Deliverable 2

PCA, CA and Clustering

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November 20, 2020

Contents

1 First setups

```
if(!is.null(dev.list())) dev.off()  # Clear plots
rm(list=ls())                       # Clean workspace
```

1.1 Load Required Packages for this deliverable

We load the necessary packages and set working directory

```
#setwd("~/Documents/uni/FIB-ADEI-LAB/deliverable2")
#filepath<-"~/Documents/uni/FIB-ADEI-LAB/deliverable2"
setwd("C:/Users/Claudia Sánchez/Desktop/FIB/TARDOR 2020-2021/ADEI/DELIVERABLE1/FIB-ADEI-LAB/deliverable2
filepath<-"C:/Users/Claudia Sánchez/Desktop/FIB/TARDOR 2020-2021/ADEI/DELIVERABLE1/FIB-ADEI-LAB/delivera

# Load Required Packages
options(contrasts=c("contr.treatment","contr.treatment"))
requiredPackages <- c("missMDA","chemometrics","mvoutlier","effects","FactoMineR","car", "factoextra","F
missingPackages <- requiredPackages[!(requiredPackages %in% installed.packages()[,"Package"])]
if(length(missingPackages)) install.packages(missingPackages)
lapply(requiredPackages, require, character.only = TRUE)
```

1.2 Load processed data from first deliverable

```
load(paste0(filepath,"/Taxi5000_del1.RData"))
```

1.3 Clean data

```
# remove some columns
#names(df)
df$lpep_pickup_datetime <- NULL
df$Lpep_dropoff_datetime <- NULL
df$Store_and_fwd_flag <- NULL
df$Ehail_fee <- NULL
df$CashTips <- NULL
df$Sum_total_amount <- NULL
df$yearGt2015 <- NULL
```

```r
# imputation
library(missMDA)
long_lat<-names(df)[c(3:6)]
imp_long_lat<-imputePCA(df[,long_lat])
df[,long_lat]<-imp_long_lat$completeObs
```

---

2 Principal Component Analysis (PCA)

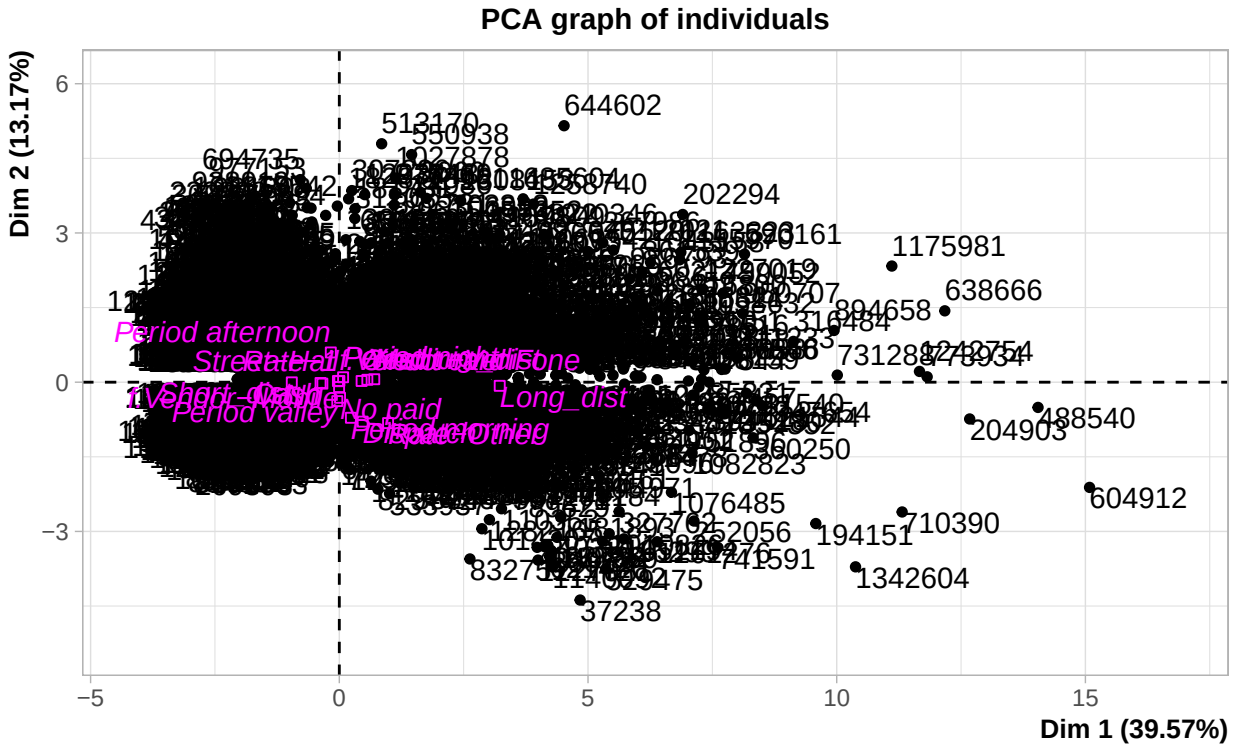
```r
names(df)
```

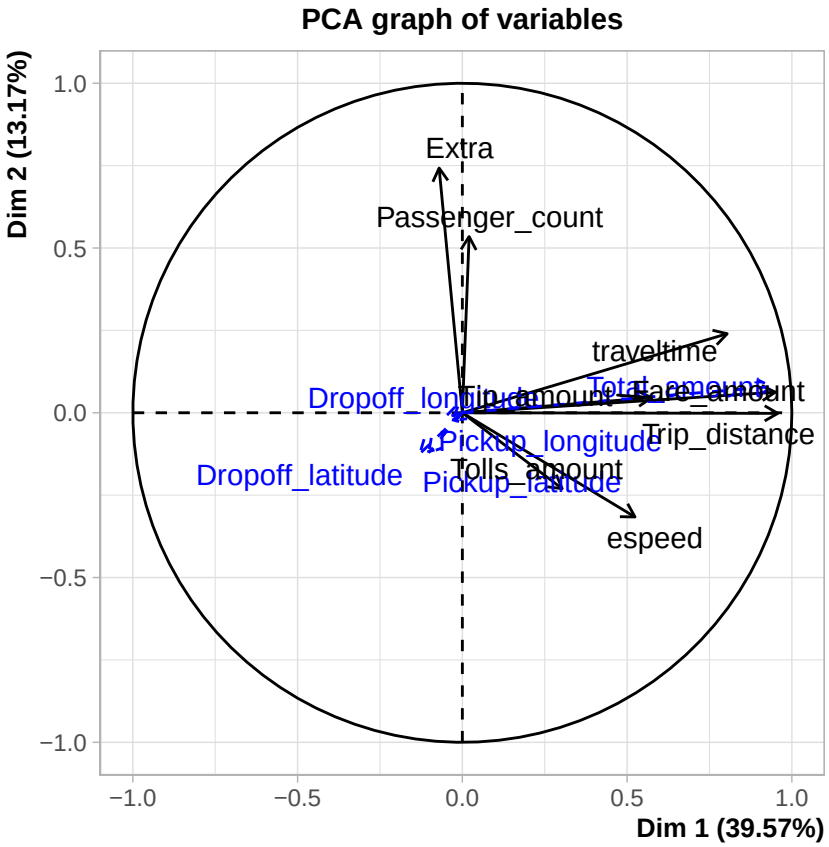
```
##  [1] "VendorID"              "RateCodeID"            "Pickup_longitude"
##  [4] "Pickup_latitude"       "Dropoff_longitude"     "Dropoff_latitude"
##  [7] "Passenger_count"       "Trip_distance"         "Fare_amount"
## [10] "Extra"                 "MTA_tax"               "Tip_amount"
## [13] "Tolls_amount"          "improvement_surcharge" "Total_amount"
## [16] "Payment_type"          "Trip_type"             "hour"
## [19] "period"                "tlenkm"                "traveltime"
## [22] "espeed"                "pickup"                "dropoff"
## [25] "Trip_distance_range"   "paidTolls"             "TipIsGiven"
## [28] "passenger_groups"
```

```r
vars_res<-names(df)[c(15,27)]
vars_quantitatives<-names(df)[c(3:10,12,20:22)]
vars_categorical<-names(df)[c(1,2,16:17,19,25,28)]
```

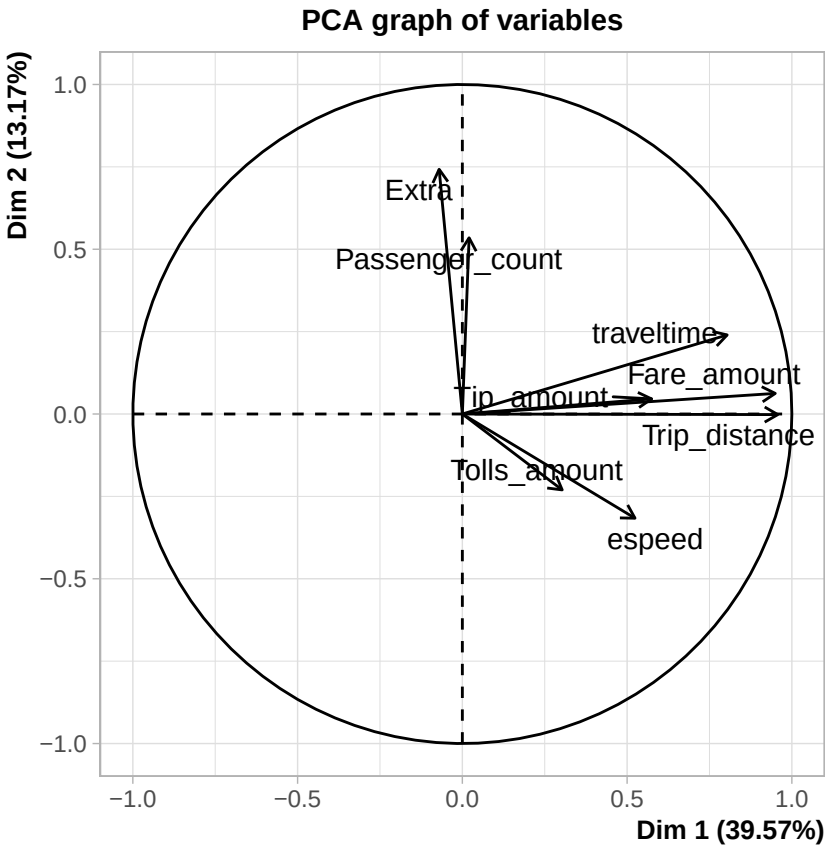
We have already seen profiling in the previous installment. So now, let's proceed to look at the main components.

```r
library(FactoMineR)
res.pca <- PCA(df[,c(1:10,12,13,15:17,19,21,22,25,27)],quanti.sup=c(3:6,13),quali.sup=c(1,2,14:16,19:20)
```

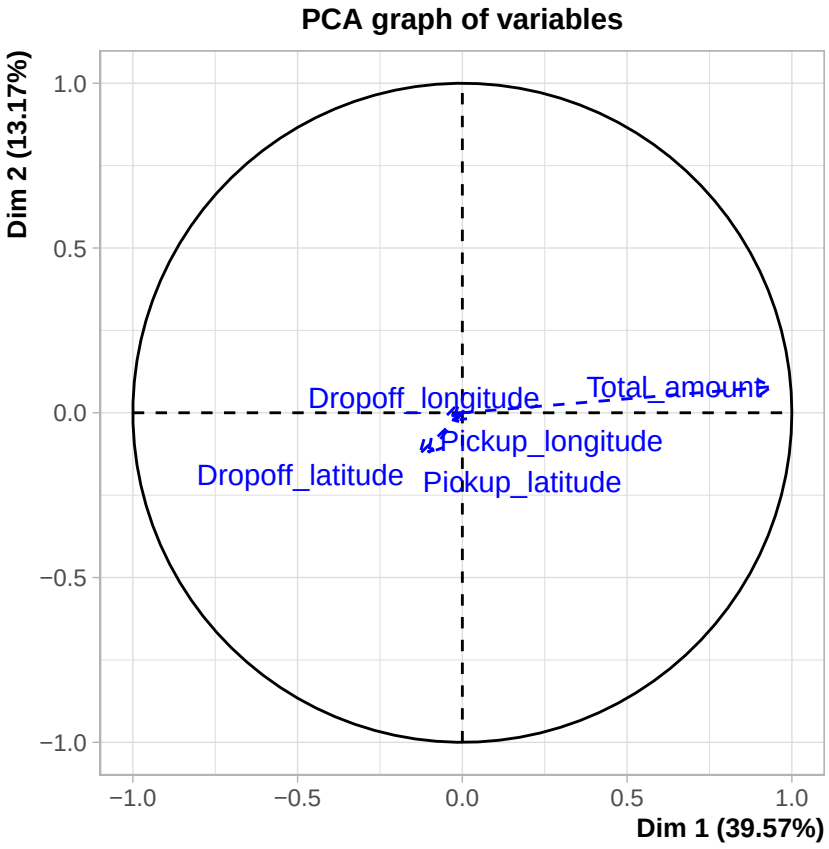




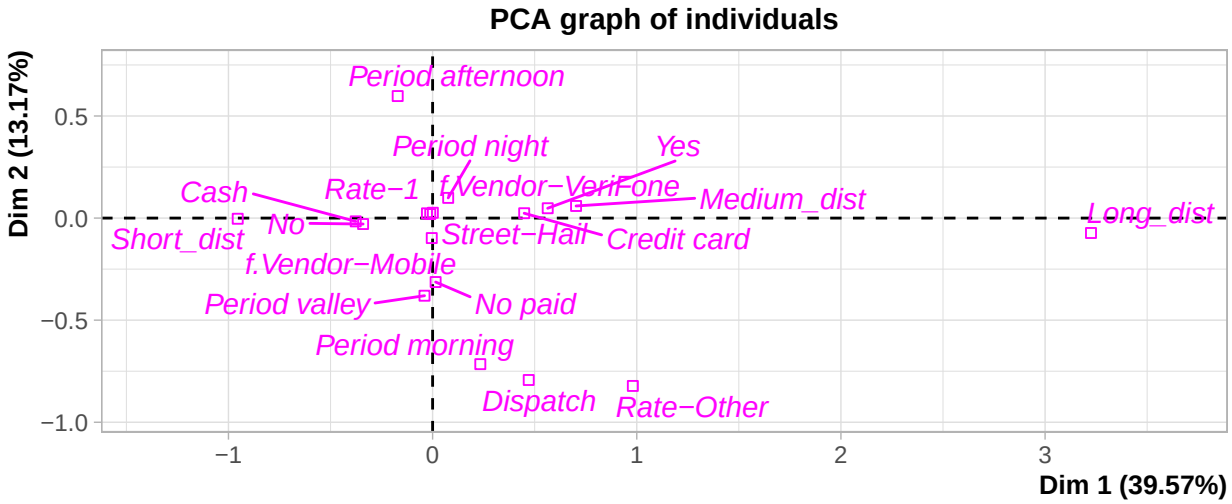

```
plot.PCA(res.pca,choix=c("var"), invisible=c("quanti.sup"))
```




```
plot.PCA(res.pca,choix=c("var"), invisible=c("var"))
```




```
plot.PCA(res.pca,choix=c("ind"), invisible=c("ind"))
```



Multivariant outliers should be included as supplementary observations: Since the data set we have is pretty good, we considered that we don't have multivariate outliers

2.1 Eigenvalues and dominant axes analysis

Eigenvalues correspond to the amount of the variation explained by each principal component (PC). Eigenvalues are large for the first PC and small for the subsequent PCs.

```
# summary(res.pca, nb.dec=2,nbind=1, nbelements = 1000, ncp=5)
```

2.1.1 How many axes we have to interpret according to Kaiser?

A PC with an eigenvalue > 1 indicates that the PC accounts for more variance than accounted by one of the original variables in standardized data. This is commonly used as a cutoff point to determine the number of PCs to retain, using the Kaiser criteria.

```
eigenvalues <- res.pca$eig
head(eigenvalues[, 1:3])
```

```
##        eigenvalue percentage of variance cumulative percentage of variance
## comp 1  3.1654602              39.568252                           39.56825
## comp 2  1.0538386              13.172983                           52.74124
## comp 3  1.0394009              12.992511                           65.73375
## comp 4  0.9538540              11.923175                           77.65692
## comp 5  0.8970712              11.213390                           88.87031
## comp 6  0.7211678               9.014597                           97.88491
```

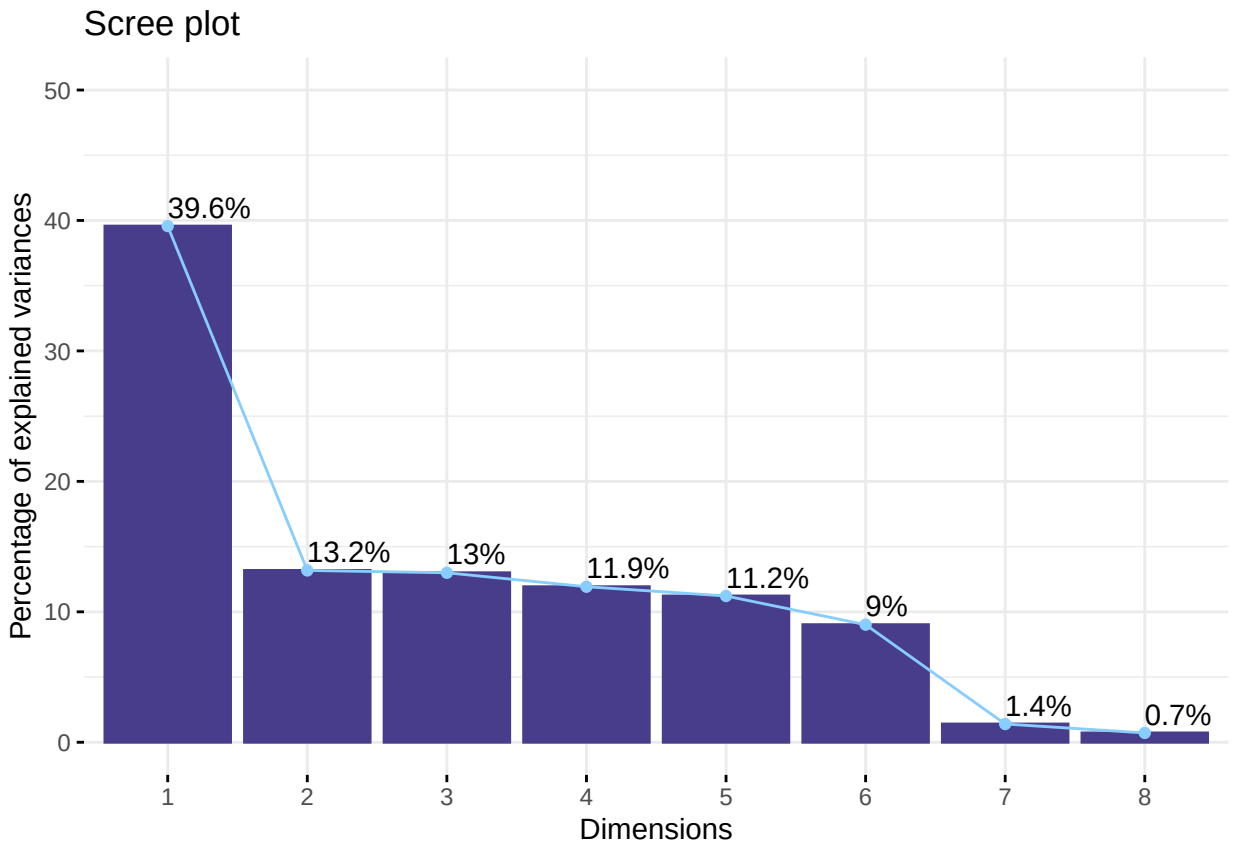
In this case, then, we will use up to dimension 3, and they will explain 65.73% of the total inertia.

2.1.2 How many axes we have to interpret according to Elbow's rule?

As a brief definition, we would say that the elbow rule is based on selecting dimensions until the difference in variance of that of the next factorial plane is almost the same as that of the current plane.

So let's look at exactly where we have this minimal difference:

```
fviz_screeplot(
  res.pca,
  addlabels=TRUE,
  ylim=c(0,50),
  barfill="darkslateblue",
  barcolor="darkslateblue",
  linecolor = "skyblue1"
)
```



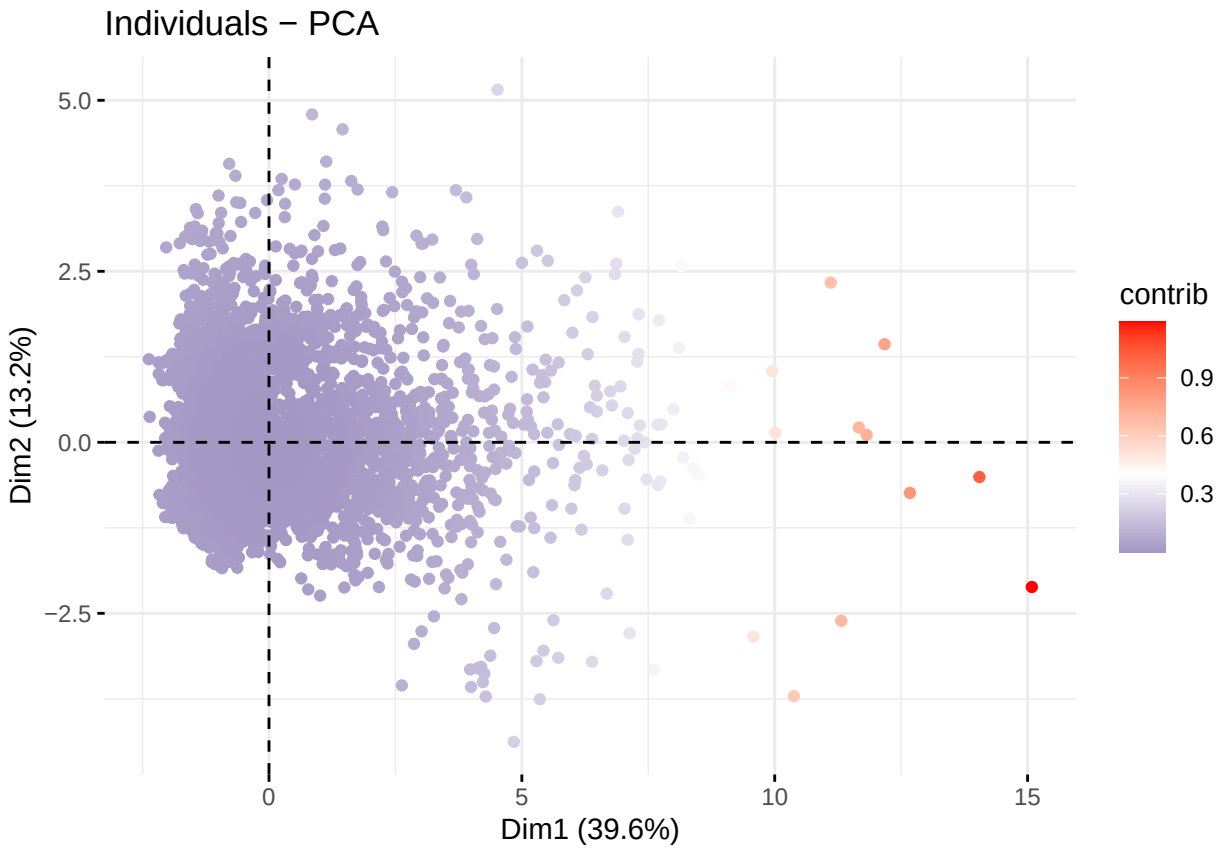
We could say, then, that there is little difference between dimension 3 and 4, or between 5 and 6. Therefore, we

could be left with 3 dimensions (as with Kasier) or 5.

2.2 Individuals point of view

2.2.1 Contribution

```
# head(res.pca$ind$contrib) # contribition of individuals to the princial components
fviz_pca_ind(res.pca, col.ind="contrib", geom = "point") +
scale_color_gradient2(low="darkslateblue", mid="white",
                      high="red", midpoint=0.40)
```

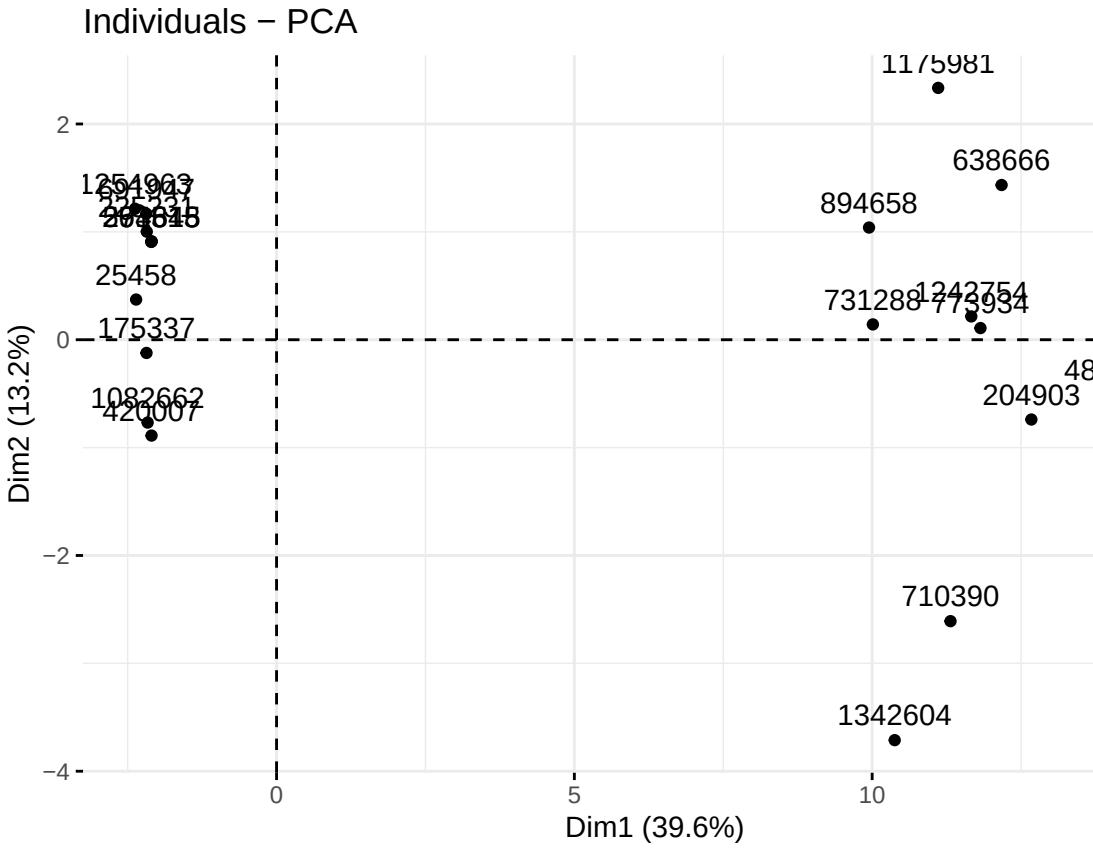


We can see that there are some individuals that are too contributive. So now, let's try to understand them better with extreme individuals.

2.2.2 Extreme individuals

```
rang<-order(res.pca$ind$coord[,1])
contrib.extremes<-c(row.names(df)[rang[1]], row.names(df)[rang[length(rang)]])

contrib.extremes<-c(row.names(df)[rang[1:10]], row.names(df)[rang[(length(rang)-10):length(rang)]])
fviz_pca_ind(res.pca, select.ind = list(names=contrib.extremes))
```



2.2.2.1 In dimension 1:

We can now have a look at them:

```
df[which(row.names(df) %in% row.names(df)[rang[(length(rang)-10):length(rang)]]), 1:28]
```

```
##                 VendorID RateCodeID Pickup_longitude Pickup_latitude
## 204903    f.Vendor-Mobile     Rate-1        -73.98677        40.70252
## 488540  f.Vendor-VeriFone     Rate-1        -73.91121        40.75299
## 604912  f.Vendor-VeriFone     Rate-1        -73.81548        40.62804
## 638666  f.Vendor-VeriFone Rate-Other        -73.80701        40.69907
## 710390  f.Vendor-VeriFone     Rate-1        -73.93688        40.81975
## 731288  f.Vendor-VeriFone     Rate-1        -73.94330        40.63695
## 773934  f.Vendor-VeriFone     Rate-1        -73.95317        40.81768
## 894658    f.Vendor-Mobile     Rate-1        -73.94506        40.79953
## 1175981 f.Vendor-VeriFone     Rate-1        -73.92376        40.76116
## 1242754 f.Vendor-VeriFone     Rate-1        -73.96619        40.58548
## 1342604   f.Vendor-Mobile Rate-Other        -73.94370        40.81538
##         Dropoff_longitude Dropoff_latitude Passenger_count Trip_distance
## 204903          -73.97940         40.64393               1      27.00000
## 488540          -73.91345         40.75084               1      30.00000
## 604912          -73.99866         40.59183               1      27.33295
## 638666          -73.81952         40.71432               1      18.21000
## 710390          -73.84977         40.67285               1      19.00000
## 731288          -73.86108         40.83635               6      19.94000
## 773934          -73.95087         40.72394               1      24.92000
## 894658          -73.94336         40.71036               1      25.70000
## 1175981         -73.90582         40.76783               5      27.76064
## 1242754         -73.87349         40.77394               1      22.46000
## 1342604         -73.94130         40.64498               1      18.30000
##         Fare_amount Extra MTA_tax Tip_amount Tolls_amount improvement_surcharge
## 204903     60.00000   0.0     Yes      14.35     0.000000                   Yes
## 488540     60.00000   0.0     Yes      17.00     0.000000                   Yes
## 604912     60.00000   0.5     Yes      17.00     5.540000                   Yes
## 638666     60.00000   1.0     Yes      17.00     3.020141                   Yes
## 710390     50.50000   0.5     Yes      11.47     5.540000                   Yes
## 731288     48.79243   0.0     Yes       0.00     5.540000                   Yes
## 773934     60.00000   0.5     Yes      13.36     0.000000                   Yes
```

```
## 894658     60.00000   1.0     Yes       0.00     0.000000                  Yes
## 1175981    60.00000   0.5     Yes       0.00     0.000000                  Yes
## 1242754    60.00000   0.0     Yes      12.86     0.000000                  Yes
## 1342604    52.00000   0.0     Yes       6.00     5.540000                  Yes
##         Total_amount Payment_type   Trip_type hour           period   tlenkm
## 204903         86.15  Credit card Street-Hail    7     Period night 43.45229
## 488540        128.76  Credit card Street-Hail    6     Period night 48.28000
## 604912        108.41  Credit card Street-Hail   20 Period afternoon 48.28000
## 638666        111.05  Credit card Street-Hail   16    Period valley 29.30615
## 710390         68.81  Credit card Street-Hail   23     Period night 30.57754
## 731288         68.84  Credit card Street-Hail   10   Period morning 32.09032
## 773934         80.16  Credit card Street-Hail    0     Period night 40.10485
## 894658         72.80         Cash Street-Hail   18 Period afternoon 41.36014
## 1175981       116.30         Cash Street-Hail   23     Period night 48.28000
## 1242754        77.16  Credit card Street-Hail   14    Period valley 36.14587
## 1342604        64.34  Credit card Street-Hail    6     Period night 29.45100
##         traveltime   espeed pickup dropoff Trip_distance_range paidTolls
## 204903    41.71667 55.00000     07      08           Long_dist        No
## 488540    49.00000 55.00000     06      07          Short_dist        No
## 604912    43.18333 55.00000     20      21          Short_dist       Yes
## 638666    60.00000 25.41608     16      17           Long_dist      <NA>
## 710390    30.53333 55.00000     23      00           Long_dist       Yes
## 731288    60.00000 31.56425     10      11           Long_dist       Yes
## 773934    36.73333 55.00000     00      01           Long_dist        No
## 894658    46.28333 53.61776     18      19           Long_dist        No
## 1175981   60.00000 55.00000     23      00          Short_dist        No
## 1242754   57.71667 37.57584     14      15           Long_dist        No
## 1342604   30.75000 55.00000     06      06           Long_dist       Yes
##         TipIsGiven passenger_groups
## 204903         Yes           Single
## 488540         Yes           Single
## 604912         Yes           Single
## 638666         Yes           Single
## 710390         Yes           Single
## 731288          No            Group
## 773934         Yes           Single
## 894658          No           Single
## 1175981         No            Group
## 1242754        Yes           Single
## 1342604        Yes           Single
```

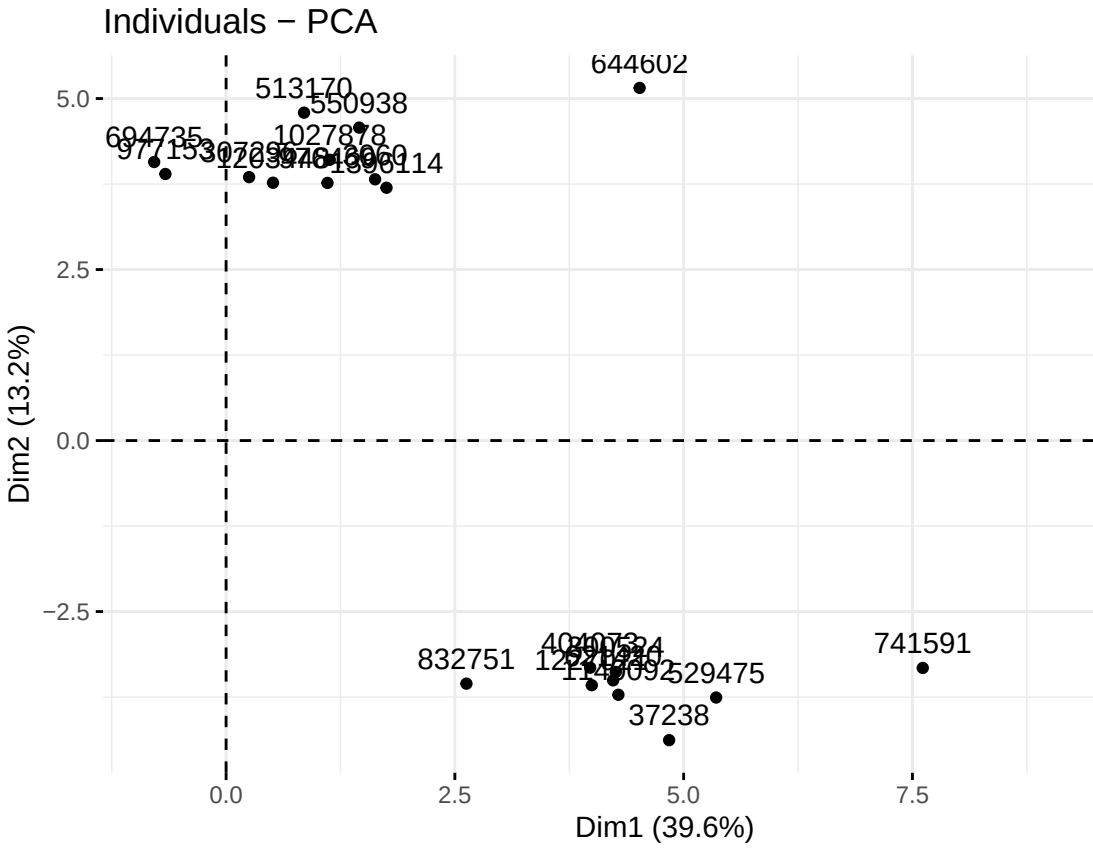
```
df[which(row.names(df) %in% row.names(df)[rang[1:10]]),1:28]
```

```
##                  VendorID RateCodeID Pickup_longitude Pickup_latitude
## 25458   f.Vendor-VeriFone     Rate-1        -73.89600        40.85568
## 175337    f.Vendor-Mobile     Rate-1        -73.85332        40.72649
## 225231  f.Vendor-VeriFone     Rate-1        -73.94785        40.80964
## 263515  f.Vendor-VeriFone     Rate-1        -73.95492        40.82026
## 274645    f.Vendor-Mobile     Rate-1        -73.94057        40.62366
## 420007    f.Vendor-Mobile     Rate-1        -73.89059        40.74692
## 591818  f.Vendor-VeriFone     Rate-1        -73.97880        40.68356
## 691947  f.Vendor-VeriFone     Rate-1        -73.80762        40.70077
## 1082662 f.Vendor-VeriFone     Rate-1        -73.93958        40.81605
## 1254963 f.Vendor-VeriFone     Rate-1        -73.99031        40.69246
##         Dropoff_longitude Dropoff_latitude Passenger_count Trip_distance
## 25458           -73.89645         40.85497               1    0.05000000
## 175337          -73.85199         40.72478               2    0.10000000
## 225231          -73.94830         40.80927               1    0.04000000
## 263515          -73.95686         40.81767               1    0.03813833
## 274645          -73.94056         40.62366               1    0.03807637
## 420007          -73.89084         40.74857               1    0.10000000
## 591818          -73.97880         40.68356               1    0.03810496
## 691947          -73.80876         40.69843               1    0.16000000
## 1082662         -73.94041         40.81475               1    0.09000000
```

```
## 1254963         -73.99083         40.69273               1    0.03000000
##         Fare_amount Extra MTA_tax Tip_amount Tolls_amount improvement_surcharge
## 25458           3.0   0.5     Yes          0            0                   Yes
## 175337          3.5   0.0     Yes          0            0                   Yes
## 225231          2.5   1.0     Yes          0            0                   Yes
## 263515          2.5   1.0     Yes          0            0                   Yes
## 274645          2.5   1.0     Yes          0            0                   Yes
## 420007          2.5   0.0     Yes          0            0                   Yes
## 591818          2.5   1.0     Yes          0            0                   Yes
## 691947          3.0   1.0     Yes          0            0                   Yes
## 1082662         3.0   0.0     Yes          0            0                   Yes
## 1254963         2.5   1.0     Yes          0            0                   Yes
##         Total_amount Payment_type   Trip_type hour           period     tlenkm
## 25458            4.3         Cash Street-Hail    4     Period night 0.08046720
## 175337           4.3         Cash Street-Hail   14    Period valley 0.16093440
## 225231           4.3         Cash Street-Hail   17 Period afternoon 0.06437376
## 263515           4.3         Cash Street-Hail   16    Period valley 0.00000000
## 274645           4.3      No paid Street-Hail   19 Period afternoon 0.00000000
## 420007           3.3         Cash Street-Hail   19 Period afternoon 0.16093440
## 591818           4.3  Credit card Street-Hail   16    Period valley 0.00000000
## 691947           4.8         Cash Street-Hail   18 Period afternoon 0.25749504
## 1082662          3.8         Cash Street-Hail   19 Period afternoon 0.14484096
## 1254963          4.3         Cash Street-Hail   18 Period afternoon 0.04828032
##         traveltime    espeed pickup dropoff Trip_distance_range paidTolls
## 25458    1.3500000  3.576320     04      04          Short_dist        No
## 175337   2.1333333  4.526280     14      14          Short_dist        No
## 225231   0.3000000 12.874752     17      17          Short_dist        No
## 263515   0.0500000 15.398313     16      16          Short_dist        No
## 274645   0.2666667 15.382913     19      19          Short_dist        No
## 420007   0.8833333 10.931393     19      19          Short_dist        No
## 591818   0.1666667 15.390021     16      16          Short_dist        No
## 691947   1.6833333  9.178041     18      19          Short_dist        No
## 1082662  1.1166667  7.782499     19      19          Short_dist        No
## 1254963  0.4166667  6.952366     18      18          Short_dist        No
##         TipIsGiven passenger_groups
## 25458           No           Single
## 175337          No           Couple
## 225231          No           Single
## 263515          No           Single
## 274645          No           Single
## 420007          No           Single
## 591818          No           Single
## 691947          No           Single
## 1082662         No           Single
## 1254963         No           Single
```

```
rang<-order(res.pca$ind$coord[,2])
contrib.extremes<-c(row.names(df)[rang[1]], row.names(df)[rang[length(rang)]])

contrib.extremes<-c(row.names(df)[rang[1:10]], row.names(df)[rang[(length(rang)-10):length(rang)]])
fviz_pca_ind(res.pca, select.ind = list(names=contrib.extremes))
```



2.2.2.2 In dimension 2:

We can now have a look at them:

```
df[which(row.names(df) %in% row.names(df)[rang[(length(rang)-10):length(rang)]]), 1:28]
```

```
##                  VendorID RateCodeID Pickup_longitude Pickup_latitude
## 3060    f.Vendor-VeriFone     Rate-1        -73.86355        40.73727
## 307296  f.Vendor-VeriFone     Rate-1        -73.95361        40.78796
## 513170  f.Vendor-VeriFone     Rate-1        -73.91908        40.75881
## 550938  f.Vendor-VeriFone     Rate-1        -73.93481        40.74301
## 644602  f.Vendor-VeriFone     Rate-1        -73.92159        40.76666
## 694735  f.Vendor-VeriFone     Rate-1        -73.98262        40.66566
## 976469  f.Vendor-VeriFone     Rate-1        -73.96669        40.80442
## 977153  f.Vendor-VeriFone     Rate-1        -73.89025        40.74623
## 1027878 f.Vendor-VeriFone     Rate-1        -73.96809        40.63953
## 1203448 f.Vendor-VeriFone     Rate-1        -73.97668        40.68291
## 1396114 f.Vendor-VeriFone     Rate-1        -73.96153        40.71631
##         Dropoff_longitude Dropoff_latitude Passenger_count Trip_distance
## 3060            -73.91945         40.74348               5          3.05
## 307296          -73.96581         40.76854               5          1.68
## 513170          -73.90479         40.77545               5          1.47
## 550938          -73.96293         40.75823               6          2.87
## 644602          -73.98792         40.73801               6          6.26
## 694735          -73.97092         40.67282               6          0.97
## 976469          -73.96804         40.76556               5          3.45
## 977153          -73.92136         40.75252               6          1.81
## 1027878         -73.98267         40.67964               6          3.58
## 1203448         -73.93872         40.69656               5          3.11
## 1396114         -73.98534         40.72356               6          2.49
##         Fare_amount Extra MTA_tax Tip_amount Tolls_amount improvement_surcharge
## 3060           14.0   0.5     Yes       0.00            0                   Yes
## 307296         14.0   1.0     Yes       3.16            0                   Yes
## 513170          8.0   1.0     Yes       0.00            0                   Yes
## 550938         19.0   1.0     Yes       4.16            0                   Yes
## 644602         32.5   1.0     Yes       6.86            0                   Yes
## 694735          9.0   1.0     Yes       2.16            0                   Yes
## 976469         18.0   1.0     Yes       2.50            0                   Yes
```

```
## 977153         10.5   1.0     Yes       0.00            0                   Yes
## 1027878        16.0   1.0     Yes       3.56            0                   Yes
## 1203448        17.0   1.0     Yes       0.00            0                   Yes
## 1396114        19.0   0.5     Yes       6.09            0                   Yes
##         Total_amount Payment_type   Trip_type hour           period    tlenkm
## 3060           15.30         Cash Street-Hail    0     Period night  4.908499
## 307296         18.96  Credit card Street-Hail   16    Period valley  2.703698
## 513170          9.80         Cash Street-Hail   18 Period afternoon  2.365736
## 550938         24.96  Credit card Street-Hail   17 Period afternoon  4.618817
## 644602         41.16  Credit card Street-Hail   18 Period afternoon 10.074493
## 694735         12.96  Credit card Street-Hail   19 Period afternoon  1.561064
## 976469         22.30  Credit card Street-Hail   16    Period valley  5.552237
## 977153         12.30         Cash Street-Hail   17 Period afternoon  2.912913
## 1027878        21.36  Credit card Street-Hail   16    Period valley  5.761452
## 1203448        18.80  Credit card Street-Hail   17 Period afternoon  5.005060
## 1396114        26.39  Credit card Street-Hail    0     Period night  4.007267
##         traveltime    espeed pickup dropoff Trip_distance_range paidTolls
## 3060      60.00000  3.864960     00      01         Medium_dist        No
## 307296    21.35000  7.598214     16      16          Short_dist        No
## 513170    60.00000  3.000000     18      18          Short_dist        No
## 550938    30.50000  9.086198     17      17         Medium_dist        No
## 644602    52.20000 11.579878     18      19           Long_dist        No
## 694735    12.08333  7.751489     19      19          Short_dist        No
## 976469    25.50000 13.064087     16      17         Medium_dist        No
## 977153    13.81667 12.649560     17      18          Short_dist        No
## 1027878   21.98333 15.724962     16      16         Medium_dist        No
## 1203448   26.13333 11.491209     17      18         Medium_dist        No
## 1396114   31.03333  7.747669     00      00          Short_dist        No
##         TipIsGiven passenger_groups
## 3060            No            Group
## 307296         Yes            Group
## 513170          No            Group
## 550938         Yes            Group
## 644602         Yes            Group
## 694735         Yes            Group
## 976469         Yes            Group
## 977153          No            Group
## 1027878        Yes            Group
## 1203448         No            Group
## 1396114        Yes            Group
```

```
df[which(row.names(df) %in% row.names(df)[rang[1:10]]),1:28]
```

```
##                  VendorID RateCodeID Pickup_longitude Pickup_latitude
## 37238   f.Vendor-VeriFone     Rate-1        -73.94037        40.79722
## 300524  f.Vendor-VeriFone     Rate-1        -73.95204        40.79805
## 404073  f.Vendor-VeriFone     Rate-1        -73.92345        40.80943
## 529475  f.Vendor-VeriFone     Rate-1        -73.95724        40.81275
## 621420  f.Vendor-VeriFone     Rate-1        -73.93903        40.81678
## 741591  f.Vendor-VeriFone     Rate-1        -73.89080        40.74696
## 832751  f.Vendor-VeriFone     Rate-1        -73.98846        40.67025
## 1140092   f.Vendor-Mobile     Rate-1        -73.91059        40.76953
## 1227021 f.Vendor-VeriFone     Rate-1        -73.89172        40.74702
## 1342604   f.Vendor-Mobile Rate-Other        -73.94370        40.81538
##         Dropoff_longitude Dropoff_latitude Passenger_count Trip_distance
## 37238           -73.87116         40.77416               1          6.29
## 300524          -73.87309         40.77436               2          7.44
## 404073          -73.87628         40.76842               1          6.70
## 529475          -73.86170         40.76838               1          7.85
## 621420          -73.87211         40.77211               1          7.33
## 741591          -74.01478         40.71557               1         11.47
## 832751          -74.01384         40.71449               1          3.66
## 1140092         -73.86433         40.84798               1          7.50
## 1227021         -73.91472         40.80377               1          6.62
```

```
## 1342604         -73.94130         40.64498               1         18.30
##         Fare_amount Extra MTA_tax Tip_amount Tolls_amount improvement_surcharge
## 37238          19.0   0.0     Yes       5.07         5.54                   Yes
## 300524         22.5   0.0     Yes       0.00         5.54                   Yes
## 404073         23.5   0.0     Yes       0.00         5.54                   Yes
## 529475         24.0   0.0     Yes       5.00         5.54                   Yes
## 621420         24.0   0.0     Yes       0.00         5.54                   Yes
## 741591         34.0   0.0     Yes       8.07         5.54                   Yes
## 832751         13.5   0.0     Yes       2.00         5.54                   Yes
## 1140092        23.5   0.0     Yes       0.00         5.54                   Yes
## 1227021        19.5   0.5     Yes       0.00         5.54                   Yes
## 1342604        52.0   0.0     Yes       6.00         5.54                   Yes
##         Total_amount Payment_type   Trip_type hour         period    tlenkm
## 37238          30.41  Credit card Street-Hail    9 Period morning 10.122774
## 300524         28.84  Credit card Street-Hail   13  Period valley 11.973519
## 404073         29.84  Credit card Street-Hail   14  Period valley 10.782605
## 529475         35.34  Credit card Street-Hail    6   Period night 12.633350
## 621420         30.34         Cash Street-Hail    8 Period morning 11.796492
## 741591         48.41  Credit card Street-Hail   15  Period valley 18.459176
## 832751         21.84  Credit card Street-Hail    9 Period morning  5.890199
## 1140092        29.84         Cash Street-Hail    8 Period morning 12.070080
## 1227021        26.34         Cash Street-Hail    5   Period night 10.653857
## 1342604        64.34  Credit card Street-Hail    6   Period night 29.450995
##         traveltime   espeed pickup dropoff Trip_distance_range paidTolls
## 37238     11.30000 53.74924     09      09           Long_dist       Yes
## 300524    17.48333 41.09120     13      13           Long_dist       Yes
## 404073    22.56667 28.66867     14      14           Long_dist       Yes
## 529475    18.20000 41.64841     06      07           Long_dist       Yes
## 621420    21.33333 33.17763     08      09           Long_dist       Yes
## 741591    27.78333 39.86385     15      15           Long_dist       Yes
## 832751    12.60000 28.04857     09      09         Medium_dist       Yes
## 1140092   19.23333 37.65363     08      09           Long_dist       Yes
## 1227021   10.46667 55.00000     05      05           Long_dist       Yes
## 1342604   30.75000 55.00000     06      06           Long_dist       Yes
##         TipIsGiven passenger_groups
## 37238          Yes           Single
## 300524          No           Couple
## 404073          No           Single
## 529475         Yes           Single
## 621420          No           Single
## 741591         Yes           Single
## 832751         Yes           Single
## 1140092         No           Single
## 1227021         No           Single
## 1342604        Yes           Single
```

2.2.3 Detection of multivariant outliers and influent data.

Since we've commented before that we don't consider multivariate outliers, no action should be taken here.

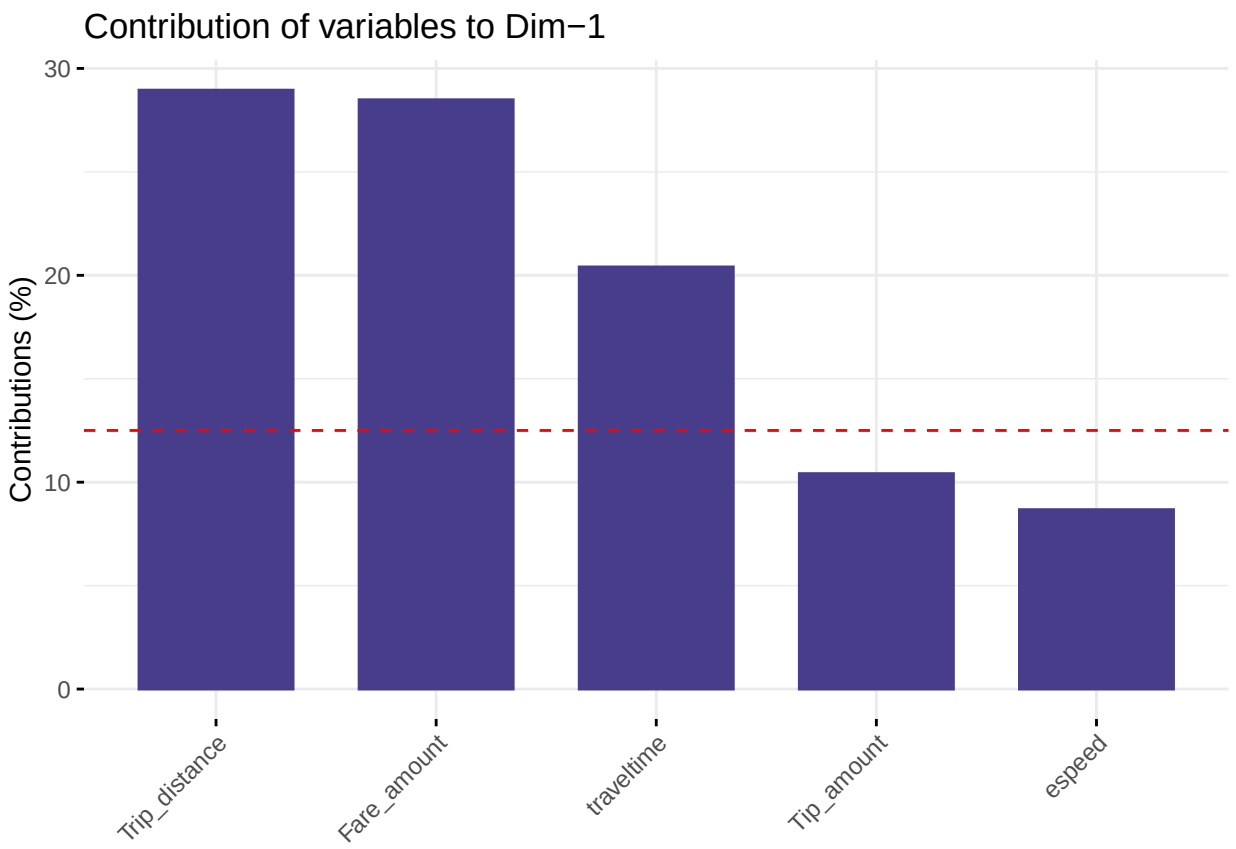
2.3 Interpreting the axes: Variables point of view coordinates, quality of representation, contribution of the variables

```
res.des <- dimdesc(res.pca)
```

2.3.1 First dimension

```
fviz_contrib(  # contributions of variables to PC1
  res.pca,
  fill = "darkslateblue",
  color = "darkslateblue",
  choice = "var",
```

```
  axes = 1,
  top = 5)
```




```
res.des$Dim.1
```

```
## $quanti
##                   correlation      p.value
## Trip_distance      0.95730706 0.000000e+00
## Fare_amount        0.94960484 0.000000e+00
## Total_amount       0.93942001 0.000000e+00
## traveltime         0.80368337 0.000000e+00
## Tip_amount         0.57415837 0.000000e+00
## espeed             0.52394674 0.000000e+00
## Tolls_amount       0.30300105 9.013310e-99
## Pickup_longitude  -0.03125024 3.360908e-02
## Dropoff_longitude -0.05426961 2.227979e-04
## Extra             -0.07041780 1.646768e-06
## Pickup_latitude   -0.10228377 3.148028e-12
## Dropoff_latitude  -0.12894697 1.345881e-18
##
## $quali
##                                R2      p.value
## Trip_distance_range 0.691017128 0.000000e+00
## TipIsGiven          0.060653567 7.774385e-65
## Payment_type        0.053034123 2.149327e-55
## RateCodeID          0.008583339 2.769847e-10
## period              0.005169311 2.569159e-05
## Trip_type           0.001738152 4.580306e-03
##
## $category
##                                    Estimate      p.value
## Trip_distance_range=Long_dist    2.23397417 0.000000e+00
## TipIsGiven=Yes                   0.45216207 7.774385e-65
## Payment_type=Credit card         0.41968655 2.271313e-56
## RateCodeID=Rate-Other            0.50422625 2.769847e-10
## period=Period morning            0.20884328 1.137211e-03
```

```
## Trip_type=Dispatch                0.24121859 4.580306e-03
## period=Period night               0.05154686 3.047979e-02
## Trip_type=Street-Hail            -0.24121859 4.580306e-03
## period=Period afternoon          -0.19586260 1.290974e-04
## RateCodeID=Rate-1                -0.50422625 2.769847e-10
## Trip_distance_range=Medium_dist -0.28824012 2.452911e-45
## Payment_type=Cash                -0.40559005 2.694846e-56
## TipIsGiven=No                    -0.45216207 7.774385e-65
## Trip_distance_range=Short_dist   -1.94573405 0.000000e+00
##
## attr(,"class")
## [1] "condes" "list "
```

In the first dimension we see that for the **quantitative** variables the most positively related, from more to less, are:

- Trip_distance (0.95)
- Fare_amount (0.94)
- Total_amount (0.93)
- traveltime (0.80)

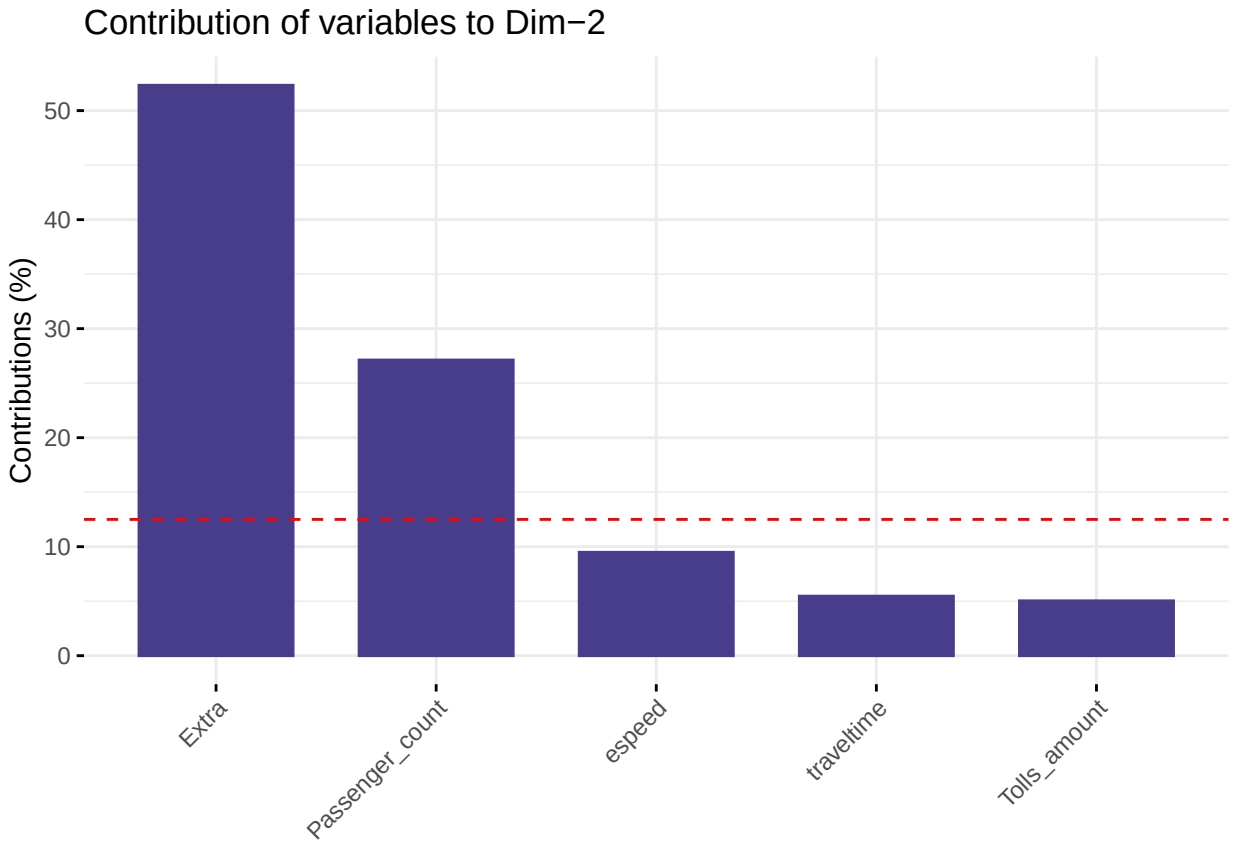
If we take look at the **qualitatives** ones, we that the most related is

- Trip_distance_range (0.69)

Finally, if we take a look at the **categories** we see that for the Trip_distance_range category long distance trips show a mean 2.23 units over the global mean and short distance ones show a mean -1.94 units under the global mean, so we can reject the H0 done in the t.Student test.

2.3.2 Second dimension

```
fviz_contrib(  # contributions of variables to PC1
  res.pca,
  fill = "darkslateblue",
  color = "darkslateblue",
  choice = "var",
  axes = 2,
  top = 5)
```



```
res.des$Dim.2
```

```
## $quanti
##                   correlation       p.value
## Extra              0.74258866  0.000000e+00
## Passenger_count    0.53463310  0.000000e+00
## traveltime         0.23990250  1.615918e-61
## Total_amount       0.07947291  6.278874e-08
## Fare_amount        0.06251197  2.105822e-05
## Tip_amount         0.04580469  1.838358e-03
## Pickup_latitude   -0.12147081  1.155632e-16
## Dropoff_latitude -0.12411309  2.469588e-17
## Tolls_amount      -0.23032359  1.024002e-56
## espeed            -0.31615982 7.834681e-108
##
## $quali
##                                R2       p.value
## period               0.184068800 2.143099e-203
## RateCodeID           0.018119629  3.862505e-20
## Trip_type            0.014819256  9.922508e-17
## VendorID             0.002425023  8.098907e-04
## TipIsGiven           0.001332968  1.304433e-02
## Trip_distance_range 0.001446882  3.527015e-02
##
## $category
##                                     Estimate       p.value
## period=Period afternoon           0.69741738 6.273330e-126
## RateCodeID=Rate-1                  0.42270813  3.862505e-20
## Trip_type=Street-Hail              0.40639535  9.922508e-17
## period=Period night                0.19868760  1.141234e-06
## VendorID=f.Vendor-VeriFone         0.06200633  8.098907e-04
## TipIsGiven=Yes                     0.03867626  1.304433e-02
## Trip_distance_range=Medium_dist    0.06499883  4.081973e-02
## Trip_distance_range=Long_dist     -0.06734957  4.739997e-02
## TipIsGiven=No                     -0.03867626  1.304433e-02
## VendorID=f.Vendor-Mobile          -0.06200633  8.098907e-04
## Trip_type=Dispatch                -0.40639535  9.922508e-17
## RateCodeID=Rate-Other             -0.42270813  3.862505e-20
## period=Period valley              -0.28051232  5.465420e-55
## period=Period morning             -0.61559267  5.765919e-69
##
## attr(,"class")
## [1] "condes" "list "
```

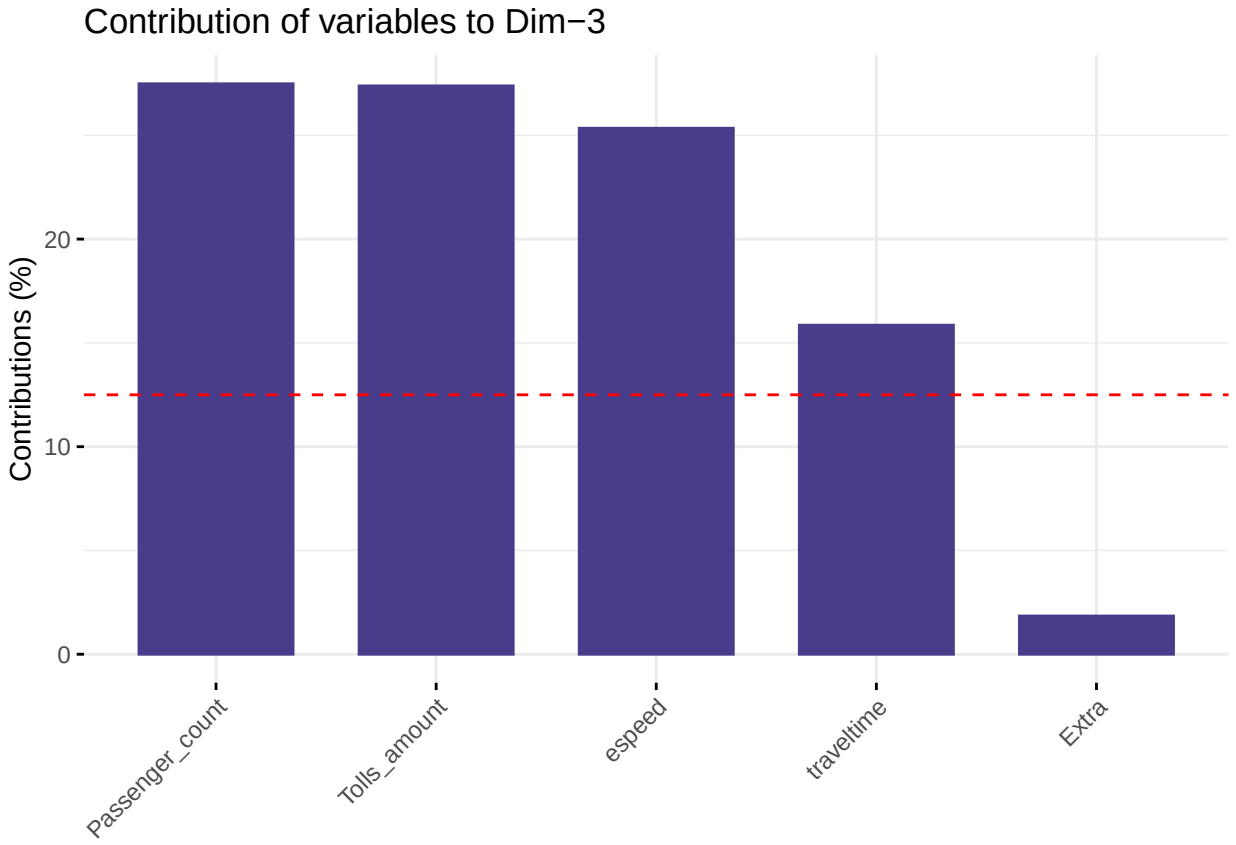
For the second dimension we see that or the **quantitative** variables Extra and Passenger_count are the most positively related ones with 0.74 and 0.53 respectively.

If we see the **qualitative** variables we notice that period is the most related with 0.18 even though it is not a very remarkable data.

And we see that for this **category**, period afternoon mean is 0.69 units over the global mean and period morning mean, on the contrary, is -0.61 units under the global mean, so we can reject the H0 done in the t.Student test.

2.3.3 Third dimension

```
fviz_contrib(  # contributions of variables to PC1
  res.pca,
  fill = "darkslateblue",
  color = "darkslateblue",
  choice = "var",
  axes = 3,
  top = 5)
```




```
res.des$Dim.3
```

```
## $quanti
##                    correlation       p.value
## Passenger_count     0.53445793  0.000000e+00
## Tolls_amount        0.53348146  0.000000e+00
## espeed              0.51322530 3.958881e-309
## Extra               0.13832221  3.460374e-21
## Dropoff_longitude   0.08626112  4.241523e-09
## Pickup_longitude    0.07649050  1.919027e-07
## Tip_amount          0.05620014  1.317391e-04
## Dropoff_latitude    0.04007164  6.431426e-03
## Pickup_latitude     0.03744970  1.088064e-02
## Total_amount       -0.06349286  1.558600e-05
## Fare_amount        -0.13644926  1.178290e-20
## traveltime         -0.40591753 6.233710e-183
##
## $quali
##                                R2      p.value
## period               0.035886226 2.283135e-36
## Trip_distance_range 0.007909240 1.080799e-08
## TipIsGiven           0.004524510 4.707055e-06
## Payment_type         0.003949701 1.070864e-04
## VendorID             0.001086215 2.503325e-02
##
## $category
##                                      Estimate      p.value
## period=Period night                0.282886526 4.247490e-30
## TipIsGiven=Yes                     0.070766034 4.707055e-06
## Payment_type=Credit card           0.121518708 2.298510e-05
## Trip_distance_range=Short_dist     0.064024746 1.353427e-04
## VendorID=f.Vendor-VeriFone         0.041213596 2.503325e-02
## VendorID=f.Vendor-Mobile          -0.041213596 2.503325e-02
## Payment_type=Cash                 -0.004578138 4.465703e-05
## TipIsGiven=No                     -0.070766034 4.707055e-06
## Trip_distance_range=Medium_dist -0.152026208 1.617657e-09
```

```
## period=Period morning           -0.205703946 2.492716e-10
## period=Period valley            -0.144508011 4.079781e-16
##
## attr(,"class")
## [1] "condes" "list "
```

For the last dimension we took into account, the third one, we see that the most related **quantitative** variables are:

- Passenger_count (0.53)
- Tolls_amount (0.53)
- espeed (0.51),

For the inversely related one, we also see that traveltime time (-0.40).

For the **quanlitatives**, we see that period is the category that is more related with 0.36, even though it is not a big relation.

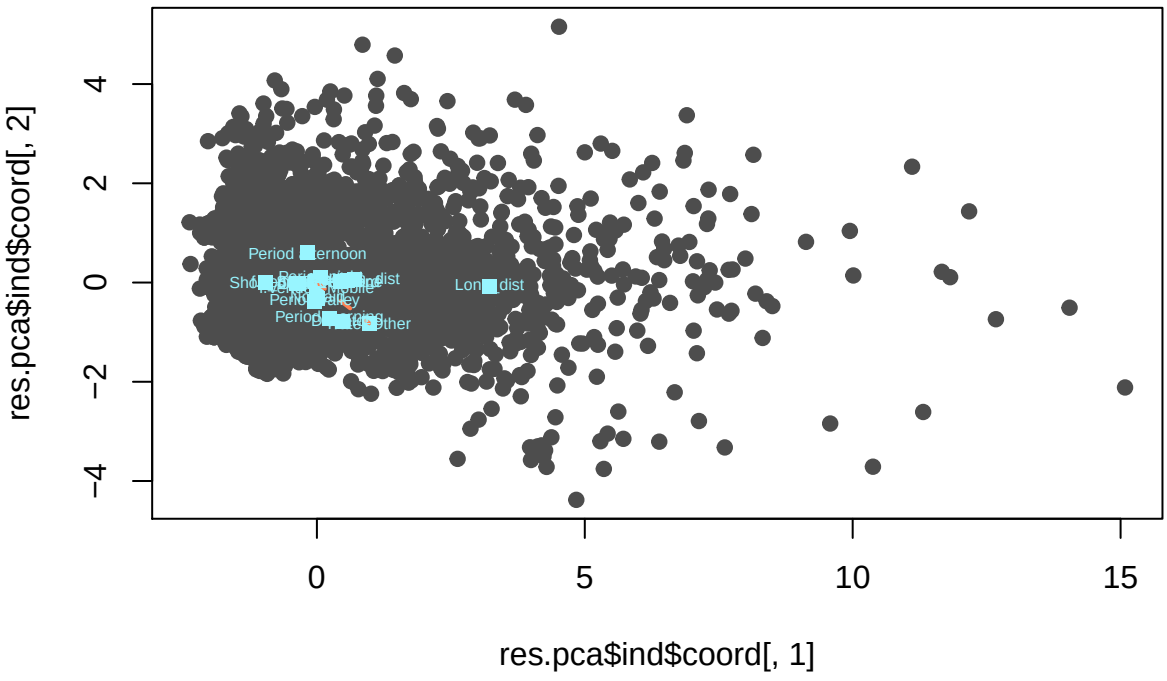
And we see that for this **category**, period afternoon mean is 0.28 units over the global mean and period valley mean, on the contrary, is -0.14 units under the global mean, hough it is not either a big relation.

We can conclude, then, that the first dimension is the one with the biggest correlations.

2.4 Perform a PCA taking into account also supplementary variables the supplementary variables can be quantitative and/or categorical

We want to take analyze the supplementary factor **kind of rate**, so we want to add lines that join the categories of this factor for the first factorial plane. With the following plot we can see it.

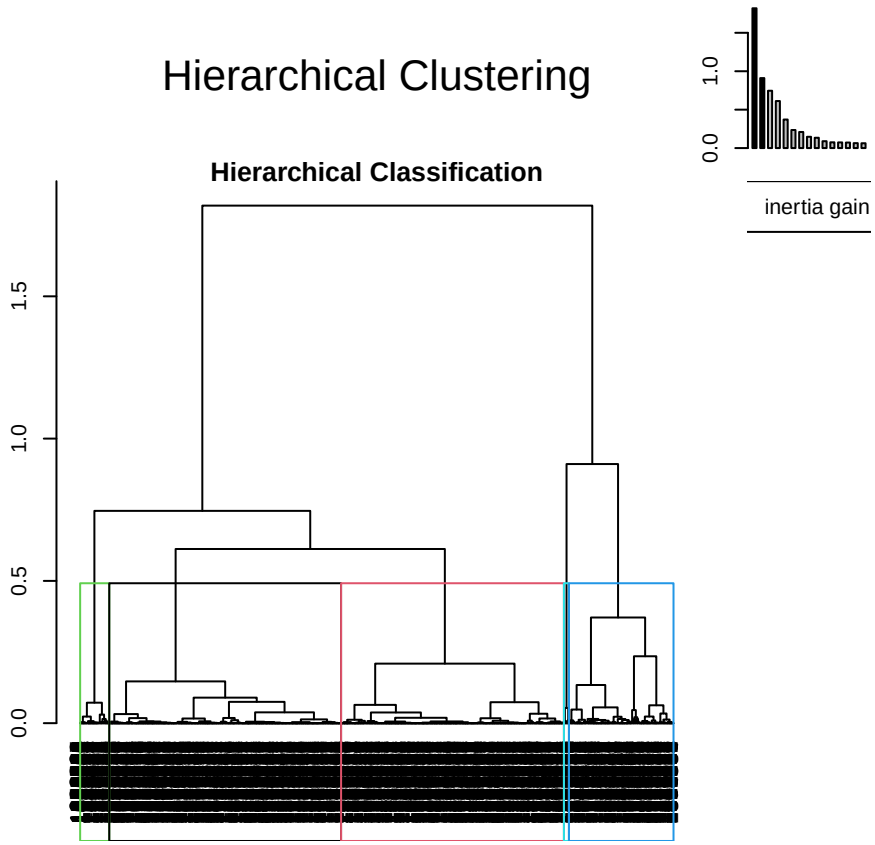
```
plot(res.pca$ind$coord[,1],res.pca$ind$coord[,2],pch=19,col="grey30") #draw all the individuals in grey
points(res.pca$quali.sup$coord[,1],res.pca$quali.sup$coord[,2],pch=15,col="cadetblue1") # points associ
lines(res.pca$quali.sup$coord[3:4,1],res.pca$quali.sup$coord[3:4,2],lwd=2,lty=2,col="coral") # draw a l
text(res.pca$quali.sup$coord[,1],res.pca$quali.sup$coord[,2],labels=names(res.pca$quali.sup$coord[,1]),c
```

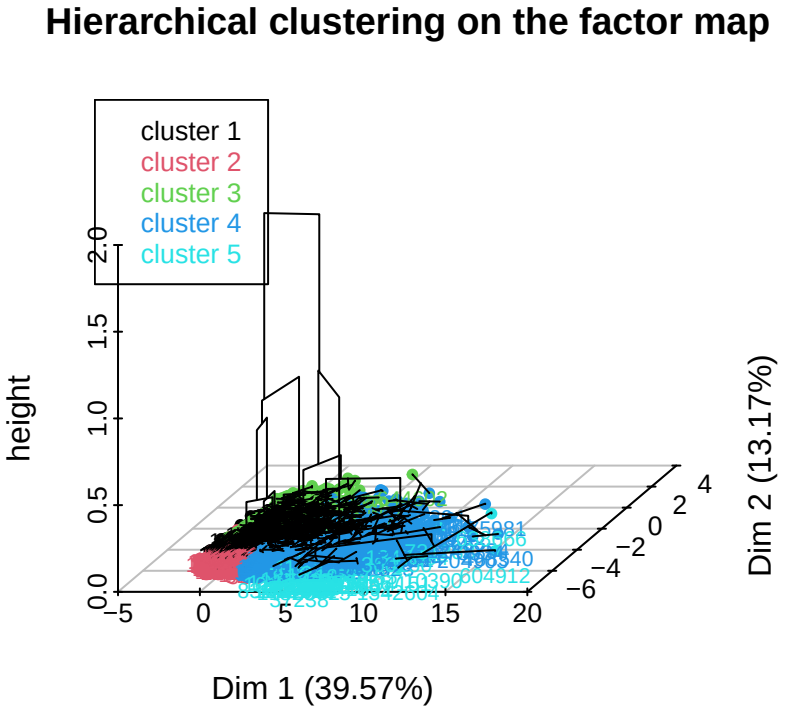


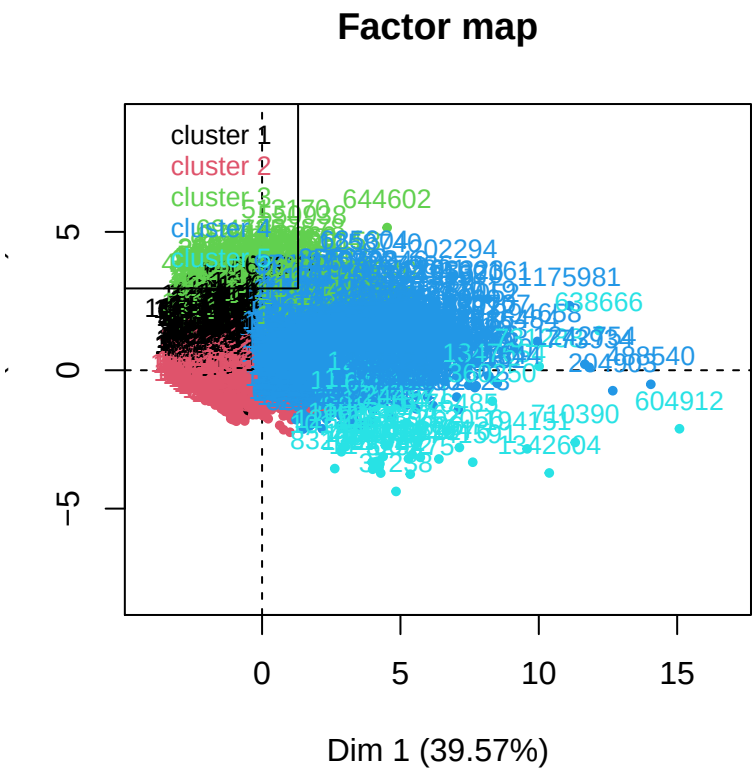

```
# res.pca$quali.sup$coord
```

3 Hierarchical Clustering

```
res.hcpc <- HCPC(res.pca,nb.clust = 5, order = TRUE)
```







Note: If we chose the default number of cluster it would be 3, as we can guess from the inertia reduction plot, that follows the Elbow's rule (number of black lines plus 1). In our case, due to the amount of data we have, the reason why we chose 5 as the number of clusters is because, after trying different numbers, we thought it was the best way to distribute the data.

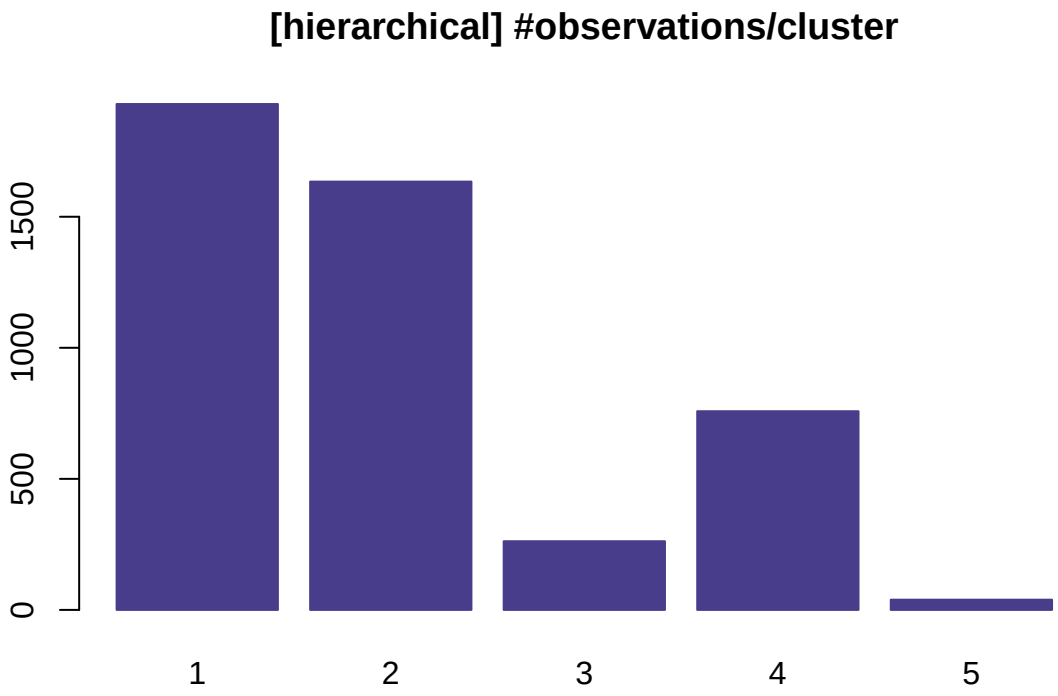
3.1 Description of clusters

Number of observations in each cluster:

```
table(res.hcpc$data.clust$clust)
```

```
##
##    1    2    3    4    5
## 1930 1634  262  758   39
```

```
barplot(table(res.hcpc$data.clust$clust), col="darkslateblue", border="darkslateblue", main="[hierarchic
```



3.2 Interpret the results of the classification

3.2.1 The description of the clusters by the variables

```
names(res.hcpc$desc.var)
```

```
## [1] "test.chi2"  "category"   "quanti.var" "quanti"     "call"
```

```
res.hcpc$desc.var$test.chi2   # categorical variables which characterizes the clusters
```

```
##                          p.value df
## period               0.000000e+00 12
## Trip_distance_range  0.000000e+00  8
## TipIsGiven           4.279197e-36  4
## Payment_type         1.274689e-28  8
## RateCodeID           4.483773e-23  4
## Trip_type            1.609776e-21  4
## VendorID             2.096463e-08  4
```

We start wit the description of the categorical variables that characterize the clusters, so in this output we do not have dimensions because it is the total association. We can see the intensity of the variables, in our case the variables that affect more to the clustering are **period** and **Trip_distance_range** because are the one with the smallest p.value. The variables associated to the clusters are the ones that appear on the output.

Next, we want to see for each cluster which are the categories that characterize them.The clusters that contain more individuals are the first, the second and the fourth one. Cluster number 4 has less individuals. We proceed to analyze them.

```
res.hcpc$desc.var$category    # description of each cluster by the categories
```

```
## $`1`
##                                    Cla/Mod      Mod/Cla    Global       p.value
## period=Period night             64.0682095  54.50777202 35.518062 7.770495e-116
## Trip_distance_range=Short_dist  50.7065949  78.08290155 64.287259  1.280121e-63
## period=Period afternoon         60.8142494  37.15025907 25.502920  6.952752e-53
## RateCodeID=Rate-1               42.9048043  99.94818653 97.252866  4.277657e-29
## Trip_type=Street-Hail           42.7843050 100.00000000 97.577331  1.936966e-27
## Payment_type=Cash               44.0128154  56.94300518 54.012546  7.116030e-04
```

```
## TipIsGiven=No                  43.6502429  65.18134715 62.340472  7.289207e-04
## Payment_type=Credit card       39.0744275  42.43523316 45.338525  7.859632e-04
## TipIsGiven=Yes                 38.5985066  34.81865285 37.659528  7.289207e-04
## Trip_type=Dispatch              0.0000000   0.00000000  2.422669  1.936966e-27
## RateCodeID=Rate-Other           0.7874016   0.05181347  2.747134  4.277657e-29
## period=Period morning           0.7380074   0.20725389 11.723989 1.260284e-129
## period=Period valley           12.4603175   8.13471503 27.255029 2.922636e-150
## Trip_distance_range=Long_dist   0.4511278   0.15544041 14.384599 2.585616e-166
##                                    v.test
## period=Period night             22.877574
## Trip_distance_range=Short_dist  16.838228
## period=Period afternoon         15.306182
## RateCodeID=Rate-1               11.195750
## Trip_type=Street-Hail           10.852664
## Payment_type=Cash                3.385069
## TipIsGiven=No                    3.378464
## Payment_type=Credit card        -3.357691
## TipIsGiven=Yes                  -3.378464
## Trip_type=Dispatch             -10.852664
## RateCodeID=Rate-Other          -11.195750
## period=Period morning          -24.223432
## period=Period valley           -26.108457
## Trip_distance_range=Long_dist  -27.485937
##
## $`2`
##                                  Cla/Mod   Mod/Cla    Global       p.value
## period=Period valley           66.587302 51.346389 27.255029 7.063369e-159
## period=Period morning          74.723247 24.785802 11.723989  1.245802e-88
## Trip_distance_range=Short_dist 42.698520 77.662179 64.287259  1.943824e-46
## Trip_type=Dispatch             73.214286  5.018360  2.422669  1.854170e-16
## RateCodeID=Rate-Other          66.141732  5.140759  2.747134  1.024771e-12
## TipIsGiven=No                  38.965996 68.727050 62.340472  2.645583e-11
## Payment_type=Cash              39.006808 59.608323 54.012546  1.570437e-08
## Payment_type=Credit card       30.963740 39.718482 45.338525  1.300378e-08
## TipIsGiven=Yes                 29.350948 31.272950 37.659528  2.645583e-11
## RateCodeID=Rate-1              34.475089 94.859241 97.252866  1.024771e-12
## Trip_type=Street-Hail          34.404788 94.981640 97.577331  1.854170e-16
## period=Period afternoon        18.999152 13.708690 25.502920  5.030711e-45
## Trip_distance_range=Long_dist   3.157895  1.285190 14.384599 1.831233e-103
## period=Period night            10.109622 10.159119 35.518062 2.015359e-175
##                                    v.test
## period=Period valley            26.856598
## period=Period morning           19.959245
## Trip_distance_range=Short_dist  14.308236
## Trip_type=Dispatch               8.231155
## RateCodeID=Rate-Other            7.127138
## TipIsGiven=No                    6.665059
## Payment_type=Cash                5.653685
## Payment_type=Credit card        -5.686015
## TipIsGiven=Yes                  -6.665059
## RateCodeID=Rate-1               -7.127138
## Trip_type=Street-Hail           -8.231155
## period=Period afternoon        -14.080144
## Trip_distance_range=Long_dist  -21.599106
## period=Period night            -28.237702
##
## $`3`
##                               Cla/Mod    Mod/Cla    Global      p.value    v.test
## VendorID=f.Vendor-VeriFone 6.767123 94.2748092 78.953061 1.557606e-12  7.069261
## period=Period night        6.942753 43.5114504 35.518062 6.033525e-03  2.745954
## RateCodeID=Rate-1          5.782918 99.2366412 97.252866 2.625621e-02  2.222401
## RateCodeID=Rate-Other      1.574803  0.7633588  2.747134 2.625621e-02 -2.222401
## period=Period valley       4.365079 20.9923664 27.255029 1.697607e-02 -2.387226
## period=Period morning      2.767528  5.7251908 11.723989 8.241798e-04 -3.344544
```

```
## VendorID=f.Vendor-Mobile   1.541624  5.7251908 21.046939 1.557606e-12 -7.069261
##
## $`4`
##                                   Cla/Mod   Mod/Cla    Global      p.value
## Trip_distance_range=Long_dist  87.5187970 76.781003 14.384599 0.000000e+00
## TipIsGiven=Yes                 24.6984492 56.728232 37.659528 2.002989e-31
## Payment_type=Credit card       22.8530534 63.192612 45.338525 3.776109e-27
## RateCodeID=Rate-Other          28.3464567  4.749340  2.747134 6.121937e-04
## period=Period night            18.2095006 39.445910 35.518062 1.401893e-02
## Trip_type=Dispatch             25.0000000  3.693931  2.422669 1.829357e-02
## period=Period morning          19.7416974 14.116095 11.723989 2.804593e-02
## VendorID=f.Vendor-Mobile       18.4994861 23.746702 21.046939 4.833228e-02
## VendorID=f.Vendor-VeriFone     15.8356164 76.253298 78.953061 4.833228e-02
## Trip_type=Street-Hail          16.1826646 96.306069 97.577331 1.829357e-02
## RateCodeID=Rate-1              16.0587189 95.250660 97.252866 6.121937e-04
## period=Period afternoon        12.9770992 20.184697 25.502920 1.834710e-04
## Payment_type=Cash              10.8930717 35.883905 54.012546 5.912321e-28
## TipIsGiven=No                  11.3809854 43.271768 62.340472 2.002989e-31
## Trip_distance_range=Short_dist  0.4710633  1.846966 64.287259 0.000000e+00
##                                    v.test
## Trip_distance_range=Long_dist         Inf
## TipIsGiven=Yes                 11.661577
## Payment_type=Credit card       10.791491
## RateCodeID=Rate-Other           3.426154
## period=Period night             2.456778
## Trip_type=Dispatch              2.359622
## period=Period morning           2.196643
## VendorID=f.Vendor-Mobile        1.974435
## VendorID=f.Vendor-VeriFone     -1.974435
## Trip_type=Street-Hail          -2.359622
## RateCodeID=Rate-1              -3.426154
## period=Period afternoon        -3.740751
## Payment_type=Cash             -10.960574
## TipIsGiven=No                 -11.661577
## Trip_distance_range=Short_dist      -Inf
##
## $`5`
##                                   Cla/Mod   Mod/Cla    Global      p.value
## Trip_distance_range=Long_dist  4.51127820 76.923077 14.384599 1.878553e-18
## Payment_type=Credit card       1.52671756 82.051282 45.338525 2.937287e-06
## TipIsGiven=Yes                 1.60827111 71.794872 37.659528 1.783365e-05
## period=Period morning          2.02952030 28.205128 11.723989 5.186239e-03
## RateCodeID=Rate-Other          3.14960630 10.256410  2.747134 2.519752e-02
## RateCodeID=Rate-1              0.77846975 89.743590 97.252866 2.519752e-02
## TipIsGiven=No                  0.38167939 28.205128 62.340472 1.783365e-05
## Payment_type=Cash              0.28033640 17.948718 54.012546 4.309549e-06
## Trip_distance_range=Short_dist 0.03364738  2.564103 64.287259 2.003816e-16
##                                    v.test
## Trip_distance_range=Long_dist    8.764351
## Payment_type=Credit card         4.675157
## TipIsGiven=Yes                   4.290419
## period=Period morning            2.795233
## RateCodeID=Rate-Other            2.238361
## RateCodeID=Rate-1               -2.238361
## TipIsGiven=No                   -4.290419
## Payment_type=Cash               -4.595866
## Trip_distance_range=Short_dist  -8.221854
```

Cluster 1

The first thing we can notice from this cluster is that **Trip_type=Street-Hail** that intervents in the 97.58% from the sample, in this cluster is the 100% of the observations, which means that all the observations in this cluster have this type of trip. We have 42.78% from the Trip_type=Street-Hail observations in this cluster. As we can see and expect, from the other trip_type that we have in this cluster is that **Trip_type=Dispatch** that intervents in the 2.42% from the sample, in this cluster is not represented, we get 0% of the observations.

Then, we can notice is the kind of rate. We can see that **RateCodeID=Rate-1**, the one that represents the standard rate, and means the 97.25% of our sample, in this cluster is the 99.95% of the observations, almost every observation from this cluster is a standard rate trip. In this cluster we have 42.90% of the observations from this category. In the other hand, we have the kind of rate, that contains the other options, represents the 2.75% of our sample, in this cluster is the 0.05% of the observations. In this cluster, we have the 0.79% of the observations from this category.

Cluster 2

The first thing we can notice from this cluster is that **RateCodeID=Rate-1** (standard rate) and **Trip_type=Street-Hail** are the most represented in the cluster. We have 94.98% of the observations in the cluster that represent street-hail trips, and we also have 94.86% of the observations in the cluster that represent the standard rate trips. We have 74.72% of the morning period trips of the observations in the sample represented in this cluster, 73.21% of the dispatch type trips of the observations in the sample represented in this cluster, 66.59% of the valley period trips of the observations in the sample represented in this cluster, we also have the 66.14% of the other kind of rates f the observations in the sample represented in this cluster. In the other hand, we only have 3.16% of the long distance trips in the sample represented in this cluster and this category only means the 1.29% of the observations in the cluster of this category. We have 10.11% of the night period trips in the sample represented in this cluster and we have almost 19% of the afternoon period trips in the sample represented in this cluster.

Cluster 3

The first thing we can notice from this cluster is that almost every observation is from standard rate kind. We can see that 99.24% of the observations in the cluster are **RateCodeID=Rate-1**, and the cluster contains the 5.78% of the observations in the sample of this kind. The rest of observations in the cluster are from **RateCodeID=Rate-Other** kind.The next thing we can notice from this cluster is that, also, almost every observation is from Verfione kind of vendor. We have the 94.27% of the observations in this cluster of **VendorID=f.Vendor-VeriFone** category. This categories represents the 78.95% from our sample, and the cluster contains the 6.77% of obervations of this kind. For the other kind of vendor, **VendorID=f.Vendor-Mobile**, that represents the 21.05% of our sample, we have that in this cluster, 5.73% of the observations are from this vendor, and the cluster contains 1.54% of observations of this kind. If we take a look at the period categories, we see that **period=Period night** represents 43.51% of the observations in the cluster, and we have the 6.94% of the observations of this kind from the sample. In this cluster the night period is over represented because this kind of period represents the 35.52% of observations from our sample. For the **period=Period valley**, we have 20.99% of the observations in the cluster of this kind of period. We have in this cluster 4.37% of the observations of this kind from our sample. The last kind of period that we have in this cluster is the moring one, that represents the 5.73% of the observations in the cluster and we have 2.77% of the observations from the sample of this kind in this cluster.

Cluster 4

In this cluster, we can see that the category more represented is **Trip_type=Street-Hail** with 96.31% of the observations in the cluster. We get 16.18% of the observations of this kind from the sample in the cluster. Another category that is very represented is the standard rate, **RateCodeID=Rate-1**, with 95.25% of the observations in the cluster. From the sample, we get in this cluster, 16.06% of the observations of this kind. We can notice that we have 87.52% of long distance trip observations from the sample in this cluster. We can see that this category is over represented in this cluster because this category represents the 14.38% of the sample, and 76.78% of the observations in the cluster are of this category. In the other hand, we can see that short distance trips that represents 1.85% of the observations in the cluster and we only got 0.47% of the observations of this kind from the sample.

Cluster 5

This cluster is the smallest one, we only have 39 observations from the sample. We can see in this cluster is that the **RateCodeID=Rate-1** represents the 89.75% of the observations in this cluster. In this cluster we only have 0.78% of the observations from the sample of this kind. The rest 10.25% are the **RateCodeID=Rate-Other** observtions in the cluster. In this case, we have a 3.15% of the observations from the sample of this kind in this cluster. Then we have that 82.05% of the observations in the cluster that paid credit card, and we got 1.53% of the observations from sample sample of this kind this cluster. The other 17.95% of the observations in the cluster paid in cash, and we got less representation from the sample in this cluster for this category, we only got 0.28% of the observations from the sample.

We now proceed to see the quantitatives variables that characterizes the clusters.

```
res.hcpc$desc.var$quanti.var  # quantitative variables which characterizes the clusters
```

```
##                         Eta2       P-value
## Passenger_count    0.781083003  0.000000e+00
## Trip_distance      0.578106343  0.000000e+00
```

```
## Fare_amount       0.575439601  0.000000e+00
## Extra             0.632538094  0.000000e+00
## Tolls_amount      0.981954788  0.000000e+00
## Total_amount      0.539522699  0.000000e+00
## traveltime        0.419905351  0.000000e+00
## espeed            0.205381252 1.391829e-228
## Tip_amount        0.202596695 4.421382e-225
## Dropoff_latitude  0.018549311  7.346910e-18
## Pickup_latitude   0.016472560  8.618675e-16
## Dropoff_longitude 0.009820162  3.006725e-09
## Pickup_longitude  0.004646807  2.504182e-04
```

We can see in the output that all the variables that appear are slightly over represented in the clusters. We can notice that the greatest represented is the Total_amount with 0.98 units over the global mean, we can also remark the Passenger_count with 0.78 units over the mean and the Extra variable with 0.63 units over the mean. The least over represented are the Pickup_longitude with 0.004 units over the mean, the Dropoff_longitude with 0.01 units over the mean, the Pickup_latitude with 0.016 units over the mean and the Dropoff_latitude with 0.02 units over the total mean.

We want to know now which variables are associated with the quantitative variables.

```
res.hcpc$desc.var$quanti      # description of each cluster by the quantitative variables
```

```
## $`1`
##                      v.test Mean in category Overall mean sd in category
## Extra              48.725143        0.6626943   0.35226044     0.23425993
## Dropoff_longitude   5.981195      -73.9299781 -73.93460830     0.04395684
## Pickup_longitude    3.321671      -73.9325877 -73.93496823     0.04237046
## Dropoff_latitude   -4.282820       40.7409033  40.74500568     0.05287830
## Pickup_latitude    -4.735737       40.7422169  40.74676502     0.05237977
## Tolls_amount       -5.433312        0.0000000   0.04769564     0.00000000
## espeed             -8.810257       19.0031003  20.33575305     6.29787224
## Tip_amount        -10.443222        0.6893179   1.02203842     1.08615941
## Passenger_count   -12.789408        1.1409326   1.37107208     0.41827819
## Total_amount      -18.789110       10.6471503  13.92640493     4.50875619
## traveltime        -19.049278        9.1670035  12.48732425     5.94179824
## Trip_distance     -20.757190        1.7205850   2.72449524     1.03949364
## Fare_amount       -22.244878        8.4204663  11.61104706     3.53352131
##                     Overall sd       p.value
## Extra              0.36668354  0.000000e+00
## Dropoff_longitude  0.04455396  2.215059e-09
## Pickup_longitude   0.04124656  8.948012e-04
## Dropoff_latitude   0.05512875  1.845399e-05
## Pickup_latitude    0.05527371  2.182601e-06
## Tolls_amount       0.50523041  5.531755e-08
## espeed             8.70570362  1.248593e-18
## Tip_amount         1.83366715  1.573775e-25
## Passenger_count    1.03565723  1.878993e-37
## Total_amount      10.04487145  9.272116e-79
## traveltime        10.03175633  6.661465e-81
## Trip_distance      2.78356770  1.055625e-95
## Fare_amount        8.25496368 1.264366e-109
##
## $`2`
##                      v.test Mean in category Overall mean sd in category
## Dropoff_latitude    8.827382       40.7546869  40.74500568     0.05701522
## Pickup_latitude     8.406078       40.7560085  40.74676502     0.05684751
## Dropoff_longitude  -2.581594      -73.9368965 -73.93460830     0.04060069
## Tolls_amount       -4.745339        0.0000000   0.04769564     0.00000000
## Tip_amount        -11.980225        0.5850122   1.02203842     0.99664574
## Passenger_count   -12.679469        1.1098324   1.37107208     0.37470104
## espeed            -13.935697       17.9222129  20.33575305     6.35570993
## traveltime        -14.229130        9.6475928  12.48732425     6.01107875
## Fare_amount       -16.360397        8.9242741  11.61104706     4.11025949
## Trip_distance     -17.849175        1.7360744   2.72449524     1.07373082
```

```
## Total_amount      -18.266469       10.2761689  13.92640493     4.94499736
## Extra             -48.289253        0.0000000   0.35226044     0.00000000
##                     Overall sd      p.value
## Dropoff_latitude   0.05512875 1.071545e-18
## Pickup_latitude    0.05527371 4.239492e-17
## Dropoff_longitude  0.04455396 9.834518e-03
## Tolls_amount       0.50523041 2.081575e-06
## Tip_amount         1.83366715 4.510961e-33
## Passenger_count    1.03565723 7.685081e-37
## espeed             8.70570362 3.844308e-44
## traveltime        10.03175633 6.042928e-46
## Fare_amount        8.25496368 3.667285e-60
## Trip_distance      2.78356770 2.933368e-71
## Total_amount      10.04487145 1.530386e-74
## Extra              0.36668354 0.000000e+00
##
## $`3`
##                     v.test Mean in category Overall mean sd in category
## Passenger_count 59.986235        5.0992366    1.3710721      0.6863440
## Extra            3.765260        0.4351145    0.3522604      0.3543457
## Total_amount    -2.537392       12.3968702   13.9264049      6.8282336
## Fare_amount     -2.616552       10.3148473   11.6110471      6.3920807
## Trip_distance   -2.945418        2.2324828    2.7244952      1.8662661
##                   Overall sd      p.value
## Passenger_count  1.0356572 0.0000000000
## Extra            0.3666835 0.0001663758
## Total_amount    10.0448715 0.0111681899
## Fare_amount      8.2549637 0.0088822891
## Trip_distance    2.7835677 0.0032251885
##
## $`4`
##                       v.test Mean in category Overall mean sd in category
## Trip_distance     49.106302       7.26458247   2.72449524     3.47580089
## Fare_amount       49.067121      25.06441195  11.61104706     9.24177619
## Total_amount      45.821920      29.21412929  13.92640493    11.86369386
## traveltime        42.874587      26.77304310  12.48732425    12.32002615
## espeed            28.378179      28.54141415  20.33575305    12.17319710
## Tip_amount        27.211285       2.67931398   1.02203842     3.09282254
## Tolls_amount      -2.295339       0.00917784   0.04769564     0.14117624
## Pickup_longitude  -3.443125     -73.93968523 -73.93496823     0.04283372
## Pickup_latitude   -4.158084      40.73913128  40.74676502     0.05714529
## Passenger_count   -4.305896       1.22295515   1.37107208     0.65713115
## Extra             -4.496790       0.29749340   0.35226044     0.33420886
## Dropoff_longitude -4.799514     -73.94171076 -73.93460830     0.05184553
## Dropoff_latitude  -5.180004      40.73552077  40.74500568     0.05408675
##                     Overall sd       p.value
## Trip_distance      2.78356770  0.000000e+00
## Fare_amount        8.25496368  0.000000e+00
## Total_amount      10.04487145  0.000000e+00
## traveltime        10.03175633  0.000000e+00
## espeed             8.70570362 3.759899e-177
## Tip_amount         1.83366715 4.775939e-163
## Tolls_amount       0.50523041  2.171371e-02
## Pickup_longitude   0.04124656  5.750332e-04
## Pickup_latitude    0.05527371  3.209275e-05
## Passenger_count    1.03565723  1.663115e-05
## Extra              0.36668354  6.898701e-06
## Dropoff_longitude  0.04455396  1.590515e-06
## Dropoff_latitude   0.05512875  2.218809e-07
##
## $`5`
##                       v.test Mean in category Overall mean sd in category
## Tolls_amount      67.367546         5.475388   0.04769564     0.39829372
## Total_amount      17.705432        42.287692  13.92640493    20.69332947
```

```
## Trip_distance    13.871930         8.882127   2.72449524     5.24509423
## Fare_amount      13.439098        29.302370  11.61104706    13.01003029
## Tip_amount       12.655167         4.722564   1.02203842     4.52414418
## espeed           10.141705        34.415339  20.33575305    11.95705914
## traveltime        7.719334        24.836325  12.48732425    11.22620743
## Pickup_longitude  1.961840       -73.922064 -73.93496823     0.04269607
##                   Overall sd      p.value
## Tolls_amount      0.50523041 0.000000e+00
## Total_amount     10.04487145 3.807483e-70
## Trip_distance     2.78356770 9.372098e-44
## Fare_amount       8.25496368 3.567598e-41
## Tip_amount        1.83366715 1.047523e-36
## espeed            8.70570362 3.607463e-24
## traveltime       10.03175633 1.169396e-14
## Pickup_longitude  0.04124656 4.978116e-02
```

Cluster 1

For this cluster, we can see that the **traveltime** is around 3 units under the overall mean, the **Fare_amount** as well and the **Total_amount** too. We can also see that the **Trip_distance** is 1 unit under the overall mean and the **espeed** as well. We see that the only variable that is over the overall mean is the variable **Extra** with less than 0.3 units over it.

Cluster 2

For the second cluster, happens something similar as with the first one. We see that the **Total_amount** is around 3.7 units under the overall mean, **espeed** around 2 units under as well, **Tip_amount** around 0.5 under the overall mean too, **traveltime** and **Fare_amount** around 3 units under the overall mean as well, **Trip_distance** around 1 unit under the mean. In this clusters the only variables ver the overall mean are **Dropoff_latitude** and **Pickup_latitude** but they are not remarkable since the increase is super light.

Cluster 3

In this cluster we can see that the most remarkable variable is **Passenger_count** with almost 4 units over the overall mean, then we also have **Total_amount** with 0.1 units over the meant. In the other hand, we have **Total_amount** and **Fare_amount** with around 1 unit under the overall mean. **Trip_distance** is around 0.5 units under the overall mean.

Cluster 4

In this cluster we can see clearly the most remarkable vairables. We have 5 variables cleary over the overall mean. These are: **Total_amount** with 26 units over the mean, **Fare_amount** and **traveltime** with 14 units over the mean, **espeed** with 8 units over the mean and **Trip_distance** with 5 units over the overall mean.

Cluster 5

In this cluster every variable is over the overall mean. Every variable except **Pickup_longitude** are remarkably over the overall mean. Firstly, we have the **Total_amount** around 30 units over, then we have **Fare_amount** 18 units over, **espeed** 14 units over, **traveltime** 12 units over, **Trip_distance** 6 units over, **Tolls_amount** 5 units over and **Tip_amount** 3.7 units over the overall mean.

3.2.2 The description of the clusters by the individuals

```
res.hcpc$desc.ind$para  # representative individuals of each cluster
```

```
## Cluster: 1
##    697423    442213    365332    655407    945065
## 0.4551377 0.4585094 0.4624702 0.4675288 0.4733316
## ------------------------------------------------------------
## Cluster: 2
##    665209    677545    343231    743541    473945
## 0.1500605 0.1502214 0.1520744 0.1533864 0.1668652
## ------------------------------------------------------------
## Cluster: 3
##    952205     21675   1090746    607516   1397283
## 0.2651094 0.3722646 0.5401477 0.5498816 0.5620526
## ------------------------------------------------------------
## Cluster: 4
##   1040597   1272173     10891   1445033    693126
```

```
## 0.5534480 0.6419473 0.6769121 0.7137618 0.7296941
## ------------------------------------------------------------
## Cluster: 5
##  1261276  1016299   327762  1010826   529475
## 1.151077 1.224596 1.305726 1.472585 1.482492
```

What we obtain are the more representative individuals,paragons, for each cluster. We get the rownames of each paragon in every single cluster.

```
res.hcpc$desc.ind$dist  # individuals distant from each cluster
```

```
## Cluster: 1
##   886530   642379    71268  1393691   560933
## 4.878069 4.760057 4.577272 4.506090 4.465229
## ------------------------------------------------------------
## Cluster: 2
##    36606   533937   535041   829742  1418974
## 4.641497 4.283722 4.264553 4.177470 3.770009
## ------------------------------------------------------------
## Cluster: 3
##   169380   644602   513170   550938   871576
## 6.214858 6.161465 5.875364 5.669044 5.651629
## ------------------------------------------------------------
## Cluster: 4
##   488540   204903   773934  1242754  1175981
## 13.32453 12.61924 12.27617 12.27616 11.95419
## ------------------------------------------------------------
## Cluster: 5
##   604912   710390   194151  1347654  1342604
## 15.93179 13.33560 12.81720 12.39681 12.21009
```

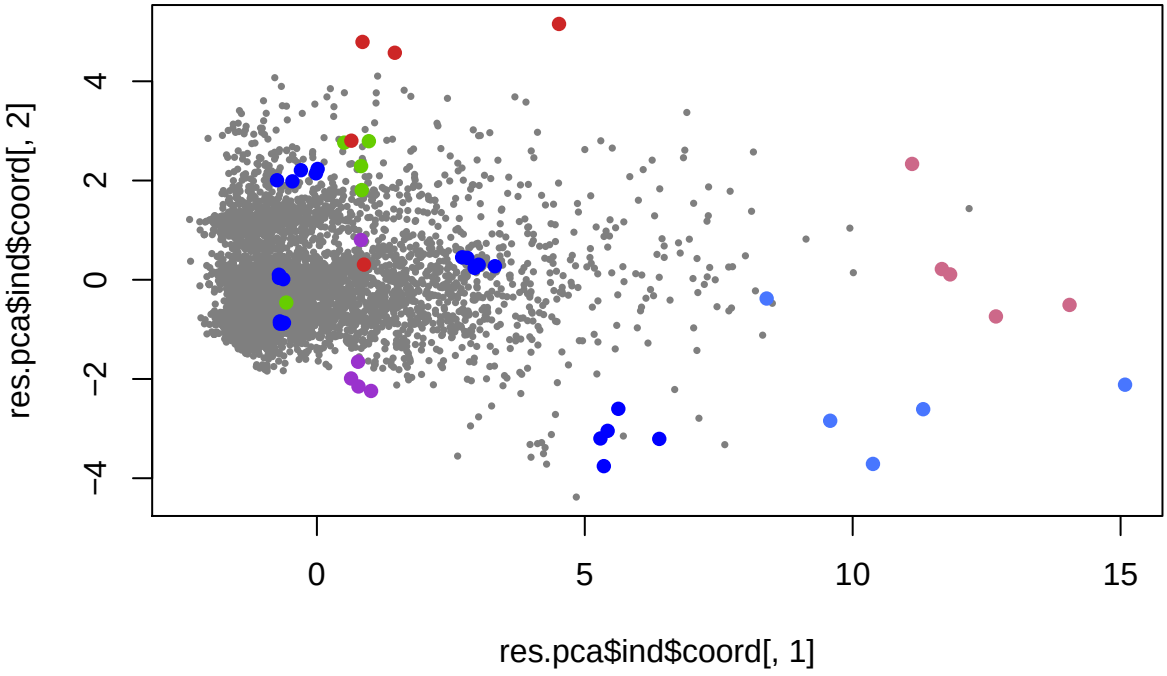
What we obtain are those individuals of each cluster that that far away in the same cluster from the rest of the individuals. We also obtain the rownames of each individual with the bigger distance respect the other ones in the cluster.

3.2.2.1 Examine the values of individuals that characterize classes

We get the grpahical representation for the individuals that characterize classes (para and dist).

```
# characteristic individuals
para1<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$para[[1]]))
dist1<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$dist[[1]]))
para2<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$para[[2]]))
dist2<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$dist[[2]]))
para3<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$para[[3]]))
dist3<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$dist[[3]]))
para4<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$para[[4]]))
dist4<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$dist[[4]]))
para5<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$para[[5]]))
dist5<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$dist[[5]]))

plot(res.pca$ind$coord[,1],res.pca$ind$coord[,2],col="grey50",cex=0.5,pch=16)
points(res.pca$ind$coord[para1,1],res.pca$ind$coord[para1,2],col="blue",cex=1,pch=16)
points(res.pca$ind$coord[dist1,1],res.pca$ind$coord[dist1,2],col="chartreuse3",cex=1,pch=16)
points(res.pca$ind$coord[para2,1],res.pca$ind$coord[para2,2],col="blue",cex=1,pch=16)
points(res.pca$ind$coord[dist2,1],res.pca$ind$coord[dist2,2],col="darkorchid3",cex=1,pch=16)
points(res.pca$ind$coord[para3,1],res.pca$ind$coord[para3,2],col="blue",cex=1,pch=16)
points(res.pca$ind$coord[dist3,1],res.pca$ind$coord[dist3,2],col="firebrick3",cex=1,pch=16)
points(res.pca$ind$coord[para4,1],res.pca$ind$coord[para4,2],col="blue",cex=1,pch=16)
points(res.pca$ind$coord[dist4,1],res.pca$ind$coord[dist4,2],col="palevioletred3",cex=1,pch=16)
points(res.pca$ind$coord[para5,1],res.pca$ind$coord[para5,2],col="blue",cex=1,pch=16)
points(res.pca$ind$coord[dist5,1],res.pca$ind$coord[dist5,2],col="royalblue1",cex=1,pch=16)
```



3.2.3 Partition quality

We are going to evaluate the partition quality.

```
#res.hcpc$call$t$within[1] = Total sum of squares
#(res.hcpc$call$t$within[1]-res.hcpc$call$t$within[5] = between sum of squares
((res.hcpc$call$t$within[1]-res.hcpc$call$t$within[5])/res.hcpc$call$t$within[1])*100
```

3.2.3.1 Gain in inertia (in %)

```
## [1] 57.49171
```

The quality of this reduction if of 57.49%.

In case we wanted to achieve an 80% of the clustering representativity we would need 18 clusters.

```
((res.hcpc$call$t$within[1]-res.hcpc$call$t$within[18])/res.hcpc$call$t$within[1])*100
```

```
## [1] 80.59951
```

3.2.4 Save the results into dataframe

```
res.hcpc$call$t$inert.gain[1:5]
```

```
## [1] 1.8187697 0.9105858 0.7460223 0.6120673 0.3712993
```

```
df$hcpck<-res.hcpc$data.clust$clust
```

---

4 K-Means Classification

4.1 Description of clusters

```
res.pca <- PCA(df[,c(1:10,12,13,15:17,19,21,22,25,27)],quanti.sup=c(3:6,13),quali.sup=c(1,2,14:16,19:20)
ppcc<-res.pca$ind$coord[,1:3] # 3 components principals (kaiser)
dim(ppcc)
```

```
## [1] 4623    3
```

4.1.1 Optimal number of clusters

```
library("factoextra")
#fviz_nbclust(ppcc, kmeans, method = "gap_stat")
```

According to the previous plot, the optimal number of clusters per k-means is 1, so we guess maybe something is wrong or missing.

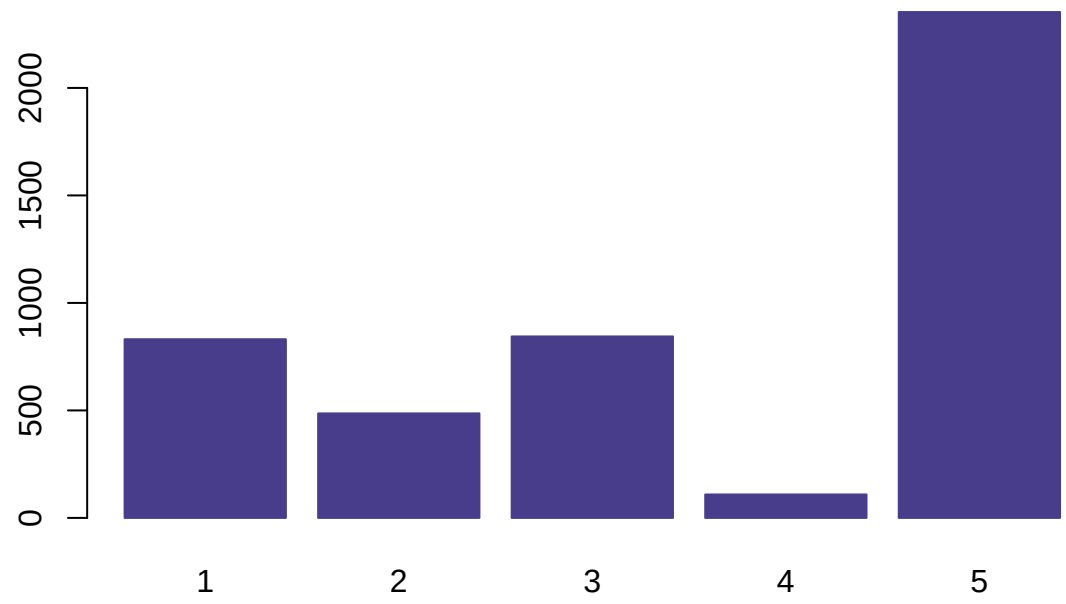
4.2 Classification

```
dist<-dist(ppcc)  # coordenates are real - Euclidean metric
kc<-kmeans(dist, 5, iter.max=30, trace=TRUE) #caclulate the distances, it turns into a matrix
```

```
## KMNS(*, k=5): iter=  1, indx=3
##  QTRAN(): istep=4623, icoun=0
##  QTRAN(): istep=9246, icoun=52
##  QTRAN(): istep=13869, icoun=6
##  QTRAN(): istep=18492, icoun=13
##  QTRAN(): istep=23115, icoun=1
##  QTRAN(): istep=27738, icoun=9
##  QTRAN(): istep=32361, icoun=27
##  QTRAN(): istep=36984, icoun=7
##  QTRAN(): istep=41607, icoun=49
##  QTRAN(): istep=46230, icoun=1
##  QTRAN(): istep=50853, icoun=6
##  QTRAN(): istep=55476, icoun=2
##  QTRAN(): istep=60099, icoun=777
## KMNS(*, k=5): iter=  2, indx=3
##  QTRAN(): istep=4623, icoun=25
##  QTRAN(): istep=9246, icoun=1
##  QTRAN(): istep=13869, icoun=5
##  QTRAN(): istep=18492, icoun=21
##  QTRAN(): istep=23115, icoun=226
##  QTRAN(): istep=27738, icoun=926
##  QTRAN(): istep=32361, icoun=3
##  QTRAN(): istep=36984, icoun=483
##  QTRAN(): istep=41607, icoun=4591
## KMNS(*, k=5): iter=  3, indx=3
##  QTRAN(): istep=4623, icoun=225
##  QTRAN(): istep=9246, icoun=690
##  QTRAN(): istep=13869, icoun=3645
## KMNS(*, k=5): iter=  4, indx=4623
```

We see from the output that in 4 iterations it has converged. We now procceed to save in the data frame the number of clusters.

```
df$claKM<-0
df$claKM<-kc$cluster
df$claKM<-factor(df$claKM)
barplot(table(df$claKM),col="darkslateblue",border="darkslateblue",main="[k-means]#observations/cluster"
```



4.2.1 Gain in inertia (in %)

The american school does the partition quality evaluation in 5 clusters is done very fast, and after executing the following chunk we get an explicability of the 77.99%

```
100*(kc$betweenss/kc$totss)
```

```
## [1] 79.40953
```

4.2.2 k-means clusters characteristics

If we want to know the characteristics of each cluster, as we did with the hierarchical, we need to execute a catdes to obtain these characteristics. In the following output we get them.

```
dim(df)
```

```
## [1] 4623   30
```

```
res.cat <-catdes(df[,c(1:28)],28)
res.cat
```

```
##
## Link between the cluster variable and the categorical variables (chi-square test)
## =================================================================================
##                            p.value df
## VendorID                1.341864e-07  2
## Trip_type               3.426063e-06  2
## improvement_surcharge   1.238067e-05  2
## period                  1.672995e-05  6
## MTA_tax                 1.861312e-05  2
## RateCodeID              8.715914e-05  2
## dropoff                 1.116565e-03 46
## pickup                  1.260864e-03 46
##
## Description of each cluster by the categories
## =============================================
## $Couple
##                               Cla/Mod    Mod/Cla    Global      p.value
## Trip_type=Dispatch          19.642857  6.4139942  2.422669 2.242380e-05
```

```
## improvement_surcharge=No   18.644068  6.4139942  2.552455 5.341037e-05
## MTA_tax=No                 18.487395  6.4139942  2.574086 6.129424e-05
## RateCodeID=Rate-Other      17.322835  6.4139942  2.747134 1.727525e-04
## VendorID=f.Vendor-Mobile    9.763618 27.6967930 21.046939 2.309436e-03
## dropoff=04                 15.094340  4.6647230  2.292883 6.411129e-03
## dropoff=02                 13.281250  4.9562682  2.768765 1.865286e-02
## pickup=02                  12.781955  4.9562682  2.876920 2.697879e-02
## pickup=04                  13.483146  3.4985423  1.925157 4.351065e-02
## period=Period morning       4.981550  7.8717201 11.723989 1.675804e-02
## dropoff=08                  2.580645  1.1661808  3.352801 1.029927e-02
## VendorID=f.Vendor-VeriFone  6.794521 72.3032070 78.953061 2.309436e-03
## pickup=08                   1.807229  0.8746356  3.590742 1.408325e-03
## RateCodeID=Rate-1           7.139680 93.5860058 97.252866 1.727525e-04
## MTA_tax=Yes                 7.126998 93.5860058 97.425914 6.129424e-05
## improvement_surcharge=Yes   7.125416 93.5860058 97.447545 5.341037e-05
## Trip_type=Street-Hail       7.115939 93.5860058 97.577331 2.242380e-05
##                               v.test
## Trip_type=Dispatch          4.239280
## improvement_surcharge=No    4.040179
## MTA_tax=No                  4.007772
## RateCodeID=Rate-Other       3.755852
## VendorID=f.Vendor-Mobile    3.047253
## dropoff=04                  2.725978
## dropoff=02                  2.352397
## pickup=02                   2.211824
## pickup=04                   2.018775
## period=Period morning      -2.391974
## dropoff=08                 -2.565616
## VendorID=f.Vendor-VeriFone -3.047253
## pickup=08                  -3.192939
## RateCodeID=Rate-1          -3.755852
## MTA_tax=Yes                -4.007772
## improvement_surcharge=Yes  -4.040179
## Trip_type=Street-Hail      -4.239280
##
## $Group
##                               Cla/Mod    Mod/Cla    Global      p.value
## VendorID=f.Vendor-VeriFone  9.589041 88.6075949 78.953061 1.756148e-07
## period=Period night        10.475030 43.5443038 35.518062 5.820838e-04
## pickup=00                  14.414414  8.1012658  4.802077 2.974700e-03
## dropoff=00                 13.452915  7.5949367  4.823708 1.168395e-02
## dropoff=22                 13.025210  7.8481013  5.148172 1.657020e-02
## dropoff=01                 13.690476  5.8227848  3.634004 2.290452e-02
## pickup=22                  12.195122  7.5949367  5.321220 4.426373e-02
## dropoff=11                  4.761905  2.2784810  4.088254 4.647029e-02
## pickup=06                   1.754386  0.2531646  1.232966 4.404955e-02
## pickup=10                   4.712042  2.2784810  4.131516 4.215942e-02
## pickup=09                   4.324324  2.0253165  4.001730 2.618077e-02
## dropoff=10                  4.278075  2.0253165  4.044992 2.356012e-02
## pickup=13                   4.022989  1.7721519  3.763790 2.010691e-02
## dropoff=09                  3.783784  1.7721519  4.001730 1.079959e-02
## period=Period valley        6.746032 21.5189873 27.255029 6.443873e-03
## period=Period morning       4.981550  6.8354430 11.723989 8.403776e-04
## VendorID=f.Vendor-Mobile    4.624872 11.3924051 21.046939 1.756148e-07
##                               v.test
## VendorID=f.Vendor-VeriFone  5.223455
## period=Period night         3.439828
## pickup=00                   2.970340
## dropoff=00                  2.521549
## dropoff=22                  2.396108
## dropoff=01                  2.275023
## pickup=22                   2.011585
## dropoff=11                 -1.991096
## pickup=06                  -2.013619
```

```
## pickup=10                  -2.031943
## pickup=09                  -2.223520
## dropoff=10                 -2.264228
## pickup=13                  -2.324347
## dropoff=09                 -2.549118
## period=Period valley       -2.724296
## period=Period morning      -3.339141
## VendorID=f.Vendor-Mobile   -5.223455
##
## $Single
##                                Cla/Mod    Mod/Cla     Global      p.value
## period=Period morning         90.03690 12.5611326 11.7239888 2.079175e-05
## pickup=08                     92.16867  3.9382239  3.5907419 1.818694e-03
## dropoff=09                    91.35135  4.3500644  4.0017305 3.296731e-03
## MTA_tax=Yes                   84.30284 97.7348777 97.4259139 4.350646e-03
## Trip_type=Street-Hail         84.28286 97.8635779 97.5773307 6.451406e-03
## RateCodeID=Rate-1             84.27491 97.5289575 97.2528661 1.259835e-02
## period=Period valley          86.19048 27.9536680 27.2550292 1.349622e-02
## improvement_surcharge=Yes     84.26193 97.7091377 97.4475449 1.438196e-02
## Payment_type=No paid          96.66667  0.7464607  0.6489293 4.121461e-02
## pickup=09                     89.18919  4.2471042  4.0017305 4.409519e-02
## pickup=14                     88.59649  5.1994852  4.9318624 4.780504e-02
## pickup=10                     89.00524  4.3758044  4.1315163 4.880281e-02
## Trip_distance_range=Long_dist 81.35338 13.9253539 14.3845987 4.426895e-02
## dropoff=02                    76.56250  2.5225225  2.7687649 2.562243e-02
## pickup=02                     76.69173  2.6254826  2.8769197 2.516991e-02
## dropoff=04                    75.47170  2.0592021  2.2928834 2.115356e-02
## improvement_surcharge=No      75.42373  2.2908623  2.5524551 1.438196e-02
## pickup=03                     75.21368  2.2651223  2.5308241 1.267203e-02
## RateCodeID=Rate-Other         75.59055  2.4710425  2.7471339 1.259835e-02
## Trip_type=Dispatch            74.10714  2.1364221  2.4226693 6.451406e-03
## MTA_tax=No                    73.94958  2.2651223  2.5740861 4.350646e-03
## period=Period night           81.30329 34.3629344 35.5180619 1.908031e-04
##                                  v.test
## period=Period morning          4.256214
## pickup=08                      3.118346
## dropoff=09                     2.938624
## MTA_tax=Yes                    2.851551
## Trip_type=Street-Hail          2.723910
## RateCodeID=Rate-1              2.494926
## period=Period valley           2.470400
## improvement_surcharge=Yes      2.447579
## Payment_type=No paid           2.041364
## pickup=09                      2.013185
## pickup=14                      1.979097
## pickup=10                      1.970310
## Trip_distance_range=Long_dist -2.011535
## dropoff=02                    -2.231887
## pickup=02                     -2.238785
## dropoff=04                    -2.305232
## improvement_surcharge=No      -2.447579
## pickup=03                     -2.492856
## RateCodeID=Rate-Other         -2.494926
## Trip_type=Dispatch            -2.723910
## MTA_tax=No                    -2.851551
## period=Period night           -3.730892
##
##
## Link between the cluster variable and the quantitative variables
## ================================================================
##                            Eta2     P-value
## Passenger_count   0.901867354 0.000000000
## Extra             0.002532301 0.002859709
## Dropoff_latitude  0.002143018 0.007043257
```

```
## Pickup_latitude   0.001945907 0.011115382
## Dropoff_longitude 0.001503016 0.030974855
##
## Description of each cluster by quantitative variables
## ======================================================
## $Couple
##                       v.test Mean in category Overall mean sd in category
## Passenger_count   11.687590          2.00000     1.371072     0.00000000
## Dropoff_longitude  2.621709        -73.92854   -73.934608     0.04597555
## Pickup_latitude   -2.561938         40.73941    40.746765     0.05013959
## Dropoff_latitude  -2.616835         40.73751    40.745006     0.05305897
##                     Overall sd      p.value
## Passenger_count   1.03565723 1.475126e-31
## Dropoff_longitude 0.04455396 8.749005e-03
## Pickup_latitude   0.05527371 1.040900e-02
## Dropoff_latitude  0.05512875 8.874928e-03
##
## $Group
##                       v.test Mean in category Overall mean sd in category
## Passenger_count 62.247250        4.4734177    1.3710721       1.109762
## Extra            3.064082        0.4063291    0.3522604       0.352331
## espeed           2.147761       21.2355484   20.3357531       9.567821
##                  Overall sd     p.value
## Passenger_count  1.0356572 0.000000000
## Extra            0.3666835 0.002183392
## espeed           8.7057036 0.031732764
##
## $Single
##                       v.test Mean in category Overall mean sd in category
## Dropoff_latitude   3.029139       40.7460763   40.7450057    0.055312145
## Pickup_latitude    2.849402       40.7477747   40.7467650    0.055913354
## espeed            -2.079800       20.2196769   20.3357531    8.583250334
## Extra             -3.233626        0.3446589    0.3522604    0.368132675
## Passenger_count  -55.870694        1.0001200    1.3710721    0.005698984
##                   Overall sd     p.value
## Dropoff_latitude 0.05512875 0.002452518
## Pickup_latitude  0.05527371 0.004380156
## espeed           8.70570362 0.037543908
## Extra            0.36668354 0.001222296
## Passenger_count  1.03565723 0.000000000
```

We proceed to explain the data obtained.

4.2.3 The description of the clusters by the variables

We start wit the description of the categorical variables that characterize the clusters, so in this output we do not have dimensions because it is the total association. We can see the intensity of the variables, in our case the variables that affect more to the clustering are **VendorID** and **Trip_type** because are the one with the smallest p.value. The variables associated to the clusters are the ones that appear on the output. Next, we want to see for each cluster which are the categories that characterize them.The clusters that contain more individuals are the first, the second and the fourth one. Cluster number 4 has less individuals. We proceed to analyze them.

??????????????????????

4.2.4 Comparison of clusters (confusion table)

We want to compare the hierarchical clustering, previously done, and the k-means clustering, so proceed to do the following.

```
table(df$hcpck,df$claKM)
```

```
##
##        1    2    3    4    5
##   1  239    7  694    0  990
##   2  261    2    8    0 1363
##   3    8  111  142    1    0
```

```
##   4  323  366    0   69    0
##   5    0    0    0   39    0
```

```
# we must do a relabel
df$hcpck<-factor(df$hcpck,labels=c("kHP-1","kHP-2","kHP-3","kHP-4","kHP-5"))
df$claKM<-factor(df$claKM,levels=c(3,5,2,1,4),labels=c("kKM-3","kKM-5","kKM-2","kKM-1","kKM-4"))
tt<-table(df$hcpck,df$claKM); tt
```

```
##
##         kKM-3 kKM-5 kKM-2 kKM-1 kKM-4
##   kHP-1   694   990     7   239     0
##   kHP-2     8  1363     2   261     0
##   kHP-3   142     0   111     8     1
##   kHP-4     0     0   366   323    69
##   kHP-5     0     0     0     0    39
```

```
100*sum(diag(tt)/sum(tt))
```

```
## [1] 54.72637
```

We have a concordance of the 54.73% so we can say that they are different, if we had a greater concordance, this would mean that they would be more similar.

---

5 CA analysis

5.1 Are there any row categories that can be combined/avoided to explain the discretization of the numeric target.

5.1.1 CA analysis for your data should contain your factor version of the numeric target (previous) in K= 7 (maximum 10) levels and 2 factors.

The first thing we need to do is factor our numeric target variable, Total_amount, and name it f.cost. We are going to set 6 different categories.

```
df$f.cost[df$Total_amount<=8] = "[0,8]"
df$f.cost[(df$Total_amount>8) & (df$Total_amount<=11)] = "(8,11]"
df$f.cost[(df$Total_amount>11) & (df$Total_amount<=18)] = "(11,18]"
df$f.cost[(df$Total_amount>18) & (df$Total_amount<= 30)] = "(18,30]"
df$f.cost[(df$Total_amount>30) & (df$Total_amount<= 50)] = "(30,50]"
df$f.cost[df$Total_amount>50] = "(50,129)"
df$f.cost<-factor(df$f.cost)
table(df$f.cost)
```

```
##
##  (11,18]  (18,30]  (30,50] (50,129)   (8,11]    [0,8]
##     1188      724      221       63     1151     1276
```

Once we have this factor, proceed to create a variable that associates the cost with the passenger groups, and we we a contingency table with 5 rows, one per kind of cost and 3 columns, one per each kind of group.

```
tt<-table(df[,c("f.cost","passenger_groups")]);tt
```

```
##           passenger_groups
## f.cost     Couple Group Single
##   (11,18]      77    89   1022
##   (18,30]      58    72    594
##   (30,50]      20    20    181
##   (50,129)      5     7     51
##   (8,11]       81   104    966
##   [0,8]       102   103   1071
```

```
chisq.test(tt,  simulate.p.value = TRUE) #to see if the rows and columns are independents. H0: Rows and
```

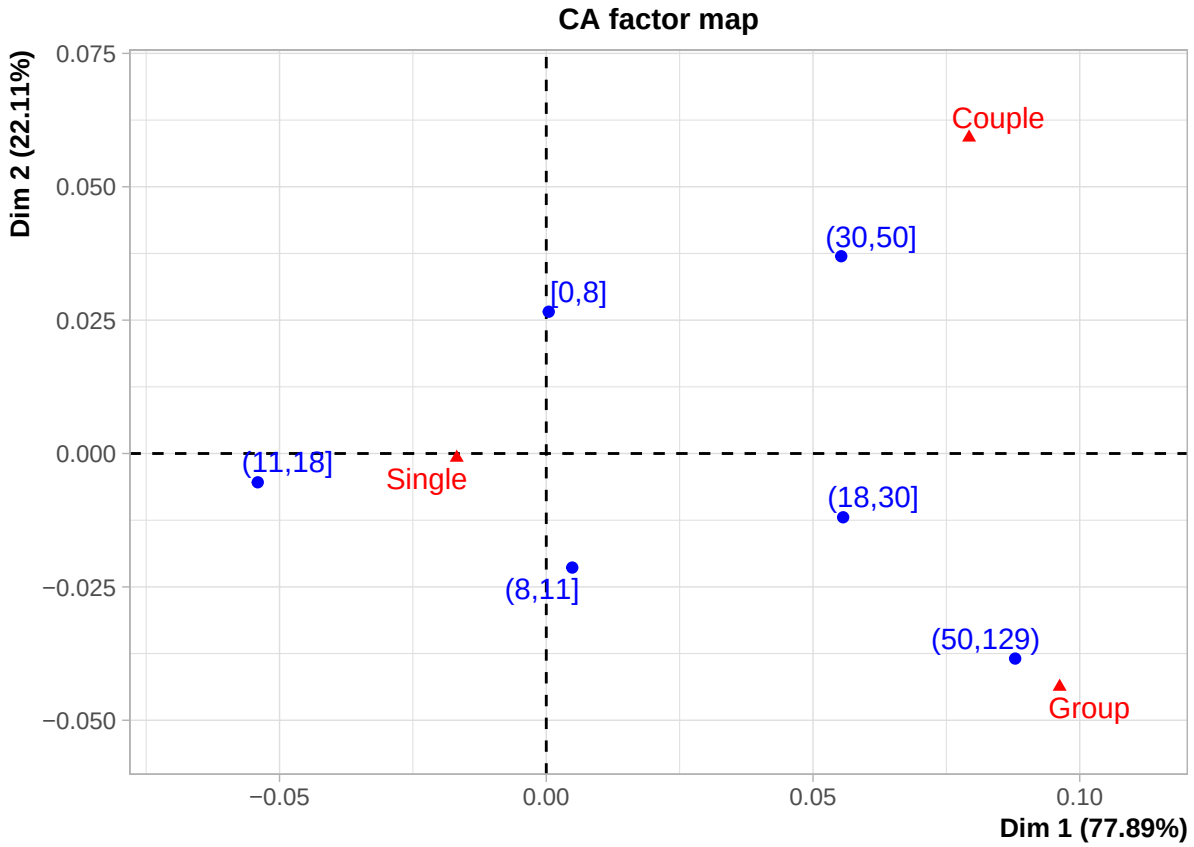
```
##
##  Pearson's Chi-squared test with simulated p-value (based on 2000
##  replicates)
##
```

```
## data:  tt
## X-squared = 8.8677, df = NA, p-value = 0.5212
```

We get a p-value greater than 0.05 so we can assume the H0. ($0.5217 < 0.05 = \text{FALSE}$).

We are now going to take a look to the simple correspondences.

```
res.ca <- CA(tt)
```



Those observations far away from the gravity center will mean that represent less observations on the sample. If rows and columns are nearby, this will mean that there is a correspondence between them, which means that they occur simultaneously in the sample.

```
summary(res.ca)
```

```
##
## Call:
## CA(X = tt)
##
## The chi square of independence between the two variables is equal to 8.867721 (p-value =  0.5447017 )
##
## Eigenvalues
##                        Dim.1   Dim.2
## Variance               0.001   0.000
## % of var.             77.890  22.110
## Cumulative % of var.  77.890 100.000
##
## Rows
##             Iner*1000    Dim.1    ctr   cos2    Dim.2    ctr   cos2
## (11,18]   |     0.759 | -0.054 50.310  0.990 | -0.005  1.763  0.010 |
## (18,30]   |     0.507 |  0.056 32.461  0.956 | -0.012  5.273  0.044 |
## (30,50]   |     0.212 |  0.055  9.782  0.691 |  0.037 15.413  0.309 |
## (50,129)  |     0.125 |  0.088  7.047  0.839 | -0.038  4.746  0.161 |
## (8,11]    |     0.120 |  0.005  0.396  0.049 | -0.021 26.828  0.951 |
## [0,8]     |     0.195 |  0.000  0.004  0.000 |  0.027 45.976  1.000 |
##
## Columns
##             Iner*1000    Dim.1    ctr   cos2    Dim.2    ctr   cos2
## Couple    |     0.726 |  0.079 31.197  0.642 |  0.059 61.383  0.358 |
```

```
## Group    |     0.955 |  0.096 52.961  0.829 | -0.044 38.494  0.171 |
## Single   |     0.237 | -0.017 15.841  0.998 | -0.001  0.122  0.002 |
```

We conclude that we can not reject the H0 for these pair of factors, and now we are going to see if we can see if there is independence between the cost and the travel time, so the first thing we are going to do is factor the travel time.

```
df$f.tt[df$traveltime<=5] = "[0,5]"
df$f.tt[(df$traveltime>5) & (df$traveltime<=10)] = "(5,10]"
df$f.tt[(df$traveltime>10) & (df$traveltime<=15)] = "(10,15]"
df$f.tt[(df$traveltime>15) & (df$traveltime<= 20)] = "(15,20]"
df$f.tt[(df$traveltime>20) & (df$traveltime<= 50)] = "(20,50]"
df$f.tt<-factor(df$f.tt)
table(df$f.tt)
```

```
##
## (10,15] (15,20] (20,50]  (5,10]    [0,5]
##     913     549     694    1511     894
```

Once we have this factor, proceed to create a variable that associates the cost with the traveltime.

```
tt<-table(df[,c("f.cost","f.tt")]);tt
```

```
##           f.tt
## f.cost     (10,15] (15,20] (20,50] (5,10] [0,5]
##   (11,18]      613     314      88    156     8
##   (18,30]      106     205     388      3    15
##   (30,50]        1      23     175      2     4
##   (50,129)       1       1      35      0     7
##   (8,11]       189       3       4    864    85
##   [0,8]          3       3       4    486   775
```

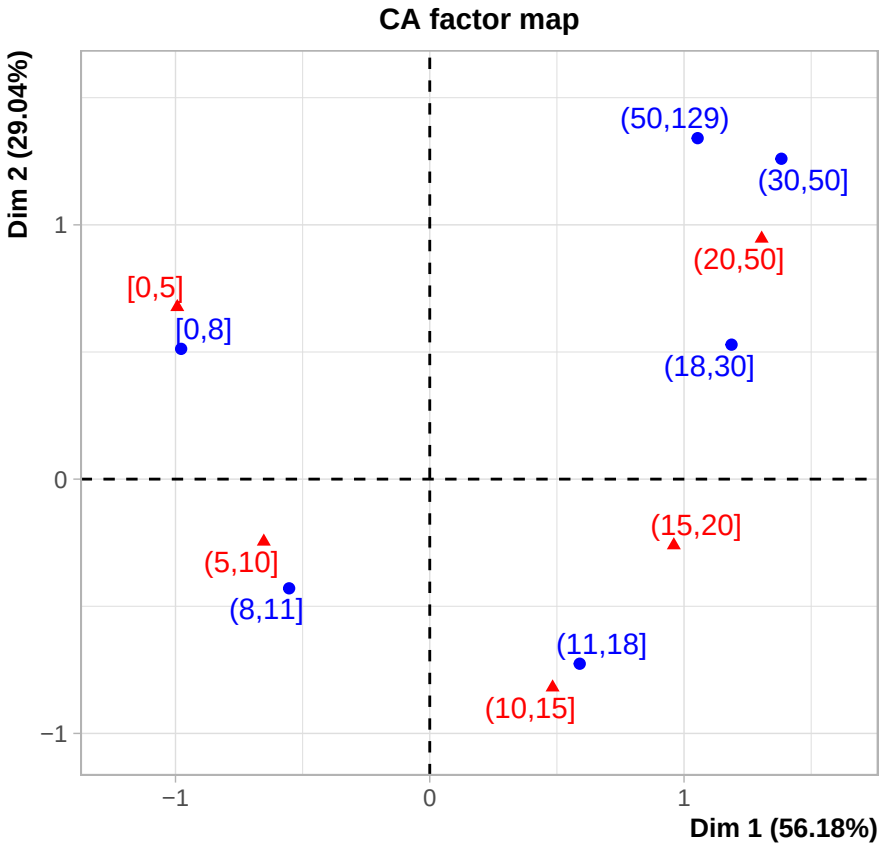
```
chisq.test(tt) #to see if the rows and columns are independents. H0: Rows and columns are independent
```

```
##
##  Pearson's Chi-squared test
##
## data:  tt
## X-squared = 6099.3, df = 20, p-value < 2.2e-16
```

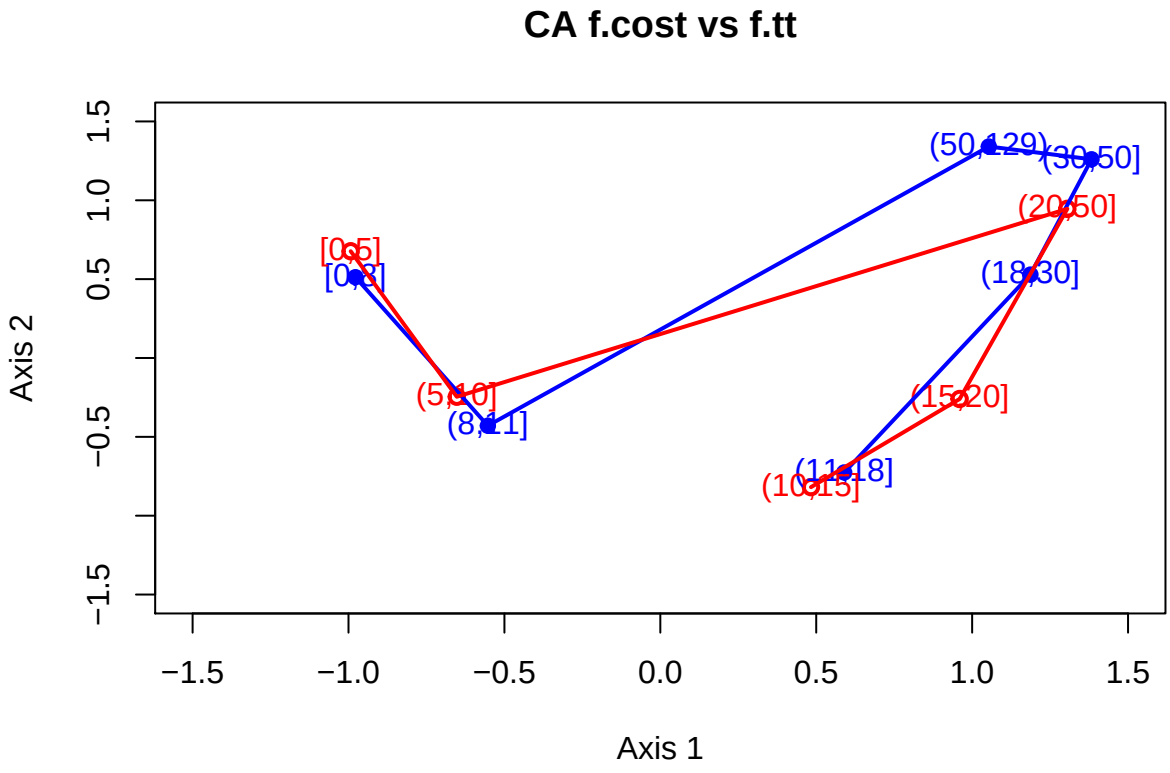
We get a p-value smaller than 0.05 so we can reject the H0. ($(< 2.2e\text{-}16) < 0.05$). So there is dependence between the traveltime and the cost, as we suspected.

We are now going to take a look to the simple correspondences.

```
res.ca <- CA(tt)
```




```
plot(res.ca$row$coord[,1],res.ca$row$coord[,2],pch=19,col="blue",xlim=c(-1.5,1.5),ylim=c(-1.5,1.5),xlab=
points(res.ca$col$coord[,1],res.ca$col$coord[,2],lwd=2,col="red")
text(res.ca$row$coord[,1],res.ca$row$coord[,2],lwd=2,col="blue",labels=levels(df$f.cost))
text(res.ca$col$coord[,1],res.ca$col$coord[,2],lwd=2,col="red",labels=levels(df$f.tt))
lines(res.ca$row$coord[,1],res.ca$row$coord[,2],lwd=2,col="blue")
lines(res.ca$col$coord[,1],res.ca$col$coord[,2],lwd=2,col="red")
```



We can see in the plot, clearly that there are some categories that occur simultaneously in the sample, for instant the trips up to 5 minutes with the cost up to 8, the trips between 5-10 minutes and the costs between 8-11, the same

happen with the trips between 10-15 minutes and the costs between 11-18. There is a clear relation between the f.cost and f.tt categories, even though we can not see a Guttman's effect from manual the relation is there.

```
summary(res.ca)
```

```
##
## Call:
## CA(X = tt)
##
## The chi square of independence between the two variables is equal to 6099.333 (p-value =  0 ).
##
## Eigenvalues
##                        Dim.1   Dim.2   Dim.3   Dim.4
## Variance               0.751   0.388   0.189   0.009
## % of var.             56.176  29.038  14.129   0.656
## Cumulative % of var.  56.176  85.215  99.344 100.000
##
## Rows
##             Iner*1000     Dim.1     ctr    cos2     Dim.2     ctr    cos2
## (11,18]  |   266.105 |   0.590  11.967   0.338 |  -0.726  35.079   0.512 |
## (18,30]  |   269.624 |   1.187  29.477   0.821 |   0.529  11.324   0.163 |
## (30,50]  |   175.119 |   1.383  11.441   0.491 |   1.260  18.373   0.407 |
## (50,129) |    31.782 |   1.054   1.425   0.337 |   1.341   4.467   0.546 |
## (8,11]   |   221.698 |  -0.553  10.223   0.346 |  -0.429  11.924   0.209 |
## [0,8]    |   372.951 |  -0.978  35.466   0.714 |   0.512  18.833   0.196 |
##             Dim.3     ctr    cos2
## (11,18]     0.391  20.884   0.148 |
## (18,30]    -0.063   0.333   0.002 |
## (30,50]    -0.582   8.062   0.087 |
## (50,129)   -0.419   0.895   0.053 |
## (8,11]     -0.627  52.158   0.445 |
## [0,8]       0.346  17.668   0.090 |
##
## Columns
##             Iner*1000     Dim.1     ctr    cos2     Dim.2     ctr    cos2
## (10,15]  |   200.286 |   0.483   6.218   0.233 |  -0.819  34.577   0.670 |
## (15,20]  |   143.488 |   0.960  14.763   0.773 |  -0.260   2.095   0.057 |
## (20,50]  |   415.261 |   1.305  34.509   0.624 |   0.946  35.059   0.328 |
## (5,10]   |   236.860 |  -0.653  18.786   0.596 |  -0.246   5.145   0.084 |
## [0,5]    |   341.385 |  -0.993  25.724   0.566 |   0.677  23.123   0.263 |
##             Dim.3     ctr    cos2
## (10,15]     0.288   8.805   0.083 |
## (15,20]     0.398  10.107   0.133 |
## (20,50]    -0.357  10.289   0.047 |
## (5,10]     -0.477  39.954   0.319 |
## [0,5]       0.545  30.844   0.171 |
```

The first thing we can see from the summary is that we have a chi square statistic of 6099.333, great enough to reject the H0, which means the intensity of the relation is high. If we take a look at the variances from the different dimensions, we can see that all together sum more than 1.

5.2 Eigenvalues and dominant axes analysis. How many axes we have to consider?

```
mean(res.ca$eig[,1])
```

```
## [1] 0.3343199
```

Following the kaiser kriteria and the value got in the output, we should retain dimensions with a variance greater than 0.3343199. In this case, the first dimension fulfills this because its variance is 0.751, but it is not enough to work with data so, we would choose 2 o 3 dimensions for this case.

---

6 MCA analysis

The Multiple correspondence analysis (MCA) is an extension of the simple correspondence analysis for summarizing and visualizing a data table containing more than two categorical variables.

MCA is generally used to analyse a data set from survey. The goal is to identify:

- A group of individuals with similar profile in their answers to the questions
- The associations between variable categories

First, we load the libraries we'll use:

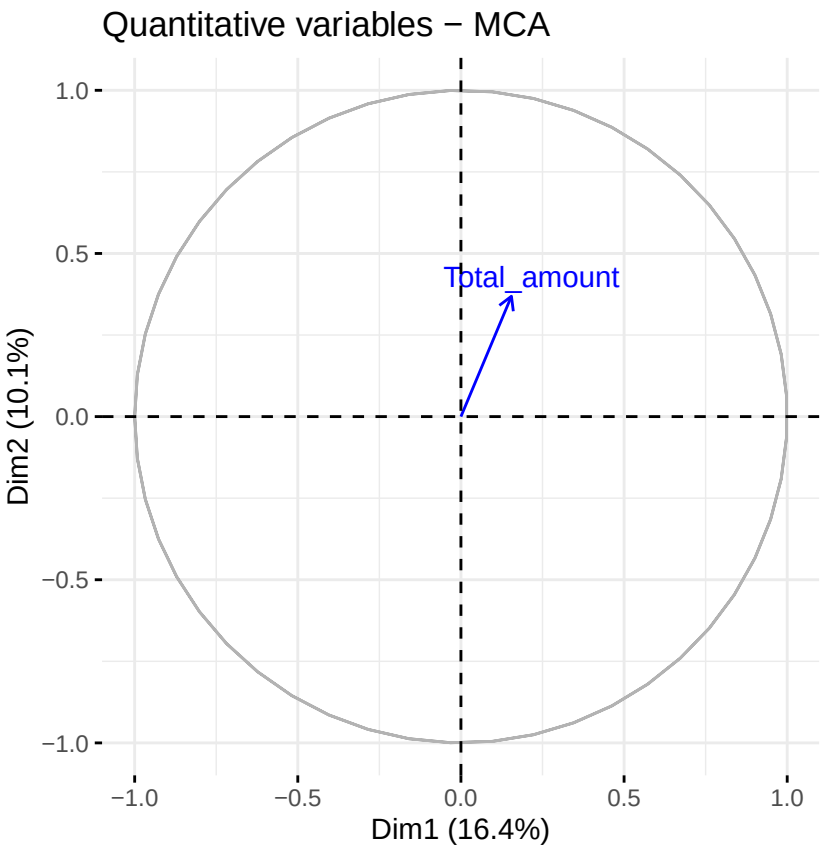
```
library(FactoMineR)
library(factoextra)
```

Now, we can start computing the MCA for our categorical variables:

```
res.mca <- MCA(
  df[,c(1:2,15:17,19,25,27:28,31)],
  quanti.sup=c(3),
  quali.sup=c(8,10),
  graph=FALSE
)
```

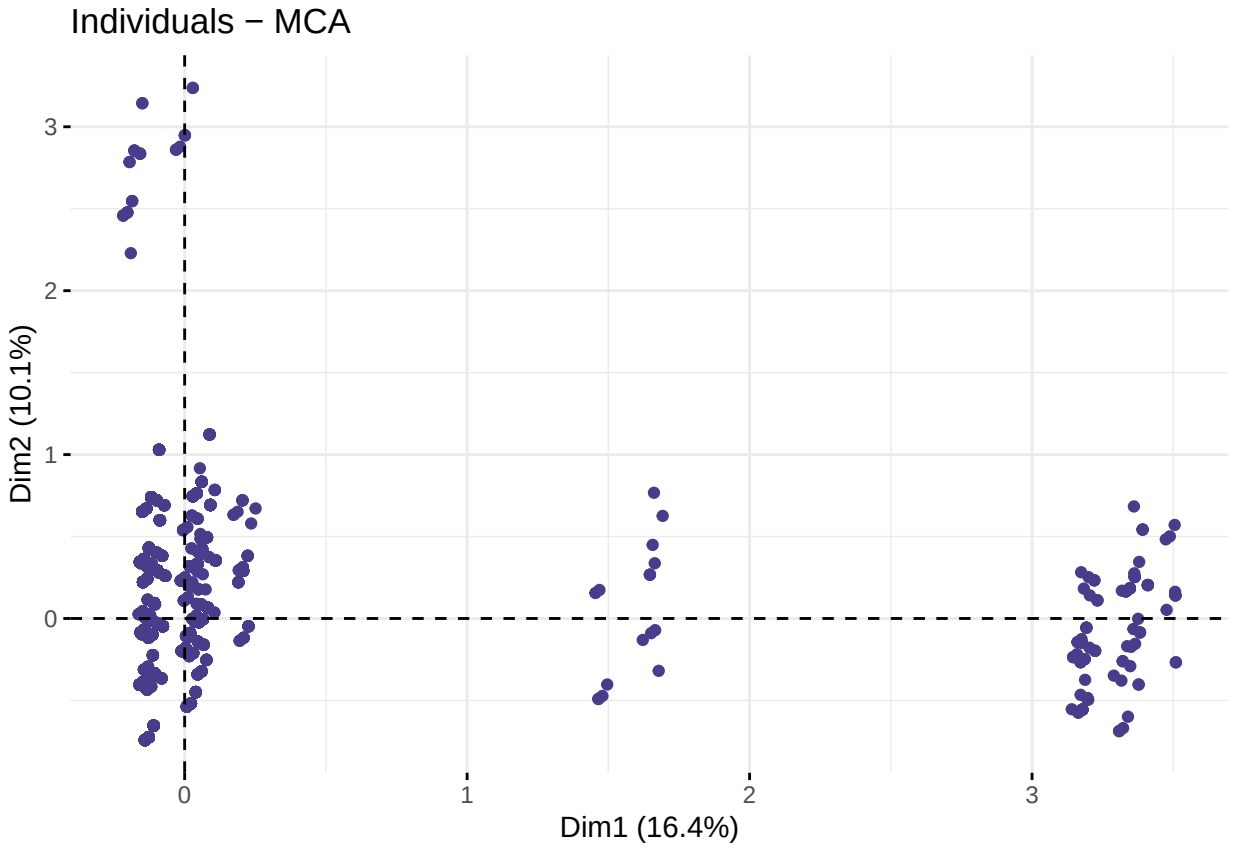
Let's look at the supplementary quantitative variable Total_amount. We can see that it is closer to the Dim2 than to the Dim1.

```
fviz_mca_var(res.mca, choice="quanti.sup", repel=TRUE, ggtheme=theme_minimal())
```



Cloud of individuals:

```
fviz_mca_ind(
  res.mca,
  geom=c("point"),
  col.ind="darkslateblue"
)
```



6.1 Eigenvalues and dominant axes analysis

How many axes we have to consider for next Hierarchical Classification stage? We consider, according to the generalized Kaiser theorem, all those dimensions such that their eigenvalue is greater than the mean. We see that the average gives us 0.1428571. Therefore, we will take up to dimension 6, which represents the 62.07% of the sample.

```
mean(res.mca$eig[,1])
```

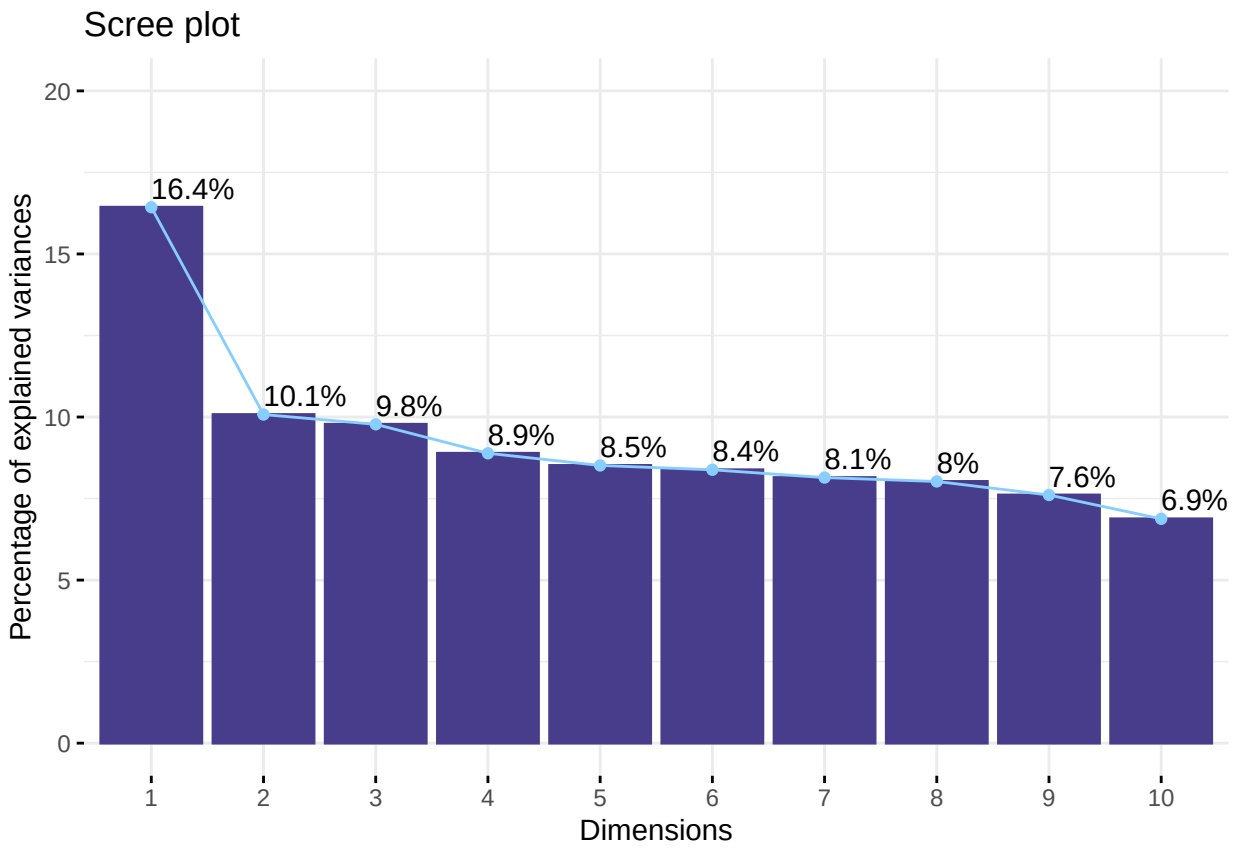
```
## [1] 0.1428571
```

```
head(get_eigenvalue(res.mca), 10)
```

```
##        eigenvalue variance.percent cumulative.variance.percent
## Dim.1   0.2817102        16.433095                    16.43310
## Dim.2   0.1727341        10.076157                    26.50925
## Dim.3   0.1676074         9.777097                    36.28635
## Dim.4   0.1523716         8.888343                    45.17469
## Dim.5   0.1459733         8.515108                    53.68980
## Dim.6   0.1436861         8.381688                    62.07149
## Dim.7   0.1396003         8.143350                    70.21484
## Dim.8   0.1375543         8.024001                    78.23884
## Dim.9   0.1304320         7.608536                    85.84738
## Dim.10  0.1179063         6.877867                    92.72524
```

We can also visualize the percentages of inertia explained by each MCA dimensions:

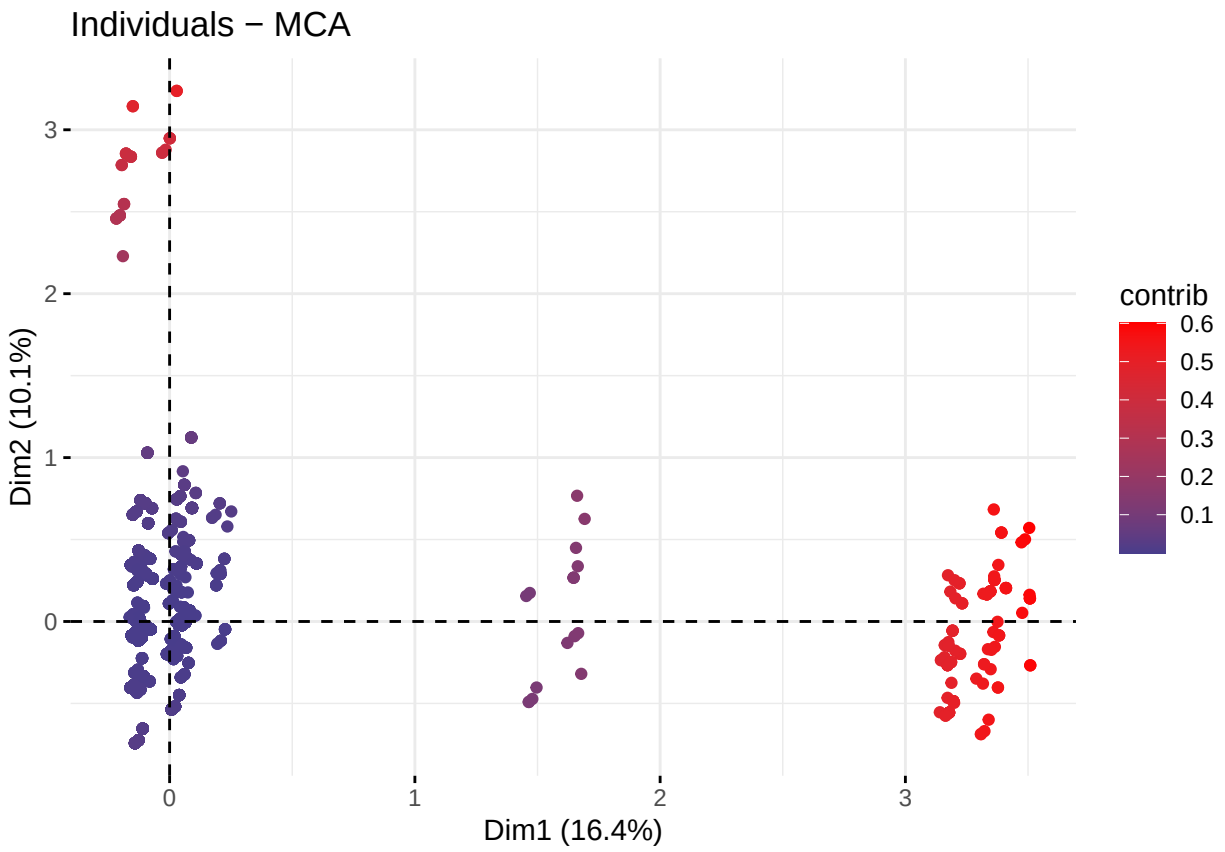
```
fviz_screeplot(
  res.mca,
  addlabels=TRUE,
  ylim=c(0,20),
  barfill="darkslateblue",
  barcolor="darkslateblue",
  linecolor="skyblue1"
)
```



6.2 Individuals point of view

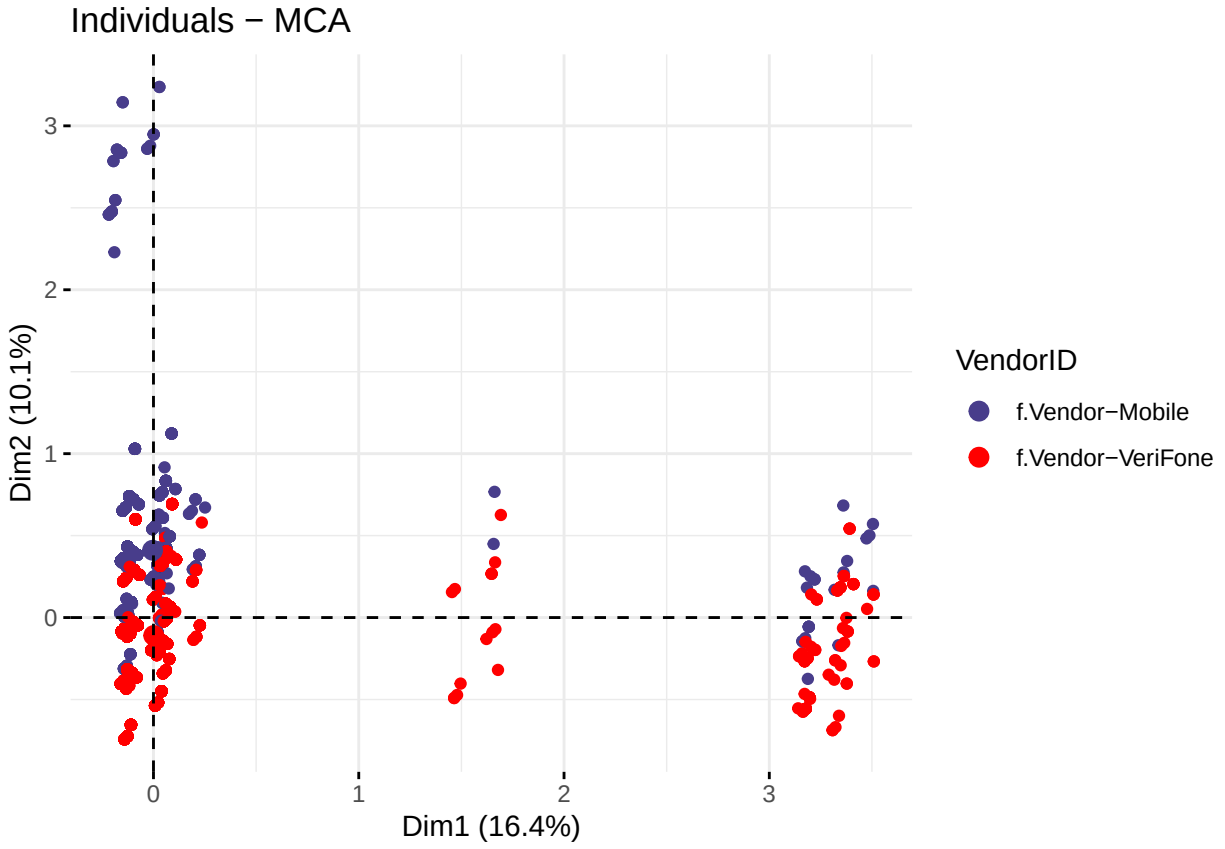
Are they any individuals "too contributive"?

```
fviz_mca_ind(
  res.mca,
  geom=c("point"),
  col.ind="contrib",
  gradient.cols=c("darkslateblue", "red")
)
```

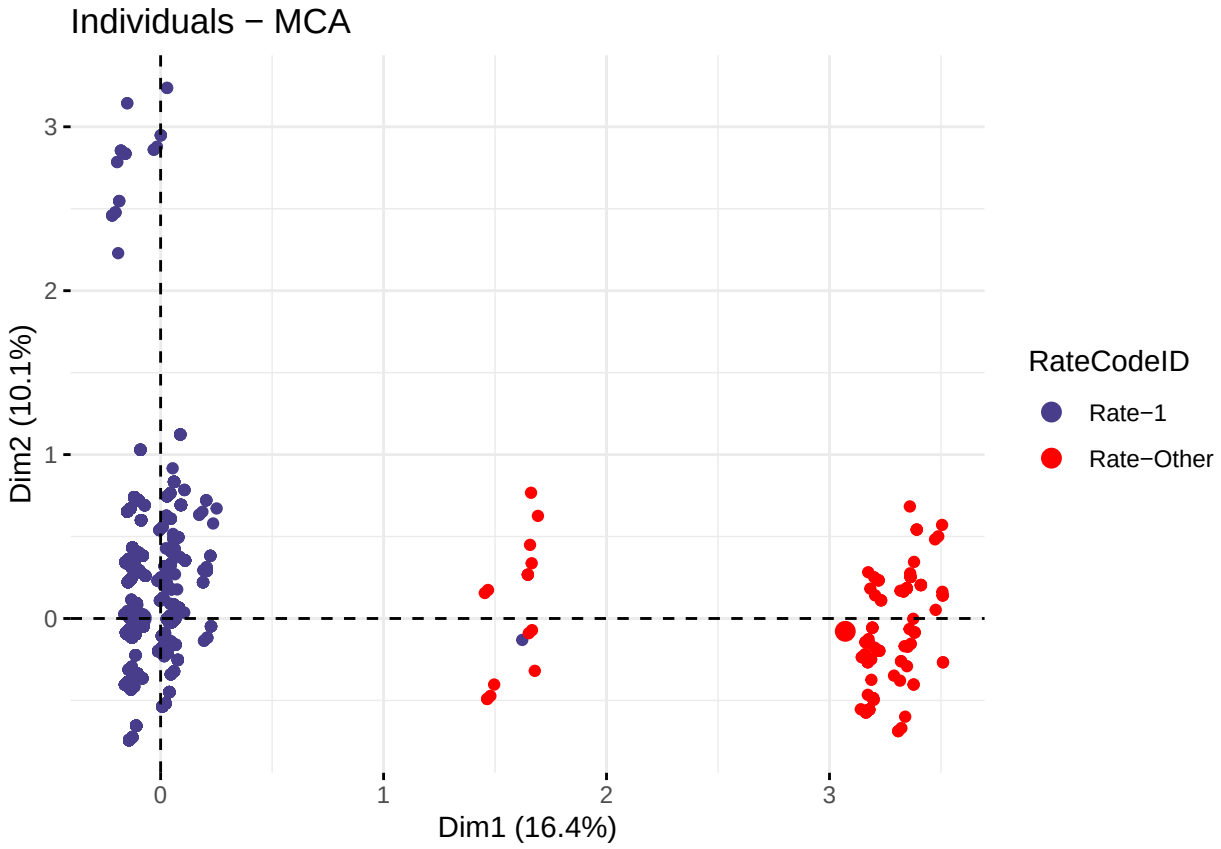


Are there any groups?

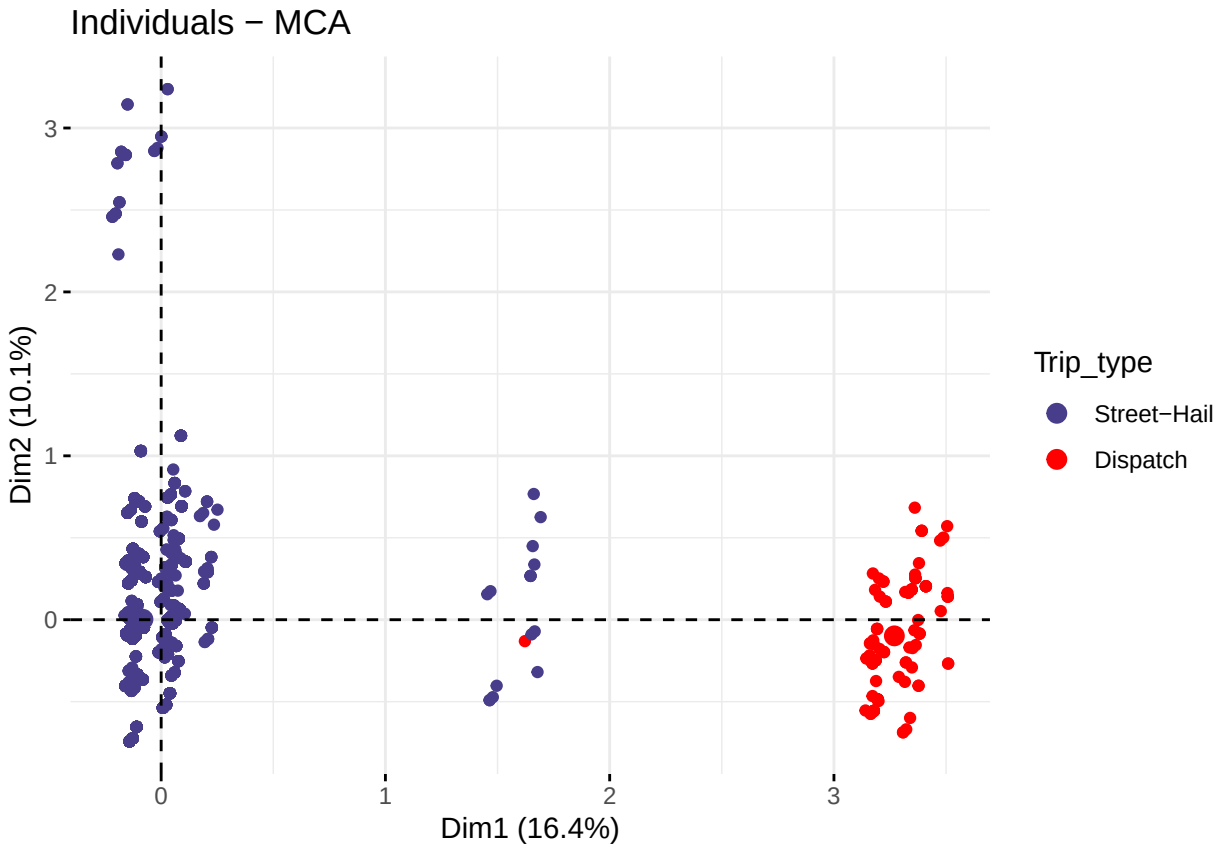
```
fviz_mca_ind(res.mca, label="none", habillage="VendorID", palette=c("darkslateblue", "red"))
```




```
fviz_mca_ind(res.mca, label="none", habillage="RateCodeID", palette=c("darkslateblue", "red"))
```




```
fviz_mca_ind(res.mca, label="none", habillage="Trip_type", palette=c("darkslateblue", "red"))
```



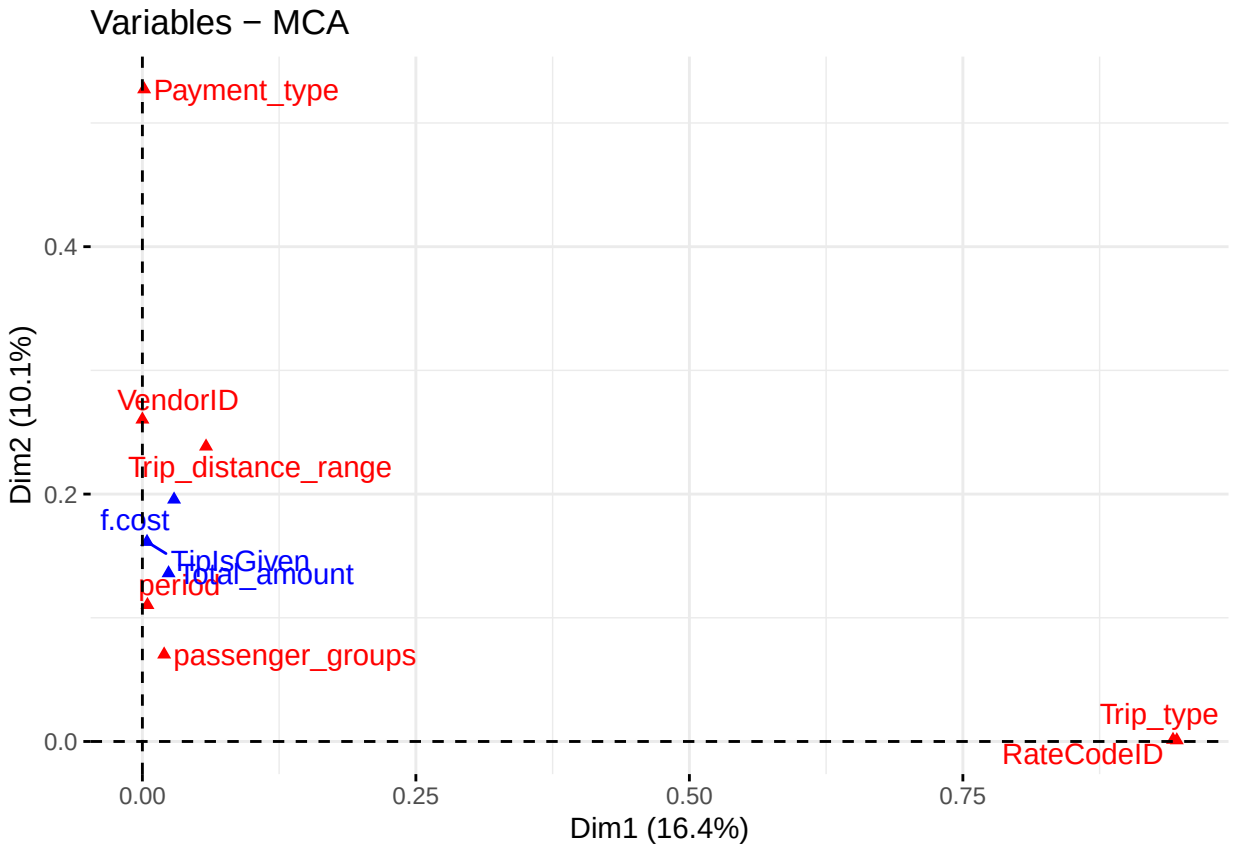
We can see that individuals are more grouped according to some variables than others. For example, the f.VendorID-Mobile is along the entire dimension 1 but also in the center of gravity. In contrast, the Rate-Other is only in the first dimension and does not touch the second at all.

6.3 Interpreting map of categories: average profile versus extreme profiles (rare categories)

Before looking at the categories, let's look at its variables:

As we can see in the plot "Variables representation", the correlation between the Payment_type factor taking into account the eta2 and the second factorial axis is a value greater than 0.5. On the other hand, we can see that something similar happens with the Trip_type factor and RateCodeID in dimension 1.

```
fviz_mca_var(res.mca, choice="mca.cor", repel=TRUE)
```



Now, let's analyze the categories.

As we can see, the "No paid" category ("Payment_type" variable) is the one farthest from the center of the plot (in dimension 2). The farther from the center of gravity, the more rarely this feature value appears in the sample represented by the dimension. In addition, we see that in dimension 1 we also have two extremes, the "Rate-Other" category ("RateCodeID" variable) and the "Dispatch" category ("Trip_type" variable). As we have said, this means that these categories are rarely represented in this dimension.

Regardering the center of mass, we can say that we find the categories most represented by the dimensions.

To give an example, let's suppose we look at the first dimension. An observation that we could find with high probability would be the following:

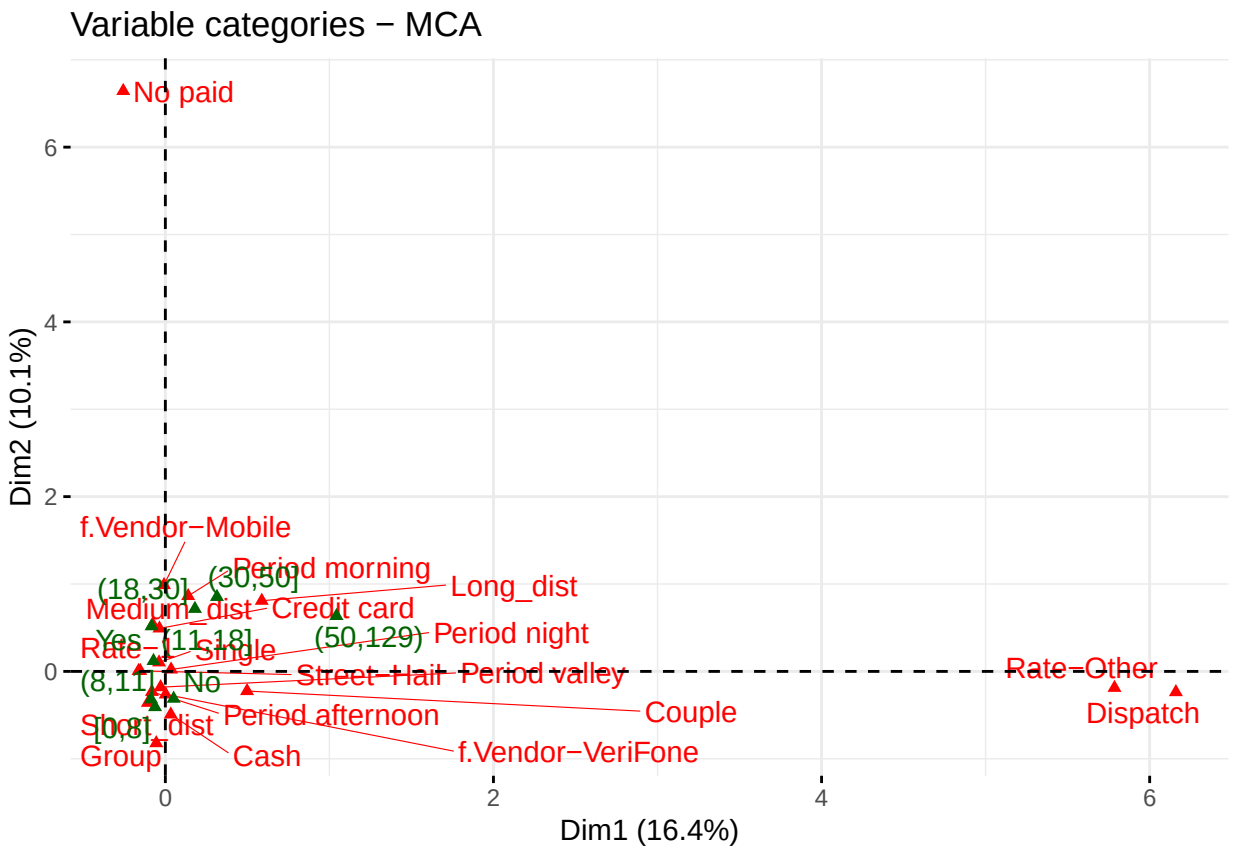
- RateCodeID = Rate-1
- Trip_type = Street-Hail

On the other hand, an observation that we could rarely find there would be...

- RateCodeID = Rate-Other
- Trip_type = Street-Dispatch

We would follow the same logic for dimension 2 considering the Payment_type variable.

```
fviz_mca_var(res.mca, repel=TRUE)
```



6.4 Interpreting the axes association to factor map

```
res.desc <- dimdesc(res.mca, axes = c(1,2))
```

6.4.1 Description of dimension 1

```
res.desc[[1]]
```

```
## $quanti
##              correlation     p.value
## Total_amount   0.1547222 3.65431e-26
##
## $quali
##                                R2      p.value
## RateCodeID           0.945537593 0.000000e+00
## Trip_type            0.942072409 0.000000e+00
## Trip_distance_range  0.058205469 6.898258e-61
## f.cost               0.028972784 1.405425e-27
## passenger_groups     0.019901125 6.814707e-21
## TipIsGiven           0.004240936 9.364240e-06
## period               0.004628593 8.564400e-05
## Payment_type         0.001608040 2.429314e-02
##
## $category
##                                      Estimate      p.value
## Trip_type=Dispatch                1.67529735 0.000000e+00
## RateCodeID=Rate-Other             1.57877258 0.000000e+00
## Trip_distance_range=Long_dist     0.24028354 4.637674e-62
## passenger_groups=Couple           0.19279452 5.856637e-22
## f.cost=(50,129)                   0.43727781 5.906344e-17
## f.cost=(30,50]                    0.05054341 1.602061e-06
## TipIsGiven=No                     0.03566808 9.364240e-06
## period=Period morning             0.06536718 5.700992e-04
## Payment_type=Cash                 0.06349408 1.434472e-02
## Payment_type=Credit card          0.02679756 2.616189e-02
```

```
## f.cost=[0,8]                    -0.14970203 8.537458e-03
## Trip_distance_range=Medium_dist -0.11215628 6.996595e-03
## f.cost=(11,18]                  -0.15476359 3.894367e-03
## period=Period afternoon         -0.05178612 1.144725e-03
## f.cost=(8,11]                   -0.16266832 6.499724e-04
## TipIsGiven=Yes                  -0.03566808 9.364240e-06
## f.cost=(18,30]                  -0.02068728 1.202545e-07
## passenger_groups=Single         -0.09190735 2.059738e-09
## Trip_distance_range=Short_dist  -0.12812726 2.015102e-22
## Trip_type=Street-Hail           -1.67529735 0.000000e+00
## RateCodeID=Rate-1               -1.57877258 0.000000e+00
##
## attr(,"class")
## [1] "condes" "list "
```

There is no info for the **quantitative** variables here.

In the first dimension we see that for the **qualitative** variables the most positively related, from more to less, are:

- RateCodeID (0.95)
- Trip_type (0.94)

If we look at the **categories**, we see that the most related are,

- for Trip_type:
  - Dispatch (1.68)
  - Long_dist (0.24)
- and for RateCodeID:
  - Rate-Other (1.58)

6.4.2 Description of dimension 2

```
res.desc[[2]]
```

```
## $quanti
##              correlation       p.value
## Total_amount   0.3688482 5.757656e-149
##
## $quali
##                               R2       p.value
## Payment_type        0.5272544813  0.000000e+00
## VendorID            0.2602830667 6.879178e-305
## Trip_distance_range 0.2384878813 4.714678e-274
## f.cost              0.1956079989 4.287815e-215
## TipIsGiven          0.1613968295 6.956769e-179
## period              0.1103532182 9.429917e-117
## passenger_groups    0.0703669803  6.304633e-74
## Trip_type           0.0013941924  1.111798e-02
## RateCodeID          0.0009990214  3.163284e-02
##
## $category
##                                    Estimate       p.value
## Payment_type=No paid             1.84096016  0.000000e+00
## VendorID=f.Vendor-Mobile         0.26007767 6.879178e-305
## TipIsGiven=Yes                   0.17229953 6.956769e-179
## Trip_distance_range=Long_dist    0.19939818 5.880829e-119
## period=Period morning            0.30980763 1.193381e-106
## f.cost=(18,30]                   0.18702736 1.831882e-102
## Trip_distance_range=Medium_dist  0.08653538  8.235254e-84
## passenger_groups=Single          0.17356325  4.157410e-60
## f.cost=(30,50]                   0.24385380  3.076322e-39
## f.cost=(50,129)                  0.15326671  3.834075e-07
## passenger_groups=Couple          0.03719691  1.495679e-05
## Trip_type=Street-Hail            0.05046600  1.111798e-02
## RateCodeID=Rate-1                0.04018420  3.163284e-02
## RateCodeID=Rate-Other           -0.04018420  3.163284e-02
```

```
## Trip_type=Dispatch              -0.05046600  1.111798e-02
## f.cost=(11,18]                  -0.06069884  1.647278e-06
## period=Period valley            -0.12396133  4.566127e-14
## period=Period afternoon         -0.14612741  8.436539e-21
## f.cost=(8,11]                   -0.24322507  1.869439e-36
## passenger_groups=Group          -0.21076016  2.204053e-67
## f.cost=[0,8]                    -0.28022396  5.282753e-68
## TipIsGiven=No                   -0.17229953 6.956769e-179
## Payment_type=Credit card        -0.71587782 4.558246e-227
## Trip_distance_range=Short_dist  -0.28593356 2.059524e-267
## VendorID=f.Vendor-VeriFone      -0.26007767 6.879178e-305
## Payment_type=Cash               -1.12508234  0.000000e+00
##
## attr(,"class")
## [1] "condes" "list "
```

There is no info for the **quantitative** variables here.

For the second dimension we see that for the **qualitative** variables the most positively related, from more to less, are:

- Payment_type (0.53)
- VendorID (0.26)

We see that they are not very large numbers, however.

If we look at the **categories**, we see that the most related are,

- for Payment_type:
  - No paid (1.84)
- and for VendorID:
  - f.Vendor-Mobile (0.26)

6.5 Perform a MCA taking into account also supplementary variables (use all numeric variables) quantitative and/or categorical. How supplementary variables enhance the axis interpretation?

```
res.mca_all <- MCA(
  df[,c(1:32)],
  quanti.sup=c(3:10, 12:13, 15, 18, 20:22),
  quali.sup=c(27,31),
  graph=FALSE
)
```

6.5.1 Description of dimensions

```
res.desc <- dimdesc(res.mca_all, axes = c(1,2))
```

```
res.desc[[1]]
```

6.5.1.1 Description of dimension 1

```
## $quanti
##                   correlation       p.value
## Fare_amount        0.34704329 5.687723e-131
## Trip_distance      0.31264071 2.305988e-105
## Total_amount       0.28704716  2.116125e-88
## tlenkm             0.28360598  2.991362e-86
## traveltime         0.23128431  3.455149e-57
## espeed             0.18449624  1.122581e-36
## Tolls_amount       0.11567250  3.040161e-15
## Tip_amount         0.10081884  6.393352e-12
## Pickup_latitude    0.09471249  1.100053e-10
## Dropoff_latitude   0.08750941  2.525109e-09
## Pickup_longitude   0.04599144  1.760667e-03
```

```
## Passenger_count  -0.06437422  1.184978e-05
## hour             -0.20861841  1.253392e-46
## Extra            -0.46952211 3.175111e-252
##
## $quali
##                                R2       p.value
## RateCodeID            0.693923341  0.000000e+00
## MTA_tax               0.711903229  0.000000e+00
## improvement_surcharge 0.698232732  0.000000e+00
## Trip_type             0.708486163  0.000000e+00
## hcpck                 0.297939266  0.000000e+00
## dropoff               0.209345234 3.392119e-214
## pickup                0.207487287 6.821630e-212
## period                0.164815275 5.012350e-180
## claKM                 0.163714821 1.972284e-177
## Trip_distance_range   0.136491381 5.970680e-148
## f.cost                0.102309739 1.704572e-105
## f.tt                  0.076192183  6.211428e-77
## paidTolls             0.019509924  1.713157e-20
## passenger_groups      0.006558016  2.507248e-07
##
## $category
##                                                    Estimate       p.value
## Trip_type=Dispatch                               1.43031511  0.000000e+00
## improvement_surcharge=improvement_surcharge_No   1.38427751  0.000000e+00
## MTA_tax=MTA_tax_No                               1.39203218  0.000000e+00
## RateCodeID=Rate-Other                            1.33153381  0.000000e+00
## Trip_distance_range=Long_dist                    0.32675153 8.100939e-136
## hcpck=kHP-2                                      0.07977521 1.681574e-104
## period=Period morning                            0.37766782 8.601718e-102
## hcpck=kHP-4                                      0.20181507  3.099380e-90
## f.tt=(20,50]                                     0.18168927  6.096325e-53
## dropoff=dropoff_09                               0.47527824  1.556093e-45
## pickup=pickup_09                                 0.43741728  3.021897e-39
## claKM=kKM-2                                      0.17416148  2.127247e-38
## f.cost=(18,30]                                   0.04742755  7.002029e-37
## f.cost=(30,50]                                   0.21181762  3.678115e-30
## pickup=pickup_10                                 0.35502449  2.166357e-28
## dropoff=dropoff_10                               0.35598916  5.081215e-28
## pickup=pickup_08                                 0.37525538  4.215535e-27
## f.cost=(50,129)                                  0.51778721  1.154869e-26
## claKM=kKM-4                                      0.40726332  3.051827e-26
## period=Period valley                             0.06316429  4.676156e-24
## dropoff=dropoff_08                               0.31036705  1.118775e-18
## claKM=kKM-1                                      0.02088140  1.810760e-16
## dropoff=dropoff_11                               0.24202770  2.191530e-15
## hcpck=kHP-5                                      0.51040471  4.740775e-15
## dropoff=dropoff_13                               0.23740406  2.794296e-14
## paidTolls=paidTolls_Yes                          0.01649022  1.300670e-13
## pickup=pickup_12                                 0.20658375  1.248113e-11
## pickup=pickup_13                                 0.20900204  1.839034e-11
## f.tt=f.tt.NA                                     0.32116637  2.544896e-10
## paidTolls=paidTolls.NA                           0.58172801  2.637481e-09
## pickup=pickup_11                                 0.18243315  3.201149e-09
## dropoff=dropoff_12                               0.17393741  1.042928e-08
## dropoff=dropoff_06                               0.34833432  4.281223e-07
## pickup=pickup_06                                 0.29293154  5.357562e-07
## dropoff=dropoff_15                               0.10947712  2.502414e-06
## pickup=pickup_14                                 0.08865893  3.225767e-05
## dropoff=dropoff_14                               0.06535148  6.420665e-04
## pickup=pickup_07                                 0.10272201  9.978763e-04
## pickup=pickup_05                                 0.18403737  1.347096e-03
## passenger_groups=Couple                          0.09533822  1.673249e-03
## pickup=pickup_15                                 0.05360616  1.924293e-03
```

```
## dropoff=dropoff_05                                  0.11200689  2.399701e-02
## dropoff=dropoff_07                                  0.04844411  4.477600e-02
## Trip_distance_range=Medium_dist                    -0.09239324  3.587226e-02
## pickup=pickup_03                                   -0.17632814  8.861076e-03
## dropoff=dropoff_16                                 -0.13845127  4.312258e-03
## pickup=pickup_16                                   -0.14870023  1.210472e-03
## dropoff=dropoff_22                                 -0.16127609  9.445790e-04
## f.tt=(15,20]                                       -0.02276355  5.656303e-04
## pickup=pickup_22                                   -0.17078247  2.323145e-04
## f.tt=(10,15]                                       -0.15233505  2.086366e-04
## dropoff=dropoff_03                                 -0.23113265  1.435539e-04
## f.cost=[0,8]                                       -0.23016247  1.876733e-05
## f.cost=(11,18]                                     -0.23321044  1.639065e-05
## pickup=pickup_21                                   -0.20005018  6.903869e-06
## dropoff=dropoff_23                                 -0.21249012  2.617862e-06
## pickup=pickup_00                                   -0.21451652  1.857404e-06
## passenger_groups=Group                             -0.11005910  1.742479e-06
## pickup=pickup_23                                   -0.22469398  9.767269e-07
## dropoff=dropoff_00                                 -0.22732617  2.822646e-07
## dropoff=dropoff_21                                 -0.22321151  3.701867e-08
## period=Period night                                -0.12234903  1.052033e-08
## hcpck=kHP-3                                        -0.34574730  5.171016e-11
## dropoff=dropoff_17                                 -0.27675451  1.836772e-12
## pickup=pickup_19                                   -0.27361333  9.619675e-15
## dropoff=dropoff_19                                 -0.28797827  1.382374e-16
## pickup=pickup_17                                   -0.31883145  6.076516e-17
## dropoff=dropoff_20                                 -0.30303289  1.825453e-17
## pickup=pickup_20                                   -0.30264483  2.466439e-18
## paidTolls=paidTolls_No                             -0.59821823  5.109733e-20
## pickup=pickup_18                                   -0.33381152  2.133837e-23
## dropoff=dropoff_18                                 -0.33632575  1.896016e-23
## f.cost=(8,11]                                      -0.31365948  7.123600e-25
## f.tt=(5,10]                                        -0.22721770  1.228615e-33
## Trip_distance_range=Short_dist                     -0.23435829  4.137407e-87
## period=Period afternoon                            -0.31848308  1.175534e-87
## claKM=kKM-3                                        -0.49342136 5.050918e-128
## hcpck=kHP-1                                        -0.44624768 2.882408e-285
## Trip_type=Street-Hail                              -1.43031511  0.000000e+00
## improvement_surcharge=improvement_surcharge_Yes -1.38427751  0.000000e+00
## MTA_tax=MTA_tax_Yes                                -1.39203218  0.000000e+00
## RateCodeID=Rate-1                                  -1.33153381  0.000000e+00
##
## attr(,"class")
## [1] "condes" "list "
```

In this dimension, since we have taken into account all the variables, we now have information for the **quantitative** variables. We see that, more or less, the most positively related are:

- Fare_amount (0.35)
- Trip_distance (0.31)
- Total_amount (0.29)

We also see that they do not contribute much given the numbers.

However, there is a little more inverse relationship with Extra, with a -0.47.

Regarding the **qualitative** variables, the new relationship is as follows:

- RateCodeID (0.69)
- MTA_tax (0.71)
- improvement_surcharge (0.70)
- Trip_type (0.71)

If we look at the **categories**, we see that the most related are,

- for Trip_type:
  - Dispatch (1.43) -> same as before but less related
- for improvement_surcharge:

  - improvement_surcharge_No (1.38)
- for MTA_tax:
  - MTA_tax_No (1.39)
- for Trip_distance_range:
  - Long_dist (0.24)
- and for RateCodeID:
  - Rate-Other (1.33) -> same as before but less related

```
res.desc[[2]]
```

6.5.1.2 Description of dimension 2

```
## $quanti
##                   correlation      p.value
## Extra              0.59540871 0.000000e+00
## Passenger_count    0.18753711 7.367467e-38
## hour               0.14546401 2.768090e-23
## Dropoff_longitude  0.10780500 1.991105e-13
## espeed             0.10518904 7.497280e-13
## Pickup_longitude   0.08329485 1.413350e-08
## Total_amount       0.04423863 2.624881e-03
## Trip_distance      0.04404583 2.740527e-03
## Fare_amount        0.03440690 1.931080e-02
## tlenkm             0.03204240 2.936007e-02
## traveltime        -0.03531017 1.635340e-02
## Tolls_amount      -0.05868397 6.539683e-05
## Dropoff_latitude  -0.08128077 3.127258e-08
## Pickup_latitude   -0.08469170 8.059026e-09
##
## $quali
##                                R2       p.value
## period                 0.7193448269  0.000000e+00
## pickup                 0.7762688275  0.000000e+00
## dropoff                0.7624477783  0.000000e+00
## hcpck                  0.4545819701  0.000000e+00
## MTA_tax                0.1619886885 1.358849e-179
## Trip_type              0.1582247481 4.316437e-175
## improvement_surcharge  0.1533670876 2.604975e-169
## RateCodeID             0.1514542007 4.820984e-167
## claKM                  0.1244134404 1.691964e-131
## passenger_groups       0.0437705123  1.254658e-45
## f.cost                 0.0076558568  1.198591e-06
## Trip_distance_range    0.0055181933  2.809998e-06
## paidTolls              0.0044565106  3.304810e-05
## f.tt                   0.0041361451  1.808199e-03
## VendorID               0.0009197986  3.920678e-02
## Payment_type           0.0012977242  4.980251e-02
##
## $category
##                                                    Estimate       p.value
## hcpck=kHP-1                                      0.31938183  0.000000e+00
## period=Period night                              0.40222038 3.365631e-247
## period=Period afternoon                          0.45882535 5.397000e-213
## MTA_tax=MTA_tax_No                               0.61577827 1.358849e-179
## Trip_type=Dispatch                               0.62682523 4.316437e-175
## improvement_surcharge=improvement_surcharge_No   0.60163400 2.604975e-169
## RateCodeID=Rate-Other                            0.57687316 4.820984e-167
## claKM=kKM-3                                      0.28367351 8.583686e-105
## dropoff=dropoff_19                               0.38381622  1.832601e-46
## pickup=pickup_19                                 0.38522256  2.503341e-46
## dropoff=dropoff_18                               0.38168754  6.015986e-46
## pickup=pickup_18                                 0.37954972  6.838557e-46
## pickup=pickup_20                                 0.37329421  3.371096e-43
```

```
## dropoff=dropoff_20                          0.37801770  3.497189e-42
## dropoff=dropoff_22                          0.38091527  1.100903e-34
## pickup=pickup_22                            0.36184277  2.051986e-32
## passenger_groups=Group                      0.13528200  1.069335e-31
## dropoff=dropoff_21                          0.32784913  6.528817e-29
## dropoff=dropoff_01                          0.40551849  1.201710e-27
## pickup=pickup_01                            0.41106345  2.203563e-27
## pickup=pickup_17                            0.32837866  2.379219e-27
## hcpck=kHP-3                                 0.32908692  2.832286e-27
## pickup=pickup_21                            0.33383417  1.161176e-26
## pickup=pickup_00                            0.33610624  2.614122e-25
## dropoff=dropoff_00                          0.32779268  3.212179e-24
## pickup=pickup_02                            0.40676906  3.883490e-22
## dropoff=dropoff_02                          0.41364408  4.972724e-22
## dropoff=dropoff_23                          0.30192512  1.126132e-20
## pickup=pickup_23                            0.30110187  3.234219e-19
## dropoff=dropoff_04                          0.42108454  4.954886e-19
## pickup=pickup_04                            0.40921819  2.566232e-15
## pickup=pickup_03                            0.35653630  2.723112e-15
## dropoff=dropoff_03                          0.33499061  5.956436e-14
## dropoff=dropoff_17                          0.22947689  6.600147e-14
## passenger_groups=Couple                     0.04411718  7.518697e-13
## claKM=kKM-2                                 0.10747201  4.561136e-12
## pickup=pickup_05                            0.35086823  4.782705e-07
## Trip_distance_range=Long_dist               0.06959039  4.957575e-07
## dropoff=dropoff_05                          0.33403293  1.329113e-06
## f.cost=(8,11]                               0.02021781  4.875813e-04
## f.tt=[0,5]                                  0.03435830  1.662342e-03
## hcpck=kHP-4                                 0.05473367  1.732551e-02
## paidTolls=paidTolls.NA                      0.36969056  2.729367e-02
## VendorID=f.Vendor-VeriFone                  0.01802595  3.920678e-02
## dropoff=dropoff_07                         -0.08624471  4.263781e-02
## VendorID=f.Vendor-Mobile                   -0.01802595  3.920678e-02
## Trip_distance_range=Short_dist             -0.03003534  2.057557e-02
## Payment_type=No paid                       -0.13844249  1.957223e-02
## claKM=kKM-4                                -0.15080413  1.234479e-02
## pickup=pickup_07                           -0.10307362  1.055184e-02
## paidTolls=paidTolls_No                     -0.03224391  4.893648e-03
## f.tt=(20,50]                               -0.06025223  3.961329e-03
## claKM=kKM-1                                -0.08122460  3.001909e-03
## paidTolls=paidTolls_Yes                    -0.33744664  6.994691e-05
## hcpck=kHP-5                                -0.30151068  3.827631e-05
## f.cost=[0,8]                               -0.08481507  7.958326e-08
## pickup=pickup_16                           -0.19161428  6.634026e-13
## dropoff=dropoff_16                         -0.26024731  6.381674e-22
## dropoff=dropoff_08                         -0.43184566  5.369589e-31
## passenger_groups=Single                    -0.17939918  2.073015e-45
## pickup=pickup_08                           -0.53102690  2.383861e-49
## pickup=pickup_11                           -0.54835024  3.477338e-53
## dropoff=dropoff_12                         -0.54861363  3.112894e-53
## dropoff=dropoff_13                         -0.53735642  6.910645e-55
## pickup=pickup_12                           -0.53762203  6.088027e-55
## pickup=pickup_13                           -0.55875049  3.267704e-57
## dropoff=dropoff_09                         -0.54245620  1.605053e-57
## pickup=pickup_09                           -0.55813145  7.767141e-61
## dropoff=dropoff_11                         -0.55595768  9.959401e-62
## dropoff=dropoff_10                         -0.59076056  7.773922e-69
## pickup=pickup_10                           -0.59157063  1.412063e-70
## claKM=kKM-5                                -0.15911679  1.682905e-71
## pickup=pickup_15                           -0.54732996  3.165865e-72
## dropoff=dropoff_15                         -0.55708943  1.053768e-72
## pickup=pickup_14                           -0.61682332  1.161024e-92
## dropoff=dropoff_14                         -0.63592139  2.251034e-94
## RateCodeID=Rate-1                          -0.57687316 4.820984e-167
```

```
## improvement_surcharge=improvement_surcharge_Yes -0.60163400 2.604975e-169
## Trip_type=Street-Hail                            -0.62682523 4.316437e-175
## MTA_tax=MTA_tax_Yes                              -0.61577827 1.358849e-179
## period=Period morning                            -0.47130282 8.452319e-206
## hcpck=kHP-2                                      -0.40169174  0.000000e+00
## period=Period valley                             -0.38974292  0.000000e+00
##
## attr(,"class")
## [1] "condes" "list "
```

In this dimension, since we have taken into account all the variables, we now have information for the **quantitative** variables. We see that, more or less, the most positively related are:

- Extra (0.59540871)
- Passenger_count (0.18753711)

For the second dimension we see that for the **qualitative** variables the most positively related, from more to less, are:

- period (0.72)
- pickup (0.78)
- dropoff (0.76)
- hcpck (0.45)
- MTA_tax (0.16)
- ...
- Payment_type (0.0013) -> we see that it has lowed down in front of the other variables
- VendorID -> it does not even appear We see that they are not very large numbers, however.

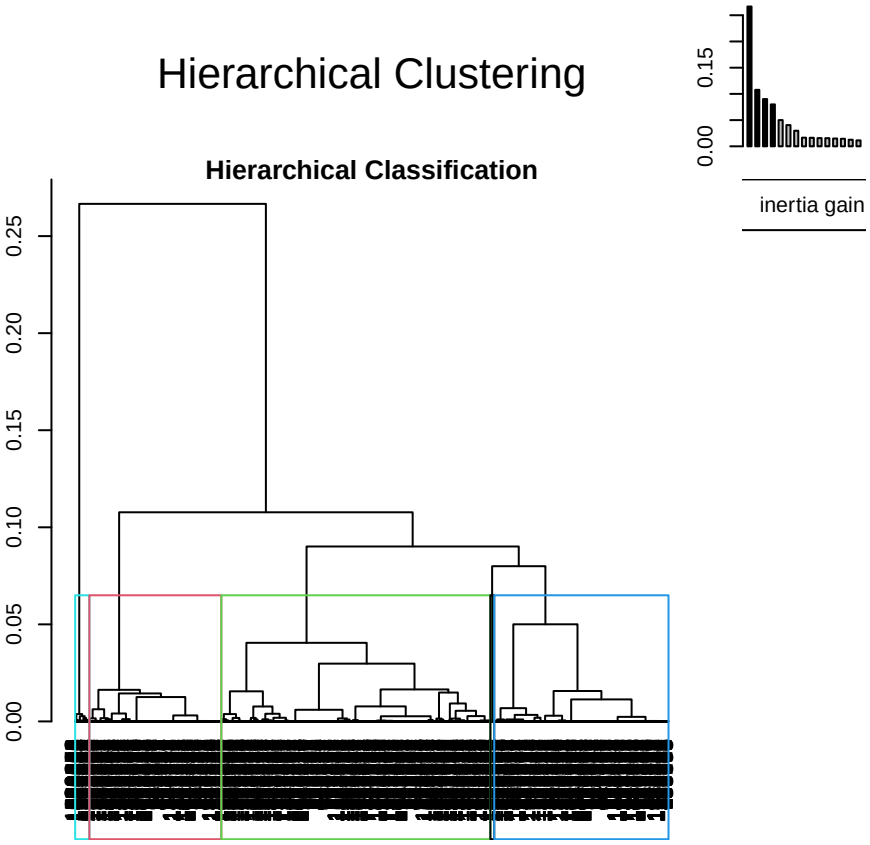
If we look at the **categories**, we see that the most related are,

- for period:
  - Period night (0.40)
  - Period afternoon (0.46)
- ...
- for Payment_type:
  - No paid (1.84) -> now it's inversed
- and for VendorID:
  - f.Vendor-Mobile -> it does not even appear

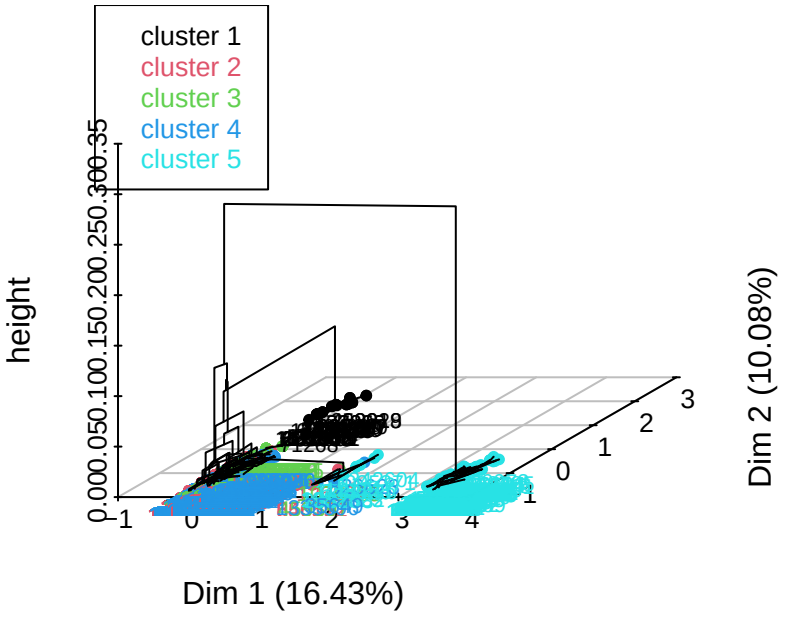
---

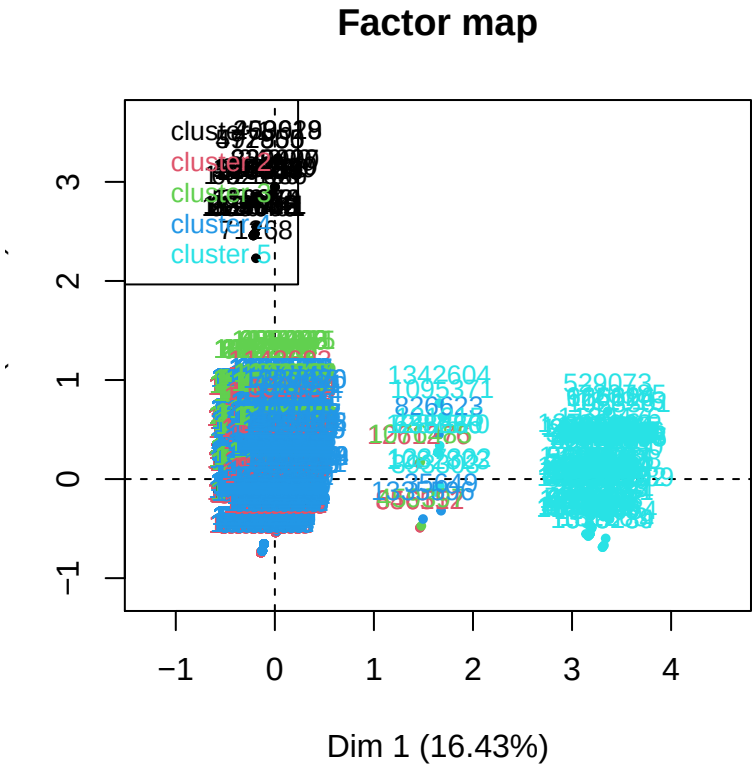
7 Hierarchical Clustering (from MCA)

```
res.hcpcMCA <- HCPC(res.mca,nb.clust = 5, order = TRUE)
```



Hierarchical clustering on the factor map





Note: If we chose the default number of cluster it would be 5, as we can guess from the inertia reduction plot, that follows the Elbow's rule (number of black lines plus 1). In our case, after trying with bigger number of clusters, we decided that the default number of cluster was fine for our case and data.

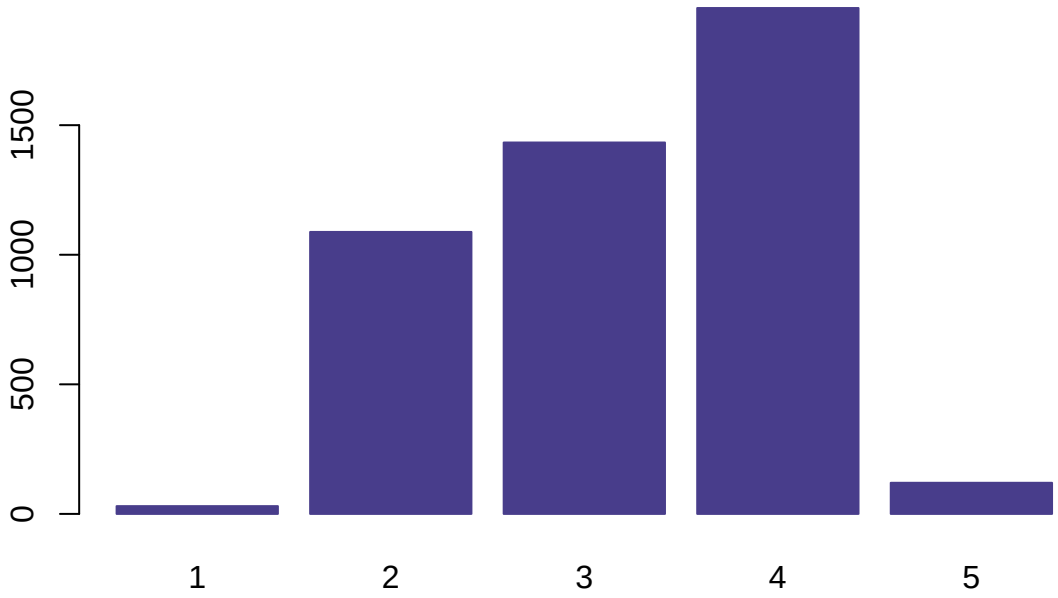
7.1 Description of clusters

Number of observations in each cluster:

```
table(res.hcpcMCA$data.clust$clust)
```

```
##
##    1    2    3    4    5
##   30 1088 1433 1952  120
```

```
barplot(table(res.hcpcMCA$data.clust$clust), col="darkslateblue", border="darkslateblue", main="[hierarc
```



7.2 Interpret the results of the classification

7.2.1 The description of the clusters by the variables

```
names(res.hcpcMCA$desc.var)
```

```
## [1] "test.chi2"  "category"   "quanti.var" "quanti"     "call"
```

```
res.hcpcMCA$desc.var$test.chi2   # categorical variables which characterizes the clusters
```

```
##                           p.value df
## RateCodeID           0.000000e+00  4
## Payment_type         0.000000e+00  8
## Trip_type            0.000000e+00  4
## period               0.000000e+00 12
## passenger_groups     2.601045e-94  8
## Trip_distance_range 6.685645e-92  8
## f.cost               1.448630e-51 20
## VendorID             2.325462e-27  4
## TipIsGiven           2.455088e-11  4
```

We start wit the description of the categorical variables that characterize the clusters, so in this output we do not have dimensions because it is the total association. We can see the intensity of the variables, in our case the variables that affect more to the clustering are **RateCodeID**, **Payment_type**, **Trip_type** and **period** because are the one with the smallest p.value. The variables associated to the clusters are the ones that appear on the output.

Next, we want to see for each cluster which are the categories that characterize them.The clusters that contain more individuals are the first, the second and the fourth one. Clusters number 1 and 5 are the ones that have less individuals. We proceed to analyze them.

```
res.hcpcMCA$desc.var$category    # description of each cluster by the categories
```

```
## $`1`
##                                Cla/Mod   Mod/Cla     Global      p.value
## Payment_type=No paid       100.0000000 100.00000  0.6489293 3.287724e-78
## VendorID=f.Vendor-Mobile     3.0832477 100.00000 21.0469392 3.471103e-21
## TipIsGiven=No                1.0409438 100.00000 62.3404716 6.580800e-07
```

```
## period=Period morning        1.4760148  26.66667 11.7239888 2.482286e-02
## passenger_groups=Single      0.7464607  96.66667 84.0363400 4.121461e-02
## TipIsGiven=Yes               0.0000000   0.00000 37.6595284 6.580800e-07
## Payment_type=Credit card     0.0000000   0.00000 45.3385248 1.248361e-08
## Payment_type=Cash            0.0000000   0.00000 54.0125460 6.774205e-11
## VendorID=f.Vendor-VeriFone   0.0000000   0.00000 78.9530608 3.471103e-21
##                                v.test
## Payment_type=No paid        18.721812
## VendorID=f.Vendor-Mobile     9.447473
## TipIsGiven=No                4.973343
## period=Period morning        2.244148
## passenger_groups=Single      2.041364
## TipIsGiven=Yes              -4.973343
## Payment_type=Credit card    -5.692987
## Payment_type=Cash           -6.525573
## VendorID=f.Vendor-VeriFone -9.447473
##
## $`2`
##                                  Cla/Mod     Mod/Cla     Global       p.value
## period=Period afternoon        88.379983  95.7720588 25.5029202  0.000000e+00
## Trip_distance_range=Short_dist 28.162853  76.9301471 64.2872594  2.073868e-24
## Trip_type=Street-Hail          24.118821 100.0000000 97.5773307  5.821121e-14
## RateCodeID=Rate-1              24.132562  99.7242647 97.2528661  1.150890e-11
## passenger_groups=Couple        37.900875  11.9485294  7.4194246  5.792479e-10
## f.cost=(11,18]                 29.461279  32.1691176 25.6975990  3.920300e-08
## f.cost=(8,11]                  28.844483  30.5147059 24.8972529  1.397923e-06
## VendorID=f.Vendor-Mobile       26.927030  24.0808824 21.0469392  5.477246e-03
## VendorID=f.Vendor-VeriFone     22.630137  75.9191176 78.9530608  5.477246e-03
## f.cost=(50,129)                 9.523810   0.5514706  1.3627515  4.760384e-03
## Payment_type=No paid            0.000000   0.0000000  0.6489293  3.099747e-04
## passenger_groups=Single        22.265122  79.5036765 84.0363400  5.081032e-06
## RateCodeID=Rate-Other           2.362205   0.2757353  2.7471339  1.150890e-11
## f.cost=(18,30]                 13.812155   9.1911765 15.6608263  1.988020e-12
## Trip_type=Dispatch              0.000000   0.0000000  2.4226693  5.821121e-14
## f.cost=(30,50]                  4.072398   0.8272059  4.7804456  5.272518e-16
## period=Period morning           4.428044   2.2058824 11.7239888  1.528422e-37
## Trip_distance_range=Long_dist   1.654135   1.0110294 14.3845987  1.258712e-66
## period=Period valley            1.746032   2.0220588 27.2550292 6.479660e-137
## period=Period night             0.000000   0.0000000 35.5180619 1.204220e-246
##                                   v.test
## period=Period afternoon              Inf
## Trip_distance_range=Short_dist  10.195634
## Trip_type=Street-Hail            7.512044
## RateCodeID=Rate-1                6.786246
## passenger_groups=Couple          6.195976
## f.cost=(11,18]                   5.494405
## f.cost=(8,11]                    4.825301
## VendorID=f.Vendor-Mobile         2.777538
## VendorID=f.Vendor-VeriFone      -2.777538
## f.cost=(50,129)                 -2.822816
## Payment_type=No paid            -3.606818
## passenger_groups=Single         -4.561414
## RateCodeID=Rate-Other           -6.786246
## f.cost=(18,30]                  -7.035322
## Trip_type=Dispatch              -7.512044
## f.cost=(30,50]                  -8.105047
## period=Period morning          -12.805447
## Trip_distance_range=Long_dist  -17.243201
## period=Period valley           -24.905542
## period=Period night            -33.541337
##
## $`3`
##                                  Cla/Mod     Mod/Cla     Global       p.value
## period=Period valley           77.222222  67.8995115 27.2550292  0.000000e+00
```

```
## period=Period morning          84.870849  32.1004885 11.7239888 2.187992e-171
## passenger_groups=Single        36.885457 100.0000000 84.0363400 7.053895e-133
## Trip_type=Street-Hail          31.766792 100.0000000 97.5773307  4.847071e-19
## RateCodeID=Rate-1              31.828292  99.8604327 97.2528661  2.899525e-18
## f.cost=[0,8]                   36.990596  32.9378925 27.6011248  7.127666e-08
## Trip_distance_range=Short_dist 33.411844  69.2951849 64.2872594  1.662139e-06
## Payment_type=Cash              33.520224  58.4089323 54.0125460  5.704677e-05
## TipIsGiven=No                  32.616239  65.5966504 62.3404716  2.137595e-03
## TipIsGiven=Yes                 28.317059  34.4033496 37.6595284  2.137595e-03
## f.cost=(18,30]                 26.104972  13.1891137 15.6608263  1.731548e-03
## Payment_type=Credit card       28.435115  41.5910677 45.3385248  5.948993e-04
## f.cost=(30,50]                 20.814480   3.2100488  4.7804456  5.532609e-04
## f.cost=(50,129)                11.111111   0.4884857  1.3627515  2.255397e-04
## Payment_type=No paid            0.000000   0.0000000  0.6489293  1.404592e-05
## Trip_distance_range=Long_dist  17.894737   8.3042568 14.3845987  1.903360e-16
## RateCodeID=Rate-Other           1.574803   0.1395673  2.7471339  2.899525e-18
## Trip_type=Dispatch              0.000000   0.0000000  2.4226693  4.847071e-19
## passenger_groups=Couple         0.000000   0.0000000  7.4194246  1.245354e-58
## passenger_groups=Group          0.000000   0.0000000  8.5442353  6.606223e-68
## period=Period afternoon         0.000000   0.0000000 25.5029202 4.668360e-228
## period=Period night             0.000000   0.0000000 35.5180619  0.000000e+00
##                                   v.test
## period=Period valley                 Inf
## period=Period morning           27.907100
## passenger_groups=Single         24.530099
## Trip_type=Street-Hail            8.915708
## RateCodeID=Rate-1                8.715315
## f.cost=[0,8]                     5.387923
## Trip_distance_range=Short_dist   4.790684
## Payment_type=Cash                4.024705
## TipIsGiven=No                    3.070418
## TipIsGiven=Yes                  -3.070418
## f.cost=(18,30]                  -3.132787
## Payment_type=Credit card        -3.433929
## f.cost=(30,50]                  -3.453549
## f.cost=(50,129)                 -3.688545
## Payment_type=No paid            -4.343142
## Trip_distance_range=Long_dist   -8.228018
## RateCodeID=Rate-Other           -8.715315
## Trip_type=Dispatch              -8.915708
## passenger_groups=Couple        -16.144309
## passenger_groups=Group         -17.412726
## period=Period afternoon        -32.241234
## period=Period night                -Inf
##
## $`4`
##                                  Cla/Mod     Mod/Cla     Global       p.value
## period=Period night            96.711328  81.3524590 35.5180619  0.000000e+00
## Trip_distance_range=Long_dist  71.578947  24.3852459 14.3845987  1.695159e-61
## passenger_groups=Group         74.430380  15.0614754  8.5442353  6.686185e-42
## Trip_type=Street-Hail          43.272002 100.0000000 97.5773307  7.579366e-28
## RateCodeID=Rate-1              43.349644  99.8463115 97.2528661  2.409545e-26
## f.cost=(30,50]                 71.493213   8.0942623  4.7804456  2.347589e-19
## f.cost=(18,30]                 56.215470  20.8504098 15.6608263  1.698775e-16
## passenger_groups=Couple        55.685131   9.7848361  7.4194246  1.982848e-07
## TipIsGiven=Yes                 46.984492  41.9057377 37.6595284  3.681425e-07
## VendorID=f.Vendor-VeriFone     43.945205  82.1721311 78.9530608  3.937983e-06
## Payment_type=Credit card       45.753817  49.1290984 45.3385248  9.740537e-06
## f.cost=(50,129)                61.904762   1.9979508  1.3627515  1.700462e-03
## f.cost=(8,11]                  39.530843  23.3094262 24.8972529  3.262945e-02
## Payment_type=Cash              39.767721  50.8709016 54.0125460  2.505066e-04
## f.cost=[0,8]                   36.912226  24.1290984 27.6011248  5.881095e-06
## VendorID=f.Vendor-Mobile       35.765673  17.8278689 21.0469392  3.937983e-06
## TipIsGiven=No                  39.347675  58.0942623 62.3404716  3.681425e-07
```

```
## Payment_type=No paid            0.000000   0.0000000  0.6489293  6.644475e-08
## f.cost=(11,18]                 35.521886  21.6188525 25.6975990  4.928571e-08
## RateCodeID=Rate-Other           2.362205   0.1536885  2.7471339  2.409545e-26
## Trip_type=Dispatch              0.000000   0.0000000  2.4226693  7.579366e-28
## Trip_distance_range=Short_dist 36.238223  55.1741803 64.2872594  2.788750e-28
## passenger_groups=Single        37.760618  75.1536885 84.0363400  1.056095e-44
## period=Period morning           5.350554   1.4856557 11.7239888  2.335274e-94
## period=Period valley           18.015873  11.6290984 27.2550292  2.460280e-99
## period=Period afternoon         9.160305   5.5327869 25.5029202 1.780977e-179
##                                   v.test
## period=Period night                  Inf
## Trip_distance_range=Long_dist   16.546560
## passenger_groups=Group          13.562453
## Trip_type=Street-Hail           10.938073
## RateCodeID=Rate-1               10.619847
## f.cost=(30,50]                   8.995687
## f.cost=(18,30]                   8.241632
## passenger_groups=Couple          5.200938
## TipIsGiven=Yes                   5.084734
## VendorID=f.Vendor-VeriFone       4.614629
## Payment_type=Credit card         4.422854
## f.cost=(50,129)                  3.138101
## f.cost=(8,11]                   -2.136613
## Payment_type=Cash               -3.661741
## f.cost=[0,8]                    -4.530620
## VendorID=f.Vendor-Mobile        -4.614629
## TipIsGiven=No                   -5.084734
## Payment_type=No paid            -5.400529
## f.cost=(11,18]                  -5.453868
## RateCodeID=Rate-Other          -10.619847
## Trip_type=Dispatch             -10.938073
## Trip_distance_range=Short_dist -11.028370
## passenger_groups=Single        -14.027639
## period=Period morning          -20.607817
## period=Period valley           -21.155413
## period=Period afternoon        -28.565936
##
## $`5`
##                                    Cla/Mod    Mod/Cla    Global       p.value
## RateCodeID=Rate-Other           93.70078740 99.1666667  2.747134 3.098738e-225
## Trip_type=Dispatch             100.00000000 93.3333333  2.422669 2.173170e-216
## Trip_distance_range=Long_dist    7.66917293 42.5000000 14.384599  3.518497e-14
## f.cost=(50,129)                 15.87301587  8.3333333  1.362751  4.263359e-06
## TipIsGiven=No                    3.33102012 80.0000000 62.340472  2.655335e-05
## passenger_groups=Couple          6.41399417 18.3333333  7.419425  7.020893e-05
## passenger_groups=Single          2.34234234 75.8333333 84.036340  1.837786e-02
## TipIsGiven=Yes                   1.37851809 20.0000000 37.659528  2.655335e-05
## Trip_distance_range=Short_dist   1.68236878 41.6666667 64.287259  3.637606e-07
## Trip_type=Street-Hail            0.17734427  6.6666667 97.577331 2.173170e-216
## RateCodeID=Rate-1                0.02224199  0.8333333 97.252866 3.098738e-225
##                                    v.test
## RateCodeID=Rate-Other           32.039255
## Trip_type=Dispatch              31.397728
## Trip_distance_range=Long_dist    7.577658
## f.cost=(50,129)                  4.598112
## TipIsGiven=No                    4.201175
## passenger_groups=Couple          3.975577
## passenger_groups=Single         -2.357916
## TipIsGiven=Yes                 -4.201175
## Trip_distance_range=Short_dist  -5.087006
## Trip_type=Street-Hail          -31.397728
## RateCodeID=Rate-1              -32.039255
```

Cluster 1 The first thing we can notice from this cluster is that all observations are of **Payment_type=No**

paid, even though this category only intervents in the sample 0.65% this cluster contains all the individuals of this payment type and all of the observations in the cluster are of **VendorID=f.Vendor-Mobile**, a category that intervents a 21.05% from the sample, but this cluster is that small that we only have a 3.08% of observations of this kind represented in the cluster. So, what is logical is that the other payment types represent a 0% in this cluster as well as the other vendor type. We can also see that all the observations in the did not left a tip, and again and because of the size of the cluster, even though the **TipIsGive=No** represents a 62.34% of the observations from sample, we only have a representation of the 1.04% of these individuals in this cluster. We can also notice that the majority of the trips are made by just one person (96.67%) and we have some morning trips (26.67%).

Cluster 2 The first thing we can see from the cluster is that all of the observations present are of the category **Trip_type=Street-Hail** and we have in this cluster a representation of the 24.12% of the observations of this category from sample. Something similar happens to the category **RateCodeID=Rate-1**. We can also see that we have the 88.38% of the observations from sample of the category **period=Period afternoon** represented in this cluster and they represent the 95.77% of the observations of the cluster. We can also notice that around the 80% of the observations in this cluster are single passengers and we have 22.27% of the observations of this category from the sample represented here.

Cluster 3 The first thing we can notice is that every observation in the cluster is of the kind of **passenger_groups=Single** and **Trip_type=Street-Hail** and we have represented the 36.89% and 31.77%, respectively, of the observations from the sample of these categories. We can also see that almost every observation in the cluster (99.86%) is of **RateCodeID=Rate-1** and we have represented in this cluster the 31.83% of the observations with this category from the sample. We can see that we have the 84.87% of the **period=Period morning** observations of the sample represented in this cluster, and the 77.22% of the **period=Period valley** observations as well. The 67.90% of the observations of the cluster are **period=Period morning**. The 69.29% of the observations in the cluster are short distance trips and the 65.60% observations in the cluster did not left any tips.

Cluster 4 The first thing we can see is that every observation in the cluster is of the kind **Trip_type=Street-Hail** and we have the 43.27% of the observations from the sample of this kind are represented in this cluster. We can also notice that almost every observation in the cluster is of the kind **RateCodeID=Rate-1** and we have 43.35% of the observations of this kind from the sample represented here. We can see that the 96.71% of the **period=Period night** observations from the sample are represented in the cluster, and the 81.35% of the observations in the cluster are of this kind too. We can see that we have represented the 74.43% of **passenger_groups=Group**, the 71.58% of **Trip_distance=Long_dist** and the 71.49% of **f.cost=(30,50]** observations of these kinds from the sample represented in this cluster.

Cluster 5 The first thing we can notice from this cluster is that we have represented in this cluster all the observations of **Trip_type=Dispatch** from the sample here and they represent the 93.33% of the observations of this kind in the cluster, so the rest are **Trip_type=Street-Hail** and we only have a representation of 0.18% of the observations from the sample in this cluster. We can also see that the 80% of the observations in the cluster did not left any tip and the other 20% left some tips, we have a very small representation of observations from the sample of these two categories in this cluster. We can also see that almost every observation in the cluster (99.17%) is of **RateCodeID=Rate-Ohter** and we have the 93.70% of the observations from the sample of this category represented in this cluster. We can see that in this cluster we have represented the 15.87% of the observations from the sample of the category **f.cost=(50,129)**.

We now proceed to see the quantitative variables that characterizes the clusters.

```
res.hcpcMCA$desc.var$quanti.var  # quantitative variables which characterizes the clusters
```

```
##                    Eta2      P-value
## Total_amount 0.03950465 3.518655e-39
```

We can see in the output that the variable that appears is slightly over represented in the clusters. We can notice that **Total_amount** is over represented with 0.04 units over the global mean. So it is practically the same as the global mean.

We want to know now which variables are associated with the quantitative variables.

```
res.hcpcMCA$desc.var$quanti      # description of each cluster by the quantitative variables
```

```
## $`1`
## NULL
##
## $`2`
##                  v.test Mean in category Overall mean sd in category Overall sd
## Total_amount -7.859152         11.83333      13.9264       7.170368   10.04487
##                    p.value
```

```
## Total_amount 3.867431e-15
##
## $`3`
##                 v.test Mean in category Overall mean sd in category Overall sd
## Total_amount -6.69081         12.45144      13.9264       7.604782   10.04487
##                    p.value
## Total_amount 2.219385e-11
##
## $`4`
##                 v.test Mean in category Overall mean sd in category Overall sd
## Total_amount 11.26398         15.87319      13.9264       11.44962   10.04487
##                    p.value
## Total_amount 1.976246e-29
##
## $`5`
##                 v.test Mean in category Overall mean sd in category Overall sd
## Total_amount 5.641927         19.03283      13.9264       19.88545   10.04487
##                    p.value
## Total_amount 1.681571e-08
```

We can notice that every cluster has remarked the Total_amount variable except the first one, that does not have any variable to be described.

Cluster 2 We can see that the **Total_amount** is around 2 units under the overall mean.

Cluster 3 We can see that the **Total_amount** is around 1 unit under the overall mean.

Cluster 4 We can see that the **Total_amount** is around 2 units over the overall mean.

Cluster 5 ### Partition quality We are going to evaluate the partition quality.

```
#res.hcpcMCA$call$t$within[1] = Total sum of squares
#(res.hcpcMCA$call$t$within[1]-res.hcpcMCA$call$t$within[5] = between sum of squares
((res.hcpcMCA$call$t$within[1]-res.hcpcMCA$call$t$within[5])/res.hcpcMCA$call$t$within[1])*100
```

7.2.1.1 Gain in inertia (in %)

```
## [1] 59.14975
```

The quality of this reduction if of 59.15%.

In case we wanted to achieve an 80% of the clustering representativity we would need 13 clusters.

```
((res.hcpcMCA$call$t$within[1]-res.hcpcMCA$call$t$within[13])/res.hcpcMCA$call$t$within[1])*100
```

```
## [1] 80.77602
```

7.3 Parangons and class-specific individuals.

7.3.1 The description of the clusters by the individuals

```
res.hcpcMCA$desc.ind$para  # representative individuals of each cluster
```

```
## Cluster: 1
##    632100   1421036     64149    154087    437922
## 0.2538258 0.2538258 0.3519479 0.3519479 0.3519479
## ------------------------------------------------------------
## Cluster: 2
##     48587     53670     55526     93463     96109
## 0.2668603 0.2668603 0.2668603 0.2668603 0.2668603
## ------------------------------------------------------------
## Cluster: 3
##     43055     85690    135038    135275    139019
## 0.1708958 0.1708958 0.1708958 0.1708958 0.1708958
## ------------------------------------------------------------
## Cluster: 4
##     1200    13382    14314    21607    22076
## 0.222467 0.222467 0.222467 0.222467 0.222467
```

```
## ------------------------------------------------------------
## Cluster: 5
##    485688   1399808   1399419    747830     27974
## 0.2623554 0.2623554 0.2979732 0.3158258 0.4450544
```

What we obtain are the more representative individuals,paragons, for each cluster. We get the rownames of each paragon in every single cluster.

```
res.hcpcMCA$desc.ind$dist  # individuals distant from each cluster
```

```
## Cluster: 1
##   881540   209928   453619    24990   329000
## 3.776488 3.763555 3.763555 3.753329 3.753329
## ------------------------------------------------------------
## Cluster: 2
##  1261276   646551   856112   187123   226984
## 1.936593 1.817659 1.817659 1.553835 1.553835
## ------------------------------------------------------------
## Cluster: 3
##   459397  1076485   128467   163845   168358
## 1.834493 1.735617 1.342113 1.342113 1.342113
## ------------------------------------------------------------
## Cluster: 4
##   826623    35649   202294   245448   321262
## 2.123598 2.034772 1.818039 1.818039 1.818039
## ------------------------------------------------------------
## Cluster: 5
##  1083301   173366   720785   131915   810930
## 3.739454 3.714631 3.708608 3.654759 3.652079
```

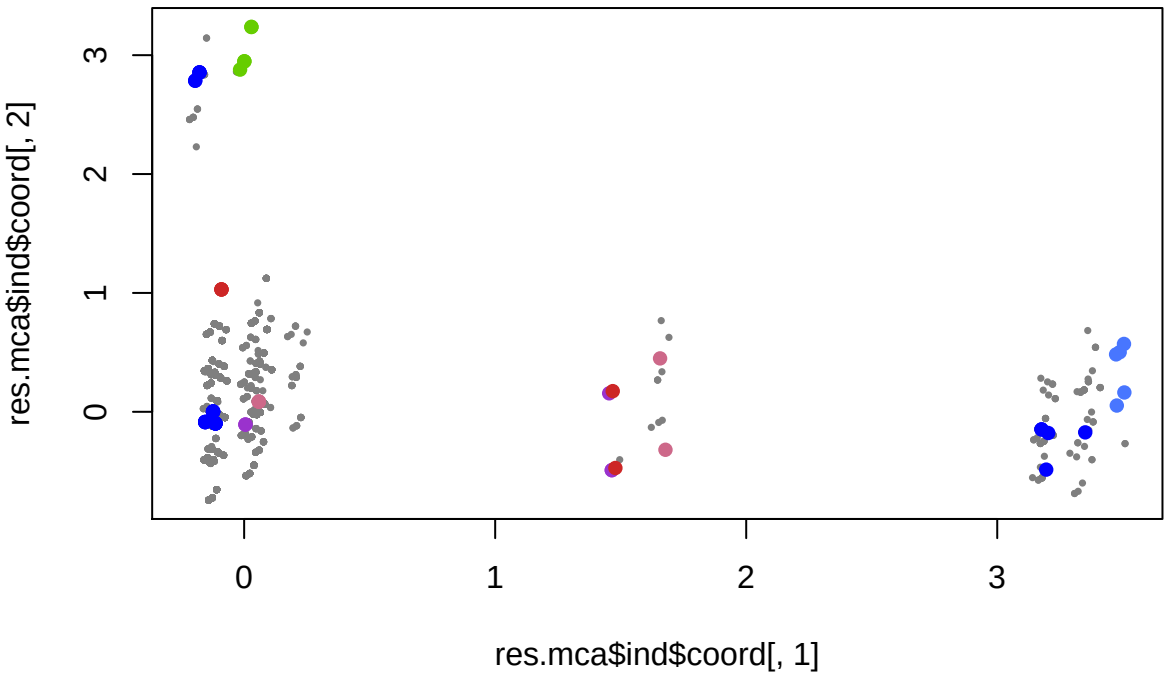
What we obtain are those individuals of each cluster that that far away in the same cluster from the rest of the individuals. We also obtain the rownames of each individual with the bigger distance respect the other ones in the cluster.

7.3.1.1 Examine the values of individuals that characterize classes

We get the grpahical representation for the individuals that characterize classes (para and dist).

```
# characteristic individuals
para1<-which(rownames(res.mca$ind$coord)%in%names(res.hcpcMCA$desc.ind$para[[1]]))
dist1<-which(rownames(res.mca$ind$coord)%in%names(res.hcpcMCA$desc.ind$dist[[1]]))
para2<-which(rownames(res.mca$ind$coord)%in%names(res.hcpcMCA$desc.ind$para[[2]]))
dist2<-which(rownames(res.mca$ind$coord)%in%names(res.hcpcMCA$desc.ind$dist[[2]]))
para3<-which(rownames(res.mca$ind$coord)%in%names(res.hcpcMCA$desc.ind$para[[3]]))
dist3<-which(rownames(res.mca$ind$coord)%in%names(res.hcpcMCA$desc.ind$dist[[3]]))
para4<-which(rownames(res.mca$ind$coord)%in%names(res.hcpcMCA$desc.ind$para[[4]]))
dist4<-which(rownames(res.mca$ind$coord)%in%names(res.hcpcMCA$desc.ind$dist[[4]]))
para5<-which(rownames(res.mca$ind$coord)%in%names(res.hcpcMCA$desc.ind$para[[5]]))
dist5<-which(rownames(res.mca$ind$coord)%in%names(res.hcpcMCA$desc.ind$dist[[5]]))

plot(res.mca$ind$coord[,1],res.mca$ind$coord[,2],col="grey50",cex=0.5,pch=16)
points(res.mca$ind$coord[para1,1],res.mca$ind$coord[para1,2],col="blue",cex=1,pch=16)
points(res.mca$ind$coord[dist1,1],res.mca$ind$coord[dist1,2],col="chartreuse3",cex=1,pch=16)
points(res.mca$ind$coord[para2,1],res.mca$ind$coord[para2,2],col="blue",cex=1,pch=16)
points(res.mca$ind$coord[dist2,1],res.mca$ind$coord[dist2,2],col="darkorchid3",cex=1,pch=16)
points(res.mca$ind$coord[para3,1],res.mca$ind$coord[para3,2],col="blue",cex=1,pch=16)
points(res.mca$ind$coord[dist3,1],res.mca$ind$coord[dist3,2],col="firebrick3",cex=1,pch=16)
points(res.mca$ind$coord[para4,1],res.mca$ind$coord[para4,2],col="blue",cex=1,pch=16)
points(res.mca$ind$coord[dist4,1],res.mca$ind$coord[dist4,2],col="palevioletred3",cex=1,pch=16)
points(res.mca$ind$coord[para5,1],res.mca$ind$coord[para5,2],col="blue",cex=1,pch=16)
points(res.mca$ind$coord[dist5,1],res.mca$ind$coord[dist5,2],col="royalblue1",cex=1,pch=16)
```



7.4 Comparison of clusters obtained after K-Means (based on PCA) and/or Hierarchical Clustering (based on PCA) focusing on f.cost target.

7.5 Comparison of clusters obtained after K-Means (based on PCA) and/or Hierarchical Clustering (based on PCA) focusing on the binary target.