# Unidad 2 parametrizado

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# Índice de contenidos:

- 1. Tabla de fortalezas/debilidades del algoritmo k-NN.
- 2. Importación de los datos.
- 3. Exploración de los datos.
- 4. Normalización.
- 5. Training y Test datasets.
- 6. Entrenamiento del modelo.
- 7. Evaluación del modelo.
- 8. Mejorando el modelo.

## 1. Tabla fortalezas/debilidades.

Fortalezas	Debilidades	
Simple y efectivo	No produce un modelo, limitando la	
	capacidad para comprender cómo las	
	características están relacionados con la clase	
No hace suposiciones sobre la distribución de	Requiere la selección de un k apropiado	
datos subyacente		
Fase de entrenamiento rápida	Características nominales y datos faltantes	
	requieren procesamiento adicional.	
	Fase de clasificación lenta.	

# 2. Importación de los datos.

```
library(readr)
wbcd <- read.csv("C:/Users/Meli/Downloads/wisc_bc_data.csv", stringsAsFactors = FALSE)
View(wbcd)
str(wbcd)</pre>
```

```
## 'data.frame': 569 obs. of 32 variables:
```

```
## $ id
                        : int 87139402 8910251 905520 868871 9012568 906539 925291 87880 862989 89827 .
## $ diagnosis
                       : chr
                                "B" "B" "B" "B" ...
                       : num 12.3 10.6 11 11.3 15.2 ...
## $ radius mean
## $ texture_mean
                                12.4 18.9 16.8 13.4 13.2 ...
                        : num
## $ perimeter_mean
                        : num
                                78.8 69.3 70.9 73 97.7 ...
## $ area_mean
                         : num 464 346 373 385 712 ...
## $ smoothness mean : num 0.1028 0.0969 0.1077 0.1164 0.0796 ...
## $ compactness_mean : num
                                0.0698 0.1147 0.078 0.1136 0.0693 ...
## $ concavity_mean : num 0.0399 0.0639 0.0305 0.0464 0.0339 ...
## $ points_mean
                         : num 0.037 0.0264 0.0248 0.048 0.0266 ...
## $ symmetry_mean : num 0.196 0.192 0.171 0.177 0.172 ...
## $ dimension_mean : num
                                0.0595 0.0649 0.0634 0.0607 0.0554 ...
                     : num
## $ radius_se
                                0.236 0.451 0.197 0.338 0.178 ...
## $ texture_se : num
## $ perimeter_se : num
                                0.666 1.197 1.387 1.343 0.412 ...
                                1.67 3.43 1.34 1.85 1.34 ...
## $ area_se
                         : num
                                17.4 27.1 13.5 26.3 17.7 ...
## $ smoothness_se : num 0.00805 0.00747 0.00516 0.01127 0.00501 ...
## $ compactness_se : num 0.0118 0.03581 0.00936 0.03498 0.01485 ...
## $ concavity_se : num  0.0168  0.0335  0.0106  0.0219  0.0155 ...
## $ points_se : num  0.01241  0.01365  0.00748  0.01965  0.00915 ..
## $ symmetry_se : num  0.0192  0.035  0.0172  0.0158  0.0165 ...
## $ dimension_se : num  0.00225  0.00332  0.0022  0.00344  0.00177 ...
                        : num 0.01241 0.01365 0.00748 0.01965 0.00915 ...
## $ radius_worst
                      : num
                                13.5 11.9 12.4 11.9 16.2 ...
                                15.6 22.9 26.4 15.8 15.7 ...
## $ texture worst
                        : num
## $ perimeter worst : num 87 78.3 79.9 76.5 104.5 ...
## $ area_worst
                         : num 549 425 471 434 819 ...
## $ smoothness_worst : num
                                0.139 0.121 0.137 0.137 0.113 ...
## $ compactness_worst: num 0.127 0.252 0.148 0.182 0.174 ...
## $ concavity_worst : num 0.1242 0.1916 0.1067 0.0867 0.1362 ...
## $ points_worst
                                0.0939 0.0793 0.0743 0.0861 0.0818 ...
                         : num
## $ symmetry_worst
                         : num
                                0.283 0.294 0.3 0.21 0.249 ...
## $ dimension_worst : num 0.0677 0.0759 0.0788 0.0678 0.0677 ...
```

### 3. Exploración de los datos.

```
#Eliminamos la columna id
wbcd <- wbcd[-1]
#tabla de frecuencias absolutas de diagnósticos
table(wbcd$diagnosis)

##
## B M
## 357 212

#Renombramos los factores
wbcd$diagnosis<- factor(wbcd$diagnosis, levels = c("B", "M"),
labels = c("Benign", "Malignant"))
#Tabla de frecuencias relativas de diagnósticos
round(prop.table(table(wbcd$diagnosis)) * 100, digits = 1)</pre>
```

```
## Benign Malignant
## 62.7 37.3
```

#### 4. Normalización de los datos.

```
#Observamos que las variables numéricas tienen rangos muy diferentes
summary(wbcd[c("radius_mean", "area_mean", "smoothness_mean")])
##
    radius_mean
                    area_mean
                                    smoothness_mean
## Min. : 6.981 Min. : 143.5 Min.
                                          :0.05263
## 1st Qu.:11.700 1st Qu.: 420.3 1st Qu.:0.08637
## Median: 13.370 Median: 551.1 Median: 0.09587
## Mean
         :14.127 Mean : 654.9 Mean
                                          :0.09636
## 3rd Qu.:15.780 3rd Qu.: 782.7 3rd Qu.:0.10530
## Max.
         :28.110 Max.
                          :2501.0 Max.
                                          :0.16340
#Creamos una función para reescalar los datos numéricos.
normalize <- function(x) {</pre>
return ((x-min(x)) / (max(x)-min(x)))
}
#Creamos un data frame con los datos numéricos normalizados
wbcd_n <- as.data.frame(lapply(wbcd[2:31], normalize))</pre>
#Comprobamos que los datos ahora están normalizados, con valores que van del 0 al 1
summary(wbcd_n$area_mean)
     Min. 1st Qu. Median
                            Mean 3rd Qu.
## 0.0000 0.1174 0.1729 0.2169 0.2711 1.0000
```

### 5. Training y Test datasets.

```
#Creamos los Training and test datasets
wbcd_train <- wbcd_n[1:469, ]
wbcd_test <- wbcd_n[470:569, ]

#Labels
wbcd_train_labels <- wbcd[1:469, 1]
wbcd_test_labels <- wbcd[470:569, 1]</pre>
```

### 6. Entrenamiento del modelo.

```
library(class)
wbcd_test_pred<- knn(train = wbcd_train, test = wbcd_test, cl= wbcd_train_labels, k=21)</pre>
```

#### 7. Evaluación del modelo.

```
library(gmodels)
CrossTable(x = wbcd_test_labels, y = wbcd_test_pred,
prop.chisq=FALSE)
##
##
##
    Cell Contents
   -----|
         N / Row Total |
         N / Col Total |
## |
        N / Table Total |
##
## Total Observations in Table: 100
##
##
               | wbcd_test_pred
##
## wbcd_test_labels | Benign | Malignant | Row Total |
  -----|-----|-----|
##
        Benign |
                    61 | 0 |
                                      61 |
                  1.000 | 0.000 |
0.968 | 0.000 |
                                    0.610 |
##
              ##
                   0.610 | 0.000 |
    -----|-----|
                          37 I
##
       Malignant |
                      2 |
                   0.051 | 0.949 |
                                    0.390 |
##
            - 1
##
                   0.032 |
                           1.000
                   0.020 | 0.370 |
##
     Column Total | 63 | 37 |
##
                 0.630 | 0.370 |
       -----|----|
##
##
##
```

### 8. Mejorando el modelo.

Con el modelo anterior se obtenían un 2% de falsos negativos. Esto no interesa, así que intentaremos mejorar el modelo: - Reescalando las variables numéricas. - Utilizando diferentes valores de k.

z-score standardization

```
wbcd_z <- as.data.frame(scale(wbcd[-1]))
#Comprobamos que los valores han sido estandarizados
summary(wbcd_z$area_mean)</pre>
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## -1.4532 -0.6666 -0.2949 0.0000 0.3632 5.2459
```

Observamos que la media de los valores es 0. Procedemos de nuevo a crear los Test y Training datasets y a evaluar el modelo:

```
wbcd_train <- wbcd_z[1:469, ]
wbcd_test <- wbcd_z[470:569, ]
wbcd_train_labels <- wbcd[1:469, 1]
wbcd_test_labels <- wbcd[470:569, 1]
wbcd_test_pred <- knn(train = wbcd_train, test = wbcd_test,
cl = wbcd_train_labels, k = 21)
CrossTable(x = wbcd_test_labels, y = wbcd_test_pred,
prop.chisq = FALSE)</pre>
```

##	Cell Contents			
##	i	N I		
##	N / Ro			
##		ol Total		
#	N / Tab			
#				
#				
#	<b></b>			
#	Total Observations	s in Table:	100	
#				
:# :#				
F# F#		wbcd_test_j	-	Dan Tatal
#	wbcd_test_labels	l penign	Malignant 	ROW TOTAL
			I .	I
##	Benign	l 61	1 0	l 61
	Benign	61 1.000	I 0.000	61 0.610
#	Benign	1.000	0.000	0.610
#	Benign	•	•	0.610
#	Benign	1.000	0.000	0.610
# # #	Benign Malignant	1.000	0.000 0.000 0.000	0.610     
# # # #		1.000 0.924 0.610	0.000   0.000   0.000 	0.610       
######		1.000 0.924 0.610	0.000   0.000   0.000 	0.610 
#########		1.000 0.924 0.610 5 0.128	0.000   0.000   0.000     34   0.872	0.610 
########	Malignant	1.000 0.924 0.610 	0.000   0.000   0.000     34   0.872   1.000   0.340	0.610 
########		1.000 0.924 0.610 5 0.128 0.076 0.050	0.000   0.000   0.000     34   0.872   1.000   0.340	0.610 

Se observa que los falsos negativos han aumentado a un 5%.

 $Valores\ alternativos\ de\ k$ 

Utilizamos diferentes valores de k con los datos normalizados:

```
wbcd_test_pred1<- knn(train = wbcd_train, test = wbcd_test, cl= wbcd_train_labels, k=1)</pre>
CrossTable(x = wbcd_test_labels, y = wbcd_test_pred1,
prop.chisq=FALSE)
##
##
##
    Cell Contents
## |
          N / Row Total |
## |
          N / Col Total |
## | N / Table Total |
## |-----|
##
## Total Observations in Table: 100
##
##
                | wbcd_test_pred1
## wbcd_test_labels | Benign | Malignant | Row Total |
## -----|-----|
          Benign | 59 | 2 | 61 |
| 0.967 | 0.033 | 0.610 |
##
##
                   0.952 | 0.053 |
0.590 | 0.020 |
##
               - 1
## -----|-----|
       Malignant | 3 | 36 | 39 |
                   0.077 | 0.923 | 0.390 |
0.048 | 0.947 | |
##
              ##
               - 1
##
                   0.030 |
                             0.360 |
               - 1
## -----|----|
     Column Total | 62 | 38 | 100 | 0.620 | 0.380 | |
##
## -----|-----|
##
##
wbcd_test_pred5<- knn(train = wbcd_train, test = wbcd_test, cl= wbcd_train_labels, k=5)</pre>
CrossTable(x = wbcd_test_labels, y = wbcd_test_pred5,
prop.chisq=FALSE)
##
##
    Cell Contents
## |-----|
## |
         N / Row Total |
N / Col Total |
## |
## |
## | N / Table Total |
```

## |-----|

```
##
##
## Total Observations in Table: 100
##
##
##
              | wbcd_test_pred5
## wbcd test labels | Benign | Malignant | Row Total |
## -----|-----|
                  60 | 1 |
          Benign |
           1
                   0.984 | 0.016 |
                    0.968 |
                             0.026 |
                   0.600 |
                           0.010 |
                    2 |
                              37 |
       Malignant |
                  0.051 | 0.949 | 0.390 |
0.032 | 0.974 | |
0.020 | 0.370 | |
##
     Column Total | 62 | 38 | 0.620 | 0.380 |
                              38 l
  -----|-----|
##
wbcd_test_pred11<- knn(train = wbcd_train, test = wbcd_test, cl= wbcd_train_labels, k=11)
CrossTable(x = wbcd_test_labels, y = wbcd_test_pred11,
prop.chisq=FALSE)
##
##
    Cell Contents
         N / Row Total |
N / Col Total |
## |
         N / Table Total |
## Total Observations in Table: 100
##
##
                | wbcd_test_pred11
##
## wbcd_test_labels | Benign | Malignant | Row Total |
                    60 |
##
          Benign |
                 0.984 | 0.016 |
##
                   0.952 |
                             0.027
              0.600 |
                           0.010 |
     -----|----|----|
       Malignant | 3 | 36 | 39 |
##
                   0.077 | 0.923 | 0.390 |
           0.048 | 0.973 | |
##
               - 1
```

```
| 0.030 | 0.360 | |
## -----|-----|
     Column Total | 63 | 37 | 100 | | 0.630 | 0.370 |
##
      -----|-----|
##
##
wbcd_test_pred15<- knn(train = wbcd_train, test = wbcd_test, cl= wbcd_train_labels, k=15)
CrossTable(x = wbcd_test_labels, y = wbcd_test_pred15,
prop.chisq=FALSE)
##
##
     Cell Contents
## |
         N / Row Total |
N / Col Total |
## |
         N / Table Total |
## |-----|
## Total Observations in Table: 100
##
##
               | wbcd_test_pred15
##
## wbcd_test_labels | Benign | Malignant | Row Total |
## -----|----|
                    61 | 0 |
          Benign |
                   1.000 | 0.000 |
0.953 | 0.000 |
0.610 | 0.000 |
             0.610 l
##
                   0.953 |
0.610 |
                ##
##
               - 1
                    3 |
##
       Malignant |
                              36 |
             ant | 0.077 | 0.923 | 0.390 | | 0.047 | 1.000 | |
##
##
               | 0.030 | 0.360 |
## --
                            36 | 100 |
     Column Total | 64 |
       0.640 |
                             0.360 |
              ---|------|
##
##
wbcd_test_pred27<- knn(train = wbcd_train, test = wbcd_test, cl= wbcd_train_labels, k=27)</pre>
CrossTable(x = wbcd_test_labels, y = wbcd_test_pred27,
prop.chisq=FALSE)
```

## ##

```
Cell Contents
##
## |
## |
          N / Row Total |
           N / Col Total |
         N / Table Total |
     -----|
##
##
  Total Observations in Table: 100
##
##
                | wbcd_test_pred27
  wbcd_test_labels | Benign | Malignant | Row Total |
          Benign |
                       61 |
##
##
                     1.000 |
                               0.000 |
                                         0.610 |
                     0.924 |
                               0.000 |
##
                     0.610 |
                               0.000 |
##
               ##
##
        Malignant |
                     5 |
                               34 |
                                         39 |
                     0.128 | 0.872 |
                     0.076 |
##
                              1.000 |
                - 1
                     0.050 I
                               0.340 l
     Column Total |
                      66 |
                                 34 |
##
         1
                   0.660 | 0.340 |
     -----|----|
##
##
```

Observamos que con k=5 se obtiene un menor número de falsos positivos.