8 Free Sorting Task

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8.1 THEORY BEHIND THE METHOD

The sorting task is a simple procedure for collecting similarity data in which each assessor groups together stimuli based on their perceived similarities. Sorting is based on categorization—a natural cognitive process routinely

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used in everyday life—and does not require a quantitative response. The final objective of the sorting task is to reveal—via statistical analyses—the structure of the product space and to interpret its underlying dimensions.

The sorting task originated in psychology (Hulin and Katz 1935) and this field has used it routinely since (see, e.g., Miller 1969; Imai 1966, for early applications; see also Coxon 1999, for a thorough review and historical perspectives). It was first used in the field of sensory evaluation in the early 1990s to investigate the perceptual structure of odors (Lawless 1989; Lawless and Glatter 1990; MacRae et al. 1992; Stevens and O'Connell 1996; Chrea et al. 2005). Lawless et al. (1995) were the first to use a sorting task with a food product.

8.2 DESIGN OF EXPERIMENTS

8.2.1 Procedure

The free sorting task is the basic method, but different variations of the sorting task emerged according to the applications and the objectives of the study.

8.2.1.1 Free Sorting Task

The sorting task is performed 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 perceived product similarities. Assessors can use the criteria they want to sort the stimuli, and they are free to make as many groups as they want and to put as many products as they want in each group.

The sorting task can be stopped at this point or can be followed by a description step where assessors are asked to describe each group of products (Lawless et al. 1995; Tang and Heymann 1999; Faye et al. 2004, 2006; Saint-Eve et al. 2004; Lim and Lawless 2005; Cartier et al. 2006; Blancher et al. 2007; Lelièvre et al. 2008, 2009; Santosa et al. 2010). This procedure is called *labeled sorting* by Bécue-Bertaut and Lê (2011). To facilitate both the assessors' task and data analysis, a preestablished list can be provided during this step to help assessors in labeling their groups (Lelièvre et al. 2008).

8.2.1.2 Variations of the Sorting Task

Several variations of the sorting task have been developed. A first variation consists in providing information on either the number and/or the nature of the groups. This type of directed sorting is very useful to evaluate if

assessors are able to discriminate between different categories of products (Ballester et al. 2009; Parr et al. 2010). For example, Lawless (1989), using citrus and woody odors, noted that when assessors had to sort the odors into only two categories, the multidimensional scaling (MDS) configuration showed only two clusters (woody and citrus), with ambiguous odors on the edges of each cluster, whereas when the assessors could use as many groups as they wished, the MDS configuration showed four groups, with the lime fragrances and ambiguous odors failing into a central cluster between woody and citrus groups.

Another variation—first proposed by Rao and Katz (1971)—is called hierarchical sorting task. In this variation, after the assessors have performed the sorting task, they are asked to successively merge the two groups that are most similar up to the time where a single group is formed (ascendant hierarchical sorting; see Coxon 1999), or inversely, the assessors are asked to separate each group into finer groups up to the time where 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 [TFS]) 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 could give more precise information than the free sorting task as it provides a more graduate measurement of the similarity between products than the 0/1 data provided by the free sorting task. According to Courcoux et al. (2012), the position of the products on the sensory map could be more stable than the one provided by the free sorting task, but further studies are needed to validate this conclusion.

8.2.2 Assessors

Who can perform a sorting task? *A priori* everybody, but the obtained results might not be perhaps exactly the same! Some studies showed that untrained and trained assessors generate similar perceptual maps (breakfast cereals, Cartier et al. 2006; beers, Lelièvre et al. 2008; Chollet et al. 2011). But other studies reported some differences between the maps generated by assessors with different levels of expertise (wine, Solomon 1997; Ballester et al. 2008; beers, Chollet and Valentin 2001; Patris et al. 2007; and fabrics, Soufflet et al. 2004). It seems that these discrepancies depend upon the nature of the products and the nature of the differences between the products. In some cases, novices tend to categorize the products according to basic sensory features, whereas experts tend to use rather higher-level types of categorization (e.g., grape variety, Ballester et al. 2008). In other cases, it was shown that experts

AQ1 are more precise in their sorting (Beguin 1993; Soufflet et al. 2004; Patris et al. 2007). Overall, it seems that untrained panelists can provide a coarse map of the products.

Concerning the number of assessors needed in sorting tasks, it has AQ2 been suggested that a large number of assessors is required (Faye 2004). However, other studies carried out with beers indicated that stable results could be reached with 20 untrained assessors (Lelièvre et al. 2008; Chollet et al. 2011). So it is likely that the stability of the results may vary with some aspects of the task, and recently, Blancher et al. (2012) have suggested that the stability of sorting task results depends on the characteristics of the product sets and on the assessor expertise level. These authors propose to evaluate these effects with a cross validation procedure and, specifically, suggest to use bootstrapping techniques to draw large numbers of samples of different sizes from the original set and compute the average R_V coefficient (which they called R_{Vb}) to determine the number of assessors necessary to obtain stable results. They consider that an average R_{Vb} at least equal to 0.95 is a good indicator of stability. All in all, although the quality of sorting task results is clearly influenced by the nature of the products, it seems that a sorting task with about 20 assessors can provide relevant and interpretable results but that this recommendation, however, may depend on the specifics of the data.

8.2.3 Products

A recurrent question when using the sorting task is: Is there a limit to the number of products that can be evaluated? Two phenomena need to be taken into account when answering this question. The first one is linked to the product itself: some products cannot be tasted in large number because of their intrinsic properties such as alcohol content or high taste persistence. It is obvious that a sorting task with 15 whiskies is likely to be problematic! The second phenomenon is linked to memory. Because of the necessity of comparing products, performing a sorting task involves short-term memory that has a capacity limited to about seven *chunks* (Miller 1956). As a consequence, when the number of products to sort exceeds the assessor's memory span, then these products have to be tasted several times and this increases the risk of confusion between products. These memory problems have previously been highlighted in an experiment where verbal data, collected after the sorting task, were analyzed in conjunction with behavioral indicators (Patris et al. 2007). Results showed that trained and untrained participants expressed difficulties to memorize beer samples during the task. Besides, the number of times that the products have to be tasted increases with the number of

products to sort but depends also on the resemblance between products: the more similar the products, the more difficult the task and the more often assessors have to taste the products.

The efficiency of the sorting task has also been shown to decrease when the number of products is too small. For example, Nava Guerra et al. (2004) report that a sorting task performed with eight beers gave poor results compared to a similar task carried out with 12 beers. So even though the optimal number of products to sort is product dependent, as a general rule of thumb, we can advise to carry out a sorting task using between 9 and 20 products with an optimum number being around 12 products. Finally, when the sorting task is carried out only with visual criteria, the number of stimuli can be considerably increased as the memory load and fatigue issues are alleviated.

But what to do when we have more than 20 products to sort? A first solution is to use incomplete block designs. But in this case, a larger number of assessors are needed (e.g., we would need 84 assessors for an entire set of 50 products with 12 products in one sort and each product being tested by at least 20 assessors). Another possibility is to split a large set of products into several smaller sets and to add in each smaller set the same product (called a prototype) and to compare the products to this prototype. Obviously, in this case, the choice of the prototype is crucial. Although these approaches have not yet given rise to any scientific publications and thus still need to be validated, comparing products to a set of references seems to be a promising idea. Some recent descriptive methods such as the pivot profile (Thuillier 2007) and the polarized sensory positioning (Teillet et al. 2010) relying on the comparison with reference products have, however, been successfully applied, respectively, to champagne and mineral water.

8.3 IMPLEMENTATION AND DATA COLLECTION

8.3.1 Example of Questionnaire

An example of instructions is shown as follows:

> You have 12 samples in front of you. Please, look at, smell, and taste these samples. Then make groups according to the similarity of these products. 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 samples as you want but please make more than one group and fewer groups than the number of products. Take as much time as you want.

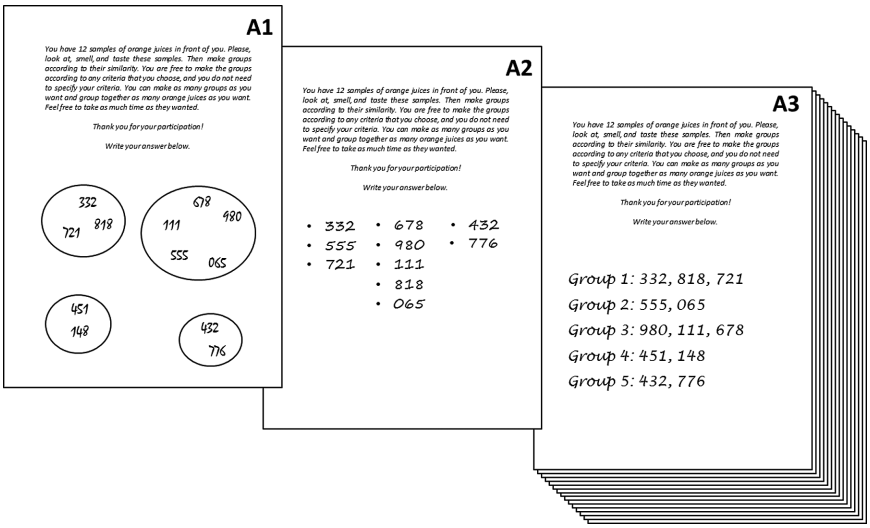


FIGURE 8.1 Example of score sheets obtained in a sorting task.

8.3.2 Example of Score Sheet

Examples of score sheets are shown in Figure 8.1.

8.3.2.1 Free Sorting Task

To analyze the sorting data with an MDS approach, the results of each assessor are encoded in an individual co-occurrence matrix where the rows and the columns are products. A value of 1 at the intersection of a row and a column indicates that the assessor sorted these two products together, whereas a value of 0 indicates that the products were not put together. All the individual matrices are then summed to obtain a global similarity matrix (Figure 8.2).

The individual matrices could also be built automatically (see Appendix) starting from a table with the products in line, the assessors in the column, and, at the intersection, the group affiliation number (products in the same group have the same affiliation number). Of course, other equivalent schemes could be used; they will all lead to the same distance matrices.

An alternative approach to analyze the sorting task is to use multiple correspondence analysis (MCA; see Abdi and Valentin 2007b; Cadoret et al. 2009). In this case, the results of the task performed by each assessor are expressed by using a group coding (also called *complete disjunctive coding*). In this scheme, each assessor is represented by as many binary vectors as there were groups of objects, and all objects in a given group are given the value of 1 in the column representing their group and a value
AQ3 of 0 for the other groups. An equivalent approach is to compute between

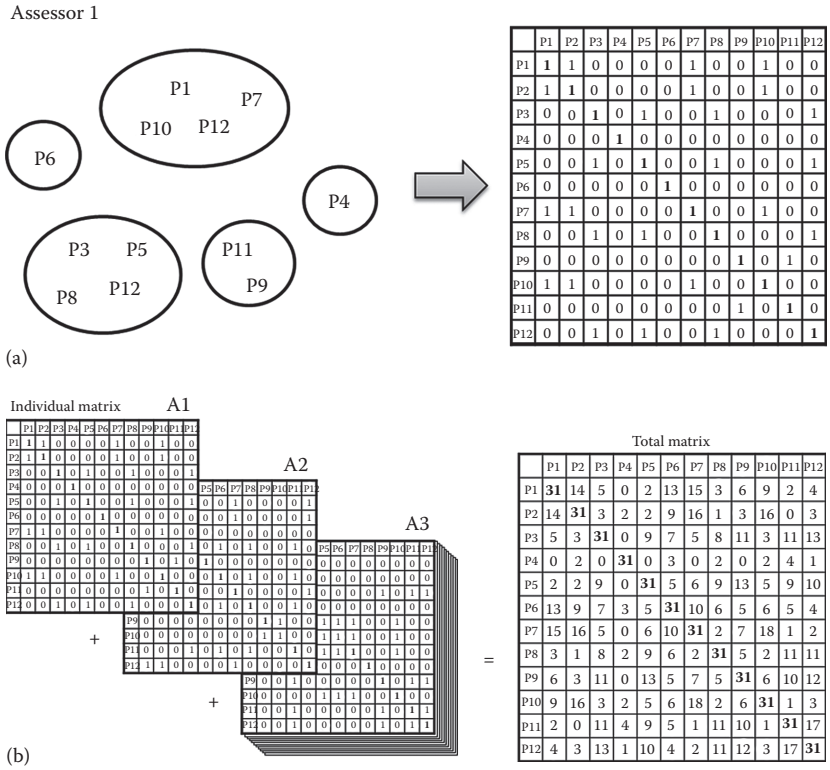


FIGURE 8.2 Example of data obtained in a free sorting task: (a) individual data and (b) group data.

product's χ^2 distance matrices for each subject and sum these matrices prior to obtain a global similarity matrix.

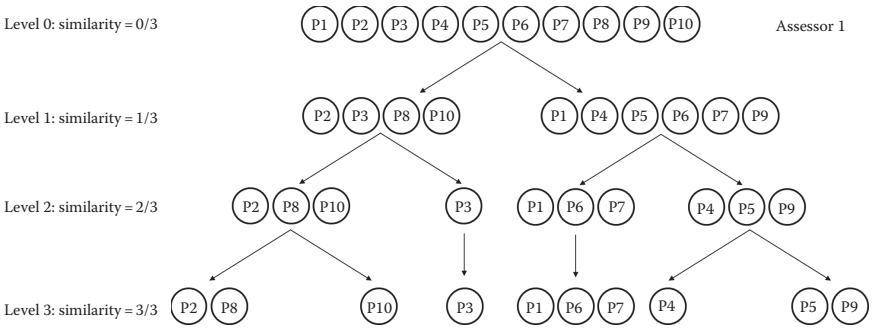
8.3.2.2 Descendant Hierarchical Sorting

In a descendant hierarchical sorting task, the similarity between products is coded as the last level at which they have been sorted together divided by the number of sorting levels. For example, two products sorted together at the third level will have a similarity score of 3/3 and two products sorted together at the second level will have a score of 2/3 (see Figure 8.3).

8.4 DATA ANALYSIS

8.4.1 Perceptual Data Analysis

The sorting similarity matrix is generally analyzed by MDS, a 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 map.



Assessor 1

	P1	P2	P3	P4	P5	P5	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 8.3 Example of individual data obtained in descendant hierarchical sorting task.

In this map, the points are arranged 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 are placed far away. 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; see Abdi 2007a,b) and nonmetric MDS. In metric MDS, the proximities are treated directly as (Euclidean) distances. The input matrix is first transformed into a cross product matrix and then submitted to an eigendecomposition (a technique equivalent to principal component analysis (PCA); see Abdi and Williams 2010). In nonmetric MDS, the proximities are treated as ordinal data. An iterative stepwise algorithm is used to create a visual representation of the objects. This algorithm (1) starts by creating an arbitrary configuration of the objects, (2) computes distances among all pairs of points, (3) 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), and (4) adjusts the position of the objects in the configuration in the direction that best decreases the stress. Steps 2 through 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 a stress value lower than 0.2 is acceptable.

In the sensory field, the similarity matrix is often analyzed with nonmetric MDS, but metric MDS is also frequently used because the sorting similarity matrix is equivalent to a squared Euclidean metric (see Abdi et al. 2007, for a proof); note that the sorting similarity matrix can also be replaced by a χ^2 distance matrix.

Multiblock analyses that take into account individual data such as DISTATIS (Abdi et al. 2007, 2012; Abdi and Valentin 2007c), MCA (Takane 1980; Cadoret et al. 2009; Abdi and Valentin 2007b), or common components and specific weights analysis (SORT CC, Qannari et al. 2009) have also been used recently. Multiple factor analysis ([MFA] Escofier and Pagès 1983; see also Abdi and Valentin 2007a; Abdi et al. in press) can also be used (see Dehlholm et al. 2012a). All 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 also provide a map of the assessors. These techniques will generally lead to similar conclusions for the relative position of the products. However, the specific χ^2 distance metric used in MCA makes salient products that are rarely associated with other products, and therefore, these rare products may define dimensions by themselves (see also the section on analysis of the example). AQ4

8.4.2 Descriptive Data Analysis

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 rows 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 to have the same meaning. If the intensity of the descriptors is evaluated as suggested by Lelièvre et al. (2008), geometric means (see Dravineks 1982) can be used instead. The resulting contingency tables are quite large and so the number of descriptors is generally reduced by grouping together terms with similar meanings and by discarding descriptors used by fewer than a certain proportion 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; Abdi and Valentin 2007c). Alternatively, the contingency table can be submitted to a correspondence analysis (CA; see Abdi and Williams 2010) 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).

8.5 ADVANTAGES AND DISADVANTAGES

8.5.1 Advantages

One of the main issues with verbal-based methods such as conventional profile 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 verbalize will be overlooked by these methods. The free sorting task alleviates this problem by relying first on a global perceptual step in which the similitude between the products is evaluated. The verbalization of the differences between products occurs only in a second step or can even be omitted.

From a practical point of view, the sorting task associated with a verbalization step is a time-effective way of describing products as long as only a coarse description of the products is required. Moreover, the sorting task can be used with both consumers and trained panelists on a relatively large set of products.

Finally, the sorting task is well adapted to select a subset of products for conducting further descriptive analysis (Giboreau et al. 2001; Piombino et al. 2004). Despite a few differences, perceptual maps obtained with a free sorting task are globally comparable with those obtained from a conventional profile (Faye et al. 2004; Saint-Eve et al. 2004) and seem to be reproducible (Falahee and MacRae 1997; Cartier et al. 2006; Lelièvre et al. 2008; Chollet et al. 2011).

8.5.2 Disadvantages

A common problem for the sorting task is that the whole set of products needs to be presented at the same time. Therefore, this method is not suitable, for example, for hot products nor for quality control.

Another aspect, rarely addressed in the literature, is the fact that vocabulary used by novices in a sorting task is often difficult to analyze and interpret. Because novices have not been trained with common references, their descriptions vary a lot from one assessor to the other, and it is often necessary to preprocess the attributes (e.g., categorization of similar terms, elimination of idiosyncratic terms) before projecting them onto the MDS maps or performing a CA. An additional problem is that assessors spontaneously qualify their attributes with various quantitative terms such as "very," "many," "slightly," "more than," and "less than," and this makes data interpretation rather cumbersome. To take into account this problem,

Lelièvre et al. (2008) suggested to provide the assessors with a predefined set of quantifiers to indicate the intensity of the perceived attributes (e.g., "not," "a little," "medium," and "very") and to analyze the data using geometric means.

Finally, authors using the sorting task generally report that this is a natural and easy task for consumers. However, even if the principle of the task is easy to understand, the task itself is not always so easy: for example, Patris et al. (2007) using a verbal report methodology showed that both trained and untrained assessors declared having memory and saturation problems when performing a sorting task on beers.

8.6 APPLICATIONS

8.6.1 Products Applications

The sorting task has been used on a large variety of food products including vanilla beans (Heymann 1994), cheese (Lawless et al. 1995), drinking waters (Falahee and MacRae 1995, 1997; Teillet et al. 2010), fruit jellies (Tang and Heyman 1999; Blancher et al. 2007), beers (Chollet and Valentin 2001; Abdi et al. 2007; Lelièvre et al. 2008, 2009), wines (Piombino et al. 2004; Ballester et al. 2005, 2008; Campo et al. 2008; Bécue-Bertaut and Lê 2011), yoghurts (Saint-Eve et al. 2004), spice aromas (Derndorfer and Baierl 2006), cucumbers and tomatoes (Deegan et al. 2010), olive oil (Santosa et al. 2010), and meat (Hoek et al. 2011). It has also been used in sensory evaluation of nonfood products such as fabrics or leathers (Giboreau et al. 2001; Picard et al. 2003; Soufflet et al. 2004; Faye et al. 2006), plastic cards (Faye et al. 2004), perfumes (Cadoret et al. 2009), or sounds (Gygi et al. 2007).

8.6.2 Usefulness of Sorting Task

The sorting task can be a very useful tool in various areas of industry including R&D, quality control, and marketing. Its role is particularly important in the development of products as well as in routine control to maintain product quality. In R&D, in addition to being a useful tool for selecting products, the sorting task could also be appropriate to determine the general characteristics of a product from a given family when we know *a priori* the relevant sensory characteristics of different members from this family. Indeed, based on the proximity structure of the members, we can deduce the membership of the studied products and thus derive its sensory characteristics. In control quality, the sorting task could be used in order to obtain an estimation of the variation of sensory characteristics according to the age of products or to the different batches. Finally, the sorting task

could also help marketing research by providing map in which products are compared to their competitors.

8.6.3 Example of Application

As an illustration, we carried out a sorting task with 16 spices, 10 individual spices (Cardamom, Chili, Cinnamon, Cloves, Coriander, Ginger, Nutmeg, Pepper, Star Anise, and Turmeric) and 6 blends of spices (Chili+Turmeric+Coriander, Chili+Turmeric, Cinnamon+Cloves+Cardamom, AQ5 Pepper+Nutmeg, Ginger+Pepper, and Ginger+Cardamom). Twenty-one French assessors participated to this experiment.

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

8.6.3.1 Metric MDS

Figure 8.4 presents the MDS representation.

Figure 8.4 suggests that there are four groups of spices: the first one composed of Cinnamon and the blend Cin+Clo+Car; the second one of Chili, Turmeric, and the blends Chi+Tum and Chi+Cor+Tum; the third one of Pepper and the blend Pep+Nut; and the last one of the other spices.

8.6.3.2 DISTATIS

To take into account individual differences, multiblock analyses such as DISTATIS are particularly well adapted (Abdi et al. 2005, 2007, 2009). AQ6 DISTATIS provides two types of MDS-like maps: (1) a map of the assessors that can be used, for example, to identify clusters among the assessors

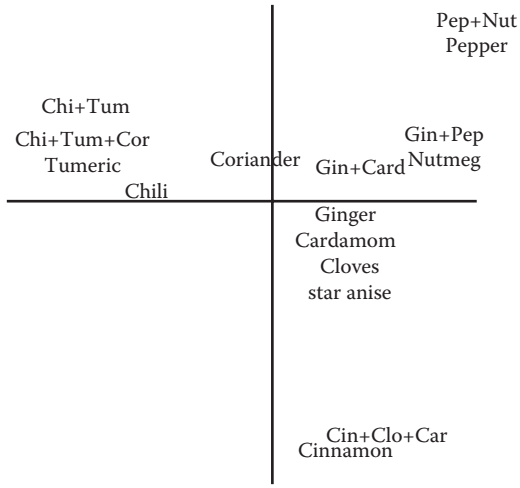


FIGURE 8.4 A 2D metric MDS map.

(in this map, assessors far to the right of dimension 1 have a large communality with the other assessors, whereas assessors close to the origin would be atypical; if a few assessors were outliers, their data may be eliminated and the analysis rerun) and (2) a map of the products that reflects how the group of assessors evaluated the products (in this map, the product positions of each assessor can also be displayed and also some confidence ellipsoids that represent the variability of the results over the assessors [when confidence intervals do not overlap, the products are perceived as different by the assessors; see Abdi et al. 2009; Dehlholm et al. 2012b; Cadoret and Husson 2013]).

Figure 8.5 shows the map of the assessors. As most of the assessors are positioned to the right, they mostly agree on their sorting. The second dimension (which account for only 7% of the variance) shows that assessors 12, 14, 15, and 16 are slightly more distant from the others.

Figure 8.6 shows the spices along with their confidence ellipsoids. We observe that for some spices, the ellipsoids are small (e.g., Pepper, Pep+Nut and Cinnamon, Cin+Clo+Car), and for others, the ellipsoids are larger (e.g., Chili, Coriander, Clove). This pattern indicates that for specific spices, the assessors are rather in agreement, whereas they tend to diverge for other spices. The first dimension opposes the spices with Chili and Turmeric to the spices with Pepper and Nutmeg. The second dimension opposes the spices with Cinnamon to the spices with Pepper. Concerning the product positioning, as can be seen by comparing Figures 8.4 and 8.6, the general solution of DISTATIS is very close to the metric MDS map. This conclusion is confirmed by computing a R_V coefficient between the factor spaces of the MDS and DISTATIS. Its value of 0.99 confirms that the two spaces are almost identical.

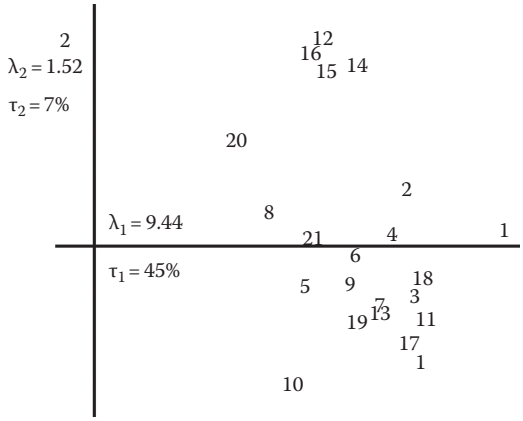


FIGURE 8.5 A 2D DISTATIS map of the assessors. The map suggests that the assessors are rather homogeneous.

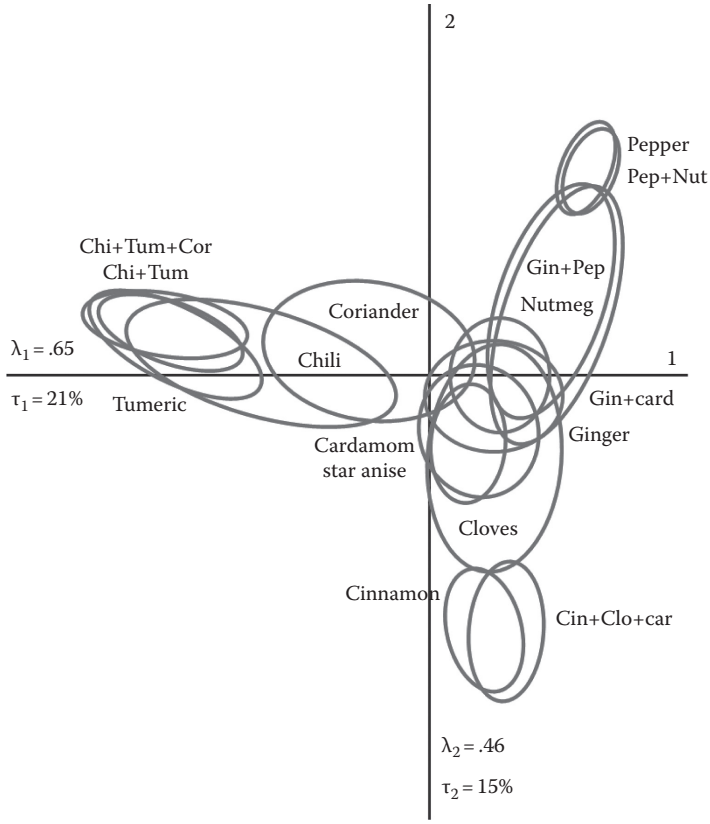


FIGURE 8.6 A 2D DISTATIS map showing the products with their 95% confidence ellipsoids. When the confidence ellipsoids of two products do not intersect, the products are perceived as significantly different by the group of assessors.

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8.A APPENDIX: ANALYSES WITH R

The techniques described in this chapter can be performed with R using the packages DistatisR (developed by Abdi, Beaton, and Chin-Fatt and available from CRAN and the senior author's homepage). The data of the example are available as a data set from this package. The analysis of the results of this chapter can be obtained with the following R commands:

```
# install the packages
install.packages("prettyGraphs")
install.packages("car")
install.packages("DistatisR")
#-----------------------------------------------------
```

```
# 1. Load the library DistatiR
library(DistatisR)
# The data to illustrate the paper are in the data set
SortingSpice
# that is provided by the package DistatisR.
data(SortingSpice)
# This data set gives the data.frame called SortSpice
that we will analyze
#-----------------------------------------------------
# 2. Create the set of distance matrices (one distance
matrix per assessor)
#    (use the function DistanceFromSort) applied to
SortSpice
DistanceCube <- DistanceFromSort(SortSpice)
#    The results will be stored into the 3D array
called DistanceCube
#-----------------------------------------------------
# 3. For the first analysis, we will performe
#    a metric multidimensional analysis
#    on the distance matrix obtained by summing
#    all the assessors' distance matrices.
#    The sum is obtained with this instruction
TotalDistance = apply(DistanceCube,c(1,2),sum)
#    The sum is stored in TotalDistance
#
# 3.1. Analyze TotalDistance with metric mds.
#      Use the function mmds (from package DistatisR)
mdsRes <- mmds(TotalDistance)
# The results of mmds are in mdsRes
# 3.2 Now a pretty plot with the prettyPlot function
from prettyGraphs
# For this plot we will use the factors scores (stored
in mdsRes$FactorScore)
PlotMDS <- prettyPlot(mdsRes$FactorScore,
           display_names = TRUE,
           display_points = TRUE,
           contributionCircles = TRUE,
           contributions = mdsRes$Contributions)
#-----------------------------------------------------
# 4. For the second analysis, we use the distatis
method
#    This is performed by the distatis function
#    (with cube of distance "DistanceCube" as a
parameter)
testDistatis <- distatis(DistanceCube)
# The factor scores for the products (i.e., spices)
are in
```

```
# testDistatis$res4Splus$F
# the factor scores for the assessors (i.e., analysis
if the RV matrix)
# are in testDistatis$res4Cmat$G
##-----------------------------------------------------
# 4.1 Inferences on the products obtained via
bootstrap
#     here we use two different bootstraps:
# 4.1.1. Bootstrap on factors (very fast but could be
too liberal
#        when the number of assessors is very large)
BootF <- BootFactorScores(testDistatis$res4Splus$Parti
alF,niter=1000)
# 4.1.2. Complete bootstrap obtained by computing sets
of compromises
#        and projecting them (could be significantly
longer because a lot
#        of computations is required)
#
 F_fullBoot <- BootFromCompromise(DistanceCube,ni
ter=1000)
#-----------------------------------------------------
# 4.2 Create the Graphics
# Get the Factor Scores and Partial Factor Scores for
the plot Routine
 LeF       <- testDistatis$res4Splus$F
 PartialFS <- testDistatis$res4Splus$PartialF
# 4.2.1. plot the Observations with the Bootstrapped
CI from the factor scores
PlotOfSplus <- GraphBootDistatisCpt(LeF,
                    BootF,PartialFS,ZeTitle='Bootstrap
on Factors')
# 4.2.2 Plot the Observations with the bootstrapped CI
from the Compromises
PlotOfSplusCpt <- GraphBootDistatisCpt(LeF, F_
fullBoot,
                          PartialFS,ZeTitle='Full
Bootstrap')
# 4.2.3 Plot the Bootstrap results with ellipses
instead of convex hulls
PlotOfSplusElli <- GraphBootDistatisEllipseCpt(Le
F,F_fullBoot,PartialFS,
      ZeTitle='Full Bootstrap 95% CI', nude=TRUE,
      color = PlotOfSplus$col)
# 4.2.4 Plot the RV map
PlotOfRvMat <- GraphDistatisRv(testDistatis$res
4Cmat$G,ZeTitle='Rv Mat')
```

```
# 5. A MCA type of approach can be obtained by
replacing step 2 by

DistanceCube <- Chi2DistanceFromSort(SortSpice)

# This will compute a Chi-2 distance for each
assessor,
# suffice to repeat steps 3 to 4 to obtain the
analysis
```

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