Data Mining Project (MaBAn 2020)

Predicting obesity levels according to daily habits

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Contents

Introduction

For this project, our objective is to predict the expected weight level (in Kg) for a given person depending on certain daily habits (eating and physical activity) and on the person's age, gender and height.

To do this, we found a quite interesting dataset (click here : http://archive.ics.uci.edu/ml/datasets/Estimation+of+obesity+levels+based+on+eating+habits+and+physical+condition+) containing 2111 observations and 17 variables (mainly categorical).

Please, find here a manually created metadata table :

```
# To adjust the page margins when knitting to PDF :

library(knitr)
opts_chunk$set(tidy.opts=list(width.cutoff=45),tidy=TRUE)
```

```r
# Used packages :

library(pander)
library(dplyr)
library(gt)
library(car)
library(ggplot2)
library(gridExtra)
library(psych)
library(corrplot)
library(ellipse)
library(dummies)
library(nnet)
library(class)
library(caret)
library(rpart)
library(rpart.plot)
library(ehaGoF)
library(forecast)
library(randomForest)


# Working Directory :

setwd("~/GitHub/CVTDM_Project_MaBAn_2020")


# Reading the data :

obesity <- read.csv("Obesity.csv", header = T,
    sep = ",")
attach(obesity)

obesity_original <- obesity


# Small metadata table :

tibble_table <- tibble(`Variable Name` = c(colnames(obesity)[1:14],
    "", colnames(obesity)[15:17]), Description = c("Gender",
    "Age", "Height", "Weight", "Has a family member suffered or suffers from overweight?
    "Do you eat high caloric food frequently?",
    "Do you usually eat vegetables in your meals?",
    "How many main meals do you have daily?",
    "Do you eat any food between meals?", "Do you smoke?",
    "How much water do you drink daily?", "Do you monitor the calories you eat daily?",
    "How often do you have physical activity?",
    "How much time do you use technological devices such as",
    "cell phone videogames, television, computer and others?",
    "How often do you drink alcohol?", "Which transportation do you usually use?",
    "Obesity level based on calculation of Mass Body Index"))

metadata <- gt(data = tibble_table)

metadata %>% tab_header(title = md("**Metadata**"),
    subtitle = "from the dataset we are using") %>%

tab_source_note(source_note = "Based on information in :

  https://www.sciencedirect.com/science/article/pii/S2352340919306985")
```

Metadata

from the dataset we are using

Variable Name	Description
Gender	Gender
Age	Age
Height	Height
Weight	Weight
family_history_with_overweight	Has a family member suffered or suffers from overweight?
FAVC	Do you eat high caloric food frequently?
FCVC	Do you usually eat vegetables in your meals?
NCP	How many main meals do you have daily?
CAEC	Do you eat any food between meals?
SMOKE	Do you smoke?
CH2O	How much water do you drink daily?
SCC	Do you monitor the calories you eat daily?
FAF	How often do you have physical activity?
TUE	How much time do you use technological devices such as cell phone videogames, television, computer and others?
CALC	How often do you drink alcohol?
MTRANS	Which transportation do you usually use?
NObeyesdad	Obesity level based on calculation of Mass Body Index

Based on information in :
https://www.sciencedirect.com/science/article/pii/S2352340919306985

Here is a small overview of the first observations :

```
pander(head(obesity))
```

Table continues below

Table continues below

Gender	Age	Height	Weight	family_history_with_overweight	FAVC	FCVC	NCP	CAEC	SMOKE	CH2O	SCC	FAF	TUE	CALC	MTRANS	NObeyesdad
Female	21	1.62	64	yes	no	2	3	Sometimes	no	2	no	0	1	no	Public_Transportation	Normal_Weight
Female	21	1.52	56	yes	no	3	3	Sometimes	yes	3	yes	3	0	Sometimes	Public_Transportation	Normal_Weight
Male	23	1.8	77	yes	no	2	3	Sometimes	no	2	no	2	1	Frequently	Public_Transportation	Normal_Weight
Male	27	1.8	87	no	no	3	3	Sometimes	no	2	no	2	0	Frequently	Walking	Overweight_Level_I
Male	22	1.78	89.8	no	no	2	1	Sometimes	no	2	no	0	0	Sometimes	Public_Transportation	Overweight_Level_II
Male	29	1.62	53	no	yes	2	3	Sometimes	no	2	no	0	0	Sometimes	Automobile	Normal_Weight

The variable of interest is "Weight", it will be our dependent variable.

This data set seems to be of high quality, because it has no missing observations, and our subsequent exploratory analysis will tell us if there are outliers to be handled with.

We will first begin with a basic data pre-processing which will be followed by a Data Exploratory Analysis. We will develop several models in order to accurately predict the level of weight of each individual.

The models will be :

1. **Multiple Linear Regression**
2. **Regression tree**
3. **k-Nearest Neighbors**
4. **Ensemble Method**

We will deploy the best model based on error metrics and prediction performance.

At the very end, we will make a **Shiny App** available, in which any user can fill-in a questionnaire concerning daily habits, age and height. Then, the App will tell the user what is the expected weight according to those characteristics, and will present the result in two forms :

- The expected weight in Kg.
- The expected obesity level based on the Body Mass Index, following the classification comming from the World Health Organisation.

The user will also be able to **select the type of model** that will predict the results. That way, it will be interesting to see with just a few clicks how each model will yield different results.

Data Pre-Processing

The first thing to do is to change the column names so that they are more visually meaningful and less confusing.

```r
# Changing column names:

names(obesity)[5] = "family_history"
names(obesity)[6] = "eat_caloric"
names(obesity)[7] = "vegetables"
names(obesity)[8] = "main_meals"
names(obesity)[9] = "food_inbetween"
names(obesity)[12] = "monitor_cal"
names(obesity)[13] = "physical_act"
names(obesity)[14] = "tech_devices"
names(obesity)[15] = "alcohol"
```

```r
# Checking the dataset structure :

pander(str(obesity))
```

'data.frame': 2111 obs. of 17 variables: $ Gender : chr "Female" "Female" "Male" "Male" … $ Age : num 21 21 23 27 22 29 23 22 24 22 … $ Height : num 1.62 1.52 1.8 1.8 1.78 1.62 1.5 1.64 1.78 1.72 … $ Weight : num 64 56 77 87 89.8 53 55 53 64 68 … $ family_history: chr "yes" "yes" "yes" "no" … $ eat_caloric : chr "no" "no" "no" "no" … $ vegetables :

num 2 3 2 3 2 2 3 2 3 2 . . . $ main_meals : num 3 3 3 3 1 3 3 3 3 3 . . . $ food_inbetween: chr “Sometimes” “Sometimes” “Sometimes” “Sometimes” . . . $ SMOKE : chr “no” “yes” “no” “no” . . . $ CH2O : num 2 3 2 2 2 2 2 2 2 2 . . . $ monitor_cal : chr “no” “yes” “no” “no” . . . $ physical_act : num 0 3 2 2 0 0 1 3 1 1 . . . $ tech_devices : num 1 0 1 0 0 0 0 1 1 . . . $ alcohol : chr “no” “Sometimes” “Frequently” “Frequently” . . . $ MTRANS : chr “Public_Transportation” “Public_Transportation” “Public_Transportation” “Walking” . . . $ NObeyesdad : chr “Normal_Weight” “Normal_Weight” “Normal_Weight” “Overweight_Level_I” . . .

```r
pander(summary(obesity[, 2:4]))
```

Age	Height	Weight
Min. :14.00	Min. :1.450	Min. : 39.00
1st Qu.:19.95	1st Qu.:1.630	1st Qu.: 65.47
Median :22.78	Median :1.700	Median : 83.00
Mean :24.31	Mean :1.702	Mean : 86.59
3rd Qu.:26.00	3rd Qu.:1.768	3rd Qu.:107.43
Max. :61.00	Max. :1.980	Max. :173.00

Since many variables are numerical and continuous between a range (for example `vegetables`, inside the range 1 to 3), we will transform them into categorical. This is, somehow, BINNING. For this, we will follow the names given in the information file refered to earlier (https://www.sciencedirect.com/science/article/pii/S2352340919306985).

To make this task easier, we created a function that bins variables. This function is called “binning”

```r
# Binning some numerical variables :


binning <- function(x) {

    # vegetables

    x$vegetables[x$vegetables <= 1] <- "Never"

    x$vegetables[x$vegetables > 1 & x$vegetables <=
        2] <- "Sometimes"

    x$vegetables[x$vegetables > 2 & x$vegetables <=
        3] <- "Always"


    # main_meals

    x$main_meals[x$main_meals >= 1 & x$main_meals <
```

```
        3] <- "Btw_1_&_2"

    x$main_meals[x$main_meals == 3] <- "Three"

    x$main_meals[x$main_meals > 3 & x$main_meals <=
        4] <- "More_than_3"


    # tech_devices

    x$tech_devices[x$tech_devices >= 0 & x$tech_devices <=
        0.5] <- "Zero_hours"

    x$tech_devices[x$tech_devices <= 1.5] <- "One_hour"

    x$tech_devices[x$tech_devices <= 2] <- "Two_hours"


    # physical_act

    x$physical_act[x$physical_act < 1] <- "I do not have"

    x$physical_act[x$physical_act >= 1 & x$physical_act <=
        2] <- "1 or 2 days"

    x$physical_act[x$physical_act >= 2 & x$physical_act <=
        4] <- "2 or 4 days"

    x$physical_act[x$physical_act >= 4 & x$physical_act <=
        5] <- "4 or 5 days"


    # CH2O

    x$CH2O[x$CH2O <= 1] <- "Less than a liter"

    x$CH2O[x$CH2O <= 2] <- "Between 1 and 2 L"

    x$CH2O[x$CH2O <= 3] <- "More than 2 L"


    return(x)

}


obesity = binning(obesity)
```

As we saw with the “str()” function, all the categorical variables are treated as “character”.Therefore, we will convert all the categorical variables to “factor” type.

Just as we did with the binning, we created a function to convert character variables to factor. This function is called “to_factor”.

```r
# Converting character variables to factor :


to_factor <- function(x) {

    x$Gender = as.factor(x$Gender)
    x$family_history = as.factor(x$family_history)
    x$eat_caloric = as.factor(x$eat_caloric)
    x$food_inbetween = as.factor(x$food_inbetween)
    x$SMOKE = as.factor(x$SMOKE)
    x$monitor_cal = as.factor(x$monitor_cal)
    x$alcohol = as.factor(x$alcohol)
    x$MTRANS = as.factor(x$MTRANS)
    x$NObeyesdad = as.factor(x$NObeyesdad)
    x$vegetables = as.factor(x$vegetables)
    x$main_meals = as.factor(x$main_meals)
    x$CH2O = as.factor(x$CH2O)
    x$physical_act = as.factor(x$physical_act)
    x$tech_devices = as.factor(x$tech_devices)

    return(x)

}

obesity = to_factor(obesity)
```

Our next step will to remove any missing values.

```r
# Checking if there are Missing Values :

sum(is.na(obesity))
```

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

There are no missing values within our dataset.

We will now proceed with the dummification of the categorical variables. All variables (with the exception of gender, age, height and weight) have already been dummyfied.

```
# Dummyfing the binary
# variables(family_history, eat_caloric,
# SMOKE, and monitor_cal) :

# Gender 1 = female, 0 = male
obesity_dummy <- cbind(dummy(obesity$Gender, sep = "_"),
    obesity[2:17])
names(obesity_dummy)[1] <- c("Gender")
obesity_dummy <- subset(obesity_dummy, select = -c(2))


# family_history 1 = yes, 0 = no
obesity_dummy <- cbind(obesity_dummy[1:4], dummy(obesity_dummy$family_hist,
    sep = "_"), obesity_dummy[6:17])
names(obesity_dummy)[6] <- c("family_hist")
obesity_dummy <- subset(obesity_dummy, select = -c(5))


# eat_caloric with 1 = yes, 0 = no
obesity_dummy <- cbind(obesity_dummy[1:5], dummy(obesity_dummy$eat_caloric,
    sep = "_"), obesity_dummy[7:17])
names(obesity_dummy)[7] <- c("eat_caloric")
obesity_dummy <- subset(obesity_dummy, select = -c(6))


# SMOKE 1 = yes, 0 = no
obesity_dummy <- cbind(obesity_dummy[1:9], dummy(obesity_dummy$SMOKE,
    sep = "_"), obesity_dummy[11:17])
names(obesity_dummy)[11] <- c("smoke")
obesity_dummy <- subset(obesity_dummy, select = -c(10))


# monitor_cal 1 = yes, 0 = no
obesity_dummy <- cbind(obesity_dummy[1:11], dummy(obesity_dummy$monitor_cal,
    sep = "_"), obesity_dummy[13:17])
names(obesity_dummy)[13] <- c("monitor_cal")
obesity_dummy <- subset(obesity_dummy, select = -c(12))



# Dummmyfying the categorical variables

# vegetables
obesity_dum <- cbind(obesity_dummy[1:6], dummy(obesity_dummy$vegetables,
    sep = "_"), obesity_dummy[8:17])
names(obesity_dum)[7:9] <- c("vegetables_never",
    "vegetables_sometimes", "vegetables_always")
```

```r
# main_meals
obesity_dum <- cbind(obesity_dum[1:9], dummy(obesity_dum$main_meals,
    sep = "_"), obesity_dum[11:19])
names(obesity_dum)[10:12] <- c("main_meals_Btw_1_2",
    "main_meals_More_than_3", "main_meals_three")

# food_in_between
obesity_dum <- cbind(obesity_dum[1:12], dummy(obesity_dum$food_inbetween,
    sep = "_"), obesity_dum[14:21])
names(obesity_dum)[13:16] <- c("food_inbetween_always",
    "food_inbetween_frequently", "food_inbetween_no",
    "food_inbetween_sometimes")

# alcohol
obesity_dum <- cbind(obesity_dum[1:21], dummy(obesity_dum$alcohol,
    sep = "_"), obesity_dum[23:24])
names(obesity_dum)[22:25] <- c("alcohol_always",
    "alcohol_frequently", "alcohol_no", "alcohol_sometimes")

# MTRANS
obesity_dum <- cbind(obesity_dum[1:25], dummy(obesity_dum$MTRANS,
    sep = "_"), obesity_dum[27])
names(obesity_dum)[26:30] <- c("mtrans_automobile",
    "mtrans_bike", "mtrans_motorbike", "mtrans_public_transportation",
    "mtrans_walking")

# CH2O
obesity_dum <- cbind(obesity_dum[1:17], dummy(obesity_dum$CH2O,
    sep = "_"), obesity_dum[19:31])
names(obesity_dum)[18:20] <- c("CH2O_less_than_a_liter",
    "CH2O_between_1_and_2", "CH2O_more_than_2")

# physical_act
obesity_dum <- cbind(obesity_dum[1:21], dummy(obesity_dum$physical_act,
    sep = "_"), obesity_dum[23:33])
names(obesity_dum)[22:24] <- c("physical_act_do_not_have",
    "physical_act_1_2", "physical_act_2_4")


# tech_devices : this one is a little bit
# tricky since there a many categories but
# only one is represented within the data!

obesity_dum <- cbind(obesity_dum[1:24], dummy(obesity_dum$tech_devices,
    sep = "_"), obesity_dum[26:35])
names(obesity_dum)[25:27] <- c("tech_0_hours",
    "tech_1_hour", "tech_2_hours_or_more")
```

```r
# remove(obesity_dum)
obesity_dum <- subset(obesity_dum[c(1:36)])
```

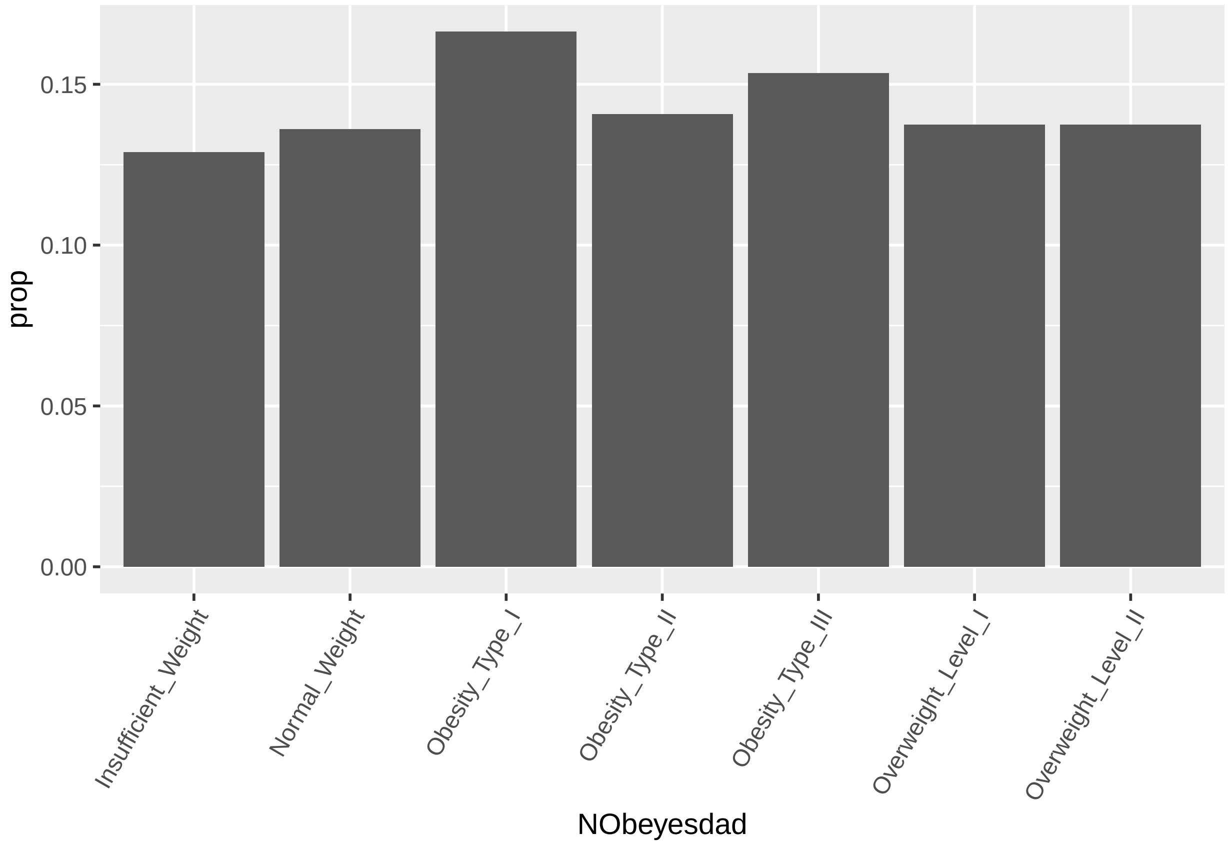
Finally, the last step in the data pre-processing is the partitionning of the data. We partitionned the data into a 60% training set and a 40% validation set. Because we have a relatively small number of observations (only 2111 observations), we thought it best to exclude a test set. However, better results could be obtained if we kept a third "test set".

```r
# Partitioning the data (60% training, 40%
# validation)

set.seed(1)

train.obs <- sample(rownames(obesity_dum), dim(obesity_dum)[1] *
    0.6)
train.set <- obesity_dum[train.obs, ]

set.seed(1)

valid.obs <- setdiff(rownames(obesity_dum), train.obs)
valid.set <- obesity_dum[valid.obs, ]
```

Now that we have finished with the data pre-processing, we can proceed with the exploratory data analysis. While we have dumyfied variables in the steps above, the original non-dummified versions of the variables will be used in the exploratory data analysis for vizualisation purposes.

Exploratory Data Analysis

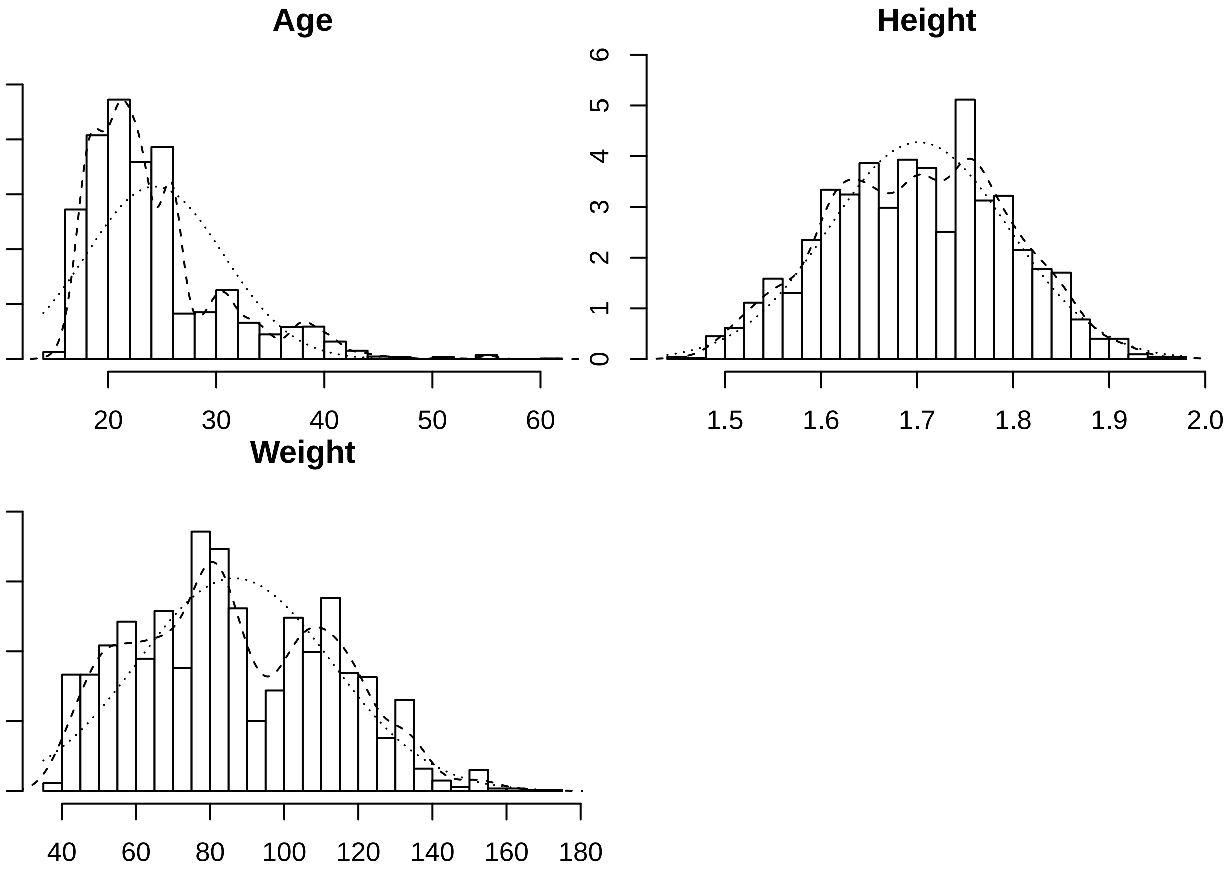
```r
ggplot(data = obesity, aes(x = NObeyesdad)) +
    geom_bar(aes(y = ..prop.., group = 1)) + theme(axis.text.x = element_text(angle = 6
    hjust = 1))
```



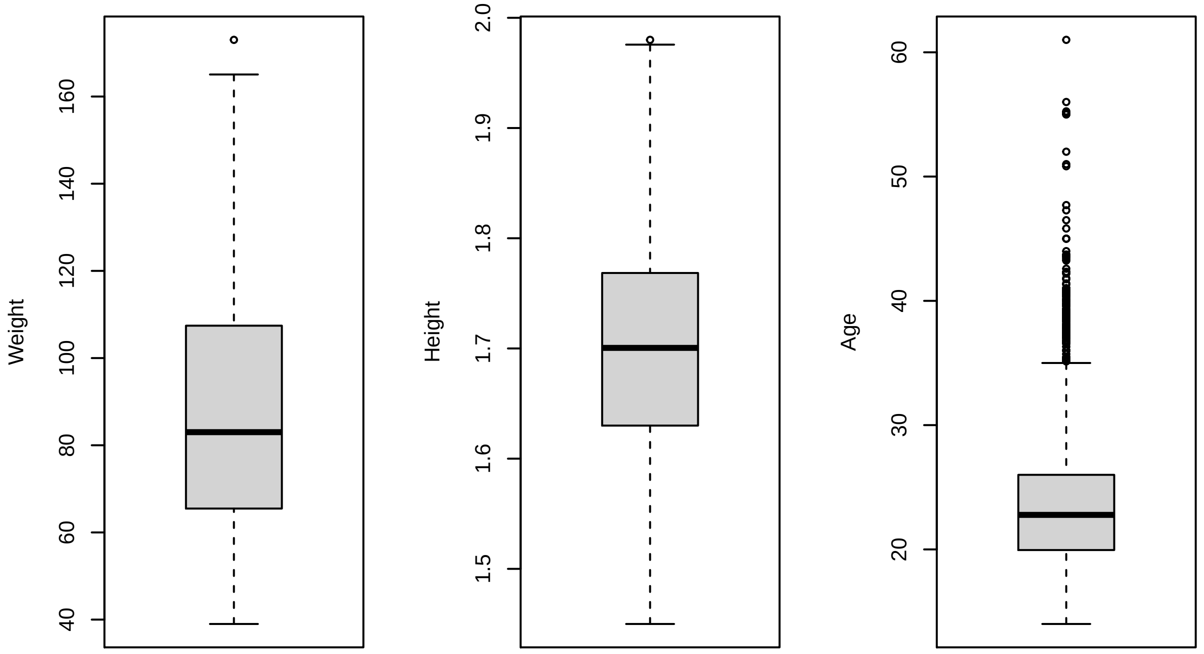
We see that the distribution of observations across the different weights is quite uniform, meaning that we do not have an unbalanced data set with respect to our variable of interest (the weight).

Let's now look at some histograms for all the continuous variables in our dataset.

```r
# Creating histograms :

multi.hist(obesity[, 2:4], density = TRUE)
```



```
# Creating boxplots :

par(mfrow = c(1, 3))

boxplot(obesity$Weight, ylab = "Weight")
boxplot(obesity$Height, ylab = "Height")
boxplot(obesity$Age, ylab = "Age")
```



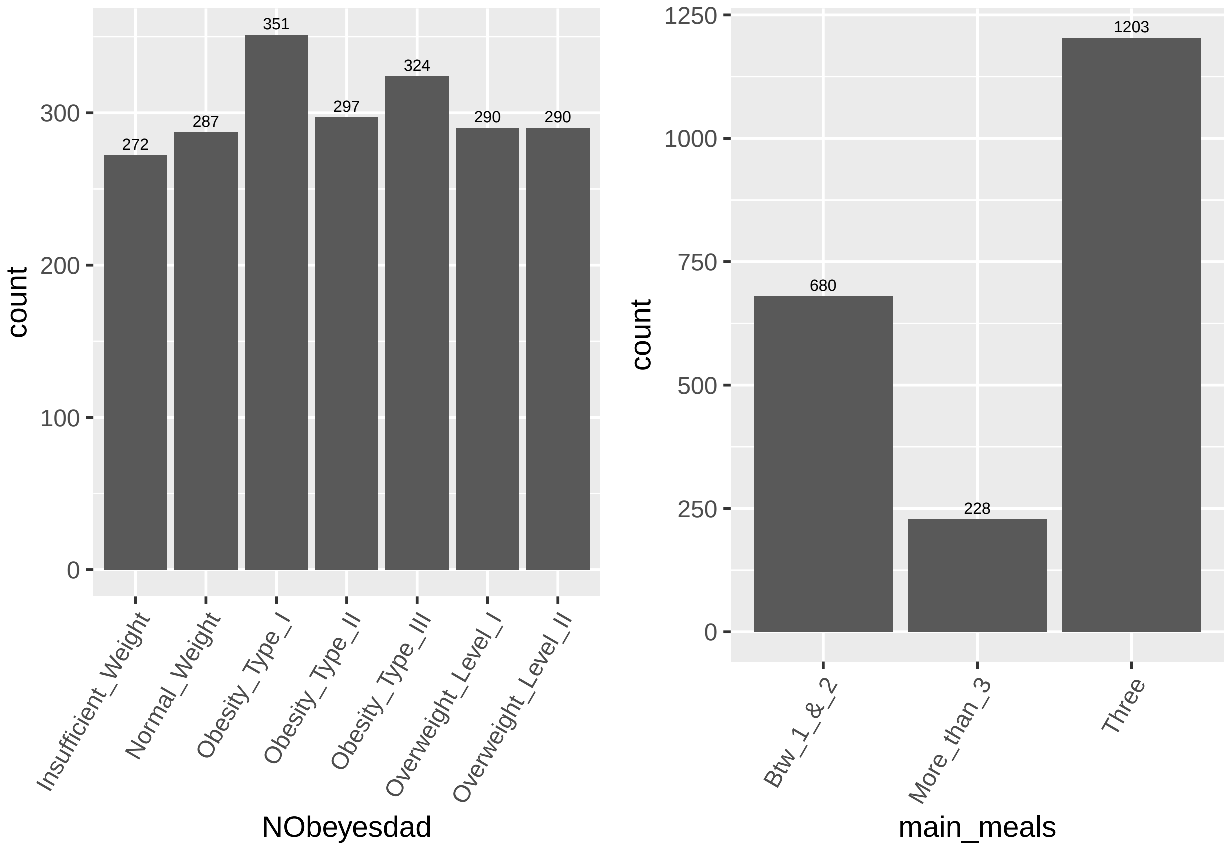
```
# We may have ONE outlier for Weight, and
# almost one for Height! Age is VERY right
# skewed!

# comment on why we are not removing the
# outliers
```

Interpretation:

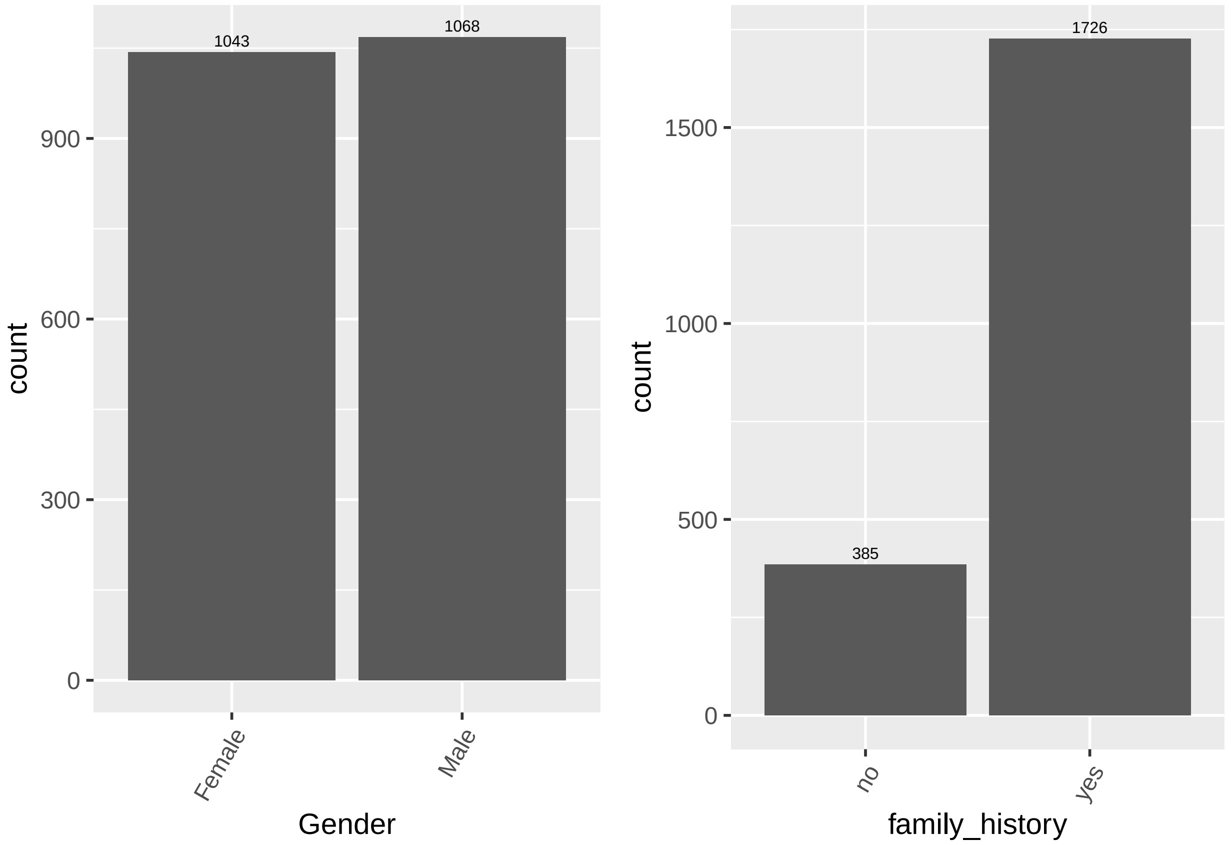
. . .

Now, let's do some barplots in order to get an idea of the distribution of each of the categorical variables.

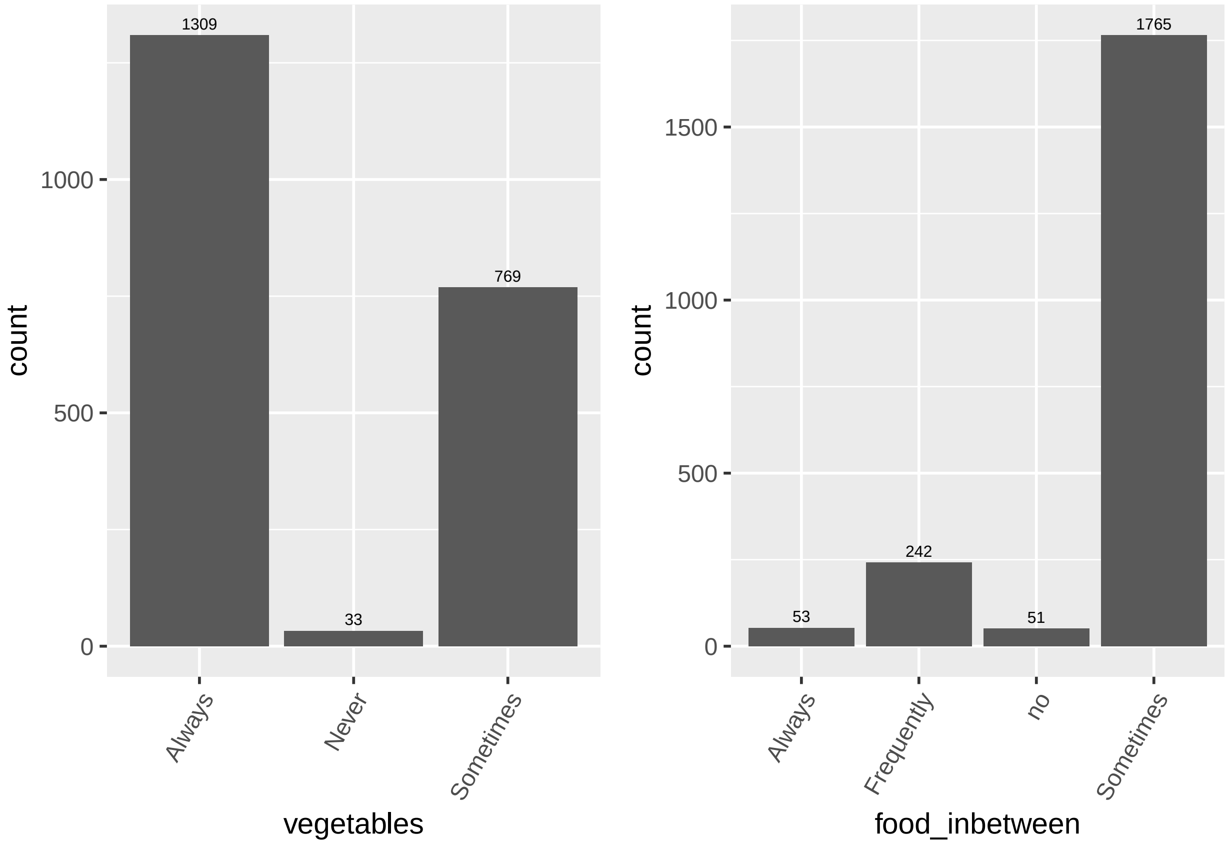
```
# Barplots :

plot_1 = ggplot(data = obesity, aes(x = NObeyesdad)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)

plot_2 = ggplot(data = obesity, aes(x = main_meals)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)

plot_3 = ggplot(data = obesity, aes(x = Gender)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)

plot_4 = ggplot(data = obesity, aes(x = family_history)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)

plot_5 = ggplot(data = obesity, aes(x = vegetables)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)

plot_6 = ggplot(data = obesity, aes(x = food_inbetween)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)

plot_7 = ggplot(data = obesity, aes(x = tech_devices)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)

plot_8 = ggplot(data = obesity, aes(x = eat_caloric)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)

plot_9 = ggplot(data = obesity, aes(x = SMOKE)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)

plot_10 = ggplot(data = obesity, aes(x = CH2O)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)

plot_11 = ggplot(data = obesity, aes(x = monitor_cal)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)

plot_12 = ggplot(data = obesity, aes(x = physical_act)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)

plot_13 = ggplot(data = obesity, aes(x = alcohol)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)

plot_14 = ggplot(data = obesity, aes(x = MTRANS)) +
    geom_bar(aes(y = ..count.., group = 1)) +
    theme(axis.text.x = element_text(angle = 60,
        hjust = 1)) + geom_text(stat = "count",
    aes(label = ..count..), vjust = -0.5, size = 2.2)


# Arranging them two-by-two :

grid.arrange(plot_1, plot_2, ncol = 2)
```



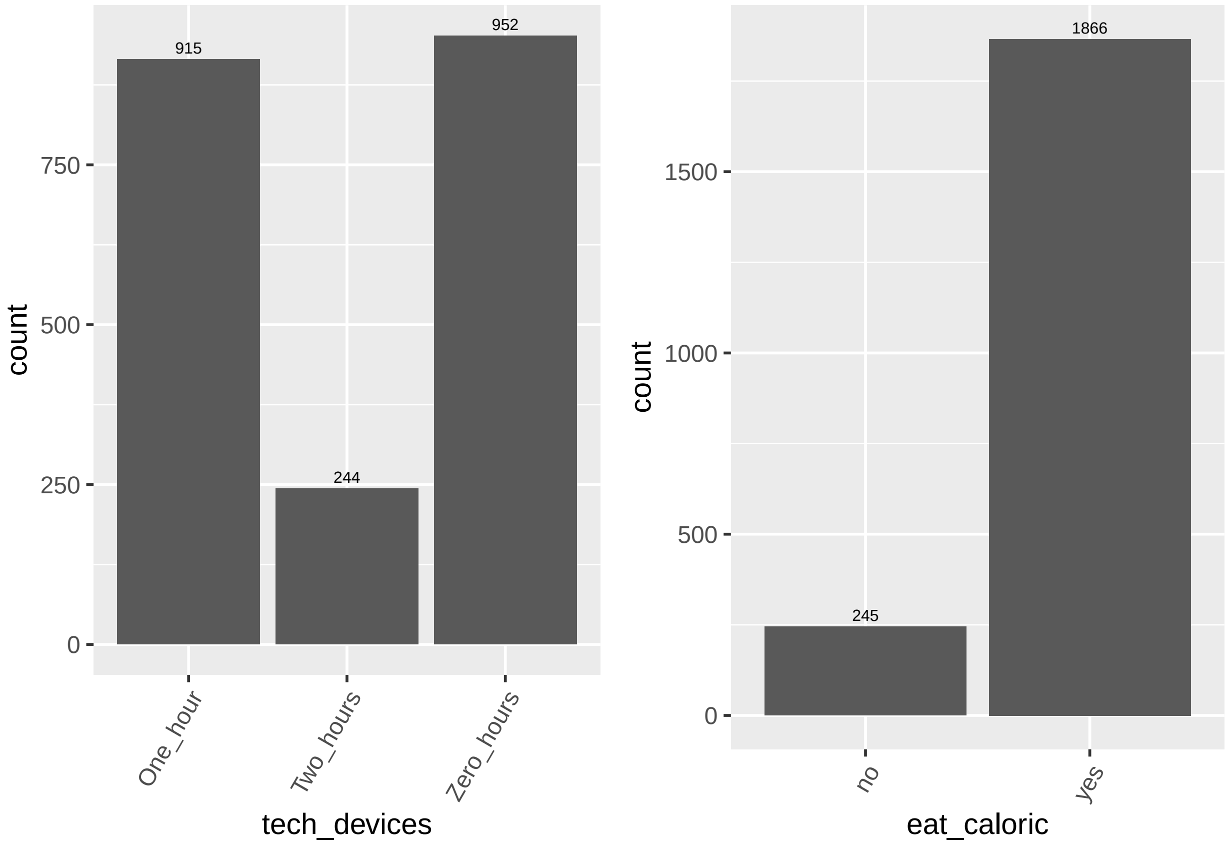
```r
grid.arrange(plot_3, plot_4, ncol = 2)
```



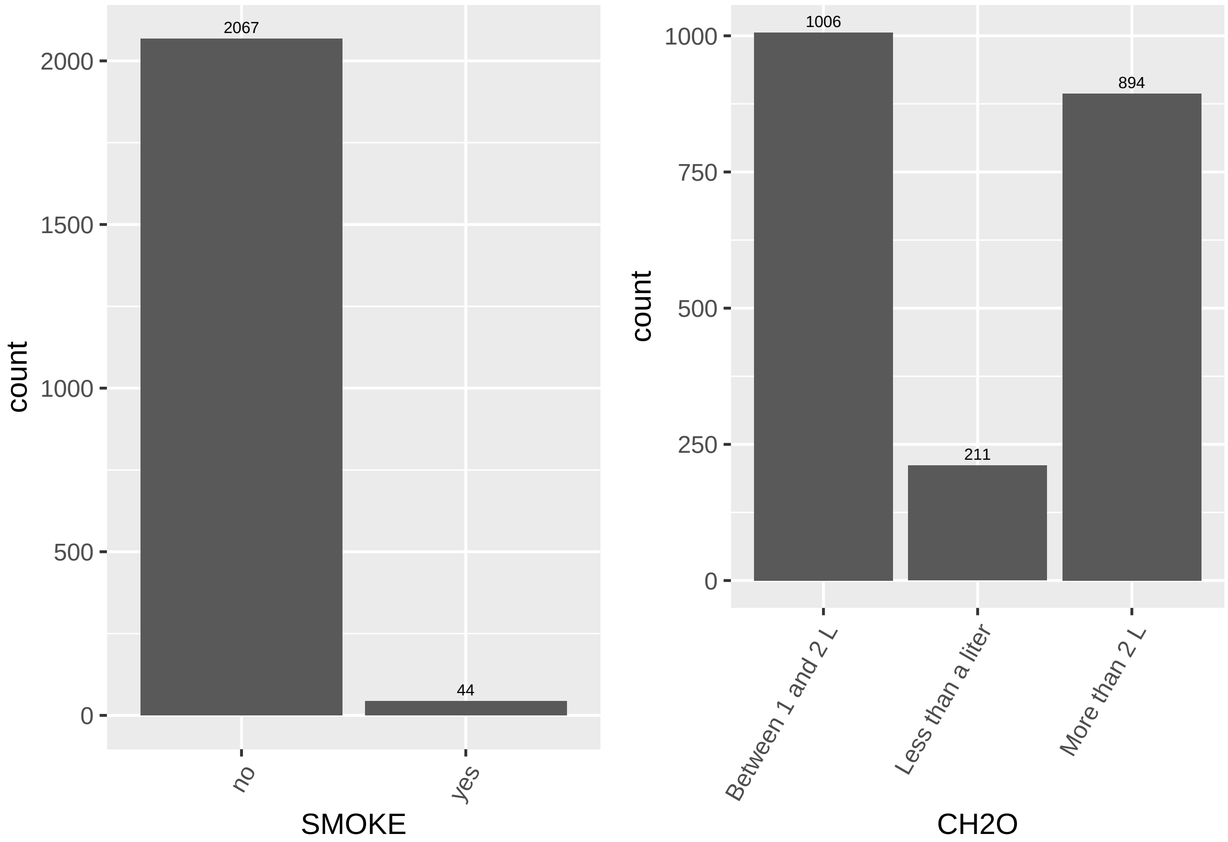
```
grid.arrange(plot_5, plot_6, ncol = 2)
```



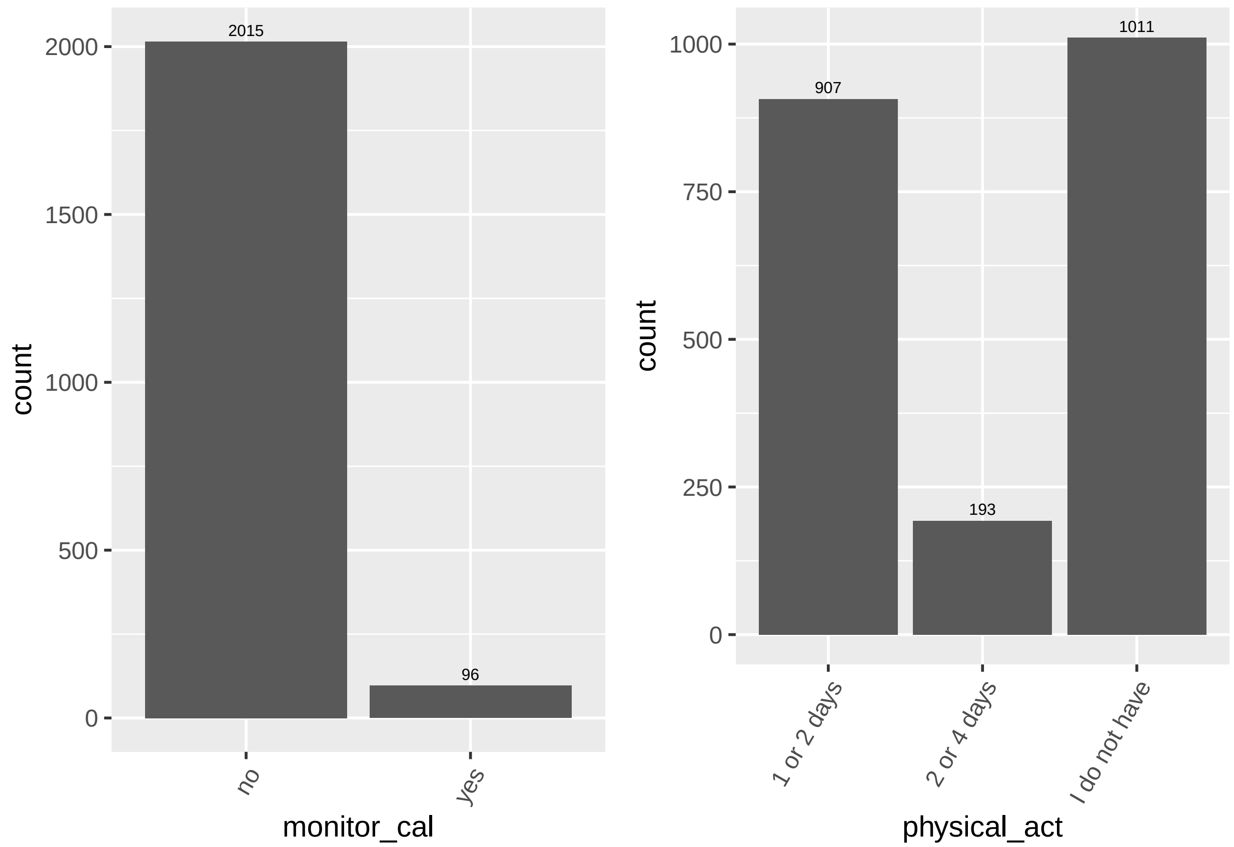
```
grid.arrange(plot_7, plot_8, ncol = 2)
```



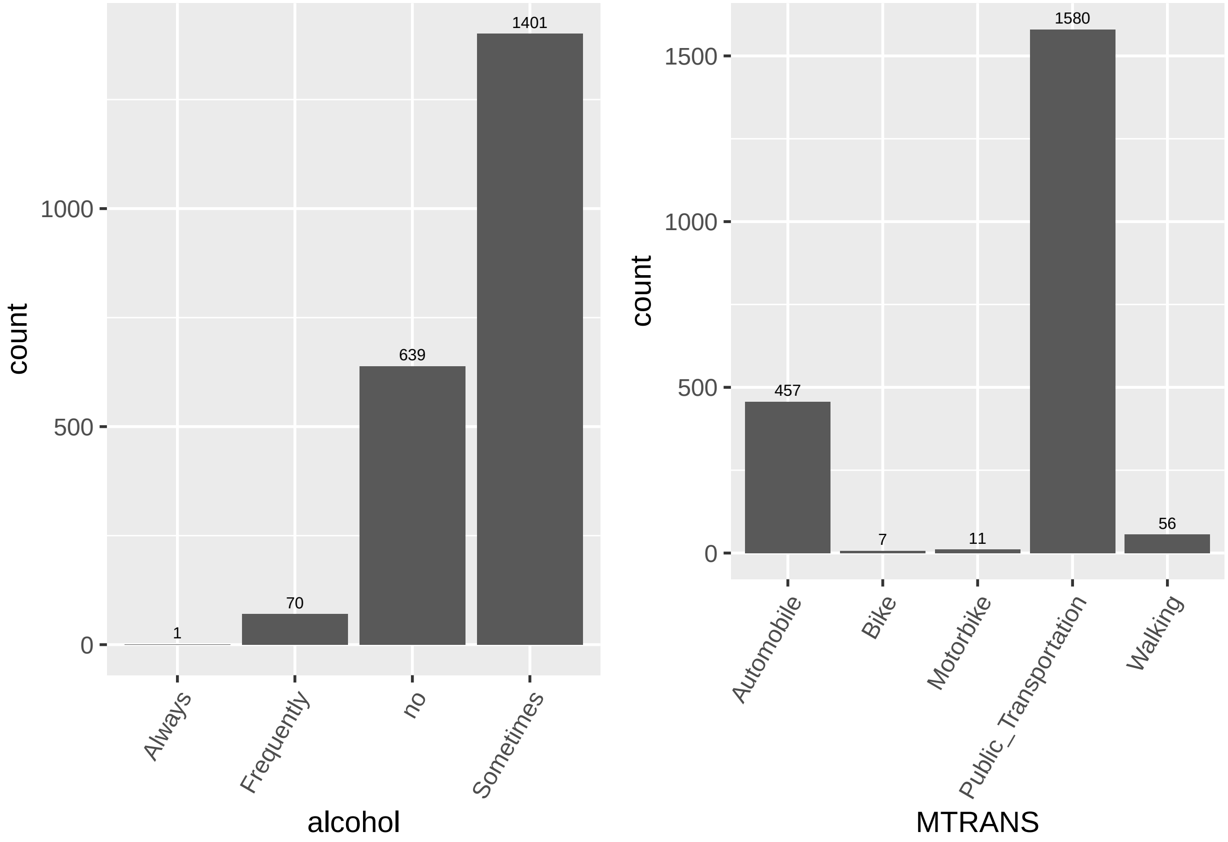
```r
grid.arrange(plot_9, plot_10, ncol = 2)
```



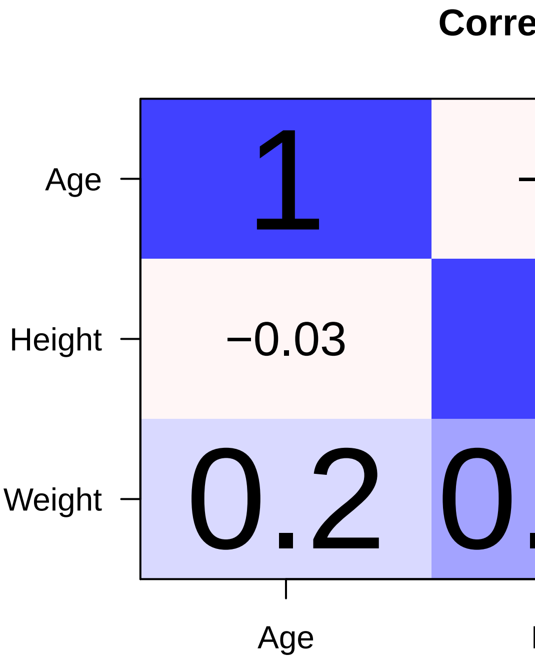
```r
grid.arrange(plot_11, plot_12, ncol = 2)
```



```r
grid.arrange(plot_13, plot_14, ncol = 2)
```



```r
# Correlation plot
cor.plot(na.omit(obesity[c(2, 3, 4)]))
```



Let's look at the correlations between the variables.

```
# comment on correlation and how we didnt do
# it for categorical variables
```

Data Analysis

Multiple Linear Regression

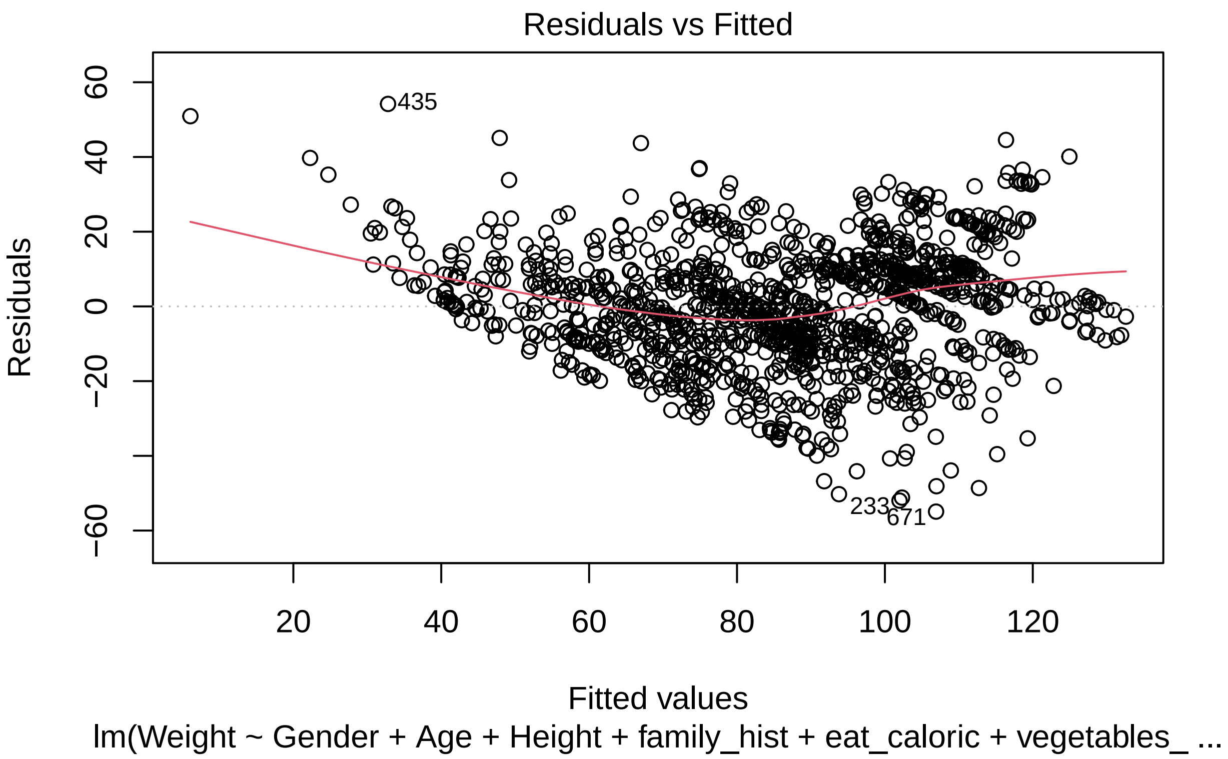
We begin with a multiple linear regression model. We will first run a full model with (n-1) dummy categories included for each variable. In most cases the dummy that was excluded from the formula this the dummy which refered to the variable category "no" or equivalent. For instance, for the variable alcohol, we excluded the variable alcohol_no from the model formula.

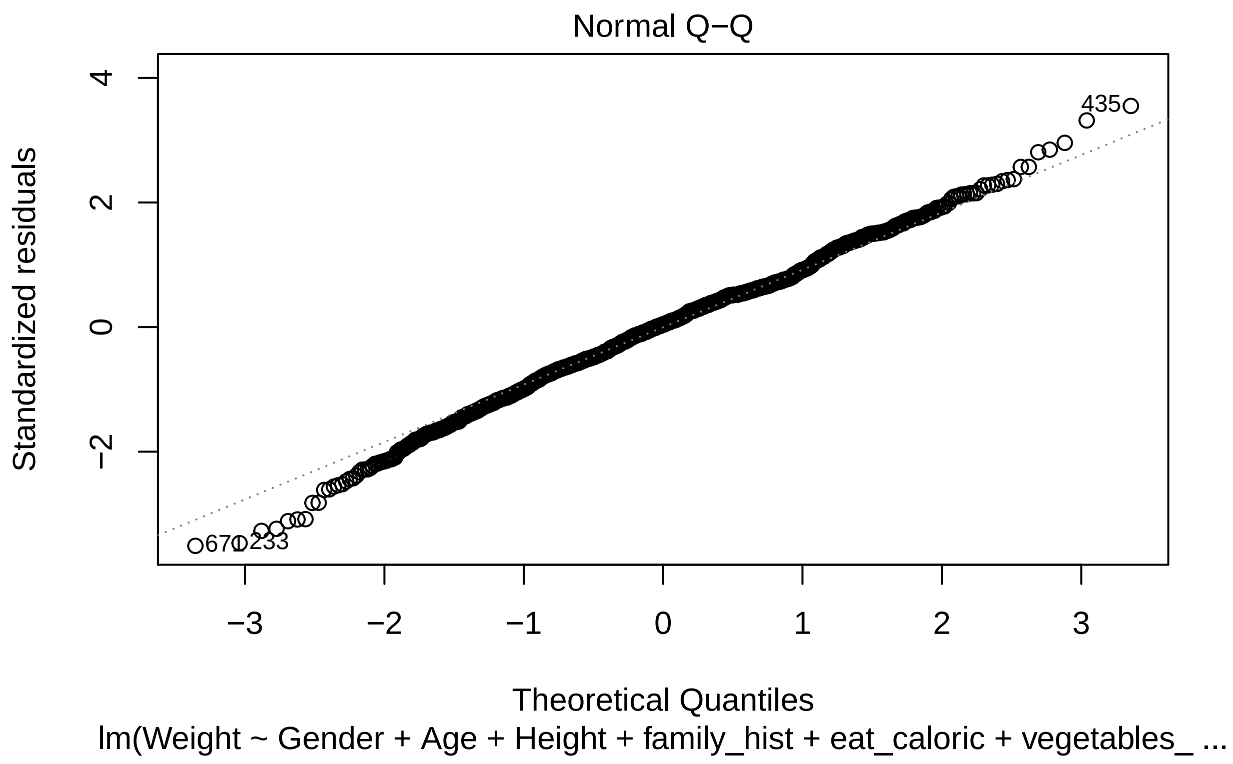
```
# Linear regression

# formula: Weight = Gender, Age, Height,

lm_weight <- lm(Weight ~ Gender + Age + Height +
    family_hist + eat_caloric + vegetables_sometimes +
    vegetables_always + main_meals_Btw_1_2 + main_meals_More_than_3 +
```

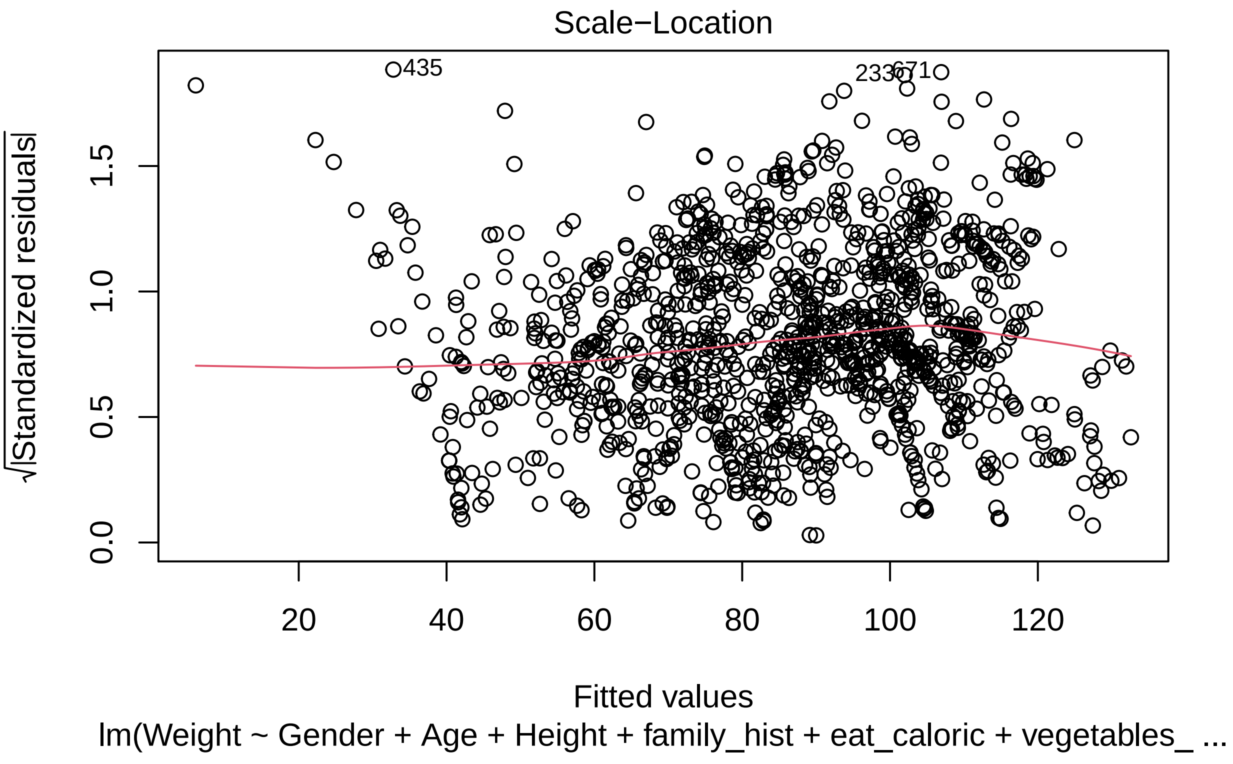
```r
    food_inbetween_always + food_inbetween_frequently +
    food_inbetween_sometimes + smoke + CH2O_between_1_and_2 +
    CH2O_more_than_2 + monitor_cal + physical_act_1_2 +
    physical_act_2_4 + tech_1_hour + tech_2_hours_or_more +
    alcohol_always + alcohol_frequently + alcohol_sometimes +
    mtrans_automobile + mtrans_bike + mtrans_public_transportation,
    data = train.set)

summary(lm_weight)
```

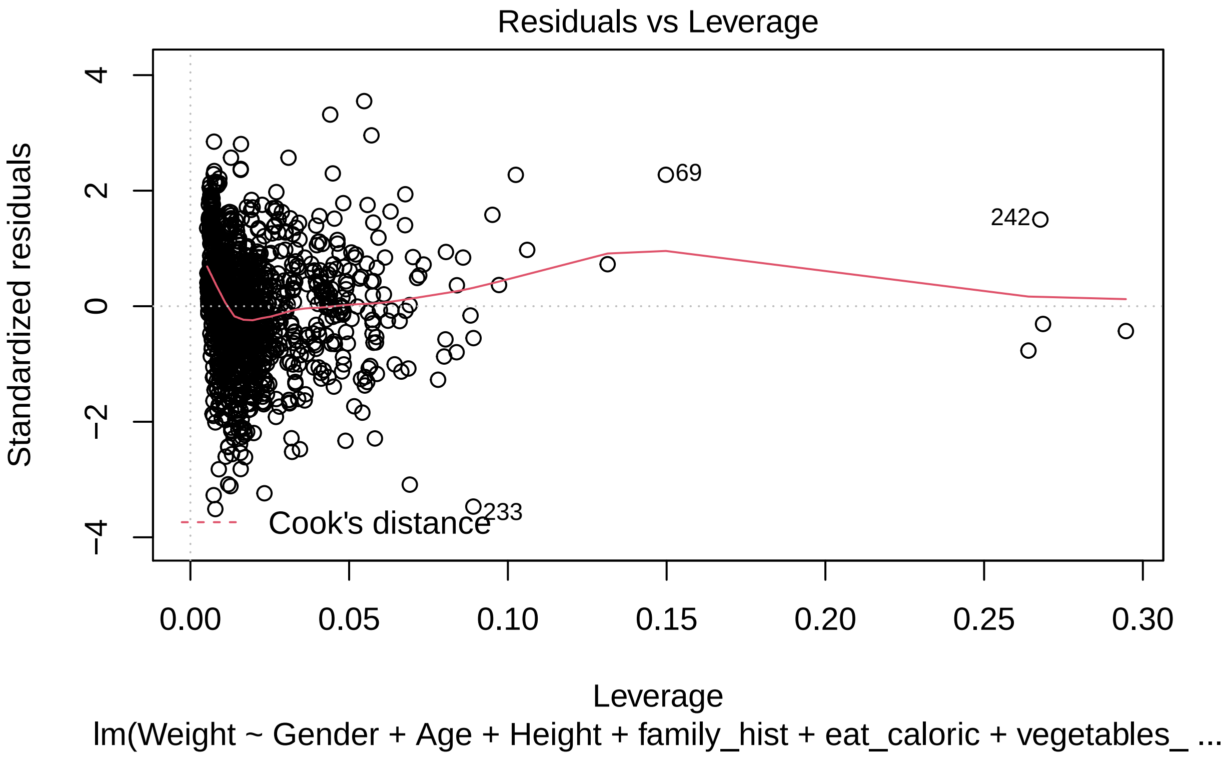
```
##
## Call:
## lm(formula = Weight ~ Gender + Age + Height + family_hist + eat_caloric +
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 +
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently +
##     food_inbetween_sometimes + smoke + CH2O_between_1_and_2 +
##     CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 +
##     tech_1_hour + tech_2_hours_or_more + alcohol_always + alcohol_frequently +
##     alcohol_sometimes + mtrans_automobile + mtrans_bike + mtrans_public_transportatio
##     data = train.set)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -54.921  -9.621   0.615   9.564  54.196
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   -156.56957   13.02841 -12.018  < 2e-16 ***
## Gender                           4.25524    1.24684   3.413 0.000664 ***
## Age                              0.81274    0.09894   8.214 5.32e-16 ***
## Height                         121.80520    7.14305  17.052  < 2e-16 ***
## family_hist                     15.29655    1.32971  11.504  < 2e-16 ***
## eat_caloric                      3.96819    1.47926   2.683 0.007404 **
## vegetables_sometimes            -9.52226    3.44567  -2.764 0.005802 **
## vegetables_always               -7.32851    0.99765  -7.346 3.70e-13 ***
## main_meals_Btw_1_2              -5.50831    1.04130  -5.290 1.45e-07 ***
## main_meals_More_than_3         -18.03950    1.53632 -11.742  < 2e-16 ***
## food_inbetween_always           -3.16154    4.25233  -0.743 0.457330
## food_inbetween_frequently      -17.21409    3.42556  -5.025 5.77e-07 ***
## food_inbetween_sometimes         0.57720    3.22714   0.179 0.858080
## smoke                           -0.22053    3.16589  -0.070 0.944476
## CH2O_between_1_and_2            -0.52713    1.59331  -0.331 0.740821
## CH2O_more_than_2                 5.35807    0.98999   5.412 7.47e-08 ***
## monitor_cal                     -4.92421    2.24731  -2.191 0.028626 *
## physical_act_1_2                -9.38751    1.63586  -5.739 1.20e-08 ***
## physical_act_2_4                 2.02866    1.00094   2.027 0.042901 *
## tech_1_hour                     -5.45663    1.55983  -3.498 0.000485 ***
## tech_2_hours_or_more            -1.47184    1.00579  -1.463 0.143621
## alcohol_always                  13.67598   16.05482   0.852 0.394473
## alcohol_frequently              -1.19652    2.63648  -0.454 0.650030
## alcohol_sometimes                4.61559    1.04280   4.426 1.04e-05 ***
## mtrans_automobile               -7.08215    2.83046  -2.502 0.012473 *
## mtrans_bike                     -4.04084    8.28314  -0.488 0.625750
## mtrans_public_transportation     4.55777    2.59702   1.755 0.079506 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15.7 on 1239 degrees of freedom
## Multiple R-squared:  0.6464, Adjusted R-squared:  0.639
## F-statistic: 87.11 on 26 and 1239 DF,  p-value: < 2.2e-16
```

```
plot(lm_weight)
```




Normal Q−Q
Standardized residuals
4
2
0
−2
435
671
233
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(Weight ~ Gender + Age + Height + family_hist + eat_caloric + vegetables_ ...


Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
435
233
671
20
40
60
80
100
120
Fitted values
lm(Weight ~ Gender + Age + Height + family_hist + eat_caloric + vegetables_ ...



Looking at the model above, we have quite a lot of variables that are significant at a confidence level of 95%. The variables that are not significant are: food_inbetween_always, food_inbetween_sometimes, smoke, CH2O_between_1_and_2, tech_1_hour,alcohol_always, alcohol_frequently, mtrans_bike and mtrans_public_transportation.

Because there are many significant variables, we will not interpret all of them, instead, we will interpret some that we find interesting.

- **Age**: An increase of 1 year of age corresponds to an average increase of 0.812 kg in weight, ceteris paribus.
- **main_meals_Btw_1_2**: An individual that eats between 1 and 2 main meals per day has an average decrease of 5.508 kg in comparison to an individual that eats three main meals per day.

Because we wish to select the best possible model for the linear regression, we will proceed with the stepwise selection method, in order to choose the most appropriate one. We will run a forward, backward, and both model selection.

```
# Stepwise model selection

# Forward
lm_forward_obesity <- step(lm_weight, direction = "forward")
```

```
## Start:  AIC=6999.41
## Weight ~ Gender + Age + Height + family_hist + eat_caloric + 
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 + 
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently + 
##     food_inbetween_sometimes + smoke + CH2O_between_1_and_2 + 
##     CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 + 
##     tech_1_hour + tech_2_hours_or_more + alcohol_always + alcohol_frequently + 
##     alcohol_sometimes + mtrans_automobile + mtrans_bike + mtrans_public_transportatio
```

```r
summary(lm_forward_obesity)
```

```
## 
## Call:
## lm(formula = Weight ~ Gender + Age + Height + family_hist + eat_caloric + 
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 + 
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently + 
##     food_inbetween_sometimes + smoke + CH2O_between_1_and_2 + 
##     CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 + 
##     tech_1_hour + tech_2_hours_or_more + alcohol_always + alcohol_frequently + 
##     alcohol_sometimes + mtrans_automobile + mtrans_bike + mtrans_public_transportatio
##     data = train.set)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -54.921  -9.621   0.615   9.564  54.196 
## 
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)    
## (Intercept)                  -156.56957   13.02841 -12.018  < 2e-16 ***
## Gender                          4.25524    1.24684   3.413 0.000664 ***
## Age                             0.81274    0.09894   8.214 5.32e-16 ***
## Height                        121.80520    7.14305  17.052  < 2e-16 ***
## family_hist                    15.29655    1.32971  11.504  < 2e-16 ***
## eat_caloric                     3.96819    1.47926   2.683 0.007404 ** 
## vegetables_sometimes           -9.52226    3.44567  -2.764 0.005802 ** 
## vegetables_always              -7.32851    0.99765  -7.346 3.70e-13 ***
## main_meals_Btw_1_2             -5.50831    1.04130  -5.290 1.45e-07 ***
## main_meals_More_than_3        -18.03950    1.53632 -11.742  < 2e-16 ***
## food_inbetween_always          -3.16154    4.25233  -0.743 0.457330    
## food_inbetween_frequently     -17.21409    3.42556  -5.025 5.77e-07 ***
## food_inbetween_sometimes        0.57720    3.22714   0.179 0.858080    
## smoke                          -0.22053    3.16589  -0.070 0.944476    
## CH2O_between_1_and_2           -0.52713    1.59331  -0.331 0.740821    
## CH2O_more_than_2                5.35807    0.98999   5.412 7.47e-08 ***
## monitor_cal                    -4.92421    2.24731  -2.191 0.028626 *  
## physical_act_1_2               -9.38751    1.63586  -5.739 1.20e-08 ***
## physical_act_2_4                2.02866    1.00094   2.027 0.042901 *  
## tech_1_hour                     -5.45663    1.55983  -3.498 0.000485 ***
## tech_2_hours_or_more            -1.47184    1.00579  -1.463 0.143621
## alcohol_always                  13.67598   16.05482   0.852 0.394473
## alcohol_frequently              -1.19652    2.63648  -0.454 0.650030
## alcohol_sometimes                4.61559    1.04280   4.426 1.04e-05 ***
## mtrans_automobile               -7.08215    2.83046  -2.502 0.012473 *
## mtrans_bike                     -4.04084    8.28314  -0.488 0.625750
## mtrans_public_transportation     4.55777    2.59702   1.755 0.079506 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15.7 on 1239 degrees of freedom
## Multiple R-squared:  0.6464, Adjusted R-squared:  0.639
## F-statistic: 87.11 on 26 and 1239 DF,  p-value: < 2.2e-16
```

```
# AIC: 6999.41 Model : Weight ~ Gender + Age +
# Height + family_hist + eat_caloric +
# vegetables_sometimes + vegetables_always +
# main_meals_Btw_1_2 + main_meals_More_than_3
# + food_inbetween_always +
# food_inbetween_frequently +
# food_inbetween_sometimes + smoke +
# CH2O_between_1_and_2 + CH2O_more_than_2 +
# monitor_cal + physical_act_1_2 +
# physical_act_2_4 + tech_1_hour +
# tech_2_hours_or_more + alcohol_always +
# alcohol_frequently + alcohol_sometimes +
# mtrans_automobile + mtrans_bike +
# mtrans_public_transportation


# Backward
lm_backward_obesity <- step(lm_weight, direction = "backward")
```

```
## Start:  AIC=6999.41
## Weight ~ Gender + Age + Height + family_hist + eat_caloric +
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 +
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently +
##     food_inbetween_sometimes + smoke + CH2O_between_1_and_2 +
##     CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 +
##     tech_1_hour + tech_2_hours_or_more + alcohol_always + alcohol_frequently +
##     alcohol_sometimes + mtrans_automobile + mtrans_bike + mtrans_public_transportatio
##
##                                Df Sum of Sq    RSS    AIC
## - smoke                         1         1 305507 6997.4
## - food_inbetween_sometimes      1         8 305514 6997.4
## - CH2O_between_1_and_2          1        27 305533 6997.5
## - alcohol_frequently           1        51 305556 6997.6
## - mtrans_bike                  1        59 305564 6997.7
## - food_inbetween_always        1       136 305642 6998.0
## - alcohol_always               1       179 305685 6998.2
## <none>                                     305506 6999.4
## - tech_2_hours_or_more         1       528 306034 6999.6
## - mtrans_public_transportation  1       759 306265 7000.6
## - physical_act_2_4             1      1013 306518 7001.6
## - monitor_cal                  1      1184 306689 7002.3
## - mtrans_automobile            1      1544 307049 7003.8
## - eat_caloric                  1      1774 307280 7004.7
## - vegetables_sometimes         1      1883 307389 7005.2
## - Gender                       1      2872 308378 7009.3
## - tech_1_hour                  1      3017 308523 7009.9
## - alcohol_sometimes            1      4831 310336 7017.3
## - food_inbetween_frequently    1      6227 311732 7023.0
## - main_meals_Btw_1_2           1      6900 312405 7025.7
## - CH2O_more_than_2             1      7223 312728 7027.0
## - physical_act_1_2             1      8120 313626 7030.6
## - vegetables_always            1     13305 318811 7051.4
## - Age                          1     16637 322143 7064.5
## - family_hist                  1     32630 338136 7125.9
## - main_meals_More_than_3       1     33997 339502 7131.0
## - Height                       1     71699 377204 7264.3
##
## Step:  AIC=6997.41
## Weight ~ Gender + Age + Height + family_hist + eat_caloric +
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 +
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently +
##     food_inbetween_sometimes + CH2O_between_1_and_2 + CH2O_more_than_2 +
##     monitor_cal + physical_act_1_2 + physical_act_2_4 + tech_1_hour +
##     tech_2_hours_or_more + alcohol_always + alcohol_frequently +
##     alcohol_sometimes + mtrans_automobile + mtrans_bike + mtrans_public_transportatio
##
##                                Df Sum of Sq    RSS    AIC
## - food_inbetween_sometimes     1         8 305515 6995.4
## - CH2O_between_1_and_2         1        27 305534 6995.5
## - alcohol_frequently           1        53 305560 6995.6
## - mtrans_bike                  1        58 305565 6995.7
## - food_inbetween_always        1       136 305643 6996.0
## - alcohol_always               1       179 305686 6996.2
## <none>                                     305507 6997.4
## - tech_2_hours_or_more         1       527 306034 6997.6
## - mtrans_public_transportation  1       760 306267 6998.6
## - physical_act_2_4             1      1012 306519 6999.6
## - monitor_cal                  1      1194 306701 7000.4
## - mtrans_automobile            1      1547 307054 7001.8
## - eat_caloric                  1      1776 307283 7002.8
## - vegetables_sometimes          1      1884 307391 7003.2
## - Gender                        1      2871 308378 7007.3
## - tech_1_hour                   1      3030 308537 7007.9
## - alcohol_sometimes             1      4830 310336 7015.3
## - food_inbetween_frequently     1      6234 311741 7021.0
## - main_meals_Btw_1_2            1      6901 312408 7023.7
## - CH2O_more_than_2              1      7315 312822 7025.4
## - physical_act_1_2              1      8119 313626 7028.6
## - vegetables_always             1     13310 318817 7049.4
## - Age                           1     17080 322587 7064.3
## - family_hist                   1     32631 338138 7123.9
## - main_meals_More_than_3        1     34024 339531 7129.1
## - Height                        1     72330 377837 7264.4
## 
## Step:  AIC=6995.45
## Weight ~ Gender + Age + Height + family_hist + eat_caloric + 
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 + 
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently + 
##     CH2O_between_1_and_2 + CH2O_more_than_2 + monitor_cal + physical_act_1_2 + 
##     physical_act_2_4 + tech_1_hour + tech_2_hours_or_more + alcohol_always + 
##     alcohol_frequently + alcohol_sometimes + mtrans_automobile + 
##     mtrans_bike + mtrans_public_transportation
## 
##                                Df Sum of Sq    RSS    AIC
## - CH2O_between_1_and_2          1        26 305541 6993.6
## - alcohol_frequently            1        54 305569 6993.7
## - mtrans_bike                   1        58 305573 6993.7
## - alcohol_always                1       179 305694 6994.2
## - food_inbetween_always         1       381 305896 6995.0
## <none>                                      305515 6995.4
## - tech_2_hours_or_more          1       548 306063 6995.7
## - mtrans_public_transportation  1       762 306277 6996.6
## - physical_act_2_4              1      1022 306537 6997.7
## - monitor_cal                   1      1192 306707 6998.4
## - mtrans_automobile             1      1543 307058 6999.8
## - eat_caloric                   1      1772 307287 7000.8
## - vegetables_sometimes          1      1935 307451 7001.4
## - Gender                        1      2917 308432 7005.5
## - tech_1_hour                   1      3022 308537 7005.9
## - alcohol_sometimes             1      4822 310337 7013.3
## - main_meals_Btw_1_2            1      6938 312453 7021.9
## - CH2O_more_than_2              1      7374 312889 7023.6
## - physical_act_1_2              1      8113 313628 7026.6
## - vegetables_always             1     13669 319185 7048.9
## - Age                           1     17150 322665 7062.6
## - family_hist                   1     33606 339121 7125.6
## - food_inbetween_frequently     1     34095 339610 7127.4
## - main_meals_More_than_3        1     34346 339862 7128.3
## - Height                        1     73963 379478 7267.9
## 
## Step:  AIC=6993.56
## Weight ~ Gender + Age + Height + family_hist + eat_caloric + 
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 + 
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently + 
##     CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 + 
##     tech_1_hour + tech_2_hours_or_more + alcohol_always + alcohol_frequently + 
##     alcohol_sometimes + mtrans_automobile + mtrans_bike + mtrans_public_transportatio
## 
##                                 Df Sum of Sq    RSS    AIC
## - mtrans_bike                    1        55 305596 6991.8
## - alcohol_frequently             1        55 305596 6991.8
## - alcohol_always                 1       184 305724 6992.3
## - food_inbetween_always          1       383 305924 6993.1
## <none>                                       305541 6993.6
## - tech_2_hours_or_more           1       557 306098 6993.9
## - mtrans_public_transportation   1       770 306311 6994.7
## - physical_act_2_4               1      1054 306595 6995.9
## - monitor_cal                    1      1176 306717 6996.4
## - mtrans_automobile              1      1543 307084 6997.9
## - eat_caloric                    1      1783 307324 6998.9
## - vegetables_sometimes           1      1952 307492 6999.6
## - Gender                         1      2918 308458 7003.6
## - tech_1_hour                    1      3031 308572 7004.1
## - alcohol_sometimes              1      4859 310400 7011.5
## - main_meals_Btw_1_2             1      6914 312455 7019.9
## - CH2O_more_than_2               1      7968 313509 7024.1
## - physical_act_1_2               1      8091 313632 7024.6
## - vegetables_always              1     13723 319264 7047.2
## - Age                            1     17130 322671 7060.6
## - main_meals_More_than_3         1     34377 339917 7126.5
## - family_hist                    1     34502 340042 7127.0
## - food_inbetween_frequently      1     35247 340787 7129.8
## - Height                         1     74497 380038 7267.8
## 
## Step:  AIC=6991.78
## Weight ~ Gender + Age + Height + family_hist + eat_caloric + 
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 + 
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently + 
##     CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 + 
##     tech_1_hour + tech_2_hours_or_more + alcohol_always + alcohol_frequently + 
##     alcohol_sometimes + mtrans_automobile + mtrans_public_transportation
## 
##                                 Df Sum of Sq    RSS    AIC
## - alcohol_frequently             1        53 305649 6990.0
## - alcohol_always                 1       192 305787 6990.6
## - food_inbetween_always          1       397 305993 6991.4
## <none>                                      305596 6991.8
## - tech_2_hours_or_more          1       569 306164 6992.1
## - mtrans_public_transportation  1       947 306542 6993.7
## - physical_act_2_4              1      1064 306660 6994.2
## - monitor_cal                   1      1193 306789 6994.7
## - mtrans_automobile             1      1495 307091 6996.0
## - eat_caloric                   1      1774 307370 6997.1
## - vegetables_sometimes          1      1940 307536 6997.8
## - Gender                        1      2966 308562 7002.0
## - tech_1_hour                   1      3036 308632 7002.3
## - alcohol_sometimes             1      4874 310470 7009.8
## - main_meals_Btw_1_2            1      6874 312469 7017.9
## - CH2O_more_than_2              1      7994 313590 7022.5
## - physical_act_1_2              1      8120 313716 7023.0
## - vegetables_always             1     13704 319299 7045.3
## - Age                           1     17101 322697 7058.7
## - main_meals_More_than_3        1     34322 339918 7124.5
## - family_hist                   1     34559 340154 7125.4
## - food_inbetween_frequently     1     35192 340787 7127.8
## - Height                        1     74674 380270 7266.6
## 
## Step:  AIC=6990
## Weight ~ Gender + Age + Height + family_hist + eat_caloric + 
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 + 
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently + 
##     CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 + 
##     tech_1_hour + tech_2_hours_or_more + alcohol_always + alcohol_sometimes + 
##     mtrans_automobile + mtrans_public_transportation
## 
##                                Df Sum of Sq    RSS    AIC
## - alcohol_always                1       194 305843 6988.8
## - food_inbetween_always         1       414 306063 6989.7
## <none>                                      305649 6990.0
## - tech_2_hours_or_more          1       548 306197 6990.3
## - mtrans_public_transportation  1       935 306584 6991.9
## - physical_act_2_4              1      1077 306725 6992.5
## - monitor_cal                   1      1230 306879 6993.1
## - mtrans_automobile             1      1519 307168 6994.3
## - eat_caloric                   1      1766 307415 6995.3
## - vegetables_sometimes          1      1957 307606 6996.1
## - Gender                        1      2968 308617 7000.2
## - tech_1_hour                   1      3005 308654 7000.4
## - alcohol_sometimes             1      5478 311127 7010.5
## - main_meals_Btw_1_2            1      6846 312495 7016.0
## - CH2O_more_than_2              1      7945 313594 7020.5
## - physical_act_1_2              1      8110 313759 7021.2
## - vegetables_always             1     13749 319398 7043.7
## - Age                           1     17050 322699 7056.7
## - main_meals_More_than_3        1     34337 339986 7122.8
## - family_hist                   1     34597 340246 7123.8
## - food_inbetween_frequently     1     35440 341089 7126.9
## - Height                        1     74647 380296 7264.6
##
## Step:  AIC=6988.81
## Weight ~ Gender + Age + Height + family_hist + eat_caloric +
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 +
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently +
##     CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 +
##     tech_1_hour + tech_2_hours_or_more + alcohol_sometimes +
##     mtrans_automobile + mtrans_public_transportation
##
##                                Df Sum of Sq    RSS    AIC
## - food_inbetween_always         1       415 306258 6988.5
## <none>                                      305843 6988.8
## - tech_2_hours_or_more          1       553 306396 6989.1
## - mtrans_public_transportation  1       834 306678 6990.3
## - physical_act_2_4              1      1049 306892 6991.1
## - monitor_cal                   1      1243 307087 6991.9
## - mtrans_automobile             1      1687 307530 6993.8
## - eat_caloric                   1      1826 307670 6994.3
## - vegetables_sometimes          1      1971 307814 6994.9
## - tech_1_hour                   1      2934 308778 6998.9
## - Gender                        1      2938 308782 6998.9
## - alcohol_sometimes             1      5449 311292 7009.2
## - main_meals_Btw_1_2            1      6764 312607 7014.5
## - CH2O_more_than_2              1      7912 313755 7019.1
## - physical_act_1_2              1      8226 314070 7020.4
## - vegetables_always             1     13705 319549 7042.3
## - Age                           1     17016 322860 7055.4
## - main_meals_More_than_3        1     34420 340264 7121.8
## - family_hist                   1     34869 340713 7123.5
## - food_inbetween_frequently     1     35247 341090 7124.9
## - Height                        1     74523 380367 7262.9
##
## Step:  AIC=6988.52
## Weight ~ Gender + Age + Height + family_hist + eat_caloric +
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 +
##     main_meals_More_than_3 + food_inbetween_frequently + CH2O_more_than_2 +
##     monitor_cal + physical_act_1_2 + physical_act_2_4 + tech_1_hour +
##     tech_2_hours_or_more + alcohol_sometimes + mtrans_automobile +
##     mtrans_public_transportation
##
##                                Df Sum of Sq    RSS    AIC
## <none>                                      306258 6988.5
## - tech_2_hours_or_more          1       574 306832 6988.9
## - mtrans_public_transportation  1       926 307184 6990.3
## - physical_act_2_4              1      1012 307270 6990.7
## - monitor_cal                   1      1335 307593 6992.0
## - mtrans_automobile             1      1602 307860 6993.1
## - eat_caloric                   1      1883 308141 6994.3
## - vegetables_sometimes          1      2252 308510 6995.8
## - tech_1_hour                   1      2952 309210 6998.7
## - Gender                        1      3001 309259 6998.9
## - alcohol_sometimes             1      5572 311830 7009.3
## - main_meals_Btw_1_2            1      6579 312837 7013.4
## - CH2O_more_than_2              1      8041 314299 7019.3
## - physical_act_1_2              1      8493 314751 7021.2
## - vegetables_always             1     13718 319976 7042.0
## - Age                           1     17193 323451 7055.7
## - food_inbetween_frequently     1     34859 341116 7123.0
## - main_meals_More_than_3        1     35162 341419 7124.1
## - family_hist                   1     36034 342292 7127.4
## - Height                        1     74621 380879 7262.6
```

```
summary(lm_backward_obesity)
```

```
## 
## Call:
## lm(formula = Weight ~ Gender + Age + Height + family_hist + eat_caloric + 
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 + 
##     main_meals_More_than_3 + food_inbetween_frequently + CH2O_more_than_2 + 
##     monitor_cal + physical_act_1_2 + physical_act_2_4 + tech_1_hour + 
##     tech_2_hours_or_more + alcohol_sometimes + mtrans_automobile + 
##     mtrans_public_transportation, data = train.set)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -54.796  -9.651   0.799   9.613  53.566 
## 
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)    
## (Intercept)                  -157.25649   12.73878 -12.345  < 2e-16 ***
## Gender                          4.32640    1.23821   3.494 0.000492 ***
## Age                             0.81187    0.09707   8.363  < 2e-16 ***
## Height                        121.98641    7.00108  17.424  < 2e-16 ***
## family_hist                    15.62919    1.29081  12.108  < 2e-16 ***
## eat_caloric                     4.07848    1.47335   2.768 0.005721 ** 
## vegetables_sometimes          -10.25052    3.38653  -3.027 0.002522 ** 
## vegetables_always              -7.35775    0.98489  -7.471 1.50e-13 ***
## main_meals_Btw_1_2             -5.33322    1.03086  -5.174 2.67e-07 ***
## main_meals_More_than_3        -18.11019    1.51417 -11.960  < 2e-16 ***
## food_inbetween_frequently     -17.48159    1.46795 -11.909  < 2e-16 ***
## CH2O_more_than_2                5.42381    0.94825   5.720 1.33e-08 ***
## monitor_cal                    -5.18724    2.22576  -2.331 0.019936 *
## physical_act_1_2               -9.53018    1.62130  -5.878 5.32e-09 ***
## physical_act_2_4                2.01635    0.99354   2.029 0.042624 *
## tech_1_hour                    -5.36631    1.54856  -3.465 0.000548 ***
## tech_2_hours_or_more           -1.51977    0.99466  -1.528 0.126783
## alcohol_sometimes               4.78278    1.00453   4.761 2.15e-06 ***
## mtrans_automobile              -6.88857    2.69795  -2.553 0.010790 *
## mtrans_public_transportation    4.79038    2.46791   1.941 0.052475 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15.68 on 1246 degrees of freedom
## Multiple R-squared:  0.6455, Adjusted R-squared:  0.6401
## F-statistic: 119.4 on 19 and 1246 DF,  p-value: < 2.2e-16
```

```
# formula: Weight ~ Gender + Age + Height +
# family_hist + eat_caloric +
# vegetables_sometimes + vegetables_always +
# main_meals_Btw_1_2 + main_meals_More_than_3
# + food_inbetween_frequently +
# CH2O_more_than_2 + monitor_cal +
# physical_act_1_2 + physical_act_2_4 +
# tech_1_hour + tech_2_hours_or_more +
# alcohol_sometimes + mtrans_automobile +
# mtrans_public_transportation

# AIC: 6988.52

# Both
lm_both_obesity <- step(lm_weight, direction = "both")
```

```
## Start:  AIC=6999.41
## Weight ~ Gender + Age + Height + family_hist + eat_caloric +
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 +
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently +
##     food_inbetween_sometimes + smoke + CH2O_between_1_and_2 +
##     CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 +
##     tech_1_hour + tech_2_hours_or_more + alcohol_always + alcohol_frequently +
##     alcohol_sometimes + mtrans_automobile + mtrans_bike + mtrans_public_transportatio
##
##                                 Df Sum of Sq    RSS    AIC
## - smoke                          1         1 305507 6997.4
## - food_inbetween_sometimes       1         8 305514 6997.4
## - CH2O_between_1_and_2           1        27 305533 6997.5
## - alcohol_frequently             1        51 305556 6997.6
## - mtrans_bike                    1        59 305564 6997.7
## - food_inbetween_always          1       136 305642 6998.0
## - alcohol_always                1       179 305685 6998.2
## <none>                                      305506 6999.4
## - tech_2_hours_or_more          1       528 306034 6999.6
## - mtrans_public_transportation  1       759 306265 7000.6
## - physical_act_2_4              1      1013 306518 7001.6
## - monitor_cal                   1      1184 306689 7002.3
## - mtrans_automobile             1      1544 307049 7003.8
## - eat_caloric                   1      1774 307280 7004.7
## - vegetables_sometimes          1      1883 307389 7005.2
## - Gender                        1      2872 308378 7009.3
## - tech_1_hour                   1      3017 308523 7009.9
## - alcohol_sometimes             1      4831 310336 7017.3
## - food_inbetween_frequently     1      6227 311732 7023.0
## - main_meals_Btw_1_2            1      6900 312405 7025.7
## - CH2O_more_than_2              1      7223 312728 7027.0
## - physical_act_1_2              1      8120 313626 7030.6
## - vegetables_always             1     13305 318811 7051.4
## - Age                           1     16637 322143 7064.5
## - family_hist                   1     32630 338136 7125.9
## - main_meals_More_than_3        1     33997 339502 7131.0
## - Height                        1     71699 377204 7264.3
##
## Step:  AIC=6997.41
## Weight ~ Gender + Age + Height + family_hist + eat_caloric +
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 +
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently +
##     food_inbetween_sometimes + CH2O_between_1_and_2 + CH2O_more_than_2 +
##     monitor_cal + physical_act_1_2 + physical_act_2_4 + tech_1_hour +
##     tech_2_hours_or_more + alcohol_always + alcohol_frequently +
##     alcohol_sometimes + mtrans_automobile + mtrans_bike + mtrans_public_transportatio
##
##                                Df Sum of Sq    RSS    AIC
## - food_inbetween_sometimes      1         8 305515 6995.4
## - CH2O_between_1_and_2          1        27 305534 6995.5
## - alcohol_frequently            1        53 305560 6995.6
## - mtrans_bike                   1        58 305565 6995.7
## - food_inbetween_always         1       136 305643 6996.0
## - alcohol_always                1       179 305686 6996.2
## <none>                                      305507 6997.4
## - tech_2_hours_or_more          1       527 306034 6997.6
## - mtrans_public_transportation  1       760 306267 6998.6
## + smoke                         1         1 305506 6999.4
## - physical_act_2_4              1      1012 306519 6999.6
## - monitor_cal                   1      1194 306701 7000.4
## - mtrans_automobile             1      1547 307054 7001.8
## - eat_caloric                   1      1776 307283 7002.8
## - vegetables_sometimes          1      1884 307391 7003.2
## - Gender                        1      2871 308378 7007.3
## - tech_1_hour                 1      3030 308537 7007.9
## - alcohol_sometimes           1      4830 310336 7015.3
## - food_inbetween_frequently   1      6234 311741 7021.0
## - main_meals_Btw_1_2          1      6901 312408 7023.7
## - CH2O_more_than_2            1      7315 312822 7025.4
## - physical_act_1_2            1      8119 313626 7028.6
## - vegetables_always           1     13310 318817 7049.4
## - Age                         1     17080 322587 7064.3
## - family_hist                 1     32631 338138 7123.9
## - main_meals_More_than_3      1     34024 339531 7129.1
## - Height                      1     72330 377837 7264.4
##
## Step:  AIC=6995.45
## Weight ~ Gender + Age + Height + family_hist + eat_caloric +
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 +
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently +
##     CH2O_between_1_and_2 + CH2O_more_than_2 + monitor_cal + physical_act_1_2 +
##     physical_act_2_4 + tech_1_hour + tech_2_hours_or_more + alcohol_always +
##     alcohol_frequently + alcohol_sometimes + mtrans_automobile +
##     mtrans_bike + mtrans_public_transportation
##
##                                 Df Sum of Sq    RSS    AIC
## - CH2O_between_1_and_2          1        26 305541 6993.6
## - alcohol_frequently            1        54 305569 6993.7
## - mtrans_bike                   1        58 305573 6993.7
## - alcohol_always                1       179 305694 6994.2
## - food_inbetween_always         1       381 305896 6995.0
## <none>                                      305515 6995.4
## - tech_2_hours_or_more          1       548 306063 6995.7
## - mtrans_public_transportation  1       762 306277 6996.6
## + food_inbetween_sometimes      1         8 305507 6997.4
## + smoke                         1         2 305514 6997.4
## - physical_act_2_4              1      1022 306537 6997.7
## - monitor_cal                   1      1192 306707 6998.4
## - mtrans_automobile             1      1543 307058 6999.8
## - eat_caloric                   1      1772 307287 7000.8
## - vegetables_sometimes          1      1935 307451 7001.4
## - Gender                        1      2917 308432 7005.5
## - tech_1_hour                   1      3022 308537 7005.9
## - alcohol_sometimes             1      4822 310337 7013.3
## - main_meals_Btw_1_2            1      6938 312453 7021.9
## - CH2O_more_than_2              1      7374 312889 7023.6
## - physical_act_1_2              1      8113 313628 7026.6
## - vegetables_always             1     13669 319185 7048.9
## - Age                           1     17150 322665 7062.6
## - family_hist                   1     33606 339121 7125.6
## - food_inbetween_frequently     1     34095 339610 7127.4
## - main_meals_More_than_3        1     34346 339862 7128.3
## - Height                         1     73963 379478 7267.9
##
## Step:  AIC=6993.56
## Weight ~ Gender + Age + Height + family_hist + eat_caloric +
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 +
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently +
##     CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 +
##     tech_1_hour + tech_2_hours_or_more + alcohol_always + alcohol_frequently +
##     alcohol_sometimes + mtrans_automobile + mtrans_bike + mtrans_public_transportatio
##
##                                 Df Sum of Sq    RSS    AIC
## - mtrans_bike                    1        55 305596 6991.8
## - alcohol_frequently             1        55 305596 6991.8
## - alcohol_always                 1       184 305724 6992.3
## - food_inbetween_always          1       383 305924 6993.1
## <none>                                       305541 6993.6
## - tech_2_hours_or_more           1       557 306098 6993.9
## - mtrans_public_transportation  1       770 306311 6994.7
## + CH2O_between_1_and_2           1        26 305515 6995.4
## + food_inbetween_sometimes       1         6 305534 6995.5
## + smoke                          1         2 305539 6995.5
## - physical_act_2_4               1      1054 306595 6995.9
## - monitor_cal                    1      1176 306717 6996.4
## - mtrans_automobile              1      1543 307084 6997.9
## - eat_caloric                    1      1783 307324 6998.9
## - vegetables_sometimes           1      1952 307492 6999.6
## - Gender                         1      2918 308458 7003.6
## - tech_1_hour                    1      3031 308572 7004.1
## - alcohol_sometimes              1      4859 310400 7011.5
## - main_meals_Btw_1_2             1      6914 312455 7019.9
## - CH2O_more_than_2               1      7968 313509 7024.1
## - physical_act_1_2               1      8091 313632 7024.6
## - vegetables_always              1     13723 319264 7047.2
## - Age                            1     17130 322671 7060.6
## - main_meals_More_than_3         1     34377 339917 7126.5
## - family_hist                    1     34502 340042 7127.0
## - food_inbetween_frequently      1     35247 340787 7129.8
## - Height                         1     74497 380038 7267.8
##
## Step:  AIC=6991.78
## Weight ~ Gender + Age + Height + family_hist + eat_caloric +
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 +
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently +
##     CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 +
##     tech_1_hour + tech_2_hours_or_more + alcohol_always + alcohol_frequently +
##     alcohol_sometimes + mtrans_automobile + mtrans_public_transportation
##
##                                 Df Sum of Sq    RSS    AIC
## - alcohol_frequently            1        53 305649 6990.0
## - alcohol_always                1       192 305787 6990.6
## - food_inbetween_always         1       397 305993 6991.4
## <none>                                      305596 6991.8
## - tech_2_hours_or_more          1       569 306164 6992.1
## + mtrans_bike                   1        55 305541 6993.6
## + CH2O_between_1_and_2          1        23 305573 6993.7
## - mtrans_public_transportation  1       947 306542 6993.7
## + food_inbetween_sometimes      1         6 305590 6993.8
## + smoke                         1         2 305594 6993.8
## - physical_act_2_4              1      1064 306660 6994.2
## - monitor_cal                   1      1193 306789 6994.7
## - mtrans_automobile             1      1495 307091 6996.0
## - eat_caloric                   1      1774 307370 6997.1
## - vegetables_sometimes          1      1940 307536 6997.8
## - Gender                        1      2966 308562 7002.0
## - tech_1_hour                   1      3036 308632 7002.3
## - alcohol_sometimes             1      4874 310470 7009.8
## - main_meals_Btw_1_2            1      6874 312469 7017.9
## - CH2O_more_than_2              1      7994 313590 7022.5
## - physical_act_1_2              1      8120 313716 7023.0
## - vegetables_always             1     13704 319299 7045.3
## - Age                           1     17101 322697 7058.7
## - main_meals_More_than_3        1     34322 339918 7124.5
## - family_hist                   1     34559 340154 7125.4
## - food_inbetween_frequently     1     35192 340787 7127.8
## - Height                        1     74674 380270 7266.6
##
## Step:  AIC=6990
## Weight ~ Gender + Age + Height + family_hist + eat_caloric +
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 +
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently +
##     CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 +
##     tech_1_hour + tech_2_hours_or_more + alcohol_always + alcohol_sometimes +
##     mtrans_automobile + mtrans_public_transportation
##
##                                Df Sum of Sq    RSS    AIC
## - alcohol_always                1       194 305843 6988.8
## - food_inbetween_always         1       414 306063 6989.7
## <none>                                      305649 6990.0
## - tech_2_hours_or_more          1       548 306197 6990.3
## + alcohol_frequently            1        53 305596 6991.8
## + mtrans_bike                   1        53 305596 6991.8
## - mtrans_public_transportation  1       935 306584 6991.9
## + CH2O_between_1_and_2          1        24 305625 6991.9
## + food_inbetween_sometimes      1         7 305642 6992.0
## + smoke                         1         4 305645 6992.0
## - physical_act_2_4              1      1077 306725 6992.5
## - monitor_cal                   1      1230 306879 6993.1
## - mtrans_automobile             1      1519 307168 6994.3
## - eat_caloric                   1      1766 307415 6995.3
## - vegetables_sometimes          1      1957 307606 6996.1
## - Gender                        1      2968 308617 7000.2
## - tech_1_hour                   1      3005 308654 7000.4
## - alcohol_sometimes             1      5478 311127 7010.5
## - main_meals_Btw_1_2            1      6846 312495 7016.0
## - CH2O_more_than_2              1      7945 313594 7020.5
## - physical_act_1_2              1      8110 313759 7021.2
## - vegetables_always             1     13749 319398 7043.7
## - Age                           1     17050 322699 7056.7
## - main_meals_More_than_3        1     34337 339986 7122.8
## - family_hist                   1     34597 340246 7123.8
## - food_inbetween_frequently     1     35440 341089 7126.9
## - Height                        1     74647 380296 7264.6
## 
## Step:  AIC=6988.81
## Weight ~ Gender + Age + Height + family_hist + eat_caloric + 
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 + 
##     main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently + 
##     CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 + 
##     tech_1_hour + tech_2_hours_or_more + alcohol_sometimes + 
##     mtrans_automobile + mtrans_public_transportation
## 
##                                 Df Sum of Sq    RSS    AIC
## - food_inbetween_always         1       415 306258 6988.5
## <none>                                      305843 6988.8
## - tech_2_hours_or_more          1       553 306396 6989.1
## + alcohol_always                1       194 305649 6990.0
## - mtrans_public_transportation  1       834 306678 6990.3
## + mtrans_bike                   1        62 305782 6990.6
## + alcohol_frequently            1        56 305787 6990.6
## + CH2O_between_1_and_2          1        28 305815 6990.7
## + food_inbetween_sometimes      1         7 305837 6990.8
## + smoke                         1         4 305839 6990.8
## - physical_act_2_4              1      1049 306892 6991.1
## - monitor_cal                   1      1243 307087 6991.9
## - mtrans_automobile             1      1687 307530 6993.8
## - eat_caloric                   1      1826 307670 6994.3
## - vegetables_sometimes          1      1971 307814 6994.9
## - tech_1_hour                   1      2934 308778 6998.9
## - Gender                        1      2938 308782 6998.9
## - alcohol_sometimes             1      5449 311292 7009.2
## - main_meals_Btw_1_2            1      6764 312607 7014.5
## - CH2O_more_than_2              1      7912 313755 7019.1
## - physical_act_1_2              1      8226 314070 7020.4
## - vegetables_always             1     13705 319549 7042.3
## - Age                           1     17016 322860 7055.4
## - main_meals_More_than_3        1     34420 340264 7121.8
## - family_hist                   1     34869 340713 7123.5
## - food_inbetween_frequently     1     35247 341090 7124.9
## - Height                        1     74523 380367 7262.9
##
## Step:  AIC=6988.52
## Weight ~ Gender + Age + Height + family_hist + eat_caloric +
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 +
##     main_meals_More_than_3 + food_inbetween_frequently + CH2O_more_than_2 +
##     monitor_cal + physical_act_1_2 + physical_act_2_4 + tech_1_hour +
##     tech_2_hours_or_more + alcohol_sometimes + mtrans_automobile +
##     mtrans_public_transportation
##
##                                Df Sum of Sq    RSS    AIC
## <none>                                      306258 6988.5
## + food_inbetween_always         1       415 305843 6988.8
## - tech_2_hours_or_more          1       574 306832 6988.9
## + food_inbetween_sometimes      1       266 305992 6989.4
## + alcohol_always                1       195 306063 6989.7
## + mtrans_bike                   1        77 306181 6990.2
## + alcohol_frequently            1        73 306185 6990.2
## - mtrans_public_transportation  1       926 307184 6990.3
## + CH2O_between_1_and_2          1        30 306228 6990.4
## + smoke                         1         9 306249 6990.5
## - physical_act_2_4              1      1012 307270 6990.7
## - monitor_cal                   1      1335 307593 6992.0
## - mtrans_automobile             1      1602 307860 6993.1
## - eat_caloric                   1      1883 308141 6994.3
## - vegetables_sometimes          1      2252 308510 6995.8
## - tech_1_hour                   1      2952 309210 6998.7
## - Gender                        1      3001 309259 6998.9
## - alcohol_sometimes             1      5572 311830 7009.3
## - main_meals_Btw_1_2            1      6579 312837 7013.4
## - CH2O_more_than_2              1      8041 314299 7019.3
## - physical_act_1_2              1      8493 314751 7021.2
## - vegetables_always             1     13718 319976 7042.0
## - Age                           1     17193 323451 7055.7
## - food_inbetween_frequently     1     34859 341116 7123.0
## - main_meals_More_than_3        1     35162 341419 7124.1
## - family_hist                   1     36034 342292 7127.4
## - Height                        1     74621 380879 7262.6
```

```r
summary(lm_both_obesity)
```

```
##
## Call:
```

```
## lm(formula = Weight ~ Gender + Age + Height + family_hist + eat_caloric +
##     vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 +
##     main_meals_More_than_3 + food_inbetween_frequently + CH2O_more_than_2 +
##     monitor_cal + physical_act_1_2 + physical_act_2_4 + tech_1_hour +
##     tech_2_hours_or_more + alcohol_sometimes + mtrans_automobile +
##     mtrans_public_transportation, data = train.set)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -54.796  -9.651   0.799   9.613  53.566
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  -157.25649   12.73878 -12.345  < 2e-16 ***
## Gender                          4.32640    1.23821   3.494 0.000492 ***
## Age                             0.81187    0.09707   8.363  < 2e-16 ***
## Height                        121.98641    7.00108  17.424  < 2e-16 ***
## family_hist                    15.62919    1.29081  12.108  < 2e-16 ***
## eat_caloric                     4.07848    1.47335   2.768 0.005721 **
## vegetables_sometimes          -10.25052    3.38653  -3.027 0.002522 **
## vegetables_always              -7.35775    0.98489  -7.471 1.50e-13 ***
## main_meals_Btw_1_2             -5.33322    1.03086  -5.174 2.67e-07 ***
## main_meals_More_than_3        -18.11019    1.51417 -11.960  < 2e-16 ***
## food_inbetween_frequently     -17.48159    1.46795 -11.909  < 2e-16 ***
## CH2O_more_than_2                5.42381    0.94825   5.720 1.33e-08 ***
## monitor_cal                    -5.18724    2.22576  -2.331 0.019936 *
## physical_act_1_2               -9.53018    1.62130  -5.878 5.32e-09 ***
## physical_act_2_4                2.01635    0.99354   2.029 0.042624 *
## tech_1_hour                    -5.36631    1.54856  -3.465 0.000548 ***
## tech_2_hours_or_more           -1.51977    0.99466  -1.528 0.126783
## alcohol_sometimes               4.78278    1.00453   4.761 2.15e-06 ***
## mtrans_automobile              -6.88857    2.69795  -2.553 0.010790 *
## mtrans_public_transportation    4.79038    2.46791   1.941 0.052475 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15.68 on 1246 degrees of freedom
## Multiple R-squared:  0.6455, Adjusted R-squared:  0.6401
## F-statistic: 119.4 on 19 and 1246 DF,  p-value: < 2.2e-16
```

```
# AIC: 6988.52 model:Weight ~ Gender + Age +
# Height + family_hist + eat_caloric +
# vegetables_sometimes + vegetables_always +
# main_meals_Btw_1_2 + main_meals_More_than_3
# + food_inbetween_frequently +
# CH2O_more_than_2 + monitor_cal +
# physical_act_1_2 + physical_act_2_4 +
# tech_1_hour + tech_2_hours_or_more +
# alcohol_sometimes + mtrans_automobile +
# mtrans_public_transportation

# Simplet model(both, backward)

# Add comments +Assumptions
```

For the forward model, the stepwise selection shows us that the best model is:

Weight ~ Gender + Age + Height + family_hist + eat_caloric + vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 + main_meals_More_than_3 + food_inbetween_always + food_inbetween_frequently + food_inbetween_sometimes + smoke + CH2O_between_1_and_2 + CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 + tech_1_hour + tech_2_hours_or_more + alcohol_always + alcohol_frequently + alcohol_sometimes + mtrans_automobile + mtrans_bike + mtrans_public_transportation

This is in fact the same model as the full model. It has an AIC of 6999.41, an R-Squared of 0.6464 and an ajusted R-Squared of 0.639.

For the backward model, the stepwise selection shows us that the best model is:

Weight ~ Gender + Age + Height + family_hist + eat_caloric + vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 + main_meals_More_than_3 + food_inbetween_frequently + CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 + tech_1_hour + tech_2_hours_or_more + alcohol_sometimes + mtrans_automobile + mtrans_public_transportation

This model is a reduced version of the full model.The AIC is 6988.52, the R-Squared is 0.6455 and the adjusted R-Squared is 0.6401.

For the both model we obtain the same results as the backward model. The best model is:

Weight ~ Gender + Age + Height + family_hist + eat_caloric + vegetables_sometimes + vegetables_always + main_meals_Btw_1_2 + main_meals_More_than_3 + food_inbetween_frequently + CH2O_more_than_2 + monitor_cal + physical_act_1_2 + physical_act_2_4 + tech_1_hour + tech_2_hours_or_more + alcohol_sometimes + mtrans_automobile + mtrans_public_transportation

This model is a reduced version of the full model.The AIC is 6988.52, the R-Squared is 0.6455 and the adjusted R-Squared is 0.6401.

When looking at all three models, the best model would seem to be the backward model(or the both model). It's adusted R-Squared is higher than the forward model by very little but is reduced and therefore favorable. We have very very similar results and insights from all three models but the backward model and the both model allow us to obtain those insights without having to drag around those variables that are not significant.

To confirm our choice of model for the linear regression, we will proceed with the validation of the accuracy of the predictions on the validation set with the help of 3 metrics: RMSE, Mean error and MAPE.

```
# Predictions on the validation set

# Forward model:
forward_pred_obesity <- predict(lm_forward_obesity,
    valid.set)

# RMSE
gofRMSE(valid.set$Weight, forward_pred_obesity,
    dgt = 3)  #16.376
```

```
## [1] 16.376
```

```
# Mean error
gofME(valid.set$Weight, forward_pred_obesity,
    dgt = 3)  #1.038
```

```
## [1] 1.038
```

```
# MAPE
gofMAPE(valid.set$Weight, forward_pred_obesity,
    dgt = 3)  #16.344
```

```
## [1] 16.344
```

```
# Backward model:
backward_pred_obesity <- predict(lm_backward_obesity,
    valid.set)

# RMSE
gofRMSE(valid.set$Weight, backward_pred_obesity,
    dgt = 3)  #16.416
```

```
## [1] 16.416
```

```
# Mean error
gofME(valid.set$Weight, backward_pred_obesity,
    dgt = 3)  #1.002
```

```
## [1] 1.002
```

```
# MAPE
gofMAPE(valid.set$Weight, backward_pred_obesity,
    dgt = 3)  #16.363
```

```
## [1] 16.363
```

```
# Both model:
both_pred_obesity <- predict(lm_both_obesity,
    valid.set)

# RMSE
gofRMSE(valid.set$Weight, both_pred_obesity, dgt = 3)  #16.416
```

```
## [1] 16.416
```

```
# Mean error
gofME(valid.set$Weight, both_pred_obesity, dgt = 3)  #1.002
```

```
## [1] 1.002
```

```
# MAPE
gofMAPE(valid.set$Weight, both_pred_obesity, dgt = 3)  #16.363
```

```
## [1] 16.363
```

```
# Add comments +Assumptions
```

Just as we had mentionned above, the backward model and the both model seem to represent the best model for our data. The difference in the three metrics for each model are very very small. This enables us to choose the backward/both model as the best model, since it yields very similar results as the full model, without all the cumbersome variables that are not relevant in the full (forward) model.

k-Nearest Neighbors

First of all, we should normalize the data, since we have different scales and big values can dominate small values! We normalize only the numerical data.

```
# Normalizing the data :

normalize <- function(x) {
    return((x - min(x))/(max(x) - min(x)))
}

train.set.norm <- as.data.frame(lapply(train.set[,
    c(2:4)], normalize))

valid.set.norm <- as.data.frame(lapply(valid.set[,
    c(2:4)], normalize))


# Regrouping into final dataset, with
# replacement of non-normalized variables :

train.final <- cbind(train.set.norm, train.set[,
    c(1, 5:36)])

valid.final <- cbind(valid.set.norm, valid.set[,
    c(1, 5:36)])
```

A “denormalize” function will be very handy when converting the predicted weight back to its normal scale :

```
denormalize <- function(x, y) {

    return((x * (max(y) - min(y))) + min(y))

}
```

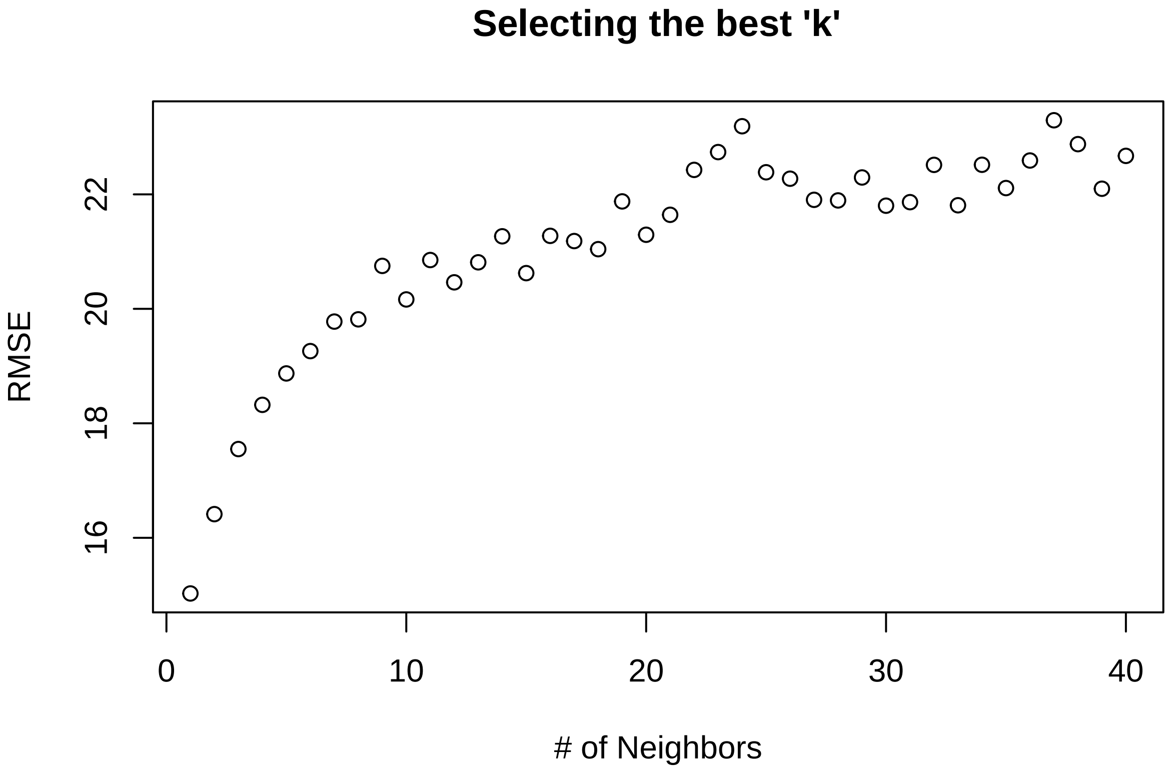
Now we will run the model JUST in order to identify different values of the **Root Mean Squared Error (RMSE)** :

```
# Creating dataframe :

rmse.df = data.frame(k = seq(1, 40, 1), RMSE = rep(0,
    40))


# Running the model :

set.seed(1)

for (i in 1:40) {

    knn.pred = knn(train = train.final[, -3],
        test = valid.final[, -3], cl = train.final[,
            3], k = i)

    k_nn = as.numeric(as.character(knn.pred))

    predicted = denormalize(k_nn, valid.set[,
        4])

    rmse.df[i, 2] = sqrt(mean((predicted - valid.set[,
        4])^2))
}


# Plotting results :

pander(rmse.df)
```

k	RMSE
1	15.03
2	16.41
3	17.55
4	18.32
5	18.87
6	19.26
7	19.78
8	19.82
9	20.75
10	20.16
11	20.85
12	20.46
13	20.81
14	21.27
15	20.62
16	21.27
17	21.18
18	21.04
19	21.88
20	21.29
21	21.64
22	22.43
23	22.74
24	23.19
25	22.39
26	22.27
27	21.9
28	21.89
29	22.3

k	RMSE
30	21.8
31	21.86
32	22.52
33	21.81
34	22.52
35	22.11
36	22.59
37	23.29
38	22.88
39	22.1
40	22.67

```r
plot(rmse.df$k, rmse.df$RMSE, xlab = "# of Neighbors",
    ylab = "RMSE", main = "Selecting the best 'k'")
```



We can see from this plot (but also fron the table above) that the best k is equal to 1. With this k = 1, we are able to minimize the RMSE.

```r
# Running the FINAL model (with k = 1):

set.seed(1)
```

```
k_nn <- knn(train = train.final[, -3], test = valid.final[,
    -3], cl = train.final[, 3], k = 1)

k_nn = as.numeric(as.character(k_nn))

predicted = denormalize(k_nn, valid.set[, 4])


RMSE = sqrt(mean((predicted - valid.set[, 4])^2))

RMSE
```

```
## [1] 15.02754
```

The resulting RMSE is equal to 15.02754.

Let's now do a Regression Tree and ultimately compare its RMSE with the one of the k-NN!

Weird! If we change the set.seed, the results for RMSE change!! So, which set.seed to choose?

Regression Tree

We will first focus on selecting the appropriate value for the Complexity Parameter (CP hereafter), which is a "penalty" factor concerning the size of the tree. A smaller CP will result in a bigger tree, and viceversa.

To do this, we will do a Cross-Validation approach. The computer will create many different partitions of the dataset into training and validation, and we want to find the CP that corresponds to the minimum Cross-Validation error.

This procedure is meant to help addressing the **tree instability** issue.

```
# First run a quite big tree (CP = 0.00001) :

set.seed(1)

tree_1 <- rpart(Weight ~ ., data = train.set,
    method = "anova", control = rpart.control(cp = 1e-05,
        minbucket = 1, maxdepth = 10))


# We do a CV : must locate in the table the
# point from which the CV error starts to rise
# :

printcp(tree_1)
```

```
##
## Regression tree:
## rpart(formula = Weight ~ ., data = train.set, method = "anova",
##     control = rpart.control(cp = 1e-05, minbucket = 1, maxdepth = 10))
##
## Variables actually used in tree construction:
##  [1] Age                         alcohol_frequently
##  [3] alcohol_no                  alcohol_sometimes
##  [5] CH2O_between_1_and_2        CH2O_less_than_a_liter
##  [7] CH2O_more_than_2            eat_caloric
##  [9] family_hist                 food_inbetween_always
## [11] food_inbetween_frequently   food_inbetween_no
## [13] food_inbetween_sometimes    Gender
## [15] Height                      main_meals_Btw_1_2
## [17] main_meals_More_than_3      main_meals_three
## [19] mtrans_automobile           mtrans_public_transportation
## [21] mtrans_walking              physical_act_1_2
## [23] physical_act_2_4            physical_act_do_not_have
## [25] smoke                       tech_0_hours
## [27] tech_1_hour                 tech_2_hours_or_more
## [29] vegetables_always           vegetables_never
## [31] vegetables_sometimes
##
## Root node error: 863970/1266 = 682.44
##
## n= 1266
##
##             CP nsplit rel error  xerror     xstd
## 1   2.3455e-01      0  1.000000 1.00155 0.031612
## 2   1.2033e-01      1  0.765455 0.76718 0.026514
## 3   9.1686e-02      2  0.645126 0.69143 0.024380
## 4   4.8885e-02      3  0.553440 0.57874 0.020532
## 5   4.7976e-02      4  0.504555 0.53189 0.020062
## 6   3.9913e-02      5  0.456579 0.50260 0.019309
## 7   3.1797e-02      6  0.416666 0.45833 0.018216
## 8   3.0705e-02      7  0.384869 0.42132 0.017611
## 9   2.9898e-02      8  0.354164 0.41031 0.017666
## 10  2.6283e-02      9  0.324267 0.39900 0.017759
## 11  2.1389e-02     10  0.297984 0.34518 0.016298
## 12  1.4922e-02     11  0.276595 0.31477 0.016084
## 13  1.3678e-02     13  0.246750 0.29319 0.015334
## 14  1.0733e-02     14  0.233073 0.27831 0.014811
## 15  6.7323e-03     15  0.222340 0.26197 0.014367
## 16  6.7285e-03     16  0.215608 0.25555 0.014318
## 17  6.4250e-03     17  0.208879 0.25484 0.014315
## 18  5.2398e-03     18  0.202454 0.24153 0.013774
## 19  5.1561e-03     19  0.197215 0.23718 0.013701
## 20  5.0756e-03     21  0.186902 0.23511 0.013704
## 21  5.0536e-03      22  0.181827 0.23474 0.013738
## 22  4.9464e-03      23  0.176773 0.23230 0.013641
## 23  4.8132e-03      24  0.171827 0.23098 0.013587
## 24  4.6777e-03      25  0.167013 0.22768 0.013597
## 25  4.5455e-03      26  0.162336 0.22770 0.013596
## 26  4.3459e-03      27  0.157790 0.22790 0.013646
## 27  4.0019e-03      28  0.153444 0.22284 0.013330
## 28  3.2234e-03      29  0.149442 0.20174 0.012413
## 29  3.0930e-03      30  0.146219 0.19889 0.012444
## 30  2.9916e-03      31  0.143126 0.19541 0.012417
## 31  2.8585e-03      32  0.140135 0.19581 0.012535
## 32  2.8075e-03      33  0.137276 0.19605 0.012634
## 33  2.4839e-03      35  0.131661 0.19153 0.012459
## 34  2.3938e-03      36  0.129177 0.19138 0.012666
## 35  2.3641e-03      38  0.124390 0.19672 0.014034
## 36  2.2876e-03      39  0.122025 0.19559 0.014017
## 37  2.1836e-03      40  0.119738 0.19980 0.014878
## 38  2.0813e-03      41  0.117554 0.20200 0.015113
## 39  2.0295e-03      43  0.113392 0.20369 0.015226
## 40  2.0205e-03      44  0.111362 0.20314 0.015217
## 41  1.9247e-03      45  0.109342 0.20182 0.015190
## 42  1.6986e-03      48  0.103567 0.19405 0.014685
## 43  1.6464e-03      50  0.100170 0.19487 0.014878
## 44  1.4059e-03      52  0.096878 0.19288 0.014810
## 45  1.4007e-03      53  0.095472 0.19279 0.015014
## 46  1.3517e-03      54  0.094071 0.19258 0.015012
## 47  1.3113e-03      55  0.092719 0.19280 0.015044
## 48  1.1903e-03      56  0.091408 0.19241 0.015191
## 49  1.1791e-03      57  0.090218 0.19372 0.015187
## 50  1.0896e-03      58  0.089039 0.19450 0.015269
## 51  1.0834e-03      59  0.087949 0.19447 0.015282
## 52  1.0806e-03      60  0.086866 0.19455 0.015281
## 53  1.0409e-03      61  0.085785 0.19446 0.015286
## 54  1.0146e-03      62  0.084744 0.19419 0.015298
## 55  1.0047e-03      63  0.083730 0.19496 0.015378
## 56  1.0036e-03      64  0.082725 0.19493 0.015378
## 57  9.9494e-04      65  0.081721 0.19493 0.015378
## 58  9.4526e-04      66  0.080726 0.19454 0.015409
## 59  9.3369e-04      67  0.079781 0.19457 0.015410
## 60  8.9659e-04      68  0.078847 0.19605 0.015490
## 61  8.8696e-04      69  0.077951 0.19705 0.015511
## 62  8.7917e-04      70  0.077064 0.19663 0.015498
## 63  8.7664e-04      71  0.076185 0.19667 0.015498
## 64  8.6872e-04      72  0.075308 0.19651 0.015504
## 65  8.5579e-04      73  0.074439 0.19666 0.015512
## 66  7.9067e-04      74  0.073584 0.19647 0.015546
## 67  7.6136e-04      75  0.072793 0.19610 0.015630
## 68  7.5874e-04      76  0.072032 0.19637 0.015648
## 69  7.3475e-04     77  0.071273 0.19719 0.015678
## 70  7.1505e-04     78  0.070538 0.19624 0.015649
## 71  7.0739e-04     79  0.069823 0.19622 0.015632
## 72  7.0003e-04     80  0.069116 0.19478 0.015445
## 73  6.9885e-04     81  0.068416 0.19442 0.015445
## 74  6.9317e-04     82  0.067717 0.19345 0.015439
## 75  6.8168e-04     86  0.064944 0.19321 0.015441
## 76  6.6291e-04     87  0.064262 0.19329 0.015462
## 77  6.4968e-04     88  0.063600 0.19127 0.015334
## 78  6.1187e-04     90  0.062300 0.19127 0.015325
## 79  5.7700e-04     92  0.061076 0.19191 0.015362
## 80  5.6197e-04     93  0.060499 0.19226 0.015343
## 81  5.6012e-04     94  0.059937 0.19295 0.015399
## 82  5.5551e-04     95  0.059377 0.19295 0.015399
## 83  5.3345e-04     96  0.058822 0.19193 0.015366
## 84  5.2949e-04     97  0.058288 0.19083 0.015368
## 85  5.2886e-04     98  0.057759 0.19080 0.015368
## 86  5.2750e-04     99  0.057230 0.19089 0.015368
## 87  5.1885e-04    100  0.056703 0.19050 0.015368
## 88  5.1087e-04    101  0.056184 0.19026 0.015362
## 89  4.9588e-04    103  0.055162 0.18986 0.015354
## 90  4.8486e-04    104  0.054666 0.19013 0.015457
## 91  4.7963e-04    107  0.053211 0.19138 0.015509
## 92  4.7509e-04    109  0.052252 0.19157 0.015508
## 93  4.5473e-04    110  0.051777 0.19067 0.015507
## 94  4.5147e-04    111  0.051322 0.19007 0.015501
## 95  4.1846e-04    113  0.050419 0.19114 0.015572
## 96  4.1701e-04    114  0.050001 0.19072 0.015578
## 97  4.0408e-04    115  0.049584 0.19061 0.015585
## 98  3.8493e-04    117  0.048776 0.18972 0.015600
## 99  3.7460e-04    118  0.048391 0.18979 0.015638
## 100 3.1367e-04    119  0.048016 0.18852 0.015599
## 101 3.0365e-04    122  0.047075 0.18864 0.015630
## 102 3.0357e-04    123  0.046772 0.18918 0.015645
## 103 3.0112e-04    124  0.046468 0.18904 0.015644
## 104 2.9037e-04    125  0.046167 0.18888 0.015646
## 105 2.8594e-04    126  0.045877 0.18885 0.015646
## 106 2.8317e-04    128  0.045305 0.18871 0.015648
## 107 2.7999e-04    129  0.045022 0.18871 0.015648
## 108 2.6409e-04    130  0.044742 0.18896 0.015658
## 109 2.6396e-04    131  0.044477 0.18867 0.015658
## 110 2.5313e-04    132  0.044213 0.18853 0.015660
## 111 2.4891e-04    133  0.043960 0.18866 0.015658
## 112 2.4321e-04    134  0.043711 0.18871 0.015661
## 113 2.2199e-04    135  0.043468 0.18916 0.015678
## 114 2.1902e-04    136  0.043246 0.18922 0.015690
## 115 2.1789e-04    137  0.043027 0.19004 0.015712
## 116 2.1609e-04    138  0.042809 0.19016 0.015713
## 117 2.0894e-04    139  0.042593 0.19264 0.015872
## 118 2.0355e-04    140  0.042384 0.19292 0.015887
## 119 2.0283e-04    141  0.042181 0.19331 0.015891
## 120 2.0174e-04    143  0.041775 0.19323 0.015892
## 121 1.9844e-04    144  0.041573 0.19336 0.015891
## 122 1.9533e-04    145  0.041375 0.19338 0.015895
## 123 1.9267e-04    146  0.041180 0.19335 0.015895
## 124 1.8506e-04    147  0.040987 0.19336 0.015896
## 125 1.7948e-04    149  0.040617 0.19340 0.015924
## 126 1.7349e-04    150  0.040437 0.19324 0.015923
## 127 1.7314e-04    151  0.040264 0.19322 0.015923
## 128 1.7105e-04    152  0.040091 0.19331 0.015925
## 129 1.6556e-04    153  0.039920 0.19332 0.015925
## 130 1.6526e-04    154  0.039754 0.19325 0.015925
## 131 1.6449e-04    155  0.039589 0.19325 0.015925
## 132 1.6278e-04    156  0.039424 0.19317 0.015926
## 133 1.6224e-04    157  0.039262 0.19342 0.015943
## 134 1.6005e-04    158  0.039099 0.19356 0.015951
## 135 1.5929e-04    160  0.038779 0.19349 0.015951
## 136 1.4593e-04    161  0.038620 0.19395 0.015975
## 137 1.4356e-04    162  0.038474 0.19491 0.016003
## 138 1.4168e-04    163  0.038330 0.19491 0.016003
## 139 1.3681e-04    164  0.038189 0.19514 0.016001
## 140 1.3370e-04    165  0.038052 0.19491 0.015997
## 141 1.3356e-04    166  0.037918 0.19483 0.015969
## 142 1.3092e-04    167  0.037785 0.19494 0.015969
## 143 1.2761e-04    168  0.037654 0.19463 0.015969
## 144 1.2457e-04    170  0.037399 0.19460 0.015969
## 145 1.2415e-04    171  0.037274 0.19461 0.015969
## 146 1.2226e-04    172  0.037150 0.19460 0.015969
## 147 1.1984e-04    173  0.037028 0.19416 0.015970
## 148 1.1818e-04    174  0.036908 0.19435 0.015969
## 149 1.1353e-04    175  0.036790 0.19450 0.016003
## 150 1.1202e-04    176  0.036676 0.19443 0.016105
## 151 1.1111e-04    177  0.036564 0.19458 0.016105
## 152 1.1067e-04    178  0.036453 0.19470 0.016110
## 153 1.0856e-04    179  0.036342 0.19469 0.016110
## 154 1.0700e-04    180  0.036234 0.19468 0.016110
## 155 1.0669e-04    181  0.036127 0.19468 0.016110
## 156 1.0508e-04    182  0.036020 0.19479 0.016116
## 157 1.0460e-04    183  0.035915 0.19477 0.016116
## 158 1.0419e-04    185  0.035706 0.19477 0.016116
## 159 1.0363e-04    186  0.035601 0.19476 0.016116
## 160 9.9800e-05    187  0.035498 0.19471 0.016117
## 161 9.9712e-05    188  0.035398 0.19461 0.016117
## 162 9.8810e-05    189  0.035298 0.19461 0.016117
## 163 9.3753e-05    190  0.035200 0.19485 0.016136
## 164 9.2613e-05    191  0.035106 0.19516 0.016135
## 165 9.0585e-05    192  0.035013 0.19517 0.016135
## 166 7.8345e-05    193  0.034923 0.19551 0.016170
## 167 7.7127e-05    194  0.034844 0.19558 0.016194
## 168 7.5068e-05    195  0.034767 0.19512 0.016138
## 169 7.1679e-05    196  0.034692 0.19509 0.016137
## 170 7.1332e-05    197  0.034620 0.19489 0.016124
## 171 7.0450e-05    198  0.034549 0.19496 0.016125
## 172 6.7110e-05    199  0.034479 0.19495 0.016125
## 173 6.4467e-05    200  0.034411 0.19497 0.016124
## 174 5.9261e-05    201  0.034347 0.19492 0.016125
## 175 5.9063e-05    202  0.034288 0.19487 0.016123
## 176 5.7612e-05    203  0.034229 0.19501 0.016124
## 177 5.7072e-05    204  0.034171 0.19490 0.016126
## 178 5.7045e-05    205  0.034114 0.19490 0.016126
## 179 5.7025e-05    206  0.034057 0.19490 0.016126
## 180 5.5750e-05    207  0.034000 0.19490 0.016126
## 181 5.5750e-05    208  0.033944 0.19487 0.016124
## 182 5.5599e-05    209  0.033888 0.19487 0.016124
## 183 5.1566e-05    210  0.033833 0.19472 0.016115
## 184 4.5550e-05    212  0.033730 0.19510 0.016122
## 185 4.3404e-05    214  0.033639 0.19526 0.016128
## 186 4.2536e-05    215  0.033595 0.19530 0.016129
## 187 3.9508e-05    216  0.033553 0.19613 0.016187
## 188 3.7810e-05    217  0.033513 0.19553 0.016148
## 189 3.7077e-05    218  0.033475 0.19558 0.016147
## 190 3.6889e-05    219  0.033438 0.19557 0.016147
## 191 3.6696e-05    220  0.033401 0.19557 0.016147
## 192 3.3334e-05    221  0.033365 0.19558 0.016148
## 193 3.2199e-05    222  0.033331 0.19567 0.016149
## 194 2.7875e-05    223  0.033299 0.19556 0.016140
## 195 2.7795e-05    224  0.033271 0.19532 0.016137
## 196 2.7779e-05    225  0.033243 0.19521 0.016132
## 197 2.5058e-05    226  0.033216 0.19520 0.016133
## 198 2.3457e-05    227  0.033191 0.19558 0.016135
## 199 2.3342e-05    228  0.033167 0.19544 0.016134
## 200 2.2630e-05    229  0.033144 0.19544 0.016134
## 201 2.1898e-05    230  0.033121 0.19544 0.016134
## 202 2.1507e-05    231  0.033099 0.19530 0.016122
## 203 2.0965e-05    232  0.033078 0.19536 0.016123
## 204 2.0395e-05    233  0.033057 0.19532 0.016123
## 205 1.9845e-05    234  0.033036 0.19526 0.016123
## 206 1.9291e-05    235  0.033017 0.19541 0.016127
## 207 1.8322e-05    237  0.032978 0.19551 0.016129
## 208 1.7738e-05    238  0.032960 0.19547 0.016127
## 209 1.7688e-05    239  0.032942 0.19549 0.016127
## 210 1.7662e-05    240  0.032924 0.19549 0.016127
## 211 1.7469e-05    241  0.032907 0.19549 0.016127
## 212 1.7358e-05    242  0.032889 0.19549 0.016127
## 213 1.7223e-05    243  0.032872 0.19524 0.016126
## 214 1.5626e-05    244  0.032855 0.19524 0.016126
## 215 1.3938e-05    246  0.032823 0.19516 0.016126
## 216 1.3206e-05    247  0.032809 0.19535 0.016125
## 217 1.2756e-05    248  0.032796 0.19535 0.016125
## 218 1.1386e-05    249  0.032783 0.19540 0.016125
## 219 1.0390e-05    250  0.032772 0.19553 0.016126
## 220 1.0000e-05    251  0.032762 0.19547 0.016127
```

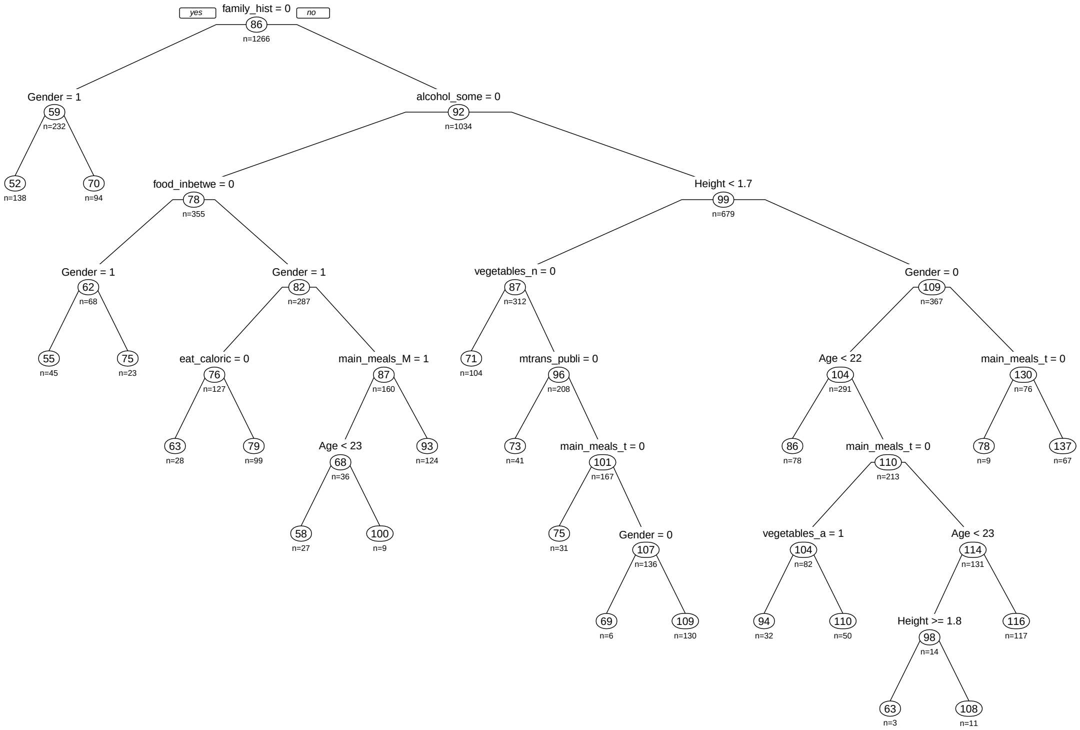
We can see from the results above that, in this case, the CV error starts to rise when CP = 0.0046777.

BUT, there is a standard error in that point estimate! If we do 0.22768+0.013597 = 0.241277

So, we can go for a SMALLER (and thus better) tree with 19 splits instead of 24, which corresponds to a CP of 0.0051561.

So now we will fit the FINAL prediction tree with a CP of 0.0051561, which is the best value for CP because we calculated it with a Cross-Validation approach!

```r
set.seed(1)

tree_2 <- rpart(Weight ~ ., data = train.set,
    method = "anova", control = rpart.control(cp = 0.0051561,
        minbucket = 1, maxdepth = 10))

plot_tree = prp(tree_2, type = 1, extra = 1, under = TRUE,
    split.font = 1, varlen = -10)
```



Now, let’s compare the RMSE for validation and training sets.

```
# First, let's create two vectors, one for the
# predicted values, and another for the actual
# values :

predicted_train <- predict(tree_2, train.set)

actual_train <- train.set$Weight


# And lastly, we make use of the RSME formula
# to calculate it :

RMSE_train = sqrt(mean((predicted_train - actual_train)^2))

RMSE_train
```

```
## [1] 11.29379
```

We have RMSE = 11.29379

Now, we do the same but for the validation set.

```
predicted_valid <- predict(tree_2, valid.set)

actual_valid <- valid.set$Weight


RMSE_valid = sqrt(mean((predicted_valid - actual_valid)^2))

RMSE_valid
```

```
## [1] 13.25937
```

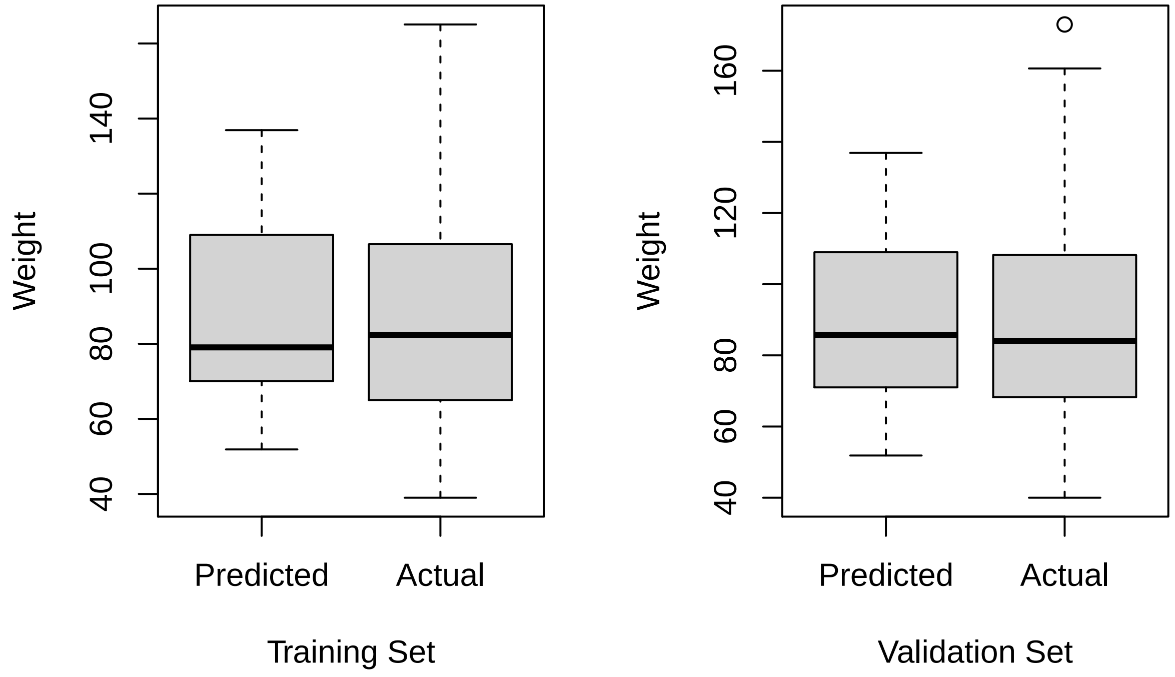
The RMSE for the validation data is 13.25937.

It is very normal that RMSE is smaller with the training data, because we have selected the optimal CP according to the training data. However, the difference seems not so big.

nyway, the RMSE which is of interest is the one for the validation set, since the validation data is "fresh and new", has not been used to adjust the model.

Let's now look at some boxplots to compare the performance of the tree on both sets (training and validation).

```
par(mfrow = c(1, 2))

boxplot(predicted_train, actual_train, names = c("Predicted",
    "Actual"), ylab = "Weight", xlab = "Training Set")

boxplot(predicted_valid, actual_valid, names = c("Predicted",
    "Actual"), ylab = "Weight", xlab = "Validation Set")
```



It is difficult to judge on which set the tree has performed better. Probably the higer RMSE for the validation set is due to the presence of an outlier!

But the training set boxplot seems a bit right skeewed, so one could conclude that the validation set did even a better job.

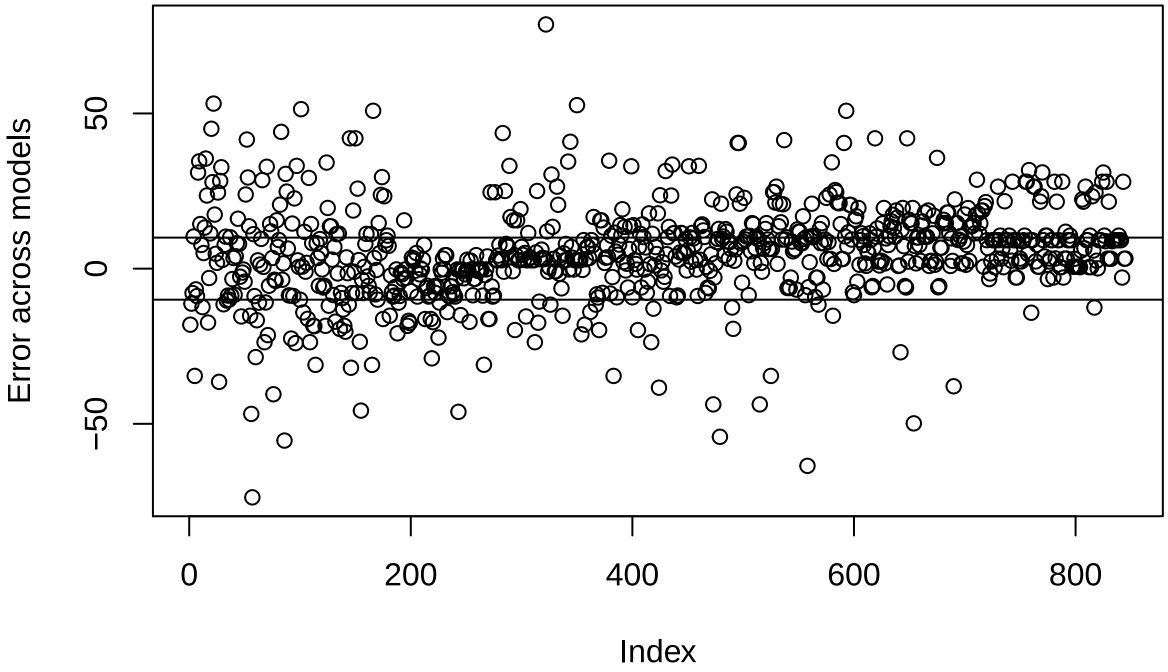
So now we are finished with the regression tree.

We can leave the CP as it is, and the tree will grow until 19 splits.

Now, let's do something quite interesting! We will do a comparison of both KNN and regression tree on the validation set.

We will plot the errors "across the models", so the difference between the predicted weights by both models.

```r
plot(predicted - predicted_valid, ylab = "Error across models")
abline(h = 10)
abline(h = -10)
```

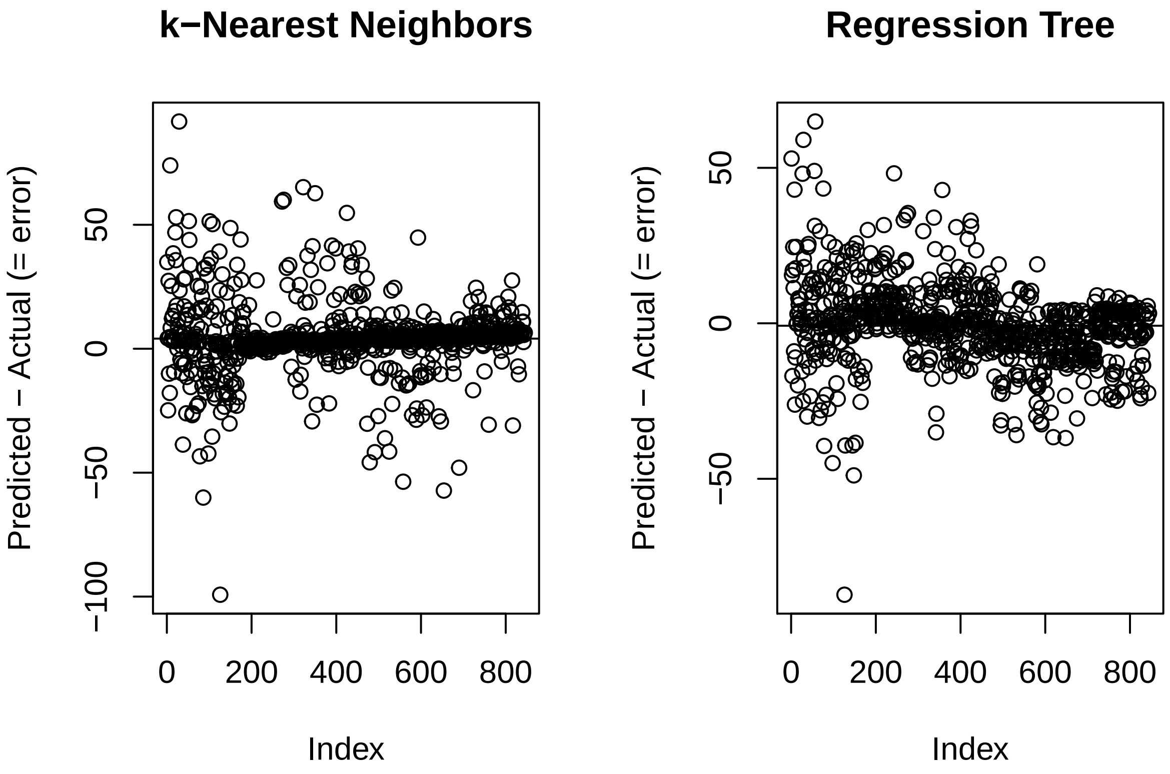


We can see that although there is quite a lot of variance, at times both models seem to behave almost equally at predicting the weight.

Inside the range of [-10 ; 10] there seems to be the majority of the points, so the range is not so big.

Let’s take a more precise look at each method compared with the validation data.

```
par(mfrow = c(1, 2))


# For KNN :
plot(predicted - valid.set[, 4], main = "k-Nearest Neighbors",
    ylab = "Predicted - Actual (= error)")
abline(h = mean(predicted - valid.set[, 4]))



# For tree :
plot(predicted_valid - valid.set[, 4], main = "Regression Tree",
    ylab = "Predicted - Actual (= error)")
abline(h = mean(predicted_valid - valid.set[,
    4]))
```



VERY INTERESTING!

Actually we can see that we have the typical **trade-off between BIAS and VARIANCE**.

Certainly, the k-NN seems to be more precise (less variance), since the points are less far apart from each other. BUT, we observe an upward trend, and the mean of the points (= errors) is at around 4, not 0!

So there is small bias in the k-NN.

However, the regression tree has a lot of variance, BUT on average it is very precise (the mean of the errros is almost at zero). Indeed :

```
# For k-NN :

mean(predicted - valid.set[, 4])
```

```
## [1] 4.079884
```

```
# For tree :

mean(predicted_valid - valid.set[, 4])
```

```
## [1] -0.7759031
```

For the regression tree, the mean is very close to zero.

So now we can discuss which model is better for us. Do we want a very accurate prediction although it may be around on average 4 Kg away from the truth? Or do we want a prediction which is very far from the truth but, taking into account all predictions, on average we are almost exactly on the target?

Probably we want something like the k-NN, since 4 Kg is not much.

The regression tree is less biased and has smaller RMSE, BUT certainly the amount of error is very big (the differences predicted - actual are quite big).

Therefore, we may prefer the k-NN after all!

Ensemble Method (MLR + k-NN + Regression Tree)

The aim of this ensemble method is to combine the Multiple Linear Regression, the k-NN and the Regression Tree in order to obtain even better results. This combination of methods will be done by taking the average prediction of the variable of interest (`Weight`).

This means that the predicted weight using this ensemble method will be obtained by running the three methods separately and then taking the average over the results.

```
# Creating dataframe :

ensemble_df <- data.frame(actual = valid.set[,
    4], MLR = backward_pred_obesity, knn = predicted,
    Regression_tree = predicted_valid, Ensemble_Method = (predicted +
        predicted_valid + backward_pred_obesity)/3)

head(ensemble_df)
```

```
##    actual       MLR       knn Regression_tree Ensemble_Method
## 2      56  63.92756  90.93895       108.99283        87.95311
## 3      77  94.05396  81.22554        92.50013        89.25988
## 4      87  82.71985  62.15660        70.03409        71.63685
## 6      53  59.01734  80.37579        70.03409        69.80907
## 10     68  87.56165  57.93629        92.50013        79.33269
## 11    105 101.38382 109.66225       116.34191       109.12933
```

```
RMSE_ensemble = sqrt(mean((ensemble_df[, 5] - valid.set[, 4])^2))

RMSE_ensemble
```

```
## [1] 11.39791
```

```
RMSE_total.df = data.frame(

    RMSE_MLR = 16.416,
    RMSE_kNN = 15.02754,
    RMSE_Tree = 13.25937,
    RMSE_Ensemble = 11.39791

  )

pander(RMSE_total.df)
```

RMSE_MLR	RMSE_kNN	RMSE_Tree	RMSE_Ensemble
16.42	15.03	13.26	11.4

Creating a person for prediction

```
# Creating a person for prediction :

example.df = obesity[1, ]

example.df$Gender = "Male"
example.df$Age = 25
example.df$Height = 1.78
example.df$Weight = 70
example.df$family_history = "no"
example.df$eat_caloric = "no"
example.df$vegetables = "Always"
example.df$main_meals = "More_than_3"
example.df$food_inbetween = "no"
example.df$SMOKE = "no"
example.df$CH2O = "Between 1 and 2 L"
example.df$monitor_cal = "no"
example.df$physical_act = "2 or 4 days"
example.df$tech_devices = "0-2_hours"
example.df$alcohol = "no"
example.df$MTRANS = "Walking"
example.df$NObeyesdad = "Normal_weight"


norm.values <- preProcess(obesity[, c(2:4)], method = "range")

example.norm <- predict(norm.values, example.df)
```

```r
example.df = to_factor(example.df)

# example.df = dummy(example.df) Create a
# SINGLE function for dummyfication (need to
# eliminate the _dummy dataset)

# predict(k_nn, example.df) predict(tree_2,
# example.df) ...

# for Multiple Linear Regression, simply
# replace coefficients and variable values
# into the formula to get the predicted
# weight. Maybe create a function called
# 'MLR()' for this!
```