Using Principal Component Analysis and Cluster Analysis to determine agricultural capacities of Algeria

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Abstract

This work aims to apply principal components analysis and cluster analysis to determine the Agricultural capacities of Algeria. We find four agricultural areas. These areas characterized by the production of citrus fruits, potatoes and potatoes, cereals and finally Livestock.

Key words

Principal Components Analysis. Cluster Analysis. Agriculture. Algeria

المخلص

يهدف هذا العمل إلى تطبيق التحليل عن طريق المركبات الأساسية والتحليل العنقودي من أجل تحديد أهم القدرات الفلاحية للجزائر. بعد تحليل النتائج وجدنا أن الجزائر تتميز بأربعة مناطق فلاحية. تتميز هذه المناطق الفلاحية بإنتاج الحمضيات والفواكه؛ البطاطا والطماطم؛ الخضر والحبوب؛ وأخيرا تربية المواشي.

الكلمات المفتاحية

التحليل عن طريق المركبات الأساسية. التحليل العنقودي. الفلاحة. الجزائر

Introduction

Principal components analysis (PCA) is a factor method, which initiated by Pearson in 1901, and developed by Hotelling in 1933 (Rotaru et al, 2012). It is a useful statistical technique for finding patterns in data of high dimension. It has found application in several fields such as agriculture, finance, economics etc. PCA is a procedure by which numbers of correlated variables are transformed into a smaller number of uncorrelated variables. It can be used to compress a high dimensional dataset into a lower dimensional dataset. PCA is based on the minimization of the mean square error in data compression, finding mutually orthogonal directions in the data having maximal variances and de-correlation of the data using orthogonal transformation. These uncorrelated variables are called Principal Components (Jyotirmoy Sarkara et al, 2014).

Cluster analysis is a collection of relatively simple descriptive statistical techniques with potential value in several fields. There are many methods of cluster analysis. One of them is the classification, which is an essential means of organizing information (Jane Clatworthy et al, 2005).

1. Data sets

We try to apply Principal Component Analysis (PCA) and Cluster Analysis (CA) on a data table of 48 individuals and 19 variables using statistical programming language R. The 48 individuals are the 48 states of Algeria. The 19 variable are a statistics about Plant wealth, Livestock and some geographical characteristics such as the geographical location, height and number of dams. The database is loaded from National Office of Statistics.

2. Finding and Discussion

2.1. The preparation of the database

Read the database using `read.csv2`:

```
setwd("C:/Users/houssem/Downloads/Colloques/Workshop-ENSSEA2017")
Agr_cap_Alg <- read.csv2("Agr_cap_Alg.csv", header = TRUE, sep = ";", check.names = FALSE,
row.names = 1)
```

- **setwd**: setting working directory. Choosing the location of the file as a working directory.
- **Agr_cap_Alg**: file's name;
- **read.csv2**: The command used to read the file. The "csv" means comma-separated values.
- **header = TRUE**: the first row represents the names of variables.
- **sep = ";"**: means that ";" separates the information.
- **check.names = FALSE**: accept the names of variables as they.
- **row.names = 1**: the first row represents the names of the individuals.

View the database using `view`:

```
View(Agr_cap_Alg)
```

Summarize and View the structure and of the database using **summary**

summary(Agr_cap_Alg)

Cows		Bulls		Sheep		Caprine	
Min.	: 58	Min.	: 70	Min.	: 22244	Min.	: 3485
1st Qu.:	7806	1st Qu.:	14590	1st Qu.:	160317	1st Qu.:	32867
Median	:18020	Median	: 33000	Median	: 385750	Median	: 65380
Mean	:21926	Mean	: 41510	Mean	: 553604	Mean	:102306
3rd Qu.:	26450	3rd Qu.:	51526	3rd Qu.:	653099	3rd Qu.:	126566
Max.	:79941	Max.	:132270	Max.	: 3113500	Max.	: 526000
NA's	:2	NA's	:2				

The **summary** command allows us to summarize the data by calculating indicators of descriptive statistics. These indicators are the minimum, the first quartile, the median, the mean, the third quartile, the maximum and the number of missing values (NA).

2.2. Manage missing data

We have several methods to replace the missing values:

- Eliminates the variables and the individuals that contain the missing values
- by the mean
- Using ("missMDA") function. We call this method Iterated Principal Component Analysis.

Install and load the package

```
install.packages("missMDA")
```

```
library(missMDA)
```

```
New_Agr_cap_Alg <- imputePCA(Agr_cap_Alg[, 1:18], scale = TRUE)
```

- New_Agr_cap_Alg : The new file that contain all the values.
- imputePCA: The command used to replace the missing values.

Save the new database in a csv file using write.csv2

```
write.csv2(New_Agr_cap_Alg, file = "New_Agr_cap_Alg.csv")
```

2.3. Execute Principal Component Analysis using FactoMiner

Install and load the package and execute the PCA analysis

```
install.packages("FactoMiner")
```

```
library(FactoMineR)
```

```
Princ_Comp_Ana <- PCA(New_Agr_cap_Alg, quali.sup = 19, quanti.sup = 16)
```

- Princ_Comp_Ana: the object that contain the results of PCA.
- **PCA**: the command used to execute the PCA analysis.
- **quali.sup = 19**: The 19th variable is a supplementary qualitative variable.
- **quanti.sup = 16**: the 16th variable is supplementary quantitative variable.

The main results of PCA are:

Figure 01: Individuals map

Source: R outputs

Figure 02: variables map

Source: R outputs

We find that the graphs are not readable and ambiguous regarding to the position of individuals and variables. We cannot interpret these maps. We will use another package to improve the results of PCA.

A summary of the main results can be obtained using `summary` function. The Eigenvalues, the coordinates (Dim), the quality of representation (cos2) and the contribution (ctr) of each variable and individual on each axe.

`summary(Princ_Comp_Ana)`

Eigenvalues

	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5	Dim.6
Variance	4.112	2.945	2.399	1.701	1.066	0.940
% of var.	24.191	17.326	14.110	10.003	6.271	5.532
Cumulative % of var.	24.191	41.517	55.627	65.630	71.901	77.433

Individuals (the 10 first)

	Dist	Dim.1	ctr	cos2	Dim.2	ctr	cos2
Adrar	2.715	-0.153	0.012	0.003	-2.253	3.592	0.689
Chlef	3.186	1.302	0.859	0.167	0.569	0.229	0.032
Laghouat	4.115	1.091	0.603	0.070	-0.111	0.009	0.001
O.E.Bouaghi	2.080	-0.497	0.125	0.057	0.023	0.000	0.000
Batna	6.283	3.210	5.219	0.261	3.792	10.171	0.364
Bejaia	5.552	-1.591	1.282	0.082	1.073	0.814	0.037
Biskra	11.692	10.893	60.106	0.868	-1.868	2.468	0.026
Bechar	2.940	-1.045	0.553	0.126	-2.235	3.534	0.578
Blida	7.517	0.205	0.021	0.001	1.095	0.848	0.021
Bouira	2.857	-1.842	1.719	0.416	0.784	0.435	0.075

Variables (the 10 first)

	Dim.1	ctr	cos2	Dim.2	ctr	cos2	Dim.3	ctr
Cows	-0.292	2.072	0.085	0.711	17.149	0.505	0.312	4.067
Bulls	-0.319	2.479	0.102	0.697	16.508	0.486	0.335	4.665
Sheep	0.290	2.050	0.084	0.345	4.043	0.119	-0.746	23.210
Caprine	0.467	5.298	0.218	0.135	0.616	0.018	-0.525	11.509
Equine	0.122	0.363	0.015	0.277	2.602	0.077	-0.633	16.728

2.4. Principal Component Analysis using `factoextra`

`install.packages("factoextra")`

`library("factoextra")`

`Princ_Comp_Ana <- princomp(New_Agr_cap_Alg)`

- Princ_Comp_Ana: the object that contain the results of PCA using **factoextra**
- **Princomp**: the command used to execute PCA.

Visualize eigenvalues (scree plot). Show the percentage of variances explained by each principal component:

fviz_eig(Princ_Comp_Ana)

Figure 03: eigenvalues

Source: R outputs

Graph of individuals using **fviz_pca_ind** function for the first and the second axes

```
fviz_pca_ind(Princ_Comp_Ana, axes = c(1,2), select.ind = list(cos2 = 20),
  col.ind = "cos2", # Color by the quality of representation
  gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
  repel = TRUE      # Avoid text overlapping
```

Figure 04: Individuals map

Source: R outputs

According to this map, the individuals who have a better representation on the first factorial plane are Tindouf, Biskra, Ghardaia, Bechar and Ouargla.

Graph of variables using `fviz_pca_var` function for the first factorial plan

```
fviz_pca_var(Princ_Comp_Ana, axes = c(1,2), select.var = list(contrib = 8),
  col.var = "contrib", # Color by contributions to the PC
  gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
  repel = TRUE # Avoid text overlapping
)
```

Figure 05: variables map

Source: R outputs

The variables that contribute the most in the construction of the first two axes are Citrus and Sheep.

Biplot of individuals and variables

```
fviz_pca_biplot(Princ_Comp_Ana, axes = c(1,2), repel = TRUE, select.ind = list(cos2 = 15), select.var = list(cos2 = 8),
  col.var = "#2E9FDF", # Variables color
  col.ind = "#696969" # Individuals color
)
```

Figure 06: Biplot of individuals and variables

Source: R outputs

We repeat the same analysis with the third and the fourth axes c(1,3), c(1,4), c(2,3) and c(3,4).

The individuals who have a better representation on the other factorial planes are Skikda and Adrar, Biskra, Blida, Djelfa, M'sila, Tiaret, Relizane and El-Oued. The variables that contribute the most in the construction of the other factorial planes are Potatoes, tomatoes and fruits.

2.5. The matrix correlation

```
install.packages("corrplot")
library(corrplot)
Cor_matrix <- cor(New_Agr_cap_Alg)
corrplot(Cor_matrix, order = "AOE", method = "color", addCoef.col = "gray",
is.corr = FALSE )
corrplot.mixed(Cor_matrix)
```

Figure 07: Correlation matrix

Source: R outputs

The most important correlation is between cows and bulls (ctr=0.98), potatoes and peppers (ctr=0.85), tomatoes and peppers (ctr=0.85) and between citrus and fruits (ctr=0.7).

2.6. Cluster Analysis

```
library(dendextend)
```

```
library(factoextra)
```

```
library(igraph)
```

```
dd <- dist(scale(New_Agr_cap_Alg), method = "euclidean")
```

```
hc <- hclust(dd, method = "ward.D2")
```

We can use the arguments main, sub, xlab, ylab to change plot titles as follow

```
fviz_dend(hc, cex = 0.5,
```

```
  main = "Dendrogram - ward.D2",
```

```
  xlab = "Objects", ylab = "Distance", sub = "")
```

```
fviz_dend(hc, k = 4, # Cut in four groups
```

```
cex = 0.5, # Label size
```

```
k_colors = c("#2E9FDF", "#00AFBB", "#E7B800", "#FC4E07"),
```

```
color_labels_by_k = TRUE, # color labels by groups
```

```
ggtheme = theme_gray() # Change theme
```

Additionally, we can plot a circular dendrogram using the option type = "circular".

```
fviz_dend(hc, cex = 0.5, k = 4,
```

```
k_colors = "jco", type = "circular")
```

Figure 08: Cluster Dendrogram

Cluster Dendrogram

Source: R outputs

Additionally, we can plot a circular dendrogram using the option type = "circular".

```
fviz_dend(hc, cex = 0.5, k = 4,
```

```
k_colors = "jco", type = "circular")
```

Figure 10: circular dendrogram

Source: R outputs

To plot a phylogenetic-like tree, we use `type = "phylogenetic"` and `repel = TRUE` (to avoid labels overplotting). This functionality requires the R package `igraph`. Make sure that it is installed before typing the following R code.

```
fviz_dend(hc, k = 4, k_colors = "jco",
type = "phylogenetic", repel = TRUE)
```

Figure 11: tree dendrogram

Source: R outputs

According to the results of the cluster analysis, we have four groups (clusters). The first cluster is Biskra. It is the most important agricultural state in Algeria. It is characterized by the production of potatoes and tomatoes in addition to the production of dates. The second cluster is Blida, Tipaza, Alger, Ain-Defla Mascara and Relizane, which characterized by the production of citrus and fruits. The third cluster is Djelfa, Laghouat and M'sila, which characterized by Livestock. The fourth is Khenchela, Batna, Constantine and Annaba, which characterized by the production of cereals.

3. Conclusion

Since its inception, R software has become an essential tool for statistics and data visualization in both the academic and corporate worlds. This exceptional development is explained by its three main qualities: it is free, very complete and in constant expansion.

Principal Component Analysis (PCA) is a dimension-reduction tool that can be used to reduce a large set of variables to a small set that still contains most of the information in the large set.

The objective of cluster analysis is to assign individuals (observations) to homogenous clusters (groups) so that observations within each group are similar to one another with respect to variables or attributes of interest.

Algeria can be divided into four agricultural regions (agricultural poles) or agricultural areas. These areas characterized by the production of citrus fruits; potatoes and potatoes; cereals; and finally Livestock.

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