

Contents

1	Introduction	5
2	Choosing and evaluating models	7
	2.1 Building and applying a logistic regression spam model	7

4 CONTENTS

Chapter 1

Introduction

This is my attempt to convert all R code encountered in $Practical\ Data\ Science\ with\ R$ to use tidyverse packages.

Chapter 2

Choosing and evaluating models

2.1 Building and applying a logistic regression spam model

```
set.seed(123)
library(tidyverse, warn.conflicts = FALSE)
## Registered S3 method overwritten by 'rvest':
    method
    read_xml.response xml2
## -- Attaching packages ----- tidyverse 1.2.1 --
## v ggplot2 3.1.0.9000
                          v purrr
                                    0.3.0
## v tibble 2.0.1
                          v dplyr 0.8.0.9000
## v tidyr 0.8.2
                          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()
Using logistic regression to classify emails into spam or non-spam:
# reading the file containing spam data
spamD <- readr::read_tsv("https://raw.githubusercontent.com/WinVector/zmPDSwR/master/Spambase/spamD.tsv</pre>
## Parsed with column specification:
    .default = col_double(),
   spam = col_character()
## )
## See spec(...) for full column specifications.
# creating training and testing datasets
spamTrain <- dplyr::filter(.data = spamD, rgroup >= 10)
spamTest <- dplyr::filter(.data = spamD, rgroup < 10)</pre>
# training the model
spamModel <- stats::glm(formula = spam =="spam" ~ .,</pre>
          family = stats::binomial(link = "logit"),
           data = dplyr::select(spamTrain, -rgroup))
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
# looking at the result
broom::tidy(spamModel)
## # A tibble: 58 x 5
##
     term
                       estimate std.error statistic p.value
##
     <chr>>
                        <dbl>
                                 0.151
                                           -10.7 1.24e-26
## 1 (Intercept)
                        -1.62
                        -0.327 0.237
## 2 word.freq.make
                                            -1.38 1.68e- 1
## 3 word.freq.address -0.155 0.0771
                                            -2.00 4.51e- 2
## 4 word.freq.all
                        0.149 0.123
                                             1.22 2.23e- 1
## 5 word.freq.3d
                         2.19 1.56
                                             1.40 1.60e- 1
                         0.476 0.102
                                            4.68 2.91e- 6
## 6 word.freq.our
## 7 word.freq.over
                        0.744 0.252
                                             2.95 3.13e- 3
## 8 word.freq.remove
                        2.34 0.349
                                              6.70 2.08e-11
## 9 word.freq.internet
                          0.801 0.220
                                              3.63 2.83e- 4
## 10 word.freq.order
                          0.645
                                 0.300
                                              2.15 3.14e- 2
## # ... with 48 more rows
# looking at the model summary
broom::glance(spamModel)
## # A tibble: 1 x 7
                                       BIC deviance df.residual
   null.deviance df.null logLik
                                  AIC
##
            <dbl> <int> <dbl> <dbl> <dbl> <dbl>
                                              <dbl>
                    4142 -807. 1730. 2097.
                                                          4085
## 1
            5556.
                                              1614.
# with predicted response on training data
spamTrain <- broom::augment(</pre>
 x = spamModel,
 newdata = spamTrain,
 type.predict = "response"
# with predicted response on test data
spamTest <- broom::augment(</pre>
 x = spamModel,
 newdata = spamTest,
 type.predict = "response"
)
# performance with the training data
table(y = spamTrain$spam, glmPred = spamTrain$.fitted > 0.5)
##
            glmPred
## y
            FALSE TRUE
##
    non-spam 2396 114
##
    spam
               178 1455
# performance with the test data
table(y = spamTest$spam, glmPred = spamTest$.fitted > 0.5)
##
            glmPred
## y
            FALSE TRUE
    non-spam 264
               22 158
##
    spam
```

Looking at actual and predicted sample responses

```
sample <- spamTest[c(7,35,224,327), c('spam', '.fitted')]</pre>
print(sample)
## # A tibble: 4 x 2
##
     spam
             .fitted
##
     <chr>
                 <dbl>
## 1 spam
              0.990
              0.480
## 2 spam
## 3 non-spam 0.000685
## 4 non-spam 0.000143
Spam confusion matrix
# performance with the test data
(cM <- table(truth = spamTest$spam, prediction = spamTest$.fitted > 0.5))
             prediction
              FALSE TRUE
## truth
##
     non-spam
                264
                      14
                 22 158
##
     spam
Entering data by hand (example of a good spam filter)
t \leftarrow as.table(matrix(data = c(288 - 1, 17, 1, 13882 - 17), nrow = 2, ncol = 2))
rownames(t) <- rownames(cM)</pre>
colnames(t) <- colnames(cM)</pre>
print(t)
            FALSE TRUE
## non-spam 287
## spam
              17 13865
```