A Latent Budget Analysis Approach to Classification: Examples from Economics

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15. September 2005

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Abstract
Latent budget analysis is a classification technique that allows clustering identification by using compositional data. This paper presents examples of how this technique deals with the unit-sum constraint by establishing an initial independence model to which subsequent models are compared in terms of their relative fitness degree. In fact, latent budget analysis does not impose linearity, homogeneity, or even specific distributions on data. Results help to understand some important relationships between capital stock composition and income or food diet composition in a heterogeneous sample of countries.

FIRST DRAFT
September, 15 2005
[COMMENTS ARE WELCOME]

1. Introduction
Compositional data have restrictions for applying traditional multivariate analysis due to, among other things, the absence of an interpretable covariance structure (Aitchison, 1986). The latent budget analysis approach of compositional data is a real alternative in terms of efficiency and versatility for dealing with the analysis of this constrained data even though the sensitive advances made it from the log-ratio approach of the CODA school research contributions.

The goal of this communication is to briefly present this methodology for classification, particularly focused in economics examples. The description of the model is heavily based on van den Ark (1999) and tries to wide the knowledge of latent budget methodology for economic research application. The work follows with section 2 where the latent budget model is described, section 3 with examples from economics and section 4 ends the paper with short conclusions.

2. The Latent Budget Model[2]
The Latent Budget Model (LBM) is a mixture model for compositional data and enables us to obtain insights in a compositional data set without the worries of a troubled covariance matrix. By performing latent budget analysis (LBA) we approximate *I* observed budgets, which may represent persons, groups or objects, by a small number of latent budgets, consisting of typical characteristics of the sample. Such approximation could be used for classification, for example.

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[2] See van den Ark (1998: 8-13)

The first insight into these kinds of models can be found initially in Goodman (1974a), in a more elaborated fashion in Clogg (1981) who interpreted a simple latent class model in an asymmetric way. Independently, de Leeuw & van der Heijden (1988) introduced the name ‘latent budget analysis’ because they used it to analyze time-budget data. In geological research the same model is know as *endmember* model (Renner 1988, 1993).

Consider and $I \times J$ compositional data matrix *P*, consisting of *I* observed budgets p_i, with components $p_{j|i}$. In the LBM the observed budgets p_i’s are approximated by expected budgets π_i, which are mixtures of *K* ($K = \min(I, J)$) *typical compositions* or *latent budgets*. The latent budgets are denoted by β_k, $k = (1, \ldots, K)$, and the model can be written as

$$\pi_i = \alpha_{1|i}\beta_1 + \ldots + \alpha_{k|i}\beta_k + \ldots + \alpha_{K|i}\beta_K \qquad (i = 1, \ldots, I)$$

where $\alpha_{k|i}$ $(i = 1, \ldots, I; k = 1, \ldots, K)$ are mixing parameters. The elements of π_i and $\pi_{j|i}$ are called expected components. The elements of β_k are $\beta_{j|k}$ $(j = 1, \ldots, J)$ and are called latent components. An alternative notation for (1) is the scalar notation

$$\pi_{j|i} = \sum_{k=1}^{K} \alpha_{k|i}\beta_{j|k} \qquad (i = 1, ..., I;\ j = 1, ..., J)$$

and the matrix notation

$$\Pi = AB^T$$

In (3) Π is a $I \times J$ matrix whose rows are the respected budgets; *A* is an $I \times K$ matrix of mixing parameters, and *B* is a $J \times K$ matrix whose columns are the latent budgets. The latent budget model with K latent budgets is denoted as LBM (K). Similar to the observed components, the parameters of the LBM are subject to the sum constraints

$$\sum_{j=1}^{J} \pi_{j|i} = \sum_{k=1}^{K} \alpha_{k|i} = \sum_{j=1}^{J} \beta_{j|k} = 1$$

and the nonnegativity constraint

$$0 \le \pi_{j|i} \le 1,$$
$$0 \le \alpha_{k|i} \le 1,$$
$$0 \le \beta_{j|k} \le 1.$$

Thus, all the parameters are proportions and this facilitates the interpretation of the model. In fact, it has been argued that its ease of interpretation is one of the main reasons to use LBA (for example, de Leeuw and van der Heijden, 1988; de Leeuw et al., 1990; van der Ark and van der Heijden, 1998).

If the data have a product-multinomial distribution, we can compute the unconditional expected probabilities π_{ij} from the expected components. The following properties hold for the expected components and the corresponding unconditional probabilities:

$$\pi_{ij} = \pi_{ij} / p_{i+},$$
$$p_{i+} = \pi_{i+},$$
$$p_{+j} = \pi_{+j}$$

(see de Leeuw *et al*., 1990).

Van der Heijden, Mooijaart, and de Leeuw (1992) proposed two ways to interpret the model, which we will call the mixture model interpretation and the MIMIC-model interpretation (Multiple Indicator Multiple Cause-model). Up to now we have treated the LBM as a mixture model and the interpretation given earlier is: the LBM writes the expected budgets as a mixture of a small number of typical, or latent, budgets. Hence, each expected budget is built up out of the *K* latent budgets, and the mixing parameters determine to what extent. The latent budgets can be characterized by comparing them with the latent budget LBM(1). LBM(1) is the independence model, with $\alpha_{1|i} = 1 \left(i = 1,\ldots,I\right)$, and $\beta_{j|1} = p_{+j} \left(j = 1,\ldots,J\right)$, in this case $\pi_i = \beta_1$ for $i = 1,\ldots,I$. Hence, if latent component $\beta_{j|k}$ is greater than that component in the independence model, p_{+j}, then β_k is characterized by the *j*-th category. On the other hand, if a $\beta_{j|k}$ is less than p_{+j} then the *j*-th category is of lesser importance. The budget proportions $\pi_k = \sum_i p_{i+}\alpha_{k|i}$ express the relative importance of each latent budget, in terms of how much of the expected data they account for. At the same time, π_k, $\left(k = 1,\ldots,K\right)$ denotes de probability of latent budget *k* when there is no information about the level of the row variable. To understand how the expected budgets are constructed from the latent budgets we must compare the mixing parameters to π_k. If $\alpha_{k|i} > \pi_k$ then the expected budget π_i is characterized more than average by latent budget β_k, and if $\alpha_{k|i} < \pi_k$ then the expected budget π_i is characterized less than average by latent budget β_k. In practice the mixture model interpretation is carried out most easily when we first characterize the latent budgets and then interpret the expected budgets in terms of the latent budgets.

Now, for interpreting the LBM as a *MIMIC*-model, we look at the observed components as conditional proportions of the row variable *X*, with *I* categories, and the column variable *Y*, with *J* categories. If we assume that the row variable and the column variable are independent given some latent variable *Z* with *K* categories, then the LBM describes the relationship between the row variable and the column variable in an asymmetric way, i.e. $\pi_{j|i} = P(Y = j \mid X = i)$ denotes the probability to respond to category *j* of *Y*, given that one belongs to the *i*-th category of *X*; these probabilities are explained by $\alpha_{k|i} = P\left(Z = k \mid X = i\right)$ which is the probability that row category *i* belongs to latent category *k*, and $\beta_{j|k} = P\left(Y = j \mid Z = k\right)$ which is the probability that a member of latent category *k* responds to the *j*-th category of *Y*.

If the compositional data do not have a product multinomial distribution then the *MIMIC*-model interpretation may be troublesome: for example, if each observed budgets represents a multivariate observation on a single subject, then it is unclear what $P(Y = j \mid Z = k)$ means. If the rows of the compositional data are not independent, for example if they denote groups, and people may belong to more than one group, then $P\left(Z = k \mid Y = i\right)$ is not well defined.

The parameters estimates of the LBM model should be identified before the latent budget solution can be analyzed. We follow with some examples from economics.

3. Examples from Economics

In this section we will present examples of application of LBA to economic data. We will define some economic problem to identify through LBA. When feasible, raw data will be presented and estimations will be interpreted. Following Ark (1998: 164) we will identify latent budgets by following three rules-of-thumb:
a) Selecting the latent budget whose proportion of lack of fit is as large from baseline model as possible.
b) The improving of adding an extra latent budget should be large enough to identify the extra effort of interpreting a larger set of parameter estimates. Ark (1998) proposes that the average improvement of fit per degree of freedom should be at least as great as the difference between the weighted Residual Sum of Squares (wRSS) of the baseline model less the observed wRSS divided by the degrees of freedom.
(c) Finally, the result should be interpretable.

For a matter of exposition we are going to follow clause c with more emphasis than advisable. We follow with the first example.

3.1 Capital composition and income classification

The first application of the latent budget analysis for a classification example is on capital composition and income. In Table 2 we see the average participation of each capital component for the 1960-1990 time periods (data were used previously in Larrosa, 2003). The definition of the components is presented in Table 1.

Table 1. Description of row variables

Code	Description
KDUR	Percentage of capital per worker allocated in durable production assets (machinery and equipment).
KOTHR	Percentage of capital per worker allocated in other buildings.
KNRES	Percentage of capital per worker allocated in non-residential building.
KRES	Percentage of capital per worker allocated in residential building.
KTRAN	Percentage of capital per worker allocated in transportation equipment.

We average and closed each capital component by income category. Data are presented in Table 2 and it shed light in the long run average capital composition of the sample of countries. Notice that poorer countries possess a lower than average transportation equipment participation on capital stock and that a high-income-OECD country and a lower-middle-income country have above average residential building capital participation. Besides, poorer countries have an above from average participation of other buildings. There are 56 countries in the sample.

Table 2. Capital composition by income category (n=56)

	KTRAN	KOTHR	KDUR	KRES	KNRES
low income [9]	0.0092	0.3204	0.1467	0.2230	0.3008
lower middle income [13]	0.0292	0.3308	0.1536	0.3279	0.1586
upper middle income [9]	0.0289	0.2389	0.1712	0.2521	0.3090
high income OECD [19]	0.0443	0.2100	0.1927	0.3424	0.2106
high income non-OECD [6]	0.0214	0.2255	0.1835	0.3244	0.2452

Source: column variables: Data from Penn World Table 5.6; row classification: 2000 World Development Indicators – The World Bank. Brackets indicate the number of countries that belongs to this category.

As the sample is not large and data have not additive lognormal distribution[3] we could not rely on maximum likelihood estimates. We use least squares for estimating latent budgets on the model (Table 2).

[3] Tests were conducted with the freeware (mvn.exe) available at http://come.to/lba/software. They are available upon request.

Table 2. Estimations of mixing parameters and identified latent budgets

Identified Mixing Parameters

	LB 1	LB 2	LB 3	*independence*
LowInc	**0.495**	0.121	**0.384**	1
LowMdIn	**0.512**	**0.285**	0.203	1
UpMidIn	0.371	0.232	**0.397**	1
HighInc	0.326	**0.402**	0.272	1
HighInc	0.347	**0.345**	0.308	1
π_k	*0.410*	*0.277*	*0.313*	1

Identified Latent Budgets

	LB 1	LB 2	LB 3	*independence*
Ktran	0	**0.096**	0	*0.027*
Kothr	**0.646**	0	0	*0.265*
Kdur	0.059	**0.284**	**0.214**	*0.17*
Kres	**0.295**	**0.620**	0.004	*0.294*
Knres	0	0	**0.783**	*0.245*

Interpretation requires going latent budget by latent budget. The first budget associates low-income countries with a higher presence of other capital al also residential capital. This would be the *low-middle income budget*. The second latent budget remarks the relation of residential capital and durable goods in OECD and non-OECD high income countries. This would be the *high income budget*. Finally, the third budget associates the non residential capital with a wider scope of countries, such middle-up and lower income countries. This would be the mid-low income budget. So far, estimations don't shed much light into the capital composition question.

We are going to see if widening the sample helps to arrive to clearer conclusions.

3.1.1 Example 1 revisited

The former example was completed by sample averaging on World Bank's income categories. We review the example by estimating latent variables that reveals capital composition among countries. So, this time, LBA is related to each country own data (see Table 3). This would help us to see any latent variable that conditioning capital composition in this sample. Since it would make no sense to assume a multinominal distribution and to apply a maximum likelihood estimation procedure, our weighted least squares approach seems reasonable. The weights used are $1\big/ p_j^{1/2}$ for the columns.

Table 3. Capital composition by country (Raw data)

Country	KTRAN	KOTHR	KDUR	KRES	KNRES
ARG	0,012	0,184	0,083	0,280	0,440
AUS	0,055	0,173	0,219	0,284	0,269
BEL	0,035	0,226	0,224	0,292	0,222
BOL	0,012	0,753	0,062	0,111	0,062
BOT	0,016	0,129	0,276	0,268	0,311
CAN	0,020	0,291	0,095	0,392	0,201
CHL	0,026	0,381	0,076	0,357	0,160
COL	0,010	0,510	0,058	0,268	0,154
DEN	0,024	0,203	0,165	0,338	0,270
DOM	0,010	0,294	0,088	0,475	0,134
ECU	0,010	0,642	0,052	0,194	0,102
FIN	0,014	0,227	0,173	0,302	0,284

FRA	0,050	0,179	0,224	0,293	0,254
GER	0,028	0,217	0,182	0,320	0,254
GRE	0,012	0,393	0,122	0,310	0,163
GUA	0,012	0,487	0,269	0,227	0,005
HKG	0,135	0,052	0,414	0,217	0,183
HON	0,174	0,194	0,417	0,122	0,091
ICE	0,018	0,071	0,112	0,613	0,185
IND	0,015	0,372	0,136	0,251	0,225
IRE	0,034	0,122	0,221	0,321	0,304
ISR	0,010	0,054	0,192	0,491	0,253
ITA	0,026	0,152	0,167	0,458	0,196
IVC	0,019	0,231	0,183	0,384	0,184
JAM	0,072	0,287	0,264	0,333	0,044
JAP	0,046	0,335	0,190	0,215	0,214
KEN	0,006	0,248	0,167	0,353	0,225
KOR	0,018	0,206	0,120	0,201	0,455
LUX	0,016	0,278	0,179	0,280	0,248
MAD	0,007	0,472	0,262	0,152	0,107
MAL	0,007	0,165	0,230	0,196	0,402
MEX	0,032	0,248	0,196	0,348	0,176
MOR	0,005	0,290	0,082	0,351	0,272
NET	0,046	0,166	0,220	0,298	0,269
NIA	0,006	0,398	0,104	0,209	0,284
NOR	0,145	0,284	0,251	0,151	0,170
NZL	0,042	0,486	0,204	0,188	0,081
OST	0,025	0,242	0,204	0,263	0,267
PAN	0,079	0,491	0,156	0,113	0,161
PAR	0,050	0,005	0,145	0,795	0,005
PER	0,011	0,387	0,112	0,485	0,005
PHI	0,005	0,044	0,148	0,220	0,584
POR	0,029	0,209	0,141	0,517	0,103
SLE	0,063	0,402	0,263	0,111	0,162
SPA	0,007	0,266	0,069	0,557	0,102
SRL	0,008	0,389	0,049	0,125	0,429
SWE	0,025	0,191	0,159	0,370	0,255
SWI	0,013	0,153	0,170	0,332	0,332
SYR	0,035	0,197	0,107	0,386	0,274
TAI	0,019	0,273	0,249	0,161	0,298
THAI	0,013	0,352	0,196	0,200	0,238
TUR	0,022	0,232	0,197	0,261	0,288
UK	0,042	0,074	0,299	0,324	0,262
USA	0,033	0,157	0,165	0,422	0,224
VEN	0,035	0,007	0,187	0,278	0,492
ZIM	0,005	0,289	0,042	0,114	0,550

Source: data processed using original data from Penn World Table 5.6

We estimate latent budgets that determine unobserved patterns in capital composition in the sample. As the sample is not large and data have not additive lognormal distribution[4] we could not rely on maximum likelihood estimates. We use instead weighted least squares. First, we try to identify the model by analyzing the dissimilarity index and the mean angular deviation (van den Ark, 1999: 126-127).

[4] Tests results are available upon request.

Table 4. Identification of model 2

Latent Budgets	LBM(K)	
	1 - D	*m.a.d.*
1/J	71.2739	0.5915
K=1	80.4209	0.3945
K=2	86.809	0.2635
K=3	90.6867	0.1955
K=4	98.4739	0.0314

As observed, as the number of latent budgets increases, the goodness-of-fit statistics (GFS) also increases. We decide for three latent budgets because of ease of interpretation and explanation of results.

Table 5. Parameter estimates of the identified mixing parameters

Country	LB 1	LB 2	LB 3
ARG	0.199	0.003	**0.797**
AUS	0.201	**0.202**	**0.597**
OST	0.282	0.141	**0.577**
BEL	0.269	**0.176**	0.555
BOL	**0.887**	0.030	0.083
BOT	0.149	**0.182**	**0.669**
CAN	**0.351**	0.036	**0.613**
CHL	**0.457**	0.036	0.507
COL	**0.604**	0.002	0.394
DEN	0.24	0.100	**0.660**
DOM	**0.365**	0.011	**0.624**
ECU	**0.758**	0.008	0.234
FIN	0.266	0.092	**0.642**
FRA	0.21	**0.198**	**0.592**
GER	0.257	0.124	**0.620**
GRE	**0.47**	0.055	0.475
HON	0.227	**0.596**	0.176
HKG	0.061	**0.511**	0.428
ICE	0.108	0.028	**0.863**
IND	**0.437**	0.072	0.491
IRE	0.142	**0.162**	**0.696**
ISR	0.078	0.087	**0.835**
ITA	0.194	0.1	**0.705**
IVC	0.284	0.109	**0.607**
JAM	**0.356**	**0.281**	0.362
JAP	**0.391**	**0.173**	0.436
KOR	0.219	0.05	**0.731**
LUX	**0.327**	0.105	**0.568**
MEX	0.302	**0.146**	0.553
NET	0.195	**0.187**	**0.619**
NZL	**0.578**	0.19	0.232

Country	1	LB 2	LB 3	
NOR	**0.325**	**0.399**	0.276	
PAN	**0.569**	**0.213**	0.218	
POR	0.271	0.086	**0.643**	
SLE	**0.468**	**0.275**	0.257	
SWE	0.229	0.095	**0.676**	
SWI	0.177	0.081	**0.741**	
SYR	0.234	0.066	**0.701**	
TAI	**0.312**	**0.175**	0.513	
THAI	**0.411**	0.122	0.467	
TUR	0.269	**0.129**	**0.602**	
UK	0.091	0.244	**0.665**	
USA	0.194	0.111	**0.694**	
VEN	0	0.123	**0.877**	
GUA	**0.592**	**0.197**	0.211	
KEN	0.299	0.074	**0.627**	
MAD	**0.562**	**0.181**	0.257	
MAL	0.179	**0.128**	**0.693**	
MOR	**0.342**	0	**0.658**	
NIA	**0.459**	0.029	0.512	
PAR	0.055	0.108	**0.837**	
PER	**0.487**	0.042	0.472	
PHI	0.022	0.04	**0.939**	
SPA	**0.336**	0	**0.664**	
SRL	**0.426**	0	**0.574**	
ZIM	0.293	0	**0.707**	
π_k	*0.312*	*0.127*	*0.561*	
Latent budgets				p_{+j}
KTRAN	0	**0.252**	0	*0.031*
KOTHR	**0.845**	0	0	*0.264*
KDUR	0.045	**0.727**	0.12	*0.174*
KRES	0.111	0	**0.475**	*0.301*
KNRES	0	0.021	**0.405**	*0.23*

Parameters can be interpreted as follows. First, we interpret the latent budgets by comparing them to the independent model. The first latent budget has greater proportions of other kinds of buildings in the capital stock. We could call it the “other buildings budget”. The second latent budget has greater values of transportation equipment and durable goods than the independent model. We could call this budget as the “durable goods budget”. Finally, residential and non residential buildings have the greater values of the third latent budget that is a sensitive preeminence of buildings. This would be the “building budget”. This finding is congruent with Larrosa (2003) results, but in that case we utilized the log-ratio approach. The interpretation of these latent budgets con each country in particular could be difficult, because quite different individuals are in the same budget. For instance, in the durable goods budget coexist India, Japan, Jamaica, Honduras, Hong

Kong, Sierra Leone, Madagascar, Malawi, Taiwan and Norway, i.e., some highly developed countries are together with some of the poorest in the World.

Another way of looking at the findings is through plotting the latent budgets in ternary diagrams. Figures 1 and 2 show the same data that Table 5. Figure 1 presents latent components estimates and Figure 2 displays the calculated LBM (3). As observed, latent budget 3 (LB 3) groups most data from countries. That is, the *building budget*. At the same time, one can see that the durable goods budget is what discriminates the sample.

Figure 1. Graphic display of latent components

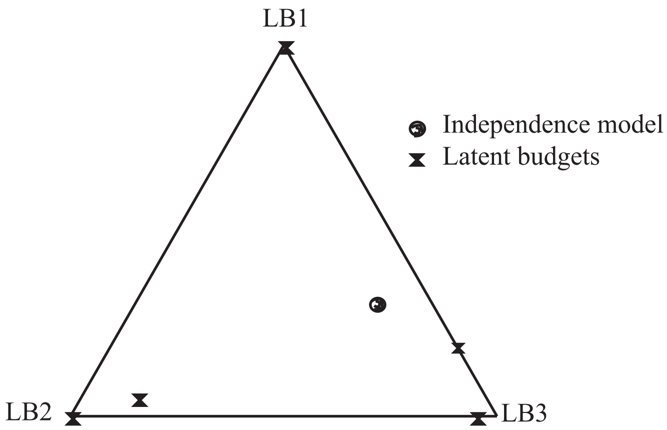
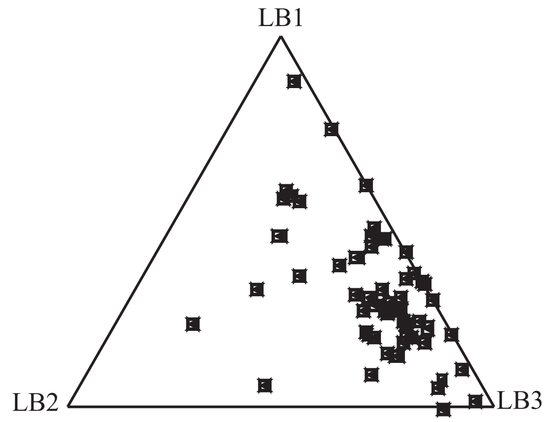


Figure 2. Graphic display of LBM (3)



3.3 Food expenditure

Food expenditure represents the money individuals from an economy spend in feeding. This is related with socioeconomic conditions but also for cultural and religious items. We have data for the 1970 total expenditure on 32 food components from Belgium (BEL), Colombia (COL), Germany (DEU), France (FRA), U.K. (GBR), Hungary (HUN), Iran (IRN), India (IND), Italy (ITA), Japan (JAP), Kenya (KEN), South Korea (KOR), Malaysia (MYS), Netherlands (NLD), Philippines (PHI), and USA (USA). The 32 food components are detailed in Table 6.

Table 6. Food components categories

Category	Labels
1	Rice
2	Flour and cereals
3	Bread
4	Other bakery products
5	Other cereal products
6	Macaroni & similar pasta
7	Beef & Veal
8	Lamb, mutton & goat meat
9	Pork meat
10	Poultry meat
11	Other fresh/frozen meat
12	Meat preparations
13	Fresh/frozen fish
14	Preserved/processed fish/seafood
15	Fresh milk

16	Preserved milk/ Other milk products/ Cheese
17	Eggs
18	Butter
19	Margarine, oils & fat
20	Fresh fruit
21	Fresh vegetables
22	Dried fruit & nuts
23	Dried/frozen/prepared vegetables
24	Potatoes & other tubers/Potato products
25	Coffees
26	Teas
27	Cocoa
28	Raw & refined sugar
29	Jam/jelly/honey/s
30	Chocolate & confetti
31	Salt, spice & sauces
32	Mineral water

We will try to find the latent diet of these countries by calculating the first three (unconstrained) latent budgets. Goodness-of-fit statistics show that four latent budgets could better identify the model but for ease of explanations and results visualization we stick on three. Table 7 shows the parameter estimates of the identified mixing parameters.

Table 7. Mixing parameters and latent components of the LBM (3) solution

Food component	**LB 1**	**LB 2**	**LB 3**	**Independ.**	**Food component**	**LB 1**	**LB 2**	**LB 3**	**Independ.**
Rice	0	**0.944**	0.056	1	Teas	0.166	0.2	**0.634**	1
Flour and cereals	0	**0.765**	**0.235**	1	Cocoa	1	0	0	1
Bread	**0.673**	0.109	**0.218**	1	Raw & refined sugar	0.331	**0.461**	**0.207**	1
Other bakery products	**0.687**	0.255	0.058	1	Jam/jelly/honey/s	0.404	**0.526**	0.07	1
Other cereal products	**0.759**	0.145	0.096	1	Chocolate & confetti	**0.898**	0.067	0.035	1
Macaroni & similar pasta	**0.489**	**0.511**	0	1	Salt, spices & sauces	0.154	**0.842**	0.004	1
Beef & Veal	**0.833**	0.129	0.038	1	Mineral water	**0.608**	0.358	0.034	1
Lamb, mutton & go	0	0	1.00	1	π_k	*0.423*	*0.449*	*0.128*	
Pork	**0.647**	0.353	0	1	**Latent budgets**				
Poultry	**0.607**	0.308	0.085	1	BEL	**0.093**	0	0	*0.042*
Other fresh-frozen meats	**0.677**	0.271	0.052	1	COL	**0.154**	0.006	0	*0.065*
Meat preparations	**0.984**	0	0.016	1	DEU	**0.091**	0	0	*0.036*
Fresh/frozen fish	0.252	**0.748**	0	1	FRA	**0.093**	0	0.01	*0.042*
Preserved/proc/dried seafood	0.266	**0.734**	0	1	GBR	**0.069**	0	**0.073**	*0.034*
Fresh milk	**0.502**	0.408	0.09	1	HUN	**0.118**	0.012	0	*0.057*
Preserved milk/Other milk products/Cheese	**0.589**	0.109	**0.302**	1	IND	0	**0.204**	0.114	*0.12*
Eggs	**0.602**	0.289	0.11	1	IRN	0	0	**0.688**	*0.085*
Butter	**0.781**	0.037	**0.182**	1	ITA	**0.099**	0.027	0.013	*0.06*
Margarine, oils & fat	0.311	0.49	**0.199**	1	JPN	0.033	**0.116**	0	*0.052*
Fresh fruit	**0.504**	0.292	**0.204**	1	KEN	0.025	**0.116**	**0.1**	*0.086*
Fresh vegetables	**0.428**	0.433	**0.139**	1	KOR	0	**0.201**	0	*0.092*
Dried fruit & nut	**0.659**	0.19	**0.151**	1	MYS	0.043	**0.107**	0	*0.065*
Dried/frozen/prepared vegetables	**0.505**	0.391	0.104	1	NLD	**0.087**	0.002	0.002	*0.04*
Potatoes & other tuber /Potato products	0.381	**0.518**	0.1	1	PHL	0.043	**0.194**	0	*0.098*
Coffees	**0.896**	0.104	0	1	USA	**0.052**	0.014	0	*0.027*

Interestingly, interpretation begins with latent budget one that represents all Western countries in the sample. This would be the *Western diet budget*. Related to this culture pattern we could match a basket of food items as represented by the mixing parameters relatively to the budgets proportions: So, Western diet budget includes meat preparations, coffee, beef and veal, chocolates, cereals, butter, other fresh meats, mineral water and other food components. The second latent budget reflects a higher value for countries other than Western. The majority are Asian countries, so this would be the *Asian diet budget*. This basket reflects higher than average presence of rice, salt and spices, fresh and processed fish, flour and cereals, potatoes, jams and jellies, pastas and sugar. Finally, the third latent budget is highly represented by a Muslim country like Iran, with low participation of other Western and African countries. The most important food component is tea. So, this would be the *tea diet budget*[5] and indicates a higher presence of, of course, tea, cheese and preserved milk, fresh fruits, floor and cereals, bread, margarine and oils and other foods components. Would you expect a clearer picture?

We end this communication with the conclusions.

4. Conclusions

Latent budget analysis is an attractive alternative for dealing with compositional data. As reported, it is easy to use and to interpret the results. It deals with highly problematic and widely available data. This report, inconclusive and still incomplete, tries to be an introduction for more insightful and in-depth texts, as van den Ark (1999) is.

As described above, LBA seems to be ideal for statistical classification and searching for unobserved patterns in data. These kinds of problem are a common in social sciences. We hope this tool rapidly enters in the syllabus of standard grade statistics course.

Acknowledgments

LB estimations were made using the freeware (lba.exe), by van den Ark, Mooijart and Van der Heijden at http://come.to/lba/software. Ternary diagrams were made it with the freeware Codapack (see Thió-Henestrosa and Martín-Fernández, 2005).

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[5] Another more precise name could be "Not-Western-Neither-Asian diet budget".

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