Flujo de análisis en clasificación supervisada

Métodos supervisados

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Contents

Comenzamos cargando los paquetes y la base de datos:

```r
library(caret)
library(mlbench)
data(Sonar)
str(Sonar, width = 85, strict.width = "cut")
```

```
## 'data.frame':    208 obs. of  61 variables:
##  $ V1   : num  0.02 0.0453 0.0262 0.01 0.0762 0.0286 0.0317 0.0519 0.0223 0.0164 ...
##  $ V2   : num  0.0371 0.0523 0.0582 0.0171 0.0666 0.0453 0.0956 0.0548 0.0375 0.017..
##  $ V3   : num  0.0428 0.0843 0.1099 0.0623 0.0481 ...
##  $ V4   : num  0.0207 0.0689 0.1083 0.0205 0.0394 ...
##  $ V5   : num  0.0954 0.1183 0.0974 0.0205 0.059 ...
##  $ V6   : num  0.0986 0.2583 0.228 0.0368 0.0649 ...
##  $ V7   : num  0.154 0.216 0.243 0.11 0.121 ...
##  $ V8   : num  0.16 0.348 0.377 0.128 0.247 ...
##  $ V9   : num  0.3109 0.3337 0.5598 0.0598 0.3564 ...
##  $ V10  : num  0.211 0.287 0.619 0.126 0.446 ...
##  $ V11  : num  0.1609 0.4918 0.6333 0.0881 0.4152 ...
##  $ V12  : num  0.158 0.655 0.706 0.199 0.395 ...
##  $ V13  : num  0.2238 0.6919 0.5544 0.0184 0.4256 ...
##  $ V14  : num  0.0645 0.7797 0.532 0.2261 0.4135 ...
##  $ V15  : num  0.066 0.746 0.648 0.173 0.453 ...
##  $ V16  : num  0.227 0.944 0.693 0.213 0.533 ...
##  $ V17  : num  0.31 1 0.6759 0.0693 0.7306 ...
##  $ V18  : num  0.3 0.887 0.755 0.228 0.619 ...
##  $ V19  : num  0.508 0.802 0.893 0.406 0.203 ...
##  $ V20  : num  0.48 0.782 0.862 0.397 0.464 ...
##  $ V21  : num  0.578 0.521 0.797 0.274 0.415 ...
##  $ V22  : num  0.507 0.405 0.674 0.369 0.429 ...
##  $ V23  : num  0.433 0.396 0.429 0.556 0.573 ...
```

```
##  $ V24  : num  0.555 0.391 0.365 0.485 0.54 ...
##  $ V25  : num  0.671 0.325 0.533 0.314 0.316 ...
##  $ V26  : num  0.641 0.32 0.241 0.533 0.229 ...
##  $ V27  : num  0.71 0.327 0.507 0.526 0.7 ...
##  $ V28  : num  0.808 0.277 0.853 0.252 1 ...
##  $ V29  : num  0.679 0.442 0.604 0.209 0.726 ...
##  $ V30  : num  0.386 0.203 0.851 0.356 0.472 ...
##  $ V31  : num  0.131 0.379 0.851 0.626 0.51 ...
##  $ V32  : num  0.26 0.295 0.504 0.734 0.546 ...
##  $ V33  : num  0.512 0.198 0.186 0.612 0.288 ...
##  $ V34  : num  0.7547 0.2341 0.2709 0.3497 0.0981 ...
##  $ V35  : num  0.854 0.131 0.423 0.395 0.195 ...
##  $ V36  : num  0.851 0.418 0.304 0.301 0.418 ...
##  $ V37  : num  0.669 0.384 0.612 0.541 0.46 ...
##  $ V38  : num  0.61 0.106 0.676 0.881 0.322 ...
##  $ V39  : num  0.494 0.184 0.537 0.986 0.283 ...
##  $ V40  : num  0.274 0.197 0.472 0.917 0.243 ...
##  $ V41  : num  0.051 0.167 0.465 0.612 0.198 ...
##  $ V42  : num  0.2834 0.0583 0.2587 0.5006 0.2444 ...
##  $ V43  : num  0.282 0.14 0.213 0.321 0.185 ...
##  $ V44  : num  0.4256 0.1628 0.2222 0.3202 0.0841 ...
##  $ V45  : num  0.2641 0.0621 0.2111 0.4295 0.0692 ...
##  $ V46  : num  0.1386 0.0203 0.0176 0.3654 0.0528 ...
##  $ V47  : num  0.1051 0.053 0.1348 0.2655 0.0357 ...
##  $ V48  : num  0.1343 0.0742 0.0744 0.1576 0.0085 ...
##  $ V49  : num  0.0383 0.0409 0.013 0.0681 0.023 0.0264 0.0507 0.0285 0.0777 0.0092 ..
##  $ V50  : num  0.0324 0.0061 0.0106 0.0294 0.0046 0.0081 0.0159 0.0178 0.0439 0.019..
##  $ V51  : num  0.0232 0.0125 0.0033 0.0241 0.0156 0.0104 0.0195 0.0052 0.0061 0.011..
##  $ V52  : num  0.0027 0.0084 0.0232 0.0121 0.0031 0.0045 0.0201 0.0081 0.0145 0.009..
##  $ V53  : num  0.0065 0.0089 0.0166 0.0036 0.0054 0.0014 0.0248 0.012 0.0128 0.0223..
##  $ V54  : num  0.0159 0.0048 0.0095 0.015 0.0105 0.0038 0.0131 0.0045 0.0145 0.0179..
##  $ V55  : num  0.0072 0.0094 0.018 0.0085 0.011 0.0013 0.007 0.0121 0.0058 0.0084 ...
##  $ V56  : num  0.0167 0.0191 0.0244 0.0073 0.0015 0.0089 0.0138 0.0097 0.0049 0.006..
##  $ V57  : num  0.018 0.014 0.0316 0.005 0.0072 0.0057 0.0092 0.0085 0.0065 0.0032 ...
##  $ V58  : num  0.0084 0.0049 0.0164 0.0044 0.0048 0.0027 0.0143 0.0047 0.0093 0.003..
##  $ V59  : num  0.009 0.0052 0.0095 0.004 0.0107 0.0051 0.0036 0.0048 0.0059 0.0056 ..
##  $ V60  : num  0.0032 0.0044 0.0078 0.0117 0.0094 0.0062 0.0103 0.0053 0.0022 0.004..
##  $ Class: Factor w/ 2 levels "M","R": 2 2 2 2 2 2 2 2 2 2 ...
```

0.1 Ejercicio propuesto

Cargamos las librerías necesarias:

```r
library(tidyverse)
library(tm)
library(SnowballC)
```

El dataset escogido se puede encontrar en (https://www.kaggle.com/c/nlp-getting-started/data). Este dataset, con 10.876 instancias, contiene 4 variables explicativas; *id*, *keyword*, *location* y *test*, y dos valores en la variable clase *target* (1 y 0). La variable clase es de tipo binaria así que vamos a aprender un modelo de clasificación binaria, y vamos a predecir si dado un tweet, este tweet trata sobre un desastre real o no. Si es un desastre real, se predice un 1. Si no, se predice un 0.

La partición inicial train-test, no se tiene que realizar, ya que las instancias de train y test ya vienen definidas en los ficheros *train.csv* y *test.csv*, proporcionados por la competición en Kaggle que se ha elegido. El conjunto de datos de train contiene 7613 instancias y el conjunto de datos de test contiene 3262 instancias.

Cargamos el dataset:

```r
train <- read.csv("train.csv", na.strings=c("","NA"))
dim(train)
```

```
## [1] 7613    5
```

```r
test <- read.csv("test.csv", na.strings=c("","NA"))
dim(test)
```

```
## [1] 3263    4
```

Cada instancia en el conjunto de train y test contiene la siguiente información:

- **id**: un identificador único para cada tweet.
- **keyword**: una palabra clave del tweet (puede estar en blanco).
- **location**: la ubicación desde la que se envió el tweet (puede estar en blanco).
- **text**: el texto del tweet.
- **target**: solo en el conjunto de datos de train porqué es la variable clase a predecir. Indica si un tweet es sobre un desastre real (1) o no (0).

```r
str(train)
```

```
## 'data.frame':    7613 obs. of  5 variables:
##  $ id      : int  1 4 5 6 7 8 10 13 14 15 ...
##  $ keyword : chr  NA NA NA NA ...
##  $ location: chr  NA NA NA NA ...
##  $ text    : chr  "Our Deeds are the Reason of this #earthquake May ALLAH Forgive us all" "Forest fi
##  $ target  : int  1 1 1 1 1 1 1 1 1 1 ...
```

```r
str(test)
```

```
## 'data.frame':    3263 obs. of  4 variables:
##  $ id      : int  0 2 3 9 11 12 21 22 27 29 ...
##  $ keyword : chr  NA NA NA NA ...
##  $ location: chr  NA NA NA NA ...
##  $ text    : chr  "Just happened a terrible car crash" "Heard about #earthquake is different cities,
```

Factorización de la variable clase, que inicialmente es de tipo entero.

```r
str(train$target)
```

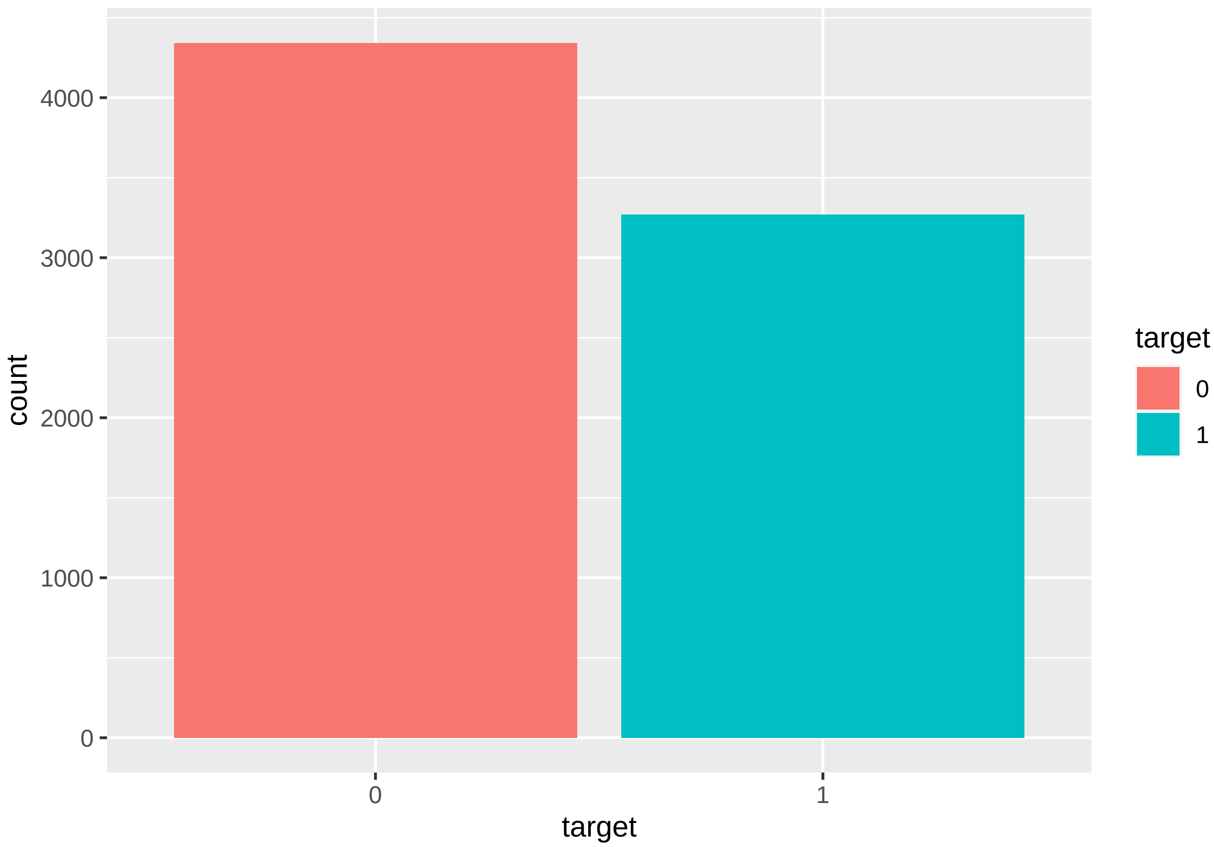
```
##  int [1:7613] 1 1 1 1 1 1 1 1 1 1 ...
```

```
train$target <- as.factor(train$target)
str(train$target)
```

```
##  Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 2 ...
```

Distribución de la variable clase:

```
ggplot(train, aes(x=target)) +
  geom_bar(aes(fill=target))
```




```
sum(train$target == "0") / dim(train)[1] * 100
```

```
## [1] 57.03402
```

```
sum(train$target == "1") / dim(train)[1] * 100
```

```
## [1] 42.96598
```

La distribución de la variable a predecir está relativamente equilibrada, donde el 57% de las instancias de los tweets son sobre un desastre no real y el 43% sobre un desastre real.

0.1.1 correlaciones entre variables explicativas

0.1.2 mética de evaluación

0.1.3 valores perdidos

```
colSums(sapply(train, is.na))
```

```
##       id  keyword location     text   target
##        0       61     2533        0        0
```

```
colSums(sapply(test, is.na))
```

```
##       id  keyword location     text
##        0       26     1105        0
```

Las variables *keyword* y *location* tienen valores perdidos. Sobretodo hay una gran cantidad de tweets, para los cuales falta la ubicación. Potencialmente, esto podría ser una buena variable predictiva en sí misma. No faltan valores en las variables *target* y *text*.

Nos ocuparemos de los valores perdidos más adelante.

Eliminamos la variable *id*.

```
train$id <- NULL
test$id <- NULL
```

0.2 keyword

```
length(unique(train$keyword))
```

```
## [1] 222
```

```
length(unique(test$keyword))
```

```
## [1] 222
```

```
train$keyword <- as.factor(train$keyword)
all.equal(levels(train$keyword), levels(test$keyword))
```

```
## [1] "Modes: character, NULL"
## [2] "Lengths: 221, 0"
## [3] "target is character, current is NULL"
```

0.3 location

```r
length(unique(train$location))
```

```
## [1] 3342
```

```r
length(unique(test$location))
```

```
## [1] 1603
```

```r
train_and_test <- rbind(train[, 1:3], test)
str(train_and_test)
```

```
## 'data.frame':    10876 obs. of  3 variables:
##  $ keyword : Factor w/ 221 levels "ablaze","accident",..: NA NA NA NA NA NA NA NA NA NA ...
##  $ location: chr  NA NA NA NA ...
##  $ text    : chr  "Our Deeds are the Reason of this #earthquake May ALLAH Forgive us all" "Forest fi
```

1. Create a corpus
2. Convert to lowercase
3. Remove punctuation
4. Remove stopwords
5. Stemming (using Porter's stemming algorithm)
6. Create document term matrix

```r
corpus_location <- Corpus(VectorSource(train_and_test$location))
corpus_location[[33]]$content
```

```
## [1] "Est. September 2012 - Bristol"
```

```r
corpus_location <- tm_map(corpus_location, tolower)
corpus_location[[33]]$content
```

```
## [1] "est. september 2012 - bristol"
```

```r
corpus_location <- tm_map(corpus_location, removePunctuation)
corpus_location[[33]]$content
```

```
## [1] "est september 2012  bristol"
```

```r
corpus_location <- tm_map(corpus_location, removeWords, stopwords("english"))
corpus_location[[33]]$content
```

```
## [1] "est september 2012  bristol"
```

```r
corpus_location <- tm_map(corpus_location, stemDocument)
corpus_location[[33]]$content
```

```
## [1] "est septemb 2012 bristol"
```

- Create document term matrix
- Reduce sparsity
- Convert to data frame

```
dtm_location <- DocumentTermMatrix(corpus_location)
dtm_location
```

```
## <<DocumentTermMatrix (documents: 10876, terms: 3840)>>
## Non-/sparse entries: 11855/41751985
## Sparsity           : 100%
## Maximal term length: 41
## Weighting          : term frequency (tf)
```

```
dtm_location <- removeSparseTerms(dtm_location, 0.9975)
dtm_location
```

```
## <<DocumentTermMatrix (documents: 10876, terms: 55)>>
## Non-/sparse entries: 3967/594213
## Sparsity           : 99%
## Maximal term length: 10
## Weighting          : term frequency (tf)
```

```
bag_of_words_location <- as.data.frame(as.matrix(dtm_location))
colnames(bag_of_words_location) <- paste0(colnames(bag_of_words_location), "_location")
str(bag_of_words_location, list.len=10)
```

```
## 'data.frame':    10876 obs. of  55 variables:
##  $ africa_location   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ london_location   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ world_location    : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ citi_location     : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ carolina_location : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ england_location  : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ohio_location     : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ india_location    : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ usa_location      : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ south_location    : num  0 0 0 0 0 0 0 0 0 0 ...
##   [list output truncated]
```

0.4 text