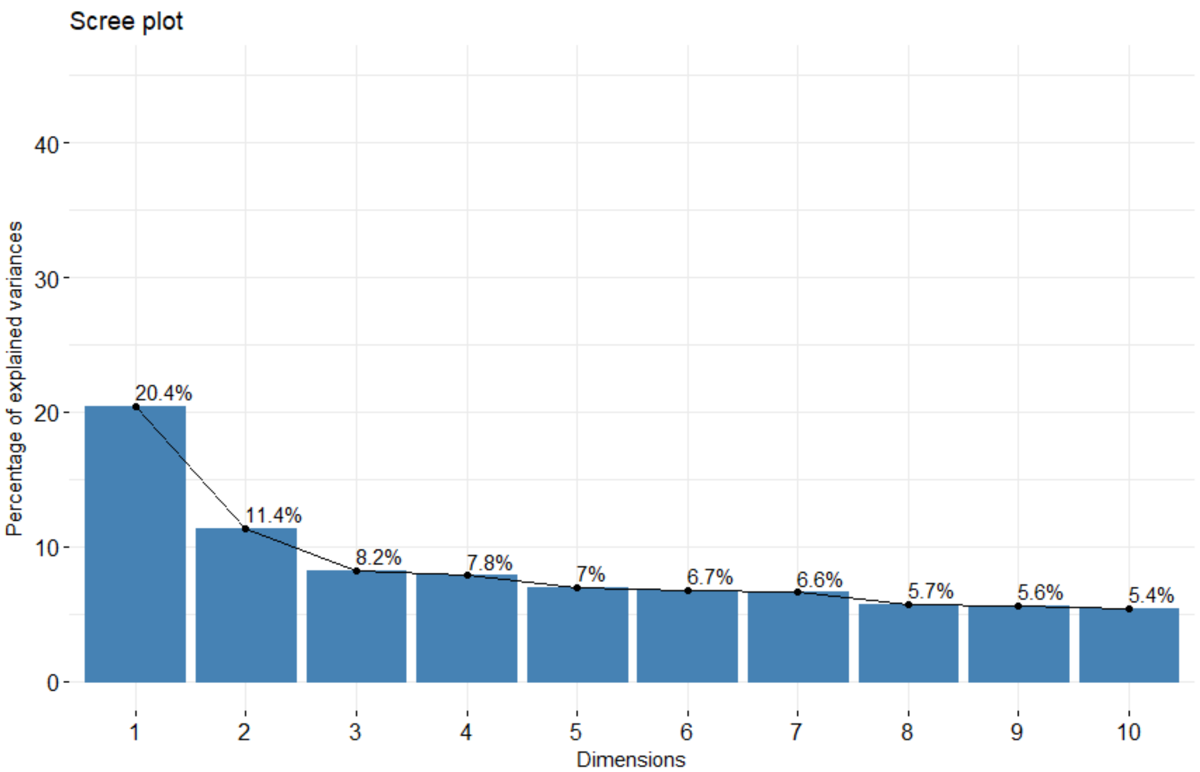
This sample R code includes MCA analysis. However, I have not attached sample dataset and just showed the plots.

##

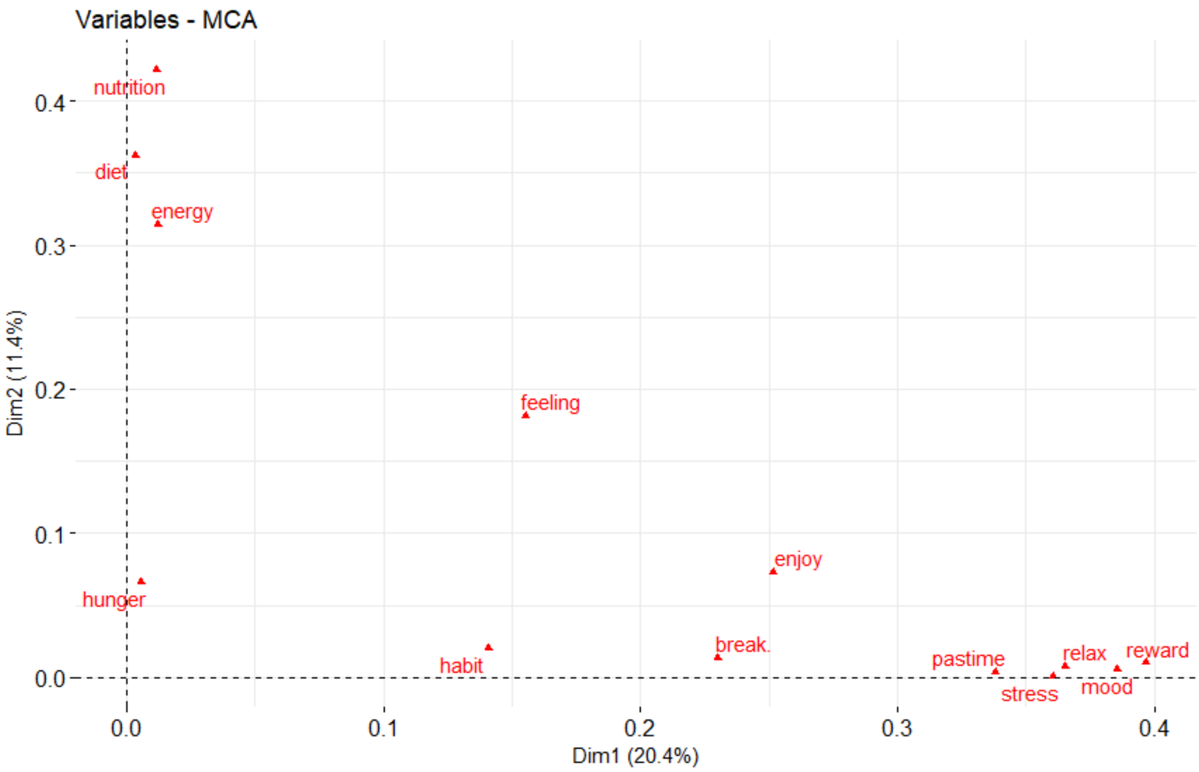
```
# Loading the packages
library("FactoMineR")
library("factoextra")
library("corrplot")

setwd("C:\\Aarhus\\Internship\\Morten\\17\\Data")

# 1 - Reason
d <- read.csv("purchase_reason_R.csv",sep = ",",header=T)
head(d[, 1:14], 3)

d.active <- d[, 1:14]

d.active$break. <- as.factor(d.active$break.)
d.active$diet <- as.factor(d.active$diet)
d.active$energy <- as.factor(d.active$energy)
d.active$enjoy <- as.factor(d.active$enjoy)
d.active$feeling <- as.factor(d.active$feeling)
d.active$habit <- as.factor(d.active$habit)
d.active$hunger <- as.factor(d.active$hunger)
d.active$mood <- as.factor(d.active$mood)
d.active$nutrition <- as.factor(d.active$nutrition)
d.active$other <- as.factor(d.active$other)
d.active$pastime <- as.factor(d.active$pastime)
d.active$relax <- as.factor(d.active$relax)
d.active$reward <- as.factor(d.active$reward)
d.active$stress <- as.factor(d.active$stress)

head(d.active, 3)

# Summary of all variables
summary(d.active)[, 1:14]

# Plotting the frequency of variable categories
plot(d.active[, 1], main=colnames(d.active)[1], ylab = "Count",
col="steelblue", las = 2)
plot(d.active[, 2], main=colnames(d.active)[2], ylab = "Count",
col="steelblue", las = 2)
plot(d.active[, 3], main=colnames(d.active)[3], ylab = "Count",
col="steelblue", las = 2)
plot(d.active[, 4], main=colnames(d.active)[4], ylab = "Count",
col="steelblue", las = 2)
plot(d.active[, 5], main=colnames(d.active)[5], ylab = "Count",
col="steelblue", las = 2)
plot(d.active[, 6], main=colnames(d.active)[6], ylab = "Count",
col="steelblue", las = 2)
plot(d.active[, 7], main=colnames(d.active)[7], ylab = "Count",
col="steelblue", las = 2)
plot(d.active[, 8], main=colnames(d.active)[8], ylab = "Count",
col="steelblue", las = 2)
plot(d.active[, 9], main=colnames(d.active)[9], ylab = "Count",
col="steelblue", las = 2)
plot(d.active[, 10], main=colnames(d.active)[10], ylab = "Count",
col="steelblue", las = 2)
plot(d.active[, 11], main=colnames(d.active)[11], ylab = "Count",
```

```
col="steelblue", las = 2)
plot(d.active[, 12], main=colnames(d.active)[12], ylab = "Count",
col="steelblue", las = 2)
plot(d.active[, 13], main=colnames(d.active)[13], ylab = "Count",
col="steelblue", las = 2)
plot(d.active[, 14], main=colnames(d.active)[14], ylab = "Count",
col="steelblue", las = 2)

# Dropping "other" since two values in it
d.active <- d.active[, c(-10)]

# Correspondence Analysis
res.mca <- MCA(d.active, ncp = 5, graph = FALSE)
print(res.mca)

# The proportion of variances retained by the different dimensions (axes)
eig.val <- get_eigenvalue(res.mca)
head(eig.val)

# Visualizing the percentages of inertia explained by each MCA dimensions
fviz_screeplot(res.mca, addlabels = TRUE, ylim = c(0, 45))
```

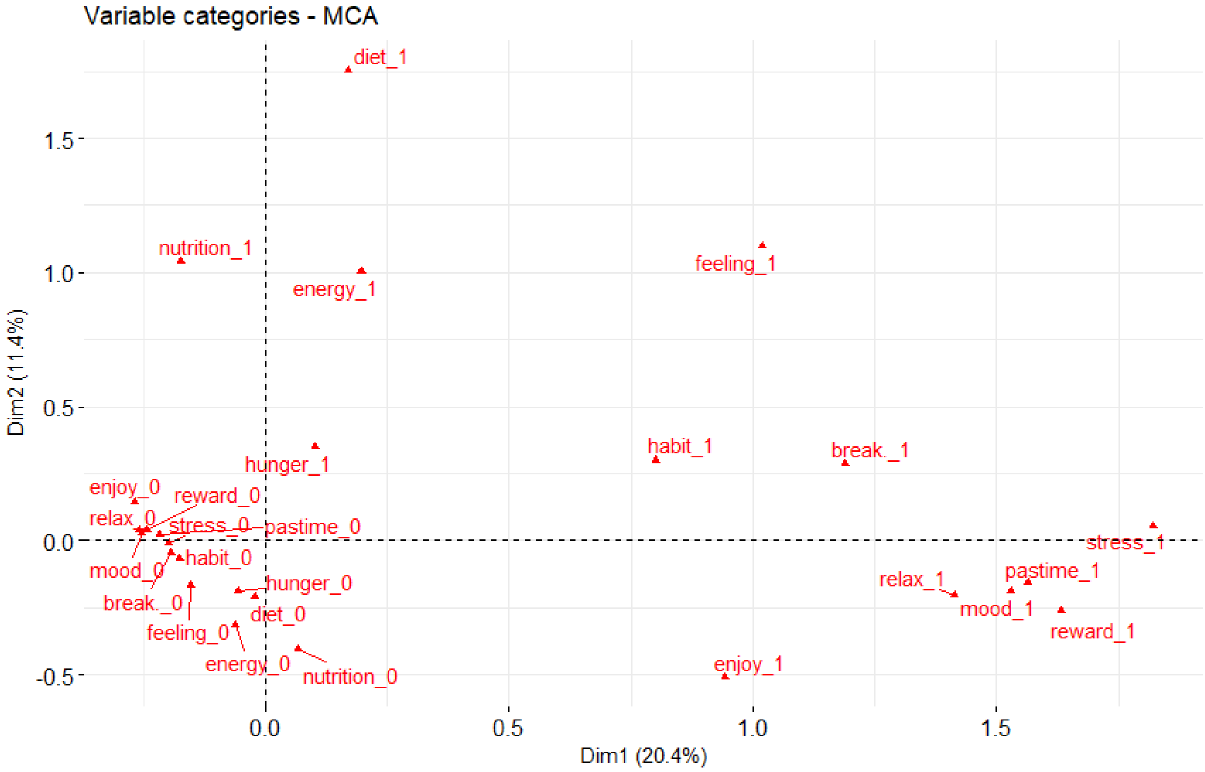



```
var <- get_mca_var(res.mca)
var

head(round(var$coord, 2), 4)   # Coordinations of each variables in each
dimension
head(round(var$cos2, 2), 4)    # The quality (the percentage of being 1) of
each variables in factor map
head(round(var$contrib, 2), 4) # Contribution of each variables in each
dimension

# Correlation between variables and principal dimensions
fviz_mca_var(res.mca, choice = "mca.cor",
```

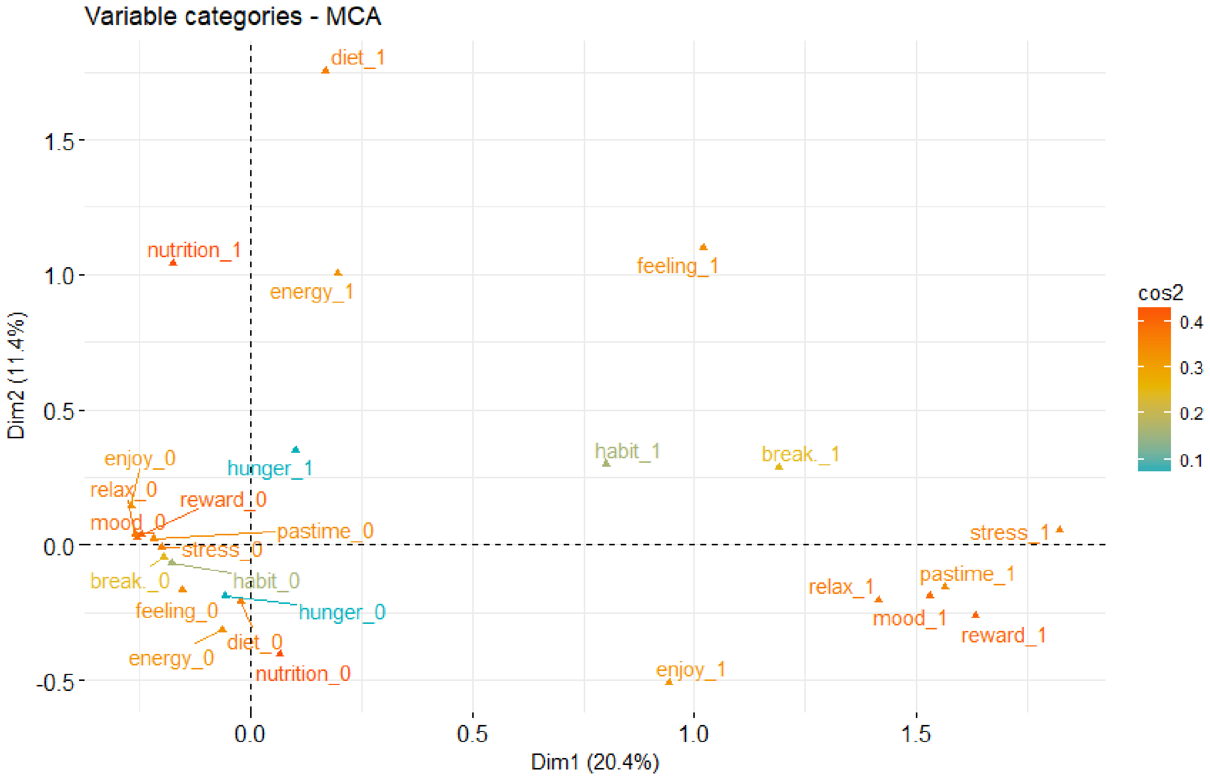
```
             repel = TRUE, # Avoid text overlapping (slow)
             ggtheme = theme_minimal())
```



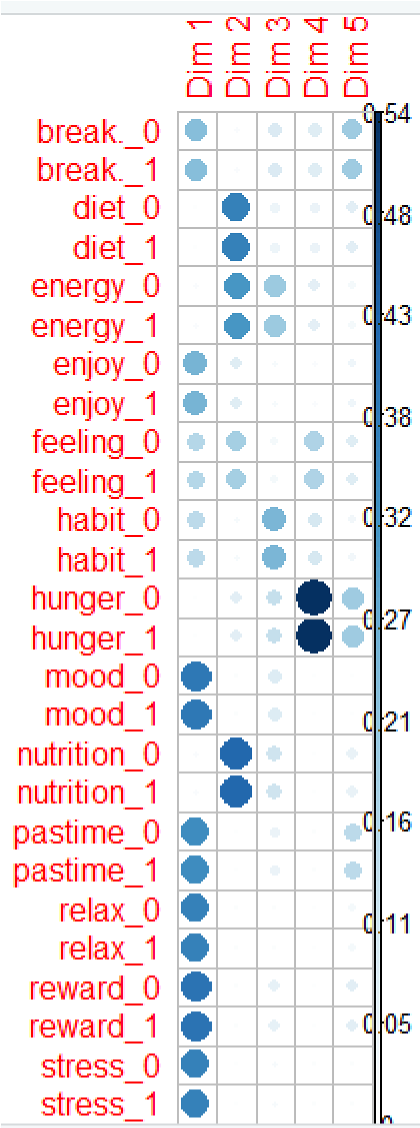

```
head(var$cos2, 4) # Coordinates of variable categories

# Visualizing variable categories
fviz_mca_var(res.mca,
             repel = TRUE, # Avoid text overlapping (slow)
             ggtheme = theme_minimal())
```



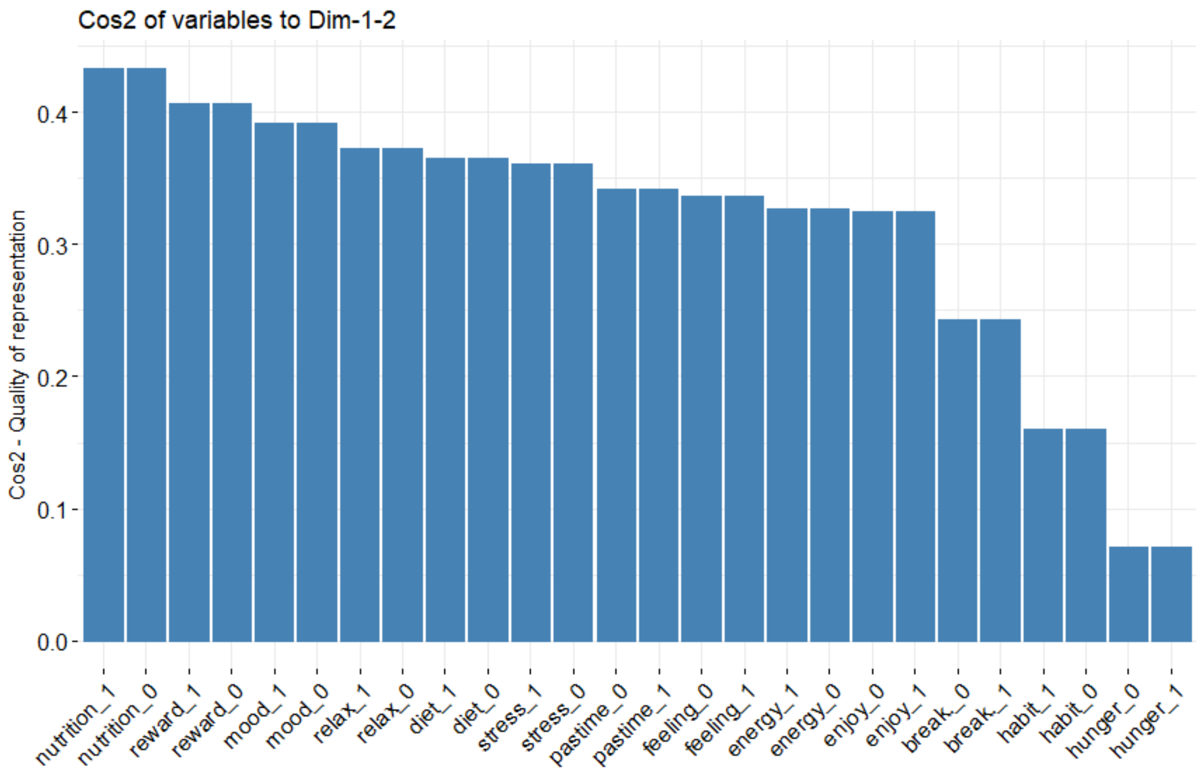

```
# Variable categories with a similar profile are grouped together.
# Negatively correlated variable categories are positioned on opposite
sides of the plot origin (opposed quadrants).
# The distance between category points and the origin measures the quality
of the variable category on the factor map. Category points that are away
from the origin are well represented on the factor map.

fviz_mca_var(res.mca, col.var = "cos2",
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE, # Avoid text overlapping
             ggtheme = theme_minimal())
```



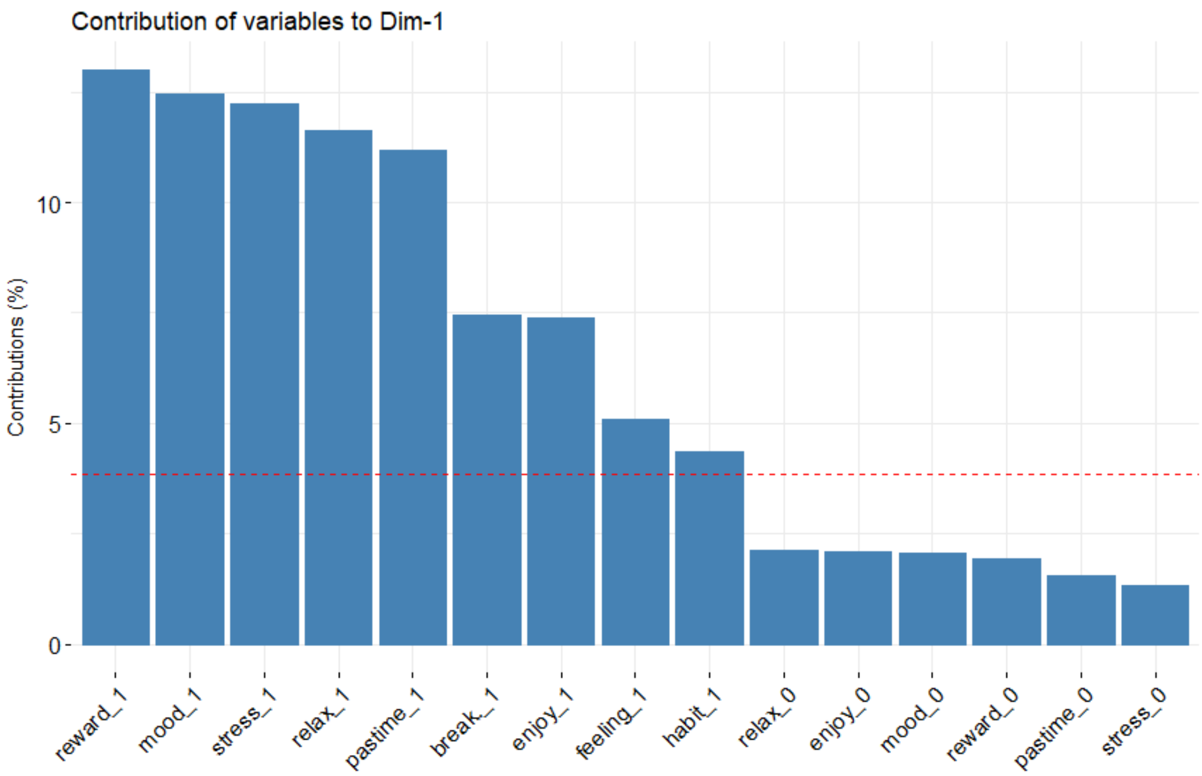

```
# cos2 shows the amount of dependencies (correlations) between the variable
and the dimension
# So, for low quality variables (less correlated with dim1 and dim2) we can
have correlation plot
corrplot(var$cos2, is.corr=FALSE)
```



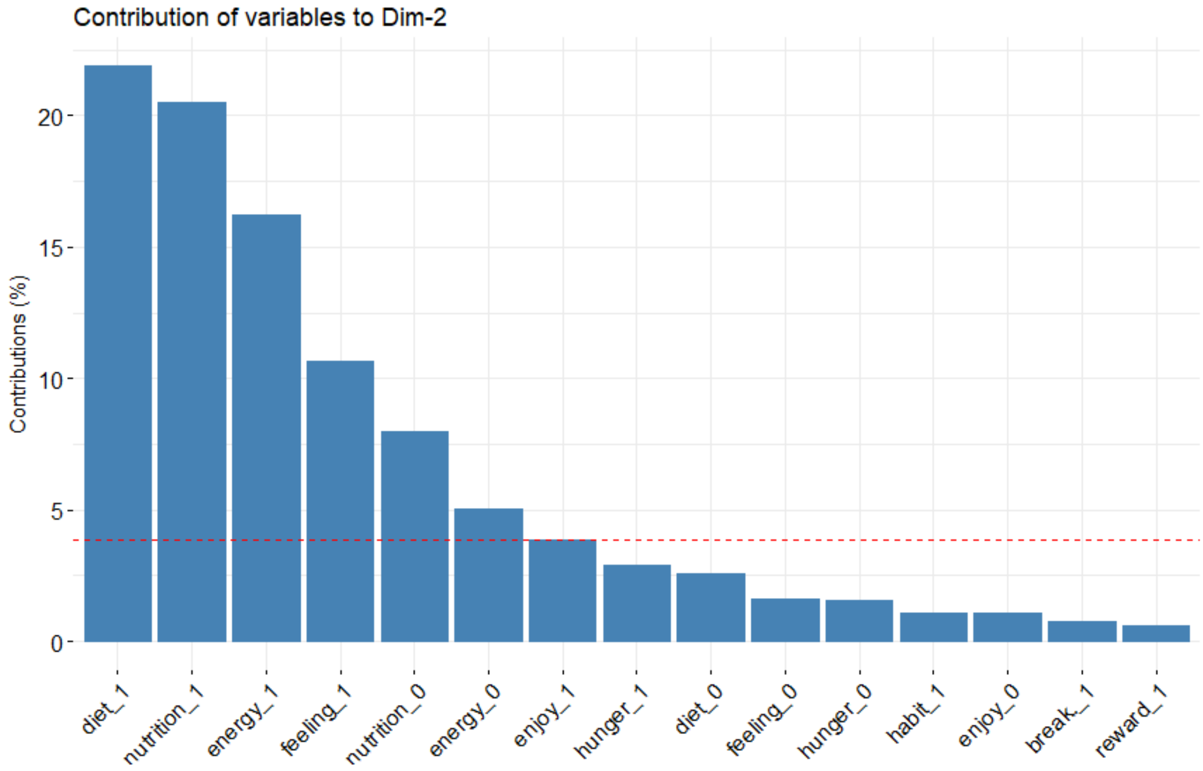

```
# Contributions of rows to dimension 1, 2
fviz_cos2(res.mca, choice = "var", axes = 1:2)
```




```
# Contributions of rows to dimension 1
fviz_contrib(res.mca, choice = "var", axes = 1, top = 15)
```




```
# Contributions of rows to dimension 2
fviz_contrib(res.mca, choice = "var", axes = 2, top = 15)
```


Contribution of variables to Dim-2
Contributions (%)
0
5
10
15
20
diet_1
nutrition_1
energy_1
feeling_1
nutrition_0
energy_0
enjoy_1
hunger_1
diet_0
feeling_0
hunger_0
habit_1
enjoy_0
break_1
reward_1