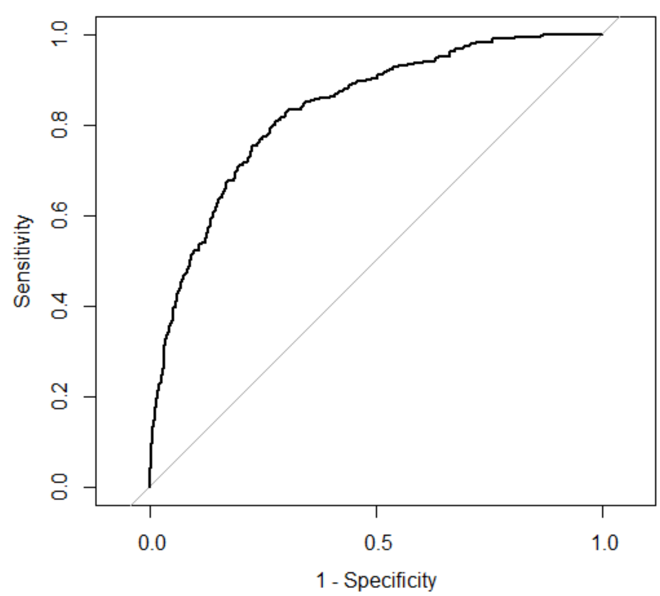
SECTION 1 **Problem 3**

a) Sensitivity, Specificity and overall misclassification rate were calculated using the confusion matrix for LDA as follows.

```
> table(LDA.pred$class, Default)
   Default
      0   1
  0 615 138
  1  85 162

sensitivity         = 162/(138+162) = 162/300   = 0.54
specificity         = 615/(615+85)  = 615/700   = 0.8785714
mc.rate = (85+138)/(615+85+138+162) = 223/1000 = 0.223
```

We observe that specificity is much higher than sensitivity and sensitivity value is close to 0.5. Which suggests that LDA performed well classifying class 1 but did poorly on class 0. ROC curve lie in between the 45-degree line and the inverted L shape we are looking for.

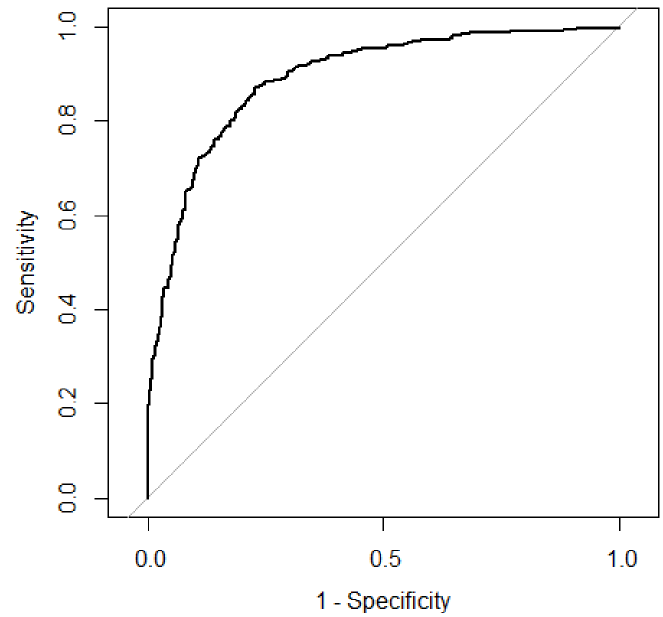


b) Sensitivity, Specificity and overall misclassification rate were calculated using the confusion matrix for QDA as follows.

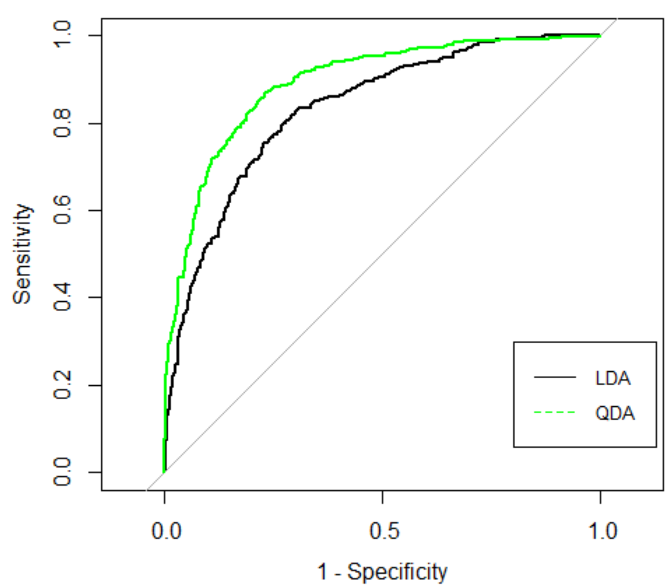
```
> table(QDA.pred$class, Default)
   Default
      0   1
  0 593  70
  1 107 230

sensitivity         = 230/(70+230)  = 230/300    = 0.7666667
specificity         = 593/(593+107) = 593/700    = 0.8471429
mc.rate = (107+70)/(593+107+70+230) = 177/1000  = 0.177
```

We observe that both the specificity and sensitivity are quite high and the overall misclassification rate is low. The model seems to be doing a good job at classification. This is further evident by the ROC curve. The shape of the ROC curve is quite close to an inverted L shape, which is the shape that we would expected under an ideal classifier.



c) When we compare the two methods, we see that QDA was a good classifier for this data set since the misclassification rate was low for QDA and even the ROC curves show that QDA curve shape is much more close to an inverted L shape. Thus, I recommend QDA classifier for this data set.



SECTION 2 **problem 3**

```
# Import data
credit.data <- read.csv(file.choose(), header = T)
attach(credit.data)

# Seperate data into respond and prodictors
train.y <- credit.data[,1]
train.x <- credit.data[,2:21]


# a)
library(MASS) # Need for LDA and QDA

# Fit LDA for the training data
LDA.fit <- lda(Default ~. , data = credit.data)

# Predictions for training data
LDA.pred <- predict(LDA.fit, credit.data)

# Confusion matrix for LDA
table(LDA.pred$class, Default)
# sensitivity = 162/(138+162) = 162/300
# specificity = 615/(615+85) = 615/700
# mc.rate = (85+138)/(615+85+138+162) = 223/1000

# install.packages("pROC")
library(pROC) # Need for roc

# Calculating and Plotting ROC curve for LDA
roc.LDA <- roc(train.y, LDA.pred$posterior[, 1], levels = c(0, 1))
plot(roc.LDA, legacy.axes = T)


# b)
# Fit QDA for the training data
QDA.fit <- qda(Default ~. , data = credit.data)

# Predictions for traning data
QDA.pred <- predict(QDA.fit, credit.data)

# Confusion matrix for QDA
table(QDA.pred$class, Default)
# sensitivity = 230/(70+230) = 230/300
# specificity = 593/(593+107) = 593/700
# mc.rate = (107+70)/(593+107+70+230) = 177/1000

# Calculating and Plotting ROC curve for QDA
roc.QDA <- roc(train.y, QDA.pred$posterior[, 1], levels = c(0, 1))
plot(roc.QDA, legacy.axes = T)


# c)
# Plotting ROC curve for LDA and QDA
plot(roc.LDA, legacy.axes = T)
plot(roc.QDA, add = T, col = "green")
legend(0.2, 0.3, legend=c("LDA", "QDA"), col=c("black", "green"), lty=1:2, cex=0.8)
```