ALY 6015 M3 Report - Thota, Sunil Raj.R

```
# Intermediate Analytics
# ALY 6015
# Module 3 - Regularization Assignment
# 02/03/2021
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# Get and set the working directories
getwd()

## [1] "G:/NEU/Coursework/2021 Q1 Winter/ALY 6015 IA/Discussions &
Assignments"

setwd('G:/NEU/Coursework/2021 Q1 Winter/ALY 6015 IA/Discussions &
Assignments')
getwd()

## [1] "G:/NEU/Coursework/2021 Q1 Winter/ALY 6015 IA/Discussions &
Assignments"

# Installed the above packages into the work space
install.packages("datasets")
install.packages("plyr")
install.packages("dplyr")
install.packages("tidyr")
install.packages("ncvreg")
install.packages("biglasso")
install.packages("bigmemory")
install.packages("glmnet")

# Loaded the below libraries into the work space

library(plyr)
library(dplyr)
library(tidyr)
require(datasets)
library(biglasso)
library(bigmemory)
library(ncvreg)


data(mtcars)
attach(mtcars)
View(mtcars)
```

```
head(mtcars)
```

```
##                    mpg cyl disp  hp drat    wt  qsec vs am gear carb
## Mazda RX4         21.0   6  160 110 3.90 2.620 16.46  0  1    4    4
## Mazda RX4 Wag     21.0   6  160 110 3.90 2.875 17.02  0  1    4    4
## Datsun 710        22.8   4  108  93 3.85 2.320 18.61  1  1    4    1
## Hornet 4 Drive    21.4   6  258 110 3.08 3.215 19.44  1  0    3    1
## Hornet Sportabout 18.7   8  360 175 3.15 3.440 17.02  0  0    3    2
## Valiant           18.1   6  225 105 2.76 3.460 20.22  1  0    3    1
```

```
tail(mtcars)
```

```
##                 mpg cyl  disp  hp drat    wt qsec vs am gear carb
## Porsche 914-2  26.0   4 120.3  91 4.43 2.140 16.7  0  1    5    2
## Lotus Europa   30.4   4  95.1 113 3.77 1.513 16.9  1  1    5    2
## Ford Pantera L 15.8   8 351.0 264 4.22 3.170 14.5  0  1    5    4
## Ferrari Dino   19.7   6 145.0 175 3.62 2.770 15.5  0  1    5    6
## Maserati Bora  15.0   8 301.0 335 3.54 3.570 14.6  0  1    5    8
## Volvo 142E     21.4   4 121.0 109 4.11 2.780 18.6  1  1    4    2
```

```
str(mtcars)
```

```
## 'data.frame':    32 obs. of  11 variables:
##  $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
##  $ cyl : num  6 6 4 6 8 6 8 4 4 6 ...
##  $ disp: num  160 160 108 258 360 ...
##  $ hp  : num  110 110 93 110 175 105 245 62 95 123 ...
##  $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
##  $ wt  : num  2.62 2.88 2.32 3.21 3.44 ...
##  $ qsec: num  16.5 17 18.6 19.4 17 ...
##  $ vs  : num  0 0 1 1 0 1 0 1 1 1 ...
##  $ am  : num  1 1 1 0 0 0 0 0 0 0 ...
##  $ gear: num  4 4 4 3 3 3 3 4 4 4 ...
##  $ carb: num  4 4 1 1 2 1 4 2 2 4 ...
```

```
summary(mtcars)
```

```
##       mpg             cyl             disp             hp       
##  Min.   :10.40   Min.   :4.000   Min.   : 71.1   Min.   : 52.0  
##  1st Qu.:15.43   1st Qu.:4.000   1st Qu.:120.8   1st Qu.: 96.5  
##  Median :19.20   Median :6.000   Median :196.3   Median :123.0  
##  Mean   :20.09   Mean   :6.188   Mean   :230.7   Mean   :146.7  
##  3rd Qu.:22.80   3rd Qu.:8.000   3rd Qu.:326.0   3rd Qu.:180.0  
##  Max.   :33.90   Max.   :8.000   Max.   :472.0   Max.   :335.0  
##       drat             wt             qsec             vs        
##  Min.   :2.760   Min.   :1.513   Min.   :14.50   Min.   :0.0000  
##  1st Qu.:3.080   1st Qu.:2.581   1st Qu.:16.89   1st Qu.:0.0000  
##  Median :3.695   Median :3.325   Median :17.71   Median :0.0000  
##  Mean   :3.597   Mean   :3.217   Mean   :17.85   Mean   :0.4375  
##  3rd Qu.:3.920   3rd Qu.:3.610   3rd Qu.:18.90   3rd Qu.:1.0000  
##  Max.   :4.930   Max.   :5.424   Max.   :22.90   Max.   :1.0000  
```

```
##        am              gear            carb      
##  Min.   :0.0000   Min.   :3.000   Min.   :1.000  
##  1st Qu.:0.0000   1st Qu.:3.000   1st Qu.:2.000  
##  Median :0.0000   Median :4.000   Median :2.000  
##  Mean   :0.4062   Mean   :3.688   Mean   :2.812  
##  3rd Qu.:1.0000   3rd Qu.:4.000   3rd Qu.:4.000  
##  Max.   :1.0000   Max.   :5.000   Max.   :8.000

# Let's perform some Regularization analysis and techniques using "mtcars"
data set. This data set is readily available in the R Studio and can be
loaded to the work space in R Studio. Or we can also install the packages by
using install.packages("packagename") command. Once it is loaded we can use
it in the code for further analysis and calculations.

# Loaded the "mtcars" data into the work space. To reduce the repetitive
usage of "mtcars" data set, "attach" is used to set it once throughout the
work space. To View the diabetes Data set we use View() command, To observe
the structure of the Data set we use str() command, and head () and tail()
shows first and last few rows in the Data set. Summary() Provides the
Descriptive Stats of the x variable in diabetes Data set.

y <- mtcars$hp
y

##  [1] 110 110  93 110 175 105 245  62  95 123 123 180 180 180 205 215 230
66  52
## [20]  65  97 150 150 245 175  66  91 113 264 175 335 109

x <- data.matrix(mtcars[, c('mpg', 'wt', 'drat', 'qsec')])
x

##                      mpg    wt drat  qsec
## Mazda RX4           21.0 2.620 3.90 16.46
## Mazda RX4 Wag       21.0 2.875 3.90 17.02
## Datsun 710          22.8 2.320 3.85 18.61
## Hornet 4 Drive      21.4 3.215 3.08 19.44
## Hornet Sportabout   18.7 3.440 3.15 17.02
## Valiant             18.1 3.460 2.76 20.22
## Duster 360          14.3 3.570 3.21 15.84
## Merc 240D           24.4 3.190 3.69 20.00
## Merc 230            22.8 3.150 3.92 22.90
## Merc 280            19.2 3.440 3.92 18.30
## Merc 280C           17.8 3.440 3.92 18.90
## Merc 450SE          16.4 4.070 3.07 17.40
## Merc 450SL          17.3 3.730 3.07 17.60
## Merc 450SLC         15.2 3.780 3.07 18.00
## Cadillac Fleetwood  10.4 5.250 2.93 17.98
## Lincoln Continental 10.4 5.424 3.00 17.82
## Chrysler Imperial   14.7 5.345 3.23 17.42
## Fiat 128            32.4 2.200 4.08 19.47
## Honda Civic         30.4 1.615 4.93 18.52
```

```
## Toyota Corolla      33.9 1.835 4.22 19.90
## Toyota Corona       21.5 2.465 3.70 20.01
## Dodge Challenger    15.5 3.520 2.76 16.87
## AMC Javelin         15.2 3.435 3.15 17.30
## Camaro Z28          13.3 3.840 3.73 15.41
## Pontiac Firebird    19.2 3.845 3.08 17.05
## Fiat X1-9           27.3 1.935 4.08 18.90
## Porsche 914-2       26.0 2.140 4.43 16.70
## Lotus Europa        30.4 1.513 3.77 16.90
## Ford Pantera L      15.8 3.170 4.22 14.50
## Ferrari Dino        19.7 2.770 3.62 15.50
## Maserati Bora       15.0 3.570 3.54 14.60
## Volvo 142E          21.4 2.780 4.11 18.60

linReg1OLS <- lm(y ~ x)
linReg1OLS

##
## Call:
## lm(formula = y ~ x)
##
## Coefficients:
## (Intercept)         xmpg          xwt        xdrat        xqsec
##     473.779       -2.877       26.037        4.819      -20.751

summary(linReg1OLS)

##
## Call:
## lm(formula = y ~ x)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -48.801 -16.007  -5.482  11.614  97.338
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  473.779    105.213   4.503 0.000116 ***
## xmpg          -2.877      2.381  -1.209 0.237319
## xwt           26.037     13.514   1.927 0.064600 .
## xdrat          4.819     15.952   0.302 0.764910
## xqsec        -20.751      3.993  -5.197 1.79e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 32.25 on 27 degrees of freedom
## Multiple R-squared:  0.8073, Adjusted R-squared:  0.7787
## F-statistic: 28.27 on 4 and 27 DF,  p-value: 2.647e-09

# Here "y" variable is taken as the response variable. Here "x" is assigned
with a matrix of predictor variables
```

```r
# In this, we need to regress "y" on the predictors in "x" using Ordinary
Least Squares(OLS). The regression model was taken between "y" and "x"

# Summary() gives us the descriptive stats and hypothesis testing values like
Standard Error, p-Value, t-Value, r-squared value, f-Statistic, Degrees of
Freedom, and etc.,

# This model is used as a baseline model to collate with the next upcoming
models

library(glmnet)

## Warning: package 'glmnet' was built under R version 4.0.3

## Loaded glmnet 4.1

lambdaSeq <- 10 ^ seq(2, -2, by = -.1)
lambdaSeq

##  [1] 100.00000000  79.43282347  63.09573445  50.11872336  39.81071706
##  [6]  31.62277660  25.11886432  19.95262315  15.84893192  12.58925412
## [11]  10.00000000   7.94328235   6.30957344   5.01187234   3.98107171
## [16]   3.16227766   2.51188643   1.99526231   1.58489319   1.25892541
## [21]   1.00000000   0.79432823   0.63095734   0.50118723   0.39810717
## [26]   0.31622777   0.25118864   0.19952623   0.15848932   0.12589254
## [31]   0.10000000   0.07943282   0.06309573   0.05011872   0.03981072
## [36]   0.03162278   0.02511886   0.01995262   0.01584893   0.01258925
## [41]   0.01000000

ridgeFit <- glmnet(x, y, alpha = 0, lambda  = lambdaSeq)
ridgeFit

##
## Call:  glmnet(x = x, y = y, alpha = 0, lambda = lambdaSeq)
##
##    Df  %Dev  Lambda
## 1   4 64.58 100.000
## 2   4 68.02  79.430
## 3   4 70.91  63.100
## 4   4 73.28  50.120
## 5   4 75.18  39.810
## 6   4 76.65  31.620
## 7   4 77.78  25.120
## 8   4 78.62  19.950
## 9   4 79.24  15.850
## 10  4 79.68  12.590
## 11  4 80.00  10.000
## 12  4 80.23   7.943
## 13  4 80.38   6.310
## 14  4 80.49   5.012
```

```
## 15  4 80.57   3.981
## 16  4 80.62   3.162
## 17  4 80.65   2.512
## 18  4 80.68   1.995
## 19  4 80.69   1.585
## 20  4 80.70   1.259
## 21  4 80.71   1.000
## 22  4 80.72   0.794
## 23  4 80.72   0.631
## 24  4 80.72   0.501
## 25  4 80.72   0.398
## 26  4 80.72   0.316
## 27  4 80.72   0.251
## 28  4 80.72   0.200
## 29  4 80.73   0.158
## 30  4 80.73   0.126
## 31  4 80.73   0.100
## 32  4 80.73   0.079
## 33  4 80.73   0.063
## 34  4 80.73   0.050
## 35  4 80.73   0.040
## 36  4 80.73   0.032
## 37  4 80.73   0.025
## 38  4 80.73   0.020
## 39  4 80.73   0.016
## 40  4 80.73   0.013
## 41  4 80.73   0.010
```

```
summary(ridgeFit)
```

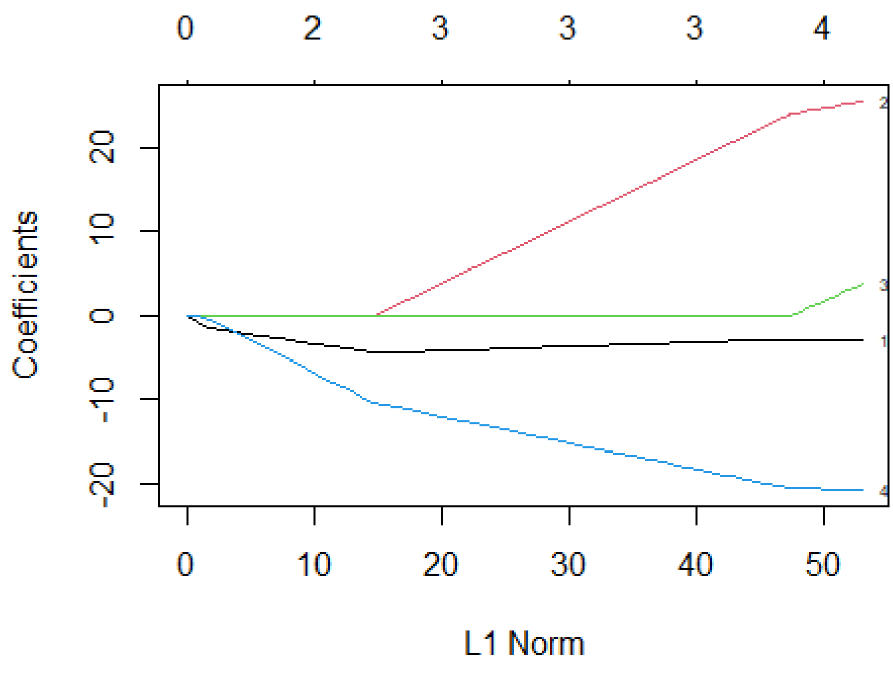
```
##           Length Class     Mode
## a0         41    -none-    numeric
## beta      164    dgCMatrix S4
## df         41    -none-    numeric
## dim         2    -none-    numeric
## lambda     41    -none-    numeric
## dev.ratio  41    -none-    numeric
## nulldev     1    -none-    numeric
## npasses     1    -none-    numeric
## jerr        1    -none-    numeric
## offset      1    -none-    logical
## call        5    -none-    call
## nobs        1    -none-    numeric
```

```
# Setting the range of lambda values and Using glmnet() method to build the
ridge regression in R. Checking the model using the Summary()

modelLASSO <- glmnet(x, y, alpha = 1)
modelLASSO
```

```
## 
## Call:  glmnet(x = x, y = y, alpha = 1) 
## 
##    Df  %Dev Lambda
## 1   0  0.00 52.380
## 2   1 10.23 47.730
## 3   2 19.52 43.490
## 4   2 29.45 39.620
## 5   2 37.71 36.100
## 6   2 44.56 32.900
## 7   2 50.24 29.970
## 8   2 54.97 27.310
## 9   2 58.89 24.880
## 10  2 62.14 22.670
## 11  2 64.84 20.660
## 12  2 67.09 18.820
## 13  3 69.32 17.150
## 14  3 71.25 15.630
## 15  3 72.84 14.240
## 16  3 74.17 12.970
## 17  3 75.27 11.820
## 18  3 76.19 10.770
## 19  3 76.95  9.815
## 20  3 77.58  8.943
## 21  3 78.10  8.148
## 22  3 78.53  7.424
## 23  3 78.90  6.765
## 24  3 79.19  6.164
## 25  3 79.44  5.616
## 26  3 79.65  5.117
## 27  3 79.82  4.663
## 28  3 79.96  4.249
## 29  3 80.08  3.871
## 30  3 80.18  3.527
## 31  3 80.26  3.214
## 32  3 80.33  2.928
## 33  3 80.39  2.668
## 34  3 80.43  2.431
## 35  3 80.47  2.215
## 36  3 80.50  2.018
## 37  3 80.53  1.839
## 38  3 80.55  1.676
## 39  3 80.57  1.527
## 40  3 80.59  1.391
## 41  3 80.60  1.268
## 42  3 80.61  1.155
## 43  3 80.62  1.052
## 44  3 80.62  0.959
## 45  3 80.63  0.874
## 46  3 80.64  0.796
```

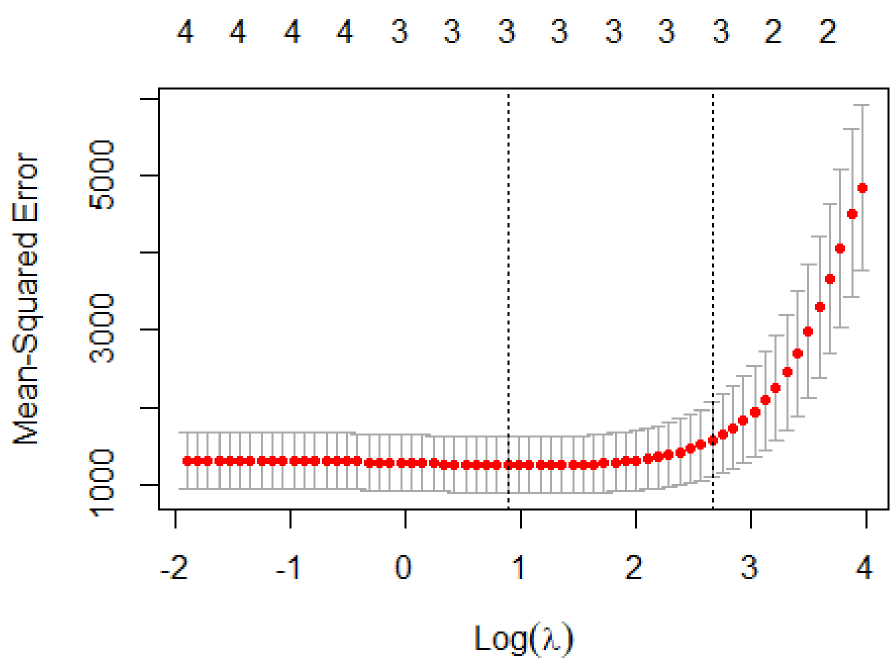
```
## 47   3 80.64  0.725
## 48   4 80.65  0.661
## 49   4 80.67  0.602
## 50   4 80.68  0.549
## 51   4 80.68  0.500
## 52   4 80.69  0.456
## 53   4 80.70  0.415
## 54   4 80.70  0.378
## 55   4 80.71  0.345
## 56   4 80.71  0.314
## 57   4 80.71  0.286
## 58   4 80.71  0.261
## 59   4 80.72  0.238
## 60   4 80.72  0.216
## 61   4 80.72  0.197
## 62   4 80.72  0.180
## 63   4 80.72  0.164
## 64   4 80.72  0.149
```

```
plot(modelLASSO,
     xvar = "norm",
     label = TRUE)
```




```
# LASSO regression is performed and for that to happen we use "glmnet"
package from the packages tab to install or simply use
install.packages("glmnet") command
```

```r
# Now, let's load the "glmnet" in our work space to regularize the model
using LASSO and plot it using plot(). This plot indicates at which stage each
coefficients shrinks to 0. and the lines depicts the values used by various
other coefficients

cvModel <- cv.glmnet(x, y, alpha = 1)
cvModel

##
## Call:  cv.glmnet(x = x, y = y, alpha = 1)
##
## Measure: Mean-Squared Error
##
##     Lambda Index Measure    SE Nonzero
## min  2.431    34    1250 362.4       3
## 1se 14.239    15    1573 485.3       3

bestLambda <- cvModel$lambda.min
bestLambda

## [1] 2.431182

plot(cvModel)
```




```r
# Here, Cross Validation is used to get the best value of lambda and plot the
curve using plot(). It is possible with cv.glmnet() method. nlambda signifies
the number of lambda values in sequence. In general, nlambda values must be
above 100.
```

```r
# Let's find optimal lambda value that minimizes test MSE and perform K-Fold
Cross validation to find optimal lambda value. At last, let's produce the
plot of test MSE by lambda value.

# From the plot we can depict that the value of lambda increased when the
number of selected variables narrows down. This tells that higher the value
of lambda, more shrink the selection is. Now, we find the min. value of
lambda to get the best fit

lambdaWithOneSE <- cvModel$lambda.1se
lambdaWithOneSE

## [1] 14.23948

latestFit <- glmnet(
  x = x,
  y = y,
  alpha = 1,
  lambda = lambdaWithOneSE
)

latestFit$beta

## 4 x 1 sparse Matrix of class "dgCMatrix"
##               s0
## mpg   -4.024702
## wt     5.766737
## drat   .
## qsec -12.842480

# Here, we use the minimum lambda value again in glmnet() function to get the
best latest fit. Now we use a higher value of lambda that is within one
standard error of the minimum to check its effect on shrinkage.

# There are 1 coefficients namely "drat" whose values have become 0. It's
clear that this variable is not so necessary to determine the value of "y".
LASSO tells that only 3 variables are necessary on which y depends. Thus the
shrinkage increases.

bestModel <- glmnet(x, y, alpha = 1, lambda = bestLambda)
coef(bestModel)

## 5 x 1 sparse Matrix of class "dgCMatrix"
##                      s0
## (Intercept) 485.152675
## mpg          -2.936266
## wt           21.698919
## drat          .
## qsec        -19.569135
```

```r
newObs <- matrix(c(21, 2.1, 3.6, 18.0), nrow = 1, ncol = 4)
newObs

##      [,1] [,2] [,3] [,4]
## [1,]   21  2.1  3.6   18

predict(bestModel, s = bestLambda, newx = newObs)

##             1
## [1,] 116.8144

yPred <- predict(bestModel, s = bestLambda, newx = x)

sstValue <- sum((y - mean(y)) ^ 2)
sseValue <- sum((yPred - y) ^ 2)

rSquaredVal <- 1 - sseValue / sstValue
rSquaredVal

## [1] 0.8043193

# To find the coefficients of best model, let's define a new observation and
use LASSO regression model to predict response value. Use fitted best model
to make predictions. Let's find SST, SSE, and R-Squared values for the new
observation
```