R-Laboratory 6

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1.Load mtcars dataset.

```
# Loading mtcars dataset.
data(mtcars)
mtcars

##                      mpg cyl  disp  hp drat    wt  qsec vs am gear carb
## Mazda RX4           21.0   6 160.0 110 3.90 2.620 16.46  0  1    4    4
## Mazda RX4 Wag       21.0   6 160.0 110 3.90 2.875 17.02  0  1    4    4
## Datsun 710          22.8   4 108.0  93 3.85 2.320 18.61  1  1    4    1
## Hornet 4 Drive      21.4   6 258.0 110 3.08 3.215 19.44  1  0    3    1
## Hornet Sportabout   18.7   8 360.0 175 3.15 3.440 17.02  0  0    3    2
## Valiant             18.1   6 225.0 105 2.76 3.460 20.22  1  0    3    1
## Duster 360          14.3   8 360.0 245 3.21 3.570 15.84  0  0    3    4
## Merc 240D           24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2
## Merc 230            22.8   4 140.8  95 3.92 3.150 22.90  1  0    4    2
## Merc 280            19.2   6 167.6 123 3.92 3.440 18.30  1  0    4    4
## Merc 280C           17.8   6 167.6 123 3.92 3.440 18.90  1  0    4    4
## Merc 450SE          16.4   8 275.8 180 3.07 4.070 17.40  0  0    3    3
## Merc 450SL          17.3   8 275.8 180 3.07 3.730 17.60  0  0    3    3
## Merc 450SLC         15.2   8 275.8 180 3.07 3.780 18.00  0  0    3    3
## Cadillac Fleetwood  10.4   8 472.0 205 2.93 5.250 17.98  0  0    3    4
## Lincoln Continental 10.4   8 460.0 215 3.00 5.424 17.82  0  0    3    4
## Chrysler Imperial   14.7   8 440.0 230 3.23 5.345 17.42  0  0    3    4
## Fiat 128            32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
## Honda Civic         30.4   4  75.7  52 4.93 1.615 18.52  1  1    4    2
## Toyota Corolla      33.9   4  71.1  65 4.22 1.835 19.90  1  1    4    1
## Toyota Corona       21.5   4 120.1  97 3.70 2.465 20.01  1  0    3    1
## Dodge Challenger    15.5   8 318.0 150 2.76 3.520 16.87  0  0    3    2
## AMC Javelin         15.2   8 304.0 150 3.15 3.435 17.30  0  0    3    2
## Camaro Z28          13.3   8 350.0 245 3.73 3.840 15.41  0  0    3    4
## Pontiac Firebird    19.2   8 400.0 175 3.08 3.845 17.05  0  0    3    2
## Fiat X1-9           27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
## Porsche 914-2       26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
## Lotus Europa        30.4   4  95.1 113 3.77 1.513 16.90  1  1    5    2
## Ford Pantera L      15.8   8 351.0 264 4.22 3.170 14.50  0  1    5    4
## Ferrari Dino        19.7   6 145.0 175 3.62 2.770 15.50  0  1    5    6
## Maserati Bora       15.0   8 301.0 335 3.54 3.570 14.60  0  1    5    8
## Volvo 142E          21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2
```

2.install ridge and glmnet packages.

```
#install.packages(ridge)
#install.packages(glmnet)

library(ridge)      # Linear and logistic ridge regression functions.
library(Matrix)
library(glmnet)     # Lasso and Elastic-Net Regularized Generalized Linear
Models

## Loaded glmnet 4.1
```

3.Perform the exploratory data analysis.

```
# Pre-processing EDA
df = mtcars

str(df)

## '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 ...
```

Insight

```
    - Totally, 32 observations of  11 variables.
    - All the 11 features are numerical datatypes.
```

```
# Summary

summary(df)

##       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
```

```
# Checking for missing values.

colSums(is.na(df))
```

```
##  mpg  cyl disp   hp drat   wt qsec   vs   am gear carb
##    0    0    0    0    0    0    0    0    0    0    0
```

```
#Checking for Empty Values

colSums(df=='')
```

```
##  mpg  cyl disp   hp drat   wt qsec   vs   am gear carb
##    0    0    0    0    0    0    0    0    0    0    0
```

```
#Checking for Duplicate values

library(tidyverse)
```

```
## ── Attaching packages ──────────────────────────────────────────────────────────────
───────────────────── tidyverse 1.3.0 ──

## ✓ ggplot2 3.3.2     ✓ purrr   0.3.4
## ✓ tibble  3.0.3     ✓ dplyr   1.0.4
## ✓ tidyr   1.1.1     ✓ stringr 1.4.0
## ✓ readr   1.4.0     ✓ forcats 0.5.1

## ── Conflicts ──────────────────────────────────────────────────────────────
──────────────────────── tidyverse_conflicts() ──
## x tidyr::expand() masks Matrix::expand()
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## x tidyr::pack()   masks Matrix::pack()
## x tidyr::unpack() masks Matrix::unpack()
```

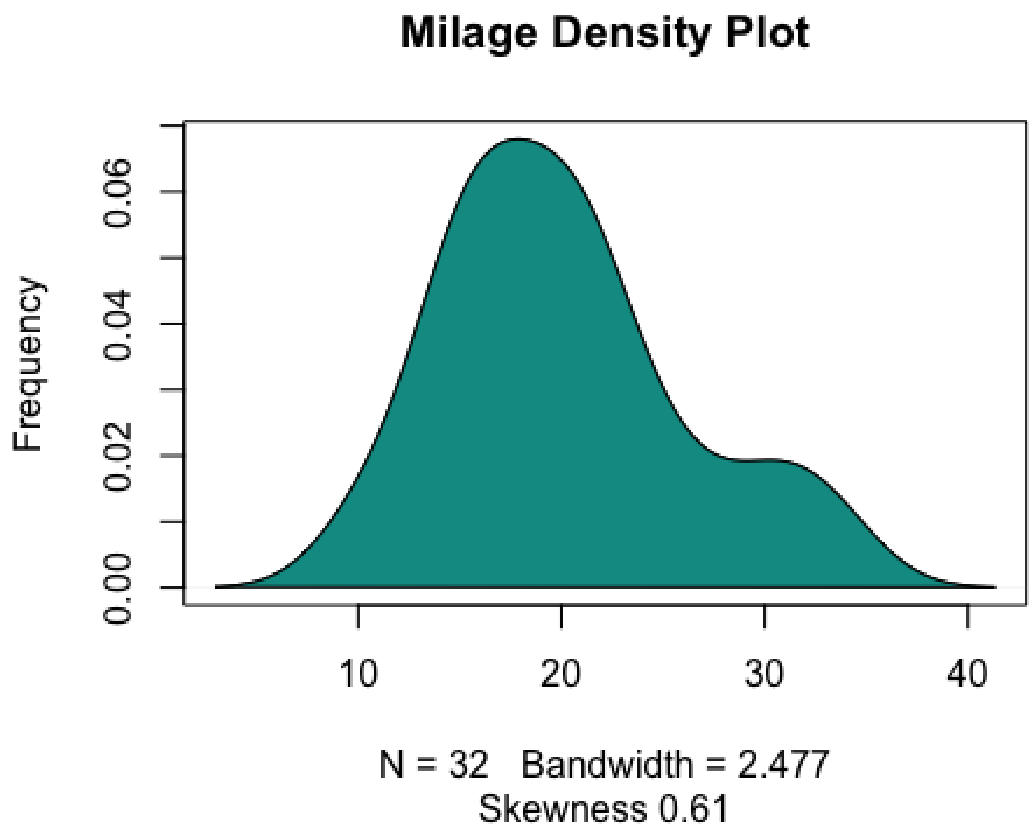
```
duplicated(df)
```

```
##  [1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [13] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
```

```
FALSE
## [25] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
```

Insight

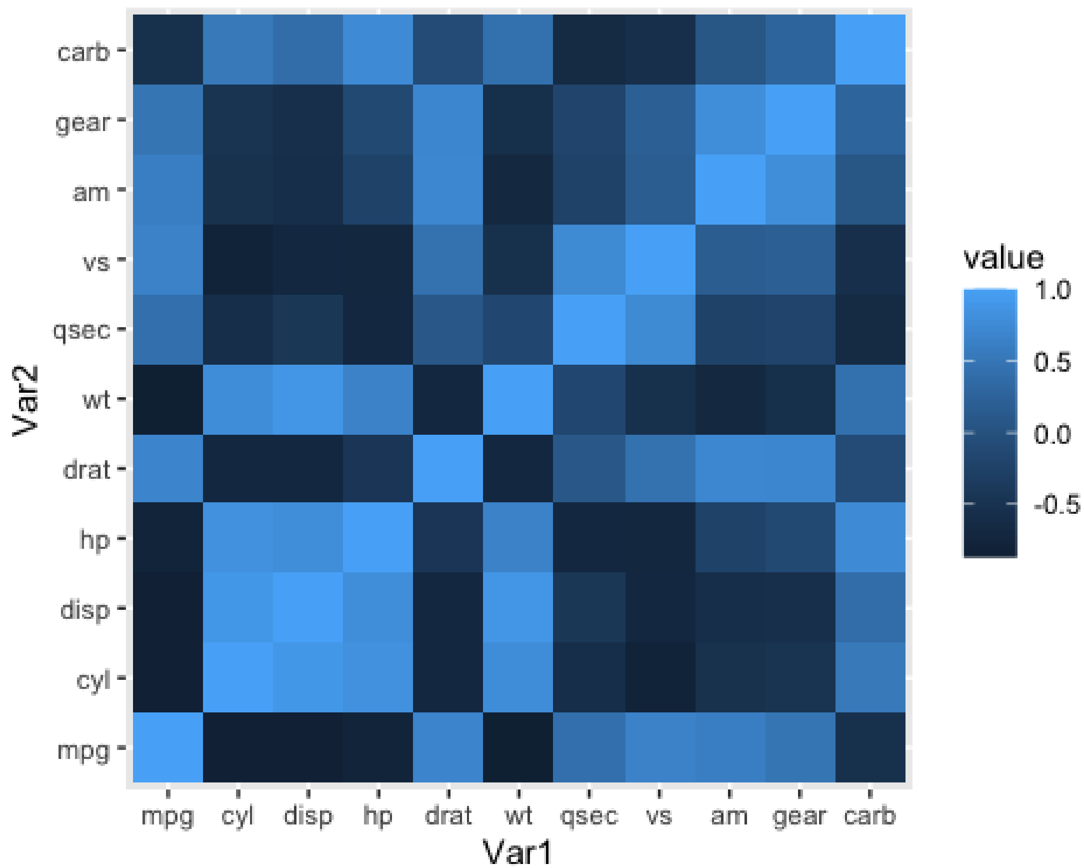
```
    - The dataset is clean, there are no missing, Empty values or duplicated
record.

# Checking Normality of Response Variable

# Using this method, we obtain predictions from the model, as well as
decision values from the binary classifiers.
library(e1071)



# plot() - Visualizing data, support vectors and decision boundaries, if
provided.
plot(density(df$mpg),
     main = "Milage Density Plot",
     ylab="Frequency",
     sub=paste("Skewness",round(e1071::skewness(df$mpg),2))
     )

polygon(density(df$mpg), col='#079992')
```



Insight

```
    - Slightly Right Skweked, which implies most of the values are posititve in nature.
```

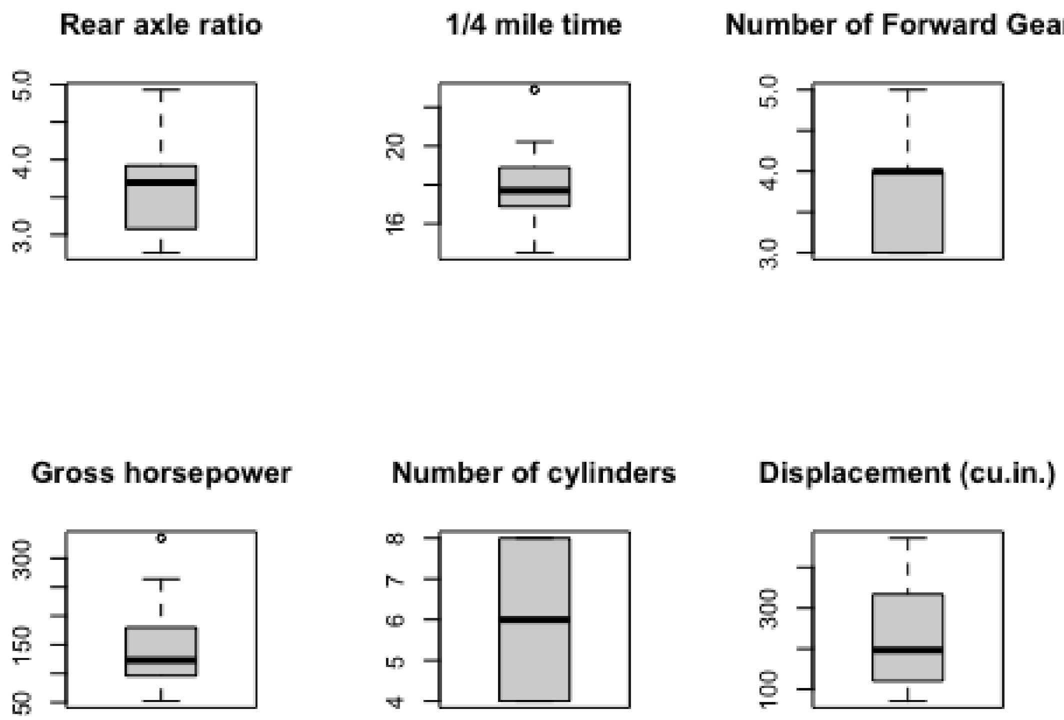
```r
#Correlation Heatmap

library(ggplot2)
library(reshape2)

##
## Attaching package: 'reshape2'

## The following object is masked from 'package:tidyr':
##
##     smiths

cormat <- round(cor(df),2)
melted_cormat <- melt(cormat)
ggplot(data = melted_cormat, aes(x=Var1, y=Var2, fill=value)) +
  geom_tile()
```



Insight

```
    - Darker shades denotes less correlationship indications.
    - Lighter shades denotes High correlationship with each variables.
    - It is evident that most of the variables possess a high correlation
with each other, thus we can assume multicollinearity is present.
```

```
#Checking for outliers in highly positive correlated values with Mileage

par(mfrow=c(2,3))

boxplot(df$drat, main = "Rear axle ratio")
boxplot(df$qsec, main = "1/4 mile time")
boxplot(df$gear, main = "Number of Forward Gears")
boxplot(df$hp,   main = "Gross horsepower")
boxplot(df$cyl, main = "Number of cylinders")
boxplot(df$disp,   main = "Displacement (cu.in.)")
```



Insight

```
    - There is an outlier found in qsec(1/4 mile time) and Gross horsepower.
```

```
#Building initial model
X = model.matrix(mpg~. , mtcars)[,-1]
Y = mtcars$mpg

#Splitting the data
set.seed(57)

trainingRow <- sample(1:nrow(df), 0.7*nrow(df))
trainset <- df[trainingRow,]
testset <- df[-trainingRow,]

lrm <- lm(trainset$mpg~., data=trainset)

summary(lrm)

##
## Call:
## lm(formula = trainset$mpg ~ ., data = trainset)
##
```

```
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -3.1759 -1.4218 -0.7548  1.0168  4.3028 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  8.55175   25.48468   0.336    0.744
## cyl         -0.07409    1.35897  -0.055    0.957
## disp         0.01402    0.02943   0.476    0.643
## hp          -0.04564    0.03718  -1.227    0.245
## drat         1.01463    2.83182   0.358    0.727
## wt          -3.66520    2.79708  -1.310    0.217
## qsec         1.22513    0.93256   1.314    0.216
## vs          -1.03224    2.89376  -0.357    0.728
## am           4.89791    2.80389   1.747    0.108
## gear        -0.76347    2.07162  -0.369    0.719
## carb         1.00937    1.36147   0.741    0.474
## 
## Residual standard error: 3.006 on 11 degrees of freedom
## Multiple R-squared:  0.8924, Adjusted R-squared:  0.7945 
## F-statistic:  9.12 on 10 and 11 DF,  p-value: 0.0005314
```

```
library(car)
```

```
## Loading required package: carData
```

```
## 
## Attaching package: 'car'
```

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

```
## The following object is masked from 'package:purrr':
## 
##     some
```

```
vif(lrm)
```

```
##       cyl      disp        hp      drat        wt      qsec        vs 
am 
## 14.567223 35.146018 19.377286  5.983737 20.942264  7.286081  4.928560 
4.627183 
##      gear      carb 
##  4.922279 12.942380
```

Insight

```
    - All the values are above 5, there is strong multi-collinearity present.
```

```r
MLR_pred <- predict(lrm,testset)
compare <- cbind(actual=testset$mpg, MLR_pred)
compare
```

```
##                      actual MLR_pred
## Mazda RX4              21.0 25.73138
## Mazda RX4 Wag          21.0 25.48283
## Hornet Sportabout      18.7 16.18709
## Merc 450SE             16.4 13.86304
## Merc 450SL             17.3 15.35424
## Dodge Challenger       15.5 15.86656
## Camaro Z28             13.3 12.02072
## Pontiac Firebird       19.2 15.22923
## Lotus Europa           30.4 25.48280
## Ferrari Dino           19.7 21.79969
```

```r
mean (apply(compare, 1, min)/apply(compare, 1, max))
```

```
## [1] 0.8654496
```

```r
RMSE = sqrt(mean((testset$mpg-MLR_pred)^2))
RMSE# calculate accuracy
```

```
## [1] 3.242592
```

Insight

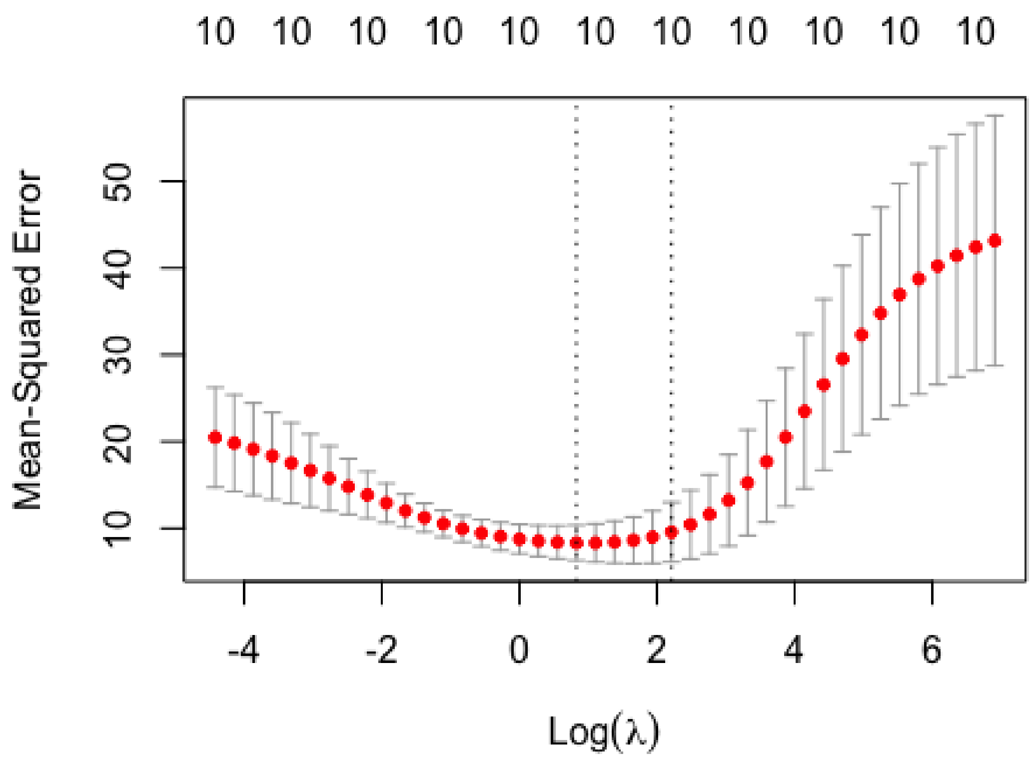
```
    - Accuracy is only 81%, which is not very efficient.
```

4.Choose optimum lamba value.

```r
#Creating a sequence with an interval of -0.12
lambda_seq = 10^seq(3, -2, by = -.12)

# Using cross validation glmnet
ridge_model1 = cv.glmnet(X[trainingRow,], Y[trainingRow],alpha = 0,
type.measure = "mse", lambda = lambda_seq, nfolds = 5)

# Best lambda value
best_lam =  ridge_model1$lambda.min
best_lam
```

```
## [1] 2.290868
```

```r
plot(ridge_model1)
```



Insight

```
- Optimum lamba value choosed and plotted.
```

5.Extract the model using k-cross validation.

```
best_fit <- ridge_model1$glmnet.fit
head(best_fit)

## $a0
##        s0        s1        s2        s3        s4        s5        s6
s7
## 20.334559 20.292781 20.239225 20.171147 20.085525 19.979298 19.849725
19.694961
##        s8        s9       s10       s11       s12       s13       s14
s15
## 19.514784 19.311363 19.089707 18.858175 18.627489 18.408886 18.213989
18.048764
##       s16       s17       s18       s19       s20       s21       s22
s23
## 17.916799 17.809536 17.713541 17.605253 17.453561 17.211267 16.889578
16.443811
##       s24       s25       s26       s27       s28       s29       s30
```

```
s31
## 15.867262 15.168862 14.373356 13.507767 12.617859 11.748121 10.943290
10.235891
##       s32       s33       s34       s35       s36       s37       s38
s39
##  9.652625  9.195744  8.862197  8.633752  8.489987  8.407891  8.371597
8.363156
##       s40       s41
##  8.371917  8.390624
##
## $beta
## 10 x 42 sparse Matrix of class "dgCMatrix"

##    [[ suppressing 42 column names 's0', 's1', 's2' ... ]]

##
## cyl  -0.0194178748 -0.0252966251 -0.0328380896 -0.0424341586 -0.0545182791
## disp -0.0002758091 -0.0003593572 -0.0004665682 -0.0006030428 -0.0007749987
## hp   -0.0004186479 -0.0005454341 -0.0007081107 -0.0009151644 -0.0011760196
## drat  0.0533808300  0.0695996484  0.0904465457  0.1170416036  0.1506476225
## wt   -0.0334154670 -0.0435648435 -0.0566082128 -0.0732447062 -0.0942618997
## qsec  0.0099463820  0.0129456398  0.0167847447  0.0216558137  0.0277673440
## vs    0.0552584274  0.0719235805  0.0932558041  0.1203216130  0.1542757009
## am    0.0480936150  0.0627816340  0.0817150371  0.1059602526  0.1367494081
## gear  0.0231786989  0.0302151718  0.0392546475  0.0507776494  0.0653217181
## carb -0.0151921901 -0.0197946406 -0.0257010946 -0.0332208008 -0.0426979387
##
## cyl  -0.0695388873 -0.087907973 -0.109928221 -0.135698629 -0.165015766
## disp -0.0009888889 -0.001250704 -0.001564942 -0.001933281 -0.002353179
## hp   -0.0015004572 -0.001897588 -0.002374333 -0.002933503 -0.003571833
## drat  0.1926063151  0.244220147  0.306569016  0.380269080  0.465207714
## wt   -0.1204958347 -0.152757675 -0.191720764 -0.237773900 -0.290863548
## qsec  0.0353274579  0.044516063  0.055444978  0.068109946  0.082345031
## vs    0.1962638343  0.247258973  0.307821869  0.377800951  0.456021858
## am    0.1754431571  0.223451530  0.282103430  0.352467645  0.435148965
## gear  0.0834498460  0.105691965  0.132453336  0.163890040  0.199763730
## carb -0.0544910930 -0.068936941 -0.086296270 -0.106686059 -0.130010072
##
## cyl  -0.197283638 -0.231536306 -0.266464233 -0.300532751 -0.332346390
## disp -0.002816699 -0.003310496 -0.003816427 -0.004313505 -0.004781762
## hp   -0.004278610 -0.005035651 -0.005819007 -0.006602703 -0.007362891
## drat  0.560329707  0.663541512  0.771838464  0.881686019  0.989424926
## wt   -0.350375086 -0.415083181 -0.483257506 -0.552919185 -0.622047734
## qsec  0.097799533  0.113949489  0.130172146  0.145876393  0.160608946
## vs    0.540065290  0.626210735  0.709690715  0.785227191  0.847558044
## am    0.530113606  0.636590523  0.753147026  0.877942427  1.008998300
## gear  0.239303462  0.281113209  0.323170856  0.362934380  0.397554449
## carb -0.155910631 -0.183762893 -0.212736212 -0.241908068 -0.270379880
##
## cyl  -0.360528450 -0.384297972 -0.402843612 -0.415951073 -0.423452517
```

```
## disp -0.005203051 -0.005565010 -0.005860181 -0.006085898 -0.006242758
## hp   -0.008082416 -0.008750542 -0.009369868 -0.009946048 -0.010492122
## drat  1.091995922  1.186915651  1.273366396  1.351086594  1.420900908
## wt   -0.689079862 -0.752763379 -0.812840558 -0.869349465 -0.923011403
## qsec  0.174252289  0.186977416  0.199466299  0.212655588  0.227820785
## vs    0.892306277  0.916099663  0.917099338  0.894707619  0.849574240
## am    1.144739301  1.284064223  1.426749223  1.573181967  1.724338051
## gear  0.424144323  0.440141829  0.443347589  0.432389871  0.406596869
## carb -0.297386038 -0.322313670 -0.344555506 -0.363509808 -0.378370411
##
## cyl  -0.425167325 -0.42005450 -0.410120588 -0.393896701 -0.371281213
## disp -0.006333105 -0.00635348 -0.006332249 -0.006253825 -0.006116423
## hp   -0.011026914 -0.01158088 -0.012176779 -0.012846804 -0.013629891
## drat  1.484296094  1.54371974  1.598688328  1.650251164  1.697789077
## wt   -0.975109142 -1.02826126 -1.081801192 -1.139297646 -1.202947602
## qsec  0.246460918  0.27054145  0.300209136  0.337137522  0.381754764
## vs    0.783255381  0.69856011  0.594295394  0.475105213  0.343307682
## am    1.881503356  2.04674980  2.218420823  2.398691570  2.587386755
## gear  0.365963926  0.31086667  0.242390790  0.162379925  0.072948414
## carb -0.388033773 -0.39096250 -0.385571567 -0.370499385 -0.344427489
##
## cyl  -0.342463622 -0.30873866 -0.270348779 -0.229806214 -0.188672924
## disp -0.005911888 -0.00561437 -0.005202658 -0.004637032 -0.003898958
## hp   -0.014564976 -0.01566547 -0.016983067 -0.018515083 -0.020283937
## drat  1.739537496  1.77200174  1.793661659  1.801191849  1.793749442
## wt   -1.274860253 -1.35695787 -1.451703556 -1.560721178 -1.684862780
## qsec  0.433804547  0.49221963  0.555823870  0.622550805  0.690414395
## vs    0.201754515  0.05567978 -0.091622500 -0.234074095 -0.368759878
## am    2.783544366  2.98484806  3.188974795  3.391538649  3.588815085
## gear -0.023108235 -0.12124949 -0.218706221 -0.310809428 -0.395541062
## carb -0.306557135 -0.25743708 -0.196781736 -0.126129760 -0.046146270
##
## cyl  -0.14959444 -0.114321523 -0.0859363880 -0.0640708118 -0.049428577
## disp -0.00296822 -0.001852804 -0.0005431506  0.0008965152  0.002426298
## hp   -0.02226644 -0.024430897 -0.0266952816 -0.0290085396 -0.031286481
## drat  1.77054264  1.732788652  1.6811238095  1.6198149498  1.551854476
## wt   -1.82401345 -1.976241190 -2.1402540939 -2.3104968329 -2.482769028
## qsec  0.75729715  0.821420677  0.8812996172  0.9360143581  0.984986034
## vs   -0.49177145 -0.601396374 -0.6940612888 -0.7717114703 -0.834179069
## am    3.77642780  3.951100196  4.1088358846  4.2489768787  4.370390310
## gear -0.47057546 -0.535317980 -0.5882799241 -0.6313053773 -0.664915963
## carb  0.04134609  0.134470039  0.2303378572  0.3267476137  0.420873237
##
## cyl  -0.040722148 -0.036836911 -0.036072576 -0.037993027 -0.040630461
## disp  0.003967958  0.005458692  0.006830848  0.008074849  0.009127739
## hp   -0.033461559 -0.035471692 -0.037271014 -0.038840130 -0.040163313
## drat  1.481742944  1.413049417  1.349248180  1.291229019  1.241674091
## wt   -2.650541028 -2.808574581 -2.951544054 -3.078901358 -3.186057739
## qsec  1.027968753  1.064995577  1.096234180  1.122274794  1.143304513
## vs   -0.883811415 -0.922412693 -0.952499479 -0.974827201 -0.992625860
```

```
## am    4.473871578  4.560469250  4.631924264  4.689726505  4.736066941
## gear -0.690910987 -0.710635426 -0.725678449 -0.736618641 -0.745245241
## carb  0.510141494  0.592324213  0.665634193  0.729630910  0.783468884
##
## cyl  -0.04406097 -0.04759208
## disp  0.01002471  0.01075943
## hp   -0.04126095 -0.04214877
## drat  1.19944143  1.16467932
## wt   -3.27637387 -3.34992102
## qsec  1.16026691  1.17361996
## vs   -1.00570722 -1.01567187
## am    4.77257000  4.80094436
## gear -0.75148098 -0.75619184
## carb  0.82821911  0.86447869
##
## $df
##  [1] 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10
10 10
## [26] 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10 10
##
## $dim
## [1] 10 42
##
## $lambda
##  [1] 1.000000e+03 7.585776e+02 5.754399e+02 4.365158e+02 3.311311e+02
##  [6] 2.511886e+02 1.905461e+02 1.445440e+02 1.096478e+02 8.317638e+01
## [11] 6.309573e+01 4.786301e+01 3.630781e+01 2.754229e+01 2.089296e+01
## [16] 1.584893e+01 1.202264e+01 9.120108e+00 6.918310e+00 5.248075e+00
## [21] 3.981072e+00 3.019952e+00 2.290868e+00 1.737801e+00 1.318257e+00
## [26] 1.000000e+00 7.585776e-01 5.754399e-01 4.365158e-01 3.311311e-01
## [31] 2.511886e-01 1.905461e-01 1.445440e-01 1.096478e-01 8.317638e-02
## [36] 6.309573e-02 4.786301e-02 3.630781e-02 2.754229e-02 2.089296e-02
## [41] 1.584893e-02 1.202264e-02
##
## $dev.ratio
##  [1] 0.06108987 0.07915888 0.10204834 0.13070259 0.16603686 0.20879069
##  [7] 0.25931876 0.31734285 0.38172109 0.45033252 0.52018246 0.58780504
## [13] 0.64985860 0.70377117 0.74818554 0.78300796 0.80915562 0.82815348
## [19] 0.84165396 0.85118415 0.85799058 0.86302353 0.86690343 0.87007810
## [25] 0.87282648 0.87530903 0.87758983 0.87972123 0.88169272 0.88350751
## [31] 0.88515014 0.88661178 0.88788129 0.88895987 0.88984982 0.89055920
## [37] 0.89110407 0.89150530 0.89179271 0.89198805 0.89211952 0.89220514
```

6.Build the final model and interpret.

```
linRidgeMod = linearRidge(trainset$mpg ~ ., data = trainset)
predicted = predict(linRidgeMod, testset) # predict on test data
compare1 = cbind (actual=testset$mpg, predicted)

mean (apply(compare1, 1, min)/apply(compare1, 1, max))
```

```
## [1] 0.9029484
```

```
summary(linRidgeMod)
```

```
##
## Call:
## linearRidge(formula = trainset$mpg ~ ., data = trainset)
##
##
## Coefficients:
##              Estimate Scaled estimate Std. Error (scaled) t value (scaled)
## (Intercept) 14.742140              NA                  NA               NA
## cyl         -0.326153       -2.753488            3.321952            0.829
## disp        -0.005767       -3.492460            2.841631            1.229
## hp          -0.015200       -5.409057            3.161192            1.711
## drat         1.757967        4.564728            3.400698            1.342
## wt          -1.322165       -6.502449            3.091123            2.104
## qsec         0.468642        4.077506            3.255874            1.252
## vs           0.103222        0.238042            3.398804            0.070
## am           2.909703        6.710119            3.236733            2.073
## gear        -0.086758       -0.279297            3.248383            0.086
## carb        -0.277200       -2.201791            3.031816            0.726
##             Pr(>|t|)
## (Intercept)       NA
## cyl           0.4072
## disp          0.2191
## hp            0.0871 .
## drat          0.1795
## wt            0.0354 *
## qsec          0.2104
## vs            0.9442
## am            0.0382 *
## gear          0.9315
## carb          0.4677
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Ridge parameter: 0.1286921, chosen automatically, computed using 3 PCs
##
## Degrees of freedom: model 5.755 , variance 4.066 , residual 7.443
```

Creating another model with only significant values.

```
linRidgeMod = linearRidge(trainset$mpg ~ ., data = trainset[, c(6,10,11)])
predicted1 = predict(linRidgeMod, testset) # predict on test data
compare2 = cbind (actual=testset$mpg, predicted1)

mean (apply(compare2, 1, min)/apply(compare2, 1, max))
```

```
## [1] 0.9464945
```

```
summary(linRidgeMod)

##
## Call:
## linearRidge(formula = trainset$mpg ~ ., data = trainset[, c(6,
##     10, 11)])
##
##
## Coefficients:
##             Estimate Scaled estimate Std. Error (scaled) t value (scaled)
## (Intercept)   27.642              NA                  NA               NA
## wt            -3.316         -16.308               4.659            3.500
## gear           1.924           6.193               4.089            1.514
## carb          -1.395         -11.082               4.262            2.600
##             Pr(>|t|)
## (Intercept)       NA
## wt          0.000465 ***
## gear        0.129929
## carb        0.009319 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Ridge parameter: 0.04208334, chosen automatically, computed using 2 PCs
##
## Degrees of freedom: model 2.698 , variance 2.457 , residual 2.939

RMSE = sqrt(mean((testset$mpg-predicted1)^2))
RMSE

## [1] 1.389815
```

Insight

```
    - The accuracy has increased from 75% to 88%.
    - Root-Mean-Square Error has decreased from 3.242 to 1.389
```