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Projective Mapping and Sorting Tasks

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Abstract Projective mapping and sorting tasks—often called "Holistic" methods—are methods that directly obtain similarity measurements between products by asking participants (who could be novices, trained assessors, or experts, adults or children) to provide a global evaluation of a set of products of interest. In projective mapping, each participant is asked to place products on a sheet of paper in such a way that the positions of the products express the products' similarity structure. In the sorting task, each participant is asked to sort the products in groups such that similar products are sorted together. For both projective mapping and sorting—in order to derive a better understanding of the similarity structure between the products—participants are also sometimes asked to verbally describe products or groups of products. The statistical analysis of projective mapping and sorting tasks used well know techniques such as: (multiple and simple) correspondence analysis, multiple factor analysis, principal component analysis, multidimensional scaling, and DISTATIS.

Keywords projective mapping, sorting task, placing, hierarchical sorting task, Napping®, categorization, multiple factor analysis, correspondence analysis, multiple correspondence analysis, similarity measurements, holistic methods, spatial arrangement procedure (SAP), DISTATIS, multidimensional scaling (MDS).

1 Introduction

Projective mapping and the sorting task are rather old techniques in Psychology (dating at least from 1935 for the sorting task, see Hulin & Katz; and 1964 and 1983 for projective mapping, but under different names, see Coombs and Dun-Rankin), but, by contrast, their use is relatively recent in sensory evaluation (1989 and 1990 for the sorting task with Lawless and with MacRae, Howgate, & Geelhoed, and 1994 for the projective mapping with Risvik et al.; for reviews see Chollet et al.,

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2011, 2014, and Valentin et al., 2012). The main purpose of these methods is to obtain similarity measurements between products from participants who, in general, are not required to be trained assessors. These methods are loosely based upon the psychological construct of categorization (see, e.g., for reviews or relevant points of view, among others, Wittengstein, 1953; Rosch, 1973, 1978; Mervis & Rosch, 1976; Tversky, 1977; Abdi, 1986, 1987; Murphy, 2002; Cohen & Lefebvre, 2005; Valentin & Chanquoy, 2012), a concept that formalizes the cognitive function of spontaneously organizing the world in meaningful and important natural categories (e.g., animate vs. inanimate, see Sha et al., 2015) or in categories statistically derived from the correlational structure of objects' properties and features (Tversky, 1977). As far as sensory evaluation is concerned, however, the very large literature on categorization and concepts boils down to indicating that categorization requires little effort (i.e., it is mostly automatic) and that it occurs very early in life (probably even right at birth if not before, see Valentin & Abdi, 2001). Practically, this indicates that tasks based on simple categorization can be performed by untrained participants (including children, see, Gombert, Fayol, & Abdi, 1990) as well as by trained assessors and experts (Chollet, Valentin, & Abdi, 2005).

Similarity measurements differ from other descriptive methods used in sensory evaluation because they seek to elicit and analyze global similarities (sometimes called "holistic") between the products rather than analytical descriptions that rely heavily on the ability to translate sensations into words and therefore can overlook hard to verbalize product characteristics. Similarity based methods rely on an overall perceptual (i.e., non-verbal) evaluation of the products. The verbalization of differences-expressed by the participants and therefore dependent upon the participants' subjective scale for perceiving and reporting such differences-between products occurs only in a second step or is altogether omitted. Similarity based methodologies also have the advantage of bypassing the costly steps of panelist selection and training. In fact, many techniques exist to measure the similarity among a set of products: pair or triadic similarity scaling, sorting tasks, and projective mapping. Pair or triadic similarity scaling involves a direct measurement of the similarity between products. In a pair similarity scaling task, panelists are provided with a pair of products and are asked to rate the degree of dissimilarity between the two products on an unstructured scale (e.g., "please rate how similar these two products are by using a scale from 1 to 7 with '1' meaning very dissimilar and '7' meaning very similar"). In a triadic similarity scaling task, panelists are provided with three products and are asked to select, in this triad of products, the most similar and the most dissimilar pair of products. By contrast, with the direct methods of similarity scaling such as pairwise or triadic approaches, projective mapping and sorting tasks are indirect similarity measurements. In projective mapping, panelists are asked to position on a large sheet of paper the products according to the products' similarities and dissimilarities. In the sorting task, panelists are asked to sort/group products according to the products' similarities. Similarity scaling techniques have the advantage of providing a direct similarity measure but these techniques can be very time consuming (and are therefore, likely to fatigue the assessors who could, consequently, produce poor quality data) because the number of pairs or triads of products to be evaluated increases as an exponential function of the number of products in the set. For example, a set of 10 products would require each panelist to perform 45 pair comparisons and 120 triads. Projective mapping and the sorting task are much less time consuming but still provide reliable inter-product similarity. In this chapter we will focus on these last two methods. After presenting these two methods in details, we discuss their advantages and disadvantages. In general, both the sorting task and projective mapping can be used with a number of products similar to standard evaluation practice, with the caveat that all products need to be simultaneously presented to the assessors and therefore that fatigue of the assessors or carry-over effects need to be taken into account when using these techniques (see, e.g., Chollet et al., 2014, for a discussion of this problem). We first describe projective mapping, then the sorting task, and finally we briefly compare these two techniques. We also illustrate these techniques with small examples.

2 Projective mapping

The idea of projective mapping was first mentioned by Dunn-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 relative positions on a plane (an equivalent idea can also be found in the classic work of Coombs, 1964). It was then reintroduced independently and simultaneously in the mid-nineties under the names of "projective mapping" by Risvik (1994, 1997) in sensory evaluation and of "spatial arrangement procedure" (SAP) by Goldstone (1994) in psychology. With projective mapping—also called more recently Napping® by Pagès (2003, 2005, see also Lê, Lê, & Cadoret, 2015), a term that reflects an amusing mixture of French and English (i.e., "nappe" means tablecloth in French and so "Napping®" means "table-clothing" rather than taking a nap...)—the assessors are asked to place the stimuli on a piece of paper in order 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 name "projective mapping" (or Napping®) has been used mostly in sensory evaluation, we will use this denomination. In a recent variation of projective mapping—called "partial napping" (Dehlohm et al., 2012; Delhom, 2015)—the assessors as asked to evaluate the products several times, according to one perceptual domain at a time (e.g., assessors can be asked to evaluate a set of wines on color, aroma, and mouthful, see, Louw et al., 2013). In partial napping, the final analysis integrates all the partial napping in to a global framework.

2.1 Methodology

Projective mapping is performed in a single session. All products (with a minimum number of eight and a maximum number depending upon the nature of the products) are presented simultaneously and are displayed on a table with a different random order for each assessor. Each assessor is presented with a large sheet of paper (often 60cm × 40cm, but, of course, any size can be used as long as it provides ample space for panelists to comfortably separate products, a computer can also be used to record the data, see Savidan & Morris, 2015, for an evaluation of the modalities used for projective mapping, and also Lê, Husson, & Lê, in press, for a new computer assisted way of collecting Napping® data). Assessors are asked first to evaluate by looking at, smelling, feeling, and/or tasting (depending on the objectives of the study and on the products) all the products. The assessors are then asked to position the products on the sheet of paper according to the products' patterns of similarities or dissimilarities. Assessors are told 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 very 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.

Additionally, panelists can be instructed to write a few attributes/descriptors that they consider as characteristic of each product or groups of products. Integration of descriptive data into the analysis can enrich the interpretation of the product map generated. If a description step is implemented, it is crucial that (for both projective mapping and sorting) the description be performed after the participants have completed the first (non-verbal) part. The importance of separating these two steps is illustrated by a—now classic-experiment—of Wilson and Schooler (1991). In this experiment, untrained participants had to rate, on a hedonic scale, five jams that had been previously evaluated by a panel of expert assessors (the experts performed this task for the magazine Consumer Reports, as part of a standard article). One group of naïve participants simply evaluated the jams and their overall evaluation was significantly similar (with an average rank correlation of $r = .55$) to the experts' evaluation. By contrast, another group of naïve participants was asked to provide reasons for their choice, and the evaluation performed by this group showed no correlation with the experts' evaluation.

2.2 Data 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 two columns representing respectively his or her X and Y coordinates (by tradition, the coordinates are measured with the upper left corner of the sheet of paper representing the origin of the measurements, but, of course, any system will do as long as the units of measurement are the same for both dimensions). The data matrix is then submitted to a multivariate analysis to provide a sensory map of the products. Originally, projective mapping data were analyzed with principal component analysis (PCA, see Abdi & Williams, 2010a; Abdi, 2007e) or generalized Procrustean analysis (GPA, see Abdi, 2003) and SAP with non-metric multidimensional scaling (MDS). More recently, Pagès (2003, 2005) proposed to use multiple factor analysis (MFA, Escoffier and Pagès, 1990, Pagès, 2014; see also, Abdi et al., 2013; Abdi & Valentin, 2007; Lê & Worch, 2015) because this technique takes into account the differences between assessors. Other equivalent methods could be used such as INDSCAL (Barcenas et al., 2004; Nestrud & Lawless, 2011), STATIS (Lavit, 1988; Abdi et al., 2012), or DISTATIS (Abdi & Valentin, 2009; Abdi et al., 2005, 2007). The common goal of all these techniques is to provide a map of the products (called the compromise map) such that the positions of the products on the map best reflect the similarity of the products as perceived by the group of assessors. The descriptors can also be projected on this map. Most techniques will also provide an indication of how each assessor interprets the common space and some techniques (e.g., STATIS, DISTATIS, and MFA) can provide, in addition, around each product, confidence ellipsoids that can be used to assess the differences between products (see, e.g., Husson, Le Dien, & Pagès, 2005; Abdi et al., 2012; Cadoret & Husson, 2013). Some of these techniques (e.g., STATIS and DISTATIS) will also provide MDS-like maps of the assessors that can be used, for example, to identify outliers or groups of assessors.

2.3 Applications

Projective mapping has been applied to diverse food products such as, for example, 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's milk cheeses (Bárcenas et al., 2004), citrus juices (Nestrud & Lawless, 2008), apples and cheese (Nestrud & Lawless, 2011), and wines (Morand & Pagès, 2006; Pagès, 2003).

2.4 An example: projective mapping and Curry powder

In this example a projective mapping was carried out to evaluate the similarity between thirteen curry powders in order to select four different curry powders for an upcoming "spiciness" scoring test. Ten untrained assessors participated in the mapping. The order of presentation of the samples was performed according to a Latin Square in order to distribute potential carry-over and adaptation effects (nevertheless, we could also use a random presentation if, for example, the number of samples is too high to allow an efficient and rapid service).

2.4.1 Instructions

Participants were provided with the following instructions:

> You have in front of you 13 curry powders. Please smell all the samples and position them on the paper in such a way that similar samples are located near one another and different samples are placed far apart. You are free to evaluate the samples according to any criteria that you choose, and you will not need to specify your criteria. Feel free to use as much of the paper as is necessary to express the differences you may perceive. When you are finished, please mark the location of each sample with the corresponding number. You are free to take all the time that you need, and, if necessary, you can smell the crook of your elbow between each sample.

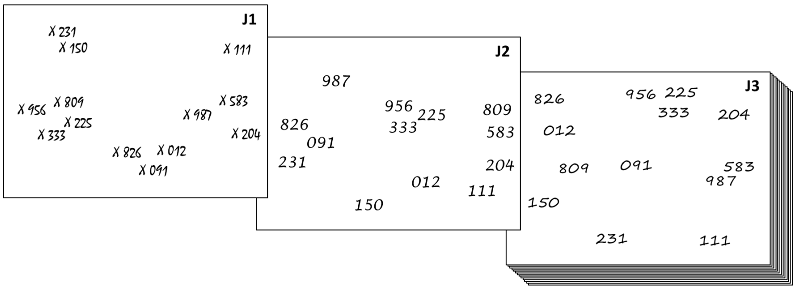
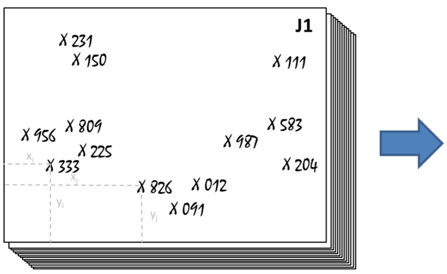


Figure 1: Example of score sheets obtained in the projective mapping test.

2.4.2 Score sheet

The score sheet was a 70cm × 55cm white sheet of paper (see Figure 1).

2.4.3 Data matrices



	J1		J2		J3		J4		J5		J6		J7		J8		J9		J10	
	X	Y	X	Y	X	Y	X	Y	X	Y	X	Y	X	Y	X	Y	X	Y	X	Y
P1	56	4	65,5	21	25,5	28,5	74,5	11,5	12	24	4,5	36,5	74	29	52	45,5	29,5	34	25,5	32
P2	48,7	30	46,5	14,8	16,2	35,5	78	6,5	15,5	45,5	22,5	26	11,5	36	2,5	2,5	9	7	17	38,5
P3	28	21,8	71,8	22,7	73,2	33	15,5	5	40	43,5	33,5	33	72,8	21,8	62	25	53	35	28	21
P4	34,5	27,5	31,5	14,8	83	33	12,5	11	56	17	47	30,8	79,5	28	79	32,5	61,5	27	43,5	28,5
P5	28	26	7	28,5	82,2	27	9,2	48	40	30	55,8	14,5	43,5	36	84,5	6	66,5	26,5	59	21,5
P6	52,2	7	62	46,2	25	35,5	6,5	30,2	55,2	44	46	54	67,5	18	39	40,5	42	10,8	15,5	42,5
P7	50	26	68,8	46,8	24,8	22	10,5	33	10,5	43,5	42,5	56	73	16,8	23	42,5	48,5	11,5	19,5	43
P8	76	23,2	20,5	36,5	72	25,8	35,5	47	52,5	21,5	57,5	17,5	42	16	82,5	23,5	72,5	42	57	27
P9	81	22,5	16	37	82	19,5	41	47	75,5	12	75	10	55,5	34,5	57,5	17	66	44,5	39	32
P10	53,8	29,2	60	21,5	36,5	35	78,8	10,5	35,2	29	48,5	21	66,5	25,5	40	47	25,5	38	45	33
P11	57,2	7	41,5	14,8	6,5	34,5	73,2	7	17	23,5	34,5	7,5	19	14,8	9,5	39	18	24	22,5	23
P12	33,5	22,5	36,5	14,8	16	28,5	7,5	8,2	17	29	10	33	31,5	35	5,5	21,5	15,5	28,5	22	19
P13	77,5	20,5	25,5	36	83,2	39	62	42,5	53	23	87	2	57,5	18,5	50	39	70,5	47	63	28

Figure 2: Example of data obtained in the projective mapping test.

For each judge, the coordinates $(X,\ Y)$ of each curry powder were measured and collected in a grand data table (see Figure 2).

2.4.4 Results

The data were analyzed with MFA, with each judge corresponding to one data table comprising two columns. As a preliminary step, an analysis of the judges was performed by first computing a matrix of the R_V coefficients computed between the judges (recall that the R_V coefficient can be interpreted as the squared coefficient of correlation between two configurations of data, see Abdi, 2007a, 2010). A PCA (specifically, an eigen-decomposition, see Abdi, 2007b) of this R_V matrix provides a map (shown in Figure 3) in which the proximity between judges represents their similarity. Figure 3 shows that Judges 2 and 7 differed from the other judges because these two judges positioned their curry powders differently than the other judges. Consequently, in the following steps of the analysis, the data of these two judges were eliminated. Even if the position of Judge 1 is rather eccentric, we decided to keep this judge because in the second analysis this judge's position was close to the other judges (and, as we did not have very many judges, we needed to keep as many judges as

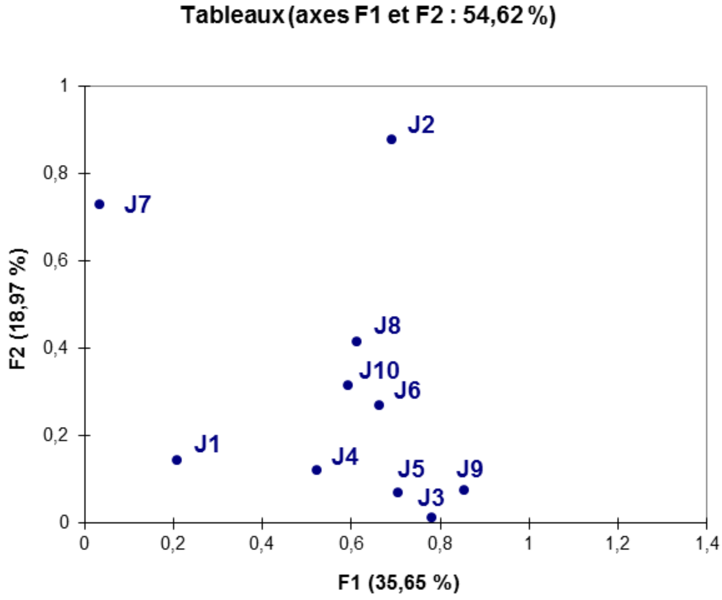


Figure 3: Map of the between judges similarity obtained from the analysis of the R_V coefficient table computed between the judges.

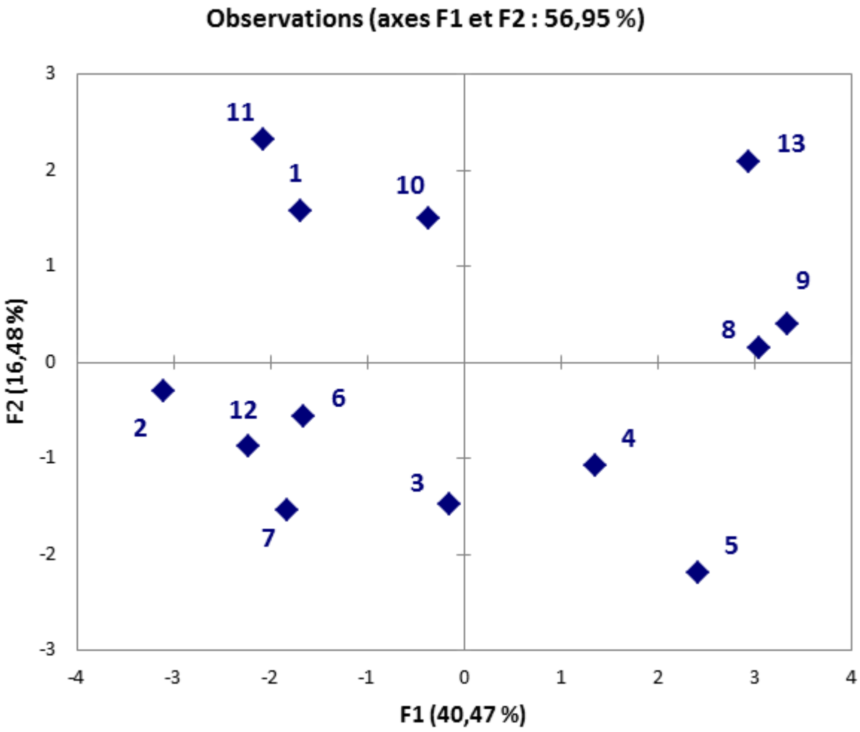


Figure 4: Compromise map for MFA. The data table of Judges 2 and 7 were not used to position the products.

possible, interestingly, however, the analysis performed without this judge was essentially the same as the analysis with this judge).

Visual inspection of Figure 4 suggests that there are four groups of curry powders: the first one is composed of P1, P10, and P11, the second one of P2, P6, P7, and P12, the third one of P3, P4, and P5, and the last one of P8, P9, and P13. From this map we can select four very different curry powders: for example P11, P13, P5, and P2, but if we wanted to select very similar products we could choose P2, P6, P7, and P12.

3 Sorting Task

The sorting task originated in Psychology (Hulin & Katz, 1935), and this field has used it routinely ever since (see Coxon, 1999, for a thorough review). The sorting task requires little effort and, actually, children as young as four year old can perform this task (Best & Ornstein, 1986). It was first used in the field of sensory evaluation in the early nineties to investigate the perceptual structure of odors (Lawless, 1989; Lawless & Glatter, 1990; MacRae et al., 1992; Stevens & OConnell, 1996; Ishii et al., 1997; Chrea et al., 2005, see also Abdi et al., 2007 for a review). Lawless et al., (1995) were the first to use a sorting task with a food product. In sensory evaluation, the focus of the analysis is to derive similarity maps between the products and, in some cases, to derive, in addition, similarity maps among the panelists. By contrast with sensory evaluation, other disciplines (e.g., Psychology, Marketing) are sometimes interested only in analyzing the similarity patterns between assessors (see, e.g., Hubert & Levin, 1976; Hubert & Arabie, 1985).

3.1 Methodology

The sorting task is performed in a single session. All products are presented simultaneously and are displayed on a table with a different random order for each assessor. Assessors are asked first to look at, smell, and/or taste (depending on the objectives of the study and the products) all the products and then to sort them in mutually exclusive groups based on product perceived similarities (see Figure 4). There is no further instruction as to how the samples should be grouped and so each assessor chooses his/her own criteria. Several variations of the sorting task exist where 1) the assessors are asked to further subdivide or regroup the products to produce a hierarchical distance matrix between objects (see Rao & Katz, 1971; see also Santosa et al., 2010, for an application to sensory evaluation), or 2) to provide several sorts (Steinberg, 1967; Rosenberg & Kim, 1975, see also Dehlholm et al., 2012, for an application to sensory evaluation under the name of Free Multiple Sorting). Both of these methods have the advantage of providing a finer grained evaluation of the products because the distances between two products can take a larger range of values than with the standard sorting task.

3.2 Data analysis

An overall similarity matrix is generated by counting the number of product co-occurrences (i.e., the number of times each pair of products was sorted in the same group). This similarity matrix is generally analyzed by Multidimensional Scaling (MDS, see Abdi 2007c,d for a review, see also Daws, 1996, and Courcoux et al., 2015, for possible alternatives), which is a technique used to visualize proximities or distances (for a definition of distances, see, e.g., Abdi, 2007d) between objects in a low dimensional space. In MDS, each object is represented by a point on a map. The points are arranged on this map so that objects that are perceived to be similar to each other are placed near each other, and objects that are perceived to be different from each other are placed far away from each other. Different algorithms can be used to obtain the visual representation of the objects. These algorithms can be classified into two main categories: metric MDS (also called classical MDS or principal coordinate analysis) 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). This method is optimum (i.e., it gives the best possible map to represent the data, see Abdi et al., 2007, for more details) when the distance matrix is a squared Euclidean distance matrix (which is the case for the distance matrix derived from a sorting task, as well as for hierarchical versions of the sorting task, see Abdi et al., 2007 for a proof). The goal of non-metric MDS is to find a map that preserves, as best as possible, the order of the distance rather than their magnitude (as metric MDS does). Non-metric MDS is best suited for the analysis of dissimilarities or non-Euclidean distances rather than for the analysis of Euclidean distances. 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 and roughly proceeds as follows: 1) the algorithm creates an arbitrary configuration; 2) the algorithm computes the distances among all pairs of points; 3) algorithm compares 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 (the stress is roughly equivalent to a non-linear coefficient of alienation or to inverse of a squared coefficient of correlation) and 4) algorithm adjusts 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. A common rule of thumb used in sensory evaluation is that any value of the Stress below 0.2 is acceptable. What method should we choose for analyzing sorting data? Because the co-occurrence matrix is equivalent to a squared Euclidean distance (see Abdi et al., 2007, for details), metric MDS will provide the best map (i.e., a 2-dimensional Euclidean distance) approximation of the data and should, therefore, be preferred. However the differences between metric or non-metric MDS are rarely of importance in practice because the solutions provided by both methods are very similar when using sorting tasks and so the choice between methods is mostly a matter of convenience, personal preferences, or habits (metric-MDS, however, makes it easier to evaluate the stability of the results by cross-validation methods). Some authors have also used additive tree representations to describe sorting data (see Abdi, 1990, for a review of these techniques, Chrea, et al., 2004, for an example, and Chollet et al., 2011, for a review concerning sensory evaluation) or hierarchical analysis performed on the products factor coordinates obtained from a metric MDS (Lelièvre et al., 2009).

Multi-block analyses that take into account individual data such as DISTATIS (Abdi et al., 2007, Mielby et al., 2014), Multiple Correspondence Analysis (MCA, Takane, 1980; Abdi & Valentin, 2007b; Cadoret et al., 2009, under the name of FAST; Lê & Worch, 2015), or common components and specific weights analysis (SORT CC, Qannari et al., 2009), have also been used recently (INDSCAL could also be used). These techniques provide a common map (often called a compromise) and also show how each assessor positions the products in the common space. Some of these techniques (i.e., DISTATIS, 2009; and FAST, see Cadoret et al., 2009) provide, in addition, a map of the assessors. The advantages of a having a map of the assessors are: 1) to be able to identify if some assessors differ from the other ones (e.g., one assessor having a cold and whose tasting ability is, consequently, reduced), 2) to be able to evaluate if groups of assessors systematically differ (e.g., do women and men differ in their way of sorting products), and 3) to discover if there are some natural groups of assessors (as can be revealed with techniques such as K-means or hierarchical analysis, see Lê & Worch, 2015; Beaton et al., 2015; Abdi & Beaton, 2016, for details).

Recall that in some cases the assessors are also asked to provide verbal descriptors for the groups of products after the sorting task has been performed. To facilitate the task, the assessors can be provided with a pre-established list of relevant terms (see Lelièvre et al., 2008). The analysis methodology of the descriptors associated to the groups of products depends upon the authors and upon the statistical techniques used for analyzing the data (unfortunately, there is no current relevant review of the literature so far to compare these methodologies). However, the current practices can essentially be regrouped in two main categories: 1) Most analyses will perform a separate analysis on the co-occurrence between words; and 2) a few analyses (i.e., DISTATIS, Abdi & Valentin, 2009; and FAST, see Cadoret et al., 2009 and Lê & Worch, 2015) will project the words directly onto the factor map of the products.

The analyses using a co-occurrence table will first build a contingency table with descriptors in row and products in columns. 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

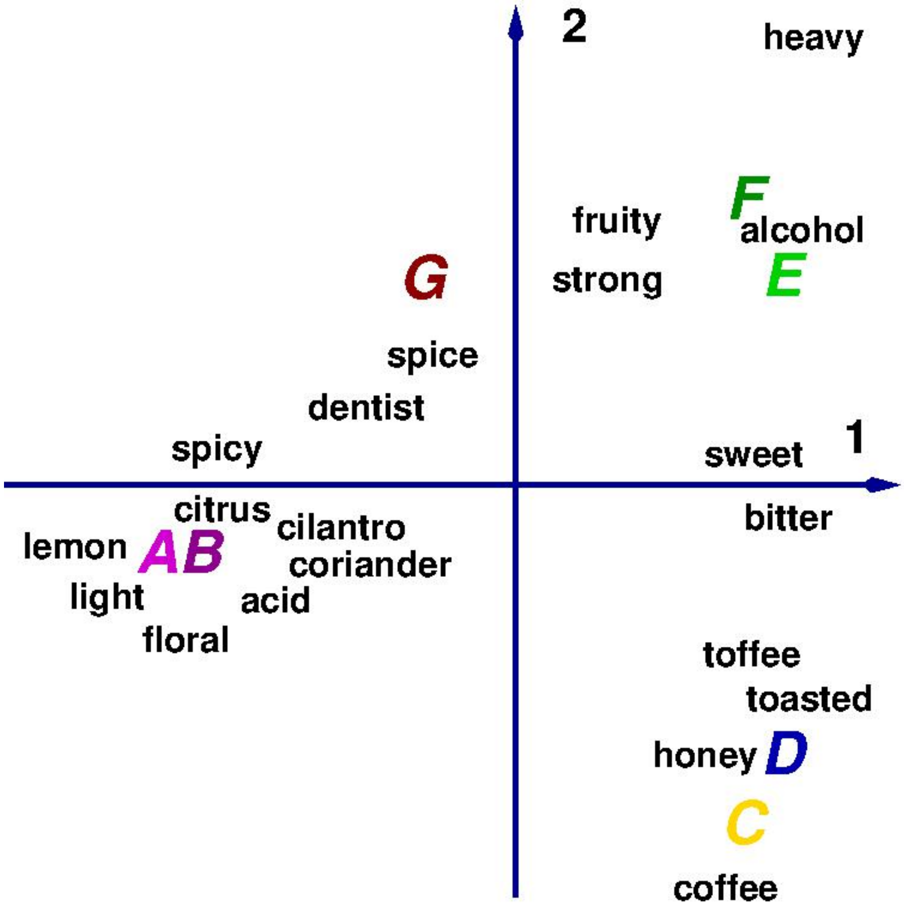


Figure 5: An example of the analysis results of a sorting task with products and descriptors. Here, seven beers (letters A to G) were sorted by eleven assessors who also described the groups of beers that they provided. The words have been lemmatized and have been projected as barycenters of the beers to which they have been associated. The analysis was performed with DISTATIS (for details and original data see Abdi & Valentin, 2007a).

to have the same meaning. The resulting contingency tables are quite large and so the list of descriptors is generally reduced by grouping together terms with similar meanings (a procedure known as lemmatization) and by discarding descriptors used by fewer than a certain number of assessors (e.g., less than 10

3.3 Application

The free sorting task is used when the investigators want to rapidly obtained a sensory map of a set of products (often without searching for any verbal description of the products). The simplicity of the sorting task made it particularly suited to be used with consumers (as opposed to trained assessors) and with participants who do not know the products to evaluate and are unable or unwilling to verbally describe them in a reliable way: such as novice consumers or even children (Lê & Worch, 2015; Valentin & Chanquoy, 2012). The sorting task has been used on a large variety of food products (see, e.g., Chollet et al., 2014) including vanilla beans (Heymann, 1994), cheese (Lawless et al., 1995; Nestrud & Lawless, 2010), drinking waters (Falahee & MacRae, 1995; Falahee & MacRae, 1997; Teillet et al., 2010), fruit jellies (Tang & Heyman, 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),

Table 1: Information about the 12 orange juices used in a sorting task (note: the names of orange juices with pulp are printed in italics).

Code	Formulation	Process	Presence of pulp
P1	Pure juice	Flash pasteurized	Yes
P2	Pure juice	Flash pasteurized	Yes
P3	Pure juice	Flash pasteurized	Yes
P4	From concentrate	Flash pasteurized	No
P5	Pure juice	Pasteurized	Yes
P6	Pure juice	Pasteurized	Yes
P7	Pure juice	Pasteurized	Yes
P8	From concentrate	Pasteurized	No
P9	From concentrate	Pasteurized	No
P10	From concentrate	Pasteurized	Yes
P11	From concentrate	Pasteurized	No
P12	From concentrate	Pasteurized	No

spice aromas (Derndorfer & Baierl, 2006), cucumbers and tomatoes (Deegan et al., 2010), apples (Nestrud & Lawless, 2010), and perfumes (Veramendi, 2013). The sorting task 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). Finally, the sorting task has been also used for the sensory evaluation of non-food products such as such, for example, as automotive fabrics (Giboreau et al., 2001; Picard et al., 2003), cloth fabrics (Souflet et al., 2004), plastic pieces (Faye et al., 2004), and pictures of products such as olive oil bottles and containers (Santosa et al., 2010; Mielby et al., 2014).

3.4 An example: sorting task and orange juice

In this example, in order to gain further insight into the development of new products, a manufacturer of orange juices wanted to know how consumers perceive the current orange juices available on the market. In particular, the manufacturer wanted to know if consumers perceived the sensory difference between, on the first hand, pure orange juices and orange juices from concentrate, and, on the other hand, between flash pasteurized and pasteurized juices. In order to answer this question, a sorting task was performed with twelve orange juices varying in term of formulation, manufacturing processes, and presence or absence of pulp (see Table 14.1 for a description of the orange juices used in this experiment). Thirty-one orange juice consumers participated in the sorting task. They received 150 mL of each sample in a plastic tumbler and were provided with mineral water for rinsing their mouth between samples if felt necessary. A tasting session lasted approximately 15 minutes.

3.4.1 Questionnaire/instructions

The participants to the experiment were given the following instructions:

> You have 12 samples of orange juices in front of you. Please, look at, smell, and taste these samples. Then make groups according to their similarity. You are free to make the groups according to any criteria that you may choose, and you do not need to specify your criteria. You can make as many groups as you want and group together as many orange juices as you want. You can take as much time as you want.

3.4.2 Score sheet

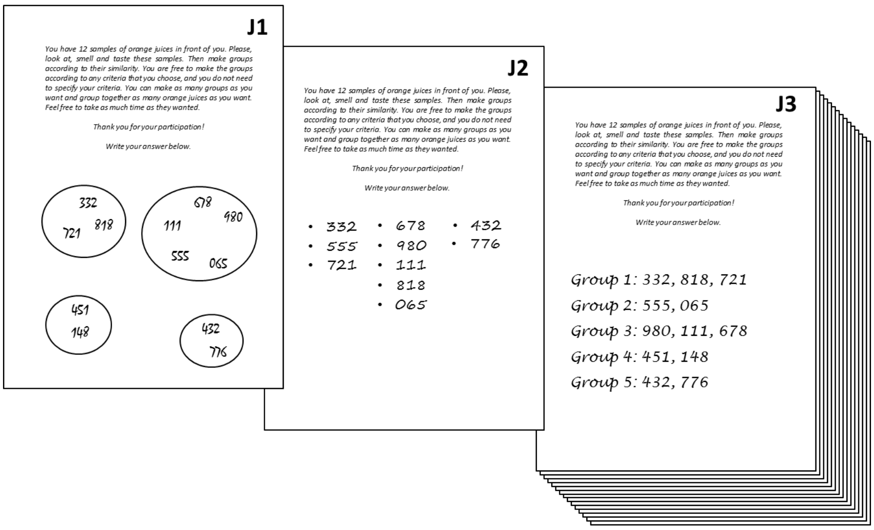


Figure 6: Example of score sheets obtained in a sorting task.

Examples of score sheets are shown in Figure 6.

3.4.3 Data matrices

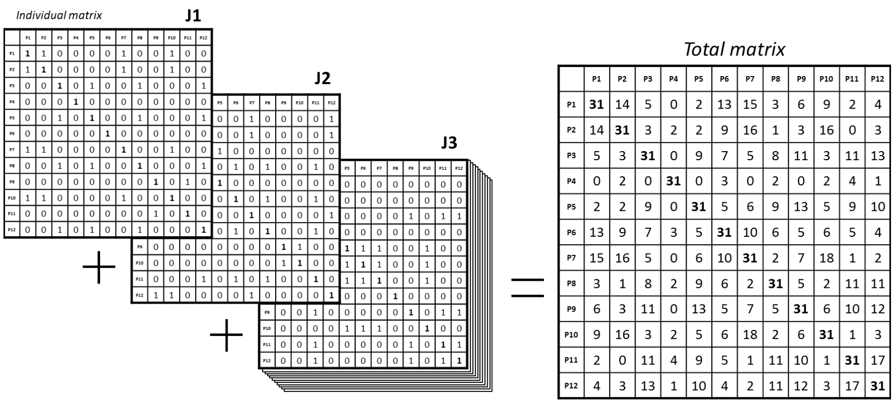


Figure 7: Example of data obtained in sorting task.

For each judge, the results of the sorting task were encoded in an individual co-occurrence matrix where both the rows and the columns represent the orange juices. In this matrix, a value of 1 at the intersection of a row and a column indicates that the judge put these two orange juices together in the same group whereas a value of 0 indicates that the orange juices were not put together. To obtain the global similarity matrix, all the individual matrices were summed (See Figure 7).

3.4.4 Results

Results were analyzed with two statistical methods: metric MDS and DISTATIS.

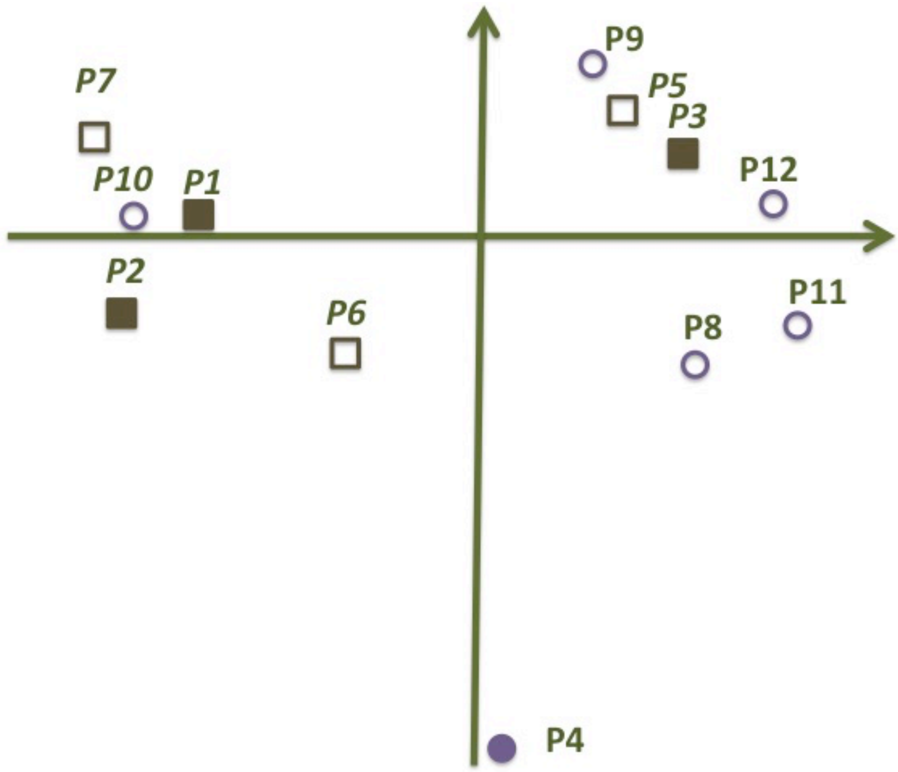


Figure 8: Two dimensional metric MDS map. Squares represent the pure juices, circles represent the juices from concentrate, full symbols represent the pasteurized juices, empty symbols represent the sterilized juices and the labels printed in italics indicate the juices.

MDS. The data were analyzed with a metric MDS performed on the global similarity matrix (we used metric MDS because the sorting task data generates a squared Euclidean distance, see Abdi et al., 2007). In this representation, two orange juices that have been often sorted together by the judges will be positioned near each other and two oranges juices that have rarely been sorted together will be positioned far apart. Figure 8 represents the MDS coordinates for the twelve orange juices used in this experiment.

Figure 8 suggests that there are three groups of orange juices: the first one composed of P1, P2, P6, P7, and P10, the second one of P3, P5, P8, P9, P11, and P12 and the last one of P4 only. The first group consists of orange juices with pulp and rather pure juices (except P10). The second group essentially consists of sterilized orange juices (except P3). Product P4—positioned alone on the bottom of Dimension 2—is characterized by a very typically chemical orange aroma.

DISTATIS. DISTATIS (see Abdi et al., 2012, 2007, 2005) is a method specifically developed for the analysis of sorting task (and projective mapping). It provides a compromise MDS-like map that optimally integrates all the judges' co-occurrence data tables in the sense that the matrix equivalent of an average squared coefficient of correlation (i.e., the R_V coefficient, see Abdi, 2007a, 2010)—computed between each judge's map and this map—is the largest possible one. On this map, we can also display 95% confidence ellipsoids for the products (obtained by using the cross-validation bootstrap technique of repeatedly sampling with replacement from the set of judges, see Abdi & Valentin, 2009, for details). In such a map, when the confidence ellipsoids of two products do not intersect, these two products can be considered as significantly different (for details, see Abdi et al., 2009). In addition, DISTATIS provides, for the judges, an MDS-like map where the proximity between the judges on the map reflects the similarity of their respective sorting data.

Figure 9 shows the products along with their confidence ellipsoids. As is often the case, the general solution of DISTATIS is very close to the metric MDS map (see, however, Mielby et al.,

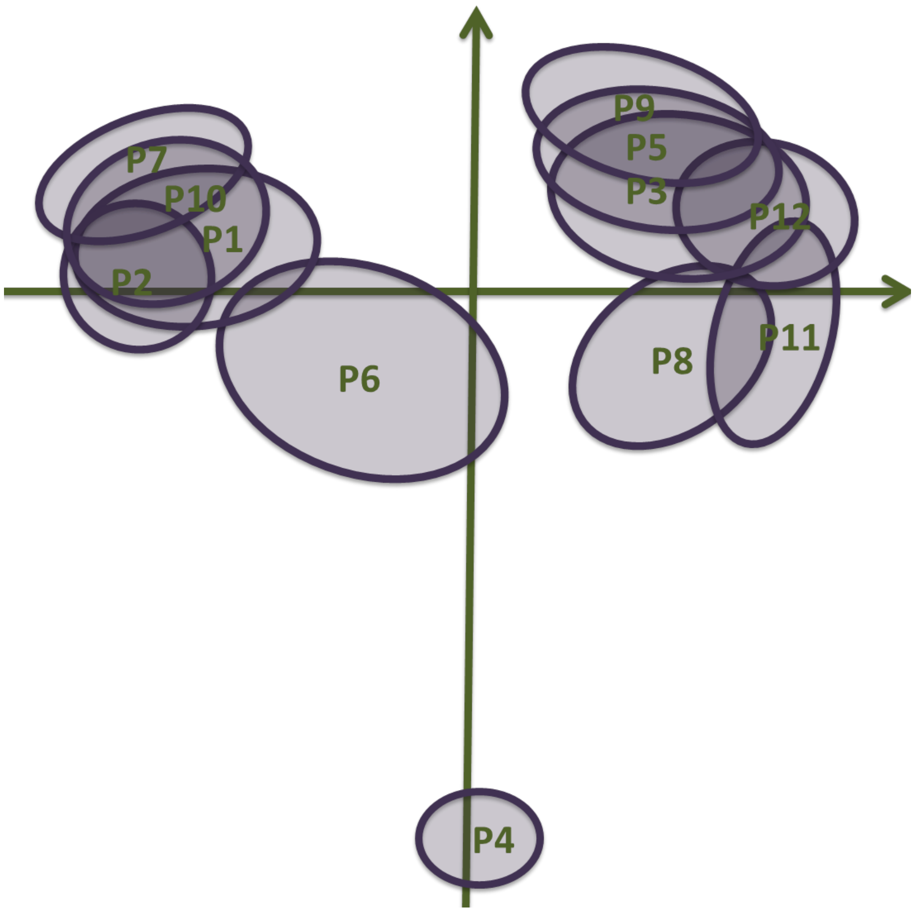


Figure 9: Two dimensional DISTATIS map showing the products with their 95% confidence ellipsoids. When the confidence ellipsoids of two products do not intersect, these two products are perceived as significantly different by the judges. The configuration of the ellipsoids suggests that there are three groups of products.

2014, for a case where DISTATIS provided a slightly different and easier to interpret result than plain metric MDS). The configuration of the ellipsoids clearly confirms that the set of the products comprises three clusters (as suggested by the MDS analysis). Figure 10 displays the map of the judges (obtained from the eigen-decomposition of the between judge R_V matrix). In this map, the judges far to the right of Dimension 1 have a large communality with the other judges whereas the judges close to the origin would be atypical. As most of the judges are positioned to the right, this indicates that the set of judges mostly agree on their sorting. If a few judges were outliers, their data may be eliminated and the analysis re-run (as was done for the projective mapping example presented above).

4 Pros and cons of projective mapping and the sorting task

Intuitively these two methods (projective napping and sorting task) are somewhat similar. The main difference is that the sorting task forces the assessors to categorize the products in an all or none fashion and provides qualitative data whereas projective mapping does not force such a categorization and provides more graded data. Accordingly, we could expect projective mapping to provide more precise data. Yet, in a recent paper, comparing the two approaches, Nestrud and Lawless (2010) reported that sorting and projective mapping of apple and cheese gave similar sensory maps but that a cluster analysis performed on the sensory maps was more easily interpretable for projective mapping than for sorting task, possibly due to a dimension reduction. However, this

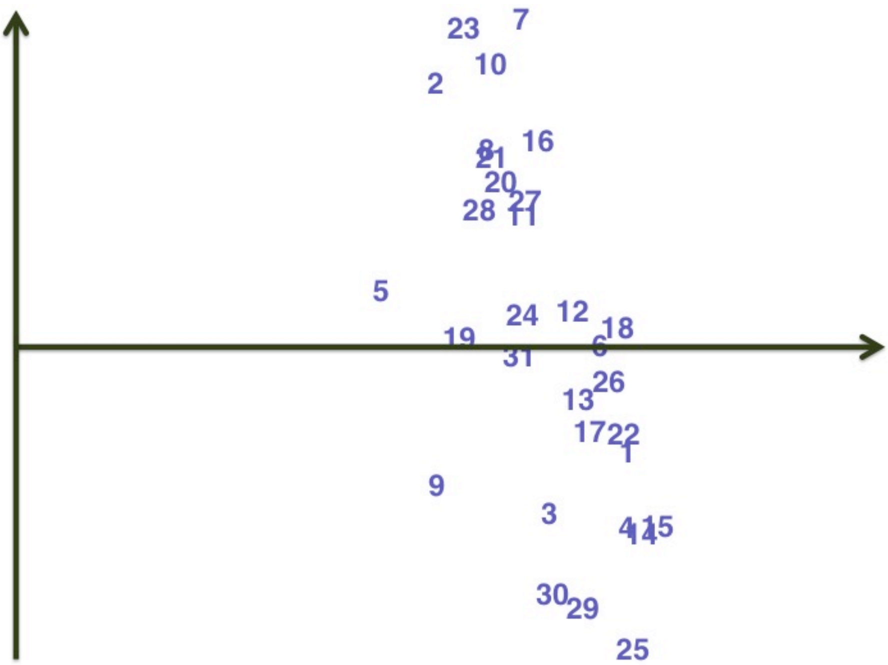


Figure 10: Two dimensional DISTATIS map of the judges. The map suggests that the judges are rather homogeneous because no judge is far from the other judges.

result still needs to be replicated and generalized to other products. As indicated by Valentin et al. (2012), a difficulty of PM is to constrain the assessors to use two dimensions to discriminate between the products but 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 nonmetric MDS, for these different techniques were highly correlated and that the solution obtained from SAP had the same dimensionality than the other methods. Recently, Nestrud and Lawless (2011) using 3D shapes reached the same conclusion.

From a practical point of view, Veinand et al., (2011) reported that projective mapping was difficult to perform especially for assessors having problems with handling spatial information. Specifically, Veinand et al., observed that, *de facto*, many assessors performed a sorting task (grouping together samples on the paper map) rather than a real projective mapping. The sorting task, however, might also not be as easy as previously suggested. For example, Patris et al., (2007) filmed trained and novice assessors performing a beer sorting task and then invited them to comment on their behavior at particular instances during the task. Both groups of assessors found the sorting task difficult to perform, especially novice assessors who reported memory difficulties as well as taste fatigue and saturation problems. The same problem might occur with projective mapping in addition to the spatial difficulties. Up to around 10% of subjects may have problems with both tasks, although these subjects are not always easy to identify in a particular study.

To sum up, both the sorting task and projective mapping completed or not with a verbalization step are time-effective ways of describing products as long as only a coarse description of the products is required. These methods can be used with both consumers and trained panelists on a relatively large set of products but might lead to memory difficulties, fatigue, and saturation problems, especially with consumers (as opposed to trained panelists) if the number of products to be evaluated is too large (see Valentin et al., 2012, and Chollet et al., 2014, for more details). Also, some products may generate carry over effects when tested simultaneously, and some types of products are likely to cause fatigue (e.g., beers or wines, because of alcohol and tannin; or, chili, mustard, and more generally products with a trigeminal effect). The number of assessors required to perform the task differs depending upon the study, the products, and the level of expertise of the participants. However, current literature (see Chollet et al., 2014) suggests that twenty untrained assessors might be sufficient to reach stable configurations even though larger numbers (i.e., from 60 to 100) of participants are often reported (see Chollet et al., 2011, 2014, and Simiqueli, 2015, for a more detailed discussion of these aspects). A common and important problem for both methods is that the whole set of products needs to be presented at the same time. Therefore, these methods are not suitable for hot products or for quality control for instance. One solution is to use an incomplete block design. But in this case, to obtain relevant results, a very large number of assessors is necessary. Another solution when evaluating products that can create fatigue—such as beers or wine—is to split the set of products in several smaller sets and to add in each smaller set the same product (called a prototype) and to compare the products to this prototype. In this case, the choice of the prototype is obviously a crucial step. For both methods, we do not need to perform replication (as in conventional profile where we, in general, study the judges' repeatability), because, several studies indicate that similar results are obtained in different replications as long as the products are quite different from each other (Chollet et al., 2011; Lelièvre et al., 2009). However, in order to have some estimation of the validity of the method, it is possible to duplicate one of the products to be evaluated and to check that these two duplicate products are close together on the product map.

All in all, projective mapping, free sorting, and their diverse avatars (see, e.g., Ares, 2014, Varela & Ares, 2014) are now becoming part of the standard toolbox of sensory evaluation and are likely to be even more relevant as the field moves to rely more on (untrained) consumers to evaluate current products and help in developing new products.

5 Summary

Projective mapping and sorting tasks are used to obtain information about the similarity structure of a set of products. These tasks can be performed by experts, untrained consumers, adults as well as children. These tasks are, in general, analyzed by statistical techniques related to PCA and provide maps that describe the similarity structure of the products under study (and, in some cases, the similarity structure of the assessors).

6 Future developments

Projective mapping, the sorting task, and the numerous variations over these techniques have been used for quite a long time in Psychology and related domains, and so these methodologies are unlikely to change much in the near future. Possible new developments then could include new ways of acquiring the data (i.e., it is likely that computers will be used more often for collecting data,) and maybe a dynamical component in the data collection (i.e., looking at how assessors organize their answers across time, see, e.g., Lê et al., in press). New interesting developments, are also likely to originate from new statistical techniques to analyze similarity data in order, for example, to reveal if different groups of assessors organize the perceptual space in different ways, or if some products can be eliminated with statistical techniques related to regularization or sparsification.

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