## Individual Assignment 6

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## R Markdown

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#Exercise 6.8: Problem 8 (parts e & f)

```
set. seed(114514)
X = c(rnorm(100))
N = c(rnorm(100))
β 0=114
β 1=514
β 2=1919
β 3=810
Y = c(β 0 + β 1*X + β 2*X^2 + β 3*X^3 + N)
df=data. frame(X, X^2, X^3, X^4, X^5, X^6, X^7, X^8, X^9, X^10, Y)
```

## #(e)

```
set.seed(114514)
library(glmnet)
```

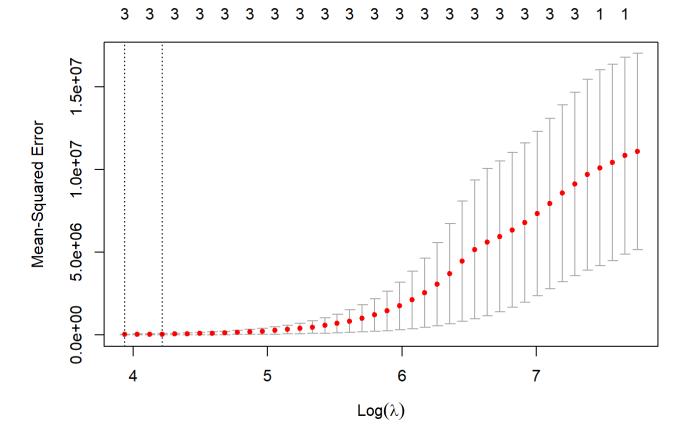
```
## 载入需要的程辑包: Matrix
```

```
## Loaded glmnet 4.1-4
```

```
x = model.matrix(Y~.,df)[,-1]
y = df$Y

train = sample(1:nrow(x), nrow(x)/2)
test = (-train)
y.test = y[test]

lasso = glmnet(x[train,], y[train], alpha=1)
cv.out = cv.glmnet(x[train,],y[train], alpha=1)
plot(cv.out)
```



```
bestlam = cv.out$lambda.min
bestlam
```

```
## [1] 51.30221
```

```
out = glmnet(x, y, alpha=1)
lasso.coef = predict(out, type="coefficients", s=bestlam)
lasso.coef
```

```
## 11 x 1 sparse Matrix of class "dgCMatrix"
##
## (Intercept)
                180. 3299
## X
                516.2386
## X.2
                1850.6751
## X.3
                782.3113
## X.4
## X.5
## X.6
## X.7
## X.8
## X.9
## X.10
```

We can find that Lasso method creates a model with  $\beta$  0,  $\beta$  1,  $\beta$  2 and  $\beta$  3, and other coef are al 1 0. That means the model is clearly provides an accurate estimation of the real model.

#(f)

```
set. seed (114514)
β7 = 100
Y2 = c(β0 + β7*X^7 + N)
df2 = data. frame (X, X^2, X^3, X^4, X^5, X^6, X^7, X^8, X^9, X^10, Y2)
```

```
#best subset
library(leaps)
regfit.full2 = regsubsets(Y2~., data=df2, nvmax=10)
reg. summary = summary(regfit.full2)
reg. summary
```

```
## Subset selection object
## Call: regsubsets.formula(Y2 ^{\sim} ., data = df2, nvmax = 10)
## 10 Variables (and intercept)
      Forced in Forced out
##
## X
         FALSE
                  FALSE
## X.2
         FALSE
                 FALSE
## X.3
         FALSE
                 FALSE
## X.4
         FALSE
                 FALSE
## X.5
         FALSE
                 FALSE
## X.6
         FALSE
                FALSE
## X.7
         FALSE
                 FALSE
## X.8
         FALSE
                FALSE
## X.9
         FALSE
                 FALSE
         FALSE
## X.10
                 FALSE
## 1 subsets of each size up to 10
## Selection Algorithm: exhaustive
            X. 2 X. 3 X. 4 X. 5 X. 6 X. 7 X. 8 X. 9 X. 10
             """"
## 1 (1)
## 2
    (1)
          """*"""*"""*
## 3 (1)
          """*"""*"""*"""*"""*""
## 4
    (1)
          ## 5
    (1)
          ## 6
    (1)
## 7
    (1)
## 8
    (1)
    (1)
## 10 (1) "*" "*" "*" "*" "*" "*" "*" "*" "*"
```

```
reg.summary$cp
```

```
## [1] -5.0955806 -3.3273523 -1.9718588 -0.4736197 1.3837341 3.1393441
## [7] 5.1329252 7.1141030 9.0834519 11.0000000
```

```
reg.summary$bic
```

```
## [1] -1870. 200 -1865. 850 -1861. 958 -1857. 912 -1853. 466 -1849. 135 -1844. 537
## [8] -1839. 953 -1835. 382 -1830. 871
```

reg.summary\$adjr2

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

According to cp and bic, they are lowest at one variable model. So the model with with the  $\hat{x7}$  term is the best choice.

```
#Lasso
x2 = model.matrix(Y2~., df2)[,-1]
y2 = df2$Y2

train2 = sample(1:nrow(x2), nrow(x2)/2)

cv.out = cv.glmnet(x[train,], y[train], alpha=1)
bestlam2 = cv.out$lambda.min

out2 = glmnet(x2, y2, alpha=1)
lasso.coef2 = predict(out2, type="coefficients", s=bestlam2)
lasso.coef2
```

We can see Lasso model also results in a model with one variable X7. Also, the model is a good estimation of the real model.