Appendice 1

Les principes de base de l'Analyse de Correspondance

et de son extension à

l'Analyse de Correspondance Multiple

A composite indicator from multidimensional qualitative data

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Contents

Abstract

Data reduction techniques, more specifically factorial correspondence analysis, is used to build a composite numerical variable from a set of qualitative (categorical) variables.

1 Foreword

The approach will be here to present a statistical technique resorting to the set of **data reduction techniques** in view of "attacking" systematically and rationally the problem of aggregating multidimensional qualitative variables. The presentation is illustrated in reference to poverty data and analysis. It is also, as much as possible, oriented on habilitating the reader to become operational with a specific statistical software offering that type of technique among its routines: we refer to the SPSS 10.1 program **Correspondence Analysis,** and its extension to Multiple Correspondence Analysis, runned with the program **Homogeneity Analysis**.

2 Problem description

- We have in hands a database consisting of a set of qualitative poverty indicators (categorical variables) measured on statistical (population) units who can be *individuals, households, communities, regions, countries,* etc. These variables generate J categories on I population units.

- Motivation: income/expenditure variables not only can be viewed as reflecting just one dimension of poverty, but are also heavy and costly to measure and may be more or less reliable due to non sampling errors (particularly recall errors). For all these reasons, light and more reliable qualitative indicators are frequently used to describe different dimensions of poverty.

- From the J categories, we would like to construct an unique indicator synthetizing the information contained in the multiple indicators.

- One of the main objectives, not necessarily the only one, is to classify the I population units according to their relative poverty level.

3 Case study: data from Vietnam survey VLSS-1

- The first Vietnam Living Standard Survey (VLSS-1) was conducted in 1992-1993. The sample consists of 4 800 households randomly selected within 150 communes, themselves randomly selected among the about 10 000 communes in Vietnam. Among the 150 selected communes, 120 are rural and 30 are urban.

- Three questionnaires were administered: a household questionnaire, a community questionnaire and a price questionnaire. The community questionnaire was administered only in the 120 rural communes. It contains

142 questions, distributed in 5 sections: demography, economy and infrastructure, education, health and agriculture.

- For our case study, we use only the community questionnaire. In view of illustrating as simply as possible the CA approach to the computation of a multidimensional poverty composite indicator, we retain only two poverty indicators, generated by the two following questions:

  section 3 (education), question #16: how many children aged 6 to 11 are enrolled?

  section 5 (agriculture), question #7: what is the proportion of each type of quality land in the land fund of this commune?

  From the education question, since the total number of children in the age-group 6-11 is available, it is possible to compute the primary enrolment rate. This rate has been transformed into a categorical indicator with the three following categories:

  category 1: rate $< 80\%$

  category 2: $80\% \leq$ rate $\leq 90\%$

  category 3: rate $> 90\%$.

  The quality land question considers seven levels of quality. We have retained only the first level, which is the best quality. The 3 categories are the following:

  category 1: percentage $= 0\%$ (no land of quality 1)

  category 2: $0\% <$ percentage $\leq 25\%$

  category 3: percentage $> 25\%$.

- The 120 communities considered here are the 120 rural communes distributed in the 7 regions:

  1. Northern Uplands : 19
  2. Red River Delta : 32
  3. North Central : 18
  4. Central Coast : 12
  5. Central Highlands : 04
  6. Southeast : 10
  7. Mekong River Delta: 25

4 Data description

- Data consists of a table $I \times J$ of positive numbers, in many cases only 0 or 1.

- Notation

  $k(i,j)$: number in cell (i,j)

  $k(i) = \sum_{j=1}^{J} k(i,j)$: total of line i

  $k(j) = \sum_{i=1}^{I} k(i,j)$: total of column j

  $k = \sum_{i=1}^{I} \sum_{j=1}^{J} k(i,j)$: the general total

- $k(i,j)$ is usually interpreted as the frequency of occurrence of category j for the unit i.

- The values of indicators for our case study are given in Annex A, Correspondence Table, pages 1-3. It is seen that the values are 1 or 0, and there are only two 1 in each line, according to the fact that for each indicator, a given commune belongs to exactly one category.

5 Data transformation

Looking at the Correspondance Table , it is difficult to "see" a poverty structure and to identify poorer and richer communes, on a rational basis. A statistical analysis is needed to try to see better the poverty content of this table, and it begins by elementary transformations of data. At the same time, some terminology and notation relative to correspondence analysis is introduced.

- relative frequency of category j for unit i : $f_j^i = \frac{k(i,j)}{k(i)}$
- relative frequency of unit i for category j : $f_i^j = \frac{k(i,j)}{k(j)}$
- **profile** of unit i : $f_J^i = \left\{ f_j^i \mid j \in J \right\}$
- **profile** of category j : $f_I = \left\{ f_i^j \mid i \in I \right\}$
- **mass** (relative weight, marginal frequency) of unit i : $f_i = \frac{k(i)}{k}$

  $f_I = \{f_i \mid i \in I\}$
- **mass** (relative weight, marginal frequency) of category j : $f_j = \frac{k(j)}{k}$

  $f_J = \{f_j \mid j \in J\}$

Remark 1 *The notion of* ***profile*** *of a population unit i allows to show the categorical structure of the unit, independently of its size. By comparing a given unit-profile f_J^i with the mean profile f_J , we can begin to view to which extent a population unit differs, structurally, from the general population structure, in regard to the observed indicators. Mutatis mutandis, the notion of* ***profile*** *of a category j allows to show the population structure of the category, independently of its importance as a social phenomena. By comparing a given category-profile f_I^j with the mean profile f_I , we can begin to view to which extent a category differs, in its demographic structure, from the general population structure, in regard to the observed population units.*

- **cluster** $N(I)$ in dim-J space

  $N(I) = \left\{ f_J^i \mid i \in I \right\}$. So, $N(I)$ is the set of the I unit-profiles in dim-J space.
- **cluster** $N(J)$ in dim-I space

  $N(J) = \left\{ f_I^j \mid j \in J \right\}$. So, $N(J)$ is the set of the J category-profiles in dim-I space.
- **centre of gravity (centroid)** of cluster $N(I)$

It's the weighted mean g_J of the I unit-profiles belonging to the cluster $N(I)$.

$g_J = \sum_{i=1}^{I} f_i f_J^i$. It's easy to see that $g_J = f_J$: the centroid of $N(I)$ is simply the mean unit-profile.

- **centre of gravity (centroid)** of cluster $N(J)$

It's the weighted mean g_I of the J category-profiles belonging to the cluster $N(J)$.

$g_I = \sum_{j=1}^{J} f_j f_I^j$. It's easy to see that $g_I = f_I$: the centroid of $N(J)$ is simply the mean category-profile.

Remark 2 *With the two clusters $N(I)$ and $N(J)$, we have now two different standpoints from which to look at the original data, corresponding to two $I \times J$ tables. We introduce so the notion of* ***duality*** *extremely important in correspondence analysis. Having now two tables instead of one, are we really on the way of simplifying our looking at the data? It must be observed that for any unit-profile f_J^i we have $\sum_{j=1}^{J} f_j^i = 1$. Thus, all unit-profiles, when represented in the J-dim euclidian space, belong, by their end-point to the (J-1)-dim unit simplex, the same for their centroid. Then the analysis of the cluster $N(I)$ can in fact be done in a (J-1)-dim subspace. Mutatis mutandis, the cluster $N(J)$ can be analyzed in a (I-1)-dim subspace. Thus, with a very simple data transformation, we have already reduced the number of dimensions relevant for data analysis.*

- Case study: the population unit profiles, the cluster $N(I)$, the centroid of $N(I)$, are given in Annex A, table "Row Profiles", pp. 4-6. The analogous elements for the category profiles are given in the table "Column Profiles", pp. 6-9.

6 Data analysis

We will now proceed to the statistical analysis of the data transformed in profiles. The analysis will be done and presented for the cluster of population units $N(I)$, but it is immediately transposable for the cluster of categories $N(J)$. At the end, the close link between both analysis, due to the duality, will clearly appear.

6.1 χ^2-Distance between profiles

The intuitive comparaison we can make between two unit-profiles i and i' needs to be formalized in a numerical measure. The distance uses in correspondence analysis goes back to the great statistician Pearson, who invented it sixty years ago to compare a sampling distribution with a theoretical probability distribution: the **chi-2 distance**, also called the **distributional distance**:

$$d^2\left(f_J^i, f_J^{i'}\right) = \sum_{j=1}^{J}\left(\frac{1}{f_j}\right)\left(f_j^i - f_j^{i'}\right)^2$$

The χ^2-distance is thus the usual distance in the I-dim euclidean space, but with a weight on axes (categories), inversely proportional to its mass. We still have a metric space.

- invariance property

If two columns (categories) are proportional, i.e have the same structure, if we replace them by a unique one, sum of both, then the distance between two lines (population units) remains unchanged.

6.2 Inertia of the cluster $N(I)$ to its centre of gravity g_J

We need also to summarize the whole variability observed in the cluster of population units $N(I)$. This is done with the concept of **inertia**, built with the χ^2-distance of each profile to the centre of gravity.

$$I_G\left[N(I)\right] = \sum_{i=1}^{I} f_i d^2\left(g_J, f_J^i\right)$$

Thus, the inertia of the cluster $N(I)$ to its centre of gravity g_J is the weighted mean of the individual profiles distances to g_J, the weight being the mass of each profile.

- Case study

The total inertia for our cluster $N(I)$ of 120 commune-profiles is 2,000, as given in the table "Summary", Annex A, p. 9.

6.3 Additive disaggregation of the total inertia

6.3.1 Normal subspaces through the centroid g_J

- In the (J-1)-simplex where lies the cluster $N(I)$, let's take any straight line $\triangle$ through the centroid g_J. In the same simplex, the (J-2)-dim subspace normal (perpendicular) to $\triangle$ is denoted $\triangle_\perp$ and called the complementary space to $\triangle$.

- $\triangle$ and $\triangle_\perp$ are thus two normal subspaces allowing to cover completely the (J-1) simplex.

6.3.2 Projections of a profile f_J^i on $\triangle$ and $\triangle_\perp$

Any centred profile $\left(f_J^i - g_J\right)$ can be projected

- perpendicularly to $\triangle$. This point determined by this projection is notated: $pr_\triangle\left(f_J^i\right)$.
- perpendicularly to $\triangle_\perp$. This point determined by this projection is notated: $pr_{\triangle_\perp}\left(f_J^i\right)$.

It is then obvious by the Pythagoras theorem that

$$d^2\left(g_J, f_J^i\right) = d^2\left(g_J, pr_\triangle\left(f_J^i\right)\right) + d^2\left(g_J, pr_{\triangle_\perp}\left(f_J^i\right)\right) \tag{1}$$

6.3.3 Total inertia disaggregation

From equation 1, by the weighted sum on all the unit-profiles, it follows that the total inertia can be disaggregated in two terms:

$$I_G\left[N\left(I\right)\right] = I_\triangle\left[N\left(I\right)\right] + I_{\triangle_\perp}\left[N\left(I\right)\right] \tag{2}$$

So, the inertia relative to the centre of gravity is the sum of the inertia relative to $\triangle$ and of the inertia relative to $\triangle_\perp$.

6.4 The first principal axis

The disaggregation process of the preceding section suggests to look for a straigth line $\triangle$ which could maximize the inertia component $I_\triangle\left[N\left(I\right)\right]$. By rotating the line $\triangle$ through the centre of gravity in the (J-1)-simplex, the value of inertia relative to that line, $I_\triangle\left[N\left(I\right)\right]$,varies. We need a computable process to find the rotation which maximizes $I_\triangle\left[N\left(I\right)\right]$. This computable process exists since a long time in statistics. It is called **principal component analysis**. Numerically, it implies the computation of the eigenvalues of a specific numerical matrix which we will not give explicitly here.

- By using principal component analysis, the line $\triangle$ catching by itself the maximal inertia from the cluster $N\left(I\right)$ is called the **first principal (or factorial) axis.** This optimal line is then denoted $\triangle_1$. Let's denote λ_1 the square root of the eigenvalue associated to the first principal axis. The value λ_1 is usually referred to as the **singular value** relative to the first principal axis.
- An important result from statistical theory is that

$$I_{\triangle_1}\left[N\left(I\right)\right] = \lambda_1^2 \tag{3}$$

Then, the inertia relative to the first principal axis is given by the associated eigenvalue λ_1^2.

- A result from correspondence analysis with the χ^2-distance is that

$$\lambda_1 \leq 1 \tag{4}$$

- Case study

  In our case study, we find in the table "Summary", Annex A, p. 9, that:

  the first principal axis has a singular value $\lambda_1 = 0,834$.

  the eigenvalue, and thus the inertia, associated to the first principal axis is $\lambda_1^2 = 0,696$.

  the proportion of the total inertia 2,000 accounted for by the first principal axis is then 0,348.

We usually say that the first principal axis **explains** 34,8% of the variability observed among the 120 population units, relatively to the 2 indicators.

6.5 The r principal (factorial) axis: complete disaggregation of inertia

Once the first principal axis $\triangle_1$ has been found, a similar process can be applied in its complementary normal subspace $\triangle_{\perp_1}$ to find the second axis $\triangle_2$, and so on repetitively until there is no more inertia to explain. Since, according to 2, the cluster $N(I)$ lies in (J-1) dimensions, the number of principal axis, denoted here by **r**, cannot exceed (J-1). But it can be much less than (J-1). In fact, it can be shown that

$$r \leq \min\left(I - 1, J - 1\right) \tag{5}$$

- The process of finding, by repetition, all the principal axis of the cluster $N(I)$ generates the **factorial disaggregation of the total inertia**. We then have for each axis (factor) the different statistics seen for the first axis.

- As one among the numerous results of the disaggregation we have:

$$I_G\left[N\left(I\right)\right] = \sum_{\alpha=1}^{r} \lambda_\alpha^2 \tag{6}$$

- We also have

$$\lambda_1 \geq \lambda_2 \geq .... \geq \lambda_r \tag{7}$$

- Case study

  In our case study, we find in the table "Summary", Annex A, p. 9, that:

  There are 4 factorial axis.

  The second axis accounts for 25,6% of the total inertia, so that the first two axis explain 60,4% of the variability found in the 2 indicators.

6.6 Scores in dimensions: discriminating between population units

The r factorial axis are perpendicular by construction and then constitute a cartesian axis system where each profile f_J^i has new coordinates: its r projections

$$pr_{\triangle_1}\left(f_J^i\right), pr_{\triangle_2}\left(f_J^i\right), ..., pr_{\triangle_r}\left(f_J^i\right)$$

These projections are called the "scores" of the population unit in the different dimensions.

Notation

The score of the population unit i on the factorial axis α is notated: $F_\alpha(i)$. Thus,

$$F_\alpha(i) = pr_{\triangle_\alpha}\left(f_J^i\right) \tag{8}$$

It can be shown that

$$\sum_{i=1}^{I} f_i F_\alpha(i) = 0 \tag{9}$$

Thus, the weighted distribution of the scores $\{F_\alpha(i)\}$ is centered on 0.

It can also be shown that

$$\sum_{i=1}^{I} f_i F_\alpha^2(i) = \lambda_\alpha^2 \tag{10}$$

Thus, the variance of the same distribution is given by the contribution λ_α^2 of the factorial axis α to the total inertia.

6.6.1 First dimension scores: numerical analysis

Since the first dimension accounts for the highest proportion of the total inertia (equation (7)), just looking at this first score can be considered as giving a good information on the differences between the population units. Here, we precisely see how a **data reduction technique** like **factorial correspondence analysis** facilitates the classification of population units represented in multidimensional data.

- Case study

In our case study, we find in the table "Overview Row points", Annex A, p. 10-12, that: The score in dimension 1 takes a small number, more precisely 8, different values. This is normal in this simple case since, with only 2 indicators of 3 categories each, the maximum number of different commune profiles is 9, but only 8 of these profiles are in fact found in the sample. The table 1 below presents the ranking of these profiles.

Table 1 Ranking of communes according to score in dimension 1

Score in dim. 1	% land quality 1	primary enrolment rate	# communes	communes id
1,824	0%	$< 80\%$	19	1,3,12,15 etc.
0,818	0%	80% - 90%	8	7,13,84,85 etc.
0,763	$\leq 25\%$	$< 80\%$	3	50,66,83
0,262	0%	$> 90\%$	30	4,5,8,9,11 etc.
-0,242	$\leq 25\%$	80% - 90%	5	6,56,70,103,104
-0,577	$> 25\%$	80% - 90%	2	102,109
-0,798	$\leq 25\%$	$> 90\%$	33	2,10,16,20 etc.
-1,133	$> 25\%$	$> 90\%$	20	19,21,27,32 etc.

We clearly see that, according to the first axis, poverty is decreasing from the highest score (1,824) to the lowest score (-1,133). The only profile not represented in the sample is a commune having $> 25\%$ of land quality 1 and a primary enrolment rate $< 80\%$.

The same table of Annex A, in column "Inertia", displays the contribution of each commune to the total inertia of 2: commune #1 contributes 0,023 while commune #109 contributes 0,048.

The same table displays the proportion of the inertia of the different axis which is contributed by each commune. Here, it has been requested only for the first two axis. So, commune #1 contributes 2,8% of the inertia of axis 1, while commune #109 contributes only 0,3%.

6.6.2 First and second dimension scores: graphical analysis

Instead of looking only at the scores on the first factorial axis, we can look at the two first dimensions. Then, the most useful and significant analysis is the one obtained by a graphical representation of the population units in a cartesian plane with the first factorial score reported on the x-axis, and the second factorial score reported on the y-axis. This graphical representation is not given here with the Correspondance Analysis program, since with the 120 communes, the graph is unreadable. But we will see below an interesting graphical capacity with the Multiple Correspondence Analysis (Homals) of the same data.

7 Duality in correspondence analysis: the key to composite indicators

With the preceding analysis, we can certainly begin to discriminate more clearly between the population units, but we have no explicit numerical relation between a population unit score and its profile on the set of the basic qualitative indicators. This relation is needed if we want to discriminate between a much larger set of population units which where not included in this specific factorial analysis, without having to recompute that type of analysis. Here the duality properties of correspondence analysis provide the required tools.

7.1 Analysis of the cluster $N(J)$

The preceding analysis of the cluster of population units (wards) $N(I)$ can be done for the cluster of categories (indicators) $N(J)$. The cluster $N(J)$ having been first transformed in category-profiles, the χ^2-distance between these profiles is defined the same way. From this follows the total inertia $I_G[N(J)]$, the calculation of the principal axis and the associated singular values, and the disaggregation of the total inertia as the sum of the principal axis inertia (eigenvalues). The beauty of the theory, due to the χ^2-distance definition, is that:

- the total inertia is the same: $I_G[N(J)] = I_G[N(I)]$
- the r singular values λ_α are the same,
- the disaggregation of the total inertia is the same $I_G[N(J)] = \sum_{\alpha=1}^{r} \lambda_\alpha^2$.

The only new element is that instead of having population unit scores, we now have category scores relative to the r factorial axis of the cluster $N(J)$. For the category j, these scores are notated $G_\alpha(j)$ and we have $G_\alpha(j) = pr_{\triangle_\alpha}\left(f_I^j\right)$. By comparing these scores, especially first one, we can see the "proximity" of different categories. Two categories having similar scores can be considered as closely correlated, and then, by this type of analysis, we have a means of eliminating redundant categories and indicators, and thus to reduce the number of indicators needed to describe our population units.

- Case study

  In our case study, we find in the table "Overview Column Points", Annex A, page 16, the value and the analysis of the score values of the 6 categories corresponding to the 2 primary indicators, for the first two factorial axis.

- the interpretation of the factorial axis from the graphical presentation

  Graphical analysis of the categories and corresponding indicators, in the two first factorial axis, is essential for understanding the meaning of these axis. More precisely, is there any poverty meaning to these axis? The relative position of the categories in such a graphical presentation reveals the underlying meaning of the axis, if there is any.

- Case study

  From the two dimensions graph given in Annex A, p. 17, we see obviously that the first axis discriminates between poorest and richest communes, according to both indicators here retained.

7.2 Linkage between both analysis: the basic duality equation

Between the only two different components of the two analysis of clusters $N(I)$ and $N(J)$, the factorial scores of population units and of primary indicators, it is shown that the following relation holds:

$$F_\alpha (i) = \sum_{j=1}^{J} f_j^i \times \frac{G_\alpha (j)}{\lambda_\alpha^2} \tag{11}$$

The equation 11 says that the factor-α score of unit i is given by multiplying its category-profile by the factor-α scores of all the ctegories, divided by the inertia (eigen) value λ_α^2 relative to this factorial axis. This is the nicest dual relation in factorial correspondence analysis: it really opens the way to build the synthetic indicator we are looking for, on a scientific basis. More than that, this relation gives us, by the relative values of the scores $G_\alpha (j)$ obtained by the categories, the "poverty dimension" represented by the factorial axis α.

7.3 Normalization and the composite indicator

From equation 11, we see that the relation between the factor-α score of unit i and the set $\{G_\alpha (j)\}$ of the indicators scores on axis α requires that these scores be deflated by the inertia (eigen) value λ_α^2,which is also the variance of the distribution of $\{G_\alpha (j)\}$ according to equation 10. It appears immediately that if we normalize the scores of the categories generated by the primary indicators, i.e. if we divide each score $G_\alpha (j)$ by λ_α^2, the relation between these catetories normalized scores and the population unit scores will be direct. So, let's define the **normalized scores** of indicator j as

$$G_{\alpha}^{*}(j)=\frac{G_{\alpha}(j)}{\lambda_{\alpha}^{2}} \tag{12}$$

We then have

$$F_{\alpha}(i)=\sum_{j=1}^{J} f_{j}^{i}\times G_{\alpha}^{*}(j) \tag{13}$$

7.3.1 Statistical definition of the composite indicator

On the basis of the objective approach recognized in the factorial correspondence analysis and of its capacity to effectively generate a simple composite indicator structure from multidimensional qualitative data, we suggest as a serious composite indicator candidate the one defined by equation 13, **for the first factorial axis**. So, the **weight** to be given to any category of a primary qualitative indicator would be its **normalized score on the first factorial axis**, as given in equation 12.

Definition 3 *A composite indicator of multiple qualitative poverty indicators, each defined as a finite set of categories, for different population units, is given by*

1. computing the profile of the population unit relatively to these primary indicators

2. applying to this profile the category-weights given by the normalized scores of these indicators on the first factorial axis coming out of correspondence analysis.

8 Multiple Correspondence Analysis

- Correspondence Analysis is a general data reduction technique applicable to the analysis of any matrix of non negative numbers. We have used it, as an example, to the analysis of two categorical variables, for us taken as poverty indicators. From this point of view, it is simply a particular case of the Multiple Correspondence Analysis (MCA), which allows to consider simultaneously any number of categorical variables. From the computational side, MCA is obtained by running a CA analysis of 0-1 indicator matrix associated to the set of categorical indicators[1].
- To illustrate the specificity and the interest of MCA, we have run here, on the same data, the SPSS program HOMALS, precisely the one that computes a MCA. The output is presented in Annex B.

[1] Equivalently, MCA is a CA applied to the Burt matrix of all contingency tables built from the indicators. See [2], chapter 7.

- We first observe the complete convergence regarding the eigenvalue (inertia) relative to each axis.
- There are important differences between the respective outputs of CA and MCA:

MCA does not produce the Correspondence Table neither the Row and Column Profiles, here taken as too simple, due to the fact that we have a 0-1 initial matrix.

MCA names "quantifications" the column (category) scores in the different dimensions, and "object scores" the row scores. Again here, we see the convergence in the scores provided by both analysis. But it does not present the inertia relative to each point (row or column).

On the other hand, MCA keeps the individuality of each indicator as a subset of the whole set of categories (columns), and presents the marginal frequencies observed for each indicator. It gives also an additional information for each indicator, its "Discrimination Measure" in each dimension, which is the variance of the quantified indicator (its different scores) in each dimension. In that sense, it is really a measure of the discrimination power of each indicator, in each dimension.

This individuality of each indicator allows to produce a graph as the one given in Annex B, p. 4, where the categories of each indicator can be linked with a line, making here quite evident the poverty meaning of the axis 1.

We notice here, Annex B, p. 7, the possibility of having a graph representing the 8 profiles taken by the 120 communes, profiles described in Table 1 above.

References

[1] Benzécri, J.P and F., *L'analyse des données, Analyse des correspondances, Exposé élémentaire,* Dunod 1980, 424 p.

[2] Greenacre, M. J., *Theory and Applications of Correspondence Analysis,* Academic Press 1984, 364 p.

Annexe A

Output SPSS de l'Analyse de Correspondance

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Two indicators: proportion of land of quality 1, primary school enrolment rate

Credit

CORRESPONDENCE
Version 1.0
by
Data Theory Scaling System Group (DTSS)
Faculty of Social and Behavioral Sciences
Leiden University, The Netherlands

Correspondence Table

Row	Column						
	Land1 >25	Land1 <=25	Land1 =0	Rate >90	Rate 80-90	Rate <80	Active Margin
1	0	0	1	0	0	1	2
2	0	1	0	1	0	0	2
3	0	0	1	0	0	1	2
4	0	0	1	1	0	0	2
5	0	0	1	1	0	0	2
6	0	1	0	0	1	0	2
7	0	0	1	0	1	0	2
8	0	0	1	1	0	0	2
9	0	0	1	1	0	0	2
10	0	1	0	1	0	0	2
11	0	0	1	1	0	0	2
12	0	0	1	0	0	1	2
13	0	0	1	0	1	0	2
14	0	0	1	1	0	0	2
15	0	0	1	0	0	1	2
16	0	1	0	1	0	0	2
17	0	0	1	1	0	0	2
18	0	0	1	1	0	0	2
19	1	0	0	1	0	0	2
20	0	1	0	1	0	0	2
21	1	0	0	1	0	0	2
22	0	1	0	1	0	0	2
23	0	0	1	0	0	1	2
24	0	1	0	1	0	0	2
25	0	0	1	1	0	0	2
26	0	1	0	1	0	0	2
27	1	0	0	1	0	0	2
28	0	0	1	1	0	0	2
29	0	1	0	1	0	0	2
30	0	0	1	1	0	0	2
31	0	1	0	1	0	0	2

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Correspondence Table

Row	Land1 >25	Land1 <=25	Land1 =0	Rate >90	Rate 80-90	Rate <80	Active Margin
32	1	0	0	1	0	0	2
33	1	0	0	1	0	0	2
34	1	0	0	1	0	0	2
35	0	1	0	1	0	0	2
36	1	0	0	1	0	0	2
37	1	0	0	1	0	0	2
38	1	0	0	1	0	0	2
39	0	1	0	1	0	0	2
40	0	1	0	1	0	0	2
41	0	1	0	1	0	0	2
42	1	0	0	1	0	0	2
43	0	0	1	1	0	0	2
44	1	0	0	1	0	0	2
45	1	0	0	1	0	0	2
46	0	0	1	1	0	0	2
47	0	1	0	1	0	0	2
48	0	1	0	1	0	0	2
49	0	1	0	1	0	0	2
50	0	1	0	0	0	1	2
51	0	0	1	1	0	0	2
52	1	0	0	1	0	0	2
53	0	1	0	1	0	0	2
54	0	0	1	1	0	0	2
55	0	1	0	1	0	0	2
56	0	1	0	0	1	0	2
57	0	1	0	1	0	0	2
58	0	1	0	1	0	0	2
59	0	1	0	1	0	0	2
60	0	1	0	1	0	0	2
61	0	0	1	1	0	0	2
62	0	0	1	1	0	0	2
63	1	0	0	1	0	0	2
64	0	0	1	1	0	0	2
65	0	0	1	1	0	0	2
66	0	1	0	0	0	1	2
67	0	0	1	1	0	0	2
68	0	1	0	1	0	0	2
69	0	0	1	0	0	1	2
70	0	1	0	0	1	0	2
71	1	0	0	1	0	0	2
72	0	1	0	1	0	0	2
73	0	0	1	0	0	1	2
74	0	1	0	1	0	0	2
75	0	0	1	0	0	1	2
76	0	1	0	1	0	0	2
77	0	1	0	1	0	0	2

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Correspondence Table

	Column						
Row	Land1 >25	Land1 <=25	Land1 =0	Rate >90	Rate 80-90	Rate <80	Active Margin
78	0	1	0	1	0	0	2
79	1	0	0	1	0	0	2
80	0	1	0	1	0	0	2
81	1	0	0	1	0	0	2
82	1	0	0	1	0	0	2
83	0	1	0	0	0	1	2
84	0	0	1	0	1	0	2
85	0	0	1	0	1	0	2
86	0	0	1	1	0	0	2
87	0	0	1	1	0	0	2
88	0	0	1	0	1	0	2
89	0	0	1	1	0	0	2
90	0	0	1	0	0	1	2
91	1	0	0	1	0	0	2
92	0	0	1	0	0	1	2
93	0	1	0	1	0	0	2
94	0	0	1	1	0	0	2
95	0	1	0	1	0	0	2
96	0	0	1	0	1	0	2
97	0	0	1	0	0	1	2
98	1	0	0	1	0	0	2
99	0	0	1	1	0	0	2
100	0	0	1	0	0	1	2
101	0	0	1	1	0	0	2
102	1	0	0	0	1	0	2
103	0	1	0	0	1	0	2
104	0	1	0	0	1	0	2
105	0	0	1	1	0	0	2
106	0	0	1	0	0	1	2
107	0	0	1	1	0	0	2
108	0	0	1	1	0	0	2
109	1	0	0	0	1	0	2
110	0	0	1	0	1	0	2
111	0	0	1	0	1	0	2
112	0	0	1	0	0	1	2
113	0	0	1	0	0	1	2
114	0	1	0	1	0	0	2
115	0	1	0	1	0	0	2
116	0	0	1	0	0	1	2
117	0	0	1	0	0	1	2
118	0	0	1	1	0	0	2
119	0	0	1	0	0	1	2
120	0	0	1	0	0	1	2
Active Margin	22	41	57	83	15	22	240

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Row Profiles

Row	Column						
	Land1 >25	Land1 <=25	Land1 =0	Rate >90	Rate 80-90	Rate <80	Active Margin
1	,000	,000	,500	,000	,000	,500	1,000
2	,000	,500	,000	,500	,000	,000	1,000
3	,000	,000	,500	,000	,000	,500	1,000
4	,000	,000	,500	,500	,000	,000	1,000
5	,000	,000	,500	,500	,000	,000	1,000
6	,000	,500	,000	,000	,500	,000	1,000
7	,000	,000	,500	,000	,500	,000	1,000
8	,000	,000	,500	,500	,000	,000	1,000
9	,000	,000	,500	,500	,000	,000	1,000
10	,000	,500	,000	,500	,000	,000	1,000
11	,000	,000	,500	,500	,000	,000	1,000
12	,000	,000	,500	,000	,000	,500	1,000
13	,000	,000	,500	,000	,500	,000	1,000
14	,000	,000	,500	,500	,000	,000	1,000
15	,000	,000	,500	,000	,000	,500	1,000
16	,000	,500	,000	,500	,000	,000	1,000
17	,000	,000	,500	,500	,000	,000	1,000
18	,000	,000	,500	,500	,000	,000	1,000
19	,500	,000	,000	,500	,000	,000	1,000
20	,000	,500	,000	,500	,000	,000	1,000
21	,500	,000	,000	,500	,000	,000	1,000
22	,000	,500	,000	,500	,000	,000	1,000
23	,000	,000	,500	,000	,000	,500	1,000
24	,000	,500	,000	,500	,000	,000	1,000
25	,000	,000	,500	,500	,000	,000	1,000
26	,000	,500	,000	,500	,000	,000	1,000
27	,500	,000	,000	,500	,000	,000	1,000
28	,000	,000	,500	,500	,000	,000	1,000
29	,000	,500	,000	,500	,000	,000	1,000
30	,000	,000	,500	,500	,000	,000	1,000
31	,000	,500	,000	,500	,000	,000	1,000
32	,500	,000	,000	,500	,000	,000	1,000
33	,500	,000	,000	,500	,000	,000	1,000
34	,500	,000	,000	,500	,000	,000	1,000
35	,000	,500	,000	,500	,000	,000	1,000
36	,500	,000	,000	,500	,000	,000	1,000
37	,500	,000	,000	,500	,000	,000	1,000
38	,500	,000	,000	,500	,000	,000	1,000
39	,000	,500	,000	,500	,000	,000	1,000
40	,000	,500	,000	,500	,000	,000	1,000
41	,000	,500	,000	,500	,000	,000	1,000
42	,500	,000	,000	,500	,000	,000	1,000
43	,000	,000	,500	,500	,000	,000	1,000
44	,500	,000	,000	,500	,000	,000	1,000
45	,500	,000	,000	,500	,000	,000	1,000
46	,000	,000	,500	,500	,000	,000	1,000

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Row Profiles

	Column						
Row	Land1 >25	Land1 <=25	Land1 =0	Rate >90	Rate 80-90	Rate <80	Active Margin
47	,000	,500	,000	,500	,000	,000	1,000
48	,000	,500	,000	,500	,000	,000	1,000
49	,000	,500	,000	,500	,000	,000	1,000
50	,000	,500	,000	,000	,000	,500	1,000
51	,000	,000	,500	,500	,000	,000	1,000
52	,500	,000	,000	,500	,000	,000	1,000
53	,000	,500	,000	,500	,000	,000	1,000
54	,000	,000	,500	,500	,000	,000	1,000
55	,000	,500	,000	,500	,000	,000	1,000
56	,000	,500	,000	,000	,500	,000	1,000
57	,000	,500	,000	,500	,000	,000	1,000
58	,000	,500	,000	,500	,000	,000	1,000
59	,000	,500	,000	,500	,000	,000	1,000
60	,000	,500	,000	,500	,000	,000	1,000
61	,000	,000	,500	,500	,000	,000	1,000
62	,000	,000	,500	,500	,000	,000	1,000
63	,500	,000	,000	,500	,000	,000	1,000
64	,000	,000	,500	,500	,000	,000	1,000
65	,000	,000	,500	,500	,000	,000	1,000
66	,000	,500	,000	,000	,000	,500	1,000
67	,000	,000	,500	,500	,000	,000	1,000
68	,000	,500	,000	,500	,000	,000	1,000
69	,000	,000	,500	,000	,000	,500	1,000
70	,000	,500	,000	,000	,500	,000	1,000
71	,500	,000	,000	,500	,000	,000	1,000
72	,000	,500	,000	,500	,000	,000	1,000
73	,000	,000	,500	,000	,000	,500	1,000
74	,000	,500	,000	,500	,000	,000	1,000
75	,000	,000	,500	,000	,000	,500	1,000
76	,000	,500	,000	,500	,000	,000	1,000
77	,000	,500	,000	,500	,000	,000	1,000
78	,000	,500	,000	,500	,000	,000	1,000
79	,500	,000	,000	,500	,000	,000	1,000
80	,000	,500	,000	,500	,000	,000	1,000
81	,500	,000	,000	,500	,000	,000	1,000
82	,500	,000	,000	,500	,000	,000	1,000
83	,000	,500	,000	,000	,000	,500	1,000
84	,000	,000	,500	,000	,500	,000	1,000
85	,000	,000	,500	,000	,500	,000	1,000
86	,000	,000	,500	,500	,000	,000	1,000
87	,000	,000	,500	,500	,000	,000	1,000
88	,000	,000	,500	,000	,500	,000	1,000
89	,000	,000	,500	,500	,000	,000	1,000
90	,000	,000	,500	,000	,000	,500	1,000
91	,500	,000	,000	,500	,000	,000	1,000
92	,000	,000	,500	,000	,000	,500	1,000

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Row Profiles

Row	Column						
	Land1 >25	Land1 <=25	Land1 =0	Rate >90	Rate 80-90	Rate <80	Active Margin
93	,000	,500	,000	,500	,000	,000	1,000
94	,000	,000	,500	,500	,000	,000	1,000
95	,000	,500	,000	,500	,000	,000	1,000
96	,000	,000	,500	,000	,500	,000	1,000
97	,000	,000	,500	,000	,000	,500	1,000
98	,500	,000	,000	,500	,000	,000	1,000
99	,000	,000	,500	,500	,000	,000	1,000
100	,000	,000	,500	,000	,000	,500	1,000
101	,000	,000	,500	,500	,000	,000	1,000
102	,500	,000	,000	,000	,500	,000	1,000
103	,000	,500	,000	,000	,500	,000	1,000
104	,000	,500	,000	,000	,500	,000	1,000
105	,000	,000	,500	,500	,000	,000	1,000
106	,000	,000	,500	,000	,000	,500	1,000
107	,000	,000	,500	,500	,000	,000	1,000
108	,000	,000	,500	,500	,000	,000	1,000
109	,500	,000	,000	,000	,500	,000	1,000
110	,000	,000	,500	,000	,500	,000	1,000
111	,000	,000	,500	,000	,500	,000	1,000
112	,000	,000	,500	,000	,000	,500	1,000
113	,000	,000	,500	,000	,000	,500	1,000
114	,000	,500	,000	,500	,000	,000	1,000
115	,000	,500	,000	,500	,000	,000	1,000
116	,000	,000	,500	,000	,000	,500	1,000
117	,000	,000	,500	,000	,000	,500	1,000
118	,000	,000	,500	,500	,000	,000	1,000
119	,000	,000	,500	,000	,000	,500	1,000
120	,000	,000	,500	,000	,000	,500	1,000
Mass	,092	,171	,238	,346	,063	,092	

Column Profiles

Row	Column						
	Land1 >25	Land1 <=25	Land1 =0	Rate >90	Rate 80-90	Rate <80	Mass
1	,000	,000	,018	,000	,000	,045	,008
2	,000	,024	,000	,012	,000	,000	,008
3	,000	,000	,018	,000	,000	,045	,008
4	,000	,000	,018	,012	,000	,000	,008
5	,000	,000	,018	,012	,000	,000	,008
6	,000	,024	,000	,000	,067	,000	,008
7	,000	,000	,018	,000	,067	,000	,008
8	,000	,000	,018	,012	,000	,000	,008
9	,000	,000	,018	,012	,000	,000	,008
10	,000	,024	,000	,012	,000	,000	,008
11	,000	,000	,018	,012	,000	,000	,008

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Column Profiles

	Column						
Row	Land1 >25	Land1 <=25	Land1 =0	Rate >90	Rate 80-90	Rate <80	Mass
12	,000	,000	,018	,000	,000	,045	,008
13	,000	,000	,018	,000	,067	,000	,008
14	,000	,000	,018	,012	,000	,000	,008
15	,000	,000	,018	,000	,000	,045	,008
16	,000	,024	,000	,012	,000	,000	,008
17	,000	,000	,018	,012	,000	,000	,008
18	,000	,000	,018	,012	,000	,000	,008
19	,045	,000	,000	,012	,000	,000	,008
20	,000	,024	,000	,012	,000	,000	,008
21	,045	,000	,000	,012	,000	,000	,008
22	,000	,024	,000	,012	,000	,000	,008
23	,000	,000	,018	,000	,000	,045	,008
24	,000	,024	,000	,012	,000	,000	,008
25	,000	,000	,018	,012	,000	,000	,008
26	,000	,024	,000	,012	,000	,000	,008
27	,045	,000	,000	,012	,000	,000	,008
28	,000	,000	,018	,012	,000	,000	,008
29	,000	,024	,000	,012	,000	,000	,008
30	,000	,000	,018	,012	,000	,000	,008
31	,000	,024	,000	,012	,000	,000	,008
32	,045	,000	,000	,012	,000	,000	,008
33	,045	,000	,000	,012	,000	,000	,008
34	,045	,000	,000	,012	,000	,000	,008
35	,000	,024	,000	,012	,000	,000	,008
36	,045	,000	,000	,012	,000	,000	,008
37	,045	,000	,000	,012	,000	,000	,008
38	,045	,000	,000	,012	,000	,000	,008
39	,000	,024	,000	,012	,000	,000	,008
40	,000	,024	,000	,012	,000	,000	,008
41	,000	,024	,000	,012	,000	,000	,008
42	,045	,000	,000	,012	,000	,000	,008
43	,000	,000	,018	,012	,000	,000	,008
44	,045	,000	,000	,012	,000	,000	,008
45	,045	,000	,000	,012	,000	,000	,008
46	,000	,000	,018	,012	,000	,000	,008
47	,000	,024	,000	,012	,000	,000	,008
48	,000	,024	,000	,012	,000	,000	,008
49	,000	,024	,000	,012	,000	,000	,008
50	,000	,024	,000	,000	,000	,045	,008
51	,000	,000	,018	,012	,000	,000	,008
52	,045	,000	,000	,012	,000	,000	,008
53	,000	,024	,000	,012	,000	,000	,008
54	,000	,000	,018	,012	,000	,000	,008
55	,000	,024	,000	,012	,000	,000	,008
56	,000	,024	,000	,000	,067	,000	,008
57	,000	,024	,000	,012	,000	,000	,008

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Column Profiles

Row	Column						
	Land1 >25	Land1 <=25	Land1 =0	Rate >90	Rate 80-90	Rate <80	Mass
58	,000	,024	,000	,012	,000	,000	,008
59	,000	,024	,000	,012	,000	,000	,008
60	,000	,024	,000	,012	,000	,000	,008
61	,000	,000	,018	,012	,000	,000	,008
62	,000	,000	,018	,012	,000	,000	,008
63	,045	,000	,000	,012	,000	,000	,008
64	,000	,000	,018	,012	,000	,000	,008
65	,000	,000	,018	,012	,000	,000	,008
66	,000	,024	,000	,000	,000	,045	,008
67	,000	,000	,018	,012	,000	,000	,008
68	,000	,024	,000	,012	,000	,000	,008
69	,000	,000	,018	,000	,000	,045	,008
70	,000	,024	,000	,000	,067	,000	,008
71	,045	,000	,000	,012	,000	,000	,008
72	,000	,024	,000	,012	,000	,000	,008
73	,000	,000	,018	,000	,000	,045	,008
74	,000	,024	,000	,012	,000	,000	,008
75	,000	,000	,018	,000	,000	,045	,008
76	,000	,024	,000	,012	,000	,000	,008
77	,000	,024	,000	,012	,000	,000	,008
78	,000	,024	,000	,012	,000	,000	,008
79	,045	,000	,000	,012	,000	,000	,008
80	,000	,024	,000	,012	,000	,000	,008
81	,045	,000	,000	,012	,000	,000	,008
82	,045	,000	,000	,012	,000	,000	,008
83	,000	,024	,000	,000	,000	,045	,008
84	,000	,000	,018	,000	,067	,000	,008
85	,000	,000	,018	,000	,067	,000	,008
86	,000	,000	,018	,012	,000	,000	,008
87	,000	,000	,018	,012	,000	,000	,008
88	,000	,000	,018	,000	,067	,000	,008
89	,000	,000	,018	,012	,000	,000	,008
90	,000	,000	,018	,000	,000	,045	,008
91	,045	,000	,000	,012	,000	,000	,008
92	,000	,000	,018	,000	,000	,045	,008
93	,000	,024	,000	,012	,000	,000	,008
94	,000	,000	,018	,012	,000	,000	,008
95	,000	,024	,000	,012	,000	,000	,008
96	,000	,000	,018	,000	,067	,000	,008
97	,000	,000	,018	,000	,000	,045	,008
98	,045	,000	,000	,012	,000	,000	,008
99	,000	,000	,018	,012	,000	,000	,008
100	,000	,000	,018	,000	,000	,045	,008
101	,000	,000	,018	,012	,000	,000	,008
102	,045	,000	,000	,000	,067	,000	,008
103	,000	,024	,000	,000	,067	,000	,008

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Column Profiles

Row	Column: Land1 >25	Land1 <=25	Land1 =0	Rate >90	Rate 80-90	Rate <80	Mass
104	,000	,024	,000	,000	,067	,000	,008
105	,000	,000	,018	,012	,000	,000	,008
106	,000	,000	,018	,000	,000	,045	,008
107	,000	,000	,018	,012	,000	,000	,008
108	,000	,000	,018	,012	,000	,000	,008
109	,045	,000	,000	,000	,067	,000	,008
110	,000	,000	,018	,000	,067	,000	,008
111	,000	,000	,018	,000	,067	,000	,008
112	,000	,000	,018	,000	,000	,045	,008
113	,000	,000	,018	,000	,000	,045	,008
114	,000	,024	,000	,012	,000	,000	,008
115	,000	,024	,000	,012	,000	,000	,008
116	,000	,000	,018	,000	,000	,045	,008
117	,000	,000	,018	,000	,000	,045	,008
118	,000	,000	,018	,012	,000	,000	,008
119	,000	,000	,018	,000	,000	,045	,008
120	,000	,000	,018	,000	,000	,045	,008
Active Margin	1,000	1,000	1,000	1,000	1,000	1,000	

Summary

Dimension	Singular Value	Inertia	Chi Square	Sig.	Proportion of Inertia: Accounted for	Proportion of Inertia: Cumulative
1	,834	,696			,348	,348
2	,715	,512			,256	,604
3	,699	,488			,244	,848
4	,551	,304			,152	1,000
Total		2,000	480,000	1,000[a]	1,000	1,000

Summary

Dimension	Confidence Singular Value: Standard Deviation	Confidence Singular Value: Correlation 2
1	,017	,057
2	,035	
3		
4		
Total		

a. 595 degrees of freedom

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Overview Row Points[a]

Row	Mass	Score in Dimension 1	Score in Dimension 2	Inertia	Contribution: Of Point to Inertia of Dimension 1	Contribution: Of Point to Inertia of Dimension 2
1	,008	1,824	-,587	,023	,028	,003
2	,008	-,798	,608	,010	,005	,003
3	,008	1,824	-,587	,023	,028	,003
4	,008	,262	-,355	,006	,001	,001
5	,008	,262	-,355	,006	,001	,001
6	,008	-,242	2,656	,037	,000	,059
7	,008	,818	1,693	,034	,006	,024
8	,008	,262	-,355	,006	,001	,001
9	,008	,262	-,355	,006	,001	,001
10	,008	-,798	,608	,010	,005	,003
11	,008	,262	-,355	,006	,001	,001
12	,008	1,824	-,587	,023	,028	,003
13	,008	,818	1,693	,034	,006	,024
14	,008	,262	-,355	,006	,001	,001
15	,008	1,824	-,587	,023	,028	,003
16	,008	-,798	,608	,010	,005	,003
17	,008	,262	-,355	,006	,001	,001
18	,008	,262	-,355	,006	,001	,001
19	,008	-1,133	-1,377	,020	,011	,016
20	,008	-,798	,608	,010	,005	,003
21	,008	-1,133	-1,377	,020	,011	,016
22	,008	-,798	,608	,010	,005	,003
23	,008	1,824	-,587	,023	,028	,003
24	,008	-,798	,608	,010	,005	,003
25	,008	,262	-,355	,006	,001	,001
26	,008	-,798	,608	,010	,005	,003
27	,008	-1,133	-1,377	,020	,011	,016
28	,008	,262	-,355	,006	,001	,001
29	,008	-,798	,608	,010	,005	,003
30	,008	,262	-,355	,006	,001	,001
31	,008	-,798	,608	,010	,005	,003
32	,008	-1,133	-1,377	,020	,011	,016
33	,008	-1,133	-1,377	,020	,011	,016
34	,008	-1,133	-1,377	,020	,011	,016
35	,008	-,798	,608	,010	,005	,003
36	,008	-1,133	-1,377	,020	,011	,016
37	,008	-1,133	-1,377	,020	,011	,016
38	,008	-1,133	-1,377	,020	,011	,016
39	,008	-,798	,608	,010	,005	,003
40	,008	-,798	,608	,010	,005	,003
41	,008	-,798	,608	,010	,005	,003
42	,008	-1,133	-1,377	,020	,011	,016
43	,008	,262	-,355	,006	,001	,001
44	,008	-1,133	-1,377	,020	,011	,016

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Overview Row Points[a]

Row	Mass	Score in Dimension		Inertia	Contribution: Of Point to Inertia of Dimension	
		1	2		1	2
45	,008	-1,133	-1,377	,020	,011	,016
46	,008	,262	-,355	,006	,001	,001
47	,008	-,798	,608	,010	,005	,003
48	,008	-,798	,608	,010	,005	,003
49	,008	-,798	,608	,010	,005	,003
50	,008	,763	,376	,027	,005	,001
51	,008	,262	-,355	,006	,001	,001
52	,008	-1,133	-1,377	,020	,011	,016
53	,008	-,798	,608	,010	,005	,003
54	,008	,262	-,355	,006	,001	,001
55	,008	-,798	,608	,010	,005	,003
56	,008	-,242	2,656	,037	,000	,059
57	,008	-,798	,608	,010	,005	,003
58	,008	-,798	,608	,010	,005	,003
59	,008	-,798	,608	,010	,005	,003
60	,008	-,798	,608	,010	,005	,003
61	,008	,262	-,355	,006	,001	,001
62	,008	,262	-,355	,006	,001	,001
63	,008	-1,133	-1,377	,020	,011	,016
64	,008	,262	-,355	,006	,001	,001
65	,008	,262	-,355	,006	,001	,001
66	,008	,763	,376	,027	,005	,001
67	,008	,262	-,355	,006	,001	,001
68	,008	-,798	,608	,010	,005	,003
69	,008	1,824	-,587	,023	,028	,003
70	,008	-,242	2,656	,037	,000	,059
71	,008	-1,133	-1,377	,020	,011	,016
72	,008	-,798	,608	,010	,005	,003
73	,008	1,824	-,587	,023	,028	,003
74	,008	-,798	,608	,010	,005	,003
75	,008	1,824	-,587	,023	,028	,003
76	,008	-,798	,608	,010	,005	,003
77	,008	-,798	,608	,010	,005	,003
78	,008	-,798	,608	,010	,005	,003
79	,008	-1,133	-1,377	,020	,011	,016
80	,008	-,798	,608	,010	,005	,003
81	,008	-1,133	-1,377	,020	,011	,016
82	,008	-1,133	-1,377	,020	,011	,016
83	,008	,763	,376	,027	,005	,001
84	,008	,818	1,693	,034	,006	,024
85	,008	,818	1,693	,034	,006	,024
86	,008	,262	-,355	,006	,001	,001
87	,008	,262	-,355	,006	,001	,001
88	,008	,818	1,693	,034	,006	,024

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Overview Row Points[a]

Row	Mass	Score in Dimension		Inertia	Contribution	
					Of Point to Inertia of Dimension	
		1	2		1	2
89	,008	,262	-,355	,006	,001	,001
90	,008	1,824	-,587	,023	,028	,003
91	,008	-1,133	-1,377	,020	,011	,016
92	,008	1,824	-,587	,023	,028	,003
93	,008	-,798	,608	,010	,005	,003
94	,008	,262	-,355	,006	,001	,001
95	,008	-,798	,608	,010	,005	,003
96	,008	,818	1,693	,034	,006	,024
97	,008	1,824	-,587	,023	,028	,003
98	,008	-1,133	-1,377	,020	,011	,016
99	,008	,262	-,355	,006	,001	,001
100	,008	1,824	-,587	,023	,028	,003
101	,008	,262	-,355	,006	,001	,001
102	,008	-,577	,671	,048	,003	,004
103	,008	-,242	2,656	,037	,000	,059
104	,008	-,242	2,656	,037	,000	,059
105	,008	,262	-,355	,006	,001	,001
106	,008	1,824	-,587	,023	,028	,003
107	,008	,262	-,355	,006	,001	,001
108	,008	,262	-,355	,006	,001	,001
109	,008	-,577	,671	,048	,003	,004
110	,008	,818	1,693	,034	,006	,024
111	,008	,818	1,693	,034	,006	,024
112	,008	1,824	-,587	,023	,028	,003
113	,008	1,824	-,587	,023	,028	,003
114	,008	-,798	,608	,010	,005	,003
115	,008	-,798	,608	,010	,005	,003
116	,008	1,824	-,587	,023	,028	,003
117	,008	1,824	-,587	,023	,028	,003
118	,008	,262	-,355	,006	,001	,001
119	,008	1,824	-,587	,023	,028	,003
120	,008	1,824	-,587	,023	,028	,003
Active Total	1,000			2,000	1,000	1,000

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Overview Row Points[a]

	Contribution		
	Of Dimension to Inertia of Point		
Row	1	2	Total
1	,833	,063	,897
2	,374	,160	,533
3	,833	,063	,897
4	,062	,083	,145
5	,062	,083	,145
6	,009	,809	,818
7	,115	,362	,477
8	,062	,083	,145
9	,062	,083	,145
10	,374	,160	,533
11	,062	,083	,145
12	,833	,063	,897
13	,115	,362	,477
14	,062	,083	,145
15	,833	,063	,897
16	,374	,160	,533
17	,062	,083	,145
18	,062	,083	,145
19	,365	,396	,761
20	,374	,160	,533
21	,365	,396	,761
22	,374	,160	,533
23	,833	,063	,897
24	,374	,160	,533
25	,062	,083	,145
26	,374	,160	,533
27	,365	,396	,761
28	,062	,083	,145
29	,374	,160	,533
30	,062	,083	,145
31	,374	,160	,533
32	,365	,396	,761
33	,365	,396	,761
34	,365	,396	,761
35	,374	,160	,533
36	,365	,396	,761
37	,365	,396	,761
38	,365	,396	,761
39	,374	,160	,533
40	,374	,160	,533
41	,374	,160	,533
42	,365	,396	,761
43	,062	,083	,145
44	,365	,396	,761

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Overview Row Points[a]

Row	Contribution: Of Dimension to Inertia of Point 1	2	Total
45	,365	,396	,761
46	,062	,083	,145
47	,374	,160	,533
48	,374	,160	,533
49	,374	,160	,533
50	,127	,023	,150
51	,062	,083	,145
52	,365	,396	,761
53	,374	,160	,533
54	,062	,083	,145
55	,374	,160	,533
56	,009	,809	,818
57	,374	,160	,533
58	,374	,160	,533
59	,374	,160	,533
60	,374	,160	,533
61	,062	,083	,145
62	,062	,083	,145
63	,365	,396	,761
64	,062	,083	,145
65	,062	,083	,145
66	,127	,023	,150
67	,062	,083	,145
68	,374	,160	,533
69	,833	,063	,897
70	,009	,809	,818
71	,365	,396	,761
72	,374	,160	,533
73	,833	,063	,897
74	,374	,160	,533
75	,833	,063	,897
76	,374	,160	,533
77	,374	,160	,533
78	,374	,160	,533
79	,365	,396	,761
80	,374	,160	,533
81	,365	,396	,761
82	,365	,396	,761
83	,127	,023	,150
84	,115	,362	,477
85	,115	,362	,477
86	,062	,083	,145
87	,062	,083	,145
88	,115	,362	,477

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Overview Row Points[a]

Row	Contribution		
	Of Dimension to Inertia of Point		
	1	2	Total
89	,062	,083	,145
90	,833	,063	,897
91	,365	,396	,761
92	,833	,063	,897
93	,374	,160	,533
94	,062	,083	,145
95	,374	,160	,533
96	,115	,362	,477
97	,833	,063	,897
98	,365	,396	,761
99	,062	,083	,145
100	,833	,063	,897
101	,062	,083	,145
102	,040	,040	,081
103	,009	,809	,818
104	,009	,809	,818
105	,062	,083	,145
106	,833	,063	,897
107	,062	,083	,145
108	,062	,083	,145
109	,040	,040	,081
110	,115	,362	,477
111	,115	,362	,477
112	,833	,063	,897
113	,833	,063	,897
114	,374	,160	,533
115	,374	,160	,533
116	,833	,063	,897
117	,833	,063	,897
118	,062	,083	,145
119	,833	,063	,897
120	,833	,063	,897
Active Total			

a. Column Principal normalization

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Overview Column Points[a]

Column	Mass	Score in Dimension 1	Score in Dimension 2	Inertia	Contribution: Of Point to Inertia of Dimension 1	Contribution: Of Point to Inertia of Dimension 2
Land1 >25	,092	-1,082	-1,191	,408	,154	,254
Land1 <=25	,171	-,616	,841	,329	,093	,236
Land1 =0	,238	,861	-,145	,263	,253	,010
Rate >90	,346	-,495	-,219	,154	,122	,032
Rate 80-90	,063	,279	1,878	,438	,007	,431
Rate <80	,092	1,679	-,456	,408	,371	,037
Active Total	1,000			2,000	1,000	1,000

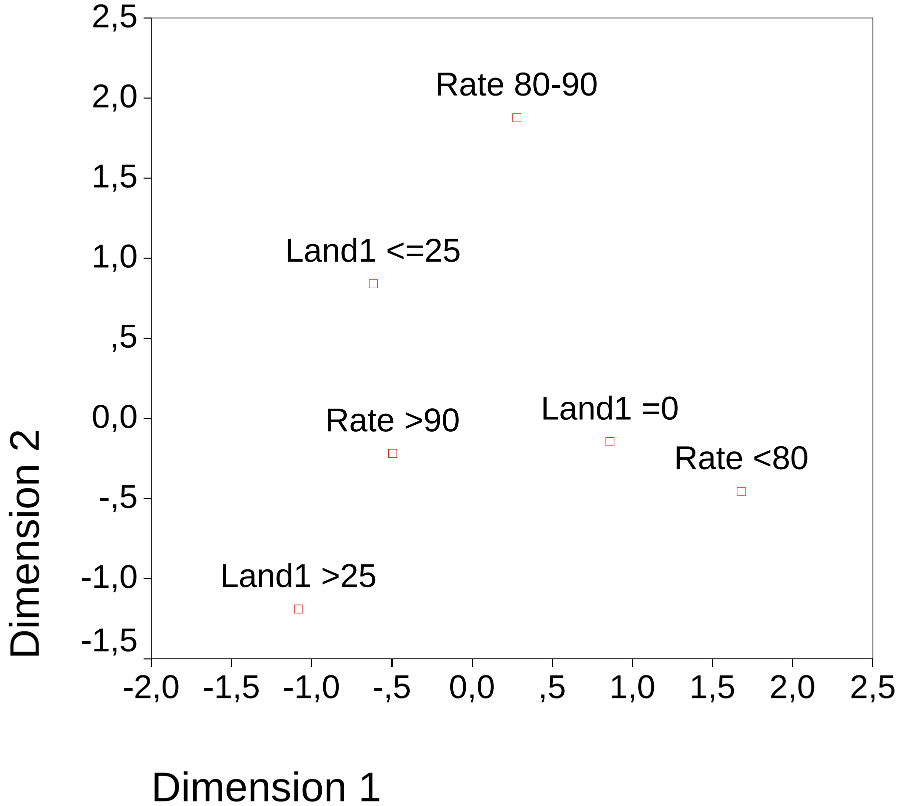
Overview Column Points[a]

Column	Contribution: Of Dimension to Inertia of Point 1	2	Total
Land1 >25	,263	,318	,581
Land1 <=25	,197	,367	,564
Land1 =0	,670	,019	,689
Rate >90	,551	,107	,658
Rate 80-90	,011	,504	,515
Rate <80	,633	,047	,680
Active Total			

a. Column Principal normalization

Column Points for Column

Column Principal Normalization



Annexe B

Output SPSS de l'Analyse de Correspondance Multiple

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Two indicators: proportion of land of quality 1, prim. school enrolment rate

Credit

HOMALS Version 1.0 by Data Theory Scaling System Group (DTSS) Faculty of Social and Behavioral Sciences Leiden University, The Netherlands

Case Processing Summary

Cases Used in Analysis	120

Marginal Frequencies

C-Proportion of land quality 1

	Marginal Frequency
Land1=0	57
Land1<=25	41
Land1>25	22
Missing	0

C-Primary enrolment rate

	Marginal Frequency
primr<80%	22
primr80-90%	15
primr>90%	83
Missing	0

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Iteration History

Iteration	Fit	Difference from the Previous Iteration
1	,032030	,032030
2	,940961	,908931
3	1,059457	,118497
4	1,147416	,087958
5	1,185088	,037673
6	1,198812	,013724
7	1,204069	,005257
8	1,206265	,002196
9	1,207241	,000977
10	1,207692	,000451
11	1,207905	,000213
12	1,208007	,000102
13	1,208056	,000049
14	1,208080	,000024
15	1,208092	,000012
16[a]	1,208097	,000006

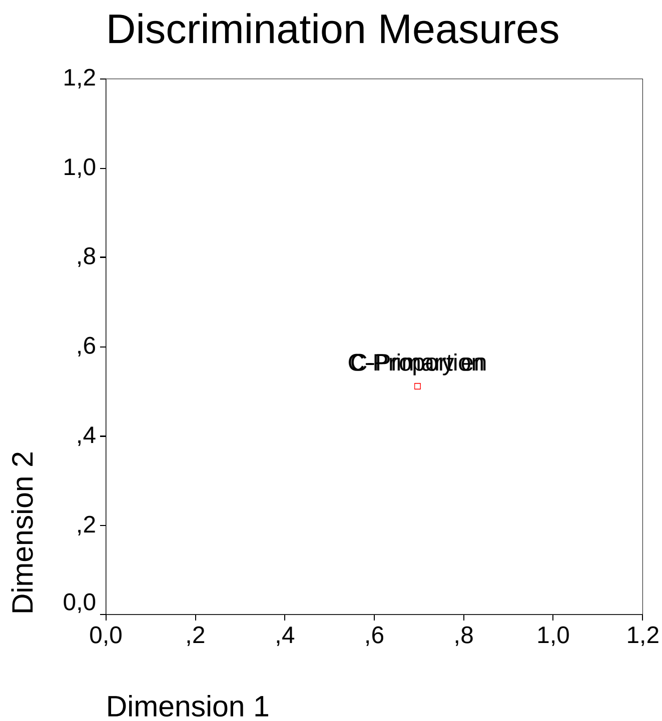
a. The iteration was terminated because convergence criteria are satisified.

Eigenvalues

Dimension	Eigenvalue
1	,696
2	,512

Discrimination Measures

	Dimension	
	1	2
C-Proportion of land quality 1	,696	,512
C-Primary enrolment rate	,696	,511



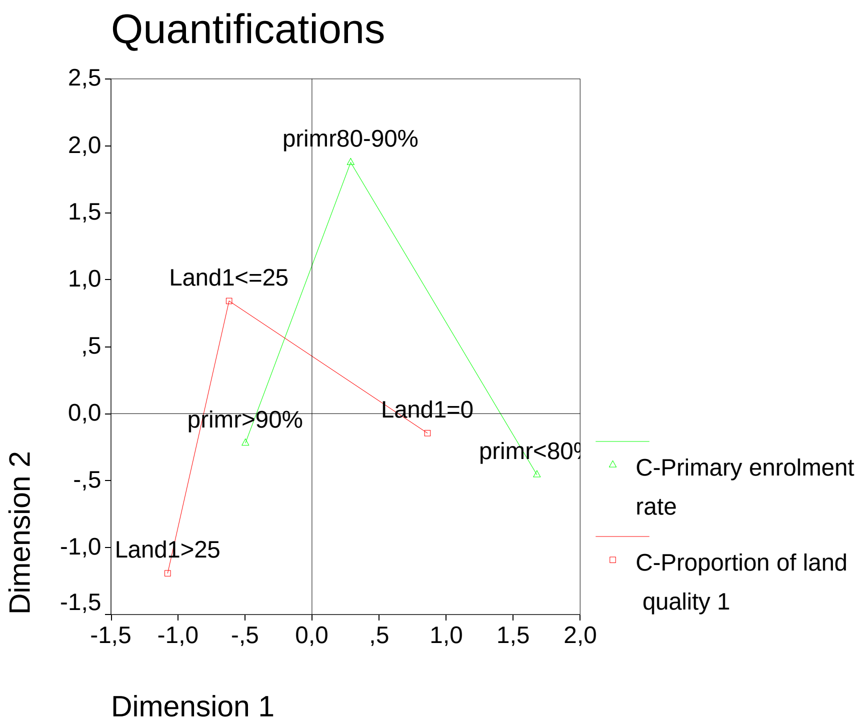
Quantifications

C-Proportion of land quality 1

	Marginal Frequency	Category Quantifications	
		Dimension	
		1	2
Land1=0	57	,862	-,146
Land1<=25	41	-,620	,841
Land1>25	22	-1,076	-1,191
Missing	0		

C-Primary enrolment rate

	Marginal Frequency	Category Quantifications	
		Dimension	
		1	2
primr<80%	22	1,677	-,455
primr80-90%	15	,288	1,877
primr>90%	83	-,497	-,219
Missing	0		



Object Scores

	Dimension	
	1	2
1	1,822	-,587
2	-,803	,609
3	1,822	-,587
4	,262	-,356
5	,262	-,356
6	-,237	2,656
7	,828	1,692
8	,262	-,356
9	,262	-,356
10	-,803	,609
11	,262	-,356
12	1,822	-,587
13	,828	1,692
14	,262	-,356
15	1,822	-,587
16	-,803	,609
17	,262	-,356
18	,262	-,356
19	-1,128	-1,377
20	-,803	,609
21	-1,128	-1,377
22	-,803	,609

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Object Scores

	Dimension	
	1	2
23	1,822	-,587
24	-,803	,609
25	,262	-,356
26	-,803	,609
27	-1,128	-1,377
28	,262	-,356
29	-,803	,609
30	,262	-,356
31	-,803	,609
32	-1,128	-1,377
33	-1,128	-1,377
34	-1,128	-1,377
35	-,803	,609
36	-1,128	-1,377
37	-1,128	-1,377
38	-1,128	-1,377
39	-,803	,609
40	-,803	,609
41	-,803	,609
42	-1,128	-1,377
43	,262	-,356
44	-1,128	-1,377
45	-1,128	-1,377
46	,262	-,356
47	-,803	,609
48	-,803	,609
49	-,803	,609
50	,757	,378
51	,262	-,356
52	-1,128	-1,377
53	-,803	,609
54	,262	-,356
55	-,803	,609
56	-,237	2,656
57	-,803	,609
58	-,803	,609
59	-,803	,609
60	-,803	,609
61	,262	-,356
62	,262	-,356
63	-1,128	-1,377
64	,262	-,356
65	,262	-,356
66	,757	,378
67	,262	-,356

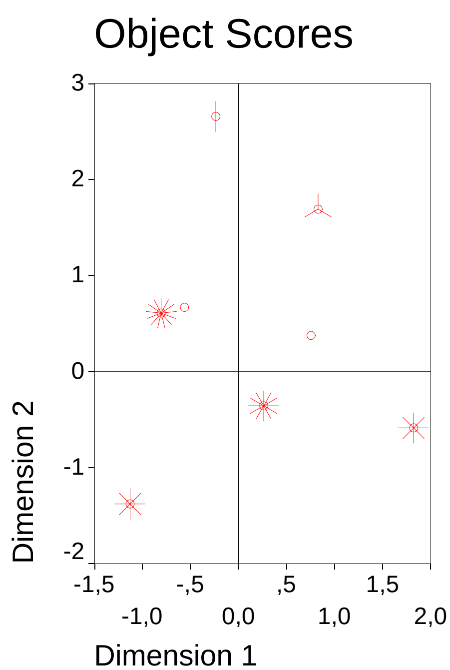
COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories

Object Scores

	Dimension	
	1	2
68	-,803	,609
69	1,822	-,587
70	-,237	2,656
71	-1,128	-1,377
72	-,803	,609
73	1,822	-,587
74	-,803	,609
75	1,822	-,587
76	-,803	,609
77	-,803	,609
78	-,803	,609
79	-1,128	-1,377
80	-,803	,609
81	-1,128	-1,377
82	-1,128	-1,377
83	,757	,378
84	,828	1,692
85	,828	1,692
86	,262	-,356
87	,262	-,356
88	,828	1,692
89	,262	-,356
90	1,822	-,587
91	-1,128	-1,377
92	1,822	-,587
93	-,803	,609
94	,262	-,356
95	-,803	,609
96	,828	1,692
97	1,822	-,587
98	-1,128	-1,377
99	,262	-,356
100	1,822	-,587
101	,262	-,356
102	-,561	,670
103	-,237	2,656
104	-,237	2,656
105	,262	-,356
106	1,822	-,587
107	,262	-,356
108	,262	-,356
109	-,561	,670
110	,828	1,692
111	,828	1,692
112	1,822	-,587

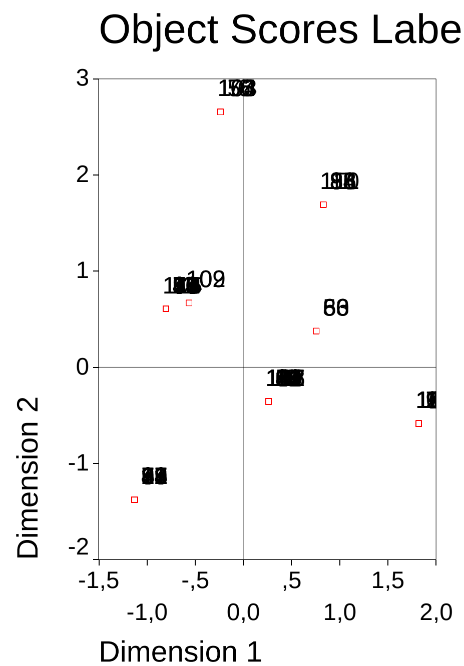
Object Scores

	Dimension	
	1	2
113	1,822	-,587
114	-,803	,609
115	-,803	,609
116	1,822	-,587
117	1,822	-,587
118	,262	-,356
119	1,822	-,587
120	1,822	-,587



Cases weighted by number of objects.

COMPOSITE POVERTY INDICATOR
VLSS-1 Communes Data
Example with 2 indicators, 6 categories



Cases weighted by number of objects.