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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.

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).

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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.
- 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 approach discussed above, the three-way structure in the data is ignored, which may obfuscate information relevant for the clustering of consumers.
- 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.

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 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:

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

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):

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

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

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

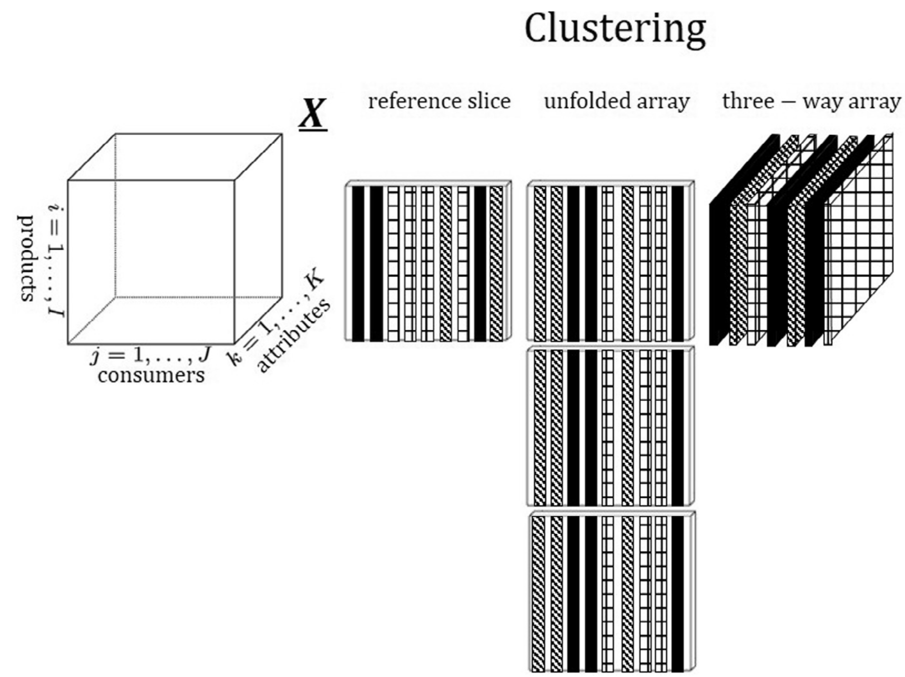

Fig. 1. Clustering schemes in the context of a three-way data structure: (1) clustering on a reference slice, (2) clustering on the unfolded array and (3) clustering the three-way array.

with all symbols as defined above and α_{jq} denoting the loading of consumer j for cluster G_q. Note that α_{jq} is undefined when consumer j does not belong to cluster G_q; in that case, α_{jq} is taken equal to 0. As pointed out above (see Footnote 1), this *CLV3W* model is mathematically 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: $cov(\boldsymbol{X}_q\boldsymbol{w}_q, \boldsymbol{t}_q) \geqslant 0$. 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).

2.3.1. 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, the cluster-specific parameters $\boldsymbol{t}_q$, α_{jq} and $\boldsymbol{w}_q$ are estimated given the consumer partition into the non-overlapping clusters G_q $(q = 1, \ldots, Q)$. This can be achieved using 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 $\underline{X}^{(q)}$ $(q = 1, \ldots, Q)$, with $\underline{X}^{(q)}$ being an array that is obtained by only taking the data slices $\boldsymbol{X}_j$ of $\underline{X}$ 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 (Andersson & Bro, 2000; Bro & De Jong, 1997; Giordani, Kiers, & Del Ferraro, 2014; Lawson & Hanson, 1974) and multiway (Helwig, 2016). In a second 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 et al., 2004), and consumer j is re-allocated to the cluster G_q for which $f_{jq} = ||\boldsymbol{X}_j - \alpha_{jq}(\boldsymbol{t}_q\boldsymbol{w}_q')||_F^2$ reaches its minimal value. After execution of the second step, a check is performed to control whether or not there

[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 De Silva & Lim, 2008; Harshman, 1970; Krijnen, Dijkstra, & Stegeman, 2008; Kroonenberg, 2008; Mitchell & Burdick, 1994; Smilde, Bro, & Geladi, 2004; Stegeman, 2006, 2007).

are empty clusters. When this is the case, the consumer who shows the weakest association with his/her cluster in terms of function value $||\boldsymbol{X}_j - \alpha_{jq}(\boldsymbol{t}_q \boldsymbol{w}_q')||_F^2$ 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 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).

2.3.2. 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.

2.3.3. 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 $\boldsymbol{Q}$

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 users 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.

3.1.1. List of terms relevant to describe aroma-induced feelings

Fifteen affective terms (see Table 1) were selected, including the six factors exhibited by Chrea et al. (2009), namely Happiness/Well-being (3 items: happy, well-being, surprised), Disgust Irritation (angry, unpleasant, irritated, disgusted, disappointed), Soothing Peacefulness (calm), Energizing Cooling (energetic), Sensory Pleasure (amused, nostalgic) and Awe Sensuality (excited); two additional terms were added: unique and free. These fifteen terms can be categorized according to the two orthogonal bipolar dimensions of pleasant-unpleasant and arousing-sleepy (Russell & Pratt, 1980); in Table 1, these fifteen terms are categorized according to the bipolar dimension of pleasant-unpleasant (see Table 1). Moreover, some of them, like excited vs calm, also refer to the arousing-sleepy dimension. 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”.

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

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

3.1.2. 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.

3.1.3. 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 staff of ONIRIS and were older than 25. No participant received any training.

3.1.4. 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).

3.1.5. 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 pillboxes, each pillbox containing drops of an aroma on a cotton in order to preserve its odorous characteristics. Pillboxes 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) to balance out the effect of order of presentation and possible carryover effect. The order of the attributes was randomized across all combina-

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

tions of participants and products. On average, participants needed 15 min to complete the questionnaire. With respect to each attribute, a three-way analysis of variance where the subject, product and order were considered as fixed factors was performed. The significance level (α) was set to 5%. Despite the design of presentation, it appears that among the fifteen emotion terms, four of them were significantly influenced by the order (i.e., angry, disgusted, unpleasant and unique).

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

3.3.1. Determining the number of clusters

The evolution of the loss criterion (2) against the number of clusters is depicted in Fig. 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.

3.3.2. Results

For the retained *CLV3W-NN* solution with two clusters, the obtained clustering of the consumers along with the consumer loadings is presented in Fig. 3, whereas the product scores (resp. attribute weights) for each cluster are depicted in Fig. 4 (resp. Fig. 5). Note that in Figs. 3–5, 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).

Inspecting the retained solution, it appears that the two clusters are equally sized as both contain 42 consumers. For each consumer, a loading is estimated that corresponds to the covariance between his/her product scores and the product scores of the cluster he/she belongs to. Indeed, as a consumer rates each product in a multi-attribute way, consumer product scores make it possible to synthesize the consumer ratings associated to the set of products. Consumer product scores are obtained using the attribute weights of the cluster he/she belongs to and depict the way a consumer globally evaluates the set of products. Thus, we can conclude that a high loading corresponds to a high covariance between the consumer product scores and the product scores of the cluster he/she belongs to. It finally reflects his/her level of agreement with his/her own cluster. In Fig. 3, the consumer loadings, arranged in an ascending order for ease of reading, are depicted. From this Figure, one can identify the most prototypical consumers for each cluster as those consumers with the highest loadings. Note that there are two consumers that have a zero value, indicating that these consumers are clearly in disagreement with the rest of the panel and therefore can be considered as rather uninformative. Those consumers could be further discarded from the partition. It is worth noting that this zero loading also appears in the "sparse LV" strategy adopted in *CLV* (Vigneau, Qannari, Navez, & Cottet, 2016)

When inspecting the product scores (see Fig. 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. These aromas belong to Roasted, Woody, Earthy and Medicinal notes. Secondly, Apricot, Flower coffee and Lemon aromas are encountered with positive scores on the two latent variables. Fruity and Floral notes encompass these three aromas. 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, associated to Spicy and Dry vegetation notes, are encountered with scores around zero for both clusters.

In Fig. 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 pleasant emotion vs unpleasant one (Chrea et al., 2009). 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 Fig. 4). In particular, the set of aromas consisting of Hazelnut, Honey and Vanilla, evokes totally opposite emotions between both consumer groups. These three aromas belong to three different notes: Spicy (Vanilla), Animal (Honey) and Roasted (Hazelnut). Inspecting the groups, it appears that the majority of men belong to this second group. This cluster is composed of 26% men compared to a percentage of 21% in the whole panel (i.e., percentages are slightly different according to a Hypergeometric test: $P[X > x] = 6.3\%$).

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.

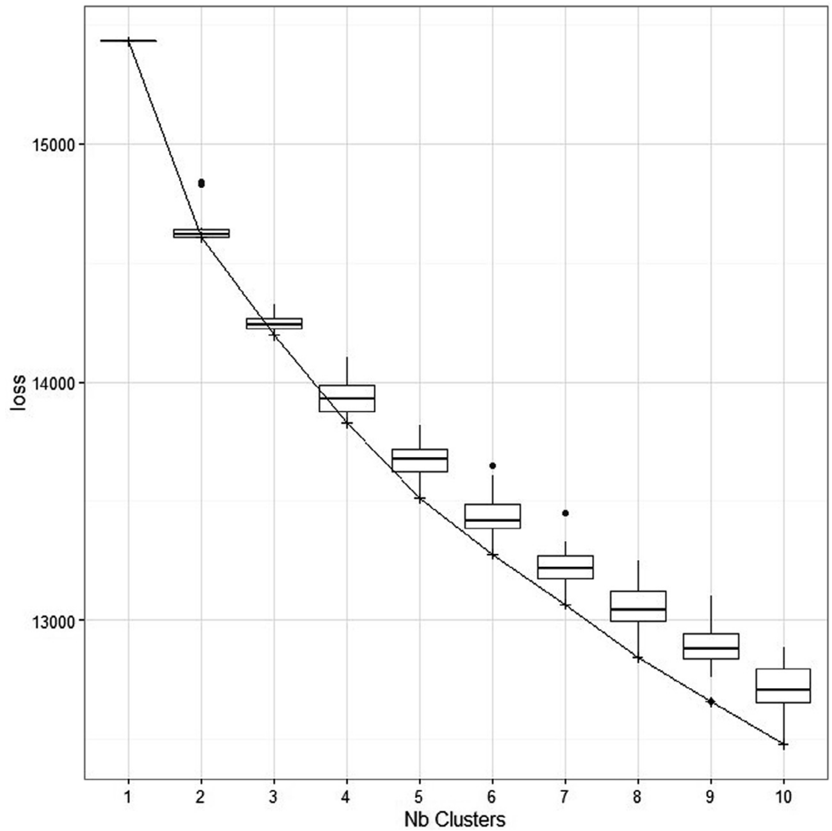

Fig. 2. Evolution of the *CLV3W-NN* loss value across increasing numbers of clusters varying from 1 up to 10; boxplots indicate the variability in loss functions values encountered across 50 random starts and a single HAC initialization.

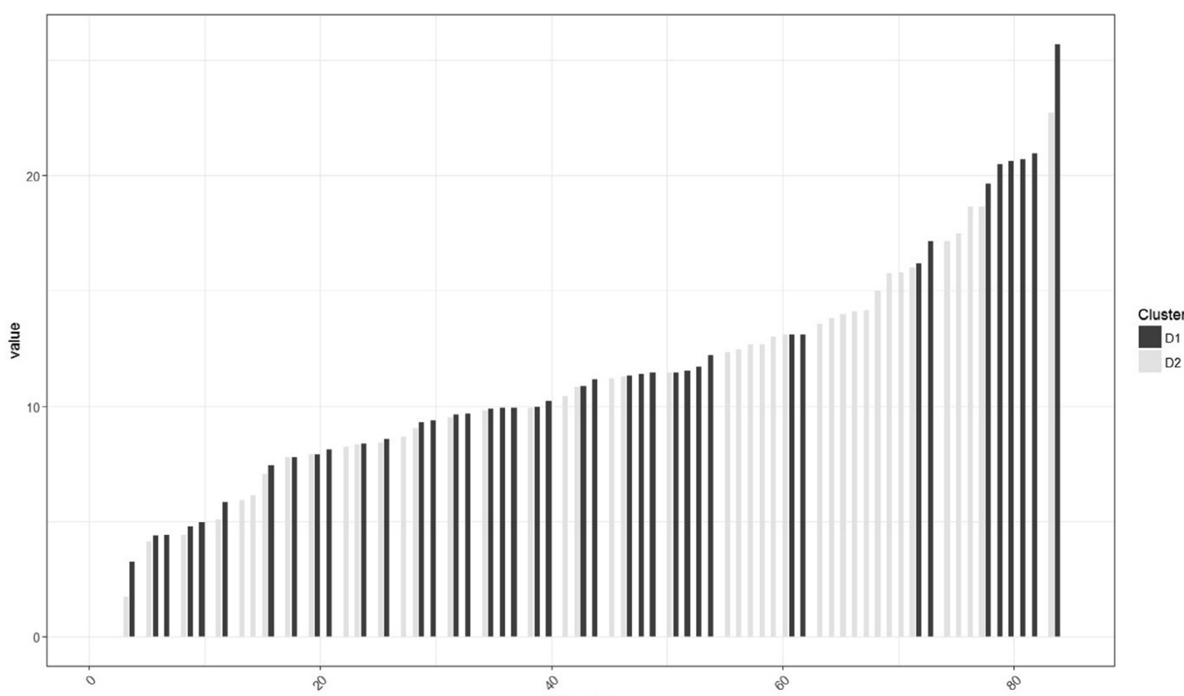

Fig. 3. Consumer loadings for the two-cluster *CLV3W-NN* solution for the coffee aromas data with D1 and D2 pertaining to the two clusters.

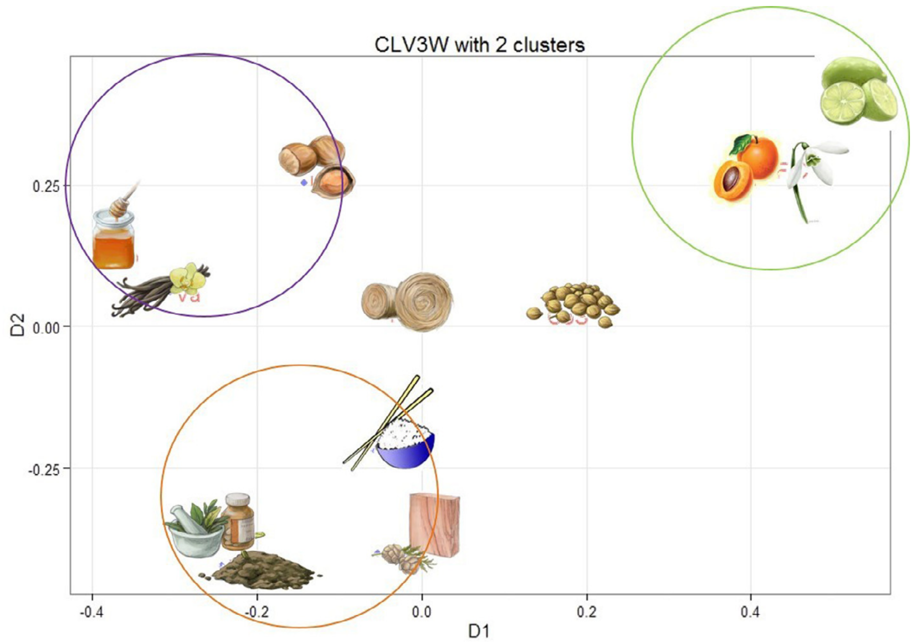

Fig. 4. Configuration of the products (i.e., product loadings) for the two-cluster *CLV3W-NN* solution for the coffee aromas data; the two axes D1 and D2 pertain to the two clusters.

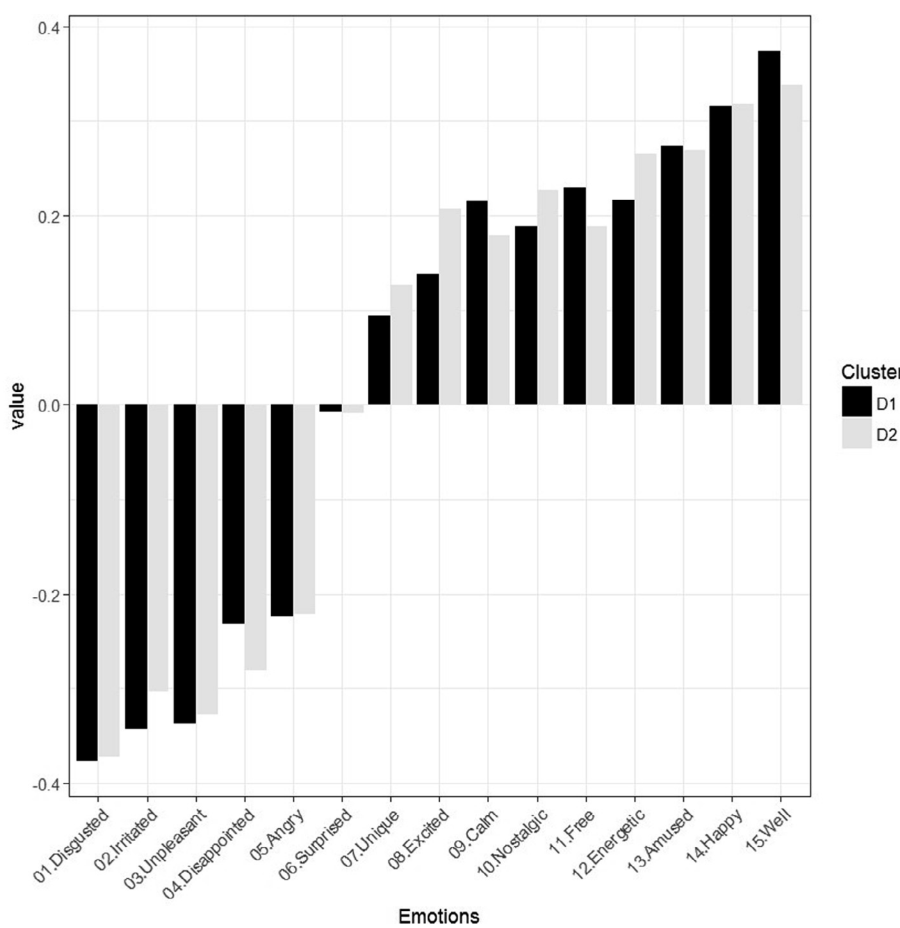

Fig. 5. Attribute weights for the two-cluster *CLV3W-NN* solution for the coffee aromas data; the two axes D1 and D2 pertain to the two clusters.

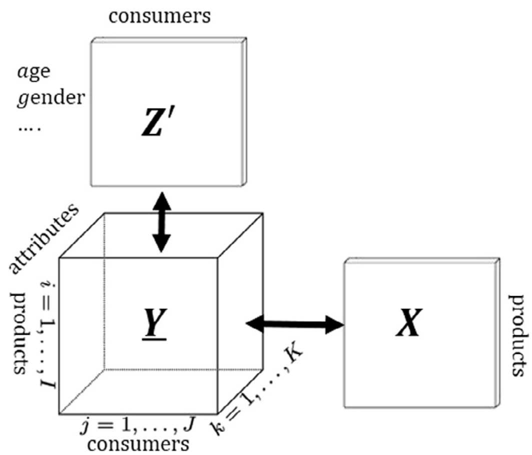

Fig. 6. An L-shaped data structure with a three-way array consumer data $\underline{\mathbf{Y}}$. $\mathbf{X}$ has common rows with $\underline{\mathbf{Y}}$ first mode and $\mathbf{Z}'$ has common columns with $\underline{\mathbf{Y}}$ second mode.

- 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, corresponding respectively to Roasted, Animal and Spicy notes. A first group associates these aromas with negative emotions, whereas a second group has positive emotions toward these aromas. This latter group is characterized by a higher percentage of men belonging to it.

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.

Further research is needed to adapt our approach to more complex data structures such as the L-shape structure integrating a three-way array. An L-shaped data structure corresponds to the case where different blocks of data have no common modes but can be rearranged such that one data array makes the connection in two different modes with the two others. This commonly occurs in consumer studies where both consumer data and sociodemographic information as well as attitudes associated to each consumer are collected together with characteristics of the products evaluated (e.g. physico-chemical characterization or alternatively sensory profile). Indeed, accounting for consumer information leads to additional information on the consumer mode while conversely accounting for product characterization provides additional information on the product mode. In order to deal with L-shape structures, Martens et al. (2005) proposed to extend PLS regression (called L-PLSR), this first approach being dedicated to factorial representation rather than consumer segmentation. Subsequently, Endrizzi, Gasperi, Calò, and Vigneau (2010) introduced consumer segmentation on the basis of the L-shape structure within the CLV framework. Nevertheless, these two approaches as well as others assumed a 2D-consumer data table (product by consumer).

Going further, an extended L-shape structure can be considered where the datasets at hand corresponds to (1) a 3D-array (product by consumer by attribute), (2) a 2D-consumer matrix with additional data on the consumers and (3) a 2D-product characteristics matrix (Fig. 6). In this context, our aim is to derive the *CLV3W-NN* criterion to perform consumer segmentation on the basis of such L-shape structure.

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