

# Compulsory exercise 2: Group 24

TMA4268 Statistical Learning V2019

Silje Anfindsen and Clara Panchaud

19 March, 2020

## Problem 1

a)

Let's find the ridge regression estimator. Remember that  $\hat{\beta}_{Ridge}$  minimizes  $RSS + \lambda \sum_{j=1}^p \beta_j^2$ . Let's rewrite this in matrix notation.

$$\begin{aligned} \min_{\beta} \{ (y - X\beta)^T (y - X\beta) + \lambda \beta^T \beta \} &= \text{develop the expression} \\ \min_{\beta} \{ y^T y - 2\beta^T X^T y + \beta^T X^T X \beta + \lambda \beta^T \beta \} & \quad \text{take the derivative with respect to beta and set equal to 0} \\ -2X^T y + 2X^T X \beta + 2\lambda \beta &= 0 \\ (X^T X + 2\lambda I) \beta &= X^T y \\ \beta &= (X^T X + \lambda I)^{-1} X^T y \end{aligned}$$

Therefore the estimator is  $\hat{\beta}_{Ridge} = (X^T X + \lambda I)^{-1} X^T y$ .

b)

To find the expected value and the variance-covariance matrix of  $\hat{\beta}_{Ridge}$  we need to remember the distribution of  $y$ ,  $y \sim N(X\beta, \sigma^2 I)$ . Therefore we get the expected value:

$$E(\hat{\beta}_{Ridge}) = E((X^T X + \lambda I)^{-1} X^T y) = (X^T X + \lambda I)^{-1} X^T E(y) = (X^T X + \lambda I)^{-1} X^T X \beta$$

and the variance-covariance matrix:

$$\begin{aligned} Var(\hat{\beta}_{Ridge}) &= Var((X^T X + \lambda I)^{-1} X^T y) = \text{by property of the variance} \\ (X^T X + \lambda I)^{-1} X^T Var(y) (X^T X + \lambda I)^{-1} X^T &= \text{develop the expression} \\ \sigma^2 (X^T X + \lambda I)^{-1} X^T X (X^T X + \lambda I)^{-1} & \end{aligned}$$

c)

TRUE, FALSE, FALSE, TRUE

d)

```
library(ISLR)
library(leaps)
library(glmnet)
```

We want to work with the *College* data. First we split it into a training and a testing set.

```
set.seed(1)

#make training and testing set
train.ind = sample(1:nrow(College), 0.5 * nrow(College))
college.train = College[train.ind, ]
college.test = College[-train.ind, ]

#the structure of the data
str(College)
```

```
## 'data.frame': 777 obs. of 18 variables:
## $ Private : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 2 2 2 2 ...
## $ Apps : num 1660 2186 1428 417 193 ...
## $ Accept : num 1232 1924 1097 349 146 ...
## $ Enroll : num 721 512 336 137 55 158 103 489 227 172 ...
## $ Top10perc : num 23 16 22 60 16 38 17 37 30 21 ...
## $ Top25perc : num 52 29 50 89 44 62 45 68 63 44 ...
## $ F.Undergrad: num 2885 2683 1036 510 249 ...
## $ P.Undergrad: num 537 1227 99 63 869 ...
## $ Outstate : num 7440 12280 11250 12960 7560 ...
## $ Room.Board : num 3300 6450 3750 5450 4120 ...
## $ Books : num 450 750 400 450 800 500 500 450 300 660 ...
## $ Personal : num 2200 1500 1165 875 1500 ...
## $ PhD : num 70 29 53 92 76 67 90 89 79 40 ...
## $ Terminal : num 78 30 66 97 72 73 93 100 84 41 ...
## $ S.F.Ratio : num 18.1 12.2 12.9 7.7 11.9 9.4 11.5 13.7 11.3 11.5 ...
## $ perc.alumni: num 12 16 30 37 2 11 26 37 23 15 ...
## $ Expend : num 7041 10527 8735 19016 10922 ...
## $ Grad.Rate : num 60 56 54 59 15 55 63 73 80 52 ...
```

Now we will apply forward selection, using *Outstate* as a response. We have 18 variables including the response so we will obtain a model including up to 17 variables.

```
nb_predictors<-17
forward<-regsubsets(Outstate~.,college.train,nvmax=17,method="forward")
sum<-summary(forward)
```

In Figure 1 we can look at the RSS and the adjusted  $R^2$  in order to pick the number of variables that gives the optimal result. Remember that if the difference is not very significant we would rather pick the simplest model. It seems like 5 variables would be good here.

```
par(mfrow=c(1,2))
plot(sum$rss,xlab="Number of Variables",ylab="RSS",type="l")
plot(sum$adjr2,xlab="Number of Variables",ylab="Adjusted RSq",type="l")
```

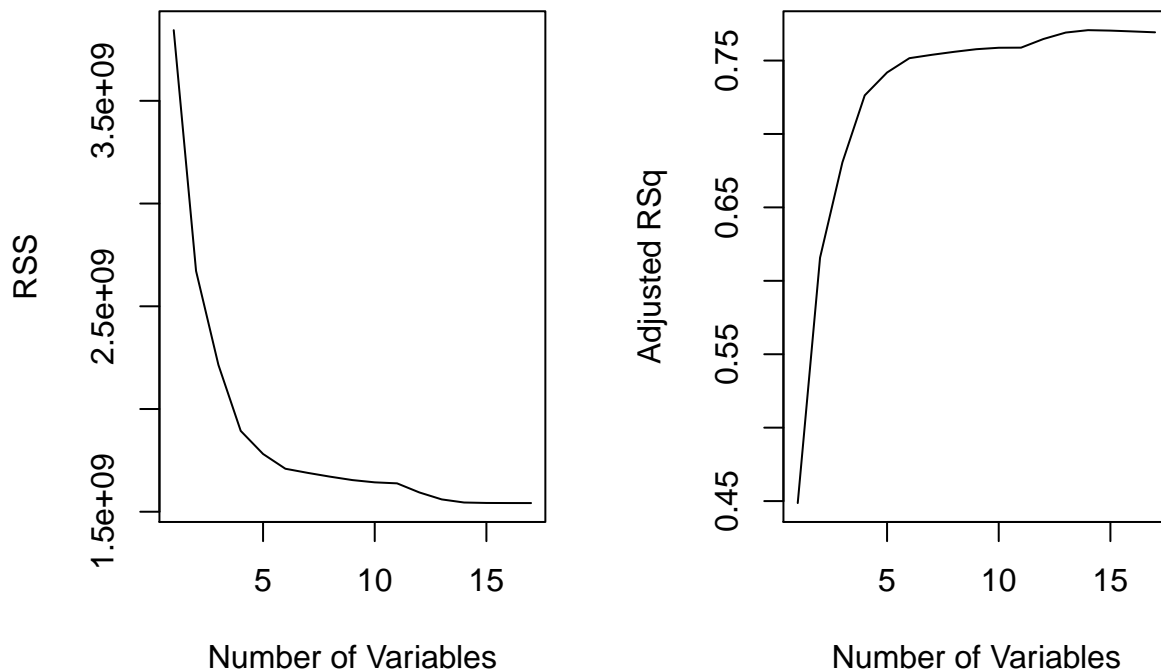


Figure 1: Comparison of models with different number of variables.

Below are the chosen variables when we decide to include 5 variables in the reduced model.

```
nb_selected_pred<-5
variables<-names( coef( forward,id=nb_selected_pred ) )
variables
```

```
## [1] "(Intercept)" "PrivateYes" "Room.Board" "perc.alumni" "Expend"
## [6] "Grad.Rate"
```

We will now find the reduced model as well as the MSE (mean squared error) on the test set.

```
#fit the reduced model
reduced.model<-lm(Outstate~Private+Room.Board+Terminal+perc.alumni+Expend,college.train)
summary(reduced.model)
```

```
##
## Call:
```

```
## lm(formula = Outstate ~ Private + Room.Board + Terminal + perc.alumni +
##      Expend, data = college.train)
##
## Residuals:
##      Min        1Q    Median        3Q        Max
## -6445.5 -1420.8  -101.8   1409.1   9608.6
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -4047.0191    712.4638  -5.680 2.67e-08 ***
## PrivateYes   2847.0626    302.6117   9.408 < 2e-16 ***
## Room.Board    1.2261     0.1226   9.998 < 2e-16 ***
## Terminal     43.0779     9.3515   4.607 5.59e-06 ***
## perc.alumni   75.1039    10.6011   7.085 6.76e-12 ***
## Expend        0.1983     0.0241   8.229 3.02e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2167 on 382 degrees of freedom
## Multiple R-squared:  0.7434, Adjusted R-squared:  0.74
## F-statistic: 221.3 on 5 and 382 DF,  p-value: < 2.2e-16
```

The reduced model is

$$\text{Outstate} = -4047.0191 + 2847.0626\text{Private} + 1.2261\text{Room.Board} \\ + 43.0779\text{Terminal} + 75.1039\text{perc.alumni} + 0.1983\text{Expend},$$

```
#find test MSE
p<-predict(reduced.model,newdata=college.test)
error1 <- mean(((college.test$Outstate)-p)^2)
error1
```

```
## [1] 4010675
```

The test MSE is

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{f}(x_i))^2 = 4010675$$

e)

We will now select a model for the same dataset as in (d) but this time with the Lasso method. Again, we use both a training and testing set for the data.

```
#Make a x matrix and y vector for both the training and testing set
x_train<-model.matrix(Outstate~.,college.train)[,-1]
y_train<-college.train$Outstate
x_test<-model.matrix(Outstate~.,college.test)[,-1]
y_test<-college.test$Outstate
```

In order to select the best value for the tuning parameter  $\lambda$  we will use cross validation.

```

set.seed(2)

#perform the Lasso method and choose the best model using CV
lasso.mod = glmnet(x_train,y_train,alpha=1) #lasso method on train set
cv.lasso = cv.glmnet(x_train,y_train,alpha=1) #CV on train set
lambda.best = cv.lasso$lambda.min #select best lambda
lambda.best

## [1] 120.4282

#do we need this plot ???
plot(cv.lasso)

```

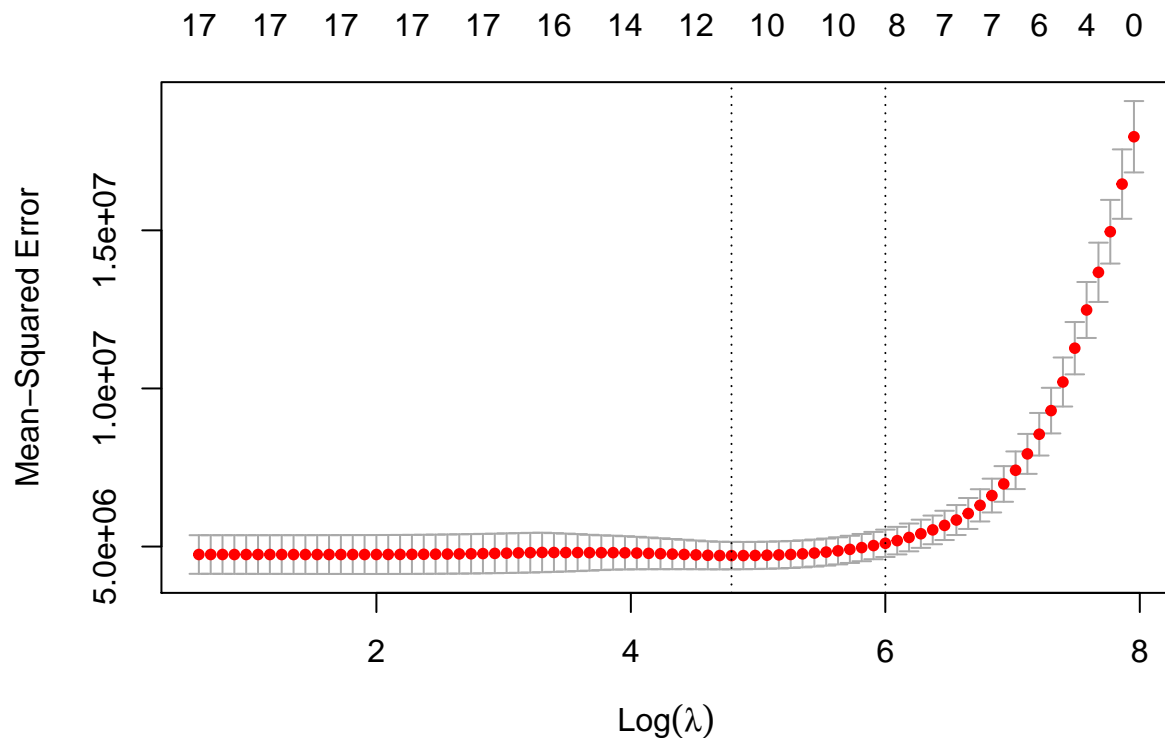


Figure 2: MSE for different values of  $\log(\lambda)$ .

```

#find the test MSE
predictions<-predict(lasso.mod,s=lambda.best,newx=x_test)
error2 <- mean((predictions-y_test)^2) #test MSE
error2

## [1] 3744943

```

From Figure 2 we can observe that the optimal tuning parameter is  $\lambda = 120.4282$  as this is the parameter that minimizes the MSE for the training set.

The test MSE is now 3744943, which is lower than what we found for the reduced model using forward selection in d).

The lasso yields sparse models which involves only a subset of variables. Lasso performs variable selection by forcing some of the coefficient estimates to be exactly zero. Theselected variables that was not put to zero are displayed below.

```
c<-coef(lasso.mod,s=lambda.best,exact=TRUE)
inds<-which(c!=0)
variables<-row.names(c)[inds]
variables
```

```
## [1] "(Intercept)" "PrivateYes" "Top10perc" "P.Undergrad" "Room.Board"
## [6] "Books" "Personal" "PhD" "Terminal" "S.F.Ratio"
## [11] "perc.alumni" "Expend" "Grad.Rate"
```

## Problem 2

a)

FALSE, FALSE, TRUE, TRUE

b)

The basis functions for a cubic spline with knots at each quartile, of variable  $X$  are,

$$\begin{aligned}b_0(X) &= 1 & b_4(X) &= (X - q_1)_+^3 \\b_1(X) &= x & b_5(x) &= (X - q_2)_+^3 \\b_2(X) &= x^2 & b_6(X) &= (X - q_3)_+^3 \\b_3(X) &= x^3\end{aligned}$$

c)

We will now investigate the relationship between Outstate and the 6 predictors as described in the problem.

//discuss which variables that seem to have a linear relationship and benefit from non-linear transformations  
- splines

d)

### **Problem 3**

a)

b)

c)

### **Problem 4**

a)

b)

c)

d)

### **Problem 5**

a)

b)

c)

d)

e)

f)

### **References**

James, G., D. Witten, T. Hastie, and R. Tibshirani. 2013. An Introduction to Statistical Learning with Applications in R. New York: Springer.