

# Ridge and Lasso

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## Introduction

### Libraries

We are going to use a few libraries:

- **glmnet**: *Lasso and Elastic-Net Regularized Generalized Linear Models*
- **tidyverse**: *Easily Install and Load the 'Tidyverse'*
- **caret**: *Classification and Regression Training*
- **ggplot2**: *Create Elegant Data Visualisations Using the Grammar of Graphics*

```
library(glmnet)    # ridge and lasso for GLMs
library(tidyverse) # data manipulation and visualization
library(caret)     # statistical learning techniques
library(ggplot2)   # plots
```

### Data

We will use the **Body Fat dataset** (which is available in the [Datasets folder](#) of our course).

The data concerns a sample of 252 men, and contains 15 variables:

1. Density of the body, determined from underwater weighing
2. Percentage of body fat, calculated as a function of the Density according to Siri's equation:  $(495/\text{Density}) - 450$ .
3. Indicator for Age group (binary; 0: up to 45 years, 1: over 45)
4. Weight (lbs)

5. Height (inches)
6. Neck circumference (cm)
7. Chest circumference (cm)
8. Abdomen circumference (cm)
9. Hip circumference (cm)
10. Thigh circumference (cm)
11. Knee circumference (cm)
12. Ankle circumference (cm)
13. Biceps circumference (cm)
14. Forearm circumference (cm)
15. Wrist circumference (cm)

We want to understand whether we can reliably describe and predict body fat percentage on the basis of these variables, using regression methods. For age, we only have a binary indicator separating men below and above 45 years. The body measurements, on the other hand, are all continuous variables. Please see the [data description file](#) for more details.

```
df <- read.table('BODY_FAT.TXT', header=TRUE)
names(df)
```

```
## [1] "Density" "SiriBF." "Over45" "Weight" "Height" "NeckC"
## [7] "ChestC" "AbdomenC" "HipC" "ThighC" "KneeC" "AnkleC"
## [13] "BicepsC" "ForearmC" "WristC"
```

We want to predict “SiriBF.” using the other features, aside from “Density”. So we drop the “Density” column.

```
df <- df[, -1]
```

## Penalized regression

We will perform ridge/lasso penalization through the **glmnet** package. Let us identify predictors and response variable

```
# getting the predictors
x_var <- data.matrix(df[, -1]) # NOTE: glmnet requires a matrix structure
# getting the response variable
y_var <- df[, "SiriBF."]
```

Let’s have a look at the glmnet function:

```
help(glmnet)
```

Note that:

- $x$ : input matrix
- $y$ : response variable
- $\alpha$  is the elastic-net mixing parameter with range  $[0, 1]$ . Namely.  $\alpha = 1$  is the lasso (default) and  $\alpha = 0$  is the ridge.
- standardize is a logical flag for  $x$  variable standardization, prior to fitting the model sequence. The coefficients are always returned on the original scale. Default is standardize=TRUE.

## Ridge

To perform ridge regression, we run `glmnet` with  $\alpha = 0$ . The  $\lambda$ 's sequence is internally computed by the package itself – although a user-defined sequence can be provided as a *lambda* argument.

```
ridge <- glmnet(x_var, y_var, alpha=0)
summary(ridge)
```

```
##          Length Class      Mode
## a0         100  -none-   numeric
## beta       1300 dgMatrix S4
## df          100  -none-   numeric
## dim           2  -none-   numeric
## lambda       100  -none-   numeric
## dev.ratio   100  -none-   numeric
## nulldev       1  -none-   numeric
## npasses       1  -none-   numeric
## jerr          1  -none-   numeric
## offset        1  -none-  logical
## call          4  -none-    call
## nobs          1  -none-   numeric
```

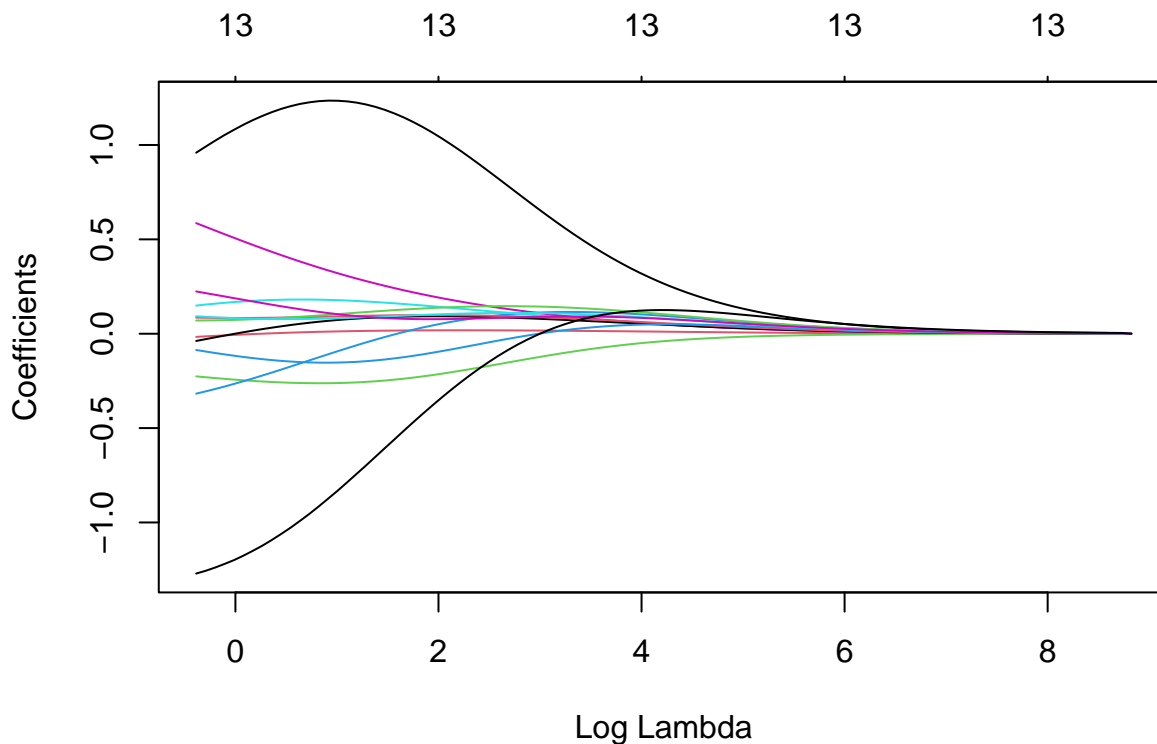
The summary is quite different than the one for linear regression, since ridge regression requires the tuning of  $\lambda$ . The code above fits a ridge regression for each  $\lambda$  value, and we have access to each of these model estimates.

We can plot the regularization path as follows:

```
dim(ridge$beta)
```

```
## [1] 13 100
```

```
plot(ridge, xvar="lambda")
```



We can automate the task of finding the optimal lambda value using the **cv.glmnet** function. This performs a k-fold cross-validation for glmnet, produces a plot, and returns “optimal”  $\lambda$  values.

```
cv_ridge <- cv.glmnet(x_var, y_var, alpha = 0)
cv_ridge
```

```
##
## Call:  cv.glmnet(x = x_var, y = y_var, alpha = 0)
##
## Measure: Mean-Squared Error
##
##      Lambda Index Measure      SE Nonzero
## min 0.6794   100   22.72 2.062        13
## 1se 1.3030    93   24.59 2.279        13
```

Two particular values of  $\lambda$  are highlighted: the minimum (min) and the largest value of lambda such that error is within 1 standard error of the minimum (1se).

```
cv_ridge$lambda.min
```

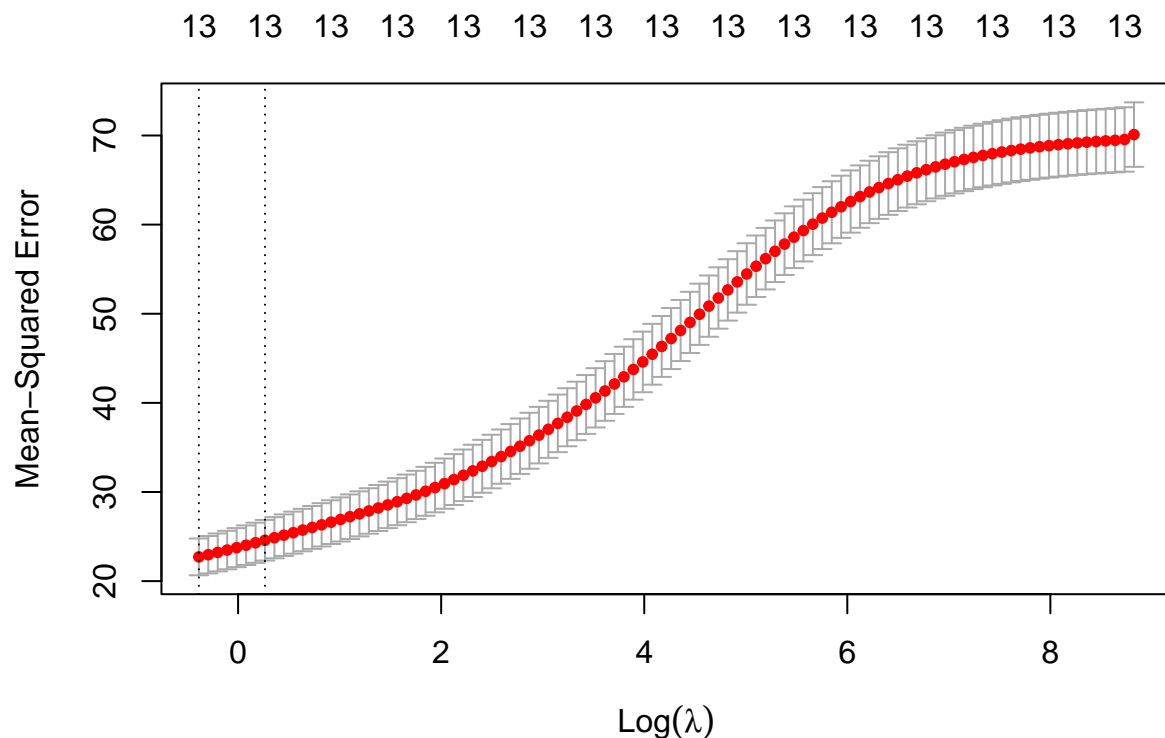
```
## [1] 0.6793883
```

```
cv_ridge$lambda.1se
```

```
## [1] 1.303006
```

We can visualize them in this way:

```
plot(cv_ridge)
```



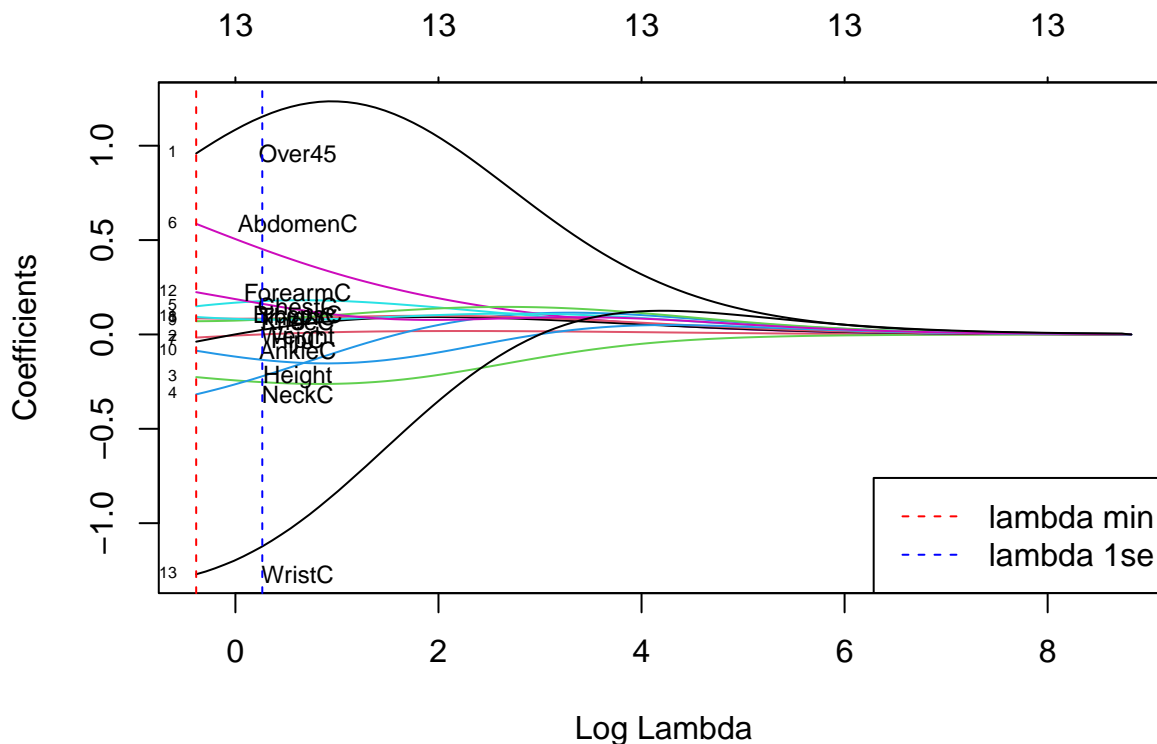
Let us see again how the regression coefficients change by modifying  $\lambda$ , highlighting the min and 1se values:

```
lbs_fun <- function(fit, offset_x=1, ...) {
  L <- length(fit$lambda)
  x <- log(fit$lambda[L])+ offset_x
```

```

y <- fit$beta[, L]
labs <- names(y)
text(x, y, labels=labs, cex=0.75, ...)
}
plot(ridge, xvar = "lambda", label=T)
lbs_fun(ridge)
abline(v=log(cv_ridge$lambda.min), col = "red", lty=2)
abline(v=log(cv_ridge$lambda.1se), col="blue", lty=2)
legend(x = "bottomright",
      legend = c("lambda min", "lambda 1se"),
      lty = c(2, 2),
      col = c("red", "blue"))

```



Let's re-fit the model and see the estimates associated to the minimum  $\lambda$ .

```

min_ridge <- glmnet(x_var, y_var, alpha=0, lambda= cv_ridge$lambda.min)
coef(min_ridge)

```

```

## 14 x 1 sparse Matrix of class "dgCMatrix"
##              s0
## (Intercept) -7.71880406
## Over45      0.95953292
## Weight     -0.01619205
## Height     -0.22630209
## NeckC      -0.31617445
## ChestC      0.14889642
## AbdomenC    0.58565111
## HipC       -0.03875703
## ThighC      0.08495378
## KneeC      0.06923480
## AnkleC     -0.08687724

```

```
## BicepsC      0.09165336
## ForearmC     0.22347815
## WristC       -1.27272327
```

We can use this model to make predictions on the training set.

```
# Make predictions on the training data
predictions <- min_ridge %>% predict(x_var) %>% as.vector()
# Model performance metrics
data.frame(
  RMSE = RMSE(predictions, y_var),
  Rsquare = R2(predictions, y_var)
)
```

```
##          RMSE  Rsquare
## 1 4.494532 0.714938
```

Be careful though! We are making predictions and assessing the goodness of fit based on training data. Is it the best choice? Do you have any other suggestions?

## Lasso

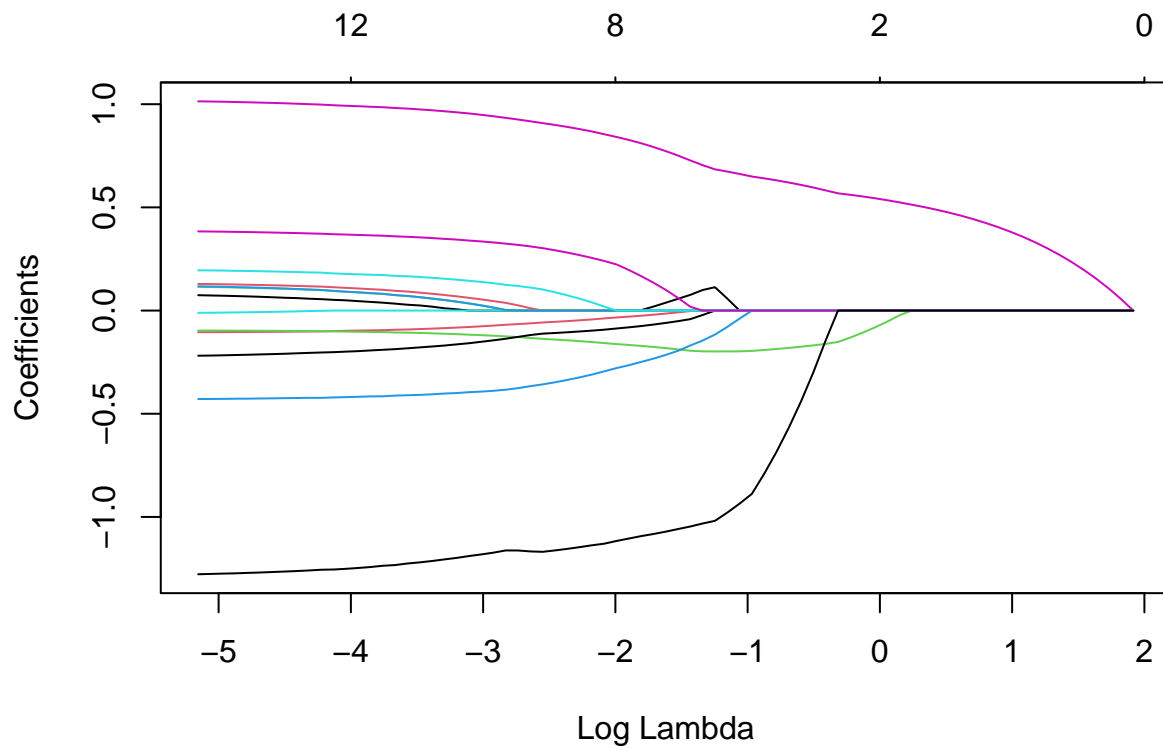
Let us now perform Lasso regression using the **glmnet** package. We follow the same approach as in Ridge regression, but set  $\alpha = 1$ .

```
lasso <- glmnet(x_var, y_var, alpha=1)
summary(lasso)
```

```
##          Length Class      Mode
## a0           77  -none-  numeric
## beta        1001 dgCMatrix S4
## df           77  -none-  numeric
## dim           2  -none-  numeric
## lambda        77  -none-  numeric
## dev.ratio      77  -none-  numeric
## nulldev        1  -none-  numeric
## npasses        1  -none-  numeric
## jerr           1  -none-  numeric
## offset         1  -none-  logical
## call           4  -none-   call
## nobs           1  -none-  numeric
```

Let's have a look at the selection path:

```
plot(lasso, xvar="lambda")
```

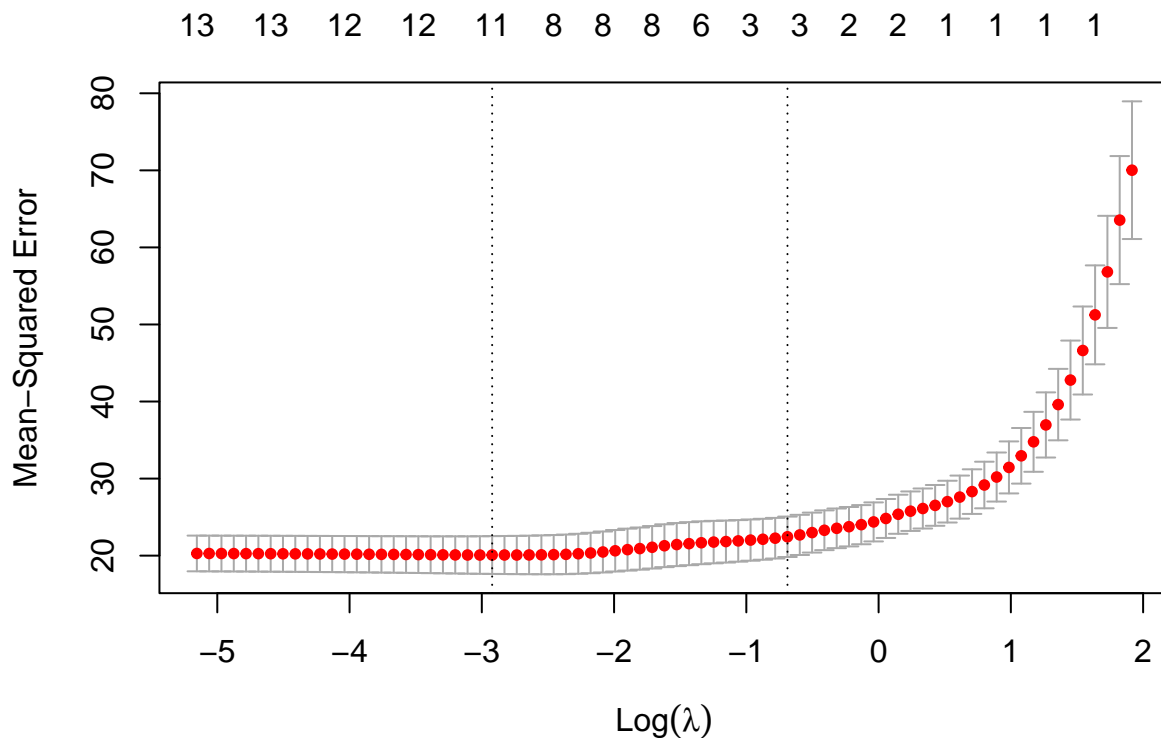


Once again, we need to tune the sparsity parameter  $\lambda$ . We use k-fold cross-validation through the `cv.glmnet` function.

```
cv_lasso <- cv.glmnet(x_var, y_var, alpha = 1)
cv_lasso

##
## Call:  cv.glmnet(x = x_var, y = y_var, alpha = 1)
##
## Measure: Mean-Squared Error
##
##      Lambda Index Measure      SE Nonzero
## min 0.0538   53  20.08 2.452      11
## 1se 0.5021   29  22.45 2.622       3

plot(cv_lasso)
```

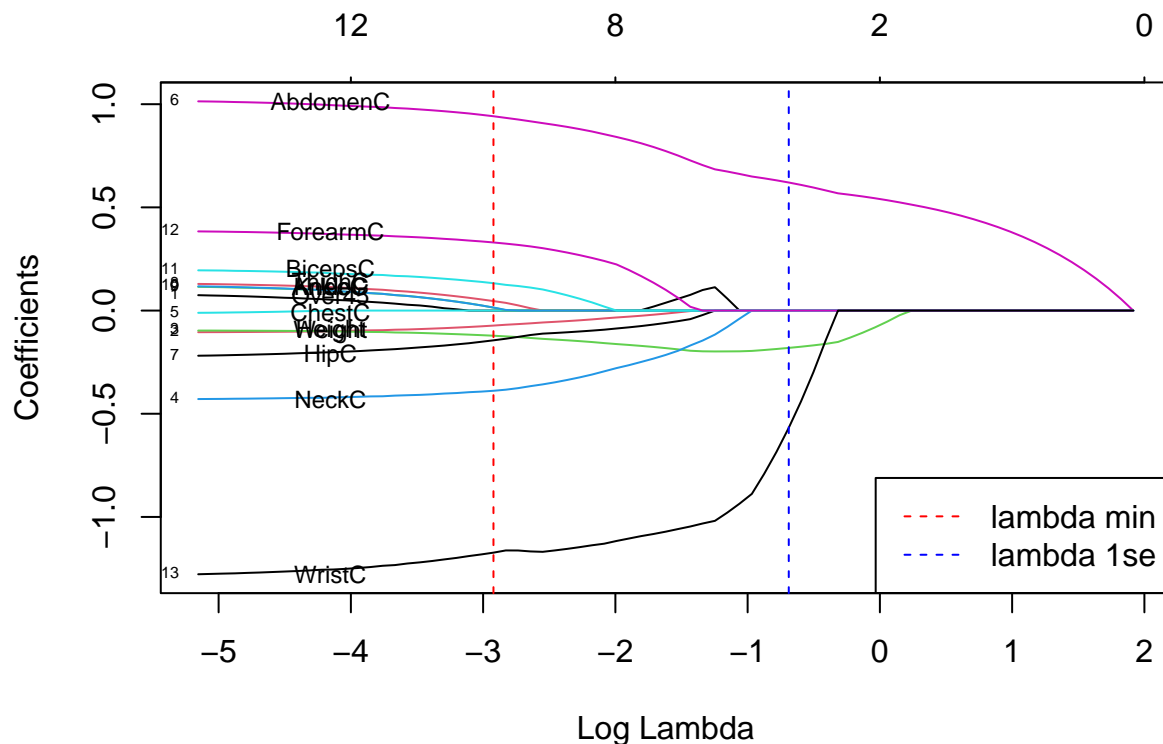


Also here, it outputs the min and the 1se  $\lambda$ . As expected, the number of non-zero coefficients (which is printed on top of the previous plot) is lower than the one for Ridge regression.

Let us see again how the regression coefficients change by modifying  $\lambda$ :

```
lbs_fun <- function(fit, offset_x=1, ...) {
  L <- length(fit$lambda)
  x <- log(fit$lambda[L]) + offset_x
  y <- fit$beta[, L]
  labs <- names(y)
  text(x, y, labels=labs, cex=0.75, ...)
}
plot(lasso, xvar = "lambda", label=T)
lbs_fun(lasso)
abline(v=log(cv_lasso$lambda.min), col = "red", lty=2)
abline(v=log(cv_lasso$lambda.1se), col="blue", lty=2)
legend(x = "bottomright",
       legend = c("lambda min", "lambda 1se"),
       lty = c(2, 2),
       col = c("red", "blue"))
```





Let us rebuild the model and compare the estimated coefficients for min and 1se  $\lambda$ .

```
min_lasso <- glmnet(x_var, y_var, alpha=1, lambda= cv_lasso$lambda.min)
se_lasso  <- glmnet(x_var, y_var, alpha=1, lambda= cv_lasso$lambda.1se)

lasso_mat <- cbind(coef(min_lasso), coef(se_lasso))
colnames(lasso_mat) <- c("min", "1se")
lasso_mat
```

```
## 14 x 2 sparse Matrix of class "dgCMatrix"
##           min      1se
## (Intercept) -13.02572407 -15.2345475
## Over45      .           .
## Weight      -0.07221900  .
## Height      -0.12199330 -0.1808351
## NeckC       -0.38887801  .
## ChestC      .           .
## AbdomenC     0.94225478  0.6205892
## HipC        -0.14771440  .
## ThighC       0.04895102  .
## KneeC       0.01204570  .
## AnkleC       0.01402466  .
## BicepsC     0.12920950  .
## ForearmC    0.32973473  .
## WristC      -1.17072511 -0.5687684
```

We can use this model to make predictions on the training set.

```
# Make predictions on the training data
predictions <- se_lasso %>% predict(x_var) %>% as.vector()
# Model performance metrics
data.frame(
```

```

RMSE = RMSE(predictions, y_var),
Rsquare = R2(predictions, y_var)
)

```

```

##      RMSE      Rsquare
## 1 4.63408 0.6976913

```

Let's try to overfit and look at the MSE increase again!

```

# take all pairwise interactions
dim(x_var)

```

```

## [1] 252 13

```

```

newx <- as.data.frame(x_var)
newx <- model.matrix(~ .^2, data=newx)
dim(newx)

```

```

## [1] 252 92

```

```

colnames(newx)

```

```

## [1] "(Intercept)"      "Over45"            "Weight"
## [4] "Height"            "NeckC"             "ChestC"
## [7] "AbdomenC"          "HipC"              "ThighC"
## [10] "KneeC"             "AnkleC"            "BicepsC"
## [13] "ForearmC"          "WristC"            "Over45:Weight"
## [16] "Over45:Height"     "Over45:NeckC"      "Over45:ChestC"
## [19] "Over45:AbdomenC"   "Over45:HipC"       "Over45:ThighC"
## [22] "Over45:KneeC"      "Over45:AnkleC"     "Over45:BicepsC"
## [25] "Over45:ForearmC"   "Over45:WristC"     "Weight:Height"
## [28] "Weight:NeckC"      "Weight:ChestC"     "Weight:AbdomenC"
## [31] "Weight:HipC"       "Weight:ThighC"     "Weight:KneeC"
## [34] "Weight:AnkleC"     "Weight:BicepsC"    "Weight:ForearmC"
## [37] "Weight:WristC"     "Height:NeckC"      "Height:ChestC"
## [40] "Height:AbdomenC"   "Height:HipC"       "Height:ThighC"
## [43] "Height:KneeC"      "Height:AnkleC"     "Height:BicepsC"
## [46] "Height:ForearmC"   "Height:WristC"     "NeckC:ChestC"
## [49] "NeckC:AbdomenC"    "NeckC:HipC"        "NeckC:ThighC"
## [52] "NeckC:KneeC"       "NeckC:AnkleC"      "NeckC:BicepsC"
## [55] "NeckC:ForearmC"    "NeckC:WristC"      "ChestC:AbdomenC"
## [58] "ChestC:HipC"       "ChestC:ThighC"     "ChestC:KneeC"
## [61] "ChestC:AnkleC"     "ChestC:BicepsC"    "ChestC:ForearmC"
## [64] "ChestC:WristC"     "AbdomenC:HipC"     "AbdomenC:ThighC"
## [67] "AbdomenC:KneeC"    "AbdomenC:AnkleC"   "AbdomenC:BicepsC"
## [70] "AbdomenC:ForearmC" "AbdomenC:WristC"   "HipC:ThighC"
## [73] "HipC:KneeC"        "HipC:AnkleC"       "HipC:BicepsC"
## [76] "HipC:ForearmC"     "HipC:WristC"       "ThighC:KneeC"
## [79] "ThighC:AnkleC"     "ThighC:BicepsC"    "ThighC:ForearmC"
## [82] "ThighC:WristC"     "KneeC:AnkleC"      "KneeC:BicepsC"
## [85] "KneeC:ForearmC"    "KneeC:WristC"      "AnkleC:BicepsC"
## [88] "AnkleC:ForearmC"   "AnkleC:WristC"     "BicepsC:ForearmC"
## [91] "BicepsC:WristC"    "ForearmC:WristC"

```

```

# take their squared terms too!
newx <- as.matrix(newx)
newx <- cbind(newx, newx[, 2:ncol(newx)]^2)

```

```
dim(newx)
```

```
## [1] 252 183
```

```
cv_lasso <- cv.glmnet(newx, y_var, alpha = 1)
cv_lasso
```

```
##
```

```
## Call: cv.glmnet(x = newx, y = y_var, alpha = 1)
```

```
##
```

```
## Measure: Mean-Squared Error
```

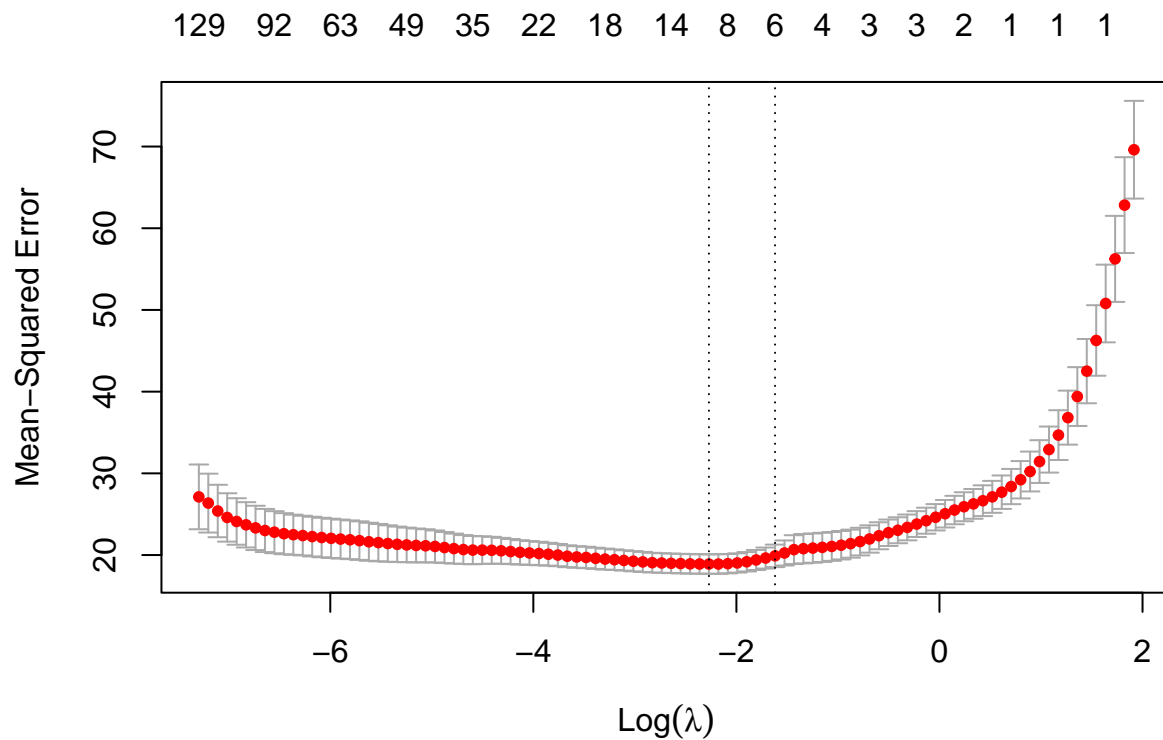
```
##
```

```
##      Lambda Index Measure      SE Nonzero
```

```
## min 0.1033   46   18.9 1.191         8
```

```
## 1se 0.1981   39   19.9 1.377         6
```

```
plot(cv_lasso)
```



```
coef(cv_lasso)
```

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

```
##                                     s1
```

```
## (Intercept)      -4.333592e+01
```

```
## (Intercept)      .
```

```
## Over45           .
```

```
## Weight           .
```

```
## Height           .
```

```
## NeckC            .
```

```
## ChestC           .
```

```
## AbdomenC         7.975966e-01
```

```
## HipC             .
```

```
## ThighC           .
```

```

## KneeC .
## AnkleC .
## BicepsC .
## ForearmC .
## WristC .
## Over45:Weight .
## Over45:Height .
## Over45:NeckC .
## Over45:ChestC .
## Over45:AbdomenC .
## Over45:HipC .
## Over45:ThighC .
## Over45:KneeC .
## Over45:AnkleC .
## Over45:BicepsC .
## Over45:ForearmC .
## Over45:WristC .
## Weight:Height .
## Weight:NeckC .
## Weight:ChestC .
## Weight:AbdomenC .
## Weight:HipC .
## Weight:ThighC .
## Weight:KneeC .
## Weight:AnkleC .
## Weight:BicepsC .
## Weight:ForearmC .
## Weight:WristC .
## Height:NeckC .
## Height:ChestC .
## Height:AbdomenC .
## Height:HipC .
## Height:ThighC .
## Height:KneeC .
## Height:AnkleC .
## Height:BicepsC .
## Height:ForearmC .
## Height:WristC .
## NeckC:ChestC .
## NeckC:AbdomenC .
## NeckC:HipC .
## NeckC:ThighC .
## NeckC:KneeC .
## NeckC:AnkleC .
## NeckC:BicepsC .
## NeckC:ForearmC .
## NeckC:WristC .
## ChestC:AbdomenC .
## ChestC:HipC .
## ChestC:ThighC .
## ChestC:KneeC .
## ChestC:AnkleC .
## ChestC:BicepsC .
## ChestC:ForearmC .

```

```

## ChestC:WristC .
## AbdomenC:HipC .
## AbdomenC:ThighC .
## AbdomenC:KneeC .
## AbdomenC:AnkleC .
## AbdomenC:BicepsC .
## AbdomenC:ForearmC 4.885119e-04
## AbdomenC:WristC .
## HipC:ThighC .
## HipC:KneeC .
## HipC:AnkleC .
## HipC:BicepsC .
## HipC:ForearmC .
## HipC:WristC .
## ThighC:KneeC .
## ThighC:AnkleC .
## ThighC:BicepsC .
## ThighC:ForearmC .
## ThighC:WristC .
## KneeC:AnkleC .
## KneeC:BicepsC .
## KneeC:ForearmC .
## KneeC:WristC .
## AnkleC:BicepsC .
## AnkleC:ForearmC .
## AnkleC:WristC .
## BicepsC:ForearmC .
## BicepsC:WristC .
## ForearmC:WristC .
## Over45 .
## Weight .
## Height .
## NeckC .
## ChestC .
## AbdomenC .
## HipC .
## ThighC .
## KneeC .
## AnkleC .
## BicepsC .
## ForearmC .
## WristC .
## Over45:Weight .
## Over45:Height .
## Over45:NeckC .
## Over45:ChestC .
## Over45:AbdomenC .
## Over45:HipC .
## Over45:ThighC .
## Over45:KneeC .
## Over45:AnkleC .
## Over45:BicepsC .
## Over45:ForearmC .
## Over45:WristC .

```

```

## Weight:Height      .
## Weight:NeckC       .
## Weight:ChestC      .
## Weight:AbdomenC    .
## Weight:HipC        -7.336356e-09
## Weight:ThighC      .
## Weight:KneeC       .
## Weight:AnkleC      .
## Weight:BicepsC     .
## Weight:ForearmC    .
## Weight:WristC      .
## Height:NeckC       -1.598837e-07
## Height:ChestC      .
## Height:AbdomenC    .
## Height:HipC        .
## Height:ThighC      .
## Height:KneeC       .
## Height:AnkleC      .
## Height:BicepsC     .
## Height:ForearmC    .
## Height:WristC      -4.686730e-06
## NeckC:ChestC       .
## NeckC:AbdomenC     .
## NeckC:HipC         .
## NeckC:ThighC       .
## NeckC:KneeC        .
## NeckC:AnkleC       .
## NeckC:BicepsC      .
## NeckC:ForearmC     .
## NeckC:WristC       -2.495760e-06
## ChestC:AbdomenC    .
## ChestC:HipC        .
## ChestC:ThighC      .
## ChestC:KneeC       .
## ChestC:AnkleC      .
## ChestC:BicepsC     .
## ChestC:ForearmC    .
## ChestC:WristC      .
## AbdomenC:HipC      .
## AbdomenC:ThighC    .
## AbdomenC:KneeC     .
## AbdomenC:AnkleC    .
## AbdomenC:BicepsC   .
## AbdomenC:ForearmC  .
## AbdomenC:WristC    .
## HipC:ThighC        .
## HipC:KneeC         .
## HipC:AnkleC        .
## HipC:BicepsC       .
## HipC:ForearmC      .
## HipC:WristC        .
## ThighC:KneeC       .
## ThighC:AnkleC      .
## ThighC:BicepsC     .

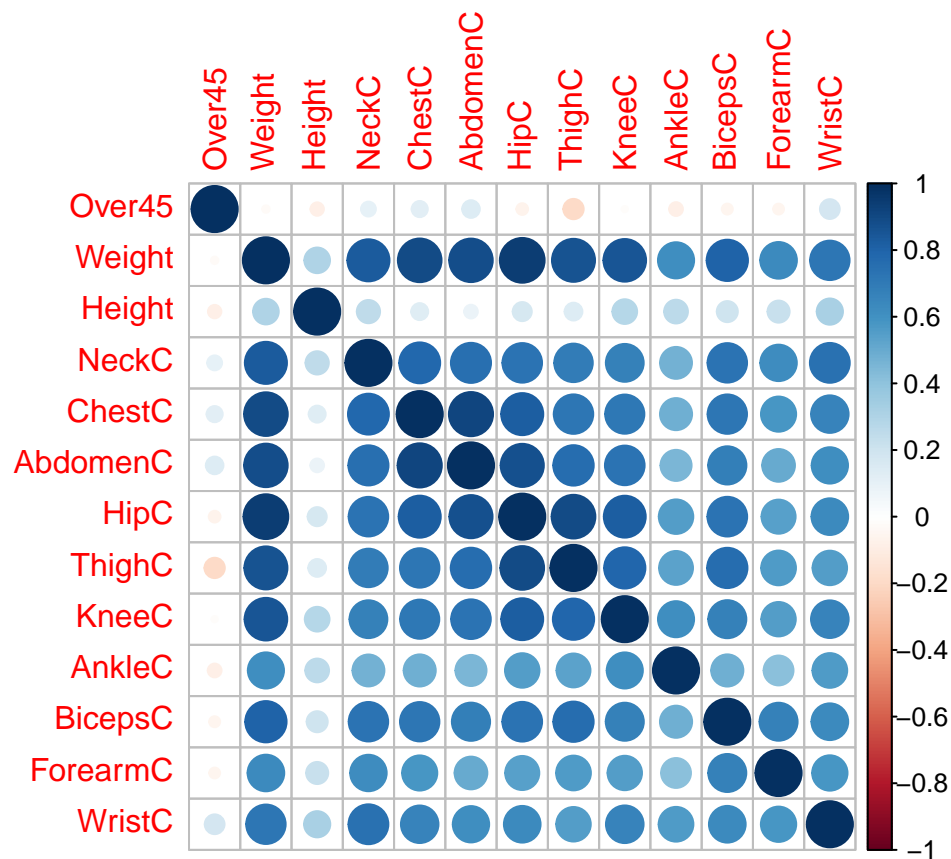
```

```
## ThighC:ForearmC .
## ThighC:WristC .
## KneeC:AnkleC .
## KneeC:BicepsC .
## KneeC:ForearmC .
## KneeC:WristC .
## AnkleC:BicepsC .
## AnkleC:ForearmC .
## AnkleC:WristC .
## BicepsC:ForearmC .
## BicepsC:WristC .
## ForearmC:WristC .
```

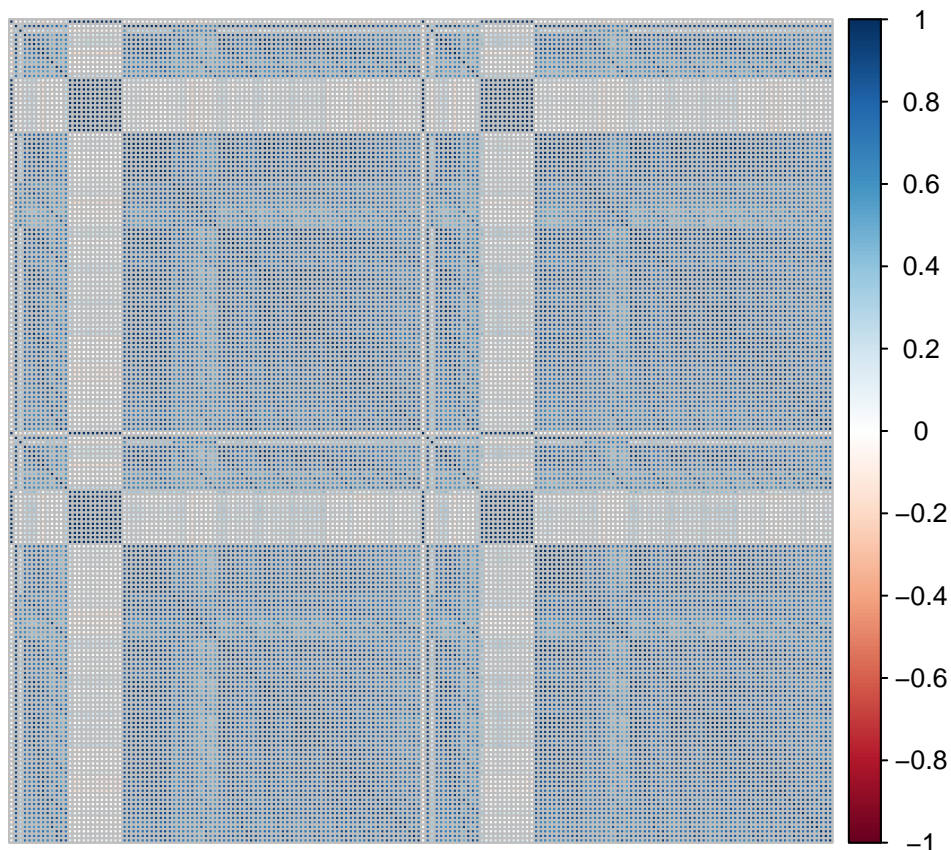
However, lasso assumptions are unlikely to hold due to strong correlations between predictors.

```
library(corrplot)
```

```
# original data
corrplot(cor(x_var))
```



```
# transformed data
newx = as.data.frame(newx[, 2:ncol(newx)])
corrplot(cor(newx), tl.pos='n')
```



## Digging in the irrepresentability condition

As you have seen before, the variance-covariance matrix can tell us whether LASSO will work (at least asymptotically) on the data at our disposal. Let's have a look at an example (available [here](#)).

```
set.seed(12345) # = Seed for replication

library(mvtnorm) # Sampling from a multivariate Normal
library(clusterGeneration) # Random matrix generation

k = 10 # = Number of Candidate Variables
p = 5 # = Number of Relevant Variables
N = 500 # = Number of observations

betas = (-1)^(1:p) # = Values for beta

sigma1 = genPositiveDefMat(k,"unifcorrmat")$Sigma # sigma1 violates irc

sigma2 = sigma1 # sigma2 satisfies irc
sigma2[(p+1):k,1:p]=0 # removing correlation among active and nonactive variables
sigma2[1:p,(p+1):k]=0

# Verify irrepresentable condition
irc1 = sort(abs(sigma1[(p+1):k,1:p] %*% solve(sigma1[1:p,1:p]) %*% sign(betas)))
irc2 = sort(abs(sigma2[(p+1):k,1:p] %*% solve(sigma2[1:p,1:p]) %*% sign(betas)))
c(max(irc1),max(irc2))
```



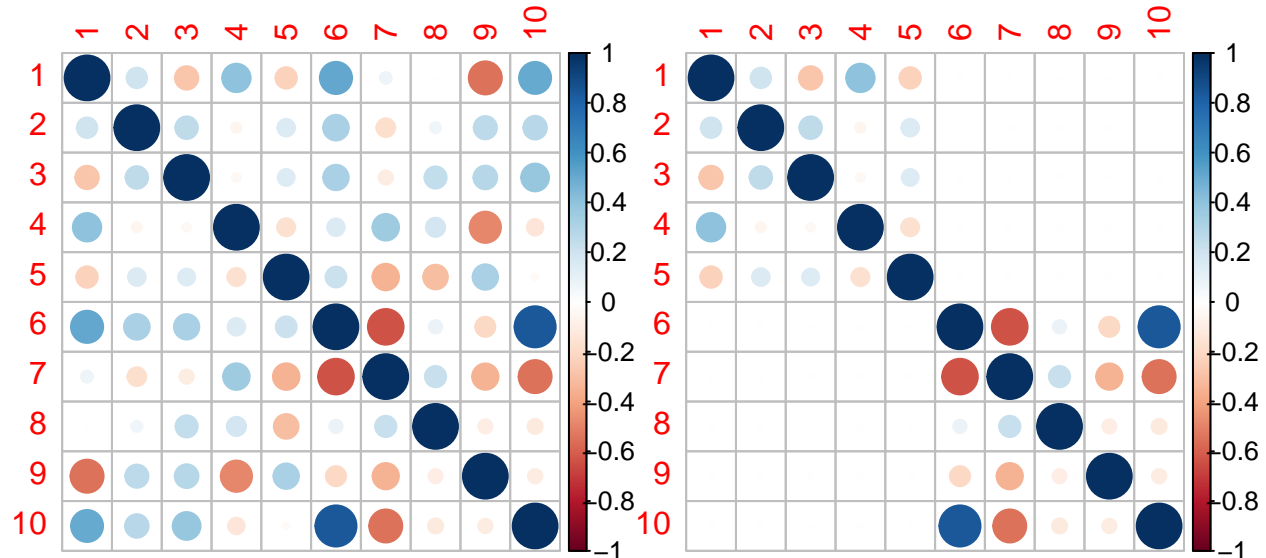
```
## [1] 3.222599 0.000000
```

```
# = Have a look at the correlation matrices
```

```
par(mfrow=c(1,2))
```

```
corrplot(cov2cor(sigma1))
```

```
corrplot(cov2cor(sigma2))
```



The first design matrix does not satisfy IRC, while the second does. Let's check it “visually”, by exploring the regularization paths!

```
X1 = rmvnorm(N,sigma = sigma1) # Variables violating IRC
```

```
X2 = rmvnorm(N,sigma = sigma2) # Variables satisfying IRC
```

```
e = rnorm(N) # Error from Standard Normal
```

```
y1 = X1[,1:p]%%betas+e # Generate y for design 1
```

```
y2 = X2[,1:p]%%betas+e # Generate y for design 2
```

```
lasso1 = glmnet(X1,y1,nlambda = 100) # Estimation for design 1
```

```
lasso2 = glmnet(X2,y2,nlambda = 100) # Estimation for design 2
```

```
# Regularization paths
```

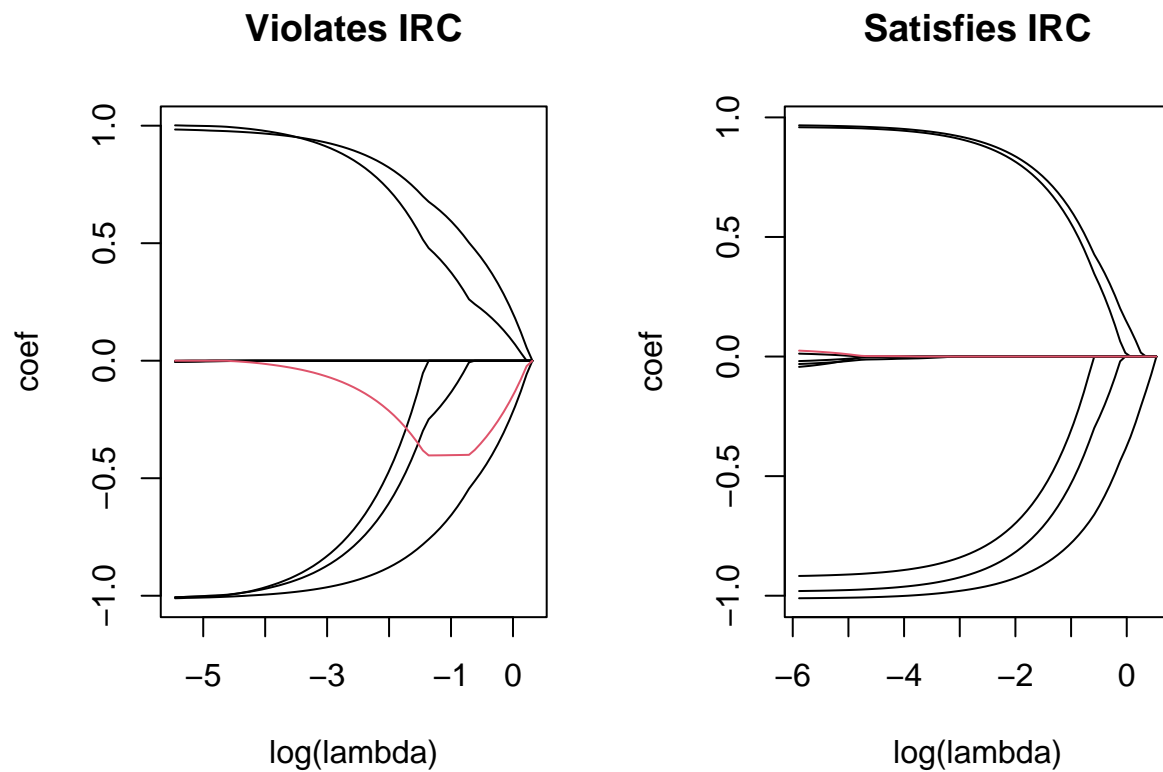
```
par(mfrow=c(1,2))
```

```
l1=log(lasso1$lambda)
```

```
matplot(as.matrix(l1),t(coef(lasso1)[-1,]),type="l",lty=1,col=c(rep(1,9),2),ylab="coef",xlab="log(lambda)
```

```
l2=log(lasso2$lambda)
```

```
matplot(as.matrix(l2),t(coef(lasso2)[-1,]),type="l",lty=1,col=c(rep(1,9),2),ylab="coef",xlab="log(lambda)
```



## Nonconvex penalization methods

If you want to try nonconvex penalization methods, have a look at the **ncvreg** package! It has a very similar syntax than glmnet.

```
library(ncvreg)

dim(newx)

## [1] 252 182

cv_scad <- cv.ncvreg(as.matrix(newx), y_var)
plot(cv_scad)
```

