Multi homing in the music platformscape

Multi-homing

There is a large literature about multi-homing, mainly from economics and focused on the competition function . Multi-homing is important because it reduce switching cost and other market barriers.

Multi-homing come from complementary between platforms. They could be vertical or horizontal, vertical when they complement different activities ; search and order, horizontal when they extend the space of choice.

Multi-homing is expected when engagement is high and usages are sophisticated. A dj need an intense level of search, a sophisticated practice of curation, and a clear willingness to contribute as a productor : playlist, even mash-up. Ordinary consumption of music favor hits and fashionable tunes that we listen as complement of others activities.

Some elements of literature :

Hong Kong University of Science and Technology et al. (2014)

Stewart and Cunningham (2017)

Ozalp and Cennamo (2017)

Haan, Zwart, and Stoffers (2021)

Scott Morton and Athey (2021)

Chen et al. (2022)

The sociology of reception has develop a theory of cultural omnivorism

Tools

```
library(tidyverse)
library(FactoMineR)
library(factoextra)
```

Data

```
df <- read_csv("MusicPlateform2.csv")%>%
  rename(ID=1,
         Rock=2,
         PopInter=3,
         HipHop=4,
         World=5,
         Salsa=6,
         Classique=7,
         Techno=8,
         HardRock=9,
         Baroque=10,
         Folk=11,
         Reggae=12,
         ChansonFrançaise=13,
         RockAlt=14,
         Dance=15,
         Jazz=16,
         AfroPop=17,
         Opera=18,
         Arabic=19,
         Blues=20,
         JK_pop=21,
         Rap=22,
         SoulFunk=23,
         S_travail=24,
         S_Live=25,
         S_Voiture=26,
         S_Menage=27,
         S_Ami=28,
         S_Bars=29,
         S_Transport=30,
```

```r
         S_Lire=31,
         S_Douche=32,
         D_Vynil=33,
         D_Streaming=34,
         D_smartphone=35,
         D_concert=36,
         D_laptop=37,
         D_ecouteurs=38,
         D_mix=39,
         D_radiotv=40,
         P_Youtube=42,
         P_Spotify=43,
         P_Deezer=44,
         P_Souncloud=45,
         P_Bandcamp=46,
         P_Discog=47,
         P_Tidal=48,
         P_Amazon=49,
         P_Mixcloud=50,
         P_AppleM=51,
         P_Qobuz=52,
         P_Pandora=53,
         P_Netease=54,
         Time=68,
         Spending=69,
         Value=70,
         Age=71,
         Genre=72)


df$Age<-factor(df$Age, ordered = TRUE,
                                levels = c("moins de 18 ans", "de 18 à 20 ans",
                                           "de 21 à 25 ans", "de 26 à 30 ans",
                                           "de 31 à 40 ans", "de 41 à 60 ans",
                                           "plus de 60 ans"))

table(df$Age)
```

```
moins de 18 ans  de 18 à 20 ans  de 21 à 25 ans  de 26 à 30 ans  de 31 à 40 ans
              5               4              71               8              14
 de 41 à 60 ans  plus de 60 ans
```

```
37                14
```

```
#color palette
col<-c("Coral","Pink","Gold","Orange")
```

The taste

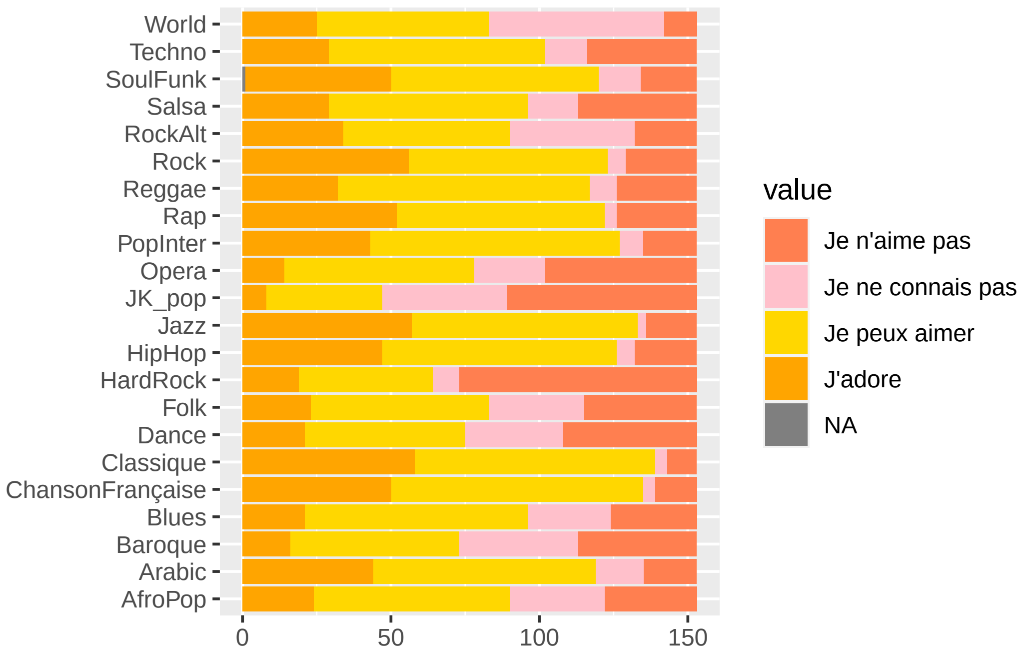
What are the styles that people like ? How they combined them ?

First step, a general view after small recoding.

Rien ne se dégage vraiment. Les adoré sont le rock, la chanson et jazz. Mais c'est pas clair. Ce qui n'est pas aimé c'est la ou la kpop, le hard rock et l'opéra. Des formes extrêmes ou exigeantes. Il ne peut pas y avoir d'analyse simple de ce type de configuration. Elle représente une moyenne et masque sans doute de grande dispersion, il va falloir segmenter, trouver des configurations plus essentielles.

```
foo<- df %>%
  select(1:23) %>%
  pivot_longer(-ID,names_to="variable", values_to = "value")

foo$value[foo$value=="J'aime beaucoup"]<-"J'adore"
foo$value[foo$value=="J'aime pas mal"]<-"Je peux aimer"
foo$value[foo$value=="J'aime un peu"]<-"Je peux aimer"
foo$value[foo$value=="J'aime pas trop"]<-"Je n'aime pas"

#variable définition
foo$value <- factor(foo$value, levels = c("Je n'aime pas",
                                          "Je ne connais pas",
                                          "Je peux aimer",
                                          "J'adore"))
#just counting
foo<-foo%>%
  group_by(variable, value)%>%
  summarise(n=n())


#plot
ggplot(foo, aes(x = reorder(variable, value), y=n, group=value))+
  geom_bar(stat="identity", aes(fill=value))+
  coord_flip()+
```

```
  labs(x=NULL, y =NULL)+
  scale_fill_manual(values=col)
```

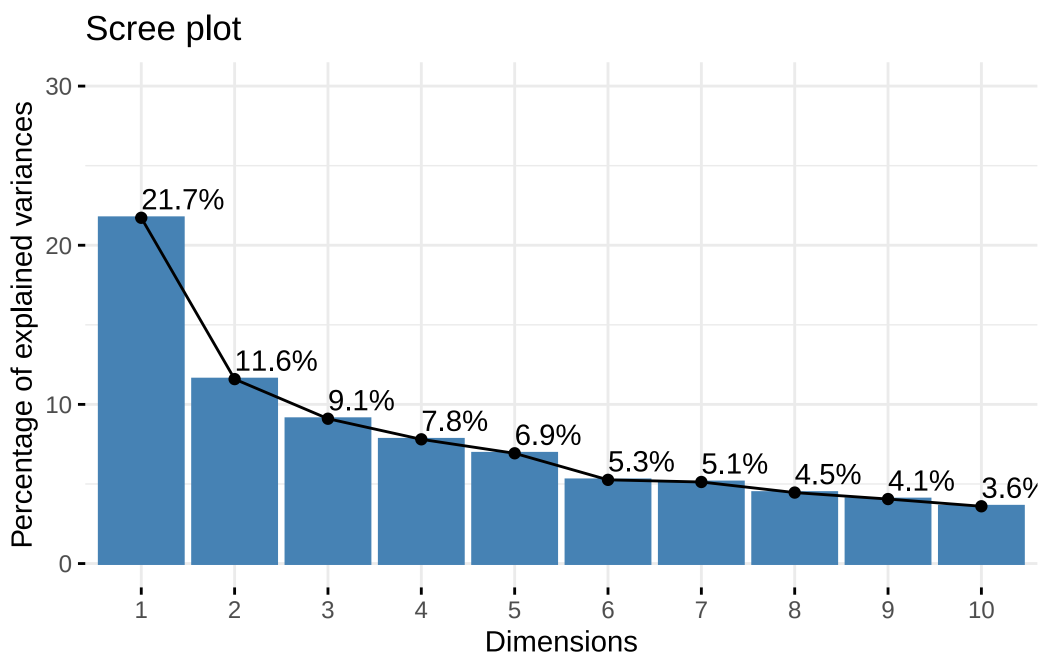


C'est ce qu'on va faire dans la série d'opérations qui suivent

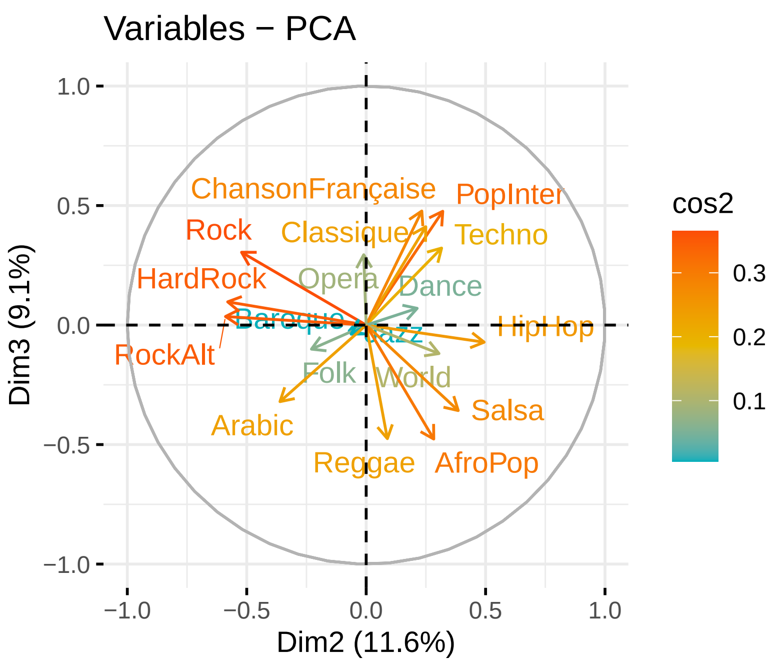
```
#construire le bon tableau

foo<- df %>%
  select(1:23) %>%
  pivot_longer(-ID,names_to="variable", values_to = "value")
table(foo$value)
```

```
               J'adore         J'aime beaucoup          J'aime pas mal
                   744                       7                       2
J'aime pas mal, J'adore          J'aime pas trop           J'aime un peu
                     1                       3                       6
          Je n'aime pas       Je ne connais pas           Je peux aimer
                   679                     446                    1478
```

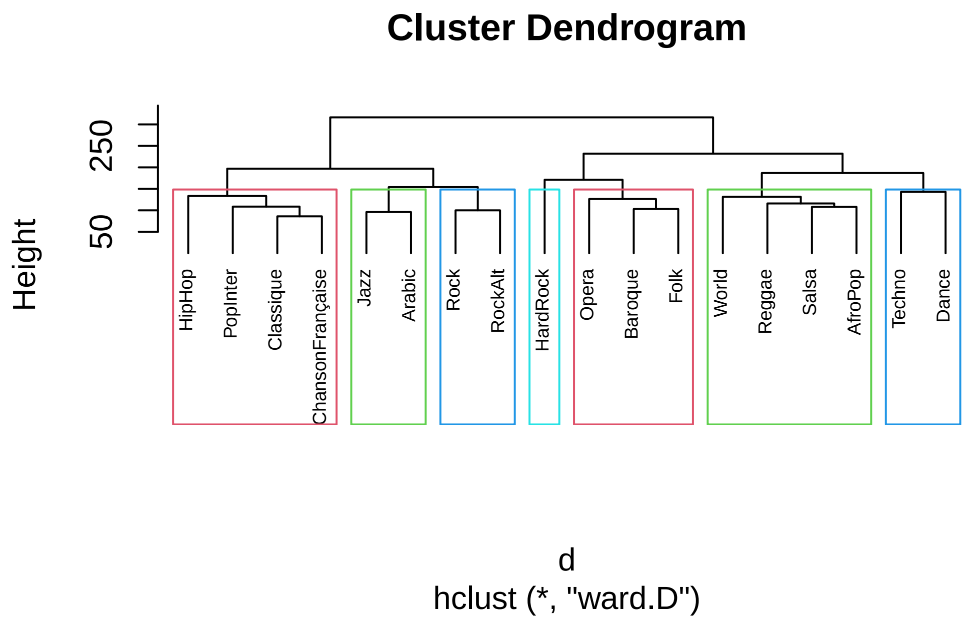
```
foo$value[foo$value=="J'aime beaucoup"]<-"J'adore"
foo$value[foo$value=="J'aime pas mal"]<-"Je peux aimer"
foo$value[foo$value=="J'aime un peu"]<-"Je peux aimer"
foo$value[foo$value=="J'aime pas trop"]<-"Je n'aime pas"

foo$value <- factor(foo$value, levels = c("Je n'aime pas",
                                          "Je ne connais pas",
                                          "Je peux aimer",
                                          "J'adore"))



foo$value2[foo$value=="Je n'aime pas"]<-1
foo$value2[foo$value=="Je ne connais pas"]<-2
foo$value2[foo$value=="Je peux aimer"]<-3
foo$value2[foo$value=="J'adore"]<-4

foo<-foo %>%
  select(-value)%>%
  pivot_wider(ID,names_from = "variable", values_from = "value2")

#PCA
fit<-PCA(foo[2:19],ncp = 4, graph =FALSE)
fviz_eig(fit, addlabels = TRUE, ylim = c(0, 30))
```



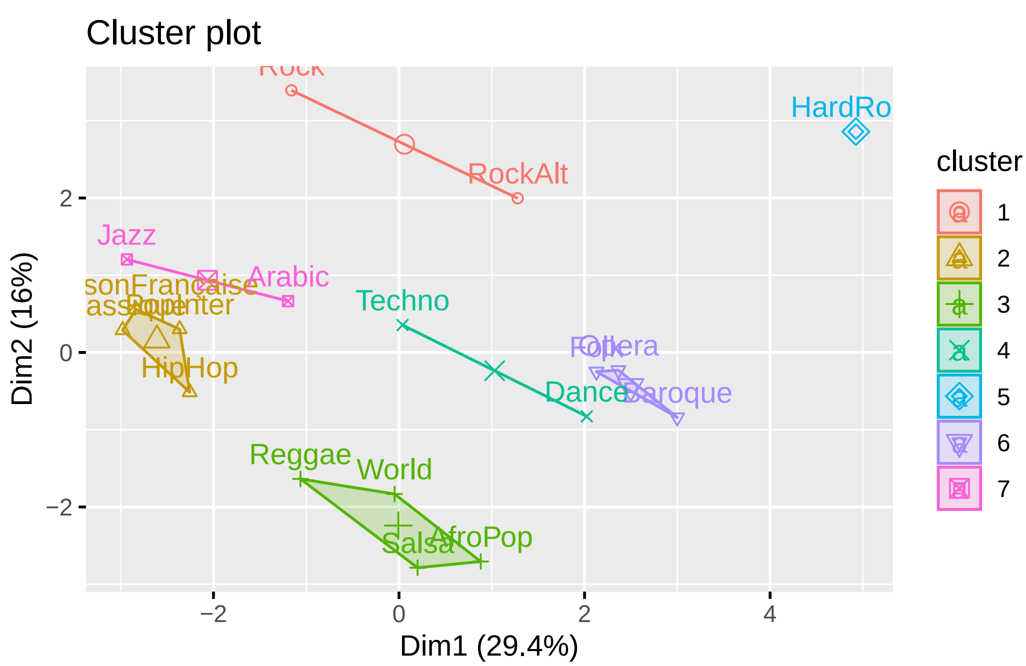

```
fviz_pca_var(fit,  axes = c(2, 3), col.var = "cos2",
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE # Évite le chevauchement de texte
             )
```




```
# Dissimilarity matrix
d <- dist(t(foo[2:19]), method = "manhattan")

# Hierarchical clustering using Ward Linkage
hc1 <- hclust(d, method = "ward" )
sub_grp <- cutree(hc1, k = 7)

# Plot the obtained dendrogram
plot(hc1, cex = 0.6, hang = -1)
rect.hclust(hc1, k = 7, border = 2:5)
```



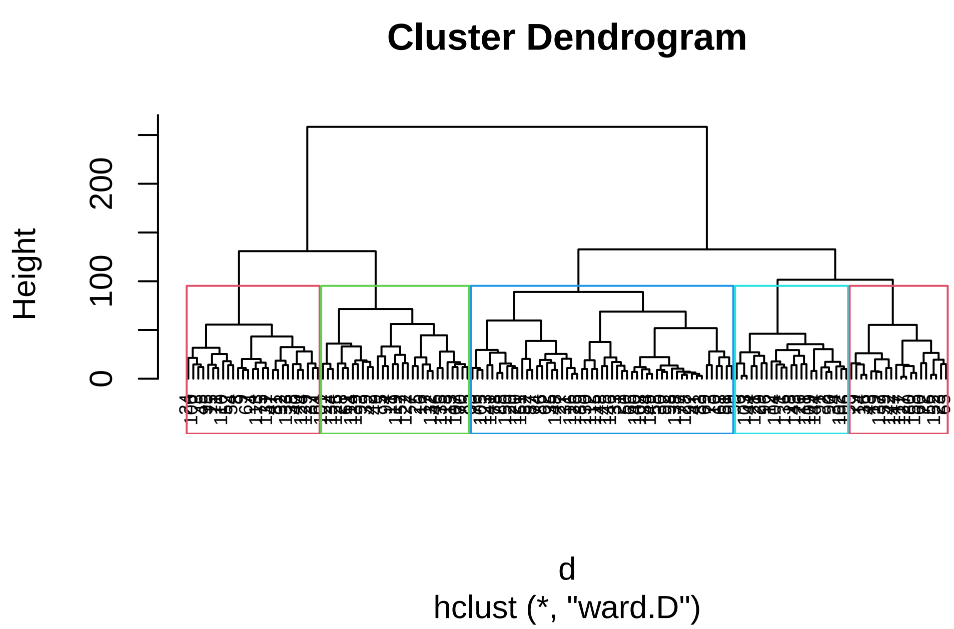

```
fviz_cluster(list(data = d, cluster = sub_grp))
```



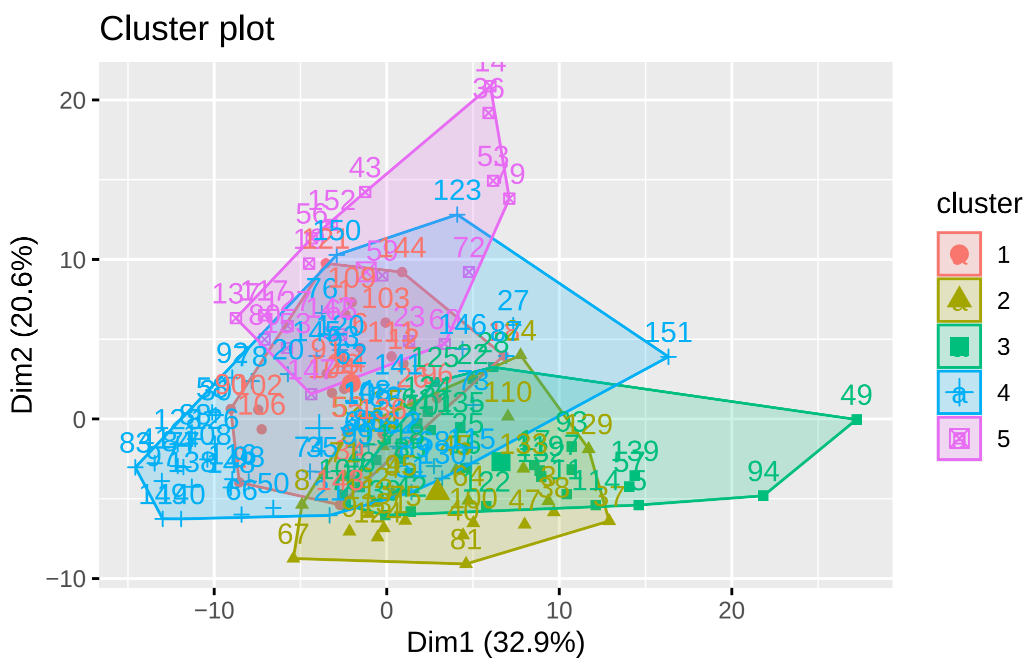
Segmentation

We want to identify groups of peaople based on the style they prefer.

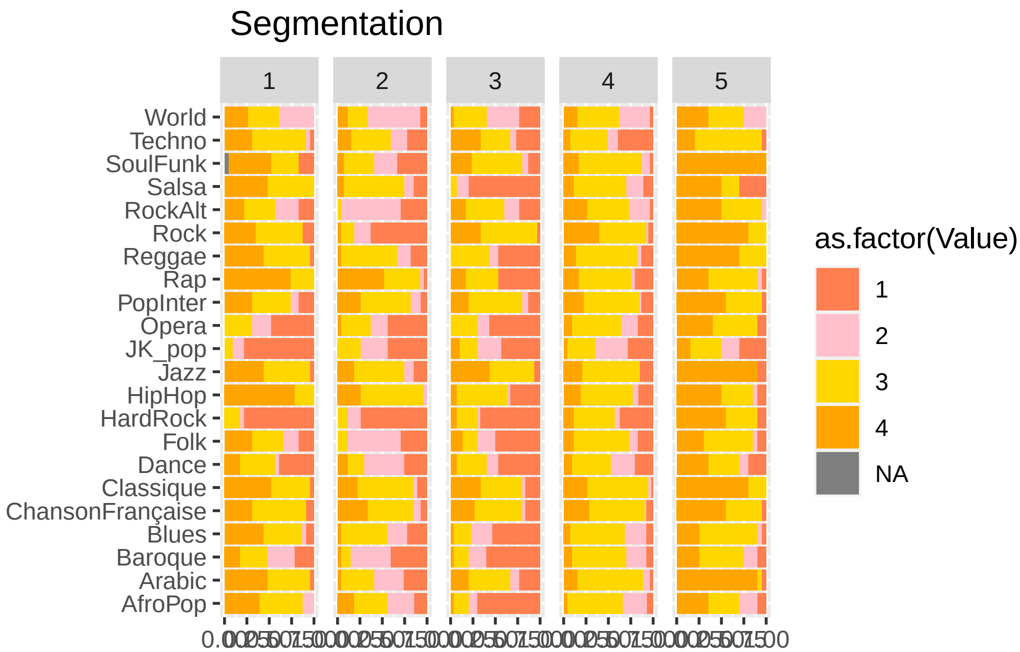
```
#number of groups
k=5

# Dissimilarity matrix
d <- dist(foo[2:23], method = "manhattan")

# Hierarchical clustering using Ward Linkage
hc1 <- hclust(d, method = "ward" )
sub_grp <- cutree(hc1, k = k)

# Plot the obtained dendrogram
plot(hc1, cex = 0.6, hang = -1)
rect.hclust(hc1, k = k, border = 2:5)
```




```
fviz_cluster(list(data = d, cluster = sub_grp))
```

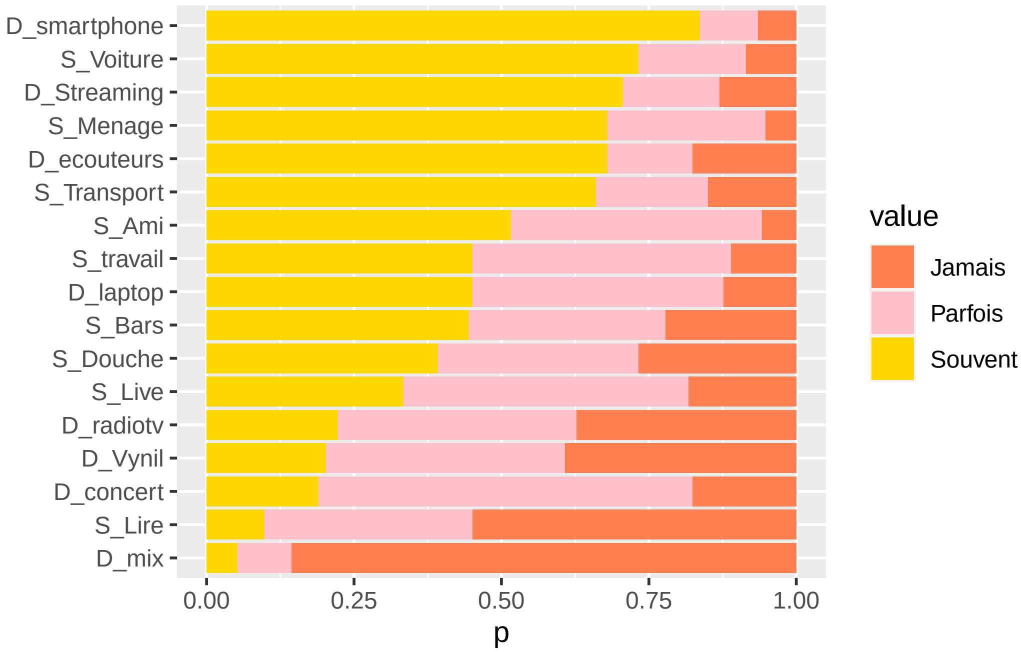



```
foo1<-cbind(foo,sub_grp)%>%
  pivot_longer(-c(ID,sub_grp),names_to="Variable", values_to="Value") %>%
  group_by(sub_grp, Variable, Value)%>%
  summarise(n=n())

foo2<-cbind(foo,sub_grp)%>%
  pivot_longer(-c(ID,sub_grp),names_to="Variable", values_to="Value") %>%
  group_by(sub_grp, Variable)%>%
  summarise(m=n())

foo3<- foo1 %>%
  left_join(foo2) %>%
  mutate(f=n / m)


ggplot(foo3, aes(x = Variable, y=f, group=Value))+
  geom_bar(stat="identity", aes(fill=as.factor(Value)))+
  facet_wrap(vars(sub_grp), ncol=5)+
  coord_flip()+
  scale_fill_manual(values = col)+
  labs(x=NULL, y=NULL, title=" Segmentation")
```

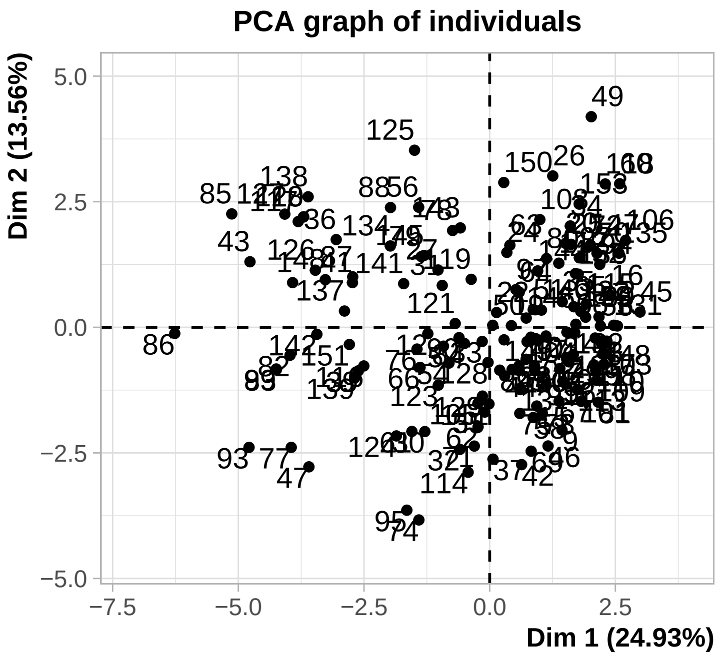


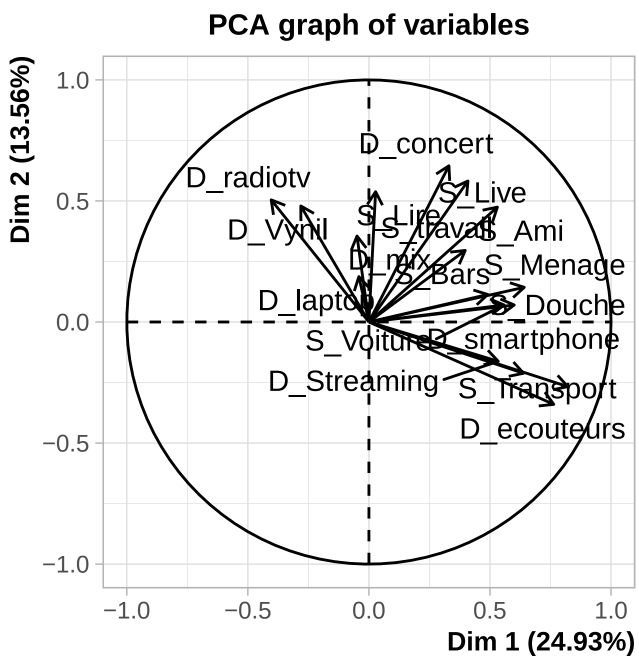
Usages

```
foo<- df %>%
  select(1,24:40)%>%
  pivot_longer(-ID,names_to="variable", values_to = "value")
foo$value[foo$value=="Fréquemment"]<-"Souvent"

foo<-foo%>%
  group_by(variable, value)%>%
  summarise(n=n(), p=n/nrow(df))%>%
  group_by(variable)%>%
  mutate(q=last(p))

ggplot(foo, aes(x = reorder(variable,q), y=p, group=value))+
  geom_bar(stat="identity", aes(fill=value))+
  coord_flip()+
  labs(x=NULL)+
  scale_fill_manual(values=col)
```

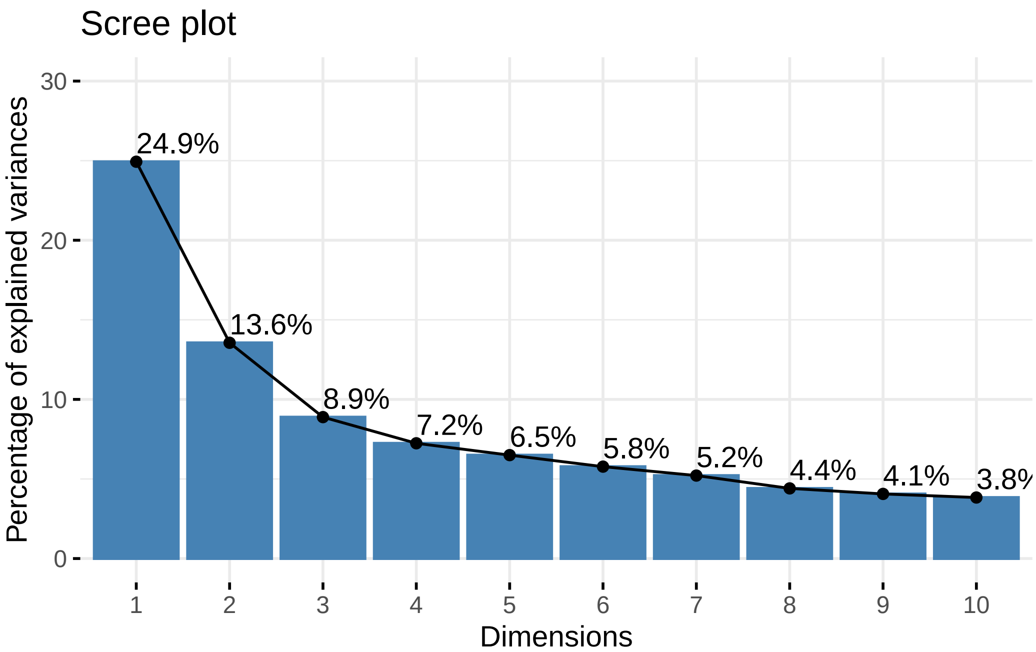



```
#data preparation
# pour le clustering

k=4
foo<- df %>%select(1, 24:40) %>%
  pivot_longer(-ID,names_to="variable", values_to = "value")

foo$value[foo$value=="Souvent"]<-2
foo$value[foo$value=="Parfois"]<-1
foo$value[foo$value=="Jamais"]<-0
foo$value<- as.numeric(foo$value)

foo<-foo %>%
  pivot_wider(ID,names_from = "variable", values_from = "value")

#PCA
fit<-PCA(foo[2:18],ncp = 4)
```

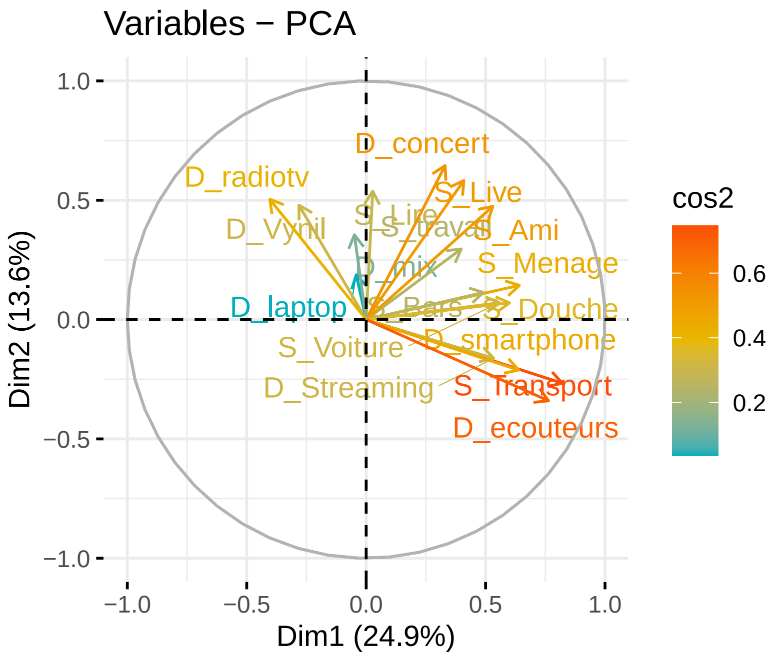




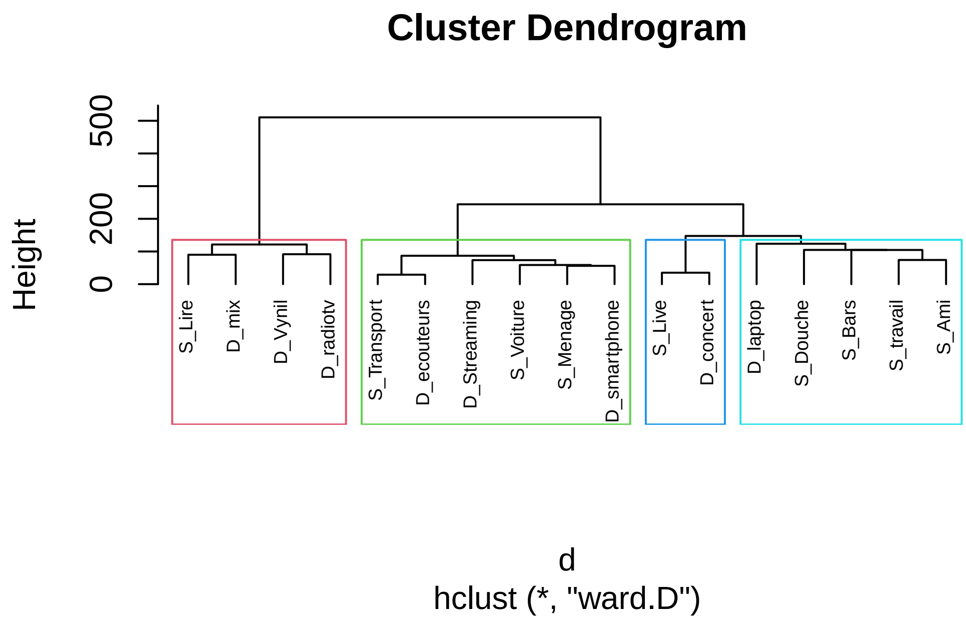

```
fviz_eig(fit, addlabels = TRUE, ylim = c(0, 30))
```



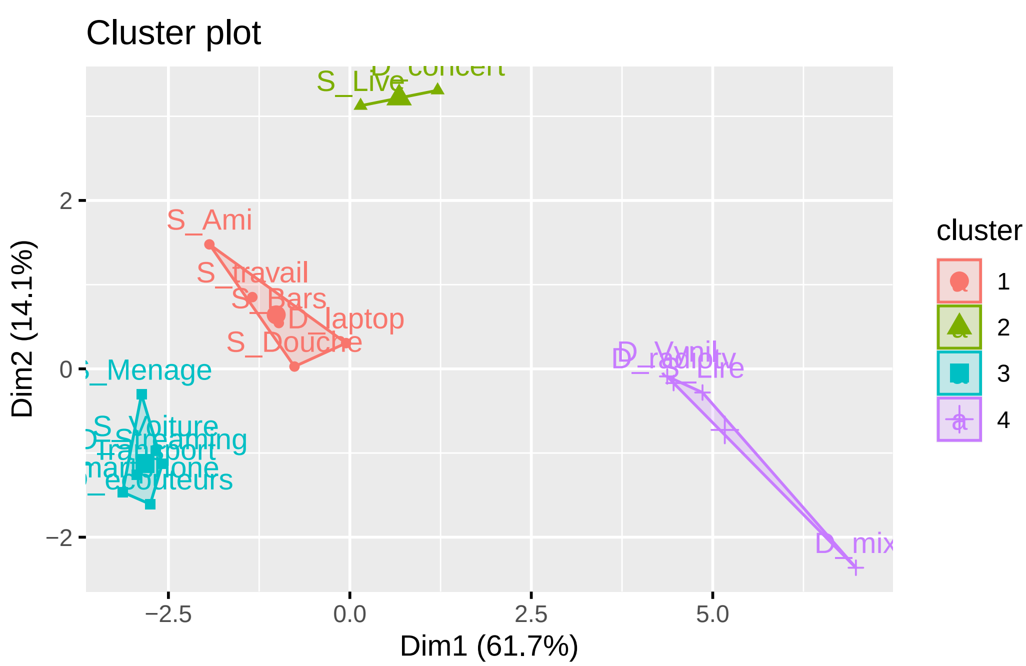

```r
fviz_pca_var(fit, col.var = "cos2",
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE # Évite le chevauchement de texte
             )
```




```
# Dissimilarity matrix
d <- dist(t(foo[2:18]), method = "manhattan")

# Hierarchical clustering using Ward Linkage
hc1 <- hclust(d, method = "ward" )
sub_grp <- cutree(hc1, k = k)

# Plot the obtained dendrogram
plot(hc1, cex = 0.6, hang = -1)
rect.hclust(hc1, k = k, border = 2:5)
```




```
fviz_cluster(list(data = d, cluster = sub_grp))
```

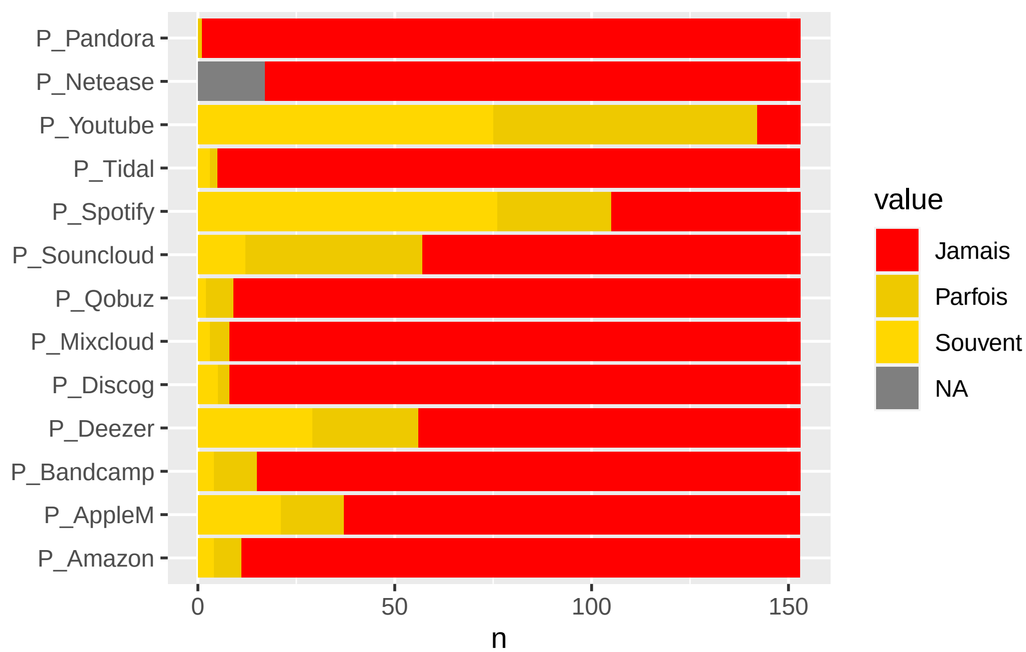


Platforms

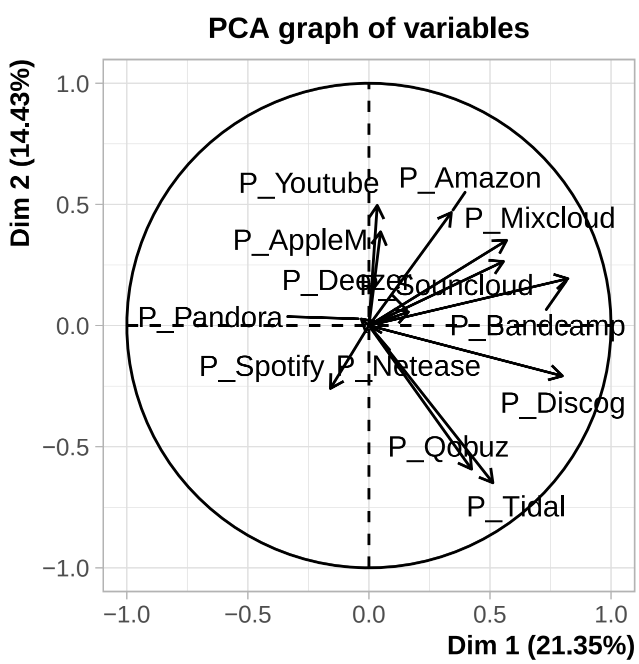
```
foo<- df %>%
  select(1,42:54)%>%
  pivot_longer(-ID,names_to="variable", values_to = "value")
table(foo$value)
```

```
Jamais Parfois Souvent
  1518     220     234
```

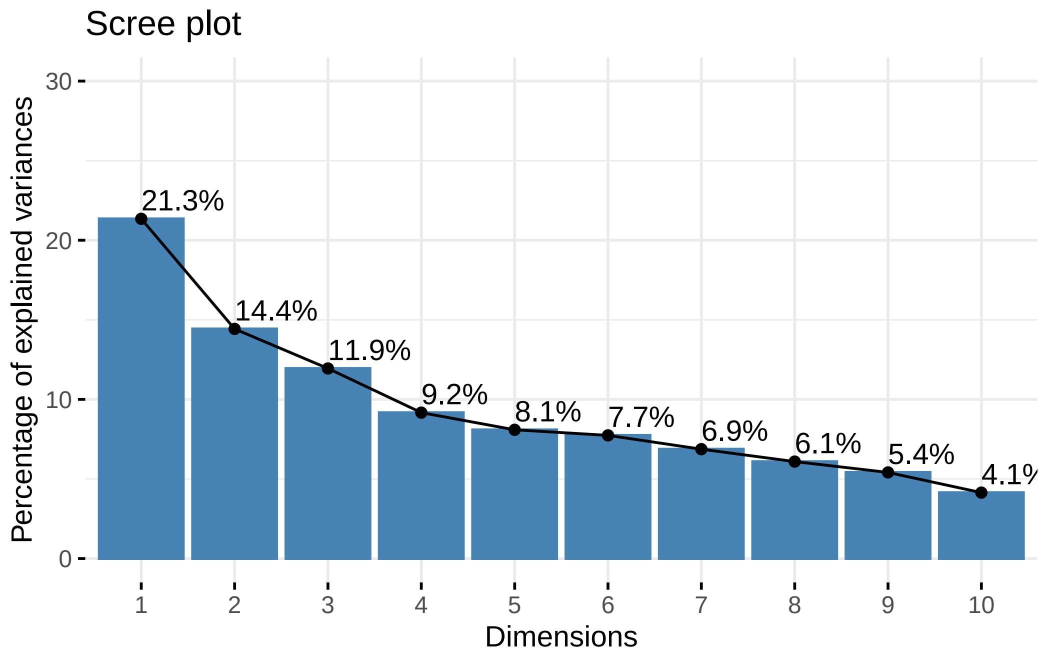
```
foo<-foo%>%
  group_by(variable, value)%>%
  summarise(n=n())
col<-c("Red","Gold2","Gold1","Darkgreen")
ggplot(foo, aes(x = reorder(variable,n), y=n, group=value))+
  geom_bar(stat="identity", aes(fill=value))+
  coord_flip()+
  labs(x=NULL)+
  scale_fill_manual(values=col)
```



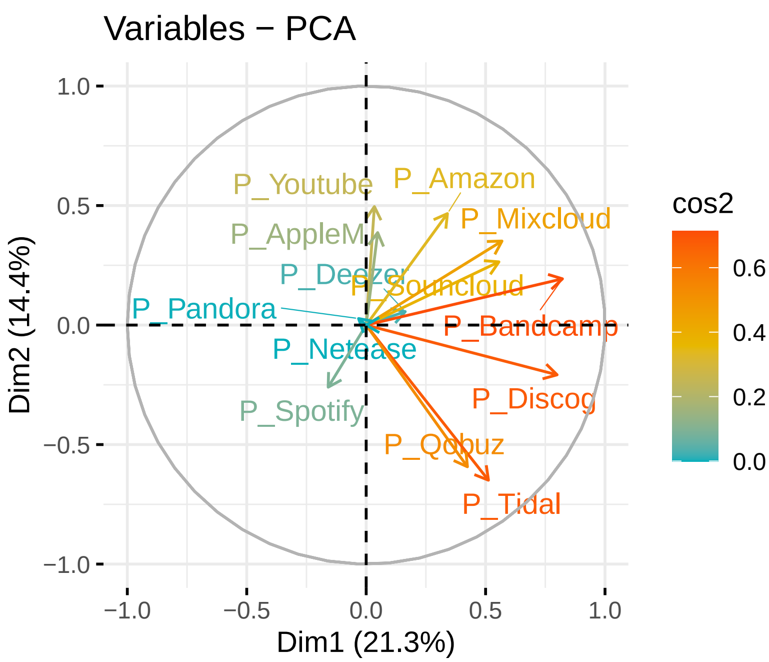
```
#data preparation
# pour le clustering

k=5
foo<- df %>%select(1, 42:54) %>%
  pivot_longer(-ID,names_to="variable", values_to = "value")

foo$value[foo$value=="Souvent"]<-2
foo$value[foo$value=="Parfois"]<-1
foo$value[foo$value=="Jamais"]<-0
foo$value<- as.numeric(foo$value)

foo<-foo %>%
  pivot_wider(ID,names_from = "variable", values_from = "value")

#PCA
fit<-PCA(foo[,2:14],ncp = 4)
```



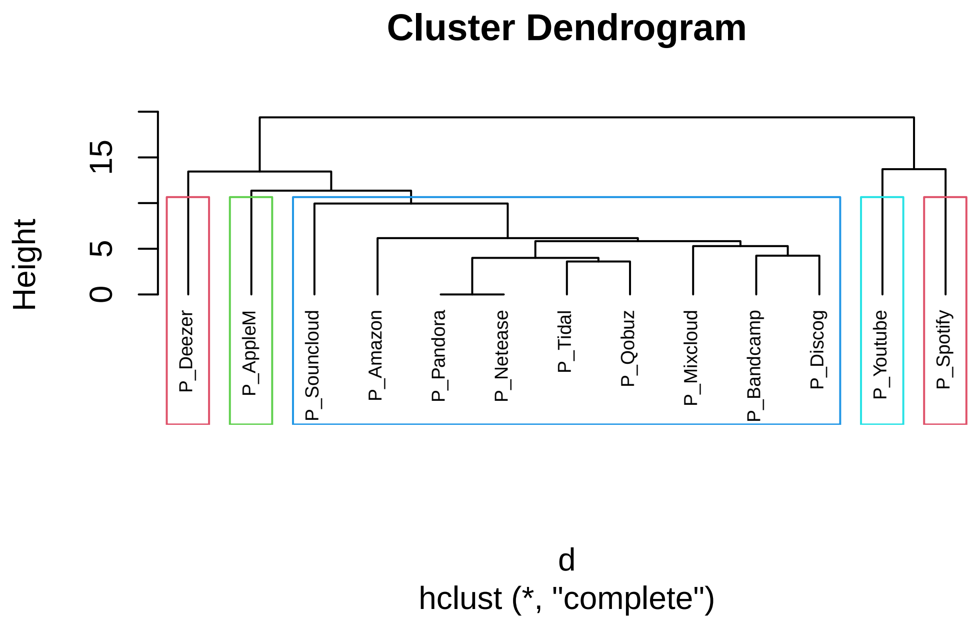

```
fviz_eig(fit, addlabels = TRUE, ylim = c(0, 30))
```



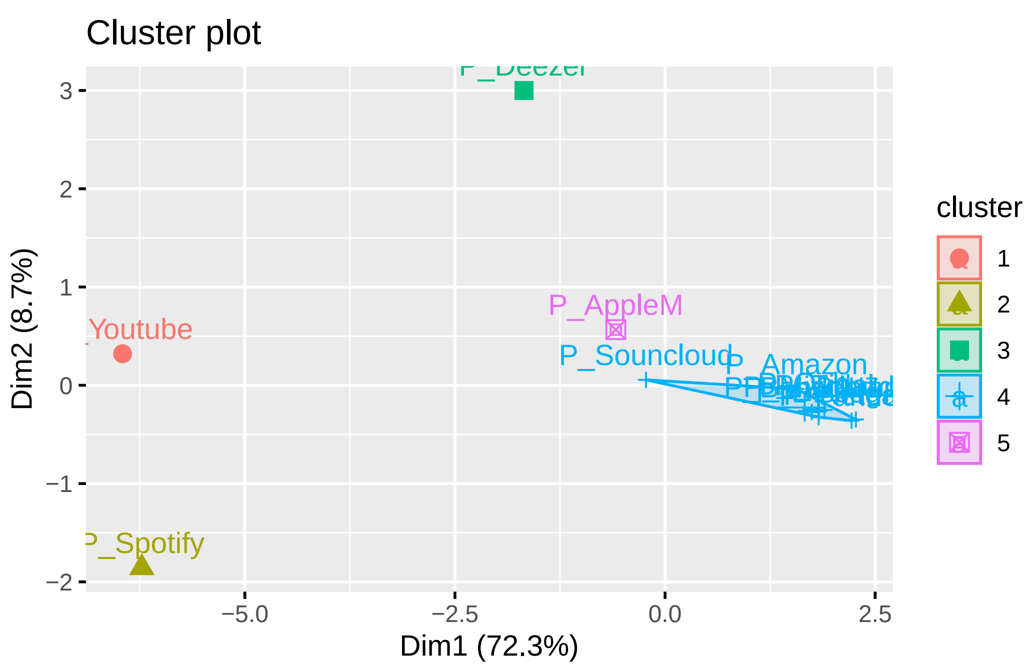

```
fviz_pca_var(fit, col.var = "cos2",
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE # Évite le chevauchement de texte
             )
```




```r
# Dissimilarity matrix
d <- dist(t(foo[2:14]), method = "euclidean")

# Hierarchical clustering using Ward Linkage
hc1 <- hclust(d )
sub_grp <- cutree(hc1, k = k)

# Plot the obtained dendrogram
plot(hc1, cex = 0.6, hang = -1)
rect.hclust(hc1, k = k, border = 2:5)
```



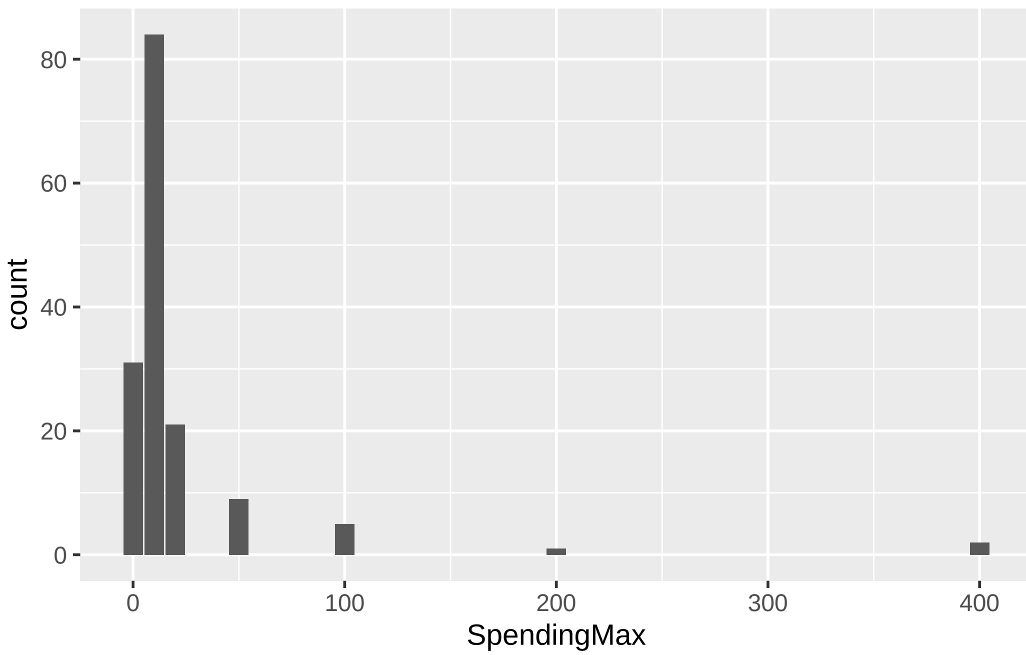

```
fviz_cluster(list(data = d, cluster = sub_grp))
```



Willingness to pay and engagement

We have two question one relevant to equipment, the other to convenient and another one about time spending.

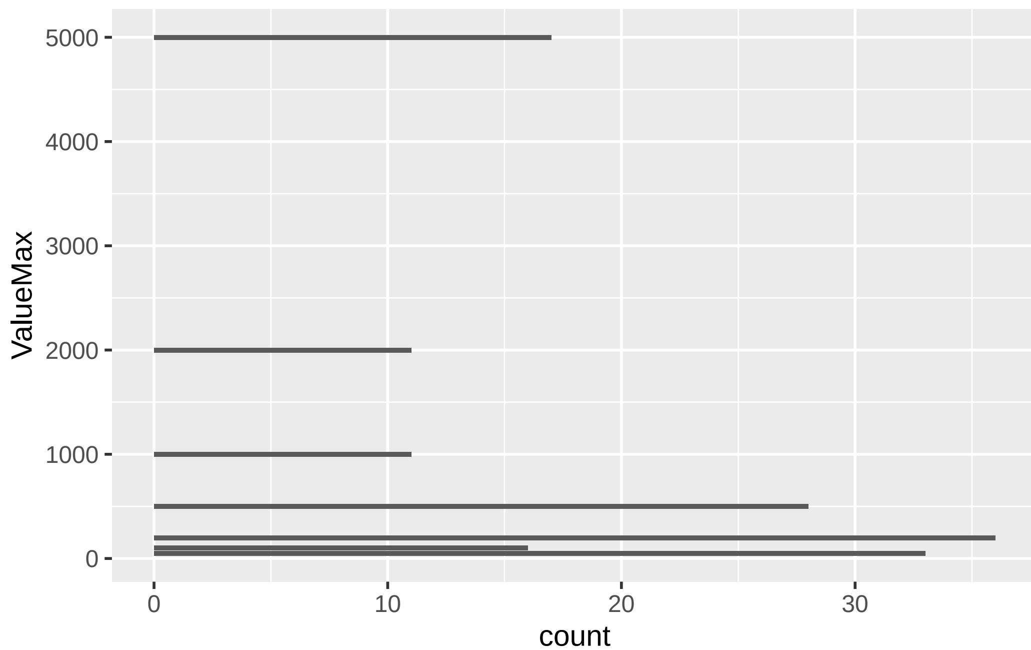
```
df$SpendingMax[df$Spending=="0 euros"] <-0
df$SpendingMax[df$Spending=="0 euros, 10 euros"] <-10
df$SpendingMax[df$Spending=="10 euros"] <-10
df$SpendingMax[df$Spending=="10 euros, 20 euros"] <-20
df$SpendingMax[df$Spending=="20 euros"] <-20
df$SpendingMax[df$Spending=="50 euros"] <-50
df$SpendingMax[df$Spending=="100 euros"] <-100
df$SpendingMax[df$Spending=="200 euros"] <-200
df$SpendingMax[df$Spending=="200 euros et plus"] <-400

ggplot(df, aes(x=SpendingMax))+geom_bar()
```



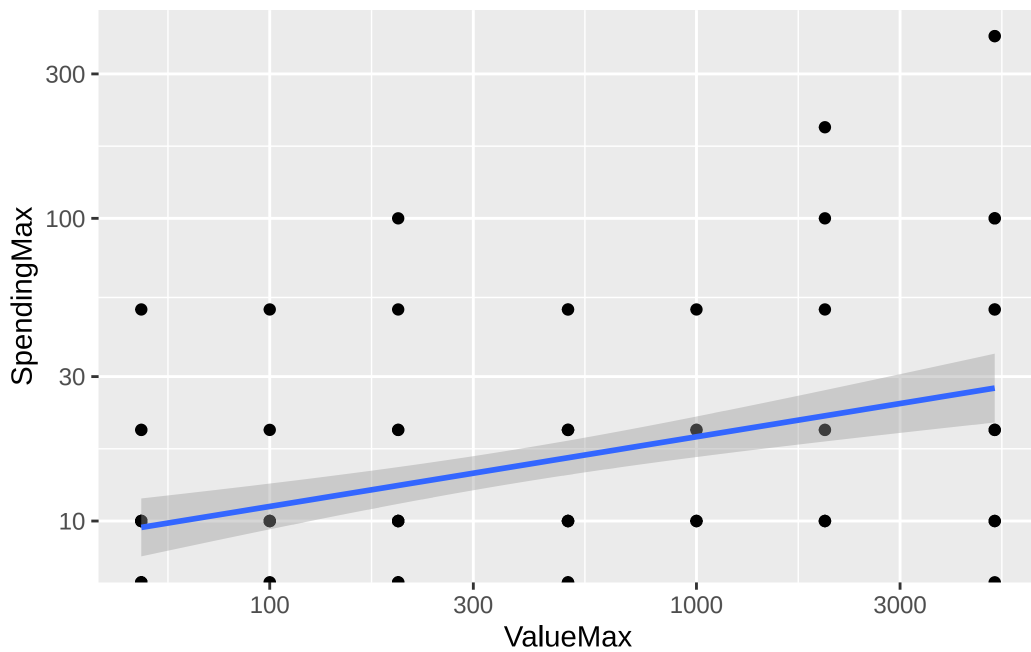

```
table(df$ValueMax)
```

```
< table of extent 0 >
```

```
df$ValueMax[df$Value=="moins de 50 euros"] <-50
df$ValueMax[df$Value=="moins de 50 euros, 100 euros"] <-100
df$ValueMax[df$Value=="100 euros"] <-100
df$ValueMax[df$Value=="200 euros"] <-200
df$ValueMax[df$Value=="500 euros"] <-500
df$ValueMax[df$Value=="1000 euros"] <-1000
df$ValueMax[df$Value=="2000 euros"] <-2000
df$ValueMax[df$Value=="200 euros, 2000 euros"] <-2000

df$ValueMax[df$Value=="2000 euros, 5000 euros et plus"] <-5000
df$ValueMax[df$Value=="5000 euros et plus"] <-5000

ggplot(df, aes(x=ValueMax))+geom_bar()+coord_flip()
```




```
ggplot(df, aes(x=ValueMax, y=SpendingMax))+
  geom_point()+
  geom_smooth(method="lm")+scale_x_log10()+scale_y_log10()
```



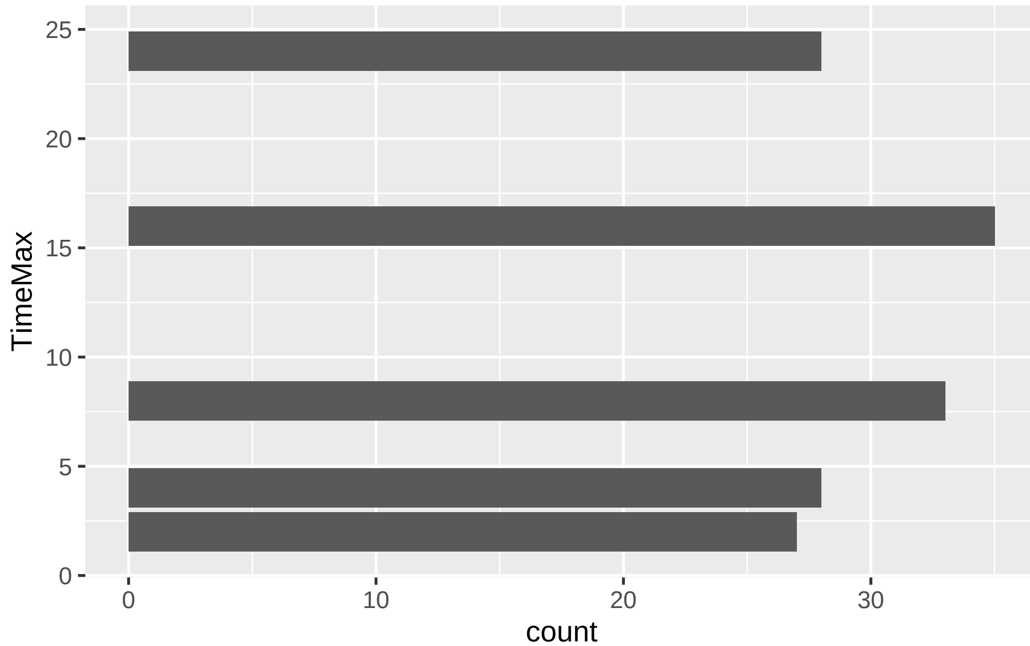

```
table(df$Time)
```

```
Entre 2 et 4h  Entre 4 et 8h Entre 8 et 16h    Moins de 2h    Plus de 16h
           28             33             35             27             28
```

```
df$TimeMax[df$Time=="Moins de 2h"] <-2
df$TimeMax[df$Time=="Entre 2 et 4h"] <-4
df$TimeMax[df$Time=="Entre 4 et 8h"] <-8
df$TimeMax[df$Time=="Entre 8 et 16h"] <-16
df$TimeMax[df$Time=="Plus de 16h"] <-24
table(df$Time)
```

```
Entre 2 et 4h  Entre 4 et 8h Entre 8 et 16h    Moins de 2h    Plus de 16h
           28             33             35             27             28
```

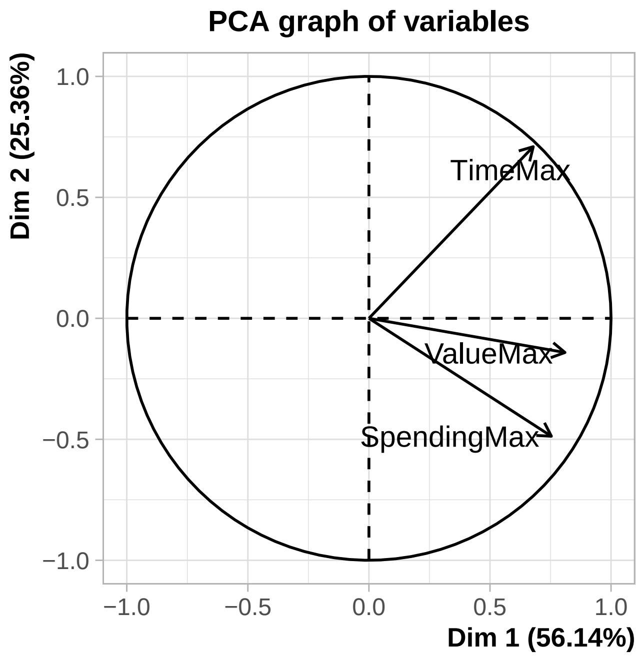
```
ggplot(df, aes(x=TimeMax))+geom_bar()+coord_flip()
```



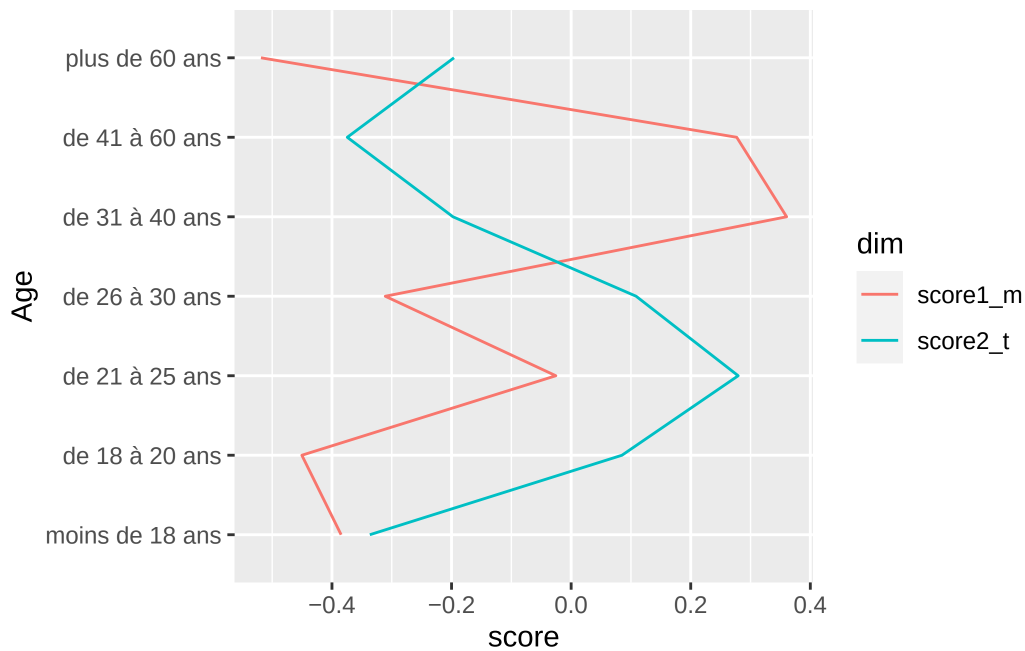

```
foo<-df%>%
  select(ValueMax, SpendingMax, TimeMax)
r<-foo %>%
  drop_na()%>%
  cor()
r
```

```
             ValueMax SpendingMax   TimeMax
ValueMax    1.0000000   0.4246352 0.3437494
SpendingMax 0.4246352   1.0000000 0.2497053
TimeMax     0.3437494   0.2497053 1.0000000
```

```
pca<-PCA(foo, scale.unit = TRUE, ncp = 2, graph = TRUE)
```




```
score<-pca$ind$coord
df<-cbind(df, score)

foo<- df%>%group_by(Age)%>%
  summarise(score1_m= mean(Dim.1, na.rm=TRUE),
            score2_t= mean(Dim.2, na.rm=TRUE)
            )%>%
  pivot_longer(-Age, names_to = "dim" , values_to = "score")
ggplot(foo, aes(x=Age,y=score,group=dim))+geom_line(aes(color=dim))+coord_flip()
```



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