## SAGA Test Problems

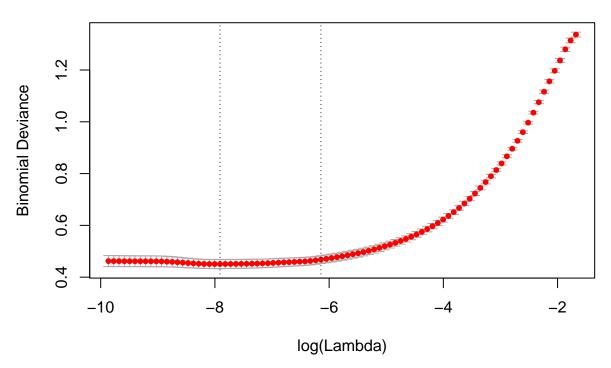
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## Easy

Use glmnet::cv.glmnet to compute a L1-regularized linear model of the spam data in library(ElemStatLearn). What features are selected for the prediction function?

```
library(ElemStatLearn)
library(glmnet)
library(pROC)
sum(is.na(spam)) # make sure data is valid
## [1] 0
p <- 57 # Each email is represented by 57 features
n <- length(spam$spam)</pre>
set.seed(123)
class <- factor(spam$spam, labels=c(0,1)) # email = 0, spam = 1</pre>
trainIdx <- sort(sample(1:n, floor(n*0.75)))</pre>
train_class <- spam$spam[trainIdx]</pre>
train_feat <- data.matrix(spam[trainIdx,1:p])</pre>
test_class <- spam$spam[-trainIdx]</pre>
test_feat <- data.matrix(spam[-trainIdx,1:p])</pre>
logistic.fitted <- cv.glmnet(train_feat,train_class,</pre>
                                family = "binomial",
                                alpha=1)
plot(logistic.fitted)
```

## 56 56 56 56 56 54 52 51 45 38 34 27 20 13 5



```
# extract coefficients
coefficients <- coef(logistic.fitted, s="lambda.1se")</pre>
names(coefficients[which(coefficients != 0),])
##
    [1] "(Intercept)" "A.1"
                                       "A.2"
                                                      "A.3"
                                                                      "A.4"
    [6] "A.5"
                        "A.6"
                                       "A.7"
                                                      "A.8"
                                                                      "A.9"
##
## [11] "A.10"
                        "A.12"
                                       "A.13"
                                                      "A.14"
                                                                      "A.15"
## [16] "A.16"
                                       "A.18"
                        "A.17"
                                                      "A.19"
                                                                      "A.20"
##
  [21] "A.21"
                        "A.22"
                                       "A.23"
                                                      "A.24"
                                                                      "A.25"
  [26] "A.26"
                        "A.27"
                                       "A.28"
                                                      "A.29"
##
                                                                      "A.30"
  [31] "A.31"
                        "A.33"
                                       "A.35"
                                                      "A.36"
                                                                      "A.39"
                                       "A.42"
  [36] "A.40"
                        "A.41"
                                                      "A.43"
                                                                      "A.44"
## [41] "A.45"
                        "A.46"
                                       "A.47"
                                                      "A.48"
                                                                      "A.49"
## [46] "A.50"
                        "A.51"
                                       "A.52"
                                                      "A.53"
                                                                      "A.54"
                        "A.57"
## [51] "A.56"
```

To reduce complexity of the model, I choose the lambda one SE away from the lambda.min.

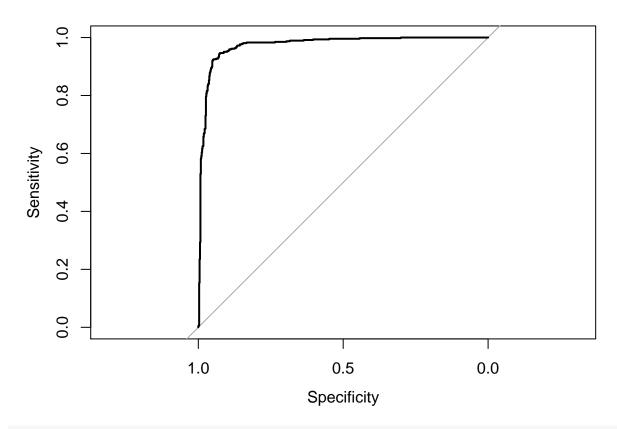
## What is the test error and test AUC of the learned model?

```
test_pred <- predict(logistic.fitted, test_feat, s="lambda.1se")
roc_lasso <- roc(test_class, test_pred)</pre>
```

## Warning in roc.default(test\_class, test\_pred): Deprecated use a matrix
## as predictor. Unexpected results may be produced, please pass a numeric

```
## vector.
```

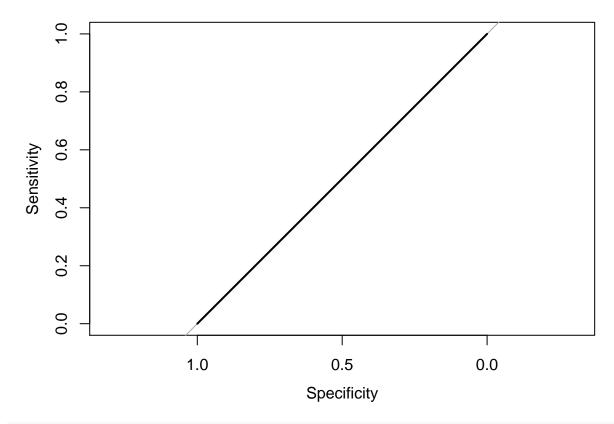
```
plot(roc_lasso)
```



```
auc(roc_lasso)
```

```
## Area under the curve: 0.974

const_pre <- rep(0,length(test_class))
roc_const <- roc(test_class, const_pre)
plot(roc_const)</pre>
```



auc(roc\_const)

## Area under the curve: 0.5

Is it significantly better than the trivial model which predicts the most frequent class in the training data? Answer these questions by using K-fold cross-validation in the spam data.

Yes, it is.