Challenge B - R Prog

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CHALLENGE B

https://github.com/charlottechemarin/Allier-Chemarin-ChallengeB.git This is the link to our repository on GitHub.

TASB 1B

QUESTION 1:

We choose to use Random Forest. We read that it is a very efficient algorithm of machine learning to check links between the different variables. It classifies the explicative variables regarding their links to the dependent variable. It produces a set of classifications on a random fraction of the data, then he makes them vote and deduces the order and the importance of the different variables.

This is the link to the website we were inpired by. http://mehdikhaneboubi.free.fr/random_forest_r.html#importation-des-donnees

QUESTION 2:

From the previous challenge, we take the datasets. We use the same code in order to clean the data (removing the missing values and changing the variables for factor ones). We choose to take Rossi's code in order to be sure there will be no mistake. We also load all the libraries we will use.

```
library(tidyverse)

library(knitr)

library(randomForest)

train <- read.csv(file.choose("train.csv"),header=T)
attach(train)

remove.vars <- train %>% summarise_all(.funs = funs(sum(is.na(.)))) %>%
gather(key = "feature", value = "missing.observations") %>%
filter(missing.observations > 100) %>% select(feature) %>% unlist
```

```r
train %>% summarise_all(.funs = funs(sum(is.na(.)))) %>% gather(key =
"feature", value = "missing.observations") %>% filter(missing.observations >
0)

##         feature missing.observations
## 1   LotFrontage                  259
## 2         Alley                 1369
## 3    MasVnrType                    8
## 4    MasVnrArea                    8
## 5      BsmtQual                   37
## 6      BsmtCond                   37
## 7  BsmtExposure                   38
## 8  BsmtFinType1                   37
## 9  BsmtFinType2                   38
## 10   Electrical                    1
## 11  FireplaceQu                  690
## 12   GarageType                   81
## 13  GarageYrBlt                   81
## 14 GarageFinish                   81
## 15   GarageQual                   81
## 16   GarageCond                   81
## 17       PoolQC                 1453
## 18        Fence                 1179
## 19  MiscFeature                 1406

train <- train %>% select(- one_of(remove.vars))

train <- train %>% filter(is.na(GarageType) == FALSE, is.na(MasVnrType) ==
FALSE, is.na(BsmtFinType2) == FALSE, is.na(BsmtExposure) == FALSE,
is.na(Electrical) == FALSE, is.na(LotFrontage) == FALSE, is.na(Alley) ==
FALSE, is.na(MasVnrType) == FALSE, is.na(MasVnrArea) == FALSE,
is.na(BsmtQual) == FALSE, is.na(BsmtCond) == FALSE, is.na(BsmtExposure) ==
FALSE, is.na(BsmtFinType1) == FALSE, is.na(BsmtFinType2) == FALSE,
is.na(Electrical) == FALSE)

#We finally remove the Id column.
train <- train[,-1]
```

Then, we chose to use the Random Forest method. We will here follw a process we found on the Internet.

```r
fit <- randomForest(train$SalePrice~., data = train)
print(fit)

##
## Call:
##  randomForest(formula = train$SalePrice ~ ., data = train)
##                Type of random forest: regression
```

```
##                      Number of trees: 500
## No. of variables tried at each split: 24
##
##           Mean of squared residuals: 684670684
##                     % Var explained: 59.85
```

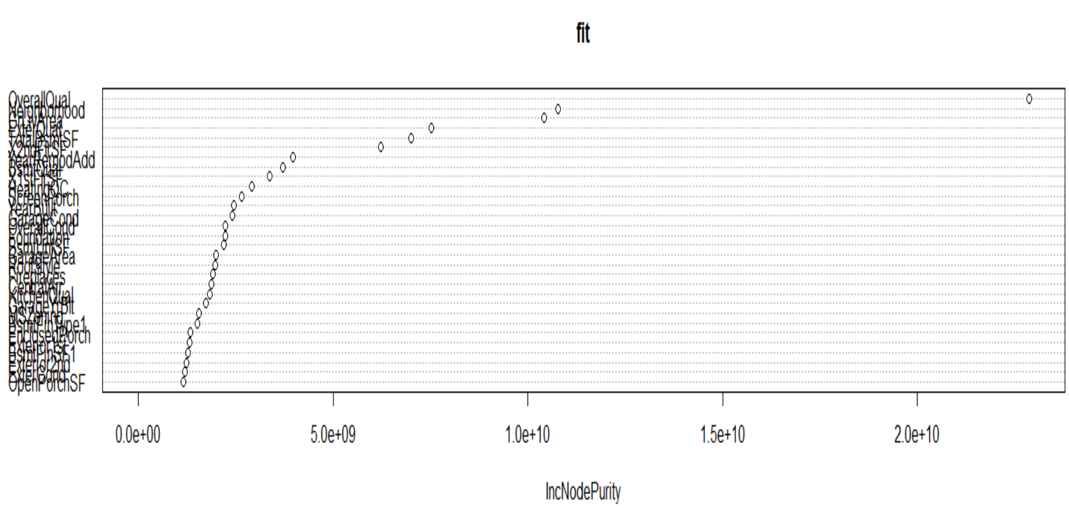
Then, we ask for the confusion matrix. In lines, we have the observations, in columns the data the model predicts.

```
summary(table(train$SalePrice, fit$predicted))
```

```
## Number of cases in table: 77
## Number of factors: 2
## Test for independence of all factors:
##  Chisq = 5236, df = 5168, p-value = 0.2506
##  Chi-squared approximation may be incorrect
```

We draw a graph to classify the explanatory variables according to their weight on the prediction.

```
varImpPlot(fit)
```



T

he command below give us the importance of each variable in an increasing way. We can see that the explanatory variables that matter the most are : utilities, street, heating, miscval, garagecond…

```
head(fit$importance[order(fit$importance[, 1], decreasing = TRUE), ])
```

```
##   OverallQual Neighborhood    GrLivArea    ExterQual  TotalBsmtSF
##   22879303096  10781099638  10413866445   7515706074   7003384426
##     X2ndFlrSF
##    6231780939
```

QUESTION 3:

We have to make predictions on the test data and compare them with the prediction we did for the last challenge. Once more, we use Rossi's code to get the first prediction of our data.

First, the code for the prediction by the linear regression:

```
test <- read.csv(file.choose("test.csv"),header=T)
attach(test)

test <- test %>% filter(is.na(GarageType) == FALSE, is.na(MasVnrType) ==
FALSE, is.na(BsmtFinType2) == FALSE, is.na(BsmtExposure) == FALSE,
is.na(Electrical) == FALSE, is.na(LotFrontage) == FALSE, is.na(Alley) ==
FALSE, is.na(MasVnrType) == FALSE, is.na(MasVnrArea) == FALSE,
is.na(BsmtQual) == FALSE, is.na(BsmtCond) == FALSE, is.na(BsmtExposure) ==
FALSE, is.na(BsmtFinType1) == FALSE, is.na(BsmtFinType2) == FALSE,
is.na(Electrical) == FALSE)


lm_model <- lm(SalePrice ~ MSZoning + LotArea + Neighborhood  + YearBuilt +
OverallQual, data = train)
summary(lm_model)

## 
## Call:
## lm(formula = SalePrice ~ MSZoning + LotArea + Neighborhood + 
##     YearBuilt + OverallQual, data = train)
## 
## Residuals:
##    Min     1Q Median     3Q    Max 
## -54123 -12726  -4308  13475 103461 
## 
## Coefficients: (1 not defined because of singularities)
##                       Estimate Std. Error t value Pr(>|t|)   
## (Intercept)         -1.366e+05  4.254e+05  -0.321  0.74919   
## MSZoningFV           1.772e+04  3.931e+04   0.451  0.65368   
## MSZoningRH           5.442e+04  4.916e+04   1.107  0.27248   
## MSZoningRL           2.066e+04  2.893e+04   0.714  0.47781   
## MSZoningRM           2.631e+04  2.498e+04   1.053  0.29622   
## LotArea              3.828e+00  1.422e+00   2.692  0.00908 **
## NeighborhoodCrawfor -7.101e+03  3.277e+04  -0.217  0.82914   
## NeighborhoodEdwards -4.829e+04  2.160e+04  -2.235  0.02896 * 
## NeighborhoodIDOTRR  -4.050e+04  2.753e+04  -1.471  0.14627   
## NeighborhoodNAmes   -2.305e+04  3.289e+04  -0.701  0.48595   
## NeighborhoodOldTown -3.152e+04  2.285e+04  -1.380  0.17259   
## NeighborhoodSomerst         NA         NA      NA       NA
```

```
## NeighborhoodSWISU   -1.182e+04  3.410e+04  -0.347  0.73008
## YearBuilt            7.294e+01  2.173e+02   0.336  0.73828
## OverallQual          1.905e+04  3.851e+03   4.948 5.89e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 27970 on 63 degrees of freedom
## Multiple R-squared:  0.6247, Adjusted R-squared:  0.5472
## F-statistic: 8.066 on 13 and 63 DF,  p-value: 3.381e-09
```

```
predict1 <- data.frame(Id = test$Id, SalePrice_predict = predict(lm_model,
test, type="response"))
```

```
head(predict1)
```

```
##     Id SalePrice_predict
## 1 1497          174140.6
## 2 1498          172992.2
## 3 1499          170423.6
## 4 1500          151442.1
## 5 1503          229379.3
## 6 1533          118440.6
```

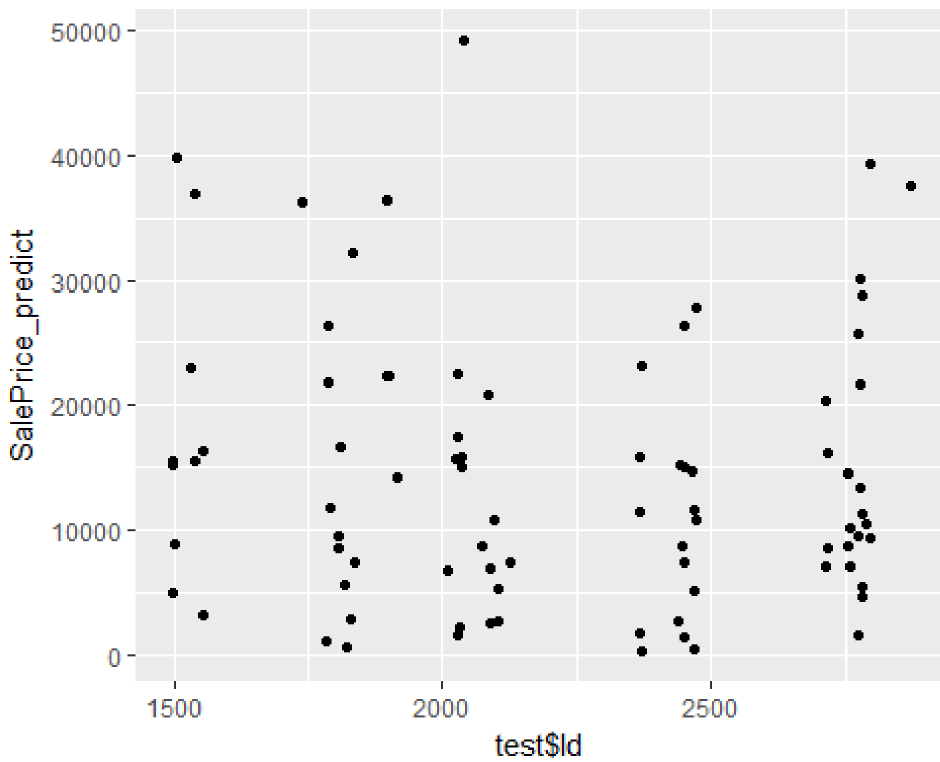
Then, with Random Forest:

```
#First, we correct the levels of the variables in order to make the two
datasets match.
levels(test$Utilities) <- levels(train$Utilities)
levels(test$Condition2) <- levels(train$Condition2)
levels(test$HouseStyle) <- levels(train$HouseStyle)
levels(test$RoofMatl) <- levels(train$RoofMatl)
levels(test$Exterior2nd) <- levels(train$Exterior2nd)
levels(test$Electrical) <- levels(train$Electrical)
levels(test$GarageQual) <- levels(train$GarageQual)
levels(test$Exterior1st) <- levels(train$Exterior1st)
levels(test$Heating) <- levels(train$Heating)

#Then, we predict
predict2 <- data.frame(Id = test$Id, SalePrice_predict = predict(fit, test,
type="response"))
head(predict2)
```

```
##     Id SalePrice_predict
## 1 1497          169052.3
## 2 1498          157502.1
## 3 1499          155245.2
## 4 1500          160368.2
## 5 1503          189545.1
## 6 1533          141489.2
```

To compare the two predictions, we make plots.

```
#First, we can compute the difference between the two predictions.
diff <- data.frame(SalePrice_predict = abs(predict1$SalePrice_predict -
predict2$SalePrice_predict))
head(diff)

##   SalePrice_predict
## 1          5088.343
## 2         15490.101
## 3         15178.386
## 4          8926.103
## 5         39834.212
## 6         23048.572

ggplot(diff, aes(x=test$Id, y=SalePrice_predict)) + geom_point()
```



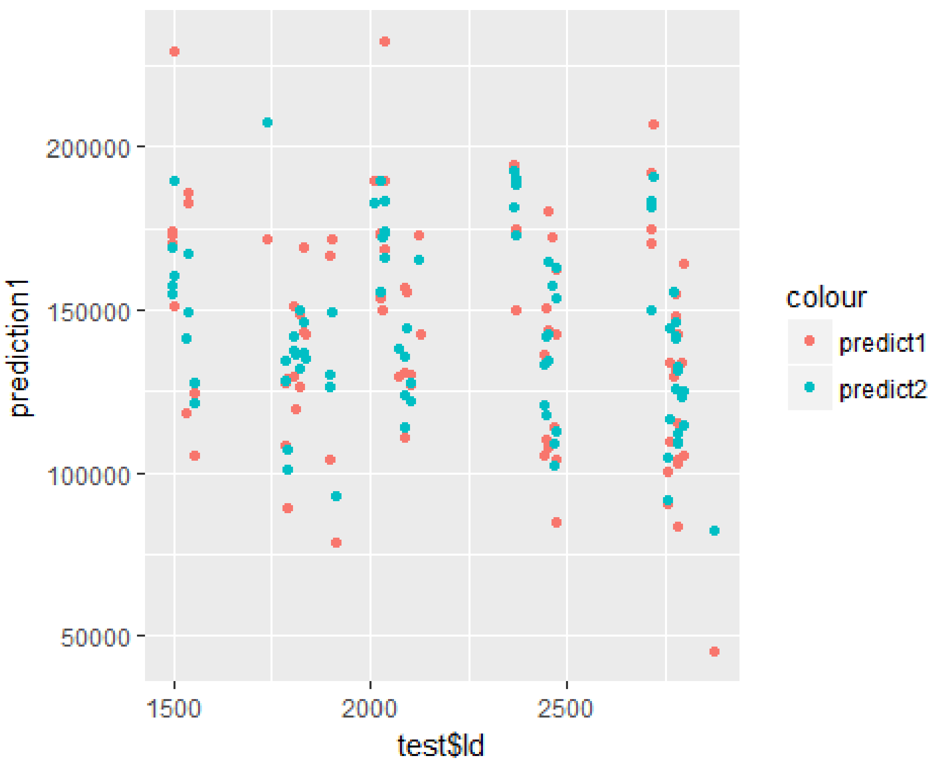

```
#We can see that the matching between the two predictions is unequal among
the observations.
```

Then, we can compare the two predictions.

```
prediction1 <- predict1$SalePrice_predict
prediction2 <- predict2$SalePrice_predict

predictions <- data.frame(test$Id, prediction1 = predict1$SalePrice_predict,
prediction2 = predict2$SalePrice_predict)
head(predictions)
```

```
##   test.Id prediction1 prediction2
## 1    1497    174140.6    169052.3
## 2    1498    172992.2    157502.1
## 3    1499    170423.6    155245.2
## 4    1500    151442.1    160368.2
## 5    1503    229379.3    189545.1
## 6    1533    118440.6    141489.2
```

```
ggplot(data= predictions) + geom_point(data = predict1, aes(x= test$Id,
y=prediction1, color = "predict1")) + geom_point(data = predict2, aes(x=Id,
y=prediction2, color = "predict2"))
```



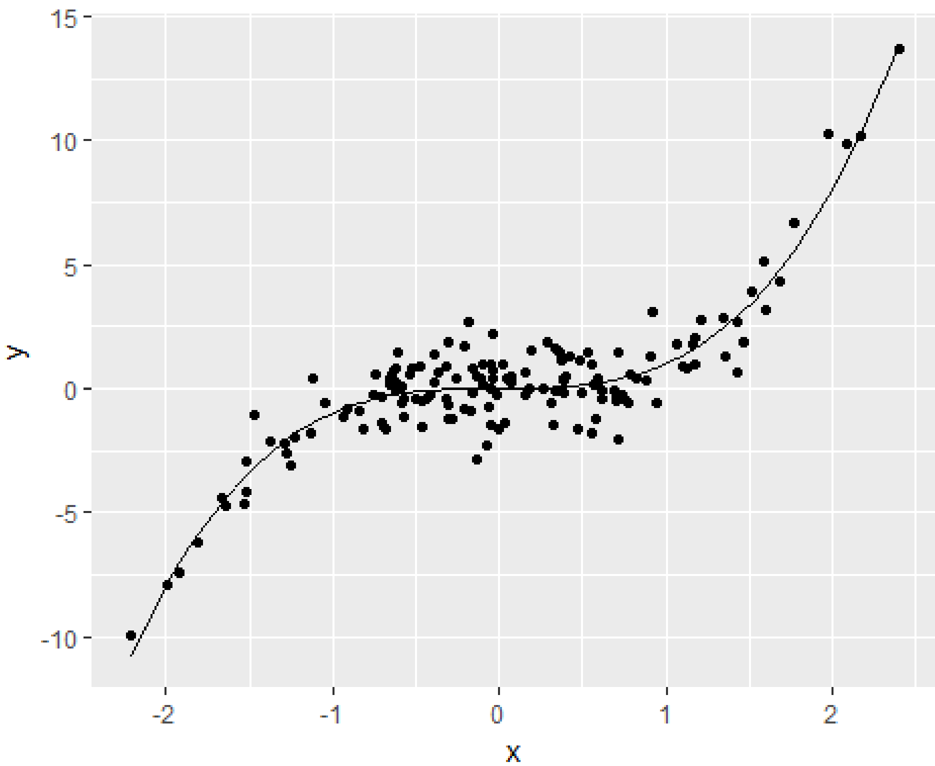
TASK 2B

We have chosen to take the correct code from the Challenge A written by Rossi Abi-Rafeh to be sure that there will be no mistakes:

Indeed, here is the code of the Challenge A:

```
# We simulate an overfit:
library(tidyverse)
library(np)

library(caret)
```

```r
# We compute the true model : y = x^3 + epsilon
set.seed(1)
Nsim <- 150
b <- c(0,1)
x0 <- rep(1, Nsim)
x1 <- rnorm(n = Nsim)

X <- cbind(x0, x1^3)
y.true <- X %*% b

eps <- rnorm(n = Nsim)
y <- X %*% b + eps

df <- tbl_df(y[,1]) %>% rename(y = value) %>% bind_cols(tbl_df(x1)) %>%
rename(x = value) %>% bind_cols(tbl_df(y.true[,1])) %>% rename(y.true =
value)

# We simulate Nsim = 100 points of (y,x)
ggplot(df) + geom_point(mapping = aes(x = x, y = y)) +
  geom_line(mapping = aes(x = x, y = y.true))
```



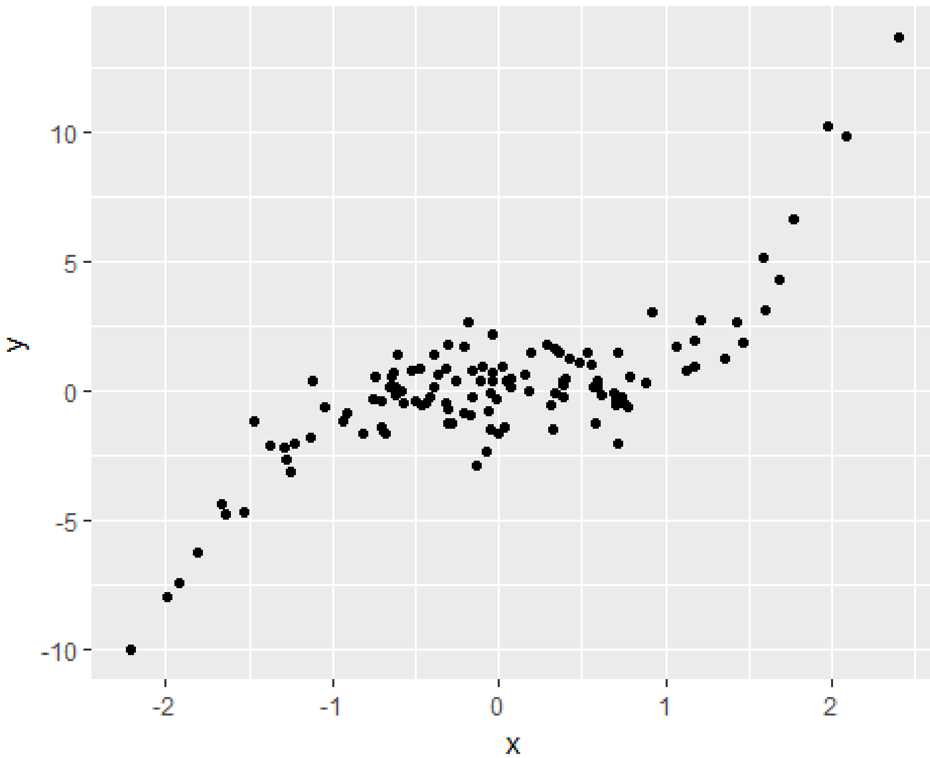

```r
# We split the sample into training and testing:
training.index <- createDataPartition(y = y, times = 1, p = 0.8)
df <- df %>% mutate(which.data = ifelse(1:n() %in% training.index$Resample1,
"training", "test"))
```

```r
training <- df %>% filter(which.data == "training")
test <- df %>% filter(which.data == "test")

# We create the model lm.fit:
lm.fit <- lm(y ~ x, data = training)
summary(lm.fit)

##
## Call:
## lm(formula = y ~ x, data = training)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.7575 -1.0695  0.0419  1.0229  7.6216
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.1950     0.1649   1.183    0.239
## x             2.4446     0.1846  13.241   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.82 on 120 degrees of freedom
## Multiple R-squared:  0.5937, Adjusted R-squared:  0.5903
## F-statistic: 175.3 on 1 and 120 DF,  p-value: < 2.2e-16

df <- df %>% mutate(y.lm = predict(object = lm.fit, newdata = df))
training <- training %>% mutate(y.lm = predict(object = lm.fit))
```

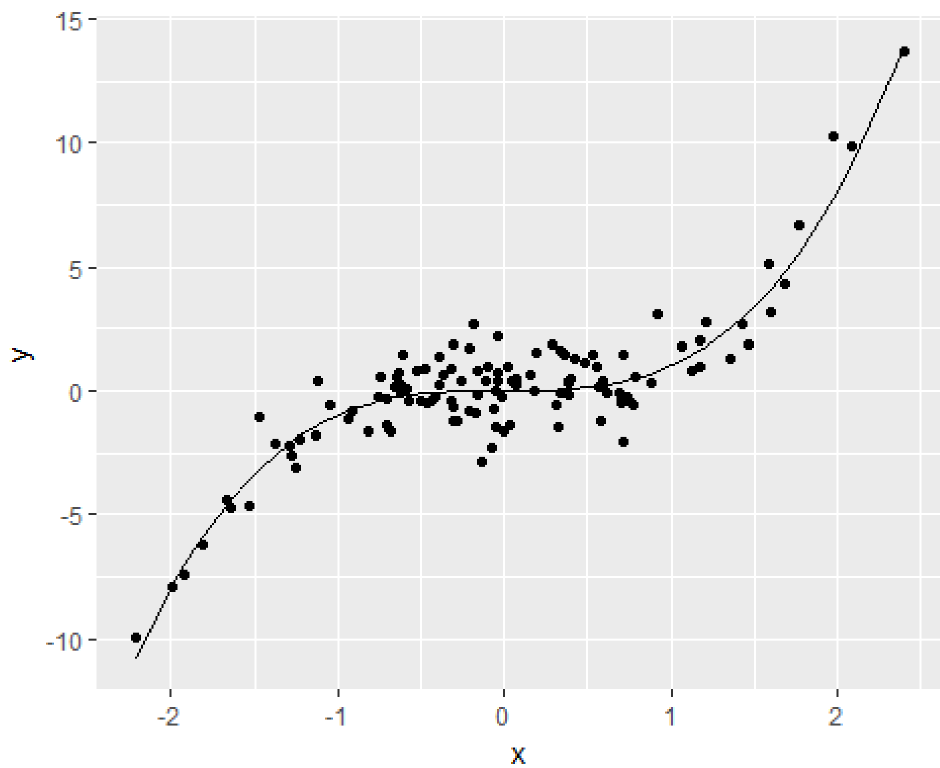
Now, we can compute all the steps of the Task 2B:

```r
#Step 1:

# We estimate a low-flexibility local linear model on the training data:
ll.fit.lowflex <- npreg(y ~ x, data = training, method = "ll", bws = 0.5)
summary(ll.fit.lowflex)

##
## Regression Data: 122 training points, in 1 variable(s)
##                 x
## Bandwidth(s): 0.5
##
## Kernel Regression Estimator: Local-Constant
## Bandwidth Type: Fixed
## Residual standard error: 1.442574
## R-squared: 0.8569977
##
## Continuous Kernel Type: Second-Order Gaussian
## No. Continuous Explanatory Vars.: 1
```

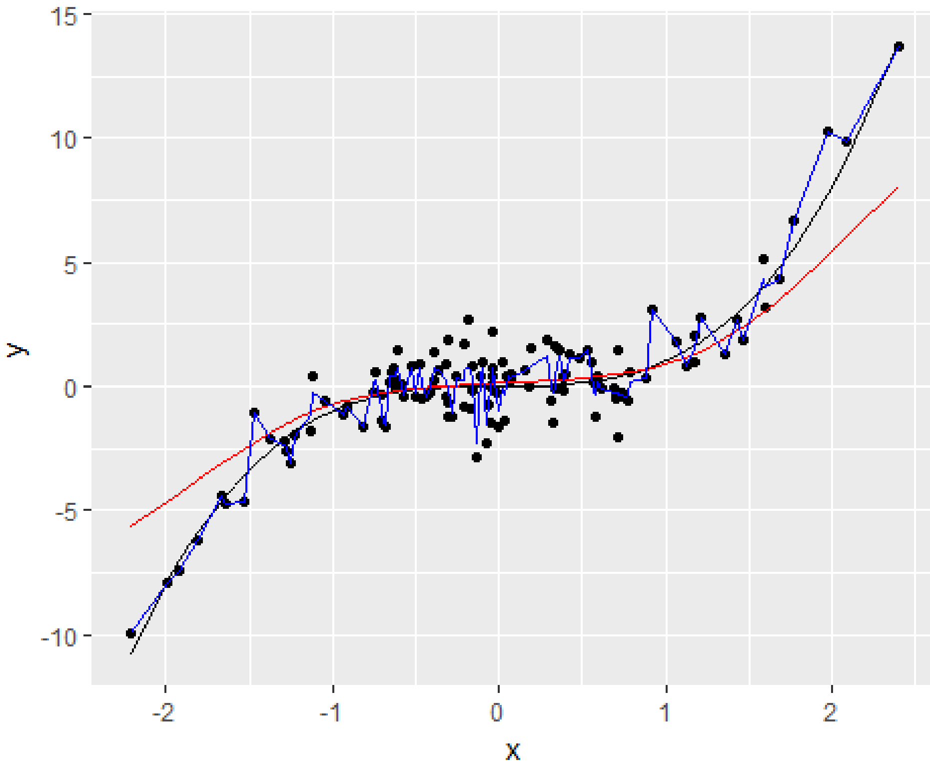
```r
#Step 2:

# We estimate a high-flexibility local linear model on the training data:
ll.fit.highflex <- npreg(y ~ x, data = training, method = "ll", bws = 0.01)
summary(ll.fit.highflex)

##
## Regression Data: 122 training points, in 1 variable(s)
##                   x
## Bandwidth(s): 0.01
##
## Kernel Regression Estimator: Local-Constant
## Bandwidth Type: Fixed
## Residual standard error: 0.5882872
## R-squared: 0.9569811
##
## Continuous Kernel Type: Second-Order Gaussian
## No. Continuous Explanatory Vars.: 1

#Step 3:

#We create the predictions of the two models above:

training <- training %>% mutate(y.ll.lowflex = predict(object =
ll.fit.lowflex, newdata = training), y.ll.highflex = predict(object =
ll.fit.highflex, newdata = training))

#Then, we plot the scatterplot of x-y on training data:

#First, we get the simple plot of training:

ggplot(training) + geom_point(mapping = aes(x = x, y = y))
```



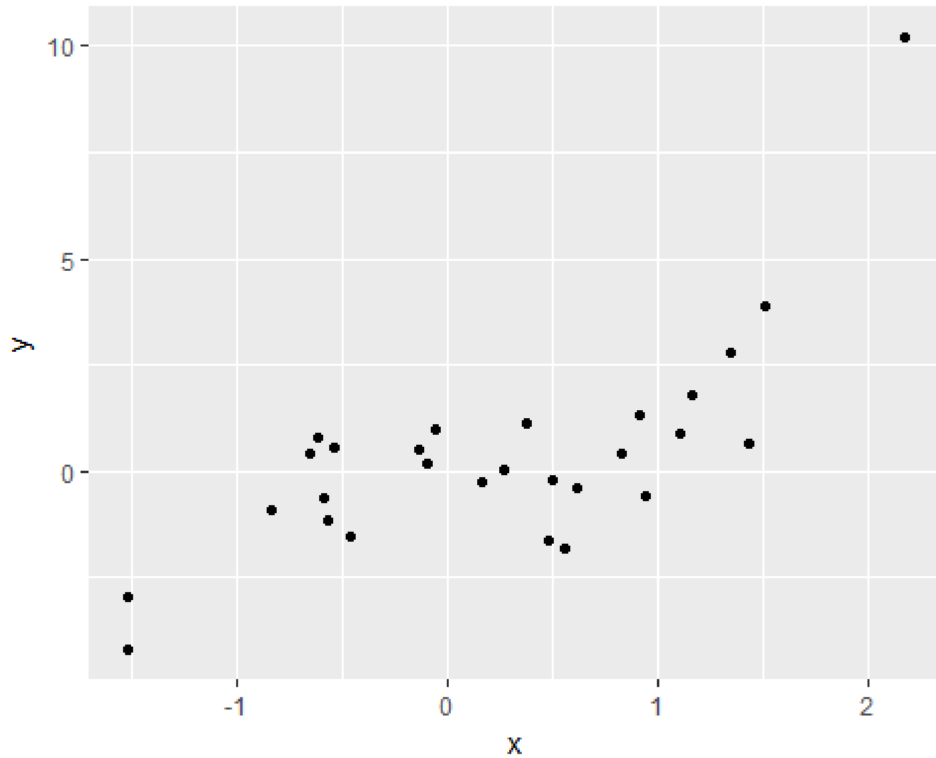

```r
#Then, we add the true regression line:

ggplot(training) + geom_point(mapping = aes(x = x, y = y)) +
  geom_line(mapping = aes(x = x, y = y.true))
```



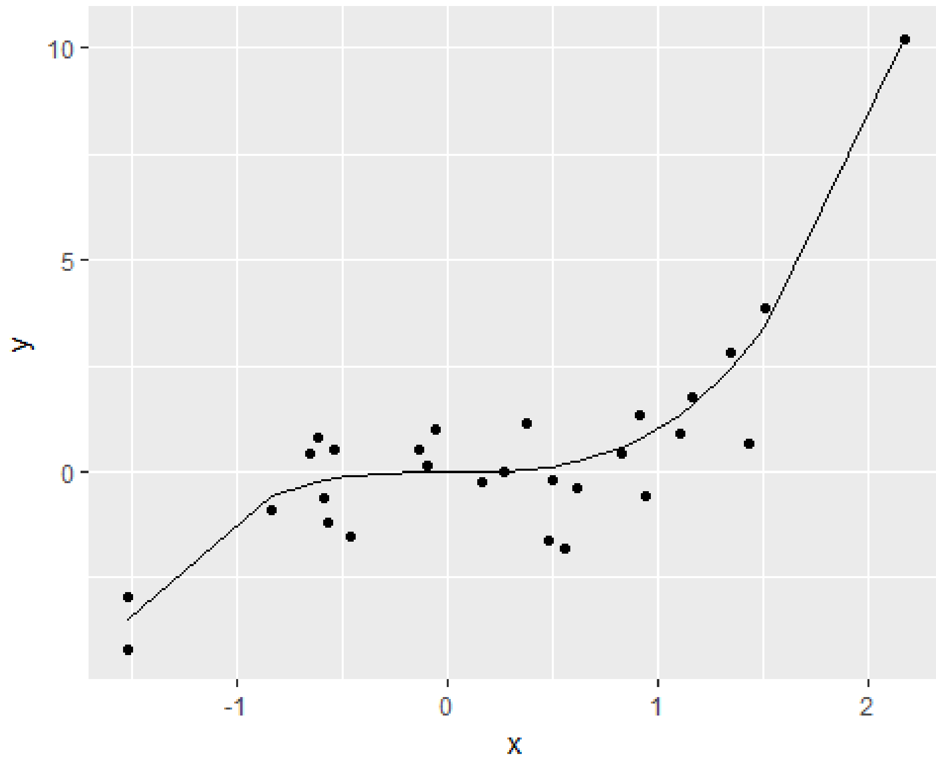

```r
#And we can get the scatterplot of x-y with the predictions of the 2 models:

ggplot(training) + geom_point(mapping = aes(x = x, y = y)) +
  geom_line(mapping = aes(x = x, y = y.true)) +
  geom_line(mapping = aes(x = x, y = y.ll.lowflex), color = "red") +
  geom_line(mapping = aes(x = x, y = y.ll.highflex), color = "blue")
```



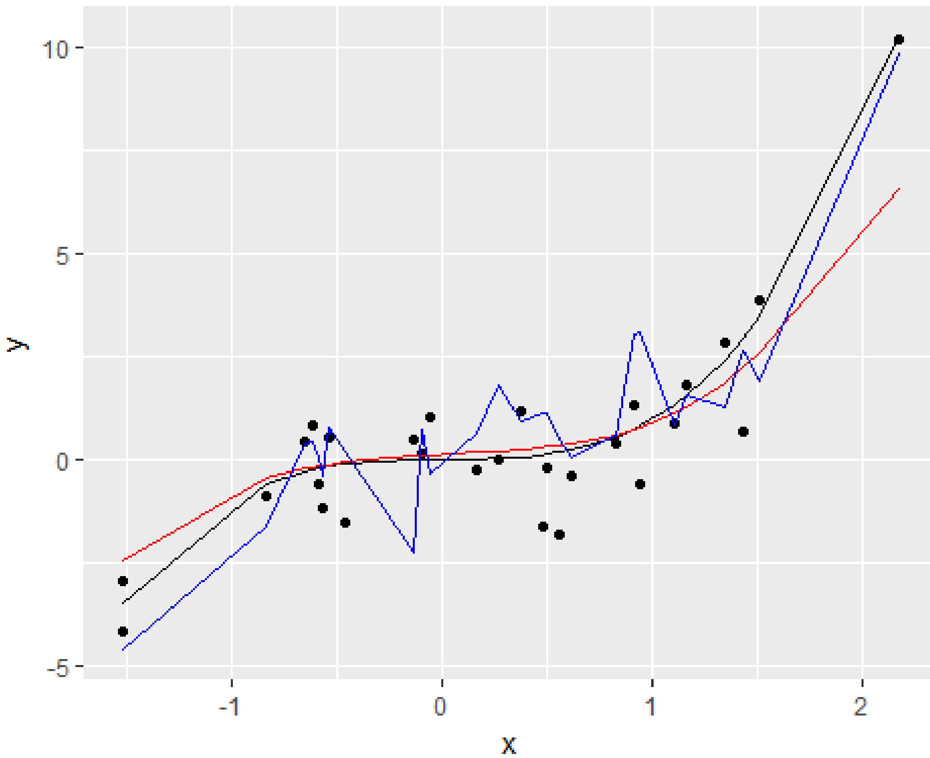

```
#Step 4:

#The predictions of fit.highflex are more variables than the predictions of fit.lowflex, indeed, we observe more variations from the fit.highflex line than from the fit.lowflex line. The predictions of fit.lowflex have then the least bias.

#Step 5:

#First, we create the predictions of the two models on the test data:

test <- test %>% mutate(y.ll.lowflex = predict(object = ll.fit.lowflex, newdata = test), y.ll.highflex = predict(object = ll.fit.highflex, newdata = test))

#Then, we plot the scatterplot of x-y on test data:

#First, we get the simple plot of test:

ggplot(test) + geom_point(mapping = aes(x = x, y = y))
```




```r
#Then, we add the true regression line:

ggplot(test) + geom_point(mapping = aes(x = x, y = y)) +
  geom_line(mapping = aes(x = x, y = y.true))
```

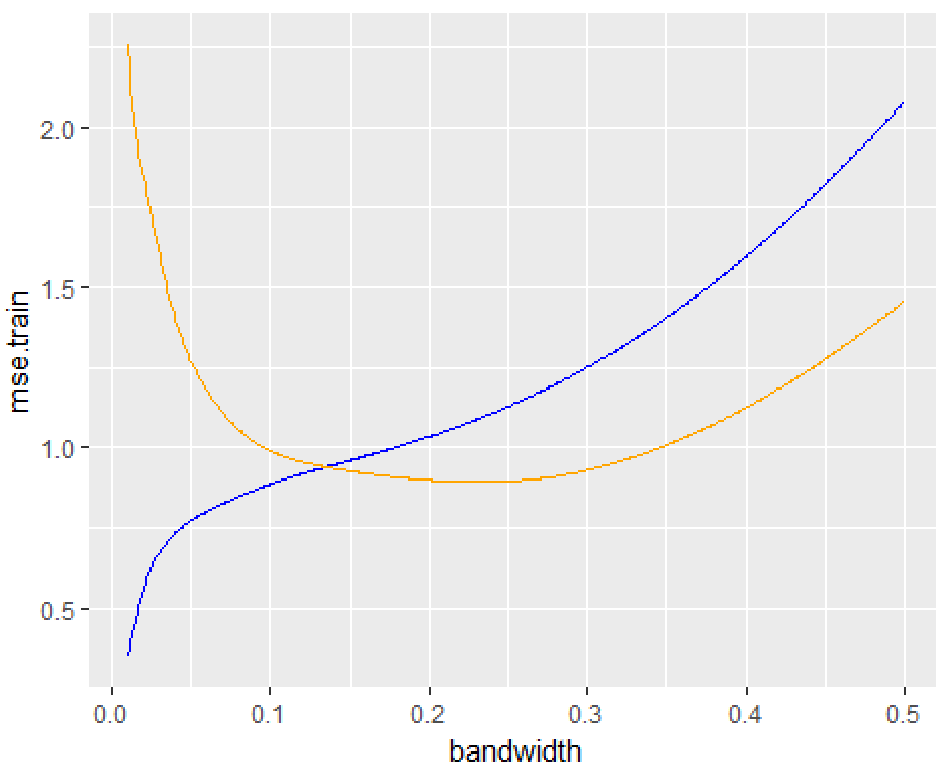



```r
#And we can get the scatterplot of x-y with the predictions of the 2 models:

ggplot(test) + geom_point(mapping = aes(x = x, y = y)) +
  geom_line(mapping = aes(x = x, y = y.true)) +
  geom_line(mapping = aes(x = x, y = y.ll.lowflex), color = "red") +
  geom_line(mapping = aes(x = x, y = y.ll.highflex), color = "blue")
```




```
#We see that the predictions of fit.highflex are more variables than the
predictions of fit.lowflex too because we observe more variations from the
fit.highflex line than from the fit.lowflex line. The predictions of
fit.lowflex have then the least bias.

#Step 6:

# We create a vector of bandwidth going from 0.01 to 0.5 with a step of
0.001:

bw <- seq(0.01, 0.5, by = 0.001)

#Step 7:

# We estimate a local linear model on the training data with each bandwidth:

llbw.fit <- lapply(X = bw, FUN = function(bw) {npreg(y ~ x, data = training,
method = "ll", bws = bw)})

#Step 8:

#We compute for each bandwidth the MSE on the training data:

mse.training <- function(fit.model){
  predictions <- predict(object = fit.model, newdata = training)
  training %>% mutate(squared.error = (y - predictions)^2) %>% summarize(mse
```

```
= mean(squared.error))
}
mse.train.results <- unlist(lapply(X = llbw.fit, FUN = mse.training))

#Step 9:

#We compute for each bandwidth the MSE on the test data:

mse.test <- function(fit.model){
  predictions <- predict(object = fit.model, newdata = test)
  test %>% mutate(squared.error = (y - predictions)^2) %>% summarize(mse =
mean(squared.error))
}
mse.test.results <- unlist(lapply(X = llbw.fit, FUN = mse.test))

#Step 10:

#We draw on the same plot how the MSE on training data and test data changes
when the bandwidth increases:

mse.df <- tbl_df(data.frame(bandwidth = bw, mse.train = mse.train.results,
mse.test = mse.test.results))

ggplot(mse.df) +
  geom_line(mapping = aes(x = bandwidth, y = mse.train), color = "blue") +
  geom_line(mapping = aes(x = bandwidth, y = mse.test), color = "orange")
```



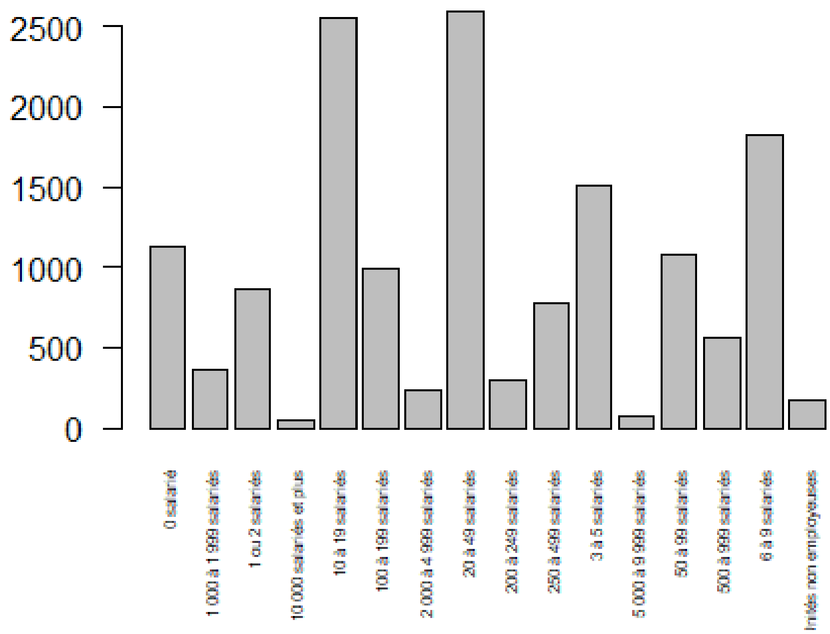
TASK 3B:

```r
#Step 1:

#We import the SIREN dataset:
library(data.table)

siren <- system.time(table1 <- fread(file.choose(),sep=";",dec=".",header =
T, select = c("SIREN", "LIBTEFEN")))



#Step 2:
library(tidyverse)

#We import the CNIL data set:
library(readr)
CNIL <- read_delim("D:/Documents/M1 Economics/rporg/Challenges/Challenge
B/OpenCNIL_Organismes_avec_CIL_VD_20171115.csv",";", escape_double = FALSE,
trim_ws = TRUE)



#First, we clean the table by removing all the NA present in it:
CNIL2<-na.omit(CNIL)
sum(is.na(CNIL2))



#Then, we create a new column called "Departement" with the first 2 numbers
of the codepost:
department <- substr(CNIL2$Code_Postal, start =1, stop=2)
CNIL2$Departement <- department

#The new column is added in the table:
head(CNIL2)

## # A tibble: 6 x 9
##       Siren                 Responsable                      Adresse
##       <chr>                       <chr>                        <chr>
## 1 788349926 "\"\"\"LA RIVE BLEUE\"\"\""               3/5 RUE BOILEAU
## 2 421715731                   01 DIRECT      58 AVENUE DE RIVESALTES
## 3 409869708                01DB-METRAVIB       200 CHEMIN DES ORMEAUX
## 4 444600464                1.2.3. SAS 57-59 -61 RUE HENRI BARBUSSE
## 5 922002968              100 % ASNIERES       70 AVENUE D'ARGENTEUIL
## 6 429621311                  1000MERCIS         28 RUE DE CHATEAUDUN
## # ... with 6 more variables: Code_Postal <chr>, Ville <chr>, NAF <chr>,
## #   TypeCIL <chr>, Portee <chr>, Departement <chr>

#We create the table with the number of CNIL by department:
table <- as.data.frame(table(department))
```

```r
colnames(table) <- c("Department", "Number of CNIL")
head(table)

##   Department Number of CNIL
## 1         01            125
## 2         02            100
## 3         03             66
## 4         04             70
## 5         05             51
## 6         06            244

#Step 3

head(table1)

##        SIREN         LIBTEFEN
## 1: 000325175        0 salarié
## 2: 005420021 10 à 19 salariés
## 3: 005420120 10 à 19 salariés
## 4: 005420120 10 à 19 salariés
## 5: 005420120 10 à 19 salariés
## 6: 005420120 10 à 19 salariés

#We remove the duplicated rows:
table1 <- table1[!duplicated(table1$SIREN),]

#We need to rename the variable Siren in SIREN in the CNIL dataset otherwise
we would not be able to merge the two datasets:
colnames(CNIL2)[colnames(CNIL2) == 'Siren'] <-'SIREN'
head(CNIL2)

## # A tibble: 6 x 9
##       SIREN                  Responsable                     Adresse
##       <chr>                        <chr>                       <chr>
## 1 788349926 "\"\"\"LA RIVE BLEUE\"\"\""                 3/5 RUE BOILEAU
## 2 421715731                    01 DIRECT      58 AVENUE DE RIVESALTES
## 3 409869708                  01DB-METRAVIB       200 CHEMIN DES ORMEAUX
## 4 444600464                     1.2.3. SAS 57-59 -61 RUE HENRI BARBUSSE
## 5 922002968                 100 % ASNIERES      70 AVENUE D'ARGENTEUIL
## 6 429621311                     1000MERCIS        28 RUE DE CHATEAUDUN
## # ... with 6 more variables: Code_Postal <chr>, Ville <chr>, NAF <chr>,
## #   TypeCIL <chr>, Portee <chr>, Departement <chr>

#We can now merge the information from the SIREN dataset into the CNIL
dataset using the merge function:
library(dplyr)

total <- merge(CNIL2, table1, by="SIREN")
head(total)
```

```
##       SIREN                             Responsable
## 1 005520176                       HERNAS CARTONNAGE
## 2 005820378                          DEMOUSELLE SAS
## 3 006380158                         ESPACE DOMICILE
## 4 007080195                        ENTREPRISES LANG
## 5 015650617                                  DURUPT
## 6 016250029 SOCIETE DES AUTOROUTES PARIS RHIN RHONE
##                       Adresse Code_Postal               Ville
## 1             50 RUE PASTEUR       80210 FEUQUIERES EN VIMEU
## 2  140 RUE DU CHATEAU D'EAU       80100           ABBEVILLE
## 3          13 AVENUE BARBARA       44570             TRIGNAC
## 4        7 RUE EUGENE CORNET       44604       SAINT NAZAIRE
## 5      4, AVENUE DE L'EUROPE       21600             LONGVIC
## 6 36 RUE DU DOCTEUR SCHMITT       21850   SAINT APOLLINAIRE
##
NAF
## 1                                 1721A Fabrication d'articles en papier
ou en carton
## 2 4321A Travaux d'installation électrique, plomberie et autres travaux
d'installation
## 3                 6820A Location et exploitation de biens immobiliers
propres ou loués
## 4                                    4399C Autres travaux de construction
spécialisés
## 5                                          4674A Autres commerces de gros
spécialisés
## 6                                           5222Z Services auxiliaires des
transports
##      TypeCIL   Portee Departement               LIBTEFEN
## 1   INTERNE  Etendue          80       50 à 99 salariés
## 2   SALARIE  Etendue          80     200 à 249 salariés
## 3   EXTERNE  Etendue          44       20 à 49 salariés
## 4 MUTUALISE Générale          44       50 à 99 salariés
## 5   SALARIE  Etendue          21       20 à 49 salariés
## 6 MUTUALISE  Etendue          21 2 000 à 4 999 salariés
```

```r
#Step 4:

#We plot the histogram of the size of the companies that nominated a CNIL:

#We first gather the variables we need in one table:
data3 <-table1[(table1$SIREN %in% CNIL2$SIREN),]

#And then we plot the histogram:
plot(factor(data3$LIBTEFEN), las=2, cex.names= 0.5)
```



2500
2000
1500
1000
500
0
0 salarié
1 000 à 1 999 salariés
1 ou 2 salariés
10 000 salariés et plus
10 à 19 salariés
100 à 199 salariés
2 000 à 4 999 salariés
20 à 49 salariés
200 à 249 salariés
250 à 499 salariés
3 à 5 salariés
5 000 à 9 999 salariés
50 à 99 salariés
500 à 999 salariés
6 à 9 salariés
Unités non employeuses