

# USED CAR PRICES CASE STUDY

## Deliverable I: Data Processing, Description, Validation and Profiling

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## 1 R libraries imports, useful functions and data loading

In this first section we will load all required packages and libraries, declare additional functions, and load our data.

### 1.1 Load required packages

```
options(contrasts=c("contr.treatment","contr.treatment"))

requiredPackages <- c("effects","FactoMineR","car",
                     "factoextra","RColorBrewer","ggplot2","dplyr","ggmap",
                     "ggthemes","knitr","treemap")

#use this function to check if each package is on the local machine
#if a package is installed, it will be loaded
#if any are not, the missing package(s) will be installed and loaded
package.check <- lapply(requiredPackages, FUN = function(x) {
  if (!require(x, character.only = TRUE)) {
    install.packages(x, dependencies = TRUE)
    library(x, character.only = TRUE)
  }
})

#verify they are loaded
search()
```

## 1.2 Sample load

```
# Clear plots
if(!is.null(dev.list())) dev.off()

# Clean workspace
rm(list=ls())

# Users file path
miquel_fp <- "C:/Users/Miquel/Documents/GitHub/ADEI/"
xavi_fp <- "~/Documents/FIB/ADEI/ADEI/"
filepath <- xavi_fp

# Set working directory
setwd(filepath)

# Load data from file
load(paste0(filepath,"MyOldCars-Raw.RData"))

# Index reset
row.names(df) <- NULL
```

## 1.3 Useful functions

```
#Mout <- which((df$tax < var_out$mouti)/(df$tax > var_out$mouts))

# Some useful functions
calcQ <- function(x) {
  s.x <- summary(x)
  iqr<-s.x[5]-s.x[2]
  list(souti=s.x[2]-3*iqr, mouti=s.x[2]-1.5*iqr, min=s.x[1], q1=s.x[2], q2=s.x[3],
       q3=s.x[5], max=s.x[6], mouts=s.x[5]+1.5*iqr, souts=s.x[5]+3*iqr ) }

countNA <- function(x) {
  mis_x <- NULL
  for (j in 1:ncol(x)) {mis_x[j] <- sum(is.na(x[,j])) }
  mis_x <- as.data.frame(mis_x)
  rownames(mis_x) <- names(x)
  mis_i <- rep(0,nrow(x))
  for (j in 1:ncol(x)) {mis_i <- mis_i + as.numeric(is.na(x[,j])) }
  list(mis_col=mis_x,mis_ind=mis_i) }

countX <- function(x,X) {
  n_x <- NULL
  for (j in 1:ncol(x)) {n_x[j] <- sum(x[,j]==X) }
  n_x <- as.data.frame(n_x)
  rownames(n_x) <- names(x)
  nx_i <- rep(0,nrow(x))
  for (j in 1:ncol(x)) {nx_i <- nx_i + as.numeric(x[,j]==X) }
  list(nx_col=n_x,nx_ind=nx_i) }
```

## 2 Data Description

During this project we will be working with a subset of the pre-treated original dataset “Uk used car dataset”. A sample of 5000 cars has been randomly selected from Mercedes, BMW, Volkswagen and Audi manufacturers and stored into a RData file *MyOldCars-Raw.RData*.

## 2.1 Original variables description

- **model:** Car model.
- **year:** Car registration year.
- **price:** Car price in £.
- **transmission:** Type of transmission ["Manual", "Automatic", "Semi-Auto"].
- **mileage:** Distance used, accumulated miles.
- **fuelType:** Type of engine fuel ["Petrol", "Diesel", "Hybrid", "Other"].
- **tax:** Applied road tax.
- **mpg:** Miles per gallon.
- **engineSize:** Engine size in liters. The cars with engine size 0 are in fact electric cars, nevertheless Mercedes C class, and other given cars are not electric cars, so data imputation is required.
- **manufacturer:** Car manufacturer ["Audi", "BMW", "Mercedes", "VW"].

```
summary(df)
```

```
##      model          year      price      transmission
## Length:5000      Min.   :1999      Min.   :   650      Length:5000
## Class :character  1st Qu.:2016      1st Qu.: 13995      Class :character
## Mode  :character  Median :2017      Median : 19498      Mode  :character
##                      Mean  :2017      Mean   : 21470
##                      3rd Qu.:2019      3rd Qu.: 26039
##                      Max.   :2020      Max.   :109990
##      mileage      fuelType      tax      mpg
## Min.   :      4      Length:5000      Min.   :   0.0      Min.   :   8.80
## 1st Qu.:  5999      Class :character  1st Qu.:125.0      1st Qu.:  44.80
## Median : 16619      Mode  :character  Median :145.0      Median :  53.30
## Mean   : 23312                      Mean   :125.3      Mean   :  53.89
## 3rd Qu.: 33834                      3rd Qu.:145.0      3rd Qu.:  61.40
## Max.   :153000                      Max.   :580.0      Max.   : 470.80
##      engineSize      manufacturer
## Min.   :0.000      Length:5000
## 1st Qu.:1.500      Class :character
## Median :2.000      Mode  :character
## Mean   :1.917
## 3rd Qu.:2.000
## Max.   :6.600
```

```
head(df, 3)
```

```
##      model year price transmission mileage fuelType tax  mpg engineSize
## 1      A1 2016 11000      Manual   29946   Petrol   30 55.4         1.4
## 2      A3 2015 10200      Manual   46112   Petrol   20 60.1         1.4
## 3      A4 2017 18500    Automatic  17418   Diesel  145 62.8         2.0
##      manufacturer
## 1          Audi
## 2          Audi
## 3          Audi
```

## 3 Univariate Descriptive Analysis

In this step of the process original numeric variables corresponding to qualitative concepts have to be converted to factors. New factors grouping original levels will be considered very positively.

Additionally original numeric variables corresponding to real quantitative concepts are kept as numeric but additional factors should also be created as a discretization of each numeric variable.

For each variable we will perform the necessary transformations and also visualize its distribution.

### 3.1 Numeric variables

#### 3.1.1 years\_sell

From **year** we can create a new variable called **years\_sell**. It will contain the same information as **year** but it will give more valuable information for a human understanding perspective.

**years\_sell** represents the years the car has been sold.

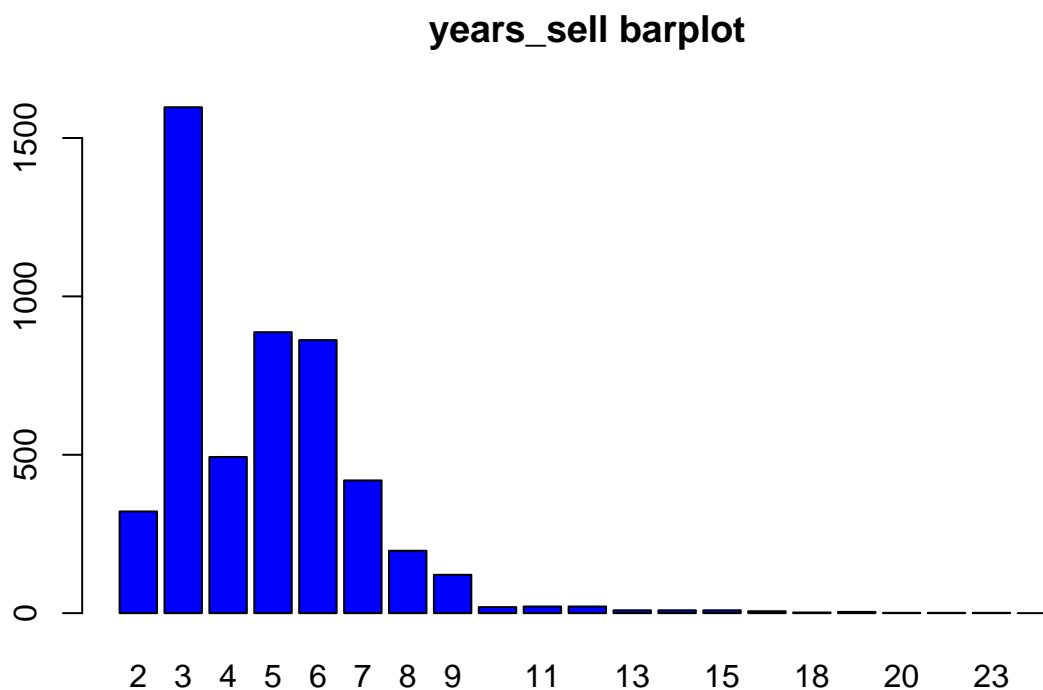
```
df$years_sell <- 2022 - df$year
summary(df$years_sell)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   2.000   3.000   5.000   4.787   6.000   23.000
```

```
table(df$years_sell,useNA="always")
```

```
##
##      2      3      4      5      6      7      8      9     10     11     12     13     14     15     16     18
## 321 1597  493  887  862  419  197  121   19   21   21    9    9    9    6    2
##   19   20   21   23 <NA>
##    4    1    1    1    0
```

```
barplot(table(df$years_sell,useNA="always"), main = "years_sell barplot", col = "blue")
```

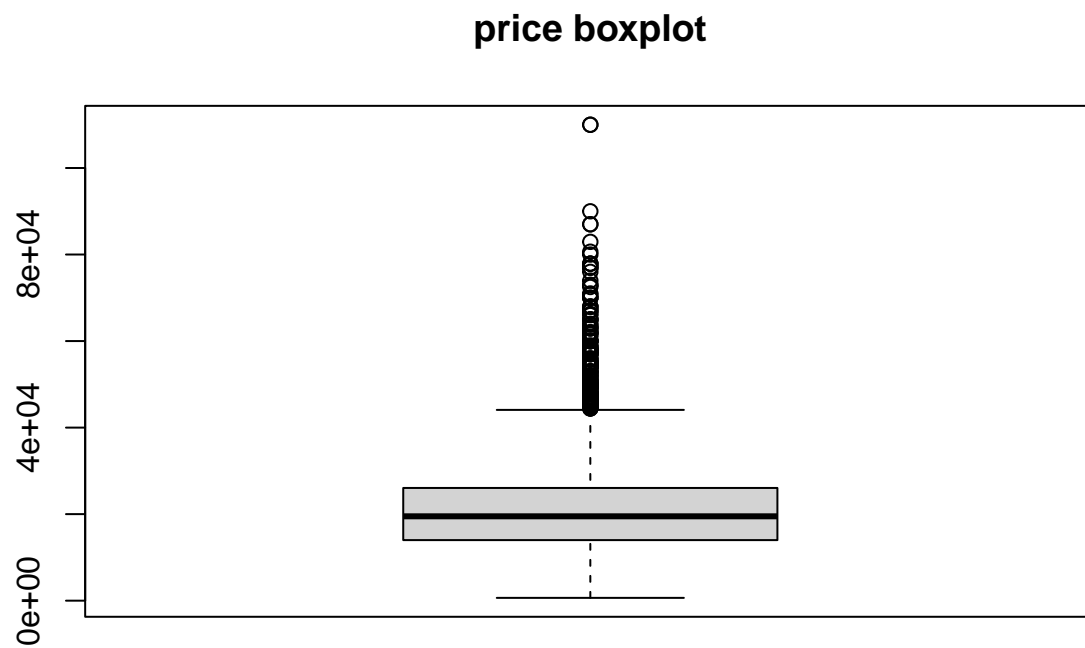


#### 3.1.2 price

```
summary(df$price)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    650   13995   19498   21470   26039  109990
```

```
boxplot(df$price, main="price boxplot")
```



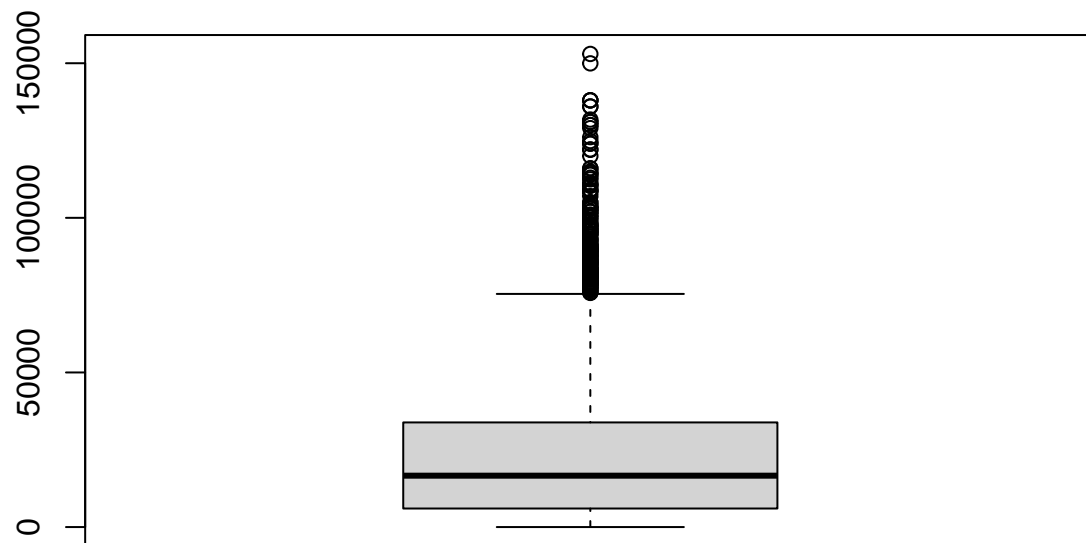
### 3.1.3 mileage

```
summary(df$mileage)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	4	5999	16619	23312	33834	153000

```
boxplot(df$mileage, main="mileage boxplot")
```

## mileage boxplot



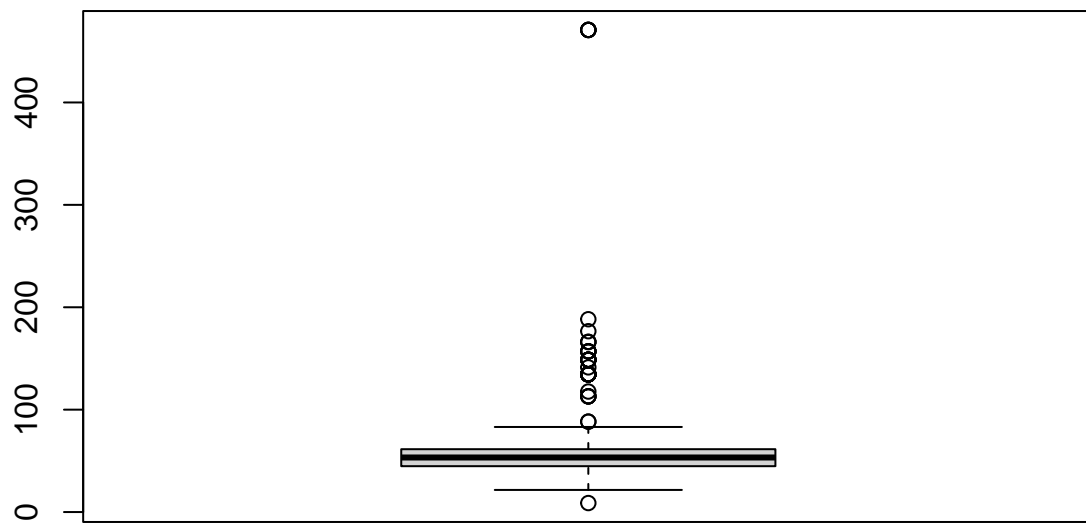
### 3.1.4 mpg

```
summary(df$mpg)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      8.80  44.80   53.30   53.89  61.40  470.80
```

```
boxplot(df$mpg, main="mpg boxplot")
```

## mpg boxplot



### 3.1.5 tax

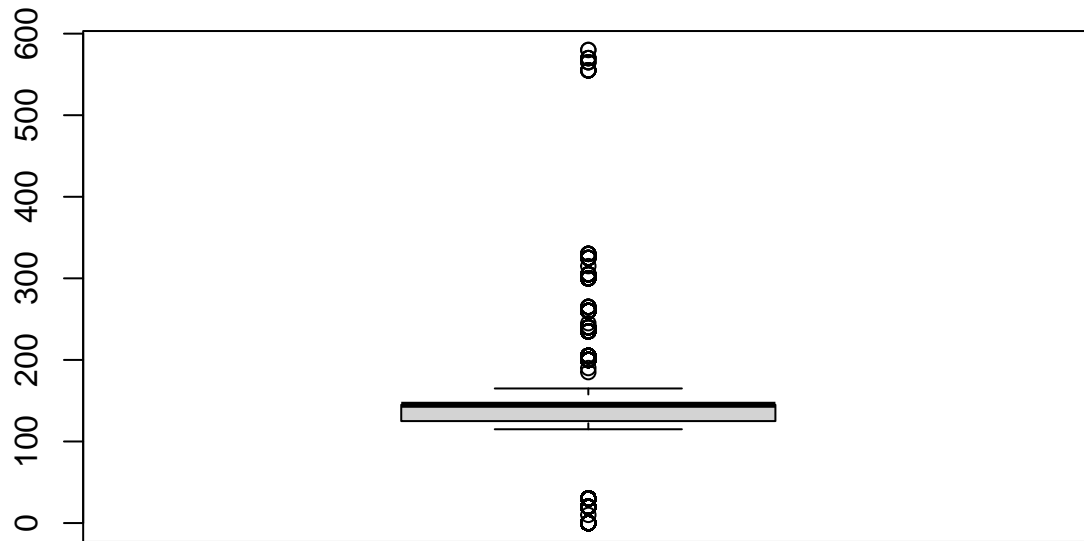
```
summary(df$tax)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0.0   125.0   145.0   125.3   145.0   580.0
```

```
boxplot(df$tax, main="tax boxplot")
```



## tax boxplot



## 3.2 Factors

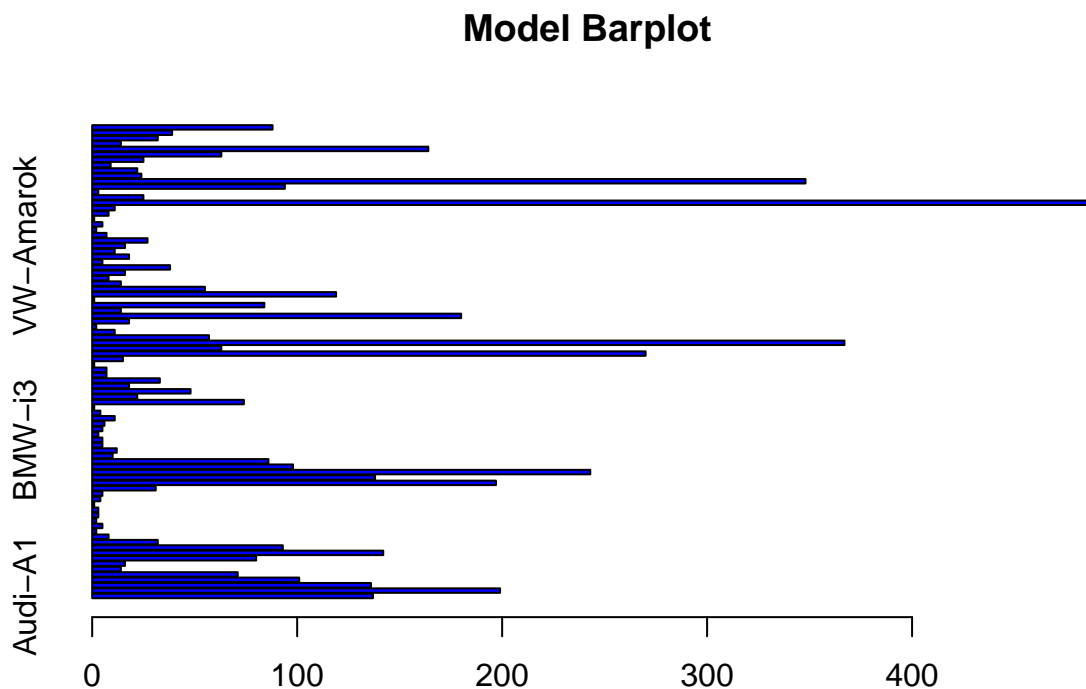
### 3.2.1 model

```
df$model<-factor(paste0(trimws(df$manufacturer),"-",trimws(df$model)))
summary(df$model)
```

```
##      Audi-A1      Audi-A3      Audi-A4      Audi-A5
##      137        199        136        101
##      Audi-A6      Audi-A7      Audi-A8      Audi-Q2
##      71          14          16          80
##      Audi-Q3      Audi-Q5      Audi-Q7      Audi-Q8
##      142         93         32          8
##      Audi-R8      Audi-RS3     Audi-RS4     Audi-RS5
##      2           5           2           3
##      Audi-RS6     Audi-S3      Audi-S4      Audi-SQ5
##      3           1           4           5
##      Audi-TT      BMW-1 Series  BMW-2 Series  BMW-3 Series
##      31          197         138         243
##      BMW-4 Series  BMW-5 Series  BMW-6 Series  BMW-7 Series
##      98           86          10          12
##      BMW-8 Series  BMW-i3      BMW-i8      BMW-M2
##      5            5           3           5
##      BMW-M3      BMW-M4      BMW-M5      BMW-M6
##      6           11          4           1
##      BMW-X1      BMW-X2      BMW-X3      BMW-X4
##      74          22          48          18
##      BMW-X5      BMW-X6      BMW-X7      BMW-Z3
##      33          7           7           1
##      BMW-Z4      Mercedes-A Class  Mercedes-B Class  Mercedes-C Class
##      15          270         63         367
##      Mercedes-CL Class Mercedes-CLA Class Mercedes-CLC Class Mercedes-CLS Class
```

```
##           57           11           2           18
## Mercedes-E Class Mercedes-GL Class Mercedes-GLA Class Mercedes-GLB Class
##          180          14          84          1
## Mercedes-GLC Class Mercedes-GLE Class Mercedes-GLS Class Mercedes-M Class
##          119          55          14          8
## Mercedes-S Class Mercedes-SL CLASS Mercedes-SLK Mercedes-V Class
##           16           38           5          18
## Mercedes-X-CLASS VW-Amarok VW-Arteon VW-Beetle
##           11           16          27           7
## VW-Caddy Life VW-Caddy Maxi Life VW-California VW-Caravelle
##            2            5            1            8
## VW-CC VW-Golf VW-Golf SV VW-Jetta
##           11          488          25           3
## VW-Passat VW-Polo VW-Scirocco VW-Sharan
##           94          348          24          22
## VW-Shuttle VW-T-Cross VW-T-Roc VW-Tiguan
##            9           25          63          164
## VW-Tiguan Allspace VW-Touareg VW-Touran VW-Up
##            14           32          39          88
```

```
barplot(summary(df$model), main = "Model Barplot", col = "blue", horiz=TRUE)
```



### 3.2.2 year

As you could imagine the distribution of years and years\_sell is the same, but moved from right to left as a result of the subtract operation. We have considered to join cars from year 1999 to 2009 because they are residual values, i.e. the amount of individuals per each one (year) is not representative enough.

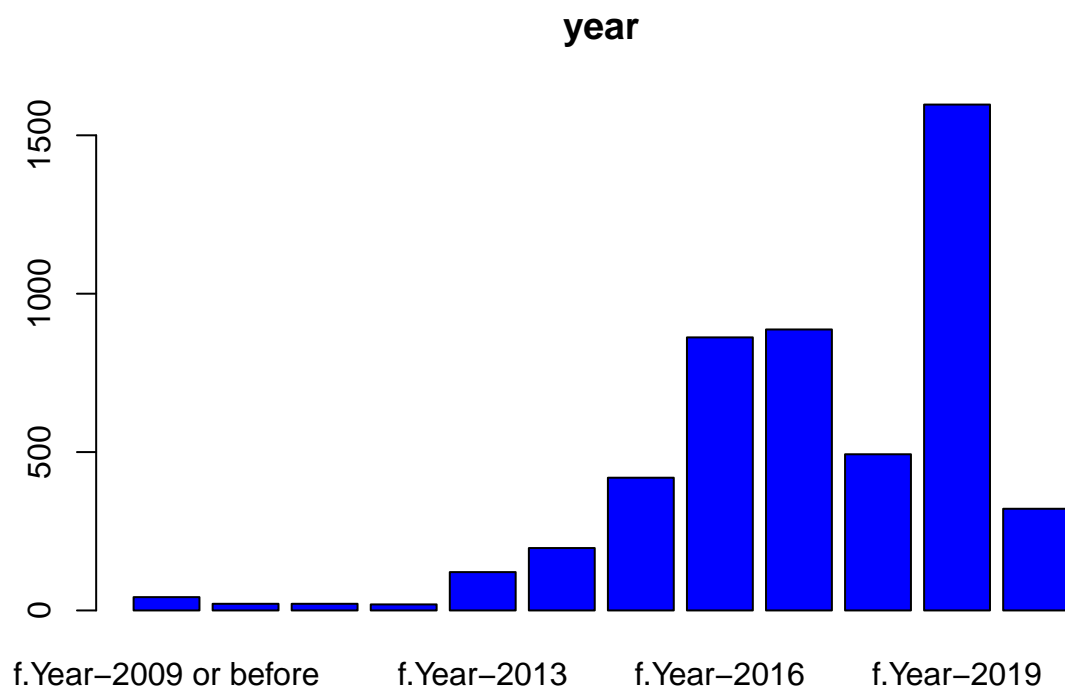
```
df[which(df$year<=2009),"year"] <- "2009 or before"

df$year <- factor(df$year)
df$year <- factor(df$year, labels = paste0("f.Year-",levels(df$year)))

summary(df$year)
```

## f.Year-2009 or before	f.Year-2010	f.Year-2011
## 42	21	21
## f.Year-2012	f.Year-2013	f.Year-2014
## 19	121	197
## f.Year-2015	f.Year-2016	f.Year-2017
## 419	862	887
## f.Year-2018	f.Year-2019	f.Year-2020
## 493	1597	321

```
barplot(summary(df$year), main = "year", col = "blue")
```



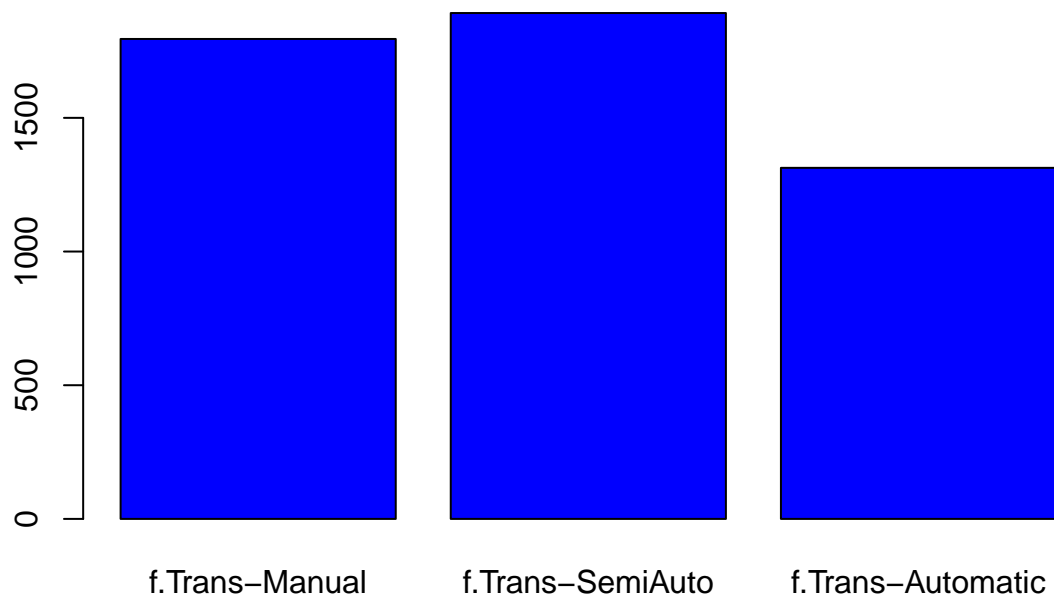
### 3.2.3 transmission

```
df$transmission<-factor(df$transmission)
df$transmission <- factor(df$transmission, levels = c("Manual","Semi-Auto","Automatic"),labels = paste0(
summary(df$transmission)
```

## f.Trans-Manual	f.Trans-SemiAuto	f.Trans-Automatic
## 1795	1892	1313

```
barplot(summary(df$transmission), main = "Transmission Barplot", col = "blue")
```

## Transmission Barplot



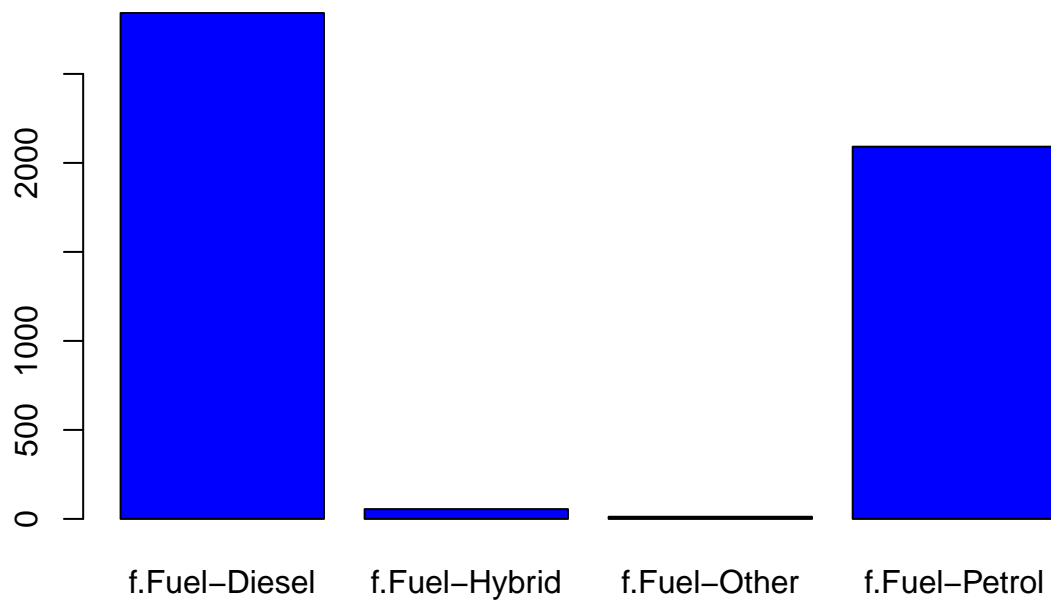
### 3.2.4 fuelType

```
df$fuelType<-factor(df$fuelType)
df$fuelType <- factor(df$fuelType, labels = paste0("f.Fuel-",levels(df$fuelType)))
summary(df$fuelType)
```

```
## f.Fuel-Diesel f.Fuel-Hybrid f.Fuel-Other f.Fuel-Petrol
##           2842           55           12           2091
```

```
barplot(summary(df$fuelType), main = "FuelType Barplot", col = "blue")
```

## FuelType Barplot



### 3.2.5 engineSize

We have considered to join cars with engineSize 4.2, 4.4, 4.7, 5, 5.2, 5.5, 6.2 and 6.6 because they are residual values, i.e. the amount of individuals per each one (engineSize) is not representative enough.

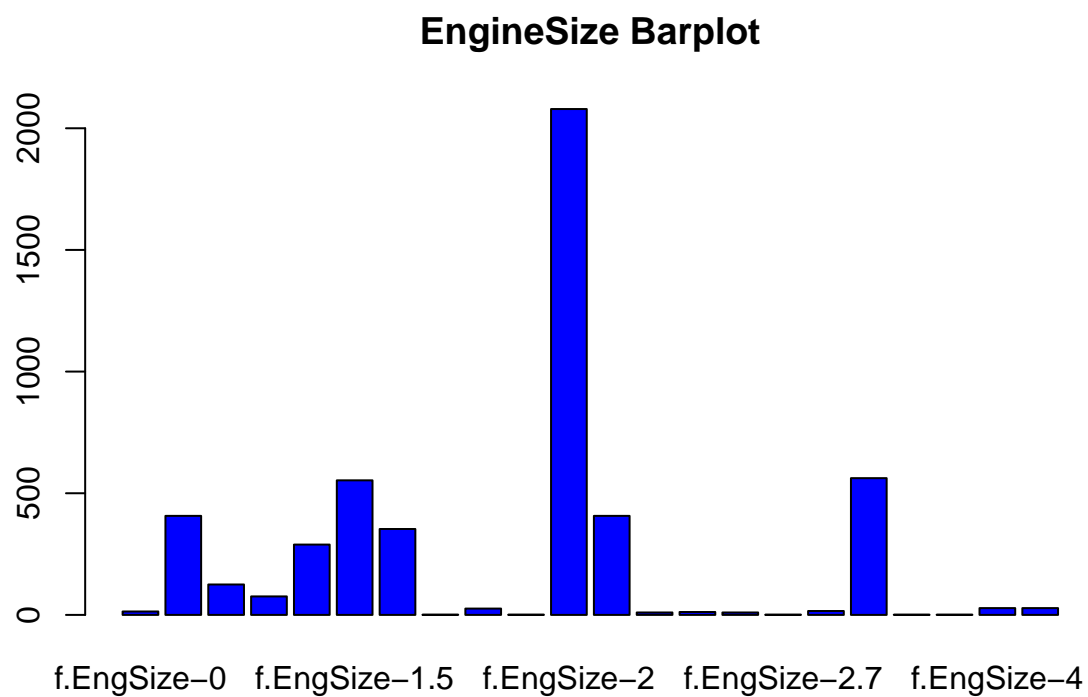
```
df[which(df$engineSize>=4.2),"engineSize"] <- "4.2 or more"

df$engineSize<-factor(df$engineSize)
df$engineSize <- factor(df$engineSize, labels = paste0("f.EngSize-",levels(df$engineSize)))

summary(df$engineSize)
```

```
##          f.EngSize-0          f.EngSize-1          f.EngSize-1.2
##              14              407              125
##    f.EngSize-1.3    f.EngSize-1.4    f.EngSize-1.5
##              76              289              553
##    f.EngSize-1.6    f.EngSize-1.7    f.EngSize-1.8
##            353              1              26
##    f.EngSize-1.9          f.EngSize-2    f.EngSize-2.1
##              1              2079          407
##    f.EngSize-2.2    f.EngSize-2.3    f.EngSize-2.5
##             10              12              10
##    f.EngSize-2.7    f.EngSize-2.9          f.EngSize-3
##              1              16              562
##    f.EngSize-3.2    f.EngSize-3.5    f.EngSize-4
##              1              1              28
## f.EngSize-4.2 or more
##              28
```

```
barplot(summary(df$engineSize), main = "EngineSize Barplot", col = "blue")
```



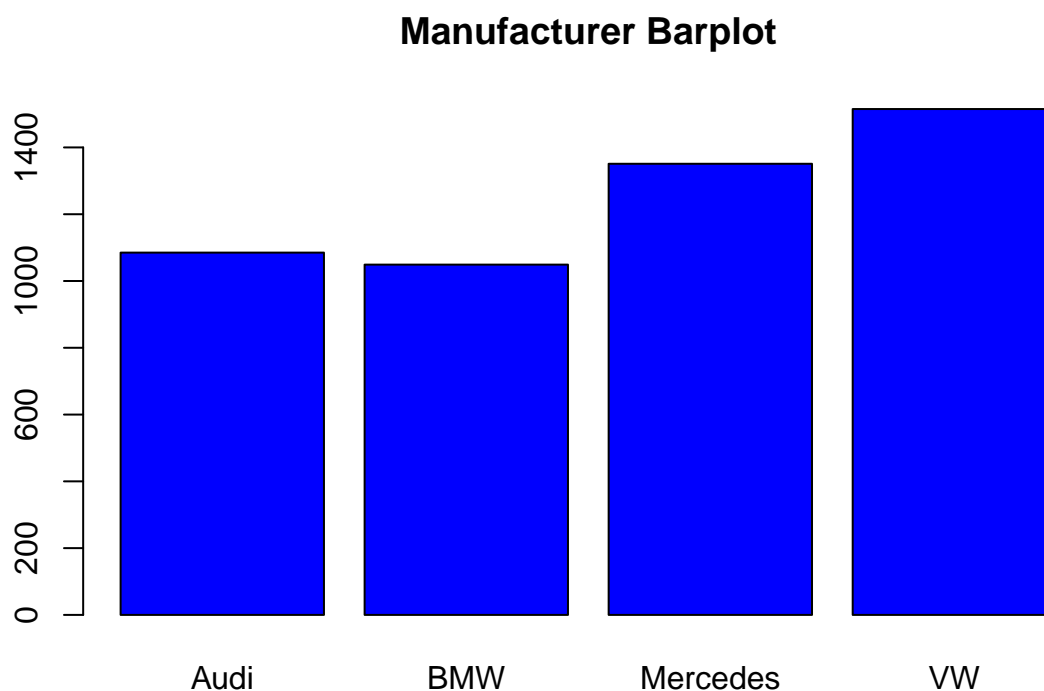
### 3.2.6 manufacturer

```
df$manufacturer<-factor(df$manufacturer)
df$manufacturer <- factor(df$manufacturer, labels = levels(df$manufacturer))

summary(df$manufacturer)
```

```
##      Audi      BMW Mercedes      VW
##      1085      1049      1351      1515
```

```
barplot(summary(df$manufacturer), main = "Manufacturer Barplot", col = "blue")
```



## 4 Data Quality Report

### 4.1 Initialization of counts for missings, outliers and errors.

```
#####
imis<-rep(0,nrow(df)) # rows - cars
jmis<-rep(0,ncol(df)) # columns - variables
#####
mis1<-countNA(df) #There are no missings at the beginning

# Number of missings for the current set of cars
sum(mis1$mis_ind)
```

```
## [1] 0
```

```
# Number of missings for the current set of variables
sum(mis1$mis_col)
```

```
## [1] 0
```

```
#####
iouts<-rep(0,nrow(df)) # rows - cars
jouts<-rep(0,ncol(df)) # columns - variables
#####

#####
ierrs<-rep(0,nrow(df)) # rows - cars
jerrs<-rep(0,ncol(df)) # columns - variables
#####
```

As you can see from the previous stats there are no missings in the variables for the random data subset.

## 4.2 Errors

After the first analysis of the samples and the provided documentation of the dataset we could say that the only visible errors are in the engineSize variable.

Engine size equal to zero is considered as an electrical vehicle so this error in the data needs to be considered and treated properly.

```
sel<-which(df$engineSize==0 & df$fuelType!="f.Fuel-Electric")
ierrs[sel]<-ierrs[sel]+1
df[sel,"engineSize"]<-NA
selmiss <- sel
jerrs[9] <- length(sel)
```

## 4.3 Univariate Outliers

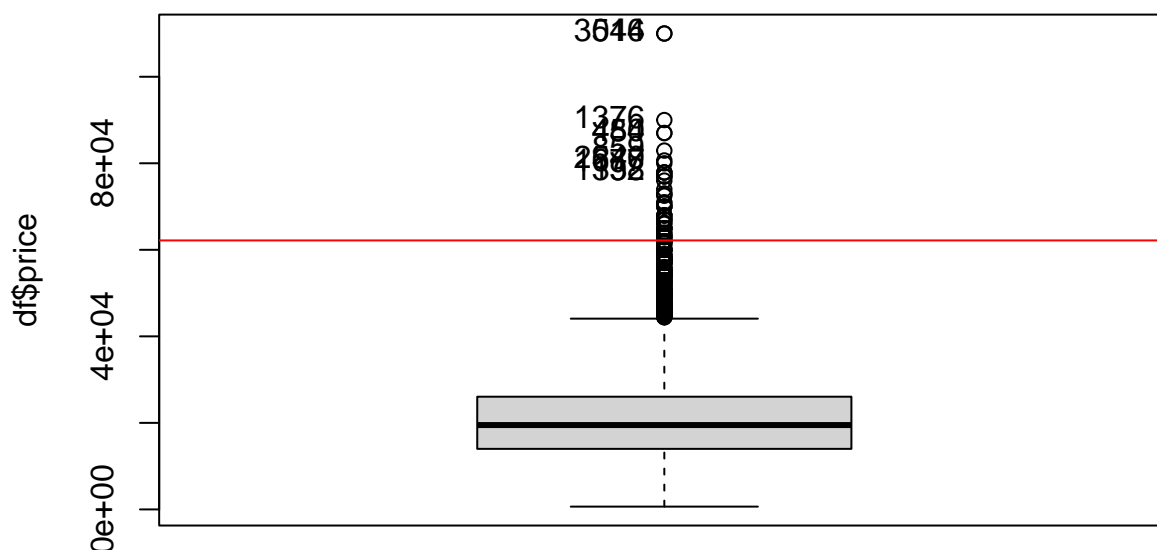
For each variable, we have executed calcQ in order to find the severe/extreme outliers (lower and upper). Then, we have recodified to/with NA the value of the variable of each individual with a value in the variable less than the under severe outlier or greater than the upper severe outlier to later apply imputation.

### 4.3.1 price

```
Boxplot(df$price)
```

```
## [1] 514 3046 1376 450 484 859 2540 1677 192 1338
```

```
var_out<-calcQ(df$price)
abline(h=var_out$souts,col="red")
abline(h=var_out$souti,col="red")
```





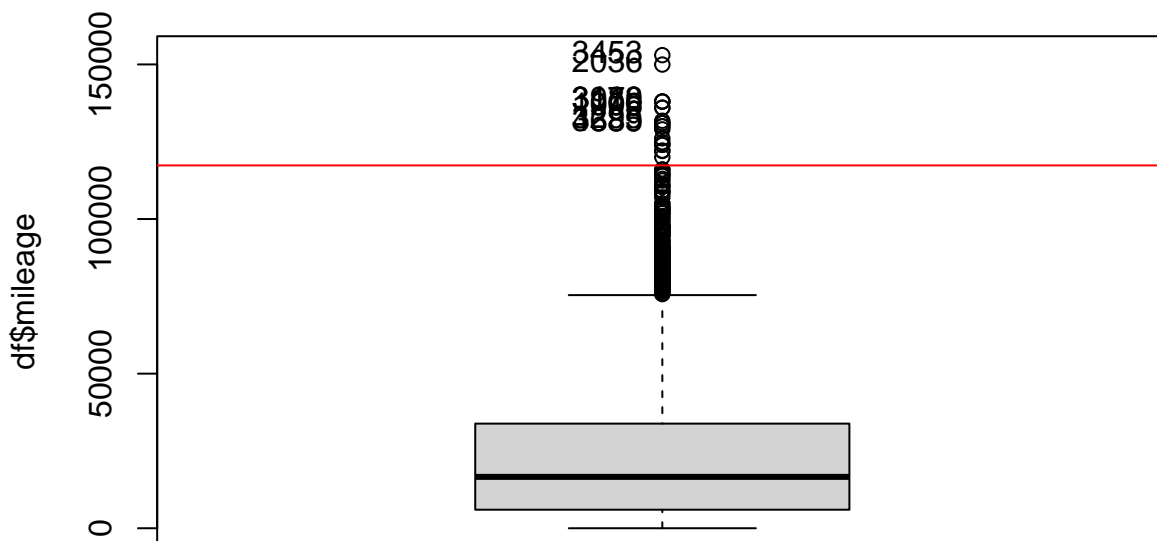
```
# Outliers:
llout_price<-which((df$price<var_out$souti)|(df$price>var_out$souts))#souts abline
iouts[llout_price]<-iouts[llout_price]+1
jouts[3]<-length(llout_price)
```

### 4.3.2 mileage

```
Boxplot(df$mileage)
```

```
## [1] 3453 2036 3113 3170 3988 995 1006 3295 3385 4689
```

```
var_out<-calcQ(df$mileage)
abline(h=var_out$souts,col="red")
abline(h=var_out$souti,col="red")
```



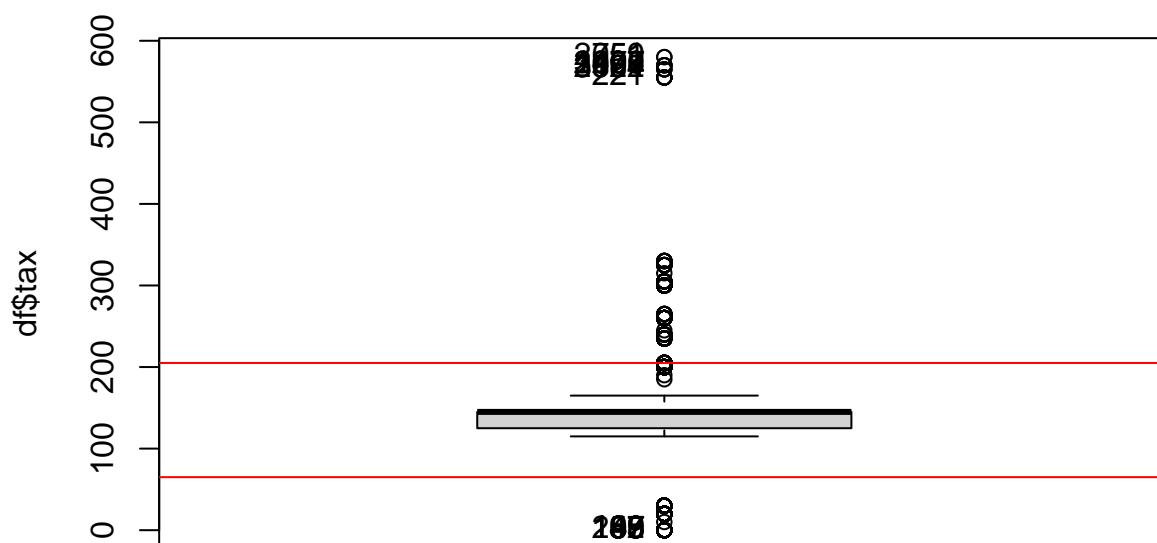
```
# Outliers:
llout_mileage<-which((df$mileage<var_out$souti)|(df$mileage>var_out$souts))#souts abline
iouts[llout_mileage]<-iouts[llout_mileage]+1
jouts[5]<-length(llout_mileage)
df[llout_mileage,"mileage"]<-NA #llout
```

### 4.3.3 tax

```
Boxplot(df$tax)
```

```
## [1] 7 33 45 47 150 169 182 197 198 209 759 2051 1008 1077 2207
## [16] 3450 2094 3184 3322 221
```

```
var_out<-calcQ(df$tax)
abline(h=var_out$souts,col="red")
abline(h=var_out$souti,col="red")
```



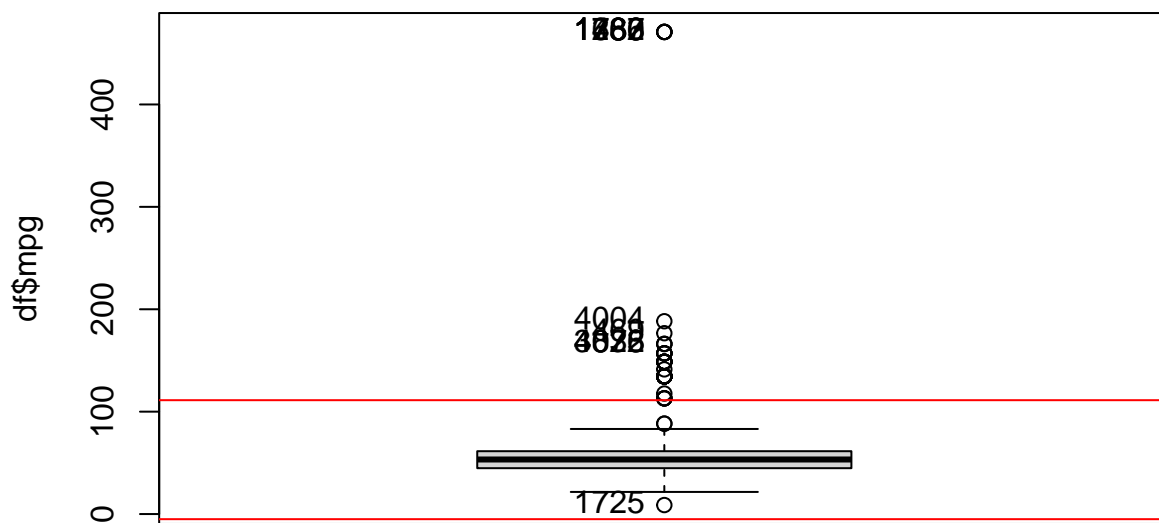
```
# Outliers:
llout_tax<-which((df$tax<var_out$souti)|(df$tax>var_out$souts))#souts abline
iouts[llout_tax]<-iouts[llout_tax]+1
jouts[7]<-length(llout_tax)
df[llout_tax,"tax"]<-NA #llout
```

#### 4.3.4 mpg

```
Boxplot(df$mpg)
```

```
## [1] 1725 1280 1487 1636 1762 1763 4004 469 3832 4026 4073
```

```
var_out<-calcQ(df$mpg)
abline(h=var_out$souts,col="red")
abline(h=var_out$souti,col="red")
```



```
# Outliers:
llout_mpg<-which((df$mpg<var_out$souti)|(df$mpg>var_out$souts))#souts abline
iouts[llout_mpg]<-iouts[llout_mpg]+1
jouts[8]<-length(llout_mpg)
df[llout_mpg,"mpg"]<-NA #llout
```

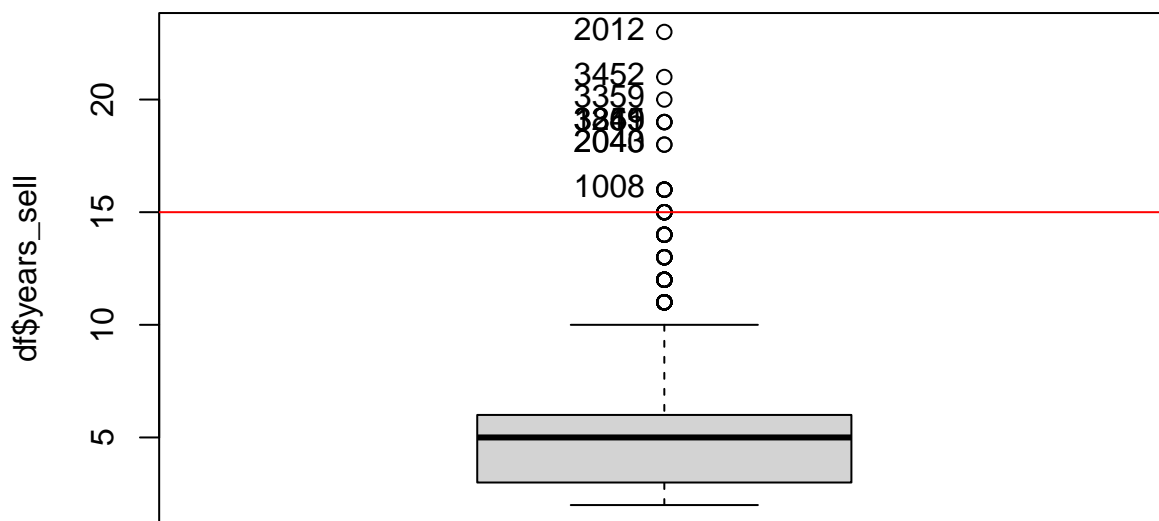
#### 4.3.5 years\_sell

He have decided not to assign NA to years\_sell because is a special variable with a low number of univariate outliers.

```
Boxplot(df$years_sell)
```

```
## [1] 2012 3452 3359 1819 3249 3355 3361 2040 2043 1008
```

```
var_out<-calcQ(df$years_sell)
abline(h=var_out$souts,col="red")
abline(h=var_out$souti,col="red")
```



```
# Outliers:
llout_years_sell<-which((df$years_sell<var_out$souti)|(df$years_sell>var_out$souts))#souts abline
iouts[llout_years_sell]<-iouts[llout_years_sell]+1
jouts[11]<-length(llout_years_sell)
#df[llout_years_sell,"years_sell"]<-NA #llout
```

## 4.4 Number of errors, missings and outliers for individual and variable

### 4.4.1 Number of missing values of each variable

```
jmis
```

```
## [1] 0 0 0 0 0 0 0 0 0 0 0 0
```

### 4.4.2 Number of errors per each variable

```
jerrs
```

```
## [1] 0 0 0 0 0 0 0 0 0 0 0 0
```

### 4.4.3 Number of outliers per each variable

```
outliers_ranking_sortlist <- sort.list(jouts, decreasing = TRUE)
for(j in outliers_ranking_sortlist) {
  if(!is.na(names(df)[j])) print(paste(names(df)[j], " : ", jouts[j]))
}
```

```
## [1] "tax : 1292"  
## [1] "mpg : 48"  
## [1] "price : 42"  
## [1] "mileage : 20"  
## [1] "years_sell : 15"  
## [1] "model : 0"  
## [1] "year : 0"  
## [1] "transmission : 0"  
## [1] "fuelType : 0"  
## [1] "engineSize : 0"  
## [1] "manufacturer : 0"
```

#### 4.4.4 Number of missing values individual

```
sum(imis)
```

```
## [1] 0
```

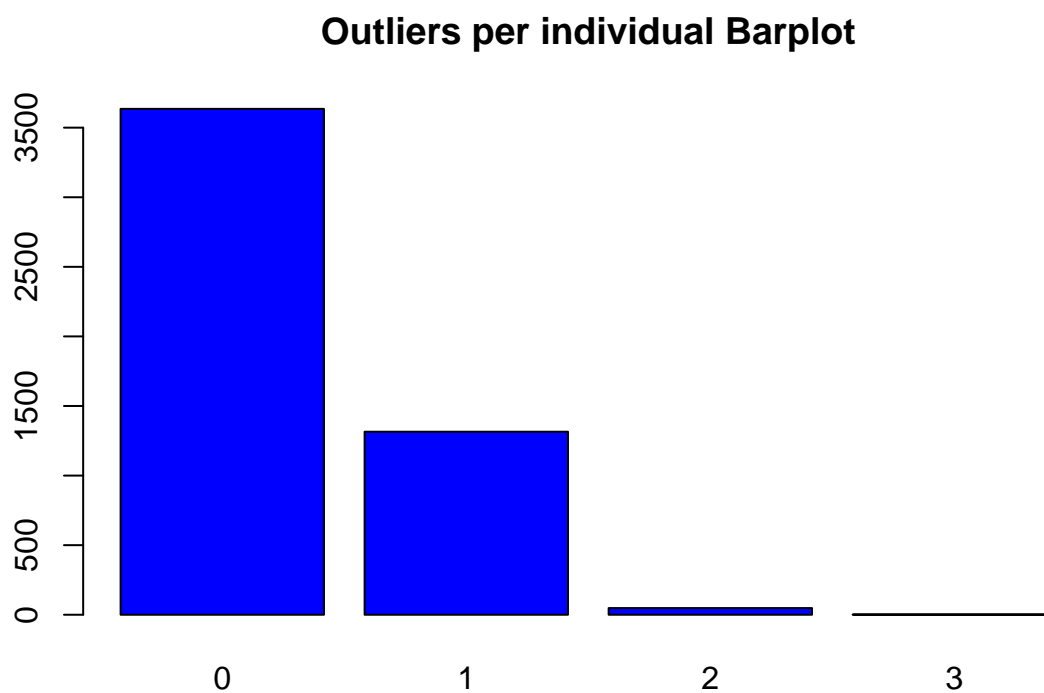
#### 4.4.5 Number of errors individual

```
sum(ierrs)
```

```
## [1] 0
```

#### 4.4.6 Number of outliers individual

```
barplot(table(iouts), main = "Outliers per individual Barplot", col = "blue")
```



#### 4.4.7 New variable adding the total number missing values, outliers and errors

We have created a new variable to know the total missing values, outliers and errors per individual.

```
df$totalMOE<- imis+iouts+ierrs
```

### 4.5 Imputation

#### 4.5.1 Imputation of numeric variables

We do imputation in order to give a value to the missings (NA's). The (regularized) iterative PCA algorithm first consists imputing missing values with initial values such as the mean of the variable.

```
library(missMDA)
```

```
names(df)
```

```
## [1] "model"      "year"      "price"      "transmission" "mileage"
## [6] "fuelType"   "tax"       "mpg"        "engineSize"  "manufacturer"
## [11] "years_sell" "totalMOE"
```

```
vars_con<-names(df)[c(5,7,8)]
vars_dis<-names(df)[c(1:2, 4, 6, 9, 10)]
vars_res<-names(df)[c(3)]
```

```
summary(df[,vars_con])
```

```
##      mileage      tax      mpg
##  Min.   :      4  Min.   :115.0  Min.   : 8.80
## 1st Qu.: 5987   1st Qu.:145.0  1st Qu.:44.10
## Median :16508   Median :145.0  Median :52.30
## Mean   :22876   Mean   :146.8  Mean   :52.71
## 3rd Qu.:33533   3rd Qu.:145.0  3rd Qu.:61.40
## Max.   :116000   Max.   :205.0  Max.   :88.30
## NA's   :20      NA's   :1292  NA's   :48
```

```
res.impca<-imputePCA(df[,vars_con],ncp=2)
summary(res.impca)
```

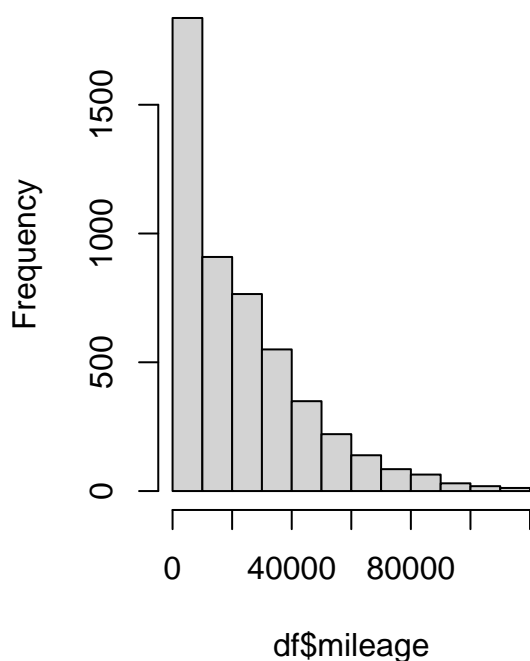
```
##           Length Class  Mode
## completeObs 15000  -none- numeric
## fittedX     15000  -none- numeric
```

We can notice a difference between the two plots, that means that the imputation has been/was correctly applied.

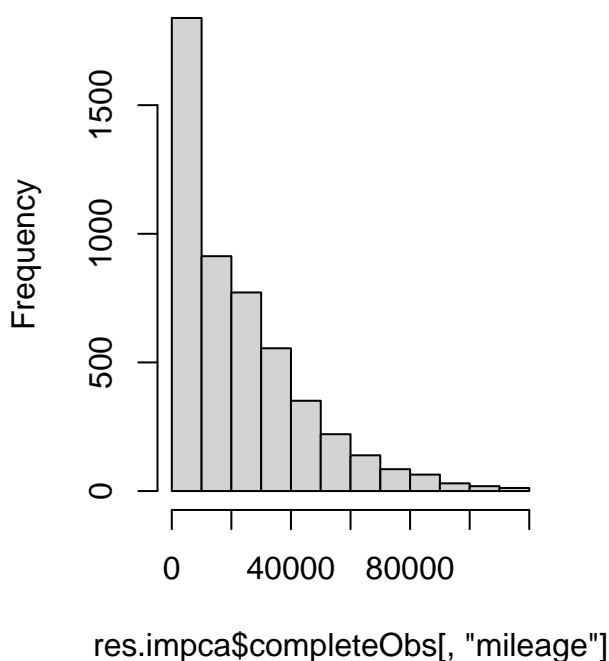
##### 4.5.1.1 mileage Plot comparison for milage variable after imputation.

```
par(mfrow = c(1,2))
hist(df$mileage)
hist(res.impca$completeObs[, "mileage"])
```

### Histogram of df\$mileage



### gram of res.impca\$completeObs[, "



```
quantile(df$mileage,seq(0,1,0.1),na.rm=T)
```

```
##      0%      10%      20%      30%      40%      50%      60%      70%
##      4.0    2000.0   4701.8   7370.7  11623.4  16508.5  22989.0  29712.1
##      80%      90%     100%
##  38260.8  52948.4 116000.0
```

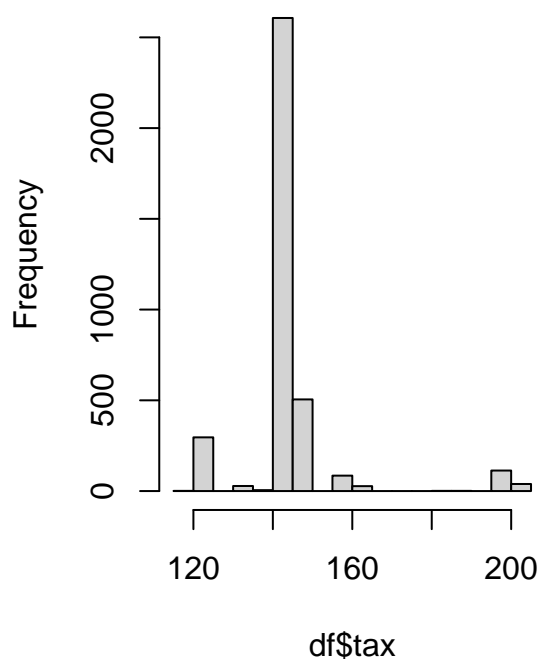
```
round(quantile(res.impca$completeObs[, "mileage"],seq(0,1,0.1),na.rm=T),dig=1)
```

```
##      0%      10%      20%      30%      40%      50%      60%      70%
##      4.0    2000.0   4714.4   7404.0  11648.6  16528.5  23000.0  29753.3
##      80%      90%     100%
##  38221.0  52770.7 116000.0
```

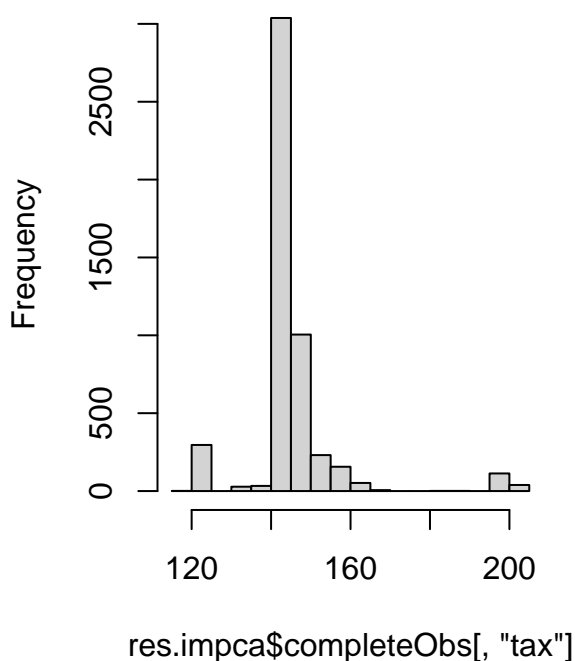
**4.5.1.2 tax** Plot comparison for tax variable after imputation.

```
par(mfrow=c(1,2))
hist(df$tax)
hist(res.impca$completeObs[, "tax"])
```

### Histogram of df\$tax



### Histogram of res.impca\$completeObs[, "tax"]



```
quantile(df$tax,seq(0,1,0.1),na.rm=T)
```

```
##    0%   10%   20%   30%   40%   50%   60%   70%   80%   90%  100%
##  115   145   145   145   145   145   145   145   150   150   205
```

```
round(quantile(res.impca$completeObs[, "tax"],seq(0,1,0.1),na.rm=T),dig=1)
```

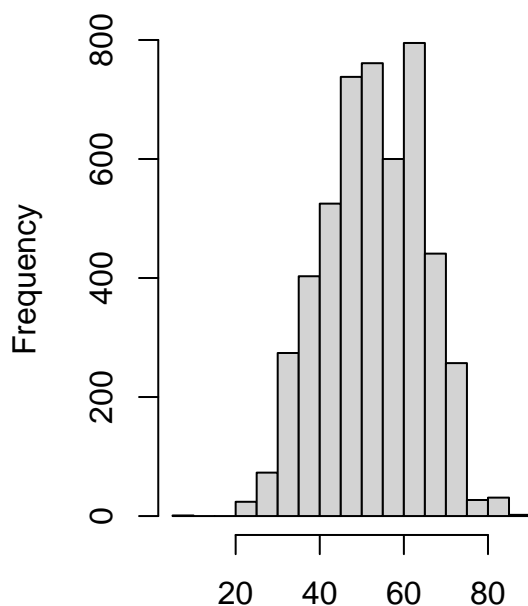
```
##    0%   10%   20%   30%   40%   50%   60%   70%   80%   90%  100%
## 115.0 142.7 145.0 145.0 145.0 145.0 145.0 145.7 150.0 151.7 205.0
```

**4.5.1.3 mpg** Plot comparison for mpg variable after imputation.

```
par(mfrow = c(1,2))
hist(df$mpg)
hist(res.impca$completeObs[, "mpg"])
```

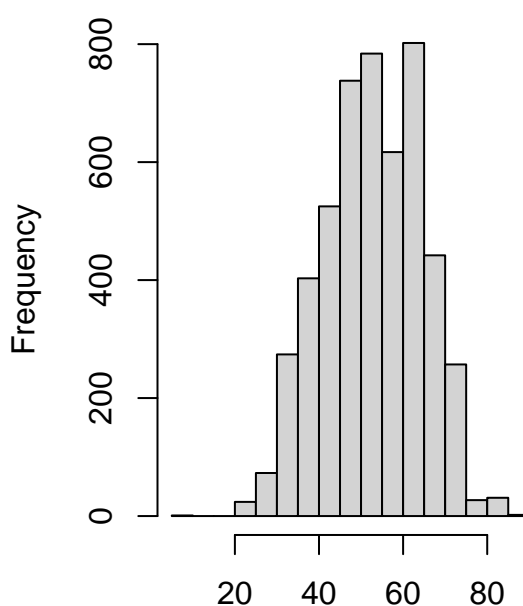


Histogram of df\$mpg



df\$mpg

Histogram of res.impca\$completeObs[,



res.impca\$completeObs[, "mpg"]

```
quantile(df$mpg,seq(0,1,0.1),na.rm=T)
```

```
##      0%   10%   20%   30%   40%   50%   60%   70%   80%   90%  100%
## 8.80 37.20 42.20 47.03 49.60 52.30 56.50 60.10 62.80 67.30 88.30
```

```
round(quantile(res.impca$completeObs[, "mpg"],seq(0,1,0.1),na.rm=T),dig=1)
```

```
##      0%   10%   20%   30%   40%   50%   60%   70%   80%   90%  100%
## 8.8 37.2 42.2 47.1 49.6 53.3 56.5 60.1 62.8 67.3 88.3
```

```
df[,vars_con]<-res.impca$completeObs
```

#### 4.5.2 Imputation of factor variables

We do imputation in order to give a value to the missings (NA's). The (regularized) iterative MCA algorithm first consists in coding the categorical variables using the indicator matrix of dummy variables. Then, in the initialization step, missing values are imputed with initial values such as the proportion of the category for each category using the non-missing entries.

```
summary(df[,vars_dis])
```

```
##           model              year      transmission
## VW-Golf           : 488  f.Year-2019:1597  f.Trans-Manual   :1795
## Mercedes-C Class: 367  f.Year-2017: 887   f.Trans-SemiAuto :1892
## VW-Polo           : 348  f.Year-2016: 862   f.Trans-Automatic:1313
## Mercedes-A Class: 270  f.Year-2018: 493
## BMW-3 Series      : 243  f.Year-2015: 419
## Audi-A3           : 199  f.Year-2020: 321
## (Other)           :3085  (Other)       : 421
##           fuelType      engineSize  manufacturer
## f.Fuel-Diesel:2842  f.EngSize-2  :2079  Audi       :1085
## f.Fuel-Hybrid: 55   f.EngSize-3  : 562  BMW         :1049
```

```
## f.Fuel-Other : 12 f.EngSize-1.5: 553 Mercedes:1351
## f.Fuel-Petrol:2091 f.EngSize-1 : 407 VW :1515
## f.EngSize-2.1: 407
## f.EngSize-1.6: 353
## (Other) : 639
```

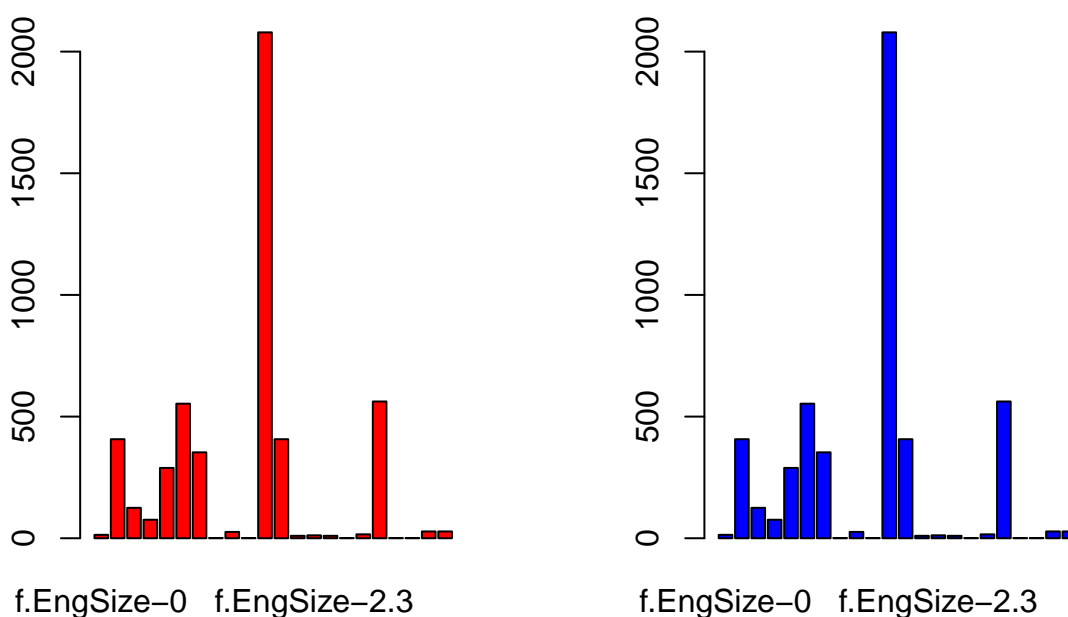
```
res.immca<-imputeMCA(df[,vars_dis],nbp=10)
summary(res.immca$completeObs)
```

```
##          model          year          transmission
## VW-Golf      : 488 f.Year-2019:1597 f.Trans-Manual  :1795
## Mercedes-C Class: 367 f.Year-2017: 887 f.Trans-SemiAuto :1892
## VW-Polo      : 348 f.Year-2016: 862 f.Trans-Automatic:1313
## Mercedes-A Class: 270 f.Year-2018: 493
## BMW-3 Series  : 243 f.Year-2015: 419
## Audi-A3      : 199 f.Year-2020: 321
## (Other)      :3085 (Other)      : 421
##          fuelType          engineSize          manufacturer
## f.Fuel-Diesel:2842 f.EngSize-2 :2079 Audi :1085
## f.Fuel-Hybrid: 55 f.EngSize-3 : 562 BMW :1049
## f.Fuel-Other : 12 f.EngSize-1.5: 553 Mercedes:1351
## f.Fuel-Petrol:2091 f.EngSize-1 : 407 VW :1515
## f.EngSize-2.1: 407
## f.EngSize-1.6: 353
## (Other) : 639
```

We can notice a difference between the two plots, that means that the imputation has been/was correctly applied.

#### 4.5.2.1 engineSize Plot comparison for engine size variable.

```
par(mfrow=c(1,2))
barplot(table(df$engineSize),col="red")
barplot(table(res.immca$completeObs[, "engineSize"]),col="blue")
```



```
df[, vars_dis ]<-res.immca$completeObs
sum(countNA(df)$mis_ind)==0
```

```
## [1] TRUE
```

## 4.6 Correlation of numeric variables with MOE

```
cor(df[,c(3,5,7,8,11)], df$totalMOE)
```

```
##           [,1]
## price      -0.29796314
## mileage     0.45404451
## tax         0.02667251
## mpg         0.32802523
## years_sell  0.52600573
```

As we can see years\_sell is one of the variables with most correlation with total\_MOE this means that as the time of a car being sold grows more tendency to have errors, outliers or/and missing increase.

## 4.7 Discretization

We do discretization in order to make it easier to understand the numeric variables.

### 4.7.1 price variable

```
quantile(df$price,seq(0,1,0.25),na.rm=TRUE)
```

```
##           0%          25%          50%          75%         100%
##    650.00   13995.00   19498.00   26039.25  109990.00
```

```
quantile(df$price,seq(0,1,0.1),na.rm=TRUE)
```

```
##           0%          10%          20%          30%          40%          50%          60%          70%
##    650.0   10318.0   12890.0   15145.5   17399.6   19498.0   21989.4   24904.5
##           80%          90%         100%
##   28000.0   33950.2  109990.0
```

```
df$aux_price<-factor(cut(df$price/1000,breaks=c(quantile(df$price,seq(0,1,0.25),na.rm=TRUE))/1000,includ
summary(df$aux_price)
```

```
## [0.65,14] (14,19.5] (19.5,26] (26,110]
##      1259      1246      1245      1250
```

```
tapply(df$price,df$aux_price,median)
```

```
## [0.65,14] (14,19.5] (19.5,26] (26,110]
##   10995.0   16950.0   22646.0   31986.5
```

```
levels(df$aux_price)<-paste("f.price-",levels(df$aux_price),sep="")
table(df$aux_price,useNA="always")
```

```
##
## f.price-[0.65,14] f.price-(14,19.5] f.price-(19.5,26] f.price-(26,110]
##              1259              1246              1245              1250
##              <NA>
##              0
```

#### 4.7.2 mileage variable

```
df$aux_mileage<-factor(cut(df$mileage,breaks=c(quantile(df$mileage,seq(0,1,0.25),na.rm=TRUE)),include.lowest=T),summary(df$aux_mileage)
```

```
##           [4,6e+03]      (6e+03,1.65e+04] (1.65e+04,3.35e+04] (3.35e+04,1.16e+05]
##           1252           1248           1250           1250
```

```
tapply(df$mileage,df$aux_mileage,median)
```

```
##           [4,6e+03]      (6e+03,1.65e+04] (1.65e+04,3.35e+04] (3.35e+04,1.16e+05]
##           2753.5           10396.0           24443.5           48095.0
```

```
levels(df$aux_mileage)<-paste("f.mileage-",levels(df$aux_mileage),sep="")
table(df$aux_mileage,useNA="always")
```

```
##
##           f.mileage-[4,6e+03]      f.mileage-(6e+03,1.65e+04]
##                               1252                               1248
## f.mileage-(1.65e+04,3.35e+04] f.mileage-(3.35e+04,1.16e+05]
##                               1250                               1250
##                               <NA>
##                               0
```

#### 4.7.3 tax variable

```
quantile(df$tax,seq(0,1,0.25),na.rm=TRUE)
```

```
##           0%           25%           50%           75%           100%
## 115.0000 145.0000 145.0000 148.0945 205.0000
```

```
df$aux_tax<-factor(cut(df$tax,breaks=c(0, 125, 145, 580),include.lowest = T ))
summary(df$aux_tax)
```

```
##           [0,125] (125,145] (145,580]
##           297       3099       1604
```

```
tapply(df$tax,df$aux_tax,median)
```

```
##           [0,125] (125,145] (145,580]
##           125       145       150
```

```
levels(df$aux_tax)<-paste("f.tax-",levels(df$aux_tax),sep="")
table(df$aux_tax,useNA="always")
```

```
##
##           f.tax-[0,125] f.tax-(125,145] f.tax-(145,580]      <NA>
##           297           3099           1604           0
```

#### 4.7.4 mpg variable

```
quantile(df$mpg,seq(0,1,0.25),na.rm=TRUE)
```

```
##           0%           25%           50%           75%           100%
##           8.8          44.8          53.3          61.4          88.3
```

```
df$aux_mpg<-factor(cut(df$mpg,breaks=c(quantile(df$mpg,seq(0,1,0.25),na.rm=TRUE)),include.lowest = T ))
summary(df$aux_mpg)
```

```
## [8.8,44.8] (44.8,53.3] (53.3,61.4] (61.4,88.3]
##      1300      1378      1188      1134
```

```
tapply(df$mpg,df$aux_mpg,median)
```

```
## [8.8,44.8] (44.8,53.3] (53.3,61.4] (61.4,88.3]
##      39.2      49.6      57.7      67.3
```

```
levels(df$aux_mpg)<-paste("f.mpg-",levels(df$aux_mpg),sep="")
table(df$aux_mpg,useNA="always")
```

```
##
## f.mpg-[8.8,44.8] f.mpg-(44.8,53.3] f.mpg-(53.3,61.4] f.mpg-(61.4,88.3]
##      1300      1378      1188      1134
##      <NA>
##      0
```

#### 4.7.5 years\_sell variable

```
df$aux_years_sell<-factor(cut(df$years_sell,breaks=c(quantile(df$years_sell,seq(0,1,0.25),na.rm=TRUE)),
summary(df$aux_years_sell)
```

```
## [2,3] (3,5] (5,6] (6,23]
## 1918 1380 862 840
```

```
tapply(df$years_sell,df$aux_years_sell,median)
```

```
## [2,3] (3,5] (5,6] (6,23]
## 3 5 6 8
```

```
levels(df$aux_years_sell)<-paste("f.years_sell-",levels(df$aux_years_sell),sep="")
table(df$aux_years_sell,useNA="always")
```

```
##
## f.years_sell-[2,3] f.years_sell-(3,5] f.years_sell-(5,6] f.years_sell-(6,23]
##      1918      1380      862      840
##      <NA>
##      0
```

## 4.8 Definition of binary outcome: Audi

Create binary target, define lists of numeric and qualitative variables and save your raw base database

We have created a binary target to know if the car is Audi or not. We will use this variable later to do profiling with it.

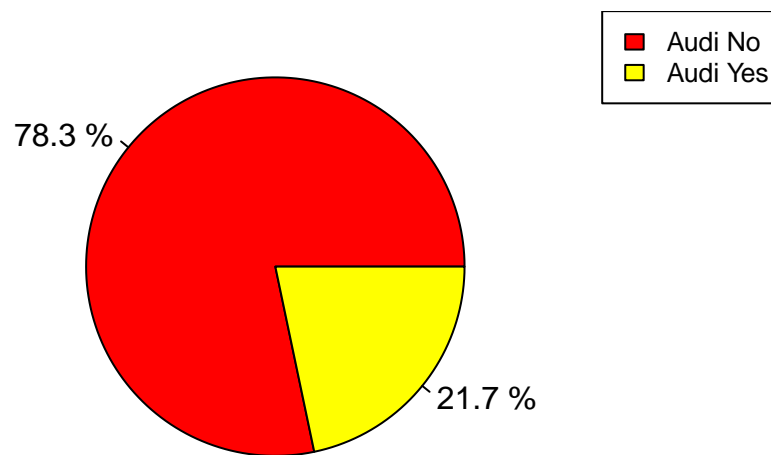
```
# Binary Target: Audi?
df$Audi<-ifelse(df$manufacturer == "Audi",1,0)
df$Audi<-factor(df$Audi,labels=paste("Audi",c("No","Yes")))
summary(df$Audi)
```

```
## Audi No Audi Yes
## 3915 1085
```

```
# Pie
piepercent<-round(100*(table(df$Audi)/nrow(df)),dig=2); piepercent

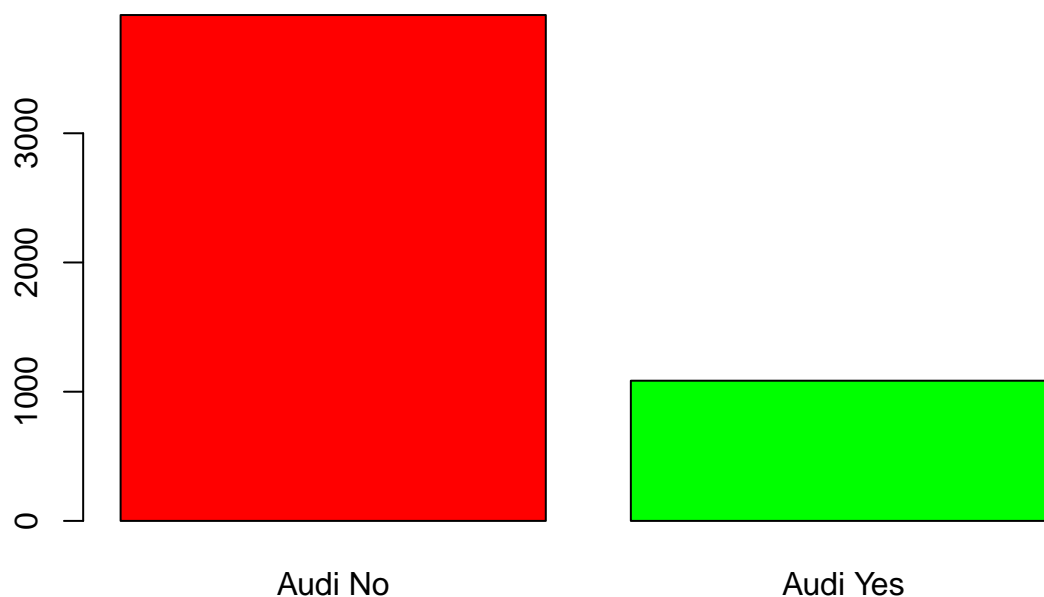
##
## Audi No Audi Yes
##      78.3      21.7

pie(table(df$Audi),col=heat.colors(2),labels=paste(piepercent,"%"))
legend("topright", levels(df$Audi), cex = 0.8, fill = heat.colors(2))
```



```
# Bar Chart
barplot(table(df$Audi),main="Barplot Binary Outcome - Factor",col=c("red","green"))
```

## Barplot Binary Outcome – Factor



### 4.9 Multivariant outliers

We have executed Moutlier function in order to find the multivariant outliers. Then, we have created a new variable (df\$mout) in order to distinguish/differentiate individuals that are multivariant outliers (they have a robust distance greater than the cutoff distance) and individuals that not.

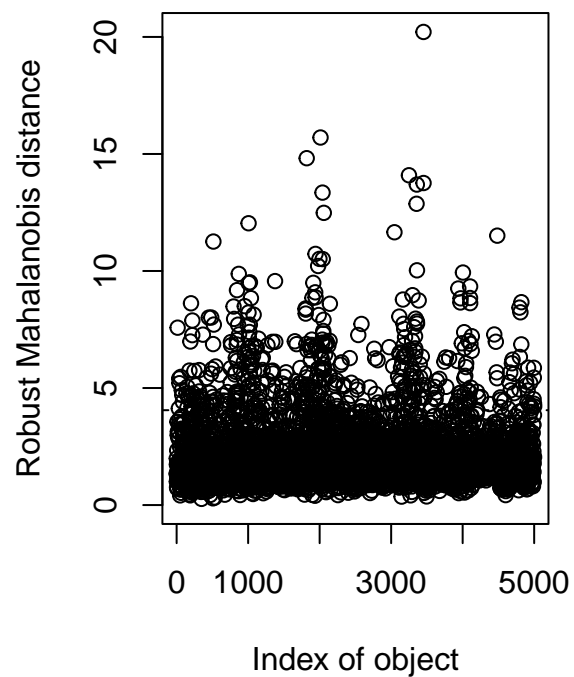
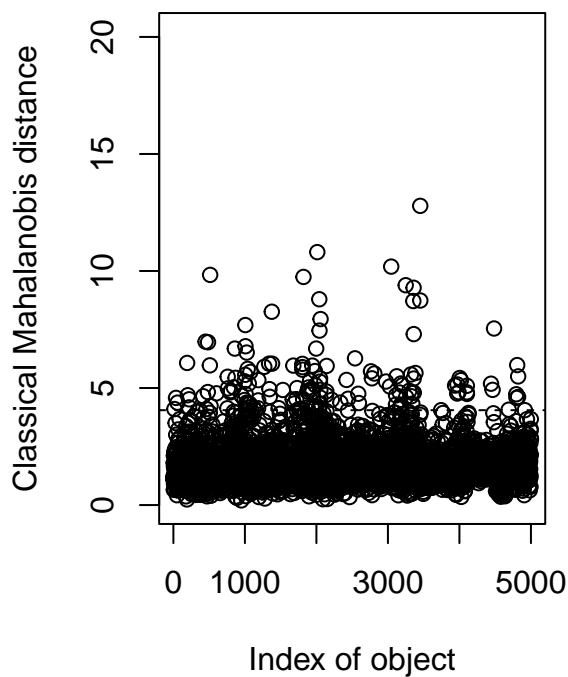
```
library(chemometrics)
```

```
## Loading required package: rpart
```

```
summary(df[,c(3, 5, 8, 11)])
```

```
##      price      mileage      mpg      years_sell
## Min.   :   650   Min.   :    4   Min.   : 8.80   Min.   : 2.000
## 1st Qu.: 13995   1st Qu.: 5999   1st Qu.:44.80   1st Qu.: 3.000
## Median : 19498   Median : 16528   Median :53.30   Median : 5.000
## Mean   : 21470   Mean   : 22888   Mean   :52.74   Mean   : 4.787
## 3rd Qu.: 26039   3rd Qu.: 33516   3rd Qu.:61.40   3rd Qu.: 6.000
## Max.   :109990   Max.   :116000   Max.   :88.30   Max.   :23.000
```

```
mout<-Moutlier(df[,c(3, 5, 8, 11)],quantile = 0.9975, plot = TRUE)
```



```
length(which(mout$rd>mout$cutoff))
```

```
## [1] 464
```

```
ll<-which(mout$rd>mout$cutoff)
Boxplot(mout$rd)
```

```
## [1] 3452 2012 1819 3249 3453 3359 2040 3355 2058 1006
```

```
df[ll[1:3],c(3,5,8,11)]
```

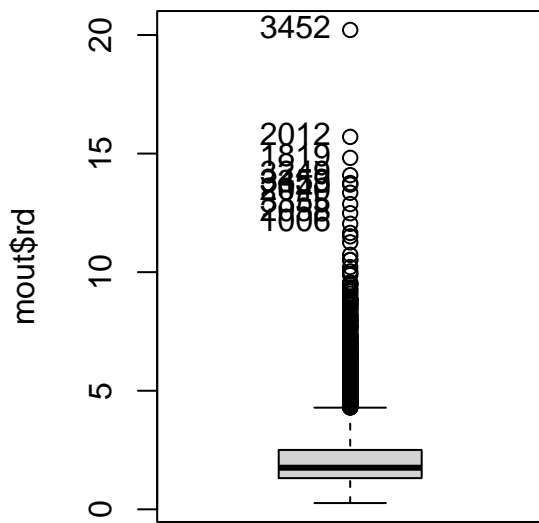
```
## price mileage mpg years_sell
## 14 16200 89334 62.8 6
## 31 56985 1510 33.2 3
## 37 63985 8450 32.8 4
```

```
df$mout <- 0
df$mout[ ll ]<-1
df$mout <- factor( df$mout, labels=c( "NoMOut", "YesMOut"))
table(df$mout)
```

```
##
## NoMOut YesMOut
## 4536 464
```

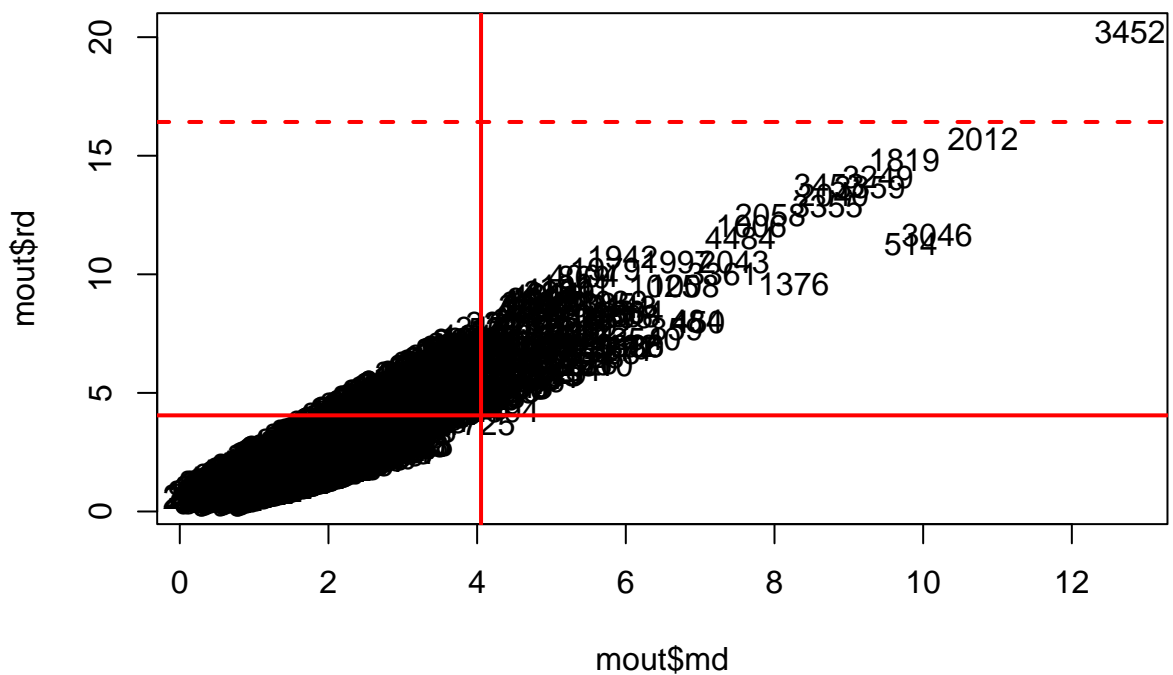
```
par(mfrow=c(1,1))
```





```
plot(mout$md,mout$rd, type="n")
text(mout$md,mout$rd,labels=rownames(df[,vars_con]))
abline(h=mout$cutoff,col="red",lwd=2)
abline(v=mout$cutoff,col="red",lwd=2)

abline(h=mout$cutoff^2,col="red",lwd=2,lty=2)
abline(v=mout$cutoff^2,col="red",lwd=2,lty=2)
```



## 4.10 Profiling

```
library(FactoMineR)
summary(df$price)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      650   13995   19498   21470   26039  109990
```

```
res.condes<-condes(df,3)
res.condes$quanti  # Global association to numeric variables
```

```
##           correlation      p.value
## totalMOE   -0.2979631 4.715577e-103
## mileage    -0.5131584 0.000000e+00
## years_sell -0.5538620 0.000000e+00
## mpg        -0.5903613 0.000000e+00
```

```
res.condes$quali  # Global association to factors
```

```
##           R2      p.value
## model      0.515041082 0.000000e+00
## year       0.353483215 0.000000e+00
## engineSize  0.413280059 0.000000e+00
## aux_price   0.731460406 0.000000e+00
## aux_mileage 0.293743806 0.000000e+00
## aux_mpg     0.300971015 0.000000e+00
## aux_years_sell 0.321950885 0.000000e+00
## transmission 0.230475968 5.322731e-285
## manufacturer 0.092467374 9.441791e-105
## aux_tax     0.089992603 4.717795e-103
## Audi       0.004668061 1.327290e-06
## fuelType    0.003656164 3.811516e-04
```

```
res.condes$category  # Partial association to significative levels in factors
```

```
##           Estimate      p.value
## aux_years_sell=f.years_sell-[2,3]  9251.70250 0.000000e+00
## aux_mpg=f.mpg-[8.8,44.8]           9723.17533 0.000000e+00
## aux_price=f.price-(26,110)         14249.54562 0.000000e+00
## aux_mileage=f.mileage-[4,6e+03]    8087.75077 3.393062e-225
## year=f.Year-2019                   12374.45389 3.012776e-202
## engineSize=f.EngineSize-3          12016.91222 5.157298e-195
## transmission=f.Trans-SemiAuto      4505.05997 1.119939e-131
## aux_tax=f.tax-(125,145)            4770.39249 1.736430e-103
## year=f.Year-2020                   16602.91086 2.019709e-77
## engineSize=f.EngineSize-4          36182.92607 1.924377e-73
## year=f.Year-2016                   469.10740 8.174011e-60
## engineSize=f.EngineSize-4.2 or more 27624.31893 3.490423e-43
## model=Audi-Q8                      43576.84832 3.318259e-41
## manufacturer=Mercedes              3039.49797 2.027962e-40
## model=Mercedes-GLE Class           10820.23923 7.120933e-37
## model=BMW-X7                       42413.20546 1.314652e-34
## model=Audi-Q7                      13708.16082 6.673097e-29
## model=Mercedes-GLC Class           3183.60042 8.847262e-28
## engineSize=f.EngineSize-2.9        28576.84571 8.454111e-27
## transmission=f.Trans-Automatic     2531.21056 7.568797e-26
## aux_mileage=f.mileage-(6e+03,1.65e+04] 2756.38254 2.237589e-25
## year=f.Year-2017                   2745.46170 1.557611e-21
## model=Audi-Q5                      2914.98273 6.957440e-21
## model=Mercedes-S Class             17293.72332 3.925870e-20
```

## model=Mercedes-GLS Class	18533.56260	1.822382e-19
## model=BMW-8 Series	35992.74832	2.204029e-19
## model=BMW-X5	8463.71195	1.821812e-17
## model=BMW-M5	37683.09832	6.285862e-17
## model=Audi-R8	56033.34832	9.515733e-17
## model=BMW-M4	18969.53014	4.519729e-16
## model=Mercedes-SL CLASS	4815.03253	2.006258e-12
## model=VW-Touareg	4073.84832	1.374518e-09
## aux_years_sell=f.years_sell-(3,5]	645.29335	1.510423e-08
## model=BMW-X6	15456.63403	2.045855e-08
## model=BMW-X3	364.01498	4.555479e-07
## model=BMW-7 Series	7855.09832	9.081694e-07
## engineSize=f.EngineSize-2	609.28213	1.057731e-06
## Audi=Audi Yes	898.85989	1.327290e-06
## manufacturer=Audi	1120.63823	1.327290e-06
## model=BMW-M2	15534.34832	2.007301e-06
## aux_price=f.price-(19.5,26]	1231.36722	2.727027e-06
## model=Audi-RS6	20839.68165	5.941713e-06
## model=VW-Caravelle	9357.72332	1.085753e-05
## model=Audi-A8	4406.53582	1.100877e-05
## model=Audi-RS5	19173.34832	2.030061e-05
## manufacturer=BMW	975.38554	2.200900e-05
## model=BMW-X4	3188.29276	2.841145e-05
## model=Audi-RS4	23962.34832	4.062218e-05
## fuelType=f.Fuel-Diesel	81.36076	6.524733e-05
## year=f.Year-2018	7588.80081	2.276380e-04
## model=BMW-i8	15037.68165	3.187854e-04
## model=Audi-S4	11958.09832	3.326456e-04
## model=BMW-X2	696.07559	3.885212e-04
## model=VW-California	29034.34832	7.553580e-04
## model=BMW-M3	4761.68165	5.636620e-03
## model=Audi-RS3	3637.14832	2.176207e-02
## engineSize=f.EngineSize-2.5	6487.23321	4.836521e-02
## model=VW-Tiguan Allspace	-1746.22311	4.737339e-02
## model=VW-Jetta	-19960.98502	4.630031e-02
## model=Mercedes-CLC Class	-23029.15168	4.266624e-02
## model=VW-Touran	-11006.95937	4.185280e-02
## model=Mercedes-X-CLASS	-771.46986	3.982262e-02
## aux_mpg=f.mpg-(44.8,53.3]	-258.09211	3.326596e-02
## model=VW-Arteon	-2896.28131	2.745189e-02
## model=VW-Golf SV	-12467.49168	2.132947e-02
## model=BMW-3 Series	-9145.48707	1.449274e-02
## model=VW-Amarok	-512.27668	9.982846e-03
## model=Mercedes-SLK	-20110.85168	9.206574e-03
## model=Mercedes-V Class	-452.42946	5.836196e-03
## model=Mercedes-CLS Class	-370.31835	5.286254e-03
## model=VW-Beetle	-18955.36597	5.108585e-03
## engineSize=f.EngineSize-1.5	-1747.80132	7.195178e-04
## model=VW-CC	-18679.10623	6.089175e-04
## model=VW-Scirocco	-15278.40168	4.165586e-04
## model=Mercedes-A Class	-10172.40353	2.833106e-05
## fuelType=f.Fuel-Petrol	-1217.90283	2.275137e-05
## engineSize=f.EngineSize-1.8	-9426.92832	1.590542e-05
## engineSize=f.EngineSize-2.1	-2501.31936	1.564794e-05
## year=f.Year-2012	-4887.18916	1.434448e-05
## model=Mercedes-C Class	-4932.22934	2.721980e-06
## Audi=Audi No	-898.85989	1.327290e-06
## model=VW-Passat	-12997.69424	6.406054e-07
## model=Audi-A3	-11593.82254	4.796664e-08
## year=f.Year-2011	-7439.76560	1.630019e-08
## model=Mercedes-E Class	-2977.47390	1.281271e-08
## year=f.Year-2010	-8897.47989	3.665675e-10
## model=Audi-A1	-14095.87796	4.173040e-13
## model=BMW-1 Series	-13141.11869	7.132624e-14

```
## aux_tax=f.tax-[0,125] -3090.21034 2.050124e-18
## year=f.Year-2009 or before -9958.24179 1.363765e-21
## model=VW-Golf -12379.53283 5.234941e-26
## engineSize=f.EngineSize-1.4 -7037.38028 4.806127e-28
## year=f.Year-2013 -5024.10129 1.983361e-29
## model=VW-Up -20805.93577 1.276864e-31
## year=f.Year-2014 -3095.45499 8.013091e-33
## engineSize=f.EngineSize-1.2 -11809.30679 7.807887e-34
## engineSize=f.EngineSize-1.6 -7001.12118 4.564378e-34
## year=f.Year-2015 -478.50193 1.365347e-36
## aux_mileage=f.mileage-(1.65e+04,3.35e+04] -3644.94145 1.161832e-43
## aux_mpg=f.mpg-(53.3,61.4] -3602.22515 5.344170e-46
## aux_years_sell=f.years_sell-(5,6] -3361.32631 8.174011e-60
## engineSize=f.EngineSize-1 -8959.45696 1.684048e-65
## aux_price=f.price-(14,19.5] -4657.16617 4.332775e-70
## aux_tax=f.tax-(145,580] -1680.18215 5.578448e-71
## model=VW-Polo -17500.47352 1.353249e-73
## manufacturer=VW -5135.52174 8.812113e-101
## aux_mpg=f.mpg-(61.4,88.3] -5862.85807 4.311250e-109
## aux_years_sell=f.years_sell-(6,23] -6535.66954 4.910168e-149
## aux_mileage=f.mileage-(3.35e+04,1.16e+05] -7199.19185 9.366109e-175
## transmission=f.Trans-Manual -7036.27053 1.829258e-279
## aux_price=f.price-[0.65,14] -10823.74668 0.000000e+00
```

As we can see in the output `condes$quanti`, price variable is related with tax, mpg, mileage and years\_sell variables because their p-values are less than 0.05. More concretely, against more price less mileage, less years\_sell and less mpg.

As we can see in the output `condes$quali`, model variable has a high correlation, i.e. certain models have high and/or low prices.

Regarding the output of `condes$category`, we can feature cars with model Audi-R8 which on average cost 56033.34832£ than baseline price, cars with model Audi-Q8 which on average cost 43576.84832£ more than baseline price and cars with model BMW-X7 which on average cost 42413.20546£ more than baseline price.

On the other hand, we can feature cars with model Mercedes-CLC Class which on average cost 23029.15168£ less than baseline price, cars with model Mercedes-SLK which on average cost 20110.85168£ less than baseline price and finally cars with model VW-Up which on average cost 20805.93577£ less than baseline price.

```
summary(df$Audi)
```

```
## Audi No Audi Yes
##      3915      1085
```

```
res.catdes<-catdes(df,18)
res.catdes$quanti.var # Global association to numeric variables
```

```
##           Eta2           P-value
## mpg      0.009703866 2.934540e-12
## price    0.004668061 1.327290e-06
## tax      0.004417699 2.552799e-06
## mileage  0.001260481 1.205183e-02
```

```
res.catdes$quanti # Partial association of numeric variables to levels of outcome factor
```

```
## $'Audi No'
##           v.test Mean in category Overall mean sd in category Overall sd
## mpg      6.964885           53.33278           52.73678           11.34995           11.49277
## mileage -2.510208          22486.99051          22887.97553          21188.80333          21454.13386
## tax     -4.699370           146.58458           146.98985           11.00856           11.58247
## price   -4.830697          21080.13921          21470.24440          10650.88867          10845.87254
##           p.value
## mpg      3.286717e-12
```

```
## mileage 1.206600e-02
## tax      2.609653e-06
## price    1.360558e-06
##
## $'Audi Yes'
##          v.test Mean in category Overall mean sd in category Overall sd
## price    4.830697      22877.85899  21470.24440   11411.69143 10845.87254
## tax      4.699370       148.45220    146.98985     13.34934   11.58247
## mileage  2.510208     24334.84772  22887.97553   22325.59521 21454.13386
## mpg      -6.964885       50.58624    52.73678     11.74518   11.49277
##          p.value
## price    1.360558e-06
## tax      2.609653e-06
## mileage  1.206600e-02
## mpg      3.286717e-12
```

```
res.catdes$test.chi2 # Global association to factors
```

```
##          p.value df
## model      0.000000e+00 87
## manufacturer 0.000000e+00 3
## engineSize  1.938026e-76 21
## aux_mpg     1.676014e-16 3
## aux_price   2.927530e-06 3
## fuelType    8.418028e-06 3
## mout        2.762592e-03 1
## transmission 4.235600e-03 2
## aux_tax     1.645093e-02 2
## aux_mileage 2.230200e-02 3
```

```
res.catdes$category # Partial association to significative levels in factors
```

```
## $'Audi No'
##          Cla/Mod      Mod/Cla Global
## manufacturer=VW      100.00000 38.69731801 30.30
## manufacturer=Mercedes 100.00000 34.50830140 27.02
## manufacturer=BMW      100.00000 26.79438059 20.98
## model=VW-Golf         100.00000 12.46487867 9.76
## engineSize=f.EngSize-2.1 100.00000 10.39591315 8.14
## model=Mercedes-C Class 100.00000 9.37420179 7.34
## model=VW-Polo         100.00000 8.88888889 6.96
## model=Mercedes-A Class 100.00000 6.89655172 5.40
## model=BMW-3 Series     100.00000 6.20689655 4.86
## model=BMW-1 Series     100.00000 5.03192848 3.94
## model=Mercedes-E Class 100.00000 4.59770115 3.60
## model=VW-Tiguan       100.00000 4.18901660 3.28
## model=BMW-2 Series     100.00000 3.52490421 2.76
## model=Mercedes-GLC Class 100.00000 3.03959132 2.38
## model=BMW-4 Series     100.00000 2.50319285 1.96
## model=VW-Passat       100.00000 2.40102171 1.88
## model=VW-Up           100.00000 2.24776501 1.76
## model=BMW-5 Series     100.00000 2.19667944 1.72
## model=Mercedes-GLA Class 100.00000 2.14559387 1.68
## engineSize=f.EngSize-1.3 100.00000 1.94125160 1.52
## model=BMW-X1          100.00000 1.89016603 1.48
## engineSize=f.EngSize-1.2 96.00000 3.06513410 2.50
## engineSize=f.EngSize-1.5 86.79928 12.26053640 11.06
## model=VW-T-Roc        100.00000 1.60919540 1.26
## model=Mercedes-B Class 100.00000 1.60919540 1.26
## aux_price=f.price-[0.65,14] 83.32010 26.79438059 25.18
## model=Mercedes-CL Class 100.00000 1.45593870 1.14
## model=Mercedes-GLE Class 100.00000 1.40485313 1.10
```

## aux_mpg=f.mpg-(61.4,88.3]	83.33333	24.13793103	22.68
## model=BMW-X3	100.00000	1.22605364	0.96
## aux_mpg=f.mpg-(53.3,61.4]	82.65993	25.08301405	23.76
## model=VW-Touran	100.00000	0.99616858	0.78
## model=Mercedes-SL CLASS	100.00000	0.97062580	0.76
## fuelType=f.Fuel-Hybrid	96.36364	1.35376756	1.10
## model=BMW-X5	100.00000	0.84291188	0.66
## model=VW-Touareg	100.00000	0.81736909	0.64
## engineSize=f.EngSize-1	84.52088	8.78671775	8.14
## model=VW-Arteon	100.00000	0.68965517	0.54
## model=VW-T-Cross	100.00000	0.63856960	0.50
## model=VW-Golf SV	100.00000	0.63856960	0.50
## model=VW-Scirocco	100.00000	0.61302682	0.48
## fuelType=f.Fuel-Diesel	79.80296	57.93103448	56.84
## mout=NoMOut	78.85802	91.36653895	90.72
## model=VW-Sharan	100.00000	0.56194125	0.44
## model=BMW-X2	100.00000	0.56194125	0.44
## aux_tax=f.tax-[0,125]	84.17508	6.38569604	5.94
## transmission=f.Trans-SemiAuto	80.23256	38.77394636	37.84
## model=Mercedes-V Class	100.00000	0.45977011	0.36
## model=Mercedes-CLS Class	100.00000	0.45977011	0.36
## model=BMW-X4	100.00000	0.45977011	0.36
## model=VW-Amarok	100.00000	0.40868455	0.32
## model=Mercedes-S Class	100.00000	0.40868455	0.32
## model=BMW-Z4	100.00000	0.38314176	0.30
## model=VW-Tiguan Allspace	100.00000	0.35759898	0.28
## model=Mercedes-GLS Class	100.00000	0.35759898	0.28
## model=Mercedes-GL Class	100.00000	0.35759898	0.28
## aux_mileage=f.mileage-(6e+03,1.65e+04]	80.28846	25.59386973	24.96
## model=Audi-RS4	0.00000	0.00000000	0.04
## model=Audi-R8	0.00000	0.00000000	0.04
## aux_years_sell=f.years_sell-(6,23]	75.11905	16.11749681	16.80
## year=f.Year-2015	73.50835	7.86717752	8.38
## model=Audi-RS6	0.00000	0.00000000	0.06
## model=Audi-RS5	0.00000	0.00000000	0.06
## aux_mileage=f.mileage-(3.35e+04,1.16e+05]	75.36000	24.06130268	25.00
## mout=YesMOut	72.84483	8.63346105	9.28
## model=Audi-S4	0.00000	0.00000000	0.08
## engineSize=f.EngSize-2.5	30.00000	0.07662835	0.20
## transmission=f.Trans-Manual	75.82173	34.76372925	35.90
## engineSize=f.EngSize-4	50.00000	0.35759898	0.56
## aux_price=f.price-(26,110]	74.96000	23.93358876	25.00
## model=Audi-SQ5	0.00000	0.00000000	0.10
## model=Audi-RS3	0.00000	0.00000000	0.10
## fuelType=f.Fuel-Petrol	75.65758	40.40868455	41.82
## model=Audi-Q8	0.00000	0.00000000	0.16
## engineSize=f.EngSize-2	74.36267	39.48914432	41.58
## model=Audi-A7	0.00000	0.00000000	0.28
## model=Audi-A8	0.00000	0.00000000	0.32
## aux_mpg=f.mpg-[8.8,44.8]	70.53846	23.42273308	26.00
## model=Audi-TT	0.00000	0.00000000	0.62
## model=Audi-Q7	0.00000	0.00000000	0.64
## engineSize=f.EngSize-1.4	47.40484	3.49936143	5.78
## model=Audi-A6	0.00000	0.00000000	1.42
## model=Audi-Q2	0.00000	0.00000000	1.60
## model=Audi-Q5	0.00000	0.00000000	1.86
## model=Audi-A5	0.00000	0.00000000	2.02
## model=Audi-A4	0.00000	0.00000000	2.72
## model=Audi-A1	0.00000	0.00000000	2.74
## model=Audi-Q3	0.00000	0.00000000	2.84
## model=Audi-A3	0.00000	0.00000000	3.98
## manufacturer=Audi	0.00000	0.00000000	21.70
##	p.value	v.test	
## manufacturer=VW	6.200610e-198	30.015283	

## manufacturer=Mercedes	4.216696e-172	27.965963
## manufacturer=BMW	5.589380e-128	24.066644
## model=VW-Golf	1.159189e-55	15.716865
## engineSize=f.EngineSize-2.1	4.367102e-46	14.251826
## model=Mercedes-C Class	1.985400e-41	13.482401
## model=VW-Polo	3.119709e-39	13.104093
## model=Mercedes-A Class	2.535101e-30	11.443480
## model=BMW-3 Series	2.812726e-27	10.818523
## model=BMW-1 Series	3.908271e-22	9.673488
## model=Mercedes-E Class	3.008936e-20	9.218639
## model=VW-Tiguan	1.765897e-18	8.771316
## model=BMW-2 Series	1.278514e-15	7.996649
## model=Mercedes-GLC Class	1.532980e-13	7.384265
## model=BMW-4 Series	2.968357e-11	6.648132
## model=VW-Passat	8.069916e-11	6.499291
## model=VW-Up	3.611143e-10	6.269971
## model=BMW-5 Series	5.947978e-10	6.191803
## model=Mercedes-GLA Class	9.794760e-10	6.112719
## engineSize=f.EngineSize-1.3	7.186080e-09	5.786517
## model=BMW-X1	1.181999e-08	5.702302
## engineSize=f.EngineSize-1.2	2.000762e-08	5.611935
## engineSize=f.EngineSize-1.5	7.077720e-08	5.389187
## model=VW-T-Roc	1.817722e-07	5.217073
## model=Mercedes-B Class	1.817722e-07	5.217073
## aux_price=f.price-[0.65,14]	3.496523e-07	5.094506
## model=Mercedes-CL Class	8.047644e-07	4.934208
## model=Mercedes-GLE Class	1.320844e-06	4.836592
## aux_mpg=f.mpg-(61.4,88.3]	1.808258e-06	4.773751
## model=BMW-X3	7.468166e-06	4.479890
## aux_mpg=f.mpg-(53.3,61.4]	2.176387e-05	4.245981
## model=VW-Touran	6.898687e-05	3.979753
## model=Mercedes-SL CLASS	8.829322e-05	3.920697
## fuelType=f.Fuel-Hybrid	1.981835e-04	3.721321
## model=BMW-X5	3.029459e-04	3.612768
## model=VW-Touareg	3.875960e-04	3.548389
## engineSize=f.EngineSize-1	1.055041e-03	3.275422
## model=VW-Arteon	1.327652e-03	3.209935
## model=VW-T-Cross	2.171678e-03	3.065691
## model=VW-Golf SV	2.171678e-03	3.065691
## model=VW-Scirocco	2.777248e-03	2.991374
## fuelType=f.Fuel-Diesel	3.165296e-03	2.951212
## mout=NoMOut	3.450461e-03	2.924468
## model=VW-Sharan	4.541297e-03	2.837889
## model=BMW-X2	4.541297e-03	2.837889
## aux_tax=f.tax-[0,125]	9.288054e-03	2.601265
## transmission=f.Trans-SemiAuto	9.456906e-03	2.595079
## model=Mercedes-V Class	1.213442e-02	2.508211
## model=Mercedes-CLS Class	1.213442e-02	2.508211
## model=BMW-X4	1.213442e-02	2.508211
## model=VW-Amarok	1.982863e-02	2.329575
## model=Mercedes-S Class	1.982863e-02	2.329575
## model=BMW-Z4	2.534506e-02	2.236102
## model=VW-Tiguan Allspace	3.239438e-02	2.139510
## model=Mercedes-GLS Class	3.239438e-02	2.139510
## model=Mercedes-GL Class	3.239438e-02	2.139510
## aux_mileage=f.mileage-(6e+03,1.65e+04]	4.802947e-02	1.977108
## model=Audi-RS4	4.705501e-02	-1.985805
## model=Audi-R8	4.705501e-02	-1.985805
## aux_years_sell=f.years_sell-(6,23]	1.539365e-02	-2.422983
## year=f.Year-2015	1.482733e-02	-2.436569
## model=Audi-RS6	1.019619e-02	-2.569104
## model=Audi-RS5	1.019619e-02	-2.569104
## aux_mileage=f.mileage-(3.35e+04,1.16e+05]	3.928202e-03	-2.883871
## mout=YesMOut	3.450461e-03	-2.924468

```

## model=Audi-S4                2.207781e-03  -3.060757
## engineSize=f.EngSize-2.5     1.574193e-03  -3.160647
## transmission=f.Trans-Manual  1.556181e-03  -3.163998
## engineSize=f.EngSize-4       1.073648e-03  -3.270481
## aux_price=f.price-(26,110]   1.069335e-03  -3.271619
## model=Audi-SQ5               4.777044e-04  -3.492956
## model=Audi-RS3               4.777044e-04  -3.492956
## fuelType=f.Fuel-Petrol       1.287964e-04  -3.828749
## model=Audi-Q8                4.818120e-06  -4.572555
## engineSize=f.EngSize-2       1.435083e-08  -5.669149
## model=Audi-A7                4.805857e-10  -6.225316
## model=Audi-A8                2.215780e-11  -6.691048
## aux_mpg=f.mpg-[8.8,44.8]    1.250134e-14  -7.710818
## model=Audi-TT                1.917911e-21  -9.509386
## model=Audi-Q7                4.068178e-22  -9.669384
## engineSize=f.EngSize-1.4     1.255775e-32  -11.895050
## model=Audi-A6                1.226198e-48  -14.656391
## model=Audi-Q2                7.866556e-55  -15.595047
## model=Audi-Q5                7.969683e-64  -16.866251
## model=Audi-A5                2.173682e-69  -17.607081
## model=Audi-A4                5.313784e-94  -20.567976
## model=Audi-A1                1.036756e-94  -20.647092
## model=Audi-Q3                2.894022e-98  -21.038835
## model=Audi-A3                1.877840e-139 -25.138712
## manufacturer=Audi            0.000000e+00  -Inf
##
## $'Audi Yes'
##
## Cla/Mod      Mod/Cla Global
## manufacturer=Audi 100.000000 100.000000 21.70
## model=Audi-A3     100.000000 18.3410138 3.98
## model=Audi-Q3     100.000000 13.0875576 2.84
## model=Audi-A1     100.000000 12.6267281 2.74
## model=Audi-A4     100.000000 12.5345622 2.72
## model=Audi-A5     100.000000 9.3087558 2.02
## model=Audi-Q5     100.000000 8.5714286 1.86
## model=Audi-Q2     100.000000 7.3732719 1.60
## model=Audi-A6     100.000000 6.5437788 1.42
## engineSize=f.EngSize-1.4 52.595156 14.0092166 5.78
## model=Audi-Q7     100.000000 2.9493088 0.64
## model=Audi-TT     100.000000 2.8571429 0.62
## aux_mpg=f.mpg-[8.8,44.8] 29.461538 35.2995392 26.00
## model=Audi-A8     100.000000 1.4746544 0.32
## model=Audi-A7     100.000000 1.2903226 0.28
## engineSize=f.EngSize-2 25.637326 49.1244240 41.58
## model=Audi-Q8     100.000000 0.7373272 0.16
## fuelType=f.Fuel-Petrol 24.342420 46.9124424 41.82
## model=Audi-SQ5    100.000000 0.4608295 0.10
## model=Audi-RS3    100.000000 0.4608295 0.10
## aux_price=f.price-(26,110] 25.040000 28.8479263 25.00
## engineSize=f.EngSize-4 50.000000 1.2903226 0.56
## transmission=f.Trans-Manual 24.178273 40.0000000 35.90
## engineSize=f.EngSize-2.5 70.000000 0.6451613 0.20
## model=Audi-S4     100.000000 0.3686636 0.08
## mout=YesMOut      27.155172 11.6129032 9.28
## aux_mileage=f.mileage-(3.35e+04,1.16e+05] 24.640000 28.3870968 25.00
## model=Audi-RS6    100.000000 0.2764977 0.06
## model=Audi-RS5    100.000000 0.2764977 0.06
## year=f.Year-2015 26.491647 10.2304147 8.38
## aux_years_sell=f.years_sell-(6,23] 24.880952 19.2626728 16.80
## model=Audi-RS4    100.000000 0.1843318 0.04
## model=Audi-R8     100.000000 0.1843318 0.04
## aux_mileage=f.mileage-(6e+03,1.65e+04] 19.711538 22.6728111 24.96
## model=VW-Tiguan Allspace 0.000000 0.0000000 0.28
## model=Mercedes-GLS Class 0.000000 0.0000000 0.28

```



## model=Mercedes-GL Class	0.000000	0.0000000	0.28
## model=BMW-Z4	0.000000	0.0000000	0.30
## model=VW-Amarok	0.000000	0.0000000	0.32
## model=Mercedes-S Class	0.000000	0.0000000	0.32
## model=Mercedes-V Class	0.000000	0.0000000	0.36
## model=Mercedes-CLS Class	0.000000	0.0000000	0.36
## model=BMW-X4	0.000000	0.0000000	0.36
## transmission=f.Trans-SemiAuto	19.767442	34.4700461	37.84
## aux_tax=f.tax-[0,125]	15.824916	4.3317972	5.94
## model=VW-Sharan	0.000000	0.0000000	0.44
## model=BMW-X2	0.000000	0.0000000	0.44
## mout=NoMOut	21.141975	88.3870968	90.72
## fuelType=f.Fuel-Diesel	20.197044	52.9032258	56.84
## model=VW-Scirocco	0.000000	0.0000000	0.48
## model=VW-T-Cross	0.000000	0.0000000	0.50
## model=VW-Golf SV	0.000000	0.0000000	0.50
## model=VW-Arteon	0.000000	0.0000000	0.54
## engineSize=f.EngineSize-1	15.479115	5.8064516	8.14
## model=VW-Touareg	0.000000	0.0000000	0.64
## model=BMW-X5	0.000000	0.0000000	0.66
## fuelType=f.Fuel-Hybrid	3.636364	0.1843318	1.10
## model=Mercedes-SL CLASS	0.000000	0.0000000	0.76
## model=VW-Touran	0.000000	0.0000000	0.78
## aux_mpg=f.mpg-(53.3,61.4]	17.340067	18.9861751	23.76
## model=BMW-X3	0.000000	0.0000000	0.96
## aux_mpg=f.mpg-(61.4,88.3]	16.666667	17.4193548	22.68
## model=Mercedes-GLE Class	0.000000	0.0000000	1.10
## model=Mercedes-CL Class	0.000000	0.0000000	1.14
## aux_price=f.price-[0.65,14]	16.679905	19.3548387	25.18
## model=VW-T-Roc	0.000000	0.0000000	1.26
## model=Mercedes-B Class	0.000000	0.0000000	1.26
## engineSize=f.EngineSize-1.5	13.200723	6.7281106	11.06
## engineSize=f.EngineSize-1.2	4.000000	0.4608295	2.50
## model=BMW-X1	0.000000	0.0000000	1.48
## engineSize=f.EngineSize-1.3	0.000000	0.0000000	1.52
## model=Mercedes-GLA Class	0.000000	0.0000000	1.68
## model=BMW-5 Series	0.000000	0.0000000	1.72
## model=VW-Up	0.000000	0.0000000	1.76
## model=VW-Passat	0.000000	0.0000000	1.88
## model=BMW-4 Series	0.000000	0.0000000	1.96
## model=Mercedes-GLC Class	0.000000	0.0000000	2.38
## model=BMW-2 Series	0.000000	0.0000000	2.76
## model=VW-Tiguan	0.000000	0.0000000	3.28
## model=Mercedes-E Class	0.000000	0.0000000	3.60
## model=BMW-1 Series	0.000000	0.0000000	3.94
## model=BMW-3 Series	0.000000	0.0000000	4.86
## model=Mercedes-A Class	0.000000	0.0000000	5.40
## model=VW-Polo	0.000000	0.0000000	6.96
## model=Mercedes-C Class	0.000000	0.0000000	7.34
## engineSize=f.EngineSize-2.1	0.000000	0.0000000	8.14
## model=VW-Golf	0.000000	0.0000000	9.76
## manufacturer=BMW	0.000000	0.0000000	20.98
## manufacturer=Mercedes	0.000000	0.0000000	27.02
## manufacturer=VW	0.000000	0.0000000	30.30
##	p.value	v.test	
## manufacturer=Audi	0.000000e+00	Inf	
## model=Audi-A3	1.877840e-139	25.138712	
## model=Audi-Q3	2.894022e-98	21.038835	
## model=Audi-A1	1.036756e-94	20.647092	
## model=Audi-A4	5.313784e-94	20.567976	
## model=Audi-A5	2.173682e-69	17.607081	
## model=Audi-Q5	7.969683e-64	16.866251	
## model=Audi-Q2	7.866556e-55	15.595047	
## model=Audi-A6	1.226198e-48	14.656391	

## engineSize=f.EngSize-1.4	1.255775e-32	11.895050
## model=Audi-Q7	4.068178e-22	9.669384
## model=Audi-TT	1.917911e-21	9.509386
## aux_mpg=f.mpg-[8.8,44.8]	1.250134e-14	7.710818
## model=Audi-A8	2.215780e-11	6.691048
## model=Audi-A7	4.805857e-10	6.225316
## engineSize=f.EngSize-2	1.435083e-08	5.669149
## model=Audi-Q8	4.818120e-06	4.572555
## fuelType=f.Fuel-Petrol	1.287964e-04	3.828749
## model=Audi-SQ5	4.777044e-04	3.492956
## model=Audi-RS3	4.777044e-04	3.492956
## aux_price=f.price-(26,110]	1.069335e-03	3.271619
## engineSize=f.EngSize-4	1.073648e-03	3.270481
## transmission=f.Trans-Manual	1.556181e-03	3.163998
## engineSize=f.EngSize-2.5	1.574193e-03	3.160647
## model=Audi-S4	2.207781e-03	3.060757
## mout=YesMOut	3.450461e-03	2.924468
## aux_mileage=f.mileage-(3.35e+04,1.16e+05]	3.928202e-03	2.883871
## model=Audi-RS6	1.019619e-02	2.569104
## model=Audi-RS5	1.019619e-02	2.569104
## year=f.Year-2015	1.482733e-02	2.436569
## aux_years_sell=f.years_sell-(6,23]	1.539365e-02	2.422983
## model=Audi-RS4	4.705501e-02	1.985805
## model=Audi-R8	4.705501e-02	1.985805
## aux_mileage=f.mileage-(6e+03,1.65e+04]	4.802947e-02	-1.977108
## model=VW-Tiguan Allspace	3.239438e-02	-2.139510
## model=Mercedes-GLS Class	3.239438e-02	-2.139510
## model=Mercedes-GL Class	3.239438e-02	-2.139510
## model=BMW-Z4	2.534506e-02	-2.236102
## model=VW-Amarok	1.982863e-02	-2.329575
## model=Mercedes-S Class	1.982863e-02	-2.329575
## model=Mercedes-V Class	1.213442e-02	-2.508211
## model=Mercedes-CLS Class	1.213442e-02	-2.508211
## model=BMW-X4	1.213442e-02	-2.508211
## transmission=f.Trans-SemiAuto	9.456906e-03	-2.595079
## aux_tax=f.tax-[0,125]	9.288054e-03	-2.601265
## model=VW-Sharan	4.541297e-03	-2.837889
## model=BMW-X2	4.541297e-03	-2.837889
## mout=NoMOut	3.450461e-03	-2.924468
## fuelType=f.Fuel-Diesel	3.165296e-03	-2.951212
## model=VW-Scirocco	2.777248e-03	-2.991374
## model=VW-T-Cross	2.171678e-03	-3.065691
## model=VW-Golf SV	2.171678e-03	-3.065691
## model=VW-Arteon	1.327652e-03	-3.209935
## engineSize=f.EngSize-1	1.055041e-03	-3.275422
## model=VW-Touareg	3.875960e-04	-3.548389
## model=BMW-X5	3.029459e-04	-3.612768
## fuelType=f.Fuel-Hybrid	1.981835e-04	-3.721321
## model=Mercedes-SL CLASS	8.829322e-05	-3.920697
## model=VW-Touran	6.898687e-05	-3.979753
## aux_mpg=f.mpg-(53.3,61.4]	2.176387e-05	-4.245981
## model=BMW-X3	7.468166e-06	-4.479890
## aux_mpg=f.mpg-(61.4,88.3]	1.808258e-06	-4.773751
## model=Mercedes-GLE Class	1.320844e-06	-4.836592
## model=Mercedes-CL Class	8.047644e-07	-4.934208
## aux_price=f.price-[0.65,14]	3.496523e-07	-5.094506
## model=VW-T-Roc	1.817722e-07	-5.217073
## model=Mercedes-B Class	1.817722e-07	-5.217073
## engineSize=f.EngSize-1.5	7.077720e-08	-5.389187
## engineSize=f.EngSize-1.2	2.000762e-08	-5.611935
## model=BMW-X1	1.181999e-08	-5.702302
## engineSize=f.EngSize-1.3	7.186080e-09	-5.786517
## model=Mercedes-GLA Class	9.794760e-10	-6.112719
## model=BMW-5 Series	5.947978e-10	-6.191803

```

## model=VW-Up                3.611143e-10  -6.269971
## model=VW-Passat            8.069916e-11  -6.499291
## model=BMW-4 Series         2.968357e-11  -6.648132
## model=Mercedes-GLC Class   1.532980e-13  -7.384265
## model=BMW-2 Series         1.278514e-15  -7.996649
## model=VW-Tiguan            1.765897e-18  -8.771316
## model=Mercedes-E Class     3.008936e-20  -9.218639
## model=BMW-1 Series         3.908271e-22  -9.673488
## model=BMW-3 Series         2.812726e-27  -10.818523
## model=Mercedes-A Class     2.535101e-30  -11.443480
## model=VW-Polo              3.119709e-39  -13.104093
## model=Mercedes-C Class     1.985400e-41  -13.482401
## engineSize=f.EngSize-2.1   4.367102e-46  -14.251826
## model=VW-Golf              1.159189e-55  -15.716865
## manufacturer=BMW           5.589380e-128  -24.066644
## manufacturer=Mercedes      4.216696e-172  -27.965963
## manufacturer=VW           6.200610e-198  -30.015283

```

As we can see in the output `catdes$quanti.var`, we can feature that  $\mu_{\text{AudiNo}}$ ,  $\mu_{\text{AudiYes}}$  and  $\mu_{\text{mpg}}$  are not the same because the p-value is less than 0.05.

As we can see in the output `catdes$quanti`, we can feature that Audi cars on average consume more, because on average they have less mpg.

As we can see in the output `catdes$test.chi2`, we can feature that Audi variable and model variable are not independent because the p-value is less than 0.05. Also, Audi variable and engineSize variable are not independent for the same reason.

As we can see in the output `catdes$category`, we can feature that VW, Mercedes and BMW cars are overrepresented in Audi No sample. Also, we can feature that engineSize 1.4, 2, 4 and 2.5 are overrepresented in Audi Yes sample and engineSize 1, 1.5, 1.2, 1.3, 2.1 are underrepresented in Audi Yes sample.