Some new and easy ways to describe, compare, and evaluate products and assessors

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Abstract

Recently, in response to industrial demand to develop faster and cheaper methods of descriptive analysis, several methods have been offered as alternatives to conventional profiling. We present three of these methods: sorting tasks, projective mapping, and flash profiling along with a new statistical method to analyze them. This new statistical method, called DISTATIS is a generalization of classical multidimensional scaling (MDS) and takes into account individual differences. DISTATIS provides two MDS-like maps: one map for the assessors, and one (compromise) map for the products. The attributes used by the assessors can also be represented on the product map as well as the specific pattern of evaluation of each assessor. Using the same statistical method to analyze different methods of descriptive analysis will facilitate their comparison.

Key words: Biplot, Bootstratp, Confidence Ellipsoid, Distance, DISTATIS, Flash Profiling, Multiple Factor Analysis, Multidimensional Scaling (MDS), "Napping", Projective Mapping, RV-coefficient, Sensory Evaluation, Sorting Tasks, STATIS,, Tablecloth Distance, Three-way analysis.

1. Introduction

Descriptive analysis is widely used in sensory evaluation for product development, quality control as well as market research. The goal of this method is to describe the sensory characteristics of a product, and to use these characteristics to quantify inter-product sensory differences (see, e.g., Lawless & Heymann, 1999, for a review). The most popular variations of descriptive analysis are the quantitative descriptive analysis or QDA (Stone, Sidel, Oliver, Woodlsey, & Singleton, 1974), the spectrum method (Meilgaard, Civille, & Carr, 1991), the texture profile (Munoz, Szczesniak, Einstein, & Schwartz, 1992) and flavour profile (Keane, 1992). All these variations provide quantitative description of sensory attributes as perceived by a group of expert panellists. These expert panellists are selected for their sensory abilities and trained to describe and evaluate sensory differences among products. The panellists first elaborate by consensus a list of attributes with precise definitions and references for each attribute. Then, they are trained to develop their sensory acuity and to use the evaluation scales. The final evaluations—which are always performed in blind condition and replicated twice—give the positioning of the different products as well as their quantified sensory characteristics. The essential parts of this training process are the elaboration of precise con-

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sensual definitions of the attributes and the development of homogeneous scaling skills. These two conditions guarantee the success of descriptive analysis in providing detailed information as well as reliable and consistent results. Yet, as a counterpart of this success, classical methods of descriptive analysis require extensive training before the panel can become 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 to perform a study and thus there is an obvious need for faster and cheaper methods.

And so, it is, maybe, not so surprising that several methods have been proposed in recent years as alternatives to classical descriptive analysis: free sorting task (Cartier, Rytz, Lecomte, Poblete, Krystlik, Belin, & Martin, 2006; Faye, Brémaud, Durand-Daubin, Courcoux, Giboreau, & Nicod, 2004; Saint-Eve, Paài, Kora, & Martin, 2003), projective mapping (Risvik, McEwan, & Redbottena, 1997) or tablecloth analysis (from the French "nappe" which is often directly translated as "napping," Pagès, 2005), and flash profiling (Dairou & Sieffermann, 2002; Delarue & Sieffermann, 2004). These methods aim at providing a quick sensory positioning of a set of products and thus bypass the time-consuming steps of attribute and scaling alignment of classical methods. These new methods build on the idea of free choice profiling (Williams & Langron, 1984) that allows judges to use their own attributes.

In a free sorting task, assessors are asked to sort together the products based on the perceived similarity between these products. Assessors are free to make as many groups as they wish and to put as many products as they want in each group. When they have sorted the products, assessors are asked to describe each group of products with a few words. In the sensory domain, sorting tasks were used on a large variety of food products as well as on non-food products (see Abdi, Valentin, Chollet, & Chrea, 2007, for a review). Sorting tasks are well adapted to obtain a coarse characterization of products or to select a subset of products for conducting further descriptive analysis (Giboreau, Navarro, Faye, & Dumortier, 2001; Piombino, Nicklaus, LeFur, Moio, & Le Quéré, 2003). Despite a few differences, perceptual maps obtained with sorting tasks are globally comparable with those obtained from classical descriptive analysis (Faye et al., 2004; Saint Eve et al., 2004) and seem to be reproducible (Cartier et al., 2006).

In projective mapping, or tablecloth analysis (a.k.a, "napping"), an assessor is asked to position the products on a two-dimensional space (an A3 sheet of white paper which plays the rôle of a tablecloth or "nappe"), according to how he or she perceives them to be related to each other. Two products are placed very close to each other if they are perceived as identical and very far one from the other if they are perceived as very different. There are no instructions as to how the samples should be separated in this space (each assessor chooses his/her own criteria), but examples of two-dimensional geographical maps can be used for illustration. 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. Assessors are free to re-taste the samples as often as they want and they can take as much time as needed to complete the task. Projective mapping gives rise to perceptual maps comparable to those obtained with classical descriptive analysis for obvious aspects of the products (Risvik, McEwan, Colwill, Rogers, & Lyon 1994; Risvick et al., 1997; Perrin, Symoneaux, Maître, Asselin, Jourjon, & Pagès, in press) and to be reproducible (Risvik et al., 1994; Risvick et al., 1997). This method seems to be well adapted for obtaining coarse descriptions of the products.

Flash profiling involves two sessions. In the first session, assessors are asked to individually generate attributes, which should be sufficiently discriminant to allow for a ranking of the samples. All the generated attributes are then pooled by the experimenter. In the second session, assessors are asked first to read the panel's list and to update their own list if desired. Then, they are asked to rank order the products from least to most for each of the chosen attributes. Ties are allowed and assessors can re-taste the samples as much as they like and take as much time as needed to complete the evaluation. Flash profiling has been use to describe food products such as red fruit jams (Dairou & Sieffermann, 2002), fruit dairy products (Delarue & Sieffermann, 2004), chewing gum (Delarue & Loescher, 2004) and fruit jelly (Blancher, Chollet, Kesteloot, Nguyen, Cuvelier, & Sieffermann, 2007) and proved to be satisfactory (compared to conventional profiling) when products are relatively different (Dairou & Sieffermann, 2002; Blancher et al., 2007) but may give different results than conventional profiling for relatively similar products such as apricot fresh cheeses (Delarue & Siefferman, 2007).

Although sorting tasks, projective mapping, and flash profiling cannot replace conventional profiling, these new descriptive methods constitute very attractive ways to provide quick descriptions of products. In this paper, we present a new statistical method, called DISTATIS, which can be used to analyze data from all three descriptive methods. DISTATIS provides two multidimensional scaling (MDS) like maps: a map for the assessors, and a compromise map for the products. The individual assessor patterns as well as the descriptors used by the assessors can be projected on this compromise space.

This method has been previously described for sorting tasks (Abdi et al., 2007) here we show how to adapt it to projective mapping and flash profiling.

2. Distatis: general principles

DISTATIS is derived from a generalization of PCA called STATIS (Escoufier, 1980; Lavit, 1988; Schlich, 1996; Abdi & Valentin, 2007b) and has the advantage of taking into account individual differences. It is a generalization of classical MDS (see, e.g., Abdi, 2007a). Specifically, DISTATIS analyzes a set of distance matrices obtained on one set of stimuli. As in MDS, the first step is to transform each distance matrix into a covariance matrix (using double centering). The similarity between covariance matrices is first evaluated using the R_v coefficient (Roberts & Escoufier, 1976, Abdi, 2007c), and this coefficient is used to create a between assessor similarity matrix. The analysis of this R_v matrix reveals the similarity structure of the assessors (i.e., are there subgroups in the assessors?) and it also provides an optimal set of weights which is then used to compute a "compromise" matrix. This compromise matrix represents the best aggregate of the original covariance matrices. The PCA of the compromise gives the position of the stimuli in the compromise space. The position of the stimuli for each distance matrix can be represented in the compromise space as supplementary points and the original distance matrices can be represented as points in a multidimensional space. Also, the attributes used to describe the products can be represented as points in the compromise space. Finally, confidence intervals can be computed for the position of the products (and the assessors but we do not illustrate this point here). These confidence intervals complete the descriptive analysis with an inferential component that identifies "significant" differences between products.

2.1. *Statistical inferences with* DISTATIS

A general problem with multivariate techniques such as MDS, PCA, STATIS, and DISTATIS is to complete these descriptive analyses with an inferential step (it is, in general, easier to publish "significant" results due to the "magic" of the .05 and .01 significance levels, see Cohen, 1994). Because the sampling distributions of the parameters optimized by these methods are rarely known, standard analytic procedures based on the normal distribution (e.g., F-tests) cannot be used, but alternative non-parametric inferential methods can be implemented via computational cross-validation techniques. One very powerful recent technique for cross-validation is the bootstrap (Efron 1979; Efron & Tibshirani, 1993). The idea of the bootstrap is to derive sampling distributions from the distribution of a large set of samples drawn with replacement from the observed data set. The bootstrapped distribution obtained from these samples is then used to estimate the sampling distribution of interest. As an illustration, in the sorting task example (described in details later), eleven assessors sorted the data and we have one distance matrix per assessor. So, the data set is composed of eleven distance matrices labeled $\mathbf{D}_1$ to $\mathbf{D}_{11}$. A possible sample of 11 distance matrices obtained by sampling with replacement from our data could be the following set of 11 distance matrices:

$$\mathbf{D}_{11},\ \mathbf{D}_{11},\ \mathbf{D}_6,\ \mathbf{D}_9,\ \mathbf{D}_2,\ \mathbf{D}_5,\ \mathbf{D}_{11},\ \mathbf{D}_9,\ \mathbf{D}_{11},\ \mathbf{D}_8,\ \mathbf{D}_1\ . \qquad (1)$$

From this set we can compute a compromise matrix.

We implemented this procedure (of sampling with replacement and computing the compromise) and repeated it 1000 times. We then projected all these 1000 compromise matrices onto the original compromise (using the projection operator defined in Equation 14 of Abdi et al., 2007) and computed for each category a confidence ellipsoid that comprised 95% of the projections of the bootstraped compromises for this category (See Figure 2). These confidence ellipsoids can be used to perform hypothesis testing: When the ellipsoids of two categories do not intersect, these two categories can be considered as statistically different at the $p = .05$ level; and when the ellipsoids of two categories intersect, these two categories cannot be considered as statistically different at the $p = .05$ level.

3. Distatis : An illustration for sorting task, projective mapping, and flash profiling

To illustrate how to use DISTATIS for sorting task, projective mapping, and flash profiling, we fabricated a small example in which seven beers (A, B, C, D, E, F, G) are described by three groups of assessors. The first group includes eleven assessors who described the beers using a sorting task. Their data are presented in Tables 1 and 2. The second group includes seven assessors who described the beers using projective mapping / napping. Their data are presented in Tables 3 and 4. The third group includes six assessors who described the beers using projective mapping / napping. Their data are presented in Tables 5 and 6.

4. Sorting

To analyze the sorting task, we derived one between beer distance matrix per assessor. In this distance ma-

Table 2. Sorting Data: The Vocabulary. For each assessor and each group of beer, the table gives the attributes listed by this assessor for this group of beers.

	Assessors										
Group	1	2	3	4	5	6	7	8	9	10	11
1	{AB} light lemon spice	{A} light lemon spice	{ABG} spice citrus dentist	{AB} floral citrus	{AB} lemon light	{AB} lemon light	{AB} dentist lemon light	{AB} spice acid light	{ABG} fruity spicy citrus	{ABG} coriander lemon light	{A} cilantro light
2	{CD} sweet honey coffee	{B} coriander lemon light	{CDE} bitter fruity toasted	{CD} toffee toasted	{CDEF} alcohol bitter spice	{G} alcohol dentist fruity	{C} sweet toffee bitter	{CD} coffee toasted	{C} toffee bitter sweet	{C} dentist acid light	{B} dentist acid lemon
3	{EF} sweet alcohol heavy	{CD} sweet coffee	{F} alcohol fruity	{EFG} fruity alcohol spice	{G} sweet coffee bitter	{CDEF} sweet toffee alcohol	{D} strong fruity	{E} alcohol fruity	{DEF} alcohol bitter fruity bitter	{DEF} honey toasted	{CD} honey
4	{G} alcohol spice	{EFG} sweet alcohol fruity					{EF} alcohol sweet fruity bitter	{FG} dentist strong fruity			{EF} alcohol
5							{G}				{G} strong

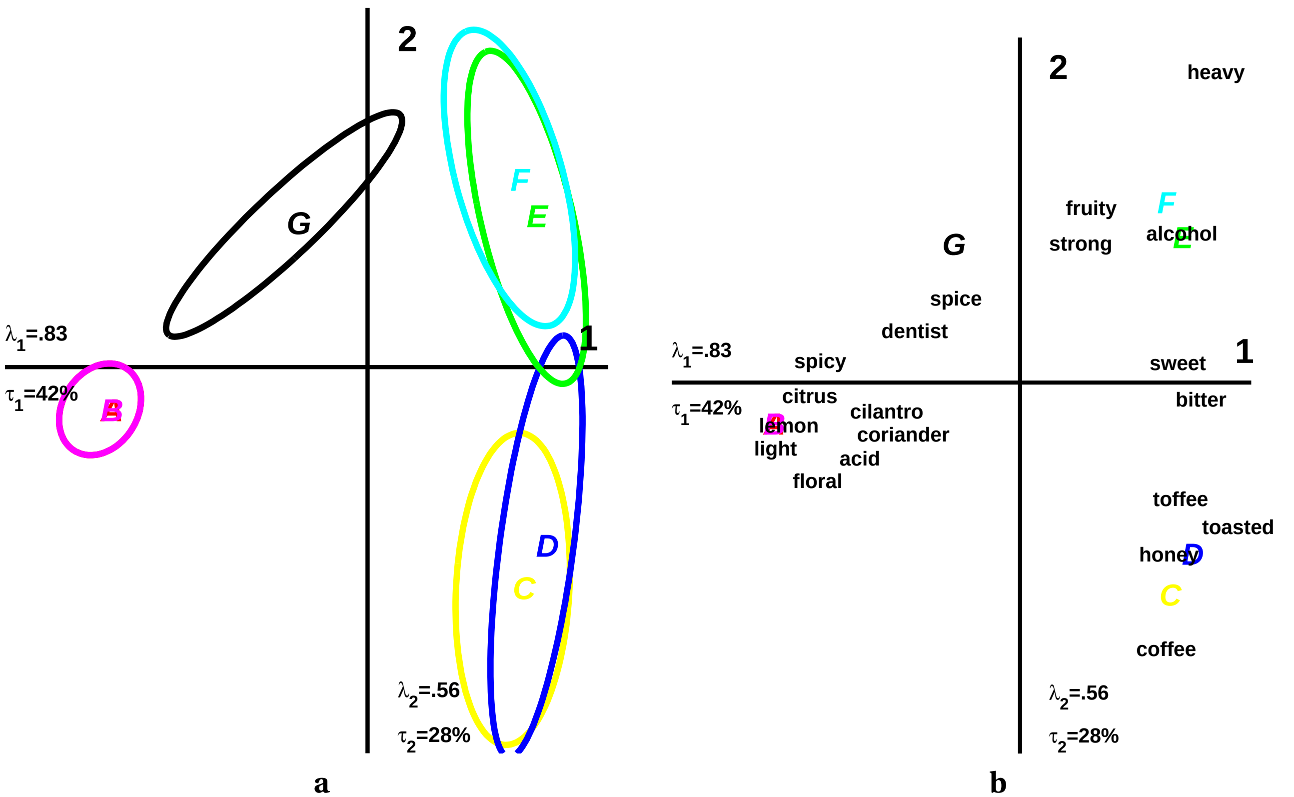

Figure 2. Sorting tasks: a) The map of the beers along with their confidence ellipsoids. b) Barycentric projections of the attributes in the beer space.

Table 1
Sorting data, the beers. Eleven assessors sorted seven beers. For each assessor, beers with the same number were sorted together

	Assessors										
Beer	1	2	3	4	5	6	7	8	9	10	11
A	1	1	1	1	1	1	1	1	1	1	1
B	1	2	1	1	1	1	1	1	1	1	2
C	2	3	2	2	2	3	2	2	2	2	3
D	2	3	2	2	2	3	3	2	3	3	3
E	3	4	2	3	2	3	4	3	3	3	4
F	3	4	3	3	2	3	4	4	3	3	4
G	4	4	1	3	3	2	5	4	1	1	5

trix, rows and columns represent the beers sorted by this assessor. A value of 1 at the intersection of a row and a column means that this assessor *did not* sort together these two beers, a value of 0 means that this assessor put these two beers in the same group (see Abdi et al., 2007, for more details). Standard DISTATIS was performed on

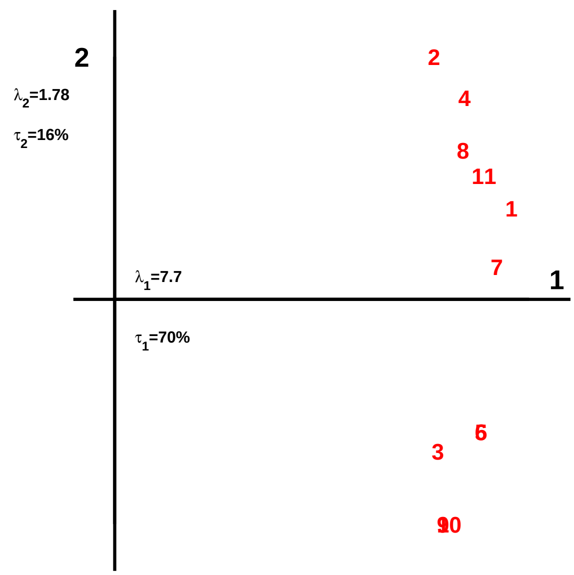

Figure 1. Sorting task: Map of the assessors. (PCA of the R_V coefficient matrix).

the set of distance matrices. The first two dimensions of the PCA of the compromise matrix explain 70% of the variance, and therefore, we limited the interpretation of the results to these two dimensions. The attributes generated by the assessors were then projected on the two-dimensional compromise map using a barycentric projection procedure (see Abdi, 2007d). Specifically, the factor coordinates of a given word were obtained by first identifying for each assessor the beer coordinates corresponding to this word, and then computing the average of these coordinates over the assessors. The results of the analysis provide three maps: One map for the assessors (Figure 1), one map for the beers with their confidence interval (Figure 2a) and the map of the attributes (Figure 2b).

The assessor map represents the PCA of the between-assessor similarity matrix (i.e., the R_V coefficient matrix). It provides an easy way to examine the relationships between the assessors. It can be used to reveal clusters of assessors and to detect atypical assessors. Here we can note two groups of assessors who seem to have behaved somewhat differently. This apparent separation in two groups of assessors could be validated using hierarchical cluster analysis or a k-mean algorithm on the coordinates of the assessors. In addition, the proportion of variance explained by the first component of the assessor map gives an indication of the quality of the compromise: The closer this value is to 100%, the better the quality of the compromise. Here the first dimension explains 70% of the variance and this reflects a relatively good consensus between assessors.

The beer and attribute maps represent the PCA of the compromise matrix. They can be interpreted as a standard PCA. Despite relatively large confidence ellipsoids, the beers seem to be organized in four groups {A,B}, {C,D},{E,F}, and {G} with some overlap of the confidence ellipsoid for Beers D and E. The relatively large size of the confidence ellipsoids for groups {C,D},{E,F} is however probably due to the nature of the sorting task which uses 0/1 values only. The first dimension which explains 42% of the variance opposes Beers A and B to Beers C, D, E, F. The second dimension which explains 28% of the variance opposes Beers C and D to Beers E, F, G. Beers A and B are described as lemon, light floral, acid, coriander, citrus spicy. Beers C and D are described as toffee, honey, toasted, coffee, and somewhat sweet and bitter. Beers E and F are described as heavy, alcohol, fruity, strong, and somewhat sweet and bitter. Finally beer G—which is in between groups {A,B} and {E,F}—has characteristics of both groups, but is mostly characterized as dentist [1] and spice.

[1] Our fake assessors were French and in France the attribute "dentist" refers to the odor of eugenol, which was used by French dentists in dental fillings.

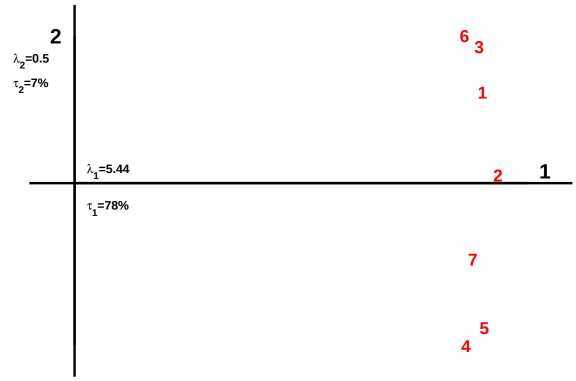

Figure 3. Projective mapping / napping: Map of the assessors (PCA of the R_V coefficient matrix).

5. Projective mapping a.k.a Tablecloth distance ("napping")

Data were collected using a coordinate system placed in the lower right hand corner of the map. The coordinates of the products are obtained as their projections on the horizontal and vertical axes. For each assessor we used the coordinates of the beers to compute a between beer distance matrix. For example, the second assessor placed Beer A at the coordinates (1,5) and Beer E at coordinates (7,9). Using these coordinates (and the Pythagorean theorem), we can compute the (squared) Euclidean distance (see, Abdi, 2007b) between these two beers as:

$$\begin{aligned} d^2_{A,E} &= (1-7)^2 + (5-9)^2 = 6^2 + 4^2 \\ &= 36 + 16 = 52. \end{aligned} \tag{2}$$

Standard DISTATIS was performed on the set of distance matrices. The first two dimensions of the PCA of the compromise matrix explain 91 % of the variance. Such a large value indicates that the interpretation of the results can be restricted to these two dimensions. The attributes were projected on the two-dimensional compromise map using a barycentric projection procedure similar to the one used for the sorting task.

Figure 3 represents the assessor map. The high proportion of variance explained by the first dimension (τ=75%) indicates that there is a good consensus among the assessors and that the compromise is a good representation of the whole group of the assessors. Yet, we can note some segmentation in the group of the assessors on the second dimension. Assessors 6 and 3 seem to have behaved differently than Assessors 4 and 5. It could thus be interesting to look at the characteristics of the assessors to explain these differences.

Figures 4a and b represent, respectively, the beer and the attribute maps. The configuration of confidence ellipsoids in Figure 4a suggests that there are

Table 3
Napping Data: The beers and their coordinates measured on a tablecloth.

	Assessor 1		Assessor 2		Assessor 3		Assessor 4		Assessor 5		Assessor 6		Assessor 7	
	Dimension		Dimension		Dimension		Dimension		Dimension		Dimension		Dimension	
Beer	D1	D2	D1	D2	D1	D2	D1	D2	D1	D2	D1	D2	D1	D2
A	1.5	4.0	1.0	5.0	6.5	2.0	1.0	2.0	8.5	5.0	1.5	5.0	5.0	1.5
B	2.5	2.0	2.5	3.0	8.5	1.0	2.0	3.0	6.5	3.5	1.0	3.0	5.5	1.5
C	8.0	1.5	6.5	5.5	6.0	5.5	7.0	2.5	2.5	3.0	8.0	1.5	0.5	5.5
D	6.0	3.0	8.0	1.0	9.0	6.5	8.0	3.0	1.0	1.5	7.0	2.0	1.0	6.0
E	7.5	7.5	7.0	9.0	3.0	8.0	7.0	5.5	3.5	6.5	8.5	5.5	9.0	8.5
F	5.5	8.5	8.0	8.5	3.5	6.0	9.0	9.0	1.5	8.5	7.0	4.5	8.0	8.0
G	4.5	6.5	4.0	8.0	1.5	3.5	2.0	7.0	6.0	9.0	5.5	6.0	9.0	2.5

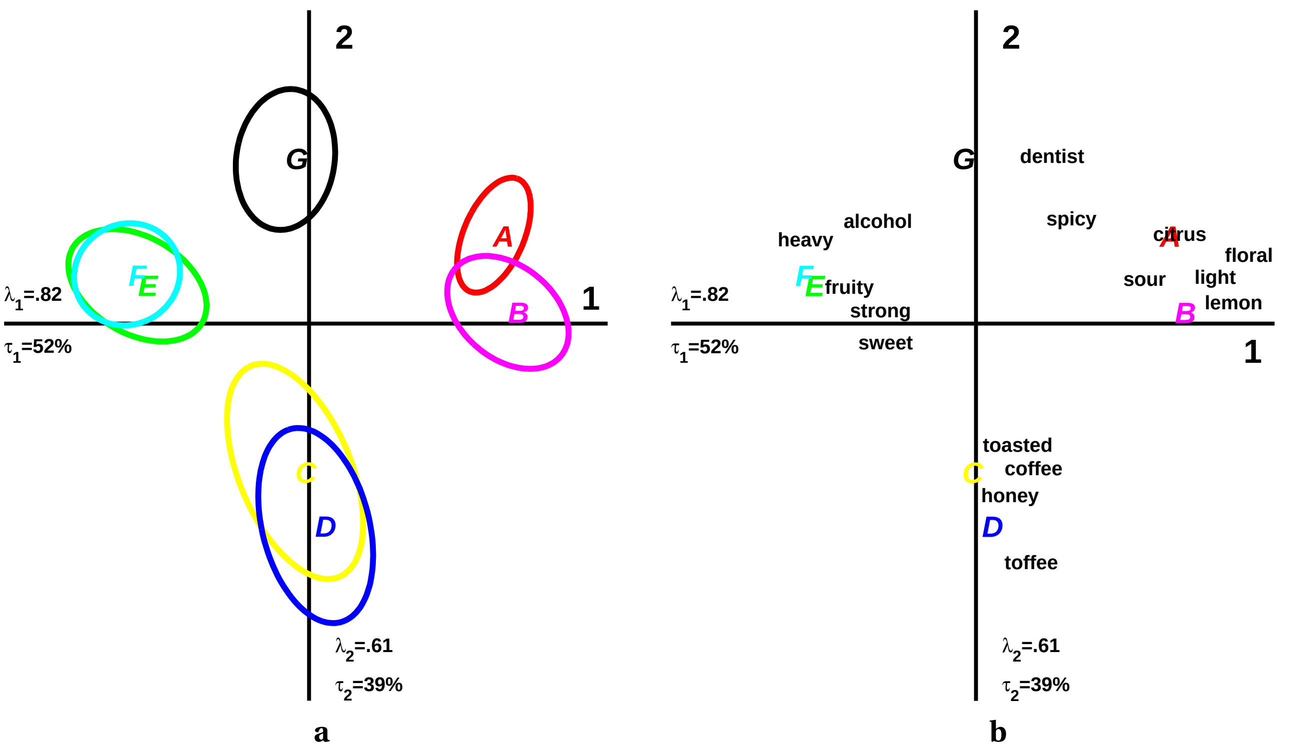

Figure 4. Napping: Tablecloth: a) The map of the beers along with their confidence ellipsoids. b) Barycentric projections of the vocabulary in the beer space.

Table 4
Napping Data: The Vocabulary.

Beer	Assessor 1	Assessor 2	Assessor 3	Assessor 4	Assessor 5	Assessor 6	Assessor 7
A	light	citrus	light	floral	dentist	light	sour
	sour		sour	spicy	citrus	floral	
				lemon	light		
B	light	floral	light	floral	citrus	light	sour
	lemon		spicy	spicy	light	floral	
				lemon			
C	toffee	sweet	toasted	sweet	coffee	sweet	toffee
	coffee	toasted	honey	toasted		strong	
	toasted		coffee			honey	
D	toffee	sweet	toasted	sweet	toffee	sweet	toffee
	coffee	honey	honey	toasted		strong	
	toasted					honey	
E	alcohol	heavy	alcohol	fruity	alcohol	sweet	alcohol
	fruity	sweet	sweet	sweet	sweet	strong	sweet
	strong	alcohol	strong			fruity	
	sweet						
F	alcohol	strong	alcohol	fruity	alcohol	sweet	alcohol
	fruity	fruity	sweet	alcohol	sweet	strong	sweet
	strong	alcoho l	strong		fruity	fruity	
	sweet						
G	alcohol	spice	alcohol	dentist	alcohol	sweet	alcohol
	fruity	alcohol	spicy	alcohol	dentist	strong	spicy
	spicy					dentist	

four groups of beers: {F,E}, {G}, {A,B}, and {C,D}. The first dimension—which explains 52% of the variance—opposes clearly Beers F and E characterized as sweet, strong, fruity, heavy, and alcoholic to Beers A and B characterized as lemon, light, floral, citrus, and sour. The second dimension opposes Beers C and D to Beer G. Beers C and D are characterized as toffee, honey, coffee, and toasted. Beer G is characterized as dentist and somewhat alcoholic and spicy.

6. Flash profiling

For each assessor, we used the ranking of the beers to compute a between beer Euclidean distance matrix. For example, the first assessor ranked Beer A as (1,1,3,1,5,4) and Beer B as (2,5,1,4,7,7). Using these ranks (and the Pythagorean theorem), we can compute the (squared) Euclidean distance between these two beers as:

Table 5
Flash Profiling: The beers

Beer Ranking According To Attributes (Assessors 1–3)

	Assessor 1						Assessor 2					Assessor 3					
	Attributes						Attributes					Attributes					
Attribute #	1	2	3	4	5	6	1	2	3	4	5	1	2	3	4	5	6
A	1	1	3	1	5	4	2	7	4	5	7	6	3	6	1	7	1
B	2	5	1	4	7	7	1	6	5	2	6	7	7	7	2	6	3
C	3	6	4	6	1	2	5	1	7	7	1	2	1	3	3	1	6
D	6	7	5	2	2	1	6	2	6	1	3	1	2	5	5	4	7
E	5	2	7	7	4	3	4	3	1	6	2	3	5	2	6	2	6
F	7	4	6	5	3	6	7	5	2	4	4	4	6	1	7	6	5
G	4	3	3	3	6	5	3	4	3	2	5	5	4	4	4	3	2

Beer Ranking According To Attributes (Assessors 4–6)

	Assessor 4							Assessor 5					Assessor 6						
	Attributes							Attributes					Attributes						
Attribute #	1	2	3	4	5	6	7	1	2	3	4	5	1	2	3	4	5	6	7
A	2	1	1	1	6	7	4	1	3	1	1	5	3	7	1	6	5	3	1
B	1	5	3	2	7	6	7	5	7	2	2	1	5	6	4	7	7	2	2
C	4	6	7	5	1	3	2	7	2	3	7	7	7	1	6	1	1	7	5
D	3	3	6	6	2	4	1	6	3	5	6	2	6	2	7	2	2	6	3
E	7	7	4	3	5	1	3	4	5	6	5	6	1	3	2	5	3	5	6
F	6	4	5	7	3	2	6	3	6	7	4	4	4	4	5	3	4	4	7
G	5	2	2	4	4	5	5	2	4	4	3	3	2	5	3	4	6	1	4

Table 6
Flash Profiling: The vocabulary.

Attributes Chosen By The Assessors

	Assessors					
	1	2	3	4	5	6
Attribute #						
1	alcohol	alcohol	coriander	ripe fruit	toasted cereal	malt
2	malt	citrus	lemon	bitter	clove	citrus
3	fruity	cereal	honey	sweet	alcohol	coriander
4	bitter	bitter	alcohol	alcohol	sweet	hop
5	spice	floral	acid	coriander	bitter	alcohol
6	hop		sweet	honey		sweet
7				hop		

$$
\begin{aligned}
d^2_{A,B} &= (1-2)^2 + (1-5)^2 + \cdots + (4-7)^2 \\
&= 1^2 + 4^2 + \cdots + 3^2 \\
&= 43.
\end{aligned} \tag{3}
$$

Standard DISTATIS was performed on the set of distance matrices. The first two dimensions of the PCA of the compromise matrix explain 72 % of the variance; we thus limited our analysis to these two dimensions. The coordinates of the attributes on the two-dimensional compromise space were obtained by computing the correlation of each attribute with the dimensions of the compromise (these coefficients of correlation are equivalent to loadings in factor analysis).

Figure 5 represents the assessor map. The very high proportion of variance explained by the first dimension (τ=89%) indicates a good consensus among the assessors and a good quality of the compromise. Yet, we can note some segmentation of the assessors on the second dimension. Specifically, Assessor 6 seems to have behaved differently from Assessor 3. The other assessors are very consensual.

Figures 6a and b represent respectively the beer and

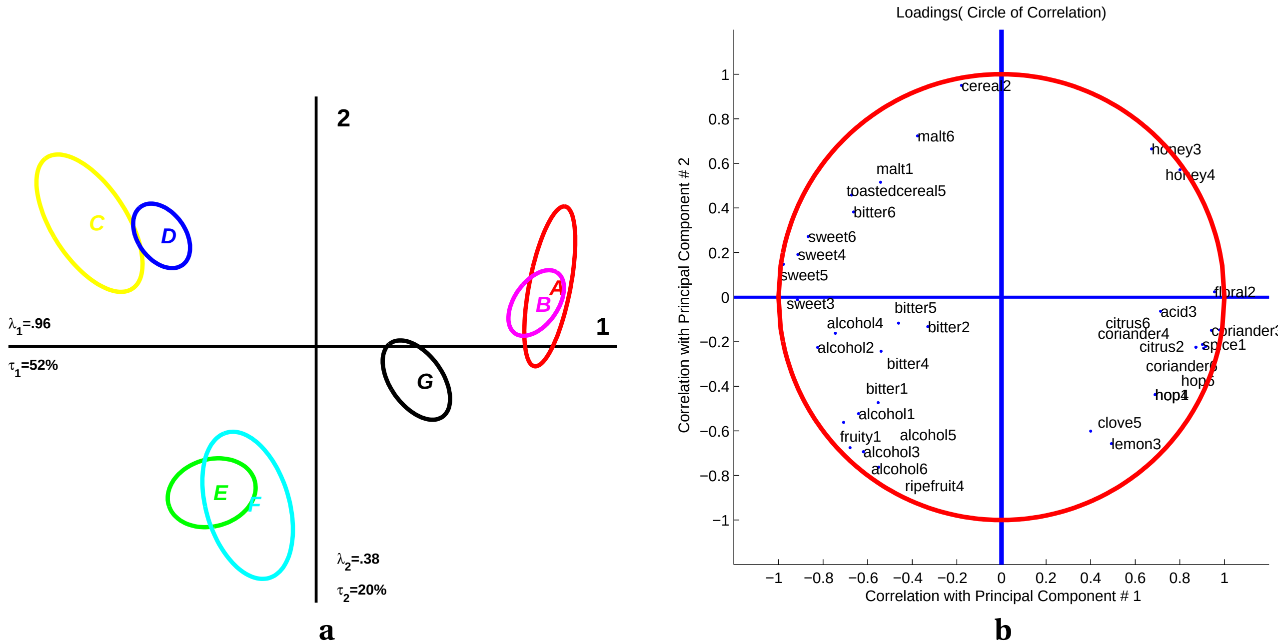

Figure 6. Flash profiling: a) The map of the beers along with their confidence ellipsoids. b) The attributes as loadings along with the circle of correlation.

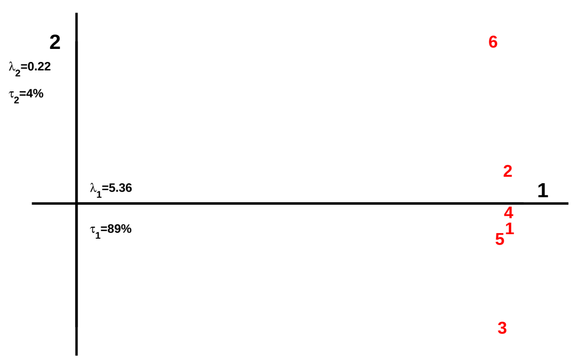

Figure 5. Flash profiling: The map of the assessors (PCA of the R_V coefficient matrix).

the attribute maps. The configuration of the confidence ellipsoids in Figure 6a reveals four groups of beers: {C,D}, {A,B}, {E,F}, and {G}. Beer G is located in between the groups {A,B} and {E,F}. The first dimension, which explains 52% of the variance, opposes Beers C and D to Beers A and B. The second dimension, which explains 39% of the variance, opposes Beers C and D to the other beers. The characterization of the groups of beers is somewhat more difficult with flash profiling than with the other two methods as all the attributes of all the assessors are preserved and sometimes the same attribute used by different assessors might project on different locations of the space. This is the case, for example, of the attribute bitter. Bitter as used by Assessor 1, is opposed on the second dimension to bitter as used by Assessor 6. Nevertheless, in our example, we can characterize Beers C and D as sweet, toasted, malt, alcohol, and maybe honey; Beers E and F are fruity, sweet, alcohol; and Beers A and B are floral, lemon, citrus, hop, coriander, spicy, and honey. Beer G is more difficult to characterize.

7. Conclusion

The main objective of this paper was to present new and easy ways to describe, compare, and evaluate products and assessors. We showed how to use a new statistical method, DISTATIS, to analyze descriptive data obtained through sorting tasks, projective mapping, and flash profiling. The advantage of using the same statistical technique to analyze data collected from different methodology is to make it easier to compare these methodologies. Here, for pedagogical reasons, we presented only small fabricated examples, so the comparisons between the three methods would be meaningless and thus these comparisons remain to be performed on real data.

Because DISTATIS provides an easy way to look at the same time at assessors, products, and attributes, we used it as the common tool to analyze the results of the sorting task, projective mapping / napping, and flash profiling. But we could have used other techniques, such as plain STATIS (Abdi & Valentin, 2007b), multiple factor analysis (Escofier & Pagès, 1998; Abdi & Valentin, 2007c), or generalized procrustean analysis (Gower & Dijksterhuis, 2004). Empirical comparisons need to be performed to evaluate the respective qualities of these alternative statistical methodologies.

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