557_Project_2BS

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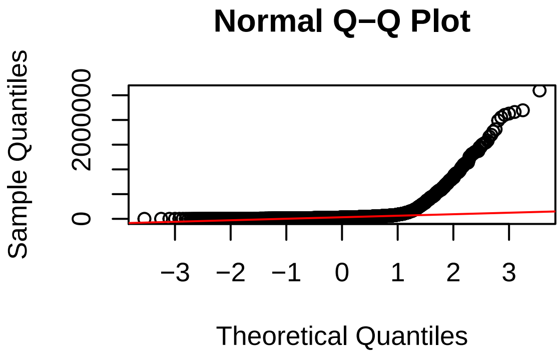
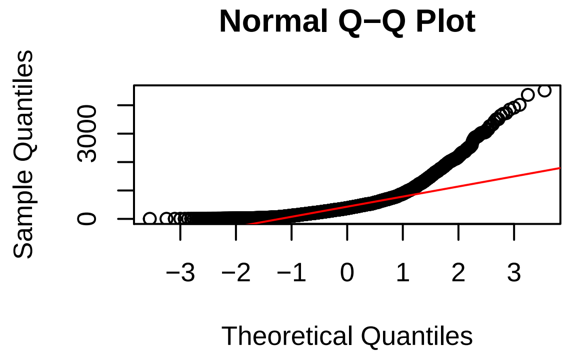
No Command Lines Ever. Whoa

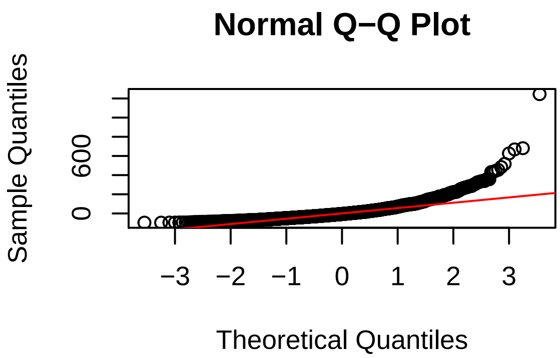
What the Factor Variables look like

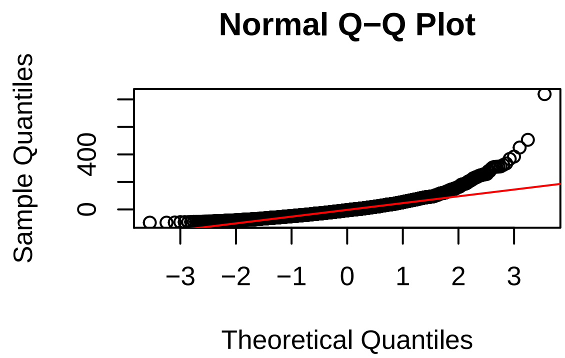
What the Continuous Variables look like

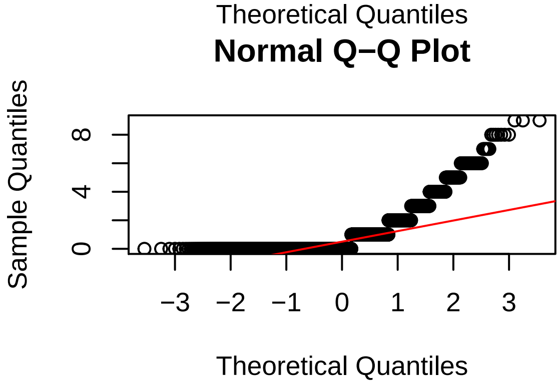
```
Call:
lm(formula = class ~ ., data = seismic)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.57549 -0.07778 -0.03812 -0.00950  1.03232 

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
(Intercept)    -2.393e-02  2.565e-02  -0.933  0.35090    
seismic         1.869e-02  1.076e-02   1.737  0.08254 .  
seismoacoustic  2.610e-03  1.002e-02   0.260  0.79457    
shift           6.190e-04  1.157e-02   0.054  0.95732    
genergy        -8.698e-08  3.459e-08  -2.514  0.01199 *  
gpuls           1.019e-04  1.670e-05   6.102  1.2e-09 ***
gdenergy       -6.943e-05  1.006e-04  -0.690  0.49009    
gdpuls         -1.942e-04  1.368e-04  -1.420  0.15583    
ghazard        -1.394e-02  1.608e-02  -0.867  0.38618    
nbumps          4.674e-01  1.680e-01   2.783  0.00543 ** 
nbumps2        -4.282e-01  1.682e-01  -2.546  0.01096 *  
nbumps3        -4.260e-01  1.681e-01  -2.535  0.01131 *  
nbumps4        -4.622e-01  1.708e-01  -2.706  0.00685 ** 
nbumps5        -2.963e-01  2.332e-01  -1.270  0.20408    
energy          2.536e-07  2.395e-06   0.106  0.91568    
maxenergy      -1.054e-06  2.333e-06  -0.452  0.65164    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2371 on 2568 degrees of freedom
Multiple R-squared:  0.09128,   Adjusted R-squared:  0.08597 
F-statistic:  17.2 on 15 and 2568 DF,  p-value: < 2.2e-16
```

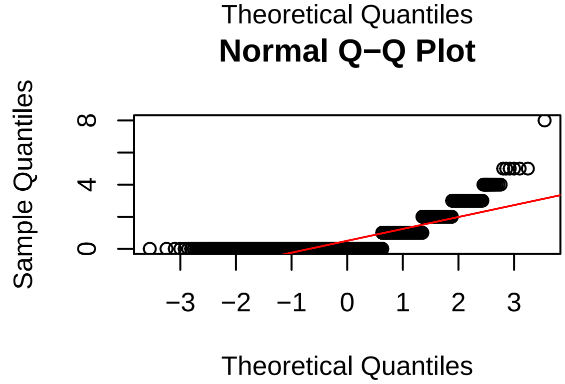

Normal Q−Q Plot
Sample Quantiles
0
2000000
−3 −2 −1 0 1 2 3
Theoretical Quantiles

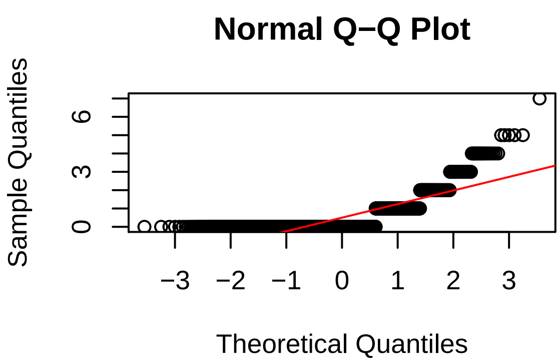

Normal Q−Q Plot
Sample Quantiles
0
3000
−3 −2 −1 0 1 2 3
Theoretical Quantiles

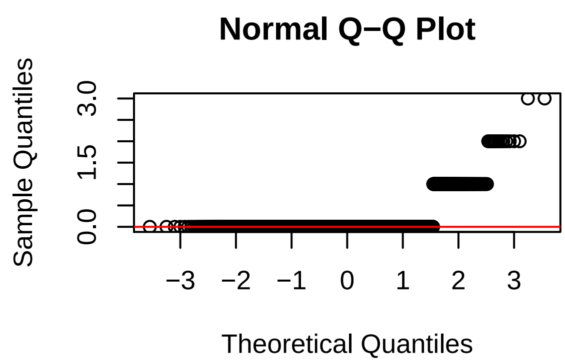

Normal Q−Q Plot
Sample Quantiles
0
600
−3 −2 −1 0 1 2 3
Theoretical Quantiles

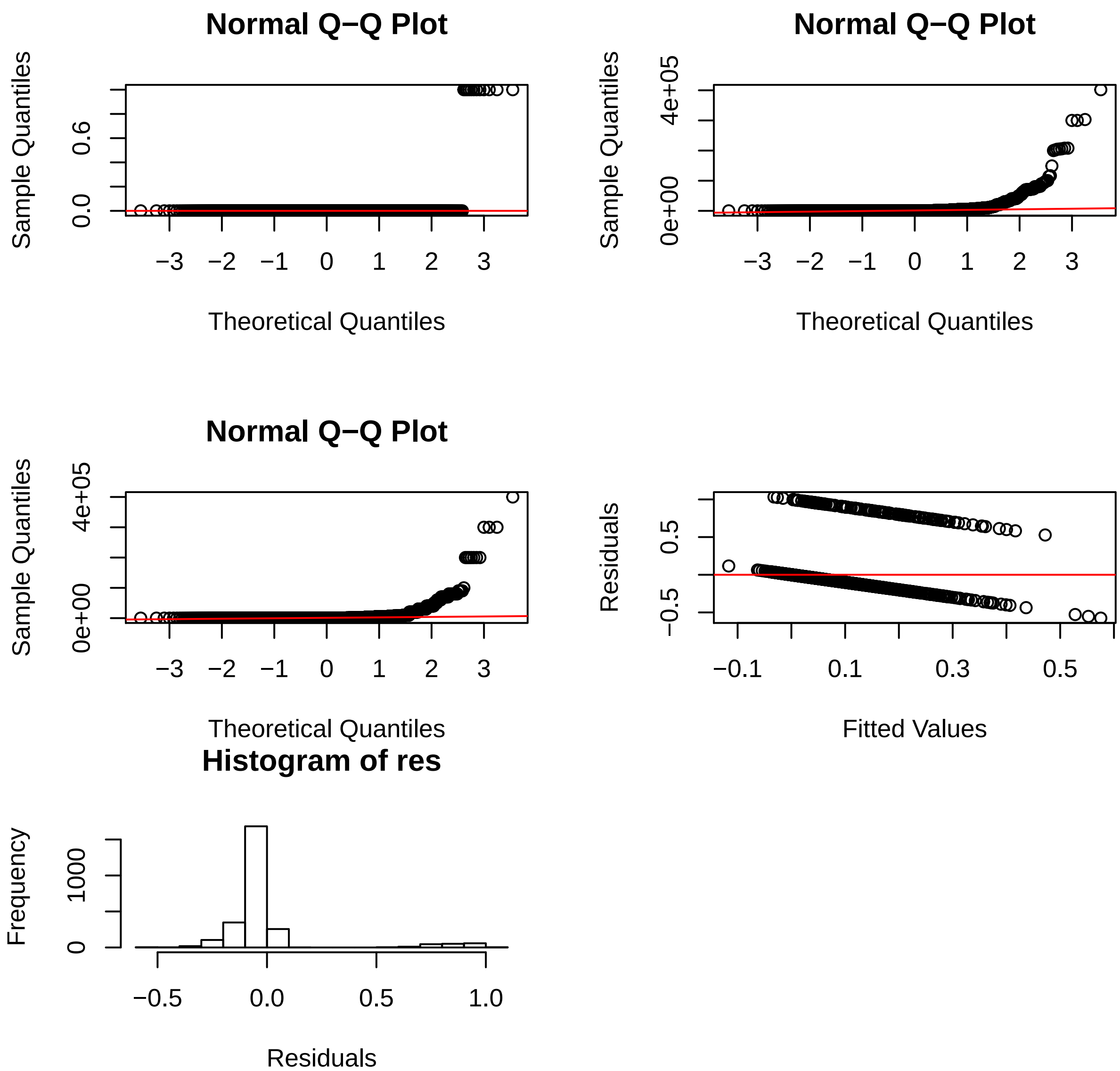

Normal Q−Q Plot
Sample Quantiles
0
400
−3 −2 −1 0 1 2 3
Theoretical Quantiles


Normal Q−Q Plot
Sample Quantiles
0
4
8
−3 −2 −1 0 1 2 3
Theoretical Quantiles


Normal Q−Q Plot
Sample Quantiles
0
4
8
−3 −2 −1 0 1 2 3
Theoretical Quantiles


Normal Q−Q Plot
Sample Quantiles
0
3
6
−3 −2 −1 0 1 2 3
Theoretical Quantiles


Normal Q−Q Plot
Sample Quantiles
0.0
1.5
3.0
−3 −2 −1 0 1 2 3
Theoretical Quantiles



Lots of multicollinearity to worry about during variable selection

```r
vif(fit)
```

```
##        seismic seismoacoustic          shift        genergy          gpuls
##       1.209814       1.286183       1.411216       2.889651       4.057018
##       gdenergy         gdpuls        ghazard         nbumps        nbumps2
##       3.000282       3.430524       1.395598    2414.689538     798.964152
##        nbumps3        nbumps4        nbumps5         energy      maxenergy
##     769.131960     104.402690      11.562237     110.283444      93.762895
```

```r
sqrt(vif(fit)) > 2
```

```
##        seismic seismoacoustic          shift        genergy          gpuls
##          FALSE          FALSE          FALSE          FALSE           TRUE
```

```
##       gdenergy         gdpuls        ghazard         nbumps        nbumps2
##          FALSE          FALSE          FALSE           TRUE           TRUE
##        nbumps3        nbumps4        nbumps5         energy      maxenergy
##           TRUE           TRUE           TRUE           TRUE           TRUE
```

Correlation of the Variables

Separating into Test and Training Sets

```
##------------------------------------
## Setting up Test and Training Sets
##------------------------------------

n <- dim(seismic)[1]
p <- dim(seismic)[2]

set.seed(2016)
test <- sample(n, round(n/4))
train <- (1:n)[-test]
seismic.train <- seismic[train,]
seismic.test <- seismic[test,]

dim(seismic)
```

```
[1] 2584   16
```

```
dim(seismic.train)
```

```
[1] 1938   16
```

```
dim(seismic.test)
```

```
[1] 646  16
```

```
#View(seismic.train)
#View(seismic.test)
```

Linear regression of an indicator matrix

```
##----------------------------------------
## Linear regression of indicator matrix
##----------------------------------------

responseY <- seismic$class
predictorX <- seismic[,-16]
```

```
# Following Le Bao's code
class1 <- which(responseY==1)
class0 <- which(responseY==0)
Y <- matrix(data = rep(0,length(responseY)*2),nrow = length(responseY))
Y[class0,1] <- 1
Y[class1,2] <- 1

betaHat <- solve(t(as.matrix(predictorX))%*%as.matrix(predictorX))%*%t(as.matrix(predictorX))%*%Y
Y1 <- as.matrix(predictorX)%*%betaHat[,1]
Y2 <- as.matrix(predictorX)%*%betaHat[,2]

pred.mx <- cbind(Y1,Y2)
pred <- rep(NA,length(Y1))
for(i in 1:length(Y1)){
  pred[i] <- which.max(pred.mx[i,]) - 1
}

# Confusion matrix
mx <- cbind(pred,responseY,pred-responseY)

confusion <- matrix(rep(NA,4), nrow = 2)
correct <- which(mx[,3] == 0)
confusion[1,1] <- length(which(mx[correct,1] == 0))
confusion[2,2] <- length(which(mx[correct,1] == 1))
confusion[1,2] <- length(which(mx[,3] == -1))
confusion[2,1] <- length(which(mx[,3] == 1))
confusion
```

```
##      [,1] [,2]
## [1,] 2411  169
## [2,]    3    1
```

```
sensitivity <- confusion[2,2]/sum(confusion[,2])
specificity <- confusion[1,1]/sum(confusion[,1])
error.rate <- (confusion[1,2] + confusion[2,1])/sum(confusion)
c(sensitivity, specificity, error.rate)
```

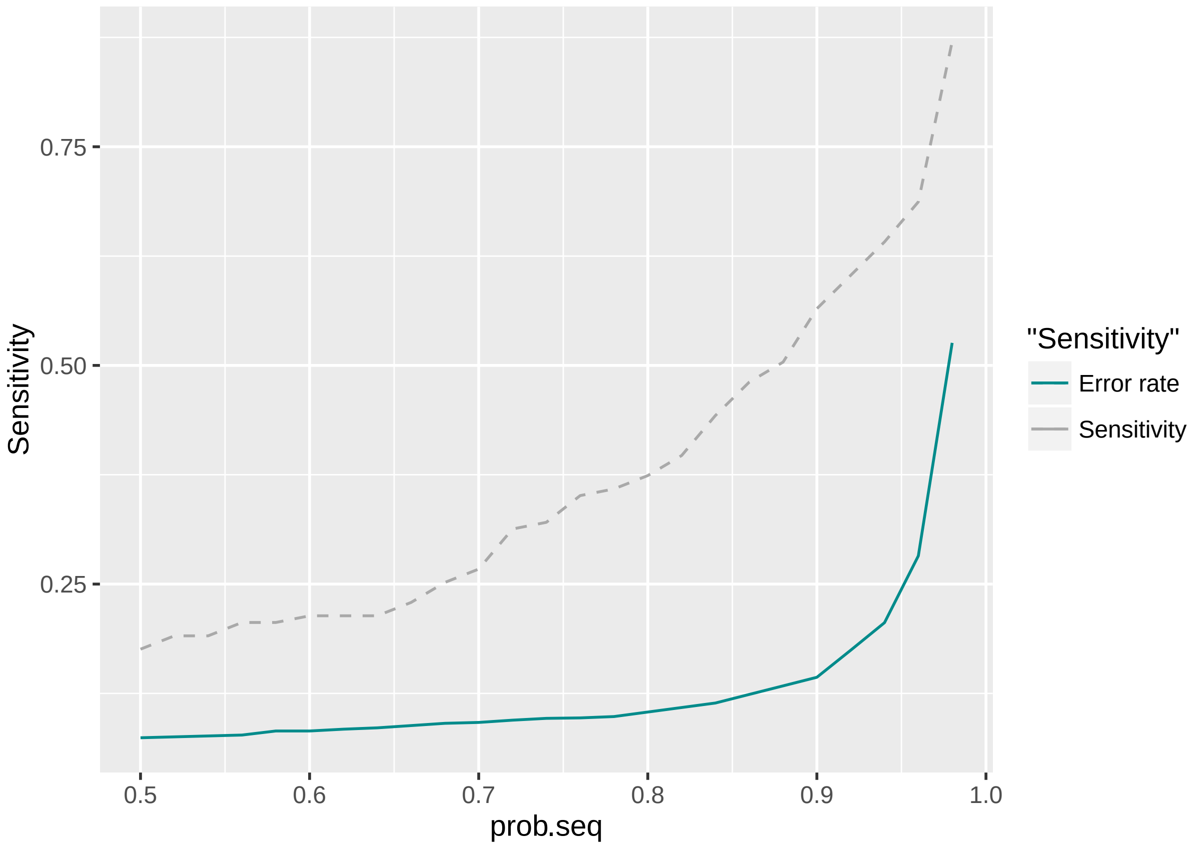
```
## [1] 0.005882353 0.998757249 0.066563467
```

Linear Discriminant Analysis on full model

```
lda.class.train    0    1
              0 1771  108
              1   36   23
```

```
[1] 0.1755725
```

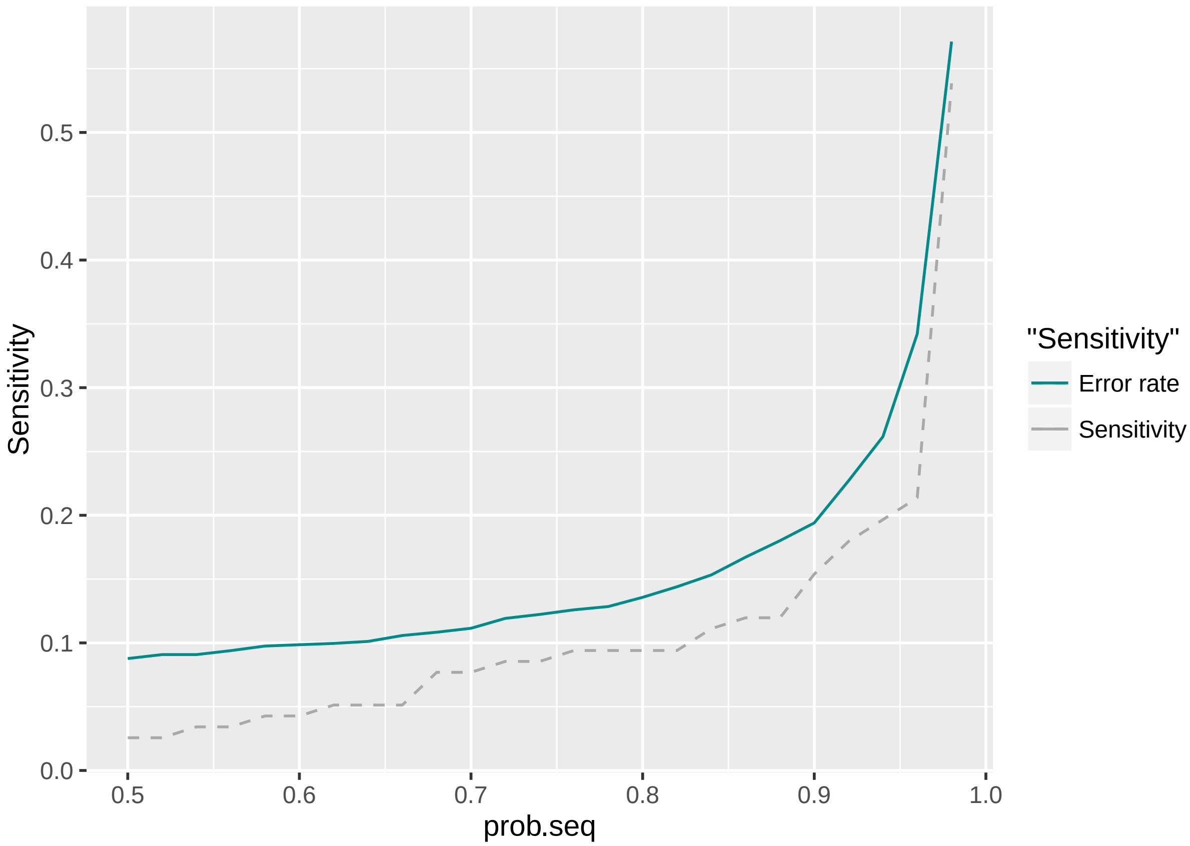
```
[1] 0.9800775
```

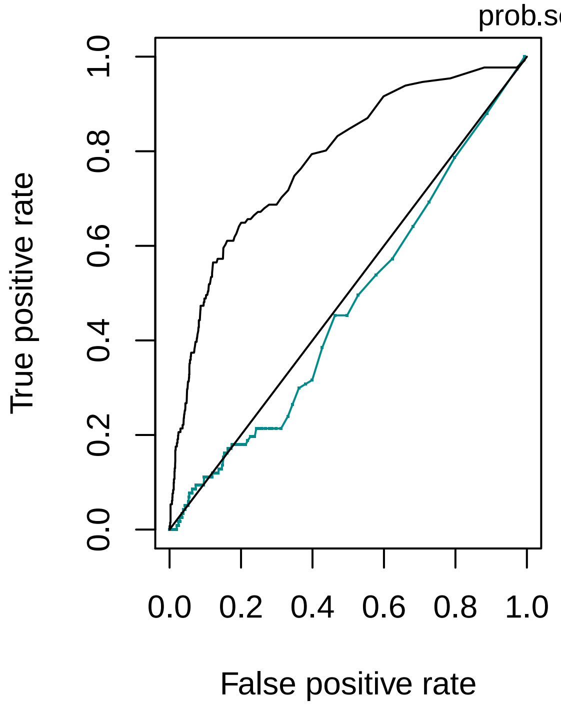



```
lda.class.test   0   1
             0 591  34
             1  16   5
```

```
[1] 0.1282051
```

```
[1] 0.9736409
```


Sensitivity
0.0
0.1
0.2
0.3
0.4
0.5
0.5
0.6
0.7
0.8
0.9
1.0
prob.seq
"Sensitivity"
Error rate
Sensitivity


True positive rate
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0
False positive rate

Quadratic Discriminant Analysis -INCOMPLETE

```
##-------------------------------------
## Fit QDA model
##-------------------------------------

## Currently, can't perform QDA.  This is probably due to multicollinearity in the model
## (can't invert covariance matrix) but should be possible after variable selection

#qda.fit <- qda(class~., data = seismic, subset = train)
```

Regularized Discriminant Analysis -INCOMPLETE

```
##-------------------------------------
## Fit RDA model
##-------------------------------------

## Currently, can't perform RDA.  This is probably due to multicollinearity in the model
## (can't invert covariance matrix) but should be possible after variable selection

par(mfrow=c(1,2))

rda.fit <- rda(class~., data=seismic.train)
rda.fit
```

```
## Call:
## rda(formula = class ~ ., data = seismic.train)
##
## Regularization parameters:
##       gamma      lambda
## 0.005757679 0.291158452
##
## Prior probabilities of groups:
##          0          1
## 0.93240454 0.06759546
##
## Misclassification rate:
##        apparent: 7.637 %
## cross-validated: 7.69 %
```

```
##
# Using  model on TRAIN Data
##
rda.pred=predict(rda.fit, seismic.train, type="response")

rda.class.train <- rda.pred$class

posterior.train <- rda.pred$posterior
truth.train <- seismic.train$class
```

```
## Confusion matrix
rda.train.confusion <- table(rda.class.train,seismic.train$class)
rda.train.sensitivity <- rda.train.confusion[2,2]/sum(rda.train.confusion[,2])
rda.train.specificity <- rda.train.confusion[1,1]/sum(rda.train.confusion[,1])

# Sensitivity, Specificity and Confusion
rda.train.confusion
```

```
##
## rda.class.train    0    1
##               0 1785  126
##               1   22    5
```

```
rda.train.sensitivity
```

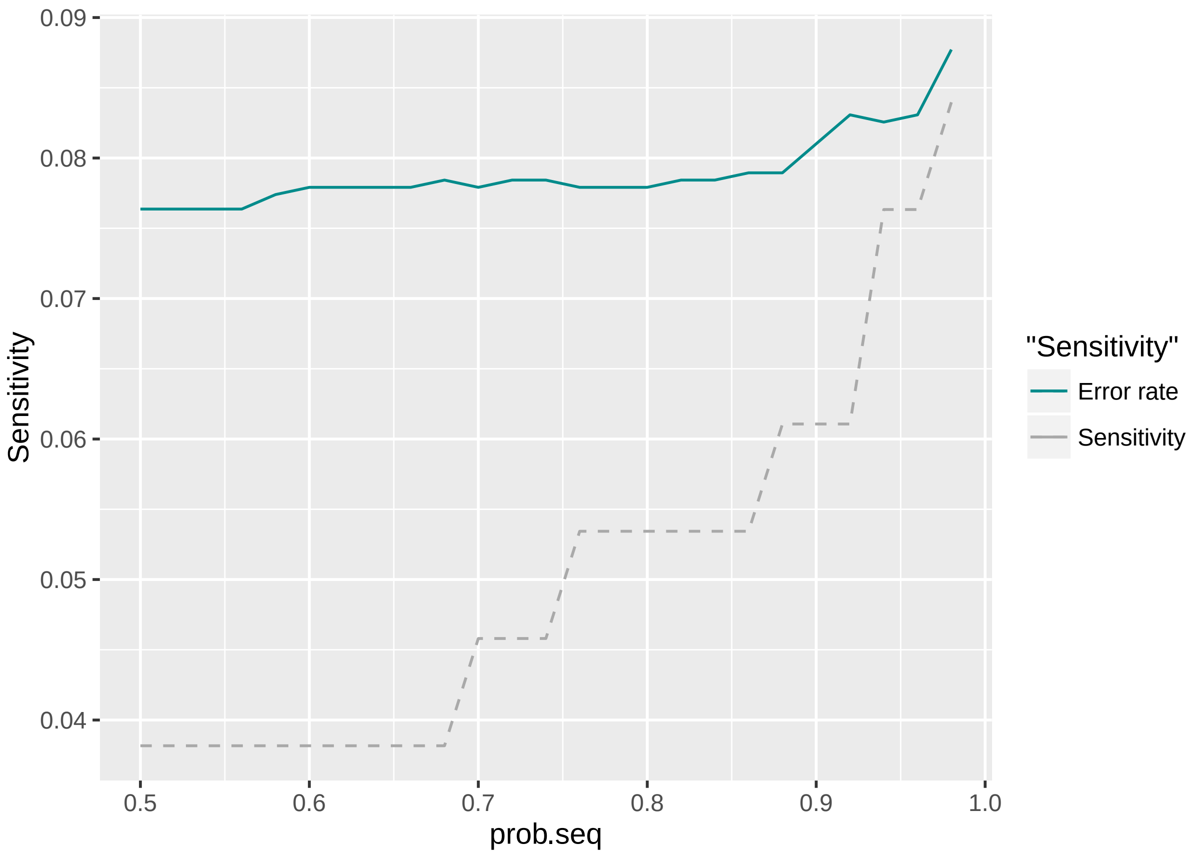
```
## [1] 0.03816794
```

```
rda.train.specificity
```

```
## [1] 0.9878251
```

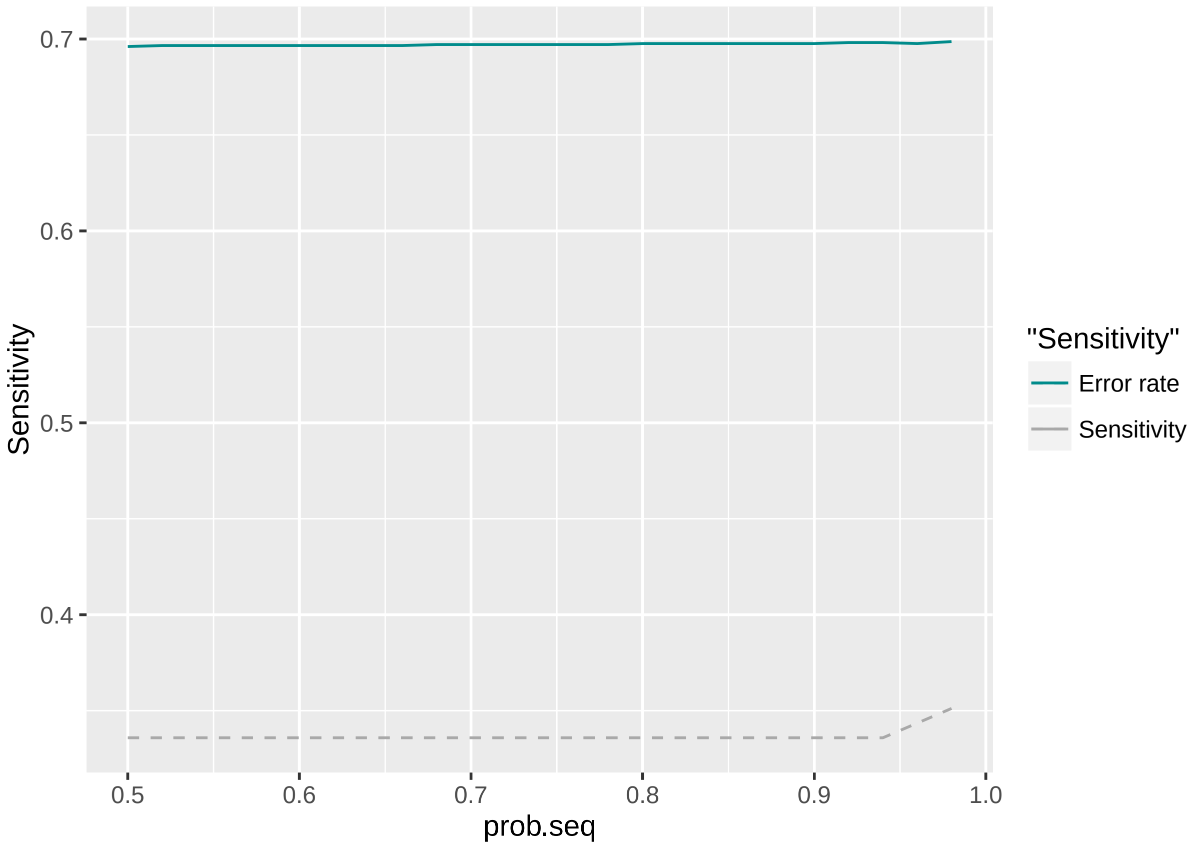
```
mod.posterior <- function(posterior, truth, prob, dimension = length(train)){
  idx0 <- which(posterior[,1] > prob)
  idx1 <- (1:dimension)[-idx0]

  prediction <- rep(NA,dimension)
  prediction[idx0] = 0
  prediction[idx1] = 1

  mx <- cbind(prediction,truth,prediction-truth)

  rda.train.confusion <- matrix(rep(NA,4), nrow = 2)
  correct <- which(mx[,3] == 0)
  rda.train.confusion[1,1] <- length(which(mx[correct,1] == 0))
  rda.train.confusion[2,2] <- length(which(mx[correct,1] == 1))
  rda.train.confusion[1,2] <- length(which(mx[,3] == -1))
  rda.train.confusion[2,1] <- length(which(mx[,3] == 1))

  sensitivity <- rda.train.confusion[2,2]/sum(rda.train.confusion[,2])
  specificity <- rda.train.confusion[1,1]/sum(rda.train.confusion[,1])
  error.rate <- (rda.train.confusion[1,2] + rda.train.confusion[2,1])/sum(rda.train.confusion)
  c(sensitivity, specificity, error.rate)
}

posterior.train <- rda.pred$posterior
truth.train <- seismic.train$class

prob.seq <- seq(.5,.98,by = .02)
output.train <- matrix(rep(NA,length(prob.seq)*2), ncol = 2)
colnames(output.train) <- c("Sensitivity", "Error.rate")
```

```r
for(i in 1:length(prob.seq)){
  output.train[i,] <- mod.posterior(posterior.train,truth.train,prob.seq[i])[c(1,3)]
}

df1 <- as.data.frame(cbind(prob.seq,output.train))

ggplot(data = df1, aes(x=prob.seq)) +
  geom_line(aes(y = Sensitivity, colour = "Sensitivity"), linetype = "dashed") +
  geom_line(aes(y = Error.rate, colour = "Error rate")) +
  scale_colour_manual(values=c("dark cyan", "dark grey"))
```




```r
##
# Using model on TEST Data
##
rda.pred=predict(rda.fit, seismic.test, type="response")

rda.class.test <- rda.pred$class

## Confusion matrix
rda.test.confusion <- table(rda.class.test,seismic.test$class)
rda.test.sensitivity <- rda.test.confusion[2,2]/sum(rda.test.confusion[,2])
rda.test.specificity <- rda.test.confusion[1,1]/sum(rda.test.confusion[,1])

mod.posterior <- function(posterior, truth, prob, dimension = length(train)){
  idx0 <- which(posterior[,1] > prob)
  idx1 <- (1:dimension)[-idx0]
```

```
  prediction <- rep(NA,dimension)
  prediction[idx0] = 0
  prediction[idx1] = 1

  mx <- cbind(prediction,truth,prediction-truth)

  rda.test.confusion <- matrix(rep(NA,4), nrow = 2)
  correct <- which(mx[,3] == 0)
  rda.test.confusion[1,1] <- length(which(mx[correct,1] == 0))
  rda.test.confusion[2,2] <- length(which(mx[correct,1] == 1))
  rda.test.confusion[1,2] <- length(which(mx[,3] == -1))
  rda.test.confusion[2,1] <- length(which(mx[,3] == 1))

  sensitivity <- rda.test.confusion[2,2]/sum(rda.test.confusion[,2])
  specificity <- rda.test.confusion[1,1]/sum(rda.test.confusion[,1])
  error.rate <- (rda.test.confusion[1,2] + rda.test.confusion[2,1])/sum(rda.test.confusion)
  c(sensitivity, specificity, error.rate)
}

posterior.train <- rda.pred$posterior
truth.train <- seismic.train$class

prob.seq <- seq(.5,.98,by = .02)
output.train <- matrix(rep(NA,length(prob.seq)*2), ncol = 2)
colnames(output.train) <- c("Sensitivity", "Error.rate")

for(i in 1:length(prob.seq)){
  output.train[i,] <- mod.posterior(posterior.train,truth.train,prob.seq[i])[c(1,3)]
}

df1 <- as.data.frame(cbind(prob.seq,output.train))

ggplot(data = df1, aes(x=prob.seq)) +
  geom_line(aes(y = Sensitivity, colour = "Sensitivity"), linetype = "dashed") +
  geom_line(aes(y = Error.rate, colour = "Error rate")) +
  scale_colour_manual(values=c("dark cyan", "dark grey"))
```




```r
# Sensitivity, Specificity and Confusion
rda.test.confusion
```

```
##
## rda.class.test   0   1
##              0 593  39
##              1  14   0
```

```r
rda.test.sensitivity
```

```
## [1] 0
```

```r
rda.test.specificity
```

```
## [1] 0.9769357
```

```r
sum(rda.pred$posterior[,1]>=.5)
```

```
## [1] 632
```

```r
sum(rda.pred$posterior[,1]<.5)
```

```
## [1] 14
```

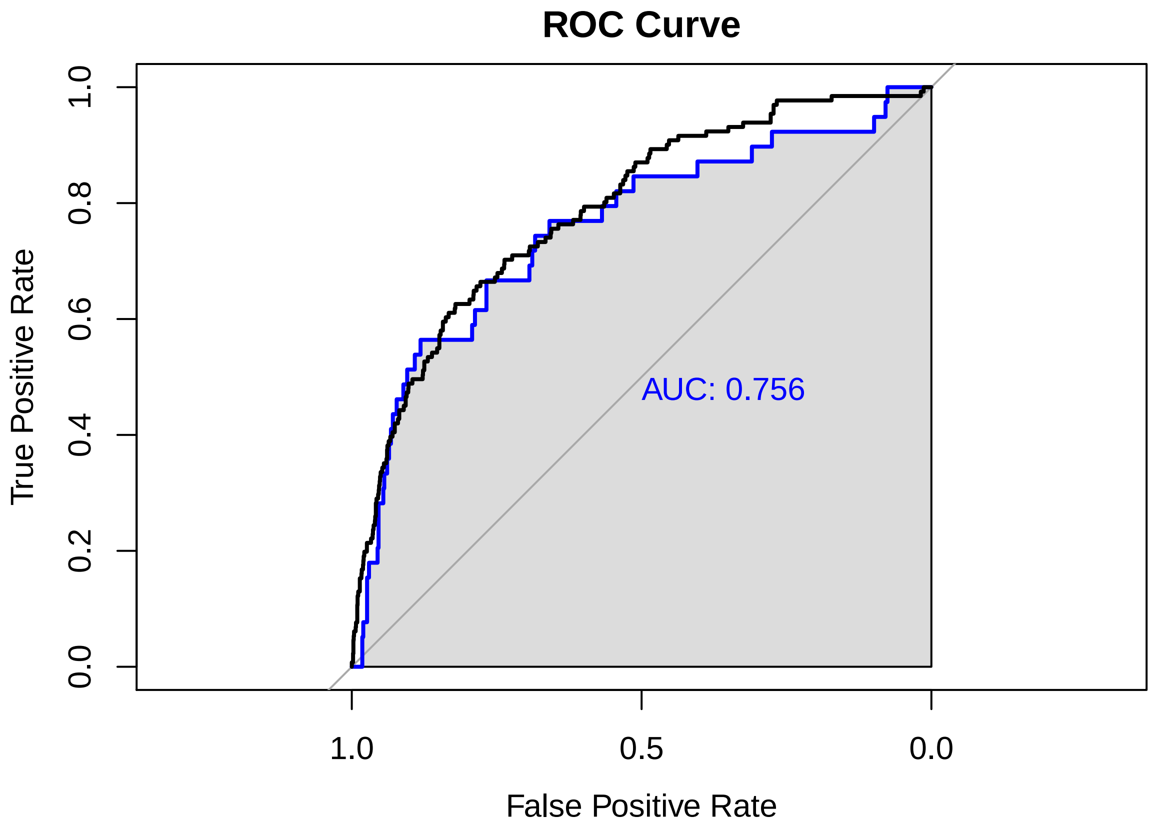
Logistic Regression.

```
Call:
glm(formula = class ~ ., family = binomial, data = seismic.train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8471  -0.3860  -0.2851  -0.1566   3.0825

Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)    -6.343e+00  7.721e-01  -8.215  < 2e-16 ***
seismic         4.808e-01  2.111e-01   2.278 0.022727 *
seismoacoustic  2.159e-01  1.993e-01   1.084 0.278524
shift           1.179e+00  3.573e-01   3.301 0.000965 ***
genergy        -2.471e-07  5.044e-07  -0.490 0.624239
gpuls           7.095e-04  2.474e-04   2.868 0.004136 **
gdenergy       -1.904e-04  2.177e-03  -0.087 0.930292
gdpuls         -2.997e-03  3.093e-03  -0.969 0.332500
ghazard        -2.335e-01  3.509e-01  -0.666 0.505671
nbumps          1.807e+01  5.354e+02   0.034 0.973080
nbumps2        -1.773e+01  5.354e+02  -0.033 0.973590
nbumps3        -1.771e+01  5.354e+02  -0.033 0.973611
nbumps4        -1.806e+01  5.354e+02  -0.034 0.973097
nbumps5        -1.604e+01  5.354e+02  -0.030 0.976095
energy          1.622e-06  4.033e-05   0.040 0.967929
maxenergy      -7.101e-06  3.969e-05  -0.179 0.858012
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 958.82  on 1937  degrees of freedom
Residual deviance: 813.40  on 1922  degrees of freedom
AIC: 845.4

Number of Fisher Scoring iterations: 12

[1] 0.9329205


glm.pred    0    1
       0 1802  125
       1    5    6

[1] 0.04580153

[1] 0.997233

[1] 0.9349845
```

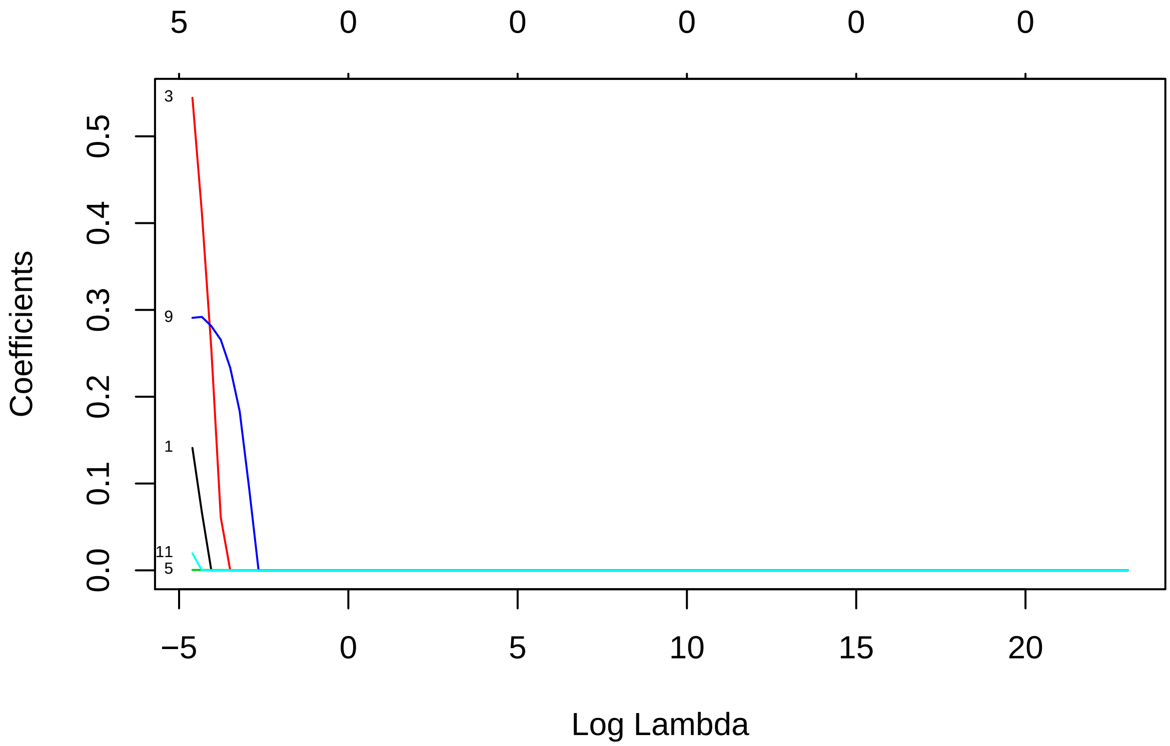
```
glm.pred   0   1
       0 604  39
       1   3   0
```

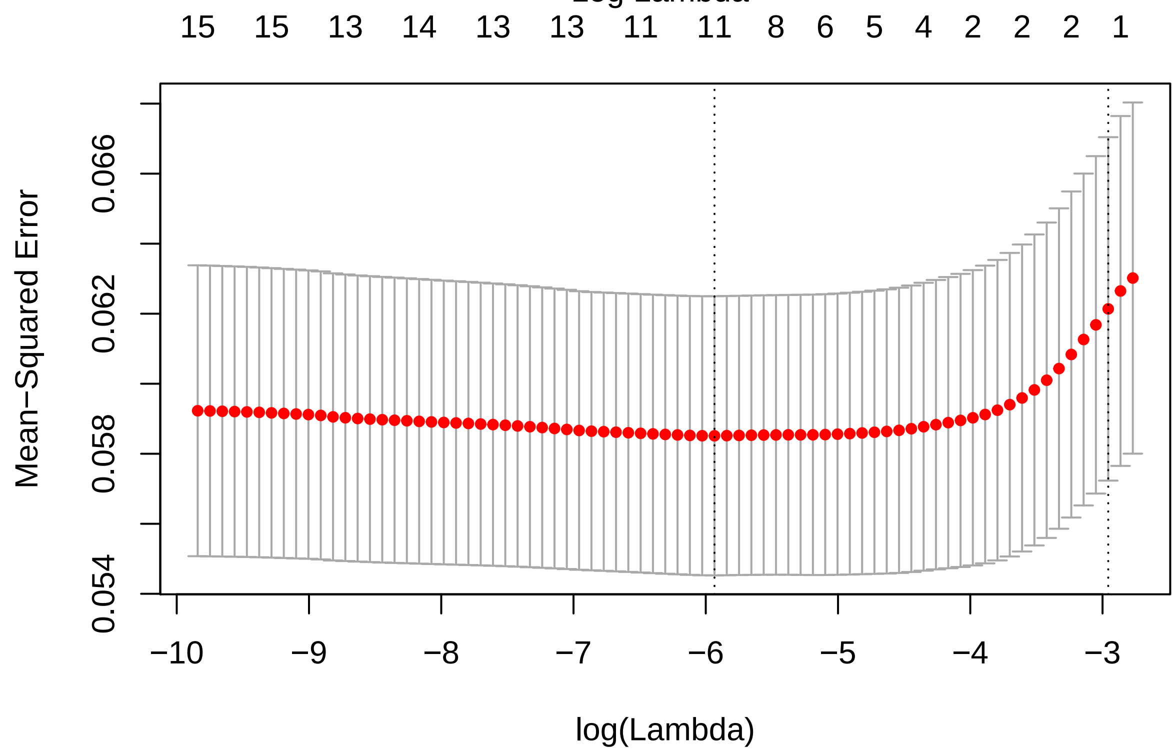
```
[1] 0
```

```
[1] 0.9950577
```



Variable Selection-LASSO





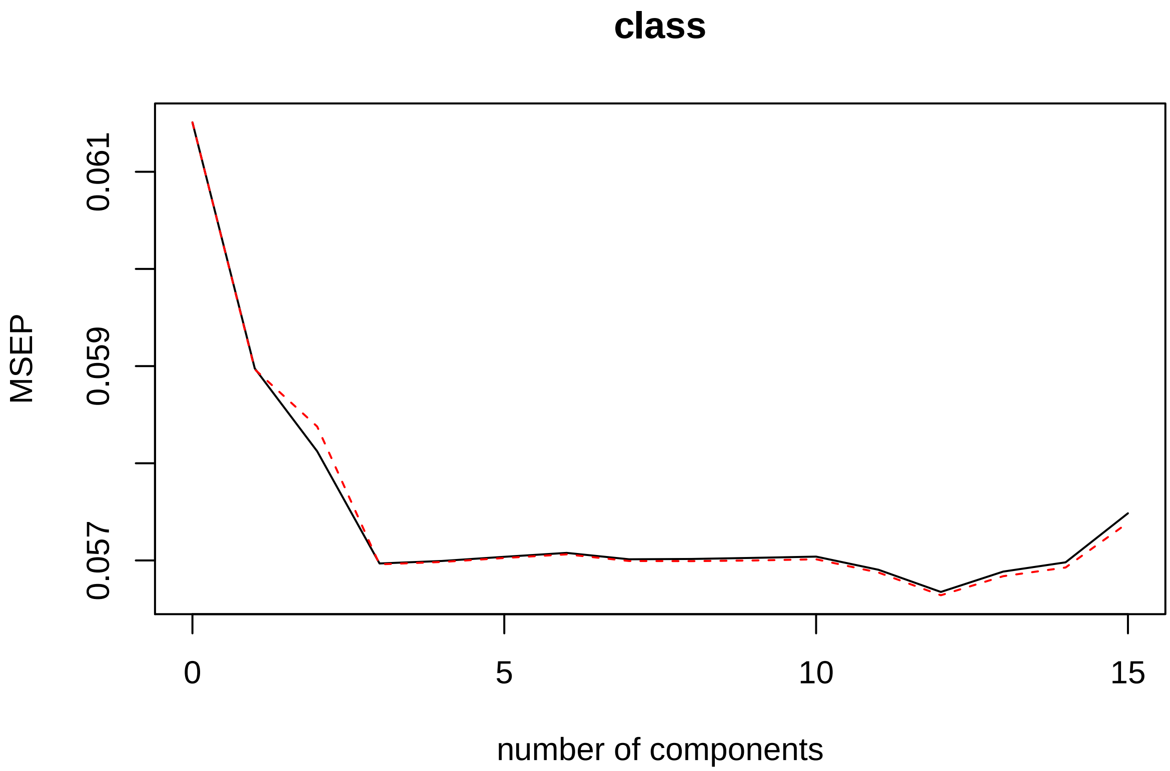

```
[1] 8.670049
```

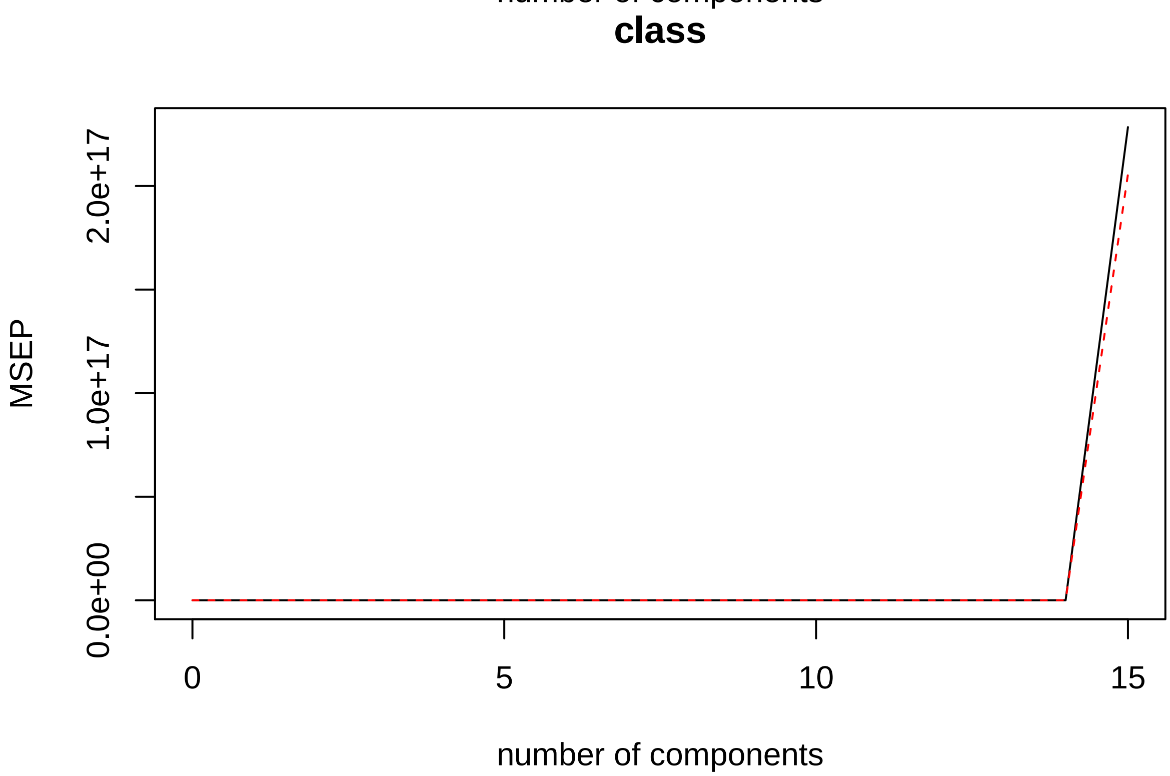
Variables selected through LASSO

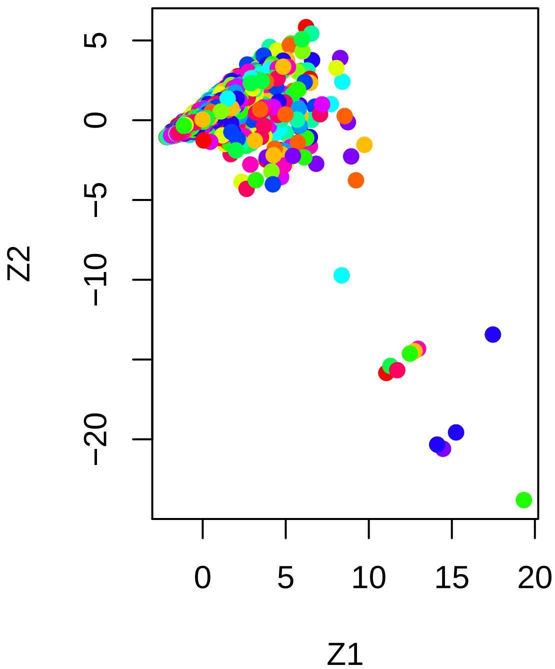
```
  (Intercept) seismic   shift gpuls  nbumps
1    -0.00814  0.0088 0.00798 5e-05 0.03118
```

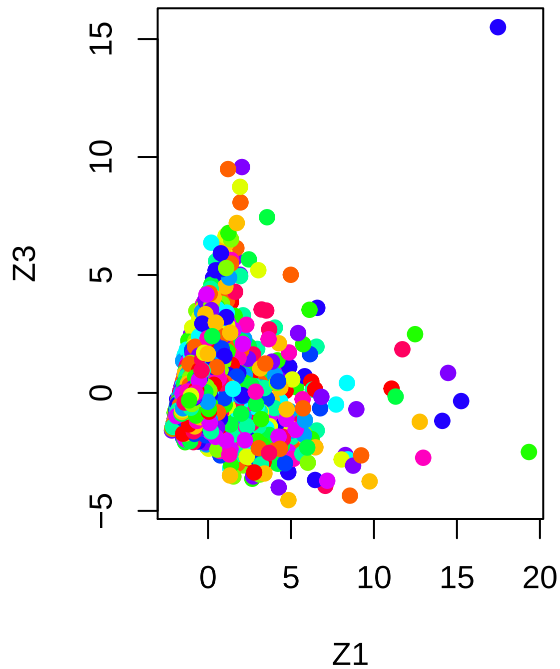
Principal Component Analysis from the Book - INCOMPLETE

```
Data:   X dimension: 2584 15
    Y dimension: 2584 1
Fit method: svdpc
Number of components considered: 15

VALIDATION: RMSEP
Cross-validated using 10 random segments.
       (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
CV           0.248   0.2428   0.2411   0.2387   0.2387   0.2388   0.2389
adjCV        0.248   0.2428   0.2416   0.2387   0.2387   0.2388   0.2389
       7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
CV      0.2388   0.2388   0.2388    0.2388    0.2385    0.2381    0.2385
adjCV   0.2387   0.2387   0.2387    0.2388    0.2385    0.2380    0.2384
       14 comps  15 comps
CV       0.2387    0.2398
adjCV    0.2386    0.2396

TRAINING: % variance explained
       1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps
X       25.306   40.680   55.704   64.926   72.401   79.396   85.185
class    4.225    5.285    7.573    7.577    7.584    7.592    7.792
       8 comps  9 comps  10 comps  11 comps  12 comps  13 comps  14 comps
X       89.627   93.557    97.005    98.398    99.294     99.97    99.998
class    7.917    8.022     8.026     8.289     8.847      8.87     8.872
       15 comps
X       100.000
class     9.128
```

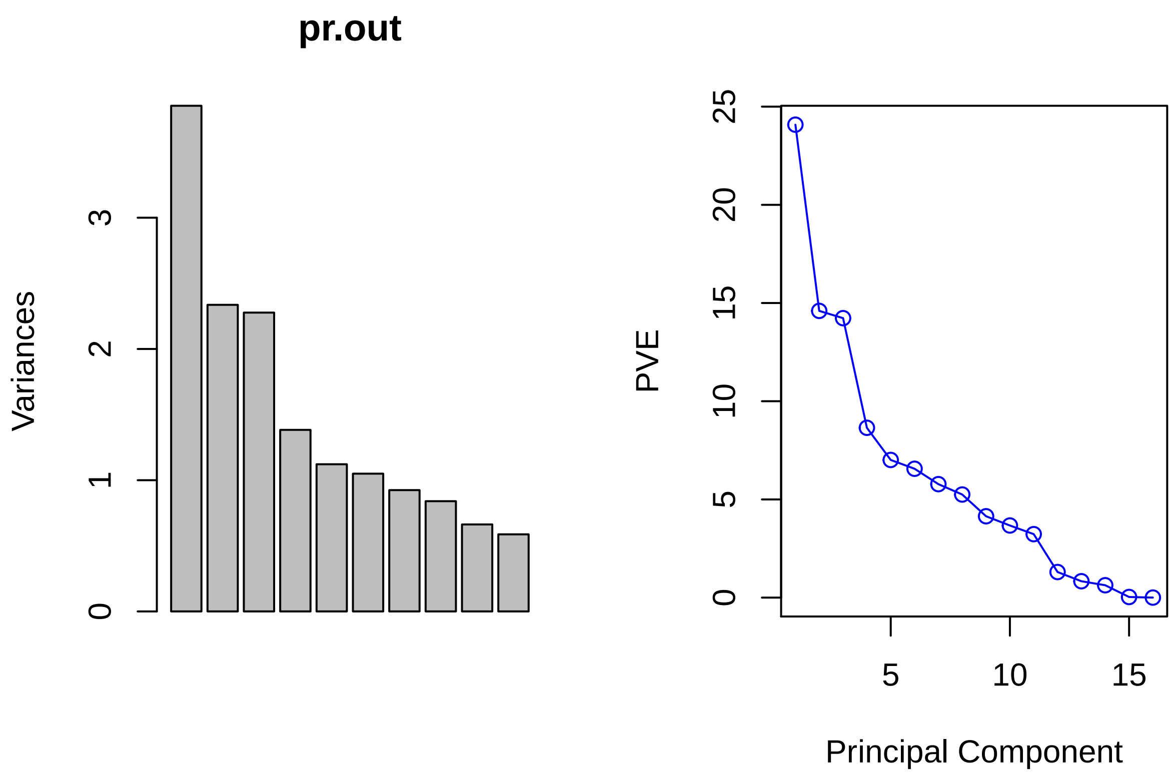

class
MSEP
0.061
0.059
0.057
0
5
10
15
number of components


class
MSEP
2.0e+17
1.0e+17
0.0e+00
0
5
10
15
number of components

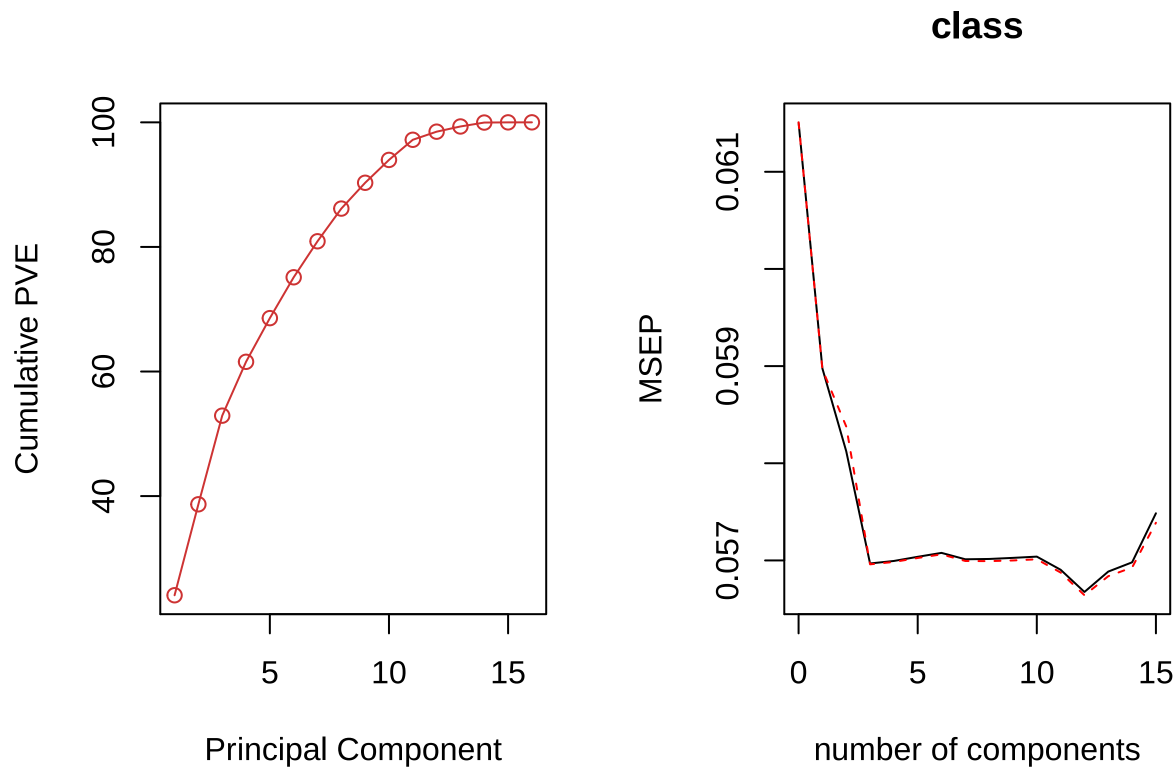




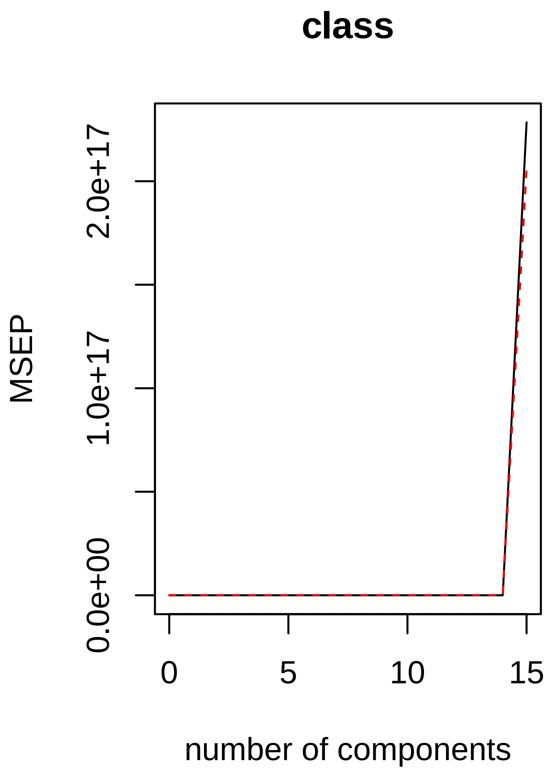

```
Importance of components:
                          PC1    PC2    PC3     PC4     PC5     PC6
Standard deviation     1.9629 1.5284 1.5089 1.17618 1.05902 1.02457
Proportion of Variance 0.2408 0.1460 0.1423 0.08646 0.07009 0.06561
Cumulative Proportion  0.2408 0.3868 0.5291 0.61559 0.68568 0.75129
                           PC7    PC8     PC9    PC10    PC11    PC12
Standard deviation     0.96145 0.9165 0.81413 0.76650 0.71908 0.45631
Proportion of Variance 0.05777 0.0525 0.04143 0.03672 0.03232 0.01301
Cumulative Proportion  0.80907 0.8616 0.90299 0.93971 0.97203 0.98504
                          PC13   PC14    PC15    PC16
Standard deviation     0.36522 0.3174 0.07039 0.01562
Proportion of Variance 0.00834 0.0063 0.00031 0.00002
Cumulative Proportion  0.99338 0.9997 0.99998 1.00000
```



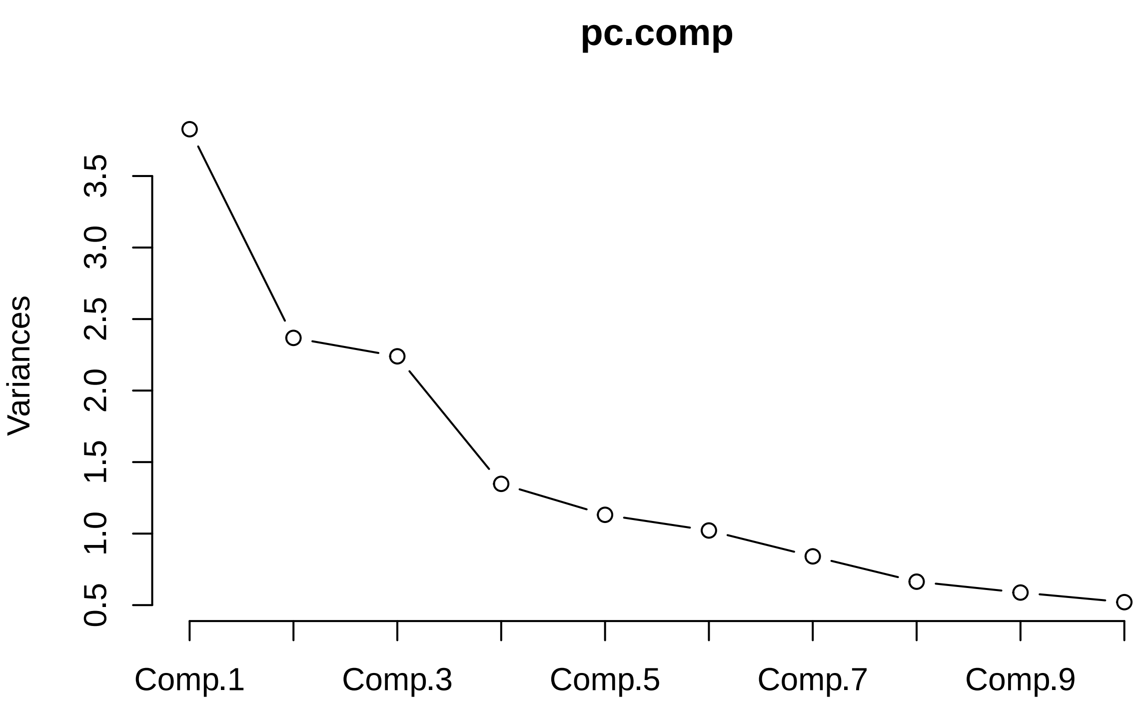

```
Data:    X dimension: 2584 15
    Y dimension: 2584 1
Fit method: svdpc
Number of components considered: 15

VALIDATION: RMSEP
Cross-validated using 10 random segments.
       (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
CV           0.248   0.2428   0.2411   0.2387   0.2387   0.2388   0.2389
adjCV        0.248   0.2428   0.2416   0.2387   0.2387   0.2388   0.2389
       7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
CV      0.2388   0.2388   0.2388    0.2388    0.2385    0.2381    0.2385
adjCV   0.2387   0.2387   0.2387    0.2388    0.2385    0.2380    0.2384
       14 comps  15 comps
CV       0.2387    0.2398
adjCV    0.2386    0.2396

TRAINING: % variance explained
       1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps
X       25.306   40.680   55.704   64.926   72.401   79.396   85.185
class    4.225    5.285    7.573    7.577    7.584    7.592    7.792
       8 comps  9 comps  10 comps  11 comps  12 comps  13 comps  14 comps
X       89.627   93.557    97.005    98.398    99.294     99.97    99.998
class    7.917    8.022     8.026     8.289     8.847      8.87     8.872
       15 comps
X       100.000
class     9.128
```



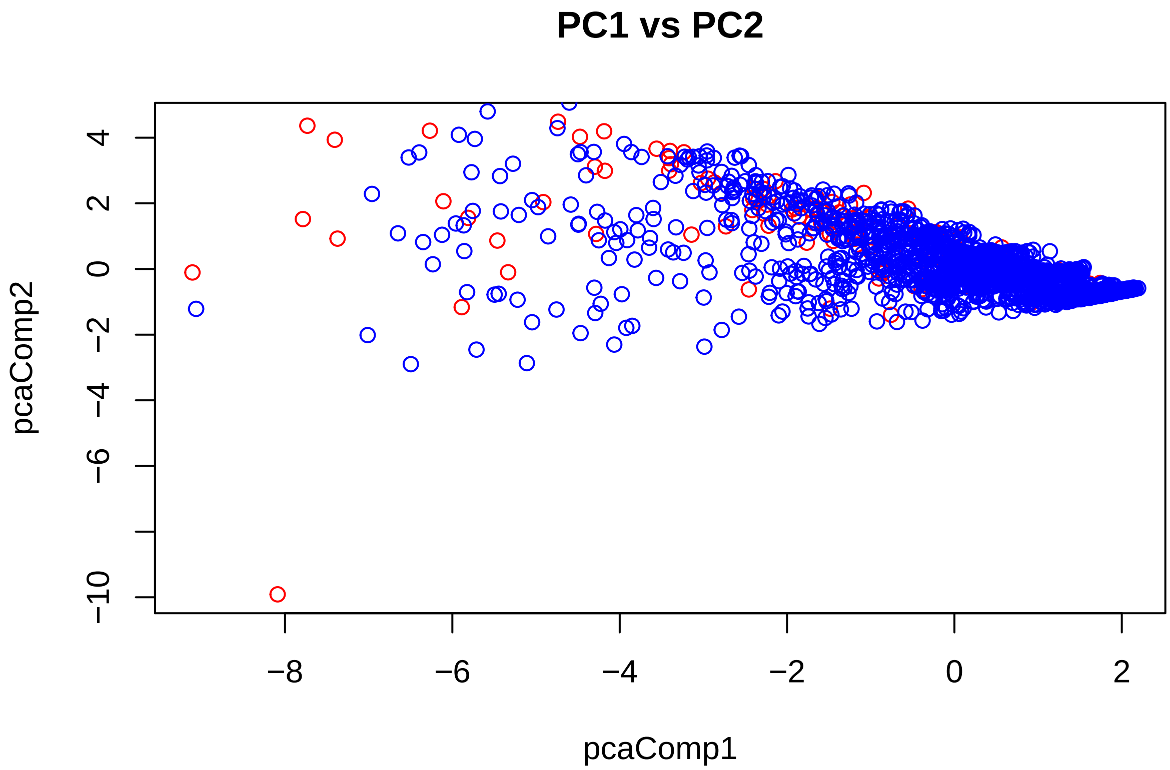

```
[1] 0.05357258

Data:   X dimension: 1938 15
    Y dimension: 1938 1
Fit method: svdpc
Number of components considered: 15

VALIDATION: RMSEP
Cross-validated using 10 random segments.
       (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
CV          0.2512   0.2454   0.2417   0.2413   0.2417   0.2417    0.242
adjCV       0.2512   0.2453   0.2415   0.2413   0.2416   0.2417    0.242
       7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
CV      0.2421   0.2421   0.2421    0.2422    0.2422    0.2420    0.2422
adjCV   0.2420   0.2420   0.2420    0.2421    0.2421    0.2419    0.2421
       14 comps   15 comps
CV       0.2431  477953634
adjCV    0.2429  453530602

TRAINING: % variance explained
       1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps
X       25.528   41.325   56.263   65.253   72.800   79.615   85.224
class    4.815    7.847    7.952    7.953    7.967    8.025    8.255
       8 comps  9 comps  10 comps  11 comps  12 comps  13 comps  14 comps
X       89.653   93.574    97.048    98.456    99.324    99.978    99.999
class    8.362    8.466     8.502     8.574     8.905     8.943     8.981
       15 comps
X       100.000
class     9.781
```

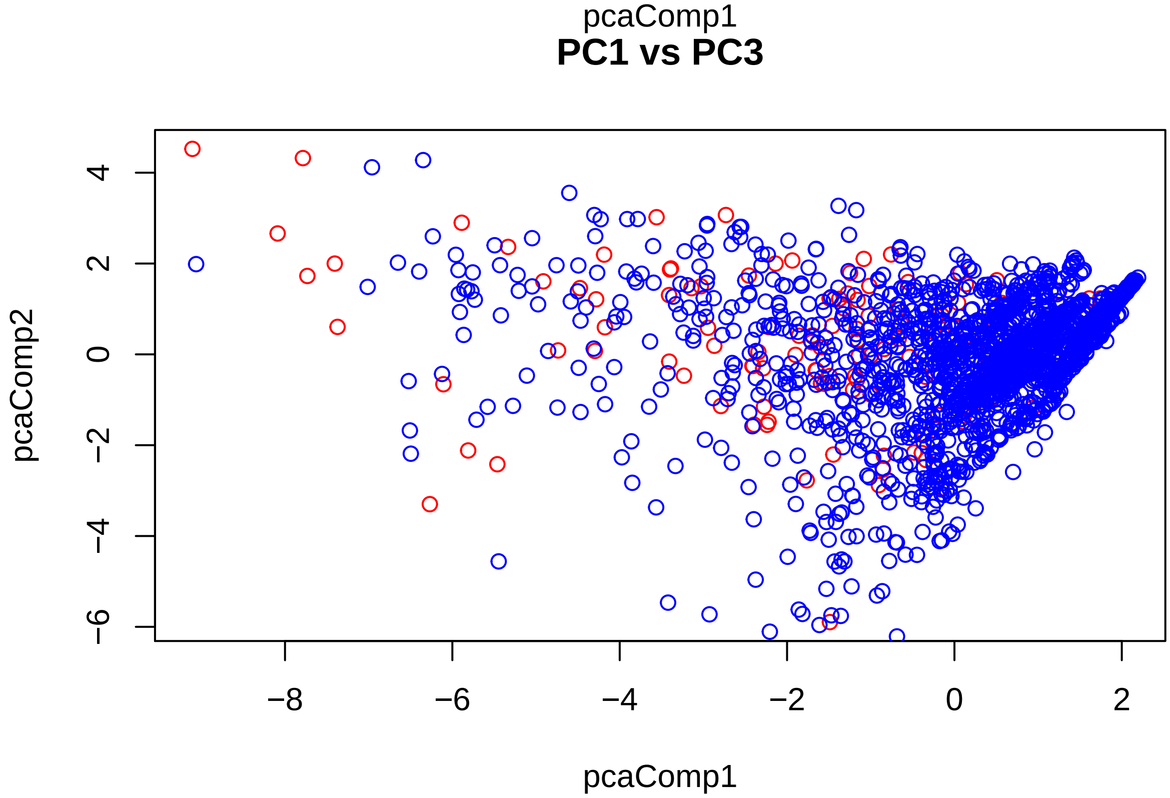


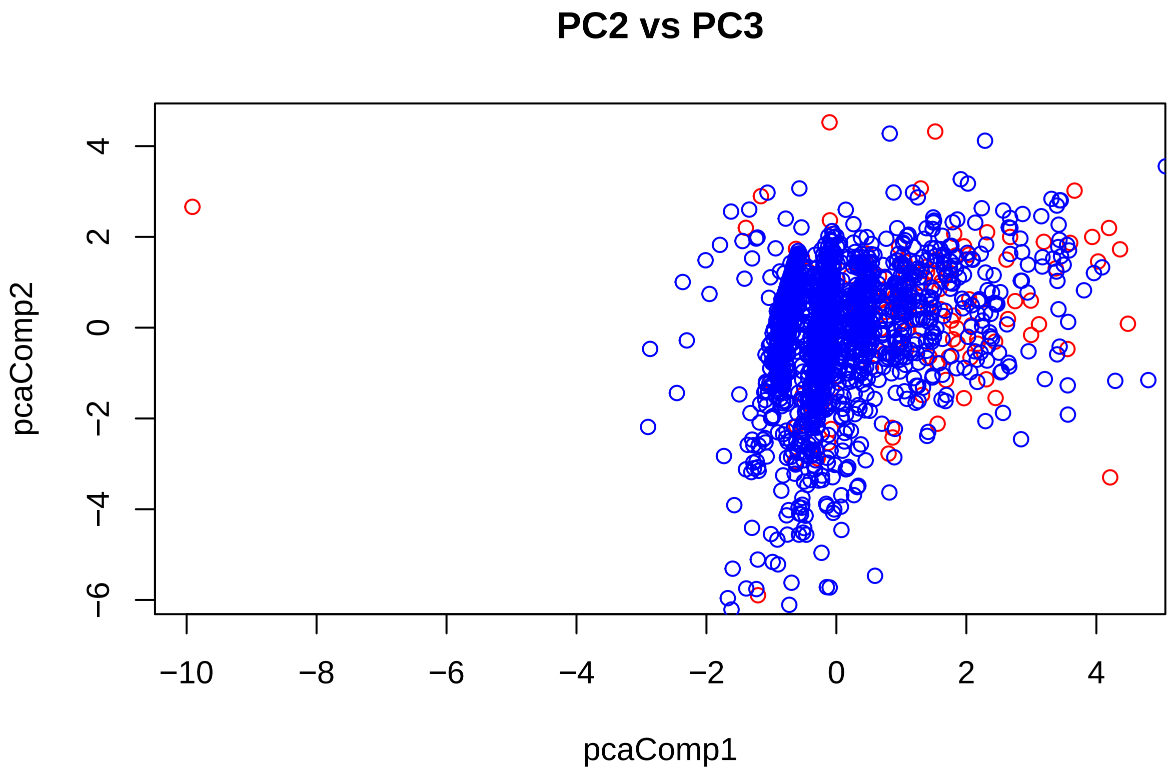
Variable Selection - PCA - INCOMPLETE



Variable Selection - PCA - INCOMPLETE








```
Data:    X dimension: 2584 15
     Y dimension: 2584 1
Fit method: svdpc
Number of components considered: 15

VALIDATION: RMSEP
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       (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
CV           0.248   0.2428   0.2411   0.2387   0.2387   0.2388   0.2389
adjCV        0.248   0.2428   0.2416   0.2387   0.2387   0.2388   0.2389
       7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
CV      0.2388   0.2388   0.2388    0.2388    0.2385    0.2381    0.2385
adjCV   0.2387   0.2387   0.2387    0.2388    0.2385    0.2380    0.2384
       14 comps  15 comps
CV       0.2387    0.2398
adjCV    0.2386    0.2396

TRAINING: % variance explained
       1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps
X       25.306   40.680   55.704   64.926   72.401   79.396   85.185
class    4.225    5.285    7.573    7.577    7.584    7.592    7.792
       8 comps  9 comps  10 comps  11 comps  12 comps  13 comps  14 comps
X       89.627   93.557    97.005    98.398    99.294     99.97    99.998
class    7.917    8.022     8.026     8.289     8.847      8.87     8.872
       15 comps
X       100.000
class     9.128
```
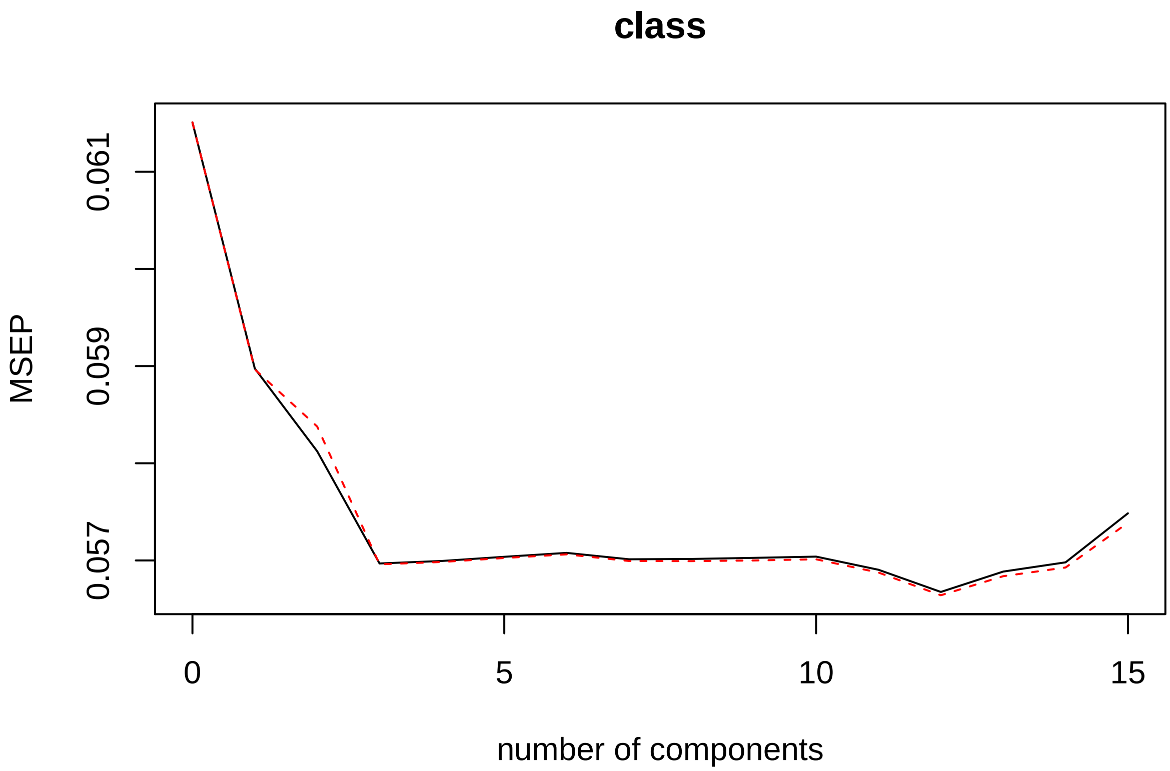
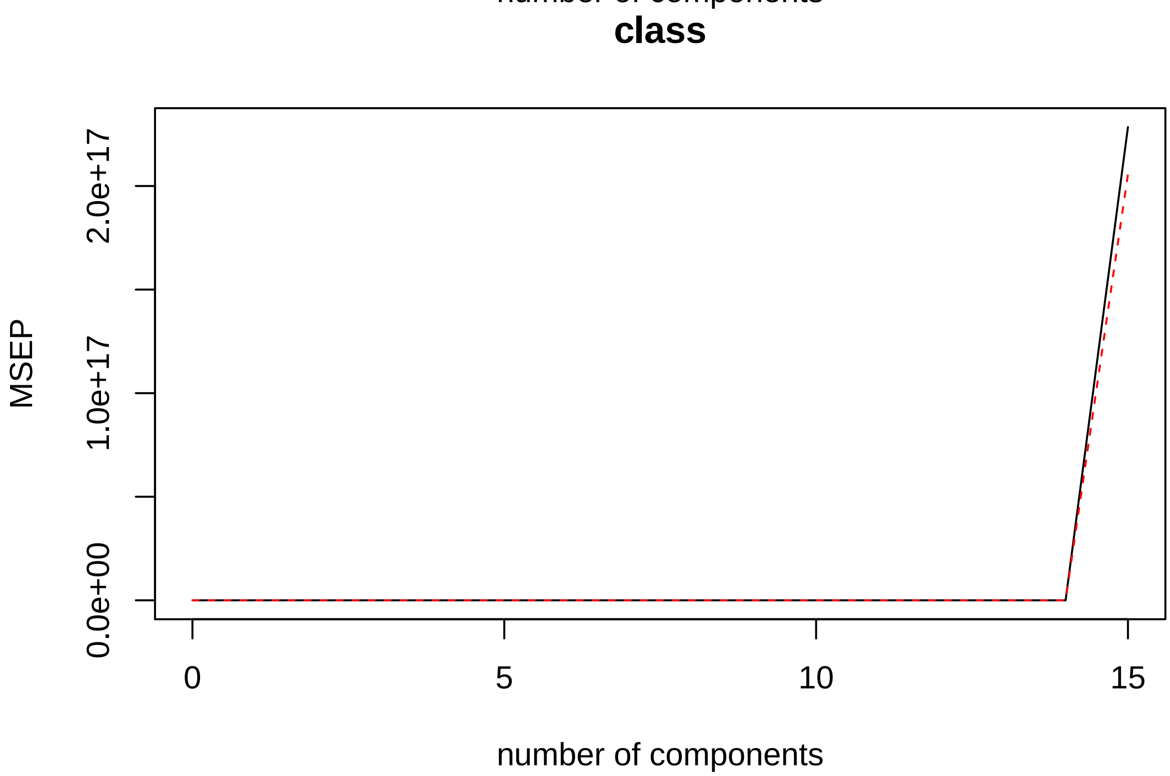
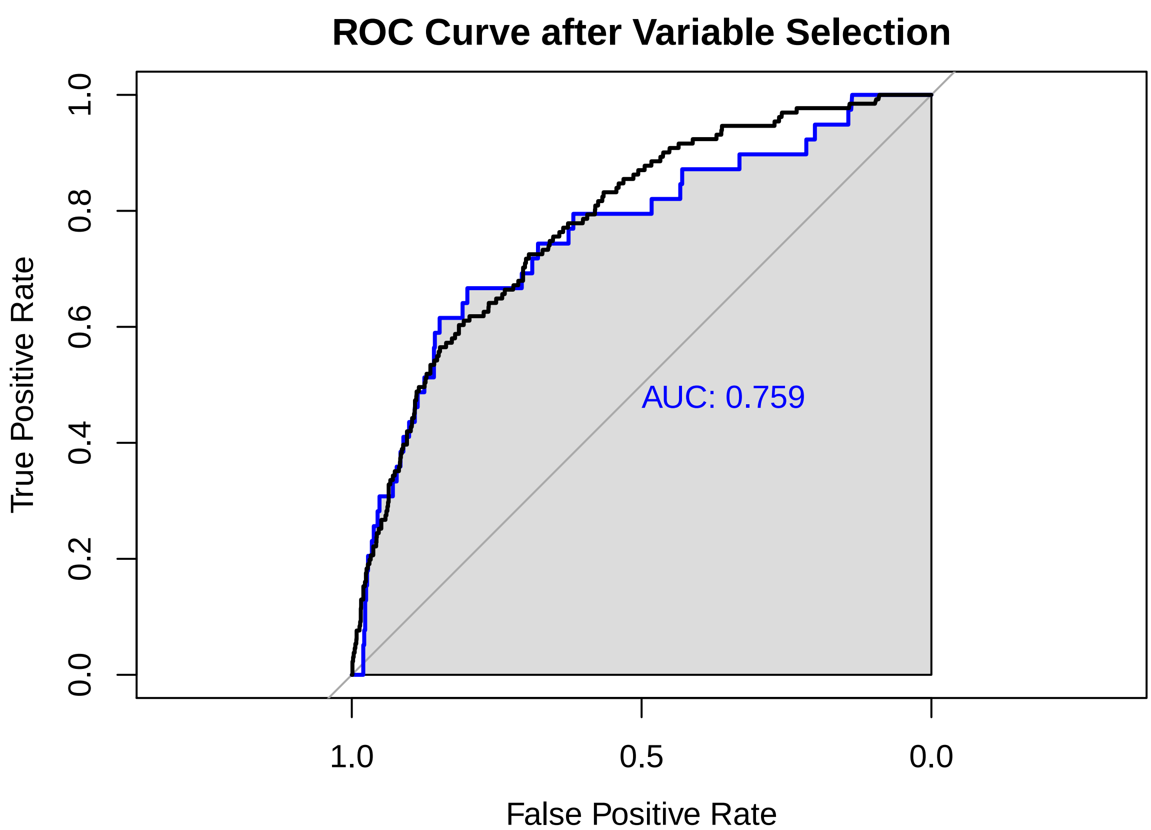


class
MSEP
0.057
0.059
0.061
0
5
10
15
number of components


class
MSEP
0.0e+00
1.0e+17
2.0e+17
0
5
10
15
number of components

```
[1] 0.05357258
```

Logistic Regression after Variable Selection

```
Call:
glm(formula = class ~ seismic + shift + gpuls + nbumps, family = binomial,
    data = seismic.train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6270  -0.3846  -0.2947  -0.1627   2.9781

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -5.9508244  0.6490468  -9.169  < 2e-16 ***
seismic      0.3641160  0.1944250   1.873 0.061098 .
shift        1.1371057  0.3402674   3.342 0.000832 ***
gpuls        0.0004913  0.0001283   3.829 0.000129 ***
nbumps       0.3231048  0.0507286   6.369  1.9e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 958.82  on 1937  degrees of freedom
Residual deviance: 828.98  on 1933  degrees of freedom
AIC: 838.98

Number of Fisher Scoring iterations: 6

[1] 0.9318885


glm.pred    0    1
       0 1803  128
       1    4    3

[1] 0.02290076

[1] 0.9977864

[1] 0.9380805


glm.pred   0   1
       0 606  39
       1   1   0

[1] 0

[1] 0.9983526
```



Quadratic Discriminant Analysis after variable selection

```
##-----------------------------------------
## Fit QDA model after variable selection
##-----------------------------------------

# Model 1
qda.fit <- qda(class~seismic+shift+gpuls+nbumps, data=seismic.train)
qda.class=predict(qda.fit,seismic.test)$class
confusion <- table(qda.class ,seismic.test$class)

sensitivity <- confusion[2,2]/sum(confusion[,2])
specificity <- confusion[1,1]/sum(confusion[,1])

confusion
```

```
##
## qda.class   0   1
##         0 565  27
##         1  42  12
```

```
sensitivity
```

```
## [1] 0.3076923
```

```
specificity
```

```
## [1] 0.9308072
```

```
# Model 2
qda.fit <- qda(class ~ genergy + gpuls + nbumps + nbumps2 + nbumps4, data=seismic.train)
qda.class=predict(qda.fit,seismic.test)$class

confusion <- table(qda.class ,seismic.test$class)

sensitivity <- confusion[2,2]/sum(confusion[,2])
specificity <- confusion[1,1]/sum(confusion[,1])

confusion
```

```
##
## qda.class   0   1
##         0 527  23
##         1  80  16
```

```
sensitivity
```

```
## [1] 0.4102564
```

```
specificity
```

```
## [1] 0.8682043
```

Regularized Discriminant Analysis after variable selection

```
rda.class   0   1
        0 595  35
        1  12   4

[1] 0.1025641

[1] 0.9802306
```

```
rda.class   0   1
        0 572  33
        1  35   6

[1] 0.1538462

[1] 0.9423394
```

Pre-Variable Selection

Model	Test Specificity	Test Sensitivity	Training Specificity	Training Sensitivity
Indicator	123	123	123	123
LDA	123	123	123	123
QDA	123	123	123	123
RDA	123	123	123	123
Log Regression	123	123	123	123

Post-Variable Selection

Model	Test Specificity	Test Sensitivity	Training Specificity	Training Sensitivity
Indicator	123	123	123	123
LDA	123	123	123	123
QDA	123	123	123	123
RDA	123	123	123	123
Log Regression	123	123	123	123