Exploratory Data Analysis

In this first phase of the data science project we performed an exploratory data analysis to:

- maximize insight into the data set
- detect outliers and missing data
- extract important variables
- test underlying assumptions
- develop a testing model and evualate all the requisites to run it.

We applyed quite simple graphical techniques like:

- plotting the raw data
- plotting simple statistics

We used R base plotting functionality because of it's convenience, but complimented with the use of `ggplot2` and `lattice` R packages.

For data wrangling tasks we used the power of the `data.table` package.

> The EDA analysis was based on a subsample of 100000 observations from the original data set. The data was partitioned running `subsample -n 100000 datos.csv -r > sample.csv` on the operating system shell.

```
knitr::opts_chunk$set(echo = TRUE,fig.align='center')

list.of.packages <- c("data.table", "dplyr","ggplot2","lubridate","lattice","scales","corrplot","caret","c
new.packages <- list.of.packages[!(list.of.packages %in% installed.packages()[,"Package"])]
if(length(new.packages)) install.packages(new.packages)
```

Loading data

```
file <- file.path('data/sample.csv')

if (file.exists(file)) {
  cat('Reading', file)
  print(paste(round(file.info(file)$size  / 2^30, 4), 'gigabytes'))
  readLines(file, n=2, skipNul = T)
  DT <- fread(file, encoding='Latin-1', na.strings=c("","NA"))
} else {
  stop("File not found.")
}
```

```
## Reading data/sample.csv[1] "0.0167 gigabytes"
```

The dataset data/sample.csv contains 50000 withdrawal requests by 33466 users. User data is missing for 15399 requests, that is, a 30.798% of the data set.

Data Type Conversion

Dates:

```
sapply(DT,class)
```

```
##                  ANO                  MES                  DIA
##          "character"          "character"          "character"
##        OP_ADQUIRENTE         ADQUIERENTE  DES_TIPO_ADQUIRENTE
##          "character"          "character"          "character"
##            OP_EMISOR               EMISOR      DES_TIPO_EMISOR
##          "character"          "character"          "character"
##           DES_AMBITO   OP_IDENT_TERMINAL OP_COD_POST_COMERCIO
##          "character"          "character"          "character"
##        DES_PROVINCIA            LOCALIDAD OP_COD_PAIS_COMERCIO
##          "character"          "character"          "character"
##            DES_MARCA             DES_GAMA         DES_PRODUCTO
##          "character"          "character"          "character"
##         TIPO_TARJETA           DES_CREDEB  DES_CLASE_OPERACION
##          "character"          "character"          "character"
##             DES_PAGO        DES_RESULTADO       PER_ID_PERSONA
##          "character"          "character"          "character"
##        PER_TIPO_PERS       PER_FECHA_ALTA          OF_COD_POST
##          "character"          "character"          "character"
##     PER_COD_PAIS_NAC      OF_COD_PAIS_RES          PER_ID_SEXO
##          "character"          "character"          "character"
##        PER_EST_CIVIL        PER_MARCA_EMP       PER_MARCA_FALL
##          "character"          "character"          "character"
##        PER_FECHA_NAC                NOPER              IMPOPER
##          "character"          "character"          "character"
```

```
DT[,FECHA:=as.Date(paste(ANO, MES, DIA, sep="-" ), tz = "Europe/Madrid")]
DT[,PER_FECHA_NAC:=as.Date(PER_FECHA_NAC, format = "%Y%m%d", tz = "Europe/Madrid")]
DT[,PER_FECHA_ALTA:=as.Date(PER_FECHA_ALTA, format = "%Y%m%d", tz = "Europe/Madrid")]
```

Categorical variables:

```
variables <- c('ANO','MES','DIA','OP_ADQUIRENTE','DES_TIPO_EMISOR','DES_PROVINCIA', 'DES_TIPO_ADQUIRENTE',
DT[,(variables):=lapply(.SD, as.factor),.SDcols=variables]
rm(variables)
```

Numerical variables:

```
variables <- c('NOPER','IMPOPER')
DT[,(variables):=lapply(.SD, as.numeric),.SDcols=variables]
```

```
## Warning in lapply(.SD, as.numeric): NAs introducidos por coerción
```

```
rm(variables)
```

Reordering columns

```
setcolorder(DT, c(ncol(DT), 1:(ncol(DT)-1)))
```

Inspecting firs row of the data set:

FECHA	ANO	MES	DIA	OP_ADQUIRENTE	ADQUIERENTE	DES_TIPO_ADQUIR
2016-03-06	2016	03	06	BM3MV1QJ1RWI6XB8W36S	Q4SRXYQNPFB8ST2BCSLT	EURO 6000

Exploratory data analysis

Missing data

```
par(mai=c(1,1.6,1,0.5), family = "Helvetica", col=viridis(1), fg = "black")
barplot(sapply(DT, function(x) sum(is.na(x))), main = "Missing Data", col=viridis(1), xlab = "Count", cex.
```

Trying to figure out what the data set "looks" like

Bank companies

The dataset contains requests from users of 70 diferent bank companies.

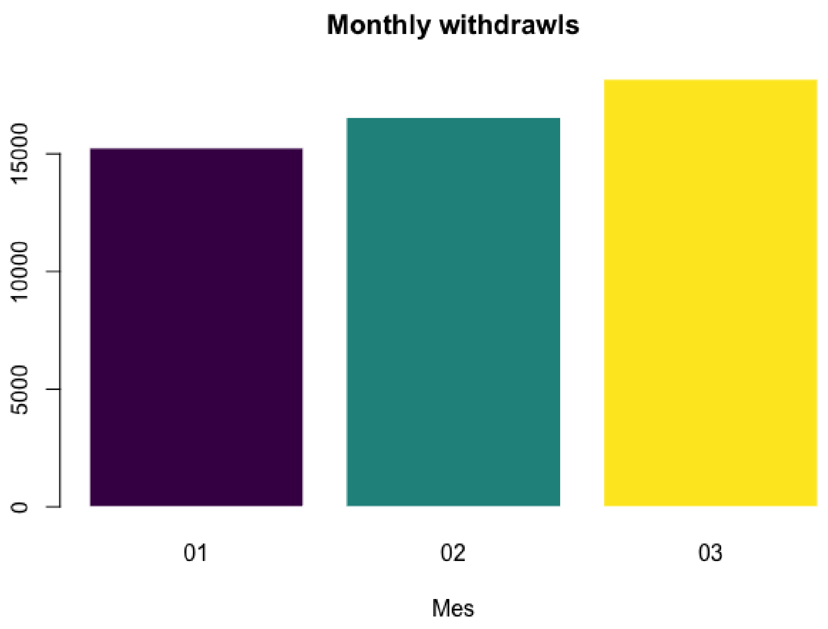
We decided to change anonymized names by friendly ones:

```
setkey(DT,OP_ADQUIRENTE)

op_adquiriente <- seq(from = 1000, to=length(unique(DT$OP_ADQUIRENTE))+999, by =1)
DT[,OP_ADQUIRENTE:=factor(OP_ADQUIRENTE,labels=op_adquiriente)]

adquirente <- paste("Entidad", op_adquiriente)
DT[,ADQUIERENTE:=factor(ADQUIERENTE,labels=adquirente)]

knitr::kable(head(DT[,c('ADQUIERENTE','OP_ADQUIRENTE'), with = FALSE]))
```

ADQUIERENTE	OP_ADQUIRENTE
Entidad 1027	1000
Entidad 1027	1000
Entidad 1027	1000
Entidad 1027	1000
Entidad 1027	1000
Entidad 1027	1000

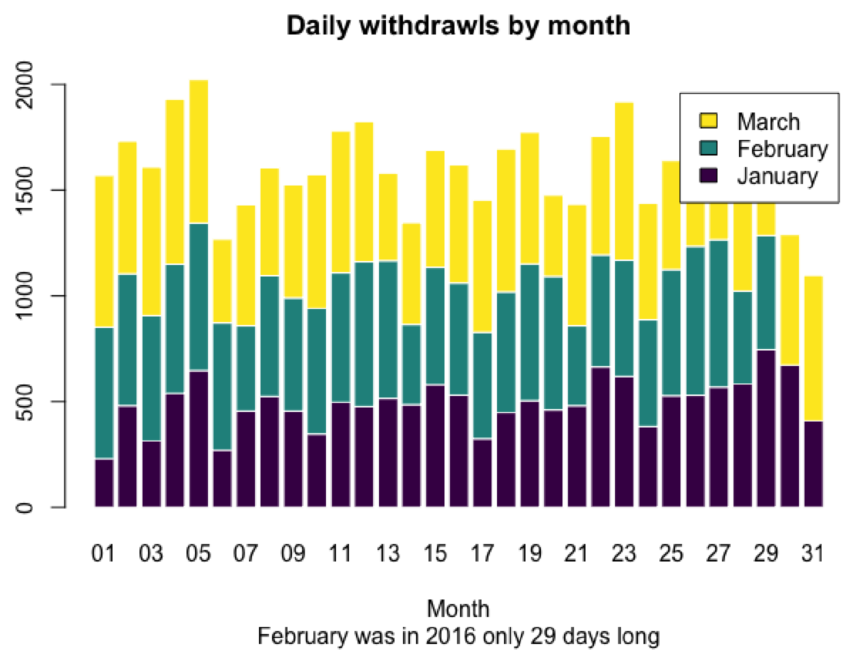
Monthly withdrawls

```
barplot(table(DT$MES), main = "Monthly withdrawls", xlab = "Mes", col=viridis(3), border = "white")
```



Daily withdrawls

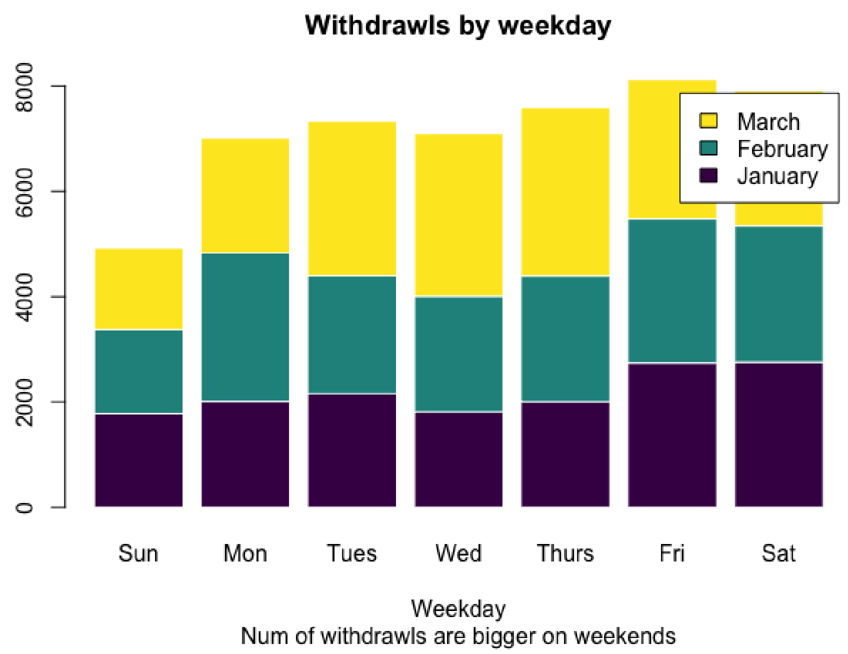
```
counts <- table(DT$MES, DT$DIA)
barplot(counts, col=viridis(3),  main = "Daily withdrawls by month", xlab = "Month", sub="February was in
```




```
rm(counts)
```

Withdrawls by weekday

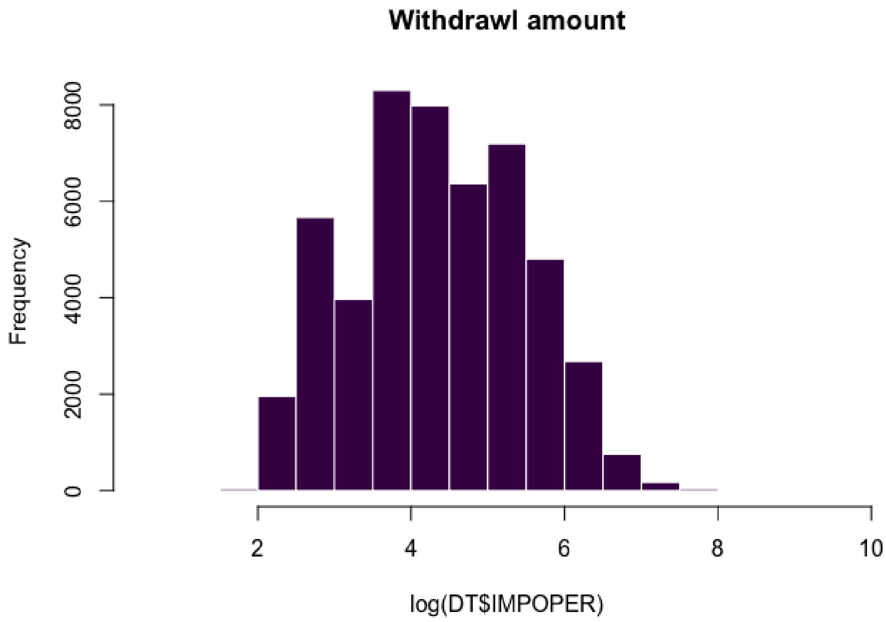
```
counts <- table(DT$MES, lubridate::wday(DT$FECHA, label = T))
barplot(counts, col=viridis(3),  main = "Withdrawls by weekday", xlab = "Weekday", sub="Num of withdrawls
```




```
rm(counts)
```

Withdrawl amount

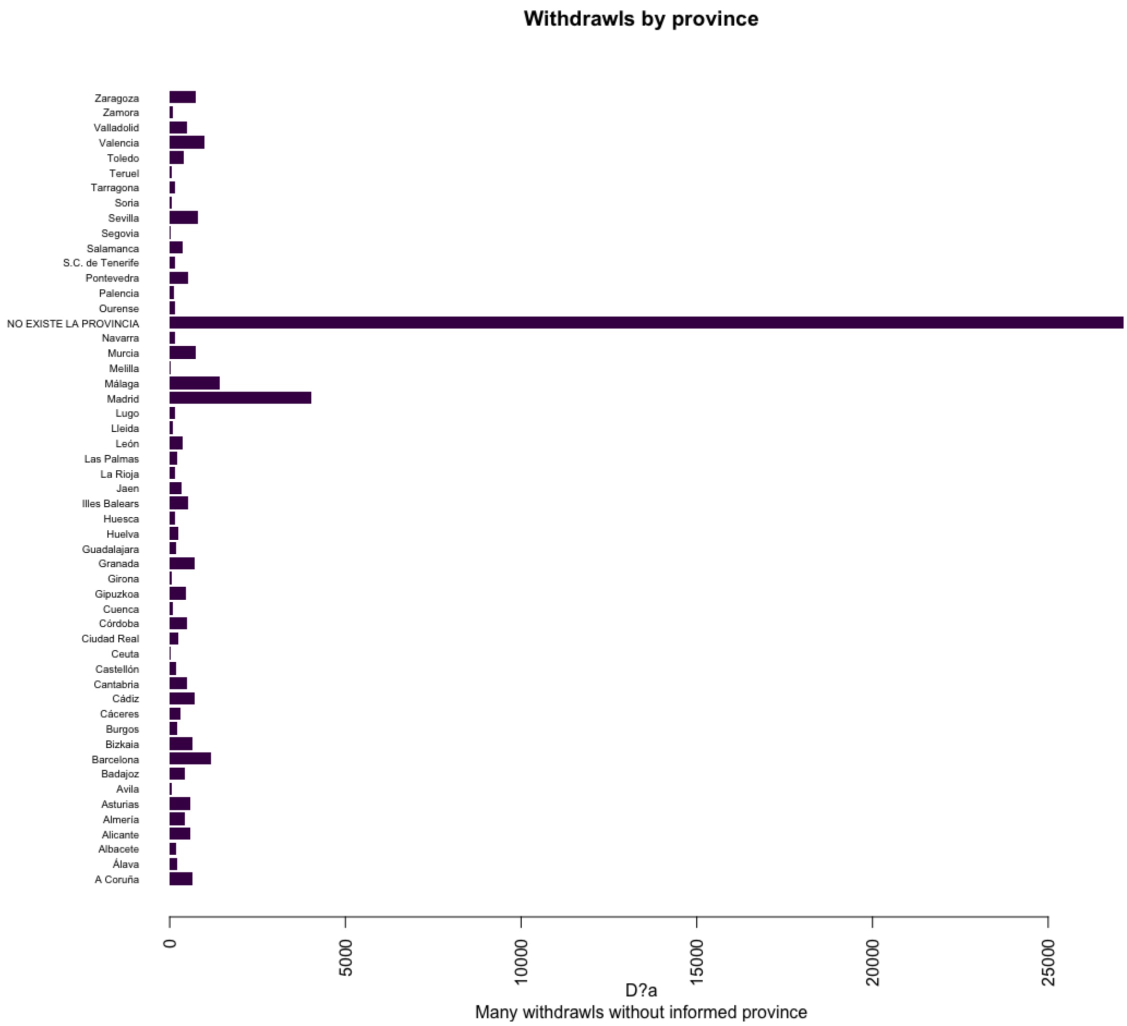
```
hist(log(DT$IMPOPER), col=viridis(1), main = "Withdrawl amount", border = "white")
```



Missing values

54.266 of observations do not have province:

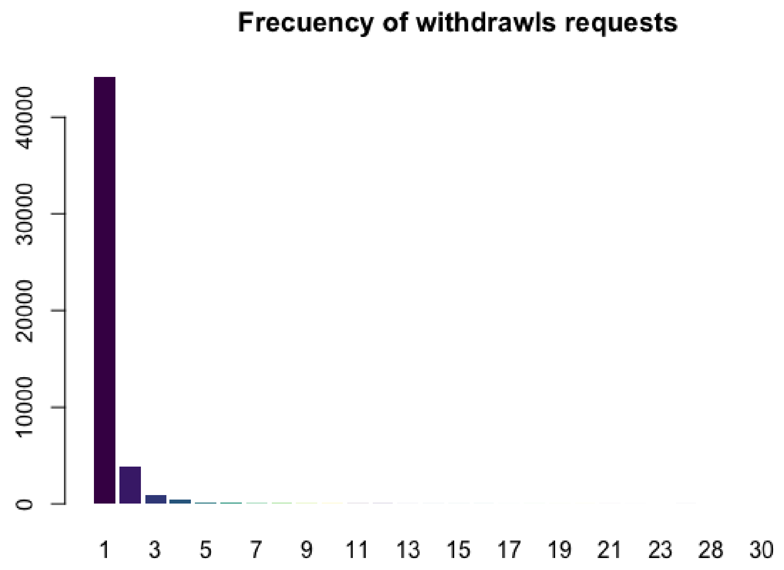
```
par(las=2)
par(mar=c(5,12,4,2))
barplot(table(DT$DES_PROVINCIA), horiz=TRUE, cex.names=0.6, col=viridis(1),  main = "Withdrawls by provinc
```



```
# Assign NA to missing data
levels(DT$DES_PROVINCIA)[levels(DT$DES_PROVINCIA)=='NO EXISTE LA PROVINCIA'] <- NA
```

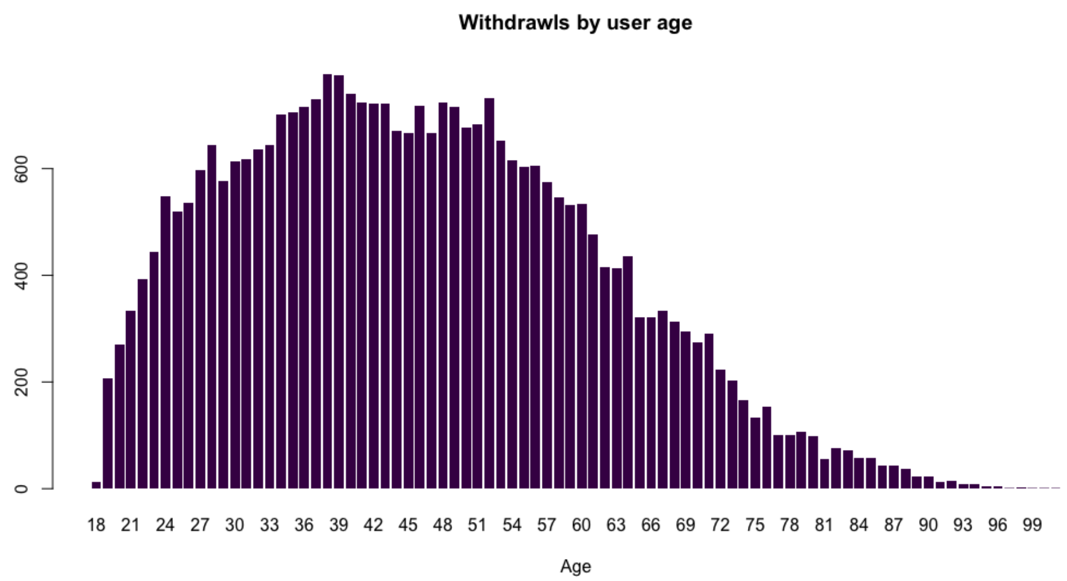
Withdrawls requests

```
barplot(table(DT$NOPER), col=viridis(10), border = NA, main="Frecuency of withdrawls requests")
```



Withdrawls by user age

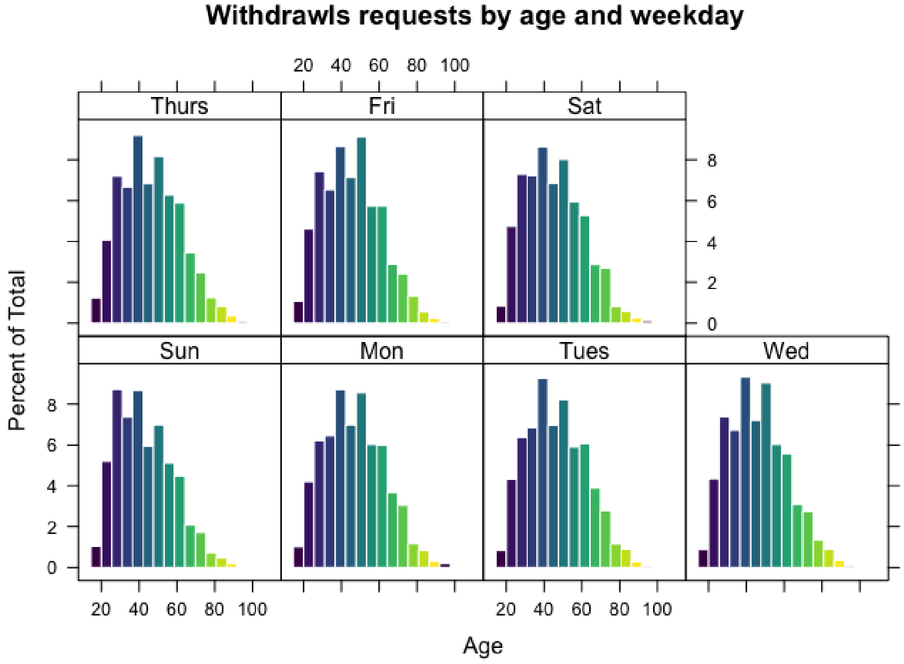
```
par(mar=c(5,5,5,5))
counts <- table(year(Sys.Date())-year(DT$PER_FECHA_NAC))
barplot(counts, col=viridis(1),  main = "Withdrawls by user age", xlab = "Age", sub="", border = NA )
```




```
rm(counts)
```

Withdrawls requests by age and weekday

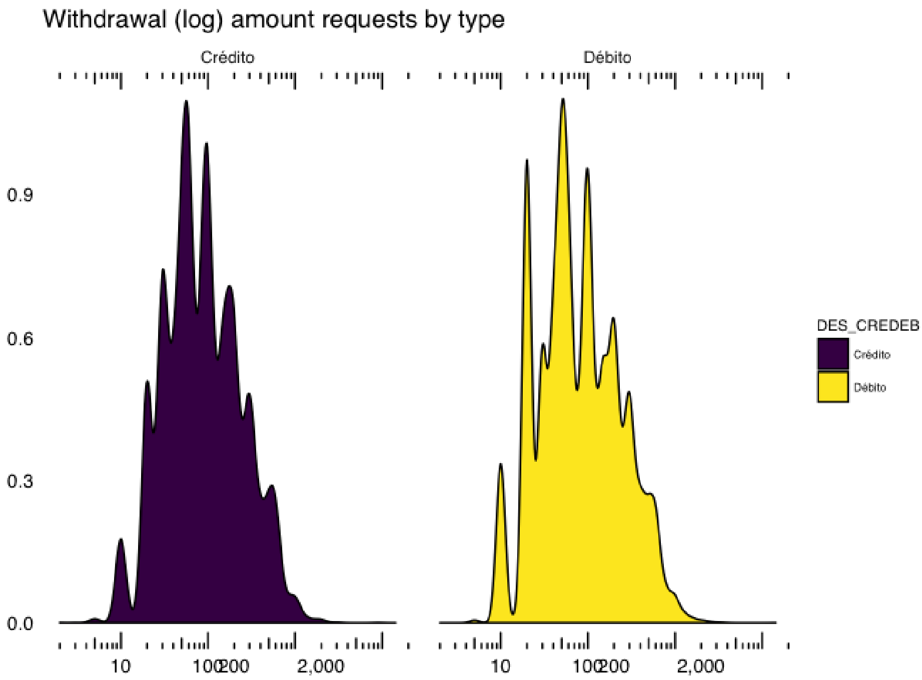
```
histogram(~ year(Sys.Date())-year(DT$PER_FECHA_NAC) | wday(DT$FECHA, label = T), data=DT, xlab = "Age", ma
```



Withdrawal amount requests by type Amount variable has been transformed into *logarithm* to reduce the effect of outliers.

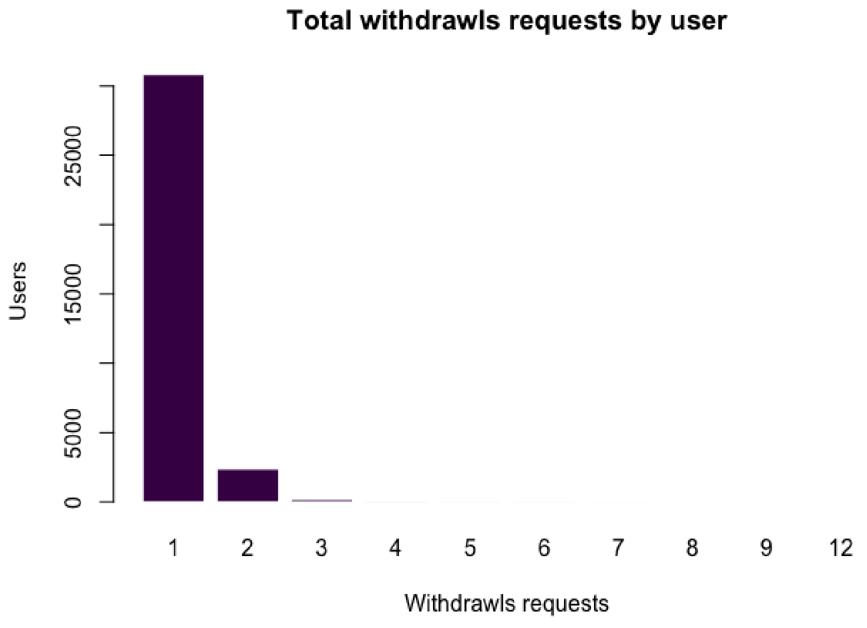
```
ggplot(DT) + geom_density(aes(x=IMPOPER, fill = DES_CREDEB), alpha = 1) + scale_x_log10(breaks=c(10,100,20
```

```
## Warning: Removed 86 rows containing non-finite values (stat_density).
```



Total withdrawls requests by user

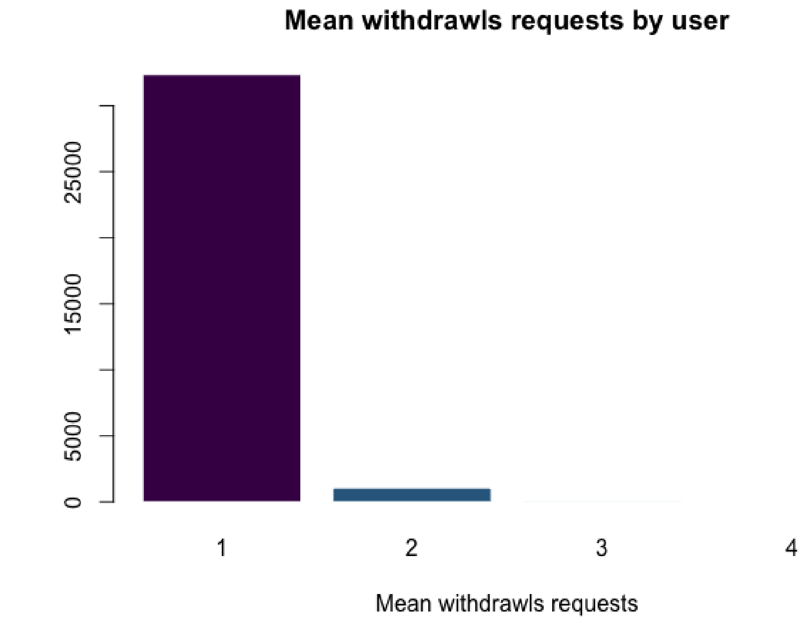
```
counts <- table(DT[!is.na(PER_ID_PERSONA),sum(NOPER), by = .(PER_ID_PERSONA)]$V1)
barplot(counts, col=viridis(1),  main = "Total withdrawls requests by user", xlab = "Withdrawls requests",
```




```
rm(counts)
```

Mean withdrawls requests by user

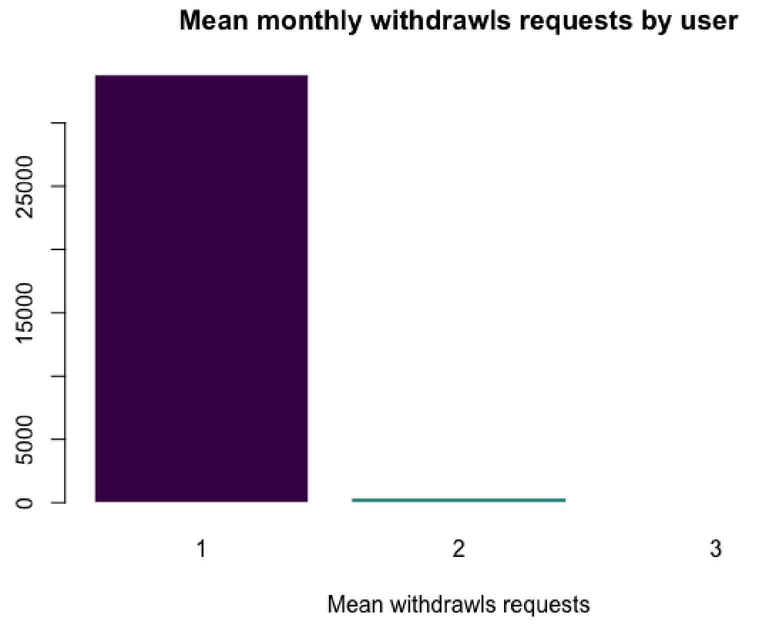
```
counts <- table(DT[!is.na(PER_ID_PERSONA),mean(na.omit(.N)), by = .(PER_ID_PERSONA)]$V1)
barplot(counts, col=viridis(4),  main = "Mean withdrawls requests by user", xlab = "Mean withdrawls reques
```




```
rm(counts)
```

Mean monthly withdrawls requests by user

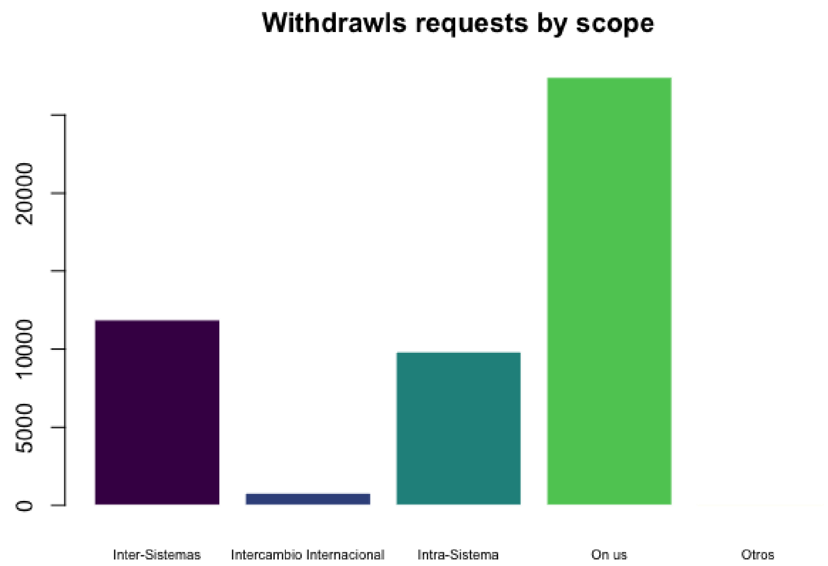
```
counts <- table(DT[!is.na(PER_ID_PERSONA),mean(na.omit(.N)), by = .(PER_ID_PERSONA, MES)]$V1)
barplot(counts, col=viridis(3),  main = "Mean monthly withdrawls requests by user", xlab = "Mean withdrawl
```




```
rm(counts)
```

Withdrawls requests by its scope

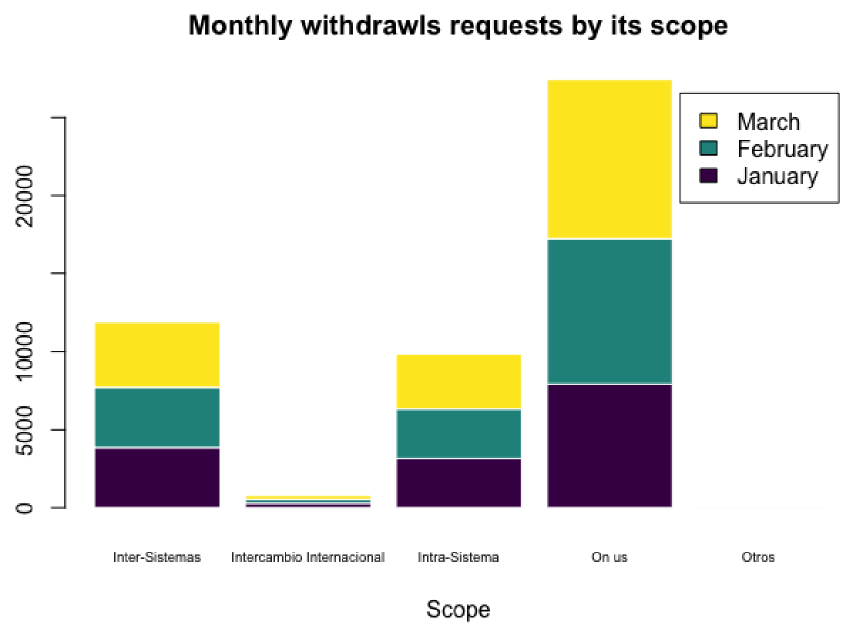
```
barplot(table(DT$DES_AMBITO), col=viridis(5), cex.names=0.6, main = "Withdrawls requests by scope", border
```



*On Us requests show withdrawls made by clients off a bank company in ATMs owned by the same company. *Inter-Sistema requests show operations between different bank companies but into the ¡ir own system (EURO 6000, Servired or 4B) *Intra-Sistema shows requests between different bank companies in different systems *Internacionales shows request between bank companies from different countries

Monthly withdrawls requests by its scope

```
counts <- table(DT$MES, DT$DES_AMBITO)
barplot(counts, col=viridis(3), cex.names=0.6, main = "Monthly withdrawls requests by its scope", xlab = "
```



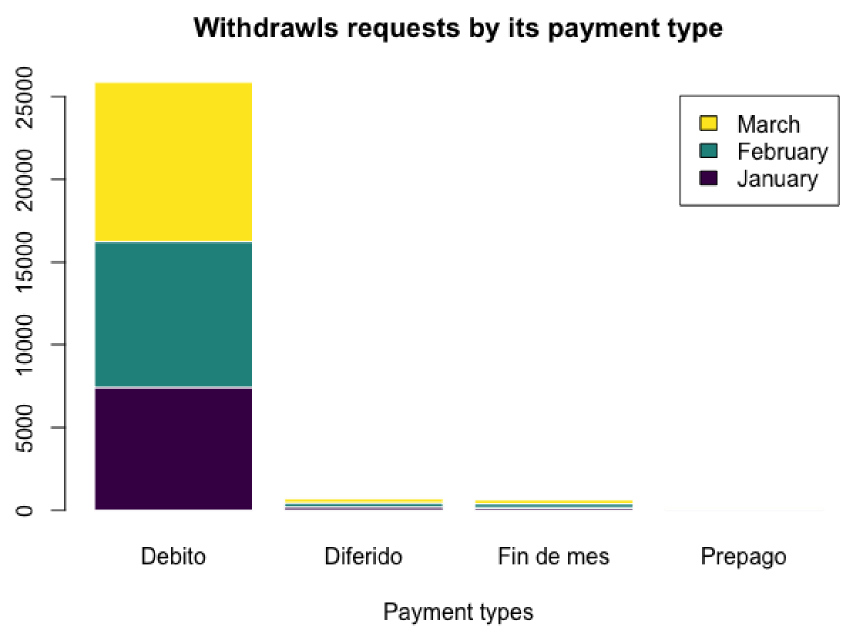

```
rm(counts)
```

Payments types

94.8% of requests are direct debit.

Withdrawls requests by its payment type

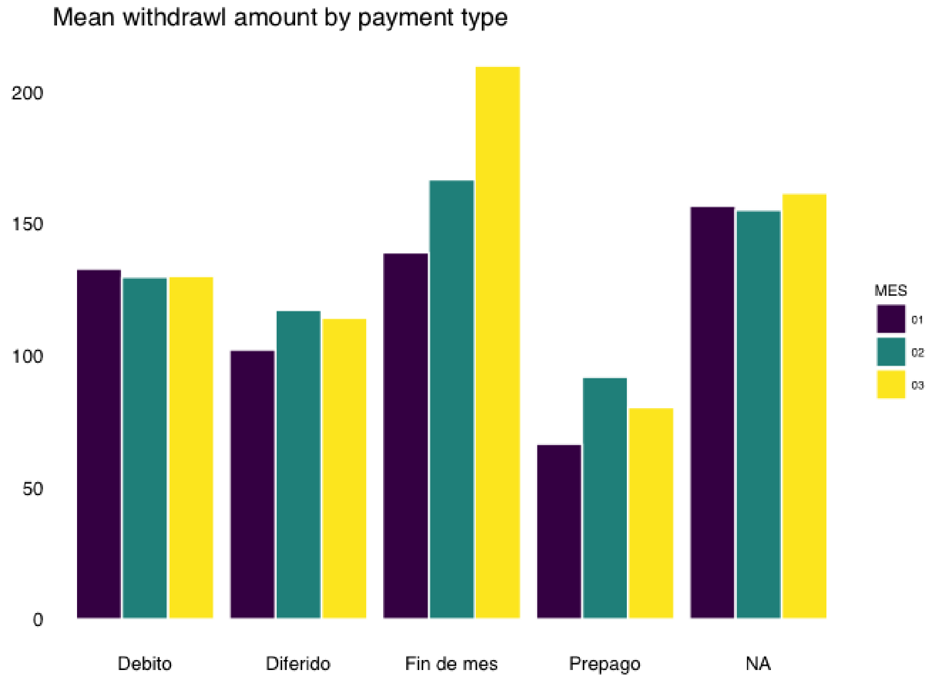
```
counts <- table(DT$MES, DT$DES_PAGO)
barplot(counts, col=viridis(3),  main = "Withdrawls requests by its payment type", xlab = "Payment types",
```




```
rm(counts)
```

Mean withdrawl amount by payment type

```
DT[,mean(na.omit(IMPOPER)), by = .(DES_PAGO, MES)] %>% ggplot(aes(x = DES_PAGO, y = V1, fill= MES)) + geom
```

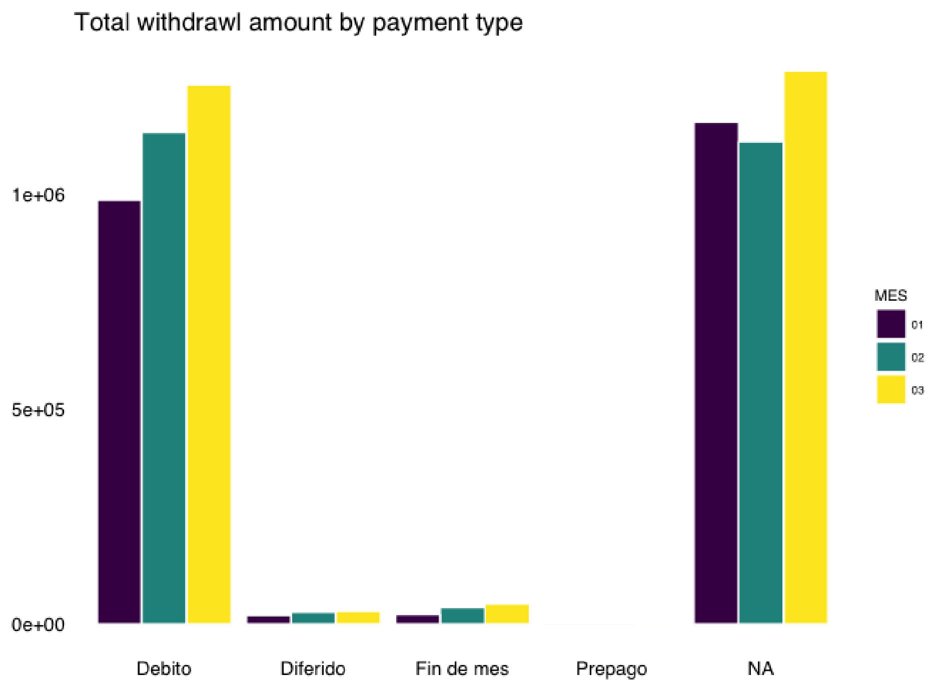



```
sum(na.omit(DT$IMPOPER))
```

```
## [1] 7146569
```

Total withdrawl amount by payment type

```
DT[,sum(na.omit(IMPOPER)), by = .(DES_PAGO, MES)] %>% ggplot(aes(x = DES_PAGO, y = V1, fill= MES)) + geom_
```



There are 86 requests without amount data, a 0.172% of the full data set.

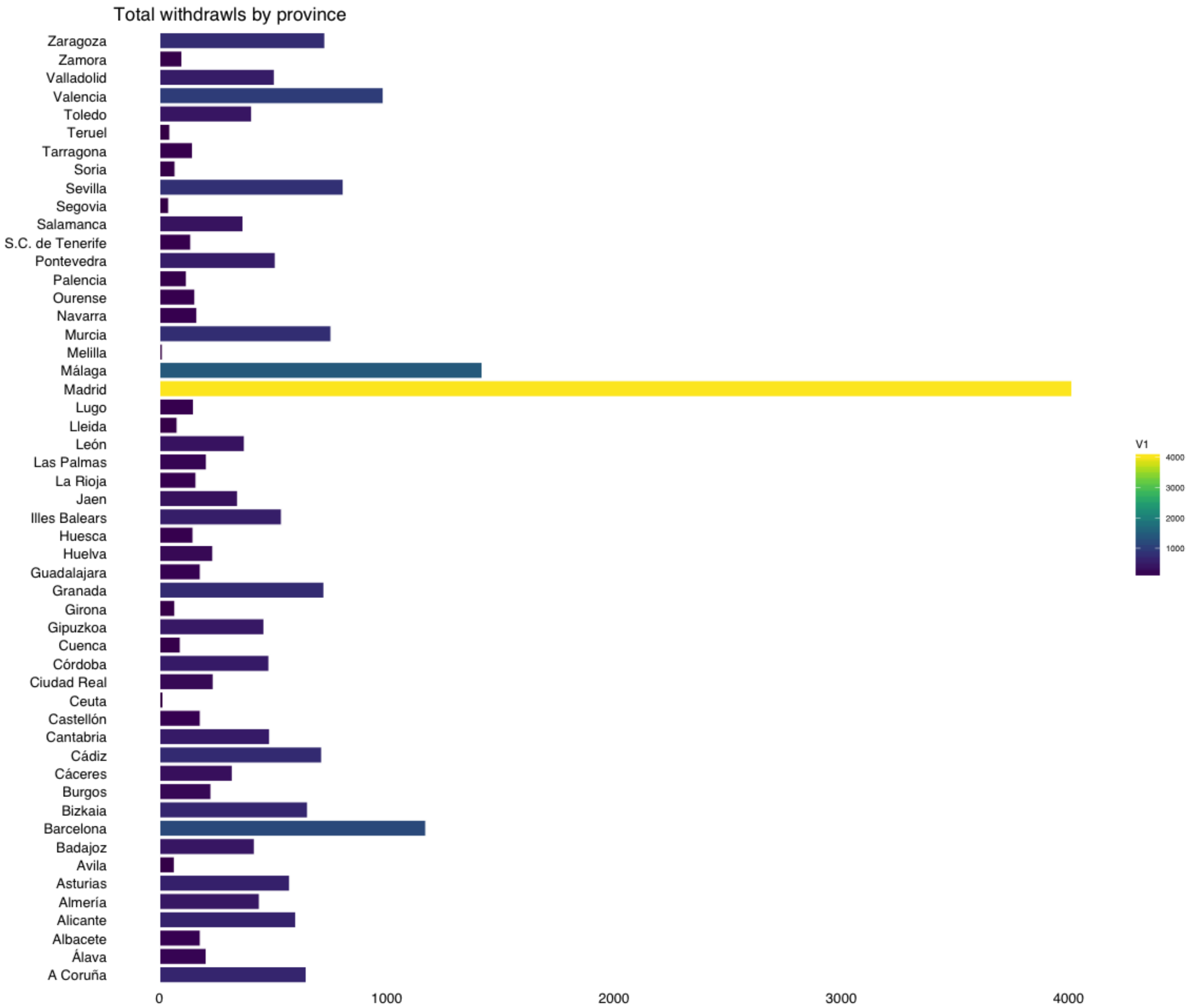
Spanish provinces

```
levels(DT$DES_PROVINCIA)[levels(DT$DES_PROVINCIA)=='NO EXISTE LA PROVINCIA'] <- NA
```

There are 27133 observations without informed province, a 54.3% of the data set.

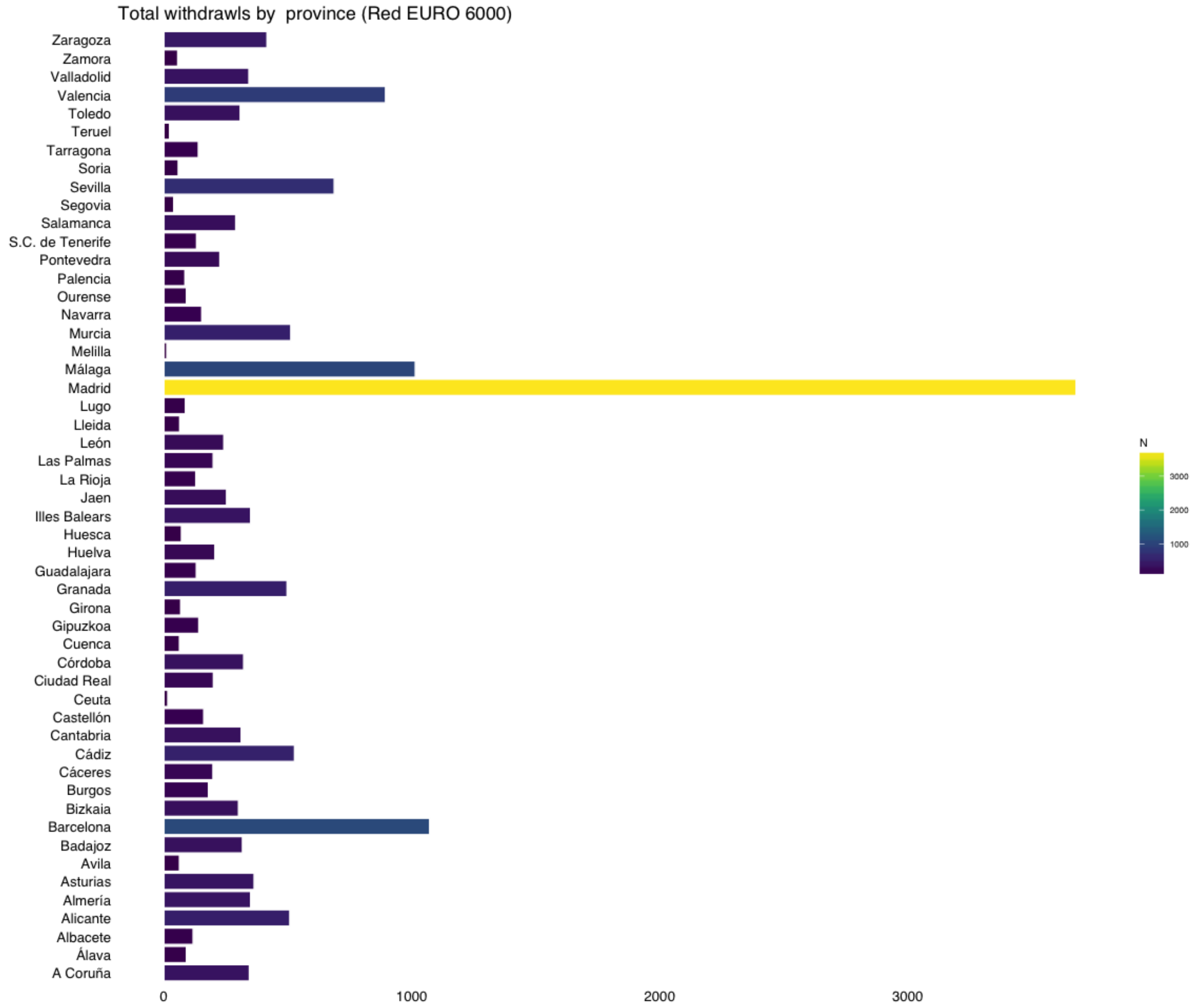
Total withdrawls by province

```
DT[!is.na(DES_PROVINCIA), (.N), by = DES_PROVINCIA] %>% ggplot(aes(x = DES_PROVINCIA, y = V1, fill= V1)) +
```



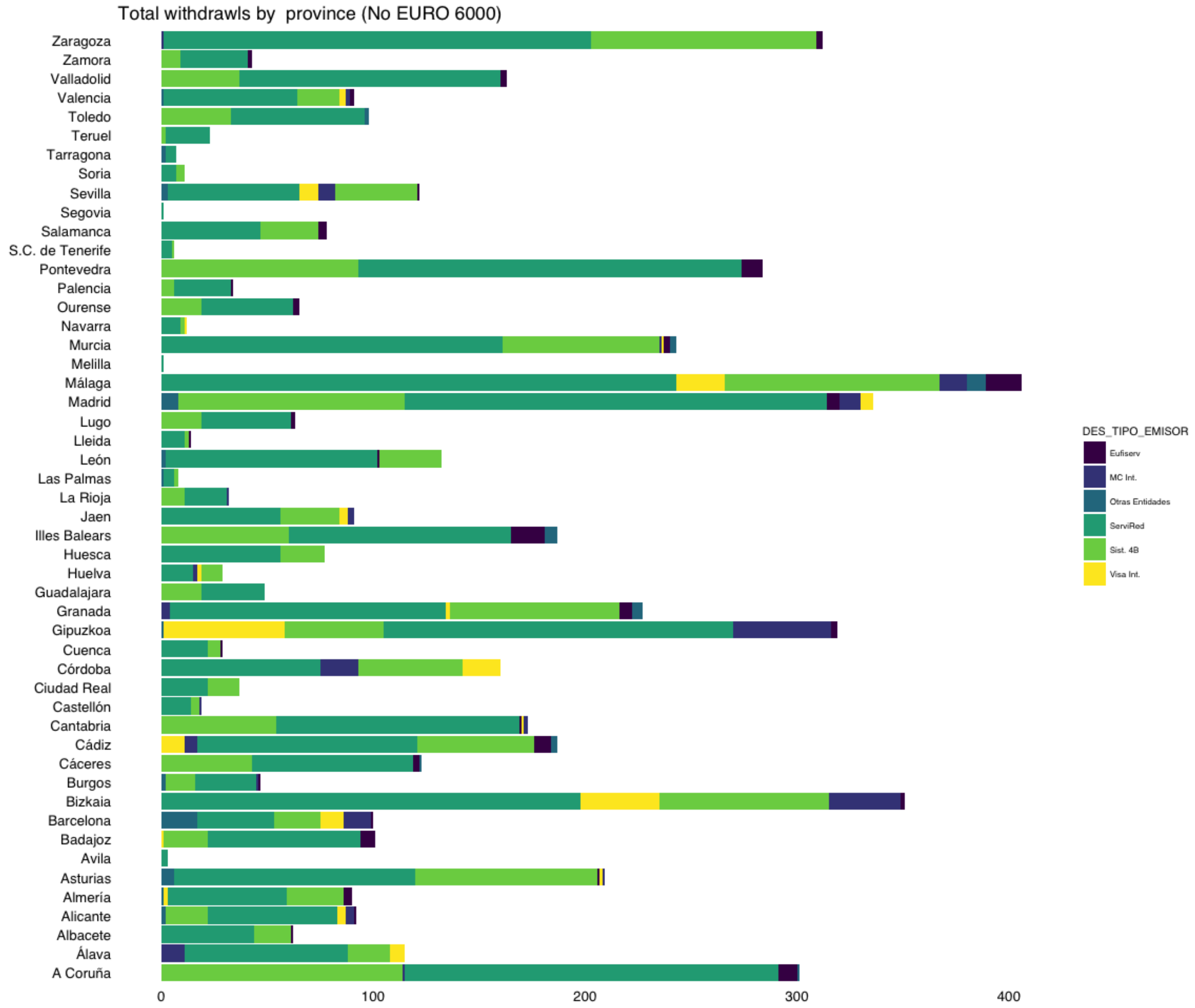
Total withdrawls by province: EURO 6000

```
DT[!is.na(DES_PROVINCIA) & DES_TIPO_EMISOR == 'EURO 6000', .N, by = .(DES_PROVINCIA, DES_TIPO_EMISOR)] %>%
```



Total withdrawls by payment province: No EURO 6000

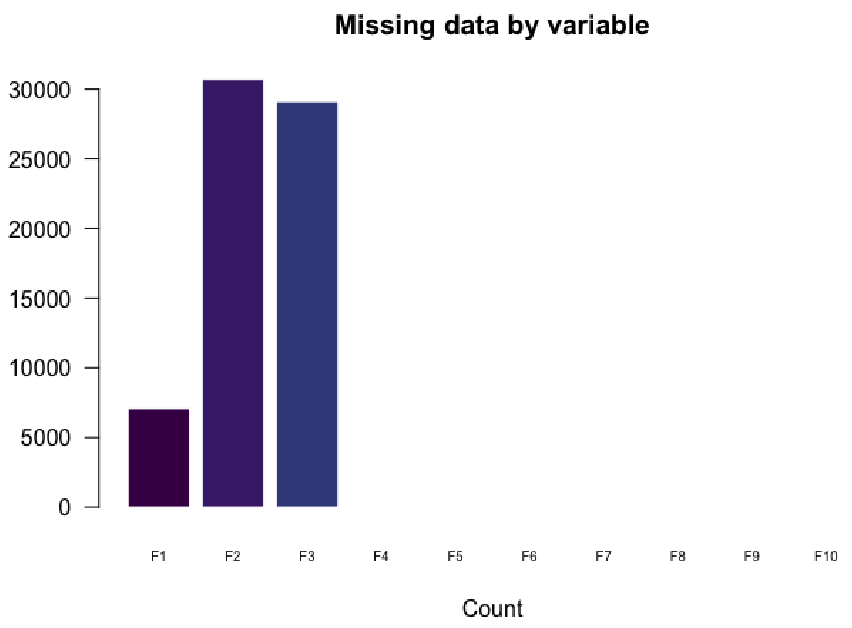
```
DT[!is.na(DES_PROVINCIA) & DES_TIPO_EMISOR != 'EURO 6000', .N, by = .(DES_PROVINCIA, DES_TIPO_EMISOR)] %>%
```



Feature engineering

Using domain knowledge of the provided data set, new variables where derived according to the main goal of this analysis.

```
# Remove no sucessfull requests and request with no user information provided
DT2 <- DT[!is.na(PER_ID_PERSONA) & DES_RESULTADO == "OK"]
rm(DT)

setkeyv(DT2,c("PER_ID_PERSONA","MES"))
DT2 <- DT2[, list(F1=median(na.omit(IMPOPER[which(DES_AMBITO == "On us")])),
                  F2=median(na.omit(IMPOPER[which(DES_AMBITO == "Inter-Sistemas")])),
                  F3=median(na.omit(IMPOPER[which(DES_AMBITO == "Intra-Sistema")]), na.rm = T),
                  F4=length(unique(.N[which(DES_AMBITO == "On us")])),
                  F5=length(unique(.N[which(DES_AMBITO == "Inter-Sistemas")])),
                  F6=length(unique(.N[which(DES_AMBITO == "Intra-Sistema")])),
                  F7=length(.N[which(DES_CREDEB == "Débito")]),
                  F8=length(.N[which(DES_CREDEB == "Crédito")]),
                  F9=sum(IMPOPER[which(DES_CREDEB == "Débito")], na.rm = T) / length(unique(MES)),
                  F10=sum(IMPOPER[which(DES_CREDEB == "Crédito")], na.rm = T) / length(unique(MES))

),
by=.(PER_ID_PERSONA)]

barplot(sapply(DT2[,c(2:11), with= FALSE], function(x) sum(is.na(x))), main = "Missing data by variable",
```




```
DT2[is.na(DT2)] <- 0

knitr::kable(head(DT2, 2))
```

PER_ID_PERSONA	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
002JN2ZPCA9DPVUE1Q7P	70	0	0	1	0	0	1	0	70	0
0034SFJMXSQT5WX8QXY1	450	0	0	1	0	0	1	0	450	0

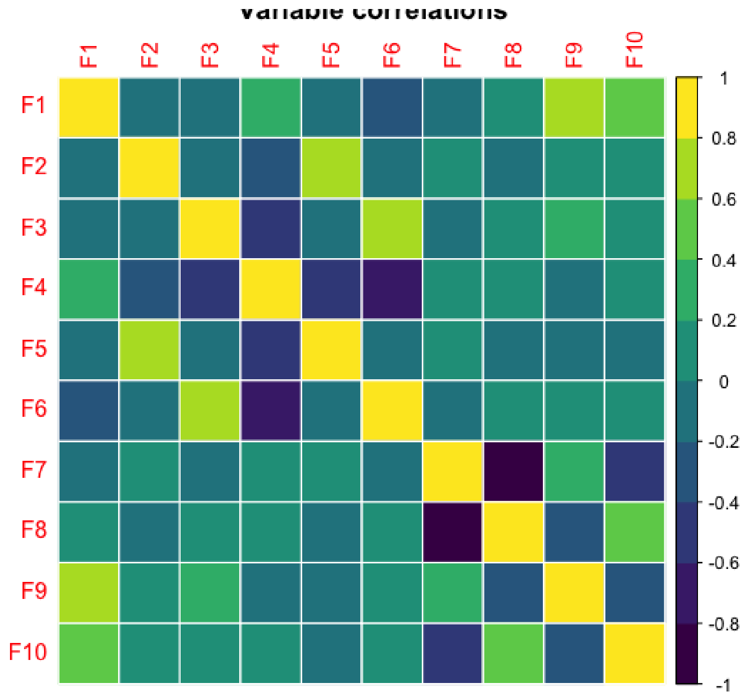
Removing high correlated variables:

Highly correlated variables usually measure the same kind of information in different ways. Many algorithms may fail of give strange results if present.

```
DT3 <- as.data.frame(DT2)
row.names(DT3) <- DT3$PER_ID_PERSONA
DT3$PER_ID_PERSONA <- NULL

correlation.mat <-cor(DT3)
knitr::kable(round(correlation.mat,2))
```

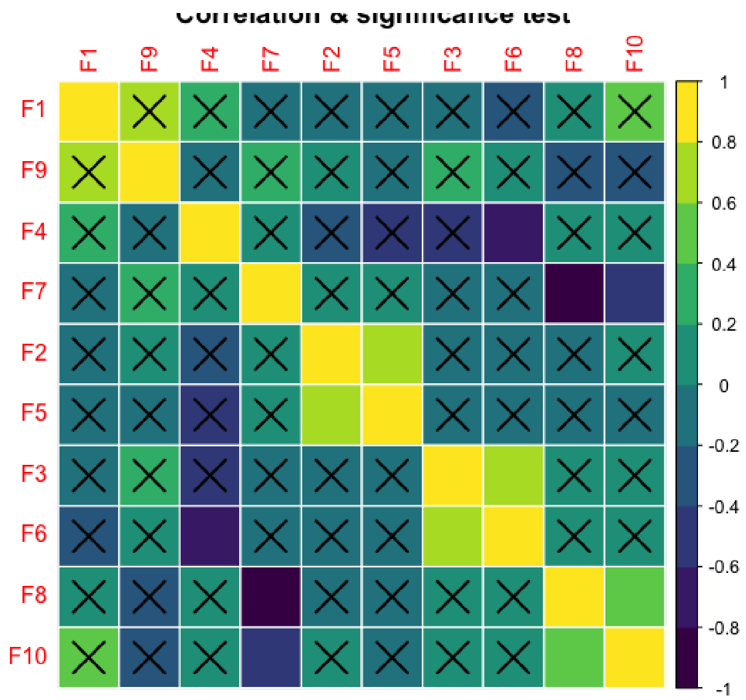
	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
F1	1.00	-0.12	-0.15	0.30	-0.19	-0.24	-0.05	0.04	0.61	0.45
F2	-0.12	1.00	-0.04	-0.33	0.61	-0.07	0.01	-0.01	0.14	0.04
F3	-0.15	-0.04	1.00	-0.43	-0.07	0.61	-0.02	0.02	0.21	0.15
F4	0.30	-0.33	-0.43	1.00	-0.53	-0.68	0.08	0.05	0.00	0.02
F5	-0.19	0.61	-0.07	-0.53	1.00	-0.11	0.03	-0.03	-0.01	-0.04
F6	-0.24	-0.07	0.61	-0.68	-0.11	1.00	-0.01	0.02	0.01	0.02
F7	-0.05	0.01	-0.02	0.08	0.03	-0.01	1.00	-0.93	0.37	-0.53
F8	0.04	-0.01	0.02	0.05	-0.03	0.02	-0.93	1.00	-0.38	0.54
F9	0.61	0.14	0.21	0.00	-0.01	0.01	0.37	-0.38	1.00	-0.22
F10	0.45	0.04	0.15	0.02	-0.04	0.02	-0.53	0.54	-0.22	1.00

```
corrplot(correlation.mat, method="color", col=viridis(10), main="Variable correlations")
```



significance test Computing the p-value of correlations:

```
cor.mtest <- function(mat, ...) {
  mat <- as.matrix(mat)
  n <- ncol(mat)
  p.mat<- matrix(NA, n, n)
  diag(p.mat) <- 0
  for (i in 1:(n - 1)) {
    for (j in (i + 1):n) {
      tmp <- cor.test(mat[, i], mat[, j], ...)
      p.mat[i, j] <- p.mat[j, i] <- tmp$p.value
    }
  }
  colnames(p.mat) <- rownames(p.mat) <- colnames(mat)
  p.mat
}

p.mat <- cor.mtest(correlation.mat)
corrplot(correlation.mat, type="ful", order="hclust", p.mat = p.mat, sig.level = 0.01, method="color", mai
```



Using the `caret` package to find correlated variables over a .9 threshold:

```
highlyCor <- findCorrelation(cor(DT3), .90, verbose = T)
```

```
## Compare row 8  and column  7 with corr  0.929
##   Means:  0.226 vs 0.21 so flagging column 8
## All correlations <= 0.9
```

High correlated variables where removed.

```
DT3$F7 <- NULL
DT3$F8 <- NULL
DT3$F9 <- NULL
DT3$F10 <- NULL
knitr::kable(head(DT3, 2))
```

	F1	F2	F3	F4	F5	F6
002JN2ZPCA9DPVUE1Q7P	70	0	0	1	0	0
0034SFJMXSQT5WX8QXY1	450	0	0	1	0	0

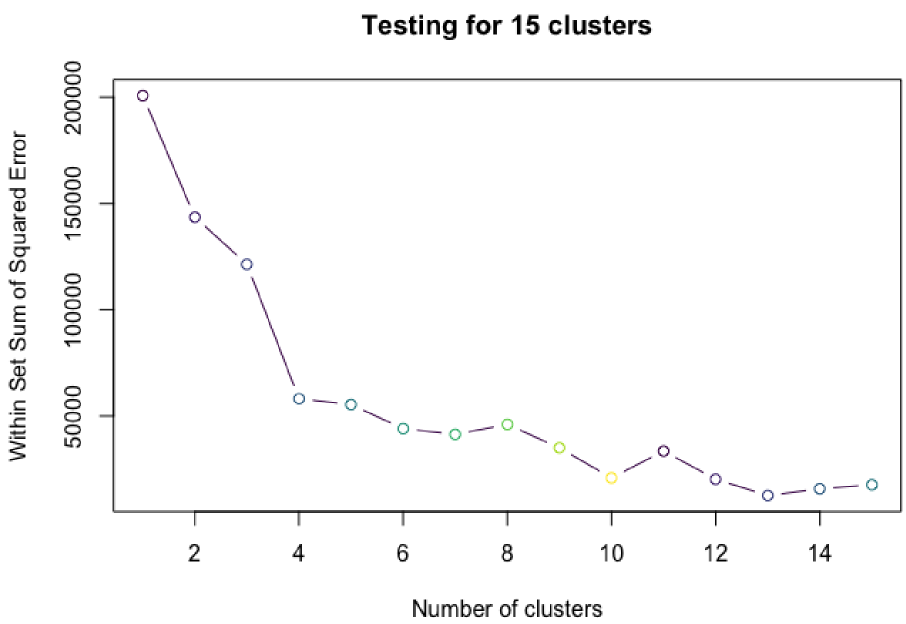
Testing the model

k-means clustering has been used as a feature learning step, in either (semi-)supervised learning or unsupervised learning.

Variable normalization

Trainning the model to find the optimal number of clusters

```
wssse <- (nrow(DT3.s)-1)*sum(apply(DT3.s,2,var))
for(i in 2:15) wssse[i]<- sum(fit=kmeans(DT3.s,centers=i,15)$withinss)
plot(1:15,wssse,type="b",main="Testing for 15 clusters",xlab="Number of clusters",ylab="Within Set Sum of
```

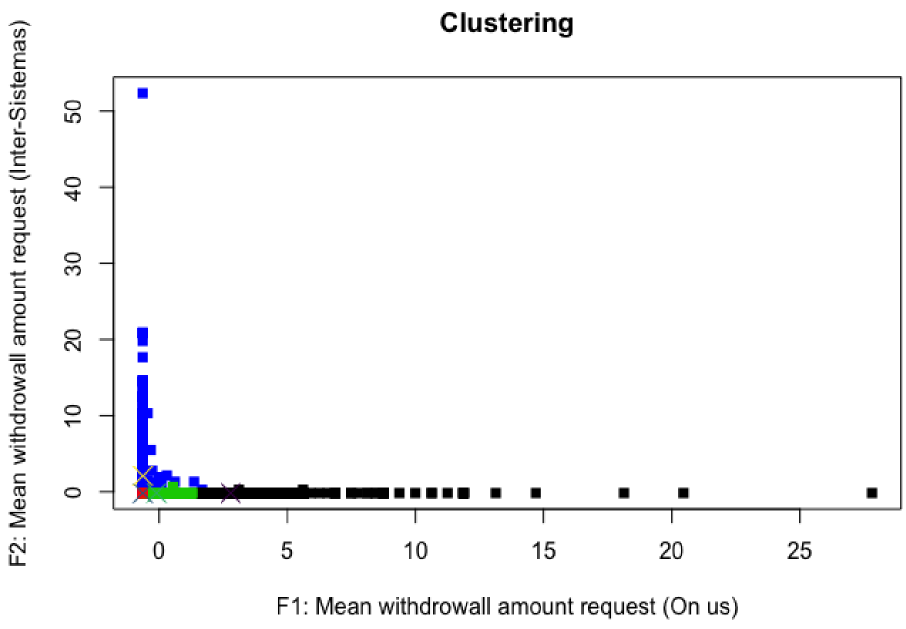


As we can see from the above output the slope of the graph changes majorly in 4th iteration, hence we consider the optimized number of cluster as 4 in which we can get the optimum result

Trainning the algorithm to find 4 clusters

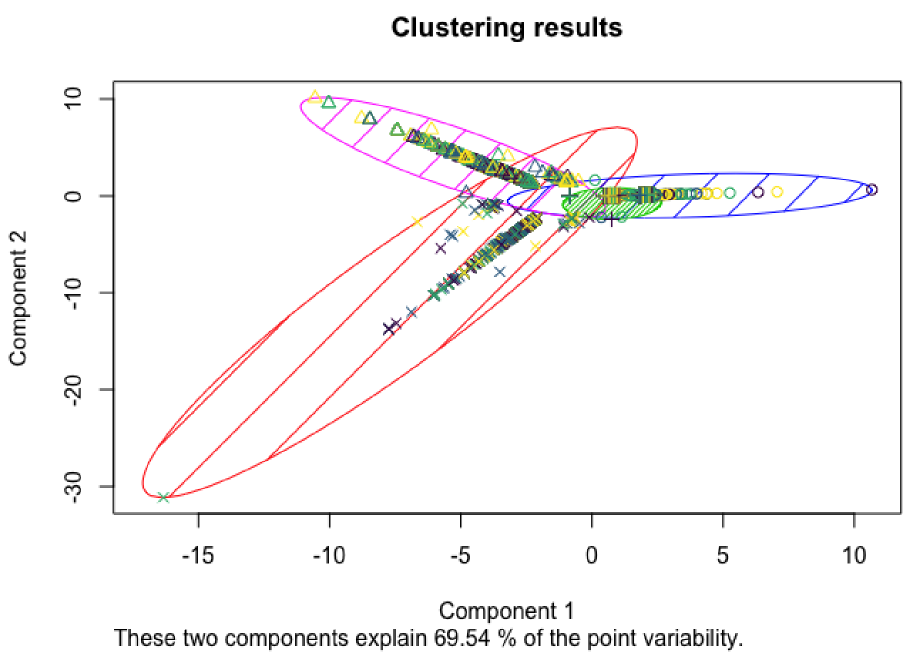
```
fit <- kmeans(DT3.s, 4)
```

```
plot(DT3.s,col=fit$cluster,pch=15, main="Clustering", xlab = "F1: Mean withdrowall amount request (On us)"
points(fit$centers,pch=4, cex = 1.9, col=viridis(4))
```



Visualizing clustering results

```
clusplot(DT3.s, fit$cluster, color=TRUE, shade=TRUE, labels=0, lines=0, col.p=viridis(4), main="Clustering
```




```
result.df <- data.frame(DT3[,c(1:6)],fit$cluster)
```

Cheking cluster composition

Group.1	F1	F2	F3	F4	F5	F6
1	548.17	0.02	0.02	1.02	0.00	0.00
2	0.63	0.00	137.87	0.01	0.00	1.02
3	85.59	0.00	0.00	1.03	0.00	0.00
4	0.74	107.33	0.68	0.01	1.01	0.01

Next steps

After this phase a R script (data_pre-processing.R) was developed to automatically process the full data set, create the new features and save them into a CSV file. This file will be uploaded to a cluster in the cloud and stored on HDFS for later usage in Spark.

The full data pre-processing phase is explained in this notebook: data_pre-processing.ipynb.