mtcars

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```
library(caret)
```

```
## Loading required package: ggplot2
```

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

```
library(glmnet)
```

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

```
## Loaded glmnet 4.1-6
```

```
# Creating 80-20 Training Testing Split, createDataPartition() returns the
indices
# Perform a basic 80/20 test-train split on the data (you may use caret, the
sample method, or manually)
initial_train = createDataPartition(mtcars$mpg,times=1,p=0.8,list=FALSE)
# Training data
training_data= mtcars[initial_train, ]
# Testing data (note the minus sign)
testing_data= mtcars[-initial_train, ]
training_data$am = factor(training_data$am)
is.factor(training_data$am)
```

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

```
# Fitting linear model
# Fit a linear model with mpg as the target response,
testing_data$am = factor(testing_data$am)
lm.fit = lm(mpg~.,data=training_data)
#MSE on test set
mean((predict(lm.fit,testing_data)-testing_data$mpg)^2)
```

```
## [1] 11.26835
```

```
# What features are selected as relevant based on resulting t-statistics?
# Analyze the t-stat and p-values to select relevant features
summary(lm.fit)
```

```
##
## Call:
## lm(formula = mpg ~ ., data = training_data)
##
## Residuals:
```

```
##     Min      1Q  Median      3Q     Max 
## -2.9424 -1.7282 -0.2225  1.0956  5.4001 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 24.62378   19.65034   1.253    0.227
## cyl         -0.41449    1.09482  -0.379    0.710
## disp         0.01090    0.01814   0.601    0.556
## hp          -0.03299    0.02539  -1.299    0.211
## drat         0.88507    1.76755   0.501    0.623
## wt          -2.73163    2.07093  -1.319    0.205
## qsec         0.18021    0.86946   0.207    0.838
## vs           0.08982    2.36188   0.038    0.970
## am1          1.15988    2.43176   0.477    0.639
## gear         0.85259    1.54799   0.551    0.589
## carb        -0.41727    0.91617  -0.455    0.655
## 
## Residual standard error: 2.632 on 17 degrees of freedom
## Multiple R-squared:  0.8699, Adjusted R-squared:  0.7934 
## F-statistic: 11.37 on 10 and 17 DF,  p-value: 1.079e-05
```

```
cat(" We will select wt as a predictor based on the statistics as it has the lowest p value.")
```

```
##  We will select wt as a predictor based on the statistics as it has the lowest p value.
```

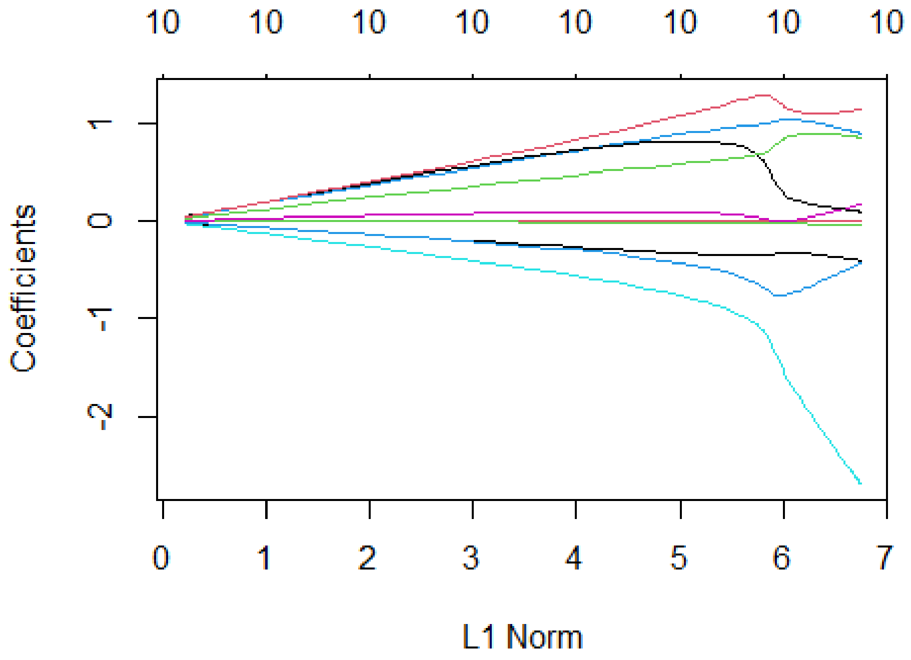
```
# coefficient values for relevant features
lm.fit$coefficients
```

```
## (Intercept)         cyl        disp          hp        drat          wt 
## 24.62378182 -0.41448777  0.01090413 -0.03298694  0.88506840 -2.73162674 
##        qsec          vs         am1        gear        carb 
##  0.18021450  0.08982164  1.15987939  0.85259465 -0.41726838
```

```
lambda_seq = 10^seq(3, -3, by= -.06)
# Perform a ridge regression using the glmnet package
ridge_regression<-glmnet(model.matrix(training_data$mpg~.,data = training_data)[, - 1],training_data$mpg,alpha=0,lambda=lambda_seq)
summary(ridge_regression)
```

```
##           Length Class     Mode   
## a0         101   -none-    numeric
## beta      1010   dgCMatrix S4     
## df         101   -none-    numeric
## dim          2   -none-    numeric
## lambda     101   -none-    numeric
## dev.ratio  101   -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

plot(ridge_regression)
```



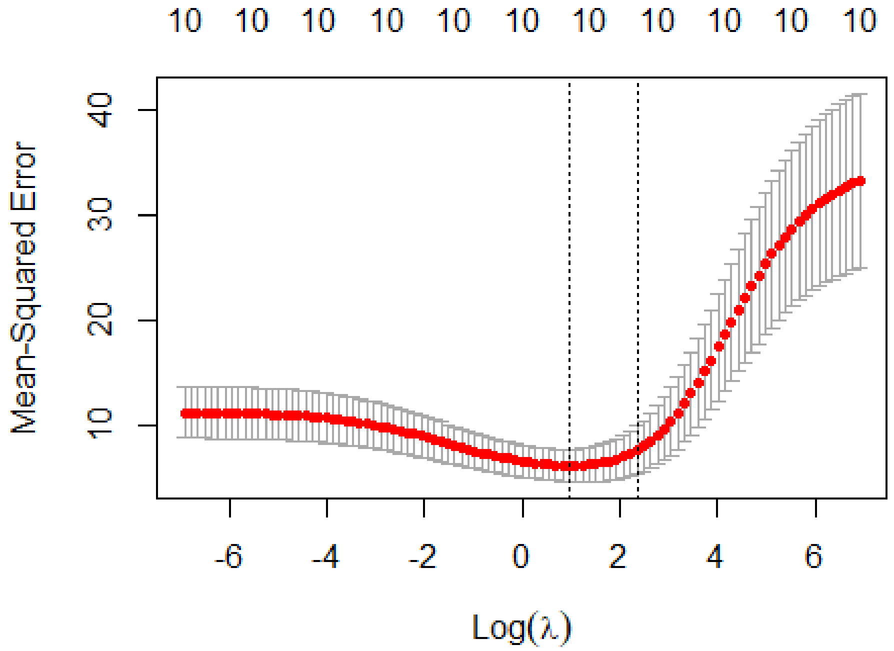
```
# Use cross-validation (via cv.glmnet) to determine the minimum value for
lambda - what do you obtain
cross_validation<-cv.glmnet(model.matrix(training_data$mpg~.,data =
training_data)[,- 1],training_data$mpg,alpha=0,lambda = lambda_seq,grouped =
FALSE)
cat("\n The best lambda: %s",cross_validation$lambda.min)

##
##  The best lambda: %s 2.630268

lambda_bst<-cross_validation$lambda.min
summary(cross_validation)

##            Length Class  Mode
## lambda     101    -none- numeric
## cvm        101    -none- numeric
## cvsd       101    -none- numeric
## cvup       101    -none- numeric
## cvlo       101    -none- numeric
## nzero      101    -none- numeric
## call         6    -none- call
## name         1    -none- character
## glmnet.fit  12     elnet  list
## lambda.min   1     -none- numeric
## lambda.1se   1     -none- numeric
## index        2     -none- numeric

# Plot training MSE as a function of lambda
plot(cross_validation)
```



```
# What is out-of-sample test set performance (using predict)
testing_predict<-predict(ridge_regression,s=lambda_bst,newx =
model.matrix(testing_data$mpg~.,data = testing_data)[, -1])
mean((testing_data$mpg-testing_predict)^2)

## [1] 11.50495

coef(cross_validation)

## 11 x 1 sparse Matrix of class "dgCMatrix"
##                       s1
## (Intercept) 20.376767880
## cyl         -0.321695828
## disp        -0.004734022
## hp          -0.010568861
## drat         0.866619485
## wt          -0.732029668
## qsec         0.091940966
## vs           0.816459140
## am1          1.039344279
## gear         0.570440867
## carb        -0.405025502
```

```
# Has ridge regression performed shrinkage, variable selection, or both?
cat("\n As we can see that new coefficients are smaller, we can say that the
ridge regression performs shrinkage.")
```

```
##
##  As we can see that new coefficients are smaller, we can say that the
ridge regression performs shrinkage.
```