UNIVERSIDADE FEDERAL FLUMINENSE

Programa de Mestrado e Doutorado em Engenharia de Produção

Multivariate Data Analysis

Correspondence Analysis

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Outline

- 1. Definition
- 2. Terminology
 - 3. CA
 - 4. MCA
- 5. Bibliography

The **CA** (Correspondence Analysis) is primarily a descriptive and visual technique designed to analyze contingency tables containing some measure of association between the rows and columns (variables) and for some situations this technique can take an exploratory character. Categorical data are the most common entries to start treatment and analysis, but continuous data can be used if they can be categorized (Ex: Age group - Age is a continuous variable, but can be grouped into categories) The **CA** is considered a special case of **PCA** and it can explore only two variables at a time, so this technique is also known as Simple Correspondence Analysis.

The MCA (Multiple Correspondence Analysis) is also a primarily descriptive and visual technique, which is used for the study of the relationship between two or more nominal or ordinal variables. A two-dimensional graphic (Biplot) typically allows a more comprehensive analysis of the data.

- The CA and MCA can graphically represent:
- The preference of certain consumers for different brands;
- Psychological profiles and social behavior;
- Animal Species and habitats;
- Good management practices and organizational performance;
- Etc.

- **Dimensions**: The maximum number of dimensions is given by the minimum between the number of lines and the number of columns, minus 1.
- Mass: Represent the marginal proportions of the row and column variables.
- Scores: Values that are used as coordinate points of the categories to plot a correspondence map.
- Inertia: It is an association measure (represented by the amount of variance) between two categorical variables. The total inertia (sum of inertia for each dimension) can be calculated as the value of chi-square statistic divided by the number of cases.
- **Eigenvalue**: The squared eigenvalue of a dimension represents its inertia.
- Contribution of categories to dimensions: The highest scores can be used to interpret a dimension, it is analogous to factor loadings.
- Contribution of dimensions to categories: They reflect how well a dimension may explain a particular category. Analogous to the coefficient of determination (proportion of explained variance).

Simple Correspondence Analysis

In order to explain a CA approach, the following dataset will be used - A sample of 100 students was collected with the following information:

- Profile of Investment (categorical variable: Aggressive, Conservative or Moderate);
- Application Type (categorical variable: BDC (Bank Deposit Certificate), Savings, or Stock Shares).

Id	Student	Profile	Application
1	Gabriela	Conservative	Savings
2	Luiz_Felipe	Conservative	Savings
3	Patrícia	Conservative	Savings
4	Gustavo	Conservative	Savings
5	Leticia	Conservative	Savings
6	Ovidio	Conservative	Savings
7	Leonor	Conservative	Savings
8	Dalila	Conservative	Savings
9	Antonio	Conservative	BDC
10	Julia	Conservative	BDC
•••			
34	Cintia	Moderate	BDC
•••			
99	Leandro	Aggressive	Stock_shares
100	Estela	Aggressive	Stock_shares

Transforming data into a contingency table (if necessary!)
my_data <- table(my_data)</pre>

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	20	2	36
Conservative	4	8	5
Moderate	16	5	4

```
library("FactoMineR")
ca <- CA(my data, ncp = 2, graph = FALSE)
# Variance Percentage (Inertia)
ca$eig
             eigenvalue
                                    percentage of variance
                                                                  cumulative percentage of variance
            0.23321487
dim 1
                                          73.42075
                                                                             73.42075
dim 2
            0.08442678
                                          26.57925
                                                                            100.00000
# Trace (Correlation Between Rows and Columns)
trace <- sqrt(sum(ca$eig[,1]))
[1] 0.5635971
# Row Mass (Row Weigths)
ca$call$marge.row
Aggressive Conservative
                           Moderate
   0.58
               0.17
                              0.25
# Column Mass (Column Weigths)
ca$call$marge.col
```

BDC

0.40

Savings

0.15

Stock_shares

0.45

Contribution of the categories in column to dimensions (Analogous to factor Loadings) ca\$col\$contrib

	ו ווווט	Dim 2
BDC	0.8650818	59.13492
Savings	67.5336283	17.46637
Stock_shares	31.6012900	23.39871

Contribution of the categories in row to dimensions (Analogous to factor Loadings) ca\$row\$contrib

	Dim 1	Dim 2
Aggressive	39.05149	2.948508
Conservative	45.10799	37.892011
Moderate	15.84052	59.159481

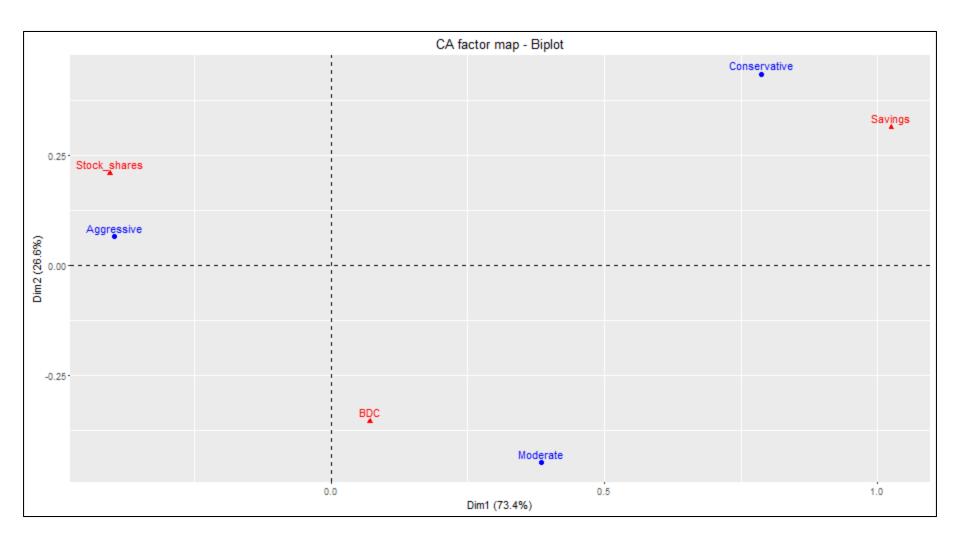
Coordinates of categories in row (Scores) ca\$row\$coord

Dim 1 Dim 2
Aggressive -0.3962625 0.06551296
Conservative 0.7866479 0.43379993
Moderate 0.3844084 -0.44697402

Coordinates of categories in column (Scores) ca\$col\$coord

Dim 1 Dim 2
BDC 0.07101935 -0.3532906
Savings 1.02469008 0.3135421
Stock shares -0.40469167 0.2095221

Biplot library("factoextra") fviz_ca_biplot(ca)



Goodness of Fit

Row and Column Sums (Weights)

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	20	2	36
Conservative	4	8	5
Moderate	16	5	4

Sum
58
17
25

Sum	40	15	45

```
# Expected Absolut Frequencies
P <- my_data
for (i in 1:3){
    for (j in 1:3){
        P[i, j] <- (sum(my_data[,j])*sum(my_data[i, ])/sum(my_data))
        }
}</pre>
```

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	23.2	8.7	26.1
Conservative	6.8	2.55	7.65
Moderate	10	3.75	11.25

Absolut Fequencies =
$$P = \frac{\sum l_i \times \sum C_j}{n}$$

Residuals E <- my_data - P

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	-3.2	-6.7	9.9
Conservative	-2.8	5.45	-2.65
Moderate	6	1.25	-7.25

 $Residuals = E = Original \ Data - P$

Chi-Squared Table Chi_Sq_Table <- (E)^2/P

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	0.44	5.16	3.75
Conservative	1.15	11.65	0.92
Moderate	3.60	0.42	4.67

Chi Squared Table =
$$\chi^2 = \frac{E^2}{P}$$

Chi-Squared Table Chi_Sq_Table <- (E)^2/P

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	0.44	5.16	3.75
Conservative	1.15	11.65	0.92
Moderate	3.60	0.42	4.67

The following hypothesis is made to test the model adequacy:

 H_0 : The association between both variables is random H_1 : The association between both variables is not random

```
# Chi-Squared Value
Chi_Sq <- sum(Chi_Sq_Table)
```

[1] 31.76416

```
Reject the null hypothesis H_0 if \chi^2_{test} > \chi^2_{(rows-1)(columns-1)}
```

```
# Chi-Squared Test
qchisq(0.95, df = 2*2)
```

[1] 9.487729

Beta Test (Association between variable is significant for values greater than 3) Beta <- $(Chi_Sq - (3 - 1)*(3 - 1))/((3 - 1)*(3 - 1))^(1/2)$

[1] 13.88208

$$Beta = \frac{\chi^2_{test} - (l-1) \times (c-1)}{\sqrt{(l-1) \times (c-1)}}$$

Standartized Residuals E_st <- E/(P)^(0.5)

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	-0.66	-2.27	1.94
Conservative	-1.07	3.41	-0.96
Moderate	1.90	0.64	-2.16

Standartized Residuals =
$$E_{st} = \frac{E}{\sqrt{P}}$$

```
# Adjusted Standartized Residuals
E_st_adj <- E_st
for (i in 1:3){
    for (j in 1:3){
        E_st_adj[i, j] <- E_st[i, j]/((1 - sum(my_data[ ,j])/sum(my_data))*(1 - sum(my_data[i, ])/sum(my_data)))^(0.5)
        }
}</pre>
```

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	-1.32	-3.80	4.03
Conservative	-1.52	4.06	-1.42
Moderate	2.83	0.81	-3.36

$$Adjusted \, Standartized \, Residuals = E_{adj} = \frac{E_{st}}{\sqrt{\left(\frac{1-\sum l_i}{n}\right) \times \left(\frac{1-\sum C_j}{n}\right)}}$$

```
# Adjusted Standartized Residuals

E_st_adj <- E_st

for (i in 1:3){
    for (j in 1:3){
        E_st_adj[i, j] <- E_st[i, j]/((1 - sum(my_data[ ,j])/sum(my_data))*(1 - sum(my_data[i, ])/sum(my_data)))^(0.5)
        }
}
```

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	-1.32	-3.80	4.03
Conservative	-1.52	4.06	-1.42
Moderate	2.83	0.81	-3.36

Values greater than 1.96 (5% of significance level), shows association between the category in row with the category in column.

```
# Quality of representation (0 = worst, 1 = Perfect) of the categories in column for each dimension (Sum of Both
Dimensions)
ca$col$cos2
                      Dim 1
                                          Dim 2
                 0.03884049
BDC
                                    0.96115951
Savings
                 0.91438756
                                     0.08561244
Stock shares
                 0.78861426
                                     0.21138574
# Quality of representation (0 = worst, 1 = Perfect) of the categories in row for each dimension (Sum of Both
Dimensions)
ca$row$cos2
                      Dim 1
                                          Dim 2
Aggressive
                 0.9733941
                                     0.02660586
Conservative
                 0.7668116
                                     0.23318836
```

0.57483119

Moderate

0.4251688

Multiple Correspondence Analysis

In order to explain a MCA approach, the following dataset will be used - A sample of 100 students was collected with the following information:

- Profile of Investment (categorical variable: Aggressive, Conservative or Moderate);
- Application Type (categorical variable: BDC (Bank Deposit Certificate), Savings, or Stock Shares).
- Marital Status (categorical variable: Married or Single).

Id	Student	Profile	Application	Marital Status
1	Gabriela	Conservative	Savings	Married
2	Luiz_Felipe	Conservative	Savings	Married
3	Patrícia	Conservative	Savings	Married
4	Gustavo	Conservative	Savings	Single
5	Leticia	Conservative	Savings	Married
6	Ovidio	Conservative	Savings	Married
7	Leonor	Conservative	Savings	Married
8	Dalila	Conservative	Savings	Married
9	Antonio	Conservative	BDC	Married
10	Julia	Conservative	BDC	Married
•••				
34	Cintia	Moderate	BDC	Married
99	Leandro	Aggressive	Stock_shares	Single
100	Estela	Aggressive	Stock_shares	Single

Transforming data into a contingency table
cont_my_data2 <- table(my_data2)</pre>

Married	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	11	0	6
Conservative	3	7	2
Moderate	10	3	1

Single	Application			
Profile	BDC Savings Stock Shares			
Aggressive	9	2	30	
Conservative	1	1	3	
Moderate	6	2	3	

```
library("FactoMineR")
mca <- MCA(my_data2, ncp = 2, graph = FALSE)
# Variance Percentage (Inertia)
mca$eig
                eigenvalue
                                   percentage of variance
                                                                  cumulative percentage of variance
dim 1
                0.6023045
                                         36.13827
                                                                              36.13827
                0.4359878
                                                                              62.29754
dim 2
                                         26.15927
dim 3
                0.2764728
                                         16.58837
                                                                              78.88591
                0.1798371
                                         10.79022
                                                                              89.67613
dim 4
dim 5
                0.1720645
                                         10.32387
                                                                             100.00000
# Column Mass (Column Weigths)
mca$call$marge.col
Aggressive
                Conservative
                                Moderate
                                                      BDC
                                                                   Savings
                                                                                       Stock shares
0.19333333
                0.05666667
                                0.08333333
                                                 0.13333333
                                                                  0.05000000
                                                                                        0.15000000
Married
                        Single
0.14333333
                      0.19000000
```

```
# Row Mass (Row Weigths) mca$call$marge.row
```

Contribution of the categories in column to dimensions (Analogous to factor Loadings) mca\$var\$contrib

	Dim 1	Dim 2
Aggressive	13.690180	0.009624243
Conservative	12.012834	28.608515192
Moderate	7.715121	18.157985111
BDC	3.852805	26.743624674
Savings	15.838730	20.321796679
Stock_shares	17.208656	5.166471138
Married	16.918554	0.565430289
Single	12.763120	0.426552674

Contribution of the categories in row to dimensions (Analogous to factor Loadings) mca\$ind\$contrib

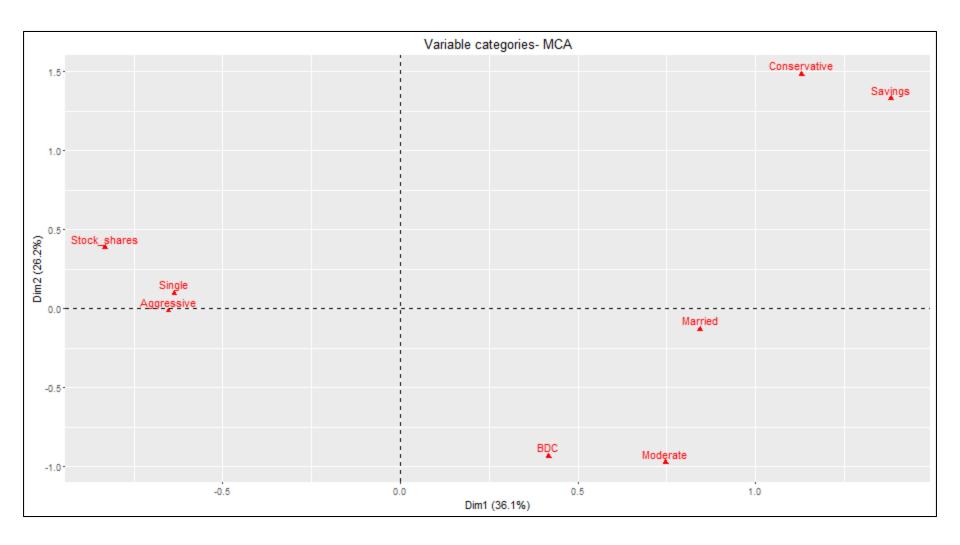
Coordinates of categories in row (Scores) ca\$row\$coord

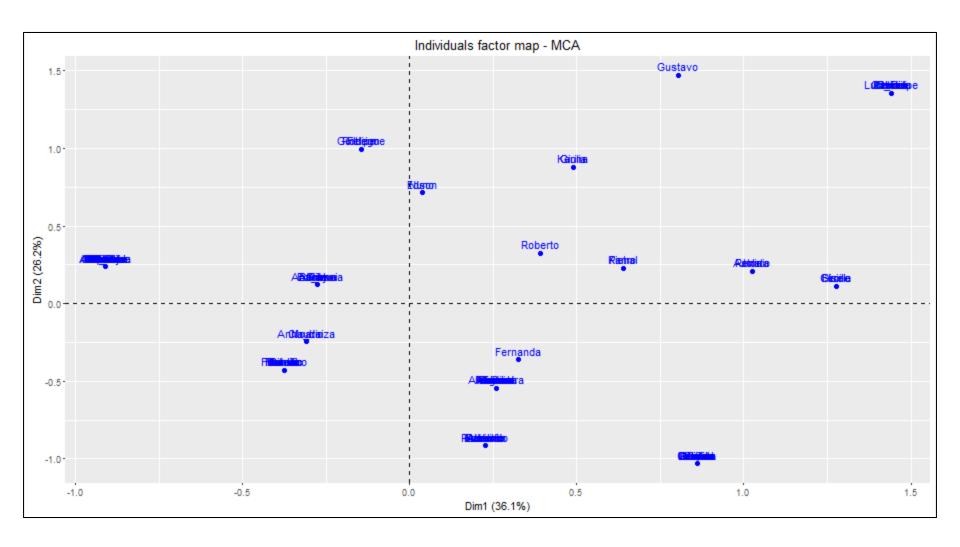
Dim 1 Dim 2
Aggressive -0.3962625 0.06551296
Conservative 0.7866479 0.43379993
Moderate 0.3844084 -0.44697402

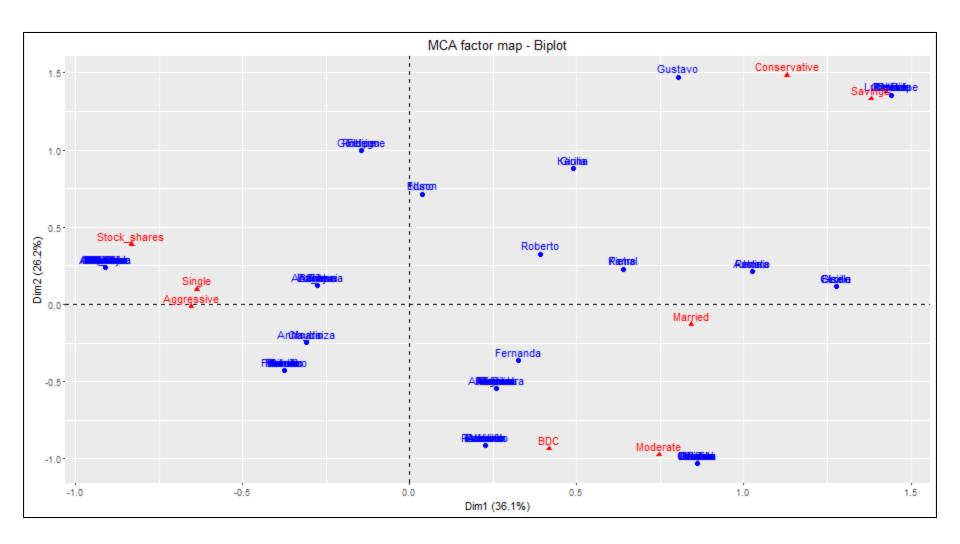
Coordinates of categories in column (Scores) ca\$col\$coord

Dim 1 Dim 2
BDC 0.07101935 -0.3532906
Savings 1.02469008 0.3135421
Stock shares -0.40469167 0.2095221

Biplot library("factoextra") fviz_mca_var(mca) fviz_mca_ind(mca) fviz_mca_biplot(mca)







Goodness of Fit

```
P <- table(my_data2[,c(1,2)])
temp <- table(my_data2[,c(1,2)])
for (i in 1:3){
    for (j in 1:3){
        P[i, j] <- (sum(temp[ ,j])*sum(temp[i, ])/sum(temp))
        }
}</pre>
```

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	23.2	8.7	26.1
Conservative	6.8	2.55	7.65
Moderate	10	3.75	11.25

E <- temp - P

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	-3.2	-6.7	9.9
Conservative	-2.8	5.45	-2.65
Moderate	6	1.25	-7.25

Chi_Sq_Table <- (E)^2/P

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	0.44	5.16	3.75
Conservative	1.15	11.65	0.92
Moderate	3.60	0.42	4.67

Chi_Sq_Table <- (E)^2/P

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	0.44	5.16	3.75
Conservative	1.15	11.65	0.92
Moderate	3.60	0.42	4.67

The following hypothesis is made to test the model adequacy:

 H_0 : The association between both variables is random H_1 : The association between both variables is not random

Chi_Sq <- sum(Chi_Sq_Table)

[1] 31.76416

Reject the null hypothesis H_0 if $\chi^2_{test} > \chi^2_{(rows-1)(columns-1)}$

qchisq(0.95, df = 2*2)

[1] 9.487729

Beta <- $(Chi_Sq - (3 - 1)*(3 - 1))/((3 - 1)*(3 - 1))^(1/2)$

[1] 13.88208

$$Beta = \frac{\chi^2_{test} - (l-1) \times (c-1)}{\sqrt{(l-1) \times (c-1)}}$$

$E_st <- E/(P)^{(0.5)}$

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	-0.66	-2.27	1.94
Conservative	-1.07	3.41	-0.96
Moderate	1.90	0.64	-2.16

```
E_st_adj <- E_st
for (i in 1:3){
    for (j in 1:3){
        E_st_adj[i, j] <- E_st[i, j]/((1 - sum(temp[ ,j])/sum(temp))*(1 - sum(temp[i, ])/sum(temp)))^(0.5)
        }
}</pre>
```

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	-1.32	-3.80	4.03
Conservative	-1.52	4.06	-1.42
Moderate	2.83	0.81	-3.36

```
E_st_adj <- E_st
for (i in 1:3){
    for (j in 1:3){
        E_st_adj[i, j] <- E_st[i, j]/((1 - sum(temp[ ,j])/sum(temp))*(1 - sum(temp[i, ])/sum(temp)))^(0.5)
        }
}
```

	Application		
Profile	BDC	Savings	Stock Shares
Aggressive	-1.32	-3.80	4.03
Conservative	-1.52	4.06	-1.42
Moderate	2.83	0.81	-3.36

```
P <- table(my_data2[,c(1,3)])
temp <- table(my_data2[,c(1,3)])
for (i in 1:3){
    for (j in 1:2){
        P[i, j] <- (sum(temp[ ,j])*sum(temp[i, ])/sum(temp))
        }
}</pre>
```

	Marital Status	
Profile	Single	Married
Aggressive	24.94	33.06
Conservative	7.31	9.69
Moderate	10.75	14.25

E <- temp - P

	Marital Status	
Profile	Single Married	
Aggressive	-7.94	7.94
Conservative	4.69	-4.69
Moderate	3.25	-3.25

Chi_Sq_Table <- (E)^2/P

	Marital Status	
Profile	Single Married	
Aggressive	2.53	1.91
Conservative	3.01	2.27
Moderate	0.98	0.74

Chi_Sq_Table <- (E)^2/P

	Marital Status	
Profile	Single Married	
Aggressive	2.53	1.91
Conservative	3.01	2.27
Moderate	0.98	0.74

The following hypothesis is made to test the model adequacy:

 H_0 : The association between both variables is random H_1 : The association between both variables is not random

Chi_Sq <- sum(Chi_Sq_Table)

[1] 11.43756

Reject the null hypothesis H_0 if $\chi^2_{test} > \chi^2_{(rows-1)(columns-1)}$

qchisq(0.95, df = 2*1)

[1] 5.991465

Beta <- $(Chi_Sq - (3 - 1)*(2 - 1))/((3 - 1)*(2 - 1))^(1/2)$

[1] 6.673365

$$Beta = \frac{\chi^2_{test} - (l-1) \times (c-1)}{\sqrt{(l-1) \times (c-1)}}$$

 $E_st <- E/(P)^{(0.5)}$

	Marital Status	
Profile	Single Married	
Aggressive	-1.59	1.38
Conservative	1.73	-1.51
Moderate	0.99	-0.86

```
E_st_adj <- E_st for (i in 1:3){
    for (j in 1:2){
        E_st_adj[i, j] <- E_st[i, j]/((1 - sum(temp[ ,j])/sum(temp))*(1 - sum(temp[i, ])/sum(temp)))^(0.5)
        }
}
```

	Marital Status	
Profile	Single	Married
Aggressive	-3.25	3.25
Conservative	2.52	-2.52
Moderate	1.52	-1.52

```
E_st_adj <- E_st
for (i in 1:3){
    for (j in 1:2){
        E_st_adj[i, j] <- E_st[i, j]/((1 - sum(temp[ ,j])/sum(temp))*(1 - sum(temp[i, ])/sum(temp)))^(0.5)
        }
}</pre>
```

	Marital Status	
Profile	Single Married	
Aggressive	-3.25	3.25
Conservative	2.52	-2.52
Moderate	1.52	-1.52

```
P <- table(my_data2[,c(2,3)])
temp <- table(my_data2[,c(2,3)])
for (i in 1:3){
    for (j in 1:2){
        P[i, j] <- (sum(temp[ ,j])*sum(temp[i, ])/sum(temp))
        }
}</pre>
```

	Marital Status	
Aplication	Single	Married
BDC	17.20	22.80
Savings	6.45	8.55
Stock Shares	19.35	25.65

E <- temp - P

	Marital Status	
Aplication	Single	Married
BDC	6.80	-6.80
Savings	3.55	-3.55
Stock Shares	-10.35	10.35

Chi_Sq_Table <- (E)^2/P

	Marital Status	
Aplication	Single	Married
BDC	2.69	2.03
Savings	1.95	1.47
Stock Shares	5.53	4.17

Chi_Sq_Table <- (E)^2/P

	Marital Status	
Aplication	Single	Married
BDC	2.69	2.03
Savings	1.95	1.47
Stock Shares	5.53	4.17

The following hypothesis is made to test the model adequacy:

 H_0 : The association between both variables is random H_1 : The association between both variables is not random

Chi_Sq <- sum(Chi_Sq_Table)

[1] 17.85666

Reject the null hypothesis H_0 if $\chi^2_{test} > \chi^2_{(rows-1)(columns-1)}$

qchisq(0.95, df = 2*1)

[1] 5.991465

Beta <- $(Chi_Sq - (3 - 1)*(2 - 1))/((3 - 1)*(2 - 1))^(1/2)$

[1] 11.21235

$$Beta = \frac{\chi^2_{test} - (l-1) \times (c-1)}{\sqrt{(l-1) \times (c-1)}}$$

 $E_st <- E/(P)^{(0.5)}$

	Marital Status	
Aplication	Single	Married
BDC	1.64	-1.42
Savings	1.39	-1.21
Stock Shares	-2.35	2.04

```
E_st_adj <- E_st
for (i in 1:3){
    for (j in 1:2){
        E_st_adj[i, j] <- E_st[i, j]/((1 - sum(temp[ ,j])/sum(temp))*(1 - sum(temp[i, ])/sum(temp)))^(0.5)
        }
}</pre>
```

	Marital Status	
Aplication	Single	Married
BDC	2.80	-2.80
Savings	2.01	-2.01
Stock Shares	-4.20	4.20

```
E_st_adj <- E_st

for (i in 1:3){

    for (j in 1:2){

        E_st_adj[i, j] <- E_st[i, j]/((1 - sum(temp[ ,j])/sum(temp))*(1 - sum(temp[i, ])/sum(temp)))^(0.5)

        }

}
```

	Marital Status	
Aplication	Single	Married
BDC	2.80	-2.80
Savings	2.01	-2.01
Stock Shares	-4.20	4.20

```
# Quality of representation (0 = worst, 1 = Perfect) of the categories in column for each dimension (Sum of Both Dimensions) mca$var$cos
```

```
Dim 2
                     Dim 1
Aggressive
                0.5889755
                                   0.000299718
Conservative
                0.2615199
                                   0.450830033
Moderate
                0.1858741
                                   0.316666416
BDC
                0.1160281
                                   0.582994735
Savings
                0.3366967
                                    0.312707855
Stock shares
                0.5653555
                                    0.122864646
Married
                0.5363222
                                   0.012974775
Single
                0.5363222
                                    0.012974775
```

Quality of representation (0 = worst, 1 = Perfect) of the categories in row for each dimension (Sum of Both Dimensions)
mca\$ind\$cos

Squared correlation between each variable and the dimensions. (Coefficient of Determination) mca\$var\$eta2

	DIM 1	Dim 2
Profile	0.6038368	0.61181462
Aplication	0.6667546	0.68317407
Marital_Status	0.5363222	0.01297477

If the absolute value of the v.test is superior to 2, then the category coordinate is significantly different from 0. mca\$var\$v.test

	Dim 1	Dim 2
Aggressive	-7.636005	-0.1722559
Conservative	5.088268	6.6807315
Moderate	4.289701	-5.5991049
BDC	3.389216	-7.5971362
Savings	5.773471	5.5639983
Stock_shares	-7.481323	3.4876353
Married	7.286693	-1.1333590
Single	-7.286693	1.1333590

If the absolute value of the v.test is superior to 2, then the category coordinate is significantly different from 0. mca\$var\$v.test

Dim 2

	DIM 1	DIM 2
Aggressive	-7.636005	-0.1722559
Conservative	5.088268	6.6807315
Moderate	4.289701	-5.5991049
BDC	3.389216	-7.5971362
Savings	5.773471	5.5639983
Stock_shares	-7.481323	3.4876353
Married	7.286693	-1.1333590
Single	-7.286693	1.1333590

Dim 1

Dimension Description (This function can be used to identify the most correlated variables with a given dimension)

dimdesc(mca, axes = 1, proba = 0.05)

\$`Dim 1`\$quali

	R2	p.value
Aplication	0.6667546	7.146026e-24
Profile	0.6038368	3.139751e-20
Marital Status	0.5363222	4.802063e-18

\$`Dim 1`\$category

	Estimate	p.value
Married	0.57400977	4.802063e-18
Savings	0.82177962	2.496427e-10
Conservative	0.56040122	5.414449e-08
Moderate	0.26298378	7.536668e-06
BDC	0.07355727	5.247853e-04
Single	-0.57400977	4.802063e-18
Stock_shares	-0.89533689	1.969490e-19
Aggressive	-0.82338500	1.249415e-20

```
dimdesc(mca, axes = 2, proba = 0.05)
```

\$`Dim 2`\$quali

R2 p.value
Aplication 0.6831741 6.163177e-25
Profile 0.6118146 1.170577e-20

\$`Dim 2`\$category

	Estimate	p.value
Conservative	0.87084816	2.083068e-14
Savings	0.70650682	1.474001e-09
Stock_shares	0.08341794	3.498686e-04
Moderate	-0.75234753	1.104083e-09
BDC	-0.78992476	2.548404e-20

MVDA

https://github.com/Valdecy/Multivariate_Data_Analysis

```
# Created by: Prof. Valdecy Pereira, D.Sc.
```

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- # Lesson: Correspondence Analysis

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repository: https://github.com/Valdecy/Multivariate_Data_Analysis

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