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Invited review

Quick and dirty but still pretty good: a review of new descriptive methods in food science

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Summary For food scientists and industrials, descriptive profiling is an essential tool that involves the evaluation of both the qualitative and quantitative sensory characteristics of a product by a panel. Recently, in response to industrial demands to develop faster and more cost-effective methods of descriptive analysis, several methods have been offered as alternatives to conventional profiling. These methods can be classified in three families: (i) verbal-based methods (flash profile and check-all-that-apply), (ii) similarity-based methods (free sorting task and projective mapping aka Napping®) and (iii) reference-based methods (polarised sensory positioning and pivot profile). We successively present these three classes of methods in terms of origin, principles, statistical analysis, applications to food products, variations of the methods and the Pros and Cons.

Keywords Check-all-that-apply, consumer research, descriptive methods, flash profile, pivot profile, polarised sensory positioning, projective mapping, sensory characterisation, sensory evaluation, sorting task.

Introduction

Food companies routinely use descriptive profile to define and quantify the sensory characteristics on which products differ because the information provided by descriptive profiles has numerous applications such as product development and improvement, quality control, advertising claim substantiation (Sidel & Stone, 1993; Lawless & Heymann, 2010), as well as understanding both consumer preferences (Greenhof & MacFie, 1994) and their relationships with instrumental data (Lee *et al.*, 1999). Several descriptive profiling techniques – some of them trademarked – can be found in the sensory evaluation literature. These include the Flavour Profile (Cairncross & Sjostrom, 1950), the Texture Profile (Brandt *et al.*, 1963), Quantitative Descriptive Analysis (QDA™; Stone *et al.*, 1974), Spectrum™ methods (Munoz & Civille, 1992) and Quantitative Flavour Profiling (Stampanoni, 1993). The most frequently used method, referred to as conventional descriptive analysis (DA), is closely related to QDA™.

Descriptive analysis is performed by a small number of panellists (from 8 to 15) who provide intensity ratings for a set of selected attributes. It involves three main steps. The *first* step is product familiarisation and development of a lexicon that comprehensively and accurately describes the product space. This is generally achieved by exposing panellists to many variations of the products and asking them to generate a set of terms that can describe differences among products. The hedonic terms are then eliminated and synonyms or antonyms regrouped in a single term. The *second* step consists in training the panellists to align and standardise the sensory concepts of the panel. This is generally achieved by associating a definition and a physical reference to each of the attributes present in the lexicon. The *third* step is scoring of the products on the basis of each descriptive attribute on an intensity scale. The performance of the panel is monitored in terms of discrimination power, agreement between panellists and reproducibility during training to achieve the most accurate, reliable and consistent results as possible.

As the first developments of sensory profiling, DA has been successfully used to evaluate a variety of food products, as evidenced by an abundant scientific literature (see, *e.g.* Stone & Sidel, 1993; Meilgaard *et al.*, 1999). DA provides good quality data but, as a counterpart of this quality, it requires extensive training before the panel can be used as a reliable sensory instrument. Because the vocabulary and associated training must be adapted to each product space, it can take from few weeks to several months – depending on

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the product – to complete a study, and thus, there is an obvious need for faster and more cost-effective methods.

Recently, in response to this demand, several methods have been offered as alternatives to DA. These alternative methods do not require a training phase and can be performed either by trained or untrained assessors. Therefore, these methods can be quite useful when a rapid access to the relative sensory positioning of a set of food products is of primary concern. These new methods can be categorised into three classes: The first class encompasses methods based on verbal descriptions of individual products; the second class includes methods based on similarity measurements between products; and the third class comprises methods based on the comparison of individual products with a (or a set of) reference(s).

Verbal-based methods

The two methods included in this section, 'flash profile (FP)' and 'check-all-that-apply (CATA)', build on the idea of free choice profiling (FCP, Williams & Langron, 1984), a technique that allows assessors to use their own attributes. Like DA, these two methods generate a direct description of the products but have the advantage of bypassing the time-consuming steps of attribute and scaling alignment of classical methods.

Flash profile

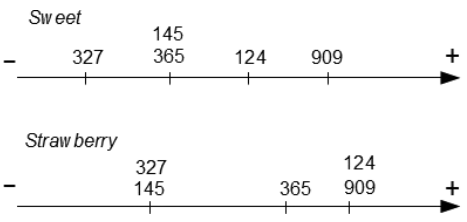
Origin and general principle

The FP was initially developed (by Sieffermann, 2000) as a method providing quick access to the relative sensory positioning of a set of products. This descriptive method is a combination of FCP and ranking methods. It relies on the often noted fact that it is easier and more natural to compare products than to evaluate them on an absolute scale.

Flash profile involves two sessions separated by an inter-session. In the *first session*, the whole set of products is presented simultaneously to each assessor who is then asked to observe, smell and/or taste the products (depending on the objectives of the study) and to generate a set of attributes, which should be sufficiently discriminant to permit ranking these products. The assessors are free to generate as many attributes as they want, but are asked to focus on descriptive terms and to avoid hedonic terms. Assessors can re-taste the products as often as they wish and can take as much time as needed. During the inter-session, the experimenter pools all the generated attributes to form a global list that is then provided to the panellists. The goal of this global list is not to obtain a consensus but to allow the panellists to update their own list if desired. They can do so by either (i) adding to their list a few terms they think are relevant but did not generate themselves or by (ii) replacing some of their own terms by terms they think are more adapted. In the *second session*, the assessors are asked to rank order the products from least to most on each of their chosen attributes (see Fig. 1 for an example).

Statistical analysis

Assessors' rank data are first collected as shown in Fig. 2 and are analysed using multivariate analysis. Initially, FP data were analysed by first performing a principal component analysis (PCA) for each assessor and then integrating these PCAs using generalised procrustean analysis (GPA, Gower, 1971; Moussaoui & Varela, 2010). GPA (see Data S1) uses an iterative algorithm to find rotation and scaling transformation of individual assessor rank matrices to maximise the



	Assessor1	
Product	Sweet	Strawberry
327	1	1,5
145	2,5	1,5
365	2,5	3
124	4	4,5
909	5	4,5

Figure 1 An example of flash profile answer sheets and data coding. Assessors were asked to select their own attributes to describe a set of five products presented simultaneously and to rank the products for each attribute.

	Assessor 1				Assessor 2							Assessor 3				
Product	A1	A2	A3	A4	A1	A2	A3	A4	A5	A6	A7	A1	A2	A3	A4	A5
327	1	1.5	4	1	2.5	1.5	5	1	1	1	4.5	1.5	4.5	3	1.5	4
145	2.5	1.5	1	4.5	1	1.5	2	4.5	2	2.5	1	4.5	2	2	1.5	1
365	2.5	3	5	2.5	2.5	4	4	2.5	3	2.5	4.5	1.5	4.5	1	3	4
124	4	4.5	2	4.5	4	3	2	4.5	4.5	4	2	4.5	1	4	4	2
909	5	4.5	3	2.5	5	5	2	2.5	4.5	5	3	3	3	5	5	4

Figure 2 An example of data table obtained with flash profile. Three assessors described five products using, respectively, four, seven and five attributes.

agreement between the assessors and to create a consensus product map. However, multiple factor analysis (MFA, see Data S2, Escofier & Pagès, 1990; Abdi & Valentin, 2007) or any multi-block analysis (*e.g.* STATIS, see Data S3, Escoufier, 1980; Abdi *et al.*, 2011; or DISTATIS, Abdi & Valentin, 2007) can also be used. Multi-block analyses give product maps similar to those obtained with PCA. The main difference is that the maps display specific terms of all the assessors rather than common terms.

Applications to food products

Although FP has become somewhat popular in food companies – mostly in France where it was developed – only a few scholarly publications referring to this new technique were available until recently. After a first application on red fruit jams (Dairou & Sieffermann, 2002), FP has been applied by the same group to describe fruit dairy products (Delarue & Sieffermann, 2004), chewing gum (Delarue & Loescher, 2004), fruit jelly (Blancher *et al.*, 2007), bread texture (Lassoued *et al.*, 2007), fruit purées (Tarea *et al.*, 2007) and lemon ice tea (Veinand *et al.*, 2011). It is currently used more widely and outside of France to address various issues. For example, Ramírez Rivera *et al.* (2009) used it in association with a Taguchi design to optimise the formulation of smoked shrimps. Albert *et al.* (2011) compared it with QDA to describe hot served foods with contrasting textural layers as fish nuggets. Jaros *et al.* (2009) combined it with a hedonic test to explore the main driving of preference of cloudy apple juices. Gómez Alvarado *et al.* (2010) evaluated the effect of origin on the sensory characteristics of Cuajada cheese, and Rason *et al.* (2006) used it to evaluate the sensory diversity of traditional dry sausages.

Variations on flash profile

A variant of FP called ranking descriptive analysis (RDA) was recently proposed by Bragato Richter *et al.* (2010). This variant is based on previous work by Rodrigue *et al.* (2000) in which untrained assessors had to rank sweet corn samples on ten pre-defined attributes. In RDA, assessors first develop a consensual vocabulary. This procedure involves four steps: (i) attribute development with selection of the most frequent terms; (ii) definition of the selected terms; (iii) development of a consensus evaluation procedure; and (iv) finally, like in FP, assessors are asked to rank the samples for all the selected terms. RDA can be seen as a compromise between DA and FP. Although not as fast as FP, it preserves the idea of using a consensual vocabulary, and this facilitates data interpretation.

Pros and Cons

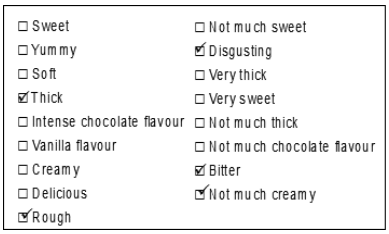
The main advantage of FP is to provide a product map in a very short time because the phases of familiarisation with the product space, attribute generation and evaluation have been integrated into a single step. Another advantage is that FP allows for a diversity of points of view because, for example, assessors from different countries and using different languages can be included in the same study. Besides these advantages, FP presents some weaknesses. First, although the authors of studies comparing FP and QDA have reported that these techniques gave similar product maps, these authors also noted that 'the interpretation of sensory terms is not always easy due to the large number of terms and the lack of definitions and evaluation procedure' (Albert *et al.*, 2011) and that 'the semantic consensus obtained in the conventional profile allowed a more accurate description of the products' (Delarue & Sieffermann, 2004). Another weakness of FP is that – as it relies on ranking – it is not suitable for large numbers of products because tasting too many products often produces saturation effects and short-term memory problems. In addition, it could be difficult to compare products that require careful temperature control or have persistent sensory characteristics. Finally – according to Delarue & Sieffermann (2004)– expert assessors are to be preferred to consumers to obtain reliable data. By 'expert assessors', these authors mean assessors having previously performed several descriptive evaluation tasks being able to understand the panel leader's instructions and to generate discriminative and non-hedonic attributes, even if these assessors were not trained on a specific product set.

Check-all-that-apply

Origin and general principle

The CATA or 'pick-any' approach originated from the work of Coomb (1964) and was first used in marketing research for studying consumers' perception of different brands (see, *e.g.* Driesener & Romaniuk, 2006). It has been recently introduced in sensory evaluation to understand consumer preference to help optimising food products (Adams *et al.*, 2007; Lancaster & Foley, 2007).

A CATA question consists of a list of attributes (words or phrases) from which assessors should select all the attributes they consider appropriate to describe a product. Products are presented one at a time to the assessors according to a balanced (*e.g.* Williams Latin square) or randomised design. Assessors are asked to evaluate each product and to check in the list the attributes that best describe the product (Fig. 3). Assessors can check as many attributes as they wish and can take as much time as needed. The attributes are not constrained to sensory aspects but could also be related to hedonic and emotional aspects as well as product usage or concept fit (Dooley *et al.*, 2010). The terms can be chosen by the assessors using, for example, a focus



Product	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17
1	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	1	1
2	1	1	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	1	0
4	0	0	1	0	0	1	1	0	0	0	0	0	1	0	0	0	0
5	1	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	1
6	0	0	0	0	1	0	1	0	1	1	0	1	0	0	0	1	0
7	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	1	1	0	0	1	0	0	0	1	1	0	0

Figure 3 An example of check-all-that-apply question (From Ares et al., 2010a,b) and data coding. Assessors are asked to check all attributes that describe a given product. Attributes (A1 to A17) that have been checked for a given product are assigned a value of one, the other attributes have a value of zero.

group (the assessors can be the same as the ones performing the CATA task or not). Alternatively, the terms can be derived from the results of open-ended questions (Aeres *et al*. 2010a). Open-ended questions are usually used in consumer tests in addition to a hedonic scale to obtain a rough product description. After evaluating their liking of the products, consumers are asked to provide a few terms to either describe the products or to indicate what they like or dislike about these products (Ares *et al*., 2010a; Symoneaux *et al*., 2012; ten Kleij & Musters, 2003).

Statistical analysis

A frequency matrix is compiled by counting the number of assessors who used each attribute to describe each product. This matrix is obtained by summing the individual 1/0 matrices depicted in Fig. 3. Correspondence analysis (CA) can then be performed on the frequency matrix to obtain a sensory map of the products. CA (see Data S4) is a generalised PCA tailored for the analysis of qualitative data. Multi-block analyses, such as MFA or multiple correspondence analysis (MCA), have also been used (Ares *et al*., 2011a,b). Recently, Popper *et al*. (2011) have also suggested using a variant of CA called multi-block Hellinger analysis that relies on the Hellinger/Bhattacharyya distance (see Abdi, 2007; Abdi *et al*., 2012) rather than the chi-square distance of CA and that can also integrate individual differences.

Applications to food products

Although CATA is a relatively recent addition to the food sensory evaluation toolbox, it seems to become popular in product optimisation where it is used to probe consumer product perception. It has been applied to salty snacks (Adams *et al*., 2007; Popper *et al*., 2011), strawberry cultivars (Lado *et al*., 2010), vanilla ice cream (Dooley *et al*., 2010), chocolate milk dessert (Ares *et al*., 2010a,b), orange-flavoured powdered drinks (Ares *et al*., 2011a,b) and texture perception of milk desserts (Bruzzone *et al*., 2011). It has also been used in addition to hedonic ratings to provide an alternative to classical external preference maps generated from sensory profiles (Dooley *et al*., 2010; Ares *et al*., 2011a,b). In a very recent paper, Plaehn (2012) proposed to use a penalty/reward analysis akin to the one used for 'Just About Right scales' (Lawless & Heymann, 2010) to analyse CATA questions in association with hedonic ratings. This new approach, although promising, still needs additional work to be better understood and validated.

Variations on check-all-that-apply question

A variant of CATA, called 'pick-*K* attributes', (or 'pick *K* over *N'*, see Coomb, 1964, pp. 66*ff*) is also used in the marketing and in the sensory domain. In this variant, assessors receive also a list of attributes, and they are asked to choose the *K* attributes that are dominant or that describe best a product. In the food sensory domain, this method had been mostly applied to describe aroma of complex products such as wines (McCloskey *et al*., 1996; Chollet & Valentin, 2000) or beers (Chollet & Valentin, 2001). The main difference between CATA and pick-*K* attributes is that when *K* is small, the pick-*K* attributes method highlights the main sensory characteristics of the products, whereas the CATA method provides a more complete description. The choice of using CATA or pick-*K* attributes thus depends on the specific objective of the study.

Pros and Cons

All publications using CATA concluded that this method was powerful enough to discriminate between samples. Compared with DA, the main advantage of CATA is its great simplicity both from the assessors and experimenter points of view. Its main limitation – as underlined by Dooley *et al*. (2010) – is that it produces counts (*i.e*. frequencies) rather than ranking or intensities, and because nominal data tend to have less power than quantitative data, CATA can require a rather large number of assessors. Also, because of the relative novelty of this method in food product description, further work is needed to assess its validity in this domain. The main issues with CATA are the choice of the list – how to optimise the list proposed to the assessors – and the choice of the number of attributes to

be used. This last problem can be crucial, because, for example, previous work by Hughson & Boakes (2002) showed that providing a short list rather than a longer list to consumers asked to describe a set of wines lead to more efficient descriptions, as measured by a matching task between descriptions and wines. A final limitation worth noting is that CATA seems to be more adapted to elicit judgments from consumers than from trained assessors because standard methods are likely to provide more information when used with trained assessors. Also, CATA seems to be better suited when used with sensory judgments than with other domains as suggested by Popper *et al*. (2011) who noted that, for unbranded products, variables describing sensory properties were more significant than variables related to domains such as emotions. These authors, however, suggested that for branded products, emotional variables would then become more relevant.

Similarity-based methods

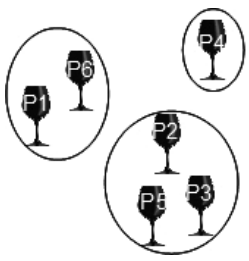
One of the main issues with verbal-based methods is that they rely heavily on an analytical perception of the products as well as on the ability to translate sensations into words. As a consequence, it is likely that product aspects difficult to verbalise will be overlooked by these methods. The methods presented in this section alleviate this problem by relying first on a global perceptual step in which the similitude between the products is evaluated. The verbalisation of the differences between products occurs only in a second step or can even be omitted.

Free sorting task

Origin and general principle

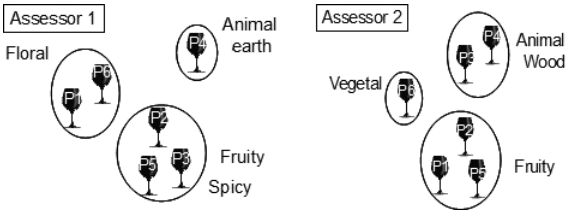
The free sorting task (FST) originated in Psychology (Hulin & Katz, 1935), a field that has used it routinely (see, *e.g*. Miller, 1969; Imai, 1966; for early applications; see also Coxon, 1999; for a thorough review and historical perspectives) to reveal – via statistical analyses – the structure of stimuli perceptual space and to interpret the underlying dimensions of these spaces. In the sensory domain, FST was first used in the early nineties to investigate the perceptual structure of odours (Lawless, 1989; Lawless & Glatter, 1990; MacRae *et al*., 1992; Stevens & O'Connell, 1996; Chrea *et al*., 2005). Lawless *et al*. (1995) were the first to use FST with a food product.

Free sorting task consists in a single session. All products are presented simultaneously and randomly displayed on a table with a different order per assessor. Assessors are asked first to look at, smell and/or taste (depending on the objectives of the study) all the products and then to sort them in mutually exclusive groups based on product-perceived similarities (Fig. 4). Assessors can use the criteria they want to perform their sorts, and they are free to make as many groups as they want and to put as many products as they want in each group. Once they are done with their groupings, assessors can be asked to provide a few terms to characterise each group they formed (Lawless *et al*., 1995; Tang & Heymann, 1999; Saint-Eve *et al*., 2004; Faye *et al*., 2004; Lim & Lawless, 2005; Faye *et al*., 2006; Cartier *et al*., 2006; Blancher *et al*., 2007; Lelièvre *et al*., 2008). This procedure (Fig. 5) is called 'labeled sorting' by Bécue-Bertaut & Lê (2011). To facilitate both the assessors' task and data analysis, a pre-established list can be provided during this step to help assessors labelling their groups (Lelièvre *et al*., 2008). An often



	P1	P2	P3	P4	P5	P6
P1	1	0	0	0	0	1
P2	0	1	1	0	1	0
P3	0	1	1	0	1	0
P4	0	0	0	1	0	0
P5	0	1	1	0	1	0
P6	1	0	0	0	0	1

Figure 4 An example of free sorting task and data coding. One assessor was asked to sort six products presented simultaneously in as many groups as needed based on products perceived similarity. The assessor grouping was then coded in a co-occurence matrix with a value of 1 if two products were grouped together and a value of 0 if two products were not grouped together. The diagonal values are set to 1 (because a product is always sorted with itself).



	Floral	Fruity	Spicy	Animal	Moldy	Vegetal	Woody
P1	1	1	0	0	0	0	0
P2	0	2	1	0	0	0	0
P3	0	1	1	1	0	0	1
P4	0	0	0	2	1	0	1
P5	0	2	1	0	0	0	0
P6	1	0	0	0	0	1	0

Figure 5 An example of labelled sorting and data coding. Assessors were asked to provide a few attributes to describe their product groups. Data are coded by counting the number of assessors who cited a given attribute for a given product.

encountered problem with labelled sorting is that assessors spontaneously qualify their attributes with various quantitative terms such as ''very', ''many', 'slightly', and this makes data interpretation rather cumbersome. To alleviate this problem, Lelièvre *et al.* (2008) suggested to provide the assessors with a pre-defined set of quantifiers to indicate the intensity of the perceived attributes (*e.g.* ''not', ''a little', ''medium and ''very').

Statistical analysis

A similarity matrix is generated by counting the number of times each pair of stimuli was sorted in the same group. This similarity matrix can be obtained by summing the individual 0/1 matrices depicted in Fig. 4. In the sensory field, this similarity matrix is generally submitted to non-metric multidimensional scaling (MDS), but metric MDS can also be used because the sorting similarity provides a Euclidean metric (see Abdi *et al.*, 2007). MDS (see Data S5) produces a spatial representation of the product similarity in which products are represented by points on a map. The points are arranged in this representation so that the distances between pairs of points reflect as well as possible the similarities among the pairs of stimuli. The coordinates of the stimuli on the spatial representation are often used as input to a cluster analysis to reveal product groupings in the MDS representation. Multi-block analyses that take into account individual data such as DISTATIS (Abdi *et al.*, 2007), MCA (Takane, 1982; Cadoret *et al.*, 2009) or common components and specific weights analysis (SORT CC, Qannari *et al.*, 2009) have also been used recently. For French readers, a presentation of these methods can be found in Faye *et al.* (2011).

The analysis of the descriptors associated to the groups of products depends upon the authors. Most analyses start by constructing a contingency table with descriptors in row and products in columns (Fig. 5). The values in the contingency table indicate the frequency at which each descriptor was employed for a stimulus. The descriptors given for a group of stimuli are assigned to each stimulus of the group and descriptors given by several assessors are assumed to have the same meaning. If the intensity of the descriptors is evaluated as suggested by Lelièvre *et al.* (2008), geometric means (Dravineks, 1982) can be used instead. The resulting contingency tables are quite large, and so the list of descriptors is generally reduced by grouping together terms with similar meanings and by discarding descriptors used by fewer than a certain number of assessors (*e.g.* 10%). The frequency data can then be projected onto the similarity maps by computing the correlations between the occurrence of descriptors and the stimuli factor scores (Faye *et al.*, 2004; Cartier *et al.*, 2006). Alternatively, the contingency table can be submitted to a CA to position both stimuli and descriptors on a descriptor-based space (Picard *et al.*, 2003; Soufflet *et al.*, 2004) or to an MCA (Cadoret *et al.*, 2009). Recently, Bécue-Bertaut & Lê (2011) used hierarchical MFA to compare sorting data collected from several panels.

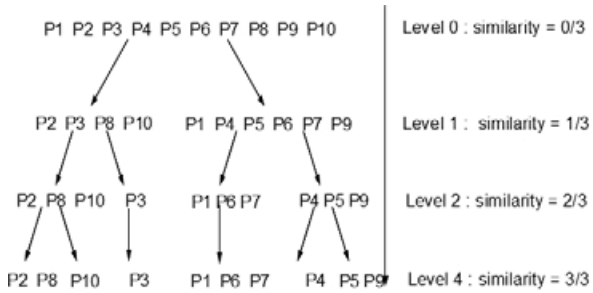
Applications to food products

Free sorting task is currently the most popular alternative method to classical descriptive analysis of food products. It has been used on a large variety of food products including vanilla beans (Heymann, 1994), cheese (Lawless *et al.*, 1995), drinking waters (Falahee & MacRae, 1995, 1997; Teillet *et al.*, 2010), fruit jellies (Tang & Heymann, 1999; Blancher *et al.*, 2007), beers (Chollet & Valentin, 2001; Abdi *et al.*, 2007; Lelièvre *et al.*, 2008, 2009), wines (Piombino *et al.*, 2004; Ballester *et al.*, 2005; Bécue-Bertaut & Lê, 2011), yoghurts (Saint-Eve *et al.*, 2004), spice aromas (Derndorfer & Baierl, 2006), cucumbers and tomatoes (Deegan *et al.*, 2010). FST has also been used to understand how consumers perceive food products such as meat or meat-substitute products (Hoek *et al.*, 2011), wine (Ballester *et al.*, 2008; Campo *et al.*, 2008) or beer (Lelièvre *et al.*, 2009).

Variations on the sorting task

A first variation on FST, referred to as 'directed sorting task' consists in providing information on either the number (*e.g.* the assessors may be asked to sort the products into two or three groups) and/or the nature (*e.g.* the assessors may be asked to sort – according to the colours red, rosé, or white – a set of wines that are presented in dark glasses) of the groups (Ballester *et al.*, 2009; Chollet *et al.*, 2011). This type of directed sorting is very useful, for example, to evaluate the effect of the region of origin on food products sensory characteristics (Parr *et al.*, 2010).

Another variation first proposed by Rao & Katz (1971) is called hierarchical sorting task (Fig. 6). In this variation, assessors are asked to form a given number of groups based on perceived similarities. Then, assessors are asked to successively merge the two groups that are most similar up to the time when a single group is formed (ascendant hierarchical sorting, see Coxon, 1999), or inversely to separate each group into finer groups up to the time when no further separation is possible (descendant hierarchical sorting, Clark, 1968) or both (Kirkland *et al.*, 2000). Ascendant hierarchical sorting has been applied to milk chocolate recently under the name of taxonomic free sorting by Courcoux *et al.* (2012). Descendant hierarchical sorting has been applied to olive oil by Santosa *et al.* (2010) and to cards by Cadoret *et al.* (2011). Hierarchical sorting seems to give more precise information than FST as it gives rise to a more graduate measurement of the similarity



	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
P1	1	0	0	0.33	0.33	1	1	0	0.33	0
P2	0	1	0.33	0	0	0	0	1	0	0.66
P3	0	0.33	1	0	0	0	0	0.33	0	0.33
P4	0.33	0	0	1	0.66	0.33	0.33	0	0.66	0
P5	0.33	0	0	0.66	1	0.33	0.33	0	1	0
P6	1	0	0	0.33	0.33	1	1	0	0.33	0
P7	1	0	0	0.33	0.33	1	1	0	0.33	0
P8	0	1	0.33	0	0	0	0	1	0	0.66
P9	0.33	0	0	0.66	1	0.33	0.33	0	1	0
P10	0	0.66	0.33	0	0	0	0	0.66	0	1

Figure 6 Example of descendant hierarchical sorting and data coding. Assessors were asked to sort ten products in two groups and then to sort each group into two subgroups up to the time they could not sort the products anymore. In this example, the assessor used three sorting levels. The similarity between products is coded as the last level at which they have been sorted together divided by the number of sorting levels. Two products sorted together at the third level will have a similarity score of 3/3, two products sorted together at the second level will have a score of 2/3 and so on.

between products than the 0/1 data provided by FST. According to Courcoux *et al.* (2012), the position of the products on the sensory map could be more stable than that provided by FST. But further studies are needed to validate this contention.

Pros and Cons

Free sorting task is well adapted to obtain a coarse characterisation of products or to select a subset of products for conducting further DA (Giboreau *et al.*, 2001; Piombino *et al.*, 2004). Despite a few differences, perceptual maps obtained with FST are globally comparable with those obtained from DA (Faye *et al.*, 2004; Saint-Eve *et al.*, 2004) and seem to be reproducible (Cartier *et al.*, 2006; Falahee & MacRae, 1997; Lelièvre *et al.*, 2008; Chollet *et al.*, 2011). FST is suitable for use with untrained assessors (Chollet *et al.*, 2011). As for FP, however, the vocabulary is difficult to interpret, and all the samples should be presented in a single session. In addition, with FST a time costly pre-processing is generally needed to analyse product descriptions. Moreover, work by Patris *et al.* (2007) suggests that FST might not be as easy a task as generally accepted. These authors filmed trained and novice assessors performing a beer sorting task and then invited them to comment on their behaviour at specific instances during the task. Both groups of assessors found the task difficult to perform, especially novice assessors who reported memory difficulties as well as saturation problems.

Placing, projective mapping, spatial arrangement procedure or Napping®

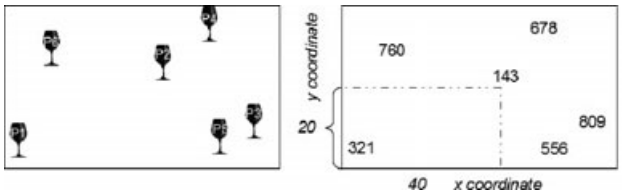
Origin and general principle

The idea of projective mapping (PM) was first mentioned by Dun-Rankin (1983) under the name of 'placing' to describe a technique in which assessors are asked to express the similarity structure of a set of stimuli by the stimuli's relative positions on a plane. It was then reintroduced independently in the mid-nineties under the names of 'PM' by Risvik *et al.* (1994, 1997) in the sensory evaluation field and of 'spatial arrangement procedure' (SAP) by Goldstone (1994) in the psychology field. With PM – also called Napping® by Pagès (2003, 2005) with an intriguing mixture of French and English (*nappe* means tablecloth in French) – the assessors are asked to place the stimuli on a piece of paper to express the similarity structure of the stimuli. The procedure in SAP is similar, but the assessors position the stimuli on a computer screen. Because the appellation of PM (or Napping®) has been used mostly in sensory evaluation (see MacKay, 2001 for an exception), we will use this denomination.

Projective mapping consists in a single session. As in FST, all products are presented simultaneously and are randomly displayed on a table with a different order for each assessor. Assessors are asked first to look at, smell and/or taste (depending on the objectives of the study) all the products and then to position the products on an A3 white sheet of paper (60 by 40 cm) according to the similarities or dissimilarities between these products (Fig. 7). Assessors are instructed that two products should be placed very close to each other if they are perceived as identical and far one from the other if they are perceived as different. There is no further instruction as to how the samples should be separated in this space, and so each assessor chooses his/her own criteria. After they have positioned the products on the map, assessors can be asked to describe each product by writing a few words directly on the sheet near the products (Fig. 8). This technique is referred to as Ultra FP by Perrin *et al.* (2008). Assessors are free to re-taste the samples as often as they want and to take as much time as needed.

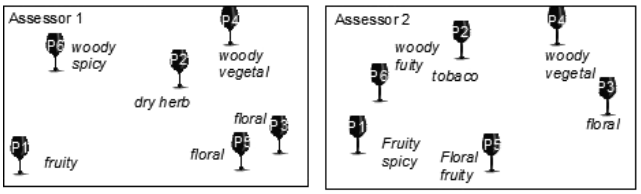
Statistical analysis

The X and Y coordinates of each sample are recorded on each assessor map and compiled in a product-by-assessors table where each assessor contributes to columns representing, respectively, his or her X and Y coordinates (Fig. 7). The matrix is then submitted to a



Product	code	x	y
P1	321	5	5
P2	143	40	20
P3	809	55	10
P4	678	45	35
P5	556	50	5
P6	760	10	30

Figure 7 An example of projective mapping (aka Napping®). An assessor was asked to taste all the samples presented on a piece of paper and to arrange them on the paper in such a way that similar samples are located near one another and different samples are placed far apart. After the assessor had positioned the products, the assessor was asked to mark the location of each sample with their corresponding three digit codes. The data are then coded by recording the coordinates of the samples on the assessor map.



	Assessor 1		Assessor 2		Attribute frequencies						
Product	*x1*	*y1*	*x2*	*y2*	fruity	woody	spicy	dry herb	floral	vegetal	tobaco
P1	5	5	7	5	10	2	0	0	0	0	0
P2	35	20	15	20	30	0	0	1	0	0	1
P3	55	10	55	10	18	0	0	0	2	2	0
P4	45	35	40	35	35	0	2	0	0	0	0
P5	50	5	35	5	5	1	0	0	2	0	0
P6	10	30	10	30	20	1	1	0	0	0	0

Figure 8 An example of data table obtained with projective mapping (aka Napping®). Two assessors positioned the products on the map and described them using seven descriptors.

multivariate analysis to provide a sensory map of the products. Originally, PM data were analysed with PCA and SAP with non-metric MDS. More recently, Pagès (2003, 2005) proposed to use MFA because this technique takes into account the differences between assessors. As usual, other equivalent methods could be used such as INDSCAL (Bárcenas *et al*., 2004; Nestrud & Lawless, 2011) or DISTATIS (Abdi & Valentin, 2007). As for FST, the coordinates of the samples on the resulting product maps can be used as input to a cluster analysis to reveal sample groupings. When a description step is used, the same approaches as the ones described for FST can be applied to characterise the samples (Fig. 8). Alternatively, Perrin *et al*. (2008) (see also, Abdi & Valentin, 2007; and Albert *et al*., 2011) proposed to add the descriptive data as supplementary variables in the MFA of PM coordinates.

Applications to food products

Although PM appeared in sensory evaluation at about the same time as FST, it has been much less used than the sorting task. A regain of interest in PM could be noted in food companies during the last decade probably as a consequence of its promotion under the name of Napping® by Pagès (2003). Despite this regain of interest, PM has given rise to a smaller number of scientific publications than FST. Yet, PM has been applied to diverse food products such as chocolate (Risvik *et al*., 1994; Kennedy & Heymann, 2009), commercial dried soup samples (Risvik *et al*., 1997), snack bars (King *et al*., 1998; Kennedy, 2010), ewe milk cheeses (Bárcenas *et al*., 2004), citrus juices (Nestrud & Lawless, 2008), wines (Morand & Pagès, 2006; Pagès, 2003, 2005; Perrin & Pagès, 2009; Perrin *et al*., 2008), hot beverages (Moussaoui & Varela, 2010), fish nugget (Albert *et al*., 2011), and apples and cheese (Nestrud & Lawless, 2010).

Variations on projective mapping

Recently, Pagès *et al*. (2010) proposed a variation in PM which they called 'sorted napping'. The idea behind sorted napping is similar to that behind hierarchical sorting. Assessors are asked first to position a set of products on a sheet of white paper. Then, they are asked to regroup similar products by circling, on the sheet of paper, products that belong to the same group. However, the benefit of this variation over PM remains to be validated.

Pros and Cons

Projective mapping gives rise to perceptual maps comparable to those obtained with DA for obvious aspects of the products (Risvik *et al*., 1994, 1997; Perrin *et al*., 2008) and seems to be reproducible at the group level (Risvik *et al*., 1994, 1997; Kennedy, 2010). As FST, PM is well adapted for obtaining product coarse descriptions. An often cited, difficulty of PM is to constrain the assessors to use two dimensions to discriminate between the products (Perrin *et al*., 2008). However, this constraint may not be too much of a problem. For example, Goldstone (1994) compared SAP with two different types of pairwise comparisons of stimuli and found that the spaces, recovered by non-metric MDS, for these different techniques were highly correlated and that the solution obtained from SAP had

the same dimensionality than the other methods. Recent work by Nestrud & Lawless (2011) using 3D shapes reached the same conclusion. Indeed, in practice, multivariate analyses (MFA or INDSCAL) of individual 2D PM configurations often seem to recover the full dimensionality of the objects. Again, the main drawback of PM as a way to describe products is the difficulty to interpret precisely the descriptions provided by the assessors (Perrin *et al*., 2008) as well as the necessity of presenting all the samples in the same session. From a practical point of view, Veinand *et al*. (2011) report that PM was somewhat difficult to perform for assessors showing spatial difficulties. They observed that *de facto* many assessors performed a FST (grouping together samples on the paper map) rather than a real PM. Also, the same memory problems as for FST are likely to occur with PM for large product sets.

Reference-based methods

The methods described previously do not enable data aggregation as all samples need to be presented at the same time. This might be problematic in circumstances when (i) the number of products to be tested is too large to be presented in a single session, (ii) a new product needs to be described or (iii) only one product is available at a time – as, for example, in quality control. The methods presented in this section propose a way to address this issue. The main idea is to keep a comparative method but instead of comparing all the products together to compare them to a (or a set of) reference(s).

Polarised sensory positioning

Origin and general principle

Polarised sensory positioning was initially proposed by Teillet *et al*. (2010) to define the sensory characteristics of water using consumers. The basic idea behind polarised sensory positioning (PSP) is to replace a large number of sensory attributes by a few prototypical products or references that will act as 'meta-attributes'.

In PSP, assessors receive first the three reference products, and then, the products to be evaluated are presented one at a time to the assessors according to a balanced (*e.g*. Williams Latin square) or randomised design. Assessors are asked to observe, smell and/or taste each product (depending on the objectives of the study) and the three reference products and to evaluate, on a continuous scale, the dissimilarity between the products to be evaluated and the three reference products (Fig. 9).

Statistical analysis

Teillet *et al*. (2010) suggest two strategies to analyse PSP. In the first one, the dissimilarities between the products and each reference product are averaged across assessors, and the resulting product-by-references matrix is submitted to MDS unfolding. This technique can recover a spatial configuration under the assumption that the intensities of the judgments of an assessor are proportional to their distances from an ideal point (see Coomb, 1964; and MacKay, 2001 for an application to food science). In the second strategy, individual data are preserved (Fig. 9) and the results analysed using STATIS or MFA.

Variation on polarised sensory positioning

Teillet *et al*. (2010) proposed a simplified version of PSP that they named Triad-PSP. In this simplified version, assessors are asked to indicate to which reference product the product under scrutiny is the most similar and to which it is the least similar. Data are then analysed using CA (MCA could be also considered). According to the authors, Triad-PSP and PSP lead to similar results, but Triad-PSP seems to be somewhat more discriminant and easier for assessors than PSP. These results, however, need to be verified in further studies.

Applications to food products

So far, PSP gave rise to only one scientific publication in the food domain where it was applied to the description of mineral waters (Teillet *et al*., 2010). The authors started using DA and FST to describe a set of commercial mineral waters and tap waters. These methods revealed a pattern – structured around a minerality gradient – suggesting (according to the authors) the presence of three main types of waters. A commercial exemplar of each type was then selected as reference product for PSP. The main advantage of PSP was then to be able to position tap water samples relative to these three stable commercial references.

Pros and Cons

Although very recently introduced in the field of sensory evaluation, PSP seems to be a very promising method whose main advantages are (i) to be easy to perform by assessors as they are only required to evaluate the global

	Assessor1			Assessor 2		
	A	B	C	A	B	C
P1	4	9	1	3	7	2
P2	2	3	7	1	4	8
P3	4	1	8	6	2	7
P4	3	4	5	2	5	4
P5	8	2	3	7	3	1

Figure 9 Example of polarised sensory positioning answer sheet and data coding. The three reference products are labelled A, B and C. The assessor was asked to compare the taste of the sample with the three references (from Theillet *et al*., 2010).

similarities between samples and reference products and (ii) to allow the compilation of data across sessions. Results obtained on mineral water (Teillet *et al.*, 2010) and on cosmetic products (Navarro *et al.*, 2011) are comparable to those obtained with standard DA. The main drawbacks of PSP is that the descriptions of the products are obtained only indirectly by deduction from the sensory characteristics of the most similar reference product and that it can be used to aggregate data only in situations where stable references can be found. Finally, this method requires a good knowledge of the product space to be able to select optimal product references. Further work will be needed to better understand this method and in particular to evaluate the effect of the number and nature of the products selected as references.

Pivot profile©

Origin and general principle

At about the same period as PSP, Thuillier (2007) developed a somewhat related method called pivot profile© (PP). PP was developed in the field of wine description and build on the idea of free description techniques often used in this field. Free description consists in asking assessors to freely write down, without any constraint, all the product attributes that they perceive. This method allows for a rich description of the products, but the data interpretation calls upon textual analyses that are often difficult to carry as well as quite time-consuming. The strategy implemented in PP to simplify data analysis and to reduce inter-individual variability is to collect free descriptions of the differences between two products: a sample product and a single reference product (the so called pivot).

In PP, assessors are first provided with the reference product, and then, the products to be evaluated are presented one at a time to the assessors according to a balanced (*e.g.* Williams Latin square) or randomised design. Assessors are asked to observe, smell and/or taste each product (depending on the objectives of the study) and the reference product and to write down each attribute that the product has in smaller or larger amount than the reference product (*e.g.* less sweet, more astringent) as shown Fig. 10. Assessors are instructed to use only descriptive words without any sentence. The negative form is not allowed (*e.g.* flat for non-effervescent). The reference product is chosen within the range of products to be evaluated.

Statistical analysis

Data analysis begins by regrouping synonyms and optionally regrouping the terms by categories. Then, negative and positive frequencies are computed for each term and each product, and the negative frequency is subtracted from the positive frequency (Fig. 11). The

	Less	More
Visual appearance	Orange, bright	Red
Smell	Fruity, spicy, alcool	Floral, honey
Taste	Sweet	Bitter
Texture	Tanin, palate weight	Springy
After taste	Short	

Figure 10 Example of pivot profile© answer sheet. The assessor is asked to indicate all the attributes that the product has in less or in more than the reference product (Thuillier *et al.*, 2007).

	Less	More
Visual appearance	Orange, bright	Red
Smell	Fruity, spicy, alcohol	Floral, honey
Taste	Sweet	Bitter
Texture	Tannin, palate weight	Springy
After-taste	Short	

	less	More
Visual appearance		Red
Smell	Fruity	Floral, honey
Taste	Sweet	
Texture	Body	
After-taste		

		Less	More	Subtraction	After translation
Visual appearance	Orange	1	0	−1	1
	Bright	1	0	−1	1
	Red	0	2	2	4
Smell	Fruity	2	0	−2	0
	Spicy	1	0	−1	1
	Alcohol	1	1	0	2
	Floral	0	2	2	4
	Honey	0	1	1	3
Taste	Sweet	2	0	−2	0
	Bitter	0	1	1	3
Texture	Tannin	1	0	−1	1
	Palate weight	1	0	−1	1
	Springy	0	1	1	3
	Body	1	0	−1	1
After-taste	Short	1	0	−1	1

Figure 11 An example of data table obtained with pivot profile©. Two assessors described one products.

resulting score is finally translated so as to obtain positive scores only. The final matrix is submitted to CA to obtain a sensory map of the products.

Applications to food products
As for PSP, PP gave rise to only one scientific publication in the food domain where it was applied to the description of a set of champagnes (Thuillier, 2007).

Pros and Cons
Pivot profile© seems to be a very promising method for complex products such as wines where a tradition of free description is relatively strong among experts. This method might provide a trade-off between experts' practice and sensory evaluation. It might prove also useful for other products because it allows for a fast direct description of the products with the possibility of aggregating data as long as a stable reference is available. As in PSP, the main difficulty of PP remains the choice of the reference product, and, here also, further work is needed to explore this issue.

Comparison between methods

As a testimony of the current interest in alternative descriptive analyses, there have been recently several comparisons between these methods and classical DA as well as between verbal- and similarity-based methods.

Comparison of alternative and conventional descriptive analysis

Consumers are often considered as being only capable of making hedonic judgments. Yet, alternative descriptive methods based on consumers were recently compared with classical DA finding similar sensory spaces with R_V coefficients (a measure of similarity between matrices akin to a squared coefficient of correlation, see Abdi, 2010) often >0.8 (Dairou & Sieffermann, 2002; Delarue & Sieffermann, 2004; Cartier *et al.*, 2006; Blancher *et al.*, 2007; Kennedy & Heymann, 2009; Moussaoui & Varela, 2010; Albert *et al.*, 2011). These studies used products varying in complexity: from simple cold products (such as jam or jelly) to complex and heterogeneous hot products (such as fish nuggets). Differences in the terms used for the samples' description were, however, observed, with consumers using a more varied and spontaneous vocabulary and trained assessors using fewer but more precise terms (Albert *et al.*, 2011). This last observation suggests that DA tends to be more accurate and reliable owing to the extensive training of the assessors. Risvik *et al.* (1997), for example, report that the largest similarity between maps obtained via PM and DA was found for the first dimension, a pattern that suggests a 'good agreement for the obvious aspects of the products'. Therefore, it seems that DA might enable to identify smaller differences between samples, particularly when dealing with complex samples and/or sensory characteristics than alternative methods. Yet, according to Albert *et al.* (2011), DA – as it requires a consensus from the panel – could potentially lead to some loss of information. Accordingly, those authors suggested that FP used with semi-trained panellists might yield a more detailed description of the samples than DA. On the other hand, as noted by Lelièvre *et al.* (2009), the interpretation of untrained consumer's sensory terms is not always easy owing to the large number of terms and the lack of definitions and evaluation procedures. Another disadvantage of all alternative methods compared with DA is that these alternative methods do not give rise to average rating scores, and thus, the assessment of least significant differences between products or the visual display of individual attributes is not possible (Albert *et al.*, 2011). Additionally, data analysis is not standard and generally more complex than for conventional DA. Further developments aiming at integrating the different stages of data analysis into a unified user-friendly software package are still needed.

Comparison of flash profile and similarity-based methods (projective mapping or free sorting task)

Blancher *et al.* (2007) were the first to compare FP and FST in a study focusing on the visual appearance and the texture of eighteen sweet jellies samples evaluated by French and Vietnamese participants. They showed that whatever the culture, FP and FST lead to similar maps, with, nevertheless, a few noticeable differences. The authors explain these small discrepancies in terms of the nature of the task (verbal methodology vs. non-verbal methodology) and assessors' strategy when performing the task. According to the authors, in FST assessors are asked to concentrate on the global similarities between the products, whereas in FP, assessors dissect their perceptions into attributes. This last point is consistent with the fact that, in an additional comparison contrasting both FP and FST to DA, FP was shown to be closer to DA than to FST.

More recently, Albert *et al.* (2011) compared FP and PM on fish nuggets with contrasting textural layers. FP was performed by ten semi-trained assessors, and PM was carried out by twenty untrained assessors. The sensory maps obtained by FP and PM were well correlated, but clusters obtained from Hierarchical Cluster Analysis (HCA) were somewhat different. According to the authors, this difference might be explained, in addition to the fact that the assessors differed for the two methods, by the fact that in FP assessors are asked to generate as many terms as possible to differentiate samples before ranking them,

whereas in PM the description is done after the mapping. This difference might focus the assessors' attention on very different dimensions of the samples and more readily accessible or global dimensions might take on a greater importance in PM than in FP. Accordingly, the authors conclude that FP gave 'more detailed information about the samples characteristics', whereas PM 'tended to summarise the information'.

Similar results were observed by Veinand *et al.* (2011) who compared FP and PM with eight lemon ice tea samples evaluated by about forty consumers for each method. In their study, despite a few differences in sample positioning, sensory maps were globally similar, but this might be in part owing to a strong opposition between two products and the other products. FP seemed to be more discriminant than PM. Both methods were repeatable. PM allowed eliciting more terms than FP. From a practical point of view, PM was on the average somewhat faster than FP (40 vs. 50 min), and the quantity of ice tea drunk by the consumers was more important for FP than for PM. And, thus, PM assessors reported to be less saturated and tired than FP assessors. In contrast, PM was more difficult to perform and to explain than FP. Veinand *et al.* concluded their paper with the suggestion that PM should probably be limited to expert panellists.

A superiority in term of discrimination and precision of descriptions of FP over PM and FST was also reported by Moussaoui & Varela (2010) in a study carried out on eight hot beverages. Twenty-four untrained assessors evaluated the samples with each method. In addition, this study showed that assessors were more repeatable – as measured using a replicated sample – with FP than PM and FST. Finally, PM was found to be more efficient – as measured by comparison with classical DA – than FST and also led to more repeatable results. Along the same lines, Nestrud & Lawless (2010) reported that, when applied to apples and cheese, PM and FST gave similar sensory maps but that a cluster analysis performed on the sensory maps was more easily interpretable for PM than for FST. However, this result still needs to be generalised to other products.

Comparison of check-all-that-apply and similarity-based methods (projective mapping or free sorting task)

Ares *et al.* (2011a) compared PM and CATA in the context of ideal products characterisation using seven samples of orange-flavoured powdered juice drinks. First, consumers evaluated the sensory characteristics of the samples using either PM or CATA. For PM, they were asked, in addition, to position their ideal product on their map, whereas for CATA they were asked to check all the terms they consider appropriate to describe their ideal product. The different approaches yielded similar information regarding the sensory characteristics of the products, but differences were observed in the positioning of the ideal product. According to the authors, PM might be more adapted to characterise ideal products than CATA because PM forces assessors to locate their ideal product within the sample space, whereas with CATA the ideal product might be located outside this space (*e.g.* the ideal product might load very high on the naturalness dimension, whereas all the samples load very low on this dimension). Moreover, locating an ideal product on a map seems to be a more intuitive and easier task than checking it for multiple attributes, as this last process might induce some rationalisation. However, from a practical point of view CATA is perceived as less difficult than PM and is, in general, less time-consuming (about 10 vs. 20 min on the average).

In another publication by the same group, Ares *et al.* (2011b) compared CATA with PM and FST using again seven powdered juice samples. For each method, fifty panellists evaluated the samples. After the evaluation, the panellists were asked to rate the difficulty of the task using a nine-point structured scale anchored with 'very easy' on the left and 'very difficult' on the right. CATA, PM and FST provided very similar information both in terms of product positioning and description except for two products for which the similarity-based methods differed from CATA. According to the authors, this difference was owing to sensory characteristics that were not included in the CATA list and so were not taken into account by assessors using this method. Difficulty score analysis showed that assessors perceived similarity-based methods as more difficult than CATA.

How to evaluate the reliability of alternative descriptive methods

Despite the fact that all the proposed approaches seem promising, further work is clearly needed to better characterise them. In particular – as noted by Blancher *et al.* (2012) – we are still lacking unified tools to evaluate the reliability of the methods. Some authors use repetitions (*e.g.* Falahee & MacRae, 1997; Cartier *et al.*, 2006; Lelièvre *et al.*, 2008), some other authors use duplicate samples (*e.g.* Moussaoui & Varela, 2010; Chollet *et al.*, 2011), other authors use R_V coefficients to compare maps obtained by several panels (Lelièvre *et al.*, 2008; Chollet *et al.*, 2011), whereas other authors use bootstrapping to draw confidence ellipses around the products (Abdi & Valentin, 2007; Ballester *et al.*, 2009; Santosa *et al.*, 2010) on the sensory map. Blancher *et al.* (2012) propose a simple tool that can be used routinely to assess whether FST results are reliable. In their paper, they considered that 'results can be considered reliable if the sorting map is stable, *i.e.,* if conducting again an experiment under similar condi-

tions (same panelists, same stimuli, and same instructions) the experimenter would get a similar sorting map'. To assess the stability of the sorting solution, Blancher *et al.* propose to use resampling techniques (see, also, *e.g.* Strother *et al.*, 2002) and to draw large numbers of samples of different sizes from the original set and to compute the average R_V coefficient (which they called R_{Vb}). These authors suggest to consider these techniques as reliable experiments for which this average R_{Vb} is at least equal to 0.95. Even though more work is needed to define a good threshold and its properties, this work constitutes a first important step that deserves to be extended to other approaches than FST.

Conclusion

To sum up, on the whole all methods presented in this review seem to be adapted when coarse descriptions are sufficient. They provide product spaces that are generally comparable to those obtained with conventional DA. Yet, DA might still be more appropriate when the objective of the researcher is to find out small differences in the intensity of specific sensory attributes as sometimes is the case, for example, in product optimisation. Further work is still needed, though, to better understand the extent to which alternative methods can be used to describe complex food products or products with small sensory differences. For such complex products, combining ideas from conventional and alternative approaches might be a good line of future research. For example, in a very recent paper, da Silva *et al.* (2012) propose to use a very short training period along with the presentation of reference materials during the evaluation to allow semi-trained panellists to quantify sensory attributes. Along the same lines, Talaverabianchi *et al.* (2010) proposed a method based on *a simplified user-friendly lexicon – which they call high identity traits (HITS) – as an alternative to traditional DA*.

Most alternative methods can be used either with trained or untrained panellists (although, some authors suggest to use experts or sensory-trained assessors for FP and PM) and all provide more or less similar product spaces. Some differences and specificities can, however, be noted. Although further work is needed to fully confirm this statement, verbal-based methods (FP and CATA) seem to provide more detailed and readily interpretable descriptions and seem to be more discriminant than similarity-based methods. Similarity-based methods seem to be more suited for providing summarised sensory information. Reference-based methods are too recent and need further explorations and comparisons with other methods. Among verbal-based methods, FP is more time-consuming and leads to more saturation problems than CATA but has the advantage of providing ordinal data rather than mere frequencies. Among similarity-based methods, PM might be more discriminant than FST but appears to be more difficult to understand and to perform. Among reference-based methods, PSP might be better suited to compare new products with known ones, and PP to describe a set of products. Ultimately, the choice between methods depends mostly on both practical issues and the specific objectives of the studies.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Data S1. Generalized procrustean analysis (GPA).
Data S2. Multiple factor analysis.
Data S3. Statis.
Data S4. Correspondance analysis (CA).
Data S5. Multidimensional scaling.

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Supplementary material 1

GENERALIZED PROCRUSTEAN ANALYSIS (GPA)

General principle

Generalized procrustean analysis (GPA) is a technique that tries to find a consensus configuration from a set of individual configurations obtained from the principal component analysis (PCA) of a set of data tables. So, the first step of GPA consists in performing a PCA of each of the data tables and to keep a small number of components (typically 2 or 3). Then, the factor scores (i.e., the coordinates of the objects on the principal components) of one table are taken as reference and the procedure tries to fit the factors scores of the other tables onto the first set of factor scores (called the "reference" set of factor scores) using procrustean analysis (PA). PA tries to fit one configuration of factor scores to the reference set by using three types of transformation: rotation, reflection, and expansion. After all the tables have been fitted to the reference, one of the fitted factor score configuration is selected and will play the role of the reference set of factors scores to which all the other sets of factors scores are now fitted using PA. The procedure is iterated till convergence is reached. The final configuration is called the consensus and it plays a role analogous to the compromise configuration of STATIS. Just like in MFA and STATIS, the fitted configurations can be projected onto the consensus configuration.

An example: Flash profile of five products (cf. section 11.2)

As an illustration a GPA was apply to the data matrix shown Figure 2 section 11.2). Figure S1 displays the products in the space of the first two principal components along with the product projections for the three assessors. The first component opposes products 307 and 385 to products 124 and 909. The second component opposes product 909 to product 145. The product projections for the three assessors show how each assessor "interprets" the product space. The lines linking the products to the color dots represents the deformation needed to transform the map of an assessor to the consensus map.

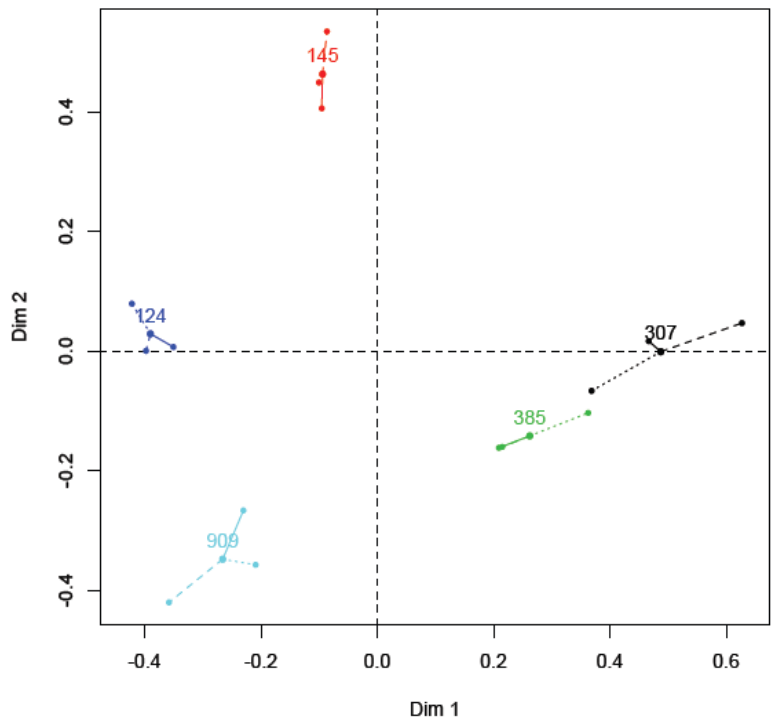

Figure S1.: The map of the products From GPA.

Supplementary material 2

MULTIPLE FACTOR ANALYSIS

General principle

Multiple factor analysis (MFA) is a generalization of principal component analysis (PCA) which allows for analyzing data tables in which a set of objects is described by several sets of variables. MFA is performed in three steps. First, a principal component analysis (PCA) is performed on each data set. Second, each data set is "normalized" by dividing all its elements by the square root of the first eigenvalue obtained from of its PCA (this normalization is akin to the *Z*-score transform used to standardize variables). This normalization balances the influence of each data set. Third, the normalized data sets are merged to form a unique matrix and a global PCA is performed on this matrix. The individual data sets are then projected onto the global analysis.

An example: Flash profile of five products (cf. section 11.2)

As an illustration a MFA was apply to the data matrix shown Figure 2 section 11.2). Figure S2a displays the products in the space of the first two principal components along with the product projections for the three assessors. The first component explains 55.15% of the inertia. It opposes products 307 and 385 to products 124 and 909. The second

component explains 36.37 % of the inertia. It opposes product 909 to product 145. The position of each product in the global analysis is the barycenter (i.e., centroid) of its positions for the assessors. The product projections for the three assessors show how each assessor "interprets" the product space. The lines linking the assessors' product projections to the global product position reveal the agreement between assessors: The shorter the lines the larger the agreement.

As in standard PCA, the variable loadings on the principal components are computed as the correlation between the original variables and the global factor scores. These loadings are plotted in Figure S2b along with the "circles of correlation."

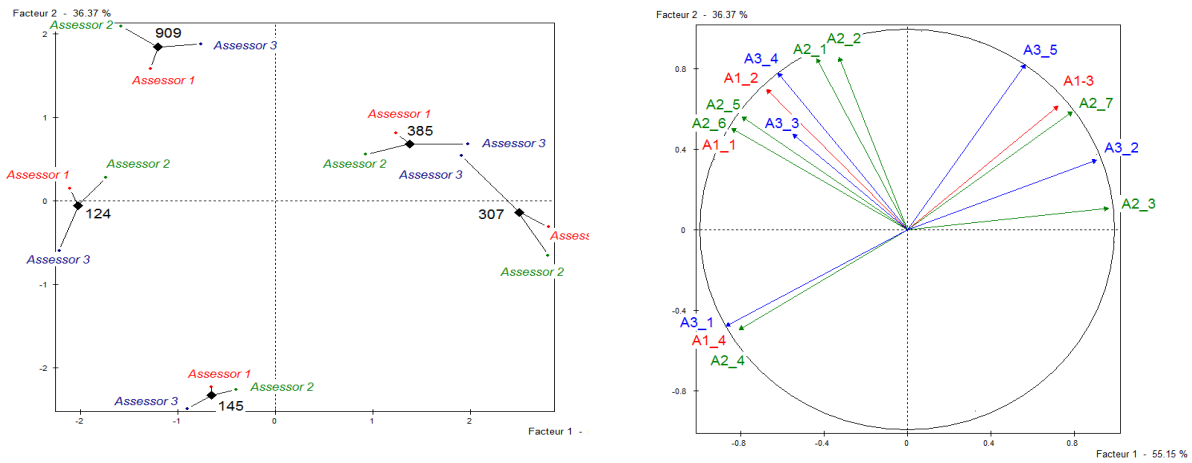

Figure S2. : a) The map of the products, b) The attributes as loadings along with the circle of correlation.

Supplementary material 3

STATIS

General principle

STATIS—an acronym that stands for the French expression *'Structuration des Tableaux à Trois Indices de la Statistique'* meaning approximately 'structuring three way statistical tables'—is a generalization of principal component analysis (PCA) which allows for analyzing data tables in which a set of objects is described by several sets of variables. STATIS is performed in two steps. First, it analyzes the relationship between the different data tables and derives from this analysis an optimal set of weights that are used to compute a linear combination (i.e., a weighted sum) of the data tables called the compromise. The weights are chosen so that the data tables agreeing the most with other data tables will have the larger weights. This is done so that the compromise will best represents the information common to the different data tables Second, the compromise is submitted to a PCA which will give an optimal map of the objects. Finally, like in MFA, the individual data sets can be projected onto the global analysis.

An example: Flash profile of five products (cf. section 11.2)

As an illustration STATIS was apply to the data matrix shown Figure 2 section 11.2)Figure S3a displays the products in the space of the first two principal components along with the product projections for the three assessors. The first component explains 55.22% of the inertia. It opposes products 307 and 385 to products 124 and 909. The second component explains 36.65% of the inertia. It opposes product 909 to product 145. The position of each product in the global analysis is the barycenter (*i.e.,* centroid) of its positions for the assessors. The product projections for the three assessors show how each assessor "interprets" the product space. The lines linking the assessors' product projections to the global product position reveal the agreement between assessors: The shorter the lines the larger the agreement.

In STATIS, the loadings (Figure S3b) are obtained from the standard loadings of a PCA (see Abdi *et al.,* for more details). Alternatively, the loadings could be obtained as correlations between the original variables and the factor scores obtained for the products.

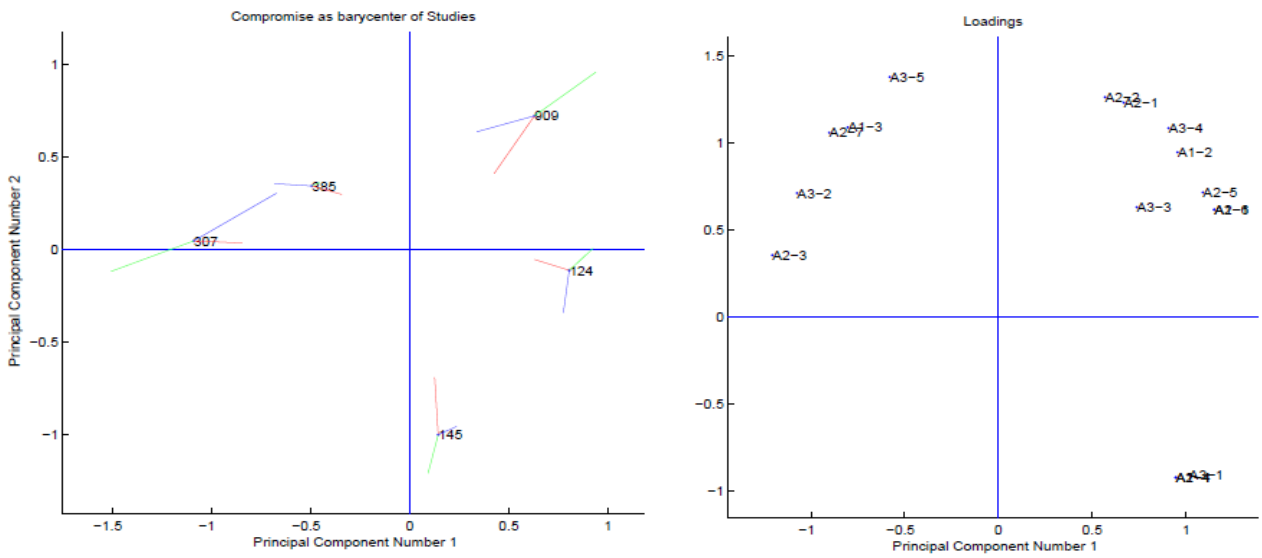

Figure S3. a) The map of the products, b) Map of the loadings for the attributes.

Supplementary material 4

CORRESPONDANCE ANALYSIS (CA)

General principle

Correspondence analysis (CA) is a generalized principal component analysis (PCA) tailored for the analysis of qualitative data. Classically, CA is used to analyze frequency tables. The first step in CA is to transform the data table into *row profiles by* dividing each row of the data matrix by its total and to assign a mass to each row and a weight to each column. The mass of each row is the proportion of this row in the total of the table and the weight of each column is inversely proportional to its use and so the mass of a row reflects its importance in the sample and the weight of a column reflects its importance for *discriminating* between the objects described in the table. The second step consists into applying a singular value decomposition to the row profile matrix This operation provides factors scores for both rows and columns which can be plotted as a map where each point represents a row or a column of the data matrix. An essential property of CA is the so-called *duality principle*, which states that we can represent the rows and the columns in the same map.

An example: Check-all-that-apply (CATA) question (cf. section II.2)

Figure S4b displays the products in the space of the first two dimension of CA. The first dimension explains 44.33% of the inertia. It opposes products P3, P1, and P6 that were more often described as bitter, rough, and disgusting to products P2, P4, and P7 that were described more often as soft, yummy, creamy delicious, and vanilla flavor. The second component explains 18.71 % of the inertia. It opposes product P5 that was more often described as very sweet and very thick to product P8 that was more often described as not much thick and not much chocolate flavor.

	P1	P2	P3	P4	P5	P6	P7	P8
Sweet	1	15	0	5	17	2	6	5
Yummy	3	15	0	3	5	1	16	6
Soft	2	16	1	17	2	3	13	4
Thick	15	3	3	4	4	2	15	2
Int choco fl	5	4	13	1	14	13	4	2
Vanilla fl	0	14	1	8	2	0	12	11
Creamy	2	12	2	10	5	9	15	12
Delicious	3	3	1	3	3	0	13	5
Rough	19	1	17	0	2	15	0	0
Not much sweet	3	2	14	2	3	16	2	14
Disgusting	19	0	4	1	0	2	0	1
Very Thick	6	2	0	2	15	20	1	2
Very Sweet	0	4	0	14	16	0	4	2
Not much thick	2	2	4	3	2	2	3	18
Not much choco fl	4	2	2	2	1	1	2	15
Bitter	16	1	13	3	1	17	0	1
not much creamy	12	3	3	2	16	2	2	3

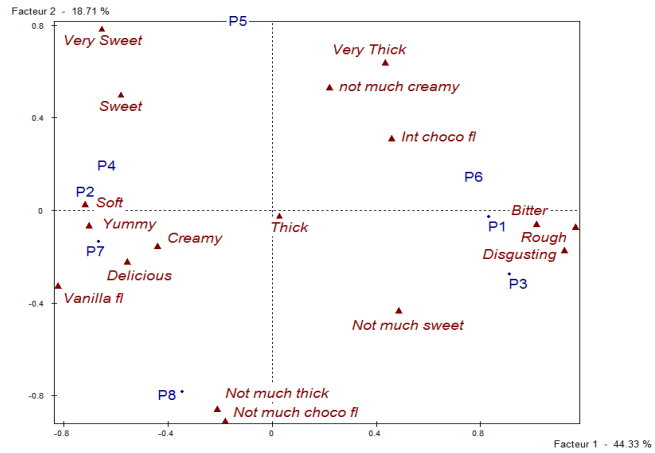

Figure S4.: a) frequency table obtained from the CATA question shown section II.2; b) products and descriptors CA map.

Supplementary material 5

MULTIDIMENSIONAL SCALING

General principle

Multidimensional scaling (MDS) is a data analysis technique used to visualize proximities or distance between objects in a low dimensional space. In MDS, each object is represented by a point in a multidimensional space. The points are arranged in this space so that objects that are perceived to be similar to each other are placed near each other on the map, and objects that are perceived to be different from each other are placed far away from each other on the map. The space is usually a two- or three-dimensional Euclidean space, but could be non-Euclidean and/or have more dimensions.

The input to MDS is a square, symmetric matrix indicating proximities among a set of objects. Different algorithms can be used to obtain the visual representation of the objects. These algorithms can be classified in to main categories: metric (also called classical) and non-metric MDS. In metric MDS, the proximities are treated directly as distances. The input matrix is first transformed into a cross-product matrix and then submitted to a principal component analysis (PCA). Like PCA, MDS can be used with supplementary or illustrative elements that are projected onto the dimensions after they have been computed. In non-metric MDS the proximities are treated as ordinal data. An iterative stepwise algorithm is used to create a visual representation of the objects. Before starting the algorithm, the dimensionality, denoted by *P,* of the solution needs to be chosen. The algorithm then proceeds with the following steps: 1) create an arbitrary configuration in *P*-dimensional space; 2) compute distances among all pairs of points; 3) compare the input matrix and the distance matrix using a stress function: the smaller the value of the stress the greater the correspondence between the two matrices (so stress is similar to one minus a squared correlation coefficient between the original data and the data on the map); and 4) adjust the object in the configuration in the direction that best decreases the stress. Steps 2 to 4 are repeated until the value of the stress is small enough or cannot be decreased any more. Different authors have different standards regarding the amount of stress to tolerate. The rule of thumb used in sensory evaluation is that anything under 0.2 is acceptable.

An example: Free Sorting task (section III.1)

A non-metric MDS was applied to the co-occurrence matrix resulting form a free sorting task performed by 14 assessors on 9 products (figure S5a). A stress value of .12 for a 2-dimensional space (Figure S5b) was judged to be satisfying.

	P1	P2	P3	P4	P5	P6	P7	P8	P9
P1	14	8	1	0	1	1	0	3	5
P2	8	14	0	0	3	1	0	3	4
P3	1	0	14	4	0	1	2	1	0
P4	0	0	4	14	1	2	9	0	0
P5	1	3	0	1	14	0	1	6	3
P6	1	1	1	2	0	14	2	0	2
P7	0	0	2	9	1	2	14	0	2
P8	3	3	1	0	6	0	0	14	0
P9	5	4	0	0	3	2	2	0	14

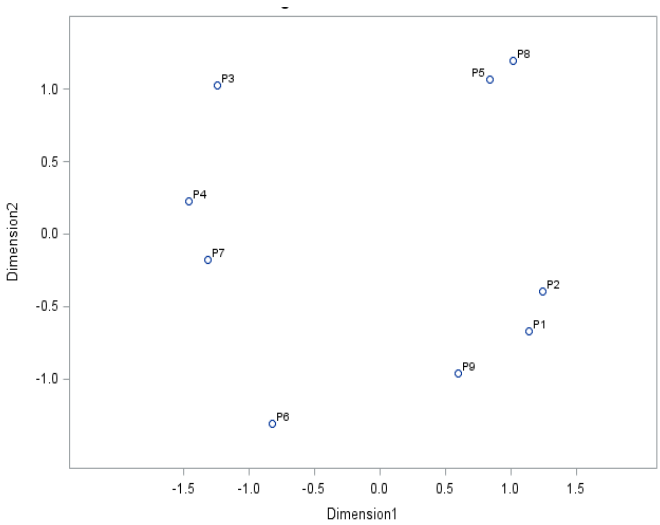

Figure S5.: a) co-occurrence matrix coding the results of the FST, b) product 2-dimensional space obtained via non-metric MDS.