

Deliverable 2

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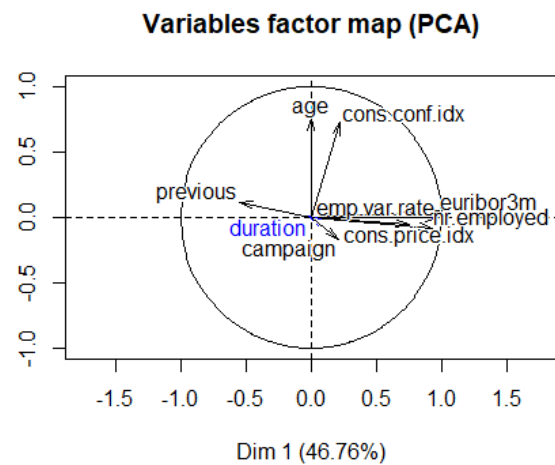
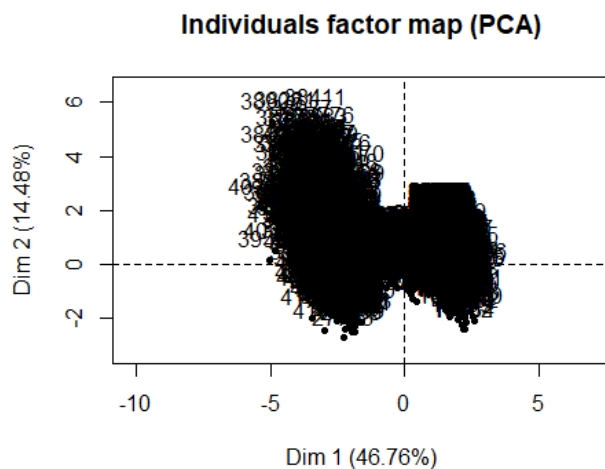
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Valores propios y ejes dominantes

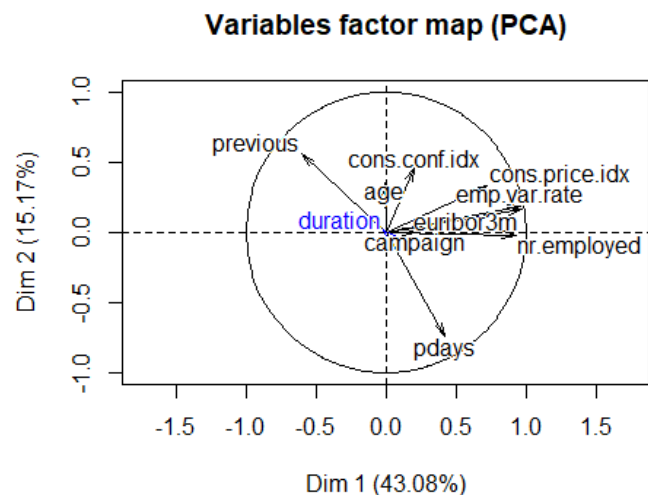
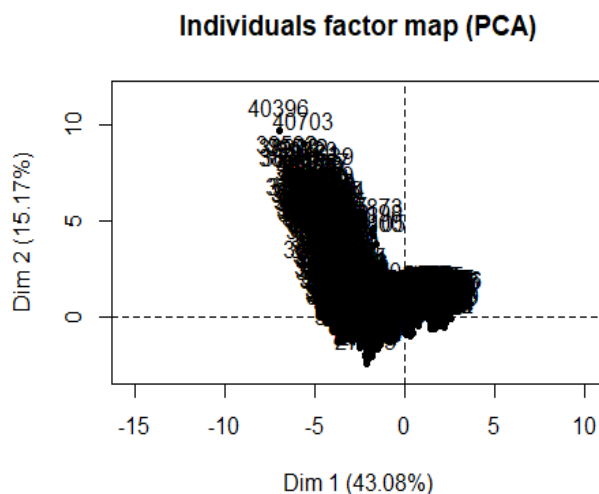
Eigenvalues and dominant axes analysis. How many axes we have to interpret according to Kaiser and Elbow's rule?

Hemos decidido probar como se ve el PCA sin y con la variable pday, ya que consideramos que es una variable con bastantes missings, aún así aporta información por lo tanto la vamos a considerar.

```
vars_num_sin_pday = vars_num[-3];  
res2.pca<-PCA(df[,c('duration',vars_num_sin_pday)],quanti.sup=1)
```



```
res.pca<-PCA(df[,c('duration',vars_num)],quanti.sup=1)
```



Vemos que con pdays existe una relación inversa con previous, respecto a los dos ejes factoriales, sin pdays se puede ver que la contribución de la variable age con el segundo eje factorial es mayor, ya que gráficamente tiene mayor magnitud además que las variables socio económicas, se ven mejor representadas en el primer eje factorial.

Por la ley de Kaiser, deberíamos utilizar los 3 primeros ejes factoriales, los cuales son mayores a 1. Por la ley de ElBow, al realizar el gráfico podemos ver que la gráfica empieza a ser plana a partir de la 2da dimensión, es decir que se cogen las 2 primeras dimensiones.

Si tomamos en cuenta el criterio del 80% se deberían coger las 4 primeras dimensiones.

```
summary(res.pca,ncp=4,nb.dec=2)
```

```
##
```

```
## Call:
```

```
## PCA(X = df[, c("duration", vars_num)], quanti.sup = 1)
```

```
##
```

```
##
```

```
## Eigenvalues
```

```
##           Dim.1 Dim.2 Dim.3 Dim.4 Dim.5 Dim.6 Dim.7
```

```
## Variance      3.88  1.36  1.10  0.97  0.83  0.43  0.39
```

```
## % of var.     43.08 15.17 12.28 10.74  9.25  4.82  4.29
```

```
## Cumulative % of var. 43.08 58.24 70.52 81.26 90.50 95.33 99.62
```

```
##           Dim.8 Dim.9
```

```
## Variance      0.02  0.01
```

```
## % of var.      0.27  0.12
```

```
## Cumulative % of var. 99.88 100.00
```

```
##
```

```
## Individuals (the 10 first)
```

```
##           Dist Dim.1 ctr cos2 Dim.2 ctr cos2 Dim.3
```

```
## 20 | 1.74 | 1.29 0.01 0.55 | 0.44 0.00 0.06 | 0.41
```

```
## 21 | 1.99 | 1.30 0.01 0.42 | 0.18 0.00 0.01 | -0.13
```

```
## 30 | 2.24 | 1.28 0.01 0.33 | 0.90 0.01 0.16 | 1.38
```

```
## 33 | 1.93 | 1.29 0.01 0.44 | 0.73 0.01 0.14 | 1.02
```

```
## 48 | 1.74 | 1.29 0.01 0.55 | 0.47 0.00 0.07 | 0.47
```

```
## 56 | 2.24 | 1.28 0.01 0.33 | 0.90 0.01 0.16 | 1.38
```

```
## 61 | 1.85 | 1.29 0.01 0.48 | 0.67 0.01 0.13 | 0.90
```

```
## 62 | 2.02 | 1.29 0.01 0.41 | 0.78 0.01 0.15 | 1.14
```

```
## 65 | 1.89 | 1.29 0.01 0.46 | 0.70 0.01 0.14 | 0.96
```

```
## 84 | 1.93 | 1.29 0.01 0.44 | 0.73 0.01 0.14 | 1.02
```

```
##           ctr cos2 Dim.4 ctr cos2
```

```
## 20 0.00 0.06 | -0.81 0.01 0.22 |
```

```
## 21 0.00 0.00 | -1.06 0.02 0.28 |
```

```
## 30 0.03 0.38 | -0.38 0.00 0.03 |
```

```
## 33 0.02 0.28 | -0.54 0.01 0.08 |
```

```
## 48 0.00 0.07 | -0.79 0.01 0.21 |
```

```
## 56 0.03 0.38 | -0.38 0.00 0.03 |
```

```
## 61 0.01 0.23 | -0.60 0.01 0.10 |
```

```
## 62 0.02 0.32 | -0.49 0.00 0.06 |
```

```
## 65 0.02 0.26 | -0.57 0.01 0.09 |
```

```
## 84 0.02 0.28 | -0.54 0.01 0.08 |
```

```
##
```

```
## Variables
```

```
##           Dim.1 ctr cos2 Dim.2 ctr cos2 Dim.3 ctr cos2
```

```
## age | -0.01 0.00 0.00 | 0.35 8.93 0.12 | 0.67 40.10 0.44
```

```
## campaign | 0.21 1.13 0.04 | 0.00 0.00 0.00 | -0.23 4.74 0.05
```

```
## pdays | 0.42 4.63 0.18 | -0.74 40.21 0.55 | 0.28 7.10 0.08
```

```
## previous | -0.60 9.37 0.36 | 0.56 22.84 0.31 | -0.30 8.38 0.09
```

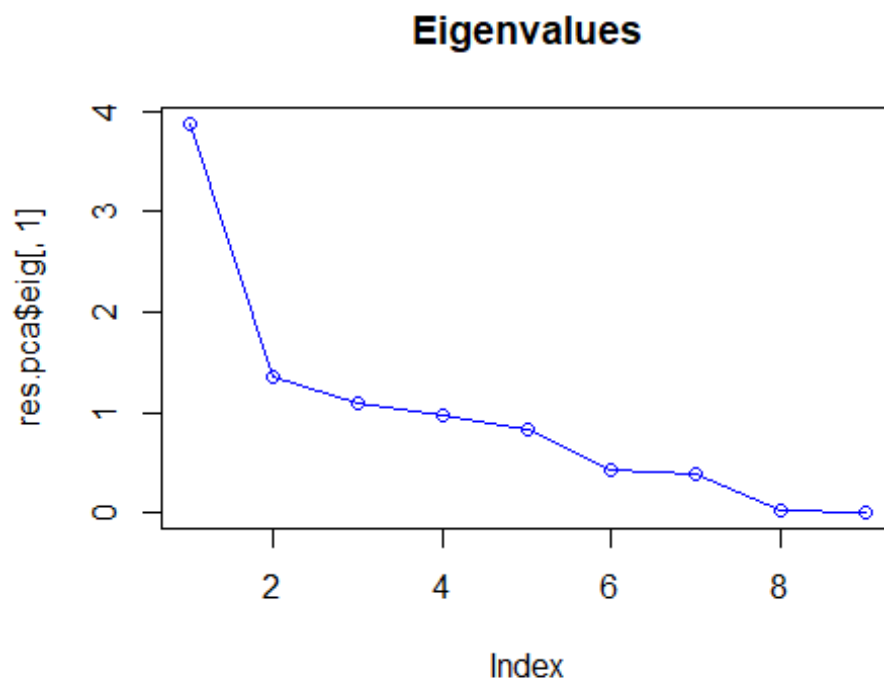
```
## emp.var.rate | 0.96 23.97 0.93 | 0.19 2.54 0.03 | -0.11 1.00 0.01
```

```
## cons.price.idx | 0.72 13.43 0.52 | 0.33 8.11 0.11 | -0.30 8.08 0.09
```

```
## cons.conf.idx | 0.20 1.06 0.04 | 0.46 15.36 0.21 | 0.58 30.44 0.34
```

```
## euribor3m      |  0.97 24.20  0.94 |  0.16  1.98  0.03 | -0.01  0.01  0.00
## nr.employed   |  0.93 22.20  0.86 | -0.02  0.03  0.00 | -0.04  0.16  0.00
##               | Dim.4   ctr  cos2
## age           |  0.28  8.23  0.08 |
## campaign      |  0.93 89.89  0.87 |
## pdays        |  0.04  0.17  0.00 |
## previous      | -0.02  0.05  0.00 |
## emp.var.rate   | -0.06  0.39  0.00 |
## cons.price.idx | -0.06  0.41  0.00 |
## cons.conf.idx  | -0.04  0.13  0.00 |
## euribor3m     | -0.07  0.51  0.00 |
## nr.employed   | -0.05  0.24  0.00 |
##
## Supplementary continuous variable
##               | Dim.1  cos2  Dim.2  cos2  Dim.3  cos2  Dim.4  cos2
## duration      | -0.02  0.00 |  0.02  0.00 |  0.00  0.00 | -0.05  0.00 |

plot(res.pca$eig[,1],main="Eigenvalues",type="o", col="blue")
```



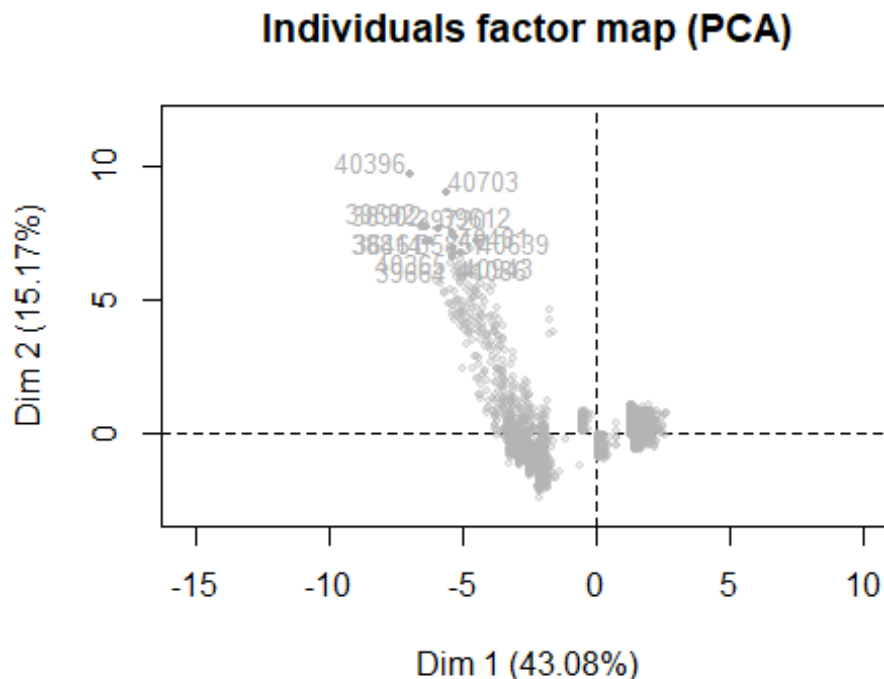
**Individuals point of view: Are they any individuals “too contributive”? To better understand the axes meaning use the extreme individuals.
Detection of multivariant outliers and influent data.**

Primero graficamos en rp los 15 individuos más contributivos en ambos ejes, luego analizamos los 5 individuos más contributivos en la dimensión 1 y 2. Al ver si estos tienen alguna relación significativa, podemos decir que para los 5 individuos de la dimension 1, vemos que

principalmente son gente mayor de 45 años, todos han comprado el producto, han sido contactados mediante el móvil, han sido contactados previamente, comprado un producto en una campaña anterior y la duración de la llamada ha sido mayor a los 300s.

Para la dimensión 2 podemos ver prácticamente las mismas características menos la duración que ha sido menor. Cabe destacar sin embargo que hay dos individuos que son muy contributivos en ambos ejes, eso hace pensar que pueden ser posibles outliers pero de igual forma los dejamos en los datos.

```
plot.PCA(res.pca, choix=c("ind"), cex=0.8, col.ind="grey70", select="contrib15", axes=c(1,2))
```



```
mas_ctr_dim1 <- sort(res.pca$ind$contrib[,1], decreasing = TRUE)[1:5]
mas_ctr_dim2 <- sort(res.pca$ind$contrib[,2], decreasing = TRUE)[1:5]
df[names(mas_ctr_dim1),]
```

##	age	job	marital	education	
## 40396	48	job.admin.	marital.divorced	education.university.degree	
## 39592	24	job.student	marital.single	education.high.school	
## 38902	83	job.retired	marital.divorced	education.basic.4y	
## 38814	65	job.retired	marital.married	education.university.degree	
## 36461	55	job.retired	marital.married	education.basic.4y	
##	default	housing	loan	contact	month
## 40396	default.no	housing.no	loan.no	contact.cellular	month.aug
## 39592	default.no	housing.yes	loan.no	contact.cellular	month.may
## 38902	default.no	housing.no	loan.no	contact.cellular	month.nov
## 38814	default.no	housing.no	loan.no	contact.cellular	month.nov

```

## 36461 default.no housing.no loan.no contact.cellular month.jun
##          day_of_week duration campaign pdays previous          poutcome
## 40396 day_of_week.thu          172          3          3          6 poutcome.success
## 39592 day_of_week.wed          258          1          3          5 poutcome.success
## 38902 day_of_week.tue          242          1          3          3 poutcome.success
## 38814 day_of_week.fri          226          1          3          3 poutcome.success
## 36461 day_of_week.tue          553          2          3          4 poutcome.failure
##          emp.var.rate cons.price.idx cons.conf.idx euribor3m nr.employed
## 40396          -1.7          94.027          -38.3          0.904          4991.6
## 39592          -1.8          93.876          -40.0          0.672          5008.7
## 38902          -3.4          92.649          -30.1          0.716          5017.5
## 38814          -3.4          92.649          -30.1          0.714          5017.5
## 36461          -2.9          92.963          -40.8          1.262          5076.2
##          y                      f.job                      f.season
## 40396 y.yes                      f.job.Admin-Managment f.season.Jun-Aug
## 39592 y.yes                      f.job.Not-working f.season.Mar-May
## 38902 y.yes f.job.Entrep-Retired-selfEmpl f.season.Sep-Dec
## 38814 y.yes f.job.Entrep-Retired-selfEmpl f.season.Sep-Dec
## 36461 y.no f.job.Entrep-Retired-selfEmpl f.season.Jun-Aug
##          f.education          f.age                      f.duration
## 40396 f.education.Professional f.age-(40,50]          f.duration-(120,180]
## 39592 f.education.High School f.age-[18,30]          f.duration-(180,300]
## 38902          f.education.Basic f.age-(50,92]          f.duration-(180,300]
## 38814 f.education.Professional f.age-(50,92]          f.duration-(180,300]
## 36461          f.education.Basic f.age-(50,92] f.duration-(300,2.1e+03]
##          f.campaign          f.pdays          f.previous
## 40396 f.campaign-(2,20] f.pdays-[0,22] f.previous-(1,6]
## 39592 f.campaign-[0,1] f.pdays-[0,22] f.previous-(1,6]
## 38902 f.campaign-[0,1] f.pdays-[0,22] f.previous-(1,6]
## 38814 f.campaign-[0,1] f.pdays-[0,22] f.previous-(1,6]
## 36461 f.campaign-(1,2] f.pdays-[0,22] f.previous-(1,6]

df[names(mas_ctr_dim2),]

##          age          job          marital          education
## 40396 48          job.admin. marital.divorced education.university.degree
## 40703 82          job.retired marital.married education.university.degree
## 39592 24          job.student marital.single          education.high.school
## 38902 83          job.retired marital.divorced          education.basic.4y
## 39612 52 job.technician marital.married education.university.degree
##          default          housing          loan          contact          month
## 40396          default.no housing.no loan.no contact.cellular month.aug
## 40703 default.unknown housing.no loan.no contact.cellular month.sep
## 39592          default.no housing.yes loan.no contact.cellular month.may
## 38902          default.no housing.no loan.no contact.cellular month.nov
## 39612          default.no housing.no loan.no contact.cellular month.may
##          day_of_week duration campaign pdays previous          poutcome
## 40396 day_of_week.thu          172          3          3          6 poutcome.success
## 40703 day_of_week.mon          81          3          3          4 poutcome.success
## 39592 day_of_week.wed          258          1          3          5 poutcome.success

```

```

## 38902 day_of_week.tue      242      1      3      3 poutcome.success
## 39612 day_of_week.thu      211      1      3      4 poutcome.success
##      emp.var.rate cons.price.idx cons.conf.idx euribor3m nr.employed
## 40396      -1.7      94.027      -38.3      0.904      4991.6
## 40703      -1.1      94.199      -37.5      0.879      4963.6
## 39592      -1.8      93.876      -40.0      0.672      5008.7
## 38902      -3.4      92.649      -30.1      0.716      5017.5
## 39612      -1.8      93.876      -40.0      0.677      5008.7
##      y      f.job      f.season
## 40396 y.yes      f.job.Admin-Managment f.season.Jun-Aug
## 40703 y.no f.job.Entrep-Retired-selfEmpl f.season.Sep-Dec
## 39592 y.yes      f.job.Not-working f.season.Mar-May
## 38902 y.yes f.job.Entrep-Retired-selfEmpl f.season.Sep-Dec
## 39612 y.yes      f.job.Serv-Tech-BlueC f.season.Mar-May
##      f.education      f.age      f.duration
## 40396 f.education.Professional f.age-(40,50] f.duration-(120,180]
## 40703 f.education.Professional f.age-(50,92] f.duration-[5,120]
## 39592 f.education.High School f.age-[18,30] f.duration-(180,300]
## 38902      f.education.Basic f.age-(50,92] f.duration-(180,300]
## 39612 f.education.Professional f.age-(50,92] f.duration-(180,300]
##      f.campaign      f.pdays      f.previous
## 40396 f.campaign-(2,20] f.pdays-[0,22] f.previous-(1,6]
## 40703 f.campaign-(2,20] f.pdays-[0,22] f.previous-(1,6]
## 39592 f.campaign-[0,1] f.pdays-[0,22] f.previous-(1,6]
## 38902 f.campaign-[0,1] f.pdays-[0,22] f.previous-(1,6]
## 39612 f.campaign-[0,1] f.pdays-[0,22] f.previous-(1,6]

```

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

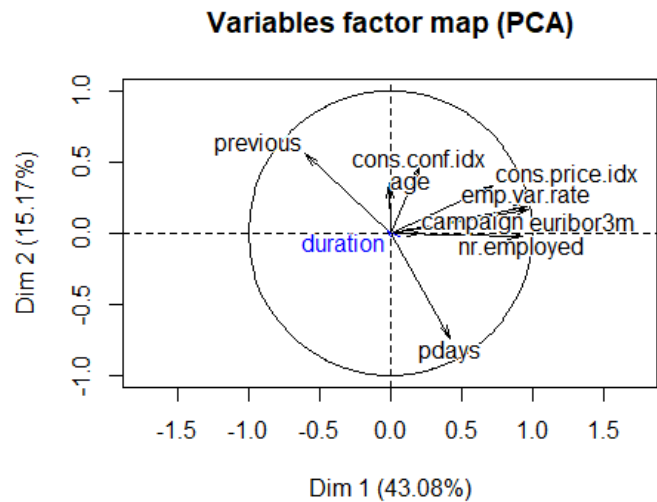
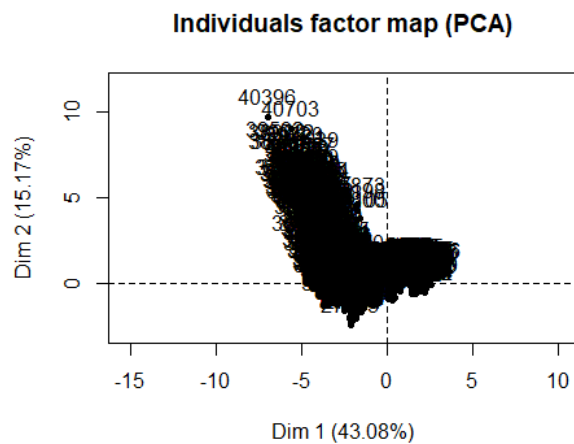
Al hacer el PCA con la variable target duration como suplementaria, podemos ver que su módulo es prácticamente nulo, esto quiere decir que la variable no se ve representada en ninguno de los ejes factoriales.

El eje horizontal está muy relacionado con las variables socio económicas, mirando el cos2 del summary podemos ver que las variables que están mejor representadas con la dimensión 1 son: euribor3m, emp.var.rate, nr.employed Para el eje vertical: pdays y previous

Para el eje vertical, podemos decir que está relacionado con las campañas previas.

Al hacer el PCA con la variable target Y como suplementaria, podemos ver que en el gráfico de rp, el factor NO, esta muy cerca del centro, por lo que no se ve representada en estos ejes factoriales. En cambio el factor SI, está a una distancia mayor del centro, aunque poco significativa.

```
res.pca<-PCA(df[,c('duration',vars_num)], quanti.sup=1)
```



```
summary(res.pca,ncp=4,nb.dec=2)
```

```
##
## Call:
## PCA(X = df[, c("duration", vars_num)], quanti.sup = 1)
##
##
## Eigenvalues
##
```

	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5	Dim.6	Dim.7
## Variance	3.88	1.36	1.10	0.97	0.83	0.43	0.39
## % of var.	43.08	15.17	12.28	10.74	9.25	4.82	4.29
## Cumulative % of var.	43.08	58.24	70.52	81.26	90.50	95.33	99.62

```
##
##
```

	Dim.8	Dim.9
## Variance	0.02	0.01
## % of var.	0.27	0.12
## Cumulative % of var.	99.88	100.00

```
##
## Individuals (the 10 first)
##
```

	Dist	Dim.1	ctr	cos2	Dim.2	ctr	cos2	Dim.3
## 20	1.74	1.29	0.01	0.55	0.44	0.00	0.06	0.41
## 21	1.99	1.30	0.01	0.42	0.18	0.00	0.01	-0.13
## 30	2.24	1.28	0.01	0.33	0.90	0.01	0.16	1.38
## 33	1.93	1.29	0.01	0.44	0.73	0.01	0.14	1.02
## 48	1.74	1.29	0.01	0.55	0.47	0.00	0.07	0.47
## 56	2.24	1.28	0.01	0.33	0.90	0.01	0.16	1.38
## 61	1.85	1.29	0.01	0.48	0.67	0.01	0.13	0.90
## 62	2.02	1.29	0.01	0.41	0.78	0.01	0.15	1.14
## 65	1.89	1.29	0.01	0.46	0.70	0.01	0.14	0.96
## 84	1.93	1.29	0.01	0.44	0.73	0.01	0.14	1.02

```
##
##
```

	ctr	cos2	Dim.4	ctr	cos2
## 20	0.00	0.06	-0.81	0.01	0.22
## 21	0.00	0.00	-1.06	0.02	0.28
## 30	0.03	0.38	-0.38	0.00	0.03


```

## 33      0.02  0.28 | -0.54  0.01  0.08 |
## 48      0.00  0.07 | -0.79  0.01  0.21 |
## 56      0.03  0.38 | -0.38  0.00  0.03 |
## 61      0.01  0.23 | -0.60  0.01  0.10 |
## 62      0.02  0.32 | -0.49  0.00  0.06 |
## 65      0.02  0.26 | -0.57  0.01  0.09 |
## 84      0.02  0.28 | -0.54  0.01  0.08 |
##
## Variables
##      Dim.1   ctr   cos2   Dim.2   ctr   cos2   Dim.3   ctr   cos2
## age      | -0.01  0.00  0.00 |  0.35  8.93  0.12 |  0.67 40.10  0.44
## campaign |  0.21  1.13  0.04 |  0.00  0.00  0.00 | -0.23  4.74  0.05
## pdays   |  0.42  4.63  0.18 | -0.74 40.21  0.55 |  0.28  7.10  0.08
## previous | -0.60  9.37  0.36 |  0.56 22.84  0.31 | -0.30  8.38  0.09
## emp.var.rate |  0.96 23.97  0.93 |  0.19  2.54  0.03 | -0.11  1.00  0.01
## cons.price.idx |  0.72 13.43  0.52 |  0.33  8.11  0.11 | -0.30  8.08  0.09
## cons.conf.idx |  0.20  1.06  0.04 |  0.46 15.36  0.21 |  0.58 30.44  0.34
## euribor3m |  0.97 24.20  0.94 |  0.16  1.98  0.03 | -0.01  0.01  0.00
## nr.employed |  0.93 22.20  0.86 | -0.02  0.03  0.00 | -0.04  0.16  0.00
##
##      Dim.4   ctr   cos2
## age      |  0.28  8.23  0.08 |
## campaign |  0.93 89.89  0.87 |
## pdays   |  0.04  0.17  0.00 |
## previous | -0.02  0.05  0.00 |
## emp.var.rate | -0.06  0.39  0.00 |
## cons.price.idx | -0.06  0.41  0.00 |
## cons.conf.idx | -0.04  0.13  0.00 |
## euribor3m | -0.07  0.51  0.00 |
## nr.employed | -0.05  0.24  0.00 |
##
## Supplementary continuous variable
##      Dim.1   cos2   Dim.2   cos2   Dim.3   cos2   Dim.4   cos2
## duration | -0.02  0.00 |  0.02  0.00 |  0.00  0.00 | -0.05  0.00 |
res.pca<-PCA(df[,c('y',vars_num)],quali.sup=1)

```



```

## 21      0.00  0.00 | -1.06  0.02  0.28 |
## 30      0.03  0.38 | -0.38  0.00  0.03 |
## 33      0.02  0.28 | -0.54  0.01  0.08 |
## 48      0.00  0.07 | -0.79  0.01  0.21 |
## 56      0.03  0.38 | -0.38  0.00  0.03 |
## 61      0.01  0.23 | -0.60  0.01  0.10 |
## 62      0.02  0.32 | -0.49  0.00  0.06 |
## 65      0.02  0.26 | -0.57  0.01  0.09 |
## 84      0.02  0.28 | -0.54  0.01  0.08 |
##
## Variables
##          Dim.1  ctr  cos2  Dim.2  ctr  cos2  Dim.3  ctr  cos2
## age          | -0.01  0.00  0.00 |  0.35  8.93  0.12 |  0.67 40.10  0.44
## campaign     |  0.21  1.13  0.04 |  0.00  0.00  0.00 | -0.23  4.74  0.05
## pdays       |  0.42  4.63  0.18 | -0.74 40.21  0.55 |  0.28  7.10  0.08
## previous     | -0.60  9.37  0.36 |  0.56 22.84  0.31 | -0.30  8.38  0.09
## emp.var.rate |  0.96 23.97  0.93 |  0.19  2.54  0.03 | -0.11  1.00  0.01
## cons.price.idx |  0.72 13.43  0.52 |  0.33  8.11  0.11 | -0.30  8.08  0.09
## cons.conf.idx |  0.20  1.06  0.04 |  0.46 15.36  0.21 |  0.58 30.44  0.34
## euribor3m    |  0.97 24.20  0.94 |  0.16  1.98  0.03 | -0.01  0.01  0.00
## nr.employed  |  0.93 22.20  0.86 | -0.02  0.03  0.00 | -0.04  0.16  0.00
##
##          Dim.4  ctr  cos2
## age          |  0.28  8.23  0.08 |
## campaign     |  0.93 89.89  0.87 |
## pdays       |  0.04  0.17  0.00 |
## previous     | -0.02  0.05  0.00 |
## emp.var.rate | -0.06  0.39  0.00 |
## cons.price.idx | -0.06  0.41  0.00 |
## cons.conf.idx | -0.04  0.13  0.00 |
## euribor3m    | -0.07  0.51  0.00 |
## nr.employed  | -0.05  0.24  0.00 |
##
## Supplementary categories
##          Dist  Dim.1  cos2 v.test  Dim.2  cos2 v.test
## y.no       |  0.23 |  0.21  0.84 21.77 | -0.08  0.13 -14.15 |
## y.yes      |  1.89 | -1.74  0.84 -21.77 |  0.67  0.13  14.15 |
##
##          Dim.3  cos2 v.test  Dim.4  cos2 v.test
## y.no       | -0.01  0.00 -1.74 |  0.01  0.00  1.09 |
## y.yes      |  0.07  0.00  1.74 | -0.04  0.00 -1.09 |

```

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

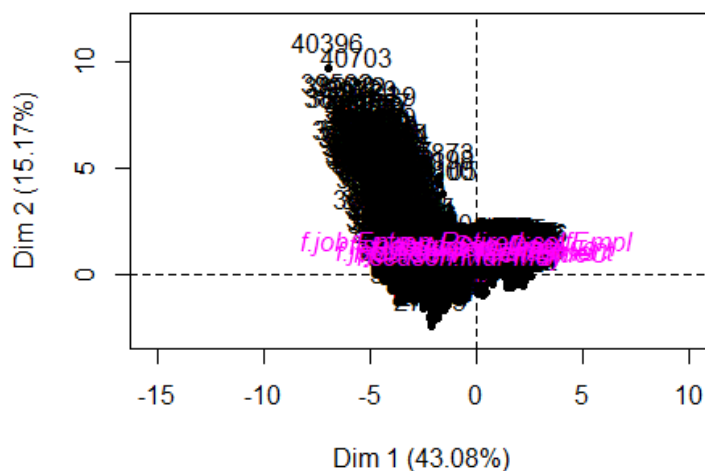
Hemos dividido el plot en diferentes partes, para así poder entender y ver mejor el resultado. Para la primera dimensión podemos ver que para los niveles mejor representados son: f.season.jun-aug, f.previous-(0.9,1], y.no, y.yes.

Para la segunda dimensión, las que se ven mejor representadas son: f.pdays-[0,22],f.pdays-[22,23], f.previous-(1,6]

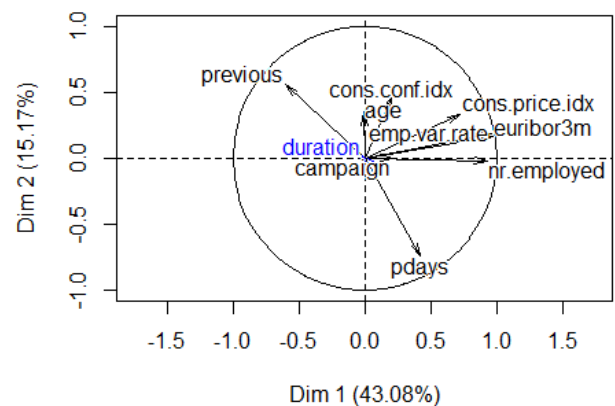
```
vars_factorizadas<- c("f.job","f.season","f.education","f.age","f.duration","f.campaign","f.pdays","f.previous","y");

res.pca<-PCA(df[,c('duration',vars_num, "f.job","f.season")],quanti.sup=1, quali.sup = c(11:12))
```

Individuals factor map (PCA)

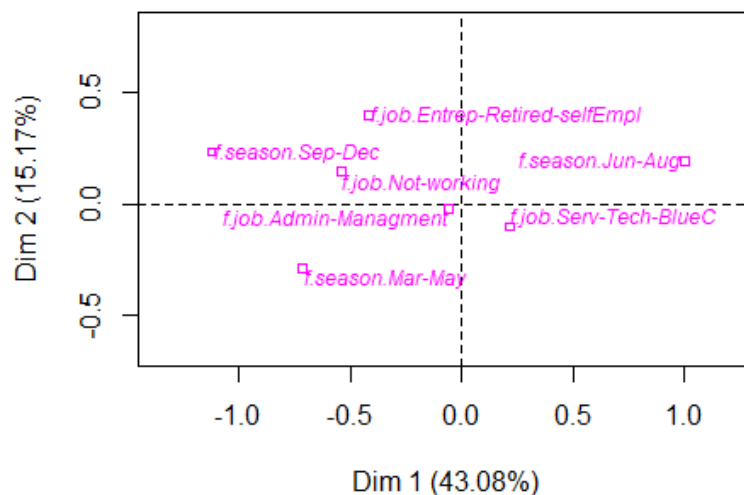


Variables factor map (PCA)



```
plot.PCA(res.pca,choix="ind",invisible="ind",cex=0.75)
```

Individuals factor map (PCA)



```
res.pca<-PCA(df[,c('duration',vars_num,"f.education","f.age")],quanti.sup=1, quali.sup = c(11:12))
```

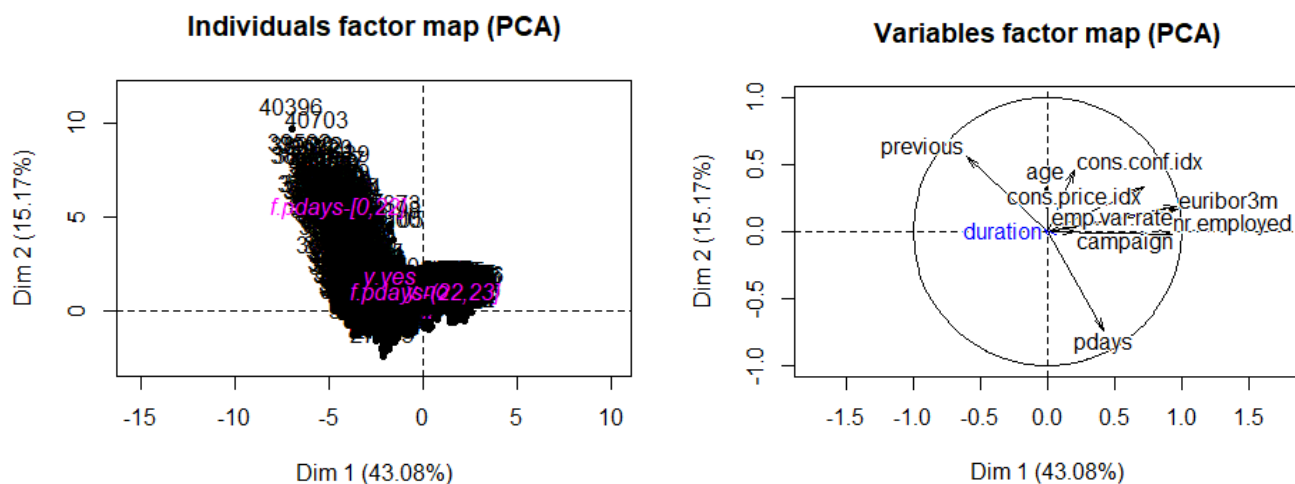
PCA plot showing the first two principal components (Dim 1 and Dim 2) for 1000 individuals. The x-axis is labeled 'Dim 1 (43.08%)' and the y-axis is labeled 'Dim 2 (15.17%)'. The plot shows a dense cloud of points, with a pink arrow pointing to a specific individual labeled 'f age (50.92)'.

```
plot.PCA(res.pca,choix="ind",invisible="ind",cex=0.75)
```

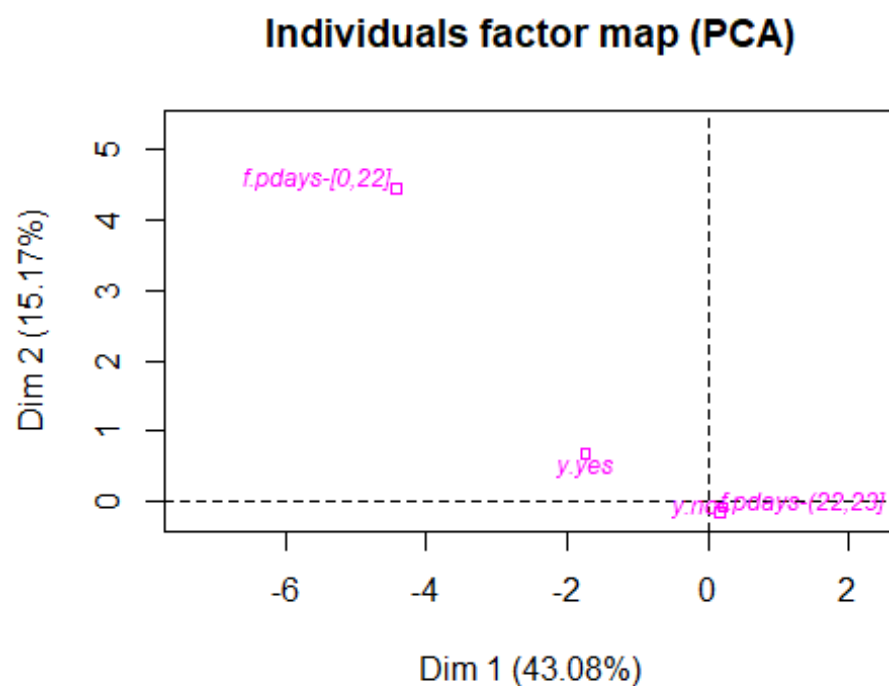
Scatter plot of the first two principal components (Dim 1 and Dim 2) for the 'f' dataset. The x-axis is Dim 1 (43.08%) and the y-axis is Dim 2 (15.17%). Data points are labeled with their corresponding variable names:

- $f.age-[50,92]$
- $f.age-[40,50]$
- $f.education-Professional$
- $f.education-Basic$
- $f.education-High\ School$
- $f.age-[30,40]$
- $f.age-[18,30]$

```
res.pca<-PCA(df[,c('duration',vars_num,"f.pdays","y")],quanti.sup=1, quali.sup =
c(11:12))
```

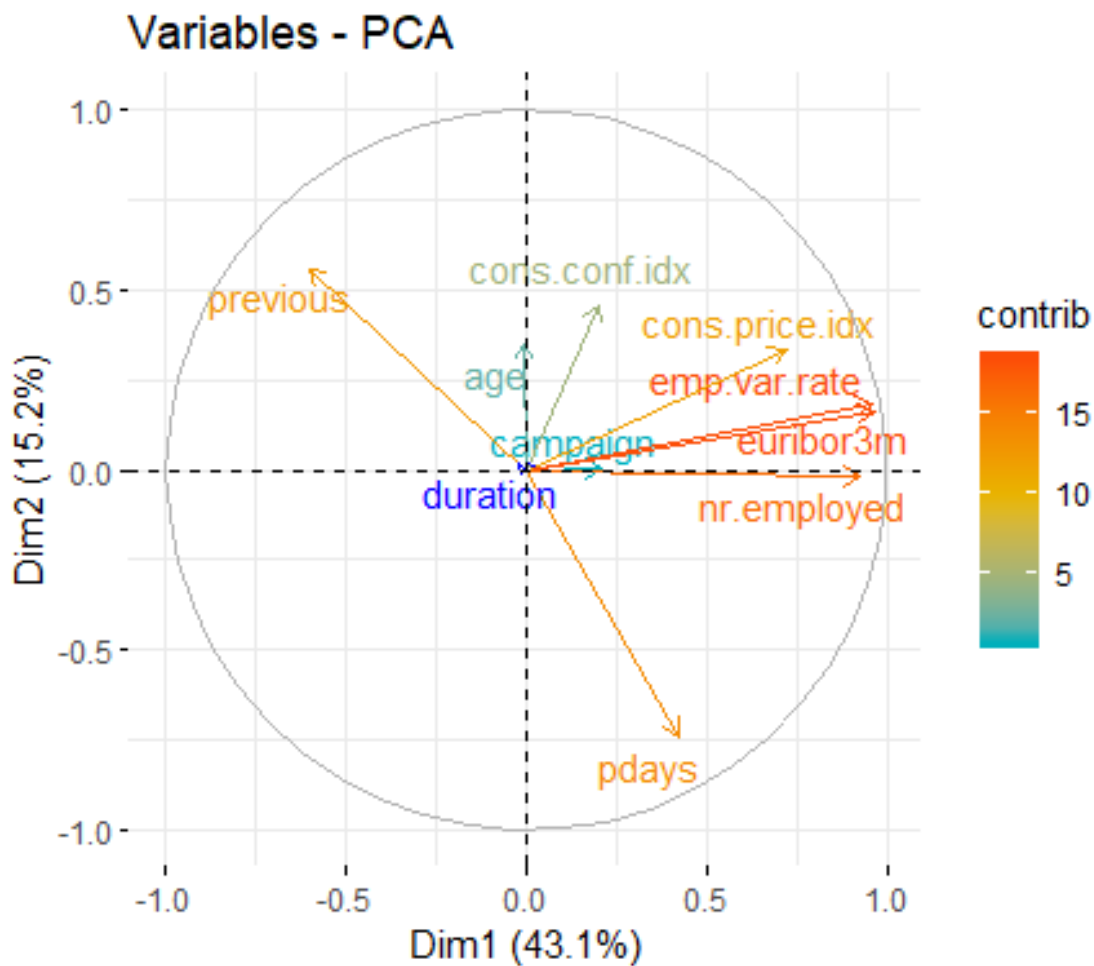


```
plot.PCA(res.pca,choix="ind",invisible="ind",cex=0.75)
```



```
res.pca<-PCA(df[,c('duration',vars_num,vars_factorizadas)],quanti.sup=1, quali.s
up = c(11:19),graph=FALSE)
```

```
fviz_pca_var(res.pca, col.var = "contrib",gradient.cols = c("#00AFBB", "#E7B800"
, "#FC4E07"),repel = TRUE)
```



```
summary(res.pca,dig = 2, nbelements= 30, nbind=3, ncp=2)
```

```
##
## Call:
## PCA(X = df[, c("duration", vars_num, vars_factorizadas)], quanti.sup = 1,
##     quali.sup = c(11:19), graph = FALSE)
##
##
## Eigenvalues
##           Dim.1   Dim.2   Dim.3   Dim.4   Dim.5   Dim.6
## Variance      3.877    1.365    1.105    0.966    0.832    0.434
## % of var.     43.078   15.166   12.276   10.736    9.246    4.823
## Cumulative % of var. 43.078   58.244   70.521   81.257   90.503   95.326
##           Dim.7   Dim.8   Dim.9
## Variance      0.386    0.024    0.010
## % of var.      4.291    0.266    0.116
## Cumulative % of var. 99.618   99.884  100.000
##
## Individuals (the 3 first)
##           Dist   Dim.1   ctr   cos2   Dim.2   ctr
## 20           | 1.739 | 1.291 0.009 0.551 | 0.441 0.003
```

```

## 21 | 1.990 | 1.295 0.009 0.424 | 0.184 0.000
## 30 | 2.240 | 1.284 0.009 0.328 | 0.898 0.012
##
##      cos2
## 20 0.064 |
## 21 0.009 |
## 30 0.161 |
##
## Variables
##
##      Dim.1   ctr   cos2   Dim.2   ctr
## age      | -0.009  0.002  0.000 |  0.349  8.933
## campaign |  0.210  1.132  0.044 |  0.003  0.001
## pdays   |  0.424  4.633  0.180 | -0.741 40.212
## previous | -0.603  9.366  0.363 |  0.558 22.836
## emp.var.rate |  0.964 23.967  0.929 |  0.186  2.544
## cons.price.idx |  0.722 13.431  0.521 |  0.333  8.109
## cons.conf.idx |  0.203  1.063  0.041 |  0.458 15.356
## euribor3m |  0.969 24.202  0.938 |  0.164  1.978
## nr.employed |  0.928 22.205  0.861 | -0.020  0.030
##
##      cos2
## age      | 0.122 |
## campaign | 0.000 |
## pdays   | 0.549 |
## previous | 0.312 |
## emp.var.rate | 0.035 |
## cons.price.idx | 0.111 |
## cons.conf.idx | 0.210 |
## euribor3m | 0.027 |
## nr.employed | 0.000 |
##
## Supplementary continuous variable
##
##      Dim.1   cos2   Dim.2   cos2
## duration | -0.022  0.000 |  0.017  0.000 |
##
## Supplementary categories
##
##      Dist   Dim.1   cos2   v.test
## f.job.Admin-Managment | 0.125 | -0.061  0.237 -1.532 |
## f.job.Entrep-Retired-selfEmpl | 1.020 | -0.418  0.168 -5.418 |
## f.job.Not-working | 0.690 | -0.541  0.615 -5.266 |
## f.job.Serv-Tech-BlueC | 0.272 |  0.217  0.637  7.570 |
## f.season.Mar-May | 0.793 | -0.719  0.821 -21.657 |
## f.season.Jun-Aug | 1.026 |  1.002  0.954 32.508 |
## f.season.Sep-Dec | 1.257 | -1.125  0.801 -16.040 |
## f.education.Basic | 0.294 |  0.125  0.181  3.071 |
## f.education.High School | 0.155 |  0.010  0.005  0.285 |
## f.education.Professional | 0.255 | -0.140  0.300 -3.384 |
## f.age-[18,30] | 1.312 | -0.436  0.111 -7.188 |
## f.age-(30,40] | 0.485 |  0.055  0.013  1.600 |
## f.age-(40,50] | 0.606 |  0.373  0.380  7.755 |
## f.age-(50,92] | 1.667 | -0.225  0.018 -3.730 |
## f.duration-[5,120] | 0.274 |  0.190  0.483  4.596 |

```


## f.duration-(120,180]	0.138	0.076	0.299	1.332
## f.duration-(180,300]	0.222	-0.180	0.658	-3.418
## f.duration-(300,2.1e+03]	0.166	-0.126	0.571	-2.781
## f.campaign-[0,1]	0.707	-0.356	0.254	-10.989
## f.campaign-(1,2]	0.221	-0.006	0.001	-0.127
## f.campaign-(2,20]	1.083	0.474	0.192	11.738
## f.pdays-[0,22]	6.580	-4.417	0.451	-30.206
## f.pdays-(22,23]	0.239	0.161	0.451	30.206
## f.previous-[0,0.9]	0.543	0.487	0.804	43.179
## f.previous-(0.9,1]	2.787	-2.633	0.893	-33.713
## f.previous-(1,6]	6.104	-4.396	0.519	-26.498
## y.no	0.231	0.212	0.844	21.769
## y.yes	1.892	-1.738	0.844	-21.769
##	Dim.2	cos2	v.test	
## f.job.Admin-Managment	-0.020	0.027	-0.869	
## f.job.Entrep-Retired-selfEmpl	0.399	0.153	8.730	
## f.job.Not-working	0.143	0.043	2.353	
## f.job.Serv-Tech-BlueC	-0.101	0.139	-5.958	
## f.season.Mar-May	-0.288	0.132	-14.633	
## f.season.Jun-Aug	0.194	0.036	10.604	
## f.season.Sep-Dec	0.234	0.035	5.626	
## f.education.Basic	0.015	0.003	0.613	
## f.education.High School	-0.066	0.180	-3.025	
## f.education.Professional	0.062	0.059	2.527	
## f.age-[18,30]	-0.400	0.093	-11.108	
## f.age-(30,40]	-0.213	0.193	-10.495	
## f.age-(40,50]	0.139	0.053	4.874	
## f.age-(50,92]	0.682	0.168	19.031	
## f.duration-[5,120]	-0.094	0.118	-3.822	
## f.duration-(120,180]	0.014	0.010	0.414	
## f.duration-(180,300]	0.085	0.147	2.721	
## f.duration-(300,2.1e+03]	0.029	0.030	1.081	
## f.campaign-[0,1]	0.003	0.000	0.167	
## f.campaign-(1,2]	0.014	0.004	0.486	
## f.campaign-(2,20]	-0.015	0.000	-0.627	
## f.pdays-[0,22]	4.435	0.454	51.122	
## f.pdays-(22,23]	-0.161	0.454	-51.122	
## f.previous-[0,0.9]	-0.181	0.111	-27.027	
## f.previous-(0.9,1]	0.442	0.025	9.534	
## f.previous-(1,6]	3.839	0.396	38.998	
## y.no	-0.082	0.126	-14.153	
## y.yes	0.671	0.126	14.153	

K-Means Classification

Hemos graficado los grupos separados en 3, 4, 5 y 6 clusters, para los cuales nos parece que gráficamente con 4 clusters los grupos están bien definidos, por lo que decidimos usar 4 clusters los cuales analizaremos seguidamente.

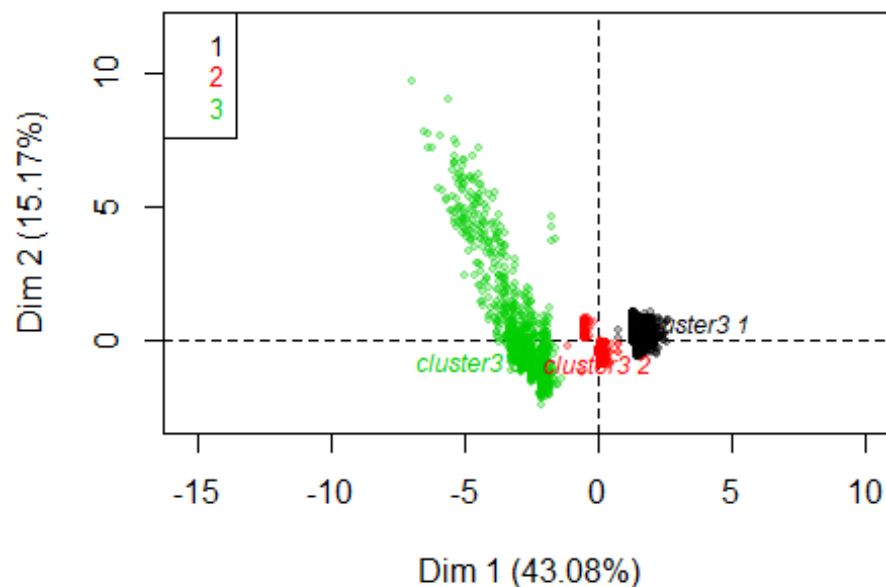
```
dclu<- res.pca$ind$coord[,1:2]; # Los dos ejes

kcla<- kmeans(dclu,4);

df$cluster3 = factor(kmeans(dclu,3)$cluster);
df$cluster4 = factor(kmeans(dclu,4)$cluster);
df$cluster5 = factor(kmeans(dclu,5)$cluster);
df$cluster6 = factor(kmeans(dclu,6)$cluster);

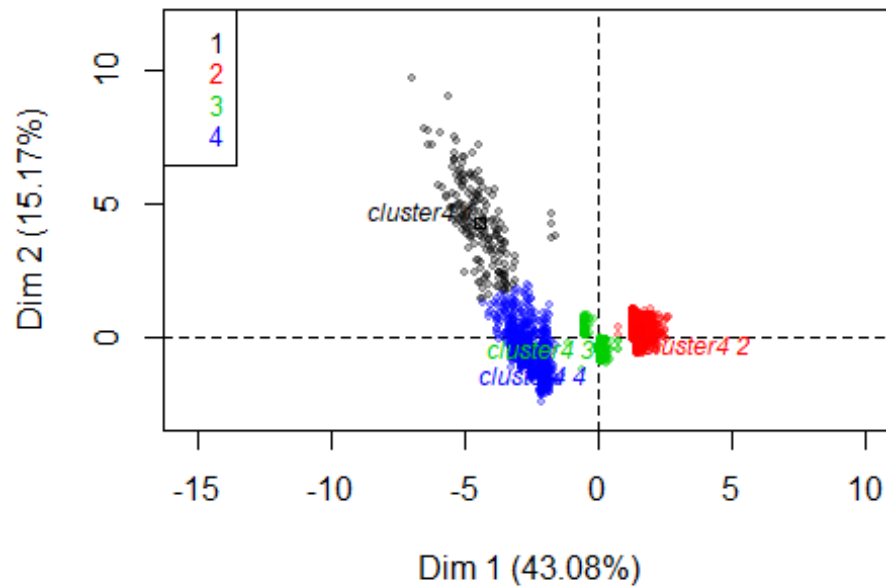
res.pca<-PCA(df[,c('duration',vars_num, "cluster3")],quanti.sup=1, quali.sup = 1
1, graph=FALSE)
plot.PCA(res.pca,choix="ind",habillage=11,select=0 ,cex=0.75)
```

Individuals factor map (PCA)



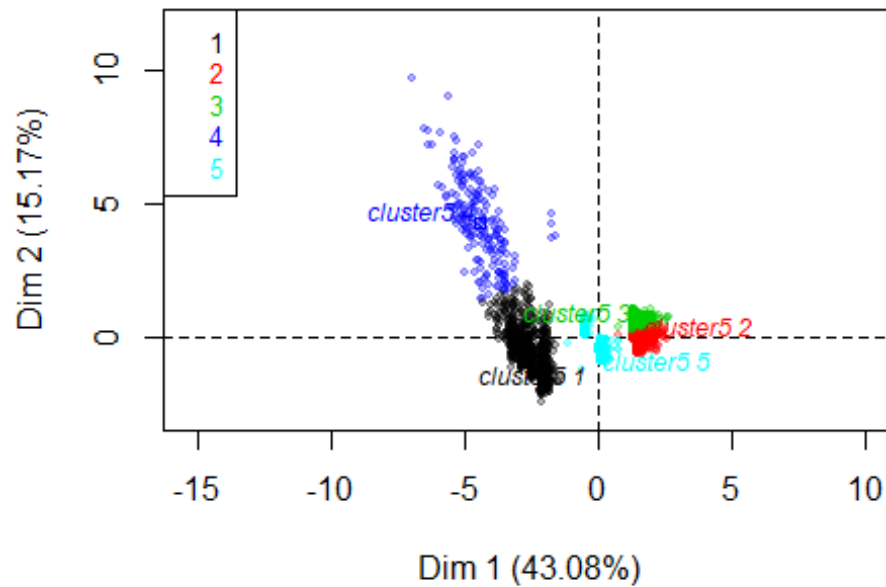
```
res.pca<-PCA(df[,c('duration',vars_num, "cluster4")],quanti.sup=1, quali.sup = 1
1, graph=FALSE)
plot.PCA(res.pca,choix="ind",habillage=11,select=0 ,cex=0.75)
```

Individuals factor map (PCA)

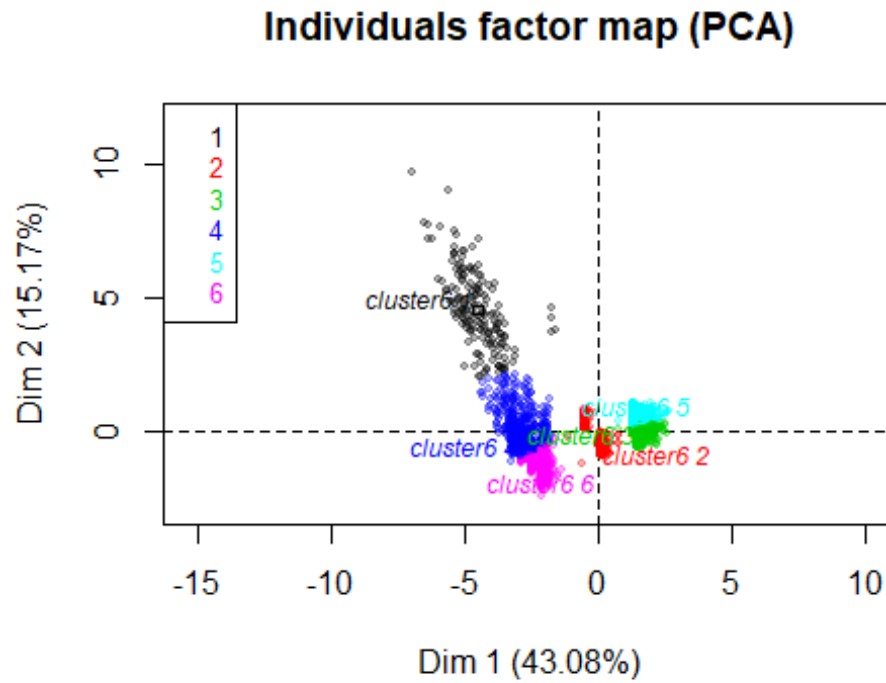


```
res.pca<-PCA(df[,c('duration',vars_num, "cluster5")],quanti.sup=1, quali.sup = 1
1, graph=FALSE)
plot.PCA(res.pca,choix="ind",habillage=11,select=0 ,cex=0.75)
```

Individuals factor map (PCA)



```
res.pca<-PCA(df[,c('duration',vars_num, "cluster6")],quanti.sup=1, quali.sup = 1
1, graph=FALSE)
plot.PCA(res.pca,choix="ind",habillage=11,select=0 ,cex=0.75)
```



```
df <- df[,c(1:29, 31)] # guardamos la clasificación en 4 clusters
```

Description of clusters

Viendo el chi-square test, podemos saber qué variables se utilizarán para caracterizar nuestros 4 clusters. Viendo las categorías donde el P-value es casi 0 podemos ver que las categorías que cumplen estas características son: month (y por extensión también f.season), poutcome, f.pdays, f.previous, contact, y, job(f.job), default, f.age, f.campaign, marital. Ahora veremos que categorías de estas variables son las que caracterizan estos clusters.

Para el catdes del cluster 1, hemos podido ver las categorías que mejor lo definen, la temporada de verano es la que mejor lo caracteriza, f.season.Jun-Aug, tenemos también un poutcome que nos indica que ninguno de los individuos ha sido contactado previamente, podemos ver que y.no representa el 95% de este cluster, han sido contactados en su mayoría por teléfono fijo, también podemos ver que este cluster está ligeramente relacionado con la categoría f.job.Serv-Tech-BlueC. En conclusión podemos decir que este cluster está caracterizado por: - Meses de jun-Ago - No han sido contactados previamente - Han sido contactados más de una vez en la campaña actual - Contactados por teléfono fijo - Trabajo normalmente es, servicio, técnicos o blue collar. - No compraron el producto en su mayoría.

Para el cluster 2, tenemos: - La temporada de mar-may están sobrerrepresentadas en este cluster - Han sido contactados en su mayoría por teléfono móvil - No han comprado el producto

en campañas anteriores - Han sido contactados en campañas previas - La categoría student está sobrerrepresentada - La aceptación del producto está sobrerrepresentada también

Para el cluster 3, tenemos: - Temporada de Sep-Dec - Contactados por móvil en su mayoría - La categoría de job.management está sobrerrepresentada - No han adquirido el producto - Una gran cantidad de individuos rechazó el producto (y.no)

Para el cluster 4, podemos ver que aglutina individuos muy bien caracterizados por las siguientes variables: - Han sido contactados previamente f.pdays[0,22] - Han comprado el producto en una campaña previa - Han comprado el producto y.yes - Temporada de Sep-Dec - Han sido contactados por móvil - Una parte importante son job.retired - Una edad de f.age-[50,92]

```
catdes(df, 30, proba = 0.001)
```

```
##
## Link between the cluster variable and the categorical variables (chi-square test)
## =====
====
##                p.value df
## month          0.000000e+00 27
## poutcome       0.000000e+00  6
## f.season       0.000000e+00  6
## f.pdays       0.000000e+00  3
## f.previous     0.000000e+00  6
## contact       4.750967e-213  3
## y             3.629487e-144  3
## job           4.108692e-67 30
## default       6.986972e-43  3
## f.age         1.030850e-26  9
## f.campaign    6.092760e-24  6
## f.job         1.806095e-19  9
## marital       1.705029e-16  6
## f.duration    1.919242e-10  9
## education     5.661192e-09 18
## f.education   8.669827e-09  6
## housing       1.403613e-07  3
## day_of_week   4.039589e-04 12
##
## Description of each cluster by the categories
## =====
## $`1`
##                Cla/Mod  Mod/Cla  Global
## f.pdays=f.pdays-[0,22] 96.5714286 88.947368 3.507014
## poutcome=poutcome.success 96.1538462 78.947368 3.126253
## f.previous=f.previous-(1,6) 75.1824818 54.210526 2.745491
## y=y.yes 21.0332103 60.000000 10.861723
## f.previous=f.previous-(0.9,1] 15.4255319 45.789474 11.302605
## f.season=f.season.Sep-Dec 11.1600587 40.000000 13.647295
```

## month=month.oct	32.5000000	13.684211	1.603206
## contact=contact.cellular	5.4011864	91.052632	64.188377
## default=default.no	4.6954315	97.368421	78.957916
## job=job.retired	15.7657658	18.421053	4.448898
## month=month.sep	25.7142857	9.473684	1.402806
## f.age=f.age-(50,92]	7.4200913	34.210526	17.555110
## month=month.mar	20.6349206	6.842105	1.262525
## job=job.student	15.5963303	8.947368	2.184369
## f.job=f.job.Entrep-Retired-selfEmpl	7.6256499	23.157895	11.563126
## f.duration=f.duration-(180,300]	6.0550459	34.736842	21.843687
## poutcome=poutcome.failure	7.3394495	21.052632	10.921844
## f.education=f.education.Professional	5.4347826	44.736842	31.342685
## education=education.university.degree	5.4347826	44.736842	31.342685
## f.job=f.job.Not-working	8.1871345	14.736842	6.853707
## f.campaign=f.campaign-[0,1]	4.9504950	55.263158	42.505010
## month=month.jun	1.6233766	5.263158	12.344689
## f.education=f.education.Basic	2.5046963	21.052632	32.004008
## f.season=f.season.Mar-May	2.7131783	29.473684	41.362725
## marital=marital.married	3.0040053	47.368421	60.040080
## f.age=f.age-(40,50]	1.9952115	13.157895	25.110220
## f.season=f.season.Jun-Aug	2.5835189	30.526316	44.989980
## education=education.basic.9y	1.3580247	5.789474	16.232465
## f.campaign=f.campaign-(2,20]	2.0496894	17.368421	32.264529
## month=month.jul	1.1560694	5.263158	17.334669
## month=month.may	1.8452381	16.315789	33.667335
## f.duration=f.duration-[5,120]	1.7341040	14.210526	31.202405
## f.job=f.job.Serv-Tech-BlueC	1.9801980	25.263158	48.577154
## job=job.blue-collar	0.8650519	5.263158	23.166333
## default=default.unknown	0.4761905	2.631579	21.042084
## contact=contact.telephone	0.9513151	8.947368	35.811623
## y=y.no	1.7086331	40.000000	89.138277
## f.previous=f.previous-[0,0.9]	0.0000000	0.000000	85.951904
## poutcome=poutcome.nonexistent	0.0000000	0.000000	85.951904
## f.pdays=f.pdays-(22,23]	0.4361371	11.052632	96.492986
##	p.value	v.test	
## f.pdays=f.pdays-[0,22]	1.259643e-281	35.860546	
## poutcome=poutcome.success	3.796871e-240	33.092604	
## f.previous=f.previous-(1,6]	1.553305e-129	24.214815	
## y=y.yes	2.494385e-64	16.934745	
## f.previous=f.previous-(0.9,1]	1.156226e-34	12.280262	
## f.season=f.season.Sep-Dec	3.391033e-20	9.205810	
## month=month.oct	3.163903e-18	8.705424	
## contact=contact.cellular	4.127348e-18	8.675225	
## default=default.no	4.787962e-14	7.537574	
## job=job.retired	2.103831e-13	7.342027	
## month=month.sep	5.701121e-11	6.551371	
## f.age=f.age-(50,92]	1.767166e-08	5.633375	
## month=month.mar	5.214842e-07	5.018235	
## job=job.student	6.469157e-07	4.976658	
## f.job=f.job.Entrep-Retired-selfEmpl	4.357820e-06	4.593544	

## f.duration=f.duration-(180,300]	3.266772e-05	4.154025	
## poutcome=poutcome.failure	3.513520e-05	4.137342	
## f.education=f.education.Professional	8.193961e-05	3.938655	
## education=education.university.degree	8.193961e-05	3.938655	
## f.job=f.job.Not-working	1.066886e-04	3.874854	
## f.campaign=f.campaign-[0,1]	3.261253e-04	3.593612	
## month=month.jun	9.887768e-04	-3.293701	
## f.education=f.education.Basic	6.774908e-04	-3.398530	
## f.season=f.season.Mar-May	5.767248e-04	-3.442331	
## marital=marital.married	3.331185e-04	-3.588083	
## f.age=f.age-(40,50]	4.090062e-05	-4.102332	
## f.season=f.season.Jun-Aug	3.480205e-05	-4.139528	
## education=education.basic.9y	1.044307e-05	-4.407790	
## f.campaign=f.campaign-(2,20]	2.688717e-06	-4.693270	
## month=month.jul	4.872344e-07	-5.031273	
## month=month.may	5.199683e-08	-5.444343	
## f.duration=f.duration-[5,120]	4.101428e-08	-5.486428	
## f.job=f.job.Serv-Tech-BlueC	2.251008e-11	-6.688740	
## job=job.blue-collar	1.081400e-11	-6.795230	
## default=default.unknown	4.787962e-14	-7.537574	
## contact=contact.telephone	4.127348e-18	-8.675225	
## y=y.no	2.494385e-64	-16.934745	
## f.previous=f.previous-[0,0.9]	2.196177e-173	-28.071291	
## poutcome=poutcome.nonexistent	2.196177e-173	-28.071291	
## f.pdays=f.pdays-(22,23]	1.259643e-281	-35.860546	
##			
## \$`2`			
##			
	Cla/Mod	Mod/Cla	Global
## f.season=f.season.Jun-Aug	87.0824053	68.47635727	44.9899800
## f.previous=f.previous-[0,0.9]	66.5656330	100.00000000	85.9519038
## poutcome=poutcome.nonexistent	66.5656330	100.00000000	85.9519038
## contact=contact.telephone	86.6256295	54.22066550	35.8116232
## month=month.jul	93.5260116	28.33625219	17.3346693
## f.pdays=f.pdays-(22,23]	59.2938733	100.00000000	96.4929860
## month=month.aug	82.3298429	22.03152364	15.3106212
## y=y.no	61.0161871	95.06129597	89.1382766
## month=month.jun	83.9285714	18.10858144	12.3446894
## default=default.unknown	75.8095238	27.88091068	21.0420842
## f.campaign=f.campaign-(2,20]	67.0807453	37.82837128	32.2645291
## f.age=f.age-(40,50]	65.5227454	28.75656743	25.1102204
## f.job=f.job.Serv-Tech-BlueC	62.1699670	52.78458844	48.5771543
## marital=marital.married	60.8144192	63.81786340	60.0400802
## housing=housing.no	61.6498464	49.21190893	45.6713427
## job=job.technician	63.7698898	18.24868651	16.3727455
## job=job.blue-collar	62.2837370	25.21891419	23.1663327
## f.education=f.education.Basic	61.1145899	34.18563923	32.0040080
## job=job.housemaid	72.2689076	3.01225919	2.3847695
## f.education=f.education.Professional	53.7084399	29.42206655	31.3426854
## education=education.university.degree	53.7084399	29.42206655	31.3426854
## f.job=f.job.Not-working	47.6608187	5.70928196	6.8537074

## month=month.may	53.4523810	31.45359019	33.6673347
## f.job=f.job.Entrep-Retired-selfEmpl	48.5268631	9.80735552	11.5631263
## job=job.retired	41.8918919	3.25744308	4.4488978
## month=month.dec	0.0000000	0.00000000	0.3607214
## f.age=f.age-[18,30]	48.6206897	14.81611208	17.4348697
## housing=housing.yes	53.4857986	50.78809107	54.3286573
## marital=marital.single	49.8936924	24.65849387	28.2765531
## job=job.student	14.6788991	0.56042032	2.1843687
## f.campaign=f.campaign-[0,1]	49.6463932	36.88266200	42.5050100
## month=month.mar	0.0000000	0.00000000	1.2625251
## month=month.oct	2.5000000	0.07005254	1.6032064
## month=month.sep	0.0000000	0.00000000	1.4028056
## default=default.no	52.2588832	72.11908932	78.9579158
## f.previous=f.previous-(1,6]	0.0000000	0.00000000	2.7454910
## y=y.yes	26.0147601	4.93870403	10.8617234
## poutcome=poutcome.success	0.0000000	0.00000000	3.1262525
## f.season=f.season.Mar-May	43.5077519	31.45359019	41.3627255
## f.pdays=f.pdays-[0,22]	0.0000000	0.00000000	3.5070140
## month=month.apr	0.0000000	0.00000000	6.4328657
## month=month.nov	0.0000000	0.00000000	10.2805611
## poutcome=poutcome.failure	0.0000000	0.00000000	10.9218437
## f.previous=f.previous-(0.9,1]	0.0000000	0.00000000	11.3026052
## contact=contact.cellular	40.8054948	45.77933450	64.1883768
## f.season=f.season.Sep-Dec	0.2936858	0.07005254	13.6472946
##	p.value	v.test	
## f.season=f.season.Jun-Aug	0.000000e+00	Inf	
## f.previous=f.previous-[0,0.9]	3.019215e-293	36.598522	
## poutcome=poutcome.nonexistent	3.019215e-293	36.598522	
## contact=contact.telephone	1.051844e-235	32.782323	
## month=month.jul	1.306801e-149	26.051114	
## f.pdays=f.pdays-(22,23]	4.293494e-67	17.305259	
## month=month.aug	3.823967e-57	15.931608	
## y=y.no	8.988442e-55	15.586531	
## month=month.jun	2.951209e-51	15.060372	
## default=default.unknown	8.402225e-45	14.043849	
## f.campaign=f.campaign-(2,20]	1.196425e-22	9.793857	
## f.age=f.age-(40,50]	4.665985e-12	6.915384	
## f.job=f.job.Serv-Tech-BlueC	5.923144e-12	6.881486	
## marital=marital.married	3.139148e-10	6.291746	
## housing=housing.no	6.199688e-09	5.811280	
## job=job.technician	3.130573e-05	4.163754	
## job=job.blue-collar	6.671792e-05	3.987697	
## f.education=f.education.Basic	1.296174e-04	3.827184	
## job=job.housemaid	6.364492e-04	3.415586	
## f.education=f.education.Professional	7.361711e-04	-3.375741	
## education=education.university.degree	7.361711e-04	-3.375741	
## f.job=f.job.Not-working	2.382353e-04	-3.674586	
## month=month.may	1.335878e-04	-3.819748	
## f.job=f.job.Entrep-Retired-selfEmpl	8.231372e-06	-4.459076	
## job=job.retired	2.872930e-06	-4.679701	

## month=month.dec	2.215519e-07	-5.180281	
## f.age=f.age-[18,30]	2.026128e-08	-5.609755	
## housing=housing.yes	6.199688e-09	-5.811280	
## marital=marital.single	6.116596e-11	-6.540860	
## job=job.student	2.122476e-20	-9.255993	
## f.campaign=f.campaign-[0,1]	1.628849e-20	-9.284227	
## month=month.mar	3.477079e-24	-10.145300	
## month=month.oct	8.502567e-27	-10.716652	
## month=month.sep	8.041008e-27	-10.721815	
## default=default.no	8.402225e-45	-14.043849	
## f.previous=f.previous-(1,6]	2.340302e-52	-15.227016	
## y=y.yes	8.988442e-55	-15.586531	
## poutcome=poutcome.success	1.057860e-59	-16.295757	
## f.season=f.season.Mar-May	8.078887e-61	-16.452266	
## f.pdays=f.pdays-[0,22]	4.293494e-67	-17.305259	
## month=month.apr	1.591937e-125	-23.831058	
## month=month.nov	3.512409e-207	-30.715702	
## poutcome=poutcome.failure	2.239752e-221	-31.760980	
## f.previous=f.previous-(0.9,1]	6.871049e-230	-32.371692	
## contact=contact.cellular	1.051844e-235	-32.782323	
## f.season=f.season.Sep-Dec	8.033924e-278	-35.615604	
##			
## \$`3`			
##	Cla/Mod	Mod/Cla	Global
## f.season=f.season.Sep-Dec	66.079295	100.000000	13.647295
## month=month.nov	86.549708	98.666667	10.280561
## contact=contact.cellular	12.425851	88.444444	64.188377
## job=job.management	17.948718	14.000000	7.034068
## f.pdays=f.pdays-(22,23]	9.345794	100.000000	96.492986
## default=default.no	10.076142	88.222222	78.957916
## y=y.no	9.622302	95.111111	89.138277
## poutcome=poutcome.failure	14.311927	17.333333	10.921844
## f.campaign=f.campaign-[0,1]	11.032532	52.000000	42.505010
## f.duration=f.duration-[5,120]	11.560694	40.000000	31.202405
## f.previous=f.previous-(0.9,1]	13.829787	17.333333	11.302605
## f.education=f.education.Professional	11.125320	38.666667	31.342685
## education=education.university.degree	11.125320	38.666667	31.342685
## job=job.entrepreneur	16.402116	6.888889	3.787575
## education=education.basic.4y	5.048544	5.777778	10.320641
## job=job.retired	2.702703	1.333333	4.448898
## f.age=f.age-[18,30]	5.747126	11.111111	17.434870
## job=job.student	0.000000	0.000000	2.184369
## job=job.blue-collar	5.795848	14.888889	23.166333
## y=y.yes	4.059041	4.888889	10.861723
## f.previous=f.previous-(1,6]	0.000000	0.000000	2.745491
## f.education=f.education.Basic	6.199123	22.000000	32.004008
## f.campaign=f.campaign-(2,20]	6.211180	22.222222	32.264529
## poutcome=poutcome.success	0.000000	0.000000	3.126253
## default=default.unknown	5.047619	11.777778	21.042084
## f.pdays=f.pdays-[0,22]	0.000000	0.000000	3.507014

## month=month.apr	0.000000	0.000000	6.432866
## month=month.jun	0.000000	0.000000	12.344689
## contact=contact.telephone	2.909905	11.555556	35.811623
## month=month.aug	0.000000	0.000000	15.310621
## month=month.jul	0.000000	0.000000	17.334669
## month=month.may	0.000000	0.000000	33.667335
## f.season=f.season.Mar-May	0.000000	0.000000	41.362725
## f.season=f.season.Jun-Aug	0.000000	0.000000	44.989980
##	p.value	v.test	
## f.season=f.season.Sep-Dec	0.000000e+00	Inf	
## month=month.nov	0.000000e+00	Inf	
## contact=contact.cellular	4.457861e-34	12.170601	
## job=job.management	4.606444e-08	5.465869	
## f.pdays=f.pdays-(22,23]	4.814305e-08	5.458036	
## default=default.no	8.895002e-08	5.347962	
## y=y.no	3.321039e-06	4.649895	
## poutcome=poutcome.failure	1.761402e-05	4.293170	
## f.campaign=f.campaign-[0,1]	2.207930e-05	4.242754	
## f.duration=f.duration-[5,120]	3.465489e-05	4.140500	
## f.previous=f.previous-(0.9,1]	6.332305e-05	4.000073	
## f.education=f.education.Professional	5.526671e-04	3.453839	
## education=education.university.degree	5.526671e-04	3.453839	
## job=job.entrepreneur	9.628257e-04	3.301170	
## education=education.basic.4y	4.140424e-04	-3.530968	
## job=job.retired	1.504256e-04	-3.790366	
## f.age=f.age-[18,30]	1.055513e-04	-3.877463	
## job=job.student	2.982402e-05	-4.174806	
## job=job.blue-collar	5.480188e-06	-4.545512	
## y=y.yes	3.321039e-06	-4.649895	
## f.previous=f.previous-(1,6]	1.972148e-06	-4.756258	
## f.education=f.education.Basic	9.408844e-07	-4.903616	
## f.campaign=f.campaign-(2,20]	9.107926e-07	-4.909994	
## poutcome=poutcome.success	3.093148e-07	-5.117681	
## default=default.unknown	8.895002e-08	-5.347962	
## f.pdays=f.pdays-[0,22]	4.814305e-08	-5.458036	
## month=month.apr	2.294108e-14	-7.632967	
## month=month.jun	8.435071e-28	-10.928369	
## contact=contact.telephone	4.457861e-34	-12.170601	
## month=month.aug	6.622682e-35	-12.325263	
## month=month.jul	6.599006e-40	-13.221438	
## month=month.may	8.848336e-86	-19.628385	
## f.season=f.season.Mar-May	8.311269e-112	-22.469179	
## f.season=f.season.Jun-Aug	2.151192e-125	-23.818443	
##			
## \$`4`			
##	Cla/Mod	Mod/Cla	Global
## f.season=f.season.Mar-May	53.779070	74.2474916	41.3627255
## month=month.apr	96.261682	20.6688963	6.4328657
## contact=contact.cellular	41.367468	88.6287625	64.1883768
## poutcome=poutcome.failure	78.348624	28.5618729	10.9218437

## f.previous=f.previous-(0.9,1]	70.744681	26.6889632	11.3026052
## month=month.may	44.702381	50.2341137	33.6673347
## y=y.yes	48.892989	17.7257525	10.8617234
## default=default.no	32.969543	86.8896321	78.9579158
## f.pdays=f.pdays-(22,23]	30.924195	99.5986622	96.4929860
## job=job.student	69.724771	5.0836120	2.1843687
## month=month.mar	79.365079	3.3444816	1.2625251
## month=month.sep	74.285714	3.4782609	1.4028056
## marital=marital.single	37.774628	35.6521739	28.2765531
## f.age=f.age-[18,30]	40.574713	23.6120401	17.4348697
## f.campaign=f.campaign-[0,1]	34.370580	48.7625418	42.5050100
## month=month.oct	60.000000	3.2107023	1.6032064
## housing=housing.yes	32.312800	58.5953177	54.3286573
## month=month.dec	72.222222	0.8695652	0.3607214
## housing=housing.no	27.161036	41.4046823	45.6713427
## f.season=f.season.Sep-Dec	22.466960	10.2341137	13.6472946
## job=job.technician	22.888617	12.5083612	16.3727455
## marital=marital.married	27.202937	54.5150502	60.0400802
## f.campaign=f.campaign-(2,20]	24.658385	26.5551839	32.2645291
## f.age=f.age-(40,50]	22.984836	19.2642140	25.1102204
## poutcome=poutcome.success	3.846154	0.4013378	3.1262525
## f.pdays=f.pdays-[0,22]	3.428571	0.4013378	3.5070140
## default=default.unknown	18.666667	13.1103679	21.0420842
## month=month.jun	14.448052	5.9531773	12.3446894
## y=y.no	27.652878	82.2742475	89.1382766
## month=month.aug	12.696335	6.4882943	15.3106212
## month=month.nov	7.797271	2.6755853	10.2805611
## f.previous=f.previous-[0,0.9]	24.761017	71.0367893	85.9519038
## poutcome=poutcome.nonexistent	24.761017	71.0367893	85.9519038
## month=month.jul	5.317919	3.0769231	17.3346693
## contact=contact.telephone	9.513151	11.3712375	35.8116232
## f.season=f.season.Jun-Aug	10.334076	15.5183946	44.9899800
##	p.value	v.test	
## f.season=f.season.Mar-May	1.214684e-211	31.047983	
## month=month.apr	2.443356e-153	26.378112	
## contact=contact.cellular	7.335999e-138	24.992718	
## poutcome=poutcome.failure	5.641457e-137	24.911094	
## f.previous=f.previous-(0.9,1]	3.761358e-101	21.351684	
## month=month.may	2.068828e-57	15.969971	
## y=y.yes	9.791179e-23	9.814096	
## default=default.no	1.504249e-20	9.292699	
## f.pdays=f.pdays-(22,23]	7.889588e-20	9.114690	
## job=job.student	6.601535e-18	8.621617	
## month=month.mar	5.354652e-16	8.103167	
## month=month.sep	1.931681e-14	7.655096	
## marital=marital.single	7.928406e-14	7.471503	
## f.age=f.age-[18,30]	1.851132e-13	7.359130	
## f.campaign=f.campaign-[0,1]	5.524740e-09	5.830543	
## month=month.oct	2.441289e-08	5.577408	
## housing=housing.yes	7.419015e-05	3.962432	

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## month=month.dec          2.959629e-04    3.618808
## housing=housing.no       7.419015e-05   -3.962432
## f.season=f.season.Sep-Dec 2.698987e-06   -4.692491
## job=job.technician       8.712805e-07   -4.918684
## marital=marital.married  2.090160e-07   -5.191135
## f.campaign=f.campaign-(2,20] 1.226294e-08   -5.696030
## f.age=f.age-(40,50]      2.434489e-10   -6.331081
## poutcome=poutcome.success 4.435265e-17   -8.400779
## f.pdays=f.pdays-[0,22]  7.889588e-20   -9.114690
## default=default.unknown   1.504249e-20   -9.292699
## month=month.jun          1.863347e-21   -9.512388
## y=y.no                    9.791179e-23   -9.814096
## month=month.aug           1.221397e-33  -12.088058
## month=month.nov           8.917776e-38  -12.847202
## f.previous=f.previous-[0,0.9] 4.885281e-80  -18.944683
## poutcome=poutcome.nonexistent 4.885281e-80  -18.944683
## month=month.jul           1.393898e-85  -19.605278
## contact=contact.telephone 7.335999e-138 -24.992718
## f.season=f.season.Jun-Aug  1.401958e-178 -28.493704
##
##
## Link between the cluster variable and the quantitative variables
## =====
##
##              Eta2          P-value
## pdays          0.833431759  0.000000e+00
## previous        0.501141537  0.000000e+00
## emp.var.rate    0.949447313  0.000000e+00
## cons.price.idx  0.574427755  0.000000e+00
## euribor3m       0.989874994  0.000000e+00
## nr.employed     0.866883329  0.000000e+00
## cons.conf.idx   0.167721928  3.916150e-198
## campaign        0.027687626  3.757869e-30
## age             0.008632187  2.197904e-09
##
## Description of each cluster by quantitative variables
## =====
## $`1`
##
##              v.test Mean in category Overall mean sd in category
## previous      45.971997          1.8210526    0.17855711    0.9567373
## cons.conf.idx  6.937479        -38.2494737   -40.54192385    7.1162952
## age           5.645279         44.3789474    40.17755511   16.9858634
## campaign      -4.322398         1.7894737     2.51503006    1.2598641
## cons.price.idx -4.817260        93.3651368    93.56373427    0.8341906
## emp.var.rate  -19.115707        -2.0936842     0.05212425    0.8565304
## euribor3m     -21.054798         0.9672263     3.58457355    0.5121394
## nr.employed   -27.122883       5025.3821053  5165.87569138   51.3340730
## pdays         -64.481704         7.8473684    22.41362725    6.4451425
##
##              Overall sd          p.value
## previous      0.5020810  0.000000e+00
## cons.conf.idx  4.6436681  3.991593e-12

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## age          10.4585324 1.649135e-08
## campaign     2.3588988 1.543422e-05
## cons.price.idx 0.5793439 1.455430e-06
## emp.var.rate  1.5774788 1.868722e-81
## euribor3m     1.7469207 2.066633e-98
## nr.employed   72.7919889 5.290316e-162
## pdays         3.1744936 0.000000e+00
##
## `$2`
##           v.test Mean in category Overall mean sd in category
## emp.var.rate 64.85040      1.304588    0.05212425    0.14415633
## euribor3m    62.64096      4.924314    3.58457355    0.05025276
## nr.employed  56.70185     5216.408091 5165.87569138   17.23254124
## cons.price.idx 52.54683     93.936445   93.56373427    0.32429720
## cons.conf.idx 25.36681     -39.099755 -40.54192385    3.04458233
## pdays        15.08725     23.000000   22.41362725    0.00000000
## campaign     11.60168      2.850088    2.51503006    2.73344964
## previous     -29.04787      0.000000    0.17855711    0.00000000
##           Overall sd           p.value
## emp.var.rate  1.5774788 0.000000e+00
## euribor3m     1.7469207 0.000000e+00
## nr.employed   72.7919889 0.000000e+00
## cons.price.idx 0.5793439 0.000000e+00
## cons.conf.idx  4.6436681 5.863605e-142
## pdays         3.1744936 1.964506e-51
## campaign     2.3588988 4.040627e-31
## previous      0.5020810 1.637199e-185
##
## `$3`
##           v.test Mean in category Overall mean sd in category
## nr.employed   9.115196     5195.713333 5165.875691    1.29710789
## euribor3m     6.818350      4.120207    3.584574    0.11552217
## pdays         4.107565     23.000000   22.413627    0.00000000
## campaign     -4.708571      2.015556    2.515030    1.58527328
## cons.conf.idx -6.997289     -42.003111 -40.541924    0.30057591
## cons.price.idx -13.833237     93.203342   93.563734    0.06359003
##           Overall sd           p.value
## nr.employed   72.7919889 7.852866e-20
## euribor3m     1.7469207 9.209193e-12
## pdays         3.1744936 3.998529e-05
## campaign     2.3588988 2.494597e-06
## cons.conf.idx  4.6436681 2.609633e-12
## cons.price.idx 0.5793439 1.606263e-43
##
## `$4`
##           v.test Mean in category Overall mean sd in category
## previous     12.312403      0.3123746    0.17855711    0.5101781
## pdays        8.075532     22.9685619   22.41362725    0.5687059
## age         -4.052007     39.2602007   40.17755511   12.0436159
## campaign    -7.780683      2.1177258    2.51503006    1.6827435

```

## cons.conf.idx	-25.921260	-43.1475585	-40.54192385	5.9781301
## cons.price.idx	-46.092491	92.9856876	93.56373427	0.4315899
## nr.employed	-55.611005	5078.2481605	5165.87569138	38.1020523
## emp.var.rate	-60.712801	-2.0210702	0.05212425	0.5356747
## euribor3m	-63.124684	1.1974843	3.58457355	0.2469009
##	Overall sd	p.value		
## previous	0.5020810	7.767580e-35		
## pdays	3.1744936	6.718328e-16		
## age	10.4585324	5.078016e-05		
## campaign	2.3588988	7.213395e-15		
## cons.conf.idx	4.6436681	3.835830e-148		
## cons.price.idx	0.5793439	0.000000e+00		
## nr.employed	72.7919889	0.000000e+00		
## emp.var.rate	1.5774788	0.000000e+00		
## euribor3m	1.7469207	0.000000e+00		

Hierarchical Clustering

Al hacer el HCPC podemos ver que el gráfico de ganancia de inercia nos da la mayoría en dos variables, y luego dos picos más pequeños.

Ahora vemos el clustering no supervisado. Vamos a clasificar estos clusters.

Para el cluster 1:

- Está caracterizado por personas que han sido contactados previamente
- Han aceptado el producto
- Se han contactado en f.season.Sep-Dec
- Tienen una sobrerrepresentación de f.job.Entrep-Retired-selfEmpl
- Llamadas de duración mayor a 3min

Para el cluster 2:

- Han sido contactados f.season.Mar-May
- Han sido contactados en campañas previas
- Han aceptado el producto (y.yes)

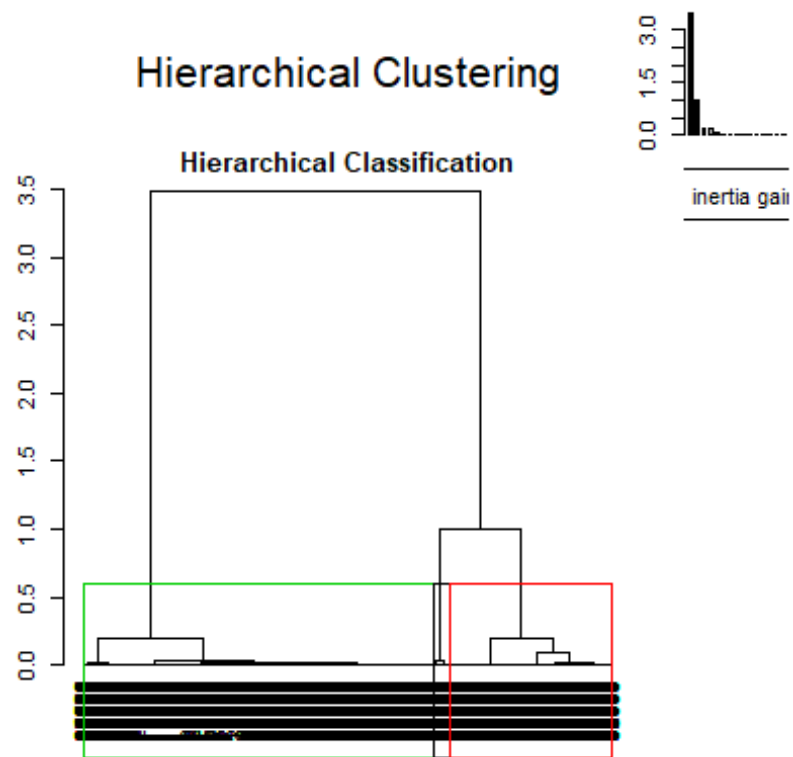
Para el cluster 3:

- Han sido contactados previamente
- No han sido contactados en campañas previas
- Han sido contactados en la temporada de f.season.Jun-Aug
- Han rechazado el producto
- Tienen una leve representación de f.job.Serv-Tech-BlueC

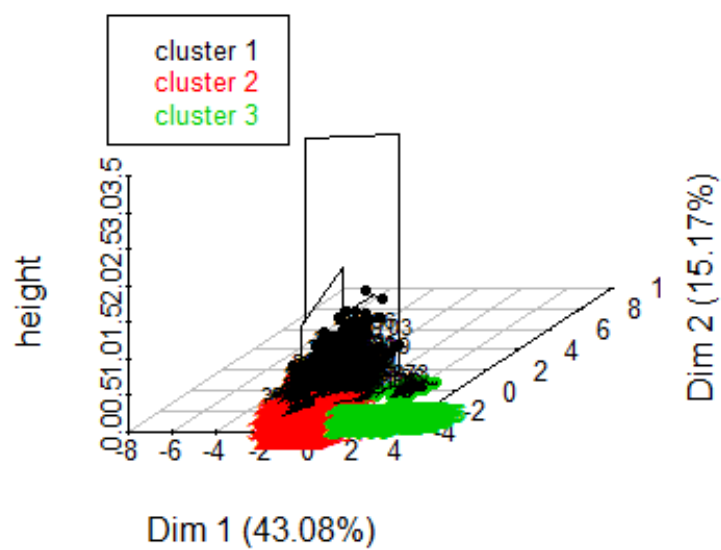
Además vemos que los parengones tienen mucho parecido a lo descrito para cada cluster.

Utilizamos el atributo nb.clust=3, después de haber visto que era el mejor corte.

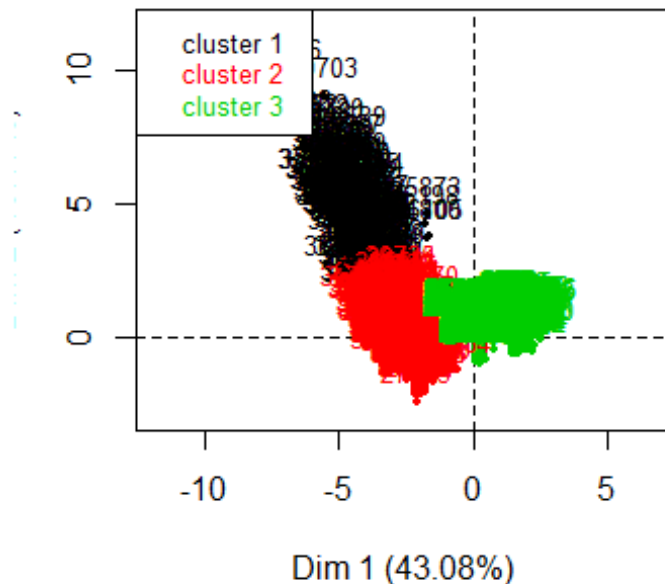
```
res.pca<-PCA(df[,c('duration',vars_num,vars_factorizadas)],quanti.sup=1, quali.s
up = c(11:19), ncp=2, graph=FALSE)
res.hcpc<-HCPC(res.pca,order=TRUE, nb.clust = 3)
```



Hierarchical clustering on the factor map



Factor map



```
attributes(res.hcpc)
```

```
## $names
## [1] "data.clust" "desc.var" "desc.axes" "call" "desc.ind"
##
## $class
## [1] "HCPC"
```

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

```
##      duration      age      campaign      pdays
## Min.   : 5.0    Min.   :18.00   Min.   : 1.000   Min.   : 0.00
## 1st Qu.:103.0   1st Qu.:32.00   1st Qu.: 1.000   1st Qu.:23.00
## Median :178.5   Median :38.00   Median : 2.000   Median :23.00
## Mean   :259.9   Mean   :40.18   Mean   : 2.515   Mean   :22.41
## 3rd Qu.:321.0   3rd Qu.:47.00   3rd Qu.: 3.000   3rd Qu.:23.00
## Max.   :2078.0   Max.   :92.00   Max.   :20.000   Max.   :23.00
##      previous      emp.var.rate      cons.price.idx      cons.conf.idx
## Min.   :0.0000    Min.   :-3.40000    Min.   :92.20    Min.   :-50.80
## 1st Qu.:0.0000    1st Qu.: -1.80000    1st Qu.:93.08    1st Qu.: -42.70
## Median :0.0000    Median : 1.10000    Median :93.44    Median : -41.80
## Mean   :0.1786    Mean   : 0.05212    Mean   :93.56    Mean   : -40.54
## 3rd Qu.:0.0000    3rd Qu.: 1.40000    3rd Qu.:93.99    3rd Qu.: -36.40
## Max.   :6.0000    Max.   : 1.40000    Max.   :94.77    Max.   : -26.90
##      euribor3m      nr.employed      f.job
## Min.   :0.634    Min.   :4964    f.job.Admin-Managment      :1647
## 1st Qu.:1.334    1st Qu.:5099    f.job.Entrep-Retired-selfEmpl: 577
```



```
## Median :4.857   Median :5191   f.job.Not-working      : 342
## Mean   :3.585   Mean   :5166   f.job.Serv-Tech-BlueC  :2424
## 3rd Qu.:4.961   3rd Qu.:5228
## Max.   :5.045   Max.   :5228
##           f.season                      f.education
## f.season.Mar-May:2064   f.education.Basic      :1597
## f.season.Jun-Aug:2245   f.education.High School :1829
## f.season.Sep-Dec: 681   f.education.Professional:1564
##
##
##
##           f.age                      f.duration
## f.age-[18,30]: 870   f.duration-[5,120]      :1557
## f.age-(30,40]:1991   f.duration-(120,180]      : 966
## f.age-(40,50]:1253   f.duration-(180,300]      :1090
## f.age-(50,92]: 876   f.duration-(300,2.1e+03]:1377
##
##
##           f.campaign                  f.pdays                  f.previous
## f.campaign-[0,1] :2121   f.pdays-[0,22] : 175   f.previous-[0,0.9]:4289
## f.campaign-(1,2] :1259   f.pdays-(22,23]:4815   f.previous-(0.9,1]: 564
## f.campaign-(2,20]:1610   f.previous-(1,6] : 137
##
##
##
##           y          clust
## y.no :4448   1: 190
## y.yes: 542   2:1497
##           3:3303
##
##
##
```

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

```
## $names
## [1] "test.chi2" "category" "quanti.var" "quanti" "call"
##
## $class
## [1] "catdes" "list "
```

```
# Factors globally related to clustering partition
res.hcpc$desc.var$test.chi2
```

```
##           p.value df
## f.pdays    0.000000e+00 2
## f.previous  0.000000e+00 4
## f.season    3.418306e-239 4
## y           2.373371e-145 2
## f.age       4.054913e-27 6
## f.job       5.294443e-17 6
```

```
## f.campaign 6.236440e-15 4
## f.duration 2.126018e-09 6
## f.education 7.523481e-04 4
```

Categories over/under represented in each cluster

```
res.hcpc$desc.var$category
```

```
## $`1`
```

	Cla/Mod	Mod/Cla	Global
## f.pdays=f.pdays-[0,22]	96.5714286	88.94737	3.507014
## f.previous=f.previous-(1,6]	75.1824818	54.21053	2.745491
## y=y.yes	21.0332103	60.00000	10.861723
## f.previous=f.previous-(0.9,1]	15.4255319	45.78947	11.302605
## f.season=f.season.Sep-Dec	11.1600587	40.00000	13.647295
## f.age=f.age-(50,92]	7.4200913	34.21053	17.555110
## f.job=f.job.Entrep-Retired-selfEmpl	7.6256499	23.15789	11.563126
## f.duration=f.duration-(180,300]	6.0550459	34.73684	21.843687
## f.education=f.education.Professional	5.4347826	44.73684	31.342685
## f.job=f.job.Not-working	8.1871345	14.73684	6.853707
## f.campaign=f.campaign-[0,1]	4.9504950	55.26316	42.505010
## f.duration=f.duration-(300,2.1e+03]	4.9382716	35.78947	27.595190
## f.age=f.age-[18,30]	5.0574713	23.15789	17.434870
## f.age=f.age-(30,40]	2.8126570	29.47368	39.899800
## f.education=f.education.Basic	2.5046963	21.05263	32.004008
## f.season=f.season.Mar-May	2.7131783	29.47368	41.362725
## f.age=f.age-(40,50]	1.9952115	13.15789	25.110220
## f.season=f.season.Jun-Aug	2.5835189	30.52632	44.989980
## f.campaign=f.campaign-(2,20]	2.0496894	17.36842	32.264529
## f.duration=f.duration-[5,120]	1.7341040	14.21053	31.202405
## f.job=f.job.Serv-Tech-BlueC	1.9801980	25.26316	48.577154
## y=y.no	1.7086331	40.00000	89.138277
## f.previous=f.previous-[0,0.9]	0.0000000	0.00000	85.951904
## f.pdays=f.pdays-(22,23]	0.4361371	11.05263	96.492986
##	p.value	v.test	
## f.pdays=f.pdays-[0,22]	1.259643e-281	35.860546	
## f.previous=f.previous-(1,6]	1.553305e-129	24.214815	
## y=y.yes	2.494385e-64	16.934745	
## f.previous=f.previous-(0.9,1]	1.156226e-34	12.280262	
## f.season=f.season.Sep-Dec	3.391033e-20	9.205810	
## f.age=f.age-(50,92]	1.767166e-08	5.633375	
## f.job=f.job.Entrep-Retired-selfEmpl	4.357820e-06	4.593544	
## f.duration=f.duration-(180,300]	3.266772e-05	4.154025	
## f.education=f.education.Professional	8.193961e-05	3.938655	
## f.job=f.job.Not-working	1.066886e-04	3.874854	
## f.campaign=f.campaign-[0,1]	3.261253e-04	3.593612	
## f.duration=f.duration-(300,2.1e+03]	1.193267e-02	2.514129	
## f.age=f.age-[18,30]	4.007463e-02	2.052979	
## f.age=f.age-(30,40]	2.422784e-03	-3.032822	
## f.education=f.education.Basic	6.774908e-04	-3.398530	
## f.season=f.season.Mar-May	5.767248e-04	-3.442331	

```

## f.age=f.age-(40,50] 4.090062e-05 -4.102332
## f.season=f.season.Jun-Aug 3.480205e-05 -4.139528
## f.campaign=f.campaign-(2,20] 2.688717e-06 -4.693270
## f.duration=f.duration-[5,120] 4.101428e-08 -5.486428
## f.job=f.job.Serv-Tech-BlueC 2.251008e-11 -6.688740
## y=y.no 2.494385e-64 -16.934745
## f.previous=f.previous-[0,0.9] 2.196177e-173 -28.071291
## f.pdays=f.pdays-(22,23] 1.259643e-281 -35.860546
##
## $`2`
## Cla/Mod Mod/Cla Global p.value
## f.season=f.season.Mar-May 53.779070 74.1482966 41.362725 9.639926e-211
## f.previous=f.previous-(0.9,1] 70.921986 26.7201069 11.302605 8.620072e-102
## y=y.yes 48.892989 17.7020708 10.861723 1.228275e-22
## f.pdays=f.pdays-(22,23] 30.965732 99.5991984 96.492986 7.200421e-20
## f.age=f.age-[18,30] 40.574713 23.5804943 17.434870 2.310583e-13
## f.campaign=f.campaign-[0,1] 34.464875 48.8309953 42.505010 3.637684e-09
## f.job=f.job.Not-working 37.134503 8.4836339 6.853707 3.388459e-03
## f.duration=f.duration-[5,120] 28.066795 29.1917168 31.202405 4.431130e-02
## f.job=f.job.Serv-Tech-BlueC 28.135314 45.5577822 48.577154 5.209983e-03
## f.season=f.season.Sep-Dec 22.760646 10.3540414 13.647295 5.972406e-06
## f.campaign=f.campaign-(2,20] 24.658385 26.5197061 32.264529 9.621448e-09
## f.age=f.age-(40,50] 22.984836 19.2384770 25.110220 1.946669e-10
## f.pdays=f.pdays-[0,22] 3.428571 0.4008016 3.507014 7.200421e-20
## y=y.no 27.697842 82.2979292 89.138277 1.228275e-22
## f.previous=f.previous-[0,0.9] 24.784332 71.0086840 85.951904 1.676131e-80
## f.season=f.season.Jun-Aug 10.334076 15.4976620 44.989980 3.526427e-179
## v.test
## f.season=f.season.Mar-May 30.981263
## f.previous=f.previous-(0.9,1] 21.420424
## y=y.yes 9.791202
## f.pdays=f.pdays-(22,23] 9.124596
## f.age=f.age-[18,30] 7.329474
## f.campaign=f.campaign-[0,1] 5.899879
## f.job=f.job.Not-working 2.930106
## f.duration=f.duration-[5,120] -2.011134
## f.job=f.job.Serv-Tech-BlueC -2.793756
## f.season=f.season.Sep-Dec -4.527364
## f.campaign=f.campaign-(2,20] -5.737271
## f.age=f.age-(40,50] -6.365490
## f.pdays=f.pdays-[0,22] -9.124596
## y=y.no -9.791202
## f.previous=f.previous-[0,0.9] -19.000910
## f.season=f.season.Jun-Aug -28.542041
##
## $`3`
## Cla/Mod Mod/Cla Global
## f.previous=f.previous-[0,0.9] 75.21567 97.668786 85.951904
## f.season=f.season.Jun-Aug 87.08241 59.188616 44.989980
## f.pdays=f.pdays-(22,23] 68.59813 100.000000 96.492986

```

```

## y=y.no          70.59353  95.065092  89.138277
## f.age=f.age-(40,50] 75.01995  28.458977  25.110220
## f.campaign=f.campaign-(2,20] 73.29193  35.725098  32.264529
## f.job=f.job.Serv-Tech-BlueC 69.88449  51.286709  48.577154
## f.duration=f.duration-[5,120] 70.19910  33.091129  31.202405
## f.duration=f.duration-(180,300] 62.66055  20.678171  21.843687
## f.duration=f.duration-(300,2.1e+03] 63.03558  26.279140  27.595190
## f.job=f.job.Entrep-Retired-selfEmpl 58.92548  10.293672  11.563126
## f.job=f.job.Not-working 54.67836  5.661520  6.853707
## f.campaign=f.campaign-[0,1] 60.58463  38.904027  42.505010
## f.age=f.age-[18,30] 54.36782  14.320315  17.434870
## f.previous=f.previous-(1,6] 0.00000  0.000000  2.745491
## y=y.yes          30.07380  4.934908  10.861723
## f.pdays=f.pdays-[0,22] 0.00000  0.000000  3.507014
## f.previous=f.previous-(0.9,1] 13.65248  2.331214  11.302605
## f.season=f.season.Mar-May 43.50775  27.187405  41.362725
##                                     p.value    v.test
## f.previous=f.previous-[0,0.9] 6.011990e-240  33.078726
## f.season=f.season.Jun-Aug 3.447463e-187  29.180312
## f.pdays=f.pdays-(22,23] 7.182640e-86  19.638980
## y=y.no          2.742424e-74  18.234602
## f.age=f.age-(40,50] 8.378911e-15  7.761714
## f.campaign=f.campaign-(2,20] 1.432305e-13  7.393298
## f.job=f.job.Serv-Tech-BlueC 8.211297e-08  5.362423
## f.duration=f.duration-[5,120] 5.127384e-05  4.049743
## f.duration=f.duration-(180,300] 5.558862e-03  -2.772728
## f.duration=f.duration-(300,2.1e+03] 3.761527e-03  -2.897497
## f.job=f.job.Entrep-Retired-selfEmpl 1.078588e-04  -3.872197
## f.job=f.job.Not-working 4.940469e-06  -4.567300
## f.campaign=f.campaign-[0,1] 6.903561e-13  -7.181332
## f.age=f.age-[18,30] 1.568440e-15  -7.971434
## f.previous=f.previous-(1,6] 6.723232e-67  -17.279410
## y=y.yes          2.742424e-74  -18.234602
## f.pdays=f.pdays-[0,22] 7.182640e-86  -19.638980
## f.previous=f.previous-(0.9,1] 1.915585e-167  -27.580337
## f.season=f.season.Mar-May 1.553439e-179  -28.570715

```

Numeric variables globally related to clustering partition

```
res.hcpc$desc.var$quanti.var
```

```

##                                     Eta2      P-value
## pdays          0.833431720  0.000000e+00
## previous       0.492162105  0.000000e+00
## emp.var.rate   0.887391268  0.000000e+00
## cons.price.idx 0.451020756  0.000000e+00
## euribor3m      0.972756054  0.000000e+00
## nr.employed    0.859965803  0.000000e+00
## cons.conf.idx  0.137891619  2.106281e-161
## campaign       0.018064870  1.813245e-20
## age            0.008646255  3.945874e-10

```

```
res.hcpc$desc.var$quanti
```

```
## `$1`
```

	v.test	Mean in category	Overall mean	sd in category
## previous	45.971997	1.8210526	0.17855711	0.9567373
## cons.conf.idx	6.937479	-38.2494737	-40.54192385	7.1162952
## age	5.645279	44.3789474	40.17755511	16.9858634
## duration	2.110371	297.6368421	259.85110220	204.0561577
## campaign	-4.322398	1.7894737	2.51503006	1.2598641
## cons.price.idx	-4.817260	93.3651368	93.56373427	0.8341906
## emp.var.rate	-19.115707	-2.0936842	0.05212425	0.8565304
## euribor3m	-21.054798	0.9672263	3.58457355	0.5121394
## nr.employed	-27.122883	5025.3821053	5165.87569138	51.3340730
## pdays	-64.481704	7.8473684	22.41362725	6.4451425
##	Overall sd	p.value		
## previous	0.5020810	0.000000e+00		
## cons.conf.idx	4.6436681	3.991593e-12		
## age	10.4585324	1.649135e-08		
## duration	251.6124483	3.482644e-02		
## campaign	2.3588988	1.543422e-05		
## cons.price.idx	0.5793439	1.455430e-06		
## emp.var.rate	1.5774788	1.868722e-81		
## euribor3m	1.7469207	2.066633e-98		
## nr.employed	72.7919889	5.290316e-162		
## pdays	3.1744936	0.000000e+00		

```
## `$2`
```

	v.test	Mean in category	Overall mean	sd in category
## previous	12.347248	0.3126253	0.17855711	0.5102106
## pdays	8.083856	22.9686039	22.41362725	0.5683270
## age	-4.063321	39.2585170	40.17755511	12.0357116
## campaign	-7.817387	2.1162325	2.51503006	1.6821146
## cons.conf.idx	-25.982635	-43.1512358	-40.54192385	5.9749813
## cons.price.idx	-46.161007	92.9853808	93.56373427	0.4313831
## nr.employed	-55.580906	5078.3791583	5165.87569138	38.2446628
## emp.var.rate	-60.699472	-2.0186373	0.05212425	0.5394336
## euribor3m	-63.098140	1.2007649	3.58457355	0.2625532
##	Overall sd	p.value		
## previous	0.5020810	5.040624e-35		
## pdays	3.1744936	6.275018e-16		
## age	10.4585324	4.837945e-05		
## campaign	2.3588988	5.393129e-15		
## cons.conf.idx	4.6436681	7.782048e-149		
## cons.price.idx	0.5793439	0.000000e+00		
## nr.employed	72.7919889	0.000000e+00		
## emp.var.rate	1.5774788	0.000000e+00		
## euribor3m	1.7469207	0.000000e+00		

```
## `$3`
```

	v.test	Mean in category	Overall mean	sd in category
--	--------	------------------	--------------	----------------

```

## euribor3m      69.642425      4.81553255      3.58457355      0.2815584
## emp.var.rate   66.534303      1.11407811      0.05212425      0.4992563
## nr.employed    64.815247    5213.61292764  5165.87569138    17.5063561
## cons.price.idx 46.665983      93.83728217      93.56373427      0.3924268
## cons.conf.idx  22.363260     -39.49118983     -40.54192385      2.9986228
## pdays          18.255882      23.00000000      22.41362725      0.0000000
## campaign       9.321541      2.73751135      2.51503006      2.6231360
## previous      -30.559574      0.02331214      0.17855711      0.1508930
##               Overall sd      p.value
## euribor3m      1.7469207  0.000000e+00
## emp.var.rate    1.5774788  0.000000e+00
## nr.employed     72.7919889  0.000000e+00
## cons.price.idx  0.5793439  0.000000e+00
## cons.conf.idx   4.6436681  8.971345e-111
## pdays           3.1744936  1.857861e-74
## campaign        2.3588988  1.146631e-20
## previous        0.5020810  4.219155e-205

### desc.ind ###
### C. The description of the clusters by the individuals ###
names(res.hcpc$desc.ind)

## [1] "para" "dist"

res.hcpc$desc.ind$para # Close to center of gravity

## Cluster: 1
##      36296      36721      40892      41007      36907
## 0.03946875 0.05735028 0.13237750 0.21737224 0.22738201
## -----
## Cluster: 2
##      30951      36346      36347      36427      36864
## 0.06134805 0.09336824 0.09336824 0.09552183 0.09624810
## -----
## Cluster: 3
##      1467      1752      331      6185      18926
## 0.01424926 0.01424926 0.01478019 0.01478019 0.01491243

res.hcpc$desc.ind$dist

## Cluster: 1
##      40396      40703      39592      38902      39612
## 11.543929 10.404680 9.652239 9.431592 9.270355
## -----
## Cluster: 2
##      37956      38026      38148      37904      38051
## 4.742178 4.688806 4.646346 4.645320 4.644823
## -----
## Cluster: 3
##      11696      8484      11485      11056      10761
## 5.265453 5.246245 5.197173 5.138562 5.009706

```

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

Eigenvalues and dominant axes analysis. How many axes we have to consider are there any row categories that can be combined/avoided to explain Duration target.

Para experimentar y para que tenga más sentido el análisis de correspondencias, refactorizaremos a 8 niveles la variable duration.

Ahora hacemos el análisis de correspondencias entre nuestra nueva duration factorizada y f.age. Para saber cuantas dimensiones debemos considerar, obtenemos la media de los eigenvalues. Vemos que solamente tiene sentido considerar el primer eje, ya que este es el único valor mayor a la media (kaiser).

Al graficar el CA, podemos ver que los 2 niveles con menores edades, son los que menos representados en ese eje. Para duration, los niveles mejor representados en el eje son los de mayor y menor duración.

Al ejecutar la función del chisq.test podemos ver que el pvalue es muy grande, lo que nos puede decir que la probabilidad de que no tengan relación es muy grande.

CA - duration vs f.age

Para duration

```
aux2<-c(5,60,120,150,180,240,300,1200,2100) # Niveles "naturales"  
duration_k8<-factor(cut(df$duration,breaks=aux2,include.lowest=T))  
table(duration_k8)
```

```
## duration_k8  
##           [5,60]           (60,120]           (120,150]           (150,180]  
##              490             1067             496             470  
##      (180,240]      (240,300]      (300,1.2e+03] (1.2e+03,2.1e+03]  
##              606             484             1311             66
```

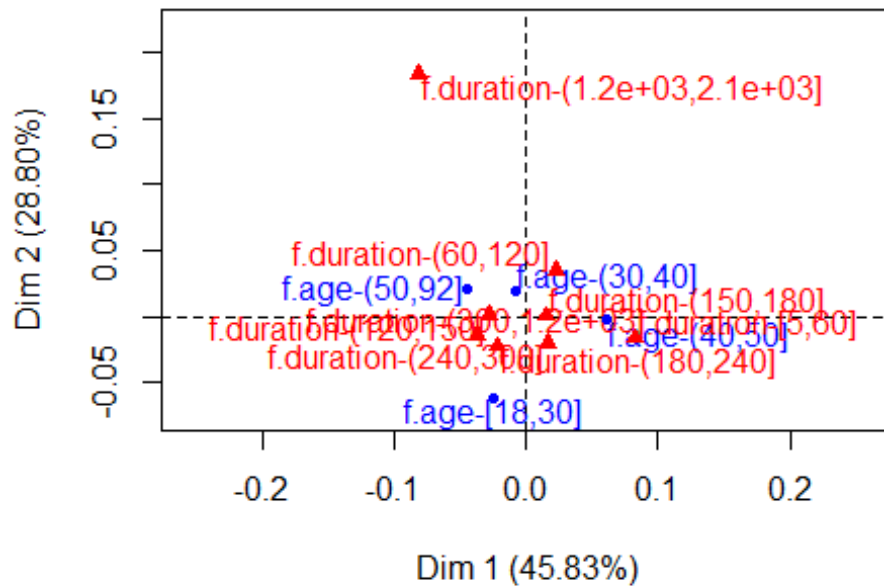
`levels(duration_k8)<-paste0("f.duration-",levels(duration_k8))` *# Hacemos las etiquetas más informativas*

```
summary(duration_k8)
```

```
##           f.duration-[5,60]           f.duration-(60,120]  
##              490             1067  
##      f.duration-(120,150]      f.duration-(150,180]  
##              496             470  
##      f.duration-(180,240]      f.duration-(240,300]  
##              606             484  
##      f.duration-(300,1.2e+03] f.duration-(1.2e+03,2.1e+03]  
##              1311             66
```

```
res.ca<-CA(table(df$f.age,duration_k8))
```

CA factor map



```
attributes(res.ca)

## $names
## [1] "eig" "call" "row" "col" "svd"
##
## $class
## [1] "CA" "list"

res.ca$eig

##          eigenvalue percentage of variance
## dim 1 0.0014130984          45.82949
## dim 2 0.0008880983          28.80273
## dim 3 0.0007821856          25.36778
##          cumulative percentage of variance
## dim 1          45.82949
## dim 2          74.63222
## dim 3         100.00000

mean(res.ca$eig[,1]) # Mean of eigenvalues

## [1] 0.001027794

sum(res.ca$eig[,1]) # Total inertia

## [1] 0.003083382
```


Rows

res.ca\$row

\$coord

	Dim 1	Dim 2	Dim 3
## f.age-[18,30]	-0.024672376	-0.061587071	0.00515479
## f.age-(30,40]	-0.007883325	0.019128850	0.02866207
## f.age-(40,50]	0.060905585	-0.002487498	-0.01655528
## f.age-(50,92]	-0.044696383	0.021246627	-0.04658344

##

\$contrib

	Dim 1	Dim 2	Dim 3
## f.age-[18,30]	7.510490	74.4623554	0.5922851
## f.age-(30,40]	1.754758	16.4394554	41.9059874
## f.age-(40,50]	65.916230	0.1749504	8.7985988
## f.age-(50,92]	24.818522	8.9232388	48.7031287

##

\$cos2

	Dim 1	Dim 2	Dim 3
## f.age-[18,30]	0.13746379	0.856535696	0.006000512
## f.age-(30,40]	0.04973439	0.292830101	0.657435510
## f.age-(40,50]	0.92975389	0.001550884	0.068695230
## f.age-(50,92]	0.43249165	0.097726640	0.469781706

##

\$inertia

[1] 0.0007720623 0.0004985776 0.0010018363 0.0008109061

Columns: the same

res.ca\$col

\$coord

	Dim 1	Dim 2	Dim 3
## f.duration-[5,60]	0.08319396	-0.0161245945	2.458294e-02
## f.duration-(60,120]	0.02249525	0.0348536919	-2.577791e-02
## f.duration-(120,150]	-0.02735408	0.0013898644	1.373241e-02
## f.duration-(150,180]	0.01565127	0.0006091358	6.835979e-05
## f.duration-(180,240]	-0.02116464	-0.0227191287	4.705510e-02
## f.duration-(240,300]	0.01669583	-0.0202658085	3.700409e-04
## f.duration-(300,1.2e+03]	-0.03694459	-0.0143453208	-2.112106e-02
## f.duration-(1.2e+03,2.1e+03]	-0.08146358	0.1836311251	1.153212e-01

##

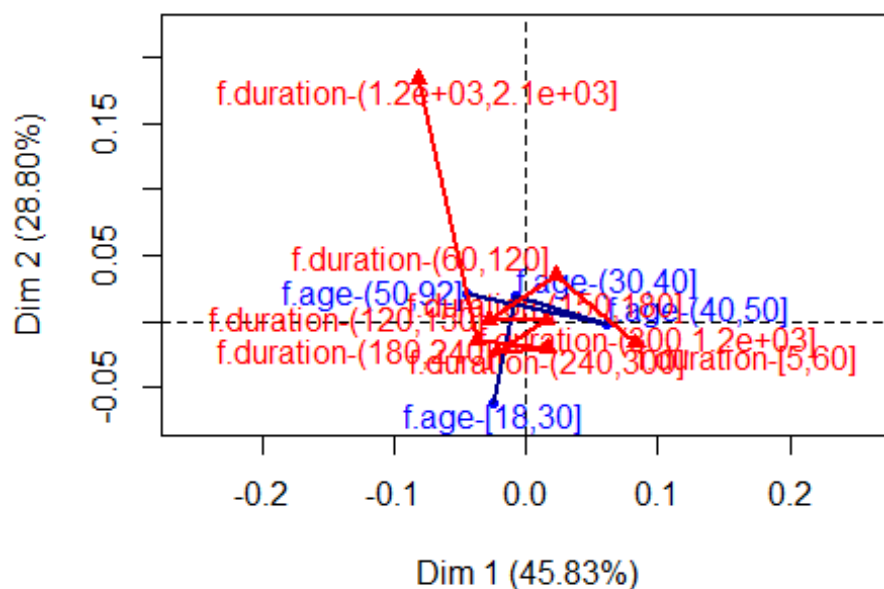
\$contrib

	Dim 1	Dim 2	Dim 3
## f.duration-[5,60]	48.095757	2.87482957	7.586705e+00
## f.duration-(60,120]	7.657254	29.24828562	1.816559e+01
## f.duration-(120,150]	5.263239	0.02162046	2.396431e+00
## f.duration-(150,180]	1.632767	0.00393518	5.627155e-05
## f.duration-(180,240]	3.849653	7.05820696	3.437761e+01
## f.duration-(240,300]	1.913324	4.48550815	1.697988e-03
## f.duration-(300,1.2e+03]	25.376484	6.08781771	1.498386e+01
## f.duration-(1.2e+03,2.1e+03]	6.211521	50.21979635	2.248806e+01

```
##
## $cos2
##
##          Dim 1      Dim 2      Dim 3
## f.duration-[5,60]    0.8889838 0.033395490 7.762072e-02
## f.duration-(60,120]  0.2121463 0.509274053 2.785796e-01
## f.duration-(120,150] 0.7970605 0.002057746 2.008818e-01
## f.duration-(150,180] 0.9984686 0.001512388 1.904743e-05
## f.duration-(180,240] 0.1409384 0.162401758 6.966599e-01
## f.duration-(240,300] 0.4042264 0.595574996 1.985675e-04
## f.duration-(300,1.2e+03] 0.6767699 0.102037507 2.211926e-01
## f.duration-(1.2e+03,2.1e+03] 0.1236833 0.628458833 2.478578e-01
##
## $inertia
## [1] 7.645138e-04 5.100466e-04 9.331130e-05 2.310800e-05 3.859799e-04
## [6] 6.688615e-05 5.298621e-04 7.096744e-04

# Link levels in rows
plot.CA(res.ca)
lines(res.ca$row$coord[,1],res.ca$row$coord[,2],lwd=2,col="darkblue")
lines(res.ca$col$coord[,1],res.ca$col$coord[,2],lwd=2,col="red")
```

CA factor map



```
# Phi2 = Intensity of the association Chisq/nbobservations
sum(res.ca$eig[,1]) # Total Inertia = Phi2

## [1] 0.003083382

# H0: f.duration - f.age independency
chisq.test(table(df$f.age,duration_k8))
```

```
##
## Pearson's Chi-squared test
##
## data: table(df$f.age, duration_k8)
## X-squared = 15.386, df = 21, p-value = 0.8031
```

CA - Education vs f.duration

Para la segunda prueba decidimos utilizar duration junto con education. Para education usaremos la variable original con todos sus niveles menos el nivel illiterate el cual nos puede causar inconvenientes.

Por kaiser vemos que las primeras dos dimensiones están por encima de la media, por lo que son las que cogemos.

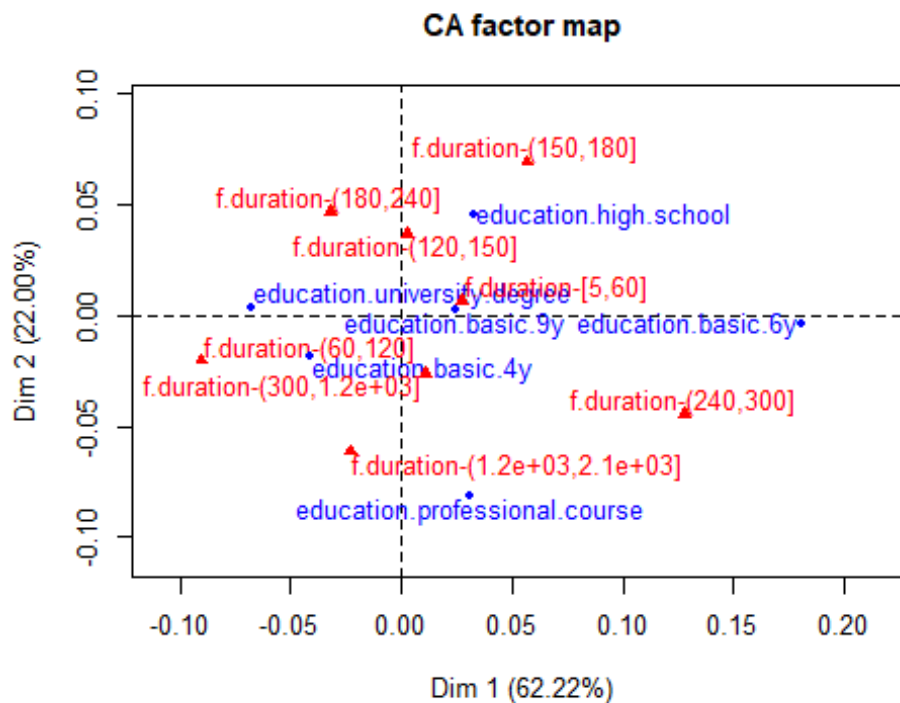
Podemos ver que para la primera dimensión los valores más lejanos del centro son los niveles de education.basic_6y, education.university.degree, para la primera dimensión. Para la segunda tenemos, f.duration(150,180], education.professional.course, esto nos puede decir qué niveles se ven mejor representados en las dimensiones.

```
#Education
table(df$education)

##
##          education.basic.4y          education.basic.6y
##                515                271
##          education.basic.9y          education.high.school
##                810                1196
##          education.illiterate education.professional.course
##                1                633
##          education.university.degree
##                1564

education_k6<-df$education
education_k6[which(education_k6=="education.illiterate")]<-"education.basic.4y"
education_k6=factor(education_k6)

par(cex=0.8)
res.ca<-CA(table(education_k6,duration_k8))
```



```
res.ca$eig
```

```
##          eigenvalue percentage of variance
## dim 1 3.865234e-03          62.2179391
## dim 2 1.366656e-03          21.9987982
## dim 3 7.963697e-04          12.8190136
## dim 4 1.318112e-04           2.1217398
## dim 5 5.234014e-05           0.8425093
##          cumulative percentage of variance
## dim 1          62.21794
## dim 2          84.21674
## dim 3          97.03575
## dim 4          99.15749
## dim 5         100.00000
```

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

```
## [1] 0.001242482
```

```
# Rows
```

```
res.ca$row
```

```
## $coord
```

	Dim 1	Dim 2	Dim 3
education.basic.4y	-0.04133205	-0.018121606	-0.058412332
education.basic.6y	0.18102401	-0.004110569	0.042729415
education.basic.9y	0.02483545	0.002685184	-0.027046691
education.high.school	0.03234069	0.045050136	-0.004194745

```

## education.professional.course 0.03069724 -0.081359937 0.007155999
## education.university.degree -0.06774789 0.003779150 0.026186751
##
## Dim 4 Dim 5
## education.basic.4y 0.010678244 -0.012189412
## education.basic.6y -0.003590873 -0.018490687
## education.basic.9y -0.022417259 0.003721054
## education.high.school 0.010664921 0.005274952
## education.professional.course 0.008039829 0.008059669
## education.university.degree -0.002700335 -0.001997413
##
## $contrib
## Dim 1 Dim 2 Dim 3 Dim 4
## education.basic.4y 4.570327 2.48475408 44.3040567 8.9453332
## education.basic.6y 46.043183 0.06714497 12.4511048 0.5312717
## education.basic.9y 2.590316 0.08563935 14.9106984 61.8866872
## education.high.school 6.485648 35.59293113 0.5295743 20.6820512
## education.professional.course 3.092616 61.44198967 0.8156972 6.2207761
## education.university.degree 37.217909 0.32754080 26.9888687 1.7338807
## Dim 5
## education.basic.4y 29.354847
## education.basic.6y 35.476433
## education.basic.9y 4.294194
## education.high.school 12.741859
## education.professional.course 15.743551
## education.university.degree 2.389116
##
## $cos2
## Dim 1 Dim 2 Dim 3
## education.basic.4y 0.2991135 0.057498362 0.597408243
## education.basic.6y 0.9371554 0.000483218 0.052214742
## education.basic.9y 0.3295023 0.003851787 0.390789233
## education.high.school 0.3233541 0.627439873 0.005439900
## education.professional.course 0.1217065 0.854941382 0.006613871
## education.university.degree 0.8658182 0.002694161 0.129359520
## Dim 4 Dim 5
## education.basic.4y 0.0199646527 0.0260152290
## education.basic.6y 0.0003687563 0.0097778938
## education.basic.9y 0.2684598606 0.0073968422
## education.high.school 0.0351637465 0.0086023464
## education.professional.course 0.0083485069 0.0083897596
## education.university.degree 0.0013755312 0.0007526117
##
## $inertia
## [1] 0.0005905913 0.0018990198 0.0003038576 0.0007752660 0.0009821731
## [6] 0.0016615026
# Columns: the same
res.ca$col

```

```

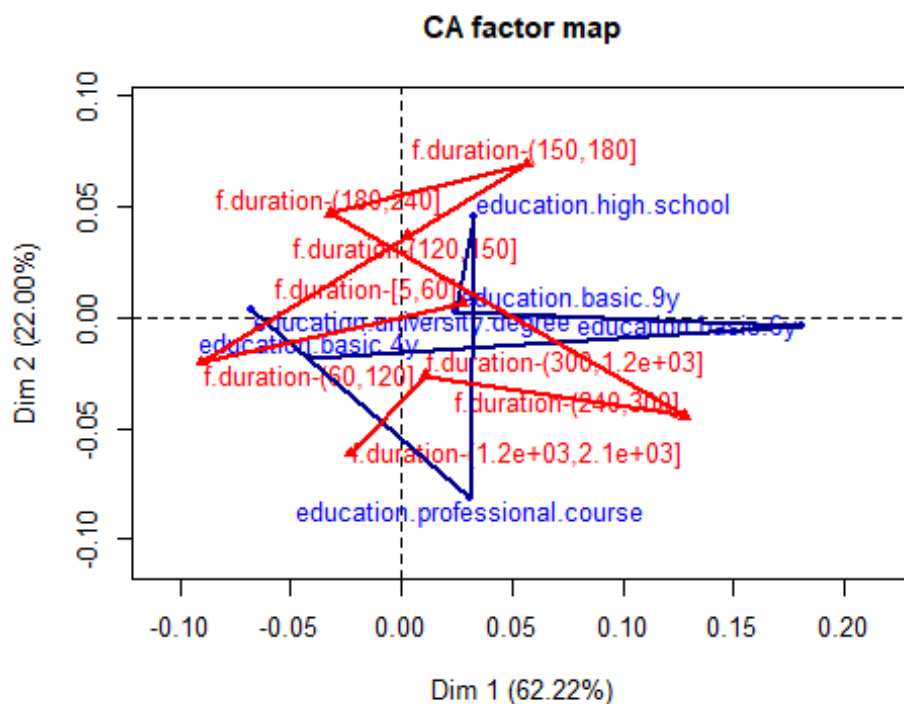
## $coord
##
##          Dim 1          Dim 2          Dim 3
## f.duration-[5,60]      0.027029115  0.006192711  0.035619391
## f.duration-(60,120]   -0.090112862 -0.020538411  0.017086167
## f.duration-(120,150]   0.002502632  0.036564696 -0.049483431
## f.duration-(150,180]   0.056880902  0.069080817  0.004342747
## f.duration-(180,240]  -0.032420109  0.046836380  0.019636428
## f.duration-(240,300]   0.127883956 -0.044401648  0.030160547
## f.duration-(300,1.2e+03] 0.010833855 -0.026353481 -0.028797208
## f.duration-(1.2e+03,2.1e+03] -0.023054621 -0.061622025 -0.029181692
##
##          Dim 4          Dim 5
## f.duration-[5,60]      0.0049402640  0.001195881
## f.duration-(60,120]   -0.0054537007  0.003195489
## f.duration-(120,150]  -0.0047413221  0.015186085
## f.duration-(150,180]  -0.0004840916 -0.004166702
## f.duration-(180,240]   0.0067808780 -0.005449376
## f.duration-(240,300]  -0.0044409552  0.006544906
## f.duration-(300,1.2e+03] -0.0015812648 -0.007781878
## f.duration-(1.2e+03,2.1e+03] 0.0922854018  0.011622914
##
## $contrib
##
##          Dim 1          Dim 2          Dim 3          Dim 4
## f.duration-[5,60]      1.85602333  0.2755485 15.6442142 1.81820805
## f.duration-(60,120]   44.92226773  6.5999164 7.8385985 4.82496535
## f.duration-(120,150]   0.01610644  9.7240230 30.5622963 1.69522671
## f.duration-(150,180]   7.88414319 32.8891869 0.2230549 0.01674558
## f.duration-(180,240]   3.30236637 19.4930424 5.8800674 4.23634841
## f.duration-(240,300]  41.03941655 13.9921319 11.0792023 1.45126036
## f.duration-(300,1.2e+03] 0.79779697 13.3511603 27.3582403 0.49837825
## f.duration-(1.2e+03,2.1e+03] 0.18187944 3.6749905 1.4143262 85.45886729
##
##          Dim 5
## f.duration-[5,60]      0.2683099
## f.duration-(60,120]   4.1716088
## f.duration-(120,150]  43.7963518
## f.duration-(150,180]   3.1242607
## f.duration-(180,240]   6.8901823
## f.duration-(240,300]   7.9381048
## f.duration-(300,1.2e+03] 30.3973777
## f.duration-(1.2e+03,2.1e+03] 3.4138039
##
## $cos2
##
##          Dim 1          Dim 2          Dim 3
## f.duration-[5,60]      0.354045576 0.01858477 0.614849014
## f.duration-(60,120]   0.915064957 0.04753484 0.032897861
## f.duration-(120,150]   0.001548393 0.33053014 0.605350244
## f.duration-(150,180]   0.402214863 0.59325319 0.002344522
## f.duration-(180,240]   0.283613187 0.59192152 0.104045298
## f.duration-(240,300]   0.847459925 0.10216102 0.047137383
## f.duration-(300,1.2e+03] 0.068871807 0.40752236 0.486604635
## f.duration-(1.2e+03,2.1e+03] 0.038426381 0.27452723 0.061565082

```

```
##
##          Dim 4          Dim 5
## f.duration-[5,60]      1.182758e-02 0.0006930612
## f.duration-(60,120]    3.351668e-03 0.0011506756
## f.duration-(120,150]   5.557584e-03 0.0570136422
## f.duration-(150,180]   2.913267e-05 0.0021582909
## f.duration-(180,240]   1.240707e-02 0.0080129231
## f.duration-(240,300]   1.021974e-03 0.0022196981
## f.duration-(300,1.2e+03] 1.467184e-03 0.0355340175
## f.duration-(1.2e+03,2.1e+03] 6.157147e-01 0.0097666035
##
## $inertia
## [1] 0.0002026283 0.0018975163 0.0004020629 0.0007576562 0.0004500643
## [6] 0.0018717928 0.0004477408 0.0001829489
```

Link levels in rows

```
plot.CA(res.ca)
lines(res.ca$row$coord[,1],res.ca$row$coord[,2],lwd=2,col="darkblue")
lines(res.ca$col$coord[,1],res.ca$col$coord[,2],lwd=2,col="red")
```



Phi2 = Intensity of the association $\text{Chisq}/\text{nbobservations}$

```
sum(res.ca$eig[,1]) # Total Inertia = Phi2
```

```
## [1] 0.00621241
```

```
chisq.test(table(education_k6,duration_k8))
```

```
## Warning in chisq.test(table(education_k6, duration_k8)): Chi-squared
## approximation may be incorrect
```

```
##
## Pearson's Chi-squared test
##
## data: table(education_k6, duration_k8)
## X-squared = 31, df = 35, p-value = 0.6617

# Traditional analysis
table(df$y,duration_k8)

##      duration_k8
##      f.duration-[5,60] f.duration-(60,120] f.duration-(120,150]
## y.no                490                1047                481
## y.yes                 0                  20                  15
##      duration_k8
##      f.duration-(150,180] f.duration-(180,240] f.duration-(240,300]
## y.no                441                550                431
## y.yes                 29                 56                 53
##      duration_k8
##      f.duration-(300,1.2e+03] f.duration-(1.2e+03,2.1e+03]
## y.no                983                25
## y.yes               328                41

chisq.test(table(df$y,duration_k8))

##
## Pearson's Chi-squared test
##
## data: table(df$y, duration_k8)
## X-squared = 643.03, df = 7, p-value < 2.2e-16
```