

Project 4 - STAT 3022

Henrique Lispector ID: 4839516 lispe001@umn.edu

April 29, 2016

Project Description

Install the library TH.data. Use the data named GlaucomaM in this library. The GlaucomaM data has 196 observations in two classes. 62 variables are derived from a confocal laser scanning image of the optic nerve head, describing its morphology. Observations are from normal and glaucomatous eyes, respectively. Use the help file to know more about the dataset. Your goal is to predict whether a person will have glaucoma based on the 62 variables. Identify the predictors and the response variable in the dataset. Randomly select 70% of the data as training data and the remaining 30% as test data. Install the package glmnet and use elastic net method on the training data to determine an appropriate model. Then use this model to do predictions on the test dataset. Report which covariates were selected in the model. You do not need to interpret any coefficient estimate. Prediction and variable selection are the main focus of your analysis.

Loading the data

```
library(TH.data)
```

```
## Loading required package: survival
```

```
## Loading required package: MASS
```

```
##
```

```
## Attaching package: 'TH.data'
```

```
## The following object is masked from 'package:MASS':
```

```
##
```

```
##      geyser
```

```
GlaucomaM_data <- GlaucomaM
```

```
head(GlaucomaM_data)
```

```
##      ag    at    as    an    ai    eag    eat    eas    ean    eai    abrg    abrt
## 2  2.220 0.354 0.580 0.686 0.601 1.267 0.336 0.346 0.255 0.331 0.479 0.260
## 43 2.681 0.475 0.672 0.868 0.667 2.053 0.440 0.520 0.639 0.454 1.090 0.377
## 25 1.979 0.343 0.508 0.624 0.504 1.200 0.299 0.396 0.259 0.246 0.465 0.209
## 65 1.747 0.269 0.476 0.525 0.476 0.612 0.147 0.017 0.044 0.405 0.170 0.062
## 70 2.990 0.599 0.686 1.039 0.667 2.513 0.543 0.607 0.871 0.492 1.800 0.431
## 16 2.917 0.483 0.763 0.901 0.770 2.200 0.462 0.637 0.504 0.597 1.311 0.394
##      abrs  abrn  abri      hic  mhcg  mhct  mhcs  mhcn  mhci  phcg
## 2  0.107 0.014 0.098  0.214  0.111 0.412  0.036  0.105 -0.022 -0.139
## 43 0.257 0.212 0.245  0.382  0.140 0.338  0.104  0.080  0.109 -0.015
## 25 0.112 0.041 0.103  0.195  0.062 0.356  0.045 -0.009 -0.048 -0.149
## 65 0.000 0.000 0.108 -0.030 -0.015 0.074 -0.084 -0.050  0.035 -0.182
```

```

## 70 0.494 0.601 0.274 0.383 0.089 0.233 0.145 0.023 0.007 -0.131
## 16 0.365 0.251 0.301 0.442 0.128 0.375 0.049 0.111 0.052 -0.088
##      phct  phcs  phcn  phci  hvc  vbsg  vbst  vbss  vbsn  vbsi  vasg
## 2   0.242 -0.053 0.010 -0.139 0.613 0.303 0.103 0.088 0.022 0.090 0.062
## 43  0.296 -0.015 -0.015 0.036 0.382 0.676 0.181 0.186 0.141 0.169 0.029
## 25  0.206 -0.092 -0.081 -0.149 0.557 0.300 0.084 0.088 0.046 0.082 0.036
## 65 -0.097 -0.125 -0.138 -0.182 0.373 0.048 0.011 0.000 0.000 0.036 0.070
## 70  0.163 0.055 -0.131 -0.115 0.405 0.889 0.151 0.253 0.330 0.155 0.020
## 16  0.281 -0.067 -0.062 -0.088 0.507 0.972 0.213 0.316 0.197 0.246 0.043
##      vast  vass  vasn  vasi  vbrg  vbrr  vbrr  vbrr  vbri  varg  vart  vars
## 2   0.000 0.011 0.032 0.018 0.075 0.039 0.021 0.002 0.014 0.756 0.009 0.209
## 43  0.001 0.007 0.011 0.010 0.370 0.127 0.099 0.050 0.093 0.410 0.006 0.105
## 25  0.002 0.004 0.016 0.013 0.081 0.034 0.019 0.007 0.021 0.565 0.014 0.132
## 65  0.005 0.030 0.033 0.002 0.005 0.001 0.000 0.000 0.004 0.380 0.032 0.147
## 70  0.001 0.004 0.008 0.007 0.532 0.103 0.173 0.181 0.075 0.228 0.011 0.026
## 16  0.001 0.005 0.028 0.009 0.467 0.136 0.148 0.078 0.104 0.540 0.008 0.133
##      varn  vari  mdg  mdt  mds  mdn  mdi  tmg  tmt  tms  tmn
## 2   0.298 0.240 0.705 0.637 0.738 0.596 0.691 -0.236 -0.018 -0.230 -0.510
## 43  0.181 0.117 0.898 0.850 0.907 0.771 0.940 -0.211 -0.014 -0.165 -0.317
## 25  0.243 0.177 0.687 0.643 0.689 0.684 0.700 -0.185 -0.097 -0.235 -0.337
## 65  0.151 0.050 0.207 0.171 0.022 0.046 0.221 -0.148 -0.035 -0.449 -0.217
## 70  0.105 0.087 0.721 0.638 0.730 0.730 0.640 -0.052 -0.105 0.084 -0.012
## 16  0.232 0.167 0.927 0.842 0.953 0.906 0.898 -0.040 0.087 0.018 -0.094
##      tmi  mr  rnf  mdic  emd  mv  Class
## 2   -0.158 0.841 0.410 0.137 0.239 0.035 normal
## 43  -0.192 0.924 0.256 0.252 0.329 0.022 normal
## 25  -0.020 0.795 0.378 0.152 0.250 0.029 normal
## 65  -0.091 0.746 0.200 0.027 0.078 0.023 normal
## 70  -0.054 0.977 0.193 0.297 0.354 0.034 normal
## 16  -0.051 0.965 0.339 0.333 0.442 0.028 normal

```

Data Pre-Processing

```
summary(GlaucomaM_data)
```

```

##      ag      at      as      an
##  Min.   :1.312  Min.   :0.2010  Min.   :0.3450  Min.   :0.3970
##  1st Qu.:2.139  1st Qu.:0.3708  1st Qu.:0.5385  1st Qu.:0.6810
##  Median :2.533  Median :0.4445  Median :0.6305  Median :0.8085
##  Mean   :2.607  Mean   :0.4590  Mean   :0.6518  Mean   :0.8359
##  3rd Qu.:2.943  3rd Qu.:0.5280  3rd Qu.:0.7382  3rd Qu.:0.9520
##  Max.   :5.444  Max.   :0.9670  Max.   :1.3400  Max.   :1.7650
##      ai      eag      eat      eas
##  Min.   :0.3690  Min.   :0.415  Min.   :0.1370  Min.   :0.0170
##  1st Qu.:0.5505  1st Qu.:1.309  1st Qu.:0.3157  1st Qu.:0.3807
##  Median :0.6320  Median :1.843  Median :0.4025  Median :0.4685
##  Mean   :0.6600  Mean   :1.874  Mean   :0.4064  Mean   :0.4864
##  3rd Qu.:0.7498  3rd Qu.:2.317  3rd Qu.:0.4833  3rd Qu.:0.6055
##  Max.   :1.3730  Max.   :4.125  Max.   :0.8480  Max.   :1.2250
##      ean      eai      abrg      abrt
##  Min.   :0.0080  Min.   :0.0980  Min.   :0.0030  Min.   :0.0030

```

##	1st Qu.:0.2805	1st Qu.:0.3725	1st Qu.:0.6817	1st Qu.:0.2450
##	Median :0.5035	Median :0.4840	Median :1.3120	Median :0.3225
##	Mean :0.5012	Mean :0.4801	Mean :1.2919	Mean :0.3248
##	3rd Qu.:0.6895	3rd Qu.:0.5948	3rd Qu.:1.7352	3rd Qu.:0.4295
##	Max. :1.5680	Max. :0.9610	Max. :4.9800	Max. :0.8270
##	abrs	abrn	abri	hic
##	Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. : -0.1890
##	1st Qu.:0.1928	1st Qu.:0.0885	1st Qu.:0.1693	1st Qu.: 0.1958
##	Median :0.3250	Median :0.2520	Median :0.3255	Median : 0.3240
##	Mean :0.3295	Mean :0.3125	Mean :0.3251	Mean : 0.3050
##	3rd Qu.:0.4512	3rd Qu.:0.4520	3rd Qu.:0.4595	3rd Qu.: 0.4190
##	Max. :1.3400	Max. :1.7650	Max. :1.2090	Max. : 0.8870
##	mhcg	mhct	mhcs	
##	Min. : -0.14700	Min. : -0.0470	Min. : -0.17200	
##	1st Qu.: 0.04675	1st Qu.: 0.1610	1st Qu.: 0.00175	
##	Median : 0.09450	Median : 0.2110	Median : 0.07050	
##	Mean : 0.09415	Mean : 0.2142	Mean : 0.06123	
##	3rd Qu.: 0.13825	3rd Qu.: 0.2742	3rd Qu.: 0.11825	
##	Max. : 0.32200	Max. : 0.4770	Max. : 0.29300	
##	mhcnc	mhcic	phcgc	phctc
##	Min. : -0.21200	Min. : -0.1610	Min. : -0.28600	Min. : -0.1210
##	1st Qu.: 0.01975	1st Qu.: -0.0035	1st Qu.: -0.13300	1st Qu.: 0.0950
##	Median : 0.07950	Median : 0.0640	Median : -0.08800	Median : 0.1540
##	Mean : 0.07380	Mean : 0.0647	Mean : -0.07853	Mean : 0.1477
##	3rd Qu.: 0.12250	3rd Qu.: 0.1300	3rd Qu.: -0.01650	3rd Qu.: 0.2052
##	Max. : 0.66000	Max. : 0.4540	Max. : 0.14500	Max. : 0.4300
##	phcsc	phcnc	phcic	hvc
##	Min. : -0.24700	Min. : -0.28500	Min. : -0.28600	Min. : 0.1100
##	1st Qu.: -0.08925	1st Qu.: -0.08900	1st Qu.: -0.11200	1st Qu.: 0.2860
##	Median : -0.02850	Median : -0.03350	Median : -0.04700	Median : 0.3470
##	Mean : -0.03105	Mean : -0.03238	Mean : -0.04238	Mean : 0.3604
##	3rd Qu.: 0.02600	3rd Qu.: 0.02400	3rd Qu.: 0.02700	3rd Qu.: 0.4283
##	Max. : 0.16000	Max. : 0.39800	Max. : 0.37100	Max. : 0.9690
##	vbsg	vbst	vbss	vbsn
##	Min. :0.0200	Min. :0.00700	Min. :0.00000	Min. :0.0000
##	1st Qu.:0.3315	1st Qu.:0.07575	1st Qu.:0.09275	1st Qu.:0.0525
##	Median :0.5960	Median :0.12200	Median :0.16800	Median :0.1185
##	Mean :0.6334	Mean :0.13399	Mean :0.18581	Mean :0.1494
##	3rd Qu.:0.8632	3rd Qu.:0.17400	3rd Qu.:0.26225	3rd Qu.:0.2157
##	Max. :2.1260	Max. :0.44600	Max. :0.81700	Max. :0.6960
##	vbsi	vasg	vast	vass
##	Min. :0.00600	Min. :0.00800	Min. :0.000000	Min. :0.0010
##	1st Qu.:0.08275	1st Qu.:0.02200	1st Qu.:0.001000	1st Qu.:0.0040
##	Median :0.15600	Median :0.03600	Median :0.001000	Median :0.0070
##	Mean :0.16420	Mean :0.04967	Mean :0.002077	Mean :0.0101
##	3rd Qu.:0.22375	3rd Qu.:0.06425	3rd Qu.:0.002000	3rd Qu.:0.0110
##	Max. :0.49000	Max. :0.75100	Max. :0.026000	Max. :0.2390
##	vasn	vasi	vbrg	vbrt
##	Min. :0.00100	Min. :0.00100	Min. :0.0000	Min. :0.00000
##	1st Qu.:0.00900	1st Qu.:0.00400	1st Qu.:0.1338	1st Qu.:0.04075
##	Median :0.01750	Median :0.00800	Median :0.3540	Median :0.08100
##	Mean :0.02561	Mean :0.01186	Mean :0.4256	Mean :0.09719
##	3rd Qu.:0.03125	3rd Qu.:0.01425	3rd Qu.:0.5540	3rd Qu.:0.13300
##	Max. :0.39700	Max. :0.10500	Max. :3.7000	Max. :0.39900

```

##          vbrs          vbrn          vbri          varg
## Min.    :0.00000  Min.    :0.00000  Min.    :0.00000  Min.    :0.0160
## 1st Qu.:0.03875  1st Qu.:0.01275  1st Qu.:0.03275  1st Qu.:0.1450
## Median :0.10150  Median :0.05650  Median :0.08750  Median :0.2780
## Mean    :0.12374  Mean    :0.09906  Mean    :0.10552  Mean    :0.2962
## 3rd Qu.:0.16475  3rd Qu.:0.14025  3rd Qu.:0.14925  3rd Qu.:0.3900
## Max.    :1.09900  Max.    :1.62000  Max.    :0.58900  Max.    :1.3250
##          vart          vars          varn          vari
## Min.    :0.00100  Min.    :0.00000  Min.    :0.00000  Min.    :0.00100
## 1st Qu.:0.00400  1st Qu.:0.03375  1st Qu.:0.06300  1st Qu.:0.03400
## Median :0.00700  Median :0.06950  Median :0.11700  Median :0.06750
## Mean    :0.01050  Mean    :0.07595  Mean    :0.12980  Mean    :0.07991
## 3rd Qu.:0.01225  3rd Qu.:0.10100  3rd Qu.:0.17800  3rd Qu.:0.11050
## Max.    :0.06500  Max.    :0.39700  Max.    :0.59700  Max.    :0.26600
##          mdg          mdt          mds          mdn
## Min.    :0.12100  Min.    :0.11700  Min.    :0.02200  Min.    :0.0230
## 1st Qu.:0.57730  1st Qu.:0.49100  1st Qu.:0.57600  1st Qu.:0.4585
## Median :0.68250  Median :0.60150  Median :0.69150  Median :0.6320
## Mean    :0.68530  Mean    :0.60950  Mean    :0.69510  Mean    :0.6115
## 3rd Qu.:0.81250  3rd Qu.:0.71830  3rd Qu.:0.81100  3rd Qu.:0.7768
## Max.    :1.29800  Max.    :1.21500  Max.    :1.35100  Max.    :1.2600
##          mdi          tmg          tmt
## Min.    :0.11600  Min.    :-0.35300  Min.    :-0.291000
## 1st Qu.:0.52980  1st Qu.: -0.16150  1st Qu.: -0.101000
## Median :0.63700  Median : -0.08100  Median : -0.018500
## Mean    :0.63650  Mean    :-0.09298  Mean    :-0.004658
## 3rd Qu.:0.74550  3rd Qu.: -0.02525  3rd Qu.: 0.087750
## Max.    :1.24700  Max.    : 0.19200  Max.    : 0.366000
##          tms          tmn          tmi          mr
## Min.    :-0.44900  Min.    :-0.51000  Min.    :-0.40500  Min.    :0.6470
## 1st Qu.: -0.13525  1st Qu.: -0.23100  1st Qu.: -0.12750  1st Qu.:0.8260
## Median : -0.03150  Median : -0.14650  Median : -0.03600  Median :0.8995
## Mean    : -0.03981  Mean    : -0.14720  Mean    : -0.03651  Mean    :0.9050
## 3rd Qu.: 0.06800  3rd Qu.: -0.05625  3rd Qu.: 0.04950  3rd Qu.:0.9685
## Max.    : 0.35800  Max.    : 0.24500  Max.    : 0.41800  Max.    :1.3170
##          rnf          mdic          emd          mv
## Min.    :-0.29700  Min.    :0.01200  Min.    :0.04700  Min.    :0.00000
## 1st Qu.: 0.11970  1st Qu.:0.14400  1st Qu.:0.23050  1st Qu.:0.02100
## Median : 0.18200  Median :0.22700  Median :0.29800  Median :0.02800
## Mean    : 0.18240  Mean    :0.23130  Mean    :0.30890  Mean    :0.03354
## 3rd Qu.: 0.23700  3rd Qu.:0.29930  3rd Qu.:0.37920  3rd Qu.:0.03825
## Max.    : 0.45100  Max.    :0.66300  Max.    :0.74300  Max.    :0.18300
##          Class
## glaucoma:98
## normal :98
##
##
##
##

```

No NA's are present in the summary of the data, so we do not need to worry about NA's.

Now let's check if the variables are coded with correct data types:

```
lapply(GlaucomaM_data, class)
```

```
## $ag
## [1] "numeric"
##
## $at
## [1] "numeric"
##
## $as
## [1] "numeric"
##
## $an
## [1] "numeric"
##
## $ai
## [1] "numeric"
##
## $eag
## [1] "numeric"
##
## $eat
## [1] "numeric"
##
## $eas
## [1] "numeric"
##
## $ean
## [1] "numeric"
##
## $eai
## [1] "numeric"
##
## $abrg
## [1] "numeric"
##
## $abrt
## [1] "numeric"
##
## $abrs
## [1] "numeric"
##
## $abrn
## [1] "numeric"
##
## $abri
## [1] "numeric"
##
## $hic
## [1] "numeric"
##
## $mhcg
## [1] "numeric"
##
```

```

## $mhct
## [1] "numeric"
##
## $mhcs
## [1] "numeric"
##
## $mhcn
## [1] "numeric"
##
## $mhci
## [1] "numeric"
##
## $phcg
## [1] "numeric"
##
## $phct
## [1] "numeric"
##
## $phcs
## [1] "numeric"
##
## $phcn
## [1] "numeric"
##
## $phci
## [1] "numeric"
##
## $hvc
## [1] "numeric"
##
## $vbsg
## [1] "numeric"
##
## $vbst
## [1] "numeric"
##
## $vbss
## [1] "numeric"
##
## $vbsn
## [1] "numeric"
##
## $vbsi
## [1] "numeric"
##
## $vasg
## [1] "numeric"
##
## $vast
## [1] "numeric"
##
## $vass
## [1] "numeric"
##

```

```
## $vasn
## [1] "numeric"
##
## $vasi
## [1] "numeric"
##
## $vbrg
## [1] "numeric"
##
## $vbrt
## [1] "numeric"
##
## $vbrs
## [1] "numeric"
##
## $vbrn
## [1] "numeric"
##
## $vbri
## [1] "numeric"
##
## $varg
## [1] "numeric"
##
## $vart
## [1] "numeric"
##
## $vars
## [1] "numeric"
##
## $varn
## [1] "numeric"
##
## $vari
## [1] "numeric"
##
## $mdg
## [1] "numeric"
##
## $mdt
## [1] "numeric"
##
## $mds
## [1] "numeric"
##
## $mdn
## [1] "numeric"
##
## $mdi
## [1] "numeric"
##
## $tmg
## [1] "numeric"
##
```

```
## $tgt
## [1] "numeric"
##
## $tms
## [1] "numeric"
##
## $tmn
## [1] "numeric"
##
## $tmi
## [1] "numeric"
##
## $mr
## [1] "numeric"
##
## $rnf
## [1] "numeric"
##
## $mdic
## [1] "numeric"
##
## $emd
## [1] "numeric"
##
## $mv
## [1] "numeric"
##
## $Class
## [1] "factor"
```

All variables are classified correctly.

Let us now create our training and test datasets so we can move on to model fitting:

```
set.seed(5) #random sample remains fixed in every run in R.
index_training <- sample(1:nrow(GlaucomaM_data), round(0.7*nrow(GlaucomaM_data)))
training_data <- GlaucomaM_data[index_training,]
test_data <- GlaucomaM_data[-index_training,]
```

Model Fitting: Elastic Net

Our response variable is “Class”, while the predictors are all the other variables.

```
X <- as.matrix(training_data[,-63])
Y <- training_data[,63]

library(glmnet)
```

```
## Warning: package 'glmnet' was built under R version 3.2.4
```

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



```
## Loading required package: foreach
```

```
## Loaded glmnet 2.0-5
```

```
fit1 <- cv.glmnet(X,Y, family='binomial')
```

The next command tells which covariates are selected. In addition, it gives the estimated coefficients. In this project, we care more about whether we have a good predictor for glaucoma or not, and not so much how individual variables affect the outcome. So we do not care much about the values of the estimated coefficients.

```
coef(fit1, s = "lambda.min")
```

```
## 63 x 1 sparse Matrix of class "dgCMatrix"
```

```
##              1
## (Intercept) -1.6431367
## ag          .
## at          .
## as          .
## an          .
## ai          .
## eag         .
## eat         .
## eas         .
## ean         .
## eai         .
## abrg        .
## abrt        .
## abrs        -1.5224756
## abrn        .
## abri        .
## hic         .
## mhcg        .
## mhct        .
## mhcs        .
## mhcnc       -0.5013093
## mhci        -6.9850653
## phcg        .
## phct        .
## phcs        .
## phcn        -1.7603040
## phci        -3.2963381
## hvc         .
## vbsg        .
## vbst        .
## vbss        .
## vbsn        .
## vbsi        .
## vasg        .
## vast        .
## vass        .
## vasn        .
## vasi        .
## vbrg        .
```

```
## vbrt      .
## vbrs      .
## vbrn      .
## vbri      .
## varg      2.6557843
## vart      .
## vars      16.1340404
## varn      .
## vari      .
## mdg      .
## mdt      .
## mds      .
## mdn      .
## mdi      .
## tmg      .
## tmt      .
## tms      -0.1314503
## tmn      .
## tmi      -1.5718128
## mr      .
## rnf      1.4466328
## mdic      .
## emd      .
## mv      .
```

The selected covariates in this model were “abrs”, “mhcn”, “mhci”, “phcn”, “phci”, “varg”, “vars”, “tms”, “tmi”, and “rnf”.

Let us see the performance in the training data first:

```
#The function "show" calculates missclassification error, i.e. how many people cases of "normal" or "glaucoma"
show <- function(tt){
  print(tt)
  cat(paste("Misclassification rate =", round(1-sum(diag(tt))/sum(tt),2),"\n"))
  invisible()
}

nx <- as.matrix(training_data[,-63])
nrow(training_data)
```

```
## [1] 137
```

```
nrow(test_data)
```

```
## [1] 59
```

```
show(with(training_data, table(actual=Y,
                                predicted=predict(fit1, newx = nx, s="lambda.min", type="class"))))
```

```
##           predicted
## actual   glaucoma normal
## glaucoma      65      8
## normal        9     55
## Misclassification rate = 0.12
```

Now let us see the performance on the test data:

```
nx <- as.matrix(test_data[,-63])
show(with(test_data, table(actual=test_data[,63],
                           predicted=predict(fit1, newx = nx, s="lambda.min", type="class"))))
```

```
##          predicted
## actual    glaucoma normal
##   glaucoma      22      3
##   normal       9      25
## Misclassification rate = 0.2
```

Conclusion

The misclassification rate overall in the training data is okay, but in the test data the misclassification rate is high. This could suggest:

- The model is overfit.
- The predictors are not good enough, i.e., we need better predictors.
- The model is not good enough.
- There is too much “randomness” in the data.

However, if we consider that the most “dangerous” prediction to be made is predict that a person would not have glaucoma, when actually the person had glaucoma, the results in the training and test data do not differ much. Only 3 people actually had glaucoma when the prediction did not say so in the test data, resulting in a misclassification rate of $0.12 = 3/(22+3)$, while in the training data this rate was around $0.109 = 8/(65+8)$.