Code Report Part 1: Model Training

Contents

[Note] The code report for Shiny App, API and other section is included in the second part of the code report with another Table of Contents, since this part is knitted directly from R Markdown file.

```
library(ggplot2)
library(caret)
library(xlsx)
library(pROC)
```

1.0 Data Wrangling

1.0.1 Introduction to the dataset

The data set we used for model training is the Z-Alizadeh Sani Data Set, which is collected for CAD diagnosis and published on the UCI Machine Learning Repository. This data set contains 303 observations and 56 features with no NA or missing value.

1.0.2 Load the dataset (No NA entry)

```
cad <- read.xlsx("DataWrangling/Z-Alizadeh sani dataset.xlsx", 1, header=TRUE)
```

1.0.3 Factorising variables in character

The categorical features in the original data set is in character format after first reading into R, we need to convert them into factors for the classification.

```
for (i in 1:length(cad)) {
  if (class(cad[,i]) == "character"){
    cad[,i] <- as.factor(cad[,i])
  }
  else if (cad[,i][1] == 0 | cad[,i][1] == 1 ){
    cad[,i] <- as.factor(cad[,i])
  }
}
str(cad)
```

```
## 'data.frame':    303 obs. of  56 variables:
##  $ Age                   : num  53 67 54 66 50 50 55 72 58 60 ...
##  $ Weight                : num  90 70 54 67 87 75 80 80 84 71 ...
```

```
##  $ Length               : num  175 157 164 158 153 175 165 175 163 170 ...
##  $ Sex                  : Factor w/ 2 levels "Fmale","Male": 2 1 2 1 1 2 2 2 1 2 ...
##  $ BMI                  : num  29.4 28.4 20.1 26.8 37.2 ...
##  $ DM                   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 2 1 2 ...
##  $ HTN                  : Factor w/ 2 levels "0","1": 2 2 1 2 2 1 1 1 1 1 ...
##  $ Current.Smoker       : Factor w/ 2 levels "0","1": 2 1 2 1 1 2 1 2 1 1 ...
##  $ EX.Smoker            : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 2 1 1 1 ...
##  $ FH                   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Obesity              : Factor w/ 2 levels "N","Y": 2 2 1 2 2 1 2 2 2 1 ...
##  $ CRF                  : Factor w/ 2 levels "N","Y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ CVA                  : Factor w/ 2 levels "N","Y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Airway.disease       : Factor w/ 2 levels "N","Y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Thyroid.Disease      : Factor w/ 2 levels "N","Y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ CHF                  : Factor w/ 2 levels "N","Y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ DLP                  : Factor w/ 2 levels "N","Y": 2 1 1 1 1 1 1 2 1 1 ...
##  $ BP                   : num  110 140 100 100 110 118 110 130 90 130 ...
##  $ PR                   : num  80 80 100 80 80 70 80 70 50 70 ...
##  $ Edema                : Factor w/ 2 levels "0","1": 1 2 1 1 1 1 1 1 1 1 ...
##  $ Weak.Peripheral.Pulse: Factor w/ 2 levels "N","Y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Lung.rales           : Factor w/ 2 levels "N","Y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Systolic.Murmur      : Factor w/ 2 levels "N","Y": 1 1 1 1 2 1 2 1 1 1 ...
##  $ Diastolic.Murmur     : Factor w/ 2 levels "N","Y": 1 1 1 2 1 1 1 1 1 1 ...
##  $ Typical.Chest.Pain   : Factor w/ 2 levels "0","1": 1 2 2 1 1 2 2 2 1 2 ...
##  $ Dyspnea              : Factor w/ 2 levels "N","Y": 1 1 1 2 2 1 1 1 2 2 ...
##  $ Function.Class       : Factor w/ 4 levels "0","1","2","3": 1 1 1 4 3 4 1 1 1 3 ...
##  $ Atypical             : Factor w/ 2 levels "N","Y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Nonanginal           : Factor w/ 2 levels "N","Y": 1 1 1 2 1 1 1 1 2 1 ...
##  $ Exertional.CP        : Factor w/ 1 level "N": 1 1 1 1 1 1 1 1 1 1 ...
##  $ LowTH.Ang            : Factor w/ 2 levels "N","Y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Q.Wave               : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 2 1 1 1 ...
##  $ St.Elevation         : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 2 1 1 1 ...
##  $ St.Depression        : Factor w/ 2 levels "0","1": 2 2 1 2 1 1 1 2 1 1 ...
##  $ Tinversion           : Factor w/ 2 levels "0","1": 2 2 1 1 1 1 2 2 1 1 ...
##  $ LVH                  : Factor w/ 2 levels "N","Y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Poor.R.Progression   : Factor w/ 2 levels "N","Y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ BBB                  : Factor w/ 3 levels "LBBB","N","RBBB": 2 2 2 2 2 2 2 2 2 1 ...
##  $ FBS                  : num  90 80 85 78 104 86 80 130 69 209 ...
##  $ CR                   : num  0.7 1 1 1.2 1 1 0.8 0.9 0.6 1.3 ...
##  $ TG                   : num  250 309 103 63 170 139 83 80 79 80 ...
##  $ LDL                  : num  155 121 70 55 110 119 85 90 90 90 ...
##  $ HDL                  : num  30 36 45 27 50 34 34 55 59 44 ...
##  $ BUN                  : num  8 30 17 30 16 13 12 19 15 16 ...
##  $ ESR                  : num  7 26 10 76 27 18 38 4 5 8 ...
##  $ HB                   : num  15.6 13.9 13.5 12.1 13.2 15.6 14.1 16.1 11.6 13.9 ...
##  $ K                    : num  4.7 4.7 4.7 4.4 4 4.2 4.8 4.3 3.4 4.6 ...
##  $ Na                   : num  141 156 139 142 140 141 139 142 139 140 ...
##  $ WBC                  : num  5700 7700 7400 13000 9200 7300 9400 12200 5100 4900 ...
##  $ Lymph                : num  39 38 38 18 55 26 58 25 49 55 ...
##  $ Neut                 : num  52 55 60 72 39 66 33 74 50 42 ...
##  $ PLT                  : num  261 165 230 742 274 194 292 410 370 380 ...
##  $ EF.TTE               : num  50 40 40 55 50 50 40 45 50 40 ...
##  $ Region.RWMA          : Factor w/ 5 levels "0","1","2","3",..: 1 5 3 1 1 1 5 5 1 3 ...
##  $ VHD                  : Factor w/ 4 levels "mild","Moderate",..: 3 3 1 4 4 3 1 1 3 3 ...
##  $ Cath                 : Factor w/ 2 levels "Cad","Normal": 1 1 1 2 2 1 1 1 2 1 ...
```

[NOTE] We observe that the feature "Exertional CP" only has one level, so we drop it from the data set, since it contains no useful information and the classifier training with ROC cannot generate probabilities for categorical feature with only one level.

```
cad <- subset(cad, select = -Exertional.CP)
```

When we train the model with metric ROC, the one-hot encoding process is embedded within the training process, so we need to set up another data set with no one-hot encoding. This data set will also following the same wrangling procedure as the other one to make sure these two data sets are consistent and contain the same features.

```
svm.df <- cad
```

1.0.4 Catrgorical Random Variables: One-Hot Encoding

The data set after one-hot encoding will contain 97 columns.

```
dummy <- dummyVars(" ~ .", data = cad)
cad <- data.frame(predict(dummy, newdata = cad))
```

1.0.5 Remove Zero Variance or Near-zero variance variable

We first examine the two data set whether they have columns with zero variance or near-zero variance (i.e. imbalanced features).

```
nz <- nearZeroVar(cad, saveMetrics = TRUE)
nz[nz$nzv,]
```

```
##                          freqRatio percentUnique zeroVar  nzv
## EX.Smoker.0               29.30000      0.660066   FALSE TRUE
## EX.Smoker.1               29.30000      0.660066   FALSE TRUE
## CRF.N                     49.50000      0.660066   FALSE TRUE
## CRF.Y                     49.50000      0.660066   FALSE TRUE
## CVA.N                     59.60000      0.660066   FALSE TRUE
## CVA.Y                     59.60000      0.660066   FALSE TRUE
## Airway.disease.N          26.54545      0.660066   FALSE TRUE
## Airway.disease.Y          26.54545      0.660066   FALSE TRUE
## Thyroid.Disease.N         42.28571      0.660066   FALSE TRUE
## Thyroid.Disease.Y         42.28571      0.660066   FALSE TRUE
## CHF.N                    302.00000      0.660066   FALSE TRUE
## CHF.Y                    302.00000      0.660066   FALSE TRUE
## Edema.0                   24.25000      0.660066   FALSE TRUE
## Edema.1                   24.25000      0.660066   FALSE TRUE
## Weak.Peripheral.Pulse.N   59.60000      0.660066   FALSE TRUE
## Weak.Peripheral.Pulse.Y   59.60000      0.660066   FALSE TRUE
## Lung.rales.N              26.54545      0.660066   FALSE TRUE
```

```
## Lung.rales.Y            26.54545      0.660066   FALSE TRUE
## Diastolic.Murmur.N      32.66667      0.660066   FALSE TRUE
## Diastolic.Murmur.Y      32.66667      0.660066   FALSE TRUE
## Function.Class.1       302.00000      0.660066   FALSE TRUE
## LowTH.Ang.N            150.50000      0.660066   FALSE TRUE
## LowTH.Ang.Y            150.50000      0.660066   FALSE TRUE
## St.Elevation.0          20.64286      0.660066   FALSE TRUE
## St.Elevation.1          20.64286      0.660066   FALSE TRUE
## Poor.R.Progression.N    32.66667      0.660066   FALSE TRUE
## Poor.R.Progression.Y    32.66667      0.660066   FALSE TRUE
## BBB.LBBB                22.30769      0.660066   FALSE TRUE
## BBB.RBBB                36.87500      0.660066   FALSE TRUE
## Region.RWMA.3           20.64286      0.660066   FALSE TRUE
## Region.RWMA.4           20.64286      0.660066   FALSE TRUE
## VHD.Severe              26.54545      0.660066   FALSE TRUE
```

```
nz.svm <- nearZeroVar(svm.df, saveMetrics = T)
nz.svm[nz.svm$nzv,]
```

```
##                        freqRatio percentUnique zeroVar  nzv
## EX.Smoker               29.30000      0.660066   FALSE TRUE
## CRF                     49.50000      0.660066   FALSE TRUE
## CVA                     59.60000      0.660066   FALSE TRUE
## Airway.disease          26.54545      0.660066   FALSE TRUE
## Thyroid.Disease         42.28571      0.660066   FALSE TRUE
## CHF                    302.00000      0.660066   FALSE TRUE
## Edema                   24.25000      0.660066   FALSE TRUE
## Weak.Peripheral.Pulse   59.60000      0.660066   FALSE TRUE
## Lung.rales              26.54545      0.660066   FALSE TRUE
## Diastolic.Murmur        32.66667      0.660066   FALSE TRUE
## LowTH.Ang              150.50000      0.660066   FALSE TRUE
## St.Elevation            20.64286      0.660066   FALSE TRUE
## Poor.R.Progression      32.66667      0.660066   FALSE TRUE
## BBB                     21.69231      0.990099   FALSE TRUE
```

There are 32 near-zero-variance features which may cause problems when the data are split into cross validation or boostraping samples (lead to samples with features only have one level), we eliminated those features.

```
nzv <- nearZeroVar(cad)
cad <- cad[,-nzv]
nzv.svm <- nearZeroVar(svm.df)
svm.df <- svm.df[,-nzv.svm]
```

1.0.6 Remove Correlated predictors

```
cad_cor <- cor(cad)
high.cor <- sum(abs(cad_cor[upper.tri(cad_cor)])>0.999)
summary(cad_cor[upper.tri(cad_cor)])
```

```
##       Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
## -1.000000 -0.063363 -0.002277 -0.008947  0.060996  0.725005
```

We observed 17 highly correlated features, all of them are generated by one-hot encoding (e.g. for a variable with 3 levels, drop one of the dummies will not lose any information), only one of them (Neut) isn't a column generated by One-Hot Encoding, and it is not having high correlation with "Cath" which is the feature that we want to predict, it has a -0.923 correlation with feature "Lymph". we drop them and the effect of removing those with absolute correlations above 0.75 are shown below:

```r
high.cor.feature <- findCorrelation(cad_cor, cutoff = 0.75)
high.cor.feature[1] = 65 #remove the Cath.Normal rather than Cath.cad
cad <- cad[, -high.cor.feature]
cad_cor2 <- cor(cad)
summary(cad_cor2[upper.tri(cad_cor2)])
```

```
##     Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -0.54585 -0.05229  0.01302  0.01417  0.06687  0.72501
```

```r
# remove the NEUT
svm.df <- svm.df[, -grep("Neut", colnames(svm.df))]
```

1.0.7 Remove features with linear dependencies:

```r
ld <- findLinearCombos(cad)
ld
```

```
## $linearCombos
## list()
##
## $remove
## NULL
```

Nothing observed so we are ok.

1.0.8 factorising binary variables:

One-hot encoding transfers some of the categorical variables into numeric form, we need to convert them back to factor form.

```r
for (i in 1:length(cad)) {
  if (cad[,i][1] == 0 | cad[,i][1] == 1 ){
    cad[,i] <- as.factor(cad[,i])
  }
}
```

1.1 Feature Selection

The data frame "cad" is used for traing the feature selection SVM.

1.1.1 Train/Test split:

```
set.seed(3164)
train.index <- createDataPartition(cad$Cath.Cad, times = 1, p = 0.8,
                                   list = FALSE)
cad.train <- cad[train.index,]
cad.test <- cad[-train.index,]
```

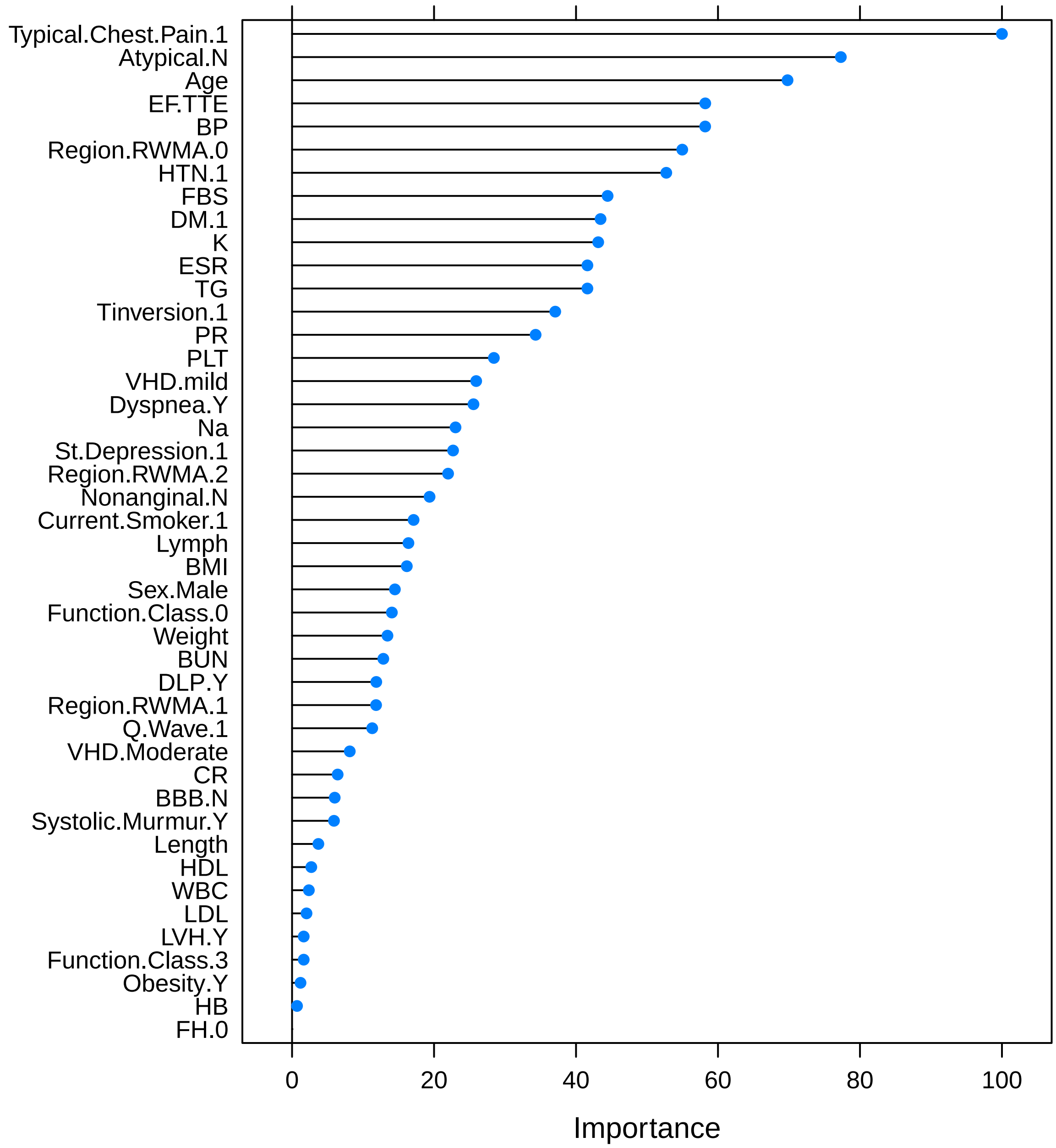
1.1.2 Set up 10-fold-cross-validation

```
parameters = trainControl(method = "repeatedcv",
                          number = 10,
                          repeats = 10,
                          classProbs = FALSE)
```

1.1.3 Feature selection by SVM

```
# train SVM
SVM = train(Cath.Cad ~ ., data = cad.train,
            method = "svmPoly",
            trControl = parameters,
            tuneGrid = data.frame(degree = 1, scale = 1, C = 1),
            preProcess = c("pca", "scale", "center"),
            na.action = na.omit)

# Ranking features by Importance
feature.rank = varImp(SVM, scale = TRUE)
plot(feature.rank)
```



1.1.4 Select features with importance > 40

Selecting feature with importance grater than 40 left with 12 predictors

```
important <- c(feature.rank$importance$X0>40, TRUE)
im <- cad[,important]
str(im)
```

```
## 'data.frame':    303 obs. of  13 variables:
```

```
##  $ Age                   : num  53 67 54 66 50 50 55 72 58 60 ...
##  $ DM.1                  : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 2 1 2 ...
##  $ HTN.1                 : Factor w/ 2 levels "0","1": 2 2 1 2 2 1 1 1 1 1 ...
##  $ BP                    : num  110 140 100 100 110 118 110 130 90 130 ...
##  $ Typical.Chest.Pain.1: Factor w/ 2 levels "0","1": 1 2 2 1 1 2 2 2 1 2 ...
##  $ Atypical.N            : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 2 ...
##  $ FBS                   : num  90 80 85 78 104 86 80 130 69 209 ...
##  $ TG                    : num  250 309 103 63 170 139 83 80 79 80 ...
##  $ ESR                   : num  7 26 10 76 27 18 38 4 5 8 ...
##  $ K                     : num  4.7 4.7 4.7 4.4 4 4.2 4.8 4.3 3.4 4.6 ...
##  $ EF.TTE                : num  50 40 40 55 50 50 40 45 50 40 ...
##  $ Region.RWMA.0         : Factor w/ 2 levels "0","1": 2 1 1 2 2 2 1 1 2 1 ...
##  $ Cath.Cad              : Factor w/ 2 levels "0","1": 2 2 2 1 1 2 2 2 1 2 ...
```

```
# train/test split
im.train <- im[train.index,]
im.test <- im[-train.index,]
```

```
# to keep two data set consistent
svm.df <- subset(svm.df, select = c(Age, DM, HTN, BP, Typical.Chest.Pain,
                                    Atypical, FBS, TG, ESR, K, EF.TTE,
                                    Region.RWMA, Cath))
str(svm.df)
```

```
## 'data.frame':    303 obs. of  13 variables:
##  $ Age               : num  53 67 54 66 50 50 55 72 58 60 ...
##  $ DM                : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 2 1 2 ...
##  $ HTN               : Factor w/ 2 levels "0","1": 2 2 1 2 2 1 1 1 1 1 ...
##  $ BP                : num  110 140 100 100 110 118 110 130 90 130 ...
##  $ Typical.Chest.Pain: Factor w/ 2 levels "0","1": 1 2 2 1 1 2 2 2 1 2 ...
##  $ Atypical          : Factor w/ 2 levels "N","Y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ FBS               : num  90 80 85 78 104 86 80 130 69 209 ...
##  $ TG                : num  250 309 103 63 170 139 83 80 79 80 ...
##  $ ESR               : num  7 26 10 76 27 18 38 4 5 8 ...
##  $ K                 : num  4.7 4.7 4.7 4.4 4 4.2 4.8 4.3 3.4 4.6 ...
##  $ EF.TTE            : num  50 40 40 55 50 50 40 45 50 40 ...
##  $ Region.RWMA       : Factor w/ 5 levels "0","1","2","3",..: 1 5 3 1 1 1 5 5 1 3 ...
##  $ Cath              : Factor w/ 2 levels "Cad","Normal": 1 1 1 2 2 1 1 1 2 1 ...
```

1.2 Claasifier Training and Testing

1.2.0 Initialising training settings

```
# set up results table
result = data.frame(Classifier = c("SVM.Poly", "SVM.Radial", "SVM.Linear",
                                   "Random Forest", "Neurual Network",
                                   "Naive Bayes", "Logistic Regression",
                                   "LDA", "KNN", "GBM", "Decision Tree",
                                   "AdaBoost Classification Tree",
                                   "Boosted Logistic Regression"),
```

```
                    Training_ROC = 0:12,
                    Testing_Accuracy = 0:12,
                    Test_AUC = 0:12)
```

```
control = trainControl(method = "repeatedcv",
                       number = 10,
                       repeats = 10,
                       classProbs = TRUE,
                       summaryFunction = twoClassSummary
                       )
```

```
# Test/ train split for SVM
set.seed(3164)
train.index.svm <- createDataPartition(svm.df$Cath, times = 1, p = 0.8,
                                       list = FALSE)
svm.train <- svm.df[train.index.svm,]
svm.test <- svm.df[-train.index.svm,]
```

1.2.1 SVM Polynomial

```
set.seed(3164)
# Train SVM polynomial with ROC metric
svm.poly= train(Cath ~ ., data = svm.train,
            method = "svmPoly",
            trControl = control,
            tuneGrid = data.frame(degree = c(1,1), scale = c(1,2), C = c(1,3)),
            preProcess = c("pca", "scale", "center"),
            metric = "ROC",
            na.action = na.omit)
print(svm.poly$results)
```

```
##   degree scale C       ROC      Sens      Spec      ROCSD     SensSD    SpecSD
## 1      1     1 1 0.9152148 0.9198693 0.6985714 0.05763243 0.06684049 0.1623053
## 2      1     2 3 0.9134314 0.9146405 0.7000000 0.05721340 0.06724725 0.1618029
```

We want to test if training with ROC will help us to achieve a better performed model, so we trained one without ROC to compare.

```
# Train without ROC
SVM = train(Cath.Cad ~ ., data = im.train,
            method = "svmPoly",
            trControl = parameters,
            tuneGrid = data.frame(degree = c(1,1), scale = c(1,2), C = c(1,3)),
            preProcess = c("pca", "scale", "center"),
            na.action = na.omit)
print(SVM$results)
```

```
##   degree scale C  Accuracy     Kappa AccuracySD   KappaSD
## 1      1     1 1 0.8643667 0.6612775 0.06272514 0.1605093
## 2      1     2 3 0.8622500 0.6564865 0.06229360 0.1579216
```

```r
# Test SVM polynomial with ROC
svm.poly.predict = predict(svm.poly, svm.test)
# confusion matrix
cm.svm.poly <- confusionMatrix(svm.poly.predict, svm.test$Cath)
print(cm.svm.poly)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     40      5
##     Normal   3     12
##
##                Accuracy : 0.8667
##                  95% CI : (0.7541, 0.9406)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.004937
##
##                   Kappa : 0.6596
##
##  Mcnemar's Test P-Value : 0.723674
##
##             Sensitivity : 0.9302
##             Specificity : 0.7059
##          Pos Pred Value : 0.8889
##          Neg Pred Value : 0.8000
##              Prevalence : 0.7167
##          Detection Rate : 0.6667
##    Detection Prevalence : 0.7500
##       Balanced Accuracy : 0.8181
##
##        'Positive' Class : Cad
##
```

```r
# Test SVM polynomial without ROC
svm.predict = predict(SVM, im.test)
# confusion matrix
cm.svm <- confusionMatrix(svm.predict, im.test$Cath.Cad)
print(cm.svm)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##          0 13  8
##          1  4 35
##
##                Accuracy : 0.8
##                  95% CI : (0.6767, 0.8922)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.09575
##
##                   Kappa : 0.5402
```

```
##
##  Mcnemar's Test P-Value : 0.38648
##
##             Sensitivity : 0.7647
##             Specificity : 0.8140
##          Pos Pred Value : 0.6190
##          Neg Pred Value : 0.8974
##              Prevalence : 0.2833
##          Detection Rate : 0.2167
##    Detection Prevalence : 0.3500
##       Balanced Accuracy : 0.7893
##
##        'Positive' Class : 0
##
```

We notice that training classifier with ROC as metric yields higher testing accuracy, thus, we'll train the left classifiers with ROC.

```
# Store the training ROC and the Testing accuracy to the result table
result$Training_ROC[1] = max(svm.poly$results$ROC)
result$Testing_Accuracy[1] = cm.svm.poly$overall[1]

# predict in probabilities
svm.poly.probs = predict(svm.poly,svm.test[,!names(svm.test) %in% c("Cath")],
                         type = "prob")
# store the testing ROC values for plotting later
svm.poly.ROC = roc(response = svm.test$Cath,
              predictor = svm.poly.probs$Cad,
              levels = levels(svm.test$Cath),
              percent = T)
# store the testing AUC to the result table
result$Test_AUC[1] = svm.poly.ROC$auc
```

1.2.2 SVM Radial

```
set.seed(3164)
# Train SVM Radial
svm.rad= train(Cath ~ ., data = svm.train,
            method = "svmRadial",
            trControl = control,
            tuneLength = 10,
            preProcess = c("pca", "scale", "center"),
            metric = "ROC",
            na.action = na.omit)
print(svm.rad$results)
```

```
##        sigma      C       ROC      Sens      Spec      ROCSD     SensSD
## 1  0.0622846   0.25 0.9048553 0.9100000 0.7085714 0.06768556 0.06919869
## 2  0.0622846   0.50 0.9000047 0.9202288 0.6371429 0.07110917 0.06684309
## 3  0.0622846   1.00 0.8957423 0.9283660 0.6271429 0.07244670 0.05976535
```

```
## 4  0.0622846   2.00 0.8927358 0.9168954 0.6414286 0.07541720 0.06588594
## 5  0.0622846   4.00 0.8882353 0.9104575 0.6400000 0.07641461 0.06862824
## 6  0.0622846   8.00 0.8802708 0.9057190 0.6214286 0.07787928 0.06998145
## 7  0.0622846  16.00 0.8840056 0.9085948 0.6142857 0.07712949 0.07069320
## 8  0.0622846  32.00 0.8633333 0.9114379 0.5700000 0.08064663 0.07697575
## 9  0.0622846  64.00 0.8471615 0.9109804 0.5457143 0.08502766 0.07488678
## 10 0.0622846 128.00 0.8317414 0.9118627 0.5071429 0.08819426 0.07386473
##       SpecSD
## 1  0.1721965
## 2  0.1820880
## 3  0.1780526
## 4  0.1630656
## 5  0.1680278
## 6  0.1678990
## 7  0.1498986
## 8  0.1471155
## 9  0.1641806
## 10 0.1641743
```

```
# Test SVM Radial
svm.rad.predict = predict(svm.rad, svm.test)
# confusion matrix
cm.svm.rad <- confusionMatrix(svm.rad.predict, svm.test$Cath)
print(cm.svm.rad)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     40      7
##     Normal   3     10
##
##                Accuracy : 0.8333
##                  95% CI : (0.7148, 0.9171)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.02687
##
##                   Kappa : 0.5582
##
##  Mcnemar's Test P-Value : 0.34278
##
##             Sensitivity : 0.9302
##             Specificity : 0.5882
##          Pos Pred Value : 0.8511
##          Neg Pred Value : 0.7692
##              Prevalence : 0.7167
##          Detection Rate : 0.6667
##    Detection Prevalence : 0.7833
##       Balanced Accuracy : 0.7592
##
##        'Positive' Class : Cad
##
```

```r
# Store the training ROC and the Testing accuracy to the result table
result$Training_ROC[2] = max(svm.rad$results$ROC)
result$Testing_Accuracy[2] = cm.svm.rad$overall[1]

# predict in probabilities
svm.rad.probs = predict(svm.rad,svm.test[,!names(svm.test) %in% c("Cath")],
                        type = "prob")
# store the testing ROC values for plotting later
svm.rad.ROC = roc(response = svm.test$Cath,
              predictor = svm.rad.probs$Cad,
              levels = levels(svm.test$Cath),
              percent = T)

# Store the testing AUC
result$Test_AUC[2] = svm.rad.ROC$auc
```

1.2.3 SVM linear

```r
set.seed(3164)
# Train SVM linear
svm.l= train(Cath ~ ., data = svm.train,
            method = "svmLinear",
            trControl = control,
            tuneLength = 10,
            preProcess = c("pca", "scale", "center"),
            metric = "ROC",
            na.action = na.omit)
print(svm.l$results)
```

```
##   C       ROC      Sens      Spec      ROCSD   SensSD    SpecSD
## 1 1 0.9152148 0.9245098 0.6885714 0.05763243 0.062564 0.1666729
```

```r
# Test SVM linear
svm.l.predict = predict(svm.l, svm.test)
# confusion matrix
cm.svm.l <- confusionMatrix(svm.l.predict, svm.test$Cath)
print(cm.svm.l)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     42      5
##     Normal   1     12
##
##                Accuracy : 0.9
##                  95% CI : (0.7949, 0.9624)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.0005383
##
```

```
##                   Kappa : 0.7349
##
##  Mcnemar's Test P-Value : 0.2206714
##
##             Sensitivity : 0.9767
##             Specificity : 0.7059
##          Pos Pred Value : 0.8936
##          Neg Pred Value : 0.9231
##              Prevalence : 0.7167
##          Detection Rate : 0.7000
##    Detection Prevalence : 0.7833
##       Balanced Accuracy : 0.8413
##
##        'Positive' Class : Cad
##
```

```
# Store the training ROC and the Testing accuracy to the result table
result$Training_ROC[3] = max(svm.l$results$ROC)
result$Testing_Accuracy[3] = cm.svm.l$overall[1]

# predict in probabilities
svm.l.probs = predict(svm.l,svm.test[,!names(svm.test) %in% c("Cath")],
                      type = "prob")
# store the testing ROC values for plotting later
svm.l.ROC = roc(response = svm.test$Cath,
              predictor = svm.l.probs$Cad,
              levels = levels(svm.test$Cath),
              percent = T)
#store the testing AUC
result$Test_AUC[3] = svm.l.ROC$auc
```

1.2.4 Random Forest

```
# train the random forest
rf <- train(Cath ~., data = svm.train,
                 method = "rf",
                 trControl = control,
                 preProc = c("center", "scale"),
                 tuneLength = 10,
                 metric = "ROC")
print(rf)
```

```
## Random Forest
##
## 243 samples
##  12 predictor
##   2 classes: 'Cad', 'Normal'
##
## Pre-processing: centered (15), scaled (15)
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 219, 218, 219, 218, 219, 218, ...
```

```
## Resampling results across tuning parameters:
##
##   mtry  ROC        Sens       Spec
##    2    0.9215780  0.9130392  0.6971429
##    3    0.9158310  0.9068301  0.7214286
##    4    0.9125934  0.9009804  0.7214286
##    6    0.9118511  0.8916993  0.7342857
##    7    0.9117787  0.8923529  0.7371429
##    9    0.9102171  0.8934967  0.7414286
##   10    0.9088772  0.8887255  0.7357143
##   12    0.9074416  0.8901307  0.7400000
##   13    0.9060224  0.8848693  0.7442857
##   15    0.9042554  0.8871895  0.7528571
##
## ROC was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 2.
```

```r
# Test the random forest
rf.predict = predict(rf, svm.test)
# confusion matrix
cm.rf <- confusionMatrix(rf.predict, svm.test$Cath)
print(cm.rf)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     40      5
##     Normal   3     12
##
##                Accuracy : 0.8667
##                  95% CI : (0.7541, 0.9406)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.004937
##
##                   Kappa : 0.6596
##
##  Mcnemar's Test P-Value : 0.723674
##
##             Sensitivity : 0.9302
##             Specificity : 0.7059
##          Pos Pred Value : 0.8889
##          Neg Pred Value : 0.8000
##              Prevalence : 0.7167
##          Detection Rate : 0.6667
##    Detection Prevalence : 0.7500
##       Balanced Accuracy : 0.8181
##
##        'Positive' Class : Cad
##
```

```r
# store the training ROC and Testing accuracy to the results table
result$Training_ROC[4] = max(rf$results$ROC)
```

```r
result$Testing_Accuracy[4] = cm.rf$overall[1]

# Save the testing ROC for plotting later
rf.probs = predict(rf,svm.test[,!names(svm.test) %in% c("Cath")],type = "prob")
rf.ROC = roc(response = svm.test$Cath,
              predictor = rf.probs$Cad,
              levels = levels(svm.test$Cath),
              percent = T)
result$Test_AUC[4] = rf.ROC$auc
```

1.2.5 Neural Network

```r
# train the neural network
cath_index = grep("Cath", colnames(svm.train))
nn = train(svm.train[, -cath_index],
            svm.train$Cath,
            method = "nnet",
            trControl = control,
            preProcess = c("scale", "center"),
            tuneLength = 5,
            verbose = F,
            trace = F,
            metric = "ROC",
            na.action = na.omit)
print(nn)
```

```
## Neural Network
##
## 243 samples
##  12 predictor
##   2 classes: 'Cad', 'Normal'
##
## Pre-processing: scaled (7), centered (7), ignore (5)
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 218, 219, 218, 219, 219, 219, ...
## Resampling results across tuning parameters:
##
##   size  decay  ROC        Sens       Spec
##   1     0e+00  0.8444935  0.8625817  0.7971429
##   1     1e-04  0.8717110  0.8568301  0.7857143
##   1     1e-03  0.8980252  0.8647386  0.7871429
##   1     1e-02  0.9149253  0.8681373  0.7914286
##   1     1e-01  0.9207843  0.8879085  0.7614286
##   3     0e+00  0.8070215  0.8605882  0.7028571
##   3     1e-04  0.8328735  0.8534641  0.7442857
##   3     1e-03  0.8578618  0.8758497  0.7200000
##   3     1e-02  0.8530439  0.8589542  0.6800000
##   3     1e-01  0.9024697  0.8878105  0.7185714
##   5     0e+00  0.7889052  0.8517647  0.6571429
##   5     1e-04  0.8278175  0.8631699  0.6600000
##   5     1e-03  0.8374510  0.8638562  0.6528571
```

```
##   5     1e-02  0.8569328  0.8715033  0.6157143
##   5     1e-01  0.9035434  0.9028431  0.6857143
##   7     0e+00  0.7809687  0.8523203  0.6571429
##   7     1e-04  0.8320121  0.8742484  0.6142857
##   7     1e-03  0.8449090  0.8684314  0.5957143
##   7     1e-02  0.8593931  0.8778758  0.6357143
##   7     1e-01  0.8979458  0.9022549  0.6871429
##   9     0e+00  0.7843044  0.8584967  0.6385714
##   9     1e-04  0.8561064  0.8838562  0.6471429
##   9     1e-03  0.8666270  0.8763072  0.6571429
##   9     1e-02  0.8732610  0.8784967  0.6385714
##   9     1e-01  0.8984687  0.8993464  0.6842857
##
## ROC was used to select the optimal model using the largest value.
## The final values used for the model were size = 1 and decay = 0.1.
```

```
# testing the neural network
nn.predict = predict(nn, svm.test)
# confusion matrix
cm.nn <- confusionMatrix(nn.predict, svm.test$Cath)
print(cm.nn)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     37      4
##     Normal   6     13
##
##                Accuracy : 0.8333
##                  95% CI : (0.7148, 0.9171)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.02687
##
##                   Kappa : 0.6037
##
##  Mcnemar's Test P-Value : 0.75183
##
##             Sensitivity : 0.8605
##             Specificity : 0.7647
##          Pos Pred Value : 0.9024
##          Neg Pred Value : 0.6842
##              Prevalence : 0.7167
##          Detection Rate : 0.6167
##    Detection Prevalence : 0.6833
##       Balanced Accuracy : 0.8126
##
##        'Positive' Class : Cad
##
```

```
# store the ROC and Testing accuracy to the results table
result$Training_ROC[5] = max(nn$results$ROC)
result$Testing_Accuracy[5] = cm.nn$overall[1]
```

```r
# plot the testing ROC
nn.probs = predict(nn,svm.test[,!names(svm.test) %in% c("Cath")],type = "prob")
nn.ROC = roc(response = svm.test$Cath,
              predictor = nn.probs$Cad,
              levels = levels(svm.test$Cath),
              percent = T)
result$Test_AUC[5] = nn.ROC$auc
```

1.2.6 Naive Bayes

```r
set.seed(3164)
# train Naive Bayes
nb <- train(Cath ~., data = svm.train,
                method = "nb",
                trControl = control,
                preProc = c("center", "scale"),
                tuneGrid = data.frame(fL = 0, usekernel = T, adjust = 1),
                metric = "ROC")
print(nb)
```

```
## Naive Bayes
##
## 243 samples
##  12 predictor
##   2 classes: 'Cad', 'Normal'
##
## Pre-processing: centered (15), scaled (15)
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 219, 219, 218, 219, 219, 218, ...
## Resampling results:
##
##   ROC        Sens       Spec
##   0.8881139  0.5108497  0.9428571
##
## Tuning parameter 'fL' was held constant at a value of 0
## Tuning
##  parameter 'usekernel' was held constant at a value of TRUE
## Tuning
##  parameter 'adjust' was held constant at a value of 1
```

```r
# Test the Naive Bayes
nb.predict = predict(nb, svm.test)
# confusion matrix
cm.nb <- confusionMatrix(nb.predict, svm.test$Cath)
print(cm.nb)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
```

```
##     Cad     24      1
##     Normal  19     16
##
##                Accuracy : 0.6667
##                  95% CI : (0.5331, 0.7831)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.8421385
##
##                   Kappa : 0.3782
##
##  Mcnemar's Test P-Value : 0.0001439
##
##             Sensitivity : 0.5581
##             Specificity : 0.9412
##          Pos Pred Value : 0.9600
##          Neg Pred Value : 0.4571
##              Prevalence : 0.7167
##          Detection Rate : 0.4000
##    Detection Prevalence : 0.4167
##       Balanced Accuracy : 0.7497
##
##        'Positive' Class : Cad
##
```

```r
# store the ROC and Testing accuracy to the results table
result$Training_ROC[6] = max(nb$results$ROC)
result$Testing_Accuracy[6] = cm.nb$overall[1]

# Save the testing ROC for plotting later
nb.probs = predict(nb,svm.test[,!names(svm.test) %in% c("Cath")],type = "prob")
nb.ROC = roc(response = svm.test$Cath,
              predictor = nb.probs$Cad,
              levels = levels(svm.test$Cath),
              percent = T)
result$Test_AUC[6] = nb.ROC$auc
```

1.2.7 Logistic Regression

```r
set.seed(3164)
# train the logistic regression
lr <- train(Cath ~., data = svm.train,
                 method = "glm",
                 family = "binomial",
                 trControl = control,
                 preProc = c("center", "scale"),
                 tuneLength = 10,
                 metric = "ROC")
print(lr)
```

```
## Generalized Linear Model
##
```

```
## 243 samples
##  12 predictor
##   2 classes: 'Cad', 'Normal'
##
## Pre-processing: centered (15), scaled (15)
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 219, 219, 218, 219, 219, 218, ...
## Resampling results:
##
##   ROC        Sens      Spec
##   0.9166153  0.905915  0.74
```

```
# Test the logistic regression
lr.predict = predict(lr, svm.test)
# confusion matrix
cm.lr <- confusionMatrix(lr.predict, svm.test$Cath)
print(cm.lr)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     39      4
##     Normal   4     13
##
##                Accuracy : 0.8667
##                  95% CI : (0.7541, 0.9406)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.004937
##
##                   Kappa : 0.6717
##
##  Mcnemar's Test P-Value : 1.000000
##
##             Sensitivity : 0.9070
##             Specificity : 0.7647
##          Pos Pred Value : 0.9070
##          Neg Pred Value : 0.7647
##              Prevalence : 0.7167
##          Detection Rate : 0.6500
##    Detection Prevalence : 0.7167
##       Balanced Accuracy : 0.8358
##
##        'Positive' Class : Cad
##
```

```
# store the ROC and Testing accuracy to the results table
result$Training_ROC[7] = max(lr$results$ROC)
result$Testing_Accuracy[7] = cm.lr$overall[1]

# Save the testing ROC for plotting later
lr.probs = predict(lr,svm.test[,!names(svm.test) %in% c("Cath")],type = "prob")
lr.ROC = roc(response = svm.test$Cath,
```

```
              predictor = lr.probs$Cad,
              levels = levels(svm.test$Cath),
              percent = T)
result$Test_AUC[7] = lr.ROC$auc
```

1.2.8 LDA

```
set.seed(3164)
# train the LDA
lda <- train(Cath ~., data = svm.train,
                 method = "lda",
                 trControl = control,
                 preProc = c("center", "scale"),
                 tuneLength = 10,
                 metric = "ROC")
print(lda)
```

```
## Linear Discriminant Analysis
##
## 243 samples
##  12 predictor
##   2 classes: 'Cad', 'Normal'
##
## Pre-processing: centered (15), scaled (15)
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 219, 219, 218, 219, 219, 218, ...
## Resampling results:
##
##   ROC        Sens       Spec
##   0.9234874  0.8832353  0.8142857
```

```
# Test the lda
lda.predict = predict(lda, svm.test)
# confusion matrix
cm.lda <- confusionMatrix(lda.predict, svm.test$Cath)
print(cm.lda)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     39      4
##     Normal   4     13
##
##                Accuracy : 0.8667
##                  95% CI : (0.7541, 0.9406)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.004937
##
##                   Kappa : 0.6717
```

```
##
##  Mcnemar's Test P-Value : 1.000000
##
##             Sensitivity : 0.9070
##             Specificity : 0.7647
##          Pos Pred Value : 0.9070
##          Neg Pred Value : 0.7647
##              Prevalence : 0.7167
##          Detection Rate : 0.6500
##    Detection Prevalence : 0.7167
##       Balanced Accuracy : 0.8358
##
##        'Positive' Class : Cad
##
```

```
# store the ROC and Testing accuracy to the results table
result$Training_ROC[8] = max(lda$results$ROC)
result$Testing_Accuracy[8] = cm.lda$overall[1]

# Save the testing ROC for plotting later
lda.probs = predict(lda,svm.test[,!names(svm.test) %in% c("Cath")],type = "prob")
lda.ROC = roc(response = svm.test$Cath,
              predictor = lda.probs$Cad,
              levels = levels(svm.test$Cath),
              percent = T)
result$Test_AUC[8] = lda.ROC$auc
```

1.2.9 KNN

```
set.seed(3164)
# train the KNN
knn <- train(Cath ~., data = svm.train,
                 method = "knn",
                 trControl = control,
                 preProc = c("center", "scale"),
                 tuneLength = 10,
                 metric = "ROC")
print(knn)
```

```
## k-Nearest Neighbors
##
## 243 samples
##  12 predictor
##   2 classes: 'Cad', 'Normal'
##
## Pre-processing: centered (15), scaled (15)
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 219, 219, 218, 219, 219, 218, ...
## Resampling results across tuning parameters:
##
##   k   ROC        Sens       Spec
```

```
##    5  0.8788235  0.8977451  0.6814286
##    7  0.8883380  0.9076144  0.7185714
##    9  0.8888025  0.9065686  0.7485714
##   11  0.8864169  0.9006536  0.7600000
##   13  0.8926471  0.9012092  0.7700000
##   15  0.8988049  0.9041503  0.7542857
##   17  0.8996615  0.9006863  0.7371429
##   19  0.8984757  0.9008170  0.7314286
##   21  0.9008730  0.9019608  0.7100000
##   23  0.8997946  0.9025490  0.7085714
##
## ROC was used to select the optimal model using the largest value.
## The final value used for the model was k = 21.
```

```
# Test the knn
knn.predict = predict(knn, svm.test)
# confusion matrix
cm.knn <- confusionMatrix(knn.predict, svm.test$Cath)
print(cm.knn)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     39      6
##     Normal   4     11
##
##                Accuracy : 0.8333
##                  95% CI : (0.7148, 0.9171)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.02687
##
##                   Kappa : 0.5745
##
##  Mcnemar's Test P-Value : 0.75183
##
##             Sensitivity : 0.9070
##             Specificity : 0.6471
##          Pos Pred Value : 0.8667
##          Neg Pred Value : 0.7333
##              Prevalence : 0.7167
##          Detection Rate : 0.6500
##    Detection Prevalence : 0.7500
##       Balanced Accuracy : 0.7770
##
##        'Positive' Class : Cad
##
```

```
# store the ROC and Testing accuracy to the results table
result$Training_ROC[9] = max(knn$results$ROC)
result$Testing_Accuracy[9] = cm.knn$overall[1]

# Save the testing ROC for plotting later
```

```r
knn.probs = predict(knn,svm.test[,!names(svm.test) %in% c("Cath")],
                    type = "prob")
knn.ROC = roc(response = svm.test$Cath,
              predictor = knn.probs$Cad,
              levels = levels(svm.test$Cath),
              percent = T)
result$Test_AUC[9] = knn.ROC$auc
```

1.2.10 GBM

```r
set.seed(3164)
# train the GBM
gbm <- train(Cath ~., data = svm.train,
                 method = "gbm",
                 trControl = control,
                 verbose = FALSE,
                 preProc = c("center", "scale"),
                 tuneLength = 10,
                 metric = "ROC")
print(gbm)
```

```
## Stochastic Gradient Boosting
##
## 243 samples
##  12 predictor
##   2 classes: 'Cad', 'Normal'
##
## Pre-processing: centered (15), scaled (15)
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 219, 219, 218, 219, 219, 218, ...
## Resampling results across tuning parameters:
##
##   interaction.depth  n.trees  ROC        Sens       Spec
##    1                  50      0.9198413  0.9299673  0.6685714
##    1                 100      0.9258497  0.9248366  0.7242857
##    1                 150      0.9243371  0.9143791  0.7300000
##    1                 200      0.9221849  0.9069281  0.7285714
##    1                 250      0.9213725  0.9085948  0.7257143
##    1                 300      0.9184407  0.9022222  0.7300000
##    1                 350      0.9167554  0.8992157  0.7157143
##    1                 400      0.9154155  0.8986928  0.7157143
##    1                 450      0.9134314  0.8963399  0.7128571
##    1                 500      0.9109104  0.8934641  0.7100000
##    2                  50      0.9195985  0.9214052  0.7085714
##    2                 100      0.9158777  0.9167320  0.7128571
##    2                 150      0.9127218  0.9107843  0.7057143
##    2                 200      0.9088936  0.9022549  0.7128571
##    2                 250      0.9083987  0.9028431  0.7042857
##    2                 300      0.9044164  0.9046732  0.6957143
##    2                 350      0.9045285  0.9017320  0.6885714
##    2                 400      0.9046359  0.8987908  0.6928571
```

```
## 2          450     0.9033894  0.8959150  0.7000000
## 2          500     0.9010131  0.8970915  0.6928571
## 3           50     0.9132213  0.9133660  0.7014286
## 3          100     0.9062325  0.9041503  0.6928571
## 3          150     0.9006863  0.9024837  0.6857143
## 3          200     0.8991690  0.8964706  0.6928571
## 3          250     0.8976657  0.8959477  0.6900000
## 3          300     0.8961625  0.8942484  0.6942857
## 3          350     0.8962792  0.8914052  0.6928571
## 3          400     0.8937628  0.8948366  0.6957143
## 3          450     0.8930812  0.8913725  0.6957143
## 3          500     0.8922782  0.8907516  0.6957143
## 4           50     0.9087162  0.9138889  0.6900000
## 4          100     0.9031746  0.9001307  0.6885714
## 4          150     0.8989356  0.8948366  0.6971429
## 4          200     0.8956022  0.8872876  0.6971429
## 4          250     0.8958870  0.8862418  0.7000000
## 4          300     0.8934500  0.8896078  0.6928571
## 4          350     0.8911251  0.8855882  0.6914286
## 4          400     0.8908450  0.8843791  0.6971429
## 4          450     0.8893184  0.8826797  0.6900000
## 4          500     0.8908310  0.8832680  0.6928571
## 5           50     0.9092810  0.9161111  0.7100000
## 5          100     0.9019468  0.8999020  0.7042857
## 5          150     0.8982446  0.8964706  0.6942857
## 5          200     0.8957516  0.8930065  0.7000000
## 5          250     0.8915033  0.8924183  0.6928571
## 5          300     0.8907563  0.8879085  0.6928571
## 5          350     0.8892764  0.8850000  0.6900000
## 5          400     0.8869608  0.8809477  0.6871429
## 5          450     0.8871382  0.8768627  0.6828571
## 5          500     0.8848880  0.8774183  0.6871429
## 6           50     0.9030019  0.9075490  0.6885714
## 6          100     0.8936181  0.8925163  0.6914286
## 6          150     0.8908777  0.8900654  0.6828571
## 6          200     0.8903688  0.8894771  0.6842857
## 6          250     0.8872782  0.8842484  0.6871429
## 6          300     0.8870962  0.8831046  0.6842857
## 6          350     0.8877591  0.8837908  0.6842857
## 6          400     0.8865453  0.8826471  0.6928571
## 6          450     0.8862792  0.8769935  0.6942857
## 6          500     0.8840289  0.8768627  0.6914286
## 7           50     0.9033707  0.9052614  0.7057143
## 7          100     0.8953455  0.8929739  0.6914286
## 7          150     0.8906162  0.8877778  0.6900000
## 7          200     0.8892390  0.8854248  0.6871429
## 7          250     0.8888329  0.8792157  0.6871429
## 7          300     0.8866387  0.8808170  0.6885714
## 7          350     0.8864939  0.8784967  0.6814286
## 7          400     0.8846545  0.8784967  0.6857143
## 7          450     0.8831979  0.8756863  0.6900000
## 7          500     0.8836461  0.8720261  0.6885714
## 8           50     0.9052007  0.9046405  0.6914286
## 8          100     0.8976797  0.8983007  0.6885714
```

```
##    8                   150      0.8928478  0.8919935  0.6928571
##    8                   200      0.8912885  0.8889869  0.7071429
##    8                   250      0.8907843  0.8866340  0.7000000
##    8                   300      0.8889683  0.8849346  0.7014286
##    8                   350      0.8888002  0.8831046  0.7014286
##    8                   400      0.8885247  0.8790523  0.7028571
##    8                   450      0.8875163  0.8791176  0.6885714
##    8                   500      0.8868861  0.8768301  0.6885714
##    9                    50      0.9036835  0.9035621  0.7028571
##    9                   100      0.8968347  0.8884641  0.6771429
##    9                   150      0.8947059  0.8845098  0.6800000
##    9                   200      0.8913632  0.8797386  0.6814286
##    9                   250      0.8891923  0.8774183  0.6957143
##    9                   300      0.8860831  0.8750654  0.6914286
##    9                   350      0.8869141  0.8733987  0.6985714
##    9                   400      0.8839683  0.8728105  0.7000000
##    9                   450      0.8834827  0.8721895  0.6957143
##    9                   500      0.8831373  0.8726797  0.6942857
##   10                    50      0.9031232  0.9000000  0.7042857
##   10                   100      0.9006956  0.8936928  0.7028571
##   10                   150      0.8959244  0.8885621  0.7014286
##   10                   200      0.8925023  0.8862092  0.6942857
##   10                   250      0.8907423  0.8833333  0.7042857
##   10                   300      0.8890009  0.8868301  0.6900000
##   10                   350      0.8884127  0.8844444  0.7000000
##   10                   400      0.8873716  0.8815686  0.6871429
##   10                   450      0.8868908  0.8785948  0.6900000
##   10                   500      0.8875724  0.8843464  0.6900000
##
## Tuning parameter 'shrinkage' was held constant at a value of 0.1
##
## Tuning parameter 'n.minobsinnode' was held constant at a value of 10
## ROC was used to select the optimal model using the largest value.
## The final values used for the model were n.trees = 100, interaction.depth =
##  1, shrinkage = 0.1 and n.minobsinnode = 10.
```

```r
# Test the gbm
gbm.predict = predict(gbm, svm.test)
# confusion matrix
cm.gbm <- confusionMatrix(gbm.predict, svm.test$Cath)
print(cm.gbm)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     38      4
##     Normal   5     13
##
##                Accuracy : 0.85
##                  95% CI : (0.7343, 0.929)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.01221
##
```

```
##                   Kappa : 0.6371
##
##  Mcnemar's Test P-Value : 1.00000
##
##             Sensitivity : 0.8837
##             Specificity : 0.7647
##          Pos Pred Value : 0.9048
##          Neg Pred Value : 0.7222
##              Prevalence : 0.7167
##          Detection Rate : 0.6333
##    Detection Prevalence : 0.7000
##       Balanced Accuracy : 0.8242
##
##        'Positive' Class : Cad
##
```

```r
# store the ROC and Testing accuracy to the results table
result$Training_ROC[10] = max(gbm$results$ROC)
result$Testing_Accuracy[10] = cm.gbm$overall[1]

# Save the testing ROC for plotting later
gbm.probs = predict(gbm,svm.test[,!names(svm.test) %in% c("Cath")],
                    type = "prob")
gbm.ROC = roc(response = svm.test$Cath,
              predictor = gbm.probs$Cad,
              levels = levels(svm.test$Cath),
              percent = T)
result$Test_AUC[10] = gbm.ROC$auc
```

1.2.11 Decision Tree

```r
set.seed(3164)
# train the decision tree
dt <- train(Cath ~., data = svm.train,
                 method = "C5.0",
                 trControl = control,
                 verbose = FALSE,
                 preProc = c("center", "scale"),
                 tuneLength = 10,
                 metric = "ROC")
print(dt)
```

```
## C5.0
##
## 243 samples
##  12 predictor
##   2 classes: 'Cad', 'Normal'
##
## Pre-processing: centered (15), scaled (15)
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 219, 219, 218, 219, 219, 218, ...
```

```
## Resampling results across tuning parameters:
##
##   model  winnow  trials  ROC        Sens       Spec
##   rules  FALSE    1      0.8246032  0.8885294  0.6857143
##   rules  FALSE   10      0.8984174  0.9158497  0.6685714
##   rules  FALSE   20      0.9100373  0.9163072  0.7014286
##   rules  FALSE   30      0.9118254  0.9144444  0.7100000
##   rules  FALSE   40      0.9131839  0.9144771  0.7085714
##   rules  FALSE   50      0.9132586  0.9157190  0.7057143
##   rules  FALSE   60      0.9143184  0.9157190  0.7171429
##   rules  FALSE   70      0.9135481  0.9157516  0.7171429
##   rules  FALSE   80      0.9142157  0.9162745  0.7114286
##   rules  FALSE   90      0.9149813  0.9156536  0.7157143
##   rules   TRUE    1      0.8276517  0.8772876  0.6785714
##   rules   TRUE   10      0.8701774  0.9000000  0.6714286
##   rules   TRUE   20      0.8764776  0.8902614  0.6900000
##   rules   TRUE   30      0.8781816  0.8884967  0.6900000
##   rules   TRUE   40      0.8780182  0.8885621  0.6957143
##   rules   TRUE   50      0.8793347  0.8896078  0.6957143
##   rules   TRUE   60      0.8799977  0.8879085  0.6957143
##   rules   TRUE   70      0.8799276  0.8890850  0.6971429
##   rules   TRUE   80      0.8818231  0.8884967  0.6957143
##   rules   TRUE   90      0.8813329  0.8884967  0.6985714
##   tree   FALSE    1      0.8182493  0.8884967  0.6771429
##   tree   FALSE   10      0.8977848  0.9040850  0.6871429
##   tree   FALSE   20      0.9047806  0.9086928  0.7100000
##   tree   FALSE   30      0.9068161  0.9064052  0.7071429
##   tree   FALSE   40      0.9090803  0.9041503  0.7171429
##   tree   FALSE   50      0.9114099  0.9063725  0.7171429
##   tree   FALSE   60      0.9103315  0.9064706  0.7100000
##   tree   FALSE   70      0.9117507  0.9064706  0.7142857
##   tree   FALSE   80      0.9124416  0.9094444  0.7200000
##   tree   FALSE   90      0.9126284  0.9065033  0.7157143
##   tree    TRUE    1      0.8200980  0.8756209  0.6814286
##   tree    TRUE   10      0.8711438  0.8913725  0.6914286
##   tree    TRUE   20      0.8765033  0.8872876  0.7000000
##   tree    TRUE   30      0.8789309  0.8872876  0.7071429
##   tree    TRUE   40      0.8789799  0.8843791  0.7085714
##   tree    TRUE   50      0.8785341  0.8837582  0.7100000
##   tree    TRUE   60      0.8787068  0.8837908  0.7085714
##   tree    TRUE   70      0.8796125  0.8826471  0.7057143
##   tree    TRUE   80      0.8797899  0.8832353  0.7057143
##   tree    TRUE   90      0.8795472  0.8849346  0.7100000
##
## ROC was used to select the optimal model using the largest value.
## The final values used for the model were trials = 90, model = rules and
##  winnow = FALSE.
```

```r
# Test the decision tree
dt.predict = predict(dt, svm.test)
# confusion matrix
cm.dt <- confusionMatrix(dt.predict, svm.test$Cath)
print(cm.dt)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     39      3
##     Normal   4     14
##
##                Accuracy : 0.8833
##                  95% CI : (0.7743, 0.9518)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.001754
##
##                   Kappa : 0.7177
##
##  Mcnemar's Test P-Value : 1.000000
##
##             Sensitivity : 0.9070
##             Specificity : 0.8235
##          Pos Pred Value : 0.9286
##          Neg Pred Value : 0.7778
##              Prevalence : 0.7167
##          Detection Rate : 0.6500
##    Detection Prevalence : 0.7000
##       Balanced Accuracy : 0.8653
##
##        'Positive' Class : Cad
##
```

```
# store the ROC and Testing accuracy to the results table
result$Training_ROC[11] = max(dt$results$ROC)
result$Testing_Accuracy[11] = cm.dt$overall[1]

# Save the testing ROC for plotting later
dt.probs = predict(dt,svm.test[,!names(svm.test) %in% c("Cath")],type = "prob")
dt.ROC = roc(response = svm.test$Cath,
              predictor = dt.probs$Cad,
              levels = levels(svm.test$Cath),
              percent = T)
result$Test_AUC[11] = dt.ROC$auc
```

1.2.12 AdaBoost Classification tree

Since the training using ROC to select the optimal model with tuneLength equal to 10 for this particular boosted model takes more than a whole night to run. We therefore adopted another approach to train this classifier, which customizing the tune grid and selecting the optimal model using accuracy.

```
set.seed(3164)
# train adaBoost Classification Tree
adaB = train(Cath ~ ., data = svm.train,
            method = "AdaBoost.M1",
            tuneGrid = data.frame(mfinal = (1:3)*5, maxdepth = c(5,5,5),
                                  coeflearn = c("Breiman", "Freund", "Zhu")),
            preProcess = c("scale", "center"),
```

```r
             na.action = na.omit)
print(adaB)
```

```
## AdaBoost.M1
##
## 243 samples
##  12 predictor
##   2 classes: 'Cad', 'Normal'
##
## Pre-processing: scaled (15), centered (15)
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 243, 243, 243, 243, 243, 243, ...
## Resampling results across tuning parameters:
##
##   coeflearn  mfinal  Accuracy   Kappa
##   Breiman     5      0.8049827  0.5145849
##   Freund     10      0.7937542  0.4847262
##   Zhu        15      0.7944090  0.4817667
##
## Tuning parameter 'maxdepth' was held constant at a value of 5
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were mfinal = 5, maxdepth = 5 and
##  coeflearn = Breiman.
```

```r
# Testing AdaBoost Classification tree
adab.tree.predict = predict(adaB, svm.test)
# confusion matrix
cm.adab.tree <- confusionMatrix(adab.tree.predict, svm.test$Cath)
print(cm.adab.tree)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     38      4
##     Normal   5     13
##
##                Accuracy : 0.85
##                  95% CI : (0.7343, 0.929)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.01221
##
##                   Kappa : 0.6371
##
##  Mcnemar's Test P-Value : 1.00000
##
##             Sensitivity : 0.8837
##             Specificity : 0.7647
##          Pos Pred Value : 0.9048
##          Neg Pred Value : 0.7222
##              Prevalence : 0.7167
##          Detection Rate : 0.6333
##    Detection Prevalence : 0.7000
```

```
##       Balanced Accuracy : 0.8242
##
##        'Positive' Class : Cad
##
```

```r
# store the ROC and Testing accuracy to the results table
result$Training_ROC[12] = paste(as.character(max(adaB$results$Accuracy)),
                                "(Accuracy)", sep = " ")
result$Testing_Accuracy[12] = cm.adab.tree$overall[1]

# Save the testing ROC for plotting later
adab.probs = predict(adaB,svm.test[,!names(svm.test) %in% c("Cath")],
                     type = "prob")
adab.ROC = roc(response = svm.test$Cath,
               predictor = adab.probs$Cad,
               levels = levels(svm.test$Cath),
               percent = T)
result$Test_AUC[12] = adab.ROC$auc
```

1.2.13 Boosted Logistic Regression

```r
set.seed(3164)
# train Boosted Logistic Regression
blr = train(Cath ~ ., data = svm.train,
            method = "LogitBoost",
            tuneGrid = data.frame(nIter = c(5,10,20,50)),
            trControl = control,
            preProcess = c("scale", "center"),
            metric = "ROC",
            na.action = na.omit)
print(blr)
```

```
## Boosted Logistic Regression
##
## 243 samples
##  12 predictor
##   2 classes: 'Cad', 'Normal'
##
## Pre-processing: scaled (15), centered (15)
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 219, 219, 218, 219, 219, 218, ...
## Resampling results across tuning parameters:
##
##   nIter  ROC        Sens       Spec
##    5     0.8263515  0.8718301  0.6014286
##   10     0.8794748  0.9193723  0.7221429
##   20     0.8829342  0.9162630  0.7043571
##   50     0.8844981  0.9043243  0.6862381
##
## ROC was used to select the optimal model using the largest value.
## The final value used for the model was nIter = 50.
```

```r
# Testing Boosted logistic regression
blr.predict = predict(blr, svm.test)
# confusion matrix
cm.blr <- confusionMatrix(blr.predict, svm.test$Cath)
print(cm.blr)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     34      4
##     Normal   5     11
##
##                Accuracy : 0.8333
##                  95% CI : (0.7071, 0.9208)
##     No Information Rate : 0.7222
##     P-Value [Acc > NIR] : 0.04242
##
##                   Kappa : 0.593
##
##  Mcnemar's Test P-Value : 1.00000
##
##             Sensitivity : 0.8718
##             Specificity : 0.7333
##          Pos Pred Value : 0.8947
##          Neg Pred Value : 0.6875
##              Prevalence : 0.7222
##          Detection Rate : 0.6296
##    Detection Prevalence : 0.7037
##       Balanced Accuracy : 0.8026
##
##        'Positive' Class : Cad
##
```

```r
# store the ROC and Testing accuracy to the results table
result$Training_ROC[13] = max(blr$results$ROC)
result$Testing_Accuracy[13] = cm.blr$overall[1]

# Save the testing ROC for plotting later
blr.probs = predict(blr,svm.test[,!names(svm.test) %in% c("Cath")],
                    type = "prob")
blr.ROC = roc(response = svm.test$Cath,
              predictor = blr.probs$Cad,
              levels = levels(svm.test$Cath),
              percent = T)
result$Test_AUC[13] = blr.ROC$auc
```

1.3 Review the Results and Plotting the ROC

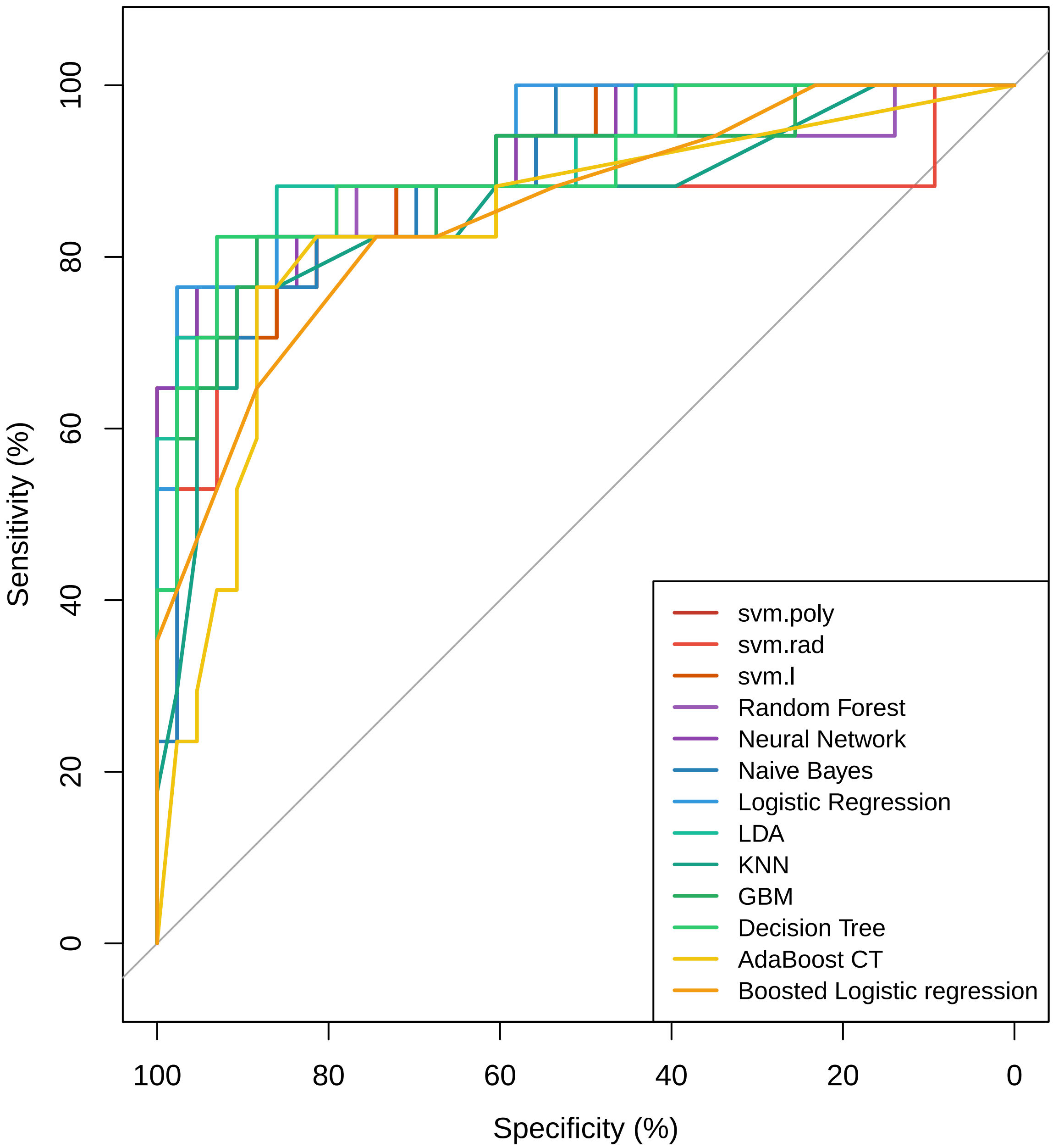
```r
# view the results
print(result)
```

```
##                       Classifier                 Training_ROC Testing_Accuracy
## 1                       SVM.Poly            0.915214752567694        0.8666667
## 2                     SVM.Radial            0.904855275443511        0.8333333
## 3                     SVM.Linear            0.915214752567694        0.9000000
## 4                  Random Forest            0.921577964519141        0.8666667
## 5                 Neurual Network            0.92078431372549        0.8333333
## 6                    Naive Bayes            0.888113912231559        0.6666667
## 7            Logistic Regression            0.916615312791783        0.8666667
## 8                            LDA            0.923487394957983        0.8666667
## 9                            KNN            0.900873015873016        0.8333333
## 10                           GBM            0.925849673202614        0.8500000
## 11                 Decision Tree            0.914981325863679        0.8833333
## 12 AdaBoost Classification Tree 0.804982729619275 (Accuracy)        0.8500000
## 13  Boosted Logistic Regression            0.884498132586368        0.8333333
##    Test_AUC
## 1  90.69767
## 2  85.36252
## 3  90.69767
## 4  89.60328
## 5  91.79207
## 6  90.01368
## 7  92.61286
## 8  91.51847
## 9  85.49932
## 10 89.05609
## 11 90.42408
## 12 83.51573
## 13 85.22572
```

```r
# ploting the ROC
plot(svm.poly.ROC,type = "S",col = "#C0392B")
plot(svm.rad.ROC,add = TRUE,col = "#E74C3C")
plot(svm.l.ROC,add = TRUE,col = "#D35400")
plot(rf.ROC,add = TRUE,col = "#9B59B6")
plot(nn.ROC,add = TRUE,col = "#8E44AD")
plot(nb.ROC,add = TRUE,col = "#2980B9")
plot(lr.ROC,add = TRUE,col = "#3498DB")
plot(lda.ROC,add = TRUE,col = "#1ABC9C")
plot(knn.ROC,add = TRUE,col = "#16A085")
plot(gbm.ROC,add = TRUE,col = "#27AE60")
plot(dt.ROC,add = TRUE,col = "#2ECC71")
plot(adab.ROC,add = TRUE,col = "#F1C40F")
plot(blr.ROC,add = TRUE,col = "#F39C12")

legend("bottomright", legend = c("svm.poly","svm.rad", "svm.l", "Random Forest",
                                 "Neural Network", "Naive Bayes",
                                 "Logistic Regression", "LDA", "KNN", "GBM",
                                 "Decision Tree", "AdaBoost CT",
                                 "Boosted Logistic regression"),
       col = c("#C0392B", "#E74C3C", "#D35400", "#9B59B6", "#8E44AD",
```

```
               "#2980B9", "#3498DB", "#1ABC9C", "#16A085", "#27AE60", "#2ECC71",
               "#F1C40F", "#F39C12"),lwd = 2, cex = 0.8)
```



1.4 Combining the models

We try to combine the classifiers we have trained to obtain a more robust ensemble model. We combine 12 classifiers we have trained, excluding the Naive Bayes classifier since its testing accuracy is only 63%.

```r
# generate a dataframe that contains the prediction results of all models
generate_ensemble_df <- function(caddataset){
  #Input: caddataset - the training dataset
  #Output: a data frame of size (nrow x 12). Each feature (column) is comprised
  #       of the predictions made by that specific model, in probabilities.
  #Runtime: Linear

  aggregate_pred.df <- as.data.frame(caddataset$Cath)
  colnames(aggregate_pred.df)=c("Cath")
  #attach predictions
  aggregate_pred.df$knnres <-  predict(knn, caddataset, type = "prob")$Cad
  aggregate_pred.df$ldares <-  predict(lda, caddataset, type = "prob")$Cad
  aggregate_pred.df$lrres <-  predict(lr, caddataset, type = "prob")$Cad
  aggregate_pred.df$rfres <-  predict(rf, caddataset, type = "prob")$Cad
  aggregate_pred.df$svmLres <-  predict(svm.l, caddataset, type = "prob")$Cad
  aggregate_pred.df$svmPres <-  predict(svm.poly, caddataset, type = "prob")$Cad
  aggregate_pred.df$svmRres <-  predict(svm.rad, caddataset, type = "prob")$Cad
  aggregate_pred.df$NNres <-  predict(nn, caddataset, type = "prob")$Cad
  aggregate_pred.df$GBMres <-  predict(gbm, caddataset, type = "prob")$Cad
  aggregate_pred.df$AdaBres <-  predict(adaB, caddataset, type = "prob")$Cad
  aggregate_pred.df$dtres <-  predict(dt, caddataset, type = "prob")$Cad
  aggregate_pred.df$blrres <-  predict(blr, caddataset, type = "prob")$Cad
  return(aggregate_pred.df)
}
```

1.4.1 Naive Voting Ensemble (Unweigthed Voting)

```r
vote_ensemble <- function(dataset, label="Cath"){
  #Input: dataset - the output dataframe from the generate_ensemble_df functino.
  #Input label - A column name to predict values for.
  #Output: a vector containing the average value of all features for each
  #       input row.
  #Converts Y or N in input df to 1 and 0 respectively.
  #To be used to take a unweighted vote of columns, aka. vote ensembling
  #when combined with generate_ensemble_df

  df = dataset[,names(dataset) != c(label)]
  num = dim(df)[2]
  vote = apply(df, 1, function(x) sum(as.numeric(x)))/num
  return(as.factor(ifelse(round(vote) == 0,"Normal","Cad")))
}
```

```r
# compute the Confusion matrix on the training data set
ensem_result <- vote_ensemble(generate_ensemble_df(svm.train))
confusionMatrix(ensem_result,svm.train$Cath)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad    163      8
```

```
##     Normal  10     62
##
##                Accuracy : 0.9259
##                  95% CI : (0.8855, 0.9555)
##     No Information Rate : 0.7119
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.8209
##
##  Mcnemar's Test P-Value : 0.8137
##
##             Sensitivity : 0.9422
##             Specificity : 0.8857
##          Pos Pred Value : 0.9532
##          Neg Pred Value : 0.8611
##              Prevalence : 0.7119
##          Detection Rate : 0.6708
##    Detection Prevalence : 0.7037
##       Balanced Accuracy : 0.9140
##
##        'Positive' Class : Cad
##
```

```r
# compute the Confusion matrix on the testing data set
ensem_result_test <- vote_ensemble(generate_ensemble_df(svm.test))
confusionMatrix(ensem_result_test,svm.test$Cath)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     39      4
##     Normal   4     13
##
##                Accuracy : 0.8667
##                  95% CI : (0.7541, 0.9406)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.004937
##
##                   Kappa : 0.6717
##
##  Mcnemar's Test P-Value : 1.000000
##
##             Sensitivity : 0.9070
##             Specificity : 0.7647
##          Pos Pred Value : 0.9070
##          Neg Pred Value : 0.7647
##              Prevalence : 0.7167
##          Detection Rate : 0.6500
##    Detection Prevalence : 0.7167
##       Balanced Accuracy : 0.8358
##
##        'Positive' Class : Cad
##
```

1.4.2 Train logistic regression on the ensemble data frame (Weighted Voting)

```r
set.seed(3164)
ensem_train <- generate_ensemble_df(svm.train)
ensem_test <- generate_ensemble_df(svm.test)

# set up 10 cross validation
control <- trainControl(method="repeatedcv",
                        number=10,
                        classProbs = TRUE,
                        summaryFunction = twoClassSummary)

# train logistic regression on result
lr_ensem<-train(Cath ~., data = ensem_train,
                method="glm",
                family = "binomial",
                trControl=control,
                metric = "ROC")

# testing the logistic regression model
ensem_lr_test=predict(lr_ensem, ensem_test)
cm.lr_ensem = confusionMatrix(ensem_lr_test, svm.test$Cath)
cm.lr_ensem
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Cad Normal
##     Cad     39      3
##     Normal   4     14
##
##                Accuracy : 0.8833
##                  95% CI : (0.7743, 0.9518)
##     No Information Rate : 0.7167
##     P-Value [Acc > NIR] : 0.001754
##
##                   Kappa : 0.7177
##
##  Mcnemar's Test P-Value : 1.000000
##
##             Sensitivity : 0.9070
##             Specificity : 0.8235
##          Pos Pred Value : 0.9286
##          Neg Pred Value : 0.7778
##              Prevalence : 0.7167
##          Detection Rate : 0.6500
##    Detection Prevalence : 0.7000
##       Balanced Accuracy : 0.8653
##
##        'Positive' Class : Cad
##
```

```r
# Save the testing ROC for plotting later
lr.ensem.probs = predict(lr_ensem, ensem_test[,2:length(ensem_test)],
                         type = "prob")
lr.ensem.ROC = roc(response = svm.test$Cath,
              predictor = lr.ensem.probs$Cad,
              levels = levels(svm.test$Cath),
              percent = T)

# display the training ROC and Testing accuracy
cat("The training ROC is:", lr_ensem$results$ROC,"\n")
```

```
## The training ROC is: 1
```

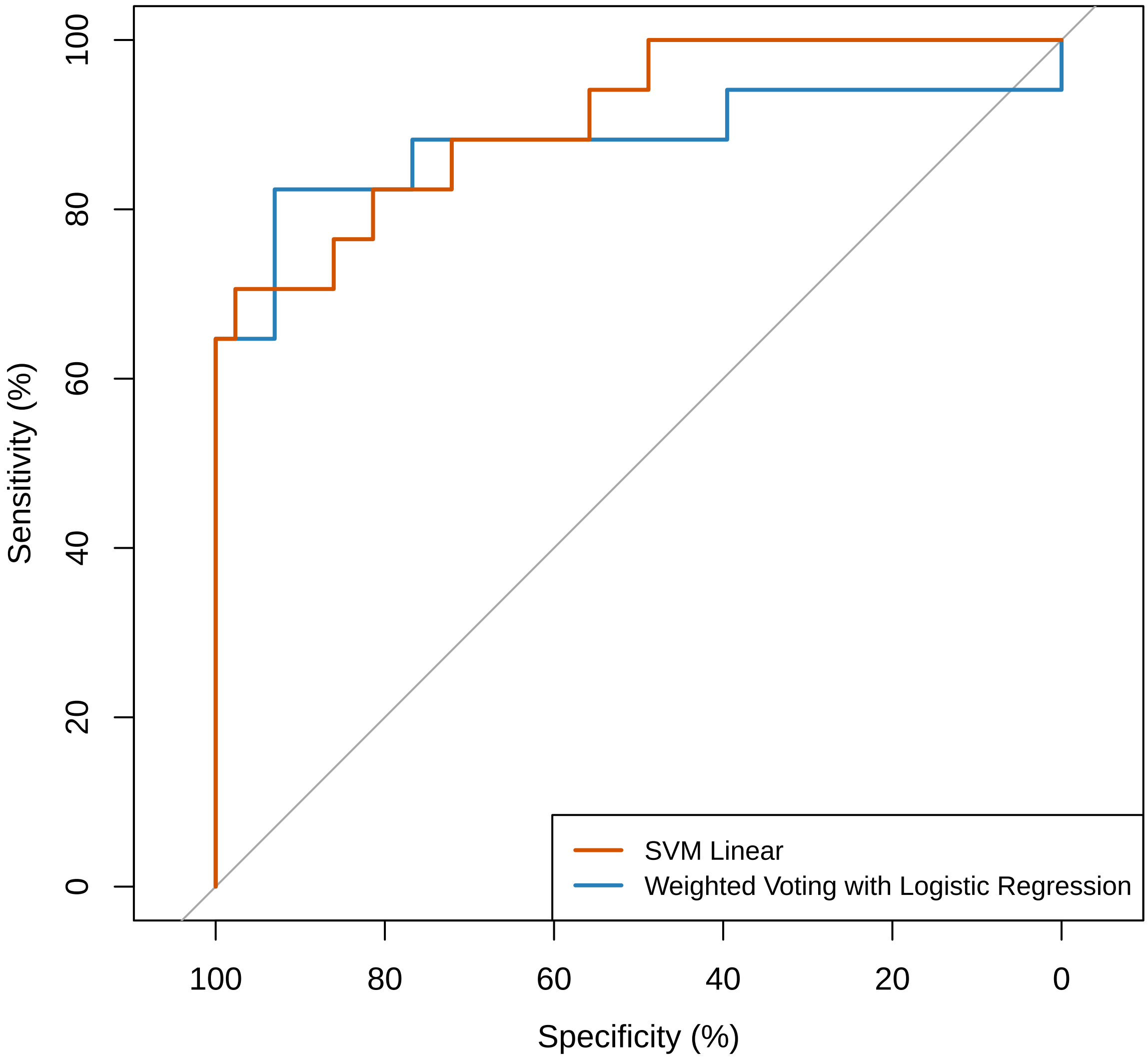
```r
cat("The Testing Accuracy is:", cm.lr_ensem$overall[1], "\n")
```

```
## The Testing Accuracy is: 0.8833333
```

```r
# display the testing AUC
cat("The test AUC is: ", as.character(lr.ensem.ROC$auc))
```

```
## The test AUC is:  88.8508891928865
```

```r
# Plot the Testing ROC curve
# and compare it with the besting performing non-ensemble classifier
plot(lr.ensem.ROC,type = "S",col = "#2980B9")
plot(svm.l.ROC,add = TRUE,col = "#D35400")
legend("bottomright",
       legend= c("SVM Linear", "Weighted Voting with Logistic Regression"),
       col = c("#D35400", "#2980B9"),lwd = 2, cex = 0.8)
```


Sensitivity (%)
Specificity (%)
SVM Linear
Weighted Voting with Logistic Regression
100
80
60
40
20
0