DATA MINING COURSE

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2025-03-19

Package

Here, we'll use FactoMineR for the analysis and factoextra for ggplot2-based visualization

```
library(FactoMineR)
library(factoextra)
library(readr)
library(corrplot)
```

Import the data set

```
data <-
read_delim("C:/Users/Jérôme/Desktop/TEYI_KODJO_JEROME_SEDOWO/ETUDE/AIMS_SENEGAL_2024-2025/Review phase Courses/Block 4/Data Mining and Big data/Tutorial_1/ACP_eaux.txt",
    delim = "\t", escape_double = FALSE,
    col_types = cols(CA = col_number(), MG = col_number(),
        `NA` = col_number(), K = col_number(),
        SUL = col_number(), NO3 = col_number(),
        HCO3 = col_number(), CL = col_number()),
    trim_ws = TRUE)
#View(data)

data_numeric <- data[6:13]
head(data_numeric)

## # A tibble: 6 × 8
##      CA    MG  `NA`     K   SUL   NO3   HCO3    CL
##   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl> <dbl>
## 1  78    24     5     1    10     3.8  357     4.5
## 2  48    11    34     1    16     4    183    50
## 3  71     5.5  11.2   3.2   5     1    250    20
## 4  89    31    17     2    47     0    360    28
## 5   4.1   1.7   2.7   0.9   1.1   0.8   25.8   0.9
## 6  85    80   385    65    25     1.9 1350   285
```

Exploratory analysis

Here we print a simple statistics for continous variables

```
summary(data_numeric)

##        CA              MG              NA                K          
##  Min.   :  1.2   Min.   : 0.20   Min.   :  0.80   Min.   :  0.00  
##  1st Qu.: 36.0   1st Qu.: 5.50   1st Qu.:  5.00   1st Qu.:  0.90  
##  Median : 63.0   Median :12.00   Median :  9.10   Median :  2.00  
##  Mean   :102.5   Mean   :25.86   Mean   : 93.85   Mean   : 11.09  
##  3rd Qu.:116.0   3rd Qu.:31.50   3rd Qu.: 36.00   3rd Qu.:  6.00  
##  Max.   :528.0   Max.   :95.00   Max.   :968.00   Max.   :130.00  
##       SUL              NO3              HCO3              CL        
##  Min.   :   1.1   Min.   : 0.000   Min.   :   4.9   Min.   :  0.30  
##  1st Qu.:   9.0   1st Qu.: 0.450   1st Qu.: 154.0   1st Qu.:  3.50  
##  Median :  16.0   Median : 1.500   Median : 236.0   Median : 14.20  
##  Mean   : 135.7   Mean   : 3.834   Mean   : 442.2   Mean   : 52.47  
##  3rd Qu.:  43.0   3rd Qu.: 4.000   3rd Qu.: 360.0   3rd Qu.: 38.00  
##  Max.   :1371.0   Max.   :35.600   Max.   :3380.5   Max.   :982.00

cor(data_numeric)

##               CA         MG          NA           K         SUL
NO3
## CA    1.00000000  0.7027224  0.11794153  0.12535483  0.91309695 -
0.06344287
## MG    0.70272239  1.0000000  0.60756895  0.66113238  0.60546334 -
0.21238801
## NA    0.11794153  0.6075689  1.00000000  0.83656419  0.06429603 -
0.11624022
## K     0.12535483  0.6611324  0.83656419  1.00000000 -0.02515575 -
0.16592834
## SUL   0.91309695  0.6054633  0.06429603 -0.02515575  1.00000000 -
0.15650372
## NO3  -0.06344287 -0.2123880 -0.11624022 -0.16592834 -0.15650372 
1.00000000
## HCO3  0.13494940  0.6197724  0.85621354  0.88156811 -0.06913651 -
0.06039047
## CL    0.27640957  0.4812610  0.58752083  0.40043988  0.31781920 -
0.12017032
##             HCO3         CL
## CA    0.13494940  0.2764096
## MG    0.61977235  0.4812610
## NA    0.85621354  0.5875208
## K     0.88156811  0.4004399
## SUL  -0.06913651  0.3178192
## NO3  -0.06039047 -0.1201703
## HCO3  1.00000000  0.1906228
## CL    0.19062285  1.0000000
```

Data Standardization

By default PCA() in **FactoMinR** standardizes the data automatically during the PCA. So we will not standardize the data manually before the PCA

```
resul_pca <- PCA(data_numeric, graph = FALSE)
print(resul_pca)
```

```
## **Results for the Principal Component Analysis (PCA)**
## The analysis was performed on 57 individuals, described by 8 variables
## *The results are available in the following objects:
##
##    name               description
## 1  "$eig"             "eigenvalues"
## 2  "$var"             "results for the variables"
## 3  "$var$coord"       "coord. for the variables"
## 4  "$var$cor"         "correlations variables - dimensions"
## 5  "$var$cos2"        "cos2 for the variables"
## 6  "$var$contrib"     "contributions of the variables"
## 7  "$ind"             "results for the individuals"
## 8  "$ind$coord"       "coord. for the individuals"
## 9  "$ind$cos2"        "cos2 for the individuals"
## 10 "$ind$contrib"     "contributions of the individuals"
## 11 "$call"            "summary statistics"
## 12 "$call$centre"     "mean of the variables"
## 13 "$call$ecart.type" "standard error of the variables"
## 14 "$call$row.w"      "weights for the individuals"
## 15 "$call$col.w"      "weights for the variables"
```

This is many information found in many different lists and matrices.

Visualization and Interpretation

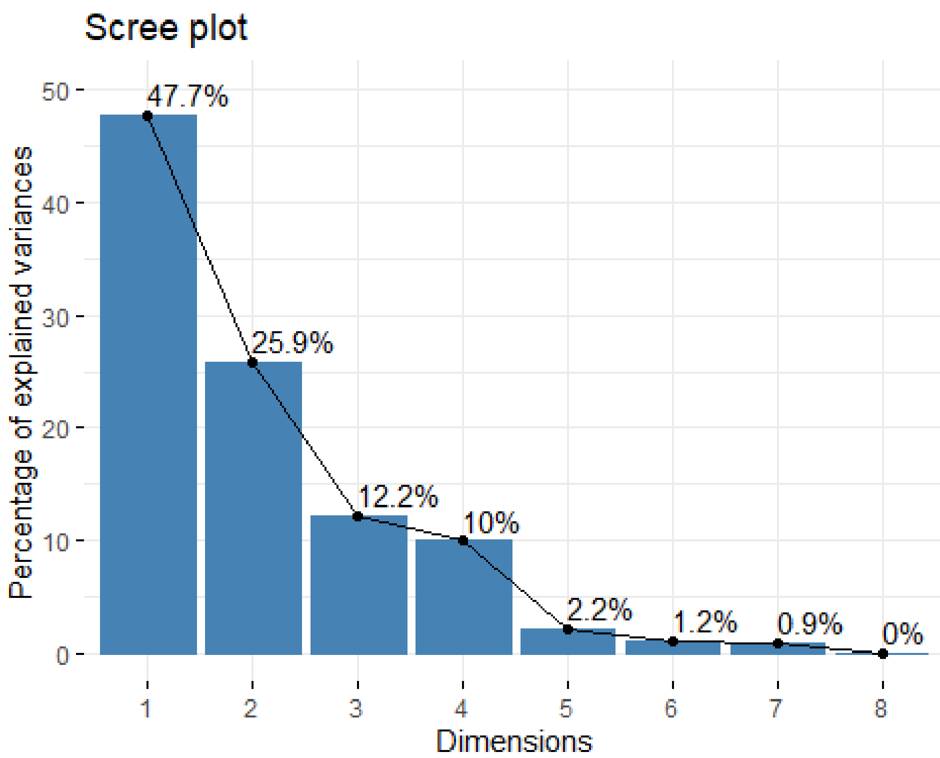
Eigenvalues

```
eig_value <- get_eigenvalue(resul_pca)
eig_value
```

```
##          eigenvalue variance.percent cumulative.variance.percent
## Dim.1 3.8167747447     47.709684309                    47.70968
## Dim.2 2.0680904354     25.851130442                    73.56081
## Dim.3 0.9728158313     12.160197892                    85.72101
## Dim.4 0.7962420036      9.953025045                    95.67404
## Dim.5 0.1792036107      2.240045134                    97.91408
## Dim.6 0.0924269941      1.155337427                    99.06942
## Dim.7 0.0740850743      0.926063429                    99.99548
## Dim.8 0.0003613058      0.004516322                   100.00000
```

Visualisation and Interpretation

```
fviz_eig(resul_pca, addlabels = TRUE, ylim = c(0,50))
```



From yhe plot above, we might want to stop at the third principal component. 68% of the information contained in the data are retained by the first Three principal components.

Graph of variables

```
var <- get_pca_var(resul_pca)
var

## Principal Component Analysis Results for variables
##  ===================================================
##   Name       Description
## 1 "$coord"   "Coordinates for the variables"
## 2 "$cor"     "Correlations between variables and dimensions"
## 3 "$cos2"    "Cos2 for the variables"
## 4 "$contrib" "contributions of the variables"
```

Coordinates of variables

```
var$coord

##           Dim.1       Dim.2        Dim.3       Dim.4        Dim.5
## CA    0.5496004  0.77641500  0.170495237 -0.17809784  0.005109279
## MG    0.9104573  0.25440564  0.036883459 -0.14815849 -0.196246861
## NA    0.8551621 -0.41427700  0.033126250  0.15439228  0.262944434
## K     0.8354674 -0.45847406 -0.005010044 -0.10636587 -0.190470398
## SUL   0.4496677  0.86757992  0.031460991 -0.02949458  0.141085221
## NO3  -0.2337948 -0.09000400  0.958423890  0.13060377 -0.026621009
## HCO3  0.7840386 -0.49889576  0.129768176 -0.31140014  0.102477046
## CL    0.6203998  0.09503392 -0.069702512  0.76975595 -0.064270252
```

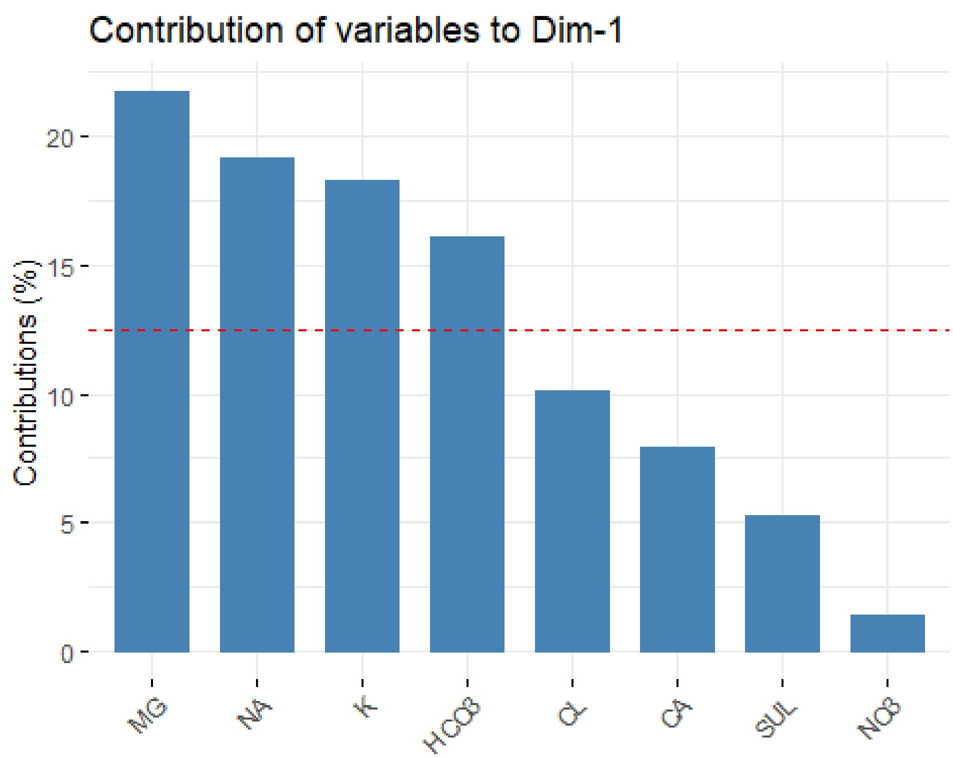
Contribution of the variables

```
var$contrib
```

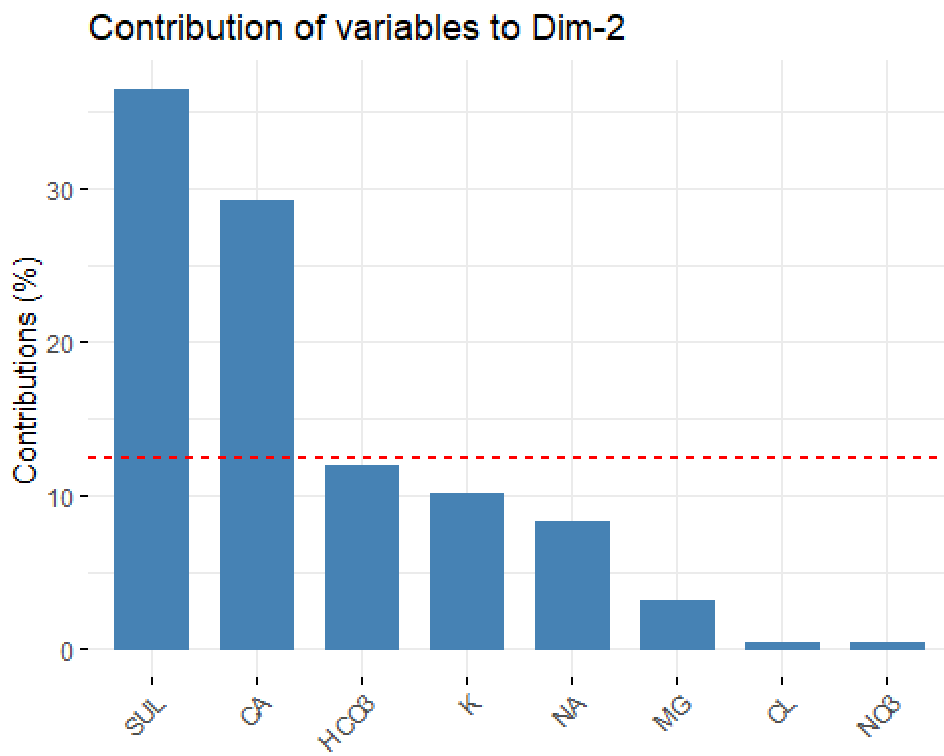
```
##          Dim.1      Dim.2        Dim.3      Dim.4       Dim.5
## CA    7.914028 29.1486404  2.988091369  3.9835677  0.01456708
## MG   21.718142  3.1295648  0.139840403  2.7568176 21.49110176
## NA   19.160213  8.2987394  0.112801250  2.9936849 38.58168659
## K    18.287845 10.1638912  0.002580194  1.4208869 20.24455434
## SUL   5.297695 36.3956481  0.101745256  0.1092545 11.10749910
## NO3   1.432099  0.3917004 94.424486502  2.1422313  0.39545973
## HCO3 16.105655 12.0351111  1.731034686 12.1784641  5.86011908
## CL   10.084322  0.4367046  0.499420338 74.4150930  2.30501232
```

Contribution of Variables to PC1

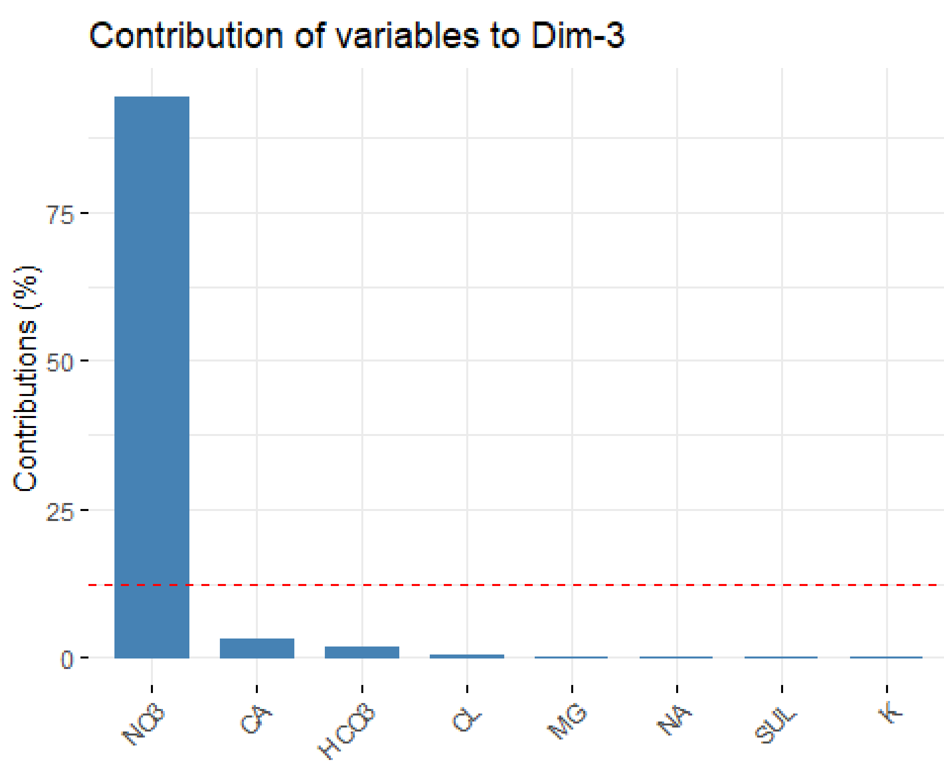
```
fviz_contrib(resul_pca, choice = "var", axes = 1)
```



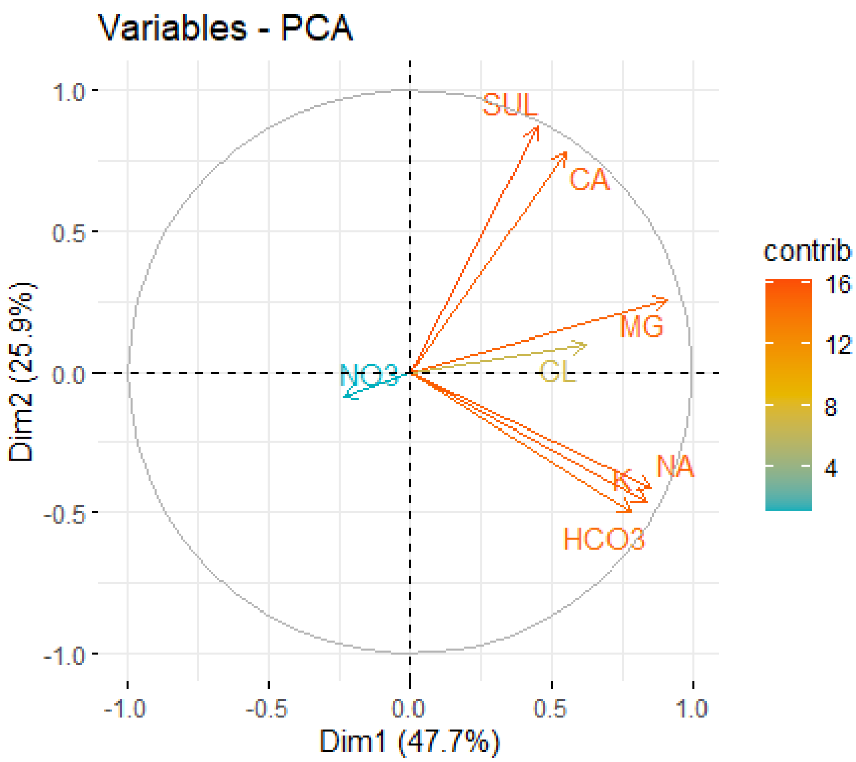

```
fviz_contrib(resul_pca, choice = "var", axes = 2)
```




```
fviz_contrib(resul_pca, choice = "var", axes = 3)
```

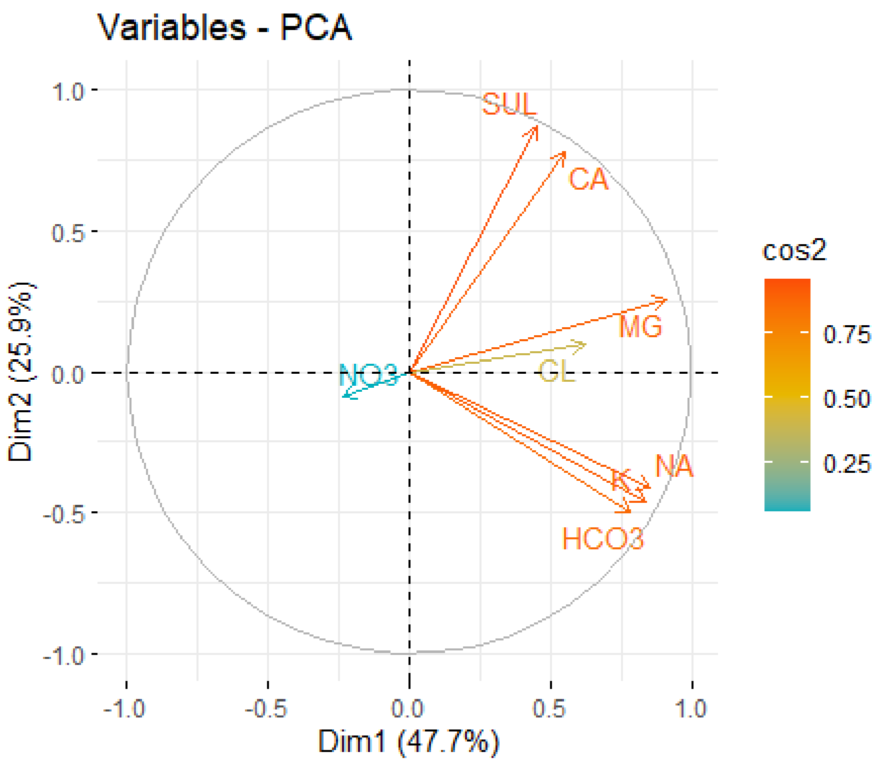


```r
fviz_pca_var(resul_pca, col.var = "contrib",
             gradient.cols = c("#00AFBB","#E7B800","#FC4E07"),
             repel = TRUE)
```



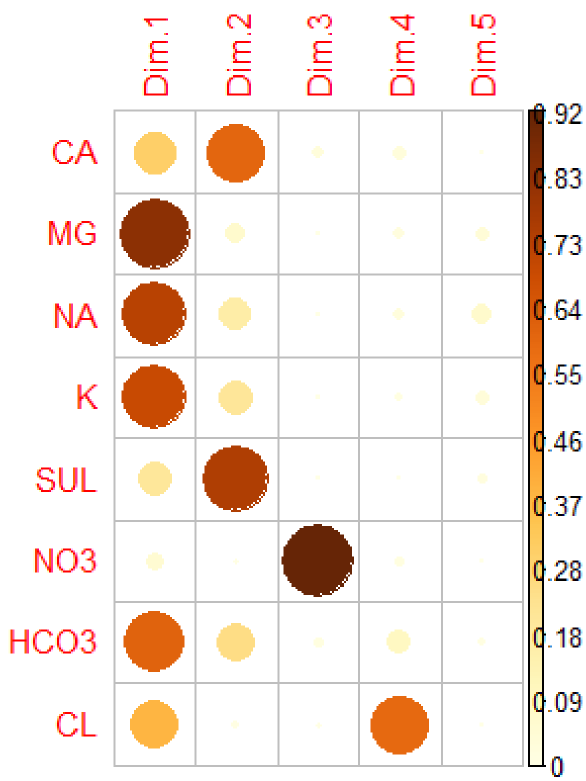
Correlation circle

```r
fviz_pca_var(resul_pca, col.var = "cos2",
             gradient.cols = c("#00AFBB","#E7B800","#FC4E07"),
             repel = TRUE)
```

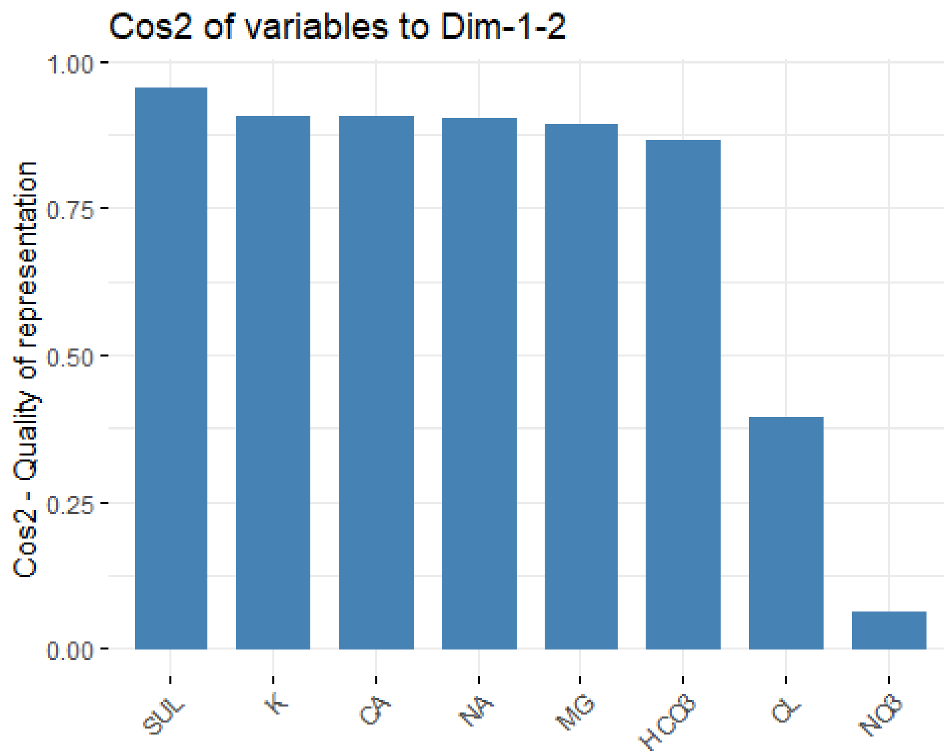


Quality of representation

```
corrplot(var$cos2, is.corr = FALSE)
```



```r
fviz_cos2(resul_pca, choice = "var", axes = 1:2)
```



Dimension description

Description of dimension 1

```r
res.desc <- dimdesc(resul_pca, axes = c(1,2), proba = 0.05)
res.desc$Dim.1

##
## Link between the variable and the continuous variables (R-square)
##
=============================================================================
====
##      correlation      p.value
## MG     0.9104573 9.573425e-23
## NA     0.8551621 2.510398e-17
## K      0.8354674 6.376416e-16
## HCO3   0.7840386 5.492255e-13
## CL     0.6203998 2.640912e-07
## CA     0.5496004 9.518680e-06
## SUL    0.4496677 4.495443e-04
```

Description of dimension 2

```r
res.desc <- dimdesc(resul_pca, axes = c(1,2), proba = 0.05)
res.desc$Dim.2
```

```
##
## Link between the variable and the continuous variables (R-square)
##
================================================================================
====
##      correlation      p.value
## SUL    0.8675799 2.528799e-18
## CA     0.7764150 1.279229e-12
## NA    -0.4142770 1.356729e-03
## K     -0.4584741 3.350678e-04
## HCO3  -0.4988958 7.814521e-05
```

Graph of individuals

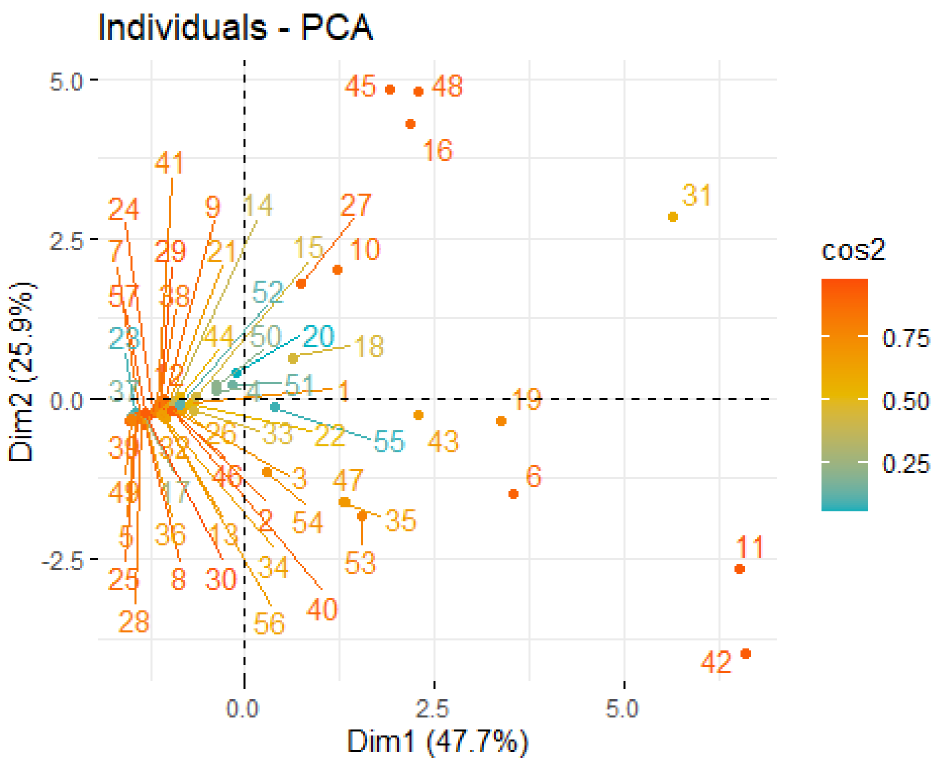
```
ind <- get_pca_ind(resul_pca)
ind

## Principal Component Analysis Results for individuals
##  ===================================================
##   Name       Description
## 1 "$coord"   "Coordinates for the individuals"
## 2 "$cos2"    "Cos2 for the individuals"
## 3 "$contrib" "contributions of the individuals"

# ind$coord
# ind$cos2
# ind$contrib
```

Quality of contribution

```
fviz_pca_ind(resul_pca, col.ind = "cos2",
             gradient.cols = c("#00AFBB","#E7B800","#FC4E07"),
             repel = TRUE)
```




```r
fviz_pca_ind(resul_pca, pointsize = "cos2",
             pointshape = 21, fill = "#E7B800",
             repel = TRUE)
```