Multilingual textual data: an approach through multiple factor analysis

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Abstract This paper focuses on the analysis of open-ended questions answered in different languages. Closed-ended questions, called contextual variables, are asked to all respondents in order to understand the relationships between the free and the closed responses among the different samples since the latter assumably affect the word choices. We have developed "Multiple Factor Analysis on Generalized Aggregated Lexical Tables" (MFA-GALT) to jointly study the open-ended responses in different languages through the relationships between the choice of words and the variables that drive this choice. MFA-GALT studies if variability among words is structured in the same way by variability among variables, and inversely, from one sample to another. An application on an international satisfaction survey shows the easy-to-interpret results that are proposed.

Keywords: Correspondence analysis, Lexical tables, Textual and contextual data, Multiple factor analysis, Generalized aggregated lexical table

1. INTRODUCTION

Socio-economic surveys benefit from introducing open-ended questions in addition to closed-ended questions because they enrich each other. Closed-ended questions inform the interpretation of open-ended questions because the meaning of words is related to the characteristics or opinions of those who speak. For

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instance, in a satisfaction survey, customers are asked to rate certain aspects of the product and then freely give their opinion on which aspects could be improved, which is clearly linked to the ratings. In a survey that includes the question "What does health mean to you?" closed-ended questions such as gender, age, education and health status will greatly assist in exploring how the definitions of health vary with these variables. In the case of international surveys, our framework, these open-ended questions raise the issue of analyzing the responses expressed in different languages by several samples.

In the case of a single language, textual statistics (Benzécri 1981; Lebart et al. 1998) offer multidimensional tools for processing free responses. Separately for each sample, the free responses are encoded in the form of a frequency table respondents $\times$ words, called a lexical table (LT). A standard methodology is to apply correspondence analysis to this LT (CA-LT; direct analysis) and to use the closed information as a complement. It is also usual to group the responses of the categories of a closed question (such as age crossed with gender or education level, called contextual variable) and to build the frequency table of the words $\times$ categories, called aggregated lexical table (ALT) which can also be analyzed by CA (CA-ALT).

This approach is extended to several quantitative or qualitative contextual variables by using linearly constrained CA methods (Takane et al. 1991). Thus, Balbi and Giordano (2001) address textual data including external information, Balbi and Misuraca (2010) propose a double projection strategy by involving external information both on documents and words while Spano and Triunfo (2012) apply canonical correspondence analysis (CCA; ter Braak (1986, 1987)) to textual data. In line with these works, Bécue-Bertaut et al. (2014) and Bécue-Bertaut and Pagès (2015) propose the method called CA on a generalized aggregated lexical table (CA-GALT). First, a table words $\times$ variables, called "Generalized Aggregated Lexical Table" (GALT), is developed by positioning the words on the variable-columns based on the values taken by the respondents who use them. Afterwards, this GALT is analyzed by means of a CCA adapted to textual data. In CA-GALT, like in any CA, both the variability of vocabulary through the variability of variables, and the variability of variables through the variability of vocabulary are explained. This fits perfectly with the perspective we have chosen to take here.

In the case of multilingual surveys, we propose to analyze simultaneously the different GALTs, one for each sample, by means of a multiple factor analysis (MFA; Escofier and Pagès 2016; Pagès 2014), tailored to process a multi-
ple GALT. This leads to the Multiple Factor Analysis for Generalized Aggregate Lexical Tables (MFA-GALT). This work outlines how to adapt MFA reasoning in order to handle a multiple GALT, and details its properties and graphical representations.

The aim of MFA-GALT is to jointly study the open-ended responses given by several samples in different languages through the relationships between the choice of words and the variables that motivate this choice. These relationships may or may not have similar structures. In other words, MFA-GALT studies whether variability among words is structured in the same way by variability among variables, and inversely, across samples.

The paper is organized as follows: Section 2 presents the data structure and the notation. Section 3 recalls the principles of CA-GALT and MFA, the methods that form the basis of our approach; Section 4 is devoted to MFA adapted to multiple GALTs (MFA-GALT) and Section 5 exposes the properties of the method. Eventually, the application of MFA-GALT to a full-scale application (Section 6) shows its capabilities. The main conclusions are presented in Section 7.

2. DATA STRUCTURE AND NOTATION

$L$ samples have answered a questionnaire with closed questions, either quantitative or categorical, all of identical type, which constitute the contextual data. They have also answered an open-ended question in different languages conforming the textual data. The $l$ sample has $I_l$ respondents who all together use $J_l$ different words in the $l$ language. From these responses, we construct the $(I_l \times J_l)$ table $Y_l$, respondents $\times$ words; $N_l$ is the grand total for this table.

The responses to the closed-ended questions, common to all samples, are encoded in the $(I_l \times K_l)$ table $X_l$, whose columns correspond either to quantitative variables or to dummy variables encoding the categories of one or more categorical variables. Whatever the type, $k$ and $K_l$ denote, respectively, the column variable $k$ and the total number of column variables. In what follows, the term variable will be used for both types. From $Y_l$, we compute the $(I_l \times J_l)$ proportion table $P_l = Y_l/N_l$.

If we consider only the sample $l$, the weights of the respondents are obtained from the margin of the rows of $P_l$, thus proportional to the length of their free answers, and stored in the $(I_l \times I_l)$ diagonal matrix $D_l$. The total weight of the respondents belonging to the same sample is equal to 1. In the same way, the weights of the words are obtained from the margin of the columns of $P_l$, thus proportional to their counts, and stored in the $(J_l \times J_l)$ diagonal matrix $M_l$. The
total weight of the words used by the same sample is equal to 1. \( X_l \) is centered and possibly normalized in the case of quantitative variables, for the weighting system \( D_l \). The data structure including the relations between words and variables is the \((J_l \times K)\) table \( Q_l = \frac{Y_l^T X_l}{N_l} = P_l^T X_l \). \( Q_l \) is called generalized aggregated lexical table.

**Remark.** The name Generalized Aggregated Lexical Table and the acronym GALT are used to emphasize the great similarity between this table and the classic aggregated lexical table (ALT) developed in the case of a single categorical variable (Lebart et al., 1998).

In fact, the calculation is exactly the same in both cases. What changes is only the expression of the matrix \( X \) itself. In the case of an ALT, this table is composed of the dummy variables corresponding to the categories of a single categorical variable.

![Diagram of coupled tables](image-url)

**Figure 1: Sequence of L coupled tables**

In the global analysis of the \( L \) samples, we have to deal with \( I = \sum_l I_l \) respon-
dents who have used \( J = \sum J_l \) different words in the \( N = \sum N_l \) occurrences that they pronounced through all the free answers. The respondent and word weights are resized so that both totals are equal to 1 for, respectively, the \( I \) respondents and \( J \) words. To this end, the respondent and word weights in sample \( l \) are multiplied by \( N_l / N \). The respondent global weights are stored in the \((I \times I)\) diagonal matrix \( D \). The word global weights are stored in the \((J \times J)\) diagonal matrix \( M \). The \((I \times K)\) global table \( X \) is obtained by juxtaposing column-wise the \( L \) tables \( X_l \), centered by set. As a consequence, table \( X \) is also centered for weighting system \( D \).

We suppose \( K < J \). In the following, the symbols \( I, I_l, J, J_l, K, L \) refer to both the set and its cardinal number.

3. METHODS USED AS A BASIS OF OUR APPROACH

3.1. DEALING WITH ONE SAMPLE

In this section, we treat only one sample and therefore consider that it is not necessary to use the index \( l \).

3.1.1. CA-GALT method

We want to analyze the GALT \( Q \). To keep, as much as possible, a CA-like approach, we use CA-GALT method \( \text{Bécue-Bertaut and Pagès [2015] Bécue-Bertaut et al. [2014]} \) that we summarize hereafter.

Let the \((K \times K)\) matrix \( C = (X^TDX) \) be the weighted correlation/covariance matrix of the variable-columns of matrix \( X \). We calculate the \((J \times K)\) matrix \( Z \), double standardized form of matrix \( Q \):

\[
Z = M^{-1}Q C^{-1}.
\] (1)

If \( C \) is not invertible, \( C^{-1} \) is substituted by the Moore-Penrose pseudoinverse \( C^\dagger \).

Then, CA-GALT is performed through a principal component analysis (PCA) in metrics \( C \) in the row space, and \( M \) in the column space, that is, PCA(\( Z, C, M \)). This involves computing the \( S (S \leq K) \) eigenvalues and eigenvectors of

\[
Z^TMZC.
\] (2)

The eigenvalues are stored into the \((S \times S)\) diagonal matrix \( \Lambda \), and the eigenvectors into the \((K \times S)\) matrix \( U \).

CA-GALT is a dual projection analysis \( \text{Bécue-Bertaut and Pagès [2015]} \) which
leads to explain, on one hand, the variability of words according to the variability of variables and, on the other hand, the variability of variables according to the variability of words.

 Remark. Metric $C^{-1}$ (or $C^*$) operates a multivariate standardization that not only separately standardizes the columns of $X$, but in addition makes them uncorrelated (Brandimarte [2011] Härdle and Simar [2012]).

3.2. MFA GENERAL SCHEME

Multiple factor analysis (Escofier and Pagès [2016], Pagès [2014]) analyzes multiple table, juxtaposing row-wise either quantitative or categorical tables. It has been further extended to frequency tables (Bécue-Bertaut and Pagès [2004]). This method analyzes a set of rows described by different sets of columns. The core of MFA is a PCA, with specific weights and metrics, applied to the multiple table dealing with the quantitative tables as in PCA, the categorical ones as in multiple correspondence analysis (MCA) and the frequency tables, in particular lexical tables, as in CA. The specific approach to each type of tables is obtained through a possible coding of the initial data and convenient choices of the weights and metrics.

In order to balance the influence of the sets on the first factorial dimension, the initial weights of the columns belonging to a given set are divided by the first eigenvalue resulting from the separate analysis of the corresponding table (PCA, MCA or CA depending on its type). Thus, the highest axial inertia of each set is normalized to 1. MFA looks for identifying the main directions of variability in the data from a description of the rows by all the different sets of columns but balancing the importance of these sets. MFA provides the classical results of principal component methods. PCA, MCA or CA characteristics and interpretation rules are kept for, respectively, the quantitative sets, the categorical sets and the frequency sets. MFA also offers graphical tools for comparing the different sets such as the superimposed global and partial representation of the rows, as induced by all the sets or separately by each of them, as well as a synthetic representation of the sets, in which each of them is represented by only one point. These graphical results allow us to compare the typologies provided by each set in a common reference space.

4. MFA ON MULTIPLE GALT

Hereafter, we tailor MFA to the case where the separate tables are GALT built from the different samples, that is to say, from the different coupled tables $(Y_1, X_1)$
It is a question of inserting GALTs, and their analysis by CA-GALT, into this approach.

MFA, as described above, is usually devoted to a set of rows described by several sets of columns. Yet, we have now to analyze several sets of row-words described by one set of column-variables. However, we are placed here in a CA-like context where the role of rows and columns is exchangeable, which we could do without altering results. In the following sections, we directly set out MFA-GALT method.

As classical MFA, MFA-GALT is performed in two steps. First, each sub-table - which is here a GALT - is analyzed separately, by applying the factorial method corresponding to its type - here CA-GALT. In the second step, a global factorial analysis on all the sets of multiple tables is performed, addressing each set as dealt with in the separate analyzes but taking into account the reweighting used to balance the influence of the sets. In this way, the different sets of rows have a similar influence on the first global axis. This reweighting consists in dividing the weights of the rows of set $l$ by the first eigenvalue obtained in the separate analyzes of this set. Therefore, the highest axial inertia of each set is standardized to 1. Among the properties of this reweighting of the rows, note that the within-sets structures are not modified and, except for very special cases, the first axis of the global analysis cannot be generated by a single table. These two steps are detailed hereafter.

First step: separate analyzes

Separate CA-GALTs are performed in each set, on the GALT $Q_l$, following Section 3.1.1 scheme except for the metric used in the row space (and weighting system in the column space). In this case, the covariance/correlation matrix computed from all the respondents, that is, $C = (X^TDX)$, is used, instead of matrices $C_l = (X_l^TDX_l)$, in all the separate analyzes. This is due to the need to place all the row sets in a same metric space. In accordance with this, $C^{-1}$ (or $C^-$, if $C$ is not invertible) is used to standardize $Q_l$. So, in this first step $Z_l = M_l^{-1}Q_lC^-$ is analyzed via PCA($Z_l,C,M_l$). The $L$ first eigenvalues $\lambda_l^1$ will be used in the second step.

Second step: global analysis

The row weighting system is updated to balance the influence of each set in
the global analysis. By construction, matrix $\mathbf{M}$ is divided into $L$ blocks. Block $l$ corresponds to the $J_l$ words used in sample $l$. The weights of the words of block $l$ are divided by $\lambda_l^1$, the first eigenvalue of the separate analysis of subtable $l$. The resulting weights are stored into the $(J \times J)$ matrix $\mathbf{M}_\lambda$.

The $(J \times K)$ multiple table $\mathbf{Q}$ juxtaposes column-wise the $L$ matrices $\mathbf{Q}_l$ but resized by multiplying them by coefficient $N_l/N$ ($\mathbf{Q}_l \times N_l/N$). A double standardization of $\mathbf{Q}_l$ on the rows and the columns, leads to the $(J \times K)$ table $\mathbf{Z} = \mathbf{M}_\lambda^{-1} \mathbf{Q} \mathbf{C}^{-1}$. If $\mathbf{C}$ is not invertible, $\mathbf{C}^{-1}$ is substituted by the by the Moore-Penrose pseudoinverse $\mathbf{C}^\dagger$. Then, MFA-GALT is performed through a non-standardized weighted PCA performed on the multiple table $\mathbf{Z}$ with $\mathbf{M}_\lambda$ as row weights and metric in the column space and $\mathbf{C}$ as column weights and metric in the row space, that is, $\text{PCA}(\mathbf{Z}, \mathbf{C}, \mathbf{M}_\lambda)$.

5. MAIN PROPERTIES OF MFA-GALT

MFA-GALT provides the classical outputs of the principal components methods:

- coordinates, contributions and quality of representation of row-words
- coordinates of categories at the centroid of the row-words used by respondents belonging to this category
- coordinates of quantitative variables as covariances and/or correlation coefficients between factors and quantitative variables

Furthermore, outputs from MFA as a partial representation of the variables, a synthetic representation of the sets and a measure of the similarity between the sets are also provided.

5.1. REPRESENTATION OF THE ROW-WORDS AND THE COLUMN-VARIABLES

$\text{PCA}(\mathbf{Z}, \mathbf{C}, \mathbf{M}_\lambda)$ involves diagonalizing the matrix $\mathbf{Z}^T \mathbf{M}_\lambda \mathbf{Z} \mathbf{C}$. The principal axis with rank $s$ corresponds to the eigenvector $\mathbf{u}_s (\|\mathbf{u}_s\|_C = 1)$ associated with the eigenvalue $\lambda_s$:

$$\mathbf{Z}^T \mathbf{M}_\lambda \mathbf{Z} \mathbf{u}_s = \lambda_s \mathbf{u}_s. \quad (3)$$

The eigenvalues $\lambda_s$ are stored into the $(S \times S)$ diagonal matrix $\Lambda$ and the eigenvectors $u_s$, dispersion axes, into the columns of the $(K \times S)$ matrix $\mathbf{U}$.

By factor $s$ we mean the vector of coordinates on axis $s$ of either the word-rows (denoted $F_s$) or the variable-columns (denoted $G_s$) (Benzécri, 1973, Pagès).
The $S$ factors on the rows are stored into the columns of the $(J \times S)$ matrix $F$, calculated as:

$$F = ZCU.$$  

(4)

The $S$ factors on the columns are stored into the columns of the $(K \times S)$ matrix $G$. Matrix $G$ is calculated through the use of the transition relations between the factors on the rows and on the columns, also found in this case as in any PCA:

$$G = Z^T M \lambda F \Lambda^{-1/2}.$$  

(5)

5.2. SUPERIMPOSED REPRESENTATION OF THE CLOUDS OF VARIABLES

According to the $L$ sets of row-words, the column-variable $k$ of $Z$ can be divided into $L$ subcolumns, named partial variables and denoted $k^l$. It is useful to represent simultaneously the $L$ partial scatter plots, each made up of the corresponding $K$ partial variables, on the same referential axes. To this end, we successively consider the $L$ matrices $Z^l$, with dimension $(J^l \times K)$, issued from matrix $Z$ by keeping only the row-words belonging to set $l$. From these matrices, the $(J \times K)$ matrices $\tilde{Z}^l$ are built by completing $Z^l$ with 0 to be the dimension of $Z$. In order to be represented on the global axes, the $K$ partial variables corresponding to the set $l$ are considered as supplementary columns in the global analysis. Their coordinates are calculated using the transition relations and stored in the $(K \times S)$ matrix $G^l$:

$$G^l = \tilde{Z}^l^T M \lambda F \Lambda^{-1/2}.$$  

(6)

Therefore, the coordinates of the partial variables corresponding to set $l$ can be calculated from the coordinates of the words used by only sample $l$. This relationship for partial variable $k^l$ is expressed very simply thanks to the structure of matrix $\tilde{Z}^l$ which contains only 0, except for the rows belonging to set $l$:

$$G_s(k^l) = \frac{1}{\sqrt{\lambda^l}} \frac{1}{\sqrt{\lambda^l}} \sum_{j \in J^l} z^l_{jk} m_{jj} F_s(j).$$  

(7)

In Eq.7, $z^l_{jk}$ denotes the generic term of $Z$ and $\frac{1}{\sqrt{\lambda^l}} m_{jj}$ denotes the generic term of matrix $M$, being $m_{jj}$ the initial weight of the word $j$ (see Section 2).

Accordingly to Eq.7, the partial variables relative to set $l$, are on the side of the words over-used in this sample by respondents having high values for these variables.

Usually, all the "partial" variables can be represented on the same scatter plot, informing about the similarities/dissimilarities among the samples.
5.3. GLOBAL REPRESENTATION OF THE SETS

Another result is to represent the \( L \) groups on the same graph, each of them being represented by a point (Pagès, 2014). To this end, the \( L_{g} \) coefficient, linkage measurement between one variable and one set of variables is used, applied here to measure the linkage between each set and the axes that are retained. First, the \( (K \times K) \) matrix of scalar products \( W_{l} \) between the \( K \) column-variables of set \( l \) is calculated as

\[
W_{l} = Z_{l}^{T} M_{\lambda}^{l} Z_{l}. \tag{8}
\]

where the diagonal matrix \( M_{\lambda}^{l}, \) equal to block \( l \) of matrix \( M_{\lambda}, \) contains the weights of the variables of set \( l, \) equal here to \( \frac{1}{n^{l}}. \) Then, \( L_{g}(l, u_{s}) \) is calculated in the following way:

\[
L_{g}(l, u_{s}) = \langle W_{l} C, u_{s} C \rangle = \text{trace}(W_{l} C u_{s}^{T} C). \tag{9}
\]

Further, \( L_{g}(l, u_{s}) \) is used as a coordinate to place set \( l \) upon axis of rank \( s. \) This coordinate always has a value between 0 and 1. Accordingly, a map of all the sets, each one represented by one point, is obtained. This map also allows for visualizing the similarity between the \( L \) set structures.

5.4. MEASURE OF THE ASSOCIATION BETWEEN VOCABULARY AND CONTEXTUAL VARIABLES

Our proposal also includes the measurement of the association between vocabulary and contextual variables, first to select the variables that actually play a role and second to interpret the results. The measures, successively performed for each sample, are detailed in Bécue-Bertaut and Pagès (2015).

Briefly, vocabulary is said to be associated with a variable if the words differ significantly from each other in the values taken by the individuals using them. The association between a categorical variable and the vocabulary is evaluated with the classical chi-square test on the frequency table crossing words and categories (=lexical table).

In the case of a quantitative variable, a one-way analysis of variance (Anova) is considered. The data table is reorganized as shown in Figure 2 before computing the one-way Anova: each row corresponds to an occurrence (i.e. a word cited by one individual). The score variable and the words variable have as many values as occurrences. Then the one-way Anova between the score and the words is performed, detecting whether relations between vocabulary and scores exist.

Note that, since the occurrences are not independent, the usual assumptions of Anova are not satisfied and it is better to use permutation tests.
6. REAL DATA APPLICATION: INTERNATIONAL SURVEY

A railway company conducted a survey to find out the level of satisfaction of its passengers with the night trains that it offers. Passengers were asked to rate their satisfaction about 13 aspects related to comfort (general, cabin, bed, seat), cleanliness (common areas, cabin, toilet), staff attention (welcome attention, trip attention, language skills) and others (cabin room, air conditioning, general aspects). Each aspect was scored on a 11 point Likert scale, from 0 (very bad) to 10 (excellent). In addition, an open-ended question was added asking for the aspects needing improvement. This question required spontaneous answers which, in this case, were expressed in English or Spanish. The data is stored into the data structure shown in Figure 3.

Preprocessing of the data includes a careful spelling correction for free responses. Stopwords are removed and then the words used at least 10 times are kept for the Spanish corpus (=all answers given in Spanish) whereas the threshold is 5 for the English corpus [Lebart et al. 1998, Murtagh 2005]. Finally, 977 respondents from the Spanish sample and 283 from the English one have no empty answers. Their response average is 3.1 long in both cases. The Spanish corpus contains 3029 occurrences corresponding to 88 distinct words and the English corpus 871 occurrences corresponding to 68 distinct words.

For the score variables, the missing values were imputed. Note that for the graphics, the grading scale has been inverted. Thus, the largest values correspond to the greatest dissatisfaction, which makes the graphs easier to read.

6.1. INITIAL FINDINGS

The most frequent words give a first overview of the complaints, which are similar in both languages and stated with homologous words. *Espacio/space* is too reduced, no place for *maletas/luggages*. *Cabinas/cabins* and *asientos/seats* lack *comodidad/comfort* while *aseos/toilets* would benefit from more *limpieza/cleanliness*. 
Figure 3: The dataset. On the left, the lexical tables; on the right contextual variables. In the example, $I_1 = 283$ (English respondents), $I_2 = 977$ (Spanish respondents), $J_1 = 68$ (English words), $J_2 = 88$ (Spanish words), $K = 13$ (satisfaction scores).
Table 1: Mean satisfaction scores and association with vocabulary ratios

| Satisfaction scores       | Spanish respondents | English respondents |
|--------------------------|---------------------|---------------------|
|                          | mean (SD)           | ass.ratio (p-value) | mean (SD)           | ass.ratio (p-value) |
| General comfort          | 6.82 (1.80)         | 0.062 (<0.001)     | 6.66 (1.95)         | 0.091 (0.148)      |
| Cabin comfort            | 6.37 (2.07)         | 0.063 (<0.001)     | 6.37 (2.03)         | 0.121 (0.010)      |
| Cabin room               | 5.33 (2.43)         | 0.089 (<0.001)     | 5.71 (2.35)         | 0.136 (<0.001)     |
| Bed comfort              | 6.70 (1.98)         | 0.050 (<0.001)     | 6.72 (2.03)         | 0.063 (0.918)      |
| Seat comfort             | 6.10 (2.20)         | 0.059 (<0.001)     | 5.99 (2.38)         | 0.123 (0.010)      |
| Air conditioning         | 6.55 (2.55)         | 0.107 (<0.001)     | 6.51 (2.71)         | 0.226 (<0.001)     |
| Common areas cleanliness | 7.41 (1.92)         | 0.043 (<0.001)     | 7.54 (1.86)         | 0.082 (0.548)      |
| Cabin cleanliness        | 7.59 (1.88)         | 0.056 (<0.001)     | 7.59 (1.81)         | 0.116 (0.036)      |
| Toilet cleanliness       | 6.21 (2.55)         | 0.090 (<0.001)     | 6.29 (2.40)         | 0.150 (<0.001)     |
| Staff welcome attention | 7.99 (1.92)         | 0.040 (0.018)      | 7.29 (2.45)         | 0.108 (0.062)      |
| Staff trip attention     | 8.07 (1.85)         | 0.038 (0.048)      | 7.34 (2.29)         | 0.092 (0.294)      |
| General aspects          | 7.77 (1.65)         | 0.038 (0.034)      | 7.48 (1.91)         | 0.079 (0.590)      |
| Staff language skills    | 7.72 (2.08)         | 0.052 (<0.001)     | 7.14 (2.52)         | 0.154 (<0.001)     |

The Aire acondicionado/Air conditioning seems to cause problems. For the English sample, the words staff and English are frequently cited. Aspects that were not asked to be evaluated are mentioned such as precio/price.

Table 1 gives first insight with the means and standard deviations of the satisfaction scores. Staff trip attention obtains the highest score (8.07) for Spanish speakers while English speakers gave the highest score to Cabin cleanliness (7.59). The lowest score is for Cabin room for both Spanish (5.33) and English speakers (5.71). It is worth noting that the three aspects related to staff (Staff welcome, Staff trip attention and Staff language skills) are clearly less appreciated by English speakers than for Spanish ones.

The association between vocabulary and a contextual variable (see Table 1 columns ass.ratio (p-value)) shows that Air conditioning obtains the highest ratio for both Spanish (0.107) and English (0.226) speakers. Toilet cleanliness ranks second for this indicator for Spanish speakers (0.090) while Staff language skill is placed second with 0.154 in the case of English ones, although Toilet cleanliness, with 0.150 is the third and not far away. Note that Staff language skill is only ranked eighth for this indicator in the case of Spanish speakers. Cabin room is ranked the third for Spanish speakers and the fourth for English speakers.

6.2. MFA-GALT ON THE MULTILINGUAL DATASET

Ranking aspects from the association-with-vocabulary ratio does not coincide with the score-average ranking. This implies that, according to passengers’ opinions, the aspects that should mostly be improved do not correspond to the
aspects they are less satisfied with. This justifies the interest in collecting information through open-ended questions, as this is different and complementary information.

MFA-GALT is applied on the multiple generalized aggregated lexical table. The total inertia is equal to 9.91. The first eigenvalue (1.75 which corresponds to 17.70% of the total inertia) is close to the number of sets, which means that the two sets share the dispersion direction corresponding to the first global axis. The second eigenvalue (1.42, 14.36% of the total inertia) and the third (1.23, 12.39% of the total inertia) are close but the following eigenvalues are much smaller, which leads us to only focus on the first three axes. To avoid overemphasizing the example, we will only interpret the first 2 axes. For a more detailed description of the results, and in particular of the 3rd dimension, the reader can refer to the thesis of Kostov (2015).

![MFA-GALT: Representation of variables (i.e. scores) and words on the plane (1,2)](image)

Figure 4: MFA-GALT: Representation of variables (i.e. scores) and words on the plane (1,2)

6.2.1. Global representation of the satisfaction scores and words

MFA-GALT provides graphical results in which each variable (each score) points to the words associated with it. It thus indicates the defects of the scored aspect, either shared or not in both languages. Figure 4a shows the best represented satisfaction scores on the first MFA-GALT principal plane through their covariances with the axes. To avoid overloading the graphics, only the scores that
are well represented are shown (here, those that have a square cosine summed on the two axes over 0.5). We first only look at the global representations of the scores which offers a three polar structure. The three poles refer to inconveniences associated with \textit{Air conditioning}, lack of \textit{Toilet cleanliness} and problems related to \textit{Cabin room}. This corresponds well with what the association-with-vocabulary ratios suggested. Figure 4b represent the words, Spanish and English, that contribute more than twice to the contribution average. We can then see words highly associated with \textit{air conditioning}, showing its drawbacks: \textit{aire}, \textit{condicionamiento}, temperature, \textit{frio} (=cold) \textit{climatización} (=air conditioner), \textit{ventilación}/\textit{ventilation} and \textit{calefacción} (=heating). On the positive part of the second axis, the lack of \textit{Toilet cleanliness} is characterized by \textit{limpieza}, \textit{toilettes}/\textit{aseos}/\textit{baños}. On the negative part, the problems with \textit{Cabin room} are described with the words \textit{size}/\textit{espacio} and \textit{cabins}/\textit{cabina}/\textit{cabinas}.

In this example, axis 3 is specific to one set, the English one, that has problems with the staff speaking poor English.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure5.png}
\caption{Representation of the sets.}
\end{figure}

\subsection*{6.2.2. Partial representation of the satisfaction scores}

Figure 4a shows the superimposed representation of the global and partial representations of the satisfaction scores on the plane (1,2). It highlights the similarities and differences between the two sets regarding the association between words and scores. \textit{Air conditioning} has a similar behavior in both sets on the first axis. On the second axis, \textit{Toilet cleanliness} and \textit{Cabin room} are more strongly associated with Spanish vocabulary than with English vocabulary, which translates into higher
covariances; the complaints of the former seem more accentuated, giving rise to more words. On the third dimension, only English speakers complain about the lack of *staff language skills*.

### 6.2.3. Representation of the sets

Similarity measures confirm that both sets share dispersion directions. The value of the RV coefficient, multivariate generalization of the squared Pearson correlation coefficient, equal to 0.74 (*p*<0.001) confirms that the partial configurations are relatively close but not homothetic.

According to the representation of the sets on the first dimension, the coordinate of Spanish sample is 0.85 whereas the coordinate of English sample takes a slightly higher value (0.91) (Figure 5). It means that the first axis provided by MFA-GALT is an axis of high importance for both sets. Consequently this is a common dispersion structure. On the other hand, the Spanish set has a much larger (0.91 vs. 0.51) coordinate on the second axis. This means that the MFA-GALT second axis is of high importance for Spanish speakers, not so much for English speakers. The opposite is observed for the third axis (0.42 for Spanish vs. 0.81 for English).

### 7. CONCLUSION

This paper proposes an original principal component method to deal with open-ended questions answered in different languages. This type of textual and contextual data leads to a sequence of coupled tables, each one made of one frequency table (=lexical table) and one quantitative/qualitative table. We tackle these data through the relations between the words and the contextual variables. Two methods are combined, CA-GALT and MFA, hence the name of the new method: *Multiple Factor Analysis on Generalized Aggregated Lexical Tables* (MFA-GALT). The first one places the words of the different sets in a same space generated by the variables, which results in the construction of the GALTs. The second one enables the simultaneous analysis of these tables in such a way that the MFA properties are preserved.

The international survey with open questions answered in different languages was analyzed with MFA-GALT. This made it possible to study similarities among words from the same language, similarities among homologous words from different languages, associations between words and satisfaction scores, similarities between satisfaction score structures (partial representations) and similarities be-
tween groups. The results of this application show that MFA-GALT provides a good synthesis of the data through easy-to-interpret outputs.

The R package *Xplortext* includes the function *LexGalt* which allows the implementation of the CA-GALT and MFA-GALT methods.

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