

Binary Classification with CARET package in R

Abstract

This R script can be easily reused to perform binary classification by CARET package in R. Machine Learning algorithms' plots, results and resampling plots are exported as output files. Few guided adjustments are required to easily reuse the script with any dataset.

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1 Introduction: Script overview

This R script can be easily reused to perform binary classification by CARET package in R. Machine Learning algorithms' plots, results and resampling plots are exported. Few guided adjustments are required to easily reuse the script with any dataset. The sample dataset is [Heart Disease UCI](#).

The R script consists of 6 chunks of code which are summarized in the table below:

Chunk	Description	Line of code
Input actions	This chunk loads libraries, imports the dataset, creates folders to save plots of interest, defines a function to plot confusion matrices, and requires few adjustments by the user to make the script suitable for any dataset.	1 - 131
ML algorithms with CARET	This chunk implements 9 Machine Learning algorithms using CARET package . It splits data into training and testing, fits and trains models, exports models' plots for variables' importance and confusion matrices with performance indicators as image file.	134 - 828
Models' resampling	This chunk resamples models, saves models' performances indicator in a dataframe which is exported as excel file, stores models' timings in order to study how script's total elapsed time is distributed.	832 - 925
Models' performances plots	This chunk creates a bar plot for each and every indicator taken into account in order to compare models' performances.	928 - 1078
Models' time elapsed plot	This chunk creates a bar chart to visualize how script's total elapsed time is distributed.	1080 - 1110
Main information storage	This chunk exports main algorithms' information in a <i>txt</i> file.	1113 - 1289

Table 1: Summary of code chunks

Following sections report details about main above mentioned code chunks.

Output files are organized as follows:

1. *figs* folder: it contains image files for confusion matrices, ROC curves, variables' importance and models' performances indicators;
2. *Console Output.txt* file: it contains total elapsed time and models' elapsed time information. It also provides models' details about classification performances and parameters' tuning;
3. *Models' Results.xlsx* file: it tables models' performance indicators which are taken into account;
4. *Time Elapsed.png* file: it plots how total elapsed time is distributed among ML algorithms.

2 Input actions

The first part of Input actions chunk sets the working directory, creates folders where to save exported plots and loads required libraries as shown in figure 1 below.

The user has to customize its own working directory on line 2 of the script.

```
1 #Set Working Directory
2 setwd("C:/Users/utente/Documents/R/GitHub_Projects/Binary_Classification_with_CARET")
3
4 library(tictoc)
5 tic("Since Star_Time")
6
7 dir.create("figs") #save plots
8 dir.create("figs/Confusion Matrices") #save Confusion Matrices' plots
9 dir.create("figs/ROC Curves") # Save ROC Curves plots
10 dir.create("figs/Models' Performances") # Save Models' Performances plots
11 dir.create("figs/Variables' Importance") # Save Variables' Importance plots
12
13 #Import packages
14 library(caret)
15 library(tidyverse)
16 library(readxl)
17 library(writexl)
18 library(dplyr)
19 library(ggplot2)
20 library(forcats)
21 library(usefun)
22 library(MLeval)
23 library(plotROC)
```

Figure 1: Set working directory and load libraries

The second part imports the case study's dataset, defines a percentage to split data into training and testing datasets, renames the target variable's column, renames target variable's outcomes as positive and negative, and sets values for the number of variables to plot and the length of the parameters' tuning grid. Related code is shown in figure 2. The user has to:

1. import its own preprocessed dataset by modifying line 25;
2. define a proportion by modifying the number on line 29;
3. rename target variable by changing the number of the column on line 32;
4. replace target variable's outcomes on lines 36 - 37;
5. set up the number of variables to display in variables' importance plots on line 45;
6. set up the value of tunelength for algorithms on line 48;

Lines of code in figure 3 coerce character columns as factors and remaining ones as numeric, then they scale and center numeric variables. The loop verifies mean and standard deviation of standardized numeric variables. The script assumes that the input dataset consists of character and numeric columns only. If it is not, the user has to modify lines 51 - 58 consequently.

If the user's dataset has just one character column, keep the code as it is.

If it has more than one character column, comment line 53 and uncomment line 54.

If the users needs, it can uncomment line 42 and replace the whole dataset with a sample of observation to test preliminary either how long the script will take to run or sampling methods for unbalanced datasets.

```

24 #Import Dataset
25 data <- read_excel("heart disease.xlsx")
26 data <- as.data.frame(data)
27
28 #Define proportion for training dataset
29 proportion <- 0.7
30
31 #Rename Target Variable
32 names(data)[14] <- "Y"
33
34 #Rename Target Variable's categories as positive or negative
35 data <- as.data.frame(data %>%
36   mutate(Y=case_when((Y == 1) ~ "Positive",
37     (Y == 0) ~ "Negative")))
38
39 table(data$Y) #Verify if your dataset is balanced or not
40
41 #Subsampling
42 #data <- sample_n(data, round(0.25*nrow(data),digits = 0))
43
44 #Set number of variables you want to be displayed in Variables' Importance plots
45 N <- ncol(data) - 1
46
47 #Set Tune Length for for tuning parameters
48 TuneLength <- 5

```

Figure 2: Input actions by the user

```

50 #Coherce character columns to factors
51 char_col <- which(unlist(lapply(data, is.character)))
52 char_col
53 data[,char_col] <- as.factor(data[,char_col])
54 #data[,char_col] <- lapply(data[,char_col], factor)
55
56 #Coherce remaining columns to numeric
57 data[,~char_col] <- sapply(data[,~char_col], as.numeric)
58 data <- as.data.frame(data)
59
60 str(data)
61
62 #Centering and scaling
63 numeric_col <- which(unlist(lapply(data, is.numeric)))
64 numeric_col
65
66 data <- data %>%
67   mutate_if(is.numeric, scale)
68
69 for (i in numeric_col) { #Verify if all numeric columns are standardized
70   print(
71     paste(
72       names(data)[i], "has mean", round(mean(data[,i]),digits = 2),
73       "and sd", sd(data[,i])
74     )
75   )
76 }
77 }

```

Figure 3: Coherce data and data centering - scaling

Lastly, figure 4 shows the function which generates confusion matrices' plots with related performance indicators.

```

79· ##### Plot Confusion Matrix Function #####
80· #####
81
82· # cm = confusionMatrix(...)
83
84· draw_CM <- function(cm,Title) {
85
86·   layout(matrix(c(1,1,2)))
87·   par(mar=c(2,2,2,2))
88·   plot(c(100, 345), c(300, 450),
89·         type = "n", xlab="", ylab="",
90·         xaxt='n', yaxt='n')
91·   title(Title, cex.main = 2.0)
92
93·   # create the matrix
94·   rect(150, 430, 240, 370, col='#72F069')
95·   text(195, 435, 'Negative', cex=1.8)
96·   rect(250, 430, 340, 370, col='#E84767')
97·   text(295, 435, 'Positive', cex=1.8)
98·   text(125, 370, 'Predicted', cex=1.9, srt=90, font=2)
99·   text(245, 450, 'Actual', cex=1.9, font=2)
100·   rect(150, 305, 240, 365, col='#E84767')
101·   rect(250, 305, 340, 365, col='#72F069')
102·   text(140, 400, 'Negative', cex=1.8, srt=90)
103·   text(140, 335, 'Positive', cex=1.8, srt=90)
104
105·   # add in the cm results
106·   res <- as.numeric(cm$table)
107·   text(195, 400, res[1], cex=1.8, font=2, col='black')
108·   text(195, 335, res[2], cex=1.8, font=2, col='black')
109·   text(295, 400, res[3], cex=1.8, font=2, col='black')
110·   text(295, 335, res[4], cex=1.8, font=2, col='black')
111
112·   # add in the specifics
113·   plot(c(100, 0), c(100, 0), type = "n", xlab="", ylab="",
114·         main = "DETAILS", xaxt='n', yaxt='n')
115·   text(10, 85, names(cm$byClass[1]), cex=1.6, font=2)
116·   text(10, 70, round(as.numeric(cm$byClass[1]), 5), cex=1.6)
117·   text(30, 85, names(cm$byClass[2]), cex=1.6, font=2)
118·   text(30, 70, round(as.numeric(cm$byClass[2]), 5), cex=1.6)
119·   text(50, 85, names(cm$byClass[5]), cex=1.6, font=2)
120·   text(50, 70, round(as.numeric(cm$byClass[5]), 5), cex=1.6)
121·   text(70, 85, names(cm$byClass[6]), cex=1.6, font=2)
122·   text(70, 70, round(as.numeric(cm$byClass[6]), 5), cex=1.6)
123·   text(90, 85, names(cm$byClass[7]), cex=1.6, font=2)
124·   text(90, 70, round(as.numeric(cm$byClass[7]), 5), cex=1.6)
125
126·   # add in the accuracy information
127·   text(30, 35, names(cm$overall[1]), cex=1.6, font=2)
128·   text(30, 20, round(as.numeric(cm$overall[1]), 3), cex=1.6)
129·   text(70, 35, names(cm$overall[2]), cex=1.6, font=2)
130·   text(70, 20, round(as.numeric(cm$overall[2]), 3), cex=1.6)
131· }

```

Figure 4: Confusion Matrix function

3 ML algorithms with CARET

This chunk of code implements 9 algorithms of supervised learning. ML algorithms are tabled below with related lines of code in the R script:

Algorithm	Lines of code
Naive Bayes	173 - 248
Linear SVM	250 - 321
Radial SVM	324 - 392
Polynomial SVM	395 - 466
Neural Network	468 - 537
Decision Tree (CART)	540 - 609
K-Nearest Neighbors	613 - 681
Logistic Regression	683 - 755
Random Forest	756 - 829

Table 2: Machine Learning algorithms for binary classification

Figure 5 reports the lines of code regarding data partitioning and the *trainControl()* function's settings. If the user is dealing with an unbalanced dataset, it can uncomment line 165 to use a sampling method. CARET provides 4 sampling methods among which 2 methods require a related library the user can load by uncommenting line 157 or 158 according to the choice it makes. The user can also customize the *trainControl()* parameters.

```

134- ##### ML Algorithms #####
135- #####
136
137 #Data Splitting
138 set.seed(120496)
139
140 inTrain <- createDataPartition(y = data$Y,
141                               p = proportion,
142                               list = FALSE)
143 training <- data[inTrain,]
144 dim(training)
145 table(training$Y)
146 testing <- data[-inTrain,]
147 dim(testing)
148 table(testing$Y)
149
150 # Class proportion in training dataset for target variable
151 table(training$Y)
152 prop.table(table(training$Y))
153- #####
154
155 #setup trainControl
156
157 #library(themis) #for SMOTE sampling for unbalanced datasets
158 #library(ROSE)  #for ROSE sampling for unbalanced datasets
159
160
161 fitControl <- trainControl(method = 'cv',
162                           number = 5,
163                           verboseIter = FALSE,
164                           classProbs = TRUE,
165                           #sampling = "down",
166                           savePredictions = TRUE,
167                           search = "grid")

```

Figure 5: Data partitioning and fit control

As reported in table 2, lines 173 - 829 implement 9 algorithms for binary classification. This guide reports an explanation about only the Naive Bayes algorithm being rationale and used functions equal and repetitive for each and every ML algorithm.

Figure 6 imports the library and defines a grid the user can customize in lines 175 - 177.

As a default option the code runs with the *tuneLength* option.

If the user prefers setting the grid manually, it can comment line 186 and uncomment line 187.

The chunk code also measures the algorithm's time elapsed by using *tic()/toc()* functions then it exports measurements on *Console Output.txt* file.

```

172 ##### Naive Bayes
173 library(naivebayes)
174
175 grid_NB <- expand.grid(laplace = seq(0,0.25,0.05),
176                       usekernel = c(TRUE,FALSE),
177                       adjust = seq(0.90,1.15,0.05))
178
179 tic("Naive Bayes")
180
181 #setup trainControl
182 NB <- train(Y ~ .,
183            data = training,
184            method = "naive_bayes",
185            trControl= fitControl,
186            #tuneGrid = grid_NB,
187            tuneLength = TuneLength)
188
189
190
191 ELT <- toc()
192
193 sink("./Console output.txt",append = TRUE)
194 print(paste(ELT$msg,(ELT$toc - ELT$tic), "sec elapsed"))
195 print(paste(ELT$msg,(ELT$toc - ELT$tic)/60, "min elapsed"))
196 print(paste(ELT$msg,(ELT$toc - ELT$tic)/3600, "hours elapsed"))
197 print_empty_line(html.output = FALSE)
198 print_empty_line(html.output = FALSE)
199 sink()

```

Figure 6: Algorithms' train control

Figure 7 outputs on console the algorithm's details by lines 201 - 205.

Lines 207 - 215 plot algorithm's ROC curve, export it as image file and it also store the AUC value.

Lines 217 - 288 plot and export as image file the variables' importance chart.

Lastly, code in figure 8 computes predictions on the testing dataset and outputs confusion matrix on console. Confusion matrix is also exported as image file.

```

201 NB
202 summary(NB)
203 NB$finalModel
204 NB$results
205 NB$bestTune
206
207 #ROC and AUC
208 x <- evalm(NB)
209 x$roc
210 ggsave(paste("ROC curve of ",NB$modelInfo$label,".png"),
211         path = "./figs/ROC Curves")
212 x$stdres
213 y<- as.data.frame(x$stdres)
214 auc_NB <- y[13,1]
215 auc_NB
216
217 #Variables' Importance
218 VarImp_NB <- varImp(NB, scale = TRUE)
219 VarImp_NB
220 CM <- plot(VarImp_NB,
221            main = paste("Variables' Importance in", NB$modelInfo$label),
222            type = "b", cex=1.3,top = N)
223 CM
224
225 png(filename = paste("./figs/Variables' Importance/",NB$modelInfo$label,".png"),
226      width = 490, height = 580, units = "px", pointsize = 15)
227 CM
228 dev.off()

```

Figure 7: Algorithms' details and ROC/AUC

```

230 #Prediction
231 prediction_NB <- predict(NB,testing)
232 prediction_NB
233
234 #Confusion matrix
235 confusion_matrix_NB <- confusionMatrix(prediction_NB,
236                                       testing$Y,
237                                       positive = "Positive")
238 confusion_matrix_NB
239
240
241 draw_CM(confusion_matrix_NB,paste("Confusion Matrix in", NB$modelInfo$label))
242
243
244 png(filename = paste("./figs/Confusion Matrices/", NB$modelInfo$label,".png"),
245      width = 900, height = 900, units = "px", pointsize = 25)
246 draw_CM(confusion_matrix_NB,paste("Confusion Matrix in", NB$modelInfo$label))
247 dev.off()

```

Figure 8: Algorithms' prediction