

# Machine learning models for cancer predictive analysis

Natalia

28 May 2019

```
data <- read.csv("C://Users//Natalia//Desktop//ITMO//R//R project//cancer data//breastcancer//cancer_data.csv")
colnames(data) <- c("id", "Class", "radius_mean", "texture_mean", "perimeter_mean", "area_mean", "smoothness_mean",
                    "compactness_worst", "concavity_worst", "concave points_worst", "symmetry_worst", "fractal_dimension_mean",
                    "radius_se", "texture_se", "perimeter_se", "area_se", "smoothness_se", "compactness_se", "concavity_se", "concave points_se", "symmetry_se", "fractal_dimension_se")
View(data)
```

## Analyse the dataset and tidy it up.

```
# Analyse the data - checking for values, NAs, data type.
summary(data)
```

```
##          id          Class      radius_mean      texture_mean
## Min.      :   8670   Min.    :0.0000   Min.     : 6.981   Min.      : 9.71
## 1st Qu.:  869222   1st Qu.:0.0000   1st Qu.:11.697   1st Qu.:16.18
## Median :   906157   Median :0.0000   Median :13.355   Median :18.86
## Mean     : 30423820   Mean     :0.3715   Mean      :14.120   Mean      :19.31
## 3rd Qu.:  8825022   3rd Qu.:1.0000   3rd Qu.:15.780   3rd Qu.:21.80
## Max.     :911320502   Max.     :1.0000   Max.      :28.110   Max.      :39.28
## perimeter_mean      area_mean      smoothness_mean      compactness_mean
## Min.      : 43.79   Min.      : 143.5   Min.      :0.05263   Min.      :0.01938
## 1st Qu.:  75.14   1st Qu.:  420.2   1st Qu.:0.08629   1st Qu.:0.06481
## Median :  86.21   Median :  548.8   Median :0.09587   Median :0.09252
## Mean      : 91.91   Mean      : 654.3   Mean      :0.09632   Mean      :0.10404
## 3rd Qu.:103.88   3rd Qu.:  782.6   3rd Qu.:0.10530   3rd Qu.:0.13040
## Max.      :188.50   Max.      :2501.0   Max.      :0.16340   Max.      :0.34540
## concavity_mean      concave_points_mean      symmetry_mean
## Min.      :0.00000   Min.      :0.00000   Min.      :0.1060
## 1st Qu.:0.02954   1st Qu.:0.02031   1st Qu.:0.1619
## Median :0.06140   Median :0.03345   Median :0.1792
## Mean      :0.08843   Mean      :0.04875   Mean      :0.1811
## 3rd Qu.:0.12965   3rd Qu.:0.07373   3rd Qu.:0.1956
## Max.      :0.42680   Max.      :0.20120   Max.      :0.3040
## fractal_dimension_mean      radius_se      texture_se      perimeter_se
## Min.      :0.04996   Min.      :0.1115   Min.      :0.3602   Min.      : 0.757
## 1st Qu.:0.05770   1st Qu.:0.2324   1st Qu.:0.8331   1st Qu.: 1.605
## Median :0.06152   Median :0.3240   Median :1.1095   Median : 2.285
## Mean      :0.06277   Mean      :0.4040   Mean      :1.2174   Mean      : 2.856
## 3rd Qu.:0.06612   3rd Qu.:0.4773   3rd Qu.:1.4743   3rd Qu.: 3.337
## Max.      :0.09744   Max.      :2.8730   Max.      :4.8850   Max.      :21.980
## area_se      smoothness_se      compactness_se      concavity_se
## Min.      : 6.802   Min.      :0.001713   Min.      :0.002252   Min.      :0.00000
## 1st Qu.: 17.850   1st Qu.:0.005166   1st Qu.:0.013048   1st Qu.:0.01506
## Median : 24.485   Median :0.006374   Median :0.020435   Median :0.02587
## Mean      : 40.138   Mean      :0.007042   Mean      :0.025437   Mean      :0.03186
## 3rd Qu.: 45.017   3rd Qu.:0.008151   3rd Qu.:0.032218   3rd Qu.:0.04176
## Max.     :542.200   Max.      :0.031130   Max.      :0.135400   Max.      :0.39600
## concave_points_se      symmetry_se      fractal_dimension_se
```

```
## Min. :0.000000 Min. :0.007882 Min. :0.0008948
## 1st Qu.:0.007634 1st Qu.:0.015128 1st Qu.:0.0022445
## Median :0.010920 Median :0.018725 Median :0.0031615
## Mean :0.011789 Mean :0.020526 Mean :0.0037907
## 3rd Qu.:0.014710 3rd Qu.:0.023398 3rd Qu.:0.0045258
## Max. :0.052790 Max. :0.078950 Max. :0.0298400
## radius_worst texture_worst perimeter_worst area_worst
## Min. : 7.93 Min. :12.02 Min. : 50.41 Min. : 185.2
## 1st Qu.:13.01 1st Qu.:21.09 1st Qu.: 84.10 1st Qu.: 515.0
## Median :14.96 Median :25.43 Median : 97.66 Median : 685.5
## Mean :16.25 Mean :25.69 Mean :107.13 Mean : 878.6
## 3rd Qu.:18.77 3rd Qu.:29.76 3rd Qu.:125.17 3rd Qu.:1073.5
## Max. :36.04 Max. :49.54 Max. :251.20 Max. :4254.0
## smoothness_worst compactness_worst concavity_worst concave points_worst
## Min. :0.07117 Min. :0.02729 Min. :0.0000 Min. :0.00000
## 1st Qu.:0.11660 1st Qu.:0.14690 1st Qu.:0.1145 1st Qu.:0.06473
## Median :0.13130 Median :0.21185 Median :0.2266 Median :0.09984
## Mean :0.13232 Mean :0.25354 Mean :0.2714 Mean :0.11434
## 3rd Qu.:0.14600 3rd Qu.:0.33760 3rd Qu.:0.3814 3rd Qu.:0.16132
## Max. :0.22260 Max. :1.05800 Max. :1.2520 Max. :0.29100
## symmetry_worst fractal_dimension_worst
## Min. :0.1565 Min. :0.05504
## 1st Qu.:0.2504 1st Qu.:0.07141
## Median :0.2821 Median :0.08002
## Mean :0.2898 Mean :0.08388
## 3rd Qu.:0.3177 3rd Qu.:0.09206
## Max. :0.6638 Max. :0.20750
```

```
str(data)
```

```
## 'data.frame': 568 obs. of 32 variables:
## $ id : int 842517 84300903 84348301 84358402 843786 844359 84458202 844981 845...
## $ Class : int 1 1 1 1 1 1 1 1 1 1 ...
## $ radius_mean : num 20.6 19.7 11.4 20.3 12.4 ...
## $ texture_mean : num 17.8 21.2 20.4 14.3 15.7 ...
## $ perimeter_mean : num 132.9 130 77.6 135.1 82.6 ...
## $ area_mean : num 1326 1203 386 1297 477 ...
## $ smoothness_mean : num 0.0847 0.1096 0.1425 0.1003 0.1278 ...
## $ compactness_mean : num 0.0786 0.1599 0.2839 0.1328 0.17 ...
## $ concavity_mean : num 0.0869 0.1974 0.2414 0.198 0.1578 ...
## $ concave_points_mean : num 0.0702 0.1279 0.1052 0.1043 0.0809 ...
## $ symmetry_mean : num 0.181 0.207 0.26 0.181 0.209 ...
## $ fractal_dimension_mean : num 0.0567 0.06 0.0974 0.0588 0.0761 ...
## $ radius_se : num 0.543 0.746 0.496 0.757 0.335 ...
## $ texture_se : num 0.734 0.787 1.156 0.781 0.89 ...
## $ perimeter_se : num 3.4 4.58 3.44 5.44 2.22 ...
## $ area_se : num 74.1 94 27.2 94.4 27.2 ...
## $ smoothness_se : num 0.00522 0.00615 0.00911 0.01149 0.00751 ...
## $ compactness_se : num 0.0131 0.0401 0.0746 0.0246 0.0335 ...
## $ concavity_se : num 0.0186 0.0383 0.0566 0.0569 0.0367 ...
## $ concave_points_se : num 0.0134 0.0206 0.0187 0.0188 0.0114 ...
## $ symmetry_se : num 0.0139 0.0225 0.0596 0.0176 0.0216 ...
## $ fractal_dimension_se : num 0.00353 0.00457 0.00921 0.00511 0.00508 ...
## $ radius_worst : num 25 23.6 14.9 22.5 15.5 ...
## $ texture_worst : num 23.4 25.5 26.5 16.7 23.8 ...
```

```
## $ perimeter_worst      : num  158.8 152.5 98.9 152.2 103.4 ...
## $ area_worst           : num  1956 1709 568 1575 742 ...
## $ smoothness_worst     : num  0.124 0.144 0.21 0.137 0.179 ...
## $ compactness_worst    : num  0.187 0.424 0.866 0.205 0.525 ...
## $ concavity_worst      : num  0.242 0.45 0.687 0.4 0.535 ...
## $ concave points_worst : num  0.186 0.243 0.258 0.163 0.174 ...
## $ symmetry_worst       : num  0.275 0.361 0.664 0.236 0.399 ...
## $ fractal_dimension_worst: num  0.089 0.0876 0.173 0.0768 0.1244 ...
```

```
data$id <- NULL
data$Cl <- ifelse(data$Class == "0", "benign", ifelse(data$Class == 1, "malignant", NA))
data$Class <- data$Cl
head(data)
```

```
##      Class radius_mean texture_mean perimeter_mean area_mean
## 1 malignant      20.57        17.77         132.90    1326.0
## 2 malignant      19.69        21.25         130.00    1203.0
## 3 malignant      11.42        20.38          77.58     386.1
## 4 malignant      20.29        14.34         135.10    1297.0
## 5 malignant      12.45        15.70          82.57     477.1
## 6 malignant      18.25        19.98         119.60    1040.0
##      smoothness_mean compactness_mean concavity_mean concave_points_mean
## 1          0.08474         0.07864         0.0869         0.07017
## 2          0.10960         0.15990         0.1974         0.12790
## 3          0.14250         0.28390         0.2414         0.10520
## 4          0.10030         0.13280         0.1980         0.10430
## 5          0.12780         0.17000         0.1578         0.08089
## 6          0.09463         0.10900         0.1127         0.07400
##      symmetry_mean fractal_dimension_mean radius_se texture_se perimeter_se
## 1          0.1812         0.05667         0.5435         0.7339         3.398
## 2          0.2069         0.05999         0.7456         0.7869         4.585
## 3          0.2597         0.09744         0.4956         1.1560         3.445
## 4          0.1809         0.05883         0.7572         0.7813         5.438
## 5          0.2087         0.07613         0.3345         0.8902         2.217
## 6          0.1794         0.05742         0.4467         0.7732         3.180
##      area_se smoothness_se compactness_se concavity_se concave_points_se
## 1      74.08      0.005225      0.01308      0.01860      0.01340
## 2      94.03      0.006150      0.04006      0.03832      0.02058
## 3      27.23      0.009110      0.07458      0.05661      0.01867
## 4      94.44      0.011490      0.02461      0.05688      0.01885
## 5      27.19      0.007510      0.03345      0.03672      0.01137
## 6      53.91      0.004314      0.01382      0.02254      0.01039
##      symmetry_se fractal_dimension_se radius_worst texture_worst
## 1      0.01389         0.003532         24.99         23.41
## 2      0.02250         0.004571         23.57         25.53
## 3      0.05963         0.009208         14.91         26.50
## 4      0.01756         0.005115         22.54         16.67
## 5      0.02165         0.005082         15.47         23.75
## 6      0.01369         0.002179         22.88         27.66
##      perimeter_worst area_worst smoothness_worst compactness_worst
## 1          158.80      1956.0         0.1238         0.1866
## 2          152.50      1709.0         0.1444         0.4245
## 3           98.87       567.7         0.2098         0.8663
## 4          152.20      1575.0         0.1374         0.2050
## 5          103.40       741.6         0.1791         0.5249
```

```
## 6          153.20      1606.0          0.1442          0.2576
##   concavity_worst concave points_worst symmetry_worst
## 1          0.2416          0.1860          0.2750
## 2          0.4504          0.2430          0.3613
## 3          0.6869          0.2575          0.6638
## 4          0.4000          0.1625          0.2364
## 5          0.5355          0.1741          0.3985
## 6          0.3784          0.1932          0.3063
##   fractal_dimension_worst      Cl
## 1          0.08902 malignant
## 2          0.08758 malignant
## 3          0.17300 malignant
## 4          0.07678 malignant
## 5          0.12440 malignant
## 6          0.08368 malignant
```

```
dim(data)
```

```
## [1] 568 32
```

```
library(tidyverse)
```

```
## -- Attaching packages ----- tidyverse 1.2
```

```
## v ggplot2 3.1.1      v purrr 0.3.2
## v tibble 2.1.1       v dplyr 0.8.0.1
## v tidyr 0.8.3        v stringr 1.4.0
## v readr 1.3.1        v forcats 0.4.0
```

```
## -- Conflicts ----- tidyverse_conflicts
```

```
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
```

```
map_int(data, function(.x) sum(is.na(.x)))
```

```
##           Class          radius_mean          texture_mean
##           0              0              0
##   perimeter_mean          area_mean          smoothness_mean
##           0              0              0
##   compactness_mean          concavity_mean          concave_points_mean
##           0              0              0
##   symmetry_mean fractal_dimension_mean          radius_se
##           0              0              0
##   texture_se          perimeter_se          area_se
##           0              0              0
##   smoothness_se          compactness_se          concavity_se
##           0              0              0
##   concave_points_se          symmetry_se          fractal_dimension_se
##           0              0              0
##   radius_worst          texture_worst          perimeter_worst
##           0              0              0
##   area_worst          smoothness_worst          compactness_worst
##           0              0              0
##   concavity_worst          concave points_worst          symmetry_worst
##           0              0              0
## fractal_dimension_worst      Cl
##           0              0
```

```
# Data type "Class" as factor:
```

```
data <- as.data.frame(data, stringsAsFactors=T)
data$Class <- as.factor(data$Class)
data$Cl <- NULL
head(data)
```

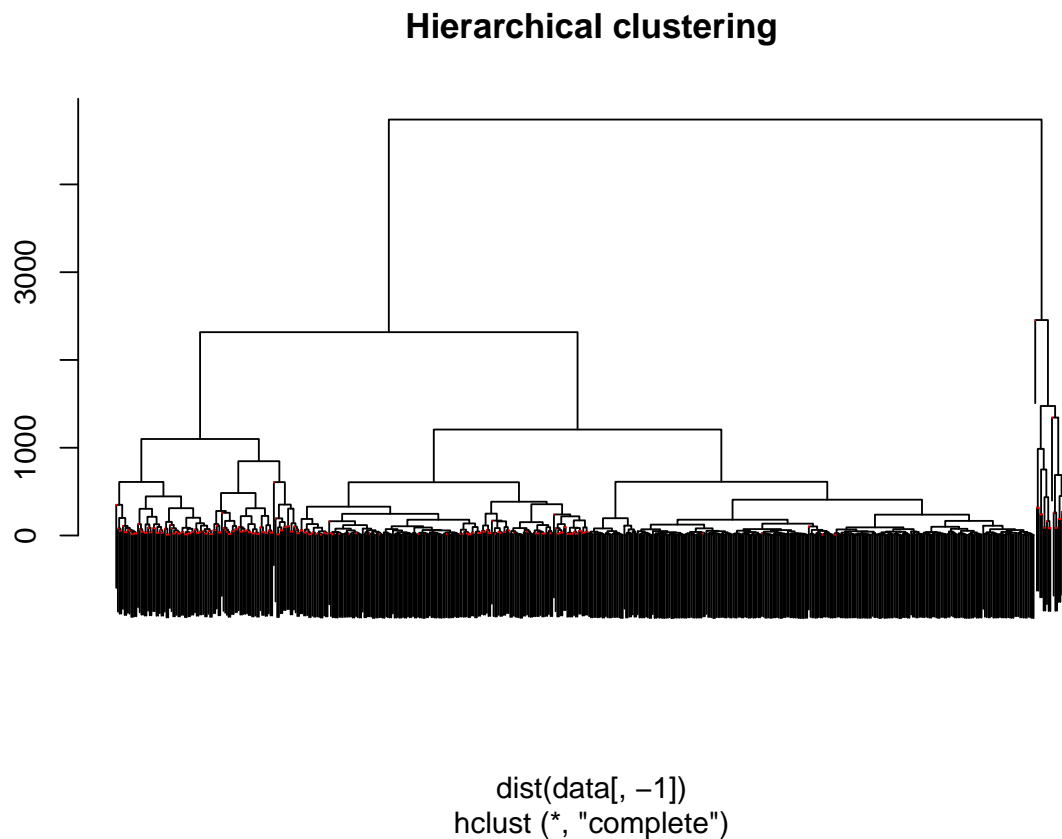
```
##      Class radius_mean texture_mean perimeter_mean area_mean
## 1 malignant      20.57       17.77       132.90    1326.0
## 2 malignant      19.69       21.25       130.00    1203.0
## 3 malignant      11.42       20.38        77.58     386.1
## 4 malignant      20.29       14.34       135.10    1297.0
## 5 malignant      12.45       15.70        82.57     477.1
## 6 malignant      18.25       19.98       119.60    1040.0
##      smoothness_mean compactness_mean concavity_mean concave_points_mean
## 1          0.08474         0.07864         0.0869         0.07017
## 2          0.10960         0.15990         0.1974         0.12790
## 3          0.14250         0.28390         0.2414         0.10520
## 4          0.10030         0.13280         0.1980         0.10430
## 5          0.12780         0.17000         0.1578         0.08089
## 6          0.09463         0.10900         0.1127         0.07400
##      symmetry_mean fractal_dimension_mean radius_se texture_se perimeter_se
## 1          0.1812         0.05667         0.5435         0.7339         3.398
## 2          0.2069         0.05999         0.7456         0.7869         4.585
## 3          0.2597         0.09744         0.4956         1.1560         3.445
## 4          0.1809         0.05883         0.7572         0.7813         5.438
## 5          0.2087         0.07613         0.3345         0.8902         2.217
## 6          0.1794         0.05742         0.4467         0.7732         3.180
##      area_se smoothness_se compactness_se concavity_se concave_points_se
## 1      74.08      0.005225      0.01308      0.01860      0.01340
## 2      94.03      0.006150      0.04006      0.03832      0.02058
## 3      27.23      0.009110      0.07458      0.05661      0.01867
## 4      94.44      0.011490      0.02461      0.05688      0.01885
## 5      27.19      0.007510      0.03345      0.03672      0.01137
## 6      53.91      0.004314      0.01382      0.02254      0.01039
##      symmetry_se fractal_dimension_se radius_worst texture_worst
## 1      0.01389         0.003532         24.99         23.41
## 2      0.02250         0.004571         23.57         25.53
## 3      0.05963         0.009208         14.91         26.50
## 4      0.01756         0.005115         22.54         16.67
## 5      0.02165         0.005082         15.47         23.75
## 6      0.01369         0.002179         22.88         27.66
##      perimeter_worst area_worst smoothness_worst compactness_worst
## 1         158.80      1956.0         0.1238         0.1866
## 2         152.50      1709.0         0.1444         0.4245
## 3          98.87       567.7         0.2098         0.8663
## 4         152.20      1575.0         0.1374         0.2050
## 5         103.40       741.6         0.1791         0.5249
## 6         153.20      1606.0         0.1442         0.2576
##      concavity_worst concave points_worst symmetry_worst
## 1          0.2416         0.1860         0.2750
## 2          0.4504         0.2430         0.3613
## 3          0.6869         0.2575         0.6638
## 4          0.4000         0.1625         0.2364
```

```
## 5      0.5355      0.1741      0.3985
## 6      0.3784      0.1932      0.3063
## fractal_dimension_worst
## 1      0.08902
## 2      0.08758
## 3      0.17300
## 4      0.07678
## 5      0.12440
## 6      0.08368
```

## DATA EXPLORATION

### Hierarchical clustering

```
library(sparcl)
hc <- hclust(dist(data[, -1]), method = "complete")
ColorDendrogram(hc, y=data$Class, main = "Hierarchical clustering", branchlength=5)
```



Not very obvious where are different clusters. It seems that “red” malignant cluster intersects with “benign” cluster.

## K-means clustering

```
fit <- kmeans(data[,c(2:31)], 2)
names(fit)

## [1] "cluster"      "centers"      "totss"        "withinss"
## [5] "tot.withinss" "betweenss"    "size"         "iter"
## [9] "ifault"

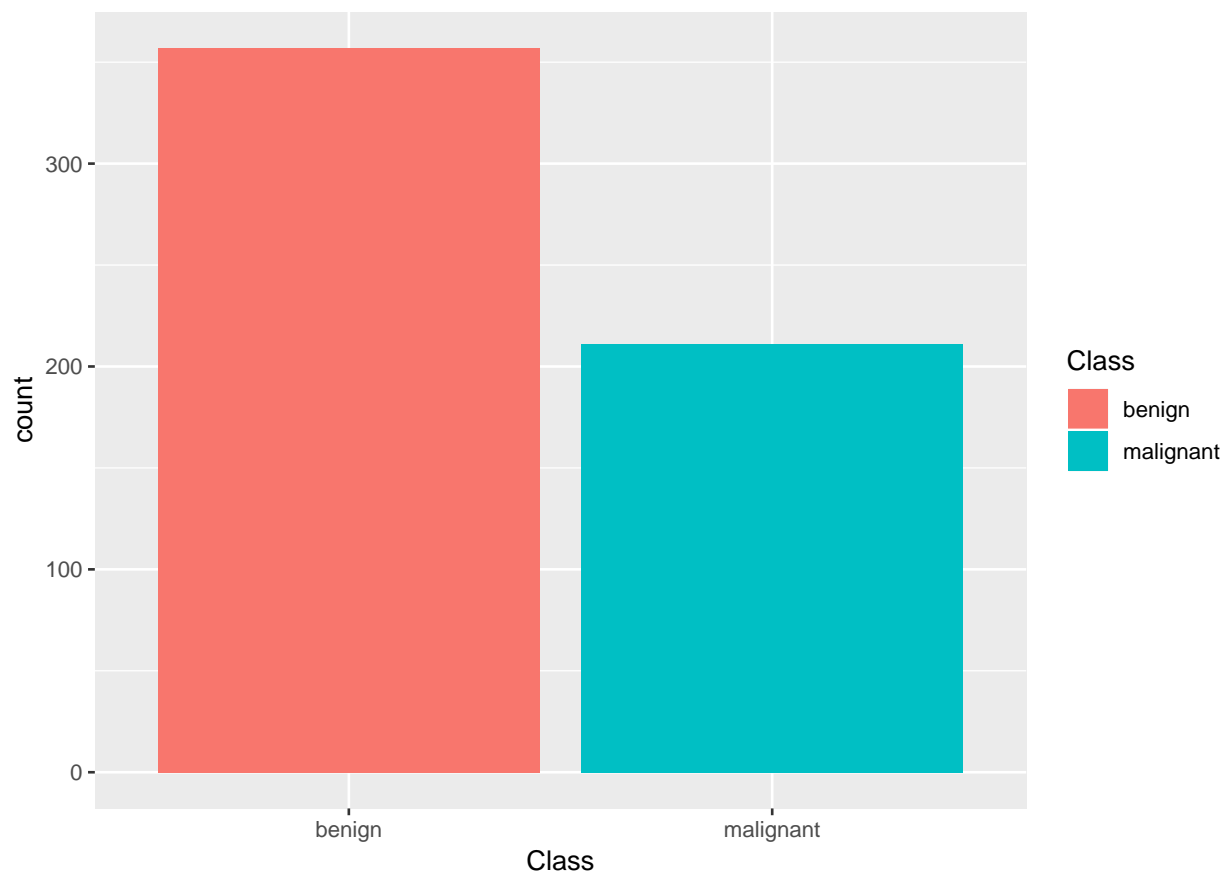
#k-means did a fairly good job
table(data.frame(fit$cluster, data[,1]))

##           data...1.
## fit.cluster benign malignant
##           1         1         129
##           2        356          82
```

## Response variable for classification.

```
library(ggplot2)

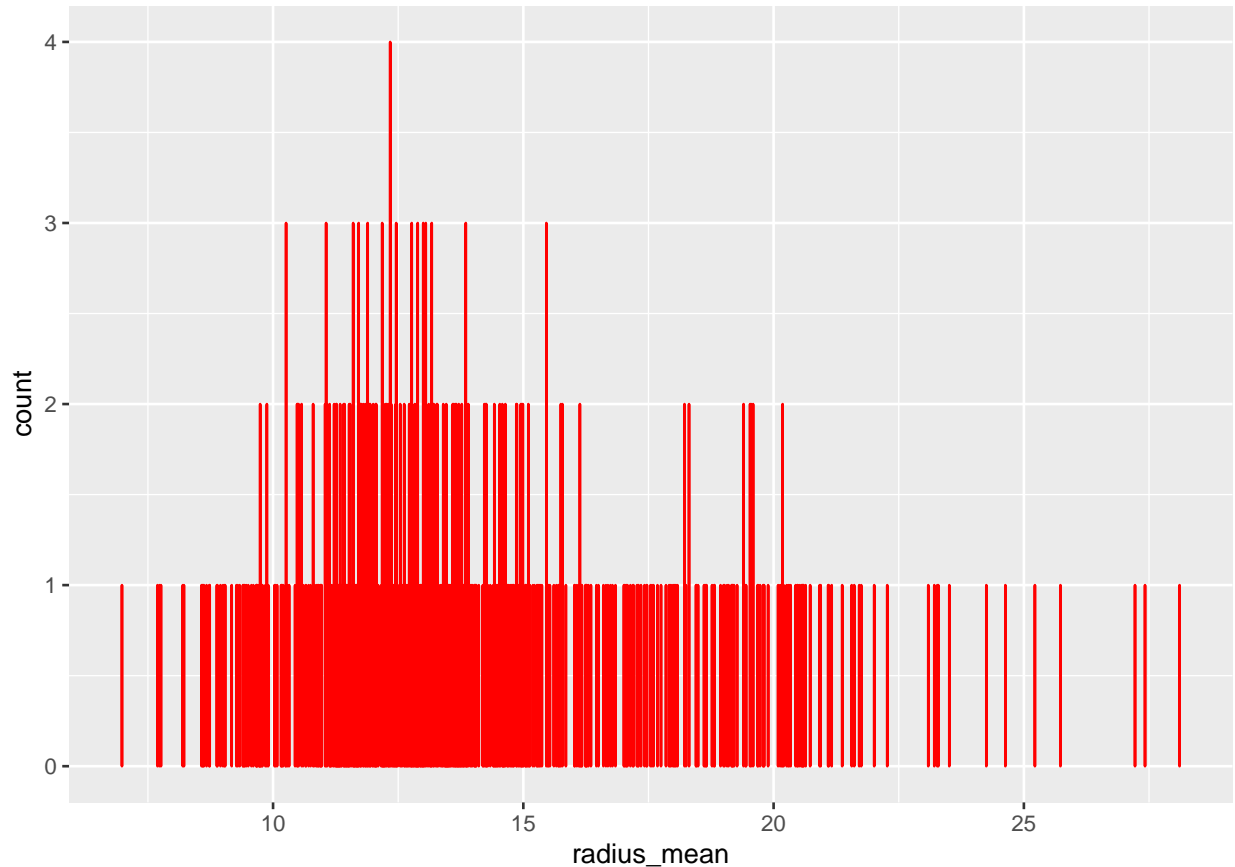
ggplot(data, aes(x = Class, fill = Class)) +
  geom_bar()
```



## Response variable for regression.

```
ggplot(data, aes(x = radius_mean)) +  
  geom_histogram(stat = "count", color = "red")
```

```
## Warning: Ignoring unknown parameters: binwidth, bins, pad
```



## Principal Component Analysis

```
library(pcaGoPromoter)
```

```
## Loading required package: ellipse
```

```
##
```

```
## Attaching package: 'ellipse'
```

```
## The following object is masked from 'package:graphics':
```

```
##
```

```
##   pairs
```

```
## Loading required package: Biostrings
```

```
## Loading required package: BiocGenerics
```

```
## Loading required package: parallel
```

```
##
```



```

## Attaching package: 'BiocGenerics'

## The following objects are masked from 'package:parallel':
##
##   clusterApply, clusterApplyLB, clusterCall, clusterEvalQ,
##   clusterExport, clusterMap, parApply, parCapply, parLapply,
##   parLapplyLB, parRapply, parSapply, parSapplyLB

## The following objects are masked from 'package:dplyr':
##
##   combine, intersect, setdiff, union

## The following objects are masked from 'package:stats':
##
##   IQR, mad, sd, var, xtabs

## The following objects are masked from 'package:base':
##
##   anyDuplicated, append, as.data.frame, basename, cbind,
##   colMeans, colnames, colSums, dirname, do.call, duplicated,
##   eval, evalq, Filter, Find, get, grep, grepl, intersect,
##   is.unsorted, lapply, lengths, Map, mapply, match, mget, order,
##   paste, pmax, pmax.int, pmin, pmin.int, Position, rank, rbind,
##   Reduce, rowMeans, rownames, rowSums, sapply, setdiff, sort,
##   table, tapply, union, unique, unsplit, which, which.max,
##   which.min

## Loading required package: S4Vectors

## Loading required package: stats4

##
## Attaching package: 'S4Vectors'

## The following objects are masked from 'package:dplyr':
##
##   first, rename

## The following object is masked from 'package:tidyr':
##
##   expand

## The following object is masked from 'package:base':
##
##   expand.grid

## Loading required package: IRanges

##
## Attaching package: 'IRanges'

## The following objects are masked from 'package:dplyr':
##
##   collapse, desc, slice

## The following object is masked from 'package:purrr':
##
##   reduce

## The following object is masked from 'package:grDevices':
##

```

```

##      windows
## Loading required package: XVector
##
## Attaching package: 'XVector'
## The following object is masked from 'package:purrr':
##
##      compact
##
## Attaching package: 'Biostrings'
## The following object is masked from 'package:base':
##
##      strsplit
library(ellipse)

data <- na.omit(data)

# perform pca and extract scores:

pcaOutput <- pca(t(data[,2:31]), printDropped = FALSE, scale = TRUE, center = TRUE)
pcaOutput2 <- as.data.frame(pcaOutput$scores)

# define groups for plotting:

pcaOutput2$groups <- data$Class

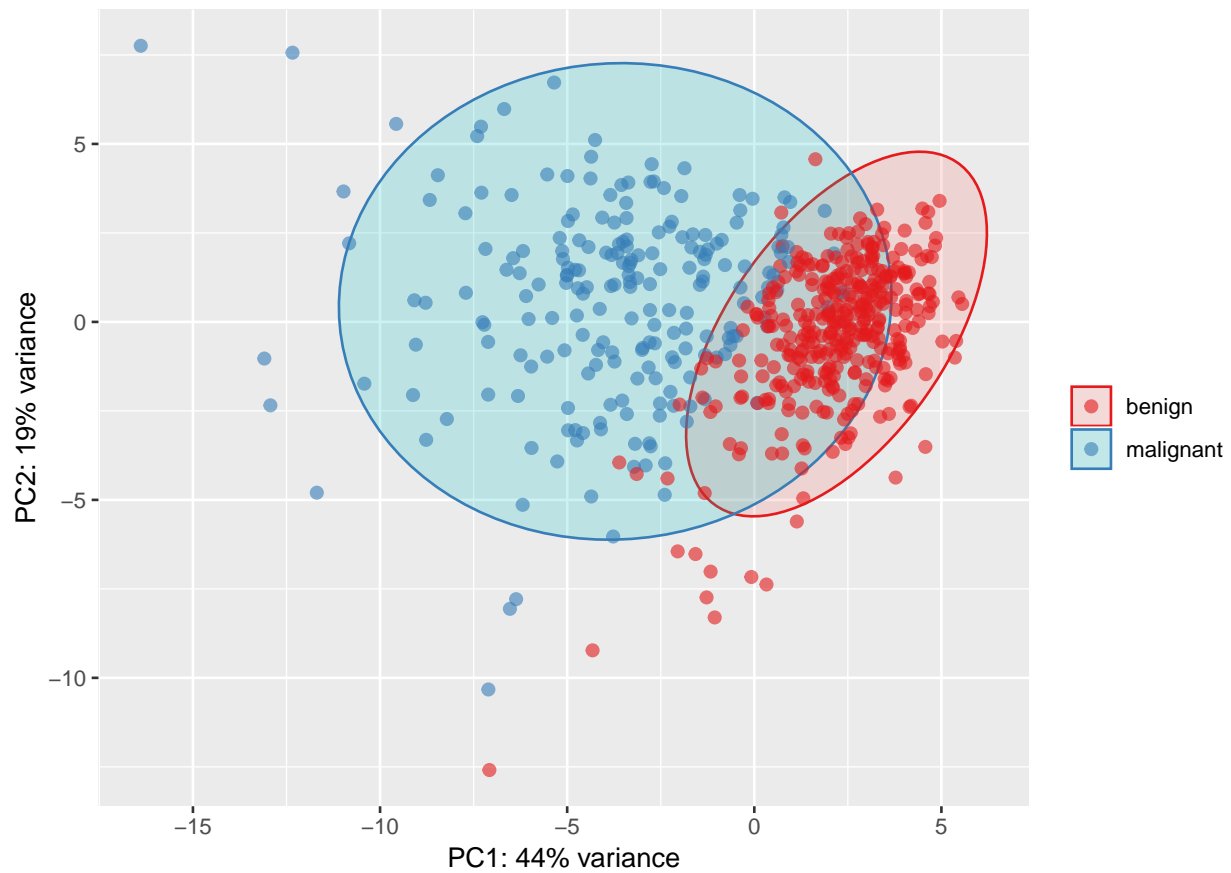
centroids <- aggregate(cbind(PC1, PC2) ~ groups, pcaOutput2, mean)

conf.rgn <- do.call(rbind, lapply(unique(pcaOutput2$groups), function(t)
  data.frame(groups = as.character(t),
    ellipse(cov(pcaOutput2[pcaOutput2$groups == t, 1:2]),
      centre = as.matrix(centroids[centroids$groups == t, 2:3]),
      level = 0.95),
    stringsAsFactors = FALSE)))

#Plot PCA with variance %:

ggplot(data = pcaOutput2, aes(x = PC1, y = PC2, group = groups, color = groups)) +
  geom_polygon(data = conf.rgn, aes(fill = groups), alpha = 0.2) +
  geom_point(size = 2, alpha = 0.6) +
  scale_color_brewer(palette = "Set1") +
  labs(color = "",
    fill = "",
    x = paste0("PC1: ", round(pcaOutput$pov[1], digits = 2) * 100, "% variance"),
    y = paste0("PC2: ", round(pcaOutput$pov[2], digits = 2) * 100, "% variance"))

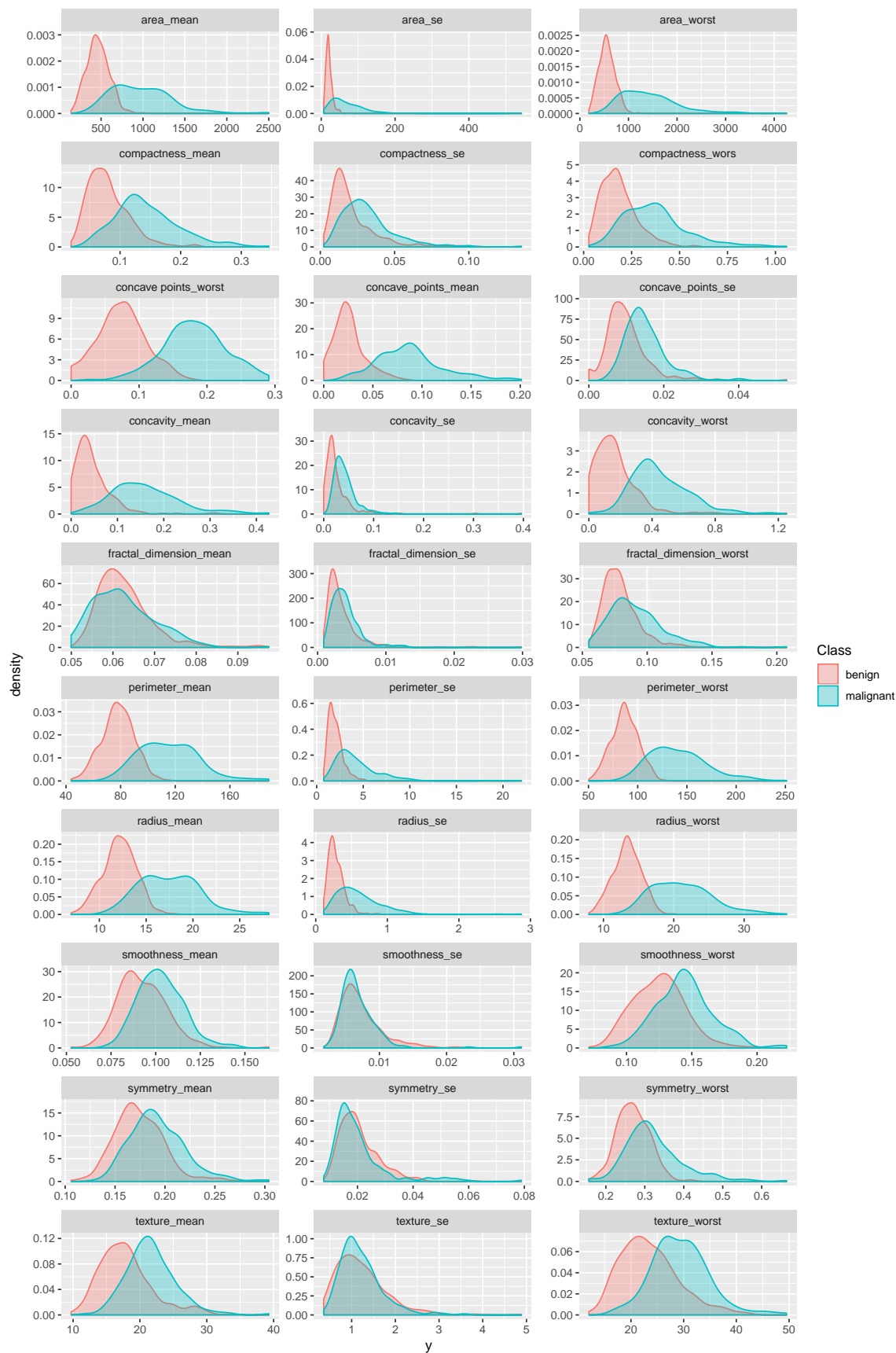
```



## Features

```
library(tidyr)

gather(data, x, y, radius_mean:fractal_dimension_worst) %>%
  ggplot(aes(x = y, color = Class, fill = Class)) +
  geom_density(alpha = 0.3) +
  facet_wrap(~ x, scales = "free", ncol = 3)
```



# MACHINE LEARNING PACKAGES FOR R

## caret

```
# configure multicore:
library(doParallel)

## Loading required package: foreach
##
## Attaching package: 'foreach'
## The following objects are masked from 'package:purrr':
##
##   accumulate, when
## Loading required package: iterators
cl <- makeCluster(detectCores())
registerDoParallel(cl)

library(caret)

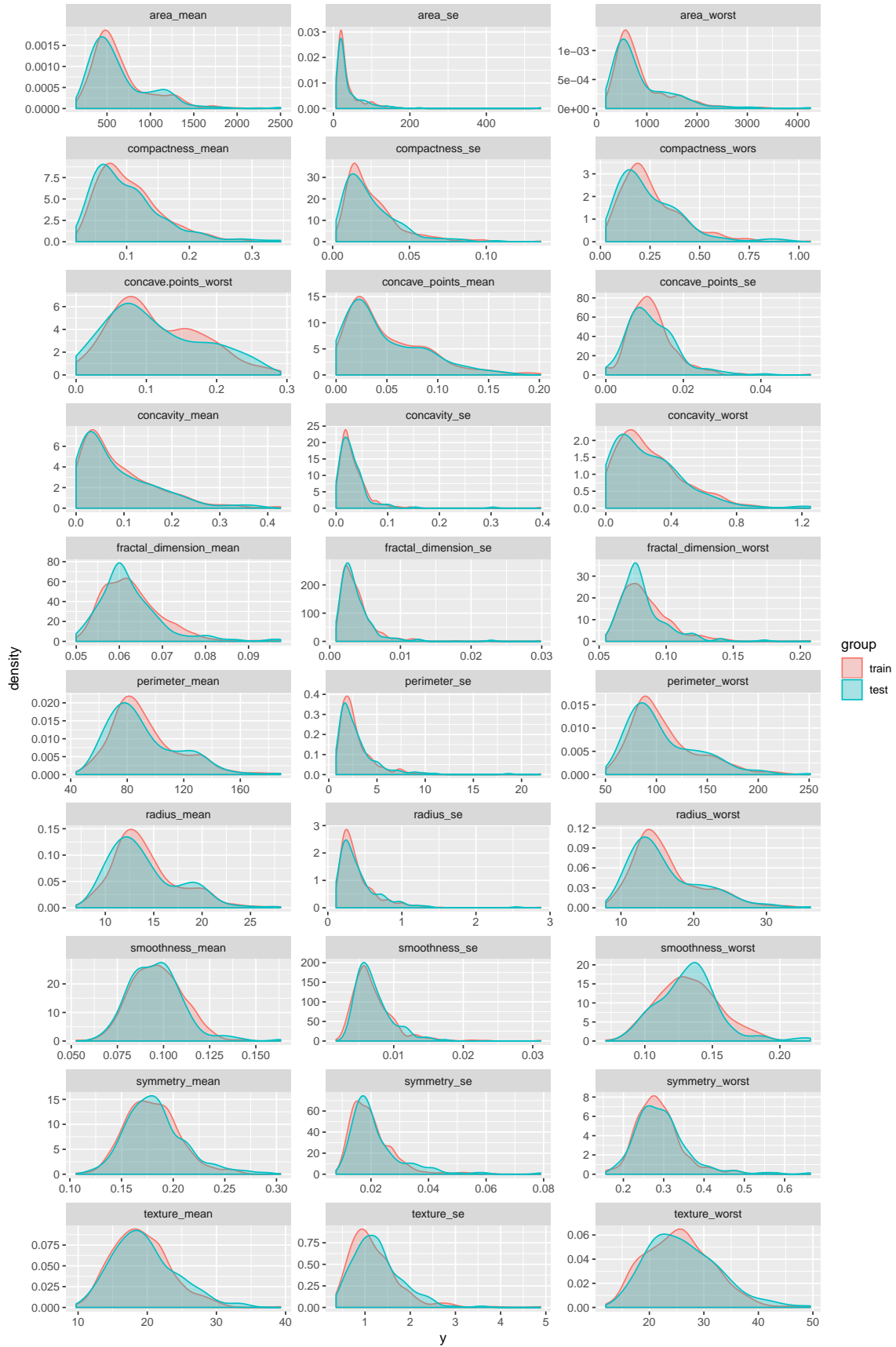
## Loading required package: lattice
##
## Attaching package: 'caret'
## The following object is masked from 'package:purrr':
##
##   lift
```

## Training, validation and test data

```
set.seed(42)
index <- createDataPartition(data$Class, p = 0.7, list = FALSE)
train_data <- data[index, ]
test_data <- data[-index, ]

library(dplyr)

rbind(data.frame(group = "train", train_data),
      data.frame(group = "test", test_data)) %>%
  gather(x, y, radius_mean:fractal_dimension_worst) %>%
  ggplot(aes(x = y, color = group, fill = group)) +
  geom_density(alpha = 0.3) +
  facet_wrap(~ x, scales = "free", ncol = 3)
```



## REGRESSION

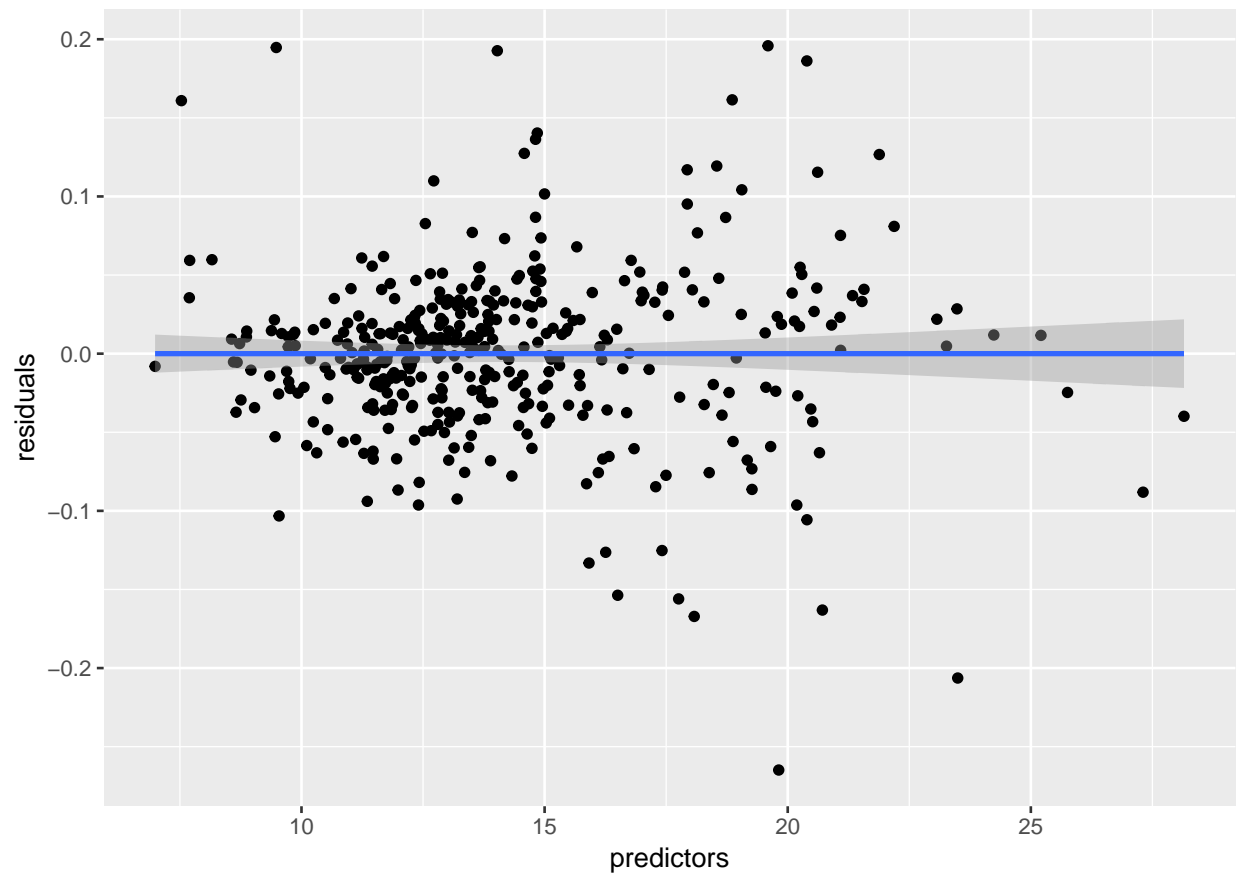
```
set.seed(42)
model_glm <- caret::train(radius_mean ~ .,
                           data = train_data,
                           method = "glm",
                           preProcess = c("scale", "center"),
                           trControl = trainControl(method = "repeatedcv",
                                                    number = 10,
                                                    repeats = 10,
                                                    savePredictions = TRUE,
                                                    verboseIter = FALSE))
```

```
model_glm
```

```
## Generalized Linear Model
##
## 398 samples
## 30 predictor
##
## Pre-processing: scaled (30), centered (30)
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 358, 358, 359, 358, 358, 358, ...
## Resampling results:
##
##      RMSE      Rsquared   MAE
## 0.06443886 0.9996674 0.04360507
```

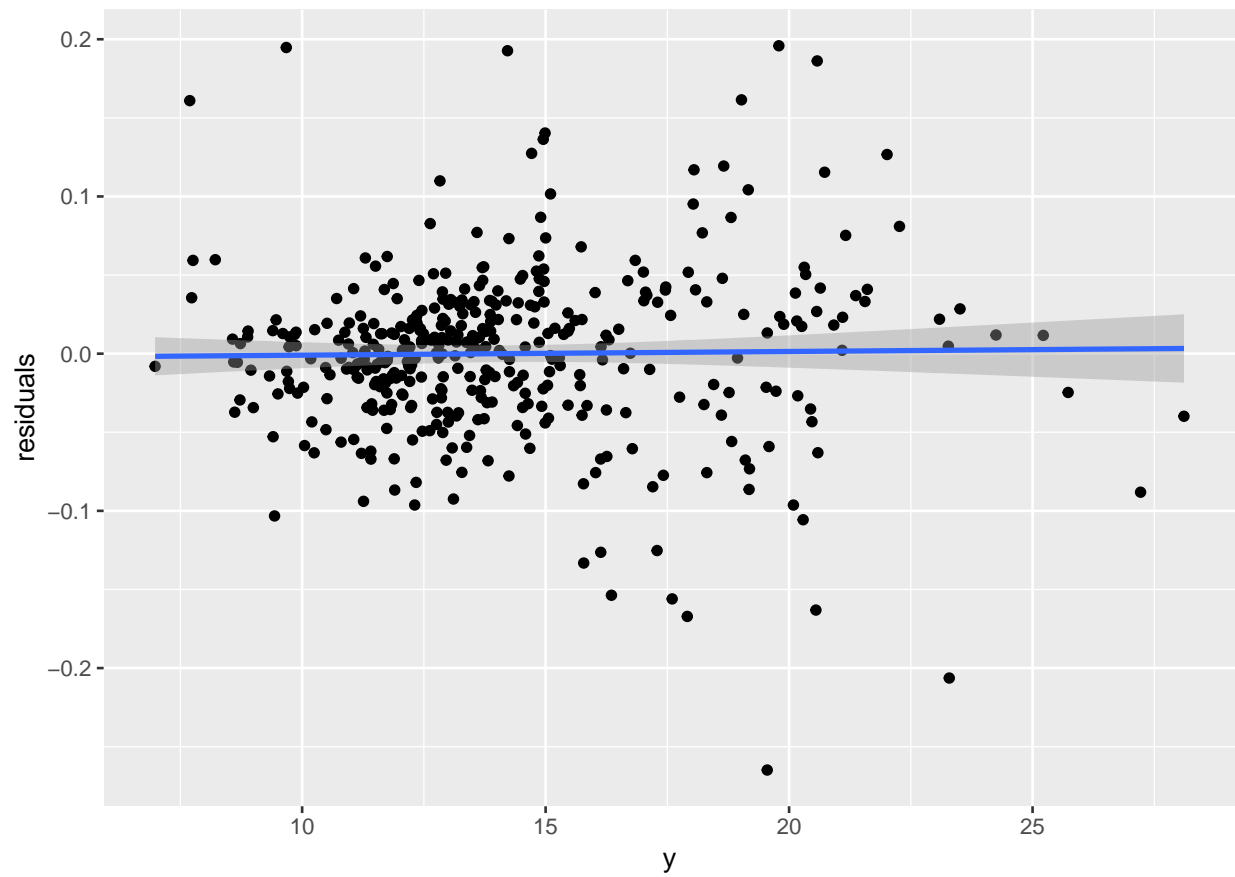
```
predictions <- predict(model_glm, test_data)
```

```
# model_glm$finalModel$linear.predictors == model_glm$finalModel$fitted.values
data.frame(residuals = resid(model_glm),
            predictors = model_glm$finalModel$linear.predictors) %>%
  ggplot(aes(x = predictors, y = residuals)) +
  geom_jitter() +
  geom_smooth(method = "lm")
```

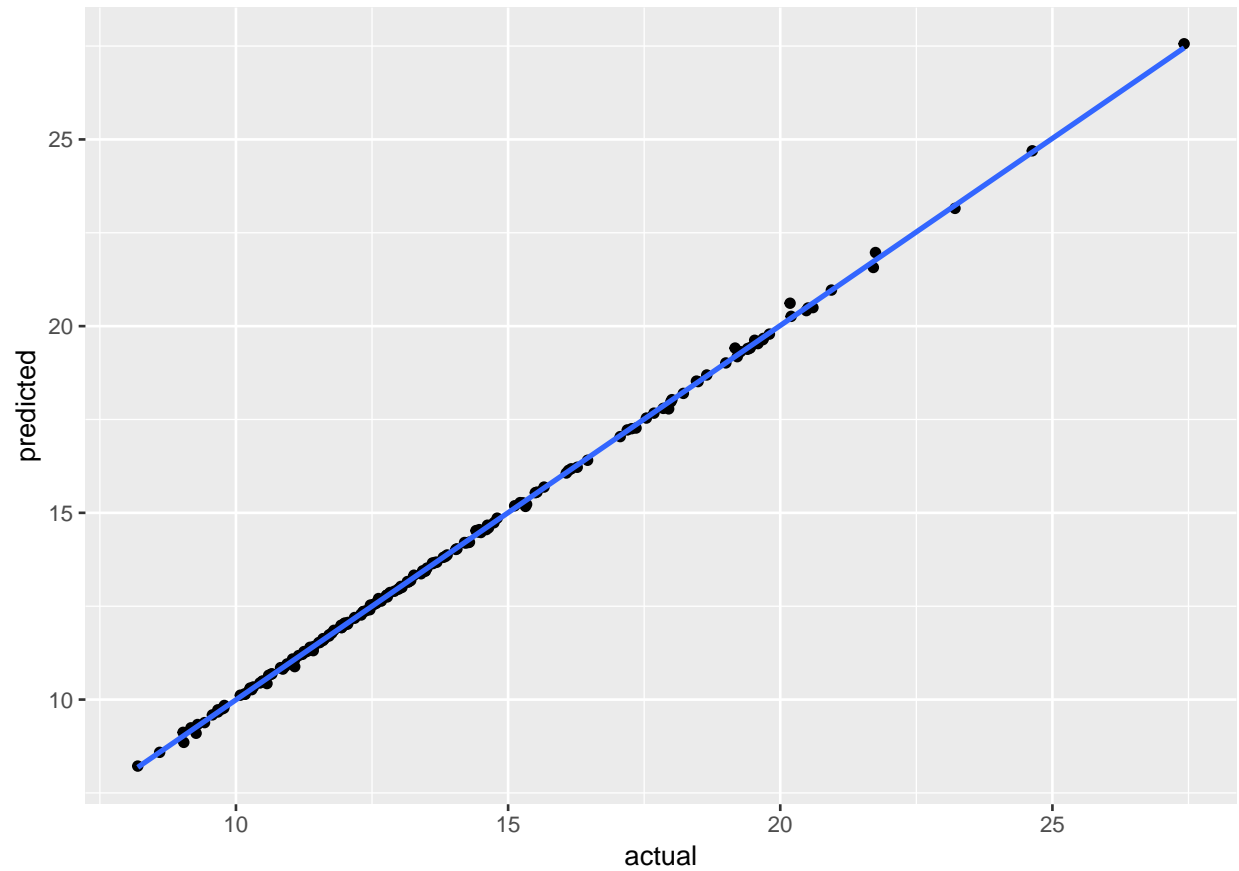


```
y <- train_data$radius_mean
data.frame(residuals = resid(model_glm),
           y = model_glm$finalModel$y) %>%
  ggplot(aes(x = y, y = residuals)) +
    geom_jitter() +
    geom_smooth(method = "lm")
```





```
data.frame(actual = test_data$radius_mean,  
            predicted = predictions) %>%  
ggplot(aes(x = actual, y = predicted)) +  
  geom_jitter() +  
  geom_smooth(method = "lm")
```



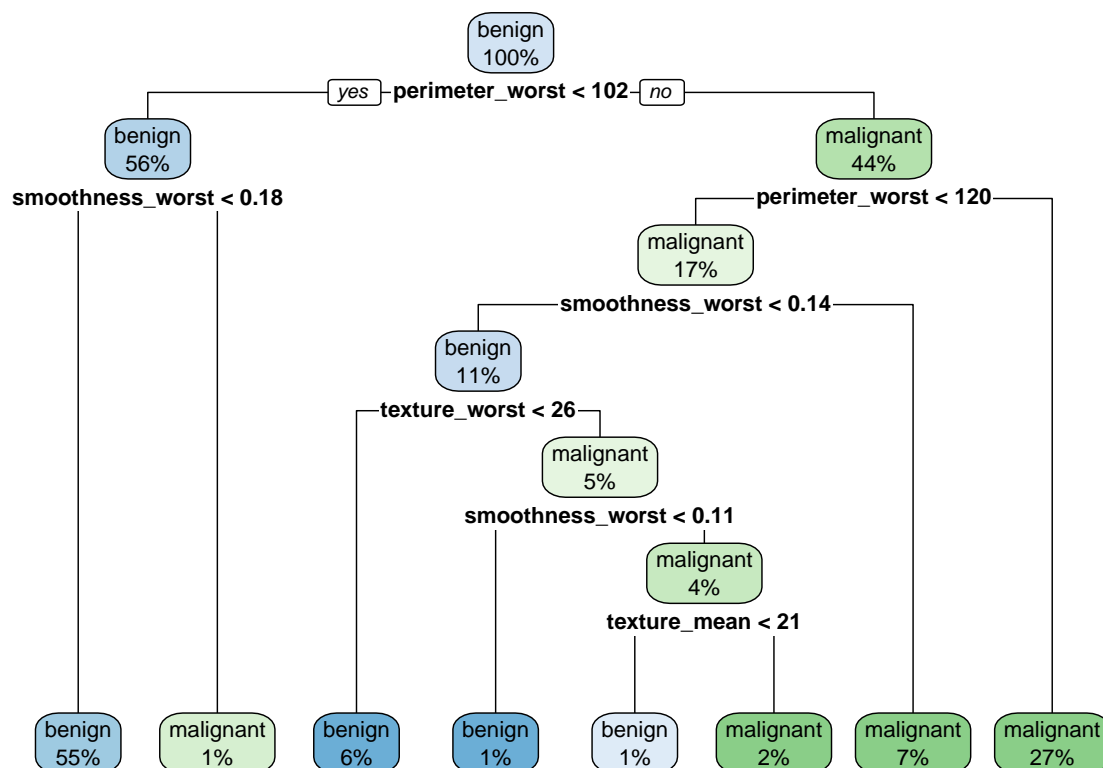
## CLASSIFICATION

### Decision trees

```
library(rpart)
library(rpart.plot)

set.seed(42)
fit <- rpart(Class ~ .,
             data = train_data,
             method = "class",
             control = rpart.control(xval = 10,
                                     minbucket = 2,
                                     cp = 0),
             parms = list(split = "information"))

rpart.plot(fit, extra = 100)
```



## RANDOM FORESTS

*#Random Forests predictions are based on the generation of  
#multiple classification trees.  
#They can be used for both, classification and regression tasks.  
#Here, it is classification task.*

```
set.seed(42)
library(randomForest)
```

```
## randomForest 4.6-14
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
##
## The following object is masked from 'package:BiocGenerics':
##
##   combine
##
## The following object is masked from 'package:dplyr':
##
##   combine
##
## The following object is masked from 'package:ggplot2':
##
```

```
##      margin
model_rf <- caret::train(Class ~ .,
                          data = train_data,
                          method = "rf",
                          preProcess = c("scale", "center"),
                          trControl = trainControl(method = "repeatedcv",
                                                    number = 10,
                                                    repeats = 10,
                                                    savePredictions = TRUE,
                                                    verboseIter = FALSE))
```

*#When savePredictions = TRUE is specified,  
#can access the cross-validation results with model\_rf\$pred.*

```
model_rf$finalModel$confusion
```

```
##           benign malignant class.error
## benign      243         7 0.02800000
## malignant    8        140 0.05405405
```

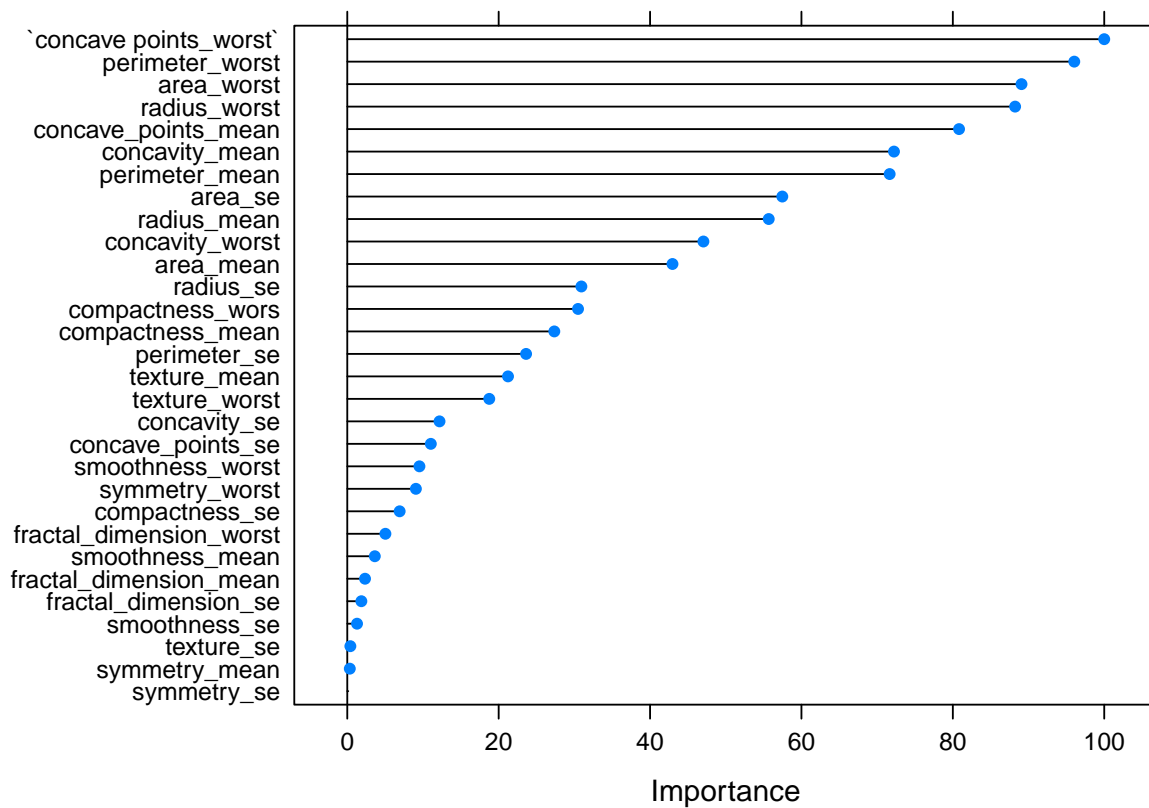
## Feature Importance

```
imp <- model_rf$finalModel$importance
imp[order(imp, decreasing = TRUE), ]
```

```
## `concave points_worst`      perimeter_worst      area_worst
##           15.841712           15.262762           14.242963
##           radius_worst      concave_points_mean      concavity_mean
##           14.119926           13.036611           11.779089
##           perimeter_mean      area_se           radius_mean
##           11.695456           9.621609           9.359654
##           concavity_worst      area_mean           radius_se
##           8.097168           7.499848           5.739611
##           compactness_wors      compactness_mean      perimeter_se
##           5.675184           5.216820           4.671186
##           texture_mean      texture_worst      concavity_se
##           4.322024           3.959726           2.999013
##           concave_points_se      smoothness_worst      symmetry_worst
##           2.830949           2.610734           2.542498
##           compactness_se      fractal_dimension_worst      smoothness_mean
##           2.228469           1.953428           1.748571
##           fractal_dimension_mean      fractal_dimension_se      smoothness_se
##           1.559781           1.488882           1.405341
##           texture_se           symmetry_mean      symmetry_se
##           1.276355           1.265452           1.216515
```

*# estimate variable importance*

```
importance <- varImp(model_rf, scale = TRUE)
plot(importance)
```



## Predicting test data

```
confusionMatrix(predict(model_rf, test_data), test_data$Class)
```

```
## Confusion Matrix and Statistics
```

```
##
```

```
##           Reference
```

```
## Prediction  benign malignant
```

```
##   benign      106         6
```

```
##   malignant     1         57
```

```
##
```

```
##           Accuracy : 0.9588
```

```
##           95% CI : (0.917, 0.9833)
```

```
##   No Information Rate : 0.6294
```

```
##   P-Value [Acc > NIR] : <2e-16
```

```
##
```

```
##           Kappa : 0.9103
```

```
##
```

```
##   McNemar's Test P-Value : 0.1306
```

```
##
```

```
##           Sensitivity : 0.9907
```

```
##           Specificity : 0.9048
```

```
##           Pos Pred Value : 0.9464
```

```
##           Neg Pred Value : 0.9828
```

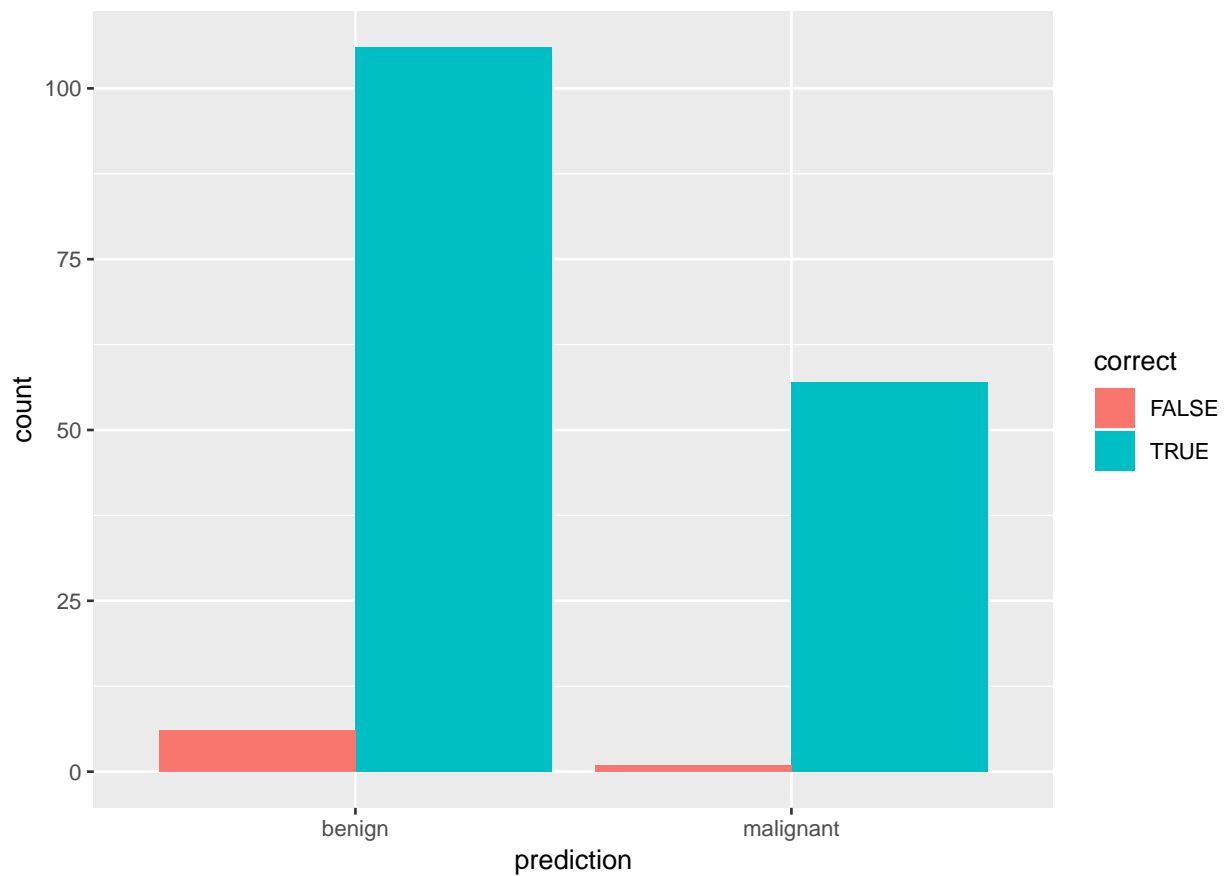
```
##           Prevalence : 0.6294
##           Detection Rate : 0.6235
##           Detection Prevalence : 0.6588
##           Balanced Accuracy : 0.9477
##
##           'Positive' Class : benign
##
```

```
results <- data.frame(actual = test_data$Class,
                      predict(model_rf, test_data, type = "prob"))

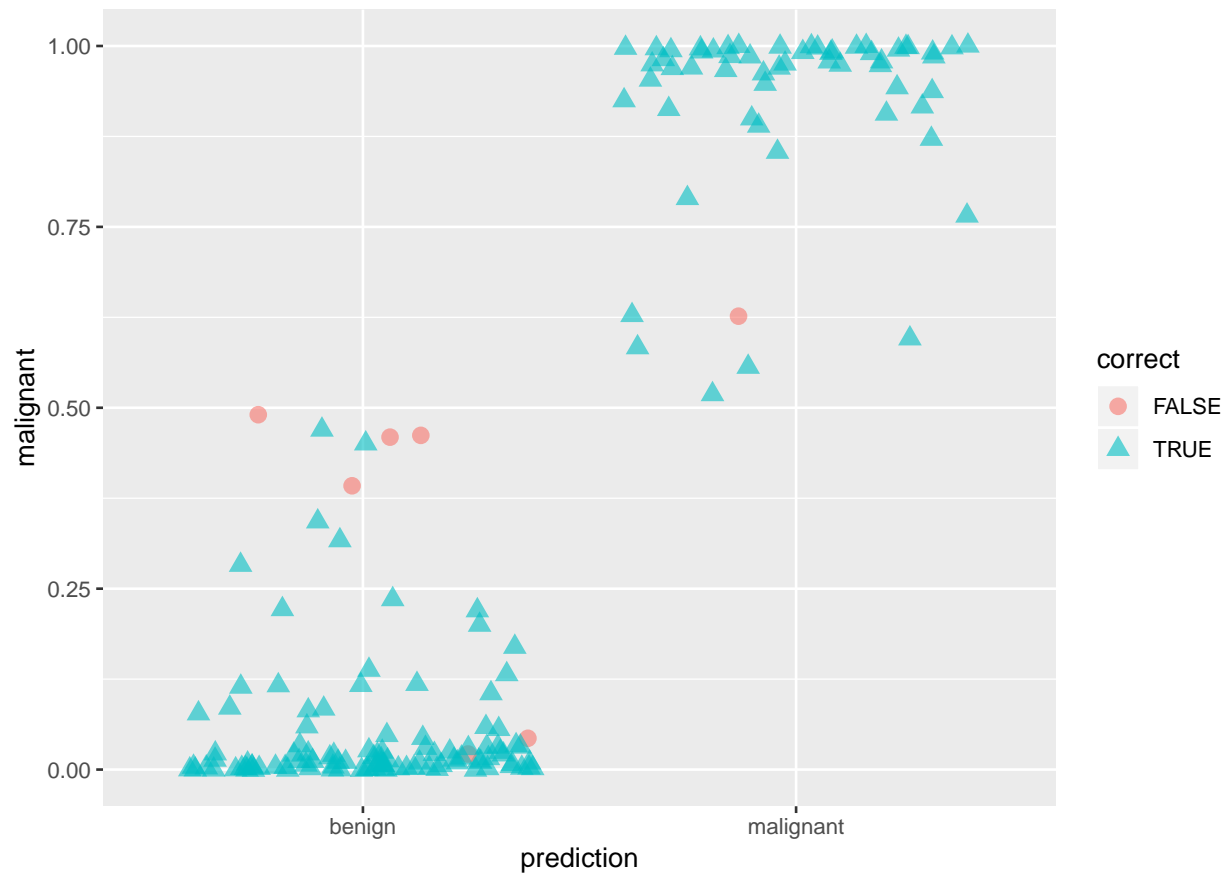
results$prediction <- ifelse(results$benign > 0.5, "benign",
                           ifelse(results$malignant > 0.5, "malignant", NA))

results$correct <- ifelse(results$actual == results$prediction, TRUE, FALSE)

ggplot(results, aes(x = prediction, fill = correct)) +
  geom_bar(position = "dodge")
```



```
ggplot(results, aes(x = prediction, y = malignant, color = correct, shape = correct)) +
  geom_jitter(size = 3, alpha = 0.6)
```



## EXTREME GRADIENT BOOSTING.

Extreme gradient boosting (XGBoost) is a faster and improved implementation of gradient boosting for supervised learning.

*#XGBoost is a tree ensemble model, which means the sum of predictions  
#from a set of classification and regression trees (CART).  
#In that, XGBoost is similar to Random Forests but it uses a different approach  
#to model training: it uses a combination of "weak" functions during iteration process,  
#for each next iteration step, the model learns using the "mistakes" data of previous steps.*

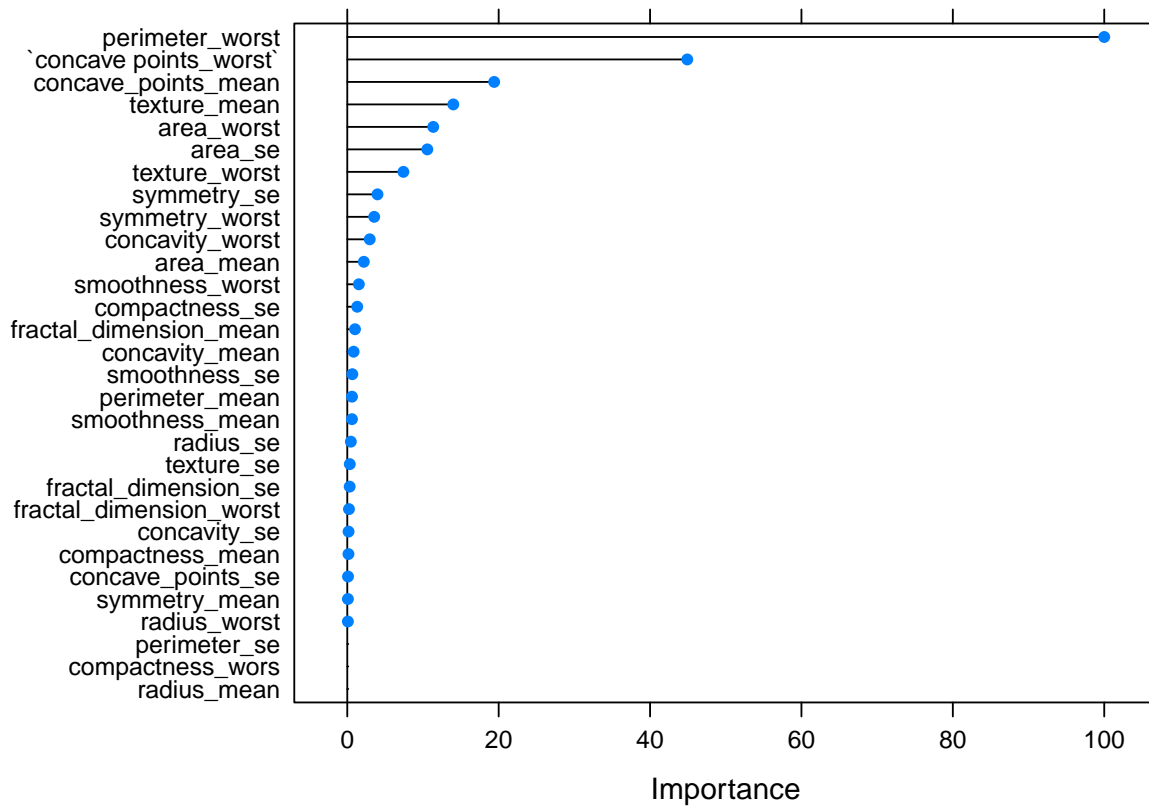
```
set.seed(42)
library(xgboost)
```

```
##
## Attaching package: 'xgboost'
##
## The following object is masked from 'package:XVector':
##
##   slice
##
## The following object is masked from 'package:IRanges':
##
##   slice
##
## The following object is masked from 'package:dplyr':
##
```

```
##      slice
model_xgb <- caret::train(Class ~ .,
                           data = train_data,
                           method = "xgbTree",
                           preProcess = c("scale", "center"),
                           trControl = trainControl(method = "repeatedcv",
                                                    number = 10,
                                                    repeats = 10,
                                                    savePredictions = TRUE,
                                                    verboseIter = FALSE))
```

## Feature Importance

```
importance <- varImp(model_xgb, scale = TRUE)
plot(importance)
```



## Predicting test data

```
confusionMatrix(predict(model_xgb, test_data), test_data$Class)
```

```
## Confusion Matrix and Statistics
```

```
##
```

```
##      Reference
```



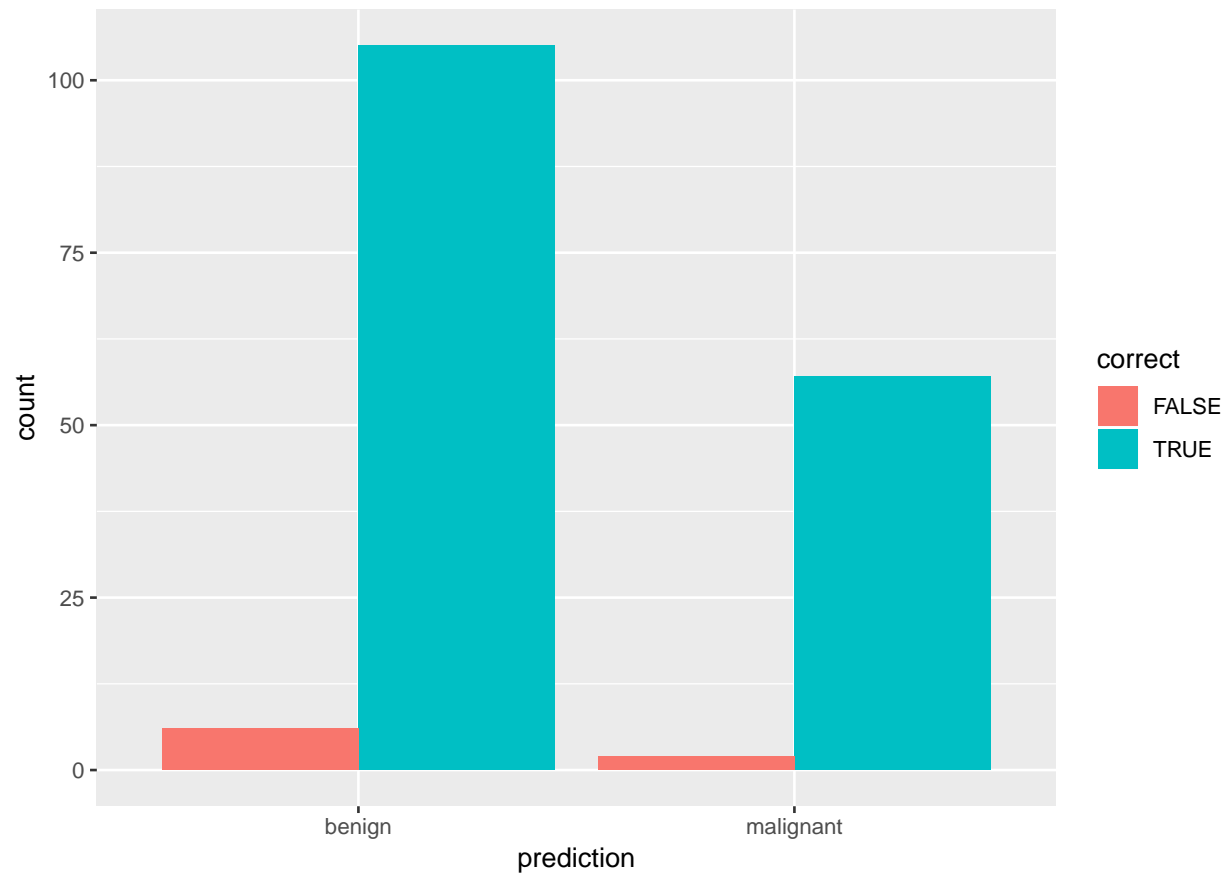
```
## Prediction  benign malignant
##   benign      105         6
##   malignant     2        57
##
##           Accuracy : 0.9529
##           95% CI : (0.9094, 0.9795)
##   No Information Rate : 0.6294
##   P-Value [Acc > NIR] : <2e-16
##
##           Kappa : 0.8978
##
## Mcnemar's Test P-Value : 0.2888
##
##           Sensitivity : 0.9813
##           Specificity : 0.9048
##           Pos Pred Value : 0.9459
##           Neg Pred Value : 0.9661
##           Prevalence : 0.6294
##           Detection Rate : 0.6176
##   Detection Prevalence : 0.6529
##           Balanced Accuracy : 0.9430
##
##   'Positive' Class : benign
##
```

```
results <- data.frame(actual = test_data$Class,
                      predict(model_xgb, test_data, type = "prob"))

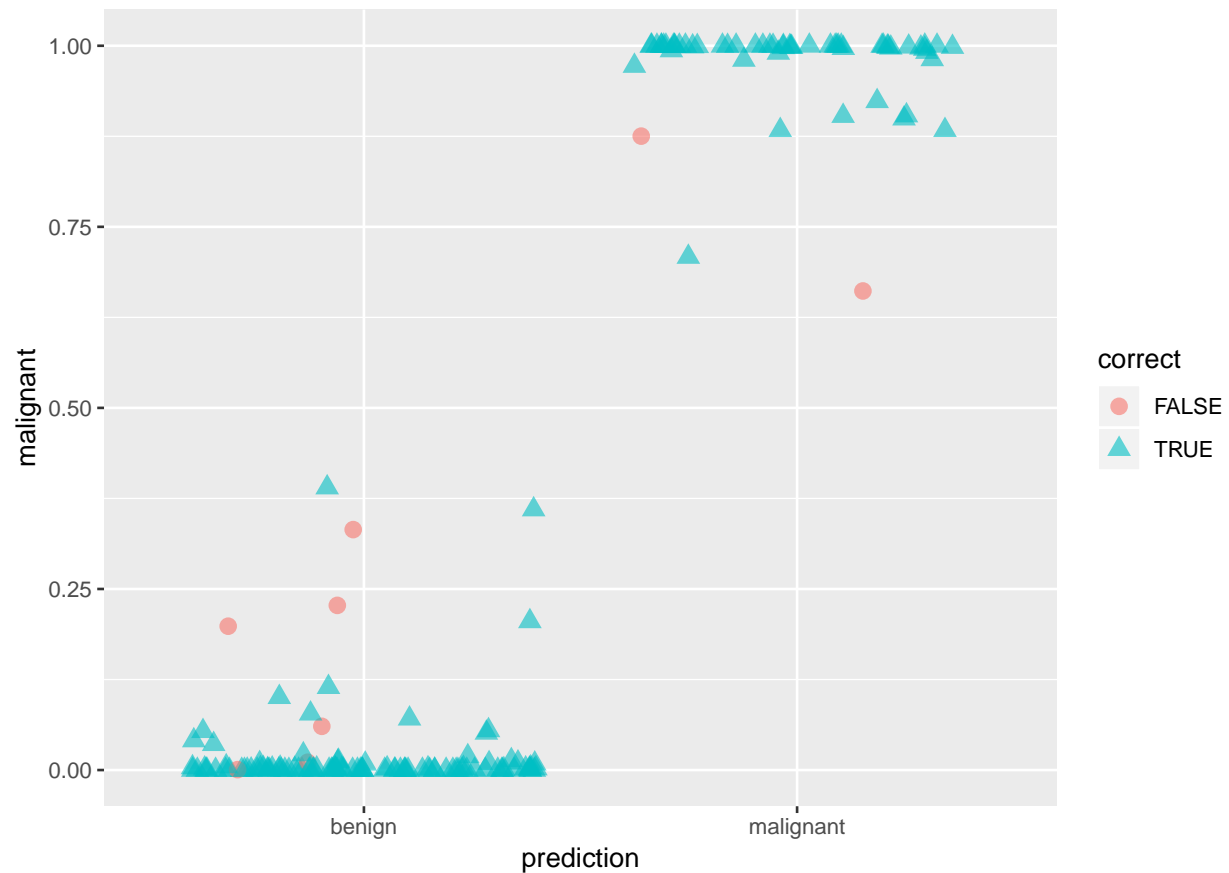
results$prediction <- ifelse(results$benign > 0.5, "benign",
                           ifelse(results$malignant > 0.5, "malignant", NA))

results$correct <- ifelse(results$actual == results$prediction, TRUE, FALSE)

ggplot(results, aes(x = prediction, fill = correct)) +
  geom_bar(position = "dodge")
```



```
ggplot(results, aes(x = prediction, y = malignant, color = correct, shape = correct)) +  
  geom_jitter(size = 3, alpha = 0.6)
```



## FEATURE SELECTION

Performing feature selection on the whole dataset would lead to prediction bias, we therefore need to run the whole modeling process on the training data alone!

## Correlation

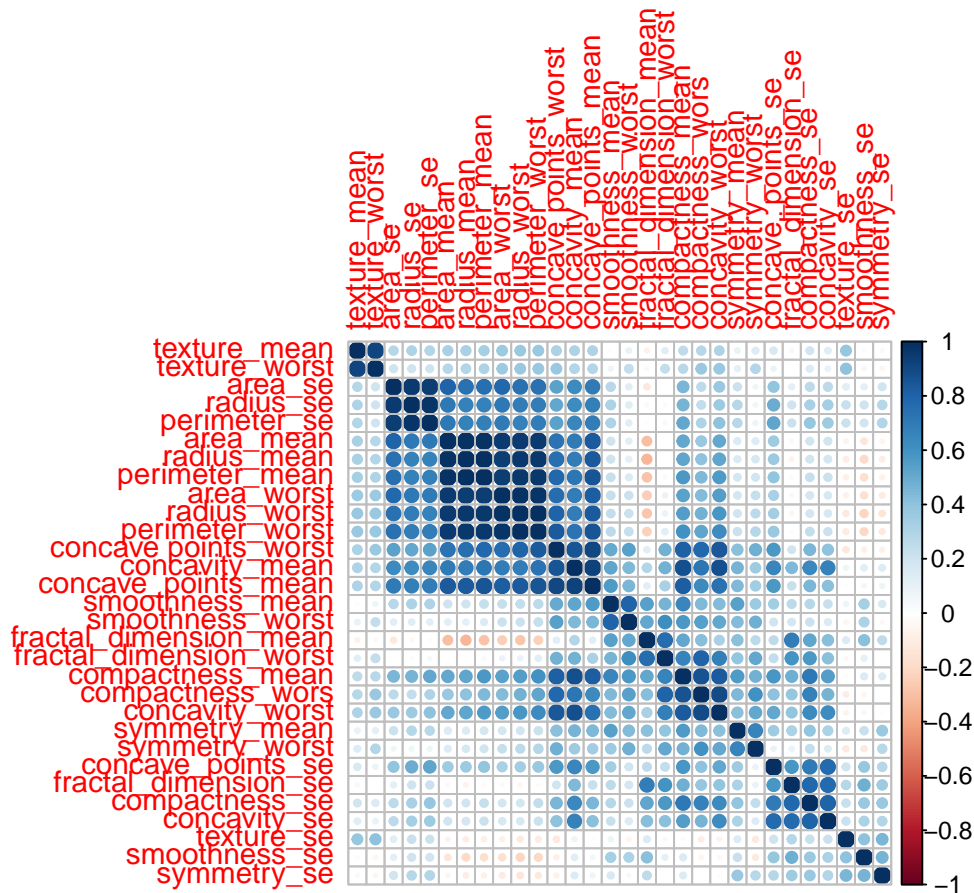
```
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```
# calculate correlation matrix
```

```
corMatMy <- cor(train_data[,2:31])
```

```
corrplot(corMatMy, order = "hclust")
```



```
#Correlations between all features are calculated and visualised.
#Removing all features with a correlation higher than 0.7,
#keeping the feature with the lower mean.
```

```
#Apply correlation filter at 0.70:
```

```
highlyCor <- colnames(train_data[, -1])[findCorrelation(corMatMy, cutoff = 0.7, verbose = TRUE)]
```

```
## Compare row 7 and column 8 with corr 0.921
## Means: 0.564 vs 0.384 so flagging column 7
## Compare row 8 and column 28 with corr 0.905
## Means: 0.534 vs 0.372 so flagging column 8
## Compare row 28 and column 6 with corr 0.819
## Means: 0.514 vs 0.36 so flagging column 28
## Compare row 6 and column 27 with corr 0.831
## Means: 0.502 vs 0.35 so flagging column 6
## Compare row 23 and column 21 with corr 0.994
## Means: 0.462 vs 0.338 so flagging column 23
## Compare row 27 and column 26 with corr 0.893
## Means: 0.443 vs 0.329 so flagging column 27
## Compare row 21 and column 3 with corr 0.967
## Means: 0.422 vs 0.319 so flagging column 21
## Compare row 3 and column 24 with corr 0.943
## Means: 0.383 vs 0.311 so flagging column 3
## Compare row 24 and column 1 with corr 0.943
## Means: 0.359 vs 0.306 so flagging column 24
```

```
## Compare row 1 and column 4 with corr 0.988
## Means: 0.315 vs 0.302 so flagging column 1
## Compare row 26 and column 30 with corr 0.803
## Means: 0.379 vs 0.3 so flagging column 26
## Compare row 4 and column 13 with corr 0.719
## Means: 0.269 vs 0.289 so flagging column 13
## Compare row 4 and column 11 with corr 0.719
## Means: 0.243 vs 0.285 so flagging column 11
## Compare row 4 and column 14 with corr 0.805
## Means: 0.213 vs 0.288 so flagging column 14
## Compare row 16 and column 18 with corr 0.709
## Means: 0.404 vs 0.289 so flagging column 16
## Compare row 18 and column 17 with corr 0.772
## Means: 0.309 vs 0.273 so flagging column 18
## Compare row 17 and column 20 with corr 0.773
## Means: 0.286 vs 0.268 so flagging column 17
## Compare row 5 and column 25 with corr 0.806
## Means: 0.322 vs 0.264 so flagging column 5
## Compare row 10 and column 30 with corr 0.761
## Means: 0.353 vs 0.255 so flagging column 10
## Compare row 22 and column 2 with corr 0.912
## Means: 0.263 vs 0.242 so flagging column 22
## All correlations <= 0.7
```

```
# which variables are flagged for removal?
```

```
highlyCor
```

```
## [1] "concavity_mean"      "concave_points_mean"
## [3] "concave points_worst" "compactness_mean"
## [5] "perimeter_worst"     "concavity_worst"
## [7] "radius_worst"        "perimeter_mean"
## [9] "area_worst"          "radius_mean"
## [11] "compactness_worst"   "perimeter_se"
## [13] "radius_se"           "area_se"
## [15] "compactness_se"      "concave_points_se"
## [17] "concavity_se"        "smoothness_mean"
## [19] "fractal_dimension_mean" "texture_worst"
```

```
#then we remove these variables
```

```
train_data_cor <- train_data[, which(!colnames(train_data) %in% highlyCor)]
```

## GRID SEARCH WITH CARET

### Automatic Grid

```
set.seed(42)
model_rf_tune_auto <- caret::train(Class ~ .,
  data = train_data,
  method = "rf",
  preProcess = c("scale", "center"),
  trControl = trainControl(method = "repeatedcv",
    number = 10,
    repeats = 10,
    savePredictions = TRUE,
```

```

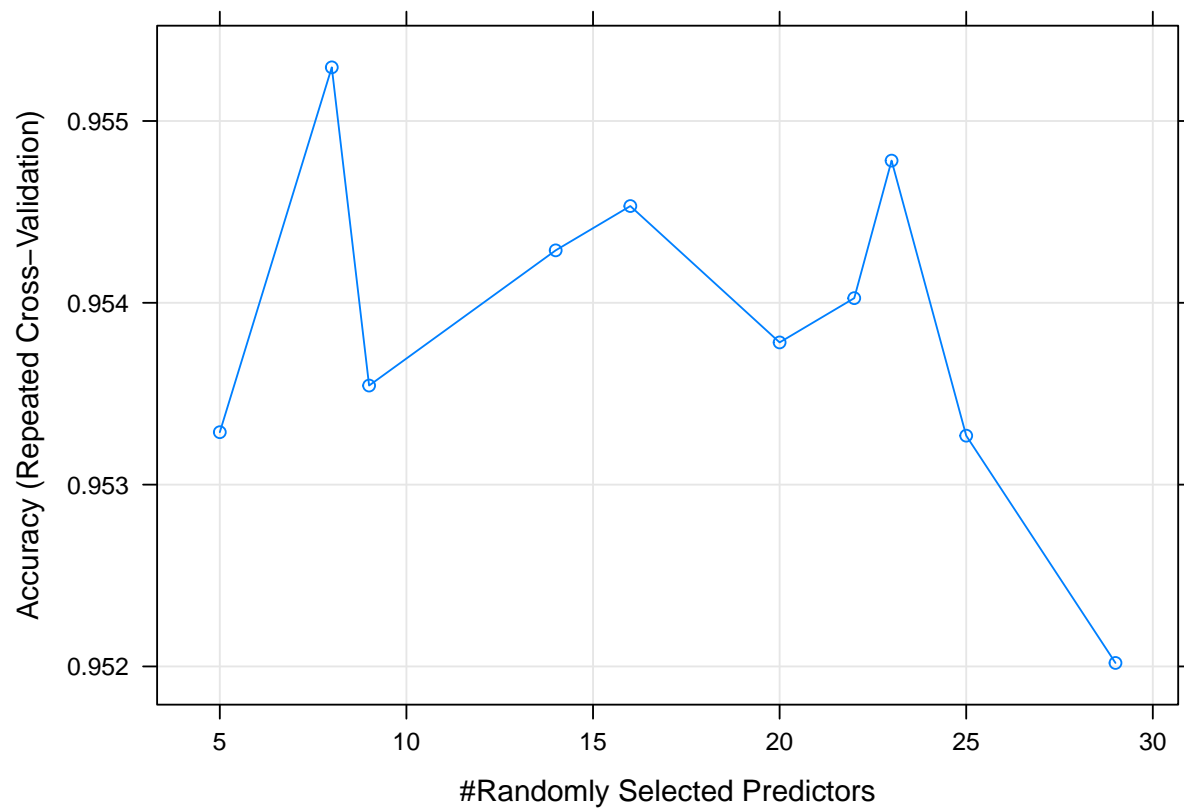
                                verboseIter = FALSE,
                                search = "random"),
                                tuneLength = 15)

model_rf_tune_auto

## Random Forest
##
## 398 samples
## 30 predictor
## 2 classes: 'benign', 'malignant'
##
## Pre-processing: scaled (30), centered (30)
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 358, 358, 359, 358, 358, 358, ...
## Resampling results across tuning parameters:
##
##  mtry  Accuracy  Kappa
##    5    0.9532885 0.8998301
##    8    0.9552949 0.9042609
##    9    0.9535449 0.9005992
##   14    0.9542885 0.9022334
##   16    0.9545321 0.9027631
##   20    0.9537821 0.9011350
##   22    0.9540256 0.9015140
##   23    0.9547821 0.9032354
##   25    0.9532692 0.9000211
##   29    0.9520192 0.8971656
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 8.

plot(model_rf_tune_auto)

```



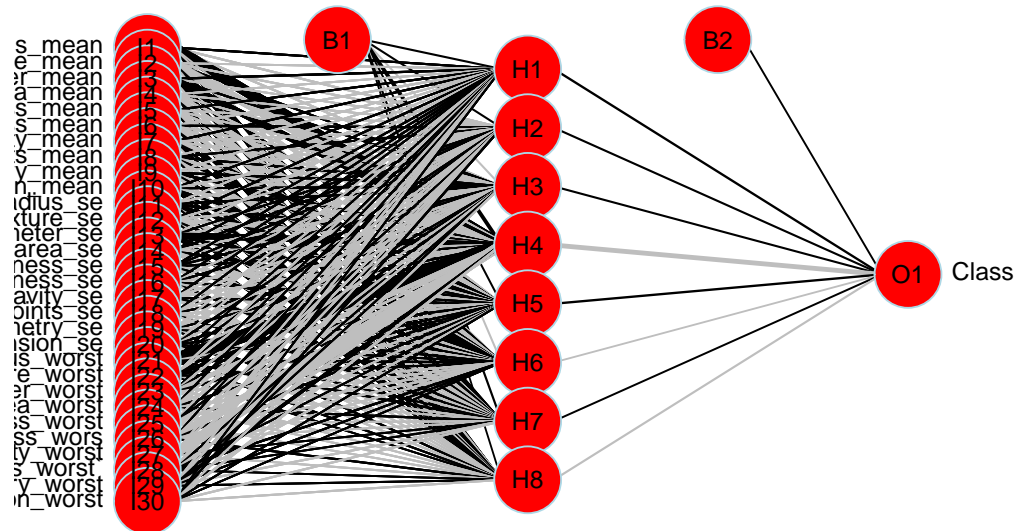
## NEURAL NETWORK MODEL

```
library(nnet)
model_nnet <- nnet(Class ~. ,
                   data= train_data,
                   size=8)
```

```
## # weights:  257
## initial  value 289.897687
## iter  10 value 249.315010
## iter  20 value 189.002331
## iter  30 value 137.130717
## iter  40 value  96.998986
## iter  50 value  79.761801
## iter  60 value  75.251591
## iter  70 value  71.625598
## iter  80 value  71.542152
## iter  90 value  71.531759
## iter 100 value  70.877250
## final   value  70.877250
## stopped after 100 iterations
```

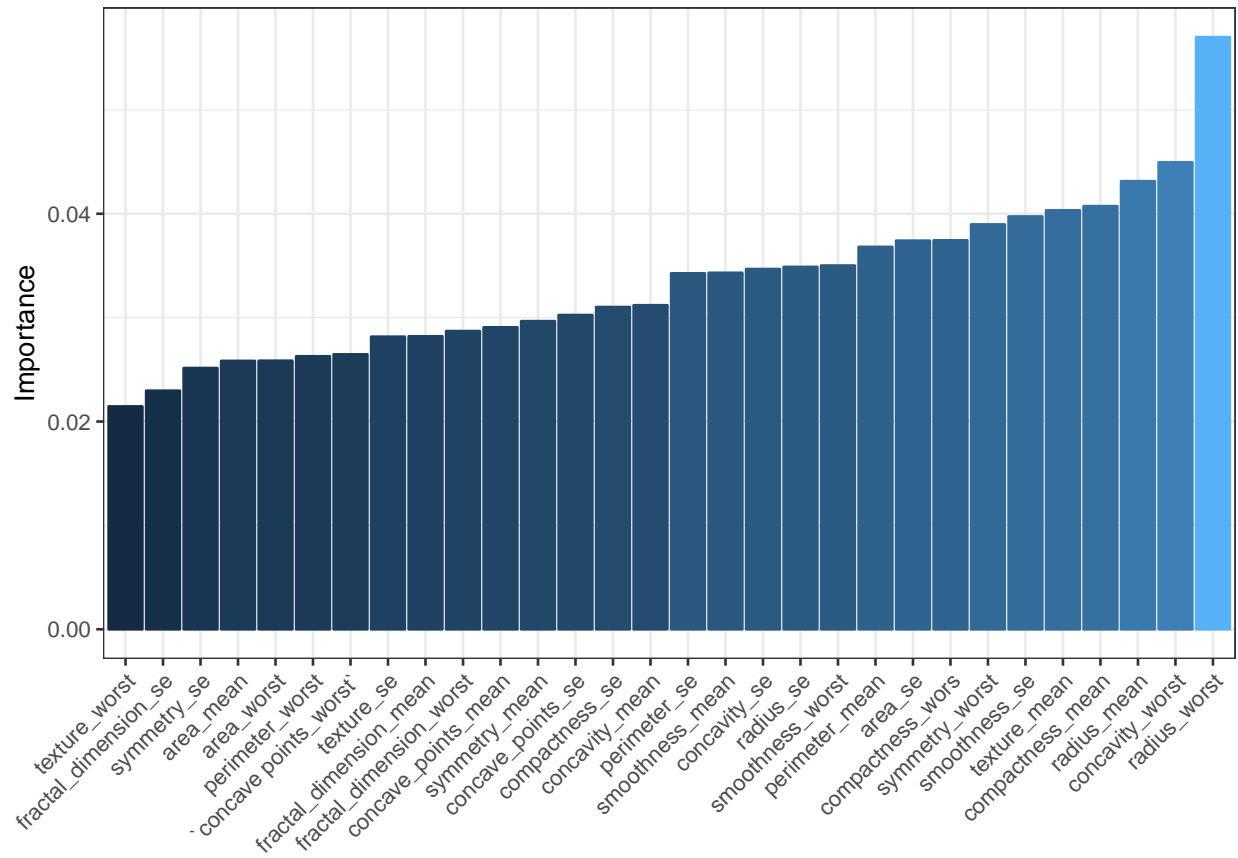
```
library(NeuralNetTools)
# Plot a neural interpretation diagram for a neural network object
```

```
plotnet(model_nnet, cex_val = .8, max_sp = T, circle_cex = 5, circle_col = 'red')
```

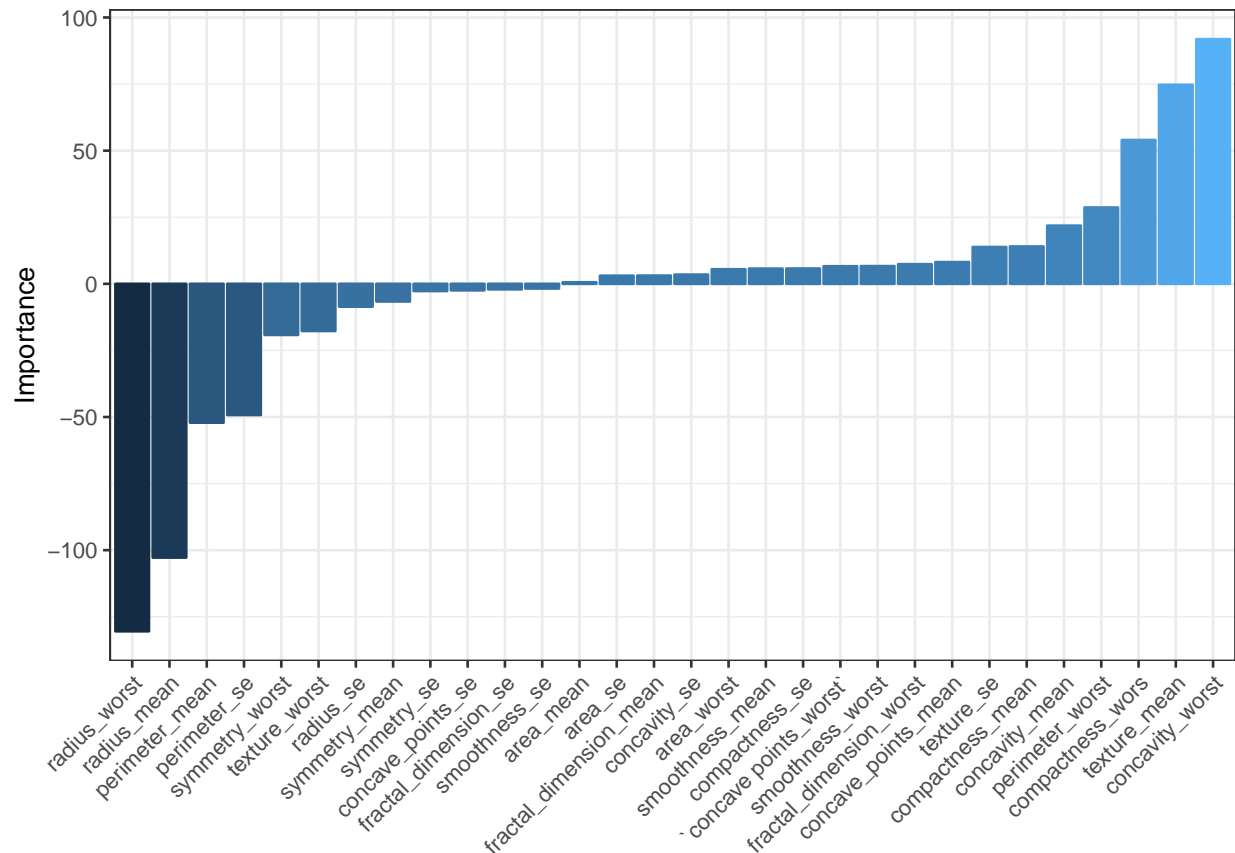


```
#Relative importance of input variables in neural networks using Garson's algorithm:
garson(model_nnet, las = 2) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```





```
olden(model_nnet) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



Here both the positive and negative value represents relative contributions of each connection weight among the variables

## Prediction

```
#Predict
predict_nnet <- predict(model_nnet,test_data, type = "class")

#Draw the crosstable

library(gmodels)
CrossTable(test_data$Class,predict_nnet,prop.chisq = F,prop.r = F,prop.c = F,dnn =c("Actual Diagnosis",

##
##
##      Cell Contents
## |-----|
## |              N |
## |              N / Table Total |
## |-----|
##
##
## Total Observations in Table:  170
##
##
```

```

##          | Predict Diagnosis
## Actual Diagnosis |      benign | malignant | Row Total |
## -----|-----|-----|-----|
##          benign |          96 |          11 |          107 |
##          |          0.565 |          0.065 |          |
## -----|-----|-----|-----|
##          malignant |           7 |          56 |          63 |
##          |          0.041 |          0.329 |          |
## -----|-----|-----|-----|
##      Column Total |          103 |          67 |          170 |
## -----|-----|-----|-----|
##
##

```