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Estimating and interpreting more than two consensus components in projective mapping: INDSCAL vs. multiple factor analysis (MFA)

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ABSTRACT

In this paper a general framework is proposed for understanding and analysing more than two consensus components in projective mapping (also known as Napping®) studies. Focus is on how two models, multiple factor analysis (MFA) and individual differences scaling (INDSCAL) based on the weighted Euclidean model (WEM), relate to each other and to the general framework. The stability of the consensus configurations of both methods are compared. The relations between the results of the two methods are investigated using the RV coefficient and an alternative index called SMI which gives equal weight to the axes regardless of the relative size of the singular values. The methods are tested and compared using three datasets and simulations.

1. Introduction

In the last couple of decades there has been an important development of new and alternative sensory techniques, sometimes referred to as rapid sensory methods (Valentin, Chollet, Lelievre, & Abdi, 2012; Varela & Ares, 2012; Varela & Ares, 2014). These methods have emerged as a response to the fact that regular quantitative descriptive analysis (QDA) can be considered quite rigid and time consuming. In this paper we will focus on the so-called projective mapping method (Risvik, McEwan, Colwill, Rogers, & Lyon, 1994), which has been later known as Napping® (Pagès, 2005). This method has several interesting characteristics since it can be used with untrained assessors and provides information that is not restricted to intensities for a number of pre-specified attributes. The method is based on asking assessors to place samples on a sheet of paper (or rectangular surface on a computer screen) according to similarities and differences. The coordinates of the samples along the "vertical" and "horizontal" directions of the sheet are then used for data analysis. Usually, the assessors are also asked to put words on the sheet that characterize the different samples or groups of samples. This last descriptive step is usually referred to as ultra-flash profiling (Perrin & Pagès, 2009).

For most applications of projective mapping, generalized Procrustes analysis (GPA, Gower, 1975; Gower & Dijksterhuis, 2004) and Multiple factors analysis (MFA, Abdi, Williams, & Valentin, 2013; Escoufier & Pagès, 1994; Pagès, 2004) are used for data analysis. GPA is based on rotating and scaling the coordinates of the assessor data before calculating the average, known as consensus configuration. MFA, on the other hand, concatenates the individual data tables after an individual scaling and performs regular principal components analysis (PCA) to obtain the consensus. Another model, which is sometimes used for interpreting projective mapping data, is individual differences scaling (INDSCAL) based on the so-called weighted Euclidean model (WEM, Barcenas, Elortondo, & Albisu, 2004; Carroll & Chang, 1970) for the distances between the objects. Husson and Pages (2006) provide an interesting discussion of some fundamental geometrical aspects of INDSCAL. In all cases it is useful to look at both the consensus and individual configurations (Tomic, Berget, & Næs, 2015).

Projective mapping data are essentially two-dimensional, but when applying statistical techniques such as MFA it is possible to extract and interpret more than two PCA components (Nestrud & Lawless, 2008). The most plausible interpretation of this is that assessors rely on different characteristics of samples for assessing their similarities and differences. In other words, they use divergent criteria, or put different emphasis on different aspects of the samples. Therefore, considering more than two dimensions can enable the identification of all the sensory characteristics responsi-

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ble for the perceived similarities and differences among samples. In this sense, Vidal et al. (2016) showed that considering only the first two dimensions of the consensus configuration can potentially underestimate the complexity of consumers' sensory perception of samples. Despite this fact, most applications of the projective mapping technique limit themselves to consider only two dimensions in the consensus configuration, although a few papers extend the interpretation up to four. As a reference point, from 46 publications in Food Quality and Preference and Food Research International that have "projective mapping" or "napping" in their tittles, abstract or keywords (Scopus search), only six go beyond the second dimension (and for the most only 3 components) for interpretation, four in product characterization applications (Cadena et al., 2014; Fariña et al., 2015; Kim, Jombart, Valentin, & Kim, 2013; Marcano, Ares, & Fiszman, 2015) and two in methodological studies (Vidal et al., 2014; Vidal et al., 2016)

This paper focuses on stability, precision and interpretation aspects when estimating more than two dimensions in the analysis of projective mapping data. In particular, we will describe a framework that can be used as a basis for better understanding of the concept of more than two underlying dimensions. The two most used methods in the area that can also handle more than two dimensions, INDSCAL and MFA, will then be related to this general framework. This will also shed some light onto conceptual differences between the two methods. The INDSCAL and MFA will then be compared both using a simulation study and using three different projective mapping data sets collected with different product categories (yoghurt, perfumes and chocolate milk). The methods will be compared with respect to how similar they are, with respect to how good they are at estimating the true consensus (in the simulations) and how stable they are with respect to the size of the data set. A random reduction is tested, but also data reduction based on poor model fit will be considered. The aim of the paper is not to propose a unique way of extracting more than two components from projective mapping data, but merely to provide some insight into the importance of incorporating more than two components and what are possible advantages and drawbacks of the methodologies tested. Focus will be on three components since one will seldom go beyond this in practical applications of projective mapping data (see also references above), but some discussion will also be given to four components. Method comparisons will be done using the RV coefficient (Robert & Escoufier, 1976) and a newly developed alternative putting equal weight on the singular vectors (the SMI, Indahl, Liland, & Næs, 2016). It must be emphasized that the method comparison in this paper is primarily based the consensus configurations and that a number of additional tools are available both for MFA and INDSCAL for assessing validity and for more detailed interpretation (see e.g Pagès (2014) and Tomic et al. (2015)).

2. Theory

2.1. The underlying mental model

Even though the underlying product space may be multidimensional, in a projective mapping task with focus on only two dimensions, each assessor is forced to focus on a subset of the dimensions, either separately or in combination (Hopfer & Heymann, 2013; Nestrud & Lawless, 2011 and Dehlholm, 2014). Since individual differences in consumers' cognitive strategies and factors related to the test can affect the sensory characteristics or dimensions used ((Jaeger, Wakeling, & MacFie, 2000; Malhotra, Pinson, & Jain, 2010; Vidal et al., 2016), the projective maps from the different assessors my turn out to be very different from each other.

In this paper we will assume that the underlying product space can be represented by *A* sensory dimensions or latent variables (the coordinates referred to as $\mathbf{X}$) that can be perceived by the assessors. One can think of these latent variables as representing scores from for instance a PCA model in *A* dimensions with each point in the space corresponding to an object. Note that the coordinates are not unique; any linear transform of $\mathbf{X}$ will play the same role in this context. In this paper boldface will be used for matrices and vectors and italics will be used for scalars.

We will here consider the individual projective mapping data $\mathbf{Y}_k$ (two columns and *N* rows, $k = 1,\ldots,K$) as individual functions f_k of the underlying latent variables $\mathbf{X}$, i.e. the data $\mathbf{Y}_k$ for assessor k can be represented as

$$\mathbf{Y}_k = f_k(\mathbf{X}) + \mathbf{E}_k \tag{1}$$

where $\mathbf{E}$ represents the random noise. The most important challenge in practice is to reveal $\mathbf{X}$ from the $\mathbf{Y}_k$ data, but the individual differences represented by f_k are also of interest in many cases (Tomic et al., 2015). We will always work with centered $\mathbf{Y}$ data, so without loss of generality we will assume that the center of $\mathbf{X}$ is zero. For the purpose of interpreting the coordinates of $\mathbf{X}$, information from the descriptive step can be useful (ultra-flash profiling).

Certain assumptions must be made on the *f's* in order to make estimation of $\mathbf{X}$ possible. The simplest assumption is that the *f*'s represent linear functions of $\mathbf{X}$. As will be shown below this assumption is needed in order to see how concrete and established methods are related to the framework in Eq. (1). With the linearity assumption, the model (1) becomes

$$\mathbf{Y}_k = \mathbf{X}\mathbf{R}_k + \mathbf{E}_k \tag{2}$$

where the $\mathbf{R_k}$'s are matrices of individual constants. In order to better understand how this model relates to individual differences in practice, it may be useful to consider a couple of examples: If for instance the $\mathbf{Y}_k$ for assessor k consists of information only along the two first dimensions of $\mathbf{X}$, the last rows (after 2 components) of $\mathbf{R_k}$ will consist of zeros only. If the columns of $\mathbf{Y}_k$ on the other hand are combinations of several underlying dimensions, the $\mathbf{R_k}$ will have at least one position different from zero in each of the actual rows.

In most practical applications of methods used for projective mapping data, focus is on 2 dimensions (see above), but in principle there can be 3 and even 4 components in the underlying space ($\mathbf{X}$). Most consumers generally use the full bi-dimensional space for building their maps. However, it has been reported that about 6–15% of the judges have "problems" with the projective mapping task, being unable to create a bi-dimensional representation of the products (Dehlholm, 2014; Hopfer & Heymann, 2013). In these cases, consumers would be sorting or ranking the samples into groups following one dimension.

In the notation below we will save the $\mathbf{X}$ for the underlying mental model above and let $\mathbf{T}$ and $\mathbf{V}$ be the coordinates for subspace estimates obtained by MFA and INDSCAL respectively.

2.2. MFA and its relation to the general framework

The MFA is defined as a PCA of the concatenated matrix $\mathbf{Y} = [\mathbf{Y}_1, \ldots, \mathbf{Y}_K]$ where each $\mathbf{Y}_k$ is first centered and divided by the first singular value of the matrix. The $\mathbf{Y}$ is then modelled by the PCA model

$$\mathbf{Y} = \mathbf{T}\mathbf{P} + \mathbf{E} \tag{3}$$

where $\mathbf{T}$ is the consensus scores matrix (also this centered since $\mathbf{Y}$ is) and the $\mathbf{P}$ is the loadings matrix of the dominating principal components. The matrix $\mathbf{E}$ represents the noise or the minor components of $\mathbf{Y}$ that one is usually not interested in. Note that other