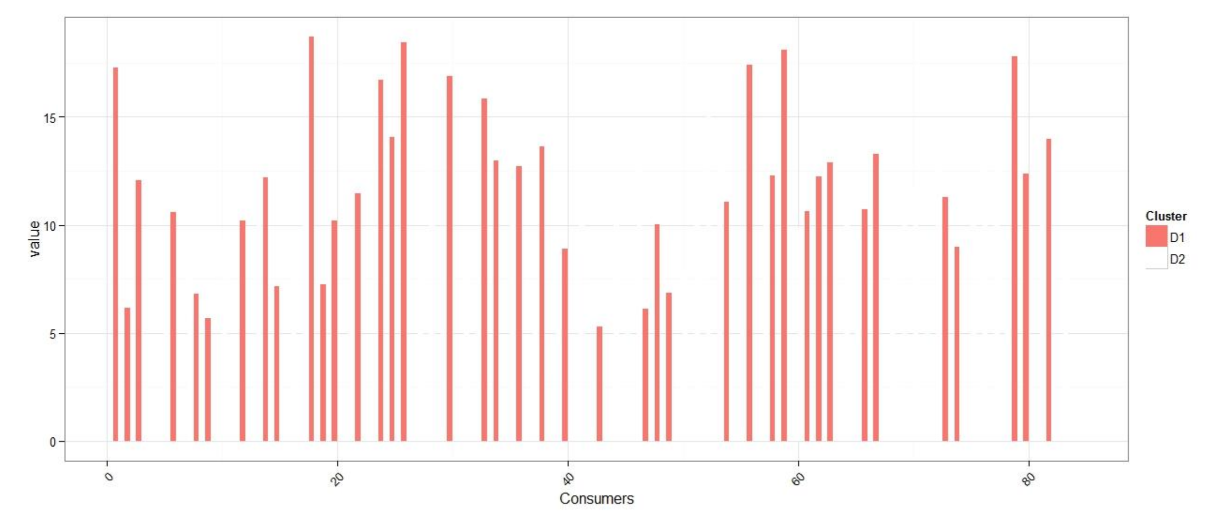
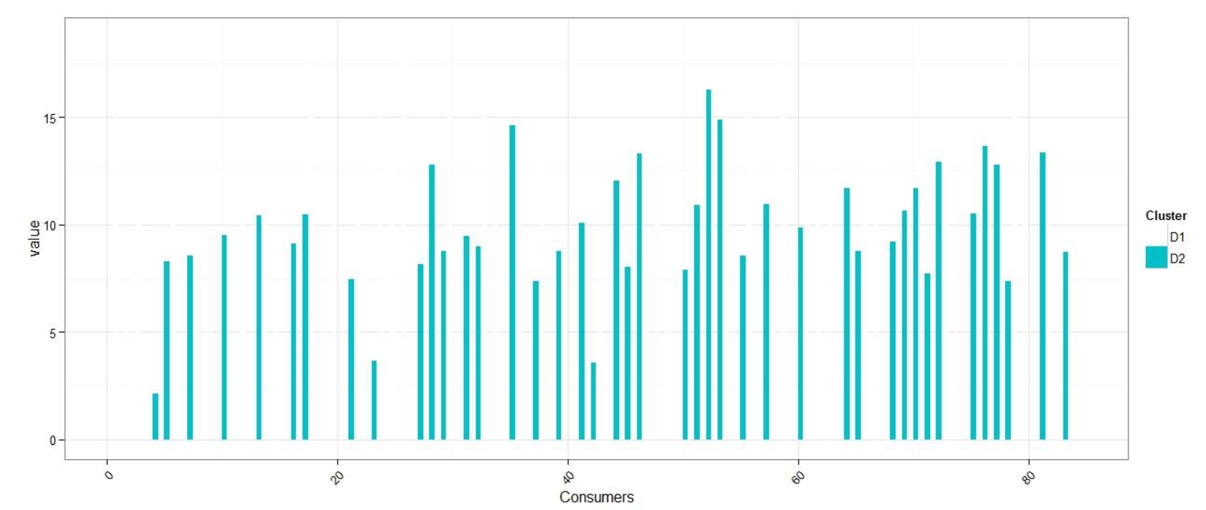


Figure 2. Evolution of the *CLV3W-NN* loss value across increasing numbers of clusters varying from 1 up to 10; boxplots indicate the variability in loss functions values encountered across 50 random starts and a single HAC initialization.



(cluster 1)



(cluster 2)

Figure 3. Consumer loadings for the two-cluster *CLV3W-NN* solution for the coffee aromas data; the two axes D1 and D2 pertain to the two clusters.

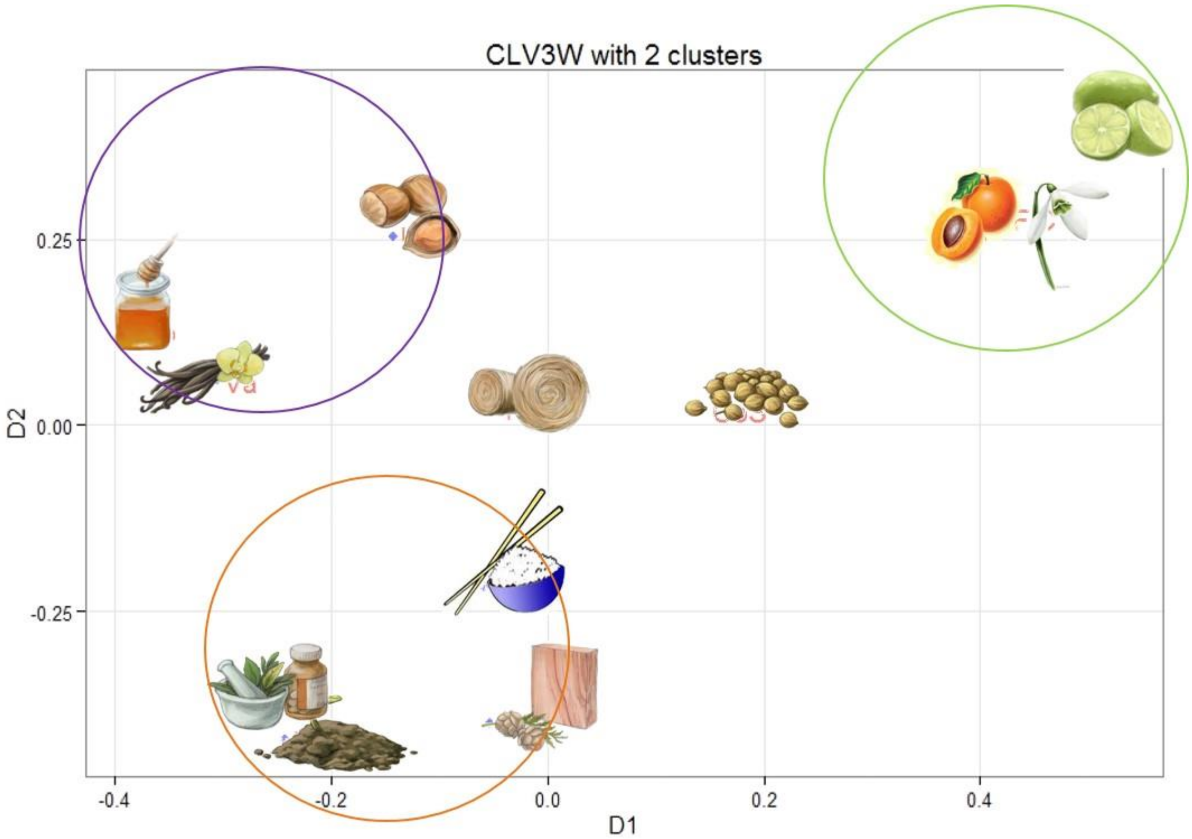


Figure 4. Configuration of the products (i.e., product loadings) for the two-cluster *CLV3W-NN* solution for the coffee aromas data; the two axes D1 and D2 pertain to the two clusters.

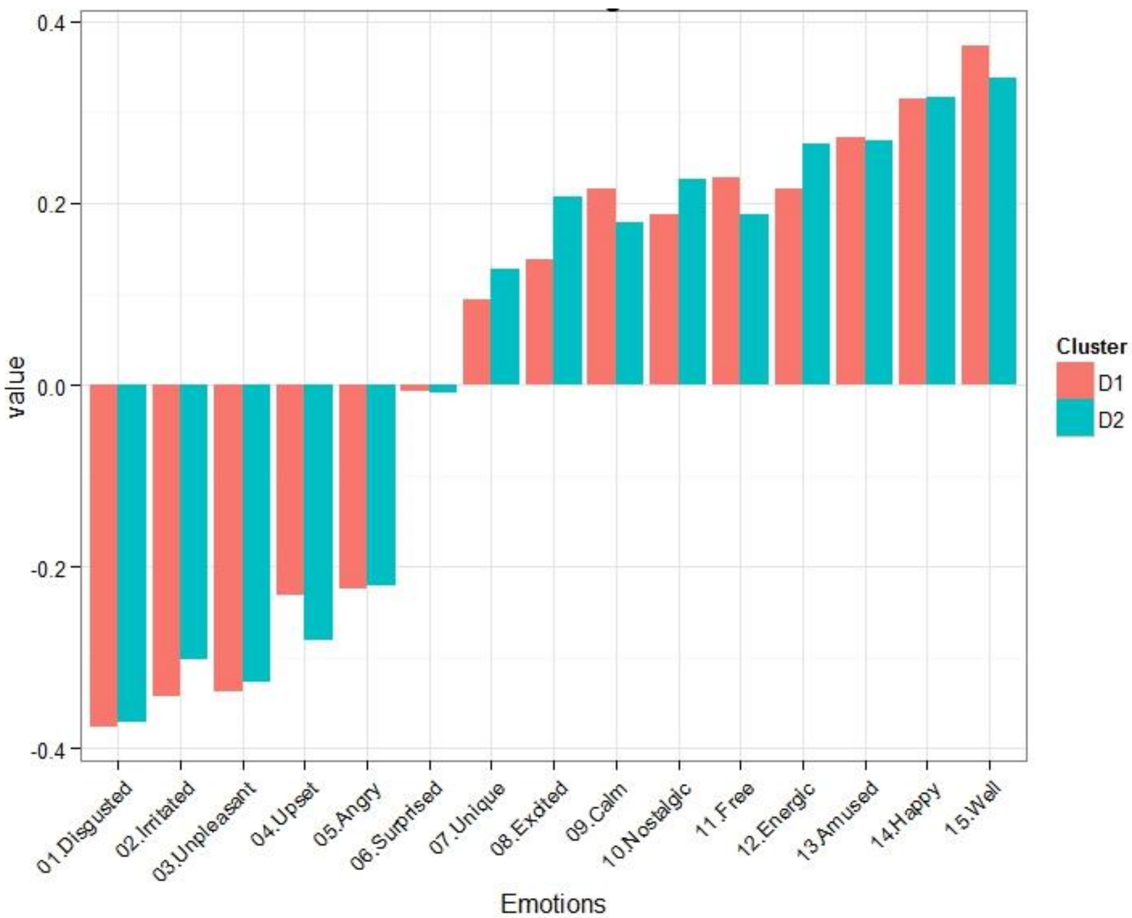


Figure 5. Attribute weights for the two-cluster *CLV3W-NN* solution for the coffee aromas data; the two axes D1 and D2 pertain to the two clusters.