Comparing discriminant rules. ROC curve and other methods

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1. Reading the data from the SPAM database using spam.R

```
spam <- read.table("spam_email_database/spambase.data", sep = ",")

spam.names <-
  c(
    read.table(
      "spam_email_database/spambase.names",
      sep = ":",
      skip = 33,
      nrows = 53,
      as.is = TRUE
    )[, 1],
    "char_freq_#",
    read.table(
      "spam_email_database/spambase.names",
      sep = ":",
      skip = 87,
      nrows = 3,
      as.is = TRUE
    )[, 1],
    "spam.01"
  )

names(spam) <- spam.names
```

2. Dividing data in training set and test set

The data is devided into a training set and a validation set wiht respectivly 2/3 and 1/3 of the data in each gorup. The aim is to get a proximatly 2/3 and 1/3 of both the spam ans the non spam emails in each group. Tho achieve this we first devide the data in to spam and no spam before deviding the data further into a test and a validation set. Before continuing the trainingset is shuffeld.

```
ind_train_spam <-
  as.numeric(sample(rownames(spam[spam$spam.01 == 1, ]), 2 / 3 * nrow(spam[spam$spam.01 == 1, ])))
ind_train_nospam <-
  as.numeric(sample(rownames(spam[spam$spam.01 == 0, ]), 2 / 3 * nrow(spam[spam$spam.01 == 0, ])))

spam_train <- spam[sample(c(ind_train_spam, ind_train_nospam)), ]
spam_test <- spam[-(c(ind_train_spam, ind_train_nospam)), ]
```

3. Classification using the Training sample

Three classification rules are considered:

-Logistic regression fitted by maximum likelihood. -Logistic regression fitted by Lasso. -k-nn binary regression and the trainingsdata is used to fix the tuning parameters and estimate the model parameters.

Logistic Regression by Maximum Likelihood

```
response <- "spam.01"
explanatory <-
  colnames(spam_train)[colnames(spam_train) != response]

# Logistic regression by maximum likelihood
ML_glm_spam <-
  glm(spam_train$spam.01 ~ .,
      family = binomial(link = "logit"),
      data = spam_train)
```

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

Logistic Regression by Lasso

```
library(glmnet)
```

```
## Loading required package: Matrix
## Loaded glmnet 3.0-2
```

```
library(Matrix)

Lasso_cv_glmnet_spam <-
  cv.glmnet(as.matrix(spam_train[, explanatory]), spam_train$spam.01, family = "binomial")
```

KNN binary regression

First the optimum k is found by calculating the number of misclassifications for each k and chose the one with the lowest misclasification rate.

```
# KNN binary regression
library(class)
library(shipunov)
```

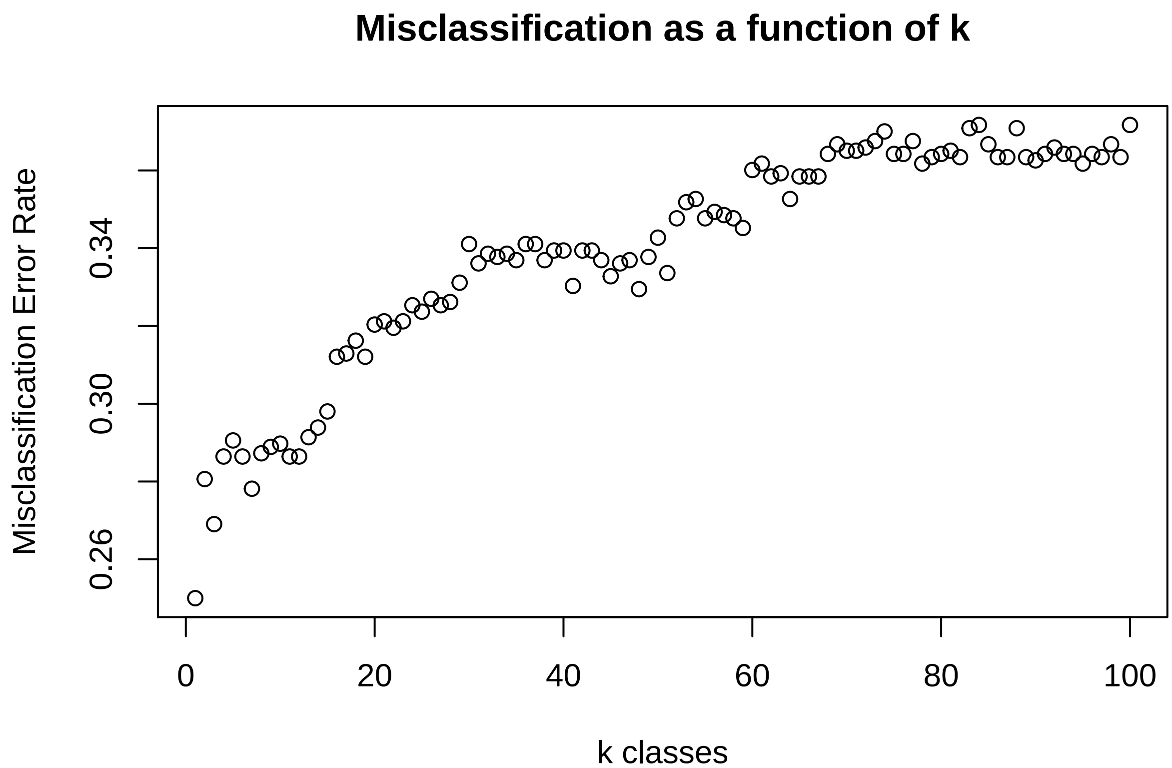
```
## package 'shipunov', version 1.6
```

```
cv_knn <- list()
misclass <- list()

for(k in 1:100) {
  cv_knn[[k]] <-
    as.numeric(knn.cv(spam_train[, explanatory], cl = spam_train$spam.01, k =
                            k)) - 1
  tmp_MCR <-
```

```r
    Misclass(cv_knn[[k]],
             spam_train$spam.01,
             quiet = TRUE,
             best = TRUE)
  misclass[[k]] <-
    mean(tmp_MCR[1, 2] / (tmp_MCR[1, 2] + tmp_MCR[2, 2]),
         tmp_MCR[2, 1] / (tmp_MCR[2, 1] + tmp_MCR[1, 1]))
}

k = which(misclass == do.call(min, misclass))[1]
plot(1:100,
     do.call(cbind, misclass),
     xlab = "k classes",
     ylab = "Misclassification Error Rate",
     main = "Misclassification as a function of k"
)
```




```r
k
```

```
## [1] 1
```

This suggests the optimum k is in fact $k = 1$ which is a bit suprising.

Now the knn classification is done with the optimum k

```r
cl <- as.factor(spam_train[, response])
knn_spam <-
  knn(spam_train[, explanatory],
      spam_test[, explanatory],
      cl = cl,
      k = k,
```

```
      prob = TRUE)

knns <- as.numeric(knn_spam) - 1
prob <- attr(knn_spam, "prob") * knns + (1 - attr(knn_spam, "prob")) * (1 - knns)
```

4. Use the test sample to compute and plot the ROC curve for each rule.

ROC curve for GLM

```
library(ROCR)
```

```
## Loading required package: gplots

##
## Attaching package: 'gplots'

## The following object is masked from 'package:stats':
##
##     lowess
```

```
library(gplots)

ML_glm_pred <- predict(ML_glm_spam, newdata = spam_test)
ML_glm_prediction <- prediction(ML_glm_pred, spam_test$spam.01)
ML_glm_performance <- performance(ML_glm_prediction, "sens", "spec")
```

ROC curve for glmnet

```
Lasso_glmnet_pred <-
  predict(Lasso_cv_glmnet_spam,
          newx = as.matrix(spam_test[, explanatory]),
          type = "response", s= "lambda.min")
Lasso_glmnet_prediction <-
  prediction(Lasso_glmnet_pred, spam_test$spam.01)
Lasso_glmnet_performance <-
  performance(Lasso_glmnet_prediction, "sens", "spec")
```

ROC curve for KNN

```
library(pROC)
```

```
## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

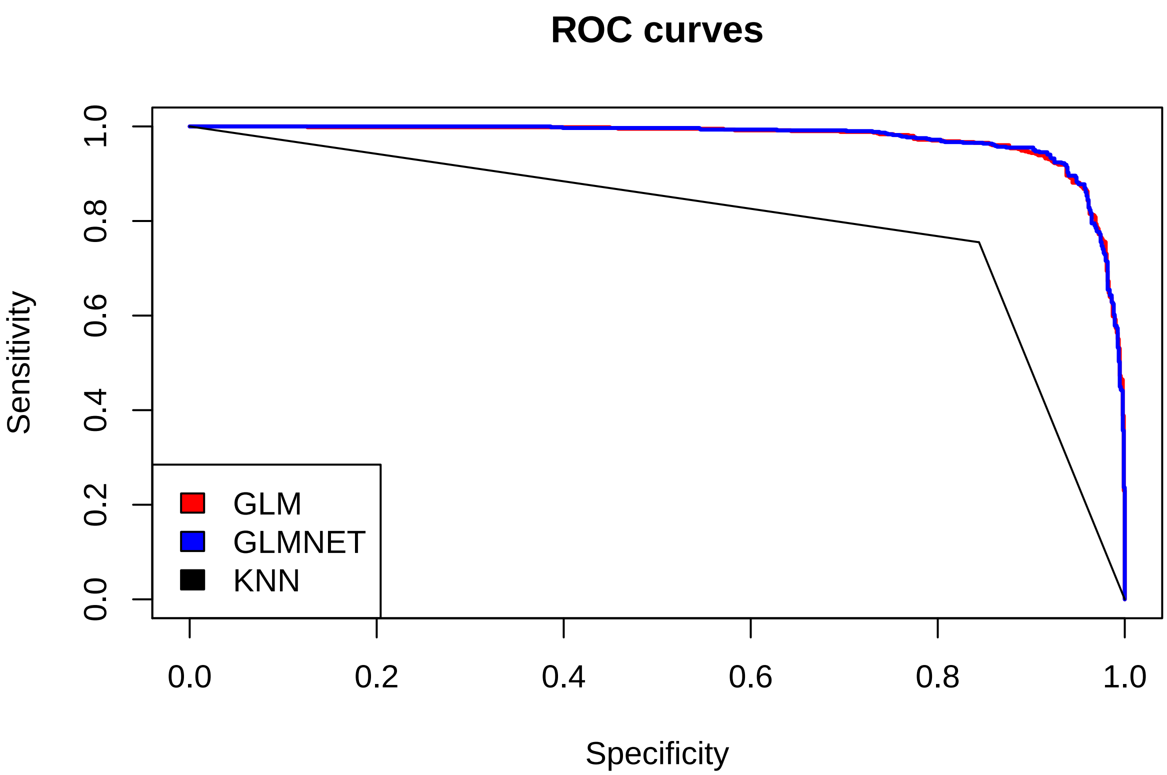
```
knns <- as.numeric(knn_spam) - 1
prob <-
```

```
  attr(knn_spam, "prob") * knns + (1 - attr(knn_spam, "prob")) * (1 - knns)

knn_prediction <- prediction(prob, spam_test$spam.01)
knn_preformance <- performance(knn_prediction, "sens", "spec")
```

Plot ROC curves for each rule

```
plot(ML_glm_performance, col = "red", lwd = 2, main = "ROC curves")
plot(
  Lasso_glmnet_performance,
  add = TRUE,
  col = "blue",
  lwd = 2
)
plot(knn_preformance, add = TRUE, col = "black")
legend("bottomleft",
       c("GLM", "GLMNET", "KNN"),
       fill = c("red", "blue", "black"))
```



As one can see the both the regression using Maximum Likelihood and the one using Lasso are very similar as well as having a high sensitivity ans specificity rate. Knn gives is worse and because of our chose of k the curve is not very smooth. This would change for different choses of k but then the misclasification rate becomes worse.

5. Compute also the misclassification rate for each rule when using the cut point c = 1/2.

```r
c = 1 / 2
library(shipunov)
```

Misclasification rate for the logistig regression using Maximum likelihood.

```r
class_ML_glm <- as.numeric(ifelse(ML_glm_pred > c,
                                  "1", "0"))

MCR_ML_glm <- Misclass(class_ML_glm, spam_test$spam.01)
```

```
## Classification table:
##     obs
## pred   0   1
##    0 894 104
##    1  36 501
## Misclassification errors (%):
##    0    1
##  3.9 17.2
## Mean misclassification error: 10.5%
```

Misclasification rate for the logistig regression using Lasso.

```r
class_Lasso_glmnet <- as.numeric(ifelse(Lasso_glmnet_pred > c,
                                        "1", "0"))

MCR_Lasso_glmnet <- Misclass(class_Lasso_glmnet, spam_test$spam.01)
```

```
## Classification table:
##     obs
## pred   0   1
##    0 882  71
##    1  48 534
## Misclassification errors (%):
##    0    1
##  5.2 11.7
## Mean misclassification error: 8.4%
```

Misclasification rate for the logistig regression using knn.

```r
class_knn <- as.numeric(ifelse(prob >= c, "1", "0"))
MCR_knn <- Misclass(class_knn, spam_test$spam.01)
```

```
## Classification table:
```

```
##      obs
## pred   0   1
##    0 784 148
##    1 146 457
## Misclassification errors (%):
##    0    1
## 15.7 24.5
## Mean misclassification error: 20.1%
```

Again we can see that the Maximim likelihood and the Lasso regreassion are similar although Lasso has a slightly smaller misclassification. The regression using Maximum likelihood has a slightly lower rate for missclasification spam emails as non spam while the Lasso regression has a lower rate for classifying non spam as spam mail. The knn is worse in every way.

6. Compute l_{val} for each rule.

```r
likelihood <- function(test, y, MCR) {
  prob <- (MCR[2, 1] + MCR[2, 2]) / nrow(test)
  l_val <- 1 / nrow(test) * sum(y * log(prob) + (1 - y) * log(1 - prob))
  return(l_val)
}

# GLM
print("ML")
```

```
## [1] "ML"
```

```r
(l_val_glm <- likelihood(spam_test, spam_test$spam.01, MCR_ML_glm))
```

```
## [1] -0.6748007
```

```r
# GLMNET
print("Lasso")
```

```
## [1] "Lasso"
```

```r
(l_val_glmnet <-
    likelihood(spam_test, spam_test$spam.01, MCR_Lasso_glmnet))
```

```
## [1] -0.6710371
```

```r
# KNN
print("KNN")
```

```
## [1] "KNN"
```

```r
(l_val_knn <- likelihood(spam_test, spam_test$spam.01, MCR_knn))
```

```
## [1] -0.6705662
```

The model that gives the highest log likelihood is the one using Lasso which corresponds the comparing of misclassification errors.