Data Mining Project 3

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Introduction

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 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.

To investigate these seismic hazards and explore more advance analysis technique 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. Table 1 in the Appendix has a listing of all 18 variables and their descriptions.

The purpose of this project is to find whether and how the other 18 variables can be used to determine the hazard status of the mine. In project 2, we utlized techniques such as the indicator matrix linear regression, logistic regression, linear discriminant analysis(LDA), quadratic discriminant qnalysis (QDA), and regularized discriminant analysis (RDA) to try and find a model that would accurately predict the hazardous state. Unfortunately, all of the five project two methods performed poorly. We felt that there were two major issues at hand for this poor performance of the five methods. First, the low incidences of "1's" in the response variable class, which indicates a hazardous state in the mine. Only 170 "1's" for class out of 2584 were observed. A difficult problem for traditional method of analyses. The second issue was multicollinearity. 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. Table 2 in the Appendix contains VIF's for the linear regression model.

Multicollinearity can be address by dimension reduction techniques such as PCA, step-wise regression, LASSO or ridge. In project 2, we utilized step-wise regression and LASSO to arrive at two candidate models. However, even with these dimension reduction techniques our models still performed poorly. Hopefully, to remedy this poor performance, we can utilize more advance techniques such as Boosting, Random Forest or Support Vector Machines.

In section 2, we report ROC curves and missclassification rates for Logistic Regression, LDA, QDA and RDA. In section 3, we report **best technique** out of the three that we tried. In section 4, we provide concluding remarks as well as future work on seismic data.

2 Logistic Regression, LDA, QDA, RDA

2.1 Logistic Regression-Full Model Logistic Regression - Step Model

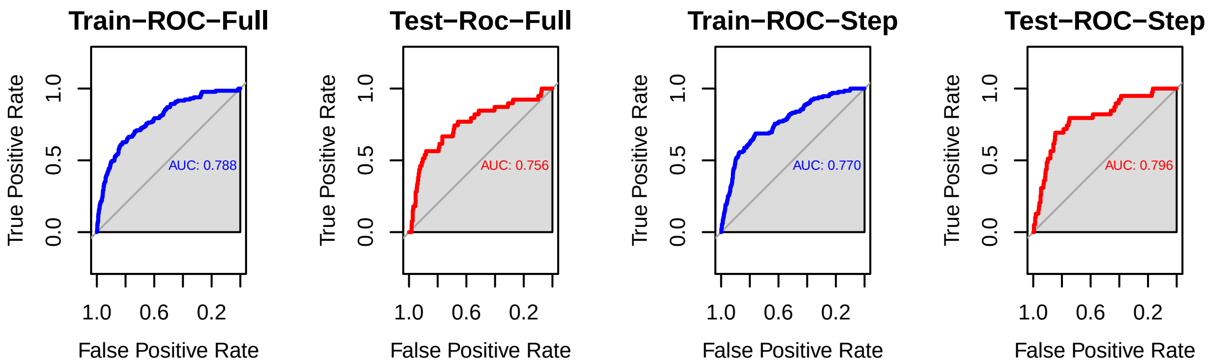


Table 1: Logistic Regression

	Full	Step
Computing Time	0.110	0.081
Train Error Rates	0.067	0.070
Test Error Rates	0.065	0.062

2.2 Linear Discriminant Analysis

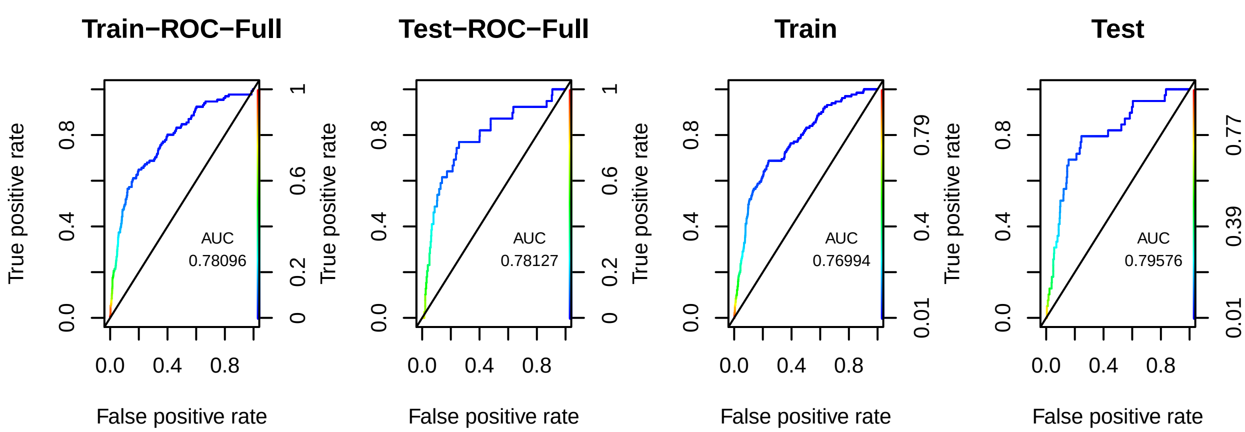


Table 2: Linear Discriminant Analysis

	Full	Step
Computing Time	0.443	1.333
Train Error Rates	0.074	0.081
Test Error Rates	0.077	0.076

2.3 Quadratic Discriminant Analysis

Full Model

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

Quadratic Discriminant Analysis - Step

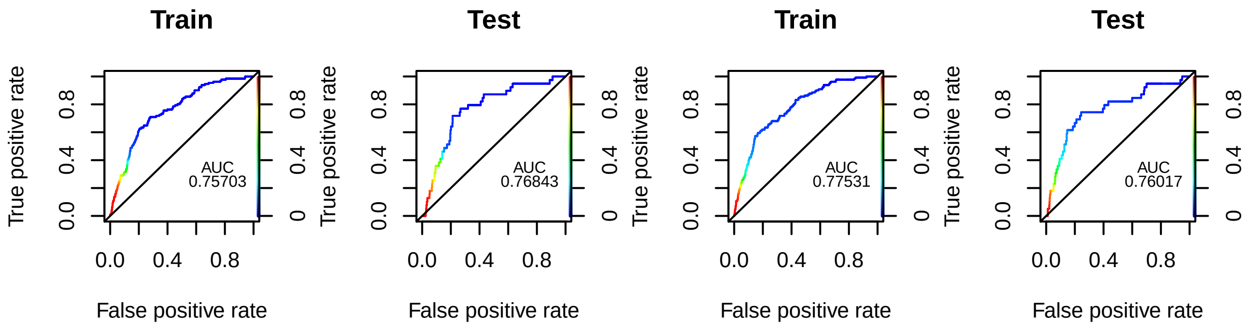


Table 3: Quadratic Discriminant Analysis

	Full	Step	Lasso
Computing Time	NA	0.443000000000001	1.283
Train Error Rates	0.149	0.109	NA
Test Error Rates	0.159	0.107	NA

2.4 Regularized Discriminant Analysis

Regularized Discriminant Analysis -Full Regularized Discriminant Analysis -Step

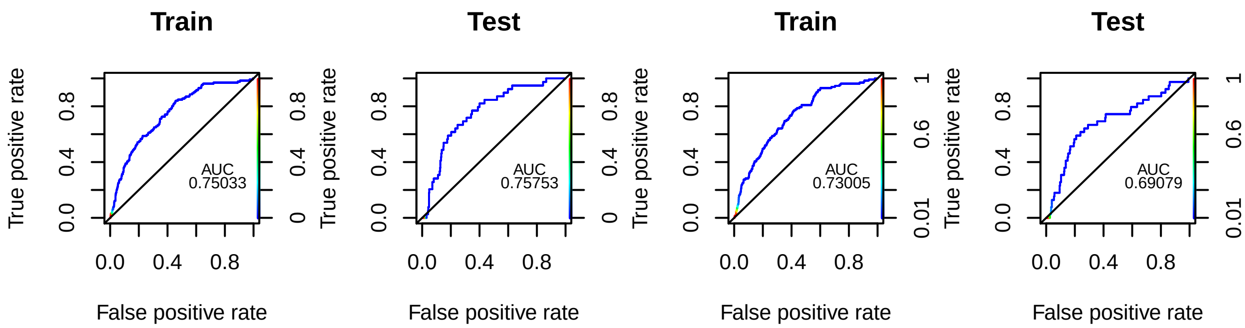
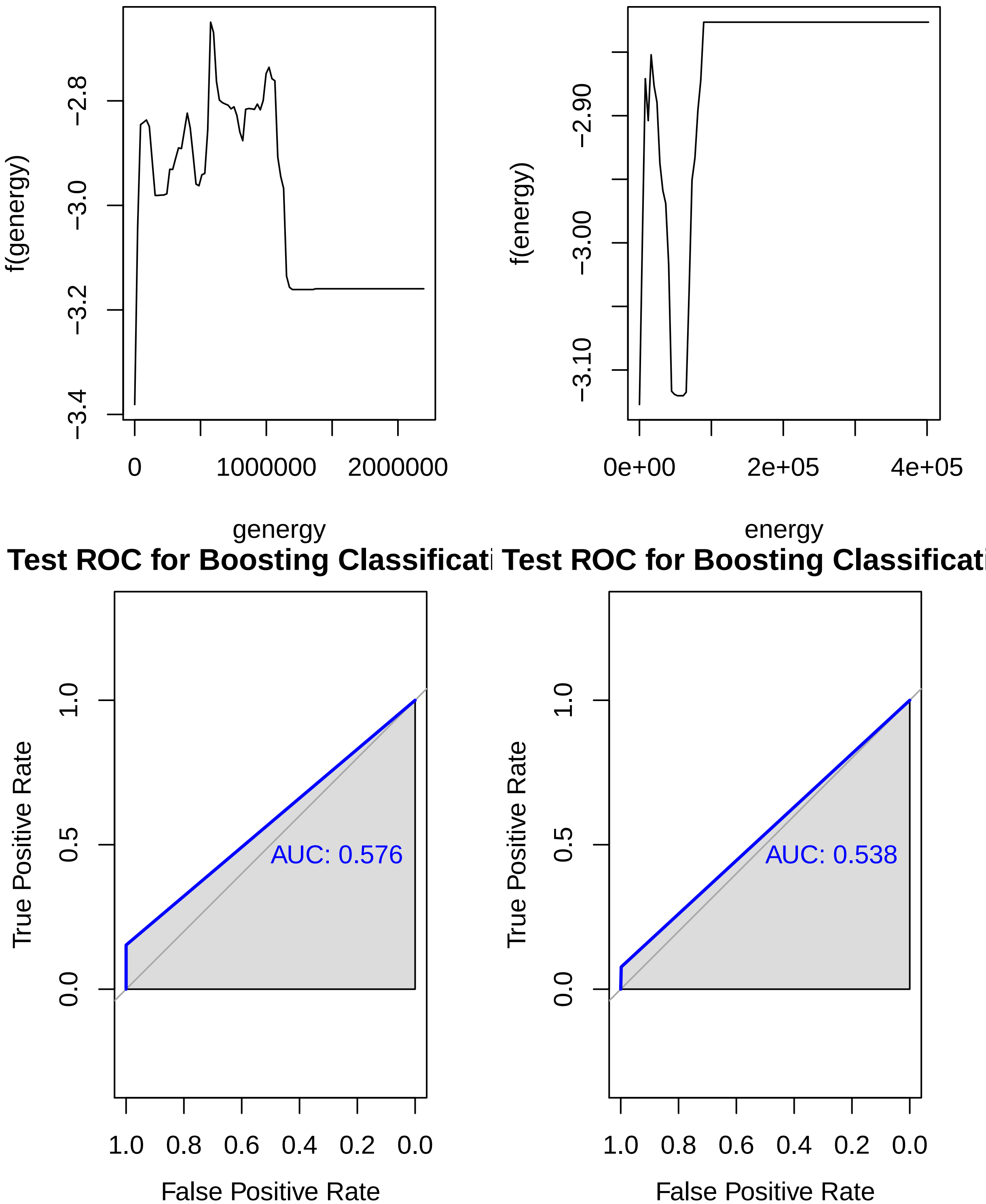


Table 4: Regularized Discriminant Analysis

	Full	Step
Computing Time	3.155	2.084
Train Error Rates	0.076	0.082
Test Error Rates	0.082	0.085

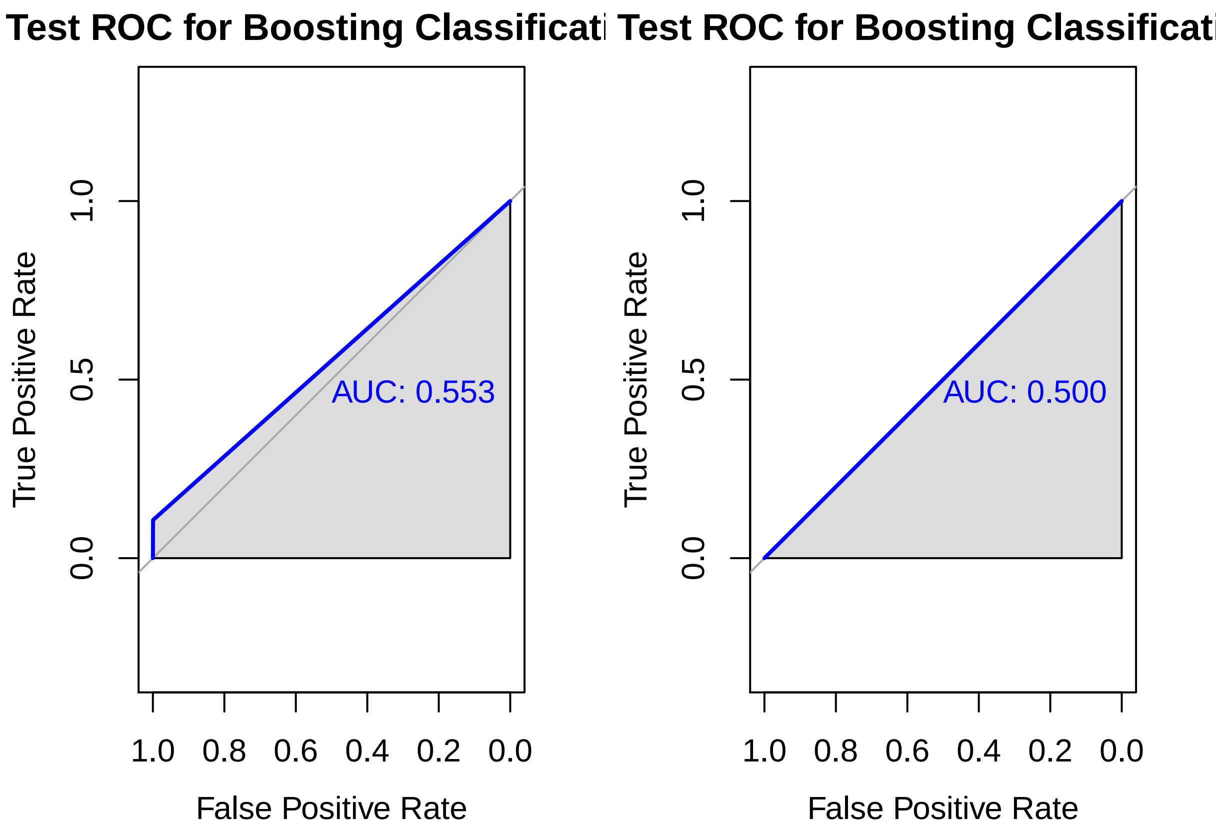
Boosting before variable selection

```
elapsed
  7.783
```



Boosting after variable selection

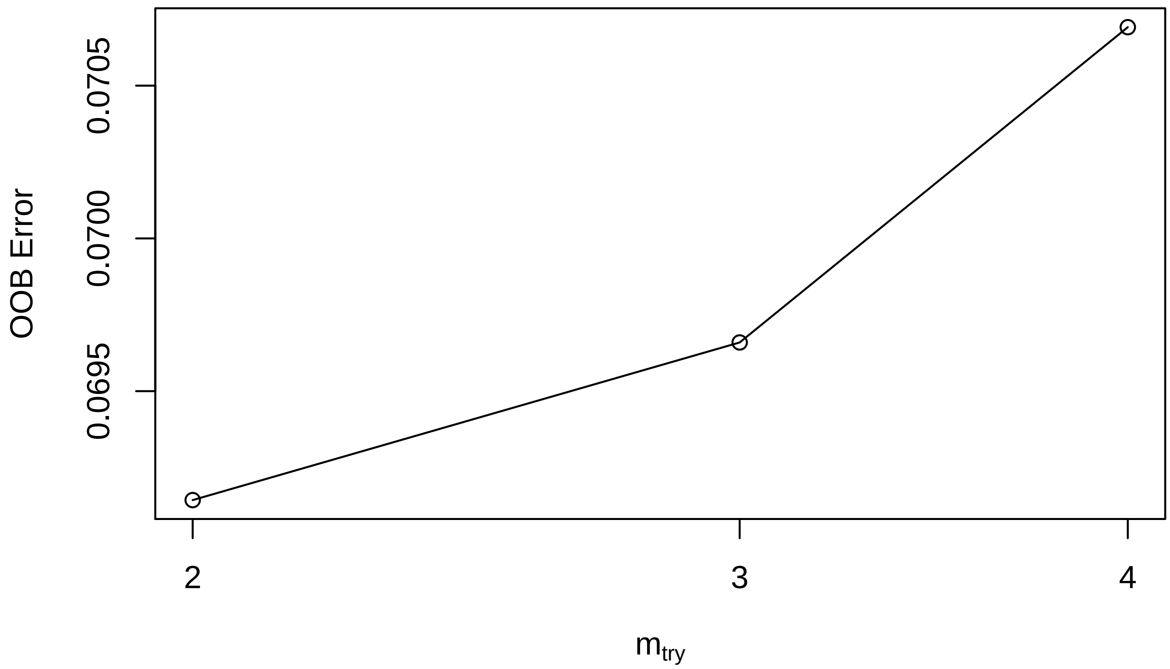
```
elapsed
  3.466
```



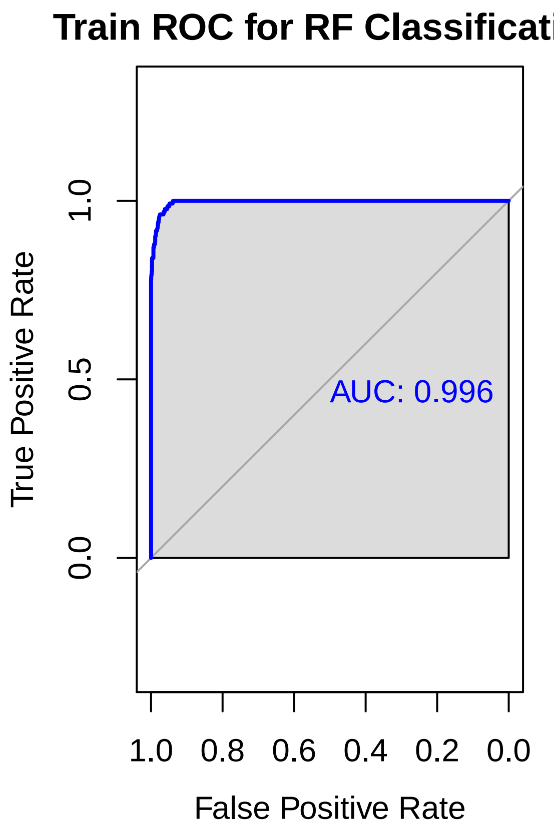
Random Forests Classification

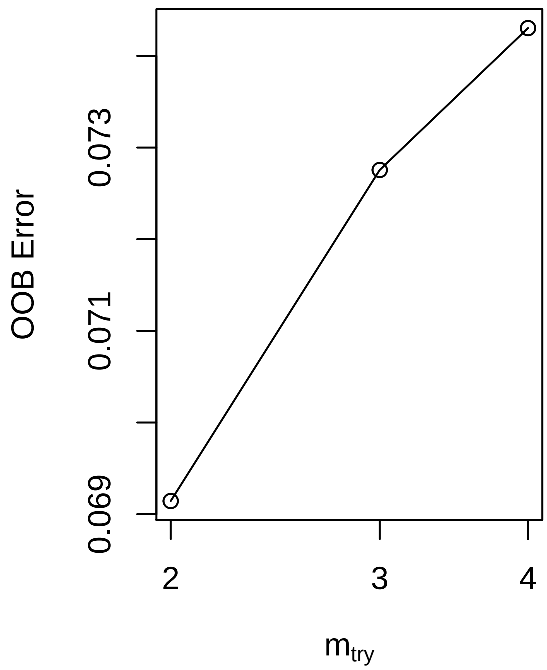
RF Classification BEFORE Variable Selection

```
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
```

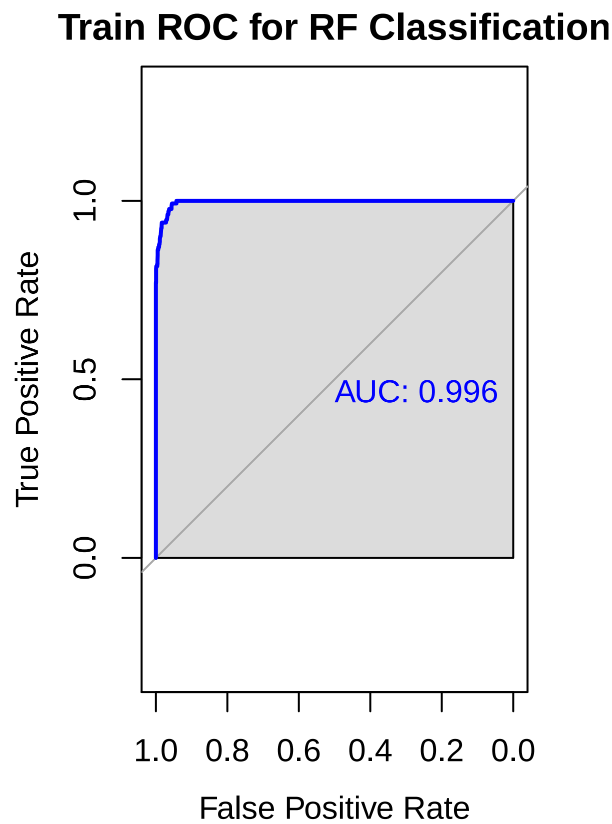





```
[1] 0
```

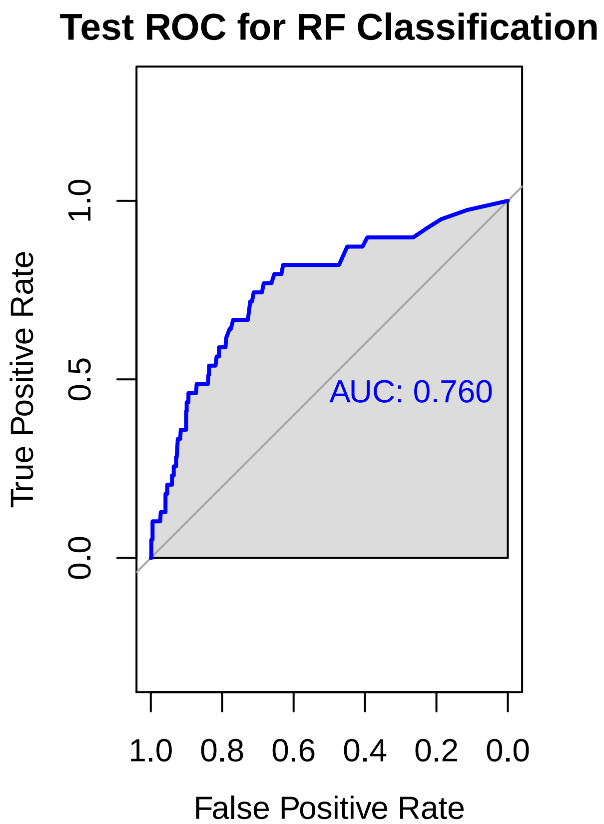
```
[1] 0.2363033
```

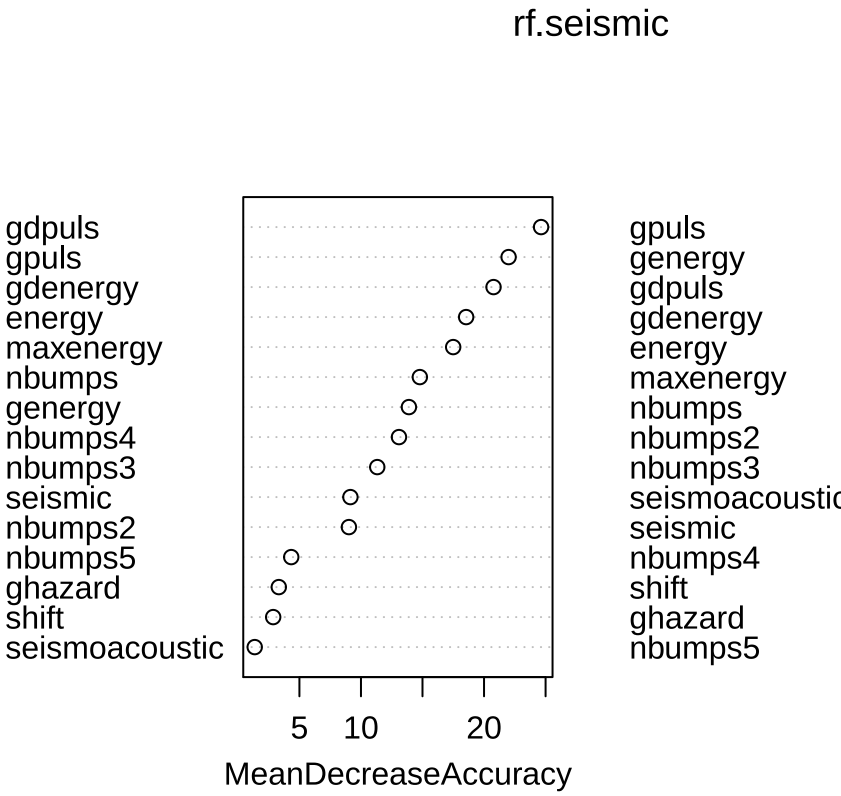
```
[1] 0.2203302
```



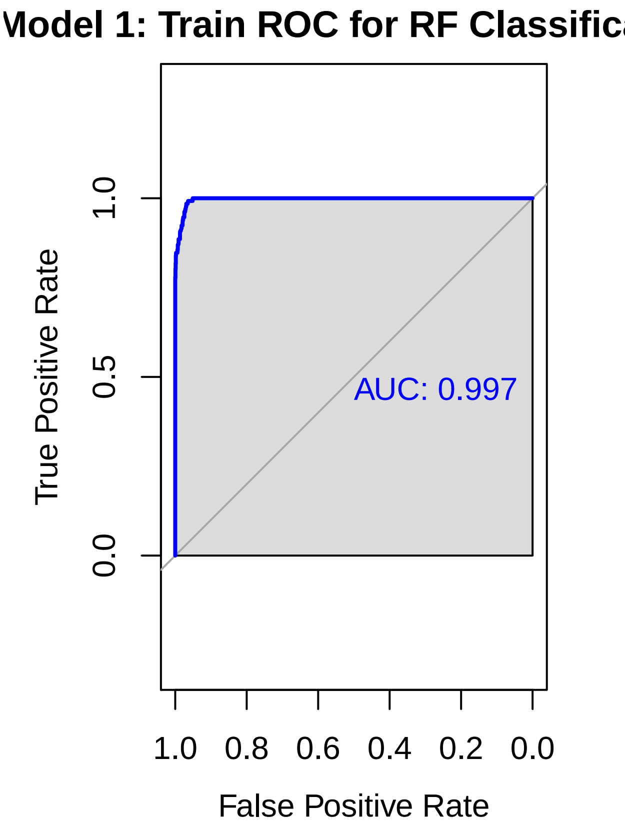

```
[1] 0.02564103

[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

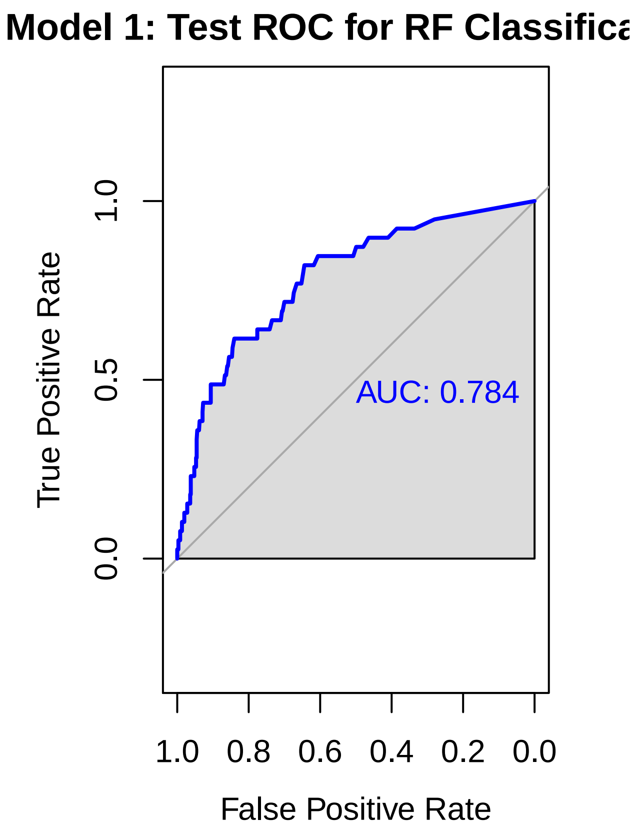

Test ROC for RF Classification
AUC: 0.760
True Positive Rate
0.0
0.5
1.0
1.0
0.8
0.6
0.4
0.2
0.0
False Positive Rate

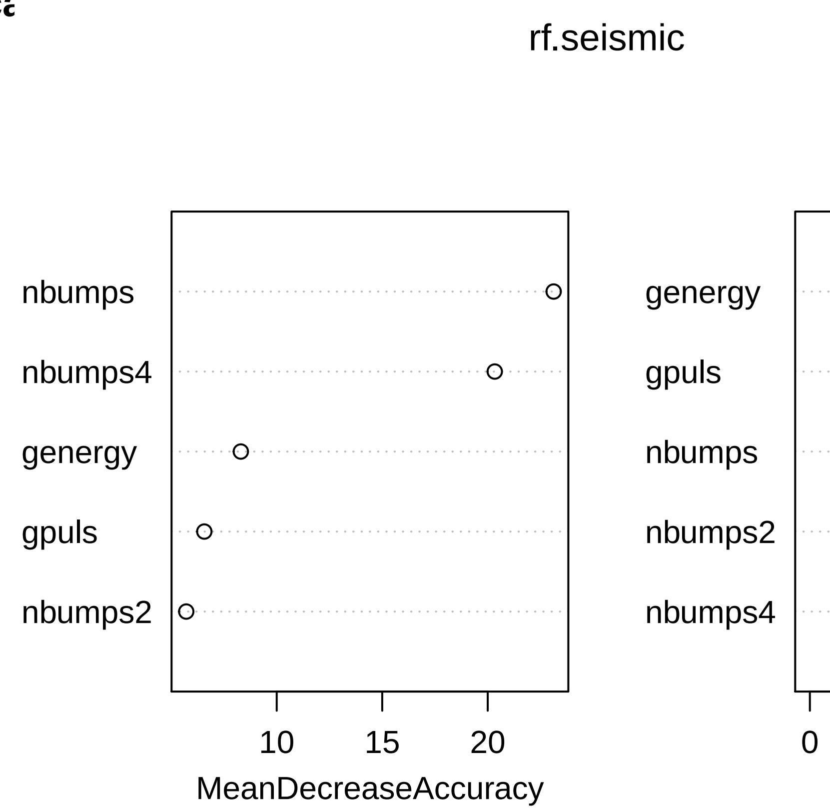

rf.seismic
gdpuls
gpuls
gdenergy
energy
maxenergy
nbumps
genergy
nbumps4
nbumps3
seismic
nbumps2
nbumps5
ghazard
shift
seismoacoustic
5
10
20
MeanDecreaseAccuracy
gpuls
genergy
gdpuls
gdenergy
energy
maxenergy
nbumps
nbumps2
nbumps3
seismoacoustic
seismic
nbumps4
shift
ghazard
nbumps5

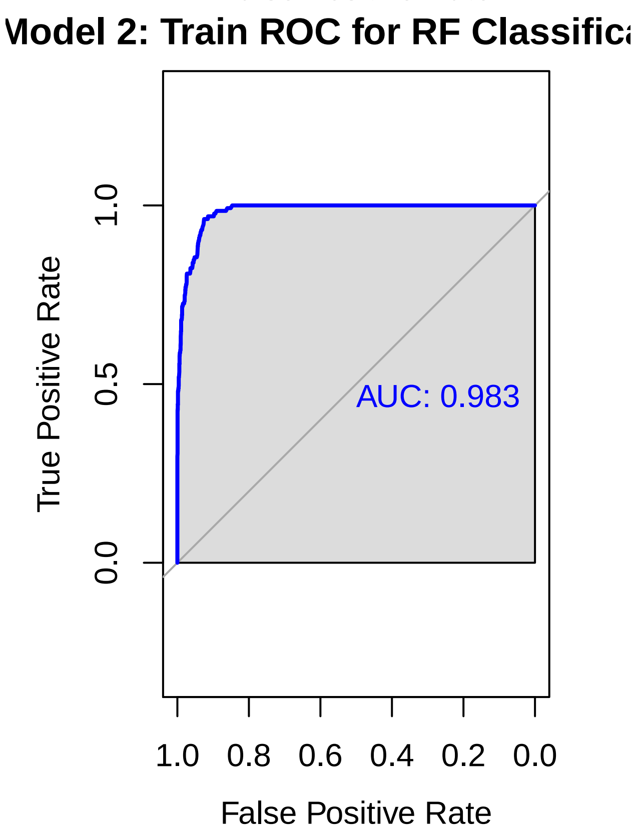
RF Classification AFTER Variable Selection




```
                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
```

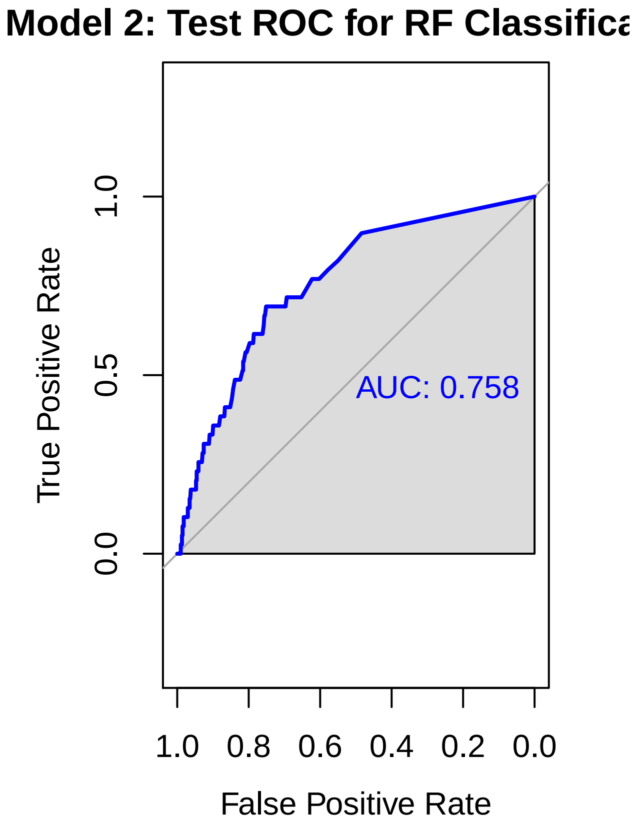


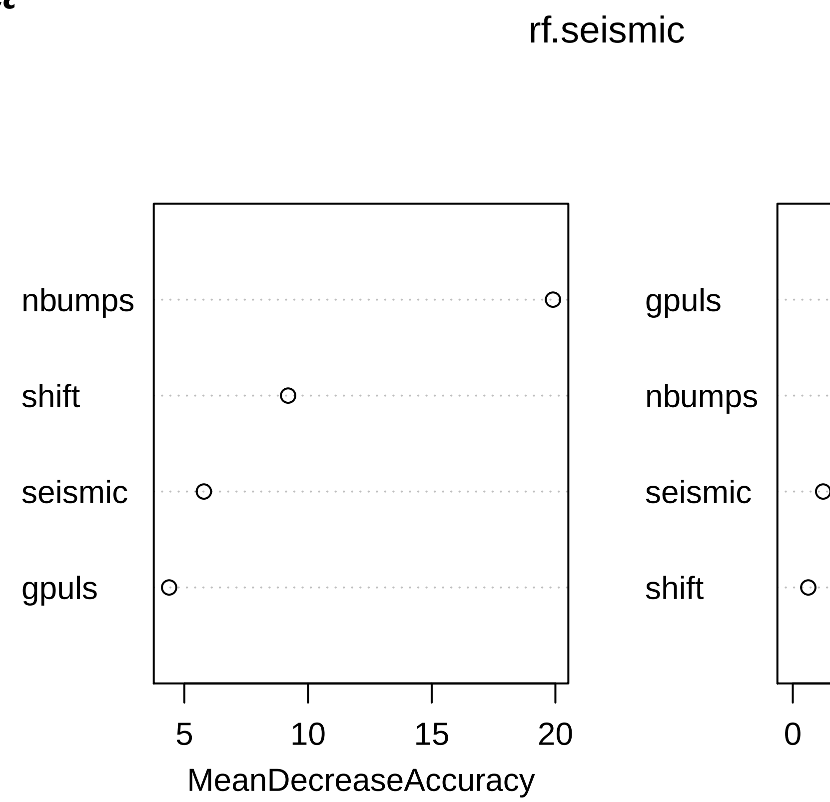




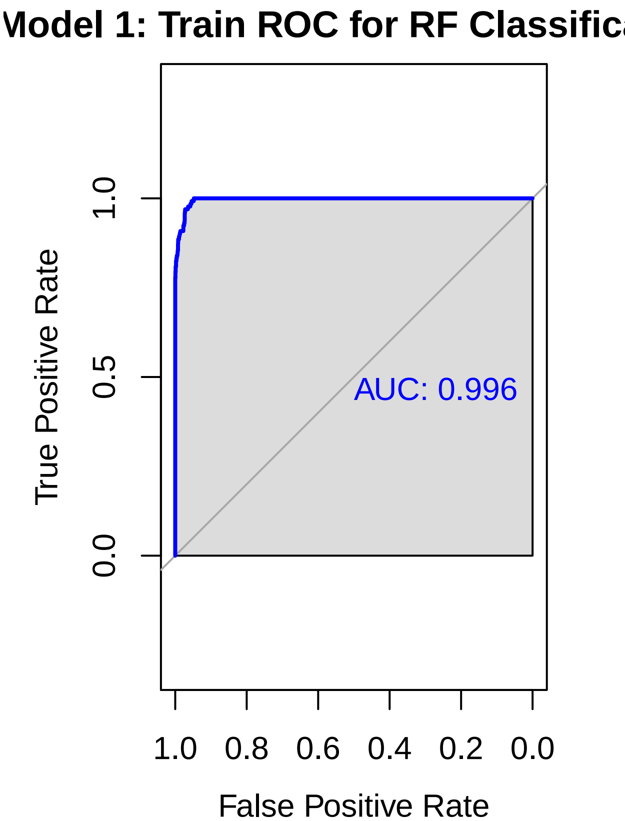

```
0           1 MeanDecreaseAccuracy MeanDecreaseGini
```

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

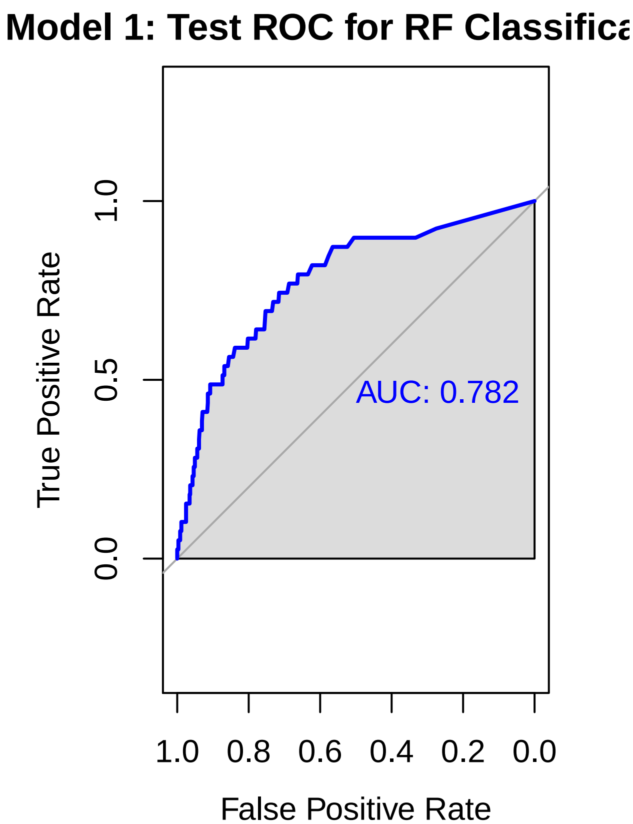


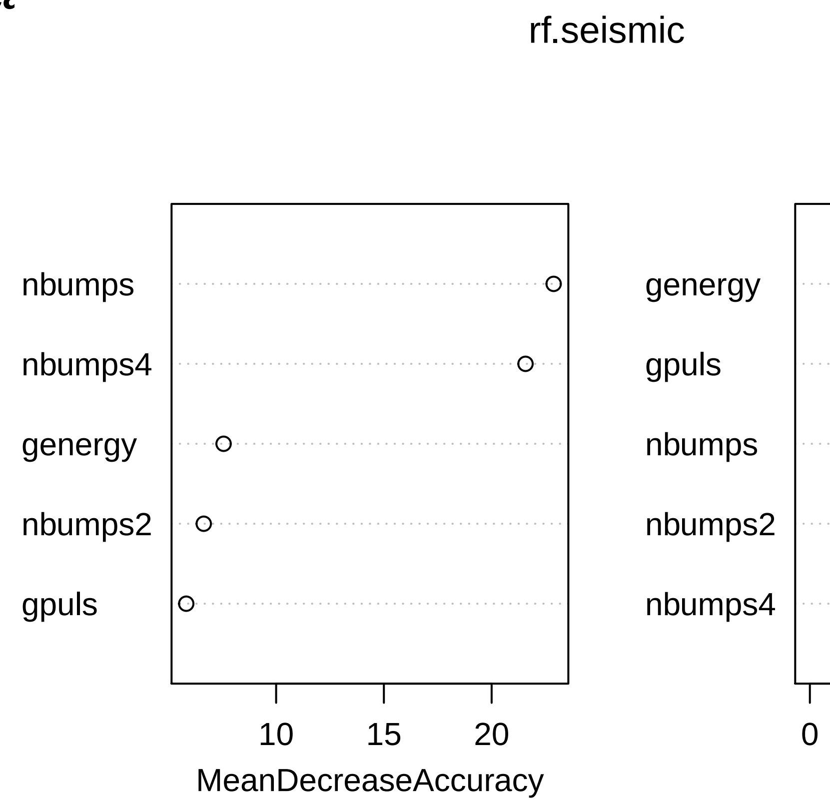


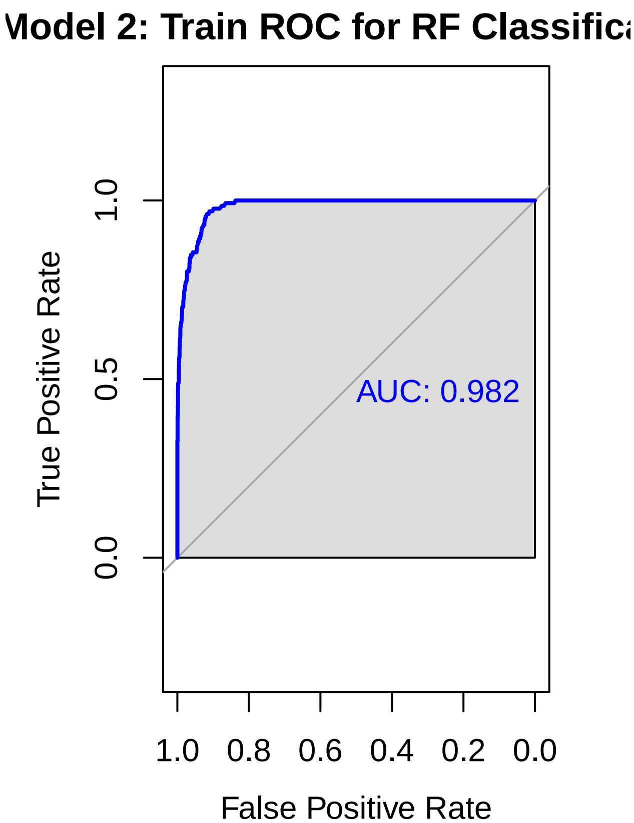
Boosting



	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

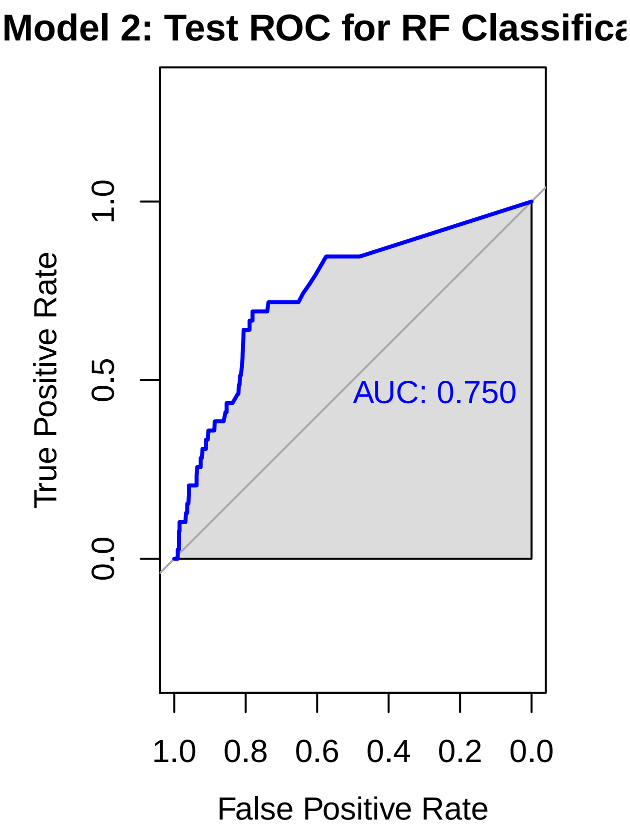


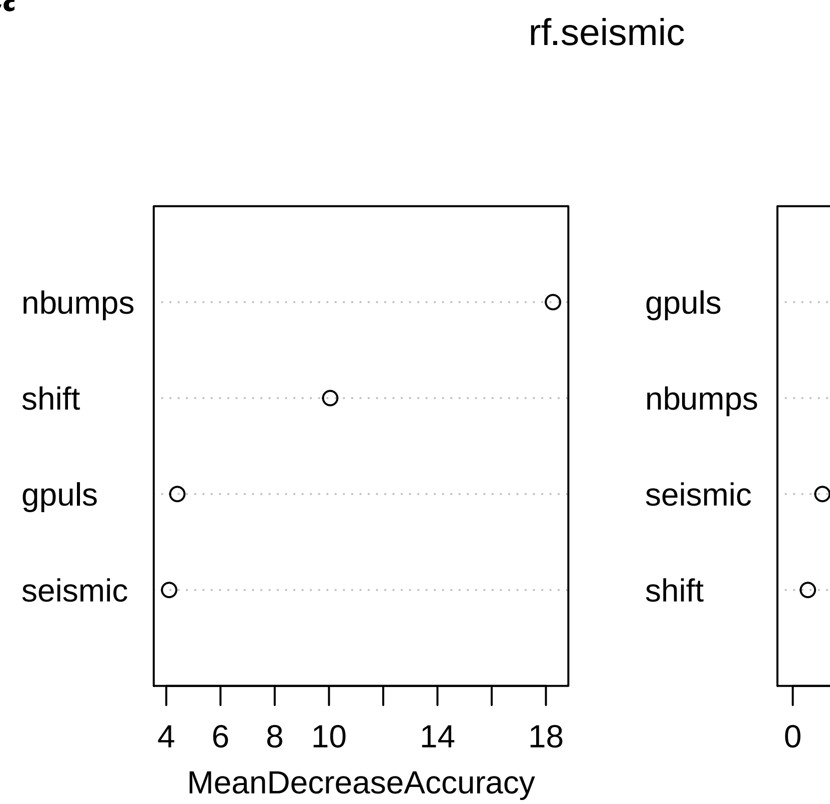





```
0          1 MeanDecreaseAccuracy MeanDecreaseGini
```

```
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
```



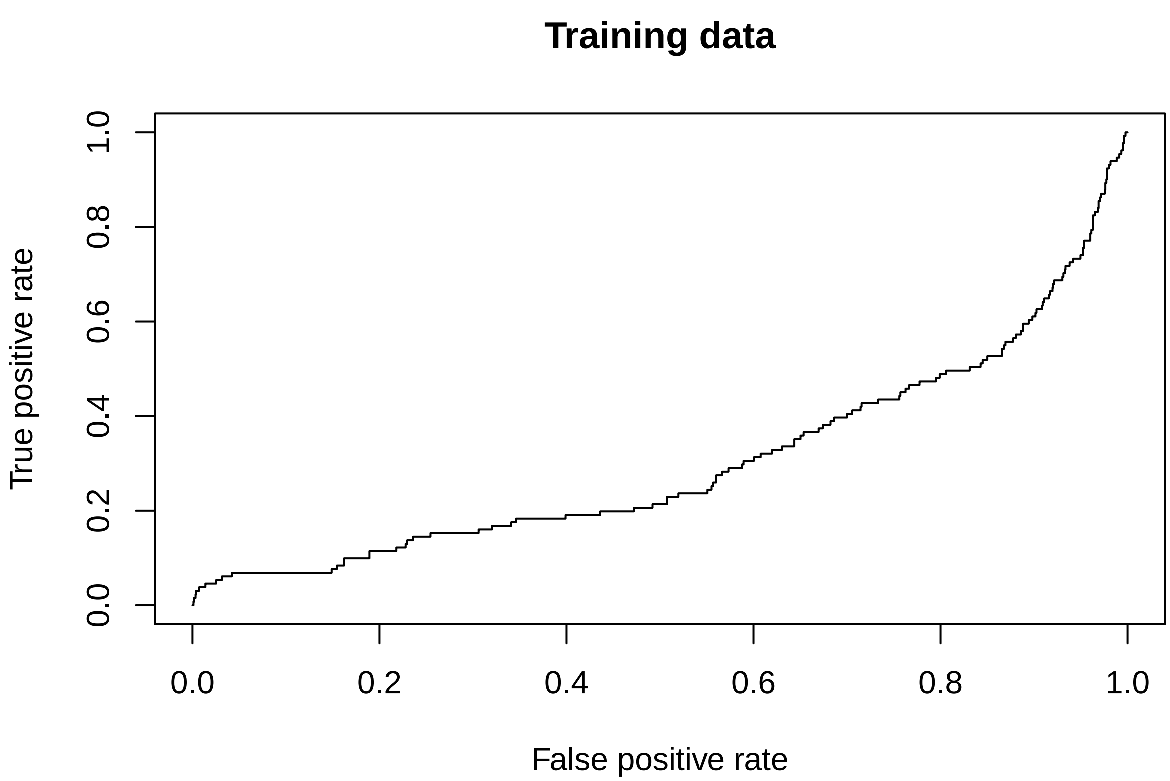


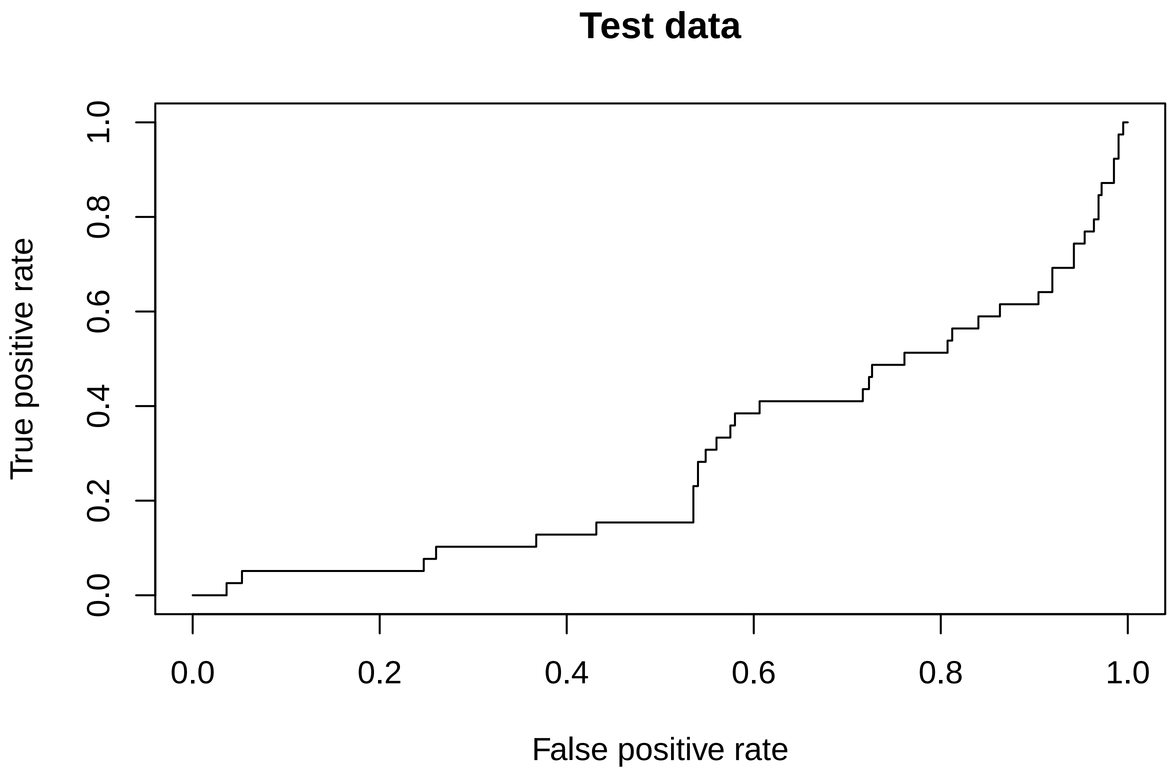
Support vector classifier and support vector machine

```
##
## 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
```

```
##
## 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
```

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

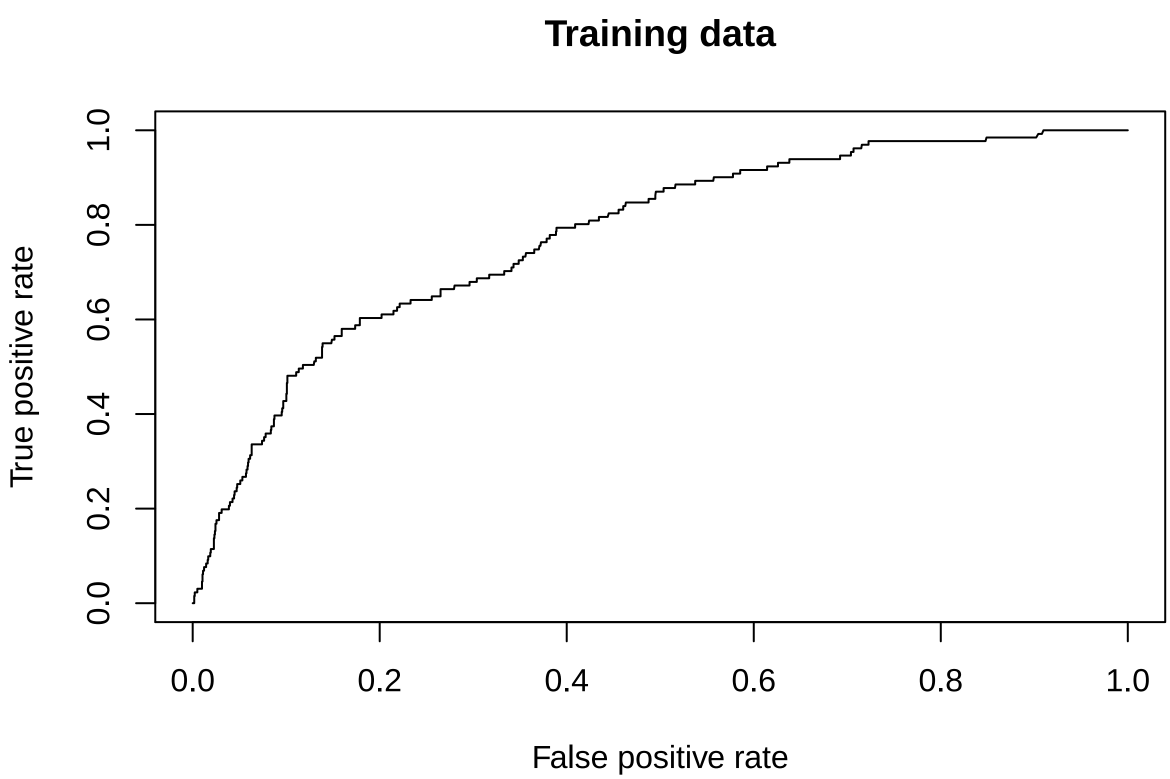


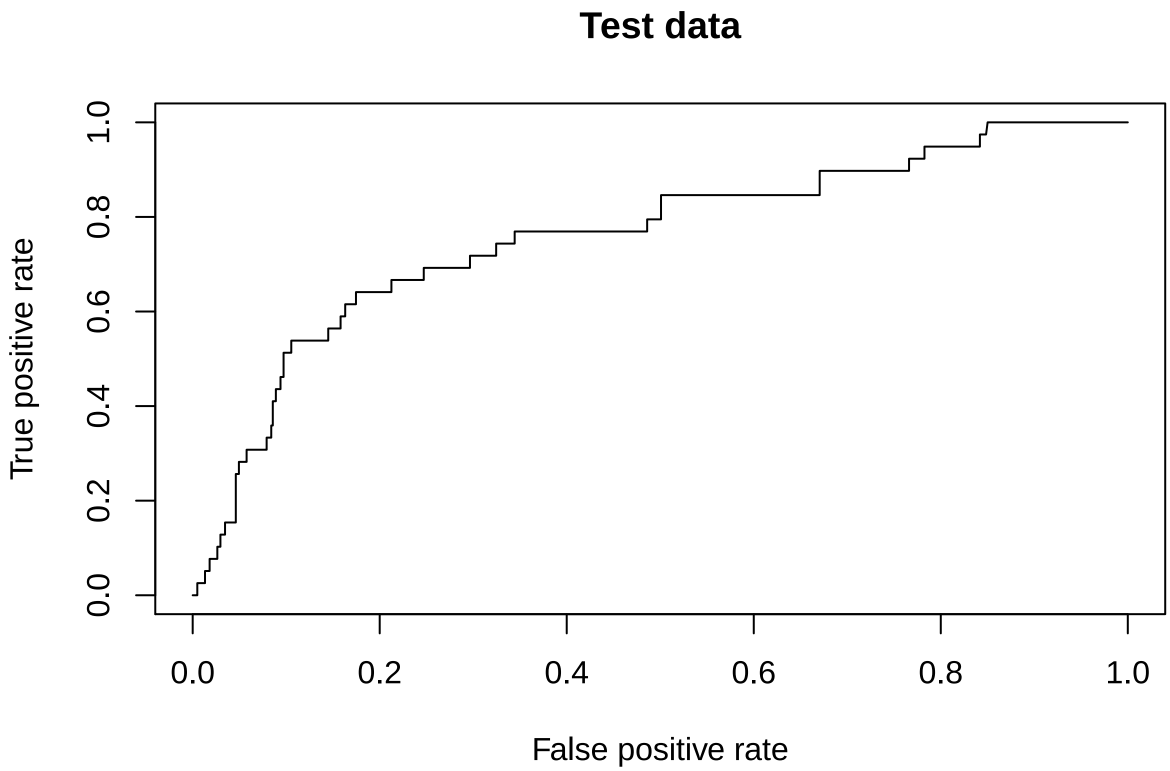



```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   cost
##  0.001
##
## - best performance: 0.0676059
##
## - Detailed performance results:
##    cost     error dispersion
## 1 0.001 0.0676059 0.01815001
## 2 0.010 0.0676059 0.01815001
## 3 0.100 0.0676059 0.01815001
## 4 1.000 0.0676059 0.01815001
## 5 5.000 0.0676059 0.01815001

##
## 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
```

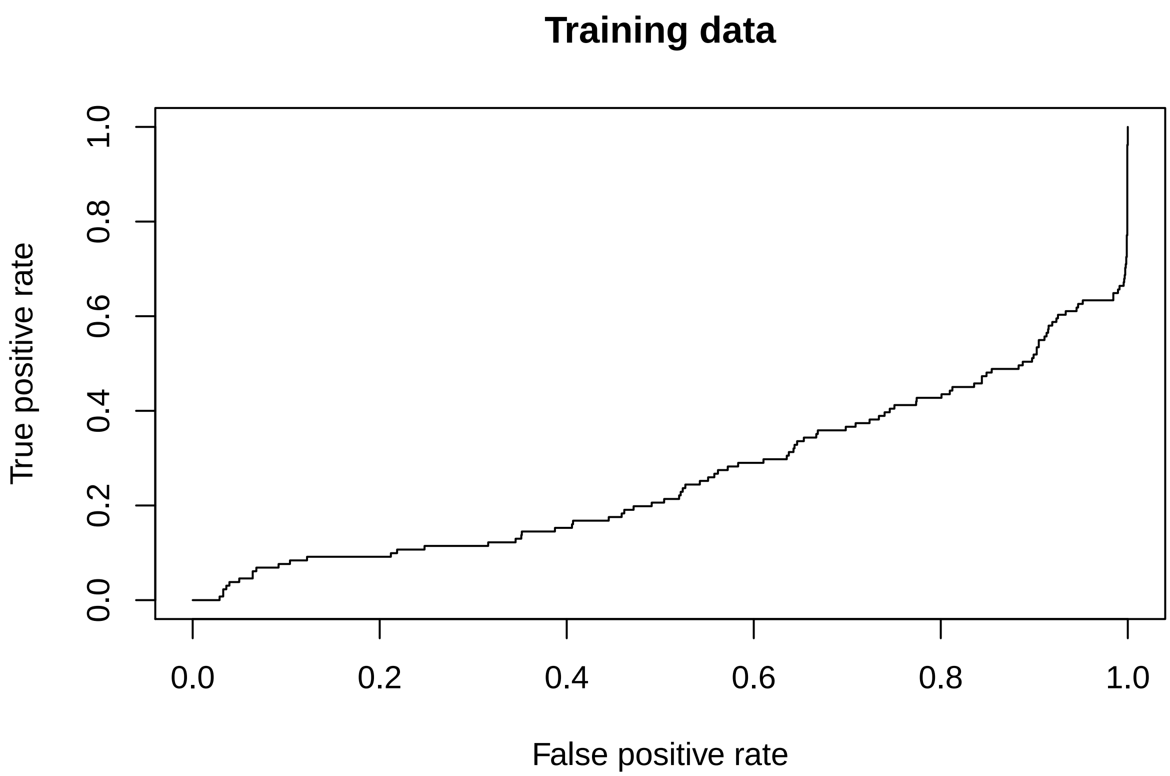
```
##        cost:  0.001
##       gamma:  0.25
##
## Number of Support Vectors:  265
##
##  ( 134 131 )
##
##
## Number of Classes:  2
##
## Levels:
##  0 1
```

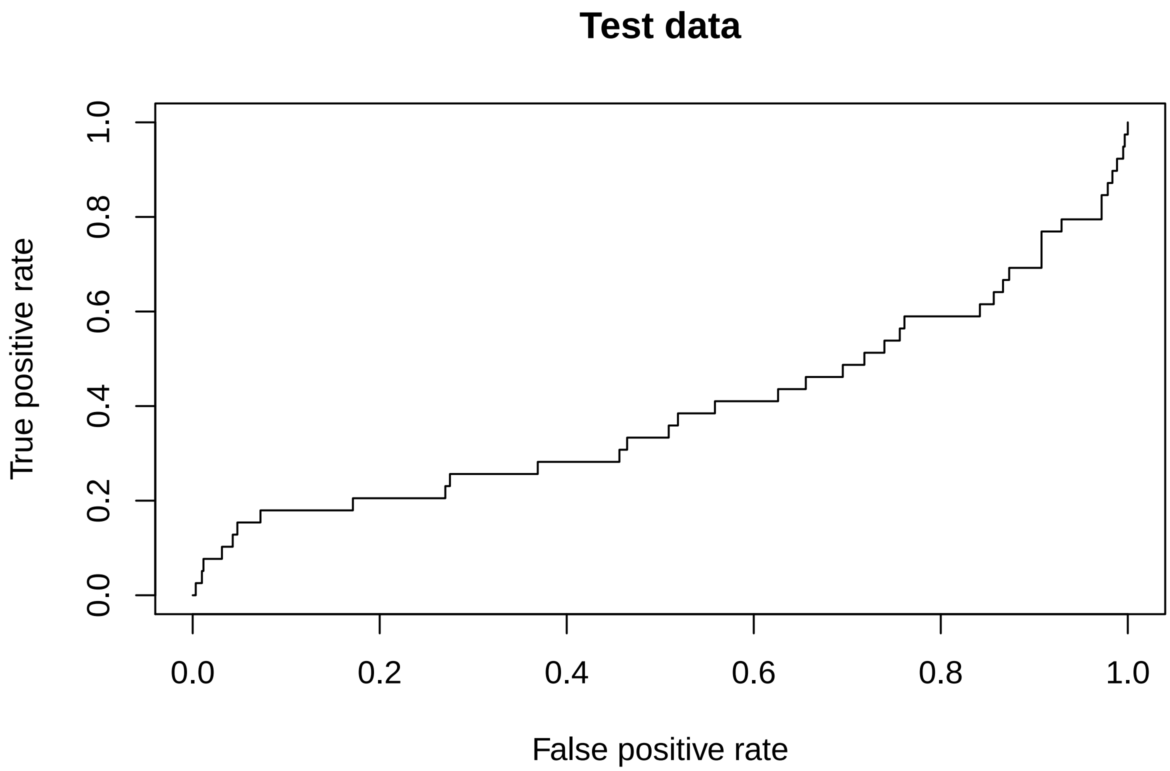
```
##        truth
## predict   0   1
##       0 607  39
##       1   0   0
```



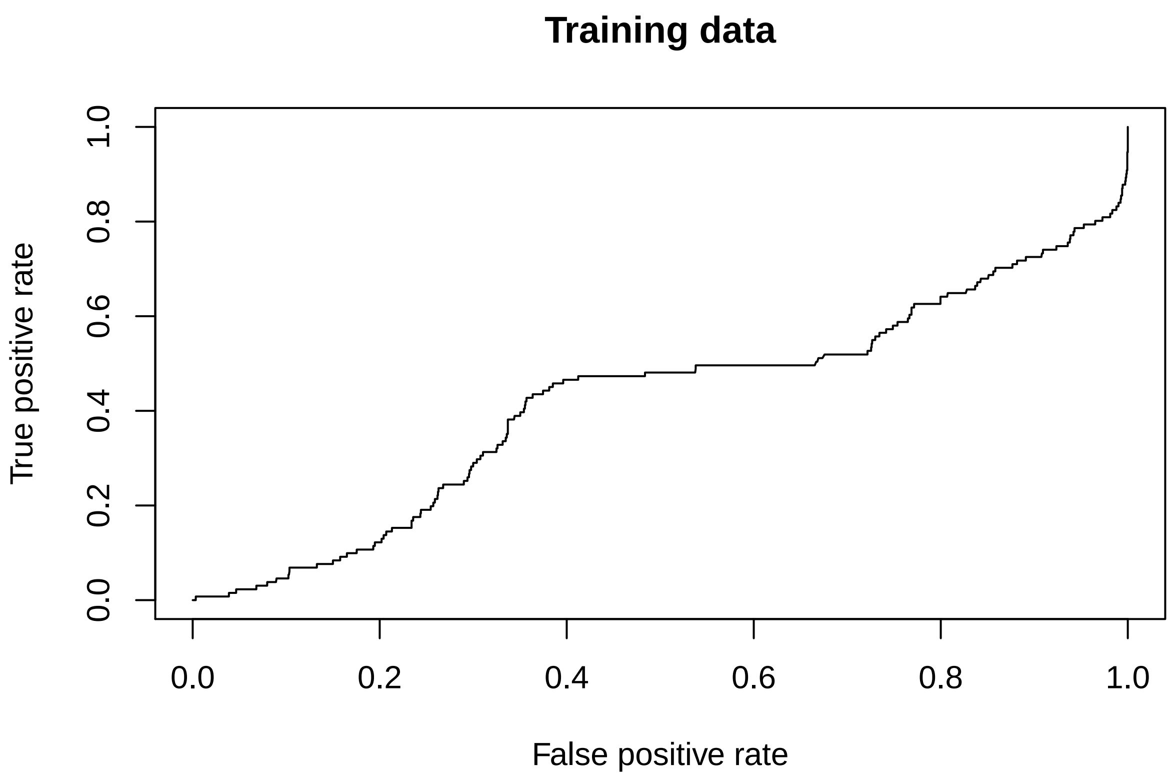


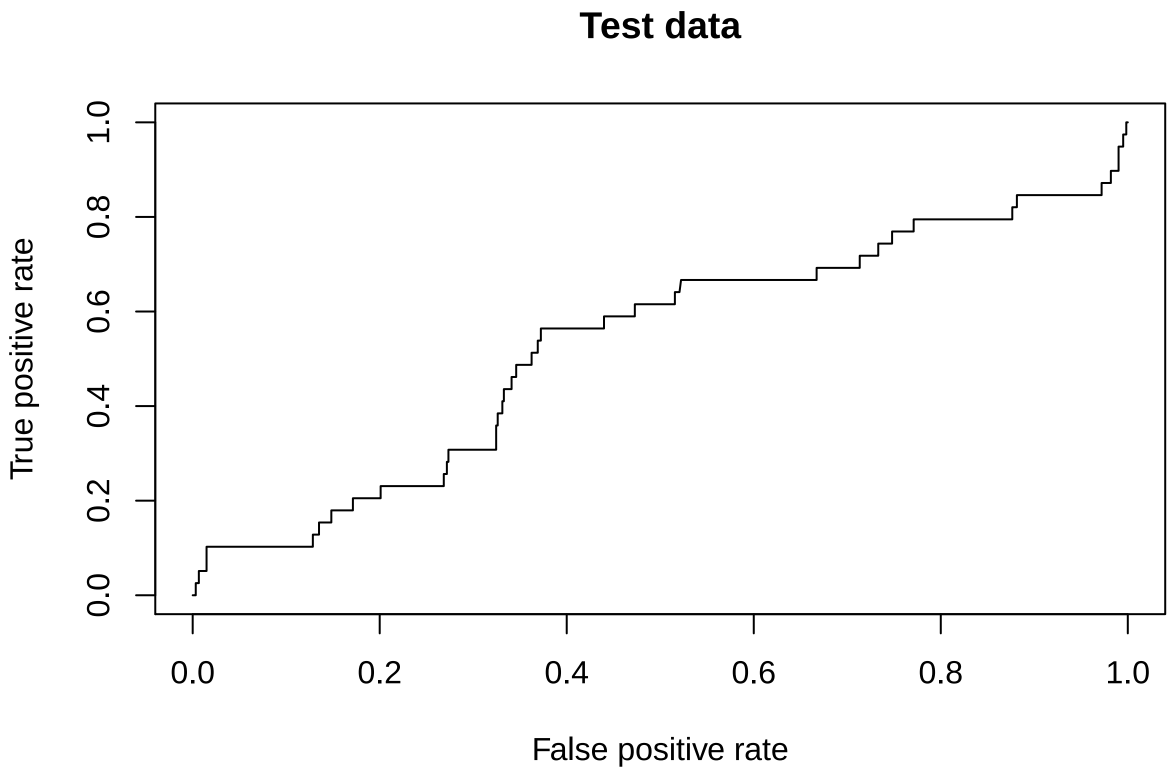

```
##         truth
## predict   0   1
##       0 607  39
##       1   0   0
```



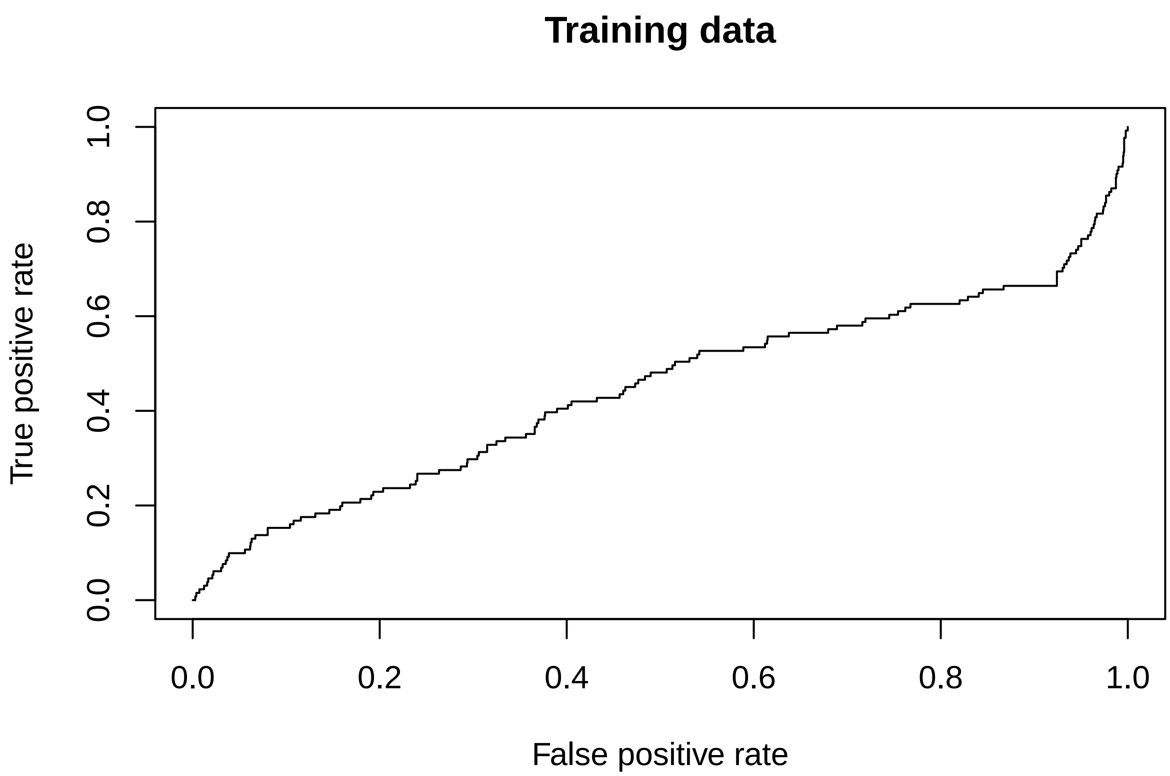


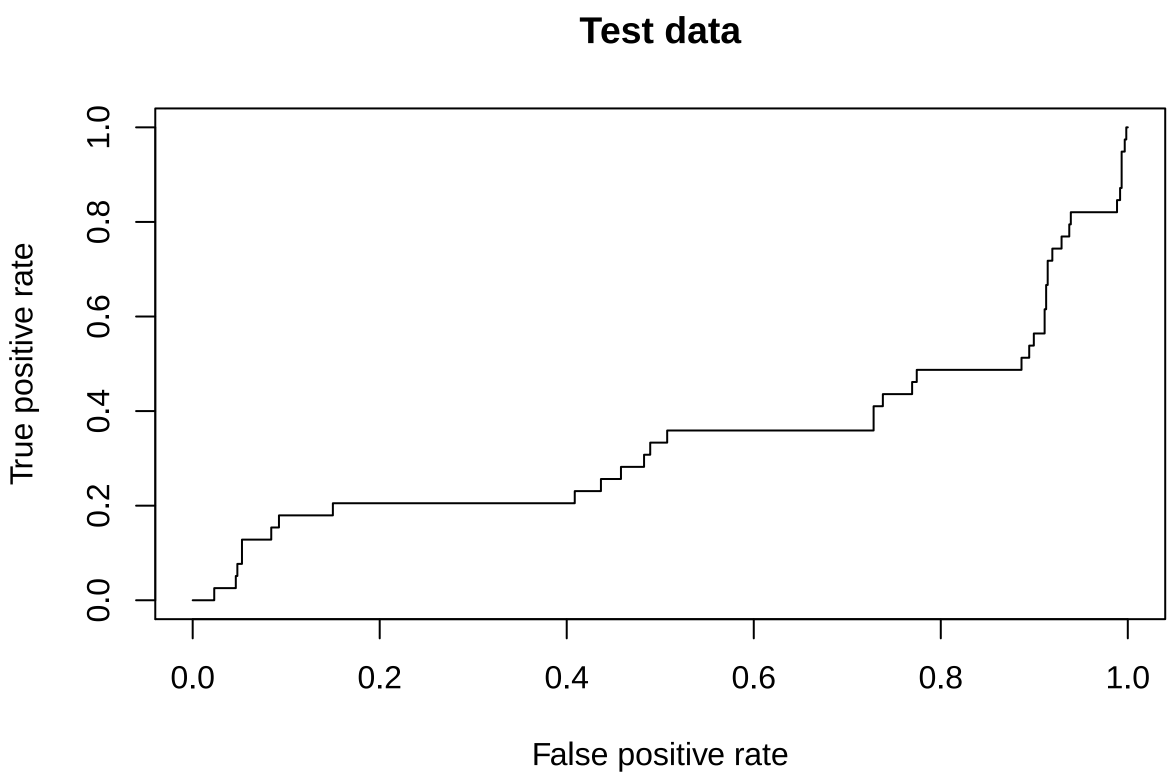

```
##          truth
## predict   0   1
##       0 607  39
##       1   0   0
```



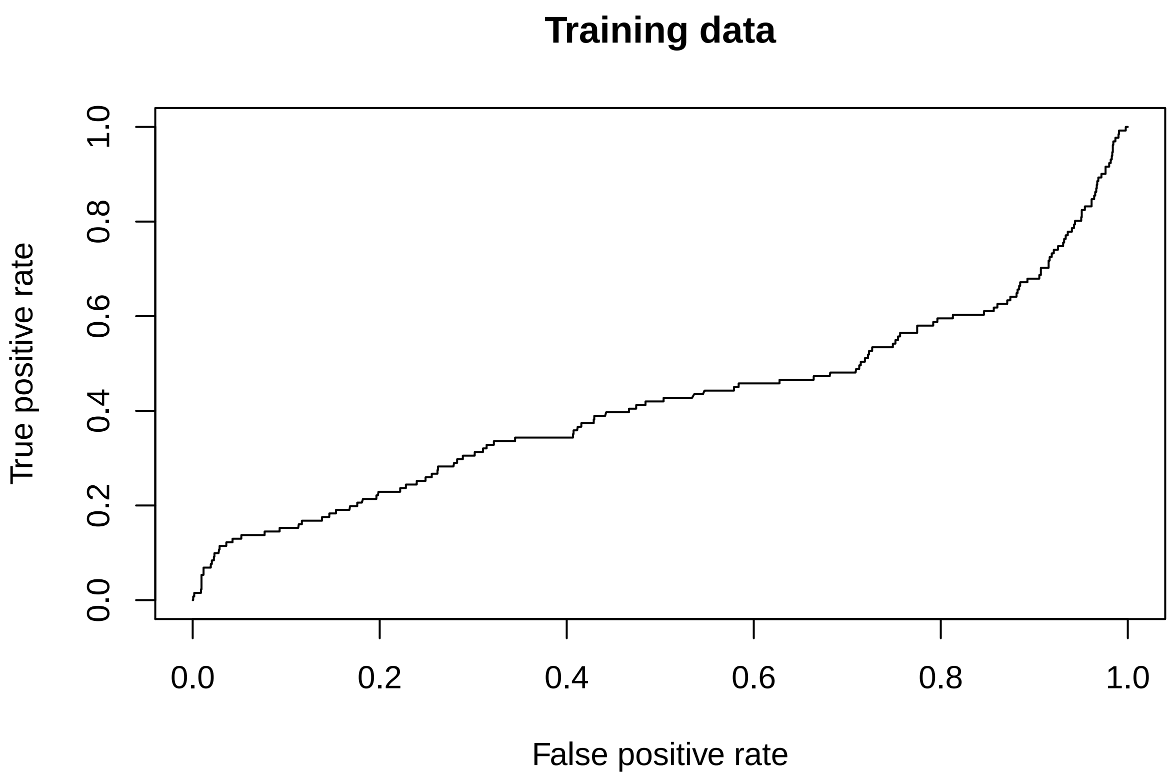


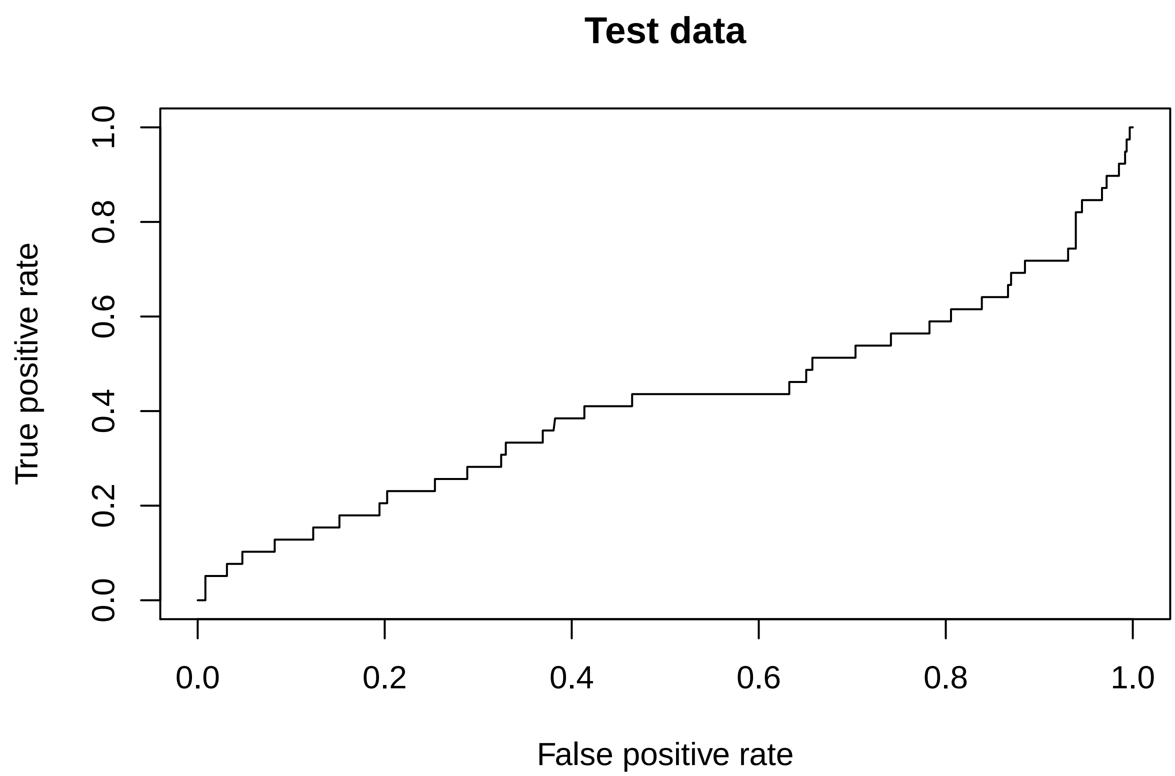

```
##         truth
## predict   0   1
##       0 607  39
##       1   0   0
```






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





	Model 1			*Model 2*		
Kernel	linear	radial	polynomial	linear	radial	polynomial
cost	.001	.001	.001	.001	.001	.001
gamma	.2	1	.2	.25	1	.25
degree	N/A	N/A	2	N/A	N/A	2
time	5.4	26.47	25.31	2.44	24.84	7.51
misclassification rate	.06	.06	.06	.06	.06	.06

How to time your code!!!

```
#--------------------------------------
# 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
```

Appendix

Table I. 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

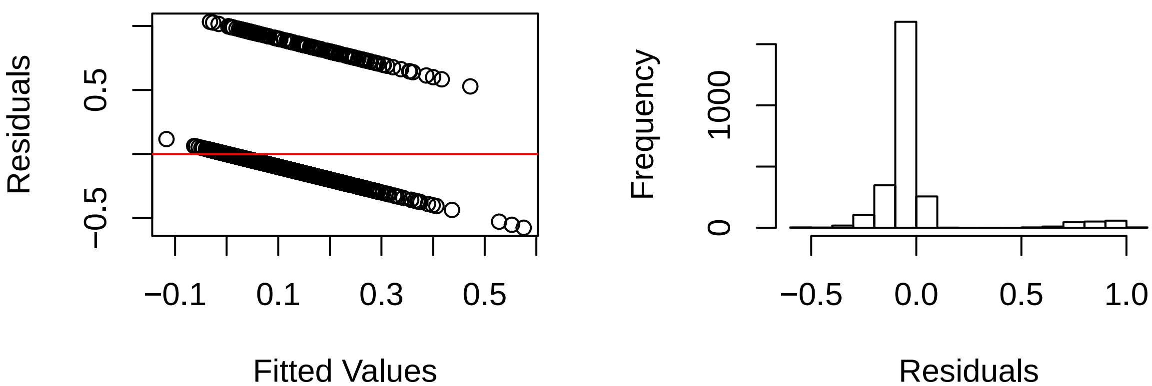


Table 7: Table II-VIFs of Linear Model

seismic	seismoacoustic	shift	genergy	gpuls	gdenergy	gdpuls
1.21	1.29	1.41	2.89	4.06	3	3.43

Table 8: Table II-VIFs of Linear Model

ghazard	nbumps	nbumps2	nbumps3	nbumps4	nbumps5	energy	maxenergy
1.4	2414.69	798.96	769.13	104.4	11.56	110.28	93.76