

MCA Analysis using Collective Action Data

Eva Wanjiru

2023-06-20

```
knitr::opts_chunk$set(message = FALSE, warning = FALSE)
```

Brief introduction

This analysis will focus on MCA for dimensionality reduction using Collective Action data collected by a scholar in Kenya. Dimension reduction usually speeds up the training, but it may not always lead to a better or simpler solution. Also, there is a likelihood that we might lose some information through MCA. The categorical features are reduced by the Multiple Correspondence Analysis (MCA), which generates a matrix with values of zero or one. This method binarized categorical variables that have more than two classes.

```
##load necessary packages
library(tidyverse)
library(naniar)
library(janitor)
library(ggplot2)
library(readxl)
library(summarytools)
library(FactoMineR)
library(factoextra)
require(ClustOfVar)
library(ltm)
library(data.table)
library(psych)
library(polycor)
```

The dataset is first loaded using the `read_excel()` function and basic checks such as structure and missing values done.

```
##load the data
MCA_data<-read_excel("MCADData.xlsx")
```

```
##clean names
df<-MCA_data %>% clean_names()

##missing values
df %>% miss_var_summary()
```

```
## # A tibble: 22 × 3
##   variable          n_miss pct_miss
##   <chr>          <int>   <dbl>
## 1 household_head_education      1  0.283
## 2 household_head_gender         0    0
## 3 household_income             0    0
## 4 registration                 0    0
## 5 membership_entry_criteria    0    0
## 6 members_gender               0    0
## 7 amalgamation                 0    0
## 8 social_networking            0    0
## 9 input_sourcing               0    0
## 10 output_marketing            0    0
## # i 12 more rows
```

```
##convert the tibble to a dataframe
```

```
df<-as.data.frame(df)
```

```
# Rename the dataframe
```

```
df_clean <- df
```

```
##check first 5 rows
```

```
#head(df_clean)
```

```
##last 5 rows
```

```
#tail(df_clean)
```

```
##recode all variables to factors
```

```
df_clean[sapply(df_clean, is.character)] <- lapply(df_clean[sapply(df_clean, is.character)],
                                                    as.factor)
```

```
##structure
```

```
str(df_clean)
```

```
## 'data.frame': 353 obs. of 22 variables:
## $ household_head_gender : Factor w/ 2 levels "Females","Males": 2 2 2 2 2 2 2 2 2 1 ...
## $ household_head_education : Factor w/ 5 levels "No formal education",...: 2 5 2 1 5 3 3 3 3 2 ...
## $ household_income : Factor w/ 7 levels ">110,001","0 to 10,000",...: 2 2 2 4 2 3 2 2 2 2 ...
## $ registration : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 2 2 1 2 ...
## $ membership_entry_criteria: Factor w/ 2 levels "Closed","Open": 2 2 2 1 2 1 1 2 1 1 ...
## $ members_gender : Factor w/ 3 levels "Females","Males on",...: 3 3 3 3 3 3 1 3 3 1 ...
## $ amalgamation : Factor w/ 2 levels "No","Yes": 1 1 1 2 1 1 1 1 1 2 ...
## $ social_networking : Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 1 ...
## $ input_sourcing : Factor w/ 2 levels "No","Yes": 1 2 1 1 1 1 1 1 1 2 ...
## $ output_marketing : Factor w/ 2 levels "No","Yes": 1 2 1 1 1 1 1 2 1 2 ...
## $ extension_services : Factor w/ 2 levels "No","Yes": 1 2 1 1 1 1 2 1 1 2 ...
## $ credit_sourcing : Factor w/ 2 levels "No","Yes": 1 1 1 2 2 1 2 1 1 2 ...
## $ savings : Factor w/ 2 levels "No","Yes": 1 1 1 2 2 1 2 1 2 2 ...
## $ informal_insurance : Factor w/ 2 levels "No","Yes": 1 1 1 2 2 1 1 1 1 1 ...
## $ social_welfare : Factor w/ 2 levels "No","Yes": 2 1 2 2 2 2 1 1 2 2 ...
## $ fine_imposing : Factor w/ 2 levels "No","Yes": 2 1 2 2 2 2 2 1 2 2 ...
## $ members_trust : Factor w/ 4 levels "Agree somewhat",...: 1 1 1 2 2 1 2 1 2 2 ...
## $ other_groups_trust : Factor w/ 4 levels "Agree somewhat",...: 1 1 4 3 2 4 3 1 3 2 ...
## $ service_providers_trust : Factor w/ 4 levels "Agree somewhat",...: 1 1 1 1 1 4 1 4 3 2 ...
## $ farm_size : Factor w/ 2 levels "< 2 acres","> 2 acres": 1 1 1 2 1 1 1 1 1 1 ...
## $ age_groups : Factor w/ 6 levels "22 to 35","3",...: 5 3 4 3 3 3 3 5 3 5 ...
## $ groupmembership : num 1 1 1 1 1 1 1 1 1 1 ...
```

There's only one missing value in the variable household education and that row can be omitted as it has no much effect on the dataset and analysis. The dataset used in this analysis consists of 353 observations and 22 variables.

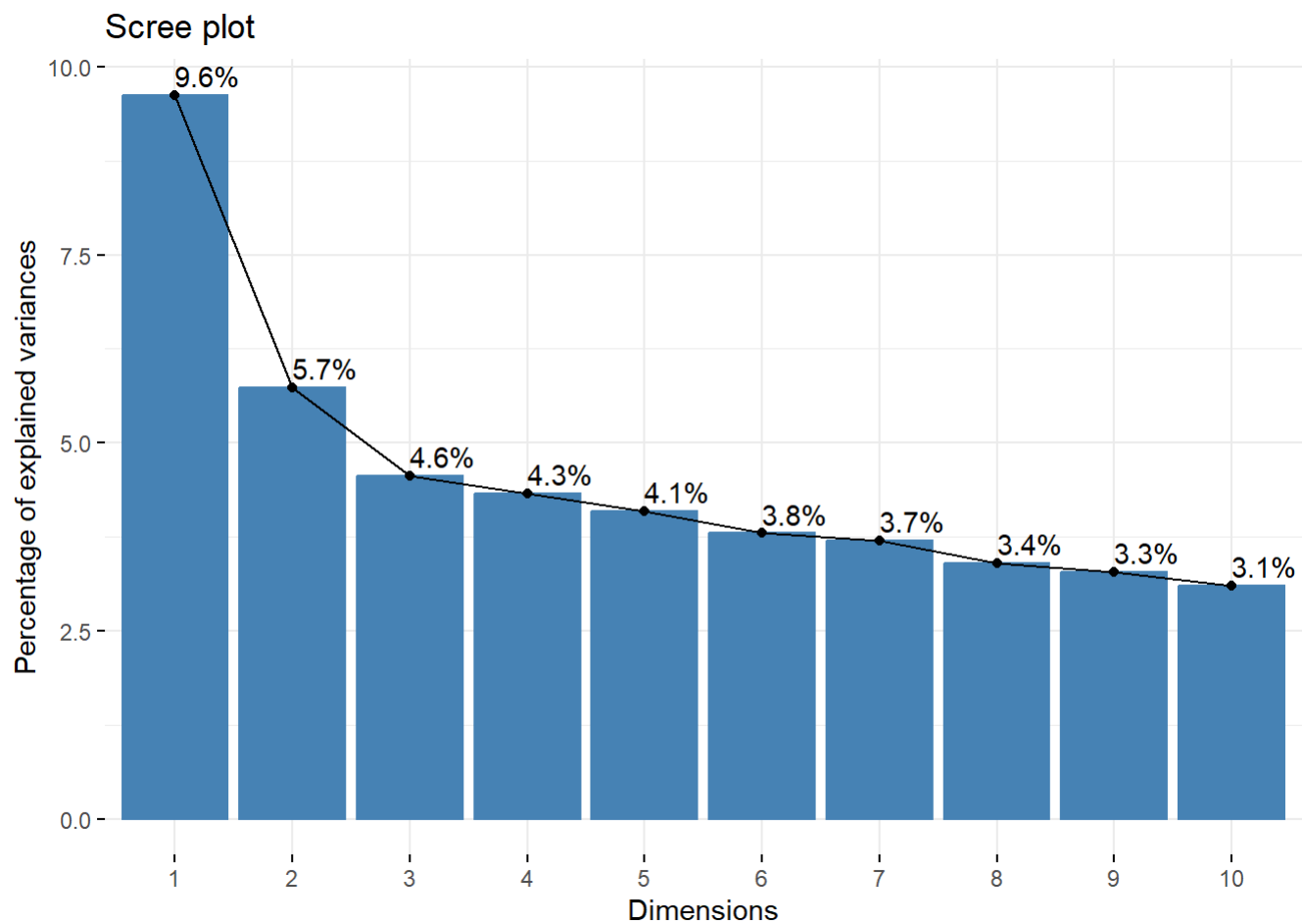
MCA

```
res.mca <- MCA(df_clean, graph = FALSE)

##Get Eigen values
eig.val <- get_eigenvalue(res.mca)
eig.val
```

##	eigenvalue	variance.percent	cumulative.variance.percent
## Dim.1	0.17939677	9.6261680	9.626168
## Dim.2	0.10697518	5.7401315	15.366299
## Dim.3	0.08508601	4.5655906	19.931890
## Dim.4	0.08059619	4.3246735	24.256564
## Dim.5	0.07631675	4.0950452	28.351609
## Dim.6	0.07079004	3.7984898	32.150099
## Dim.7	0.06895564	3.7000585	35.850157
## Dim.8	0.06342515	3.4033006	39.253458
## Dim.9	0.06125064	3.2866197	42.540077
## Dim.10	0.05772304	3.0973340	45.637411
## Dim.11	0.05604685	3.0073921	48.644804
## Dim.12	0.05188210	2.7839174	51.428721
## Dim.13	0.05067236	2.7190049	54.147726
## Dim.14	0.04899204	2.6288410	56.776567
## Dim.15	0.04673430	2.5076941	59.284261
## Dim.16	0.04592465	2.4642497	61.748511
## Dim.17	0.04468232	2.3975881	64.146099
## Dim.18	0.04278260	2.2956516	66.441750
## Dim.19	0.04261722	2.2867775	68.728528
## Dim.20	0.04084406	2.1916327	70.920161
## Dim.21	0.03965092	2.1276105	73.047771
## Dim.22	0.03802769	2.0405103	75.088281
## Dim.23	0.03647962	1.9574428	77.045724
## Dim.24	0.03529091	1.8936585	78.939383
## Dim.25	0.03496281	1.8760534	80.815436
## Dim.26	0.03269428	1.7543272	82.569763
## Dim.27	0.03260025	1.7492818	84.319045
## Dim.28	0.02889982	1.5507218	85.869767
## Dim.29	0.02783426	1.4935456	87.363312
## Dim.30	0.02703882	1.4508633	88.814176
## Dim.31	0.02554774	1.3708542	90.185030
## Dim.32	0.02452055	1.3157367	91.500767
## Dim.33	0.02319166	1.2444303	92.745197
## Dim.34	0.02240244	1.2020821	93.947279
## Dim.35	0.02080948	1.1166063	95.063885
## Dim.36	0.01919624	1.0300424	96.093928
## Dim.37	0.01778916	0.9545404	97.048468
## Dim.38	0.01726955	0.9266589	97.975127
## Dim.39	0.01474924	0.7914224	98.766549
## Dim.40	0.01248958	0.6701724	99.436722
## Dim.41	0.01049746	0.5632783	100.000000

```
##find percentages explained by MCA dimensions
fviz_screplot(res.mca, addlabels = TRUE)
```



As shown in the screeplot above, the first two dimensions do not account for more than 20% and all our components have eigen values that are less than 1 and inertia percentage less than 10% hence we need to work around the data to get great results.

```
##Get variable contributions to the MCA dimensions  
var <- get_mca_var(res.mca)  
  
round(var$contrib,2)
```

##	Dim 1	Dim 2	Dim 3	Dim 4	Dim 5
## household_head_gender_Females	0.40	0.19	0.77	8.96	3.13
## household_head_gender_Males	0.18	0.08	0.34	4.00	1.40
## household_head_education.NA	0.02	0.11	0.46	1.43	0.64
## No formal education	0.48	1.02	2.70	8.84	0.06
## Primary	0.01	4.54	0.08	1.47	3.88
## Secondary	0.23	0.32	3.63	0.74	0.61
## University	0.01	0.01	13.67	0.18	0.03
## Vocational	0.15	0.88	0.10	0.01	0.04
## >110,001	0.01	0.25	0.48	0.56	2.20
## 0 to 10,000	0.15	0.71	1.35	2.12	0.21
## 10,001 to 30,000	0.35	1.93	2.29	0.99	0.28
## 30,001 to 50,000	0.20	0.82	3.68	6.85	0.00
## 50,001 to 70,000	0.00	0.98	0.01	0.88	0.71
## 70,001 to 90,000	0.03	0.00	0.08	7.65	7.23
## 90,001 to 110,000	0.00	0.32	0.01	0.27	0.48
## registration_No	1.25	3.57	1.61	0.10	0.87
## registration_Yes	0.18	0.52	0.24	0.01	0.13
## Closed	0.00	1.49	0.05	0.01	0.02
## Open	0.01	11.04	0.35	0.07	0.15
## members_gender_Females	4.28	0.69	0.08	0.17	0.50
## members_gender_Males on	0.02	0.05	0.03	6.87	10.24
## members_gender_Mixed	5.39	0.78	0.09	0.00	0.05
## amalgamation_No	2.20	0.28	0.04	0.10	0.11
## amalgamation_Yes	10.54	1.36	0.20	0.47	0.51
## social_networking_No	2.56	0.33	0.00	0.58	0.18
## social_networking_Yes	7.70	0.99	0.00	1.74	0.55
## input_sourcing_No	1.72	0.06	0.02	0.06	0.00
## input_sourcing_Yes	11.79	0.43	0.13	0.41	0.03
## output_marketing_No	3.29	0.00	0.34	0.00	0.00
## output_marketing_Yes	14.60	0.00	1.50	0.00	0.00
## extension_services_No	1.36	0.00	0.02	0.06	0.01
## extension_services_Yes	9.57	0.01	0.15	0.44	0.07
## credit_sourcing_No	0.37	4.50	1.16	0.00	0.04
## credit_sourcing_Yes	0.56	6.77	1.75	0.00	0.06
## savings_No	3.04	4.21	3.06	0.80	0.00
## savings_Yes	1.61	2.22	1.61	0.42	0.00
## informal_insurance_No	0.16	0.04	0.28	2.16	4.40
## informal_insurance_Yes	0.38	0.10	0.65	5.10	10.39
## social_welfare_No	2.86	0.74	0.00	0.27	0.68
## social_welfare_Yes	2.65	0.69	0.00	0.25	0.63
## fine_imposing_No	2.49	4.13	1.44	0.02	9.59
## fine_imposing_Yes	0.31	0.51	0.18	0.00	1.19
## members_trust_Agree somewhat	1.46	9.02	4.70	0.63	0.13
## members_trust_Agree strongly	0.32	3.43	1.56	0.10	0.00
## members_trust_Disagree strongly	0.01	1.50	1.46	0.52	0.00
## members_trust_Neither agree nor di	0.15	1.28	3.39	1.14	2.22
## other_groups_trust_Agree somewhat	0.92	3.39	5.81	0.02	0.92
## other_groups_trust_Agree strongly	0.01	10.88	0.22	0.47	0.48
## other_groups_trust_Disagree strongly	0.58	1.10	8.50	7.93	1.24
## other_groups_trust_Neither agree nor di	0.45	3.34	0.09	3.07	1.74
## service_providers_trust_Agree somewhat	0.03	1.46	0.26	0.09	7.27

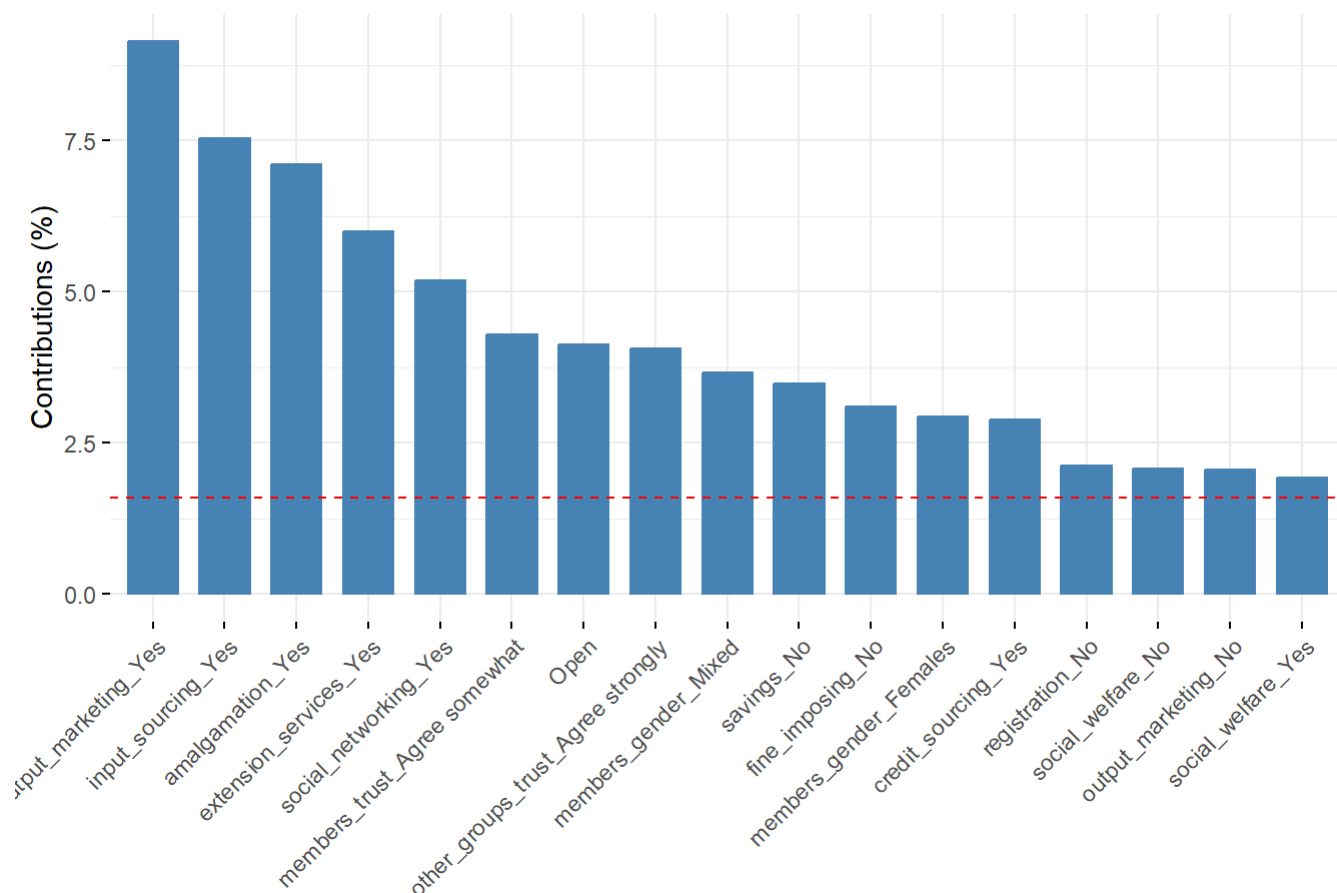
## service_providers_trust_Agree strongly	0.04	4.28	2.69	1.41	0.00
## service_providers_trust_Disagree strongly	0.46	0.91	9.75	7.02	0.04
## service_providers_trust_Neither agree nor di	0.00	0.36	9.25	0.06	8.39
## < 2 acres	0.04	0.02	0.22	0.48	0.54
## > 2 acres	0.54	0.31	3.08	6.60	7.41
## 22 to 35	0.72	0.01	0.41	0.03	0.93
## 3	0.04	0.05	2.95	0.02	2.53
## 36 to 49	0.30	0.14	0.11	2.67	0.24
## 50 to 63	0.00	0.19	0.09	0.42	0.59
## 64 to 77	0.50	0.58	0.23	0.08	4.05
## Above 70	0.31	0.02	0.63	2.16	0.00
## 1	0.00	0.00	0.00	0.00	0.00

Variables that have higher associations (higher cosine similarity) with specific dimensions are more strongly related to those dimensions. This information can help identify the variables that contribute most to each dimension and understand the underlying patterns in the data.

Total contribution to dimension 1 and 2

```
# Total contribution to dimension 1 and 2
fviz_contrib(res.mca, choice = "var", axes = 1:2, top = 17)
```

Contribution of variables to Dim-1-2



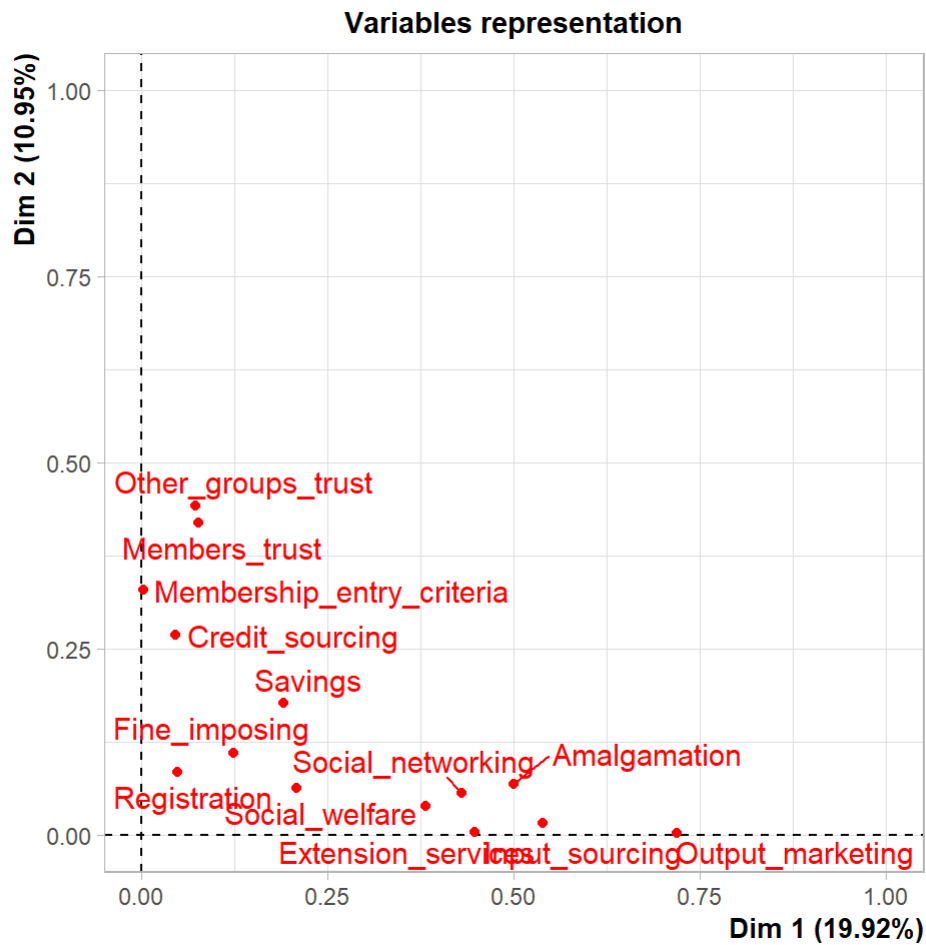
Using the plot above, the variables making up for the total contributions to dimension 1 and 2 are shown above. The red dotted line in the graph above shows the expected average values, if the contributions were uniform. The graph shows the variables that have a high contribution to both dimension 1 and 2 are in order of importance (only

the top 15 variables are chosen). We can therefore drop the other variables and see if there is a difference in the contribution to inertia on the scree plot.

Select top 15 variables

```
##choose only the top 15 variables  
my_data<-MCA_data[,c(4:13,15:18)]  
res.mca1 <- MCA(my_data)
```

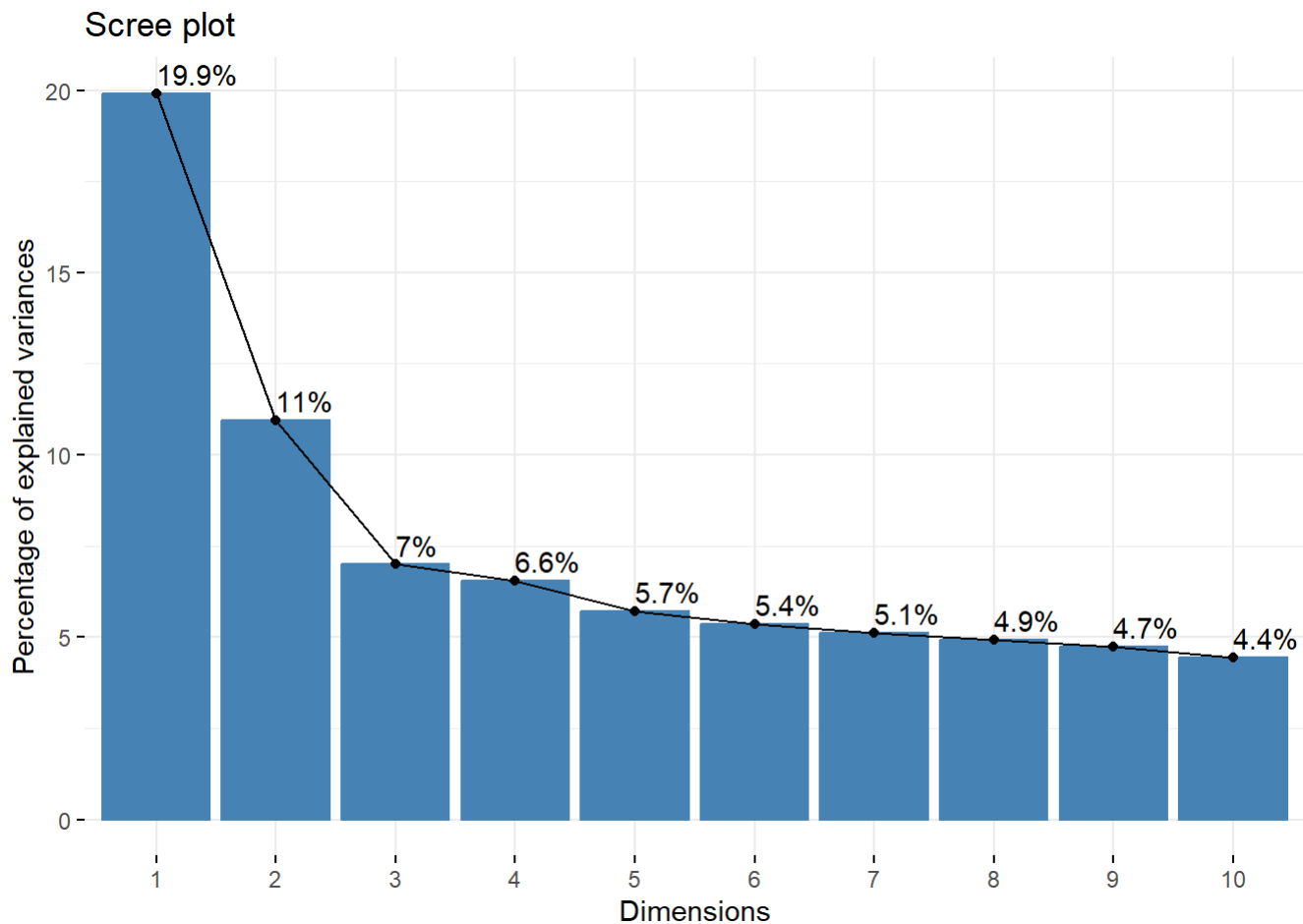

Figure 2: PCA plot of 313 samples. The x-axis is labeled 'Dim 1 (19.92%)' and the y-axis is labeled 'Dim 2 (10.95%)'. The plot shows a dense cluster of points, with a dashed vertical line at Dim 1 = 0 and a dashed horizontal line at Dim 2 = 0. The points are numbered, and the plot is divided into four quadrants by these dashed lines.



```
##Get Eigen values
eig.val1 <- get_eigenvalue(res.mca1)
eig.val1
```

##	eigenvalue	variance.percent	cumulative.variance.percent
## Dim.1	0.27032067	19.918365	19.91837
## Dim.2	0.14866906	10.954562	30.87293
## Dim.3	0.09494094	6.995648	37.86858
## Dim.4	0.08896708	6.555469	44.42404
## Dim.5	0.07752691	5.712509	50.13655
## Dim.6	0.07284383	5.367440	55.50399
## Dim.7	0.06948536	5.119974	60.62397
## Dim.8	0.06699849	4.936731	65.56070
## Dim.9	0.06444373	4.748486	70.30918
## Dim.10	0.06025728	4.440010	74.74919
## Dim.11	0.05616004	4.138108	78.88730
## Dim.12	0.05088870	3.749693	82.63700
## Dim.13	0.04665217	3.437528	86.07452
## Dim.14	0.04175455	3.076651	89.15118
## Dim.15	0.03797632	2.798256	91.94943
## Dim.16	0.03488435	2.570426	94.51986
## Dim.17	0.03257279	2.400100	96.91996
## Dim.18	0.02334605	1.720235	98.64019
## Dim.19	0.01845453	1.359807	100.00000

```
##find percentages explained by MCA dimensions  
fviz_screplot(res.mca1, addlabels = TRUE)
```



Now from the screeplot above, the percentage of inertia explained by each MCA dimension has increased significantly hence we can continue with the analysis.

Variable contribution to the dimensions

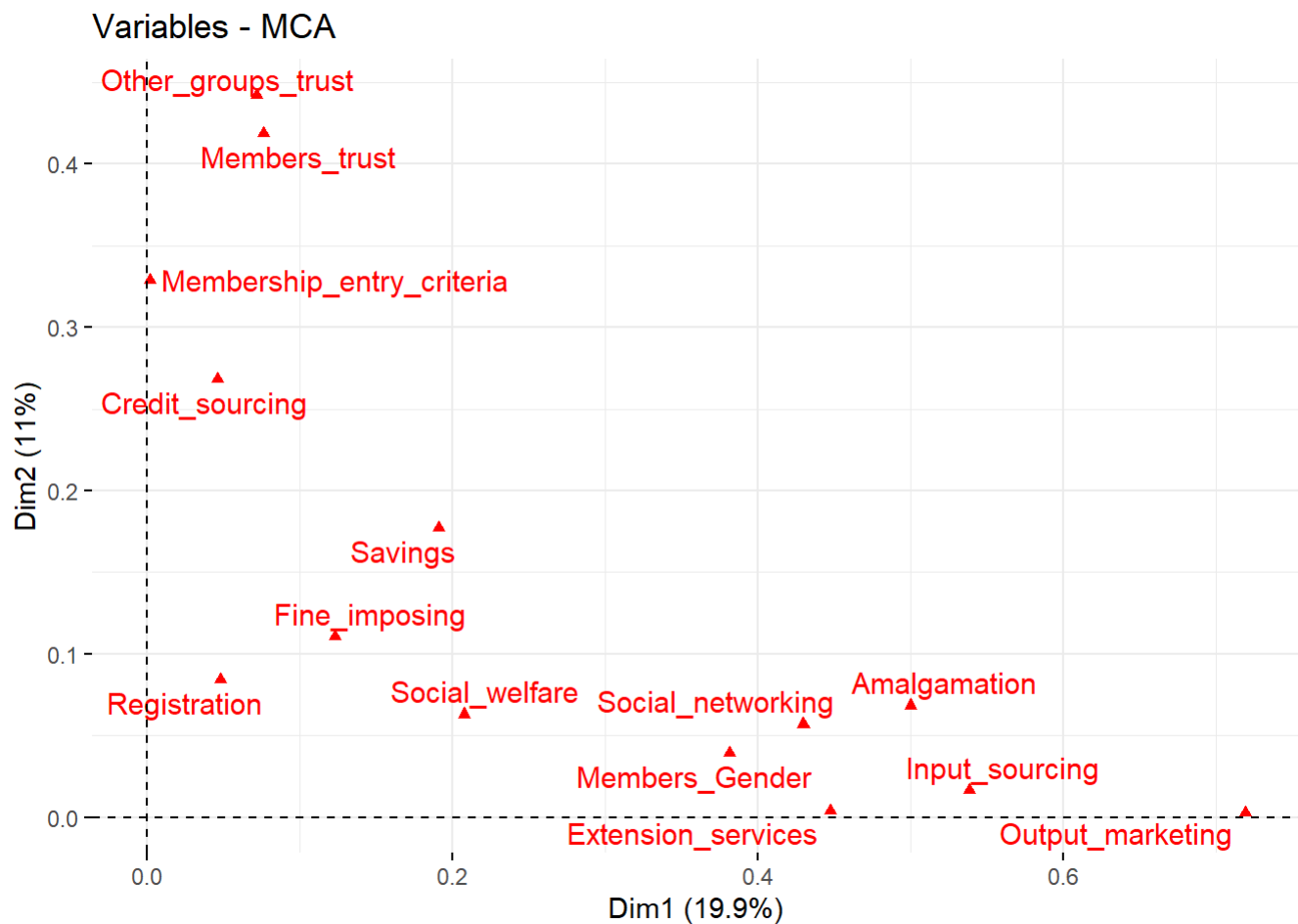
```
##Get variable contributions to the MCA dimensions  
var_contrib <- get_mca_var(res.mca1)  
  
round(var_contrib$contrib,2)
```

##	Dim 1	Dim 2	Dim 3	Dim 4	Dim 5
## Registration_No	1.11	3.54	6.01	15.88	9.11
## Registration_Yes	0.16	0.52	0.88	2.32	1.33
## Closed	0.01	1.88	0.05	0.09	0.22
## Open	0.05	13.92	0.38	0.64	1.63
## Females	4.40	0.86	0.11	1.01	2.36
## Males on	0.06	0.02	0.02	0.33	53.72
## Mixed	5.62	1.01	0.15	1.03	0.15
## Amalgamation_No	2.28	0.57	0.37	0.12	0.23
## Amalgamation_Yes	10.93	2.72	1.75	0.57	1.10
## Social_networking_No	2.83	0.68	0.19	0.11	1.16
## Social_networking_Yes	8.53	2.06	0.59	0.33	3.49
## Input_sourcing_No	1.81	0.10	0.00	0.00	0.03
## Input_sourcing_Yes	12.41	0.68	0.00	0.00	0.20
## Output_marketing_No	3.50	0.03	0.35	0.01	0.13
## Output_marketing_Yes	15.51	0.11	1.54	0.04	0.59
## Extension_services_No	1.47	0.02	0.03	0.05	0.06
## Extension_services_Yes	10.36	0.16	0.24	0.37	0.41
## Credit_sourcing_No	0.49	5.15	3.51	0.12	0.00
## Credit_sourcing_Yes	0.73	7.75	5.28	0.17	0.00
## Savings_No	3.31	5.57	6.05	0.14	5.47
## Savings_Yes	1.75	2.94	3.19	0.07	2.89
## Social_welfare_No	2.85	1.57	0.98	2.12	0.09
## Social_welfare_Yes	2.65	1.46	0.91	1.97	0.08
## Fine_imposing_No	2.90	4.72	6.72	3.65	1.63
## Fine_imposing_Yes	0.36	0.59	0.83	0.45	0.20
## Members_trust_Agree somewhat	1.54	11.22	13.95	0.49	0.08
## Members_trust_Agree strongly	0.34	4.49	1.66	0.06	0.12
## Members_trust_Disagree strongly	0.01	2.05	11.92	6.70	0.81
## Members_trust_Neither agree nor di	0.13	2.37	1.35	32.09	5.75
## Other_groups_trust_Agree somewhat	1.01	3.99	17.28	1.83	0.40
## Other_groups_trust_Agree strongly	0.00	12.19	0.65	0.42	0.97
## Other_groups_trust_Disagree strongly	0.49	0.84	12.23	11.30	1.72
## Other_groups_trust_Neither agree nor di	0.41	4.24	0.83	15.53	3.88

Variables that have higher associations (higher cosine similarity) with specific dimensions are more strongly related to those dimensions. This information can help identify the variables that contribute most to each dimension and understand the underlying patterns in the data.

Correlation between variables and principal dimensions

```
fviz_mca_var(res.mca1, choice = "mca.cor",
             repel = TRUE, # Avoid text overlapping (slow)
             ggtheme = theme_minimal())
```

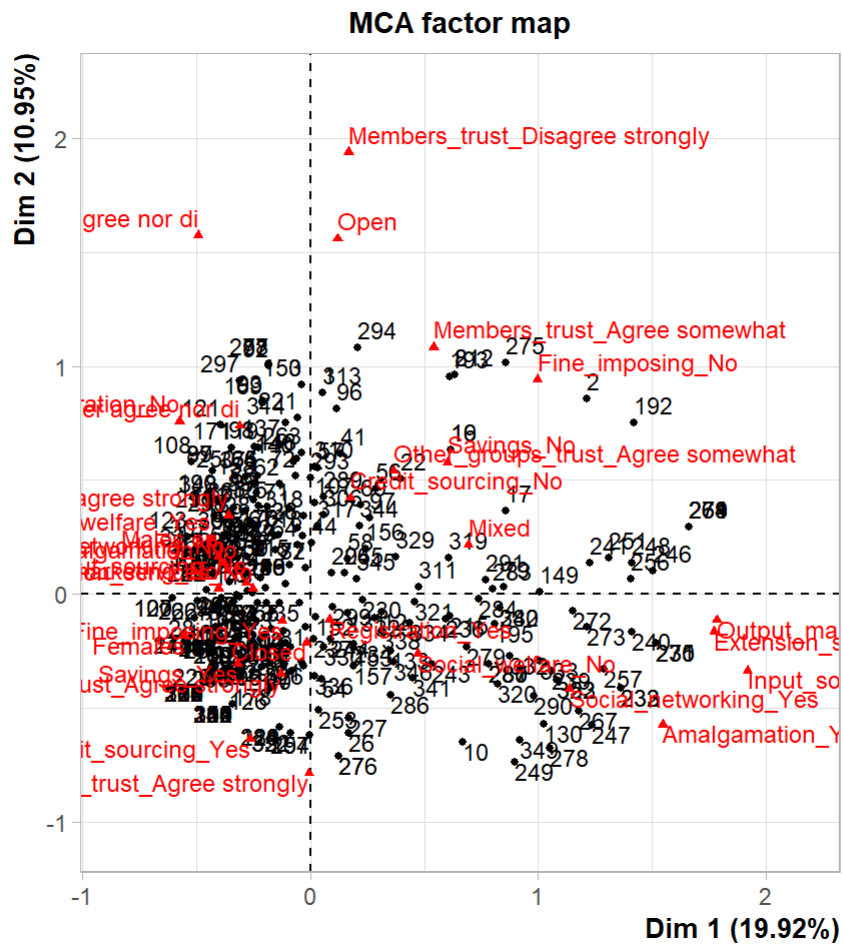


- The plot above helps to identify variables that are the most correlated with each dimension. The squared correlations between variables and the dimensions are used as coordinates.
- It can be seen that, the variables extension services and output marketing are the most correlated with dimension 1. Similarly, the variables membership entry criteria and fine imposing are the most correlated with dimension 2.

Biplot

A biplot, which combines the dimension plot with the variable plot. This plot allows you to visualize both the relationships between categories and the relationships between variables in the same plot. It helps interpret the associations between categories, variables, and dimensions simultaneously. This can lead to a better understanding of the relationships and provide valuable information for further analysis or decision-making.

```
plot.MCA(res.mca1, cex = 0.8, repel = TRUE)
```



```
var <- get_mca_var(res.mca1)
# Coordinates of variables
var$coord
```

##	Dim 1	Dim 2	Dim 3
## Registration_No	-0.574353873	0.76014376	0.791888834
## Registration_Yes	0.083915339	-0.11105996	-0.115698044
## Closed	-0.016234532	-0.21077189	0.027965773
## Open	0.120212842	1.56071568	-0.207079889
## Females	-0.553067643	-0.18115968	-0.050975390
## Males on	-0.405035012	0.16648442	-0.123683607
## Mixed	0.693680528	0.21762972	0.066703160
## Amalgamation_No	-0.323175411	0.11948590	-0.076588141
## Amalgamation_Yes	1.547003607	-0.57196530	0.366618642
## Social_networking_No	-0.377878263	0.13755920	-0.058657293
## Social_networking_Yes	1.137928859	-0.41424078	0.176638439
## Input_sourcing_No	-0.280483436	0.04885134	0.001822715
## Input_sourcing_Yes	1.919753298	-0.33436026	-0.012475469
## Output_marketing_No	-0.402911029	0.02561246	-0.075155692
## Output_marketing_Yes	1.785205790	-0.11348288	0.332997526
## Extension_services_No	-0.252507721	0.02347714	0.022759253
## Extension_services_Yes	1.773292860	-0.16487352	-0.159832028
## Credit_sourcing_No	0.175157505	0.42255972	0.278718126
## Credit_sourcing_Yes	-0.263357383	-0.63533802	-0.419065550
## Savings_No	0.601903640	0.57907709	0.482313056
## Savings_Yes	-0.317888502	-0.30583292	-0.254728107
## Social_welfare_No	0.473084345	-0.26041560	-0.164838191
## Social_welfare_Yes	-0.439477260	0.24191613	0.153128374
## Fine_imposing_No	0.997454575	0.94304648	-0.898920397
## Fine_imposing_Yes	-0.123887670	-0.11712998	0.111649349
## Members_trust_Agree somewhat	0.542093702	1.08535698	-0.966811512
## Members_trust_Agree strongly	-0.129297167	-0.34839420	0.169369584
## Members_trust_Disagree strongly	0.167555486	1.93892946	3.739337104
## Members_trust_Neither agree nor di	-0.492564525	1.57607366	0.950132941
## Other_groups_trust_Agree somewhat	0.367388072	0.54132189	-0.900497656
## Other_groups_trust_Agree strongly	-0.005613923	-0.78595497	0.145300038
## Other_groups_trust_Disagree strongly	-0.359413507	0.34706016	1.060791122
## Other_groups_trust_Neither agree nor di	-0.308678940	0.73914409	0.261068646
##	Dim 4	Dim 5	
## Registration_No	1.245767616	-0.8807474633	
## Registration_Yes	-0.182011502	0.1286806359	
## Closed	0.034834107	-0.0521256988	
## Open	-0.257938271	0.3859783887	
## Females	0.152389652	-0.2169710731	
## Males on	-0.536022057	6.4157223053	
## Mixed	-0.170376300	0.0614091956	
## Amalgamation_No	0.042516706	0.0547897779	
## Amalgamation_Yes	-0.203522595	-0.2622723795	
## Social_networking_No	0.042458413	0.1294233759	
## Social_networking_Yes	-0.127857722	-0.3897408479	
## Input_sourcing_No	-0.002270277	0.0188305727	
## Input_sourcing_Yes	0.015538786	-0.1288848084	
## Output_marketing_No	-0.011165390	-0.0420009463	
## Output_marketing_Yes	0.049471267	0.1860965004	
## Extension_services_No	-0.027312802	0.0270208857	
## Extension_services_Yes	0.191810360	-0.1897603106	

## Credit_sourcing_No	-0.048978383	-0.0002467934
## Credit_sourcing_Yes	0.073641257	0.0003710653
## Savings_No	-0.070506730	0.4143078058
## Savings_Yes	0.037237321	-0.2188119147
## Social_welfare_No	0.234297296	0.0449864846
## Social_welfare_Yes	-0.217653226	-0.0417907234
## Fine_imposing_No	0.641515026	-0.4007716475
## Fine_imposing_Yes	-0.079678618	0.0497773702
## Members_trust_Agree somewhat	0.175952029	0.0645977481
## Members_trust_Agree strongly	0.030366141	0.0419529848
## Members_trust_Disagree strongly	2.712906573	-0.8791619198
## Members_trust_Neither agree nor di	-4.489694087	-1.7737723658
## Other_groups_trust_Agree somewhat	0.283329725	-0.1241190097
## Other_groups_trust_Agree strongly	-0.112210894	0.1597558833
## Other_groups_trust_Disagree strongly	0.986818753	0.3597305674
## Other_groups_trust_Neither agree nor di	-1.094564022	-0.5105080885

```
# Cos2: quality of representation on the factore map
var$cos2
```


##	Dim 1	Dim 2	Dim 3
## Registration_No	4.819710e-02	0.0844215385	9.161999e-02
## Registration_Yes	4.819710e-02	0.0844215385	9.161999e-02
## Closed	1.951599e-03	0.3289549973	5.791149e-03
## Open	1.951599e-03	0.3289549973	5.791149e-03
## Females	3.647807e-01	0.0391379834	3.098821e-03
## Males on	2.357089e-03	0.0003982336	2.197936e-04
## Mixed	3.810460e-01	0.0375054849	3.523313e-03
## Amalgamation_No	4.999535e-01	0.0683417894	2.807864e-02
## Amalgamation_Yes	4.999535e-01	0.0683417894	2.807864e-02
## Social_networking_No	4.299986e-01	0.0569826315	1.036113e-02
## Social_networking_Yes	4.299986e-01	0.0569826315	1.036113e-02
## Input_sourcing_No	5.384590e-01	0.0163339452	2.273922e-05
## Input_sourcing_Yes	5.384590e-01	0.0163339452	2.273922e-05
## Output_marketing_No	7.192791e-01	0.0029065752	2.502666e-02
## Output_marketing_Yes	7.192791e-01	0.0029065752	2.502666e-02
## Extension_services_No	4.477701e-01	0.0038707579	3.637658e-03
## Extension_services_Yes	4.477701e-01	0.0038707579	3.637658e-03
## Credit_sourcing_No	4.612902e-02	0.2684682548	1.168012e-01
## Credit_sourcing_Yes	4.612902e-02	0.2684682548	1.168012e-01
## Savings_No	1.913382e-01	0.1771008379	1.228587e-01
## Savings_Yes	1.913382e-01	0.1771008379	1.228587e-01
## Social_welfare_No	2.079098e-01	0.0629987357	2.524140e-02
## Social_welfare_Yes	2.079098e-01	0.0629987357	2.524140e-02
## Fine_imposing_No	1.235723e-01	0.1104590131	1.003639e-01
## Fine_imposing_Yes	1.235723e-01	0.1104590131	1.003639e-01
## Members_trust_Agree somewhat	7.268760e-02	0.2913780333	2.312039e-01
## Members_trust_Agree strongly	5.613864e-02	0.4075920565	9.632848e-02
## Members_trust_Disagree strongly	3.217747e-04	0.0430882228	1.602595e-01
## Members_trust_Neither agree nor di	4.908493e-03	0.0502545008	1.826378e-02
## Other_groups_trust_Agree somewhat	5.334941e-02	0.1158218931	3.205123e-01
## Other_groups_trust_Agree strongly	2.197038e-05	0.4306257474	1.471757e-02
## Other_groups_trust_Disagree strongly	2.181484e-02	0.0203410212	1.900304e-01
## Other_groups_trust_Neither agree nor di	1.834836e-02	0.1052062066	1.312480e-02
##	Dim 4	Dim 5	
## Registration_No	2.267440e-01	1.133351e-01	
## Registration_Yes	2.267440e-01	1.133351e-01	
## Closed	8.985049e-03	2.011939e-02	
## Open	8.985049e-03	2.011939e-02	
## Females	2.769404e-02	5.614086e-02	
## Males on	4.128156e-03	5.914008e-01	
## Mixed	2.298671e-02	2.986243e-03	
## Amalgamation_No	8.653110e-03	1.436985e-02	
## Amalgamation_Yes	8.653110e-03	1.436985e-02	
## Social_networking_No	5.428636e-03	5.044158e-02	
## Social_networking_Yes	5.428636e-03	5.044158e-02	
## Input_sourcing_No	3.527735e-05	2.426975e-03	
## Input_sourcing_Yes	3.527735e-05	2.426975e-03	
## Output_marketing_No	5.523660e-04	7.816229e-03	
## Output_marketing_Yes	5.523660e-04	7.816229e-03	
## Extension_services_No	5.238878e-03	5.127492e-03	
## Extension_services_Yes	5.238878e-03	5.127492e-03	

## Credit_sourcing_No	3.606830e-03	9.157649e-08
## Credit_sourcing_Yes	3.606830e-03	9.157649e-08
## Savings_No	2.625482e-03	9.065548e-02
## Savings_Yes	2.625482e-03	9.065548e-02
## Social_welfare_No	5.099556e-02	1.880018e-03
## Social_welfare_Yes	5.099556e-02	1.880018e-03
## Fine_imposing_No	5.111503e-02	1.994936e-02
## Fine_imposing_Yes	5.111503e-02	1.994936e-02
## Members_trust_Agree somewhat	7.657732e-03	1.032158e-03
## Members_trust_Agree strongly	3.096443e-03	5.910301e-03
## Members_trust_Disagree strongly	8.435372e-02	8.858747e-03
## Members_trust_Neither agree nor di	4.078077e-01	6.365283e-02
## Other_groups_trust_Agree somewhat	3.172954e-02	6.089142e-03
## Other_groups_trust_Agree strongly	8.777578e-03	1.779174e-02
## Other_groups_trust_Disagree strongly	1.644516e-01	2.185334e-02
## Other_groups_trust_Neither agree nor di	2.307095e-01	5.018667e-02

```
# Contributions to the dimensions
var$contrib
```

##	Dim 1	Dim 2	Dim 3
## Registration_No	1.111193311	3.53900071	6.014294603
## Registration_Yes	0.162349672	0.51706179	0.878711874
## Closed	0.006135612	1.88045285	0.051839140
## Open	0.045432749	13.92430566	0.383856486
## Females	4.396182633	0.85763203	0.106332517
## Males on	0.061400673	0.01886227	0.016301893
## Mixed	5.619033259	1.00562875	0.147931671
## Amalgamation_No	2.282850482	0.56740460	0.365047731
## Amalgamation_Yes	10.927743291	2.71610070	1.747441596
## Social_networking_No	2.832485468	0.68249872	0.194327226
## Social_networking_Yes	8.529643738	2.05525184	0.585189943
## Input_sourcing_No	1.813773917	0.10004152	0.000218088
## Input_sourcing_Yes	12.414274811	0.68472862	0.001492691
## Output_marketing_No	3.499683704	0.02571412	0.346704905
## Output_marketing_Yes	15.506290874	0.11393331	1.536169423
## Extension_services_No	1.474775115	0.02318064	0.034112868
## Extension_services_Yes	10.356943419	0.16279129	0.239565370
## Credit_sourcing_No	0.486868141	5.15215266	3.510023560
## Credit_sourcing_Yes	0.732028695	7.74649904	5.277482232
## Savings_No	3.308504775	5.56812872	6.048693968
## Savings_Yes	1.747348842	2.94074331	3.194548330
## Social_welfare_No	2.848026798	1.56913241	0.984483285
## Social_welfare_Yes	2.645707955	1.45766399	0.914547314
## Fine_imposing_No	2.904483119	4.72071169	6.716620674
## Fine_imposing_Yes	0.360747903	0.58633043	0.834229956
## Members_trust_Agree somewhat	1.539801578	11.22328300	13.945221321
## Members_trust_Agree strongly	0.340380694	4.49352747	1.662966462
## Members_trust_Disagree strongly	0.008406114	2.04673058	11.920458892
## Members_trust_Neither agree nor di	0.127128317	2.36661566	1.346823038
## Other_groups_trust_Agree somewhat	1.010341286	3.98830030	17.282593650
## Other_groups_trust_Agree strongly	0.000342073	12.19101874	0.652443946
## Other_groups_trust_Disagree strongly	0.493147642	0.83609642	12.231329737
## Other_groups_trust_Neither agree nor di	0.406543341	4.23847615	0.827995612
##	Dim 4	Dim 5	
## Registration_No	1.588380e+01	9.110876e+00	
## Registration_Yes	2.320686e+00	1.331134e+00	
## Closed	8.582972e-02	2.205510e-01	
## Open	6.355486e-01	1.633127e+00	
## Females	1.014098e+00	2.359118e+00	
## Males on	3.267407e-01	5.371628e+01	
## Mixed	1.029938e+00	1.535452e-01	
## Amalgamation_No	1.200522e-01	2.287846e-01	
## Amalgamation_Yes	5.746759e-01	1.095165e+00	
## Social_networking_No	1.086529e-01	1.158554e+00	
## Social_networking_Yes	3.271934e-01	3.488826e+00	
## Input_sourcing_No	3.610575e-04	2.850510e-02	
## Input_sourcing_Yes	2.471238e-03	1.951016e-01	
## Output_marketing_No	8.165978e-03	1.326036e-01	
## Output_marketing_Yes	3.618156e-02	5.875361e-01	
## Extension_services_No	5.242747e-02	5.888470e-02	
## Extension_services_Yes	3.681838e-01	4.135312e-01	

## Credit_sourcing_No	1.156679e-01	3.370140e-06
## Credit_sourcing_Yes	1.739119e-01	5.067160e-06
## Savings_No	1.379396e-01	5.465764e+00
## Savings_Yes	7.285121e-02	2.886680e+00
## Social_welfare_No	2.122518e+00	8.979617e-02
## Social_welfare_Yes	1.971738e+00	8.341721e-02
## Fine_imposing_No	3.650448e+00	1.634946e+00
## Fine_imposing_Yes	4.533996e-01	2.030665e-01
## Members_trust_Agree somewhat	4.928951e-01	7.623907e-02
## Members_trust_Agree strongly	5.704479e-02	1.249509e-01
## Members_trust_Disagree strongly	6.695725e+00	8.069424e-01
## Members_trust_Neither agree nor di	3.209220e+01	5.748289e+00
## Other_groups_trust_Agree somewhat	1.825796e+00	4.020883e-01
## Other_groups_trust_Agree strongly	4.152465e-01	9.658875e-01
## Other_groups_trust_Disagree strongly	1.129569e+01	1.722541e+00
## Other_groups_trust_Neither agree nor di	1.553192e+01	3.877260e+00

R2 and p values

R2 tells you how well the model explains the variation in the data. If R2 is low, then your independent variable isn't helping to explain very much about the dependent variable. A p-value for a tells us if the intercept is statistically significantly different from 0 or not

```
dimdesc(res.mca1)
```

```

## `$Dim 1`
##
## Link between the variable and the categorical variable (1-way anova)
## =====
##
##          R2          p.value
## Output_marketing  0.71927910 7.451905e-99
## Input_sourcing    0.53845900 6.780434e-61
## Amalgamation      0.49995353 9.007620e-55
## Extension_services 0.44777014 3.499334e-47
## Social_networking 0.42999858 9.265198e-45
## Members_Gender    0.38134849 3.184663e-37
## Social_welfare    0.20790981 1.586427e-19
## Savings           0.19133825 6.253374e-18
## Fine_imposing     0.12357232 1.050416e-11
## Members_trust     0.07628459 4.132315e-06
## Other_groups_trust 0.07229792 8.545235e-06
## Registration      0.04819710 3.168649e-05
## Credit_sourcing   0.04612902 4.730598e-05
##
## Link between variable and the categories of the categorical variables
## =====
##
##                                     Estimate
## Output_marketing=Output_marketing_Yes 0.56882692
## Input_sourcing=Input_sourcing_Yes     0.57197763
## Amalgamation=Amalgamation_Yes         0.48617522
## Extension_services=Extension_services_Yes 0.52663089
## Social_networking=Social_networking_Yes 0.39405204
## Members_Gender=Mixed                  0.40648741
## Social_welfare=Social_welfare_No      0.23723121
## Savings=Savings_No                   0.23911088
## Fine_imposing=Fine_imposing_No        0.29150622
## Members_trust=Members_trust_Agree somewhat 0.27043667
## Other_groups_trust=Other_groups_trust_Agree somewhat 0.23082931
## Registration=Registration_Yes          0.17112489
## Credit_sourcing=Credit_sourcing_No    0.11399715
## Other_groups_trust=Other_groups_trust_Neither agree nor di -0.12067397
## Other_groups_trust=Other_groups_trust_Disagree strongly -0.14705207
## Credit_sourcing=Credit_sourcing_Yes   -0.11399715
## Registration=Registration_No            -0.17112489
## Members_trust=Members_trust_Agree strongly -0.07863536
## Fine_imposing=Fine_imposing_Yes        -0.29150622
## Savings=Savings_Yes                   -0.23911088
## Social_welfare=Social_welfare_Yes     -0.23723121
## Members_Gender=Females                 -0.24172654
## Social_networking=Social_networking_No -0.39405204
## Extension_services=Extension_services_No -0.52663089
## Amalgamation=Amalgamation_No          -0.48617522
## Input_sourcing=Input_sourcing_No       -0.57197763
## Output_marketing=Output_marketing_No  -0.56882692
##
##                                     p.value
## Output_marketing=Output_marketing_Yes 7.451905e-99
## Input_sourcing=Input_sourcing_Yes     6.780434e-61

```

```

## Amalgamation=Amalgamation_Yes 9.007620e-55
## Extension_services=Extension_services_Yes 3.499334e-47
## Social_networking=Social_networking_Yes 9.265198e-45
## Members_Gender=Mixed 1.873095e-38
## Social_welfare=Social_welfare_No 1.586427e-19
## Savings=Savings_No 6.253374e-18
## Fine_imposing=Fine_imposing_No 1.050416e-11
## Members_trust=Members_trust_Agree somewhat 2.703553e-07
## Other_groups_trust=Other_groups_trust_Agree somewhat 1.167075e-05
## Registration=Registration_Yes 3.168649e-05
## Credit_sourcing=Credit_sourcing_No 4.730598e-05
## Other_groups_trust=Other_groups_trust_Neither agree nor di 1.084310e-02
## Other_groups_trust=Other_groups_trust_Disagree strongly 5.428784e-03
## Credit_sourcing=Credit_sourcing_Yes 4.730598e-05
## Registration=Registration_No 3.168649e-05
## Members_trust=Members_trust_Agree strongly 6.793058e-06
## Fine_imposing=Fine_imposing_Yes 1.050416e-11
## Savings=Savings_Yes 6.253374e-18
## Social_welfare=Social_welfare_Yes 1.586427e-19
## Members_Gender=Females 1.815311e-36
## Social_networking=Social_networking_No 9.265198e-45
## Extension_services=Extension_services_No 3.499334e-47
## Amalgamation=Amalgamation_No 9.007620e-55
## Input_sourcing=Input_sourcing_No 6.780434e-61
## Output_marketing=Output_marketing_No 7.451905e-99
##
## $`Dim 2`
##
## Link between the variable and the categorical variable (1-way anova)
## =====
##
## R2 p.value
## Other_groups_trust 0.44237144 5.444182e-44
## Members_trust 0.41898240 6.888407e-41
## Membership_entry_criteria 0.32895500 2.903008e-32
## Credit_sourcing 0.26846825 1.213844e-25
## Savings 0.17710084 1.388858e-16
## Fine_imposing 0.11045901 1.501767e-10
## Registration 0.08442154 2.696940e-08
## Amalgamation 0.06834179 6.320707e-07
## Social_welfare 0.06299874 1.790691e-06
## Social_networking 0.05698263 5.766439e-06
## Members_Gender 0.03917388 9.179939e-04
## Input_sourcing 0.01633395 1.628037e-02
##
## Link between variable and the categories of the categorical variables
## =====
##
## Estimate
## Membership_entry_criteria=Open 0.341521782
## Members_trust=Members_trust_Agree somewhat 0.008623606
## Credit_sourcing=Credit_sourcing_No 0.203950130
## Savings=Savings_No 0.170600149
## Other_groups_trust=Other_groups_trust_Agree somewhat 0.127598406

```

## Fine_imposing=Fine_imposing_No	0.204389441
## Other_groups_trust=Other_groups_trust_Neither agree nor di	0.203873951
## Registration=Registration_No	0.167957739
## Amalgamation=Amalgamation_No	0.133303586
## Social_welfare=Social_welfare_Yes	0.096843598
## Social_networking=Social_networking_No	0.106380489
## Members_trust=Members_trust_Neither agree nor di	0.197832314
## Members_trust=Members_trust_Disagree strongly	0.337740897
## Members_Gender=Mixed	0.057828048
## Other_groups_trust=Other_groups_trust_Disagree strongly	0.052695692
## Input_sourcing=Input_sourcing_No	0.073878647
## Input_sourcing=Input_sourcing_Yes	-0.073878647
## Members_Gender=Females	-0.095935681
## Social_networking=Social_networking_Yes	-0.106380489
## Social_welfare=Social_welfare_No	-0.096843598
## Amalgamation=Amalgamation_Yes	-0.133303586
## Registration=Registration_Yes	-0.167957739
## Fine_imposing=Fine_imposing_Yes	-0.204389441
## Savings=Savings_Yes	-0.170600149
## Credit_sourcing=Credit_sourcing_Yes	-0.203950130
## Membership_entry_criteria=Closed	-0.341521782
## Members_trust=Members_trust_Agree strongly	-0.544196818
## Other_groups_trust=Other_groups_trust_Agree strongly	-0.384168050
##	p.value
## Membership_entry_criteria=Open	2.903008e-32
## Members_trust=Members_trust_Agree somewhat	4.380972e-28
## Credit_sourcing=Credit_sourcing_No	1.213844e-25
## Savings=Savings_No	1.388858e-16
## Other_groups_trust=Other_groups_trust_Agree somewhat	5.080135e-11
## Fine_imposing=Fine_imposing_No	1.501767e-10
## Other_groups_trust=Other_groups_trust_Neither agree nor di	4.319520e-10
## Registration=Registration_No	2.696940e-08
## Amalgamation=Amalgamation_No	6.320707e-07
## Social_welfare=Social_welfare_Yes	1.790691e-06
## Social_networking=Social_networking_No	5.766439e-06
## Members_trust=Members_trust_Neither agree nor di	2.126687e-05
## Members_trust=Members_trust_Disagree strongly	8.527705e-05
## Members_Gender=Mixed	2.518112e-04
## Other_groups_trust=Other_groups_trust_Disagree strongly	7.277928e-03
## Input_sourcing=Input_sourcing_No	1.628037e-02
## Input_sourcing=Input_sourcing_Yes	1.628037e-02
## Members_Gender=Females	1.834335e-04
## Social_networking=Social_networking_Yes	5.766439e-06
## Social_welfare=Social_welfare_No	1.790691e-06
## Amalgamation=Amalgamation_Yes	6.320707e-07
## Registration=Registration_Yes	2.696940e-08
## Fine_imposing=Fine_imposing_Yes	1.501767e-10
## Savings=Savings_Yes	1.388858e-16
## Credit_sourcing=Credit_sourcing_Yes	1.213844e-25
## Membership_entry_criteria=Closed	2.903008e-32
## Members_trust=Members_trust_Agree strongly	8.261470e-42
## Other_groups_trust=Other_groups_trust_Agree strongly	7.631914e-45

```

##
## $`Dim 3`
##
## Link between the variable and the categorical variable (1-way anova)
## =====
##               R2      p.value
## Other_groups_trust 0.41196874 5.544267e-40
## Members_trust      0.38380498 1.879904e-36
## Savings            0.12285869 1.215072e-11
## Credit_sourcing    0.11680116 4.165479e-11
## Fine_imposing      0.10036388 1.138992e-09
## Registration       0.09161999 6.493745e-09
## Amalgamation       0.02807864 1.580420e-03
## Social_welfare     0.02524140 2.758461e-03
## Output_marketing   0.02502666 2.877576e-03
##
## Link between variable and the categories of the categorical variables
## =====
##                                     Estimate
## Other_groups_trust=Other_groups_trust_Disagree strongly 0.283205453
## Members_trust=Members_trust_Disagree strongly          0.852375101
## Savings=Savings_No                                     0.113550357
## Credit_sourcing=Credit_sourcing_No                     0.107502253
## Fine_imposing=Fine_imposing_Yes                        0.155690837
## Registration=Registration_No                            0.139825045
## Amalgamation=Amalgamation_Yes                          0.068281517
## Social_welfare=Social_welfare_Yes                     0.048986704
## Output_marketing=Output_marketing_Yes                 0.062881079
## Other_groups_trust=Other_groups_trust_Agree strongly   0.001119880
## Other_groups_trust=Other_groups_trust_Neither agree nor di 0.036791068
## Members_trust=Members_trust_Neither agree nor di      -0.007048075
## Output_marketing=Output_marketing_No                  -0.062881079
## Social_welfare=Social_welfare_No                      -0.048986704
## Amalgamation=Amalgamation_No                          -0.068281517
## Registration=Registration_Yes                          -0.139825045
## Members_trust=Members_trust_Agree strongly            -0.247620685
## Fine_imposing=Fine_imposing_No                       -0.155690837
## Credit_sourcing=Credit_sourcing_Yes                  -0.107502253
## Savings=Savings_Yes                                    -0.113550357
## Members_trust=Members_trust_Agree somewhat            -0.597706340
## Other_groups_trust=Other_groups_trust_Agree somewhat  -0.321116401
##                                                         p.value
## Other_groups_trust=Other_groups_trust_Disagree strongly 8.331720e-18
## Members_trust=Members_trust_Disagree strongly          5.102758e-15
## Savings=Savings_No                                     1.215072e-11
## Credit_sourcing=Credit_sourcing_No                     4.165479e-11
## Fine_imposing=Fine_imposing_Yes                        1.138992e-09
## Registration=Registration_No                            6.493745e-09
## Amalgamation=Amalgamation_Yes                          1.580420e-03
## Social_welfare=Social_welfare_Yes                     2.758461e-03
## Output_marketing=Output_marketing_Yes                 2.877576e-03
## Other_groups_trust=Other_groups_trust_Agree strongly   2.262773e-02

```



```
## Other_groups_trust=Other_groups_trust_Neither agree nor di 3.140459e-02
## Members_trust=Members_trust_Neither agree nor di 1.102890e-02
## Output_marketing=Output_marketing_No 2.877576e-03
## Social_welfare=Social_welfare_No 2.758461e-03
## Amalgamation=Amalgamation_No 1.580420e-03
## Registration=Registration_Yes 6.493745e-09
## Members_trust=Members_trust_Agree strongly 2.547389e-09
## Fine_imposing=Fine_imposing_No 1.138992e-09
## Credit_sourcing=Credit_sourcing_Yes 4.165479e-11
## Savings=Savings_Yes 1.215072e-11
## Members_trust=Members_trust_Agree somewhat 7.995338e-22
## Other_groups_trust=Other_groups_trust_Agree somewhat 2.638512e-31
```

Cronbach test

Please note that while Cronbach's alpha is commonly used for assessing the internal consistency of variables measured on a numerical scale, it can also be applied to factor scores derived from MCA as an approximate measure of internal consistency. However, keep in mind that MCA deals with categorical data, and Cronbach's alpha may not be the most appropriate measure in this context.

This coefficient represents the internal consistency reliability of the factor scores. It ranges from 0 to 1, with higher values indicating greater internal consistency. Generally, a Cronbach's alpha value above 0.6 is considered acceptable.

##Cronbach test for the dimensions

```
##cronbach test of dimensions
factor_scores <- res.mca1$ind$coord
alpha_result <- alpha(factor_scores, check.keys = TRUE)
alpha_result
```

```
##
## Reliability analysis
## Call: alpha(x = factor_scores, check.keys = TRUE)
##
##   raw_alpha std.alpha G6(smc) average_r   S/N   ase mean   sd median_r
##   1.4e-15   1.9e-15 1.8e-15    4e-16 2e-15 0.081 0.15 0.17  2.5e-16
##
##   95% confidence boundaries
##           lower alpha upper
## Feldt    -0.17     0  0.16
## Duhachek -0.16     0  0.16
##
## Reliability if an item is dropped:
##           raw_alpha std.alpha G6(smc) average_r   S/N alpha se   var.r   med.r
## Dim 1-    1.6e-15   1.8e-15 1.4e-15    4.4e-16 1.8e-15   0.086 2.5e-31  4.1e-16
## Dim 2     1.9e-15   2.4e-15 1.9e-15    5.9e-16 2.4e-15   0.082 3.6e-31  5.7e-16
## Dim 3-    1.0e-15   1.5e-15 1.2e-15    3.7e-16 1.5e-15   0.083 4.9e-31  9.1e-17
## Dim 4     1.5e-15   1.5e-15 1.1e-15    3.7e-16 1.5e-15   0.083 3.0e-31  2.5e-16
## Dim 5     3.0e-16   5.9e-16 4.4e-16    1.5e-16 5.9e-16   0.083 2.2e-31 -3.5e-17
##
## Item statistics
##           n raw.r std.r   r.cor r.drop   mean   sd
## Dim 1- 353  0.63  0.45 1.4e-08 5.0e-16 3.8e-01 0.52
## Dim 2  353  0.47  0.45 6.1e-09 9.8e-17 1.1e-16 0.39
## Dim 3- 353  0.37  0.45 2.3e-08 7.0e-16 3.8e-01 0.31
## Dim 4  353  0.36  0.45 1.6e-08 4.8e-16 4.7e-17 0.30
## Dim 5  353  0.34  0.45 3.2e-08 1.5e-15 3.1e-17 0.28
```

##Cronbach test for the variables

```
##cronbach test of variables
variables<-my_data[,]
variables <- na.omit(variables) # Remove rows with missing values
variables1 <- lapply(variables, factor)

##correlation matrix of the variables
cor_matrix <- hetcor(variables1, method = "polychoric", use = "pairwise.complete.obs")$correlations
cor_matrix <- as.matrix(cor_matrix,check.keys = TRUE)

##calculate the output from the diagonals of the correlation matrix
cov_matrix <- cor_matrix * outer(sqrt(diag(cor_matrix))), sqrt(diag(cor_matrix)))

##replace any missing values in the correlation matrix with zero
cov_matrix[is.na(cov_matrix)] <- 0

##get the results of the cronbach test
alpha_result_var <- alpha(cov_matrix,check.keys = TRUE)
alpha_result_var
```

```
##
## Reliability analysis
## Call: alpha(x = cov_matrix, check.keys = TRUE)
##
##   raw_alpha std.alpha G6(smc) average_r S/N median_r
##       0.84      0.84      0.9      0.26 5.4      0.23
##
##   95% confidence boundaries
##       lower alpha upper
## Feldt  0.7  0.84  0.94
##
## Reliability if an item is dropped:
##               raw_alpha std.alpha G6(smc) average_r S/N var.r med.r
## variables1          0.84      0.84      0.90      0.27 5.3 0.073 0.25
## Membership_entry_criteria 0.86      0.86      0.91      0.30 5.9 0.072 0.26
## Members_Gender          0.82      0.82      0.89      0.24 4.5 0.079 0.20
## Amalgamation            0.82      0.82      0.88      0.25 4.6 0.071 0.23
## Social_networking        0.83      0.83      0.88      0.25 4.8 0.074 0.23
## Input_sourcing           0.81      0.81      0.98      0.23 4.3 0.066 0.21
## Output_marketing         0.80      0.80      0.87      0.23 4.1 0.065 0.21
## Extension_services       0.82      0.82      0.88      0.24 4.4 0.074 0.21
## Credit_sourcing-        0.85      0.85      0.91      0.28 5.5 0.079 0.26
## Savings-                0.83      0.83      0.89      0.26 4.9 0.082 0.23
## Social_welfare-         0.83      0.83      0.92      0.27 5.0 0.078 0.23
## Fine_imposing-          0.83      0.83      0.91      0.26 5.0 0.084 0.21
## Members_trust-          0.84      0.84      0.91      0.28 5.3 0.086 0.26
## Other_groups_trust-     0.85      0.85      0.91      0.28 5.5 0.084 0.27
## method                  0.86      0.86      0.91      0.30 6.1 0.076 0.29
##
## Item statistics
##               r r.cor r.drop
## variables1      0.44 0.46 0.332
## Membership_entry_criteria 0.19 0.13 0.073
## Members_Gender   0.77 0.77 0.717
## Amalgamation     0.75 0.77 0.686
## Social_networking 0.66 0.65 0.583
## Input_sourcing    0.87 0.79 0.834
## Output_marketing  0.96 1.02 0.952
## Extension_services 0.80 0.82 0.754
## Credit_sourcing-  0.34 0.25 0.226
## Savings-          0.59 0.55 0.507
## Social_welfare-   0.54 0.57 0.447
## Fine_imposing-    0.56 0.51 0.466
## Members_trust-    0.43 0.36 0.327
## Other_groups_trust- 0.37 0.30 0.258
## method            0.12 0.00 0.000
```

Variable clustering

```

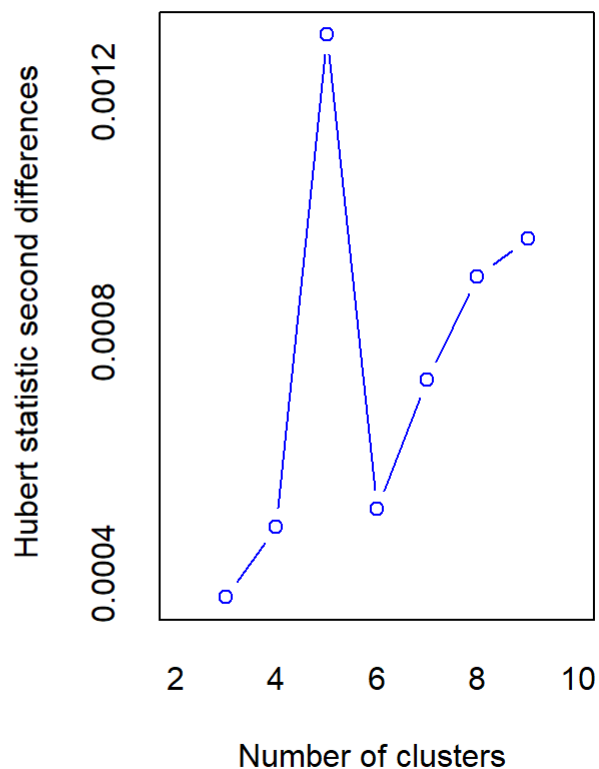
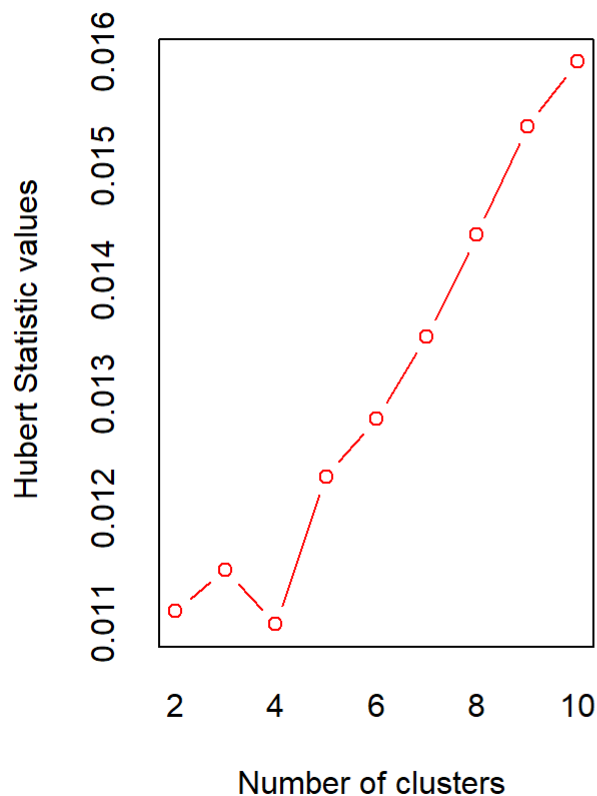
# Extract MCA coordinates of the individuals
mca_coords <- res.mca1$ind$coord

# Load the NbClust package
library(NbClust)

# Set the number of repetitions for stability analysis
set.seed(123) # for reproducibility
num_reps <- 10

# Compute the optimal number of clusters using NbClust
nbclust_result <- NbClust(mca_coords, diss = NULL, min.nc = 2, max.nc = 10,
                          method = "kmeans", index = "all", alphaBeale = 0.1)

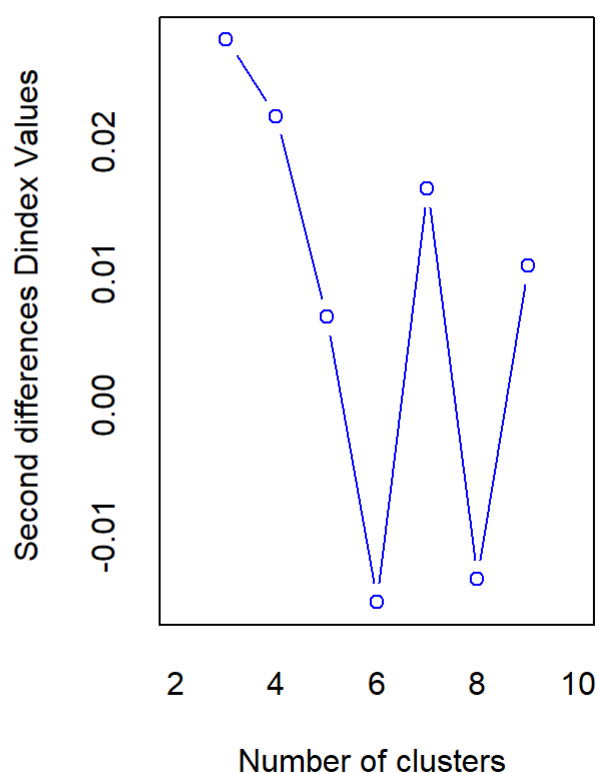
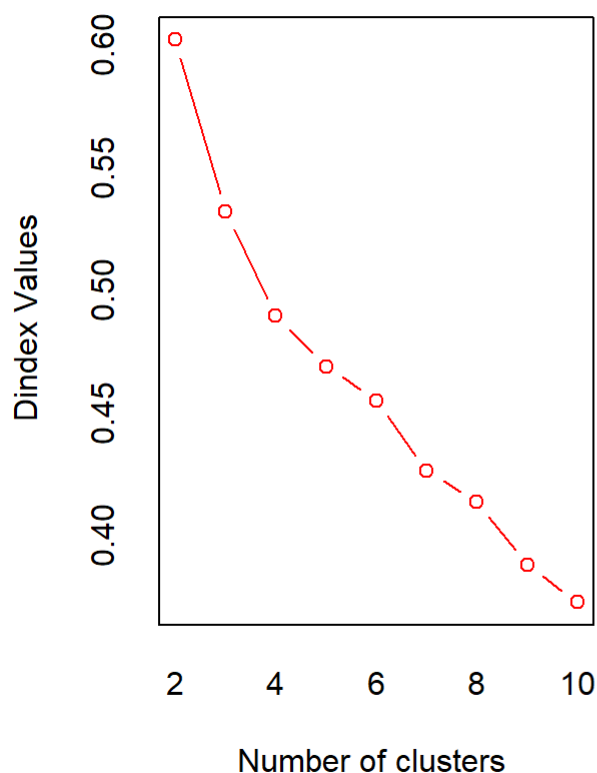
```



```

## *** : The Hubert index is a graphical method of determining the number of clusters.
##           In the plot of Hubert index, we seek a significant knee that corresponds to a
##           significant increase of the value of the measure i.e the significant peak in
Hubert
##           index second differences plot.
##

```



```
## *** : The D index is a graphical method of determining the number of clusters.
##           In the plot of D index, we seek a significant knee (the significant peak in D
index
##           second differences plot) that corresponds to a significant increase of the va
lue of
##           the measure.
##
## *****
## * Among all indices:
## * 9 proposed 2 as the best number of clusters
## * 6 proposed 3 as the best number of clusters
## * 2 proposed 5 as the best number of clusters
## * 1 proposed 6 as the best number of clusters
## * 1 proposed 8 as the best number of clusters
## * 2 proposed 9 as the best number of clusters
## * 3 proposed 10 as the best number of clusters
##
##           ***** Conclusion *****
##
## * According to the majority rule, the best number of clusters is  2
##
##
## *****
```

```
# Get the optimal number of clusters based on the majority rule
```

```
optimal_clusters <- nbclust_result$Best.nc[1]
```

```
# Print the optimal number of clusters
```

```
cat("Optimal number of clusters:", optimal_clusters, "\n")
```

```
## Optimal number of clusters: 2
```

```
##more parameters related to clusters
```

```
Index<-nbclust_result$All.index
```

```
Index
```

```
##      KL      CH Hartigan      CCC      Scott      Marriot      TrCovW      TraceW
## 2  2.9006 159.4464  76.8683  0.9383  551.9975 120794838 1213.8749 165.1626
## 3  1.5565 135.2302  52.1119  1.0091  897.9486 102001977  855.4002 135.4905
## 4  0.5575 120.6016  49.7556  2.0673 1124.7035  95391673  545.6230 117.9315
## 5  2.2659 115.4536  33.9127  3.8917 1375.1075  73326258  416.9826 103.2164
## 6  0.5798 107.8355  35.4355  4.5458 1541.5392  65896396  393.5751  94.0510
## 7  0.4287 104.6431  52.6573  5.9088 1692.8733  58421081  291.3604  85.3365
## 8  1.1991 110.5466  46.7887  9.9297 1978.3050  33992878  196.7579  74.0647
## 9  2.5655 115.3598  26.8572 13.2905 2282.4206  18177781  142.0996  65.2196
## 10 2.3762 113.2019  18.4372 14.2098 2367.5629  17632162  124.5248  60.4965
##      Friedman  Rubin Cindex      DB Silhouette      Duda Pseudot2      Beale  Ratkowsky
## 2    3.7207  1.4543  0.2652  1.1589      0.4279  2.7595 -95.0054 -1.9629      0.1464
## 3    5.1233  1.7727  0.2177  1.6454      0.3186  1.0054  -0.8174 -0.0165      0.2464
## 4    6.1588  2.0367  0.2238  1.5355      0.2846  0.7481  34.6846  1.0436      0.2674
## 5    7.0857  2.3271  0.1859  1.4944      0.3298  1.3358 -16.5917 -0.7720      0.2963
## 6    8.0231  2.5538  0.2203  1.4275      0.2876  2.2264 -55.6355 -1.6881      0.2967
## 7    9.0132  2.8146  0.2201  1.3625      0.2750  0.5715  89.9805  2.3113      0.2843
## 8   12.5536  3.2430  0.2231  1.2841      0.2345  1.0475  -2.3592 -0.1392      0.2802
## 9   15.4184  3.6828  0.2138  1.2319      0.2436  2.0697 -31.5267 -1.5800      0.2759
## 10  16.0251  3.9703  0.2095  1.1811      0.2549  1.8915 -31.5787 -1.4431      0.2661
##      Ball Ptbiserial      Frey McClain      Dunn Hubert SDindex Dindex      SDbw
## 2  82.5813      0.5672  1.4298  0.2296  0.0607  0.0111  5.3971  0.6019  0.7482
## 3  45.1635      0.5567  2.6350  0.7303  0.0547  0.0115  5.9872  0.5318  0.7267
## 4  29.4829      0.4692 -0.3894  1.2682  0.0591  0.0110  5.7107  0.4894  0.5714
## 5  20.6433      0.5812  2.9628  1.0752  0.0583  0.0123  5.9558  0.4689  0.6958
## 6  15.6752      0.5272  4.6488  1.3948  0.0773  0.0128  6.1712  0.4550  0.6633
## 7  12.1909      0.4570 -0.1565  1.9637  0.0723  0.0135  6.0093  0.4261  0.4415
## 8   9.2581      0.4785  0.8299  1.8896  0.0773  0.0144  7.6336  0.4136  0.4567
## 9   7.2466      0.4516  0.8397  2.2376  0.0756  0.0153  7.0906  0.3879  0.3414
## 10  6.0496      0.4241  0.5066  2.6448  0.0782  0.0159  6.8390  0.3727  0.2957
```

```
##critical values
```

```
cric_val<-nbclust_result$All.CriticalValues
```

```
cric_val
```

##	CritValue_Duda	CritValue_PseudoT2	Fvalue_Beale
## 2	0.6374	84.7619	1.0000
## 3	0.6836	70.8151	1.0000
## 4	0.6901	46.2456	0.3912
## 5	0.6206	40.3531	1.0000
## 6	0.6080	65.1117	1.0000
## 7	0.6463	65.6580	0.0439
## 8	0.6133	32.7920	1.0000
## 9	0.5934	41.7988	1.0000
## 10	0.6025	44.2121	1.0000

```
##best partition  
best_part<-nbclust_result$Best.partition  
best_part
```

```
## 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
## 2 1 2 2 2 2 2 1 2 1 2 2 2 2 2 1 1 2 1 2
## 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40
## 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60
## 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80
## 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99 100
## 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120
## 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## 121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140
## 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2
## 141 142 143 144 145 146 147 148 149 150 151 152 153 154 155 156 157 158 159 160
## 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2
## 161 162 163 164 165 166 167 168 169 170 171 172 173 174 175 176 177 178 179 180
## 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## 181 182 183 184 185 186 187 188 189 190 191 192 193 194 195 196 197 198 199 200
## 2 2 2 2 2 2 2 2 2 2 2 1 1 2 1 2 2 2 2
## 201 202 203 204 205 206 207 208 209 210 211 212 213 214 215 216 217 218 219 220
## 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2
## 221 222 223 224 225 226 227 228 229 230 231 232 233 234 235 236 237 238 239 240
## 2 2 2 2 2 2 2 2 2 2 1 1 1 2 1 1 2 2 1
## 241 242 243 244 245 246 247 248 249 250 251 252 253 254 255 256 257 258 259 260
## 1 2 1 2 2 1 1 1 1 2 1 2 2 2 2 1 1 2 2 2
## 261 262 263 264 265 266 267 268 269 270 271 272 273 274 275 276 277 278 279 280
## 2 2 2 2 2 2 1 1 1 1 1 1 1 1 1 2 2 1 1
## 281 282 283 284 285 286 287 288 289 290 291 292 293 294 295 296 297 298 299 300
## 1 1 1 1 1 2 1 2 2 1 1 2 2 2 2 2 2 2 2
## 301 302 303 304 305 306 307 308 309 310 311 312 313 314 315 316 317 318 319 320
## 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 1
## 321 322 323 324 325 326 327 328 329 330 331 332 333 334 335 336 337 338 339 340
## 1 2 1 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 1
## 341 342 343 344 345 346 347 348 349 350 351 352 353
## 1 2 2 2 2 2 2 2 1 2 2 1 2
```

```
##get the metrics
metrics<-nbclust_result$Best.nc
metrics
```


##	KL	CH	Hartigan	CCC	Scott	Marriot	TrCovW
## Number_clusters	2.0000	2.0000	3.0000	10.0000	3.0000	9	3.0000
## Value_Index	2.9006	159.4464	24.7564	14.2098	345.9511	15269476	358.4747
##	TraceW	Friedman	Rubin	Cindex	DB	Silhouette	Duda
## Number_clusters	3.0000	8.0000	9.0000	5.0000	2.0000	2.0000	2.0000
## Value_Index	12.1132	3.5404	-0.1523	0.1859	1.1589	0.4279	2.7595
##	PseudoT2	Beale	Ratkowsky	Ball	PtBiserial	Frey	McClain
## Number_clusters	2.0000	2.0000	6.0000	3.0000	5.0000	3.000	2.0000
## Value_Index	-95.0054	-1.9629	0.2967	37.4178	0.5812	2.635	0.2296
##	Dunn	Hubert	SDindex	Dindex	SDbw		
## Number_clusters	10.0000	0	2.0000	0	10.0000		
## Value_Index	0.0782	0	5.3971	0	0.2957		

The best number of clusters is 2 according to the majority rule. The values associated with the metrics are also shown in the output above.

The above output shows the different metrics which are measures used to assess the quality of the MCA solution. These metrics are typically used to determine the number of dimensions (components) to retain in the analysis. To explain a few;

*KL (Kaiser-Like criterion): KL is based on the eigenvalues of the MCA solution. It considers the proportion of variance explained by each dimension and compares it to a random expectation. The KL criterion suggests retaining dimensions that explain more variance than would be expected by chance.

*CH (Cattell-Horn criterion): CH is also based on the eigenvalues of the MCA solution. It compares the eigenvalues of the observed data to the eigenvalues of a simulated random dataset. The CH criterion recommends retaining dimensions with eigenvalues larger than those obtained from the random dataset.

*Hartigan: The Hartigan criterion is based on the eigenvalues of the MCA solution. It compares the observed eigenvalues to a null distribution obtained by random permutations of the original data. The Hartigan criterion suggests retaining dimensions with eigenvalues that are significantly larger than the expected values under the null distribution.

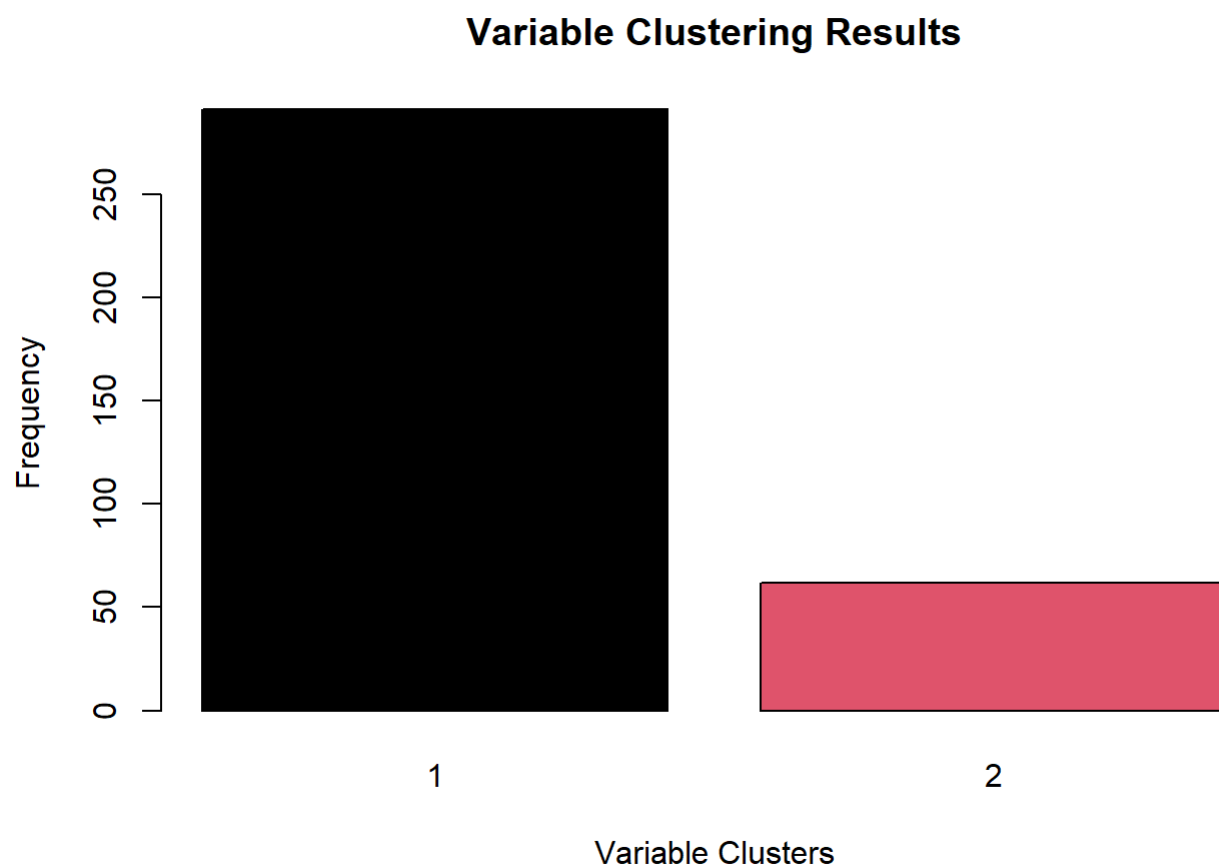
These metrics provide different approaches to determine the appropriate number of dimensions to retain in MCA. Researchers typically compare these metrics and consider other factors such as interpretability and the specific research question to make a final decision on the number of dimensions to retain in the analysis.

K-means clustering

K-means clustering is a popular unsupervised machine learning algorithm used for partitioning a dataset into K distinct clusters. It is a simple yet effective algorithm that aims to group similar data points together based on their feature similarities. K-means clustering is widely used in various fields for tasks such as customer segmentation, image compression, anomaly detection, and recommendation systems. However, it has some limitations, such as sensitivity to the initial centroid selection and being prone to converging to local optima. Several variations and improvements to the basic K-means algorithm have been proposed to address these limitations.

```
# Perform K-means clustering on the MCA coordinates of variables
set.seed(123) # for reproducibility
kmeans_result <- kmeans(mca_coords, centers = optimal_clusters)
variable_cluster_assignments <- kmeans_result$cluster

# Create a bar plot of the variable clustering results
barplot(table(variable_cluster_assignments), col = 1:optimal_clusters,
        xlab = "Variable Clusters", ylab = "Frequency", main = "Variable Clustering Results")
```



The optimal number of clusters is 2 and hence the analysis continues to investigate the variables contributing to the two clusters.

Dendrogram

Dendrogram is a tree that is used to visualize the objects in the different clusters.

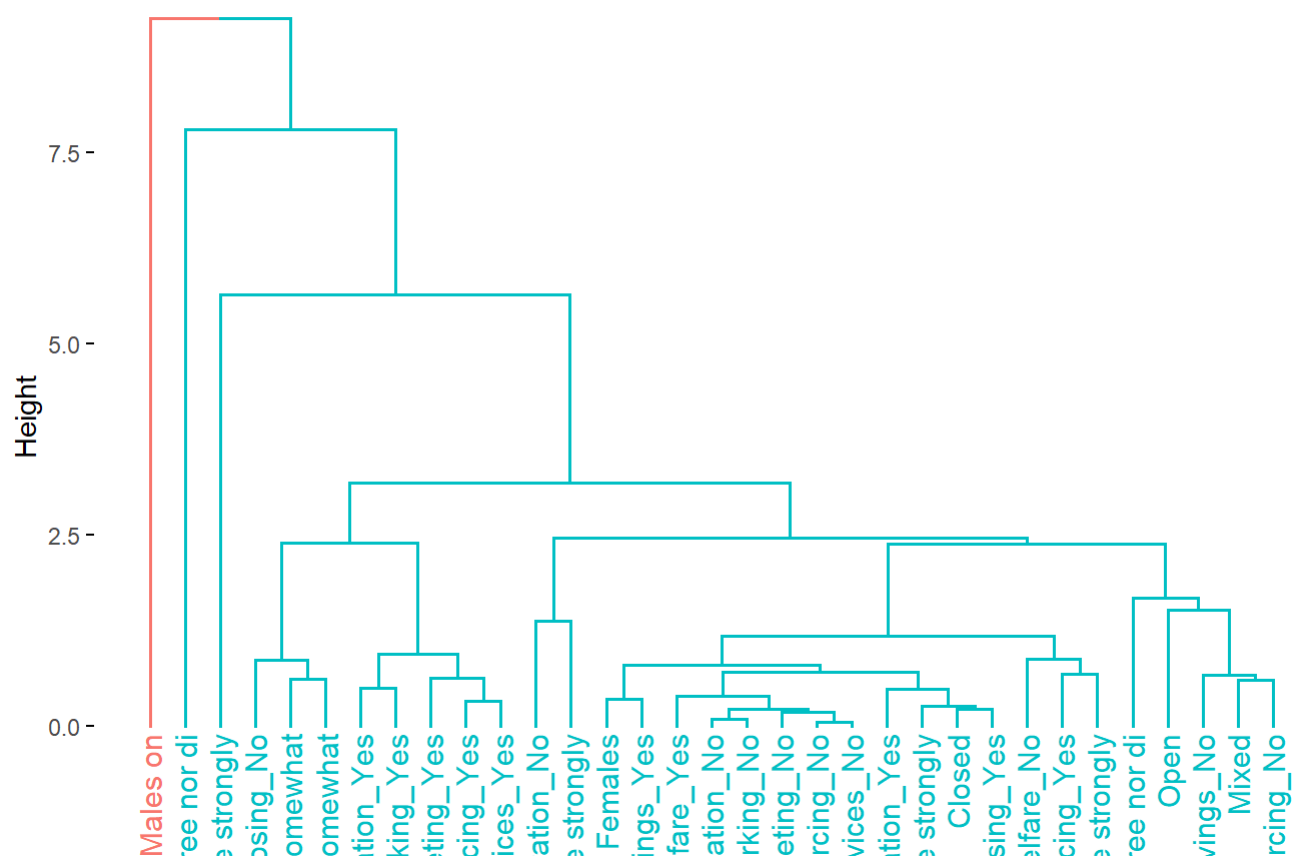
```
# Extract coordinates of categories
coord <- res.mca1$var$coord

# Perform variable clustering using MCA results
hc <- hclust(dist(coord))

clustering_res <- cutree(hc,k=2) # Adjust the number of clusters as needed

# Plot variable clustering dendrogram
fviz_dend(hc, k = 2, cex = 0.8)
```

Cluster Dendrogram



Finding the clusters

```

# Extract MCA coordinates of the variables
mca_coords <- res.mca1$var$coord

# Perform K-means clustering on the MCA coordinates of variables
k <- optimal_clusters
set.seed(123) # for reproducibility
kmeans_result <- kmeans(mca_coords, centers = k)
variable_cluster_assignments <- kmeans_result$cluster

# Create a data frame with variable names and their cluster assignments
variable_clusters <- data.frame(Variable = rownames(mca_coords), Cluster = variable_cluster_assignments)

# Compute summary statistics by cluster
summary_stats <- aggregate(Variable ~ Cluster, data = variable_clusters, FUN = function(x) paste(unique(x), collapse = ", "))

# Print the summary statistics
data.table(summary_stats)

```

```

##      Cluster
## 1:         1
## 2:         2
##
Variable
## 1: Registration_Yes, Closed, Open, Females, Males on, Mixed, Amalgamation_No, Social_networking_No, Input_sourcing_No, Output_marketing_No, Extension_services_No, Credit_sourcing_No, Credit_sourcing_Yes, Savings_No, Savings_Yes, Social_welfare_No, Social_welfare_Yes, Fine_imposing_Yes, Members_trust_Agree somewhat, Members_trust_Agree strongly, Members_trust_Neither agree nor disagree, Other_groups_trust_Agree somewhat, Other_groups_trust_Agree strongly, Other_groups_trust_Neither agree nor disagree
## 2:
Registration_No, Amalgamation_Yes, Social_networking_Yes, Input_sourcing_Yes, Output_marketing_Yes, Extension_services_Yes, Fine_imposing_No, Members_trust_Disagree strongly, Other_groups_trust_Disagree strongly

```

The clusters are shown in the results above and the analysis continues to check the summary statistics of the clusters.

Summary statistics of the clusters

```

# Assuming you have performed MCA and obtained the MCA results in 'mca_result'
# Assuming you have obtained the cluster membership in 'cluster_membership'
# Perform variable clustering using k-means algorithm on MCA results
num_clusters <- 2 # Specify the number of clusters
clusters <- kmeans(res.mca1$var$coord, centers = num_clusters)

# Cluster membership of each variable
cluster_membership <- clusters$cluster
# Combine cluster membership and variable coordinates
data <- data.frame(cluster_membership, res.mca1$var$coord)

# Calculate mean and standard deviation of variables in each cluster
means <- aggregate(. ~ cluster_membership, data, FUN = mean)
# Calculate standard deviation for clusters with at least 2 non-NA values
sds <- aggregate(. ~ cluster_membership, data, FUN = function(x) {
  if (sum(!is.na(x)) >= 2) {
    sd(x, na.rm = TRUE)
  } else {
    0
  }
})

# Print the means and standard deviations
print("Means:")

```

```
## [1] "Means:"
```

```
print(means)
```

```
##   cluster_membership   Dim.1   Dim.2   Dim.3   Dim.4   Dim.5
## 1                1 -0.06810927 0.1887170 -0.0309520 -0.2580567 0.2090524
## 2                2  0.93271412 0.2655841  0.5996715  0.6124942 -0.2872791
```

```
print("Standard Deviations:")
```

```
## [1] "Standard Deviations:"
```

```
print(sds)
```

```
##   cluster_membership   Dim.1   Dim.2   Dim.3   Dim.4   Dim.5
## 1                1  0.3725776 0.5961527 0.3874165 0.9429293 1.3836601
## 2                2  0.9590055 0.8187519 1.3042628 0.9366201 0.4189032
```

The mean and standard deviation of variables in both cluster 1 and cluster 2 are as shown in the output above. However the standard deviation for the variables in cluster 2 are all zeros. If a cluster has fewer than 2 non-missing values, the standard deviation is set to 0.

```

# Extract the coordinates of the individuals from the MCA results
individual_coordinates <- res.mca1$ind$coord

# Perform K-means clustering on the individual coordinates
k <- 2 # Number of clusters
clusters <- kmeans(individual_coordinates, centers = k)

# Get the cluster assignments for each individual
individual_clusters <- clusters$cluster

# Combine individual cluster assignments with the original dataframe
data <- data.frame(individual_clusters, my_data)

# Combine individual cluster assignments with the original dataframe
data <- data.frame(individual_clusters, my_data)
# Convert all variables to factors
data <- data %>%
  mutate_all(as.factor)

##write out the csv file
write.csv(data,"clustered_data.csv")

```

Summary statistics of variables

```

# Group by the grouping column and calculate the proportion of each factor level
##Registration
data %>%
  count(individual_clusters, Registration) %>%
  group_by(individual_clusters) %>%
  mutate(proportion = n / sum(n))

```

```

## # A tibble: 4 × 4
## # Groups:   individual_clusters [2]
##   individual_clusters Registration    n proportion
##   <fct>          <fct>      <int>      <dbl>
## 1 1            No           1      0.0161
## 2 1            Yes          61      0.984
## 3 2            No          44      0.151
## 4 2            Yes         247      0.849

```

```

# Print the summary statistics
print(summary_stats)

```

```
## Cluster
## 1      1
## 2      2
##
Variable
## 1 Registration_Yes, Closed, Open, Females, Males on, Mixed, Amalgamation_No, Social_networkin
g_No, Input_sourcing_No, Output_marketing_No, Extension_services_No, Credit_sourcing_No, Credit_
sourcing_Yes, Savings_No, Savings_Yes, Social_welfare_No, Social_welfare_Yes, Fine_imposing_Yes,
Members_trust_Agree somewhat, Members_trust_Agree strongly, Members_trust_Neither agree nor di,
Other_groups_trust_Agree somewhat, Other_groups_trust_Agree strongly, Other_groups_trust_Neither
agree nor di
## 2
Registration_No, Amalgamation_Yes, Social_networking_Yes, Input_sourcing_Yes, Output_marketing_Y
es, Extension_services_Yes, Fine_imposing_No, Members_trust_Disagree strongly, Other_groups_trus
t_Disagree strongly
```

```
##membership entry criteria
```

```
data %>%
  count(individual_clusters,Membership_entry_criteria) %>%
  mutate(proportion = n / sum(n))
```

```
## individual_clusters Membership_entry_criteria  n proportion
## 1              1          Closed  54 0.15297450
## 2              1           Open   8 0.02266289
## 3              2          Closed 257 0.72804533
## 4              2           Open  34 0.09631728
```

```
##Members gender
```

```
data %>%
  count(individual_clusters,Members_Gender) %>%
  mutate(proportion = n / sum(n))
```

```
## individual_clusters Members_Gender  n proportion
## 1              1      Females   1 0.002832861
## 2              1      Mixed   61 0.172804533
## 3              2      Females 191 0.541076487
## 4              2      Males on   5 0.014164306
## 5              2      Mixed   95 0.269121813
```

```
##Amalgamation
```

```
data %>%
  count(individual_clusters,Amalgamation) %>%
  mutate(proportion = n / sum(n))
```

```
## individual_clusters Amalgamation n proportion
## 1 1 No 19 0.05382436
## 2 1 Yes 43 0.12181303
## 3 2 No 273 0.77337110
## 4 2 Yes 18 0.05099150
```

##socialnetworking

```
data %>%
  count(individual_clusters,Social_networking) %>%
  mutate(proportion = n / sum(n))
```

```
## individual_clusters Social_networking n proportion
## 1 1 No 16 0.04532578
## 2 1 Yes 46 0.13031161
## 3 2 No 249 0.70538244
## 4 2 Yes 42 0.11898017
```

##input sourcing

```
data %>%
  count(individual_clusters,Input_sourcing) %>%
  mutate(proportion = n / sum(n))
```

```
## individual_clusters Input_sourcing n proportion
## 1 1 No 24 0.06798867
## 2 1 Yes 38 0.10764873
## 3 2 No 284 0.80453258
## 4 2 Yes 7 0.01983003
```

##Output marketing

```
data %>%
  count(individual_clusters,Output_marketing) %>%
  mutate(proportion = n / sum(n))
```

```
## individual_clusters Output_marketing n proportion
## 1 1 No 6 0.01699717
## 2 1 Yes 56 0.15864023
## 3 2 No 282 0.79886686
## 4 2 Yes 9 0.02549575
```

##Extension services

```
data %>%
  count(individual_clusters,Extension_services) %>%
  mutate(proportion = n / sum(n))
```



```
## individual_clusters Extension_services n proportion
## 1 1 No 27 0.07648725
## 2 1 Yes 35 0.09915014
## 3 2 No 282 0.79886686
## 4 2 Yes 9 0.02549575
```

```
##credit sourcing
data %>%
  count(individual_clusters,Credit_sourcing) %>%
  mutate(proportion = n / sum(n))
```

```
## individual_clusters Credit_sourcing n proportion
## 1 1 No 47 0.13314448
## 2 1 Yes 15 0.04249292
## 3 2 No 165 0.46742210
## 4 2 Yes 126 0.35694051
```

```
##savings
data %>%
  count(individual_clusters,Savings) %>%
  mutate(proportion = n / sum(n))
```

```
## individual_clusters Savings n proportion
## 1 1 No 45 0.12747875
## 2 1 Yes 17 0.04815864
## 3 2 No 77 0.21813031
## 4 2 Yes 214 0.60623229
```

```
##social welfare
data %>%
  count(individual_clusters,Social_welfare) %>%
  mutate(proportion = n / sum(n))
```

```
## individual_clusters Social_welfare n proportion
## 1 1 No 57 0.16147309
## 2 1 Yes 5 0.01416431
## 3 2 No 113 0.32011331
## 4 2 Yes 178 0.50424929
```

```
##fine imposing
data %>%
  count(individual_clusters,Fine_imposing) %>%
  mutate(proportion = n / sum(n))
```

```
## individual_clusters Fine_imposing n proportion
## 1 1 No 19 0.05382436
## 2 1 Yes 43 0.12181303
## 3 2 No 20 0.05665722
## 4 2 Yes 271 0.76770538
```

```
##members trust
data %>%
  count(individual_clusters,Members_trust) %>%
  mutate(proportion = n / sum(n))
```

```
## individual_clusters Members_trust n proportion
## 1 1 Agree somewhat 22 0.062322946
## 2 1 Agree strongly 39 0.110481586
## 3 1 Disagree strongly 1 0.002832861
## 4 2 Agree somewhat 48 0.135977337
## 5 2 Agree strongly 233 0.660056657
## 6 2 Disagree strongly 3 0.008498584
## 7 2 Neither agree nor di 7 0.019830028
```

```
##other groups trust
data %>%
  count(individual_clusters,Other_groups_trust) %>%
  mutate(proportion = n / sum(n))
```

```
## individual_clusters Other_groups_trust n proportion
## 1 1 Agree somewhat 26 0.07365439
## 2 1 Agree strongly 27 0.07648725
## 3 1 Disagree strongly 5 0.01416431
## 4 1 Neither agree nor di 4 0.01133144
## 5 2 Agree somewhat 74 0.20963173
## 6 2 Agree strongly 118 0.33427762
## 7 2 Disagree strongly 46 0.13031161
## 8 2 Neither agree nor di 53 0.15014164
```

The proportions of each variable in the different clusters is shown in the outputs above.