

Assignment_9.R

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2020-11-10

GitHub Link:

.R File: [https://github.com/kunwangRU/Survival-Analysis-of-Patients-with-Heart-Failure/blob/master/LDA%20\(Assignment%209\).R](https://github.com/kunwangRU/Survival-Analysis-of-Patients-with-Heart-Failure/blob/master/LDA%20(Assignment%209).R)

#Loading Packages

```
library(dplyr)
```

```
##
```

```
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
```

```
##
```

```
## filter, lag
```

```
## The following objects are masked from 'package:base':
```

```
##
```

```
## intersect, setdiff, setequal, union
```

```
library(psych)
```

```
## Warning: package 'psych' was built under R version 3.6.3
```

```
library(cluster)
```

```
## Warning: package 'cluster' was built under R version 3.6.3
```

```
library(fpc)
```

```
## Warning: package 'fpc' was built under R version 3.6.3
```

```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 3.6.3
```

```
##
```

```
## Attaching package: 'ggplot2'
```

```
## The following objects are masked from 'package:psych':
```

```
##
```

```
## %+%, alpha
```

```
library(MASS)
```

```
##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##      select

library(ROCR)

## Warning: package 'ROCR' was built under R version 3.6.3

library(klaR)

#Loading dataset
rawdata <- read.csv("C:/Users/wangk/Desktop/Rutgers/Rutgers Courseware/Fall
2020/Multivariate Analysis/heart_failure_clinical_records_dataset.csv")
View(rawdata)

#Identifying different columns names
names(rawdata)

## [1] "age" "anaemia"
## [3] "creatinine_phosphokinase" "diabetes"
## [5] "ejection_fraction" "high_blood_pressure"
## [7] "platelets" "serum_creatinine"
## [9] "serum_sodium" "sex"
## [11] "smoking" "time"
## [13] "DEATH_EVENT"

#Data Summary
str(rawdata)

## 'data.frame': 299 obs. of 13 variables:
## $ age : num 75 55 65 50 65 90 75 60 65 80 ...
## $ anaemia : int 0 0 0 1 1 1 1 0 1 ...
## $ creatinine_phosphokinase: int 582 7861 146 111 160 47 246 315 157 123
## ...
## $ diabetes : int 0 0 0 0 1 0 0 1 0 0 ...
## $ ejection_fraction : int 20 38 20 20 20 40 15 60 65 35 ...
## $ high_blood_pressure : int 1 0 0 0 0 1 0 0 0 1 ...
## $ platelets : num 265000 263358 162000 210000 327000 ...
## $ serum_creatinine : num 1.9 1.1 1.3 1.9 2.7 2.1 1.2 1.1 1.5 9.4
## ...
## $ serum_sodium : int 130 136 129 137 116 132 137 131 138 133
## ...
## $ sex : Factor w/ 2 levels "Female","male": 2 2 2 2 1
2 2 2 1 2 ...
## $ smoking : int 0 0 1 0 0 1 0 1 0 1 ...
## $ time : int 4 6 7 7 8 8 10 10 10 10 ...
## $ DEATH_EVENT : Factor w/ 2 levels "Death","No Death": 2 2 2
2 2 2 2 2 2 ...
```

```
summary(rawdata)
```

```
##      age      anaemia      creatinine_phosphokinase
## Min.   :40.00   Min.   :0.0000   Min.    : 23.0
## 1st Qu.:51.00   1st Qu.:0.0000   1st Qu.: 116.5
## Median :60.00   Median :0.0000   Median : 250.0
## Mean   :60.83   Mean    :0.4314   Mean    : 581.8
## 3rd Qu.:70.00   3rd Qu.:1.0000   3rd Qu.: 582.0
## Max.   :95.00   Max.    :1.0000   Max.    :7861.0
##      diabetes      ejection_fraction      high_blood_pressure      platelets
## Min.   :0.0000   Min.   :14.00   Min.    :0.0000   Min.    : 25100
## 1st Qu.:0.0000   1st Qu.:30.00   1st Qu.:0.0000   1st Qu.:212500
## Median :0.0000   Median :38.00   Median :0.0000   Median :262000
## Mean   :0.4181   Mean    :38.08   Mean    :0.3512   Mean    :263358
## 3rd Qu.:1.0000   3rd Qu.:45.00   3rd Qu.:1.0000   3rd Qu.:303500
## Max.   :1.0000   Max.    :80.00   Max.    :1.0000   Max.    :850000
## serum_creatinine serum_sodium      sex      smoking
## Min.   :0.500   Min.   :113.0   Female:105   Min.    :0.0000
## 1st Qu.:0.900   1st Qu.:134.0   male  :194   1st Qu.:0.0000
## Median :1.100   Median :137.0                   Median :0.0000
## Mean   :1.394   Mean    :136.6                   Mean    :0.3211
## 3rd Qu.:1.400   3rd Qu.:140.0                   3rd Qu.:1.0000
## Max.   :9.400   Max.    :148.0                   Max.    :1.0000
##      time      DEATH_EVENT
## Min.   : 4.0   Death    :203
## 1st Qu.:73.0   No Death: 96
## Median :115.0
## Mean   :130.3
## 3rd Qu.:203.0
## Max.   :285.0
```

```
head(rawdata)
```

```
##      age anaemia creatinine_phosphokinase diabetes ejection_fraction
## 1    75      0           582      0           20
## 2    55      0          7861      0           38
## 3    65      0          146      0           20
## 4    50      1          111      0           20
## 5    65      1          160      1           20
## 6    90      1           47      0           40
##      high_blood_pressure platelets serum_creatinine serum_sodium      sex
## 1              1    265000          1.9          130   male
## 2              0    263358          1.1          136   male
## 3              0    162000          1.3          129   male
## 4              0    210000          1.9          137   male
## 5              0    327000          2.7          116 Female
## 6              1    204000          2.1          132   male
##      smoking time DEATH_EVENT
## 1      0      4   No Death
## 2      0      6   No Death
```

```

## 3      1      7      No Death
## 4      0      7      No Death
## 5      0      8      No Death
## 6      1      8      No Death

dim(rawdata)

## [1] 299 13

#Data Cleaning

#Checking for missing values
is.null(rawdata)

## [1] FALSE

##The "FALSE" output shows there is no missing data in the dataset.

data <- as.matrix(rawdata[,c(1,3,5,7,8,9,12)])
dim(rawdata)

## [1] 299 13

dim(data)

## [1] 299 7

dataset <- cbind(data, as.numeric(rawdata$DEATH_EVENT)-1)
dim(dataset)

## [1] 299 8

colnames(dataset)[8] <- "death"

View(dataset)
str(dataset)

## num [1:299, 1:8] 75 55 65 50 65 90 75 60 65 80 ...
## - attr(*, "dimnames")=List of 2
## ..$ : NULL
## ..$ : chr [1:8] "age" "creatinine_phosphokinase" "ejection_fraction"
## "platelets" ...

# Lets cut the data into two parts
smp_size_raw <- floor(0.75 * nrow(dataset))
train_ind_raw <- sample(nrow(dataset), size = smp_size_raw)
train_raw.df <- as.data.frame(dataset[train_ind_raw, ])
test_raw.df <- as.data.frame(dataset[-train_ind_raw, ])
# We have a training and a test set. Training is 75% and test is 25%

```

```
dataset.lda <- lda(formula = train_raw.df$death ~ ., data = train_raw.df)
dataset.lda
```

```
## Call:
## lda(train_raw.df$death ~ ., data = train_raw.df)
##
## Prior probabilities of groups:
##      0      1
## 0.6696429 0.3303571
##
## Group means:
##      age creatinine_phosphokinase ejection_fraction platelets
## 0 58.51111          524.4333          41.07333      274711
## 1 65.40091          577.7027          32.78378      264309
##      serum_creatinine serum_sodium      time
## 0      1.175133      137.1267 154.18000
## 1      1.825811      135.2838  68.78378
##
## Coefficients of linear discriminants:
##                                LD1
## age                2.099868e-02
## creatinine_phosphokinase 7.198031e-05
## ejection_fraction    -4.598699e-02
## platelets            2.220684e-07
## serum_creatinine      3.152938e-01
## serum_sodium          -2.596675e-02
## time                 -1.193570e-02
```

```
summary(dataset.lda)
```

```
##      Length Class  Mode
## prior      2    -none- numeric
## counts     2    -none- numeric
## means     14    -none- numeric
## scaling    7    -none- numeric
## lev        2    -none- character
## svd         1    -none- numeric
## N           1    -none- numeric
## call        3    -none- call
## terms       3    terms  call
## xlevels     0    -none- list
```

```
print(dataset.lda)
```

```
## Call:
## lda(train_raw.df$death ~ ., data = train_raw.df)
##
## Prior probabilities of groups:
##      0      1
## 0.6696429 0.3303571
##
```



```
View(dataset.lda.predict)  
dataset.lda.predict$x
```

```
##          LD1  
## 1  1.77283231  
## 2  1.32158942  
## 3  1.18085883  
## 4  1.79210926  
## 5  1.97850321  
## 6  1.18386128  
## 7  1.19499836  
## 8  1.50028178  
## 9  1.17551727  
## 10 1.57263752  
## 11 1.31404519  
## 12 1.84632784  
## 13 0.62829563  
## 14 1.33248189  
## 15 -0.08220599  
## 16 0.50167386  
## 17 1.67836521  
## 18 0.10520202  
## 19 1.12624607  
## 20 -0.05581531  
## 21 0.43100048  
## 22 -0.94366567  
## 23 1.20367843  
## 24 0.99582475  
## 25 0.87891896  
## 26 -0.42548970  
## 27 -0.86757743  
## 28 1.56579281  
## 29 -0.20059261  
## 30 1.10428398  
## 31 -0.03733506  
## 32 0.12002184  
## 33 0.41892436  
## 34 0.63568386  
## 35 0.32532663  
## 36 0.08670294  
## 37 -0.11959639  
## 38 0.38097103  
## 39 1.00267756  
## 40 -0.31447150  
## 41 0.05353679  
## 42 -0.21252017  
## 43 -1.51949666  
## 44 -0.26084694  
## 45 -1.16251832  
## 46 0.49900431
```

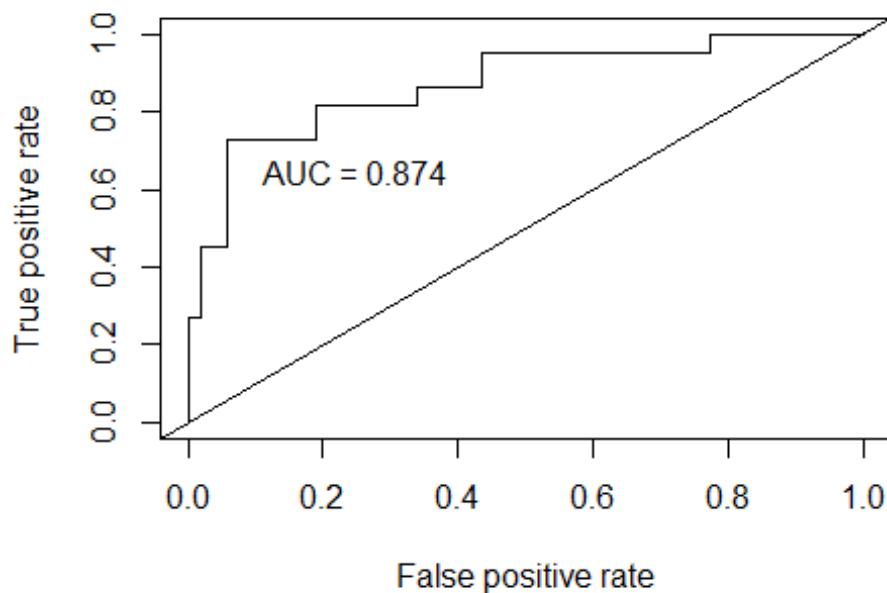
```

## 47 -0.70681931
## 48 -1.37787276
## 49 -1.38300714
## 50 -0.08273190
## 51 -0.53465769
## 52 -1.69099749
## 53 -1.00363963
## 54 -0.70984865
## 55 -1.55468559
## 56 -0.57211393
## 57 -1.09491722
## 58 -1.05918353
## 59 -1.21633471
## 60 -1.14937040
## 61 -1.68649907
## 62 -1.44410078
## 63 -0.40172670
## 64 -1.54662511
## 65 -1.78830983
## 66 -2.25248497
## 67 -1.45747720
## 68 -1.31497705
## 69 -1.71142594
## 70 -1.52057671
## 71 -1.26038873
## 72 -1.54707427
## 73 -1.86985773
## 74 -2.13635845
## 75 -2.34897960

# Get the posteriors as a dataframe.
dataset.lda.predict.posterior <-
as.data.frame(dataset.lda.predict$posterior)

#create ROC/AUC curve
pred <- prediction(dataset.lda.predict.posterior[,2], test_raw.df$death)
roc.perf = performance(pred, measure = "tpr", x.measure = "fpr")
auc.train <- performance(pred, measure = "auc")
auc.train <- auc.train@y.values
plot(roc.perf)
abline(a=0, b= 1)
text(x = .25, y = .65 ,paste("AUC = ", round(auc.train[[1]],3), sep = ""))

```

#Since the AUC value 0.82 is close to 1.0, we can say, it is a good model

```
summary(dataset.lda)
```

```
##           Length Class  Mode
## prior      2      -none- numeric
## counts     2      -none- numeric
## means     14      -none- numeric
## scaling    7      -none- numeric
## lev        2      -none- character
## svd         1      -none- numeric
## N           1      -none- numeric
## call        3      -none- call
## terms       3      terms call
## xlevels     0      -none- list
```

```
(prop = dataset.lda$svd^2/sum(dataset.lda$svd^2))
```

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

#we can use the singular values to compute the amount of the between-group variance that is explained by each linear discriminant.

#We see that the first linear discriminant (dataset.lda) explains almost all of the between-group variance in the dataset

```
data2<- as.data.frame(dataset)
```

```
View(data2)
```

```

dataset.lda2 <- lda(formula = death ~ ., data = data2, CV = TRUE)
dataset.lda2

## $class
## [1] 1 1 1 1 1 1 1 0 0 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1
0
## [36] 1 1 0 1 1 1 1 1 1 0 1 1 0 1 1 1 1 0 1 1 1 0 0 0 1 1 1 1
1
## [71] 0 0 1 0 1 1 0 0 1 0 1 0 1 1 0 0 0 0 0 0 0 0 1 0 0 1 0 1 0 1 1
0
## [106] 1 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 1 0 1 0 0 0 0 1 0 0 1 0
0
## [141] 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
0
## [176] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
## [211] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0
0
## [246] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
## [281] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## Levels: 0 1
##
## $posterior
##           0           1
## 1  0.0179741183 0.9820258817
## 2  0.0818920058 0.9181079942
## 3  0.0438234013 0.9561765987
## 4  0.0900721530 0.9099278470
## 5  0.0078978522 0.9921021478
## 6  0.0495485966 0.9504514034
## 7  0.0359811561 0.9640188439
## 8  0.6479695126 0.3520304874
## 9  0.6995478474 0.3004521526
## 10 0.0001731388 0.9998268612
## 11 0.0237996127 0.9762003873
## 12 0.1737865410 0.8262134590
## 13 0.2761567756 0.7238432244
## 14 0.4112232438 0.5887767562
## 15 0.2944061933 0.7055938067
## 16 0.2560491258 0.7439508742
## 17 0.1771974576 0.8228025424
## 18 0.0844280524 0.9155719476
## 19 0.1370342377 0.8629657623
## 20 0.4048626531 0.5951373469
## 21 0.1081968278 0.8918031722
## 22 0.1419476488 0.8580523512
## 23 0.2975498733 0.7024501267
## 24 0.7957060295 0.2042939705
## 25 0.0716034594 0.9283965406

```

26 0.1837559784 0.8162440216
27 0.1540106078 0.8459893922
28 0.3591955618 0.6408044382
29 0.0235606150 0.9764393850
30 0.0848719425 0.9151280575
31 0.0645559940 0.9354440060
32 0.0773591483 0.9226408517
33 0.3355171612 0.6644828388
34 0.3342967284 0.6657032716
35 0.6284449498 0.3715550502
36 0.0517658579 0.9482341421
37 0.3012797349 0.6987202651
38 0.5100966908 0.4899033092
39 0.0669054479 0.9330945521
40 0.2105032665 0.7894967335
41 0.0514107856 0.9485892144
42 0.3407811544 0.6592188456
43 0.4216099380 0.5783900620
44 0.4516074089 0.5483925911
45 0.8279629449 0.1720370551
46 0.3510097399 0.6489902601
47 0.1994406652 0.8005593348
48 0.5517036015 0.4482963985
49 0.0067972052 0.9932027948
50 0.4311130020 0.5688869980
51 0.1928818194 0.8071181806
52 0.2464312761 0.7535687239
53 0.0929493327 0.9070506673
54 0.5781551848 0.4218448152
55 0.2381177386 0.7618822614
56 0.0512207566 0.9487792434
57 0.1612050422 0.8387949578
58 0.6105366907 0.3894633093
59 0.2853939248 0.7146060752
60 0.1329823221 0.8670176779
61 0.2196064148 0.7803935852
62 0.4009659385 0.5990340615
63 0.5714771335 0.4285228665
64 0.7838333229 0.2161666771
65 0.9781299059 0.0218700941
66 0.0553625134 0.9446374866
67 0.3148673593 0.6851326407
68 0.2991800021 0.7008199979
69 0.3167386599 0.6832613401
70 0.2204277321 0.7795722679
71 0.8436355331 0.1563644669
72 0.5855824149 0.4144175851
73 0.0911759526 0.9088240474
74 0.7092078756 0.2907921244
75 0.1733953052 0.8266046948

76 0.4014011531 0.5985988469
77 0.8869095071 0.1130904929
78 0.8141266733 0.1858733267
79 0.4349613816 0.5650386184
80 0.8151002204 0.1848997796
81 0.4460590743 0.5539409257
82 0.7180389749 0.2819610251
83 0.1665911237 0.8334088763
84 0.4654653211 0.5345346789
85 0.5019391842 0.4980608158
86 0.9120458636 0.0879541364
87 0.6351321949 0.3648678051
88 0.9156792617 0.0843207383
89 0.8557839420 0.1442160580
90 0.5233252900 0.4766747100
91 0.6977813065 0.3022186935
92 0.6784926566 0.3215073434
93 0.9447273066 0.0552726934
94 0.3073240315 0.6926759685
95 0.7910902946 0.2089097054
96 0.9340809068 0.0659190932
97 0.2992716559 0.7007283441
98 0.8622578668 0.1377421332
99 0.4207813828 0.5792186172
100 0.7185316381 0.2814683619
101 0.4415035014 0.5584964986
102 0.6120615389 0.3879384611
103 0.2699941283 0.7300058717
104 0.3853794560 0.6146205440
105 0.7695612352 0.2304387648
106 0.4073064625 0.5926935375
107 0.7710234455 0.2289765545
108 0.7114043816 0.2885956184
109 0.5511150431 0.4488849569
110 0.7656266992 0.2343733008
111 0.7698229954 0.2301770046
112 0.6508287223 0.3491712777
113 0.4513454377 0.5486545623
114 0.8855008713 0.1144991287
115 0.5052502157 0.4947497843
116 0.7597527787 0.2402472213
117 0.9380953874 0.0619046126
118 0.5065318068 0.4934681932
119 0.9303197912 0.0696802088
120 0.2900197077 0.7099802923
121 0.8762469195 0.1237530805
122 0.6562349108 0.3437650892
123 0.7913926174 0.2086073826
124 0.6769816452 0.3230183548
125 0.2943767018 0.7056232982

126 0.9024941057 0.0975058943
127 0.2197899184 0.7802100816
128 0.9524498008 0.0475501992
129 0.6584631712 0.3415368288
130 0.5007868714 0.4992131286
131 0.9503428972 0.0496571028
132 0.0594016209 0.9405983791
133 0.8468115465 0.1531884535
134 0.9528408304 0.0471591696
135 0.1850029100 0.8149970900
136 0.6260130965 0.3739869035
137 0.9360457533 0.0639542467
138 0.2019130396 0.7980869604
139 0.7005363271 0.2994636729
140 0.7116072544 0.2883927456
141 0.5202886300 0.4797113700
142 0.8679471830 0.1320528170
143 0.6880012832 0.3119987168
144 0.8481525558 0.1518474442
145 0.3552152762 0.6447847238
146 0.8324205891 0.1675794109
147 0.7709292332 0.2290707668
148 0.9180917356 0.0819082644
149 0.3374567274 0.6625432726
150 0.6506772918 0.3493227082
151 0.5780003874 0.4219996126
152 0.9602812631 0.0397187369
153 0.9054540578 0.0945459422
154 0.7571257986 0.2428742014
155 0.7499123386 0.2500876614
156 0.5519648779 0.4480351221
157 0.7911794274 0.2088205726
158 0.7071806788 0.2928193212
159 0.6721506882 0.3278493118
160 0.8985860876 0.1014139124
161 0.7544045486 0.2455954514
162 0.8970084114 0.1029915886
163 0.8313440672 0.1686559328
164 0.8613763087 0.1386236913
165 0.8012029594 0.1987970406
166 0.6090743099 0.3909256901
167 0.9744315100 0.0255684900
168 0.3749285278 0.6250714722
169 0.8616927583 0.1383072417
170 0.7522325223 0.2477674777
171 0.8456721196 0.1543278804
172 0.8555584637 0.1444415363
173 0.9744217305 0.0255782695
174 0.7978700455 0.2021299545
175 0.8444181228 0.1555818772

176 0.9775656146 0.0224343854
177 0.7896187178 0.2103812822
178 0.9730222579 0.0269777421
179 0.9809357386 0.0190642614
180 0.9344377311 0.0655622689
181 0.9075614793 0.0924385207
182 0.7699686000 0.2300314000
183 0.7022155808 0.2977844192
184 0.6577454496 0.3422545504
185 0.8350403132 0.1649596868
186 0.8486675651 0.1513324349
187 0.9836070238 0.0163929762
188 0.7555848625 0.2444151375
189 0.9336095181 0.0663904819
190 0.9859017641 0.0140982359
191 0.6324127477 0.3675872523
192 0.9753070015 0.0246929985
193 0.9527811974 0.0472188026
194 0.8511080740 0.1488919260
195 0.8263895236 0.1736104764
196 0.9350839623 0.0649160377
197 0.9639865589 0.0360134411
198 0.9079292916 0.0920707084
199 0.8454005263 0.1545994737
200 0.5016117565 0.4983882435
201 0.9526571582 0.0473428418
202 0.9940657110 0.0059342890
203 0.9856193717 0.0143806283
204 0.5448776639 0.4551223361
205 0.9255989422 0.0744010578
206 0.9787164294 0.0212835706
207 0.9866608404 0.0133391596
208 0.8571001357 0.1428998643
209 0.9414641629 0.0585358371
210 0.9341447866 0.0658552134
211 0.7072253502 0.2927746498
212 0.9956254562 0.0043745438
213 0.9515033744 0.0484966256
214 0.9073656272 0.0926343728
215 0.9305733762 0.0694266238
216 0.8577356263 0.1422643737
217 0.9746651353 0.0253348647
218 0.8393664987 0.1606335013
219 0.8910507507 0.1089492493
220 0.9687978296 0.0312021704
221 0.6320548773 0.3679451227
222 0.9864512329 0.0135487671
223 0.9795485129 0.0204514871
224 0.9303742255 0.0696257745
225 0.9192786249 0.0807213751

226 0.9573609923 0.0426390077
227 0.8707680972 0.1292319028
228 0.9410644577 0.0589355423
229 0.2378807811 0.7621192189
230 0.8219283103 0.1780716897
231 0.8626109698 0.1373890302
232 0.9205132600 0.0794867400
233 0.9834681811 0.0165318189
234 0.9644300105 0.0355699895
235 0.9826669891 0.0173330109
236 0.9716732475 0.0283267525
237 0.9861211540 0.0138788460
238 0.8681099855 0.1318900145
239 0.9583214393 0.0416785607
240 0.9825174111 0.0174825889
241 0.9430699104 0.0569300896
242 0.9066555794 0.0933444206
243 0.9813522995 0.0186477005
244 0.9568365679 0.0431634321
245 0.9478161233 0.0521838767
246 0.9603449460 0.0396550540
247 0.9208437091 0.0791562909
248 0.7838893776 0.2161106224
249 0.9870006142 0.0129993858
250 0.9657050314 0.0342949686
251 0.9616396017 0.0383603983
252 0.9800085608 0.0199914392
253 0.9850410320 0.0149589680
254 0.9185694745 0.0814305255
255 0.9959470671 0.0040529329
256 0.9735660505 0.0264339495
257 0.9539034748 0.0460965252
258 0.9827115384 0.0172884616
259 0.9714533601 0.0285466399
260 0.9942952131 0.0057047869
261 0.9868455406 0.0131544594
262 0.9778359422 0.0221640578
263 0.8951768541 0.1048231459
264 0.9957505117 0.0042494883
265 0.9802195378 0.0197804622
266 0.9890130746 0.0109869254
267 0.8918317008 0.1081682992
268 0.9816230977 0.0183769023
269 0.9928248084 0.0071751916
270 0.9870081265 0.0129918735
271 0.9632881503 0.0367118497
272 0.9880764803 0.0119235197
273 0.9687555046 0.0312444954
274 0.9957991830 0.0042008170
275 0.9704102363 0.0295897637

```

## 276 0.9924543896 0.0075456104
## 277 0.9745783511 0.0254216489
## 278 0.9751537120 0.0248462880
## 279 0.9802495084 0.0197504916
## 280 0.9853134108 0.0146865892
## 281 0.9626822211 0.0373177789
## 282 0.9288911886 0.0711088114
## 283 0.8736427610 0.1263572390
## 284 0.9745992507 0.0254007493
## 285 0.9947810570 0.0052189430
## 286 0.9876192662 0.0123807338
## 287 0.9765987237 0.0234012763
## 288 0.9973408493 0.0026591507
## 289 0.9821014319 0.0178985681
## 290 0.9731778282 0.0268221718
## 291 0.9986496566 0.0013503434
## 292 0.9815515499 0.0184484501
## 293 0.9932623187 0.0067376813
## 294 0.9868891226 0.0131108774
## 295 0.9926371630 0.0073628370
## 296 0.9889101553 0.0110898447
## 297 0.9993780933 0.0006219067
## 298 0.9923538772 0.0076461228
## 299 0.9960970251 0.0039029749
##
## $terms
## death ~ age + creatinine_phosphokinase + ejection_fraction +
##      platelets + serum_creatinine + serum_sodium + time
## attr(,"variables")
## list(death, age, creatinine_phosphokinase, ejection_fraction,
##      platelets, serum_creatinine, serum_sodium, time)
## attr(,"factors")
##
##      age creatinine_phosphokinase ejection_fraction
## death      0                    0                  0
## age        1                    0                  0
## creatinine_phosphokinase  0                    1                  0
## ejection_fraction      0                    0                  1
## platelets      0                    0                  0
## serum_creatinine      0                    0                  0
## serum_sodium      0                    0                  0
## time          0                    0                  0
##
##      platelets serum_creatinine serum_sodium time
## death      0                    0              0  0
## age        0                    0              0  0
## creatinine_phosphokinase  0                    0              0  0
## ejection_fraction      0                    0              0  0
## platelets      1                    0              0  0
## serum_creatinine      0                    1              0  0
## serum_sodium      0                    0              1  0
## time          0                    0              0  1

```



```

## attr(,"term.labels")
## [1] "age" "creatinine_phosphokinase"
## [3] "ejection_fraction" "platelets"
## [5] "serum_creatinine" "serum_sodium"
## [7] "time"
## attr(,"order")
## [1] 1 1 1 1 1 1 1
## attr(,"intercept")
## [1] 1
## attr(,"response")
## [1] 1
## attr(,".Environment")
## <environment: R_GlobalEnv>
## attr(,"predvars")
## list(death, age, creatinine_phosphokinase, ejection_fraction,
##      platelets, serum_creatinine, serum_sodium, time)
## attr(,"dataClasses")
##      death      age creatinine_phosphokinase
##      "numeric"  "numeric" "numeric"
##      ejection_fraction platelets serum_creatinine
##      "numeric"  "numeric" "numeric"
##      serum_sodium      time
##      "numeric"  "numeric"
##
## $call
## lda(formula = death ~ ., data = data2, CV = TRUE)
##
## $xlevels
## named list()

head(dataset.lda2$class)

## [1] 1 1 1 1 1 1
## Levels: 0 1

#the Maximum a Posteriori Probability (MAP) classification (a factor)
#posterior: posterior probabilities for the classes.
head(dataset.lda2$posterior, 3)

##      0      1
## 1 0.01797412 0.9820259
## 2 0.08189201 0.9181080
## 3 0.04382340 0.9561766

#Dividing the data into two parts 50% each
train <- sample(1:299, 150)

# training model
dataset.lda3 <- lda(death ~ .,
                    data2,
                    prior = c(1,1)/2,

```

```

subset = train)

# predictions
plda = predict(object = dataset.lda3,
               newdata = data2[-train, ])
head(plda$class)

## [1] 1 1 1 0 1 1
## Levels: 0 1

# posterior prob
head(plda$posterior, 6)

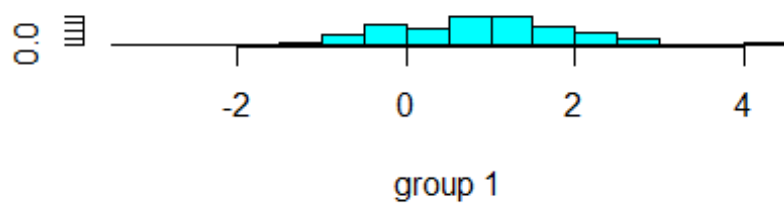
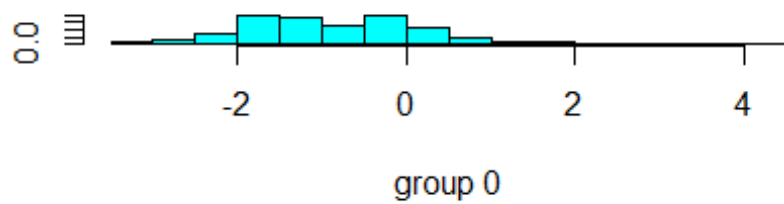
##           0           1
## 3  0.03260689 0.9673931
## 4  0.03598577 0.9640142
## 7  0.01966265 0.9803374
## 8  0.61393675 0.3860633
## 18 0.04882990 0.9511701
## 20 0.35848051 0.6415195

head(plda$x, 3)

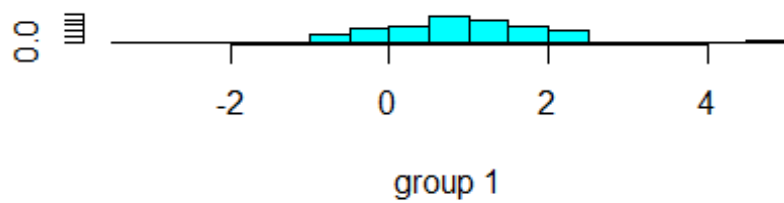
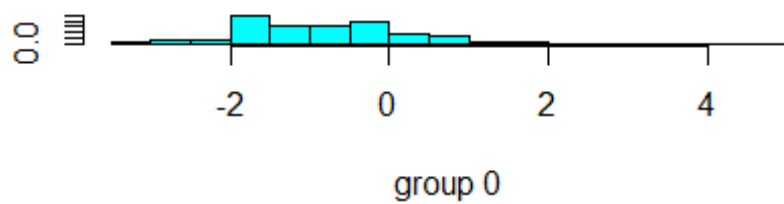
##           LD1
## 3 1.876900
## 4 1.820374
## 7 2.164294

plot(dataset.lda)

```



```
plot(dataset.lda3)
```



```
dataset.lda <- lda(death ~ .,
  data2,
  prior = c(1,1)/2)
prop.lda = dataset.lda$svd^2/sum(dataset.lda$svd^2)
plda <- predict(object = dataset.lda,
  newdata = data2)
data3 = data.frame(death = data2[, "death"], lda = plda$x)
```

Dividing the dataset using second approach

```
set.seed(101) # Nothing is random!!
sample_n(data2, 10)
```

```
##   age creatinine_phosphokinase ejection_fraction platelets
## 1   58                      144                38    327000
## 2   60                      2281               40    283000
## 3   61                       80                38    282000
## 4   58                      200                60    300000
## 5   53                      1808               60    249000
## 6   45                      582                55    543000
## 7   65                      157                65    263358
## 8   73                      1185               40    220000
## 9   85                      910                50    235000
## 10  50                      196                45    395000
##   serum_creatinine serum_sodium time death
## 1             0.7         142    83     0
## 2             1.0         141   187     0
## 3             1.4         137   213     0
## 4             0.8         137   104     0
## 5             0.7         138   106     0
## 6             1.0         132   250     0
## 7             1.5         138    10     1
## 8             0.9         141   213     0
## 9             1.3         134   121     0
## 10            1.6         136   285     0
```

Dividing dataset into 75/25 using Dplyr preserves class

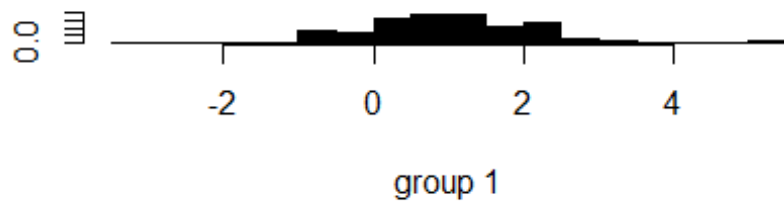
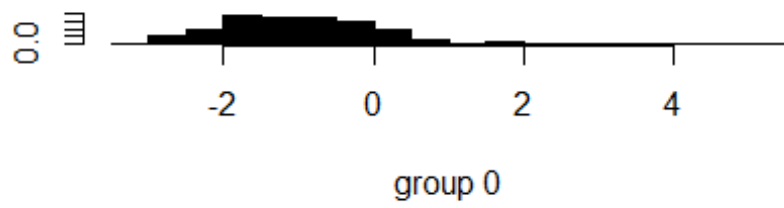
```
training_sample <- sample(c(TRUE, FALSE), nrow(data2), replace = T, prob =
c(0.75, 0.25))
train <- data2[training_sample, ]
test <- data2[!training_sample, ]
```

Lets run LDA like before

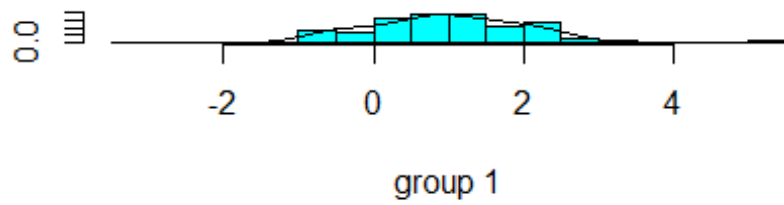
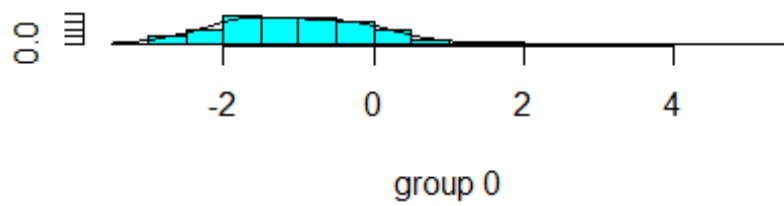
```
lda.data2 <- lda(death ~ ., train)
```

Plotting the data to better understand the model

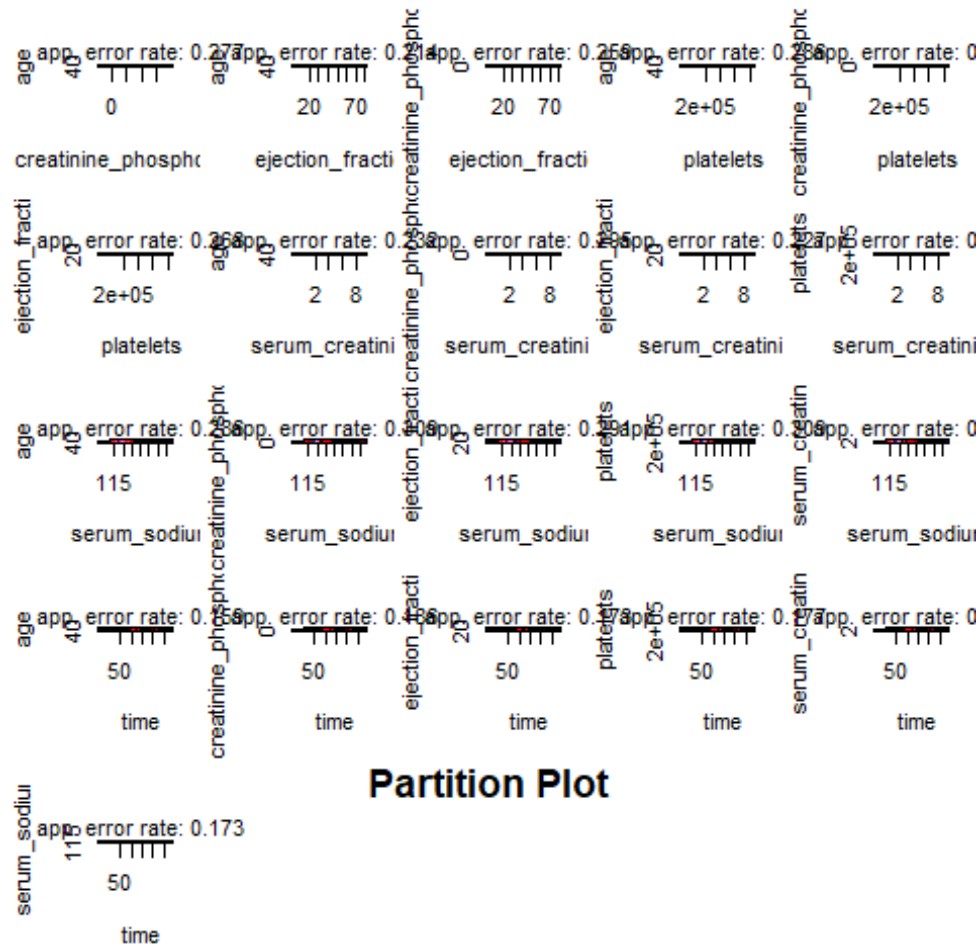
```
plot(lda.data2, col = as.integer(train$death))
```



```
plot(lda.data2, dimen = 1, type = "b")
```



```
View(data2)
# Partition plots
partimat(death ~ age + creatinine_phosphokinase + ejection_fraction +
platelets + serum_creatinine + serum_sodium + time, data=train, method="lda")
```



```
# Checking the accuracy for training set to understand how good the model is
lda.train <- predict(lda.data2)
train$lda <- lda.train$class
table(train$lda,train$death)
```

```
##
##      0  1
##  0 141 19
##  1   9 51
```

```
#Checking the accuracy for testing set to understand how good the model is
lda.test <- predict(lda.data2,test)
test$lda <- lda.test$class
table(test$lda,test$death)
```

```
##
##      0  1
##  0 39  6
##  1 14 20
```