SPerveen_Homework2

Sadia Perveen

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- 1. Download the classification output data set (attached in Blackboard to the assignment).
- 2. The data set has three key columns we will use: ② class: the actual class for the observation ② scored.class: the predicted class for the observation (based on a threshold of 0.5) ② scored.probability: the predicted probability of success for the observation Use the table() function to get the raw confusion matrix for this scored dataset. Make sure you understand the output. In particular, do the rows represent the actual or predicted class? The columns?

```
cod <-
read.csv("https://raw.githubusercontent.com/sperveen/DATA621/main/classificat
ion-output-data.csv")
head(cod, 10)
      pregnant glucose diastolic skinfold insulin
##
                                                      bmi pedigree age class
## 1
                    124
                                                             0.161
                                                                    37
             7
                               70
                                         33
                                                215 25.5
             2
## 2
                    122
                               76
                                         27
                                                200 35.9
                                                             0.483 26
                                                                            0
## 3
             3
                    107
                               62
                                         13
                                                 48 22.9
                                                             0.678 23
                                                                            1
                                                  0 29.2
## 4
             1
                    91
                               64
                                                             0.192 21
                                         24
                                                                            0
## 5
             4
                    83
                               86
                                         19
                                                  0 29.3
                                                             0.317
                                                                    34
                                                                            0
## 6
             1
                    100
                               74
                                         12
                                                 46 19.5
                                                             0.149
                                                                    28
                                                                            0
             9
                    89
                               62
                                          0
                                                  0 22.5
                                                             0.142
                                                                    33
                                                                            0
## 7
             8
## 8
                    120
                               78
                                          0
                                                  0 25.0
                                                             0.409
                                                                    64
                                                                            0
## 9
             1
                    79
                                         42
                                                 48 43.5
                                                                    23
                               60
                                                             0.678
                                                                            0
## 10
                    123
                               48
                                         32
                                                165 42.1
                                                             0.520 26
                                                                            0
##
      scored.class scored.probability
## 1
                            0.32845226
## 2
                  0
                            0.27319044
## 3
                  0
                            0.10966039
                  0
## 4
                            0.05599835
## 5
                  0
                            0.10049072
                 0
## 6
                            0.05515460
## 7
                  0
                            0.10711542
## 8
                  0
                            0.45994744
                  0
## 9
                            0.11702368
## 10
                            0.31536320
confusionMatrix <- data.frame(table("scored.class" = cod$scored.class,</pre>
"class" = cod$class))
confusionMatrix
```

```
## scored.class class Freq
## 1 0 0 119
## 2 1 0 5
## 3 0 1 30
## 4 1 1 27
```

3. Write a function that takes the data set as a dataframe, with actual and predicted classifications identified, and returns the accuracy of the predictions. TP + TN Accuracy = TP + FP + TN + FN

```
accuracyPredictions <- function(confusionMatrix){
  tp <- confusionMatrix[confusionMatrix$class==1 &
confusionMatrix$scored.class==1,]$Freq
  tn <- confusionMatrix[confusionMatrix$class==0 &
confusionMatrix$scored.class==0,]$Freq
  fp <- confusionMatrix[confusionMatrix$class==0 &
confusionMatrix$scored.class==1,]$Freq
  fn <- confusionMatrix[confusionMatrix$class==1 &
confusionMatrix$scored.class==0,]$Freq
  total <- tp + tn + fp + fn
  return((tp+tn)/total)
}
accuracyPredictionsValue <- accuracyPredictions(confusionMatrix)
accuracyPredictionsValue</pre>
```

4. Write a function that takes the data set as a dataframe, with actual and predicted classifications identified, and returns the classification error rate of the predictions. *FP* + *FN Classification Error Rate* = *TP* + *FP* + *TN* + *FN* Verify that you get an accuracy and an error rate that sums to one.

```
errorRate <- function(confusionMatrix){
  tp <- confusionMatrix[confusionMatrix$class==1 &
  confusionMatrix$scored.class==1,]$Freq
  tn <- confusionMatrix[confusionMatrix$class==0 &
  confusionMatrix$scored.class==0,]$Freq
  fp <- confusionMatrix[confusionMatrix$class==0 &
  confusionMatrix$scored.class==1,]$Freq
  fn <- confusionMatrix[confusionMatrix$class==1 &
  confusionMatrix$scored.class==0,]$Freq
  total <- tp + tn + fp + fn
  return((fp+fn)/total)
}
errorRateValue <- errorRate(confusionMatrix)
errorRateValue</pre>
```

5. Write a function that takes the data set as a dataframe, with actual and predicted classifications identified, and returns the precision of the predictions. TP Precision = TP + FP

```
percision <- function(confusionMatrix){
   tp <- confusionMatrix[confusionMatrix$class==1 &
   confusionMatrix$scored.class==1,]$Freq
   fp <- confusionMatrix[confusionMatrix$class==0 &
   confusionMatrix$scored.class==1,]$Freq
   return(tp/(tp+fp))
}

percisionValue <- percision(confusionMatrix)
percisionValue
## [1] 0.84375</pre>
```

6. Write a function that takes the data set as a dataframe, with actual and predicted classifications identified, and returns the sensitivity of the predictions. Sensitivity is also known as recall. TP Sensitivity = TP + FN

```
sensitivity <- function(confusionMatrix){
  tp <- confusionMatrix[confusionMatrix$class==1 &
  confusionMatrix$scored.class==1,]$Freq
  fn <- confusionMatrix[confusionMatrix$class==1 &
  confusionMatrix$scored.class==0,]$Freq
  return(tp/(tp+fn))
}
sensitivityValue <- sensitivity(confusionMatrix)
sensitivityValue</pre>
## [1] 0.4736842
```

7. Write a function that takes the data set as a dataframe, with actual and predicted classifications identified, and returns the specificity of the predictions. TN Specificity = TN + FP

```
specificity <- function(confusionMatrix){
  tn <- confusionMatrix[confusionMatrix$class==0 &
  confusionMatrix$scored.class==0,]$Freq
  fp <- confusionMatrix[confusionMatrix$class==0 &
  confusionMatrix$scored.class==1,]$Freq
  return(tn/(tn+fp))
}

specificityValue <- specificity(confusionMatrix)
specificityValue
## [1] 0.9596774</pre>
```

8. Write a function that takes the data set as a dataframe, with actual and predicted classifications identified, and returns the F1 score of the predictions. 2 × *Precision* × *Sensitivity Precision* + *Sensitivity*

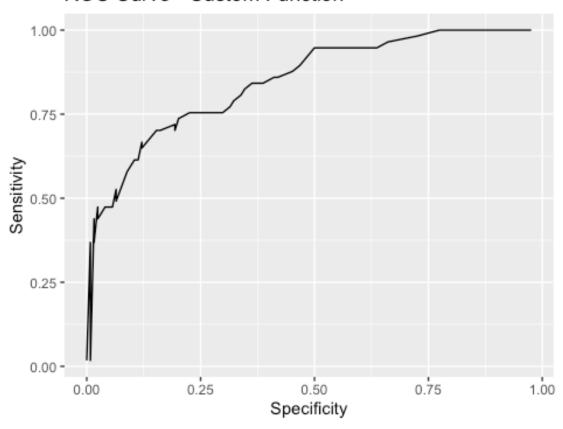
```
f1Score <- function(confusionMatrix){
  percisionValue <- percision(confusionMatrix)
  sensitivityValue <- sensitivity(confusionMatrix)
  return((2 * percisionValue * sensitivityValue)/(percisionValue +
  sensitivityValue))
}
f1ScoreValue <- f1Score(confusionMatrix)
f1ScoreValue
## [1] 0.6067416</pre>
```

- 9. Before we move on, let's consider a question that was asked: What are the bounds on the F1 score? Show that the F1 score will always be between 0 and 1. (Hint: If 0 < a < 1 and 0 < b < 1 then ab < a.)
- 10. Write a function that generates an ROC curve from a data set with a true classification column (class in our example) and a probability column (scored.probability in our example). Your function should return a list that includes the plot of the ROC curve and a vector that contains the calculated area under the curve (AUC). Note that I recommend using a sequence of thresholds ranging from 0 to 1 at 0.01 intervals.

```
rocPlot <- function(cod){</pre>
  cod2 <- cod
  thresholds \leftarrow seq(0,1,0.01)
  sensitivityPoints <- c()</pre>
  specificityPoints <- c()</pre>
  for (t in thresholds) {
    cod2$scored.class <- ifelse(cod2$scored.probability > t,1,0)
    specificityPoints <- append(specificityPoints,1-</pre>
specificity(data.frame(table("scored.class" = cod2$scored.class, "class" =
cod2$class))))
    sensitivityPoints <-
append(sensitivityPoints,sensitivity(data.frame(table("scored.class" =
cod2$scored.class, "class" = cod2$class))))
  codDf <- data.frame(X=specificityPoints,Y=sensitivityPoints)</pre>
  codDf <- na.omit(codDf)</pre>
  g <- ggplot(codDf,aes(X,Y)) + geom_line() + ggtitle('ROC Curve - Custom</pre>
Function') +
    xlab('Specificity') + ylab('Sensitivity')
  height = (codDf_{Y}[-1]+codDf_{Y}[-length(codDf_{Y})])/2
  width = -diff(codDf$X)
  area = sum(height*width)
  return(list(Plot =g,AUC = area))
}
```

```
rocPlot(cod)
## $Plot
```

ROC Curve - Custom Function



```
## ## $AUC
## [1] 0.8247029
```

11. Use your created R functions and the provided classification output data set to produce all of the classification metrics discussed above.

```
functionName <- c('Accuracy','Classification Error Rate', 'Precision',</pre>
'Sensitivity', 'Specificity', 'F1 Score')
functionValue <- c(accuracyPredictions(confusionMatrix),</pre>
errorRate(confusionMatrix), percision(confusionMatrix),
sensitivity(confusionMatrix), specificity(confusionMatrix),
f1Score(confusionMatrix))
functionOutputs <- as.data.frame(cbind(functionName, functionValue))</pre>
functionOutputs
##
                   functionName
                                     functionValue
## 1
                       Accuracy 0.806629834254144
## 2 Classification Error Rate 0.193370165745856
                      Precision
## 3
                                           0.84375
```

```
## 4 Sensitivity 0.473684210526316
## 5 Specificity 0.959677419354839
## 6 F1 Score 0.606741573033708
```

12. Investigate the caret package. In particular, consider the functions confusionMatrix, sensitivity, and specificity. Apply the functions to the data set. How do the results compare with your own functions?

```
require("caret")
## Loading required package: caret
## Loading required package: lattice
##
## Attaching package: 'caret'
## The following objects are masked by '.GlobalEnv':
##
##
       sensitivity, specificity
caret::confusionMatrix(table(cod$class,cod$scored.class))
## Confusion Matrix and Statistics
##
##
##
         0
             1
##
     0 119 5
     1 30 27
##
##
##
                  Accuracy : 0.8066
##
                    95% CI: (0.7415, 0.8615)
       No Information Rate: 0.8232
##
##
       P-Value [Acc > NIR] : 0.7559
##
##
                     Kappa: 0.4916
##
    Mcnemar's Test P-Value: 4.976e-05
##
##
##
               Sensitivity: 0.7987
               Specificity: 0.8438
##
            Pos Pred Value: 0.9597
##
##
            Neg Pred Value : 0.4737
                Prevalence: 0.8232
##
##
            Detection Rate: 0.6575
      Detection Prevalence : 0.6851
##
         Balanced Accuracy: 0.8212
##
##
          'Positive' Class : 0
##
##
```

13. Investigate the pROC package. Use it to generate an ROC curve for the data set. How do the results compare with your own functions?

```
require("pROC")
## Loading required package: pROC
## Type 'citation("pROC")' for a citation.
##
## Attaching package: 'pROC'
## The following objects are masked from 'package:stats':
##
## cov, smooth, var
plot(pROC::roc(cod$class, cod$scored.probability), main="ROC Curve - pROC")
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases</pre>
```

