

# Classificação de tumores usando kNN

## 2. Bibliotecas utilizadas

More on tidyverse here.

More on caret here.

More on class here.

```
library(tidyverse)
library(caret)
library(class)
```

## 3. Importando os dados

You can also embed plots, for example:

```
data <- read.csv("wisc_bc_data.csv")[,-1]
data$diagnosis <- factor(data$diagnosis, levels = c("B","M"), ordered = T)
data[,2:ncol(data)] <- sapply(data[,2:ncol(data)], as.numeric)
row.names(data) <- as.numeric(row.names(data))
```

## 4. Análise exploratória dos dados

### 4.1 Verificando os tipos dos dados e ausência de valores

Verificando as primeiras linhas da tabela:

```
head(data)
```

| ##   | diagnosis | radius_mean | texture_mean | perimeter_mean | area_mean |
|------|-----------|-------------|--------------|----------------|-----------|
| ## 1 | M         | 17.99       | 10.38        | 122.80         | 1001.0    |
| ## 2 | M         | 20.57       | 17.77        | 132.90         | 1326.0    |
| ## 3 | M         | 19.69       | 21.25        | 130.00         | 1203.0    |
| ## 4 | M         | 11.42       | 20.38        | 77.58          | 386.1     |
| ## 5 | M         | 20.29       | 14.34        | 135.10         | 1297.0    |
| ## 6 | M         | 12.45       | 15.70        | 82.57          | 477.1     |

  

| ##   | smoothness_mean | compactness_mean | concavity_mean | concave.points_mean |
|------|-----------------|------------------|----------------|---------------------|
| ## 1 | 0.11840         | 0.27760          | 0.3001         | 0.14710             |
| ## 2 | 0.08474         | 0.07864          | 0.0869         | 0.07017             |
| ## 3 | 0.10960         | 0.15990          | 0.1974         | 0.12790             |
| ## 4 | 0.14250         | 0.28390          | 0.2414         | 0.10520             |
| ## 5 | 0.10030         | 0.13280          | 0.1980         | 0.10430             |
| ## 6 | 0.12780         | 0.17000          | 0.1578         | 0.08089             |

  

| ##   | symmetry_mean | fractal_dimension_mean | radius_se | texture_se | perimeter_se |
|------|---------------|------------------------|-----------|------------|--------------|
| ## 1 | 0.2419        | 0.07871                | 1.0950    | 0.9053     | 8.589        |
| ## 2 | 0.1812        | 0.05667                | 0.5435    | 0.7339     | 3.398        |
| ## 3 | 0.2069        | 0.05999                | 0.7456    | 0.7869     | 4.585        |
| ## 4 | 0.2597        | 0.09744                | 0.4956    | 1.1560     | 3.445        |
| ## 5 | 0.1809        | 0.05883                | 0.7572    | 0.7813     | 5.438        |
| ## 6 | 0.2087        | 0.07613                | 0.3345    | 0.8902     | 2.217        |

```
##      area_se smoothness_se compactness_se concavity_se concave.points_se
## 1  153.40      0.006399      0.04904      0.05373      0.01587
## 2   74.08      0.005225      0.01308      0.01860      0.01340
## 3   94.03      0.006150      0.04006      0.03832      0.02058
## 4   27.23      0.009110      0.07458      0.05661      0.01867
## 5   94.44      0.011490      0.02461      0.05688      0.01885
## 6   27.19      0.007510      0.03345      0.03672      0.01137
##      symmetry_se fractal_dimension_se radius_worst texture_worst
## 1    0.03003      0.006193      25.38      17.33
## 2    0.01389      0.003532      24.99      23.41
## 3    0.02250      0.004571      23.57      25.53
## 4    0.05963      0.009208      14.91      26.50
## 5    0.01756      0.005115      22.54      16.67
## 6    0.02165      0.005082      15.47      23.75
##      perimeter_worst area_worst smoothness_worst compactness_worst
## 1      184.60      2019.0      0.1622      0.6656
## 2      158.80      1956.0      0.1238      0.1866
## 3      152.50      1709.0      0.1444      0.4245
## 4       98.87      567.7      0.2098      0.8663
## 5      152.20      1575.0      0.1374      0.2050
## 6      103.40      741.6      0.1791      0.5249
##      concavity_worst concave.points_worst symmetry_worst
## 1      0.7119      0.2654      0.4601
## 2      0.2416      0.1860      0.2750
## 3      0.4504      0.2430      0.3613
## 4      0.6869      0.2575      0.6638
## 5      0.4000      0.1625      0.2364
## 6      0.5355      0.1741      0.3985
##      fractal_dimension_worst
## 1      0.11890
## 2      0.08902
## 3      0.08758
## 4      0.17300
## 5      0.07678
## 6      0.12440
```

Verificando a existência de *missing values*:

```
colSums(is.na(data))
```

```
##      diagnosis      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
##          0
```

## 4.2 Verificando quantidade da variável dependente no dataset

Total de Benignos e Malignos:

```
table(data$diagnosis)
```

```
##
##  B   M
## 357 212
```

Benignos e Malignos em %:

```
round(prop.table(table(data$diagnosis))*100, digits = 2)
```

```
##
##      B      M
## 62.74 37.26
```

## 4.3 Normalizando as variáveis quantitativas

### 4.3.1 Normalização Min-Max

$$x_{\text{norm}} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

```
norm.minmax <- function(x) {
  return((x - min(x))/(max(x) - min(x)))
}
```

---

### 4.3.2 Normalização Z-score

$$x_{\text{norm}} = \frac{x - \text{mean}(x)}{\text{sd}(x)}$$

```
norm.zscore <- function(x) {
  return((x - mean(x))/sd(x))
}
```

---

### 4.3.3 Normalizando os dados

```
data_norm1 <- as.data.frame(lapply(data[,2:ncol(data)], norm.minmax))
data_norm2 <- as.data.frame(lapply(data[,2:ncol(data)], norm.zscore))
```

## 5. Construindo o modelo de Classificação k-NN

### 5.1 Criando dataset de treino e teste

```
test.size <- 0.20
split_row <- as.integer((1 - test.size) * nrow(data))
```

Dataset de treino e teste utilizando a normalização min-max:

```
train1 <- data_norm1[1:split_row,]
test1 <- data_norm1[(split_row+1):nrow(data_norm1),]
```

Dataset de treino e teste utilizando o Z-score para normalização dos dados:

```
train2 <- data_norm2[1:split_row,]
test2 <- data_norm2[(split_row+1):nrow(data_norm2),]
```

Criando as labels de saída:

```
label.train <- data[1:split_row, 1]
label.test <- data[(split_row+1):nrow(data), 1]
```

### 5.2 Criando o modelo k-NN

Uma sugestão acadêmica para a escolha do  $k$  é calcular a raiz quadrada do tamanho da amostra e usar o valor obtido:

```
k <- ceiling(sqrt(nrow(data)))
```

Modelo com normalização min-max:

```
#label.train
data_pred1 <- knn(train = train1, test = test1, cl = label.train, k = k)
```

Modelo normalizado com Z-score:

```
data_pred2 <- knn(train = train2, test = test2, cl = label.train, k = k)
```

#### 5.2.1 Matriz de Confusão usando o modelo normalizado com min-max

```
confusionMatrix(data_pred1, label.test)

## Confusion Matrix and Statistics
##
##              Reference
## Prediction  B  M
##           B 88  2
##           M  0 24
##
##              Accuracy : 0.9825
##              95% CI : (0.9381, 0.9979)
##      No Information Rate : 0.7719
##      P-Value [Acc > NIR] : 9.116e-11
##
##              Kappa : 0.9488
##
##  Mcnemar's Test P-Value : 0.4795
##
##              Sensitivity : 1.0000
```

```
##           Specificity : 0.9231
##           Pos Pred Value : 0.9778
##           Neg Pred Value : 1.0000
##           Prevalence : 0.7719
##           Detection Rate : 0.7719
##           Detection Prevalence : 0.7895
##           Balanced Accuracy : 0.9615
##
##           'Positive' Class : B
##
```

---

## 5.2.2 Matriz de Confusão usando o modelo por Z-score

```
confusionMatrix(data_pred2, label.test)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  B  M
##           B 88  2
##           M  0 24
##
##           Accuracy : 0.9825
##           95% CI : (0.9381, 0.9979)
##           No Information Rate : 0.7719
##           P-Value [Acc > NIR] : 9.116e-11
##
##           Kappa : 0.9488
##
##           Mcnemar's Test P-Value : 0.4795
##
##           Sensitivity : 1.0000
##           Specificity : 0.9231
##           Pos Pred Value : 0.9778
##           Neg Pred Value : 1.0000
##           Prevalence : 0.7719
##           Detection Rate : 0.7719
##           Detection Prevalence : 0.7895
##           Balanced Accuracy : 0.9615
##
##           'Positive' Class : B
##
```

---

## Extra: Tuning $k$

```
##
## Attaching package: 'mltools'
## The following object is masked from 'package:tidyr':
##
##     replace_na
```

```

scores <- c()
ks <- 2:as.integer(sqrt(nrow(data)))

for (k in ks) {
  preds <- knn(train = train1, test = test1, cl = label.train, k = k)
  f1 <- as.numeric(confusionMatrix(preds, label.test)$byClass["F1"])
  scores <- append(scores, f1)
}

ymin <- 0.95
ymax <- 1.00

plot(ks, scores, type = "l", lwd=2,
     main="F1 Score per num. of neighbors",
     xlab = "# neighbors", ylab = "Score", ylim = c(ymin, ymax))

# Best k
points(ks[which.max(scores)], max(scores), pch=21, col="red")

# Vertical line
lines(x = c(ks[which.max(scores)], ks[which.max(scores)]),
      y = c(ymin, max(scores)),
      lty=3, col="darkgray", lwd=1.5)

# Horizontal line
lines(x = c(min(ks), ks[which.max(scores)]),
      y = c(max(scores), max(scores)),
      lty=3, col="darkgray", lwd=1.5)

legend("bottomright", pch=21, col="red", legend = "Best k")

```

**F1 Score per num. of neighbors**

