Multi-block methods in sensory analysis: a comparison of consensus methods by means of a flavor language case study

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Cross-cultural comparisons of sensory data are often required in product development. Free choice profiling permits each evaluator the freedom to use language and scaling procedures with which he feels comfortable. The data are usually analyzed by Generalized Procrustes Analysis (GPA). There are, however, other multi-block consensus methods: e.g. Consensus Principal Component Analysis (C-PCA) (Westerhuis et. al, 1998) and Multi-block Component Analysis (MBCA) (Smilde et. al, 2000). All three of these techniques were applied to a recent project aimed at developing savory flavors for the Asian market.

One aspect that these explorative methods have in common is that data from different tables (blocks) are jointly decomposed into a low dimensional sub-representation by pursuing a consensus between the blocks. C-PCA consensus scores can be obtained by means of a singular value decomposition of scaled block variables or with the multi-block NIPALS projections, as originally proposed by Wold. GPA tries to iteratively match the blocks into a centroid configuration by applying block transformations, rotations and isotropic scaling of the various blocks, followed by PCA to compute the consensus scores. The MBCA consensus scores are obtained by an algorithm based on Principal Covariate Regression (PCovR) (Jong, 1992), which tries to find covariates describing most variance in the predictors and dependent variables simultaneously. The same theoretical concept was elaborated by Smilde (Smilde et. al, 2000) for multi-block data analysis. The objective of MBCA is to find a good balance between finding block summarizers and a cross-block summarizer (consensus scores). The added value of MBCA compared to C-PCA and GPA is that the theory allows data blocks of different rank and even of different block dimensions.

In the present study three data blocks of different rank were examined. The Australian team of flavorists and product developers produced data of rank 2 whereas their Japanese counterpart's data was of rank 3. The Naarden sensory research panel had data of rank 4. GPA and C-PCA failed to summarize the data on a block level, yielding an under- or overfit of the data. On the other hand, MBCA allowed imposing different ranks per block, yielding a better fit of the data and improved insights in the data structures at higher dimensions.

Keywords: C-PCA; GPA; MBCA; FCP

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