Analytics 512 Homework 5

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Analytics 512 HW #5

Exercise 6.8 2b

The ridge regression relative to leasr squares is: less flexible and hence will give improved prediction accu- racy when its increase in bias is less than its decrease in variance. As λ increases, the flexibility of the ridge regression fit decreases.

Exercise 6.8 3

Part A

Decrease Steadily, as S increases,the model better fits to the training data, which lowers the value of the residuals, thus lowering the RSS.

Part B

Decrease initially, and then eventually start increasing in a U shape. This is because at a certain point, the model will be overfitted, which results in an increase in the value of the residuals.

Part C

Increase Steadily. As the value of S increase, there are more non-zero values of β_i, the more the variance increases.

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Part A

In [1]:
```
library(ISLR)
attach(College)
train = sample(nrow(College), nrow(College)*.70, replace = F)
training = College[train,]
testing = College[-train,]
```

Part B

In [2]:
```
college.lm = lm(Apps~.,data=training)
est.lm = predict(college.lm, testing)
#MSE
mean((testing$Apps - est.lm)^2)
```

Out[2]: 1279215.06275523

Part C

In [3]:
```
library(glmnet)
grid=10^seq(10,-2,length=100)

x=model.matrix(Apps~., data = training)
y = training$Apps
college.ridge = cv.glmnet(x,y,alpha=0,lambda=grid)
ridge.pred = predict(college.ridge,
                     newx=model.matrix(Apps~., data = testing),
                     s=college.ridge$lambda.min)
mean((testing$Apps - ridge.pred)^2)
```

```
Loading required package: Matrix
Loading required package: foreach
Loaded glmnet 2.0-2
```

Out[3]: 1278474.46643965

In [4]:
```
college.ridge$lambda.min
```

Out[4]: 0.01

Part D

In [5]:
```
college.lasso = cv.glmnet(x,y,alpha=1,lambda=grid)
college.lasso$lambda.min
```

Out[5]: 0.123284673944206

In [6]:
```
lasso.pred = predict(college.lasso,
                     newx=model.matrix(Apps~., data = testing),
                     s=college.lasso$lambda.min)
mean((testing$Apps - lasso.pred)^2)
```

Out[6]: 1275583.45516865

Exercise 6.8 11

In [7]:
```
library(MASS)
Boston$crim = log10(as.numeric(Boston$crim))
dim(Boston)
```

Out[7]: 506 14

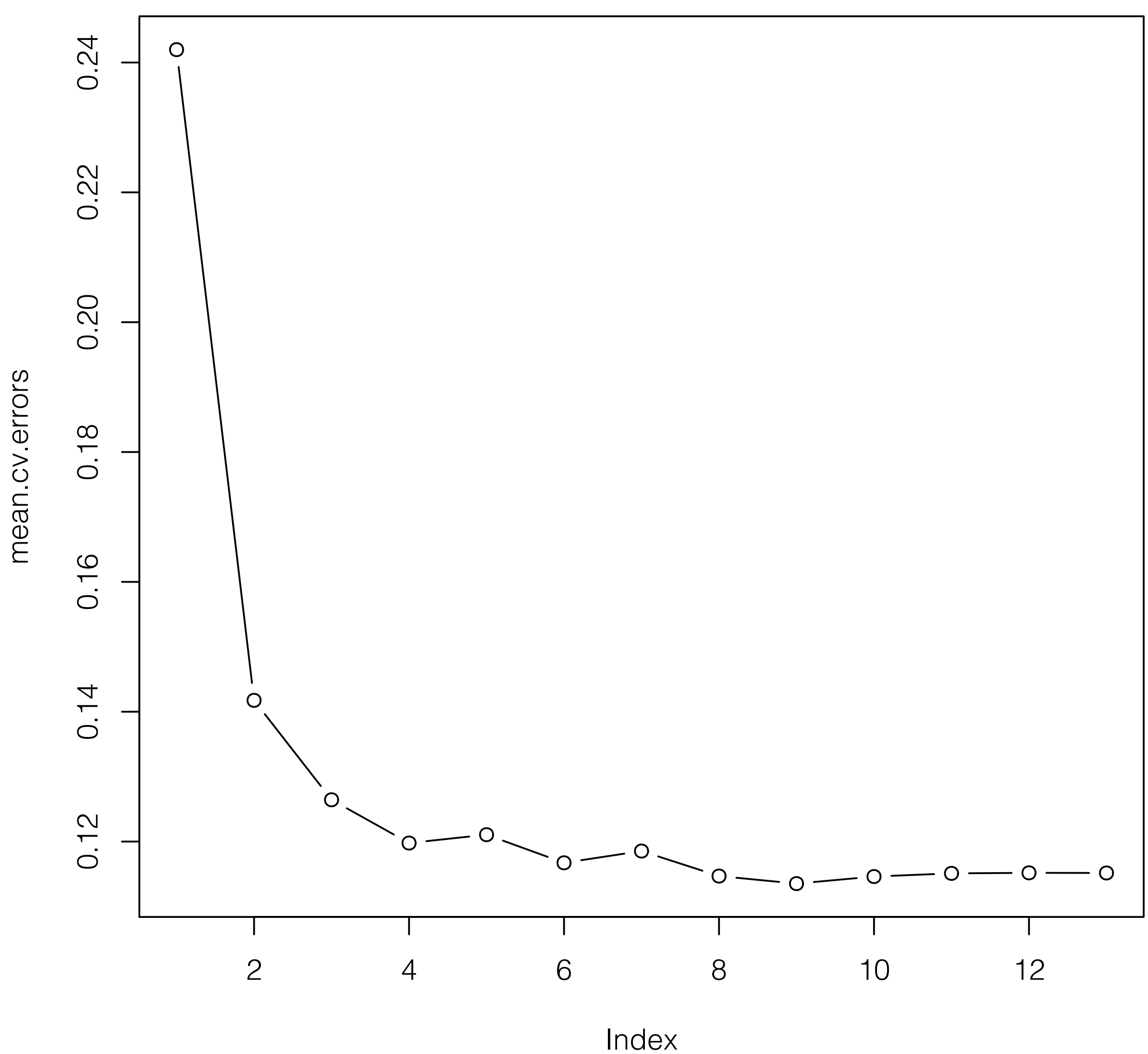
Part A

In [8]:
```
library(leaps)
Boston.bestsubset = regsubsets(crim~.,data=Boston)
```

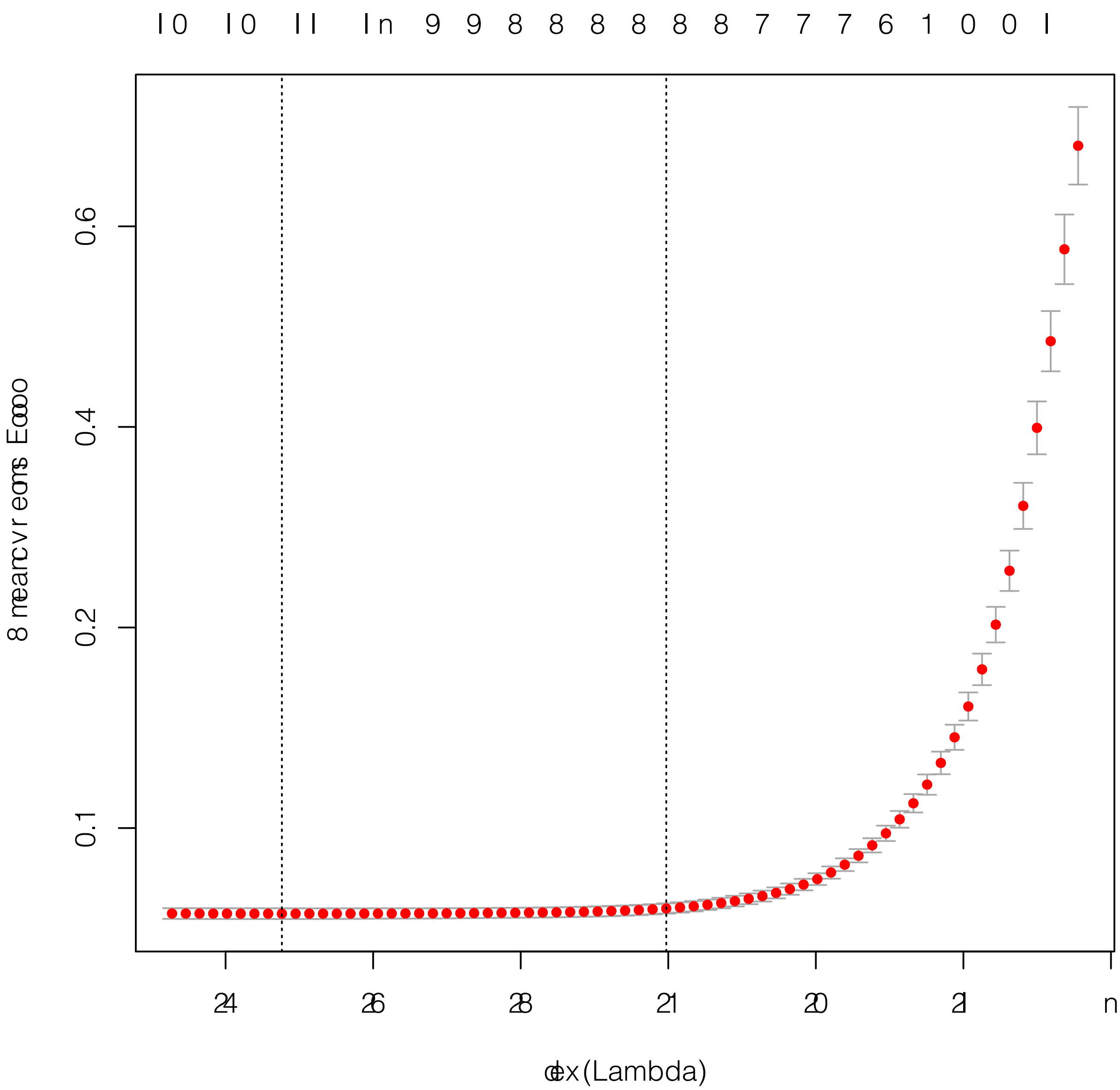
In [9]:
```
predict.regsubsets <- function(object, newdata, id, ...) {
    form <- as.formula(object$call[[2]])
    mat <- model.matrix(form, newdata)
    coefi <- coef(object, id = id)
    xvars <- names(coefi)
    mat[, xvars] %*% coefi
}

k=10
set.seed (1)
folds=sample(1:k,nrow(Boston),replace=TRUE)
cv.errors=matrix(NA,k,13, dimnames=list(NULL, paste(1:13)))
```

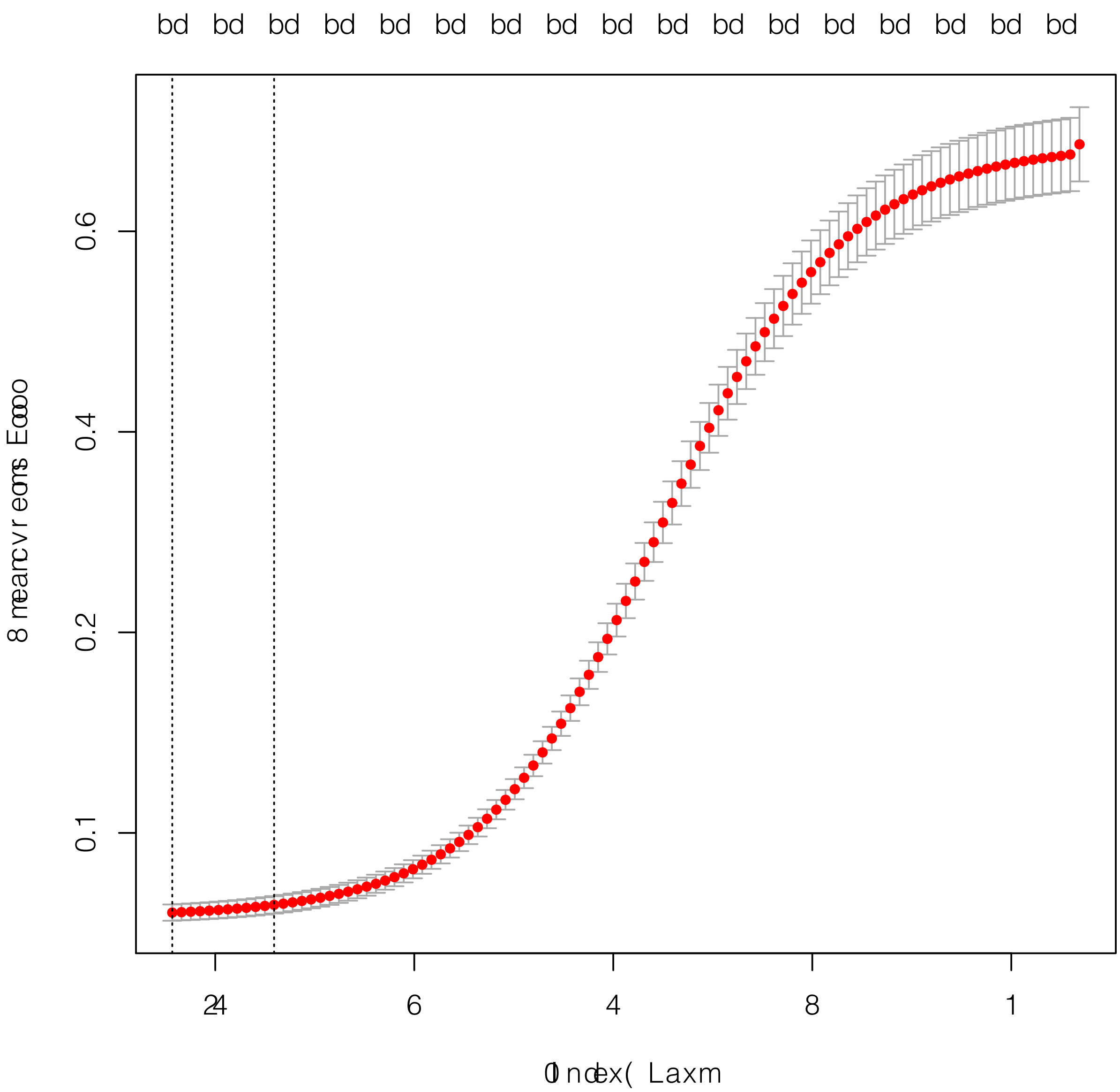
In [10]:
```
for(j in 1:k){
    best.fit = regsubsets(crim~.,data=Boston[folds!=j,],
                          nvmax=13)
    for(i in 1:13){
        pred = predict(best.fit,Boston[folds==j,],id=i)
        cv.errors[j,i] = mean( (Boston$crim[folds==j]-pred)^2)
        }
    }
mean.cv.errors=apply(cv.errors ,2,mean)
plot(mean.cv.errors ,type='b')
```



In [11]:
```
cv.lasso = cv.glmnet(model.matrix(crim ~ ., Boston),
                     Boston$crim, alpha = 1, type.measure = "mse")
plot(cv.lasso)
```



```
In [12]: cv.ridge = cv.glmnet(model.matrix(crim ~ ., Boston),
                              Boston$crim, alpha = 0, type.measure = "mse")
         plot(cv.ridge)
```



Part B

Based off the the the graphs, it's easy to infer which the minimun Mean Sqared Error occurs for Best Subset Selection, lasso, and Ridge Regression. After looking at the Mean Sqare errors generated by various examples of each model, the best model, based of MSE, would be Best Subset Selection with 9 variables.

In [24]:
```
which(mean.cv.errors == min(mean.cv.errors))
min(mean.cv.errors)
cv.lasso$lambda.min
cv.lasso$cvm[cv.lasso$lambda == cv.lasso$lambda.min]
cv.ridge$lambda.min
cv.ridge$cvm[cv.ridge$lambda == cv.ridge$lambda.min]
```

Out[24]: **9:** 9

Out[24]: 0.113525982496003

```
[1] "Lambda is"
```

Out[24]: 0.11462334668151

Out[24]: 0.0878578829939546

Out[24]: 0.120528283513175