BostonHousingExample_Classification

STAT380

2023-10-12

#Loading the BostonHousing Datya

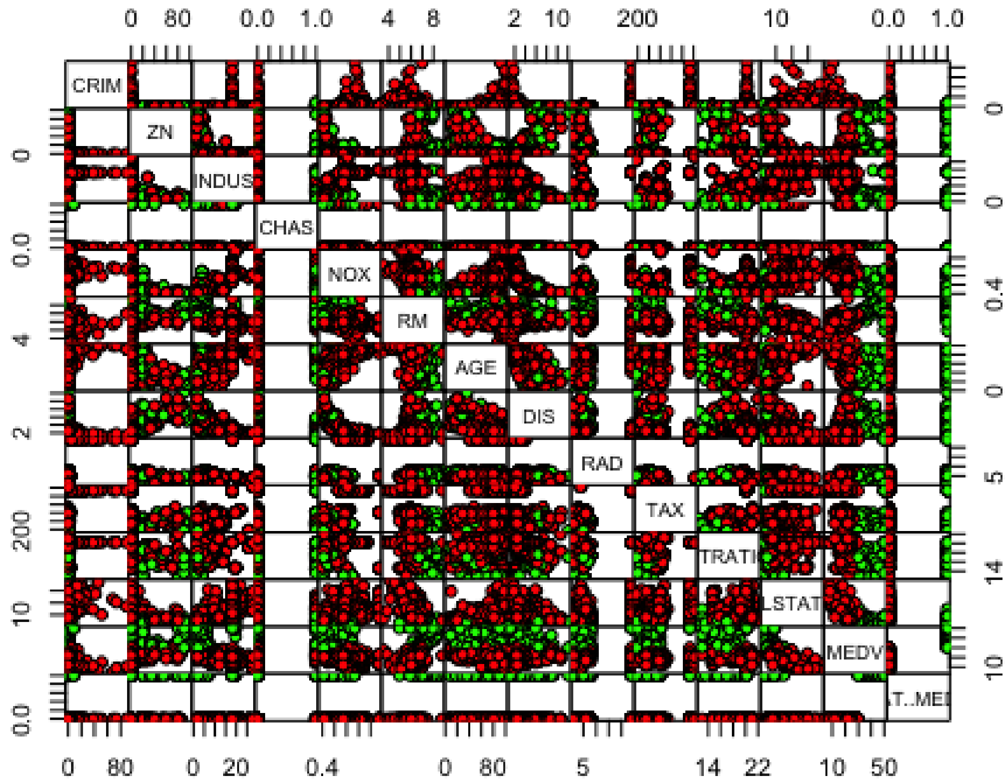
```
### Example 2: Boston data with binary classifier
BostonH<-
read.csv(url("https://raw.githubusercontent.com/subhadippal2019/STAT380UAEU/m
ain/BostonHousing.csv"))
set.seed(12)
attach(BostonH)
library(caret)
```

```
## Loading required package: lattice

## Loading required package: ggplot2
```

```
inTrain = createDataPartition(BostonH$CRIM, p = 0.8, list = FALSE)
train = BostonH[inTrain, ]
vali = BostonH[-inTrain,]
```

```
# Creating scatter plot for the numerical variables:
pairs(BostonH,
             gap = 0,
             bg = c("red", "green", "blue")[as.factor(CAT..MEDV)],
             pch = 21)
```




```
#Discriminant analysis with one predictor: CRIM
library(MASS)
formulas = as.factor(CAT..MEDV) ~ CRIM
MEDV_lda.1 = lda(formulas, train)
p  = predict(MEDV_lda.1, train)
#ldahist(data = p$x[,1], g = train$CAT..MEDV)
###Discriminant analysis density plots
#p.df = data.frame(LD1 = p$x, class = p$class)
#print(p.df) # Not necessary
#ggplot(p.df) + geom_density(aes(LD1, fill = class), alpha = 0.2)

#### Note: Clearly, based on the histograms and density plots, the prediction
was not good.

#Discriminant analysis with all predictors
formulas = as.factor(CAT..MEDV) ~ CRIM + INDUS + NOX + RM + AGE + DIS +
PTRATIO + LSTAT + MEDV
MEDV_lda = lda(formulas, train)
MEDV_lda

## Call:
## lda(formulas, data = train)
##
```

```
## Prior probabilities of groups:
##         0         1 
## 0.8349754 0.1650246 
## 
## Group means:
##        CRIM     INDUS       NOX       RM      AGE      DIS  PTRATIO
LSTAT
## 0 4.1644690 12.292802 0.5647018 6.067617 70.64307 3.702458 18.86460
14.281003
## 1 0.7836348  5.551493 0.4981940 7.305507 57.77463 4.273193 16.35821
5.148209
##       MEDV
## 0 19.27404
## 1 39.17463
## 
## Coefficients of linear discriminants:
##                  LD1
## CRIM     0.034964242
## INDUS   -0.045230244
## NOX      1.972884240
## RM       0.587544779
## AGE      0.004018909
## DIS      0.032399356
## PTRATIO -0.025705505
## LSTAT    0.072827463
## MEDV     0.202243942
```

```
p  = predict(MEDV_lda, train)
#ldahist(data = p$x[,1], g = train$CAT..MEDV)
#ggord(MEDV_lda, train$CAT..MEDV, ylim =c(-10,10) )
###Discriminant analysis density plots
p.df = data.frame(LD1 = p$x, class = p$class)
print(p.df)
```

```
##              LD1 class
## 1    0.223550574     0
## 2   -0.380832844     0
## 3    2.273761394     1
## 4    1.972099516     1
## 5    2.835025688     1
## 6    0.904901711     0
## 8    1.558457816     0
## 9   -0.095840381     0
## 10  -0.367260541     0
## 11  -0.665159889     0
## 12  -0.668985523     0
## 13  -0.197902681     0
## 14  -1.015529854     0
## 15  -1.144883857     0
## 16  -1.197077016     0
```

```
## 17  -0.722598963     0
## 18  -1.040314495     0
## 19  -1.220585278     0
## 20  -1.366174777     0
## 23  -1.074459237     0
## 25  -1.291408400     0
## 26  -1.839701689     0
## 27  -1.271756573     0
## 28  -1.321936264     0
## 32  -1.626768485     0
## 33  -0.970158175     0
## 35  -1.300157433     0
## 36  -1.194654951     0
## 37  -0.925844316     0
## 38  -0.973134384     0
## 39  -0.102541974     0
## 40   1.108216243     0
## 41   1.995151785     1
## 42   0.208004136     0
## 43  -0.322023201     0
## 44  -0.299761351     0
## 45  -0.804029244     0
## 46  -1.410923668     0
## 47  -0.922725208     0
## 49  -0.792968164     0
## 50  -0.854454711     0
## 51  -0.760526480     0
## 52  -0.734249771     0
## 53  -0.061752877     0
## 54  -0.456273990     0
## 55  -0.940269393     0
## 56   2.604352826     1
## 57   0.124016402     0
## 59  -0.460917834     0
## 62  -1.264098990     0
## 63  -0.375635083     0
## 64   0.499149291     0
## 65   2.438734977     1
## 66  -0.520079600     0
## 67  -1.185436362     0
## 70  -1.095577694     0
## 71  -0.627283354     0
## 72  -1.124407758     0
## 73  -1.199692722     0
## 75  -0.795203433     0
## 76  -1.010878720     0
## 77  -0.973276570     0
## 78  -1.131564207     0
## 79  -0.785256490     0
## 81   0.629282660     0
```

```
## 83  -0.168844534     0
## 84  -0.516656453     0
## 85   0.030274780     0
## 87  -0.259668292     0
## 89   0.288558758     0
## 91  -0.111473264     0
## 94  -0.653657127     0
## 95  -1.008857267     0
## 96   0.940341381     0
## 99   4.447305804     1
## 100  2.359379975     1
## 101  0.903453684     0
## 102  0.572262679     0
## 103 -0.974725355     0
## 104 -0.778533243     0
## 105 -0.681534532     0
## 107 -0.534423446     0
## 108 -0.545446766     0
## 109 -0.537686195     0
## 110 -0.538993019     0
## 111 -0.425318962     0
## 112  0.069030527     0
## 114 -0.566010023     0
## 116 -0.873587805     0
## 117 -0.468123852     0
## 118 -1.048571166     0
## 119 -0.571824863     0
## 120 -1.027440039     0
## 122 -1.235271165     0
## 124 -1.071262056     0
## 125 -1.329253113     0
## 126 -0.969991695     0
## 127 -1.406301095     0
## 128 -1.792497147     0
## 129 -1.111584997     0
## 130 -2.103177173     0
## 132 -1.036870716     0
## 133 -0.423686047     0
## 134 -1.406931539     0
## 136 -1.018051701     0
## 137 -1.426666598     0
## 138 -1.337811515     0
## 140 -1.093581742     0
## 141 -1.461467878     0
## 142 -1.245797830     0
## 143 -0.960957780     0
## 144 -0.476894770     0
## 146 -0.411311474     0
## 147 -1.158929262     0
## 148 -0.847233796     0
```

```
## 149 -0.142135324     0
## 150 -0.867980219     0
## 151  0.113853402     0
## 152 -0.747594117     0
## 153 -1.992592440     0
## 154 -0.408222604     0
## 155 -0.727302389     0
## 156 -0.984028112     0
## 159 -0.431746012     0
## 161  0.123857198     0
## 163  5.476562121     1
## 164  5.890827466     1
## 165 -0.480432898     0
## 167  5.679112242     1
## 168 -0.274006190     0
## 169 -0.015205028     0
## 171 -1.361605320     0
## 172 -1.141305772     0
## 173  0.041902873     0
## 174  0.209724813     0
## 175 -0.336430478     0
## 176  0.998833334     0
## 178  0.129783122     0
## 179  1.559182625     0
## 180  2.899419174     1
## 181  4.167503487     1
## 182  2.535328675     1
## 184  1.902040944     1
## 185  0.690026399     0
## 187  5.937815281     1
## 188  1.735041220     0
## 189  0.981552953     0
## 192  1.306945558     0
## 195  0.805099905     0
## 196  5.894599677     1
## 197  2.278463568     1
## 198  1.906158376     1
## 199  2.735518822     1
## 201  1.951585374     1
## 202 -0.071123355     0
## 203  4.054194012     1
## 204  5.508102499     1
## 205  5.844335082     1
## 206 -0.761071031     0
## 207  0.003732497     0
## 208 -0.101259429     0
## 209  0.138024953     0
## 210 -0.397887906     0
## 211 -0.156817207     0
## 212 -0.494104373     0
```

```
## 214  0.567461850     0
## 215  0.483902347     0
## 216 -0.123734616     0
## 217 -0.296096757     0
## 219 -0.154979410     0
## 220 -0.134194081     0
## 221  1.110057159     0
## 222  0.511186267     0
## 223  1.224745565     0
## 224  1.439691474     0
## 225  5.090297793     1
## 226  6.473622110     1
## 227  3.473501480     1
## 228  1.954526278     1
## 229  4.886379225     1
## 231  0.140626592     0
## 232  2.044690229     1
## 233  4.408933792     1
## 235  1.262453521     0
## 236  0.057105426     0
## 237  0.585201575     0
## 238  1.936409172     1
## 239 -0.277773750     0
## 240 -0.116071907     0
## 242 -0.599920448     0
## 243 -0.133103464     0
## 244 -0.428713318     0
## 245 -1.391845606     0
## 246 -0.794558691     0
## 247 -0.136720133     0
## 248 -0.590788946     0
## 249  0.164413525     0
## 250  0.334032629     0
## 251 -0.247569018     0
## 252 -0.377590090     0
## 253  0.929619160     0
## 254  4.381406328     1
## 255 -0.701968243     0
## 256 -0.897633296     0
## 257  4.232546528     1
## 258  6.976265853     1
## 259  3.591273475     1
## 260  2.048254997     1
## 261  3.130633541     1
## 262  5.059297646     1
## 263  6.642404052     1
## 264  2.818030944     1
## 265  3.603778770     1
## 268  6.703017113     1
## 269  4.546227746     1
```

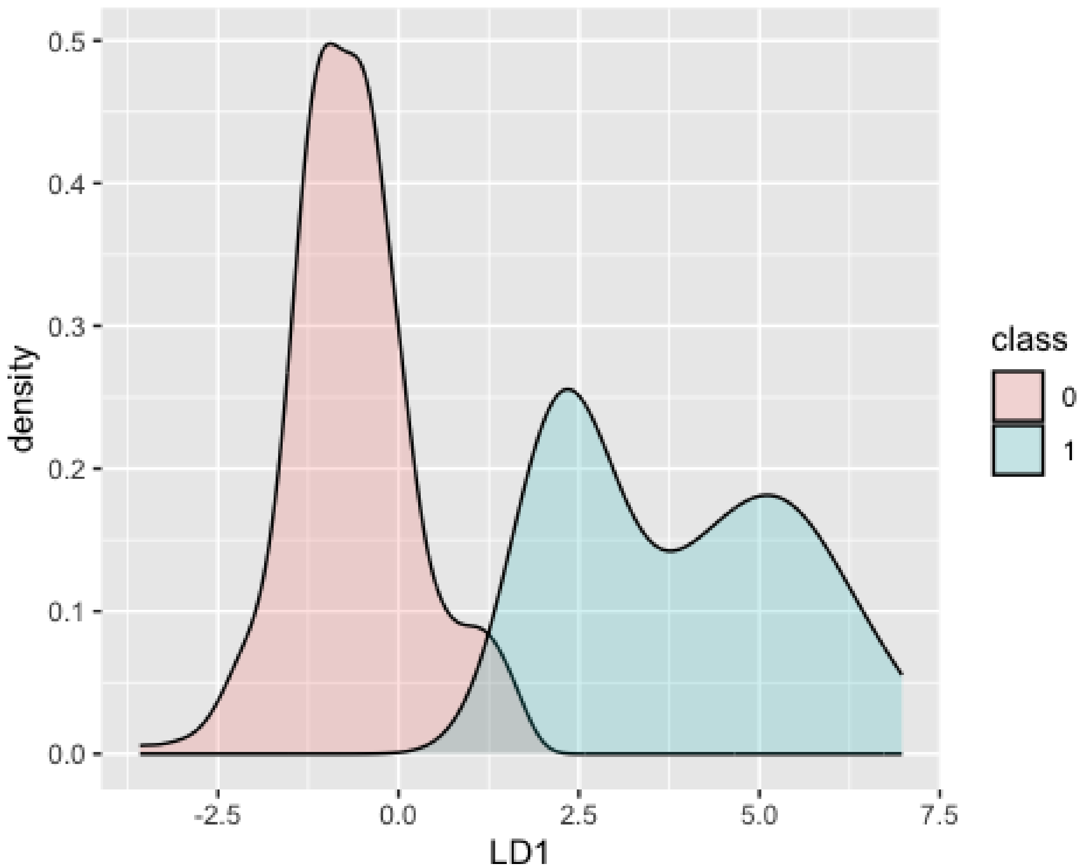
```
## 270 -0.655934715     0
## 272 -0.234568410     0
## 273  0.013916413     0
## 275  1.371761327     0
## 276  1.354530886     0
## 277  2.105524025     1
## 278  1.603475067     0
## 280  2.249622414     1
## 281  4.988549448     1
## 282  2.434116499     1
## 284  5.860621696     1
## 285  2.016160892     1
## 286 -0.336603447     0
## 287 -0.513446341     0
## 288 -0.458481769     0
## 289 -0.486999144     0
## 290  0.213265679     0
## 291  0.595667778     0
## 292  2.561519190     1
## 293  0.420326612     0
## 294 -0.679738863     0
## 295 -0.965430986     0
## 296  0.493814512     0
## 297  0.273555075     0
## 298 -0.889422258     0
## 299 -0.530028743     0
## 300  1.135830324     0
## 301  0.433290889     0
## 302 -0.294870635     0
## 304  1.753465753     0
## 306  1.170997167     0
## 307  2.522842198     1
## 308  1.208258901     0
## 309 -0.365566542     0
## 311 -2.237790203     0
## 312 -0.834579257     0
## 314 -0.588747598     0
## 315  0.166116756     0
## 316 -1.747245371     0
## 317 -0.777343490     0
## 318 -0.672168327     0
## 319 -0.087390149     0
## 321 -0.203008442     0
## 323 -1.077802336     0
## 324 -1.267784202     0
## 325 -0.082542545     0
## 326 -0.314566900     0
## 327 -0.569178782     0
## 328 -0.324650649     0
## 330 -0.421323175     0
```

```
## 332 -1.611891915     0
## 334 -0.573901354     0
## 335 -0.801729856     0
## 338 -1.155795314     0
## 339 -0.899561212     0
## 340 -1.143732823     0
## 341 -1.194290250     0
## 343 -1.033371966     0
## 344  0.220997397     0
## 345  1.524994806     0
## 346 -1.329026520     0
## 347 -1.285666212     0
## 348 -0.263985938     0
## 350  0.779076711     0
## 351 -0.185533794     0
## 353 -1.340422811     0
## 354  1.372867756     0
## 355 -1.624749564     0
## 357 -0.327476588     0
## 359 -0.001142007     0
## 362 -0.327826216     0
## 363 -0.950710857     0
## 364 -1.192851054     0
## 365  0.753514656     0
## 366 -0.998574105     0
## 367 -0.817808011     0
## 368 -1.071585753     0
## 369  3.978514564     1
## 370  5.034115238     1
## 371  5.201880753     1
## 372  5.313467320     1
## 373  5.061954745     1
## 374 -0.800534008     0
## 375 -0.761536527     0
## 377 -0.465250145     0
## 378 -0.815591462     0
## 379 -0.447024739     0
## 380 -1.451751068     0
## 381  1.148318626     0
## 382 -1.240934037     0
## 383 -1.740349607     0
## 384 -1.520890692     0
## 385 -2.079130055     0
## 386 -1.942678354     0
## 387 -1.552675888     0
## 388 -1.808336591     0
## 389 -1.656753929     0
## 390 -2.021791075     0
## 391 -1.419111638     0
## 392  0.429004710     0
```

```
## 393 -2.128549683     0
## 394 -1.518338387     0
## 395 -1.661656344     0
## 396 -1.329245991     0
## 397 -1.437808573     0
## 398 -2.520150411     0
## 400 -2.182108686     0
## 401 -1.856331647     0
## 403 -1.305789989     0
## 404 -2.215846184     0
## 405 -0.975074227     0
## 406 -0.938520374     0
## 407 -2.150139457     0
## 408  0.830063478     0
## 409 -0.573667497     0
## 411 -0.586565529     0
## 412 -0.096668129     0
## 413 -0.022248963     0
## 414 -0.731541471     0
## 415 -0.966129140     0
## 416 -1.367119157     0
## 417 -1.630369095     0
## 418 -1.334570510     0
## 420 -1.592952002     0
## 421 -0.648009786     0
## 424 -1.295029266     0
## 425 -2.456587843     0
## 427 -2.632334920     0
## 428 -1.213493641     0
## 429 -1.748055194     0
## 430 -1.614783006     0
## 431 -1.343845805     0
## 432 -0.901482829     0
## 434 -1.267528283     0
## 435 -1.686956300     0
## 437 -1.696214970     0
## 438 -1.397525625     0
## 439 -1.138468405     0
## 440 -1.366761631     0
## 441 -1.337555849     0
## 442 -0.251159048     0
## 443 -0.444076250     0
## 444 -0.580434258     0
## 449 -1.143655505     0
## 450 -1.211009726     0
## 452 -0.809088207     0
## 453 -0.908481550     0
## 454  0.183977519     0
## 455 -0.625020639     0
## 457 -1.681516998     0
```

```
## 459 -1.150598423     0
## 460 -0.392405441     0
## 462 -0.785350360     0
## 463 -0.416766787     0
## 464 -0.428743290     0
## 467 -0.706055927     0
## 468 -0.440964013     0
## 469 -0.418963389     0
## 471 -0.585817137     0
## 472 -0.935621303     0
## 473  0.031786351     0
## 475 -1.955794220     0
## 476 -1.248366253     0
## 477 -0.772345788     0
## 478 -1.599282370     0
## 479 -1.224516691     0
## 481 -0.427009248     0
## 482 -0.171502106     0
## 483  0.232776894     0
## 484 -1.156338813     0
## 485 -1.042790322     0
## 486 -0.769195918     0
## 487 -0.821556657     0
## 488 -1.047656104     0
## 489 -2.353710992     0
## 490 -3.583682384     0
## 491 -3.132157255     0
## 492 -2.341294829     0
## 493 -1.423914873     0
## 494 -0.655243936     0
## 495  0.092454143     0
## 496 -0.094531071     0
## 497 -0.507762508     0
## 498 -1.073177928     0
## 500 -1.301820773     0
## 501 -1.200643492     0
## 502 -0.295054243     0
## 503 -0.956225010     0
## 504  0.017715931     0
## 505 -0.410257264     0
## 506 -2.832420084     0
```

```
ggplot(p.df) + geom_density(aes(LD1, fill = class), alpha = 0.2)
```




```
#####################################################################
# Classifier Performance
####################################################################

## Run logit model: Medianvalue0 /1 ~ LowerPopul.+ Numberofrooms+Teacher
/Pupilratio

fit = glm(CAT..MEDV~LSTAT+RM+PTRATIO,data=train,family = "binomial")
summary(fit)

##
## Call:
## glm(formula = CAT..MEDV ~ LSTAT + RM + PTRATIO, family = "binomial",
##     data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.0326  -0.1810  -0.0442  -0.0038   3.2965
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -11.7543     5.0132  -2.345 0.019043 *
## LSTAT        -0.4110     0.1100  -3.736 0.000187 ***
```

```
## RM            2.8482     0.5976   4.766 1.88e-06 ***
## PTRATIO      -0.3213     0.1164  -2.761 0.005759 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 363.70  on 405  degrees of freedom
## Residual deviance: 130.07  on 402  degrees of freedom
## AIC: 138.07
##
## Number of Fisher Scoring iterations: 8
```

```
#Create predictions-training vs.validation set
pred_t = predict(fit,newdata = train,type ="response")
pred_v = predict(fit,newdata = vali,type ="response")

#Evaluate performance-training vs.validation set
#Training-logit model
confusionMatrix(as.factor(ifelse(pred_t > 0.5,1,0)),
as.factor(train$CAT..MEDV))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 330  10
##          1   9  57
##
##                Accuracy : 0.9532
##                  95% CI : (0.9279, 0.9716)
##     No Information Rate : 0.835
##     P-Value [Acc > NIR] : 1.712e-13
##
##                   Kappa : 0.8292
##
##  Mcnemar's Test P-Value : 1
##
##             Sensitivity : 0.9735
##             Specificity : 0.8507
##          Pos Pred Value : 0.9706
##          Neg Pred Value : 0.8636
##              Prevalence : 0.8350
##          Detection Rate : 0.8128
##    Detection Prevalence : 0.8374
##       Balanced Accuracy : 0.9121
##
##        'Positive' Class : 0
##
```

```r
#Or
pred_t_c = ifelse(pred_t > 0.5,1,0); head(pred_t_c); length(pred_t_c)

## 1 2 3 4 5 6
## 1 0 1 1 1 0

## [1] 406

confusionMatrix(as.factor(train$CAT..MEDV), as.factor(pred_t_c))

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 330   9
##          1  10  57
##
##                Accuracy : 0.9532
##                  95% CI : (0.9279, 0.9716)
##     No Information Rate : 0.8374
##     P-Value [Acc > NIR] : 4.045e-13
##
##                   Kappa : 0.8292
##
##  Mcnemar's Test P-Value : 1
##
##             Sensitivity : 0.9706
##             Specificity : 0.8636
##          Pos Pred Value : 0.9735
##          Neg Pred Value : 0.8507
##              Prevalence : 0.8374
##          Detection Rate : 0.8128
##    Detection Prevalence : 0.8350
##       Balanced Accuracy : 0.9171
##
##        'Positive' Class : 0
##

#Validation-logit model
confusionMatrix(as.factor(ifelse(pred_v>0.5,1,0)), as.factor(vali$CAT..MEDV))

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 82  2
##          1  1 15
##
##                Accuracy : 0.97
##                  95% CI : (0.9148, 0.9938)
##     No Information Rate : 0.83
```

```
##     P-Value [Acc > NIR] : 1.309e-05
##
##                   Kappa : 0.8911
##
##  Mcnemar's Test P-Value : 1
##
##             Sensitivity : 0.9880
##             Specificity : 0.8824
##          Pos Pred Value : 0.9762
##          Neg Pred Value : 0.9375
##              Prevalence : 0.8300
##          Detection Rate : 0.8200
##    Detection Prevalence : 0.8400
##       Balanced Accuracy : 0.9352
##
##        'Positive' Class : 0
##
```

```r
## Validation

#Naive benchmark:the average
y_fit_naive = median(train$CAT..MEDV)
#Create predictions
pred_v_reg = predict(fit,newdata = vali,type ="response")
pred_v_naiv = rep(y_fit_naive,length(vali$MEDV))

#Evaluate performance-validation set
#Validation-logit model vs naive benchmark
confusionMatrix(as.factor(ifelse(pred_v_reg > 0.5, 1,0)),
as.factor(vali$CAT..MEDV))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 82  2
##          1  1 15
##
##                Accuracy : 0.97
##                  95% CI : (0.9148, 0.9938)
##     No Information Rate : 0.83
##     P-Value [Acc > NIR] : 1.309e-05
##
##                   Kappa : 0.8911
##
##  Mcnemar's Test P-Value : 1
##
##             Sensitivity : 0.9880
##             Specificity : 0.8824
##          Pos Pred Value : 0.9762
```

```
##          Neg Pred Value : 0.9375
##              Prevalence : 0.8300
##          Detection Rate : 0.8200
##    Detection Prevalence : 0.8400
##       Balanced Accuracy : 0.9352
##
##        'Positive' Class : 0
##
```

```
confusionMatrix(as.factor(ifelse(pred_v_naiv > 0.5, 1,0)),
as.factor(vali$CAT..MEDV))
```

```
## Warning in confusionMatrix.default(as.factor(ifelse(pred_v_naiv > 0.5, 1,
:
## Levels are not in the same order for reference and data. Refactoring data
to
## match.
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 83 17
##          1  0  0
##
##                Accuracy : 0.83
##                  95% CI : (0.7418, 0.8977)
##     No Information Rate : 0.83
##     P-Value [Acc > NIR] : 0.5643017
##
##                   Kappa : 0
##
##  Mcnemar's Test P-Value : 0.0001042
##
##             Sensitivity : 1.00
##             Specificity : 0.00
##          Pos Pred Value : 0.83
##          Neg Pred Value :  NaN
##              Prevalence : 0.83
##          Detection Rate : 0.83
##    Detection Prevalence : 1.00
##       Balanced Accuracy : 0.50
##
##        'Positive' Class : 0
##
```

```
## We check the overall classification accuracy

predicted.classes = as.factor(ifelse(pred_v_reg > 0.5, 1, 0))
observed.classes  = as.factor(vali$CAT..MEDV)
#Estimated accuracy-logit model
```

```r
accuracy = mean (observed.classes == predicted.classes)
accuracy

## [1] 0.97

#Estimated miss-classification rate-logit model
error <-mean (observed.classes != predicted.classes)
error

## [1] 0.03

#Confusion matrix, proportion of cases-logit model
table(observed.classes, predicted.classes)

##                  predicted.classes
## observed.classes  0  1
##                 0 82  1
##                 1  2 15

prop.table(table(observed.classes, predicted.classes))

##                  predicted.classes
## observed.classes    0    1
##                 0 0.82 0.01
##                 1 0.02 0.15

## We check the graphical representation of the logit accuracy
#Compute the receiver operating characteristics curve (roc)-logit model using
library(pROC)

#library(pROC)
#res.roc = roc(observed.classes, pred_v_reg)
#plot.roc(res.roc, print.auc = TRUE)

#### we repeat the same functions with the Iris data example:

### Confusion matrix and accuracy - training data
data("iris")
str(iris)

## 'data.frame':    150 obs. of  5 variables:
##  $ Sepal.Length: num  5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
##  $ Sepal.Width : num  3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
##  $ Petal.Length: num  1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
##  $ Petal.Width : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
##  $ Species     : Factor w/ 3 levels "setosa","versicolor",..: 1 1 1 1 1 1
1 1 1 1 ...

head(iris)

##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1          5.1         3.5          1.4         0.2  setosa
```

```
## 2          4.9         3.0          1.4         0.2  setosa
## 3          4.7         3.2          1.3         0.2  setosa
## 4          4.6         3.1          1.5         0.2  setosa
## 5          5.0         3.6          1.4         0.2  setosa
## 6          5.4         3.9          1.7         0.4  setosa

set.seed(134)
ind = sample(2, nrow(iris), replace = TRUE, prob = c(0.6, 0.4))
training = iris[ind==1,]
testing = iris[ind==2,]

iris_lda = lda(Species~., training)

p1 = predict(iris_lda, training)$class
tab = table(Predicted = p1, Actual = training$Species)
tab

##             Actual
## Predicted    setosa versicolor virginica
##   setosa         33          0         0
##   versicolor      0         34         0
##   virginica       0          0        31

p2 = predict(iris_lda, testing)$class
tab1 = table(Predicted = p2, Actual = testing$Species)
tab1

##             Actual
## Predicted    setosa versicolor virginica
##   setosa         17          0         0
##   versicolor      0         14         0
##   virginica       0          2        19

n = sum(tab) # number of instances
nc = nrow(tab) # number of classes
diag = diag(tab) # number of correctly classified instances per class
rowsums = apply(tab, 1, sum) # number of instances per class
colsums = apply(tab, 2, sum) # number of predictions per class
p = rowsums / n # distribution of instances over the actual classes
q = colsums / n # distribution of instances over the predicted classes

n = sum(tab1) # number of instances
nc = nrow(tab1) # number of classes
diag = diag(tab1) # number of correctly classified instances per class
rowsums = apply(tab1, 1, sum) # number of instances per class
colsums = apply(tab1, 2, sum) # number of predictions per class
p = rowsums / n # distribution of instances over the actual classes
q = colsums / n # distribution of instances over the predicted classes

accuracy = sum(diag) / n
```