557_Project

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4/11/2017

Data overview

Mining activity has long been associated with mining hazards, such as fires, floods, and toxic contaminants (Dozolme, P., 2016). Among these hazards, seismic hazards are the hardest to detect and predict (Sikora & Wróbel, 2010). Minimizing loss from seismic hazards requires both advanced data collection and analysis. In recent years, more and more advanced seismic and seismoacoustic monitoring systems have come about. Still, the disproportionate number of low-energy versus high-energy seismic phenomena (e.g. $> 10^4$J) renders traditional analysis methods insufficient.

In this project, we used the seismic-bumps dataset provided by Sikora & Wróbel (2010), found in the UCI Machine Learning Repository. This seismic-bumps dataset comes from a coal mine located in Poland and contains 2584 observations of 19 attributes. Each observation summarizes seismic activity in the rock mass within one 8-hour shift. Note that the decision attribute, named "class", has values 1 and 0. This variable is the response variable we use in this project. A class value of "1" is categorized as "hazardous state", which essentially indicates a registered seismic bump with high energy ($>10^4$J) in the next shift. A class value "0" represents non-hazardous state in the next shift. According to Bukowska (2006), a number of factors having an effect on seismic hazard occurrence were proposed. Among other factors, the occurrence of tremors with energy $> 10^4$J was listed. The purpose is to find whether and how the other 18 variables can be used to determine the hazard status of the mine.

Table 1. Attribute information of the seismic-bumps dataset

Data Attributes	Description
seismic	result of shift seismic hazard assessment: 'a' - lack of hazard, 'b' - low hazard, 'c' - high hazard, 'c
seismoacoustic	result of shift seismic hazard assessment
shift	type of a shift: 'W' - coal-getting, 'N' - preparation shift
genergy	seismic energy recorded within previous shift by active geophones (GMax) monitoring the longwal
gpuls	number of pulses recorded within previous shift by GMax
gdenergy	deviation of recorded energy within previous shift from average energy recorded during eight prev
gdpuls	deviation of recorded pulses within previous shift from average number of pulses recorded during e
ghazard	result of shift seismic hazard assessment by the seismoacoustic method based on registration comi
nbumps	the number of seismic bumps recorded within previous shift
nbumps$i$, $i \in \{1, \ldots, 5\}$	the number of seismic bumps ($10^i - 10^{i+1}$ J) registered within previous shift
energy	total energy of seismic bumps registered within previous shift
maxenergy	maximum energy of the seismic bumps registered within previous shift
class	the decision attribute: '1' - high energy seismic bump occurred in the next shift ('hazardous state

Exploratory Data Analysis

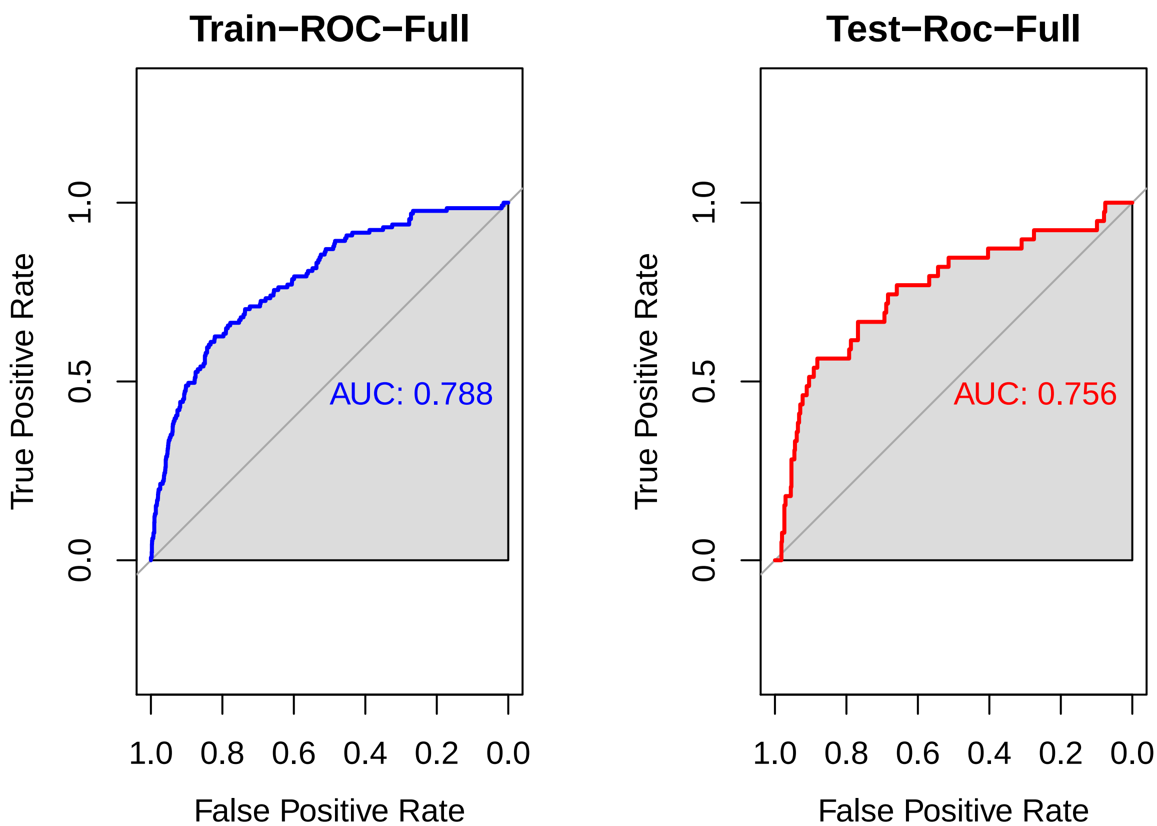
The state of the mine was indeed deemed hazardous infrequently − only 170 shifts out of 2584 − a difficult problem in our analyses. We want to examine which observations of seismic activity can help in the prediction of the hazard state of the mine during the next shift. Regression diagnostics indicate that the data, in general, meet most assumptions. However, we see that that data are somewhat skewed right, and there is severe multicollinearity (VIF > 10) between some of the covariates, as shown below.

Classification before Variable Selection

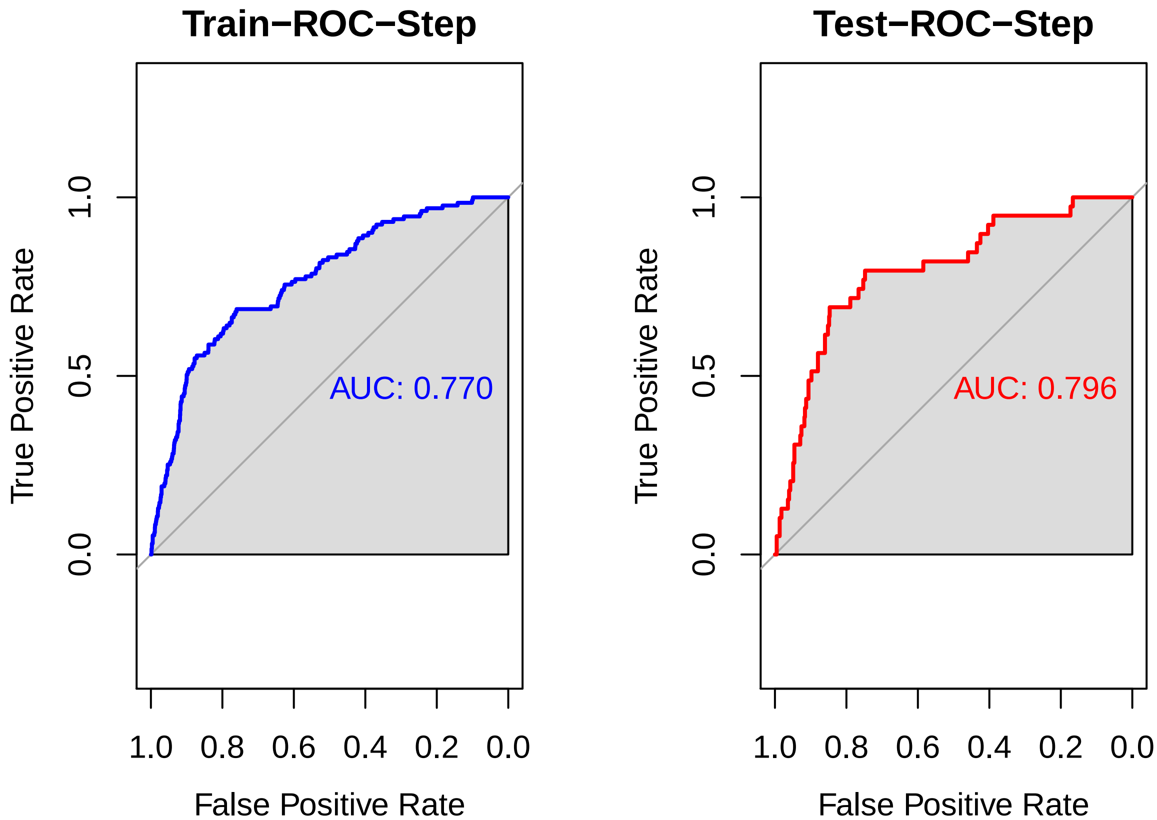
We first take the seismic-bumps dataset and partition the data into training (75%) and test (25%) datasets. The next steps involve examining multiple classification methods on the training and test datasets separately. The goal is to examine which classification method outputs comparatively better prediction for seismic hazards based on available predictors.

Logistic Regression

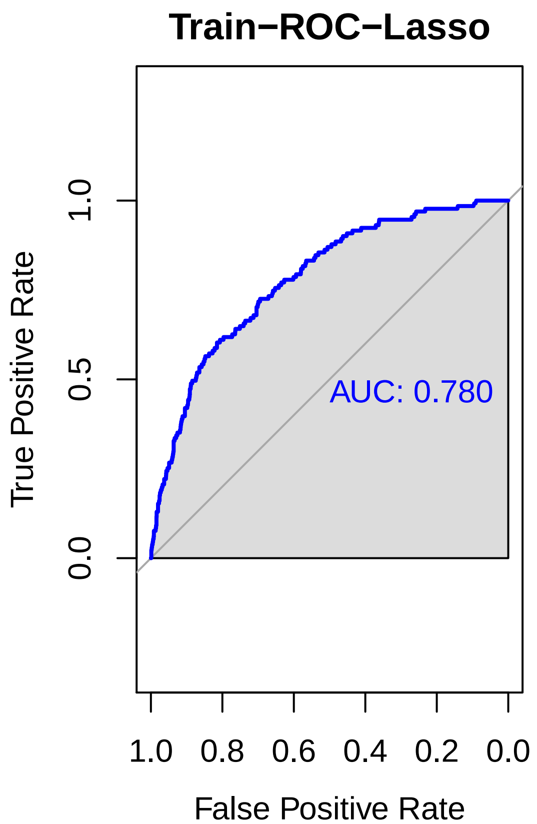
Full Model

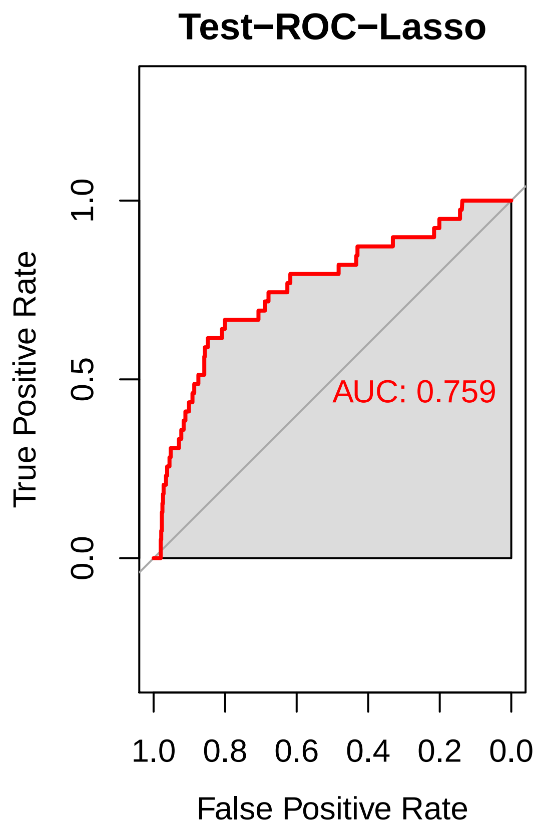


Logistic Regression - Step Model



Logistic Regression - Lasso Model

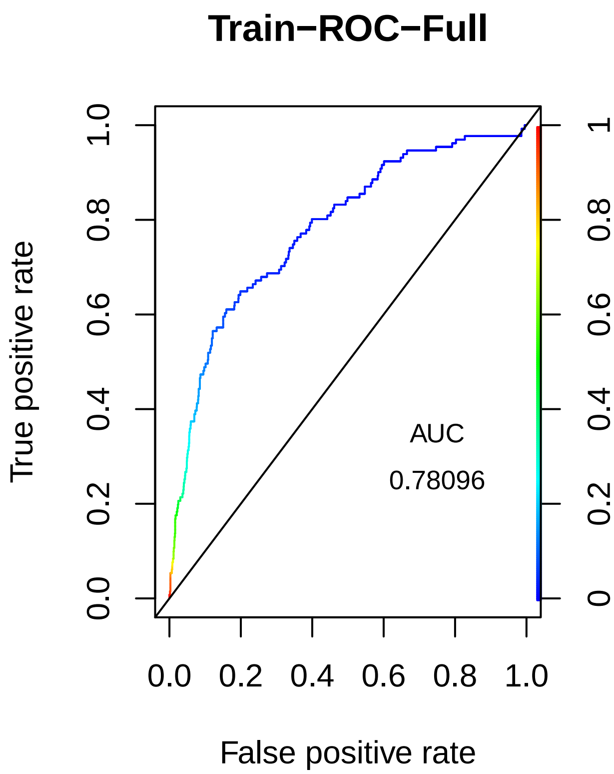


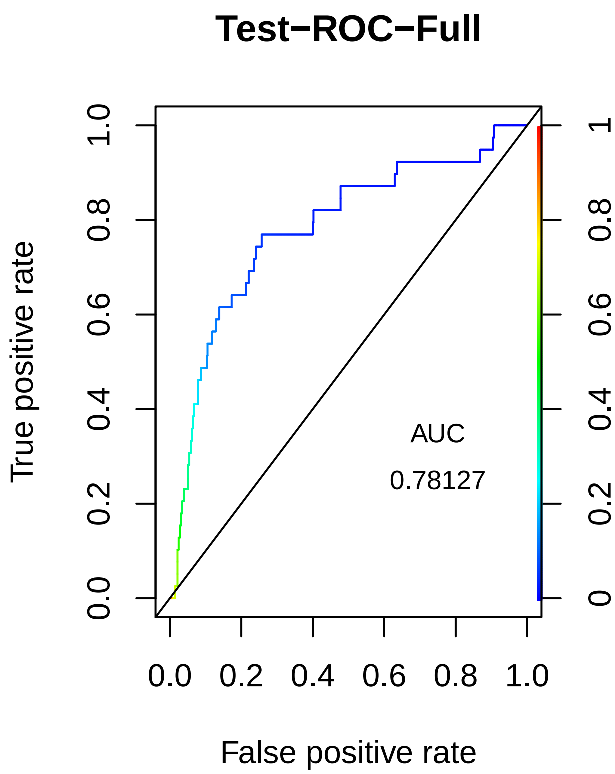



```
        time1 time2 time3
elapsed 0.123 0.195 0.073

     rate1.train rate3.train rate5.train
[1,]       0.067        0.07       0.068

     rate2.test rate4.test rate6.test
[1,]      0.065      0.062      0.062
```

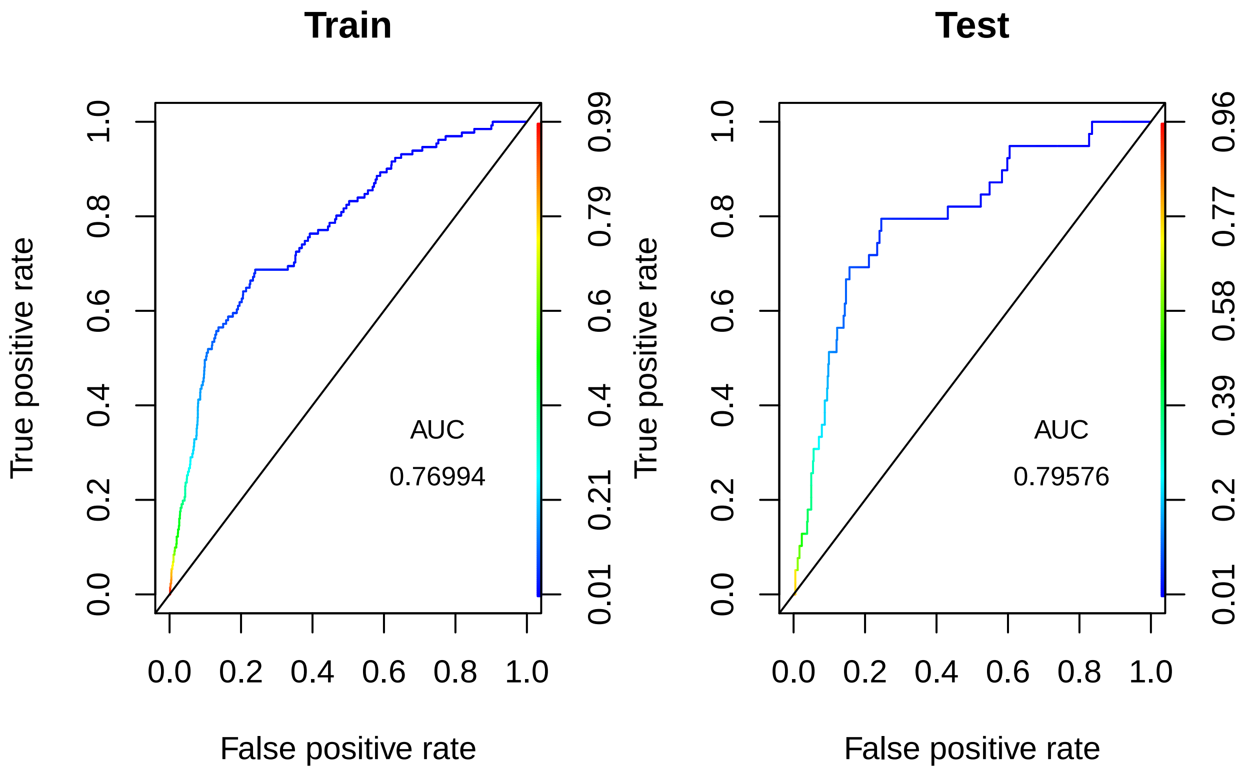
Linear Discriminant Analysis

Full Model

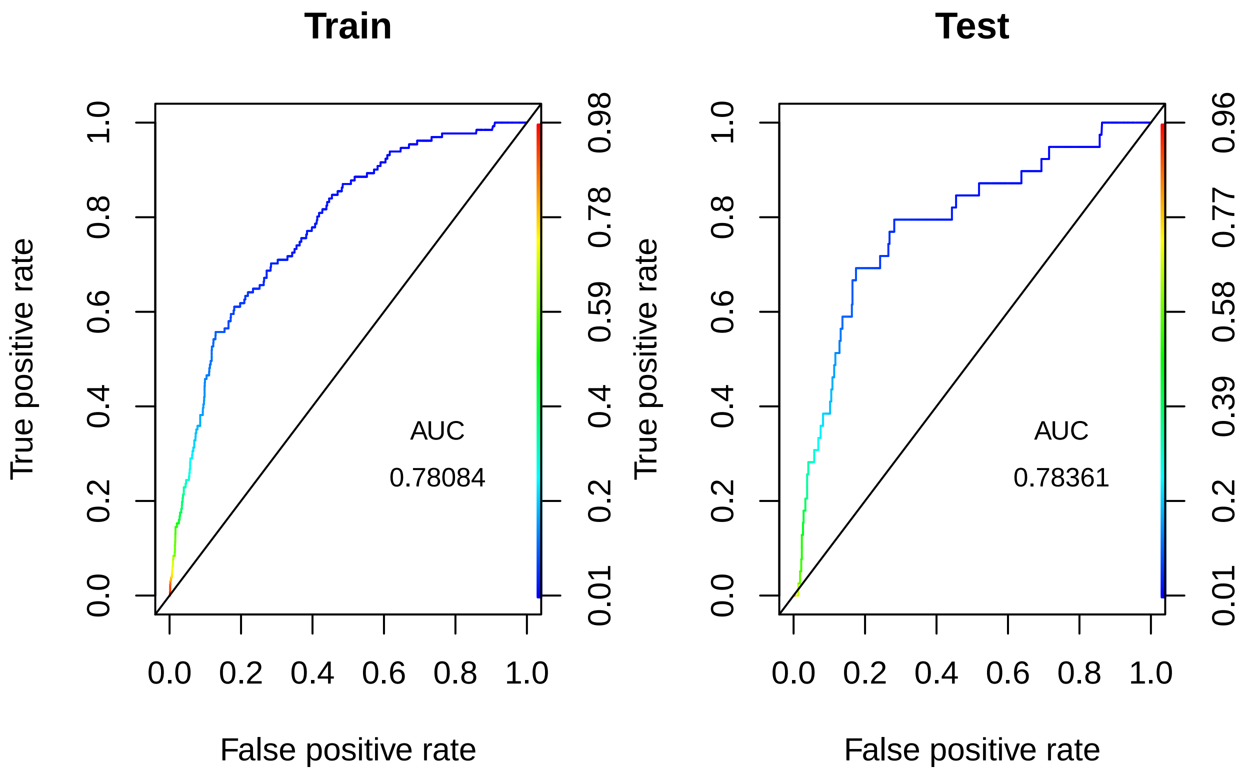




Linear Discriminant Analysis - Step



Linear Discriminant Analysis - Lasso



```
        time1 time2 time3
elapsed 0.841 0.819 0.737
```

```
     rate1.train rate3.train rate5.train
[1,]       0.074       0.081       0.077
```

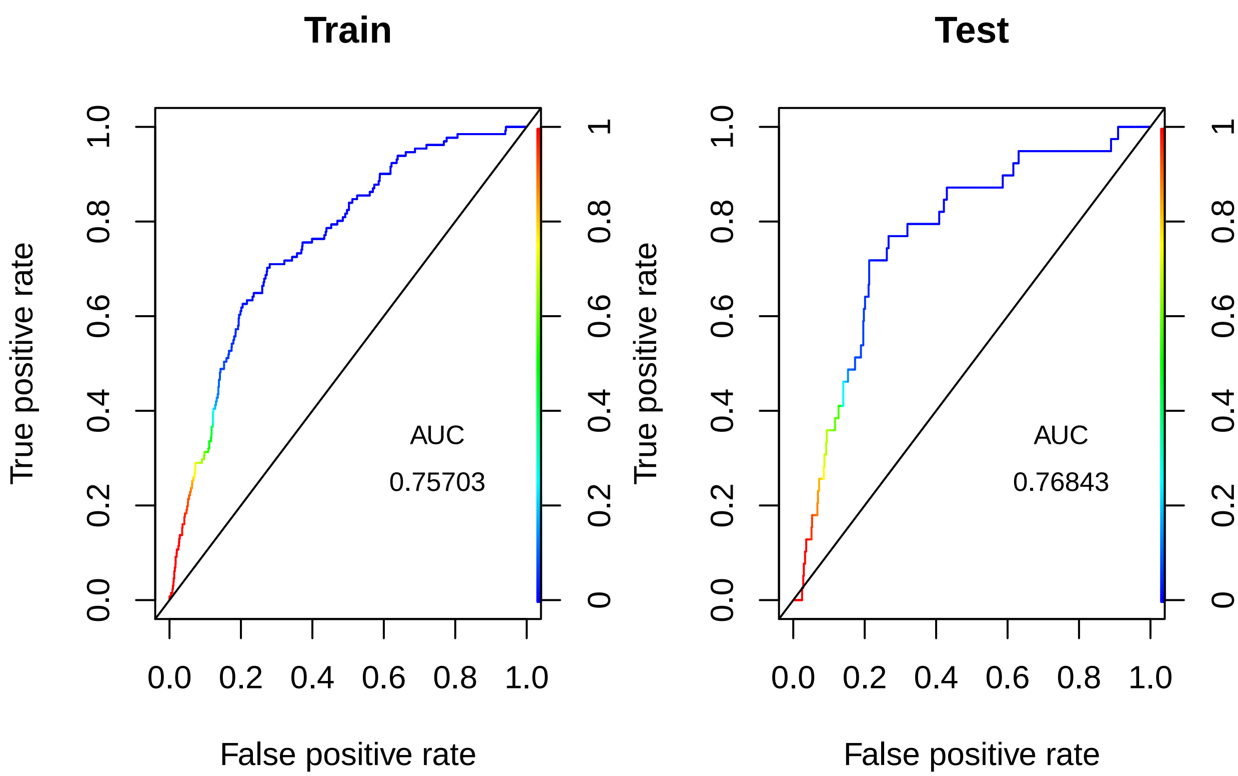
```
     rate2.test rate4.test rate6.test
[1,]      0.077      0.076      0.076
```

Quadratic Discriminant Analysis

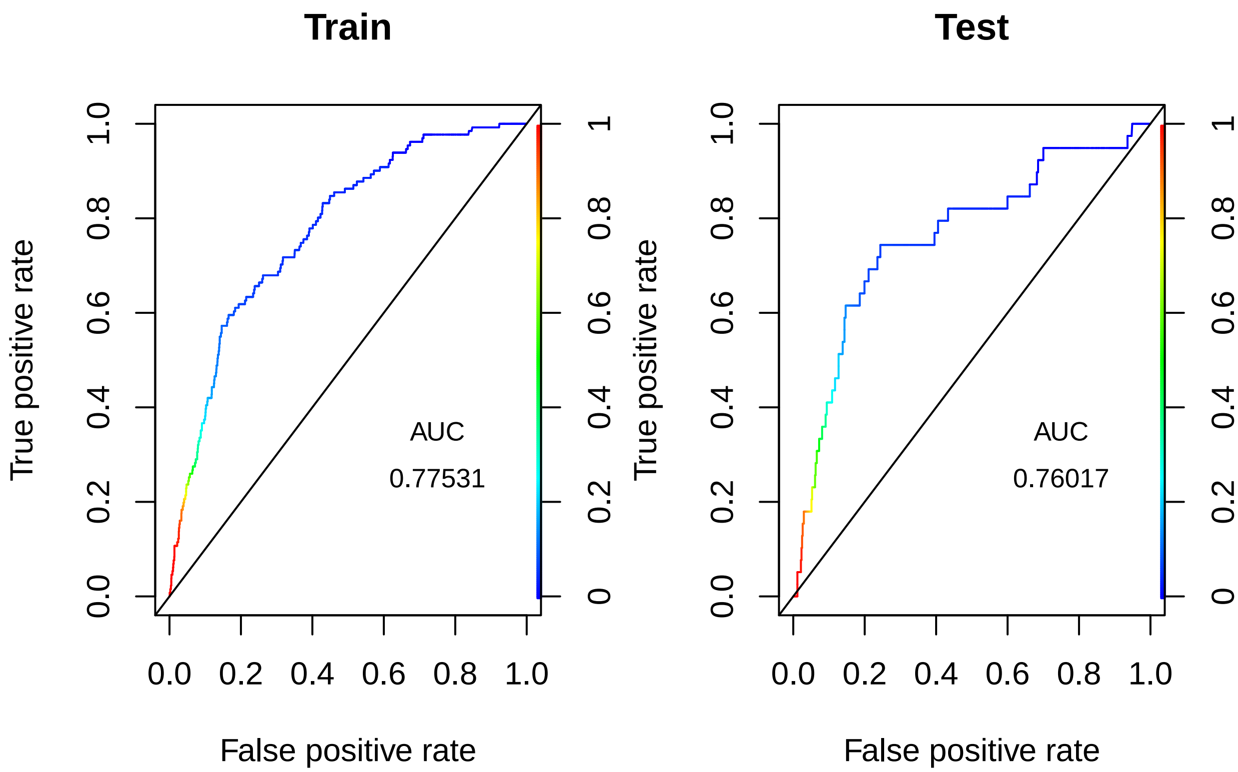
Full Model

Full Model not able to handle the multicollinearity of the data.

Quadratic Discriminant Analysis - Step

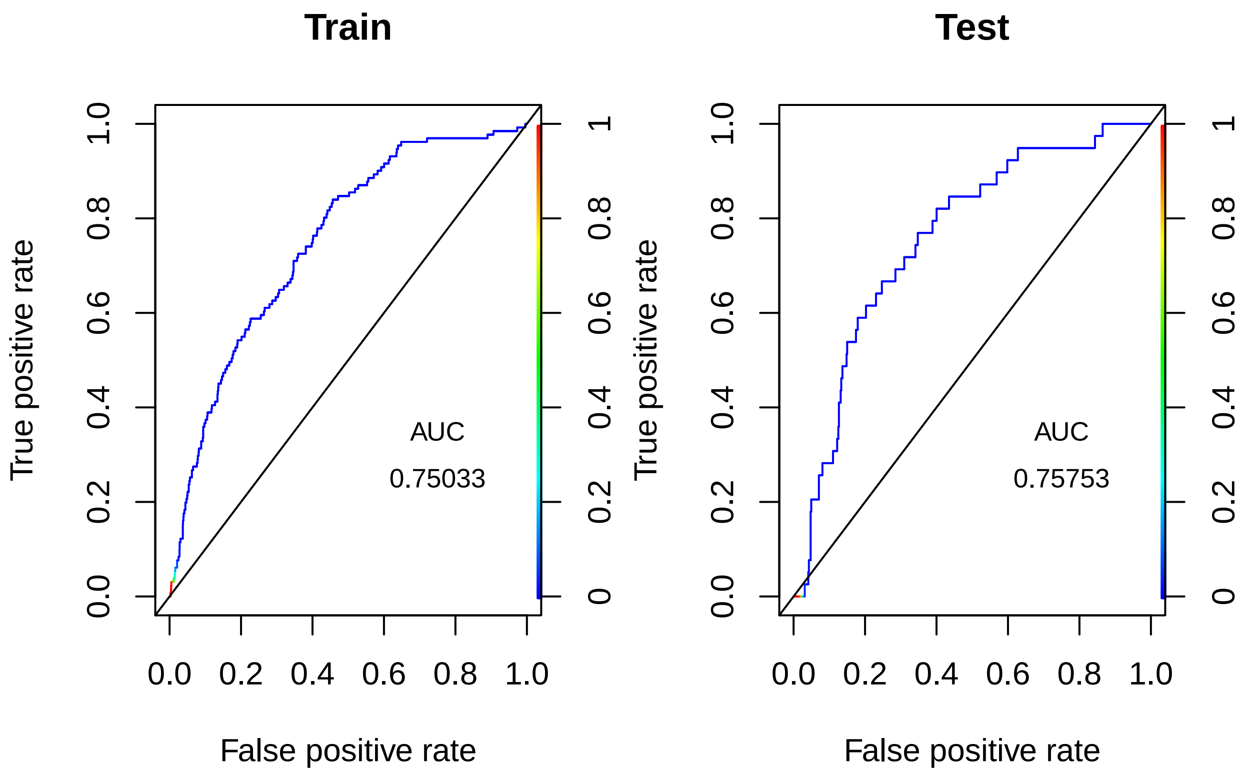


Quadratic Discriminant Analysis - LASSO

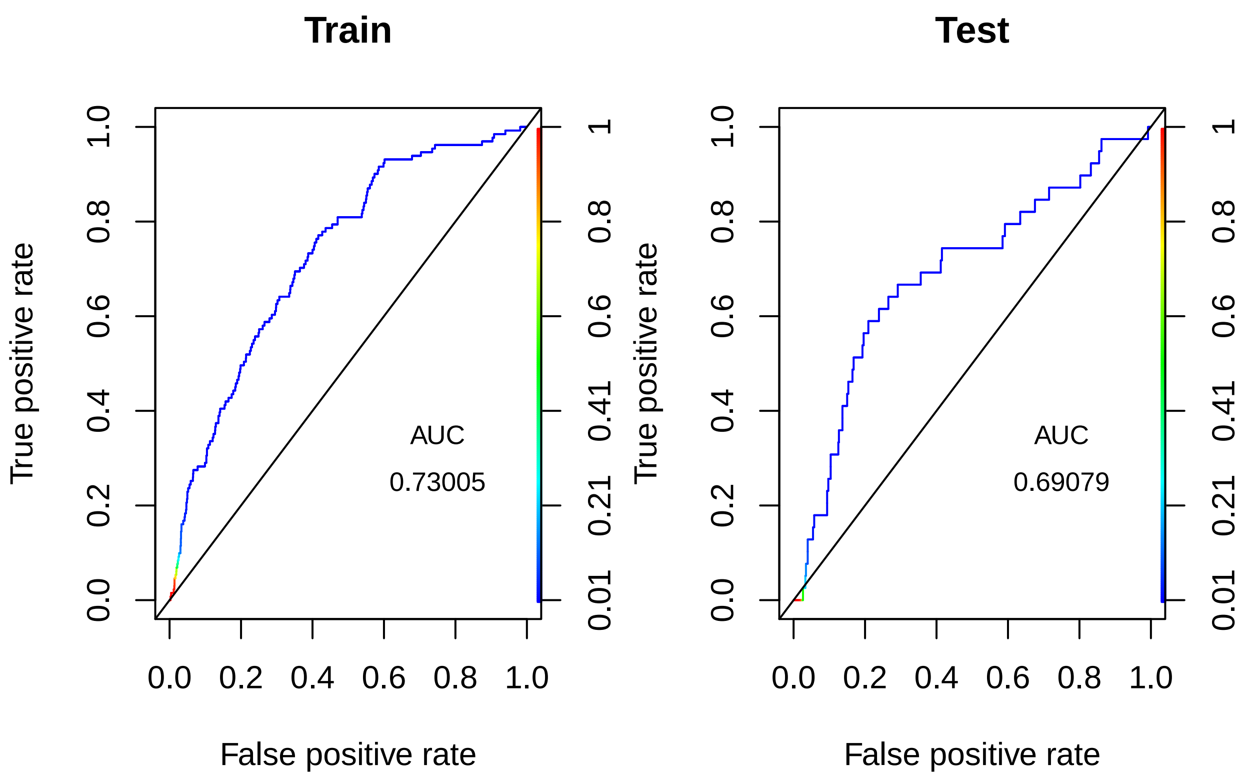



```
        time1 time2
elapsed  0.84 0.704

     rate1.train rate3.train rate5.train
[1,]       0.149       0.109       0.077

     rate2.test rate4.test rate6.test
[1,]      0.159      0.107      0.076
```

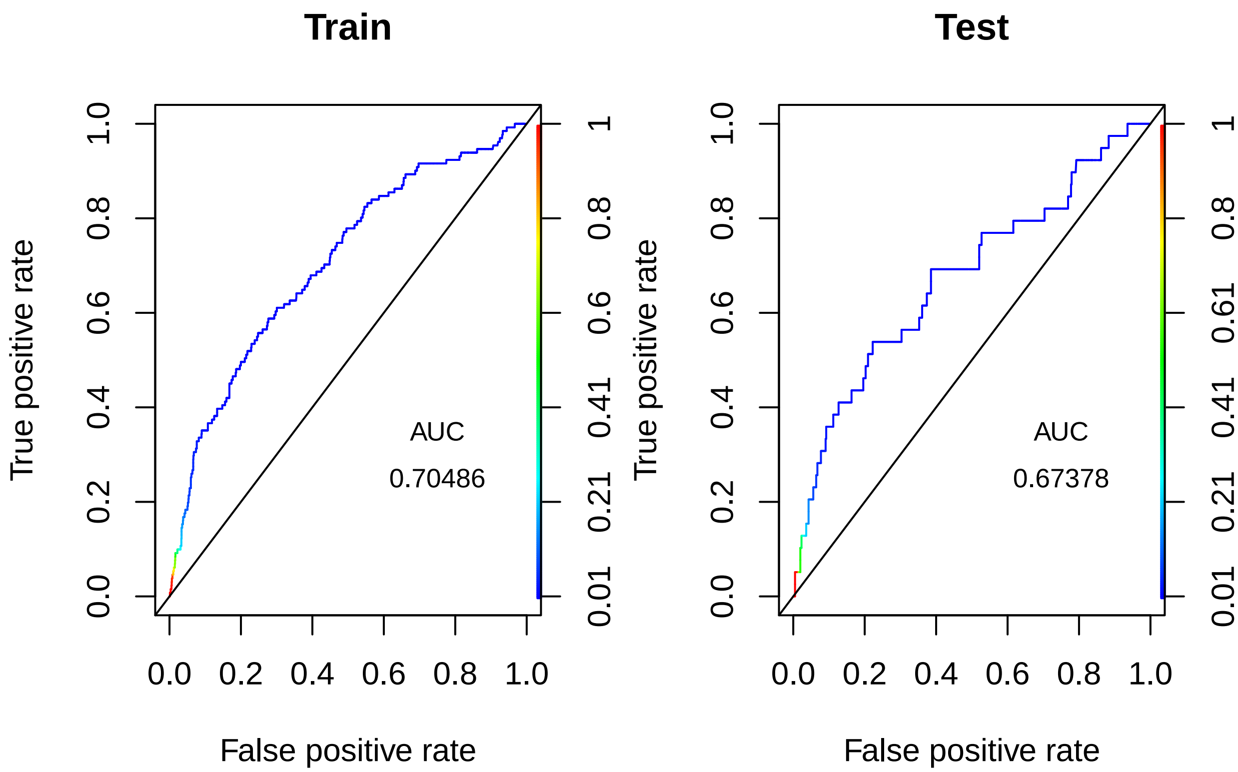
Regularized



Regularized Discriminant Analysis - Step



Regularized Discriminant Analysis - Lasso



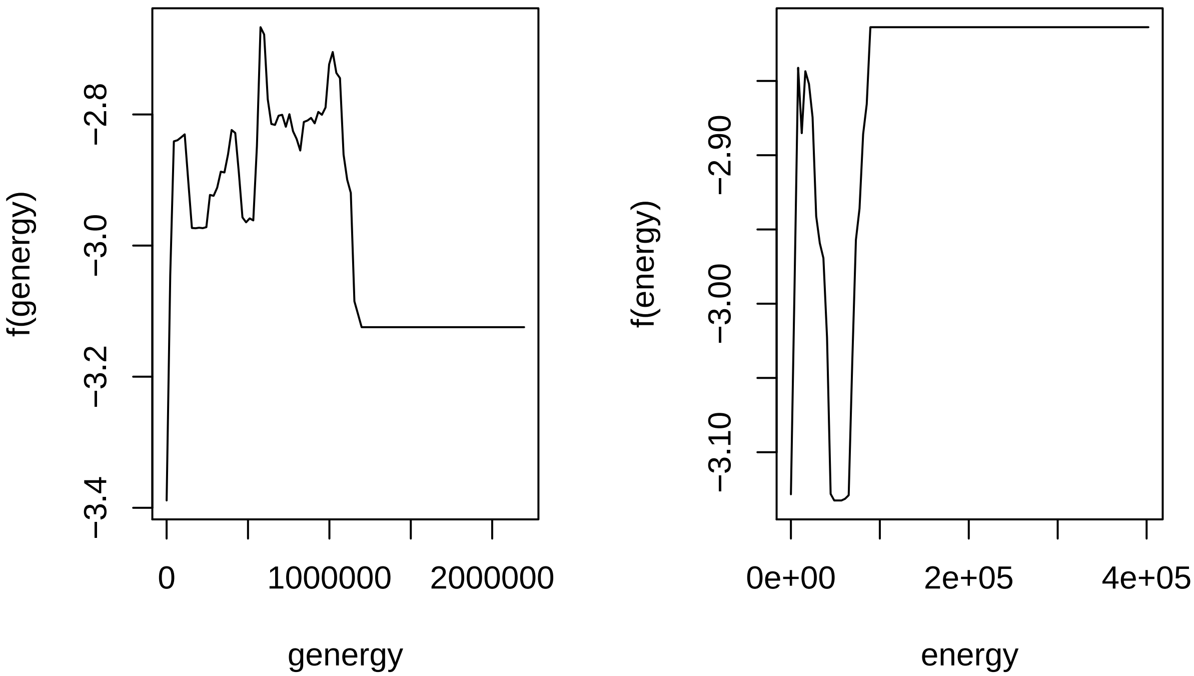

```
        time1 time2
elapsed 3.468 1.654
```

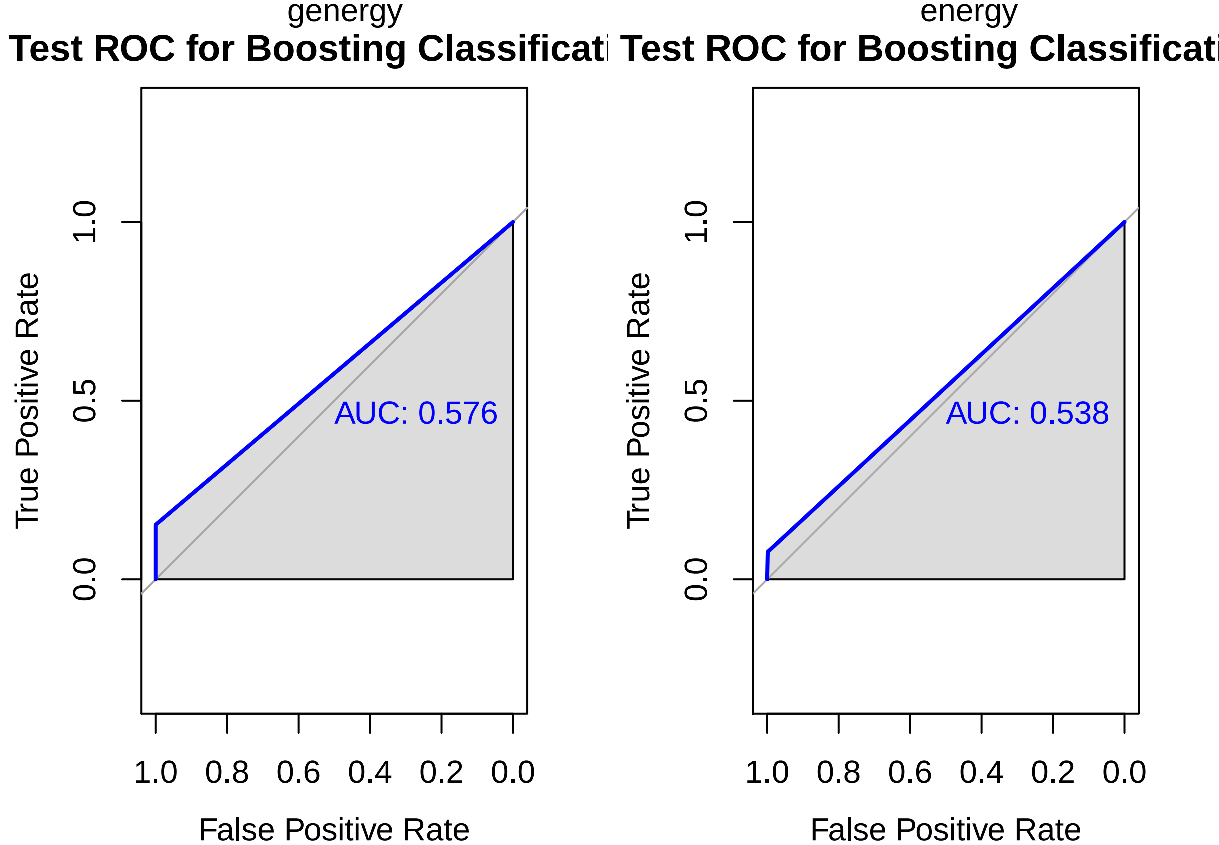
```
     rate1.train rate3.train rate5.train
[1,]       0.076       0.082       0.077
```

```
     rate2.test rate4.test rate6.test
[1,]      0.082      0.085      0.074
```

<<<<<<< HEAD # Boosting before variable selection

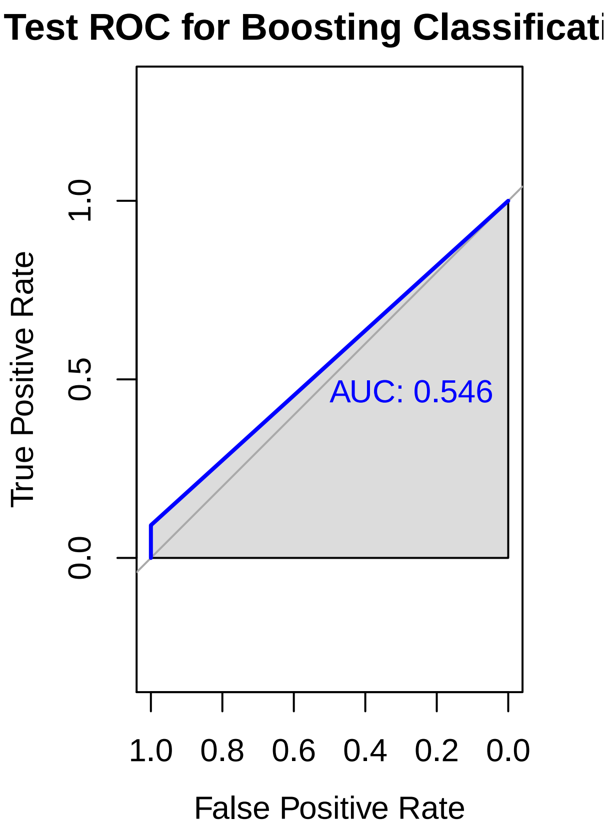
```
elapsed
  7.816
```

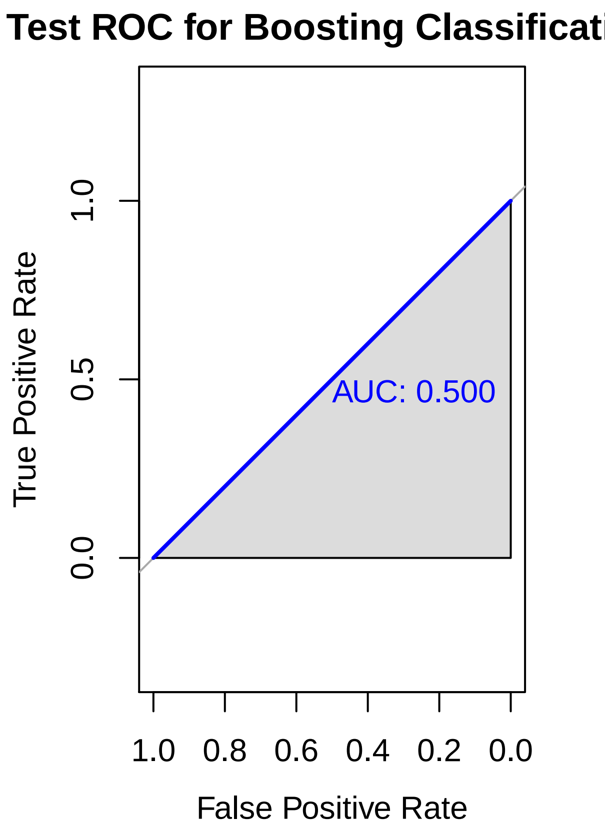




Boosting after variable selection

```
elapsed
  3.589
```

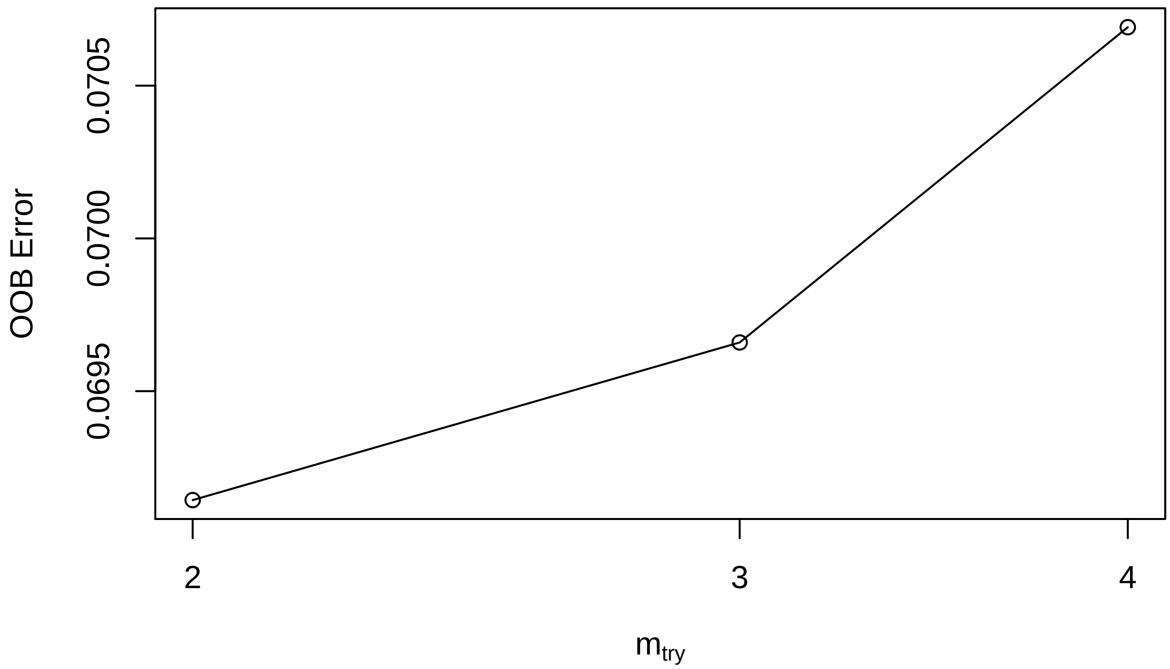




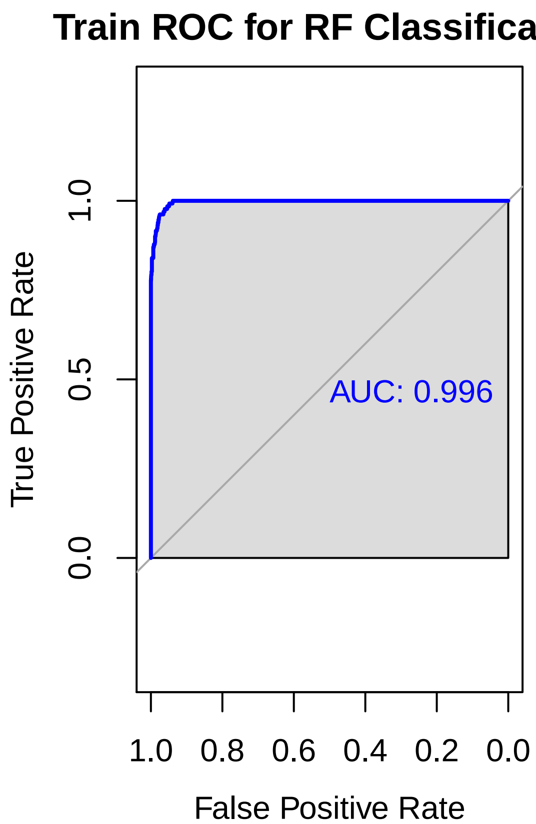
Random Forests Classification

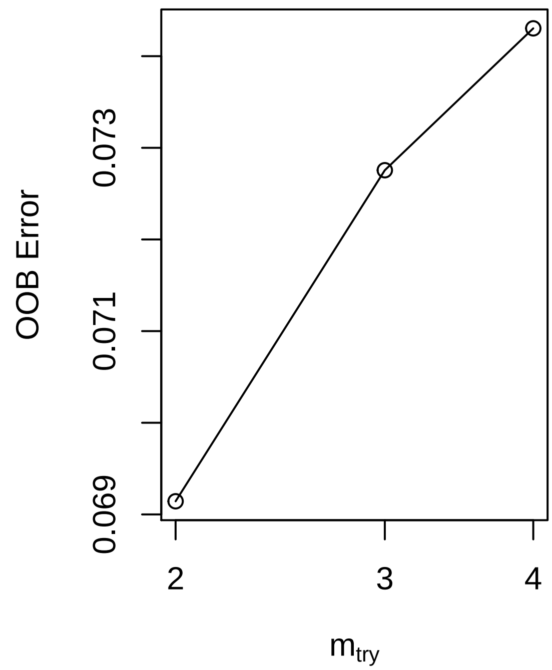
RF Classification BEFORE Variable Selection

```
mtry = 3  OOB error = 6.97%
Searching left ...
mtry = 2    OOB error = 6.91%
0.007407407 0.01
Searching right ...
mtry = 4    OOB error = 7.07%
-0.01481481 0.01
```

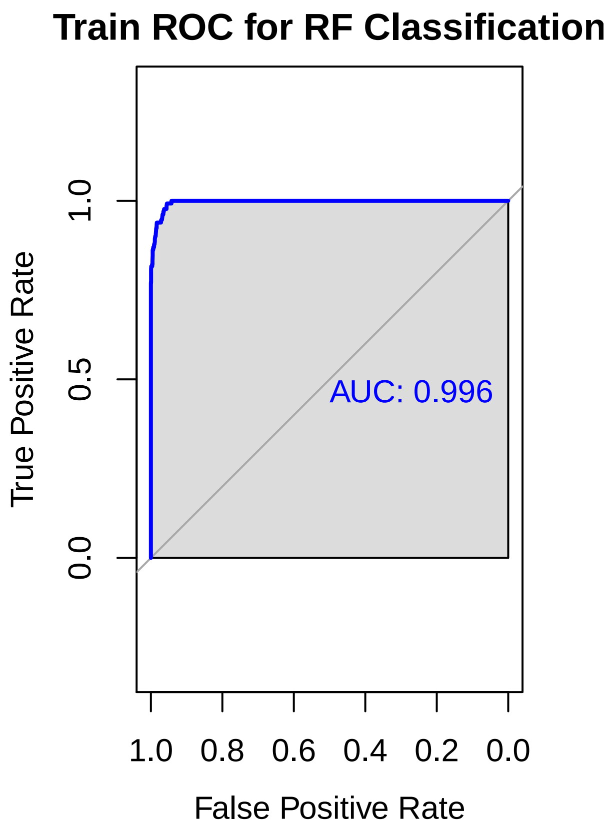



```
mtry = 3  OOB error = 7.28%
Searching left ...
mtry = 2    OOB error = 6.91%
0.04964539 0.01
Searching right ...
mtry = 4    OOB error = 7.43%
-0.07462687 0.01
```



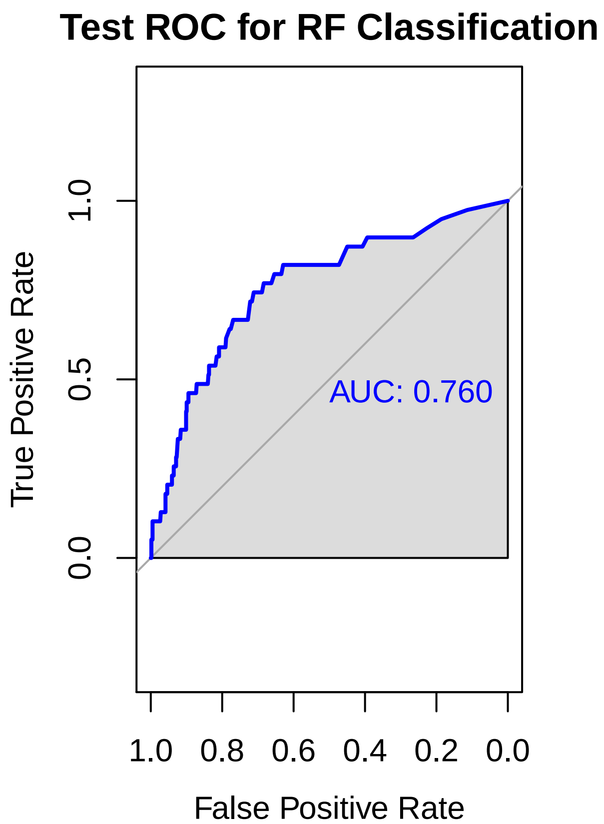


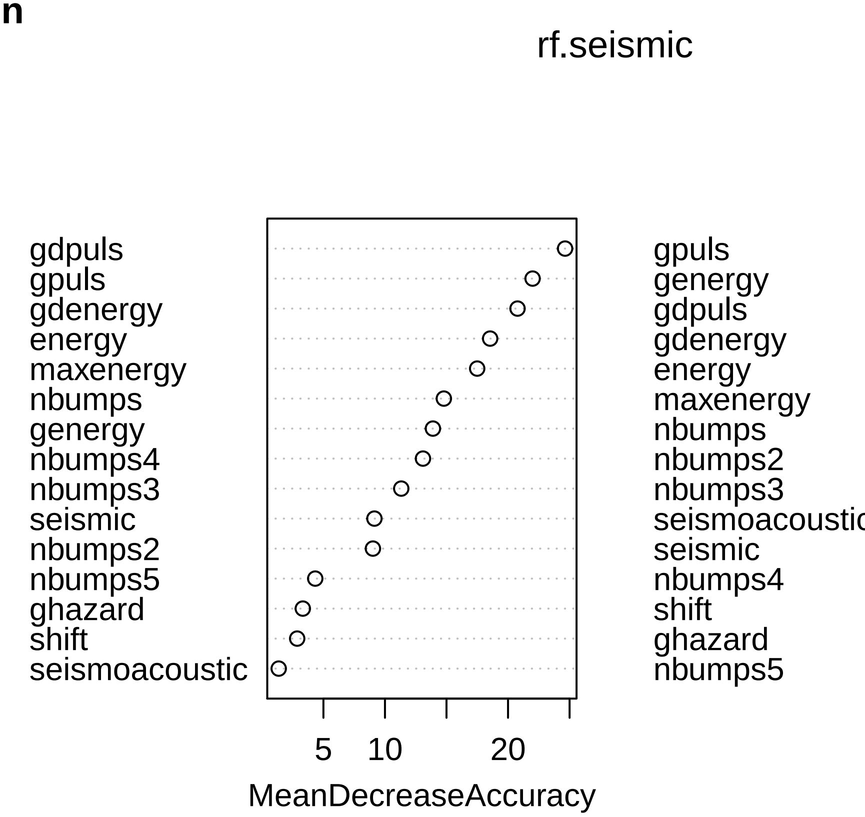

```
[1] 0

[1] 0.2363033

[1] 0.2203302
```




```
[1] 0.02564103

[1] 0.1136738

[1] 0.1083591
```

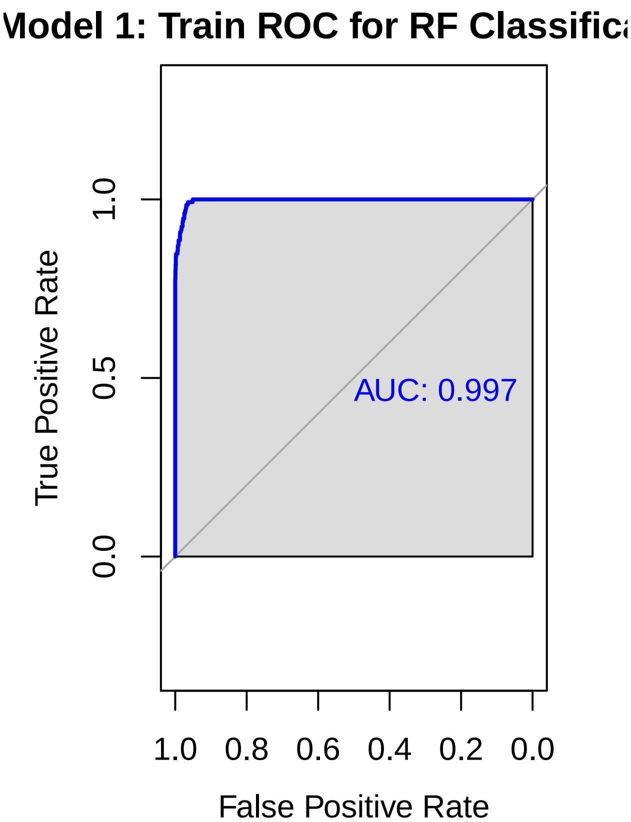
	0	1	MeanDecreaseAccuracy	MeanDecreaseGini
seismic	7.639190	5.1409941	9.142981	4.2665367
seismoacoustic	1.581907	-0.2409790	1.368947	4.5015275
shift	2.486616	0.7266865	2.869017	2.4176743
genergy	12.086539	2.4284640	13.895572	25.1355203
gpuls	18.476810	13.6828191	21.994591	26.7512211
gdenergy	22.120246	-8.0739569	20.771536	20.7055737
gdpuls	25.688347	-7.5341551	24.634248	20.8810289
ghazard	4.587309	-2.7149240	3.327211	1.9414849
nbumps	13.977076	5.3373298	14.784089	11.5360046
nbumps2	6.668420	8.5245738	9.021708	8.5027181
nbumps3	9.531100	5.9025441	11.324696	7.3784317
nbumps4	14.878958	-10.0707066	13.088679	2.7869821
nbumps5	4.832149	-2.6126517	4.336337	0.3214691
energy	17.725076	-1.2777291	18.544822	18.4047305
maxenergy	17.086692	-5.1894493	17.493649	13.4764157


Test ROC for RF Classification
True Positive Rate
0.0
0.5
1.0
AUC: 0.760
1.0
0.8
0.6
0.4
0.2
0.0
False Positive Rate

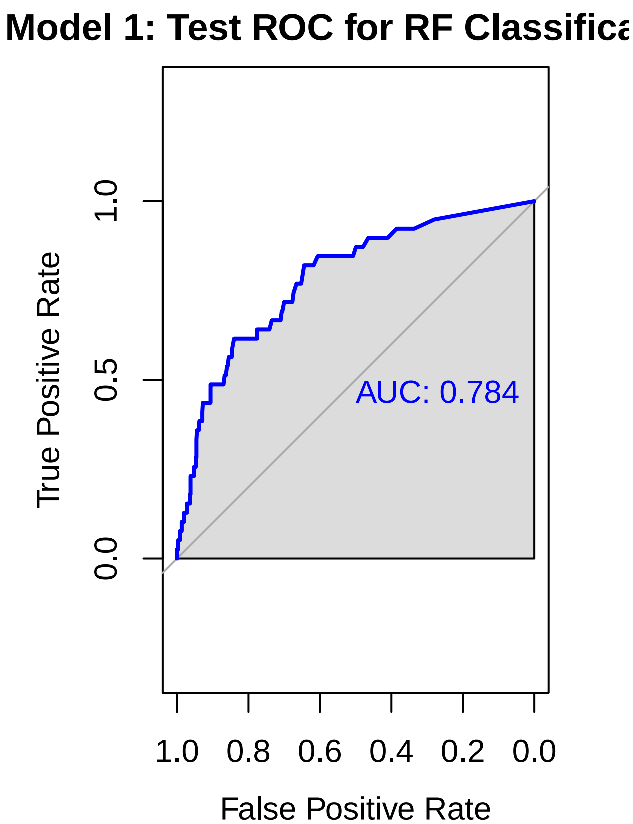

rf.seismic
gdpuls
gpuls
gdenergy
energy
maxenergy
nbumps
genergy
nbumps4
nbumps3
seismic
nbumps2
nbumps5
ghazard
shift
seismoacoustic
5
10
20
MeanDecreaseAccuracy
gpuls
genergy
gdpuls
gdenergy
energy
maxenergy
nbumps
nbumps2
nbumps3
seismoacousti
seismic
nbumps4
shift
ghazard
nbumps5

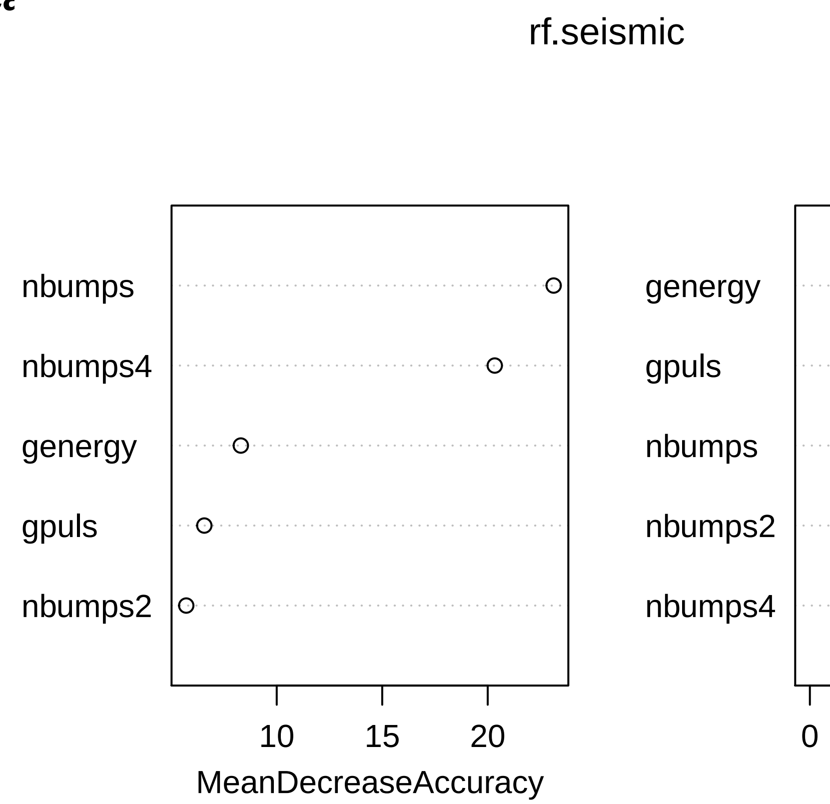
RF Classification AFTER Variable Selection

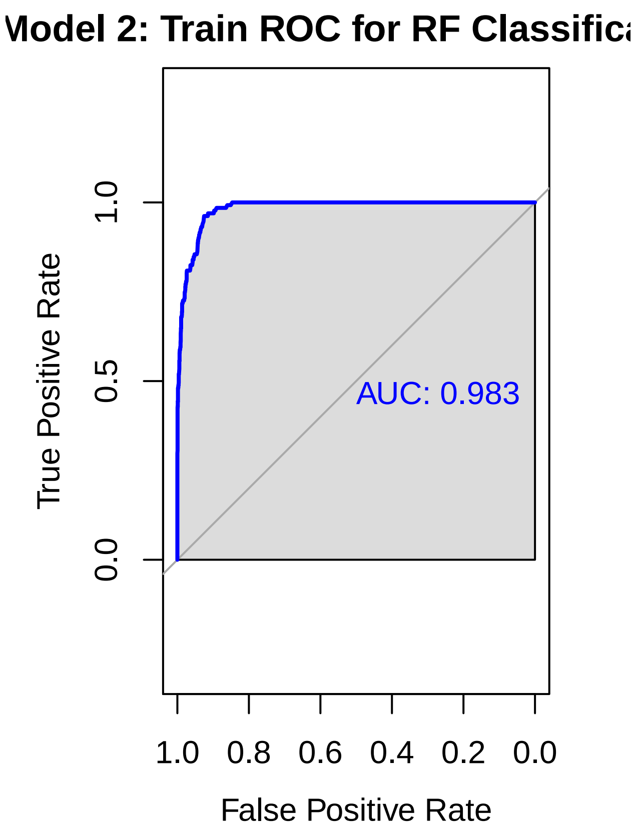
RF Classification AFTER Variable Selection



	0	1	MeanDecreaseAccuracy	MeanDecreaseGini
genergy	6.564781	3.001198	8.298559	68.418908
gpuls	1.086896	18.312691	6.567174	66.430515
nbumps	15.305794	31.873589	23.124064	26.073064
nbumps2	2.285010	8.816717	5.711204	14.121004
nbumps4	23.265875	-8.649932	20.332543	7.037393

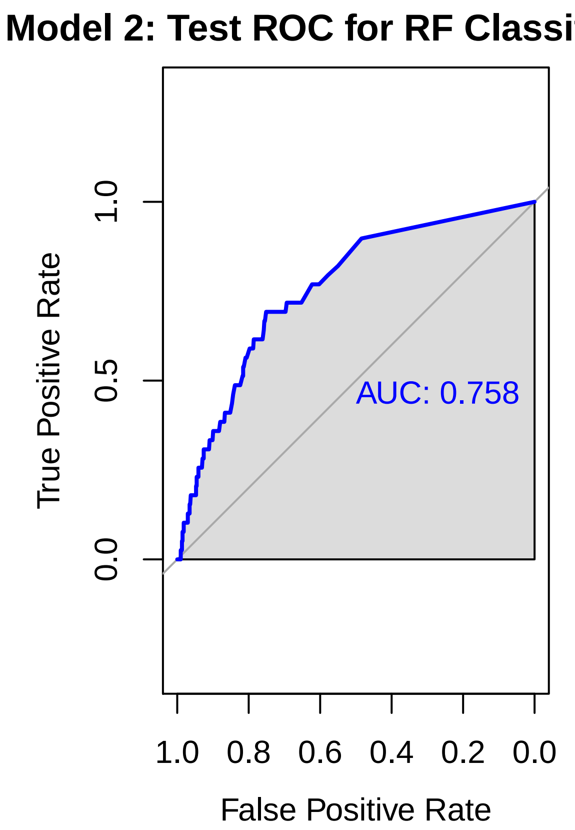




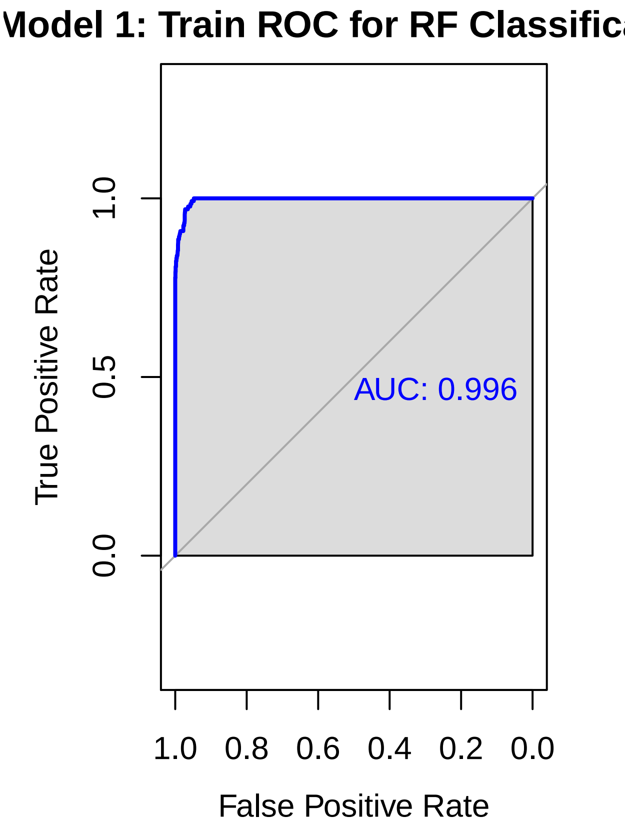



```
0          1 MeanDecreaseAccuracy MeanDecreaseGini
```

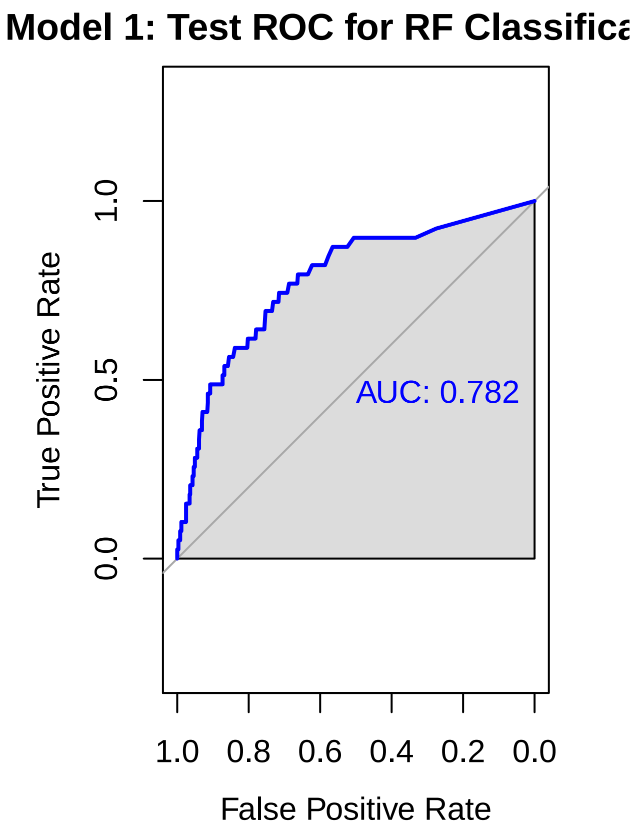
```
seismic  2.624006  11.019565            5.789011          5.976086
shift   11.051096 -11.510160            9.194394          3.050479
gpuls    1.478515   7.540176            4.383246         75.482383
nbumps  13.186473  22.919363           19.903187         27.608000
```

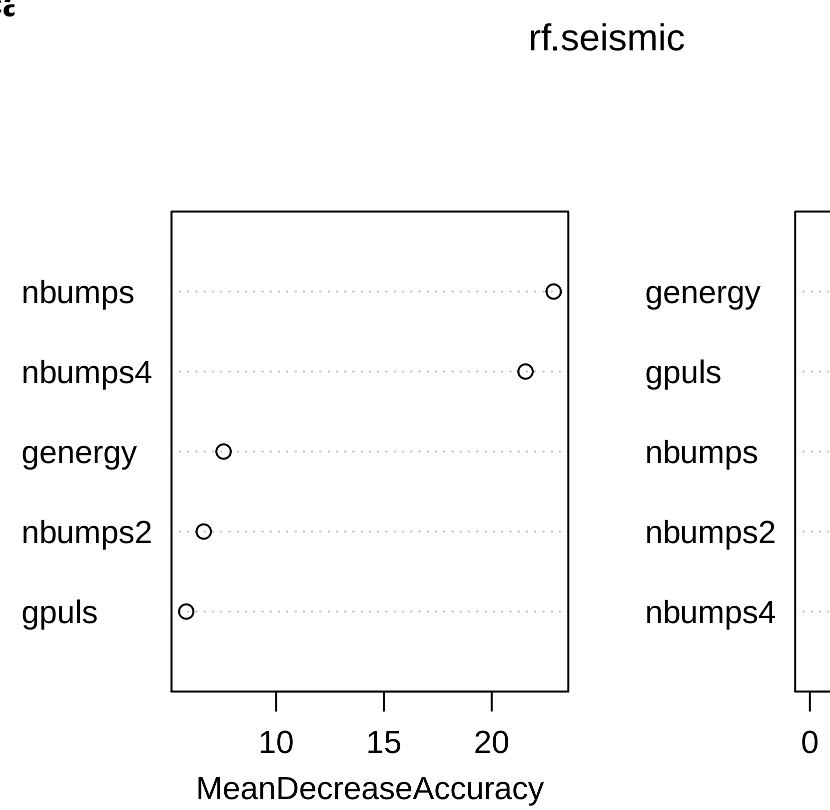


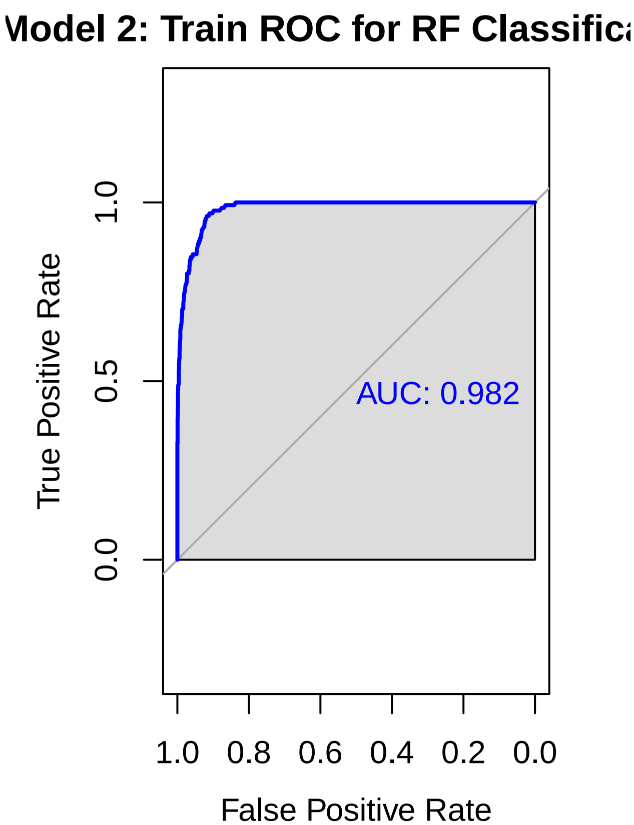
Boosting



	0	1	MeanDecreaseAccuracy	MeanDecreaseGini
genergy	5.1300375	5.586820	7.563177	68.556399
gpuls	0.0700258	19.539698	5.829128	66.551265
nbumps	14.9000236	32.868947	22.877694	26.059296
nbumps2	3.0991937	9.011757	6.641027	14.385561
nbumps4	24.1165725	-8.627134	21.572093	7.176123

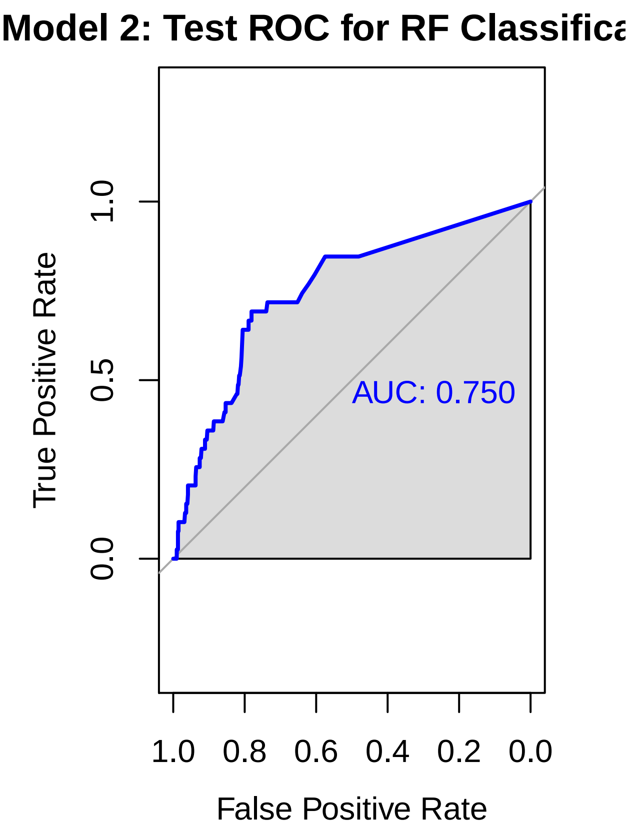


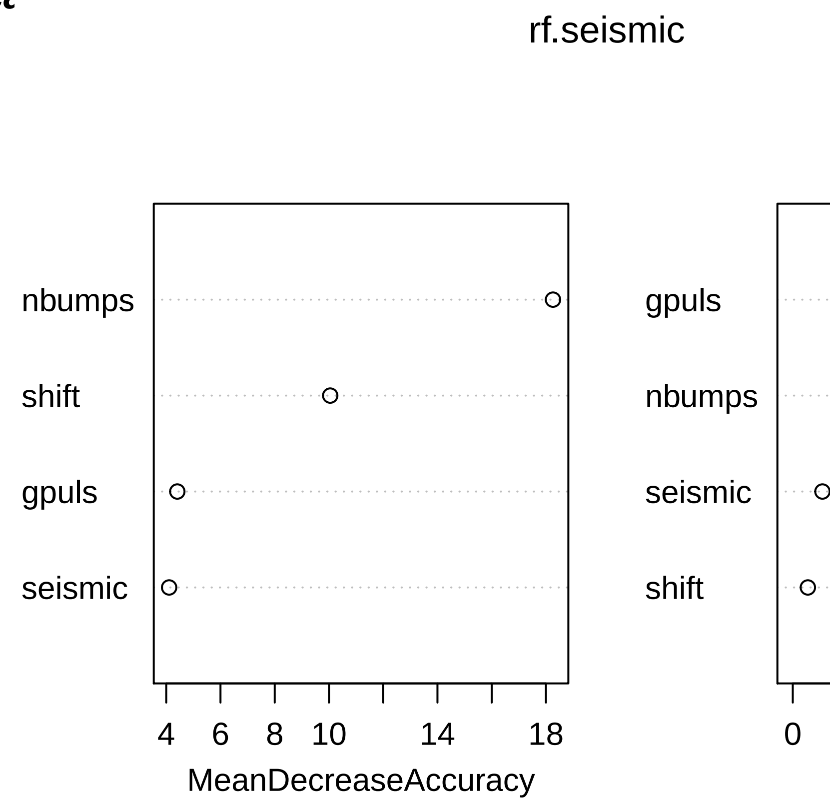





```
0          1 MeanDecreaseAccuracy MeanDecreaseGini
```

```
seismic   0.7571748  9.478397           4.105877        5.821832
shift    11.4969471 -9.940458          10.045574        2.959784
gpuls     1.6136431  7.619120           4.407885       75.308097
nbumps   12.7174931 21.298900          18.259825       27.149236
```





Support vector classifier and support vector machine

```
# Variable selection and refitting
#model1 = genergy + gpuls + nbumps + nbumps2 + nbumps4 #Step
#model2 = seismic + shift + gpuls + nbumps #Lasso

library(e1071)

# We can modify this by using kernel = radial, which involves changing choice of gamma
# or by choosing kernel = polynomial, where we can also modify the degree
# Using a linear kernel is technically a support vector classifier

#--------------------------------------------------
# Get the ROC curve for svm
library(ROCR)

rocplot <- function(pred, truth, ...){
  predob <- prediction(pred, truth)
  perf <- performance(predob, "tpr", "fpr")
```

```r
  plot(perf,...)
}
#---------------------------------------------------

#---------------------------------------------------
# Start with just the linear kernel
#---------------------------------------------------

##
## Model 1
##

start.time <- proc.time()

tune.out <- tune(svm, factor(class)~genergy + gpuls + nbumps + nbumps2 + nbumps4, data = seismic[train,]

# Look for a best model
summary(tune.out)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   cost
##  0.001
##
## - best performance: 0.06760857
##
## - Detailed performance results:
##    cost      error dispersion
## 1 0.001 0.06760857 0.01645615
## 2 0.010 0.06760857 0.01645615
## 3 0.100 0.06760857 0.01645615
## 4 1.000 0.06760857 0.01645615
## 5 5.000 0.06760857 0.01645615
```

```r
bestmod <- tune.out$best.model
summary(bestmod)
```

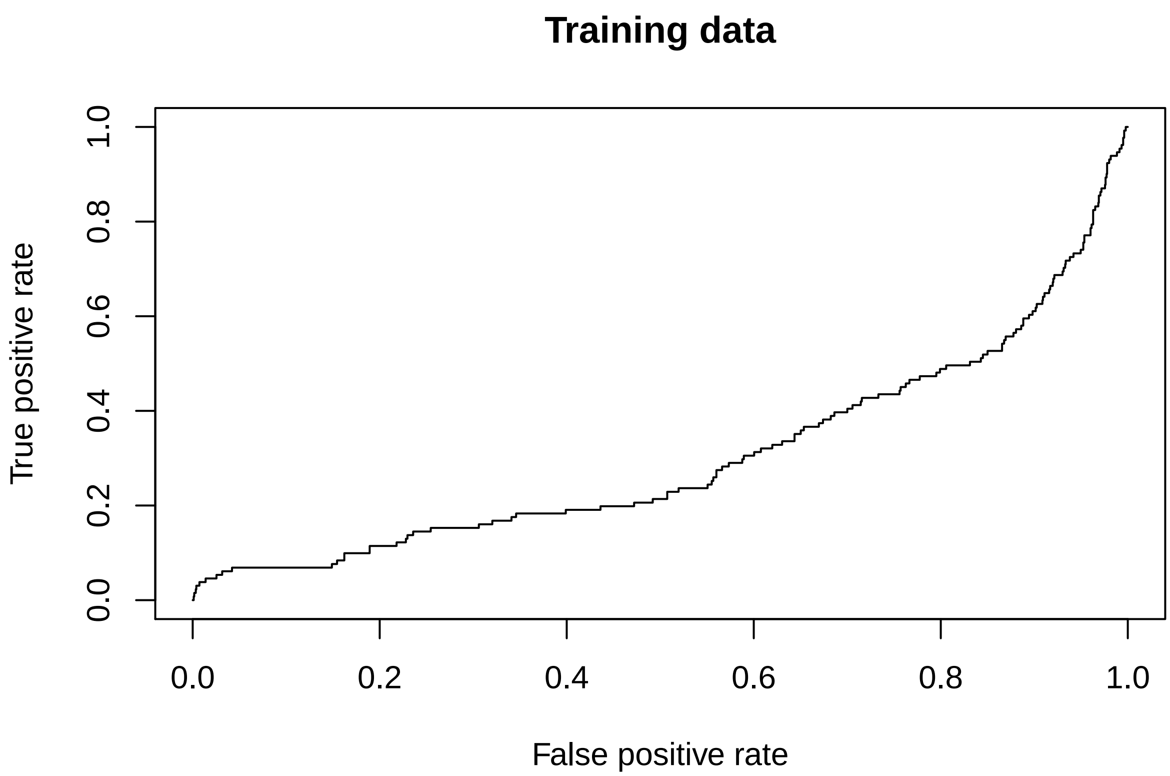
```
##
## Call:
## best.tune(method = svm, train.x = factor(class) ~ genergy + gpuls +
##     nbumps + nbumps2 + nbumps4, data = seismic[train, ], ranges = list(cost = c(0.001,
##     0.01, 0.1, 1, 5)), kernel = "linear")
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  0.001
```

```
##       gamma:  0.2
##
## Number of Support Vectors:  268
##
##  ( 137 131 )
##
##
## Number of Classes:  2
##
## Levels:
##  0 1
```

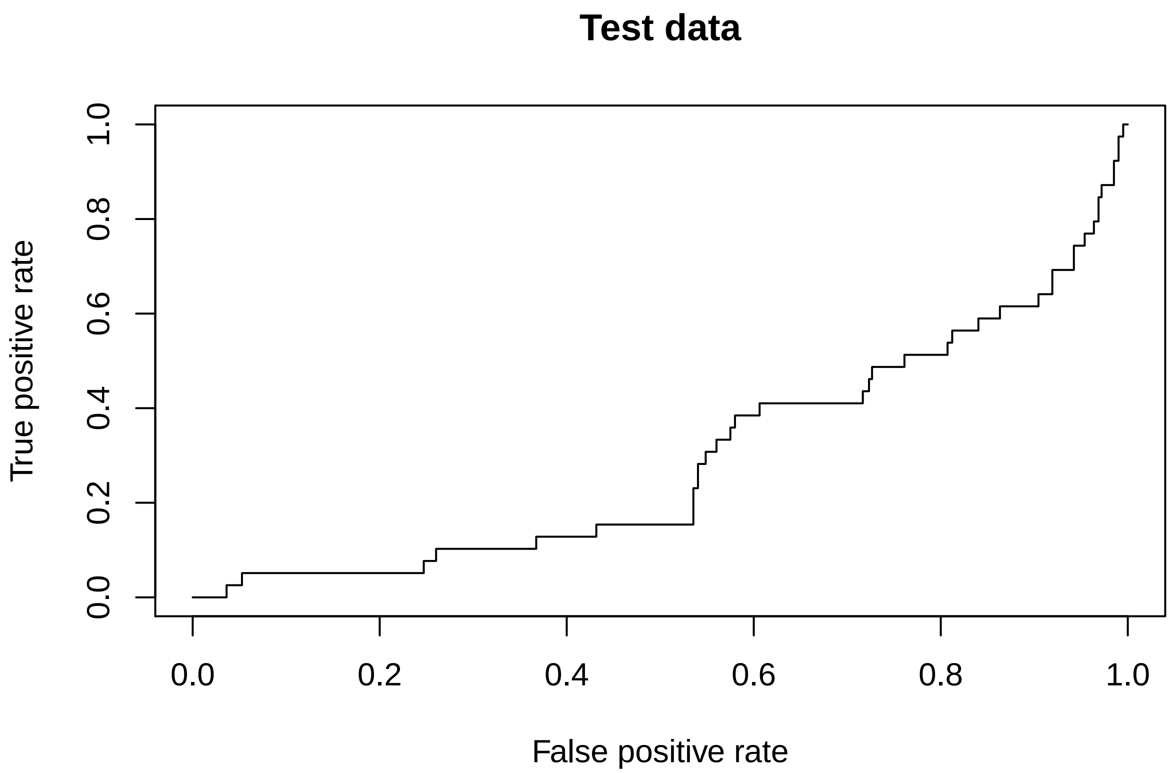
```
ypred <- predict(bestmod, seismic[-train,])
table(predict = ypred, truth = seismic$class[-train])
```

```
##        truth
## predict   0   1
##       0 607  39
##       1   0   0
```

```
svmfit.best1 <- svm(factor(class)~genergy + gpuls + nbumps + nbumps2 + nbumps4, data = seismic[train,],
fitted1 <- attributes(predict(svmfit.best1, seismic[train,], decision.values = T))$decision.values
fitted.test1 <- attributes(predict(svmfit.best1, seismic[-train,], decision.values = T))$decision.values

# It is unsurprising that this doesn't work well, because we are using a linear classifier
# However, we have reason to believe that a non-linear classifier would be more appropriate
rocplot(fitted1, seismic[train,"class"], main = "Training data")
```



```r
rocplot(fitted.test1, seismic[-train,"class"], main = "Test data")
```




```r
total.time <- proc.time() - start.time
time1 <- total.time[3]

##
## Model 2
##

start.time <- proc.time()

tune.out <- tune(svm, factor(class)~seismic + shift + gpuls + nbumps, data = seismic[train,], kernel =

# Look for a best model
summary(tune.out)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   cost
##  0.001
##
## - best performance: 0.0676059
##
## - Detailed performance results:
```

```
##    cost     error dispersion
## 1 0.001 0.0676059 0.01815001
## 2 0.010 0.0676059 0.01815001
## 3 0.100 0.0676059 0.01815001
## 4 1.000 0.0676059 0.01815001
## 5 5.000 0.0676059 0.01815001
```

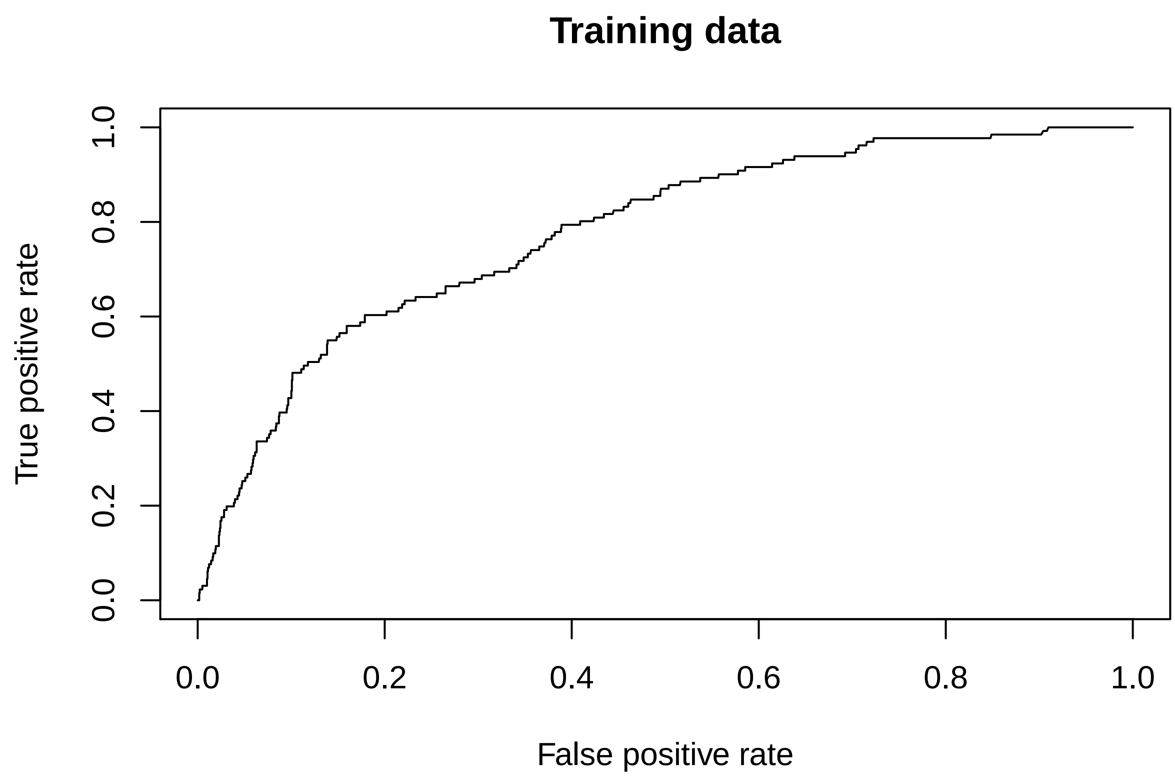
```
bestmod <- tune.out$best.model
summary(bestmod)
```

```
##
## Call:
## best.tune(method = svm, train.x = factor(class) ~ seismic + shift +
##     gpuls + nbumps, data = seismic[train, ], ranges = list(cost = c(0.001,
##     0.01, 0.1, 1, 5)), kernel = "linear")
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  0.001
##       gamma:  0.25
##
## Number of Support Vectors:  265
##
##  ( 134 131 )
##
##
## Number of Classes:  2
##
## Levels:
##  0 1
```

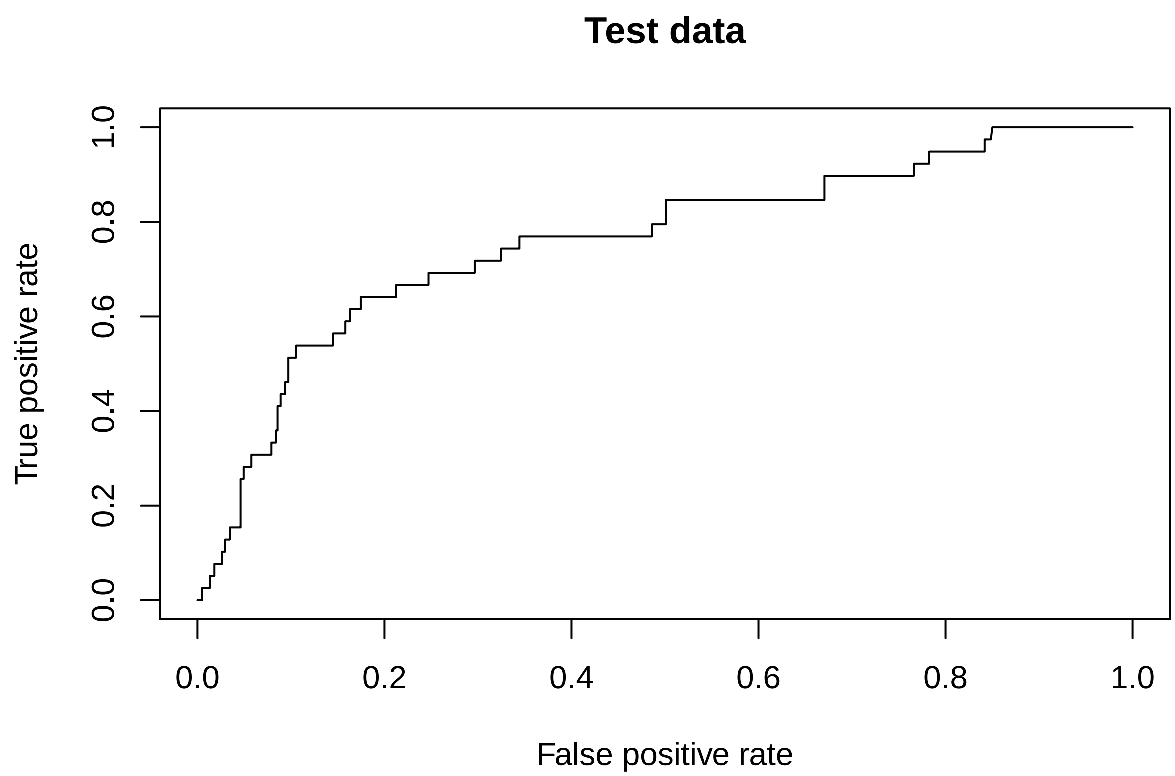
```
ypred <- predict(bestmod, seismic[-train,])
table(predict = ypred, truth = seismic$class[-train])
```

```
##        truth
## predict   0   1
##       0 607  39
##       1   0   0
```

```
svmfit.best2 <- svm(factor(class)~seismic + shift + gpuls + nbumps, data = seismic[train,], kernel = "li
fitted2 <- attributes(predict(svmfit.best2, seismic[train,], decision.values = T))$decision.values
fitted.test2 <- attributes(predict(svmfit.best2, seismic[-train,], decision.values = T))$decision.values

# This one shows a much better ROC curve
# But it still looks bad just from the original table produced
rocplot(fitted2, seismic[train,"class"], main = "Training data")
```



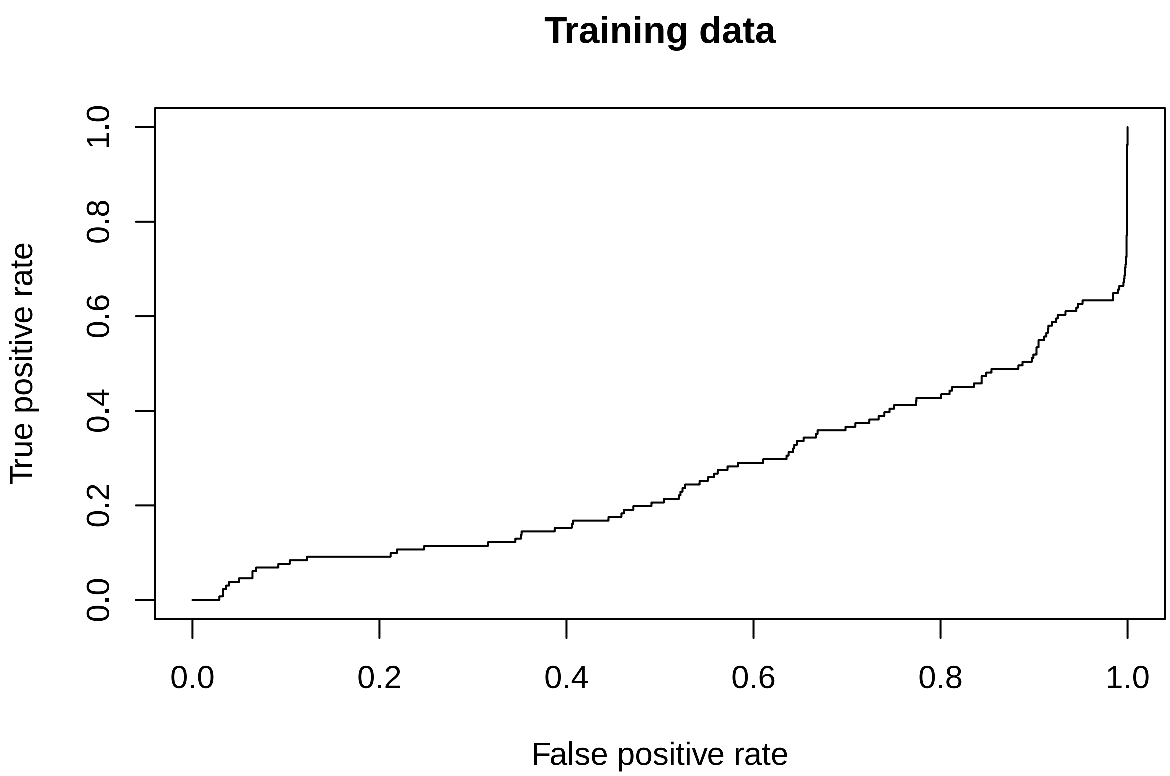

```r
rocplot(fitted.test2, seismic[-train,"class"], main = "Test data")
```



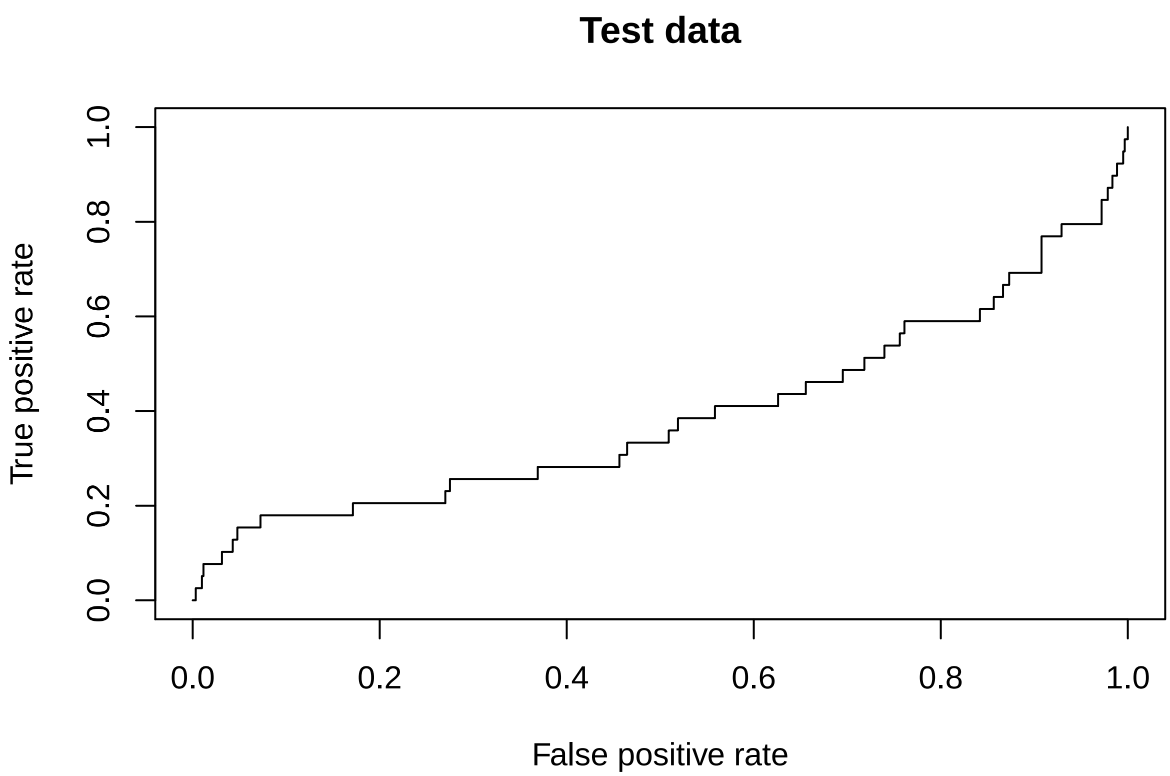
```r
total.time <- proc.time() - start.time
time2 <- total.time[3]

#---------------------------------------------------
# Implement with the radial kernel
#---------------------------------------------------

##
## Model 1
##

start.time <- proc.time()

tune.out2 <- tune(svm, factor(class)~genergy + gpuls + nbumps + nbumps2 + nbumps4, data = seismic[train

bestmod <- tune.out2$best.model
ypred <- predict(bestmod, seismic[-train,])
table(predict = ypred, truth = seismic$class[-train])
```

```
##        truth
## predict   0   1
##       0 607  39
##       1   0   0
```

```r
svmrad2 <- svm(factor(class)~genergy + gpuls + nbumps + nbumps2 + nbumps4, data = seismic[train,], kerne
fitted2 <- attributes(predict(svmrad2, seismic[train,], decision.values = T))$decision.values
fitted.test2 <- attributes(predict(svmrad2, seismic[-train,],decision.values = T))$decision.values

rocplot(fitted2, seismic[train,"class"], main = "Training data")
```



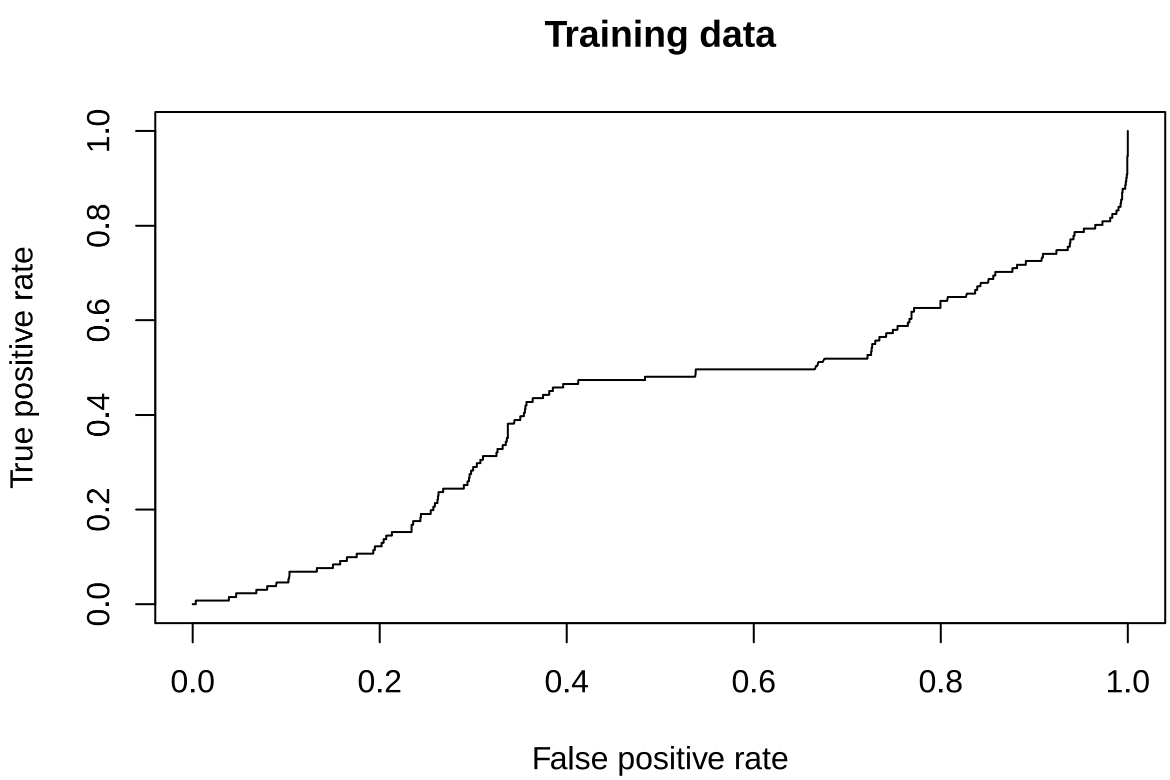

```r
rocplot(fitted.test2, seismic[-train,"class"], main = "Test data")
```



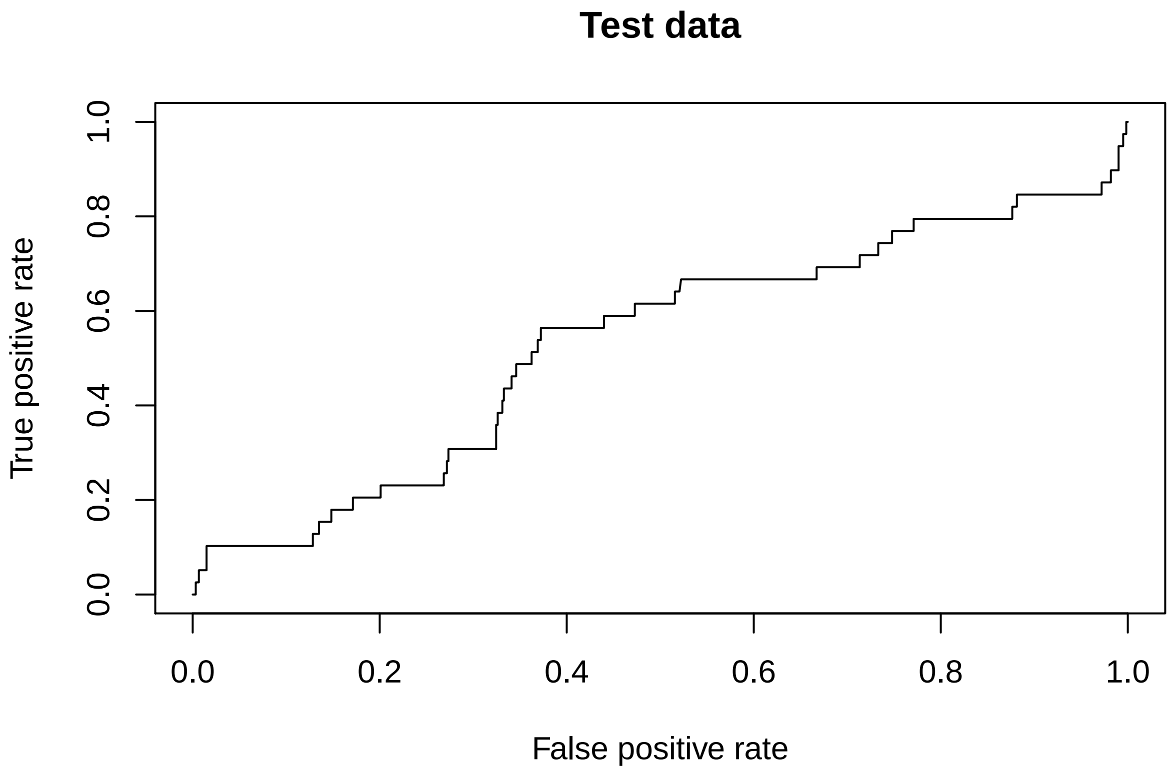
```r
total.time <- proc.time() - start.time
time3 <- total.time[3]

##
## Model 2
##

start.time <- proc.time()

tune.out3 <- tune(svm, factor(class)~seismic + shift + gpuls + nbumps, data = seismic[train,], kernel =

bestmod <- tune.out3$best.model
ypred <- predict(bestmod, seismic[-train,])
table(predict = ypred, truth = seismic$class[-train])
```

```
##        truth
## predict   0   1
##       0 607  39
##       1   0   0
```

```r
svmrad3 <- svm(factor(class)~seismic + shift + gpuls + nbumps, data = seismic[train,], kernel = "radial
fitted3 <- attributes(predict(svmrad3, seismic[train,], decision.values = T))$decision.values
fitted.test3 <- attributes(predict(svmrad3, seismic[-train,],decision.values = T))$decision.values

rocplot(fitted3, seismic[train,"class"], main = "Training data")
```



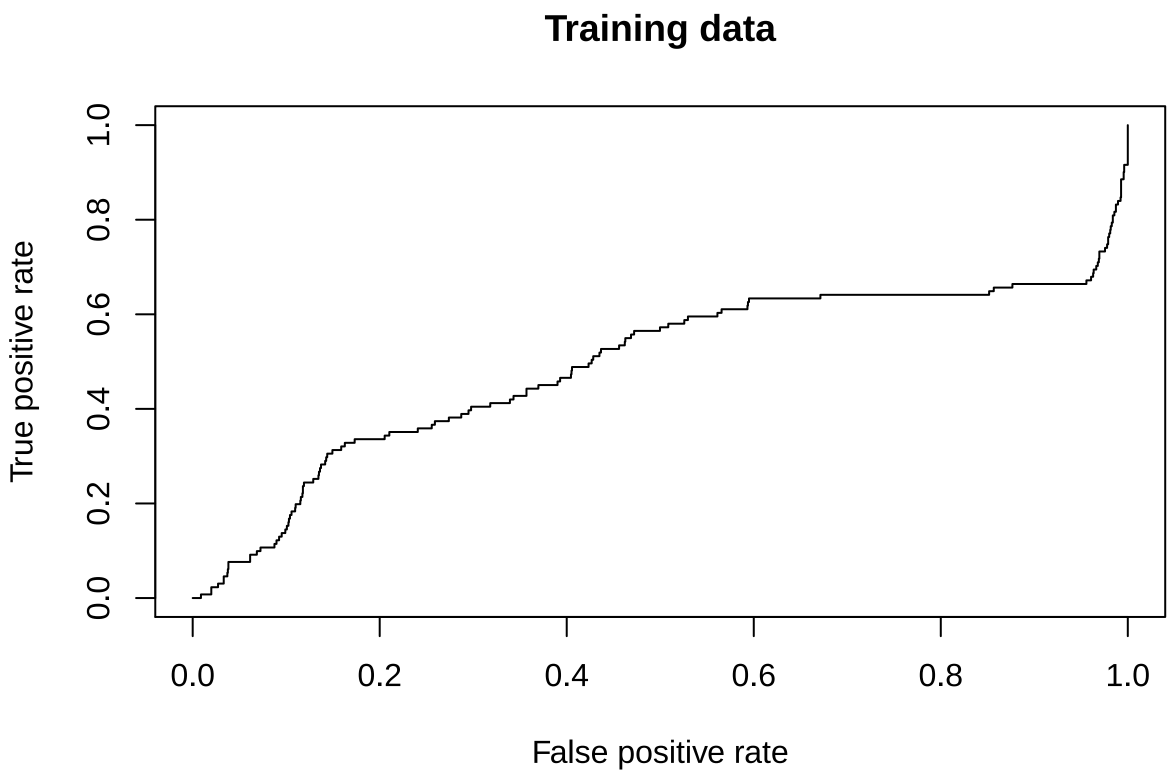
```
rocplot(fitted.test3, seismic[-train,"class"], main = "Test data")
```



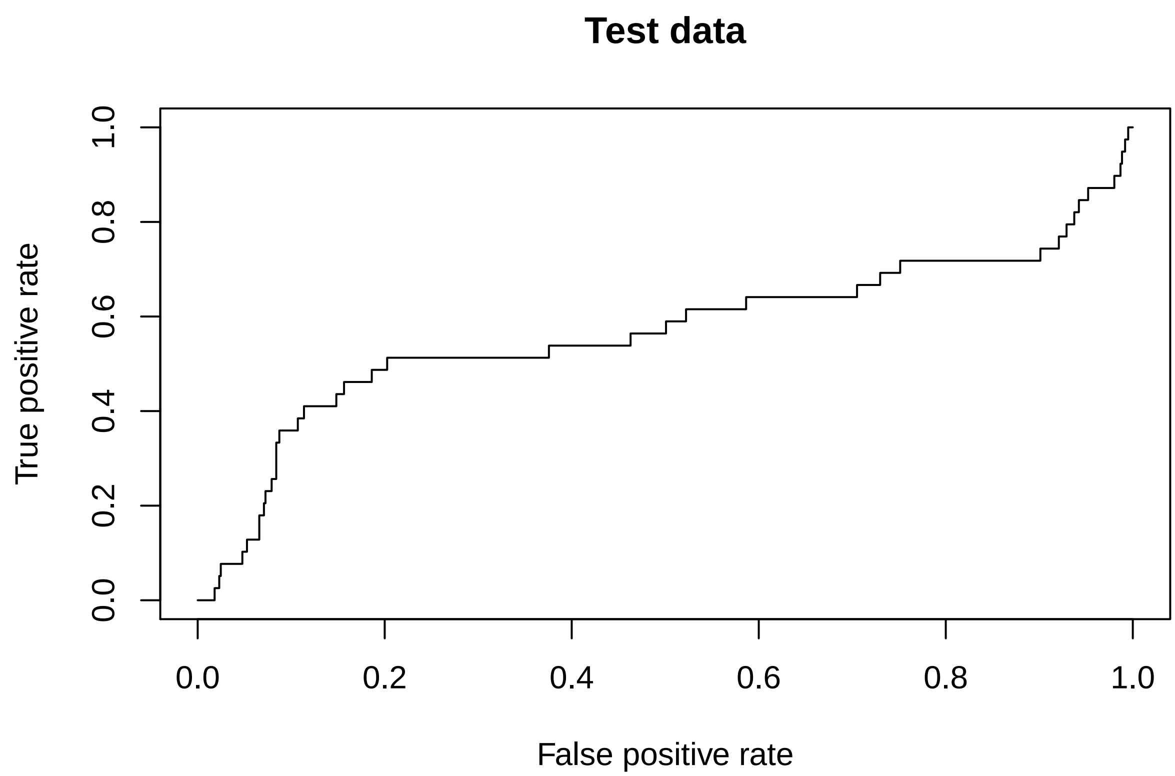

```
total.time <- proc.time() - start.time
time4 <- total.time[3]

#--------------------------------------------------
# Implement with the polynomial kernel
#--------------------------------------------------

##
## Model 1
##

start.time <- proc.time()

tune.out4 <- tune(svm, factor(class)~genergy + gpuls + nbumps + nbumps2 + nbumps4, data = seismic[train

bestmod <- tune.out4$best.model
ypred <- predict(bestmod, seismic[-train,])
table(predict = ypred, truth = seismic$class[-train])
```

```
##         truth
## predict   0   1
##       0 606  39
##       1   1   0
```

```r
svmpoly4 <- svm(factor(class)~genergy + gpuls + nbumps + nbumps2 + nbumps4, data = seismic[train,], kern
fitted4 <- attributes(predict(svmpoly4, seismic[train,], decision.values = T))$decision.values
fitted.test4 <- attributes(predict(svmpoly4, seismic[-train,],decision.values = T))$decision.values

rocplot(fitted4, seismic[train,"class"], main = "Training data")
```



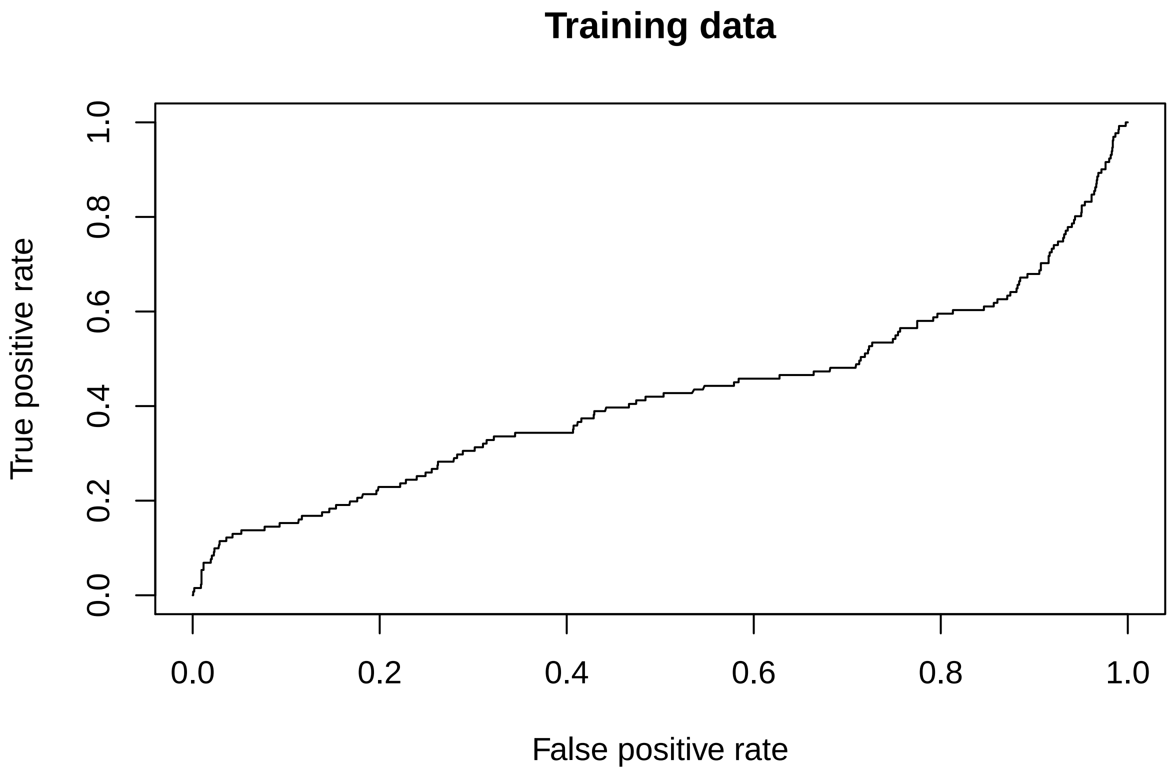

```r
rocplot(fitted.test4, seismic[-train,"class"], main = "Test data")
```



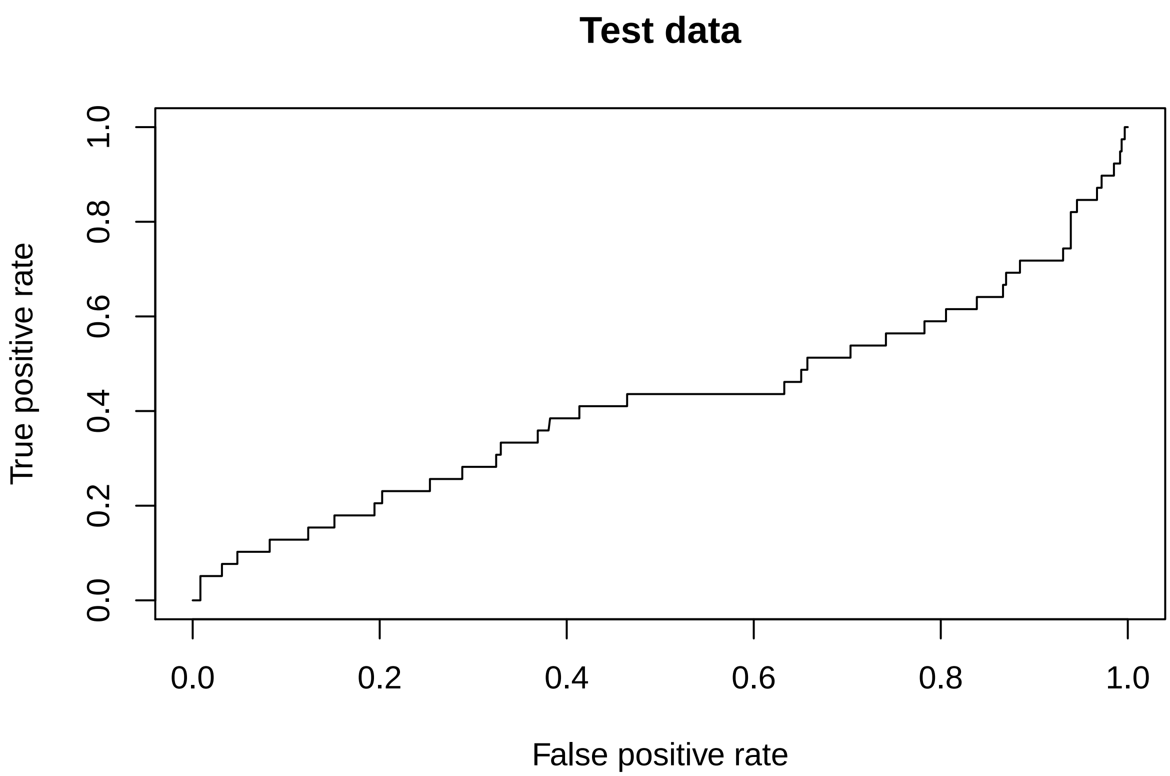

```
total.time <- proc.time() - start.time
time5 <- total.time[3]

##
## Model 2
##

start.time <- proc.time()

tune.out5 <- tune(svm, factor(class)~seismic + shift + gpuls + nbumps, data = seismic[train,], kernel =

bestmod <- tune.out5$best.model
ypred <- predict(bestmod, seismic[-train,])
table(predict = ypred, truth = seismic$class[-train])
```

```
##        truth
## predict   0   1
##       0 607  39
##       1   0   0
```

```
svmpoly5 <- svm(factor(class)~seismic + shift + gpuls + nbumps, data = seismic[train,], kernel = "polyno
fitted5 <- attributes(predict(svmpoly5, seismic[train,], decision.values = T))$decision.values
fitted.test5 <- attributes(predict(svmpoly5, seismic[-train,],decision.values = T))$decision.values

rocplot(fitted5, seismic[train,"class"], main = "Training data")
```




```
rocplot(fitted.test5, seismic[-train,"class"], main = "Test data")
```



```r
total.time <- proc.time() - start.time
time6 <- total.time[3]
```

How to time your code!!!

```r
#-------------------------------------
# How to time your method
#-------------------------------------

# Put this before your method
start.time <- proc.time()

## the thing you are computing, like random forest or SVM goes here ##

total.time <- proc.time() - start.time

total.time[3] # the elapsed time
```

```
## elapsed
##   0.001
```