POM681 Business Analytics & Data Mining
Prof. Rai

Template for Assignment 6: Classification and Prediction

Student Name:

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Overview: In this analysis you will develop logistic regression model based on the data set provided to predict whether or not the specimens are genuine.

Data Set Information: Data (A6DATA.txt) were extracted from images that were taken from genuine and forged banknote-like specimens. For digitization, an industrial camera usually used for print inspection was used. The final images have 400x 400 pixels. Due to the object lens and distance to the investigated object gray-scale pictures with a resolution of about 660 dpi were gained. Wavelet Transform tool were used to extract features from images.

Attribute Information:
V1: variance of Wavelet Transformed image (continuous)
V2: skewness of Wavelet Transformed image (continuous)
V3: kurtosis of Wavelet Transformed image (continuous)
V4: entropy of image (continuous)
V5: class (0-forged, 1-genuine)

1. (5 points) Read the A6DATA.csv data file into RStudio. Run set.seed(222) for partitioning of the dataset into training (50%) and testing (50%). Report on the number of forged and genuine banknote-like specimens in the training and testing data.

```
# Read the data
data <- read.csv("/Users/pranavvinod/downloads/A6DATA.txt", header = F)
data$V5 <- as.factor(data$V5)

summary(data)        # 762 forged banknotes and 610 genuine banknotes

##        V1                V2                V3                V4
##  Min.   :-7.0421   Min.   :-13.773   Min.   :-5.2861   Min.   :-8.54
82
##  1st Qu.:-1.7730   1st Qu.: -1.708   1st Qu.:-1.5750   1st Qu.:-2.41
35
##  Median : 0.4962   Median :  2.320   Median : 0.6166   Median :-0.58
67
##  Mean   : 0.4337   Mean   :  1.922   Mean   : 1.3976   Mean   :-1.19
17
##  3rd Qu.: 2.8215   3rd Qu.:  6.815   3rd Qu.: 3.1793   3rd Qu.: 0.39
48
##  Max.   : 6.8248   Max.   : 12.952   Max.   :17.9274   Max.   : 2.44
95
```

```
##   V5
##   0:762
##   1:610
##
##
##
##

set.seed(222)

# Partitioning the data
indices <- sample(1:nrow(data), size = nrow(data)*0.5)
train <- data[indices,]
test <- data[-indices,]

# Data description
summary(train)      # 381 forged banknotes and 305 genuine banknotes

##         V1                  V2                  V3                  V4
##   Min.   :-7.0364   Min.   :-13.773   Min.   :-5.2133   Min.   :-7.78
53
##   1st Qu.:-1.8180   1st Qu.: -2.502   1st Qu.:-1.2489   1st Qu.:-2.03
81
##   Median : 0.3345   Median :  1.883   Median : 0.7679   Median :-0.51
68
##   Mean   : 0.3549   Mean   :  1.673   Mean   : 1.5917   Mean   :-1.09
93
##   3rd Qu.: 2.6627   3rd Qu.:  6.623   3rd Qu.: 3.3064   3rd Qu.: 0.43
85
##   Max.   : 6.5633   Max.   : 12.952   Max.   :17.9274   Max.   : 2.44
95
##   V5
##   0:381
##   1:305
##
##
##
##

summary(test)       # 381 forged banknotes and 305 genuine banknotes
```

```
##         V1                  V2                  V3
V4
##   Min.   :-7.0421   Min.   :-13.678   Min.   :-5.2861   Min.
:-8.5482
##   1st Qu.:-1.7448   1st Qu.: -1.017   1st Qu.:-1.8191   1st
Qu.:-2.6168
##   Median : 0.5404   Median :  2.872   Median : 0.3065   Median
:-0.7160
##   Mean   : 0.5126   Mean   :  2.172   Mean   : 1.2035   Mean
:-1.2840
```

```
##  3rd Qu.: 2.9713   3rd Qu.:  6.937   3rd Qu.: 3.1330   3rd
Qu.: 0.3408
##  Max.   : 6.8248   Max.   : 12.378   Max.   :17.6772   Max.
: 2.1625
##  V5
##  0:381
##  1:305
```

There are 381 forged and 305 genuine banknotes in both the training and testing dataset.

2. (20 points) Develop a logistic regression model using the training data. Provide final logistic regression model (with only significant variables), equation for calculating probability that specimen is genuine, confusion matrix for both training & testing data, misclassification error for both training & testing data, and discuss performance of the model.

```
# Create model for 50:50 split
m1 <- glm(formula = V5 ~., data = train, family = 'binomial')

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

summary(m1)

##
## Call:
## glm(formula = V5 ~ ., family = "binomial", data = train)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.21019   0.00000   0.00000   0.00008   2.34895
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   9.5831     3.7680   2.543  0.01098 *
## V1           -9.2371     3.3643  -2.746  0.00604 **
## V2           -3.7759     1.2996  -2.905  0.00367 **
## V3           -5.2246     1.8005  -2.902  0.00371 **
## V4            0.9020     0.8068   1.118  0.26358
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 942.561  on 685  degrees of freedom
## Residual deviance:  21.758  on 681  degrees of freedom
## AIC: 31.758
##
## Number of Fisher Scoring iterations: 13
```

```r
# we can see that V4 is not a significant variable for predictions, so
we drop it
m1.best <- glm(formula = V5 ~.-V4, data = train, family = 'binomial')

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

summary(m1.best)

##
## Call:
## glm(formula = V5 ~ . - V4, family = "binomial", data = train)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.34409   0.00000   0.00000   0.00013   2.03675
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)    8.094      2.613   3.098 0.001951 **
## V1            -8.616      2.688  -3.205 0.001349 **
## V2            -3.948      1.174  -3.364 0.000770 ***
## V3            -5.217      1.585  -3.291 0.000999 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 942.561  on 685  degrees of freedom
## Residual deviance:  23.373  on 682  degrees of freedom
## AIC: 31.373
##
## Number of Fisher Scoring iterations: 12

# Final equation :  log(p) = 8.094 - 8.616*V1 - 3.948*V2 - 5.217*V3

# Confusion matrices
p1 <- predict(m1.best, train, type = 'response')
pred1 <- ifelse(p1>0.5,1,0)
cm1 <- table(pred1, train$V5) # for training data
cm1

##
## pred1   0   1
##     0 377   4
##     1   4 301

p1 <- predict(m1.best, test, type = 'response')
pred1 <- ifelse(p1>0.5,1,0)
cm2 <- table(pred1, test$V5)     # for testing data
cm2
```

```
##
## pred1   0   1
##     0 377   3
##     1   4 302
```

```
# Misclassification Error/Accuracy
errorTrain <- (377+301)/(377+301+8)        # 98.8% / 1.2%
errorTest <- (377+302)/(377+301+7)      # 99.1% /  1.9%

# Specificity, sensitivity and accuracy
Spec1 <- cm1[1]/(cm1[1]+cm1[3])             # 0.989
sens1 <- cm1[4]/(cm1[2]+cm1[4])             #0.986

Spec2 <- cm2[1]/(cm2[1]+cm2[3])             # 0.992
sens2 <- cm2[4]/(cm2[2]+cm2[4])             # 0.986
```

The equation for calculating if the specimen is genuine is given by the best model:

$$\boldsymbol{p} = \frac{\boldsymbol{exp}(\mathbf{8.094 - 8.616*V1 - 3.948*V2 - 5.217*V3})}{\mathbf{1+}\boldsymbol{exp}(\mathbf{8.094 - 8.616*V1 - 3.948*V2 - 5.217*V3})}$$

Here log(p) is the log of probability that the sample is genuine.

With a misclassification error of 1.2% and 1.9% for training and testing data respectively, we can say that the model performs very well.

It also has very high specificity and sensitivity for both the testing and training data.

3. (40 points) Develop logistic regression models with 60%/40%, 70%/30%, and 80%/20% partitioning into training and testing data sets using set.seed(222). Summarize training and testing accuracy, sensitivity and specificity for each in the table below and compare with 50%/50% performance using the table below. Recommend and comment on the best model for future use based on model accuracy. (No need to reproduce codes here as they are similar to part 1 and 2.)

Partitioning	Accuracy %	Sensitivity %	Specificity %
Training - 50%	98.8	98.6	98.9
Testing – 50%	99.1	98.6	99.2
Training - 60%	99.6	99.4	99.7
Testing – 40%	98.7	98.7	98
Training - 70%	99.5	99.5	99.6

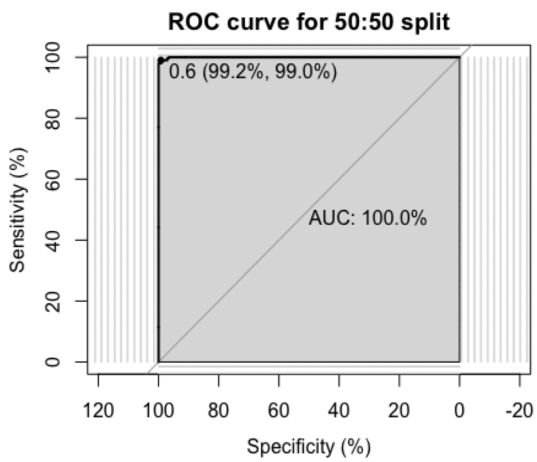
Testing – 30%	97.8	98.4	97.1
Training - 80%	99.1	99.1	99.1
Testing – 20%	98.9	99.1	98.7

4. (20 points) Compare the best and the worst logistic regression model in the previous question using ROC curve, AUC and best threshold values based on testing data. Discuss your results.

```
r <- multiclass.roc(test$V5, p1, percent = TRUE)

## Setting direction: controls < cases

roc <- r[['rocs']]
r1 <- roc[[1]]
plot.roc(r1,print.auc = T,
         print.thres = T,
         auc.polygon = T,
         grid = c(0.1,0.2),
         main = "ROC curve for 50:50 split")
```

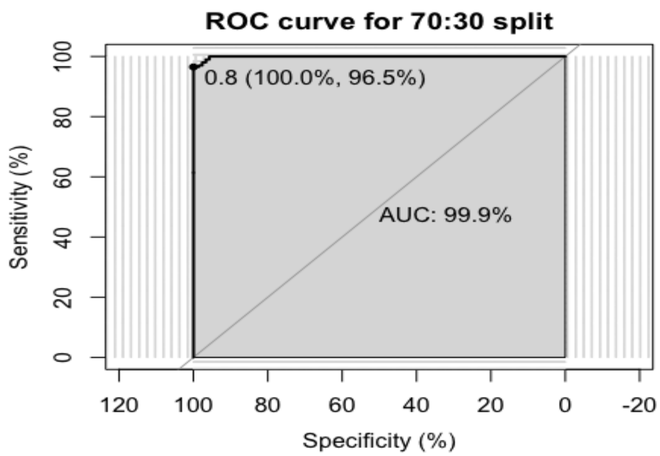



```
r <- multiclass.roc(test$V5, p3, percent = TRUE)

## Setting direction: controls < cases

roc <- r[['rocs']]
r3 <- roc[[1]]
plot.roc(r3,print.auc = T,
         print.thres = T,
         auc.polygon = T,
```

```
        grid = c(0.1,0.2),
        main = "ROC curve for 70:30 split")
```



Based on testing data, we can conclude that the split 50:50 (model 1) performs best in terms of accuracy, while the worst performing model is the one with 70:30 (model 2) split. Even though the difference is not large, with model 1 having AUC=100% and model 2 having AUC=99.9%
Both are good ROC curves because they hug the top left corner of the graph.
The best threshold for model 1 is 0.6 whereas for model 2 it is 0.8.

DELIVERABLE

5. (15 points) Create R Markdown file for this assignment and knit it in a Word format. Submit a single PDF based on the knitted file covering all five questions, code, output and comments.