

140.644 - Statistical Machine Learning

Final Project

Martin Skarzynski

March 18, 2018

Part 1: A prediction model for the age in months at time of examination, RIDAGEEX

```
load("nhanes2003-2004.Rda")

#Explore the dataset
dim(nhanes2003_2004)

## [1] 10122    813

#head(nhanes2003_2004)
#names(nhanes2003_2004)
#library(purrr, help)
#map(nhanes2003_2004, class)
library(dplyr, help)

##
## 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

#glimpse(nhanes2003_2004)

#Remove all rows with NAs in the outcome variable column
condition <- !is.na(nhanes2003_2004$RIDAGEEX)
length(condition)

## [1] 10122

nhanes2003_2004 <- nhanes2003_2004[condition,]
#Next, remove all variables with NAs
nhanes2003_2004 <- nhanes2003_2004[,colMeans(is.na(nhanes2003_2004))<=0.00]
# nhanes2003_2004 <- nhanes2003_2004[rowMeans(is.na(nhanes2003_2004))<=0.00,]

#Double check that removeing NAs worked
sum(!is.na(nhanes2003_2004))

## [1] 226320

sum(is.na(nhanes2003_2004))

## [1] 0
```

```

dim(nhanes2003_2004)

## [1] 9430 24

#glimpse(nhanes2003_2004)

# Remove factors with fewer than two levels
#str(nhanes2003_2004)
n_lev <- sapply(nhanes2003_2004, nlevels)
#head(n_lev)
nhanes2003_2004 <- nhanes2003_2004[ , n_lev>=2]

which(names(nhanes2003_2004)=="RIDAGEEX")

## [1] 9

#names(nhanes2003_2004)

#Turn all variables to numeric for now
nhanes2003_2004 <- sapply( nhanes2003_2004, as.numeric )
nhanes2003_2004 <- as.data.frame( nhanes2003_2004 )

"RIDAGEEX" %in% names(nhanes2003_2004)

## [1] TRUE
## nhanes2003_2004$RIDAGEEX <- as.numeric(nhanes2003_2004$RIDAGEEX)

set.seed(20180318)

nhanes <-
  nhanes2003_2004 %>%
  rowwise() %>%
  mutate(splt = sample(
    c("train", "test"),
    1,
    replace = TRUE,
    prob = c(0.75, 0.25) # Set weights for each group here
  ))
#head(nhanes)

train <- nhanes %>%
  filter(splt == "train") %>%
  select(-SEQN, -splt)

test <- nhanes %>%
  filter(splt == "test") %>%
  select(-SEQN, -splt)

index_train <- which(nhanes$splt=="train")
index_test <- which(nhanes$splt=="test")
dim(nhanes[index_train,-c(1,24)])

## [1] 7056 22

```

```
all(nhanes[index_train,-c(1,24)]==train)
```

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

```
dim(train)
```

```
## [1] 7056 22
```

```
#names(nhanes)
```

```
lin <- lm(formula = RIDAGEEX ~ .,  
          data = train,  
          na.action = na.omit) #NAs were already removed
```

When λ is zero, we should obtain the same results with linear, ridge and lasso regression.

```
library(glmnet, help)
```

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

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

```
## Loaded glmnet 2.0-13
```

```
#convert response variable to vector
```

```
y_train <- train$RIDAGEEX
```

```
mod_mat <- model.matrix(object = RIDAGEEX ~ ., data = train)
```

```
#mod_mat %>% head
```

```
rid_cv <- cv.glmnet(mod_mat, y_train, alpha = 0)
```

```
rid_lam <- rid_cv$lambda.min
```

```
rid_mod <- glmnet(x = mod_mat,  
                 y = y_train,  
                 alpha = 0,  
                 lambda = rid_lam)
```

```
las_cv <- cv.glmnet(mod_mat, y_train, alpha = 1)
```

```
las_lam <- las_cv$lambda.min
```

```
las_mod <- glmnet(x = mod_mat,  
                 y = y_train,  
                 alpha = 1,  
                 lambda = las_lam)
```

```
#make predictions
```

```
pred_lm <- predict(object = lin, newdata = test)
```

```
## Warning in predict.lm(object = lin, newdata = test): prediction from a
```

```
## rank-deficient fit may be misleading
```

```
mean((pred_lm - test$RIDAGEEX)^2)
```

```
## [1] 2779.574
```

```
test_mat <- model.matrix(RIDAGEEX ~ ., data = test)
```

```
rid_pred <- predict(rid_mod, s = rid_lam, newx = test_mat)
```

```
mean((rid_pred - test$RIDAGEEX)^2)
```

```
## [1] 3967.504
```

```
las_pred <- predict(las_mod, s = las_lam, newx = test_mat)
mean((las_pred - test$RIDAGEEX)^2)
```

```
## [1] 2787.77
```

```
coef(lin)
```

```
## (Intercept)      BMDSTATS      PEASCST1      RIDSTATR      RIDEXMON
## 3.210740e+01 -2.225614e-01 2.969798e+00      NA 1.221872e+00
## RIAGENDR      RIDAGEYR      RIDAGEMN      RIDRETH1      RIDRETH2
## -1.097913e-01 1.651047e-01 9.629433e-01 -9.632279e-01 1.166802e+00
## DMBORN      DMDCITZN      DMDHHSIZ      SIALANG      SIAPROXY
## 2.319925e-01 -8.185409e+00 -7.772925e-01 7.090095e+00 2.096446e+00
## SIAINTRP      WTINT2YR      WTMEC2YR      SDMVPSU      SDMVSTRA
## -1.072850e+01 7.094412e-04 -4.627857e-04 1.053173e-01 -1.423998e-01
## DR1DRSTZ      DR2DRSTZ
## -3.693276e+00 1.648239e+00
```

```
predict(rid_mod, s = rid_lam, exact = T, type = 'coefficients')
```

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

```
## 1
## (Intercept) 80.144337253
## (Intercept) .
## BMDSTATS 1.186328299
## PEASCST1 3.010562140
## RIDSTATR .
## RIDEXMON 2.055698820
## RIAGENDR -0.239904524
## RIDAGEYR 1.359788106
## RIDAGEMN 0.787370334
## RIDRETH1 -1.544006037
## RIDRETH2 0.824958488
## DMBORN 1.307483464
## DMDCITZN -13.547197571
## DMDHHSIZ -4.052524492
## SIALANG 11.954839886
## SIAPROXY 8.938828888
## SIAINTRP -17.312545231
## WTINT2YR -0.001575854
## WTMEC2YR -0.001138606
## SDMVPSU 0.654504185
## SDMVSTRA -0.192694936
## DR1DRSTZ -0.800713161
## DR2DRSTZ 0.660650015
```

```
predict(las_mod, s = las_lam, exact = T, type = 'coefficients')
```

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

```
## 1
## (Intercept) 13.5902482
## (Intercept) .
## BMDSTATS .
## PEASCST1 .
## RIDSTATR .
## RIDEXMON .
```

```
## RIAGENDR      .
## RIDAGEYR      0.1332356
## RIDAGEMN      0.9606375
## RIDRETH1      .
## RIDRETH2      .
## DMDDBORN      .
## DMDCITZN      .
## DMDHHSIZ      .
## SIALANG      .
## SIAPROXY      .
## SIAINTRP      .
## WTINT2YR      .
## WTMEC2YR      .
## SDMVPSU      .
## SDMVSTRA      .
## DR1DRSTZ      .
## DR2DRSTZ      .
```

The MSEs I obtained are really low, unfortunately, looking at the coefficients it appears that a few of the variables are driving the models. Upon further inspection, RIDAGEMN and RIDAGEYR is the age in months and years, respectively. I will rerun the models after removing these variables.

```
train2 <- train %>%
  select(-RIDAGEMN, -RIDAGEYR)

test2 <- test %>%
  select(-RIDAGEMN, -RIDAGEYR)

lin2 <- lm(formula = RIDAGEEX ~ .,
  data = train2,
  na.action = na.omit) #NAs were already removed

#convert response variable to vector
y_train2 <- train2$RIDAGEEX
mod_mat2 <- model.matrix(object = RIDAGEEX ~ ., data = train2)
#mod_mat2 %>% head

rid_cv2 <- cv.glmnet(mod_mat2, y_train2, alpha = 0)
rid_lam2 <- rid_cv2$lambda.min
rid_mod2 <- glmnet(x = mod_mat2,
  y = y_train2,
  alpha = 0,
  lambda = rid_lam2)

las_cv2 <- cv.glmnet(mod_mat2, y_train2, alpha = 1)
las_lam2 <- las_cv2$lambda.min
las_mod2 <- glmnet(x = mod_mat2,
  y = y_train2,
  alpha = 1,
  lambda = las_lam2)

#make predictions
pred_lm2 <- predict(object = lin2, newdata = test2)
```

```
## Warning in predict.lm(object = lin2, newdata = test2): prediction from a
```

```

## rank-deficient fit may be misleading
mean((pred_lm2 - test2$RIDAGEEX)^2)

## [1] 67086.84

test_mat2 <- model.matrix(RIDAGEEX ~ ., data = test2)

rid_pred2 <- predict(rid_mod2, s = rid_lam2, newx = test_mat2)
mean((rid_pred2 - test2$RIDAGEEX)^2)

## [1] 67170.32

las_pred2 <- predict(las_mod2, s = las_lam2, newx = test_mat2)
mean((las_pred2 - test2$RIDAGEEX)^2)

## [1] 67092.88

coef(lin2)

##      (Intercept)      BMDSTATS      PEASCST1      RIDSTATR      RIDEXMON
## 644.59400668    14.70610782    16.73483133           NA    13.06993171
##      RIAGENDR      RIDRETH1      RIDRETH2      DMBORN      DMDCITZN
## 6.56668458    -7.92154819   -10.88664541    43.10342921  -120.17079744
##      DMDHHSIZ      SIALANG      SIAPROXY      SIAINTRP      WTINT2YR
## -47.43690898    92.46659665   106.06749533   -96.62026334   -0.01568087
##      WTMEC2YR      SDMVPSU      SDMVSTRA      DR1DRSTZ      DR2DRSTZ
## -0.02159239     0.16133156   -0.83021491    12.12515026   -9.09910450

predict(rid_mod2, s = rid_lam2, exact = T, type = 'coefficients')

## 21 x 1 sparse Matrix of class "dgCMatrix"
##              1
## (Intercept) 634.55798922
## (Intercept) .
## BMDSTATS    14.76046516
## PEASCST1    16.31810247
## RIDSTATR    .
## RIDEXMON    12.06962470
## RIAGENDR    6.37345939
## RIDRETH1    -7.73782378
## RIDRETH2    -10.43609440
## DMBORN      38.12304130
## DMDCITZN    -106.13660962
## DMDHHSIZ    -45.76005969
## SIALANG     83.21932075
## SIAPROXY    103.97270981
## SIAINTRP    -92.53809987
## WTINT2YR    -0.01770495
## WTMEC2YR    -0.01981538
## SDMVPSU     0.34838774
## SDMVSTRA    -0.88199384
## DR1DRSTZ    10.87664069
## DR2DRSTZ    -8.27157724

predict(las_mod2, s = las_lam2, exact = T, type = 'coefficients')

## 21 x 1 sparse Matrix of class "dgCMatrix"

```

```
##                                1
## (Intercept) 637.63512973
## (Intercept) .
## BMDSTATS    14.43356411
## PEASCST1    15.97926172
## RIDSTATR    .
## RIDEXMON    12.29523129
## RIAGENDR    5.91603651
## RIDRETH1    -7.40621496
## RIDRETH2    -10.24691339
## DMDBORN     40.73254601
## DMDCITZN    -114.86491424
## DMDHHSIZ    -47.34453189
## SIALANG     90.00730520
## SIAPROXY    105.84308716
## SIAINTRP    -93.24053506
## WTINT2YR    -0.01565267
## WTMEC2YR    -0.02138917
## SDMVPSU     .
## SDMVSTRA    -0.76740007
## DR1DRSTZ    10.77998070
## DR2DRSTZ    -8.08346165
```

```
library(randomForest)
```

```
## randomForest 4.6-12
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
##
```

```
## Attaching package: 'randomForest'
```

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

```
##
```

```
##      combine
```

```
rf_mod <- randomForest(RIDAGEEX ~ ., data = train, mtry = ncol(train)-2, ntree = 500)
dim(train)
```

```
## [1] 7056  22
```

```
rf_pred <- predict(rf_mod, newdata = test)
length(rf_pred)
```

```
## [1] 2374
```

```
length(test$RIDAGEEX)
```

```
## [1] 2374
```

```
mean((rf_pred - test$RIDAGEEX)^2)
```

```
## [1] 924.8965
```

```
rf_mod2 <- randomForest(RIDAGEEX ~ ., data = train2, mtry = ncol(train2)-2, ntree = 500)
dim(train)
```

```
## [1] 7056  22
```

```
rf_pred2 <- predict(rf_mod2, newdata = test2)
length(rf_pred2)
```

```
## [1] 2374
```

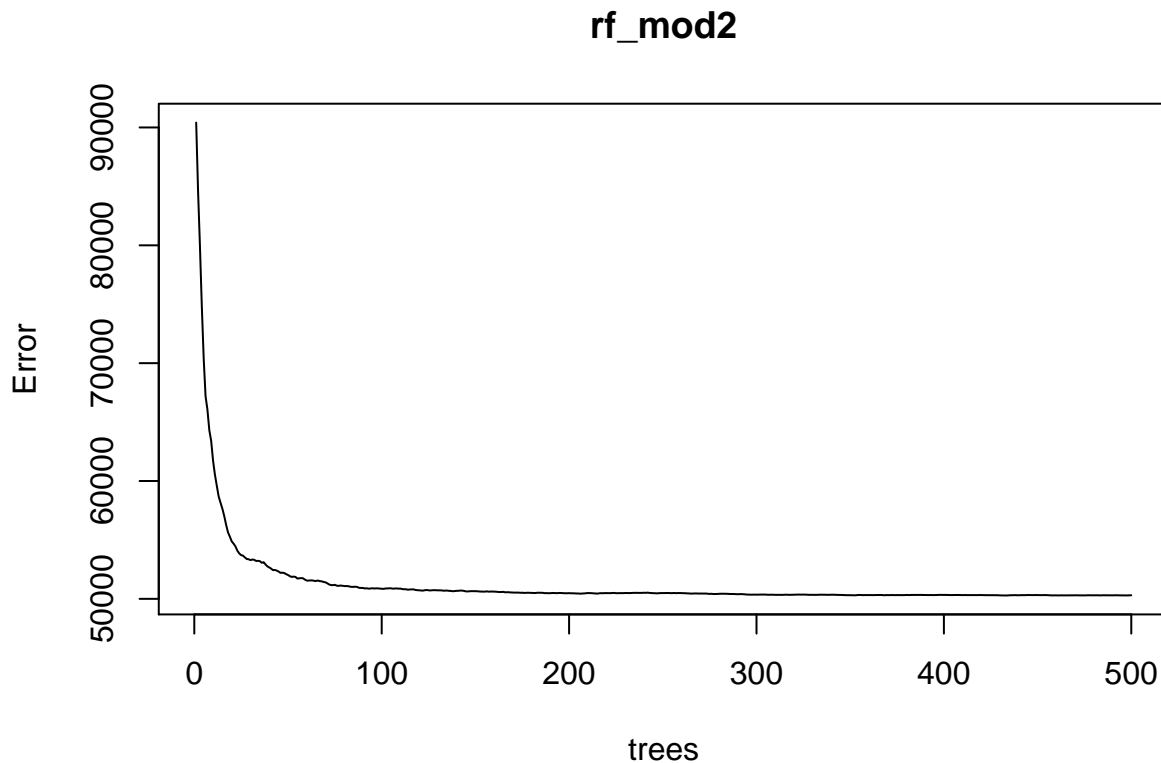
```
length(test2$RIDAGEEX)
```

```
## [1] 2374
```

```
mean((rf_pred2 - test2$RIDAGEEX)^2)
```

```
## [1] 50638.12
```

```
plot(rf_mod2)
```



```
#boosting
library(gbm)
```

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

```
## Loading required package: lattice
```

```
## Loading required package: splines
```

```
## Loading required package: parallel
```

```
## Loaded gbm 2.1.3
```

```
lambdas <- 10^seq(-10, -0.2, by = 0.1)
```

```
train_err <- rep(NA, length(lambdas))
```

```
for (i in 1:length(lambdas)) {
  boost <- gbm(RIDAGEEX ~ .,
               data = train2,
               distribution = "gaussian",
```


}

```
## w, : variable 3: RIDSTATR has no variation.
```

```
## Warning in gbm.fit(x, y, offset = offset, c
## w, : variable 3: RIDSTATR has no variation.
```

```
## Warning in gbm.fit(x, y, offset = offset, c
## w, : variable 3: RIDSTATR has no variation.
```

```
## w, : variable 3: RIDSTATR has no variation.
```

```
## w, : variable 3: RIDSTATR has no variation.
```

```
## w, : variable 3: RIDSTATR has no variation.
```

```
## w, : variable 3: RIDSTATR has no variation.
```

```
## w, : variable 3: RIDSTATR has no variation.
```

```
## w, : variable 3: RIDSTATR has no variation.
```

```
## w, : variable 3: RIDSTATR has no variation.
```

```
## w, : variable 3: RIDSTATR has no variation.
```

```
## w, : variable 3: RIDSTATR has no variation.
```

```
## w, : variable 3: RIDSTR has no variation.
```

```
## Warning in gbm.fit(x, y, offset = offset, c
## w, : variable 3: RIDSTATR has no variation.
```

```
## w, : variable 3: RIDSTATR has no variation.
```

```
## w, : variable 3: RIDSTATR has no variation.
```


[illegible]

[illegible]

[illegible]

```
## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.

## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.

## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.

## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.

## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.

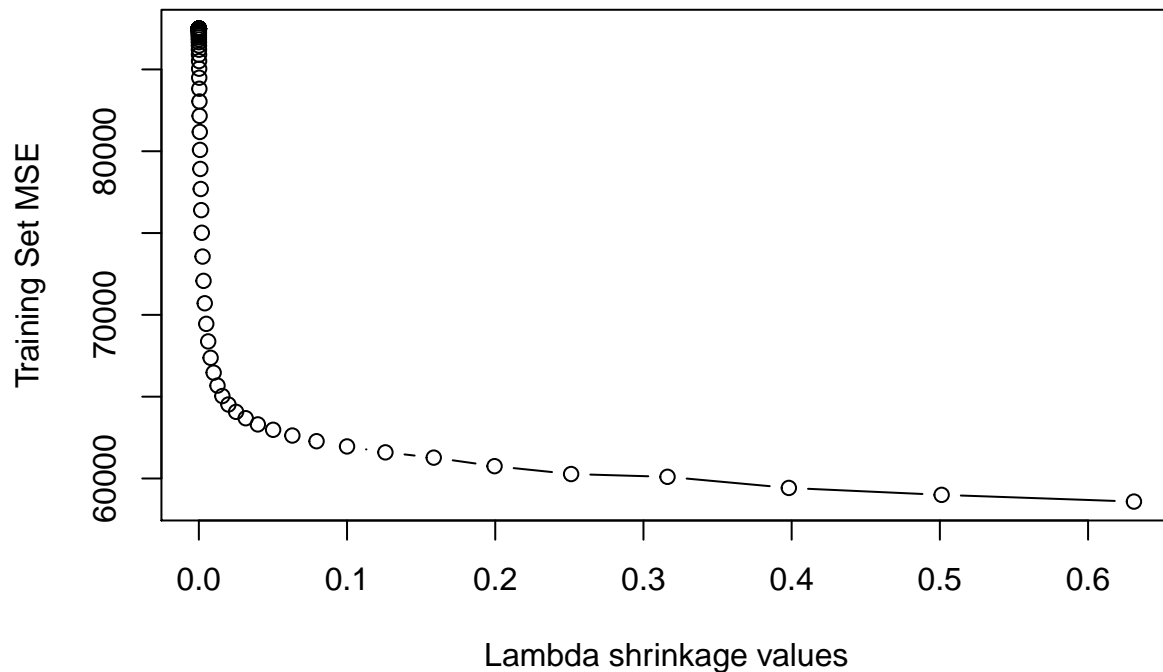
## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.

## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.

## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.

## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.
```

```
plot(lambdas,
     train_err,
     type = "b",
     xlab = "Lambda shrinkage values",
     ylab = "Training Set MSE")
```



Now I will produce a plot with different shrinkage values on the x -axis and the corresponding test set MSE on the y -axis.

```
test_err <- rep(NA, length(lambdas))
for (i in 1:length(lambdas)) {
  boost <- gbm(RIDAGEEX ~ .,
               data = train2,
               distribution = "gaussian",
               n.trees = 500,
               shrinkage = lambdas[i])
  pred_test <- predict(boost, test2, n.trees = 500)
  test_err[i] <- mean((pred_test - test2$RIDAGEEX)^2)
}
```

```
## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.
```

```
## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.
```

```
## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.
```

```
## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.
```

```
## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.
```

```
## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.
```

```
## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
```


[illegible]

[illegible]

```
## w, : variable 3: RIDSTATR has no variation.

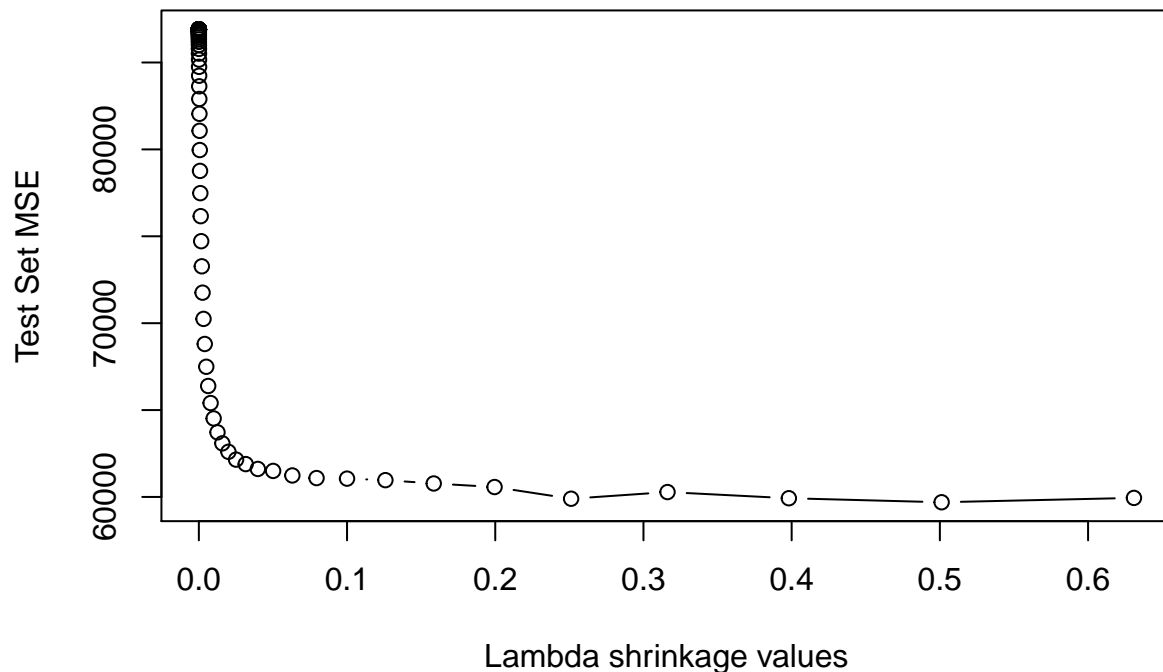
## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.

## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.

plot(lambdas,
     test_err,
     type = "b",
     xlab = "Lambda shrinkage values",
     ylab = "Test Set MSE")
which.min(test_err)

## [1] 98

abline(h = which.min(test_err), lty = 2, col = "red")
```



```
lambdas[which.min(test_err)]
```

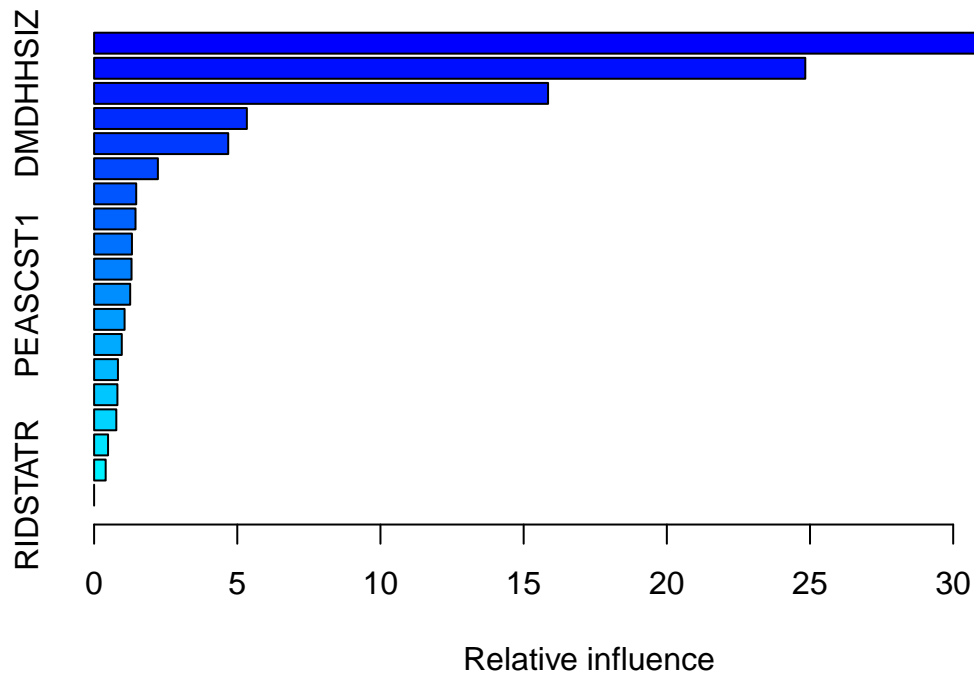
```
## [1] 0.5011872
```

The minimum test MSE is 98, which was obtained with λ of 0.501. The test MSE for boosting is (98).

```
library(gbm)
boost <- gbm(RIDAGEEX ~ .,
             data = train2,
             distribution = "gaussian",
             n.trees = 1000,
             shrinkage = lambdas[which.min(test_err)])
```

```
## Warning in gbm.fit(x, y, offset = offset, distribution = distribution, w =
## w, : variable 3: RIDSTATR has no variation.
```

```
summary(boost)
```



```
##          var      rel.inf
## WTINT2YR WTINT2YR 34.9185137
## WTMEC2YR WTMEC2YR 24.8350773
## DMDHHSIZ DMDHHSIZ 15.8527183
## SDMVSTRA SDMVSTRA  5.3338751
## SIAPROXY SIAPROXY  4.6830020
## RIDRETH1 RIDRETH1  2.2273256
## SIAINTRP SIAINTRP  1.4706002
## RIDRETH2 RIDRETH2  1.4463935
## DR1DRSTZ DR1DRSTZ  1.3213961
## SDMVPSU  SDMVPSU  1.3074629
## PEASCST1 PEASCST1  1.2595944
## DMDBORN  DMDBORN  1.0646520
## BMDSTATS BMDSTATS  0.9665995
## SIALANG  SIALANG  0.8323435
## DR2DRSTZ DR2DRSTZ  0.8138287
## DMDCITZN DMDCITZN  0.7756094
## RIAGENDR RIAGENDR  0.4869990
## RIDEXMON RIDEXMON  0.4040086
## RIDSTATR RIDSTATR  0.0000000
```

From the results above, it appears that WTINT2YR and WTMEC2YR are the most important and second most important variables, respectively. # Part 2: For participants 50 years and older, build a prediction model for the final mortality status, mortstat

```
load("nhanes2003-2004.Rda")
#head(nhanes2003_2004)
#Turn all variables to numeric
nhanes2003_2004 <- sapply( nhanes2003_2004, as.numeric )
nhanes2003_2004 <- as.data.frame( nhanes2003_2004 )
#Remove all rows with NAs in the outcome variable column
```

```

nhanes <- nhanes2003_2004 %>%
  filter(RIDAGEYR > 50) %>%
  filter(!is.na(mortstat))

#Next, remove all variables with NAs
nhanes <- nhanes[,colMeans(is.na(nhanes))<=0.00]
# nhanes2003_2004 <- nhanes2003_2004[rowMeans(is.na(nhanes2003_2004))<=0.00,]

#Double check that removeing NAs worked
sum(!is.na(nhanes))

## [1] 137268

sum(is.na(nhanes))

## [1] 0

dim(nhanes)

## [1] 2214    62

glimpse(nhanes)

## Observations: 2,214
## Variables: 62
## $ SEQN      <dbl> 5, 8, 11, 16, 17, 29, 32, 33, 35, 46, 47, 50, 51, 54,...
## $ BPQ010     <dbl> 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,...
## $ BPQ060     <dbl> 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 2, 1, 1, 2, 1,...
## $ SDDSRVYR   <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,...
## $ RIDSTATR   <dbl> 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,...
## $ RIAGENDR   <dbl> 1, 1, 1, 2, 2, 2, 2, 1, 2, 1, 1, 2, 2, 1, 1, 1, 2, 2,...
## $ RIDAGEYR   <dbl> 52, 61, 83, 52, 71, 54, 85, 85, 84, 67, 52, 56, 72, 7...
## $ RIDRETH1   <dbl> 3, 4, 3, 4, 3, 4, 3, 3, 3, 3, 3, 3, 1, 4, 3, 1, 2, 3,...
## $ RIDRETH2   <dbl> 1, 2, 1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 3, 2, 1, 3, 5, 1,...
## $ DMQMILIT   <dbl> 2, 2, 1, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 1,...
## $ DMDDBORN   <dbl> 1, 1, 1, 1, 3, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 2, 1, 1,...
## $ DMDCITZN   <dbl> 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1,...
## $ DMDEDUC2   <dbl> 3, 3, 4, 2, 3, 3, 2, 1, 3, 3, 3, 4, 1, 1, 2, 1, 3, 1, 1,...
## $ DMDEDUC    <dbl> 2, 2, 3, 1, 2, 2, 1, 1, 2, 2, 2, 3, 1, 1, 1, 1, 2, 1, 1,...
## $ DMDHHSIZ   <dbl> 2, 2, 2, 2, 1, 1, 1, 1, 1, 2, 2, 2, 1, 2, 2, 4, 2, 1, 1,...
## $ DMDHRGND   <dbl> 1, 1, 2, 1, 2, 2, 2, 1, 2, 1, 1, 2, 2, 1, 1, 2, 2, 2, 2,...
## $ DMDHRAGE   <dbl> 40, 48, 67, 45, 57, 42, 70, 70, 69, 54, 40, 44, 58, 3...
## $ SIALANG     <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1,...
## $ SIAPROXY    <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,...
## $ SIAINTRP    <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,...
## $ WTINT2YR    <dbl> 3505, 243, 550, 1049, 1976, 881, 626, 582, 455, 2529,...
## $ WTMEC2YR    <dbl> 5064, 405, 953, 1622, 1, 1332, 1116, 986, 846, 4009, ...
## $ SDMVPSU     <dbl> 2, 2, 2, 1, 2, 1, 1, 2, 2, 2, 2, 2, 2, 2, 1, 1, 2, 2, 2,...
## $ SDMVSTRA    <dbl> 3, 5, 5, 10, 11, 13, 10, 11, 2, 4, 2, 11, 8, 13, 5, 1...
## $ DIQ010      <dbl> 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,...
## $ DIQ050      <dbl> 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,...
## $ DIQ090      <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,...
## $ DIQ100      <dbl> 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 1, 1, 2, 2, 1, 1, 2, 2,...
## $ DIQ120      <dbl> 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 1, 1, 2, 2, 1, 2, 2, 1,...
## $ DIQ140      <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 2, 1, 2, 2, 2, 2, 1, 1,...
## $ HSAQUEX     <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,...

```

```
## $ MCQ010 <dbl> 2, 2, 1, 1, 1, 2, 2, 2, 2, 2, 2, 1, 2, 2, 1, 2, 2, 1, ...
## $ MCQ053 <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, ...
## $ MCQ092 <dbl> 2, 2, 1, 2, 1, 2, 2, 1, 2, 1, 2, 2, 2, 2, 1, 2, 2, 2, ...
## $ MCQ140 <dbl> 2, 2, 1, 2, 2, 2, 2, 1, 2, 2, 2, 1, 1, 2, 2, 2, 2, 2, ...
## $ MCQ160A <dbl> 2, 1, 1, 2, 1, 2, 2, 2, 1, 1, 1, 2, 1, 1, 2, 2, 1, 1, ...
## $ MCQ160B <dbl> 2, 2, 2, 2, 1, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, ...
## $ MCQ160C <dbl> 2, 2, 1, 2, 1, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, ...
## $ MCQ160D <dbl> 2, 2, 2, 2, 1, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, ...
## $ MCQ160E <dbl> 2, 2, 1, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, ...
## $ MCQ160F <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, ...
## $ MCQ160G <dbl> 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, ...
## $ MCQ160J <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 1, 1, 2, 1, 2, 2, 2, 1, 2, 1, ...
## $ MCQ160K <dbl> 2, 2, 2, 1, 1, 1, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 1, ...
## $ MCQ160L <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, ...
## $ MCQ160M <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, ...
## $ MCQ220 <dbl> 2, 2, 1, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, ...
## $ MCQ245A <dbl> 1, 1, 2, 1, 2, 1, 2, 2, 2, 2, 1, 1, 1, 2, 2, 2, 1, 2, ...
## $ MCQ250A <dbl> 2, 2, 2, 2, 1, 1, 2, 2, 2, 3, 1, 2, 2, 2, 1, 2, 3, 1, ...
## $ MCQ250B <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 2, 3, 2, 1, 2, 2, 2, 2, 3, 2, ...
## $ MCQ250C <dbl> 2, 2, 1, 1, 2, 2, 2, 2, 2, 3, 1, 2, 2, 2, 2, 2, 3, 2, ...
## $ MCQ250E <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 3, 1, 2, 2, 1, 2, 2, 2, 3, 2, ...
## $ MCQ250F <dbl> 2, 1, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 3, 1, ...
## $ MCQ250G <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 3, 2, ...
## $ MCQ265 <dbl> 4, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 4, 2, ...
## $ SSQ011 <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, ...
## $ SSQ051 <dbl> 1, 1, 1, 2, 2, 1, 1, 1, 2, 2, 1, 1, 2, 1, 1, 1, 1, 2, ...
## $ SSQ061 <dbl> 15, 2, 3, 20, 20, 24, 3, 11, 24, 5, 12, 2, 1, 22, 20, ...
## $ WHQ030 <dbl> 1, 2, 3, 3, 1, 1, 3, 3, 1, 1, 1, 1, 3, 1, 3, 1, 1, 1, ...
## $ WHQ040 <dbl> 2, 1, 3, 3, 2, 2, 3, 3, 2, 2, 2, 2, 3, 2, 3, 2, 2, 2, ...
## $ WHQ090 <dbl> 2, 2, 2, 2, 1, 1, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, ...
## $ mortstat <dbl> 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, ...
```

```
# Remove factors with fewer than two levels
str(nhanes)
```

```
## 'data.frame': 2214 obs. of 62 variables:
## $ SEQN : num 5 8 11 16 17 29 32 33 35 46 ...
## $ BPQ010 : num 2 1 1 1 1 1 1 1 1 1 ...
## $ BPQ060 : num 1 1 1 1 1 1 2 1 1 1 ...
## $ SDDSRVYR: num 1 1 1 1 1 1 1 1 1 1 ...
## $ RIDSTATR: num 2 2 2 2 1 2 2 2 2 2 ...
## $ RIAGENDR: num 1 1 1 2 2 2 2 1 2 1 ...
## $ RIDAGEYR: num 52 61 83 52 71 54 85 85 84 67 ...
## $ RIDRETH1: num 3 4 3 4 3 4 3 3 3 3 ...
## $ RIDRETH2: num 1 2 1 2 1 2 1 1 1 1 ...
## $ DMQMILIT: num 2 2 1 2 2 2 2 1 2 2 ...
## $ DMDBORN : num 1 1 1 1 3 1 1 1 1 1 ...
## $ DMDCITZN: num 1 1 1 1 2 1 1 1 1 1 ...
## $ DMDEDUC2: num 3 3 4 2 3 3 2 1 3 3 ...
## $ DMDEDUC : num 2 2 3 1 2 2 1 1 2 2 ...
## $ DMDHHSIZ: num 2 2 2 2 1 1 1 1 1 2 ...
## $ DMDHRGND: num 1 1 2 1 2 2 2 1 2 1 ...
## $ DMDHRAGE: num 40 48 67 45 57 42 70 70 69 54 ...
## $ SIALANG : num 1 1 1 1 1 1 1 1 1 1 ...
## $ SIAPROXY: num 2 2 2 2 2 2 2 2 2 2 ...
```



```
## $ SIAINTRP: num 2 2 2 2 2 2 2 2 2 ...
## $ WTINT2YR: num 3505 243 550 1049 1976 ...
## $ WTMEC2YR: num 5064 405 953 1622 1 ...
## $ SDMVPSU : num 2 2 2 1 2 1 1 2 2 2 ...
## $ SDMVSTRA: num 3 5 5 10 11 13 10 11 2 4 ...
## $ DIQ010 : num 2 2 2 2 1 2 2 2 2 2 ...
## $ DIQ050 : num 2 2 2 2 1 2 2 2 2 2 ...
## $ DIQ090 : num 2 2 2 2 2 2 2 2 2 2 ...
## $ DIQ100 : num 2 2 2 2 1 2 2 2 2 2 ...
## $ DIQ120 : num 2 2 2 2 1 2 2 2 2 2 ...
## $ DIQ140 : num 2 2 2 2 2 2 2 2 2 1 ...
## $ HSAQUEX : num 2 2 2 2 2 2 2 2 2 2 ...
## $ MCQ010 : num 2 2 1 1 1 2 2 2 2 2 ...
## $ MCQ053 : num 2 2 2 2 2 2 2 2 2 2 ...
## $ MCQ092 : num 2 2 1 2 1 2 2 1 2 1 ...
## $ MCQ140 : num 2 2 1 2 2 2 2 1 2 2 ...
## $ MCQ160A : num 2 1 1 2 1 2 2 2 1 1 ...
## $ MCQ160B : num 2 2 2 2 1 2 2 2 2 1 ...
## $ MCQ160C : num 2 2 1 2 1 2 2 2 2 1 ...
## $ MCQ160D : num 2 2 2 2 1 2 2 2 2 1 ...
## $ MCQ160E : num 2 2 1 2 2 2 2 2 2 1 ...
## $ MCQ160F : num 2 2 2 2 2 2 2 2 2 2 ...
## $ MCQ160G : num 2 2 2 2 1 2 2 2 2 2 ...
## $ MCQ160J : num 2 2 2 2 2 2 2 2 1 1 ...
## $ MCQ160K : num 2 2 2 1 1 1 2 2 1 2 ...
## $ MCQ160L : num 2 2 2 2 2 2 2 2 2 2 ...
## $ MCQ160M : num 2 2 2 2 2 2 2 2 1 1 ...
## $ MCQ220 : num 2 2 1 2 2 1 2 2 2 2 ...
## $ MCQ245A : num 1 1 2 1 2 1 2 2 2 2 ...
## $ MCQ250A : num 2 2 2 2 1 1 2 2 2 3 ...
## $ MCQ250B : num 2 2 2 2 2 2 2 2 2 3 ...
## $ MCQ250C : num 2 2 1 1 2 2 2 2 2 3 ...
## $ MCQ250E : num 2 2 2 2 2 2 2 2 3 1 ...
## $ MCQ250F : num 2 1 2 1 2 2 2 2 2 2 ...
## $ MCQ250G : num 2 2 2 2 2 2 2 2 2 2 ...
## $ MCQ265 : num 4 2 2 2 2 2 2 2 2 2 ...
## $ SSQ011 : num 1 1 1 1 1 1 1 1 1 1 ...
## $ SSQ051 : num 1 1 1 2 2 1 1 1 2 2 ...
## $ SSQ061 : num 15 2 3 20 20 24 3 11 24 5 ...
## $ WHQ030 : num 1 2 3 3 1 1 3 3 1 1 ...
## $ WHQ040 : num 2 1 3 3 2 2 3 3 2 2 ...
## $ WHQ090 : num 2 2 2 2 1 1 2 2 1 2 ...
## $ mortstat: num 0 0 1 0 1 0 1 1 0 0 ...
```

```
unique(nhanes$SDDSRVYR)
```

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

```
unique(nhanes$mortstat)
```

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

```
"mortstat" %in% names(nhanes)
```

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

```

nhanes2003_2004$RIDAGEEX <- as.numeric(nhanes2003_2004$RIDAGEEX)

set.seed(20180318)

nhanes <-
  nhanes %>%
  rowwise() %>%
  mutate(splt = sample(
    c("train", "test"),
    1,
    replace = TRUE,
    prob = c(0.75, 0.25) # Set weights for each group here
  ))
#head(nhanes)

train <- nhanes %>%
  filter(splt == "train")%>%
  # select(-SEQN, -splt, -SDDSRVYR)

test <- nhanes %>%
  filter(splt == "test")%>%
  # select(-SEQN, -splt, -SDDSRVYR)
train <- train[,-c(1,3,ncol(train))]
test <- test[,-c(1,3,ncol(test))]

index_train <- which(nhanes$splt=="train")
index_test <- which(nhanes$splt=="test")

logis <- glm(formula = mortstat ~ .,
  family = binomial,
  data = train,
  na.action = na.omit) #NAs were already removed

```

When λ is zero, we should obtain the same results with linear, ridge and lasso regression.

```

library(glmnet, help)

#convert response variable to vector
y_train <- train$mortstat
mod_mat <- model.matrix(object = mortstat ~ ., data = train)
#mod_mat %>% head

rid_cv <- cv.glmnet(mod_mat, y_train, alpha = 0)
rid_lam <- rid_cv$lambda.min
rid_mod <- glmnet(x = mod_mat,
  y = y_train,
  family = "binomial",
  alpha = 0,
  lambda = rid_lam)

las_cv <- cv.glmnet(mod_mat, y_train, alpha = 1)
las_lam <- las_cv$lambda.min
las_mod <- glmnet(x = mod_mat,
  y = y_train,

```

```

        family = "binomial",
        alpha = 1,
        lambda = las_lam)

#make predictions
y_test <- test$mortstat
prob_logis <- predict(object = logis, newdata = test, type = "response")

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading

pred_logis <- rep(0,length(y_test))
pred_logis[prob_logis>.5]=1
table(pred_logis,y_test)

##           y_test
## pred_logis    0    1
##           0 325  81
##           1  60  86

#prediction accuracy
mean(pred_logis==y_test)*100

## [1] 74.45652

#missclassification rate
(1-mean(pred_logis==y_test))*100

## [1] 25.54348

test_mat <- model.matrix(mortstat ~ ., data = test)

rid_prob <- predict(rid_mod, s = rid_lam, newx = test_mat, type = "response")
rid_pred <- rep(0, length(y_test))
rid_pred[rid_prob>.5]=1
table(rid_pred,y_test)

##           y_test
## rid_pred    0    1
##           0 339  87
##           1  46  80

#prediction accuracy
mean(rid_pred==y_test)*100

## [1] 75.9058

#missclassification rate
(1-mean(rid_pred==y_test))*100

## [1] 24.0942

las_prob <- predict(las_mod, s = las_lam, newx = test_mat, type = "response")
las_pred <- rep(0, length(y_test))
las_pred[las_prob>.5]=1
table(las_pred,y_test)

##           y_test
## las_pred    0    1

```

```
##          0 337 82
##          1 48 85

#prediction accuracy
mean(las_pred==y_test)*100

## [1] 76.44928

#missclassification rate
(1-mean(las_pred==y_test))*100

## [1] 23.55072

exp(coef(logis))

## (Intercept)      BPQ010      SDDSRVYR      RIDSTATR      RIAGENDR
## 1.338503e+04 9.914407e-01          NA 4.182160e-01 6.189123e-01
##      RIDAGEYR      RIDRETH1      RIDRETH2      DMQMILIT      DMDBORN
## 1.114684e+00 8.563293e-01 9.264521e-01 8.634467e-01 7.101031e-01
##      DMDCITZN      DMDEDUC2      DMDEDUC      DMDHHSIZ      DMDHRGND
## 1.040911e+00 1.150674e+00 8.766823e-01 8.670911e-01 1.234636e+00
##      DMDHRAGE      SIALANG      SIAPROXY      SIAINTRP      WTINT2YR
## 9.780151e-01 7.504155e-01 3.507126e-01 1.028543e+00 9.997589e-01
##      WTMEC2YR      SDMVPSU      SDMVSTRA      DIQ010      DIQ050
## 9.999094e-01 7.683430e-01 1.004613e+00 7.731992e-01 4.071165e-01
##      DIQ090      DIQ100      DIQ120      DIQ140      HSAQUEX
## 3.347229e-01 1.271025e+00 8.991786e-01 7.080853e-01          NA
##      MCQ010      MCQ053      MCQ092      MCQ140      MCQ160A
## 8.551744e-01 7.069943e-01 6.595456e-01 7.384368e-01 9.375922e-01
##      MCQ160B      MCQ160C      MCQ160D      MCQ160E      MCQ160F
## 5.564638e-01 9.781467e-01 1.117502e+00 8.091150e-01 8.140195e-01
##      MCQ160G      MCQ160J      MCQ160K      MCQ160L      MCQ160M
## 3.709946e-01 9.540182e-01 6.910058e-01 8.340894e-01 1.267628e+00
##      MCQ220      MCQ245A      MCQ250A      MCQ250B      MCQ250C
## 9.035755e-01 1.623616e+00 1.012003e+00 1.014368e+00 9.102191e-01
##      MCQ250E      MCQ250F      MCQ250G      MCQ265      SSQ011
## 1.040810e+00 9.447993e-01 9.712902e-01 8.398450e-01 1.200370e+00
##      SSQ051      SSQ061      WHQ030      WHQ040      WHQ090
## 1.003854e+00 1.013731e+00 1.326810e+00 8.088459e-01 1.386947e+00
```

```
exp(predict(rid_mod, s = rid_lam, exact = T, type = 'coefficients'))
```

```
## 61 x 1 Matrix of class "dgeMatrix"
##          1
## (Intercept) 798.2331029
## (Intercept) 1.0000000
## BPQ010      0.9810742
## SDDSRVYR    1.0000000
## RIDSTATR    0.5828499
## RIAGENDR    0.7976910
## RIDAGEYR    1.0527695
## RIDRETH1    0.9449378
## RIDRETH2    0.9302608
## DMQMILIT    0.7975303
## DMDBORN     0.8457229
## DMDCITZN    0.9438924
## DMDEDUC2    1.0108619
```

```

## DMDDEDUC      1.0010844
## DMDHHSIZ      0.9435363
## DMDHRGND      1.1481368
## DMDHRAGE      1.0071956
## SIALANG        0.8527956
## SIAPROXY       0.4777184
## SIAINTRP       1.0378410
## WTINT2YR       0.9998252
## WTMEC2YR       0.9998780
## SDMVPSU        0.8655845
## SDMVSTRA       0.9995056
## DIQ010         0.8305113
## DIQ050         0.5706851
## DIQ090         0.4975548
## DIQ100         1.0983771
## DIQ120         0.9331856
## DIQ140         0.8475899
## HSAQUEX        1.0000000
## MCQ010         0.8968256
## MCQ053         0.7290153
## MCQ092         0.7486695
## MCQ140         0.7709688
## MCQ160A        0.9219354
## MCQ160B        0.6075462
## MCQ160C        0.9250233
## MCQ160D        1.0072005
## MCQ160E        0.8560984
## MCQ160F        0.8225180
## MCQ160G        0.4742283
## MCQ160J        1.0411908
## MCQ160K        0.7875970
## MCQ160L        0.9486981
## MCQ160M        1.1266722
## MCQ220         0.8755903
## MCQ245A        1.5586635
## MCQ250A        1.0299147
## MCQ250B        1.0238114
## MCQ250C        0.9229038
## MCQ250E        1.0556966
## MCQ250F        0.9989832
## MCQ250G        1.0022665
## MCQ265         0.9322941
## SSQ011         1.0901229
## SSQ051         0.9924645
## SSQ061         1.0080422
## WHQ030         1.1628070
## WHQ040         0.9650176
## WHQ090         1.2782109

```

```
exp(predict(las_mod, s = las_lam, exact = T, type = 'coefficients'))
```

```

## 61 x 1 Matrix of class "dgeMatrix"
##              1
## (Intercept) 299.4966713
## (Intercept) 1.0000000

```

## BPQ010	1.0000000
## SDDSRVYR	1.0000000
## RIDSTATR	0.4770661
## RIAGENDR	0.6910605
## RIDAGEYR	1.0981468
## RIDRETH1	0.9964678
## RIDRETH2	0.9994903
## DMQMILIT	0.8647099
## DMDBORN	0.7455959
## DMDCITZN	1.0000000
## DMDDEDUC2	1.0156403
## DMDDEDUC	1.0000000
## DMDHHSIZ	0.9385592
## DMDHRGND	1.1201018
## DMDHRAGE	0.9942549
## SIALANG	0.8820657
## SIAPROXY	0.4880736
## SIAINTRP	1.0000000
## WTINT2YR	0.9998336
## WTMEC2YR	0.9999115
## SDMVPSU	0.8574278
## SDMVSTRA	1.0000000
## DIQ010	0.8135888
## DIQ050	0.4941549
## DIQ090	0.3954753
## DIQ100	1.0169715
## DIQ120	0.9912958
## DIQ140	0.8126362
## HSAQUEX	1.0000000
## MCQ010	0.9342817
## MCQ053	0.7751238
## MCQ092	0.6977869
## MCQ140	0.7876512
## MCQ160A	0.9924716
## MCQ160B	0.5850207
## MCQ160C	1.0000000
## MCQ160D	1.0000000
## MCQ160E	0.8876824
## MCQ160F	0.8956696
## MCQ160G	0.3983468
## MCQ160J	1.0000000
## MCQ160K	0.7320843
## MCQ160L	0.9577582
## MCQ160M	1.0929697
## MCQ220	0.9534763
## MCQ245A	1.4699759
## MCQ250A	1.0000000
## MCQ250B	1.0000000
## MCQ250C	0.9548581
## MCQ250E	1.0000000
## MCQ250F	1.0000000
## MCQ250G	1.0000000
## MCQ265	0.9157886
## SSQ011	1.0478959

```
## SSQ051      1.0000000
## SSQ061      1.0089709
## WHQ030      1.1587417
## WHQ040      0.9731150
## WHQ090      1.2478374
```

```
#head(train)
library(MASS, help)
```

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

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

```
#fit_lda <- lda(mortstat ~ ., data = train)
#fit_lda
#pred_lda <- predict(fit_lda, Weekly_20092010)
#table(pred_lda$class, mortstat_20092010)
#
#fit_qda <- qda(mortstat ~ ., data = Weekly, subset = train)
#fit_qda
#pred_qda <- predict(fit_qda, Weekly_20092010)
#table(pred_qda$class, mortstat_20092010)
```