DIMENSION REDUCTION AND SHRINKAGE

Part II. Ridge Regression and LASSO

3. LASSO and RIDGE REGRESSION in package GLMNET

```
> library(glmnet)
```

 # This package requires X-variables in a matrix

```
> X = model.matrix( medv ~ ., data=Boston )
> Y = medv
> ridgereg = glmnet(X, Y, alpha=0, lambda = seq(0,10,0.01))
```

 # alpha is a "mixing parameter". It combines Lasso and Ridge Regression. We only need the extreme values for now,

alpha=0 => ridge regression
alpha=1 => lasso

 # So, which lambda is it best to choose? Run cross-validation…

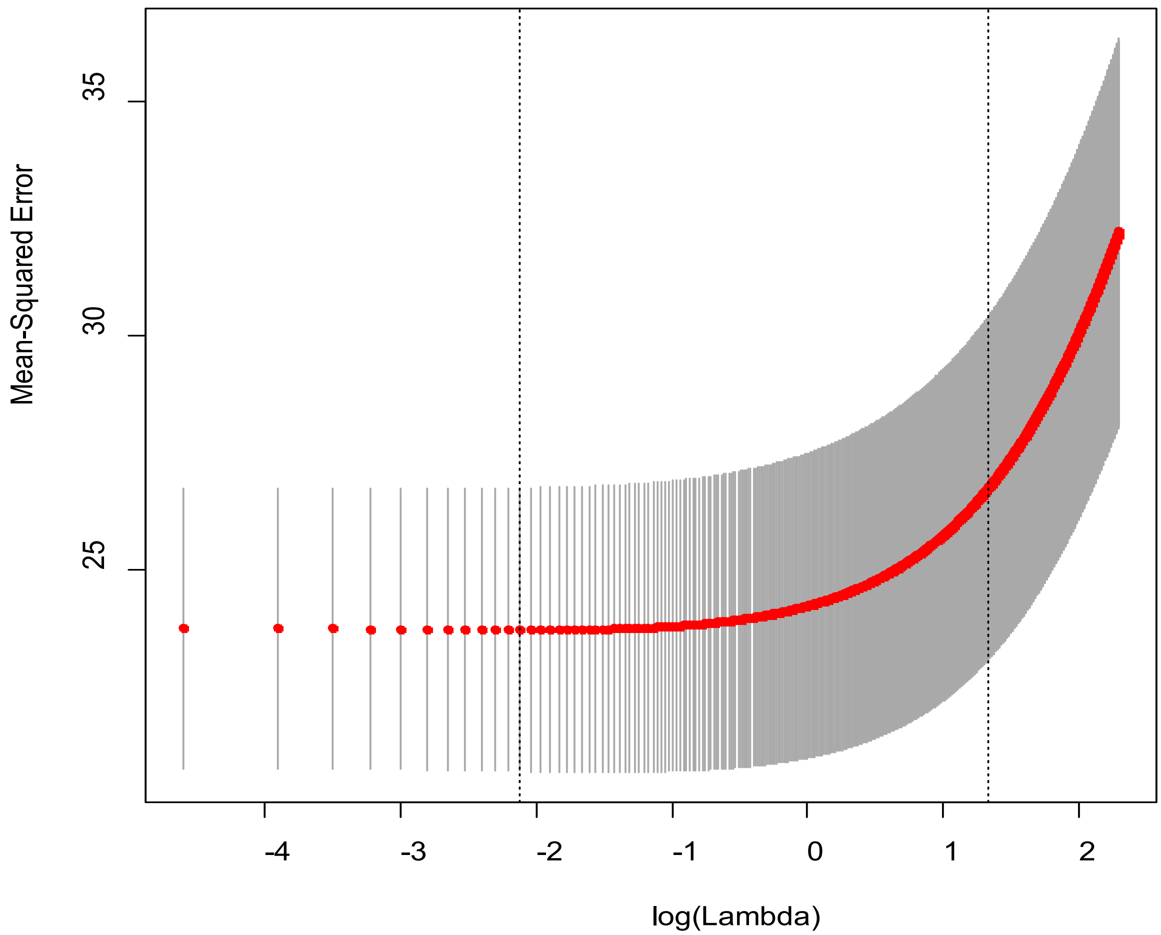
```
> cv_ridge = cv.glmnet(X,medv,alpha=0,lambda=seq(0,10,0.01))
> names(cv_ridge)
 [1] "lambda"     "cvm"        "cvsd"       "cvup"       "cvlo"       "nzero"      "name"       "glmnet.fit"
 [9] "lambda.min" "lambda.1se"
```

 # For the selected values of lambda, we get

"cvm" = the mean cross-validation error
"cvsd" = its estimated standard error
"cvlo" = cvm – cvsd (lower curve)
"cvup"= cvm + cvsd (upper curve)

 # All these can be plotted…

```
> plot(cv_ridge)
```



 # Which lambda minimized the MSE?

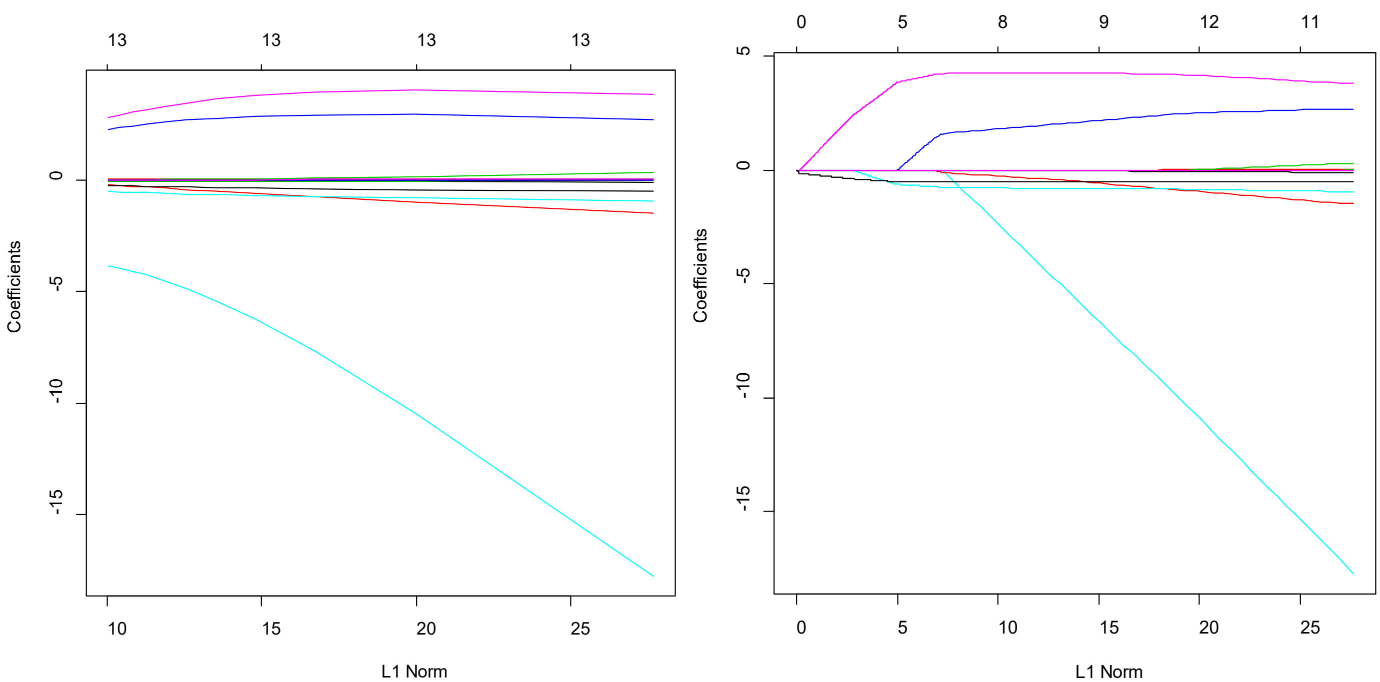
```
> cv_ridge$lambda.min
[1] 0.12
> predict( ridgereg, cv_ridge$lambda.min, type="coefficients" )

(Intercept) 20.863586526
crim        -0.068099108
zn           0.020536577
indus       -0.068164404
chas         2.777651593
nox         -5.514335229
rm           3.645249869
age         -0.007642606
dis         -0.532994082
rad          0.034679405
tax         -0.002916331
ptratio     -0.676296397
black        0.007674913
lstat       -0.351786530
```

 # Similarly with LASSO, only choose alpha=1

```
> lasso = glmnet(X, Y, alpha=1, lambda = seq(0,10,0.01))
```

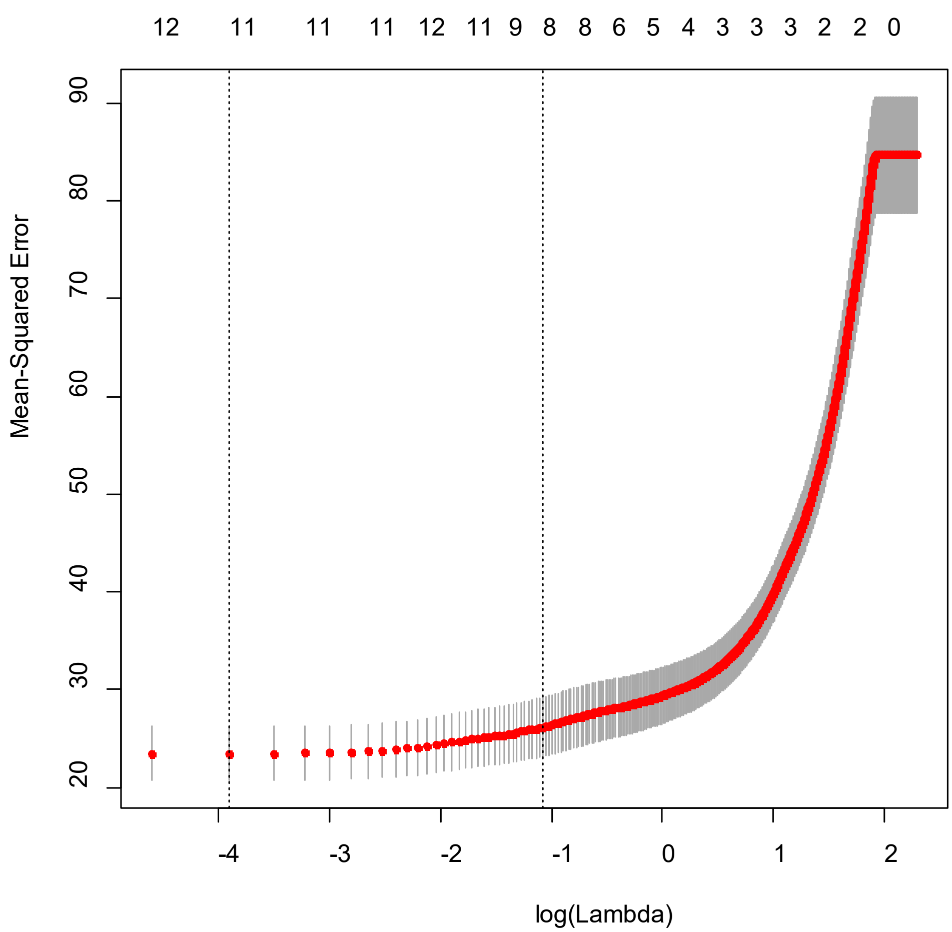
 # Compare the slopes estimated by ridge regression and by lasso

```
> plot(ridgereg)
> plot(lasso)
```



 # Ridge regression uses all the variables – all slopes are not 0 for all lambda. Conversely, lasso does variable selection and sends some slopes to 0. The number of non-zero slopes is printed in the top.

> cv.lasso = cv.glmnet(X, medv, alpha=1, lambda=seq(0,10,0.01))
> plot(cv.lasso)



> cv.lasso$lambda.min
[1] 0.02
> predict(lasso,cv. lasso$lambda.min, type="coefficients")

```
(Intercept) 18.739101467
crim        -0.024356546
zn           .
indus        .
chas         2.009577446
nox         -4.667589527
rm           4.273554725
age          .
dis         -0.401567952
rad          .
tax          .
ptratio     -0.803881292
black        0.006716721
lstat       -0.518576315
```

 # For LASSO, the best lambda to use is 0.02. Some coefficients are 0 – these variables are removed from the model.

 # Prediction for new values of X and cross-validation

> n = length(medv)
> Z = sample(n,n/2)

> lasso = glmnet(X[Z,], medv[Z], alpha=1, lambda=seq(0,10,0.01))
> Yhat = predict(lasso, cv.lasso$lambda.min, newx=X[-Z,])
> mean((Yhat - medv[-Z])^2)
[1] 23.62894

 # This is the test MSE, estimated by the validation set approach.