ds2_hw3

Ruihan Zhang

2023-03-21

```
library(caret)
```

```
## Loading required package: ggplot2
```

```
## Loading required package: lattice
```

```
library(knitr)
library(glmnet)
```

```
## Loading required package: Matrix
```

```
## Loaded glmnet 4.1-4
```

```
library(mlbench)
library(splines)
library(mgcv)
```

```
## Loading required package: nlme
```

```
## This is mgcv 1.8-40. For overview type 'help("mgcv-package")'.
```

```
library(pROC)
```

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

```
##
## Attaching package: 'pROC'
```

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

```
library(MASS)
library(earth)
```

```
## Loading required package: Formula
```

```
## Loading required package: plotmo

## Loading required package: plotrix

## Loading required package: TeachingDemos
```

```
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.2 --

## v tibble  3.1.8      v dplyr   1.0.10
## v tidyr   1.3.0      v stringr 1.5.0
## v readr   2.1.2      v forcats 0.5.2
## v purrr   1.0.1
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::collapse() masks nlme::collapse()
## x tidyr::expand()   masks Matrix::expand()
## x dplyr::filter()   masks stats::filter()
## x dplyr::lag()      masks stats::lag()
## x purrr::lift()     masks caret::lift()
## x tidyr::pack()     masks Matrix::pack()
## x dplyr::select()   masks MASS::select()
## x tidyr::unpack()   masks Matrix::unpack()
```

```
library(ggplot2)
library(pdp)
```

```
##
## Attaching package: 'pdp'
##
## The following object is masked from 'package:purrr':
##
##     partial
```

```
library(vip)
```

```
##
## Attaching package: 'vip'
##
## The following object is masked from 'package:utils':
##
##     vi
```

```
library(klaR)
```

```
##
## Attaching package: 'klaR'
##
## The following object is masked from 'package:TeachingDemos':
##
##     triplot
```

```r
library(AppliedPredictiveModeling)
```

```r
auto=read_csv("./auto.csv") %>%
  janitor::clean_names() %>%
  na.omit() %>%
  mutate(mpg_cat = as.factor(mpg_cat),
         year = as.factor(year),
         origin = as.factor(origin),
         mpg_cat = fct_relevel(mpg_cat, c("low", "high")))
```

```
## Rows: 392 Columns: 8
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (1): mpg_cat
## dbl (7): cylinders, displacement, horsepower, weight, acceleration, year, or...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
set.seed(2023)
train_index=createDataPartition(y=auto$mpg_cat, p=0.7, list = FALSE)
train=auto[train_index,]
test=auto[-train_index,]
#training data
x1=model.matrix(mpg_cat~.,train)[,-1]
y1=train$mpg_cat
#testing data
x2=model.matrix(mpg_cat~.,test)[,-1]
y2=auto$mpg_cat[-train_index]
```

```r
#1.
glm_fit=glm(mpg_cat~., data = auto, subset = train_index, family =binomial(link = "logit"))
summary(glm_fit)
```

```
##
## Call:
## glm(formula = mpg_cat ~ ., family = binomial(link = "logit"),
##     data = auto, subset = train_index)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0585  -0.0673   0.0028   0.1359   3.4148
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  22.287033   6.589777   3.382 0.000719 ***
## cylinders    -0.873335   0.724940  -1.205 0.228319
## displacement  0.007416   0.021833   0.340 0.734095
## horsepower   -0.027269   0.039025  -0.699 0.484702
## weight       -0.005532   0.002191  -2.524 0.011594 *
## acceleration -0.192443   0.249056  -0.773 0.439706
## year71        0.318705   2.397011   0.133 0.894226
```

```
## year72       -1.206294   1.362235  -0.886 0.375873
## year73       -1.735417   1.452223  -1.195 0.232084
## year74        1.975910   1.809505   1.092 0.274850
## year75        1.167625   1.497279   0.780 0.435490
## year76        2.213028   1.621090   1.365 0.172207
## year77        1.388917   1.823066   0.762 0.446145
## year78        1.544688   1.505540   1.026 0.304890
## year79        4.607034   1.941760   2.373 0.017663 *
## year80        5.194261   2.073119   2.506 0.012227 *
## year81        4.785045   1.801277   2.656 0.007896 **
## year82        3.532248   1.690508   2.089 0.036666 *
## origin2       1.201654   1.163232   1.033 0.301590
## origin3       0.341372   1.139917   0.299 0.764581
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 382.62  on 275  degrees of freedom
## Residual deviance:  78.48  on 256  degrees of freedom
## AIC: 118.48
##
## Number of Fisher Scoring iterations: 8
```

```
pred_prob=predict(glm_fit, newdata = auto[-train_index,],
                          type = "response")
pred=rep("low", length(pred_prob))
pred[pred_prob>0.5]="high"
cm=confusionMatrix(data = factor(pred, levels = c("low","high")),
                reference = auto$mpg_cat[-train_index],
                positive = "high")
kable(cm$table,"simple")
```

	low	high
low	52	5
high	6	53

```
cm$byClass["Balanced Accuracy"]
```

```
## Balanced Accuracy
##         0.9051724
```

```
#caret
ctrl=trainControl(method = "cv",
                    summaryFunction = twoClassSummary,
                    classProbs = TRUE)
glm_model=train(x1,y1,,method="glm",metric="ROC", trControl=ctrl)
```

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

```r
summary(glm_model)
```

```
##
## Call:
## NULL
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0585  -0.0673   0.0028   0.1359   3.4148
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  22.287033   6.589777   3.382 0.000719 ***
## cylinders    -0.873335   0.724940  -1.205 0.228319
## displacement  0.007416   0.021833   0.340 0.734095
## horsepower   -0.027269   0.039025  -0.699 0.484702
## weight       -0.005532   0.002191  -2.524 0.011594 *
## acceleration -0.192443   0.249056  -0.773 0.439706
## year71        0.318705   2.397011   0.133 0.894226
## year72       -1.206294   1.362235  -0.886 0.375873
## year73       -1.735417   1.452223  -1.195 0.232084
## year74        1.975910   1.809505   1.092 0.274850
## year75        1.167625   1.497279   0.780 0.435490
## year76        2.213028   1.621090   1.365 0.172207
## year77        1.388917   1.823066   0.762 0.446145
## year78        1.544688   1.505540   1.026 0.304890
## year79        4.607034   1.941760   2.373 0.017663 *
## year80        5.194261   2.073119   2.506 0.012227 *
## year81        4.785045   1.801277   2.656 0.007896 **
## year82        3.532248   1.690508   2.089 0.036666 *
## origin2       1.201654   1.163232   1.033 0.301590
## origin3       0.341372   1.139917   0.299 0.764581
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 382.62  on 275  degrees of freedom
## Residual deviance:  78.48  on 256  degrees of freedom
## AIC: 118.48
##
## Number of Fisher Scoring iterations: 8
```

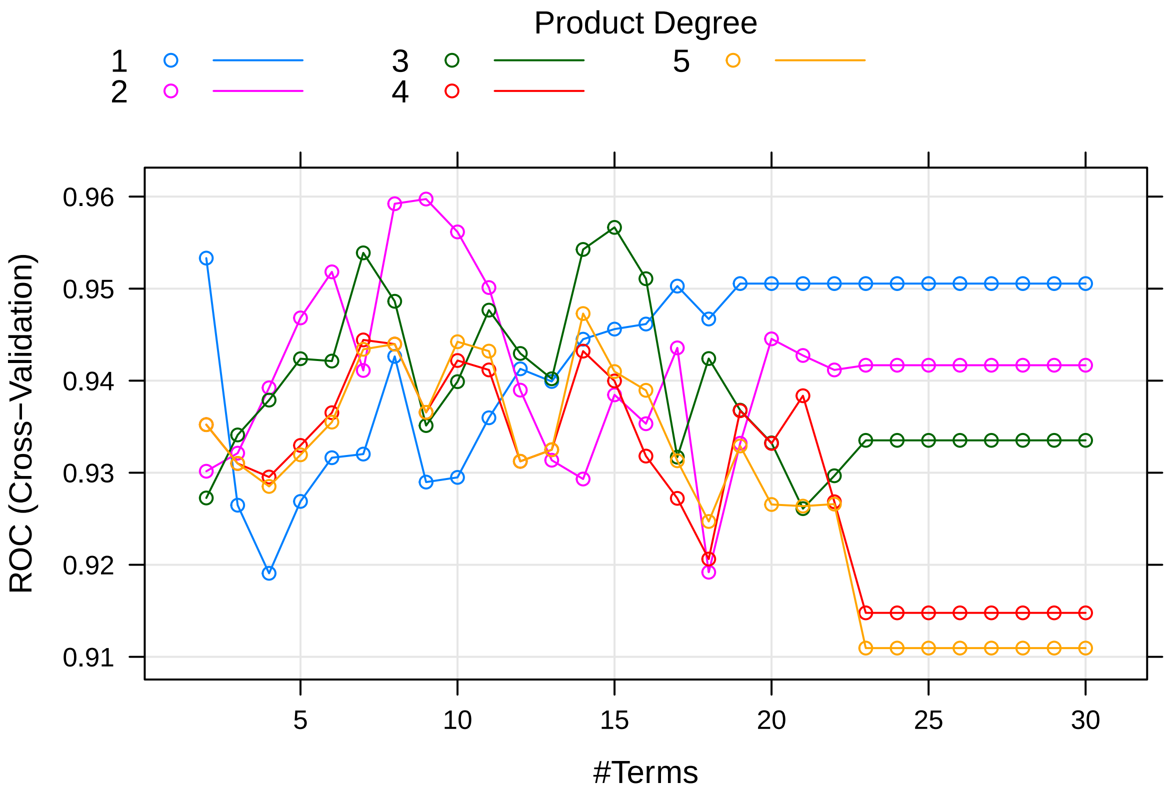
```r
#2.
set.seed(2023)

mars.fit=train(auto[train_index,1:7],
                    auto$mpg_cat[train_index],
                    method = "earth",
                    tuneGrid = expand.grid(degree = 1:5,
                                           nprune = 2:30),
                    metric = "ROC",
                    trControl = ctrl)
```

```r
summary(mars.fit)
```

```
## Call: earth(x=tbl_df[276,7], y=factor.object, keepxy=TRUE,
##             glm=list(family=function.object, maxit=100), degree=2, nprune=9)
##
## GLM coefficients
##                                                    high
## (Intercept)                                    -4.39379
## h(6-cylinders)                                  4.39334
## h(6-cylinders) * year72                     -1144.02683
## h(250-displacement) * year72                   17.57656
## h(250-displacement) * year73                   -0.02805
## h(4-cylinders) * h(250-displacement)           -0.07958
## h(cylinders-4) * h(250-displacement)            0.02873
## h(250-displacement) * h(weight-2671)           -0.00006
## h(250-displacement) * h(14.3-acceleration)      0.02364
##
## GLM (family binomial, link logit):
##  nulldev  df       dev  df   devratio     AIC iters converged
##  382.617 275   63.2795 267      0.835   81.28    21         1
##
## Earth selected 9 of 33 terms, and 6 of 19 predictors (nprune=9)
## Termination condition: Reached nk 39
## Importance: displacement, cylinders, year72, year73, weight, acceleration, ...
## Number of terms at each degree of interaction: 1 1 7
## Earth GCV 0.04144919    RSS 9.76534    GRSq 0.8354025    RSq 0.8584733
```

```r
plot(mars.fit)
```




```r
kable(mars.fit$bestTune,"simple")
```

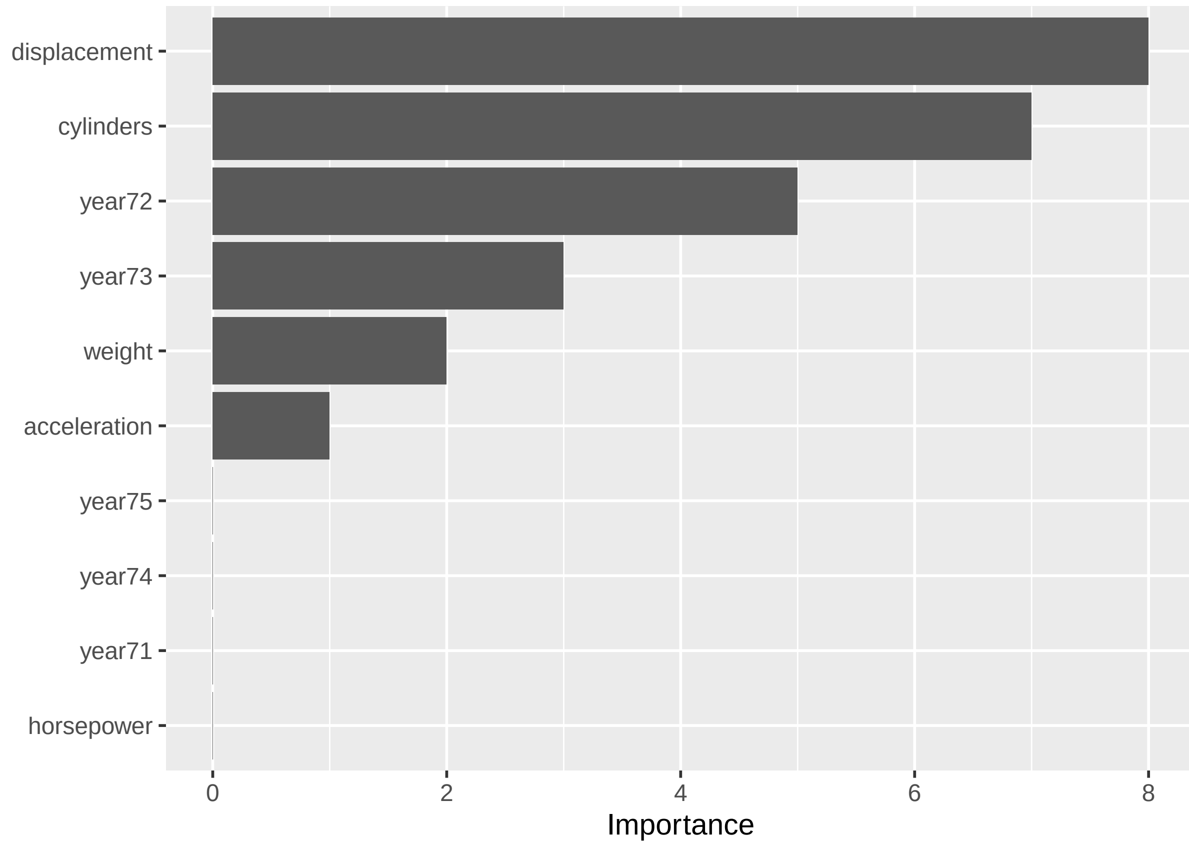
	nprune	degree
37	9	2

```r
coef(mars.fit$finalModel)
```

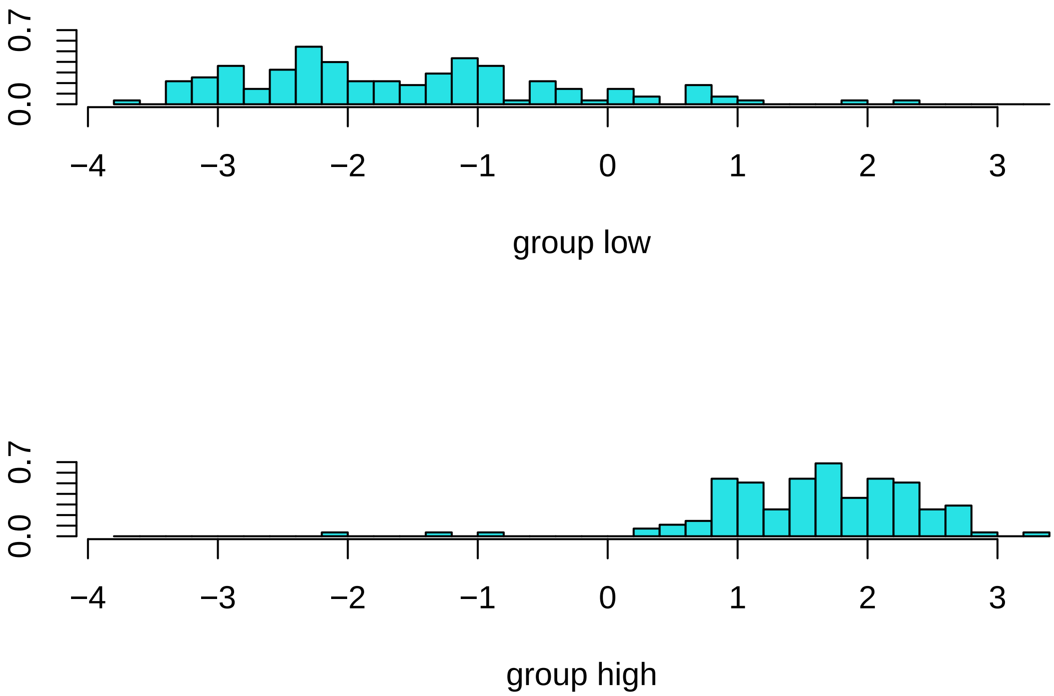
```
##                                (Intercept)
##                              -4.393787e+00
##        h(cylinders-4) * h(250-displacement)
##                               2.873138e-02
##        h(4-cylinders) * h(250-displacement)
##                              -7.957990e-02
## h(250-displacement) * h(14.3-acceleration)
##                               2.364000e-02
##                h(250-displacement) * year72
##                               1.757656e+01
##                h(250-displacement) * year73
##                              -2.805051e-02
##                              h(6-cylinders)
##                               4.393339e+00
##        h(250-displacement) * h(weight-2671)
##                              -6.454739e-05
```

```
##                      h(6-cylinders) * year72
##                                -1.144027e+03
```

```
vip(mars.fit$finalModel)
```




```
#3.
set.seed(2023)
lda_fit=lda(mpg_cat~., data=auto, subset=train_index)
plot(lda_fit)
```




```r
lda_fit$scaling
```

```
##                        LD1
## cylinders    -0.6330461045
## displacement -0.0006067008
## horsepower    0.0101564649
## weight       -0.0009549525
## acceleration -0.0635785096
## year71        0.4736405821
## year72        0.0179567748
## year73       -0.0758425539
## year74        0.9473677997
## year75        0.2649570035
## year76        0.6429583548
## year77        0.7169187913
## year78        0.2963530158
## year79        1.2533575787
## year80        1.5369245404
## year81        1.6226917506
## year82        1.5570246564
## origin2       0.4476293185
## origin3       0.2628033617
```

```r
lda.pred=predict(lda_fit,newdata = test)
head(lda.pred$posterior)
```

```
##          low         high
## 1 0.9996787 0.0003212537
## 2 0.9994263 0.0005736901
## 3 0.9997312 0.0002688218
## 4 0.9993203 0.0006796832
## 5 0.9987197 0.0012803443
## 6 0.9996102 0.0003897596
```

```
#use caret
set.seed(2023)
lda_fit2=train(mpg_cat~., data=train,method="lda",metric="ROC",trControl=ctrl)
lda_fit2$results
```

```
##   parameter       ROC      Sens      Spec      ROCSD    SensSD     SpecSD
## 1      none 0.9657771 0.8763736 0.9703297 0.05623982 0.1221558 0.03834799
```

```
coef(lda_fit2$finalModel)
```

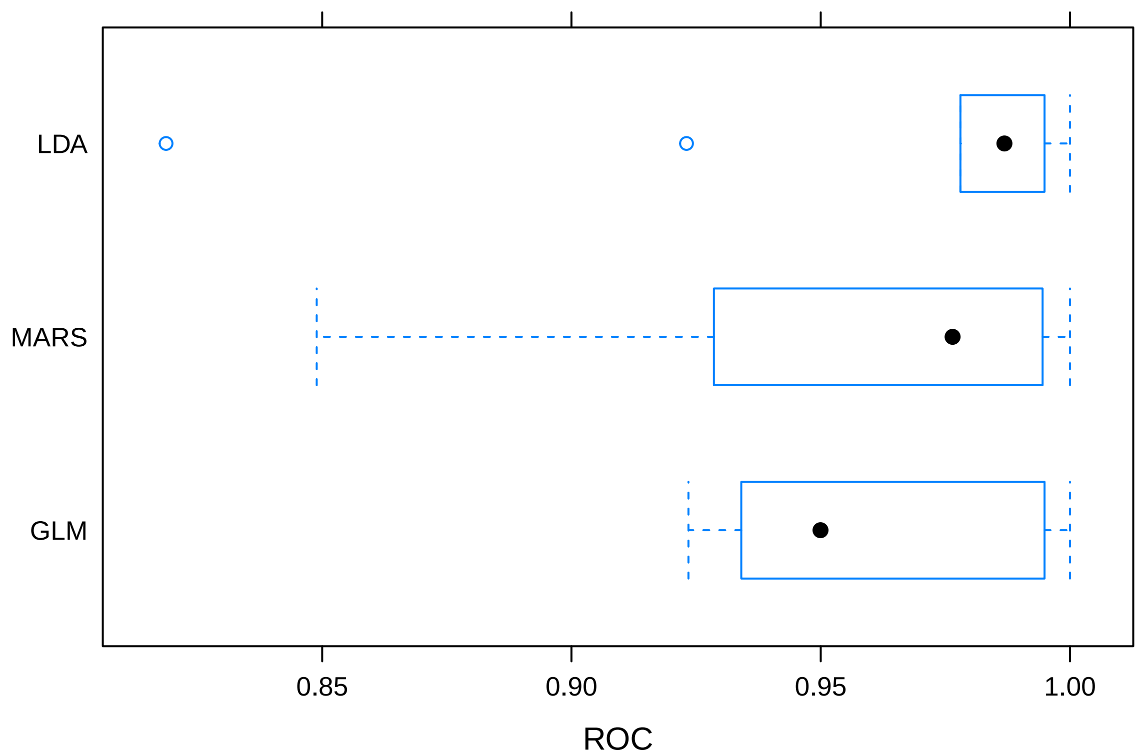
```
##                        LD1
## cylinders    -0.6330461045
## displacement -0.0006067008
## horsepower    0.0101564649
## weight       -0.0009549525
## acceleration -0.0635785096
## year71        0.4736405821
## year72        0.0179567748
## year73       -0.0758425539
## year74        0.9473677997
## year75        0.2649570035
## year76        0.6429583548
## year77        0.7169187913
## year78        0.2963530158
## year79        1.2533575787
## year80        1.5369245404
## year81        1.6226917506
## year82        1.5570246564
## origin2       0.4476293185
## origin3       0.2628033617
```

```
#4.
set.seed(2023)
res=resamples(list(GLM=glm_model,MARS=mars.fit,LDA=lda_fit2))
summary(res)
```

```
##
## Call:
## summary.resamples(object = res)
##
## Models: GLM, MARS, LDA
## Number of resamples: 10
##
## ROC
```

```
##            Min.   1st Qu.    Median      Mean   3rd Qu. Max. NA's
## GLM  0.9234694 0.9365188 0.9499608 0.9614207 0.9947998    1    0
## MARS 0.8489011 0.9362245 0.9764521 0.9597331 0.9933281    1    0
## LDA  0.8186813 0.9784144 0.9868524 0.9657771 0.9936224    1    0
##
## Sens
##            Min.   1st Qu.    Median      Mean   3rd Qu. Max. NA's
## GLM  0.7142857 0.8571429 0.8901099 0.8851648 0.9285714    1    0
## MARS 0.8461538 0.8736264 0.9285714 0.9340659 1.0000000    1    0
## LDA  0.6428571 0.8461538 0.8928571 0.8763736 0.9821429    1    0
##
## Spec
##            Min.   1st Qu.    Median      Mean   3rd Qu. Max. NA's
## GLM  0.7857143 0.9244505 0.9285714 0.9351648 1.0000000    1    0
## MARS 0.7857143 0.8571429 0.9258242 0.9126374 0.9821429    1    0
## LDA  0.9230769 0.9285714 1.0000000 0.9703297 1.0000000    1    0
```

```
bwplot(res,metric = "ROC")
```

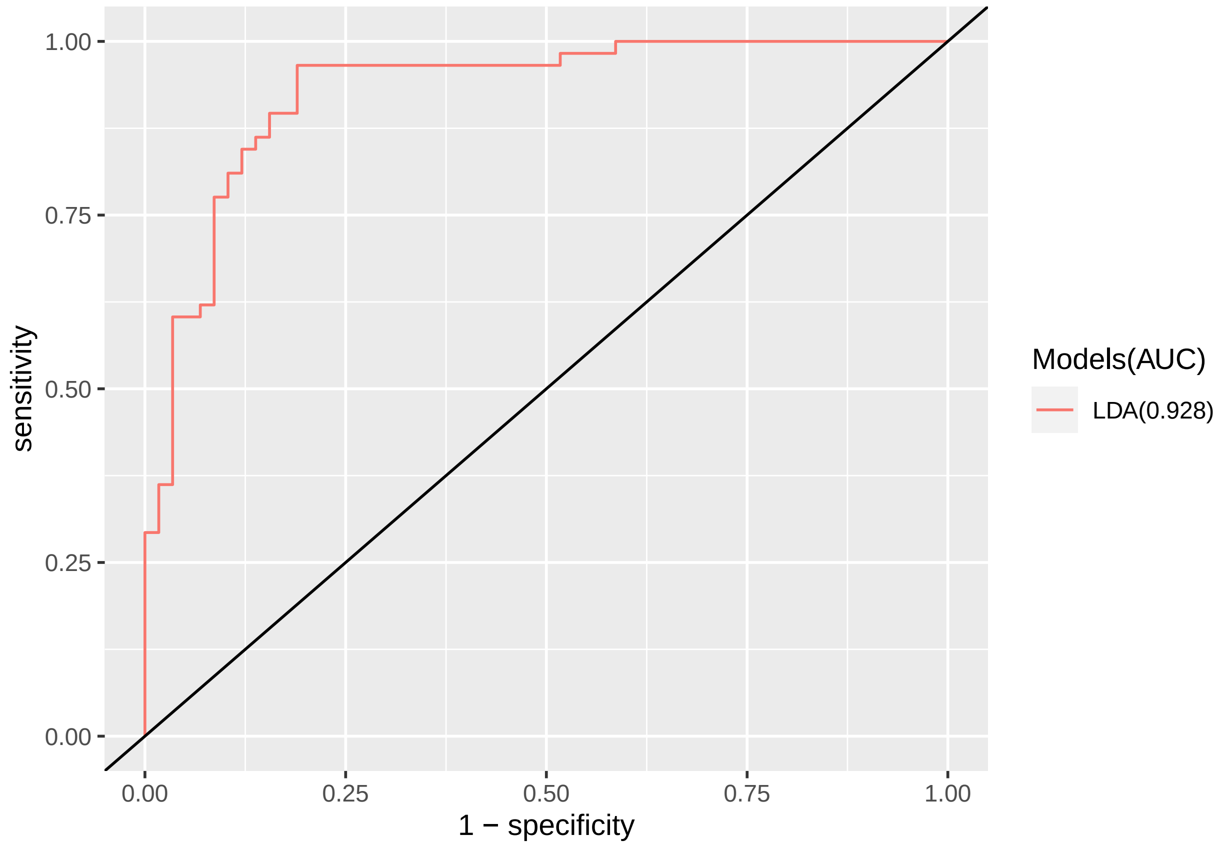



```
lda_pred=predict(lda_fit2, newdata = test,type = "prob")[,2]
lda_roc=roc(test$mpg_cat, lda_pred)
```

```
## Setting levels: control = low, case = high
```

```
## Setting direction: controls < cases
```

```r
lda_auc=lda_roc$auc[1]
modelName=c("LDA")
ggroc(list(lda_roc), legacy.axes = TRUE) + scale_color_discrete(labels=paste0(modelName,"(", round(lda_a
```




```r
test_pred_lda=predict(lda_fit2,newdata = test,type = "prob")
test_pred_prob=predict(glm_fit,newdata = test, type = "response")
pred2=rep("low",length(lda_pred))
pred2[lda_pred>0.5]="high"
confusionMatrix(data = as.factor(pred2),reference=test$mpg_cat,positive="high")
```

```
## Warning in confusionMatrix.default(data = as.factor(pred2), reference =
## test$mpg_cat, : Levels are not in the same order for reference and data.
## Refactoring data to match.
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction low high
##       low   46    2
##       high  12   56
##
##                Accuracy : 0.8793
##                  95% CI : (0.8058, 0.9324)
##     No Information Rate : 0.5
```

```
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.7586
##
##  Mcnemar's Test P-Value : 0.01616
##
##             Sensitivity : 0.9655
##             Specificity : 0.7931
##          Pos Pred Value : 0.8235
##          Neg Pred Value : 0.9583
##              Prevalence : 0.5000
##          Detection Rate : 0.4828
##    Detection Prevalence : 0.5862
##       Balanced Accuracy : 0.8793
##
##        'Positive' Class : high
##
```

The misclassification rate of the LDA model is 1-0.8793=0.1207.